Wearable Biosensors to Understand Construction Workers' Mental and Physical Stress

by

Houtan Jebelli

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Doctoral Committee:

Associate Professor SangHyun Lee, Chair
Professor Vineet R. Kamat
Associate Professor Carol C. Menassa
Professor Clayton Scott

Houtan Jebelli

hjebelli@umich.edu

ORCID iD: 0000-0003-4786-7616

Dedication

This dissertation is dedicated to:

My Lovely Mother, Nahid,
for the million wonderful things she gave me, for being my first and best teacher.
Half of my heart lives in heaven. Miss you Mom, every day!

My Gorgeous Sister, Rasha,
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ABSTRACT

Occupational stress is defined as harmful physical and mental responses when job requirements are greater than a worker's capacity. Construction is one of the most stressful occupations because it involves physiologically and psychologically demanding tasks performed in a hazardous environment this stress can jeopardize construction safety, health, and productivity. Various instruments, such as surveys and interviews, have been used for measuring workers' perceived mental and physical stress. However valuable, such instruments are limited by their invasiveness, which prevents them from being used for continuous stress monitoring. The recent advancement of wearable biosensors has opened a new door toward the non-invasive collection of a field worker's physiological signals that can be used to assess their mental and physical status. Despite these advancements, challenges remain: acquiring physiological signals from wearable biosensors can be easily contaminated from diverse sources of signal noise. Further, the potential of these devices to assess field workers' mental and physical status has not been examined in the naturalistic work environment. To address these issues, this research aims to propose and validate a comprehensive and efficient stress-measurement framework that recognizes workers mental and

physical stress in a naturalistic environment. The focus of this research is on two wearable biosensors. First, a wearable EEG headset, which is a direct measurement of brain waves with the minimal time lag, but it is highly vulnerable to various artifacts. Second, a very convenient wristband-type biosensor, which may be used as a means for assessing both mental and physical stress, but there is a time lag between when subjects are exposed to stressors and when their physiological signals change. To achieve this goal, five interrelated and interdisciplinary studies were performed to; 1) acquire high-quality EEG signals from the job site; 2) assess construction workers' emotion by measuring the valence and arousal level by analyzing the patterns of construction workers' brainwaves; 3) recognize mental stress in the field based on brain activities by applying supervised-learning algorithms;4) recognize real-time mental stress by applying Online Multi-Task Learning (OMTL) algorithms; and 5) assess workers' mental and physical stress using signals collected from a wristband biosensor. To examine the performance of the proposed framework, we collected physiological signals from 21 workers at five job sites. Results yielded a high of 80.13% mental stress-recognition accuracy using an EEG headset and 90.00% physical stress-recognition accuracy using a wristband sensor. These results are promising given that stress recognition with wired physiological devices within a controlled lab setting in the clinical domain has, at best, a similar level of accuracy. The proposed wearable biosensor-based, stress-recognition framework is expected to help us better understand workplace stressors and improve worker safety, health, and productivity through early detection and mitigation of stress at human-centered, smart and connected construction sites.

Chapter 1:

Introduction

1.1 Job stress at Construction Sites

Job stress has been defined as the harmful psychological and physical response to various stressors, is a critical factor that adversely affects work performance such as safety, health, productivity, and quality (NIOSH 1999). Construction is known as one of the most stressful occupations because of physically and psychologically demanding tasks performed in a hazardous work environment (Jones and Saad 2003; Loosemore et al. 2003; Petersen and Zwerling 1998; Xiang et al. 2014). Workers' excessive occupational stress has been proven to increase the likelihood of errors, incidents, injuries, and health problems, and is linked to stagnant/declined productivity (Abbe et al. 2011; Leung et al. 2008, 2015; Loosemore and Waters 2004). All of these issues are prevalent in the construction industry. Further, it was reported that 68% of construction workers suffer from excessive stress as a result of working in the construction industry (Campbell 2006). Because of long working hours, unpleasant working conditions, and heavy workloads, the adverse effects of fatigue can be exacerbated (Abdelhamid and Everett 2002; Hallowell and others 2010; Sluiter 2006; Toole 2005). Therefore, a large number of construction workers suffer from significant levels of mental and physical stress that can increase error rates and cause unsafe actions (Sluiter

2006). Excessive physical stress may also cause work-related musculoskeletal disorders (WMSDs) and productivity loss (Hallowell and others 2010; Sluiter 2006; Toole 2005).

A number of studies have attempted to assess individual mental stress by evaluating individuals' psychological and physiological responses to various stressors. Specifically, a number of instruments for subjective estimations of stress (e.g., International Survey of Stress) have been used to measure the individual's perceived stress (Abbe et al. 2011; Bowen et al. 2013; Goldenhar et al. 2003; Gutierrez and Ostermann 1999; Leung et al. 2010; Love et al. 2009; Seo and Lee 2010). In contrast, physiological measures for biochemical responses (e.g., stress hormones) have been used widely in the clinical domain as reliable markers for monitoring mental stress levels. Stress-related hormones (e.g., cortisol and glucocorticoids) change in response to stressors , so tracking the changes in these hormones provides meaningful insight of individuals' stress (Levine et al. 2007; Ranabir and Reetu 2011; Russell et al. 2012; Sharma and Gedeon 2012).

In addition, there has been significant research to assess worker physical stress prior to work through the development of subjective physical stress assessments to measure perceived fatigue levels (Borghini et al. 2014; De Vries et al. 2003; Dittner et al. 2004; Fang et al. 2015; Michielsen et al. 2003; Rosa 1995), empirical assessments (e.g., regression equations) and theoretical models of endurance using physiological or mechanical mechanisms (e.g., mathematical equations) along with simulation-based assessment of workers' fatigue under varying degrees of work intensity (Liu et al. 2002; Ma et al. 2009; Manenica 1986; Perez et al. 2014; Rohmert et al. 1986; Rose et al. 1992; Sato et al. 1984; Seo et al. 2016; Xia and Law 2008).

1.2 Physiological Signals

Physiological signals are defined as measurements generated by the physiological processes of individuals (Ritter 2009). Physiological signals can be categorized into two groups: electrical physiological signals (e.g., Electrodermal activity [EDA], Electroencephalography [EEG], Photoplethysmography [PPG], and Electrocardiography [ECG]) and non-electrical physiological signals (e.g., Inertial Measurement Units [IMU] and potential of Hydrogen [pH]) (Lazakidou 2008). Previous studies have reported changes in electrical physiological signals are highly associated with stress levels (Healey and Picard 2005; Hosseini and Khalilzadeh 2010; Kim et al. 2004; de Santos Sierra et al. 2011). Among various electrical physiological signals, EEG, PPG, EDA, and ST are four highly informative signals that may be used as a means to assess subjects' mental and physical conditions.

EEG measures the electrical activity of the brain recorded from the scalp by EEG electrodes placed on the scalp (Szafir and Signorile 2011). These electrodes capture the action potential of the neurons in the brain, which provides rich information about the activity of the central nervous system. PPG represents cardiac activity by measuring the volumetric change of the heart. This change is calculated by measuring the light transmission and reflection of the blood pulse (Allen 2007). The difference between the light transmitted and reflected by a PPG sensor is proportional to the changes of blood pulse in the arteries, which represent cardiac activity (Shelley 2007). EDA is a signal that can be acquired from a wristband type biosensor. EDA indicates the electrical properties of the skin by measuring the variation of the skin conductance (Boucsein 2012). An EDA sensor placed in a wristband type sensor applies a low constant voltage. Then changes in this voltage resulting from the activity of sweat glands is measured. ST is a signal measured by an infrared thermopile placed in a wristband type sensor. An infrared thermopile measures skin temperature by detecting its infrared energy. Higher infrared energy is proportional to a higher temperature.

1.2.1 Physiological Response and Mental Stress

Physiological response is defined as a metric that measures the changes and reactions of physiological signals in response to different stressors (Hosseini and Khalilzadeh 2010; Renaud and Blondin 1997). When human beings are exposed to various stressors, their physiological signals will be affected by these stressors. As a result, we are able to recognize stress by examining patterns of physiological response. Due to the rich information provided by EEG signals about the central nervous system activities, there is a considerable amount of attention to recognize individuals' stress using EEG signals (Hou et al. 2015a; Liu and Sourina 2014). In order to recognize different brainwave patterns under various stressors, previous researchers extracted and calculated different EEG signal features in time and frequency domain (Blaiech et al. 2013; Frantzidis et al. 2008; Huang et al. 2012; Jirayucharoensak et al. 2014; Khosrowabadi et al. 2014; Liu et al. 2013; Oude Bos 2006). The EEG signal features in these domains showed a high potential to distinguish different EEG signal patterns while individuals are facing different stressors (Davidson et al. 1990; Li and Lu 2009; Louwerse and Hutchinson 2012; Xu and Plataniotis 2012). In addition, by analyzing PPG signals, various responses can be extracted (e.g., heart rate [HR] and heart rate variability [HRV]), associated with an individual's stress. Previous researchers showed higher stress usually leads to higher HR (Abbe et al. 2011). HRV is another parameter that can be extracted from a PPG signal to provide information about stress levels. HRV shows the interval between heartbeats, the variation in interbeat intervals, which shows the time interval between individual heartbeats (Acharya et al. 2006). Previous researchers showed that higher stress might lead to lower HRV (Castaldo et al. 2015; Salahuddin and Kim 2006; Tan et al. 2011). In the case of EDA, two main physiological responses can be extracted: electrodermal level (EDL) and electrodermal response (EDR) (Boucsein 2012). EDL shows slow changes in EDA and is associated with an individual's stress for an extended period (Braithwaite et al. 2013). On the other hand, EDR is a short-term phasic component of EDA that shows rapid changes in an individual's stress over a short period (Horvath 1978; Kurniawan et al. 2013; Lawler 1980; Shi et al. 2007a; b; Sime 1977; Villarejo et al. 2012). In addition to the metrics extracted from PPG and EDA signals, there are indications that an individual's peripheral body temperature is associated with their stress level (Boregowda et al. 2017; Briese 1995; Kleitman and Jackson 1950; Marazziti et al. 1992; Oka and Oka 2007; Vinkers et al. 2010).

1.2.2 Physiological Signals and Physical Stress

Highly physically demanding activities increase the risk of physical stress (Hwang and Lee 2017) leading up the to temporary inability of a muscle to maintain its optimal performance (Chaffin 1973; Hultman and Greenhaff 1991; Taylor and Gandevia 2008). High physical stress is closely associated with intense physical activities (Bogdanis 2012; Convertino et al. 1997; Ebaugh et al. 2006) and can be understood as the body's response to conscious (e.g., physical exertion) and subconscious factors (e.g., environmental factors) that are present during highly physically demanding activities (De Vries et al. 2003; Edwards 1981). When the body is exposed to a high degree of physical demand, it makes physiological adaptations (e.g., heart rate and respiration increase, the release of hormones, and adjustment of body temperature) to cope with these stressors. Without these responses, the body would not survive (Nielsen et al. 1993; Noakes 2000). Therefore, examining changes in physiological responses can provide useful information about individual physical-demand levels. The body's physiological responses can be examined by studying the changes in the pattern of physiological signals. Previous researchers confirmed the potential of various physiological responses (e.g., heart rate, heart-rate variability, electrodermal activity, electrodermal response, body temperature) that are calculated from various physiological signals (photoplethysmography [PPG], electrodermal activity [EDA], skin temperature [ST]) to assess individual physical fatigue (Acharya et al. 2006; Earnest et al. 2004; Heiden et al. 2005; Ibrahimy et al. 2003; Roja et al. 2006; Segerstrom and Nes 2007).

PPG provides rich information about cardiovascular-system activity (Allen 2007) by measuring the blood-volume variations in vascular tissues (Saquib et al. 2015; Shelley 2007). When individuals experience intense physical activities, their brains innervate heart-related activities, which result in changes in blood volume. Previous studies have reported that there is an association between physical fatigue and various PPG-based metrics, such as heart rate (Caspersen et al. 1985; Ceesay et al. 1989; Jouven et al. 2005; Keytel et al. 2005; Livingstone et al. 1992; Meijer et al. 1989; Rennie et al. 2001; Spurr et al. 1988), %HRR (Bos et al. 2004; Esposito et al. 2004; Freedson and Miller 2000; Hwang and Lee 2017; Richmond et al. 2008; Sluiter 2006), and heart-rate variability (Acharya et al. 2006; Aubert et al. 2003; Nakamura et al. 1993; Pichot et al. 2000).

Electrodermal activity (EDA) also referred to as galvanic skin response (GSR). It represents the skin conductance by continuous measurement of changes in the electrical properties of the skin (Boucsein 2012; Braithwaite et al. 2013). If the sympathetic nervous system is activated by physical demands or mental stress, sweat-gland activity increases, which in turn increases skin conductance. Despite the fact that previous researchers reported that EDA activation happens mostly as the result of mental stress (Critchley 2002; Horvath 1978; Kurniawan et al. 2013; Picard et al. 2016; Venables and Christie 2012; Villarejo et al. 2012) and cognitive load (Haapalainen et al. 2010; Nourbakhsh et al. 2012; Setz et al. 2010; Shi et al. 2007).

Peripheral skin temperature (ST) is another physiological signal that can be measured using an infrared thermopile. ST provides valuable information on the body’s thermoregulation resulting from physical activity (Romanovsky 2014). ST is measured in relation to core body temperature

(Cheng et al. 2012; Kelly 2006; Niedermann et al. 2014), as well as ambient temperature (Elebute 1976; Petrofsky et al. 2012; Thiele and Van Senden 1966). Both are associated with individual physical demand levels (Bakshi 2003; Bergh and Ekblom 1979; Galloway and Maughan 1997; Sumowski and Leavitt 2014).

1.3 Challenges of Collecting Physiological Signals in the Field

Despite the potential of physiological signals to provide rich information on construction workers' mental and physical status (Ahn et al. 2019; Abdelhamid and Everett 2002; Aryal et al. 2017; Chen et al. 2016, 2017b; Cheng et al. 2012; Gatti et al. 2014; Ghahramani et al. 2018; Hwang et al. 2016; Jebelli et al. 2018b; Choi et al. 2019; Lee and Migliaccio 2018), these signals are mostly collected in a laboratory environment, not in everyday situations (Ritter 2009). Acquiring physiological signals in a controlled environment using traditional wired EEG devices leads to high-quality signals because of minimal movement by the subjects, high-quality wired sensors, and multiple sensors placed in different locations by a well-trained staff. In addition, the quality of EEG recordings using wearable EEG headsets in a controlled lab environment is acceptable with the help of a few commercially available EEG acquiring and pre-processing software (e.g., Emotiv Pro) as long as the signal has not interfered with intrinsic signal artifacts (e.g., eye blinking, eye movement, facial muscle movement, etc.). Although the high quality of physiological signals collected from controlled environments broadens our understanding of the relationship between stress and physiological responses, its application is limited to construction sites because lab environments are limited to reproducing only certain work conditions and tasks in construction sites.

In addition to wearable EEG headsets, recent advancements in technology, including several types of wearable biosensors (e.g., chest straps, wristbands, etc.), are available as a means to monitor workers' mental status. Chest strap sensors have been used mostly for monitoring the cardiac activity (e.g., heart rate) of construction workers (Seoane et al. 2014). Despite their success in monitoring workers' cardiac activity in the field, these devices they remain limited in their acquisition of electrical activity of the heart (Electrocardiography [ECG]). Quite recently, a few researchers attempted to assess workers' mental stress (Hwang et al. 2018a; Jebelli et al. 2018b; e; Wang et al. 2019) and cognitive load (Chen et al. 2015, 2017b) based on brain waves collected from an EEG headset. Although the main advantage of EEG headsets is their ability to rapidly indicate changes in workers' mental status (Herwig et al. 2003), the process of capturing high quality EEG signals in the field is more challenging compared to other physiological signals due to several intrinsic artifacts (e.g., eye blinking, facial muscle movement, etc.). Among different types of wearable biosensors, wristband-type biosensors allow us to acquire multiple physiological signals (e.g., PPF, EDA, and ST) without interrupting workers' ongoing tasks. However, measuring physiological signals using a wristband-type biosensor at real construction sites remains challenging due to the large number of extrinsic signal artifacts and distortions that come from workers' movement, sensor displacement, environmental noises and lower quality of sensor electrodes compared with wired biosensors (Hwang et al. 2016; Jebelli et al. 2017; Tamura et al. 2014; Wei et al. 2008). To address this issue, this study proposes a framework to reduce physiological signal artifacts while preserving the features of the original signal by applying signal processing and filtering, followed by pattern recognition to assess workers' mental stress, achieved with supervised learning. Then, the performance of the proposed framework will be examined using the physiological signals acquired in the field using a wristband-type biosensor.Limitation of Current Methods and Problem Statements

Any subjective assessment of worker mental and physical stress has two important limitations for the field. First, stopping workers during their tasks to have them fill out questionnaires interrupts their work. Second, these methods are subjective and rely on imprecise memory and reconstructions of the past (Larson and Csikszentmihalyi 1983). In addition, despite the validity of physiological measures for biochemical responses (e.g., stress hormones), this method is not viable for continuous stress monitoring because measuring stress-related hormones requires the collection of serum, saliva, urine, or hair samples. Given dynamic changes in work environments, continuous monitoring of stress is particularly meaningful in construction sites. Furthermore, analyzing collected samples require laboratory processing, which is difficult to apply in the field. On the other hand, the empirical estimation and theoretical models of worker stress do not have the limitations of subjective methods. However, they are limited to individual factors (the body's capabilities, age, experience, varying trades, etc.) and site conditions (temperature, humidity, differences from indoor to outdoor, etc.) that can affect workers' physical demands. Each worker is unique with different personal characteristics (e.g., age, experience, physiological characteristics, gender, etc.) and therefore workers do not respond the same to a certain task. For instance, the same tasks that require a low physical demand (or low mental stress) for one worker may cause a higher physical demand (or higher mental stress) for another worker, or even for the same worker in a different environment (Astrand et al. 2003; Gatti et al. 2014; Mohamed and Alginahi 2009). As such, in order to appropriately assess each worker's stress, rather than how much the task physically demands, to what extent the worker responds to the stressors is more important and indeed, accurately reflect workers' mental and physical status.

1.4 Research Objectives and Approaches

Given this background, the overall goal of this research is to promote safe construction sites and healthy and productive workers by developing measurable frameworks for continuous monitoring of workers' mental and physical stress. We will do so using noninvasive, low-cost, wearable biosensors. It involves quantifying workers' physiological signal responses to stressors on site. The better understanding of the causes of stress and fatigue contributes critically to enhancing the safety of construction sites and improving worker health and productivity. To achieve these goals, outlines of the objectives of this research follow:

1.4.1 Research Objective 1

Investigating physiological signals can be useful in understanding human psychosocial and physiological aspects of work, such as mental stress, emotional exhaustion, burnout, mental fatigue, and physical stress. Recently, wireless, off-the-shelf wearable biosensors, lightweight and affordable, have become available, so that researchers can measure construction workers' physiological signals in the field without interfering with their ongoing work. However, physiological signals can be contaminated by many sources, such as body and sensor movement, respiration, and muscle-movement artifacts. These artifacts are especially serious in the field because of the noise construction sites generate and workers' frequent movement during physically demanding tasks. Further, the relatively low recording resolutions, e.g., 4-256 Hz, of wearable biosensors, compared to one that is wired, make the analysis of these signals more challenging. To address this problem, <u>*the first objective of this research is to acquire high-quality physiological signals in the field.*</u>

1.4.2 Research Objective 2

Construction workers' emotional states (e.g., pleasure, displeasure, excitement, relaxation) are known to be a critical factor affecting workers' performance (e.g., safety, health, and productivity). To prevent their adverse impacts on work performance, measuring emotional states should take precedence to better understand how workers' emotions vary while they are working. Among many methods available to measure these states, the electroencephalogram (EEG) has great potential for quantitative measurement and overcoming any bias from a subjective assessment of emotions. While EEG-based measurement of emotion has been tested and applied in a laboratory environment, recent advancements in wearable EEG sensors make them portable, wireless, and affordable and open a door to non-intrusive measurement of emotion in the field . After looking into capturing and processing high-quality physiological signals in the field, this chapter investigates the feasibility of measuring workers' emotions in the field using a wearable EEG sensor. *To do this, the second objective to develop and validate a bipolar dimensional emotion model, which consists of two dimensions of valence (displeasure to pleasure) and arousal (relaxation to excitement); it was applied to quantify workers' emotional states.*

1.4.3 Research Objective 3

Taking into account that many construction workers suffer from excessive stress, which adversely impacts their safety and health, early recognition of stress is an essential step toward stress management. In this regard, an electroencephalogram (EEG) has been widely applied to assess individuals' stress by analyzing brain waves in the clinical domains. With recent advancements in wearable EEG devices, the EEG's utility can be extended to field workers, particularly by non-invasively assessing construction workers' stress. *The third objective of this research, then, is to* *develop a procedure to automatically recognize workers' stress at construction sites using EEG signals.*

1.4.4 Research Objective 4

Recognizing the factors that cause stress is a crucial step toward early detection of stressors. In this regard, several studies recognize individuals' stress using an electroencephalogram (EEG). However, current EEG-based stress-recognition frameworks have several drawbacks. First, they are mostly designed to recognize individuals' stress only in a controlled laboratory environment. Second, they do not take into account the changes in the EEG signals of different subjects under the same stressors. Third, most of the current stress recognition algorithms occur in an offline setting. To address these issues, *the fourth objective of this research is to develop and validate an EEG-based stress recognition framework that takes into account each subject's brainwave patterns to train the stress-recognition classifier and continuously update this classifier based on new signals in near real-time.*

1.4.5 Research Objective 5.

In the second study, our framework achieved high mental- stress recognition based on EEG signals. For the third study, we examined the potential of our framework to measure workers' mental and physical stress using other physiological signals collected from a convenient wristband biosensor. To address this problem, *the fifth objective of this research is to develop a framework for continuous, automatic measurement of worker mental stress and physical demand by examining changes in workers' physiological signals collected from a wristband biosensor.*

1.6 Dissertation Structure

This dissertation is the result of compiling studies to achieve the research objective mentioned. In terms of the organization of content, chapters 2 – 7 elaborate stand-alone studies to reach the aforementioned objectives. The following is an outline of the chapters of this dissertation:

- ***Chapter 1 – Introduction***

Chapter 1 provides preliminary background information, clarifies the focus of the dissertation, specifies the research goal, and highlights a specific research methodology and its objectives.

Chapter 2 –An EEG Signal-Processing Framework to Obtain High-Quality Brainwaves from an Off-the-shelf, Wearable EEG Device

Capturing high-quality brainwave signals from a wearable EEG device can be very challenging on construction sites due to signal artifacts generated from body movement during physically demanding work. To address this issue, this chapter proposes an EEG signal-processing framework that can acquire high-quality EEG signals from construction sites using a wearable EEG device. Specifically, the signal-processing framework reduces noises and thereby can extract quality EEG signals.

- ***Chapter 3 –Measurement of Workers' Emotional State Using a Wearable EEG during Construction Tasks***

This chapter presents an EEG-based, emotion-measurement framework to assess construction workers' emotions based on EEG signals acquired in the field. Workers' valence and arousal levels were measured using a wearable EEG sensor during ongoing tasks. The validity of the EEG-based emotion measurement was examined by comparison with cortisol levels obtained from workers' saliva samples, accepted as a reliable measure. The results demonstrate the applicability of a wearable EEG sensor to measuring workers' emotions, particularly valence levels, crucial to understanding workers' emotional states.

- ***Chapter 4 –Recognition of Workers' Stress Using an EEG at Construction Sites***

To manage excessive occupational stress, recognizing workers' stress on site is an essential step. This chapter applies several supervised-learning algorithms to recognize workers' stress while they are working. Time and frequency domain features from EEG signals are calculated using fixed- and sliding-window approaches. Salivary cortisol, a stress hormone, was also collected to label low- or high-stress levels when they work. The results show that the fixed-window approach and the Gaussian Support Vector Machine (SVM) yielded the classification accuracy of 80.32%, very promising given the similar accuracy of stress recognition in clinical domains where extricate and wired EEG devices were used and the subjects engaged in minimal body movement.

- ***Chapter 5 – A Continuously Updated, Computationally Efficient, Stress-Recognition Framework Using EEG by Applying Online, Multi-Task Learning Algorithms (OMTL).***

This chapter proposes a framework to recognize individuals' stress in near real time and for new stressful conditions. The proposed framework extracts a broad range of EEG signal features and then applies different Online Multi-Task Learning (OMTL) algorithms. The proposed framework was applied on the EEG collected in two environments—first on that collected in a controlled lab environment using a wired EEG and second, on the EEG collected in the field using a wearable EEG device. The OMTL-Von Neuman method resulted in the best prediction accuracy on both datasets (71.14% on the first dataset and 77.61% on second) among all tested algorithms.

- ***Chapter 6 – Wristband-type Wearable Biosensor to Assess Construction Workers' Mental Stress***

This chapter examines the potential of other physiological signals (e.g., PPG, EDA, and ST) acquired from a wristband-type biosensor. This chapter proposes a framework for continuous and automatic measurement of worker stress by examining the changes in workers' physiological signals collected from a wristband type biosensor. The framework applies various filtering methods to reduce physiological signal noises and extract patterns of physiological signals as workers experience various stress levels. Then, the framework learns these patterns by applying a supervised-learning algorithm. To examine the performance of the proposed framework, I collected physiological signals from ten construction workers in the field. The proposed framework resulted in a stress-prediction accuracy of 84.48% in distinguishing between low and high stress levels and 73.28% in distinguishing among low, medium, and high stress levels. The results confirmed the potential of the proposed framework for assessing workers' stress in the field using other physiological signals collected from a wristband type sensor.

- ***Chapter 7 –Wristband-type Wearable Biosensor to Assess Construction Workers' Physical Demand***

This chapter develops and examines a procedure for automatic predictions of demand levels based on physiological signals collected from workers. Workers physiological signals were captured using a wristband-type biosensor while they performed regular tasks in the field. Various physiological responses were extracted from the artifact-corrected signals. The rate of energy expenditure was used as a baseline to separate tasks into low, moderate, and high-intensity activities. Then, a supervised machine-learning model was trained by applying a Gaussian kernel-support vector machine. The results led to a prediction accuracy of 90% in recognizing low and high physical-intensity levels and 87% for a more detailed low, moderate, and high physical-intensity levels.

- ***Chapter 8 – Conclusions***

The final chapter draws conclusions and summarizes the main points of various chapters. It provides a brief summary of the key findings and offers an overview of the important contributions of this research. Chapter 8 ends with possible follow-up research that can build upon this dissertation.

1.7 References

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Chapter 2:

An EEG Signal-Processing Framework to Obtain High-Quality Brainwaves from an Off-the-Shelf, Wearable EEG device[1]

2.1 Introduction

The construction industry has one of the highest rates of workers' psychosocial problems (EU-OSHA 2013). A psychosocial disorder is a mental illness usually caused or influenced by life experiences as well as mal-adjusted cognitive and behavioral processes (Üstün and Sartorius 1995), such as stress, emotional exhaustion, burnout, and mental fatigue (EU-OSHA 2013). Specifically, stress in construction has been known as a critical psychosocial problem because construction is one of the most stressful occupations (Di Martino 1992; Petersen and Zwerling 1998), which results from physiologically and psychologically demanding tasks in a hazardous environment (Jones and Saad 2003; Loosemore et al. 2003; Xiang et al. 2014). High occupational stress increases the likelihood of errors, incidents and injuries and is linked to stagnant or declining productivity prevalent in the construction industry (Abbe et al. 2011; Djebarni 1996; Goldenhar et al. 2003; Leung et al. 2008, 2015; Loosemore et al. 2003; Love et al. 2009). In addition, emotional

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exhaustion—the degree to which individuals do not feel emotionally secure and relaxed—can cause workers' stress and burnout in the long run due to a lack of emotional resources and energy from having too many things to do in a limited time e. Other psychosocial problems in construction sites include: burnout defined as a syndrome of emotional exhaustion, cynicism, and changes in personal accomplishment (Burke and Richardsen 1996; Maslach et al. 2001); and mental fatigue which is an exhaustion of mental and physical strength that results from bodily labor or mental exertion (Lewis and Wessely 1992). Burnout has been identified as a major effect of job stress (Cordes and Dougherty 1993; Lee and Ashforth 1993) while mental fatigue may lead to a significant decrease in motivation and vigilance e, as well as potential accidents and injuries (Swaen et al. 2003).

As such, these psychosocial problems of construction workers may adversely affect project performances including productivity, quality (Abbe et al. 2011; Leung et al. 2008, 2015), and safety (Brewer and Clippard 2002; Maslach et al. 2001; Nyssen et al. 2003). Thus, monitoring workers' psychosocial status is very helpful to avoid its negative influence on performances. Particularly, this monitoring can help construction project and safety managers investigate and manage excessive job demands or potentially hazardous working conditions that can cause serious psychosocial problems, which can eventually improve workers' safety and health as well as productivity and work quality.

To detect the psychosocial problems of the human subjects, several physical and physiological measures (i.e., biometrics) have been widely used. The use of these bio-metrics as an indicator of psychosocial problems include: electromyographm (EMG) illustrated as electrical activities produced by active muscles (Healey and Picard 2005; Luijcks et al. 2014); skin temperature (ST) (Reisman 1997; Zhai and Barreto 2006); electro-dermal activity (EDA) produced by the activity of the sweat glands and reflecting sympathetic nervous system activity (Ferreira et al. 2008; Healey and Picard 2005; Labbé et al. 2007; Selye 1956); heart rate variability (HRV) represented as the variation between heartbeats (Acharya et al. 2006; Dishman et al. 2000; Ferreira et al. 2008; Niskanen et al. 2004); blood volume pulse (BVP), the change of blood flow after each heart beat (Healey and Picard 2005; Reisman 1997); and electroencephalogram (EEG) presenting the electrical activity along the scalp produced by the firing of neurons in the brain (Chen et al. 2015, 2016; Hosseini and Khalilzadeh 2010; Hou et al. 2015; Jovanov et al. 2003; Szafir and Signorile 2011).

Among them, EEG has been widely used in neuroscience, cognitive psychology, neurolinguistics, and psychophysiological areas to assess psychosocial status (Collerton 2015; Kable 2011; Wada 2015). A particular strength of EEG is that it can accurately monitor the neural activities and brain-wave patterns by directly capturing the response of central nervous system, while other biometrics (i.e., EMG, ST, EDA, HRV, and BVP) are physiological signs originated from peripheral nervous system activities such as sympathetic and parasympathetic activations in the autonomic nervous system (Zhai et al. 2005). Therefore, EEG could provide richer and more detailed information on psychosocial status than others. Also, according to EEG's high temporal resolution, low instructive equipment, rapid indication of changes in brain activity, and capability to record complex electrical waveforms at the scalp during different emotions (Novák et al. 2004), EEG has been introduced as a very useful tool for monitoring a range of psychosocial problems such as stress (Goodman et al. 2013; Hou et al. 2015; Lee et al. 2014; Putman et al. 2014; Singh and Sharma 2015); emotional exhaustion (Blaiech et al. 2013; Eaton et al. 2014; Sokka et al. 2014); burnout (Broeke et al. 2013; Martinez et al. 2015; Ryu et al. 2015; Sokka et al. 2014, 2016; Tement et al. 2016), and mental fatigue (Borghini et al. 2012, 2014; Charbonnier et al. 2016; Trejo et al. 2015).

Despite the capacity of EEG to provide rich and detailed information on psychosocial status of subjects, it has been applied and tested only in a controlled laboratory environment using a clinical EEG recording device (e.g., electrode cap), not in real workplaces like construction because this device typically comes with many wired nodes, which can interfere with workers' ongoing work. The recent introduction of a wearable EEG device can open a new door to non-intrusively measure field (construction) workers' EEG because it is wireless (no hard wires), lightweight and affordable. However, EEG recording is highly vulnerable to various forms and sources of noise, which are very common and even severe in real-world work environments. Specifically, one of the biggest challenges is the low signal-to-noise ratio in the record of the brain signals. When subjects are relatively stationary, EEG artifacts (i.e., noises obscuring the signal of interest) are relatively small and can thus be identified and corrected (Urigüen and Garcia-Zapirain 2015). On the other hand, when subjects in the field are frequently moving around, which is typical for construction workers, EEG artifacts significantly increase.

To apply a wearable EEG device to construction workers, the first logical step should be to ensure that high-quality brain waves from construction workers can be obtained at the field where the sources of EEG artifacts are prevalent (e.g., noise from body movements). As such, I propose a signal-processing framework for removing the most common EEG artifacts recorded from workers at the real construction sites while they are performing their tasks. Then, I investigate whether high-quality EEG signals can be acquired from construction field workers applying the proposed framework to raw EEG signals recorded from a wearable EEG device. Specifically, changes in brain activation in the EEG while subjects are working at real sites will be monitored and recorded for this purpose.

2.2 Electroencephalography

Electroencephalography (EEG) is a non-invasive medical imaging technique method to collect electrical activity of the brain. In 1875, Richard Caton discovered the electrical activity of the brain. Caton detected EEG from the exposed brains of rabbits and monkeys. EEG is defined as an alternating type of electrical activity recorded from the scalp surface (Niedermeyer and da Silva 2005). There are two general sources for EEG to be measured. The first one is Electrocorigrom that is directly measured from the cortical surface (from the scalp surface non-invasively). The second one is Electrogram that can be used to measure EEG by inserting a depth probe directly in the brain tissue. Electrogram is not possible to be used in the non-clinical research area. This research will thus refer only to EEG measured from the scalp (i.e., Electrocorigrom). In this method, the voltage fluctuation generated by neurons activity located on the surface of the brain will be recorded (Khalil and Misulis 2006; Sanei and Chambers 2013). To collect these voltage fluctuations, multiple electrodes are usually placed on the scalp.

Information that can be provided by the EEG strongly depends on the location of the brain that EEG electrodes were placed (Koessler et al. 2007). Particularly, the cerebral cortex area has the highest impact to EEG electrical activity and each region of the cerebral cortex area (e.g., frontal lobes, motor cortex, parietal lobe, etc. as shown in A of Figure 2.1) controls different function (Teplan 2002). For example, the frontal lobe controls emotions and the capacity of attention (Rusinov 2012). In addition, a motor cortex region is involved in controlling voluntary movements, which can be used to monitor the activation of the brain from workers' physical movements (Rusinov 2012). Therefore, the off-the-shelf wearable devices (e.g., Emotiv EPOC+

that this study used as denoted by B in Figure 2.1) have multiple electrodes (e.g., 14 scalp electrodes as denoted by C in Figure 2.1) to provide diverse information of EEG detected from different locations in the cerebral cortex area of the brain.

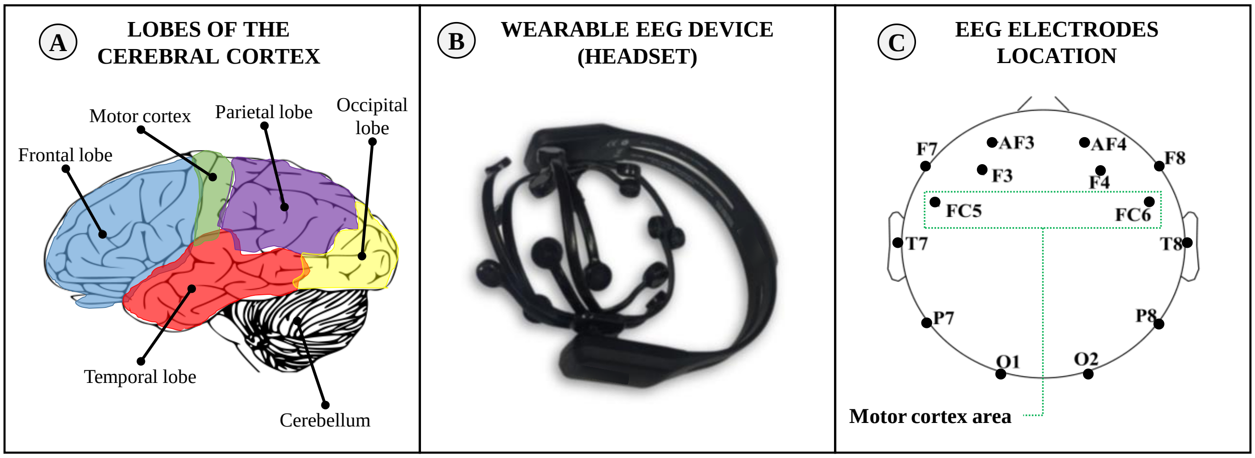

Figure 2.1. An overview of wearable EEG: (a) the cerebral cortex of the brain; (b) an example of the wearable EEG device; and (c) EEG electrode placements.

EEG is typically described in terms of a rhythmic activity. This rhythmic activity is usually categorized into five basic groups by their different frequency range including: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and Gamma (>30 Hz) bands (Borghini et al. 2014; Jasper and Andrews 1938; Walter and Dovey 1944). Delta and theta frequency ranges are usually observed in infants, children, and sleeping adults. An alpha frequency range bands conscious thinking and subconscious mind, which promotes a feeling of deep relaxation. A beta frequency range is the usual walking rhythm of the brain associated with active thinking and attention, the beta the beta frequency range can clearly show the activation of the brain during a motor cortex activity (McFarland et al. 2000; Pfurtscheller and Neuper 1997). Gamma frequency range has a very low amplitude, and thus, the occurrence of gamma frequency range in normal adults is rare. The gamma frequency range is usually observed in clinical domains to detect certain brain diseases. As such, our target in this research (i.e., stress) would be beta frequency bands.

2.3 Challenges in the Use of EEG at Construction Field

EEG signals recorded from electrodes placed on the scalp have a frequency range from 0.01 to 100 Hz and varies from a few microvolts to approximately 100 microvolts (Nunez and Srinivasan 2006). Because of this small amplitude, recording of any EEG is very vulnerable to various forms of signal artifacts which refer to signal distortions appearing within desired or pure signal waveforms (Teplan 2002). When subjects are relatively stationary, EEG artifacts that obscure the signal of interest are small in scale, and can thus be identified and corrected (Urigüen and Garcia-Zapirain 2015). Some artifacts are extrinsic—generated from environmental or physical factors such as electrode popping, high impedance, movement artifacts, environmental noise, and wiring noise in the EEG device. On the other hand, some artifacts are intrinsic—generated within the body's physiology such as eye movements, blinking, and facial muscle movement (Jung et al. 2000; Kar et al. 2010; Shao et al. 2009; Szafir and Signorile 2011; Urigüen and Garcia-Zapirain 2015). Although many existing EEG signal processing methods have been used in clinical domains such as neural science and cognitive psychology, they collected EEG signals only in a controlled laboratory environment using an exquisite clinical EEG recording device (e.g., wired electrode cap) while subjects' are in the stationary postures to minimize extrinsic artifacts (Jahankhani et al. 2006; Ortolani et al. 2002). However, these methods cannot be applied in the real site due to significant extrinsic artifacts from hardware limitations of a wearable EEG device (i.e., vulnerable to signal noises) and subjects' intensive movement during working. Such methods also require preparation of the scalp skin such as removing the hairs and applying conductive gels, which are not practical to be used in the construction sites. Further, most of the existing EEG signal processing methods require collecting other bio-signals such as electromyogram (EMG) and electrocorticogram (ECoG), in order to remove these intrinsic artifacts. Collecting other bio-signals such as EMG and ECoG is not also practical in the field. Recently, Chen et al. (2016) demonstrated the capability of a EEG device for monitoring construction workers' mental workloads in a controlled environment using four EEG electrodes. One of the main challenges they faced was dealing with the noise of EEG recording even in a controlled environment; for example, they mentioned that sweat as a factor that changes the conductivity of skin could show up intermittent slow wave artifacts on the EEG signals. In real construction sites, there are several factors that can more intensify artifacts in EEG signals (e.g., sweating, movement artifacts, environmental sounds, drifts in electrode impedance, and data aliasing), by significantly affecting the quality of EEG recording from construction workers. Due to these reasons, EEG has not been applied and tested on site. Therefore, acquiring high-quality EEG signals by dealing with artifacts should take precedence so that a wearable EEG is used to explore construction workers' psychosocial status.

2.4 Research Objective and Scope

To acquire high-quality EEG signals from real construction sites using an off-the-shelf wearable EEG device, this chapter proposes a signal processing framework that can remove the most common EEG artifacts and obtain quality brain waves from field construction workers at a real construction environment, one of the most noise-prone job sites for acquiring neural signals.

In addition, one reliable way to validate the processed EEG signals is to capture the activation of the motor cortex area of the brain (see C in Figure 2.1) caused by body movements (Brown 2000; Brümmer et al. 2011; Ganguly et al. 2009; Gwin et al. 2011; Lotze et al. 1999; Miller et al. 2007; Rabe et al. 2008; Schneider et al. 2013; Umilta et al. 2012). This method has been widely used to examine the reliability of the EEG signals in recognizing activation of the brain because the physical movement task is the most identifiable, visible, and easy-to-simulating stimulus to induce brain activations among diverse stimuli used in the EEG research field (e.g., emotional tasks that induce a certain emotional state such as watching a horror movie clop, cognitive tasks such as Stroop word-color matching test, etc.). Furthermore, the intrinsic artifacts (e.g., eye blinking, vertical eye movements and facial muscle movements) in the EEG signals from the motor cortex area are much more significant than ones from the frontal area (AF3, F7, F3, and FC5) (Figure 2.1). This study's focus is thus whether the significant artifacts in the EEG signals from the motor cortex area can be corrected to capture the brain activation. Specifically, the EEG beta frequency range clearly shows the activation of the brain during motor cortex (while subjects are moving) (McFarland et al. 2000; Pfurtscheller and Neuper 1997). Capturing changes of the activation in the EEG beta frequency while a subject is working will demonstrate the potential of a wearable EEG device to monitor workers' brain wave patterns at the real construction site. As such, I examine whether the EEG signal processed by the proposed framework can capture brain motor cortex area activation between working (active) and none-working (inactive) conditions.

2.5 Proposed EEG Signal Processing Framework

Figure 2.2 shows the overall EEG signal-processing framework that has been developed in this study. In this framework, the recorded data are first labeled and then cut for different experimental datasets, in order to match the recorded EEG signals with different tasks (Pre-Processing denoted by A in Figure 2.2). Then, filtering methods are used to remove extrinsic artifacts (e.g., sweating and drift in the electrode impedance) while intrinsic artifacts (e.g., eye movement, blinking, and facial muscle activity artifacts) were removed using an independent component analysis (ICA) that can remove intrinsic ones such as ocular and muscle artifacts from EEG signals (Artifacts Removal denoted by B in Figure 2.2). After cleaning the EEG signals, mean power spectral density (PSD) on the beta frequency range is calculated for the electrodes near the motor cortex while the subjects are working (active) and not working (inactive) by measuring the strength of energy variation as a function of beta frequency range (Power Spectral Analysis denoted by C in Figure 2.2). This will provide criteria for the existence of the brain waves in the EEG signals. Artifacts removal and power spectral analysis steps (B and C in Figure 2.2) in this framework will be further discussed in the following sections.

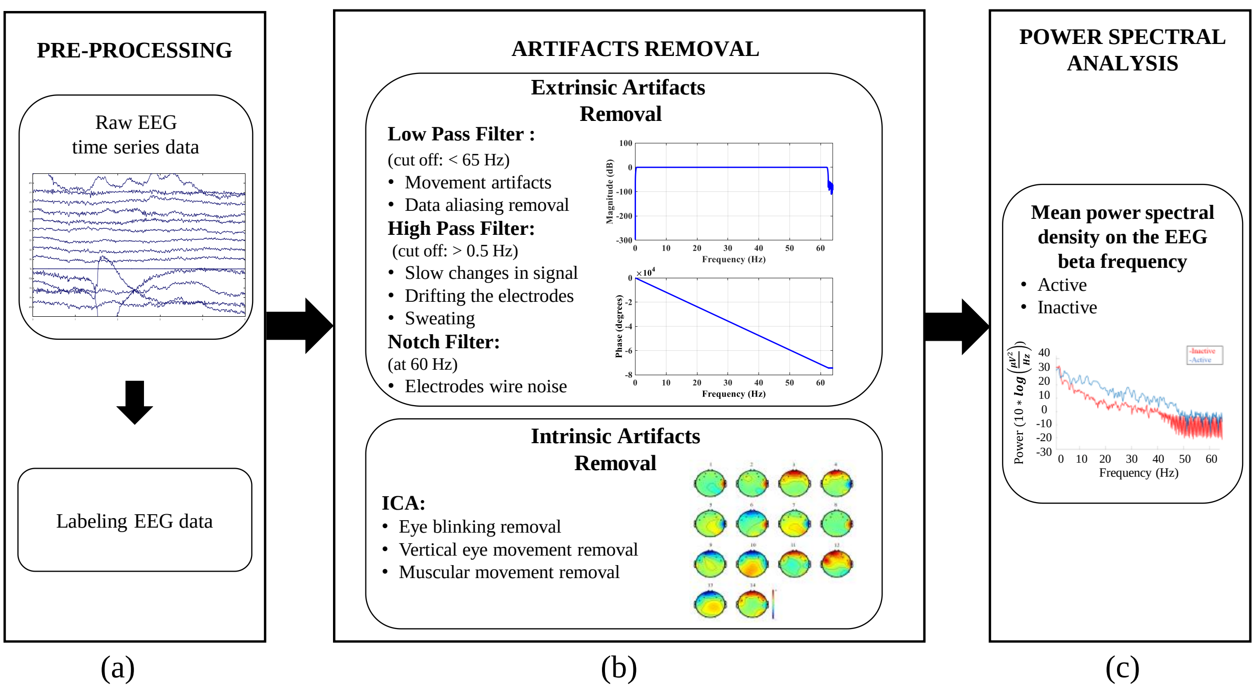

Figure 2.2. EEG signal processing framework: (a) pre-processing and data labeling across 14 different EEG electrodes; (b) signal artifacts removal steps to remove extrinsic and intrinsic artifacts; and (c) power spectra analysis.

2.5.1 Extrinsic Artifacts Removal

Filtering methods are applied to remove a number of extrinsic artifacts such as sweating and drift in the electrode impedance. Specifically, a bandpass filter allows signals between cutoff frequencies (e.g., 0.5 Hz–65 Hz) to pass and prevents signals to pass at other frequencies (Christiano and Fitzgerald 2003). Band pass filters with a higher cutoff of 65 Hz (i.e., low pass filter that passes the frequencies lower than 65 Hz) and a lower cutoff of 0.5 Hz (i.e., high pass filter that passes the frequencies higher than 0.5 Hz) are used to remove the factors that cause rapid changes (i.e., the frequencies higher than 65 Hz) and slow changes (i.e., the frequencies lower than 0.5 Hz) in the EEG. In addition, there is a noise from the electrodes' wire generated as a result of the power line interference signal (Teplan 2002), which usually has a very narrow frequency range (e.g., 60Hz). In such a case, a notch filter is applied, which allows signals to pass within a very narrow band of frequencies (Teplan 2002). EEG signal baseline difference might be also caused by variation in temperature or bias in the EEG (Reddy and Narava 2013). To remove the effect of the factors that cause the baseline difference among different dataset, EEG signals are normalized.

2.5.2 Intrinsic Artifacts Removal

Intrinsic artifacts also have to be removed to obtain quality EEG signals. For example, ocular artifacts like eye movement and blinking contaminate EEG signals (Croft and Barry 2000; Manoilov 2006; Romero et al. 2009). In addition, another important source of the artifacts in recording EEG signals during movement is muscle activity. Muscle artifacts usually derive from head and neck muscles that become active during head movement or other motions (Gwin et al. 2011), which are typical for construction field work.

Such eye movement and muscle artifacts are the most difficult to deal with because their spectrum is similar to non-artifactual EEG components (Brown 2000). The independent component analysis (ICA) method has been proposed to remove eye movement and blinking artifacts, as well as muscular movement in EEG signals (Comon 1994). ICA method can isolate both artifactual and neutrally generated EEG noises from the original EEG (Jung et al. 2000). Separating the artifactual EEG sources facilitates to remove these artifacts and then to extract and mix non-artifactual components to achieve a clean EEG signal. ICA method is widely used in EEG research in the clinical domain to remove ocular (including eye movement and blinking) and muscle artifacts (Delorme and Makeig 2004; Makeig et al. 1996; Reddy and Narava 2013; Vigário 1997; Zhukov et al. 2000).

ICA method assumes a set of EEG-signals from electrodes at a time instant t (Equation 1) to be a combination of j unknown underlying sources that are statistically independent (Equation 2). It assumes that the mixing of the source is linear (Equation 3) and the number of underlying sources is smaller or equal to the number of EEG electrodes (in this chapter, i=j=14), as shown in following equations based on the concepts suggested by Comon (1994):

$$E(t) = [\, E_1(t), E_2(t), E_3(t), \dots, E_i(t)]^T \tag{1}$$

$$S(t) = [\, S_1(t), S_2(t), S_3(t), \dots, S_j(t)]^T \tag{2}$$

$$E(t) = A\, S(t) \tag{3}$$

where $E_i(t)$ shows the i*th* EEG electrode, $S_j(t)$ shows the j*th* underlying source, and A is a full-rank j×i mixing matrix that defines the weight for each source contribution to the EEG signals at each electrode. ICA method attempts to recover the original source S(t) by analyzing E(t), so in order to achieve S(t) from E(t), first step is to calculate the separating or de-mixing matrix W using Equation 4, as follows:

$$S(t) = W\, E(t). \tag{4}$$

There are several approaches to find the demixing matrix and calculate independent components. These include Extended Infomax (Lee 1998), Pearson (Karvanen and Koivunen 2002), Infomax (Bell and Sejnowski 1995), ERICA (Cruces et al. 2002), Fast ICA (Hyvärinen and Oja 2000), JADE (Cardoso 1999), FOBI (Cardoso 1999), etc. Delorme et al. (2007) compared 20 ICA algorithms to 71 EEG channel data recorded from 14 subjects, they found that Extended Infomax ICA method and Fast ICA method ranked highest. Furthermore, Extended Infomax ICA and Fast ICA methods are most widely used in the literature. The Fast ICA method is based on maximizing non-Gaussianity as a measure of statistical independence based on an iterative method. The Extended Infomax ICA method minimizes the mutual information among different components by using a neural network to maximize the joint entropy out of a neural processor. Extended Infomax ICA switches to a different type of distribution among different sources as its learning rule (Bell and Sejnowski 1995; Makeig et al. 1996). Previous studies have shown that Extended Infomax ICA usually performs better than Fast ICA (Delorme et al. 2007). The Extended Infomax method has thus been implemented in the EEGLAB Tool Box that has been widely used for EEG signal processing (Delorme and Makeig 2004).

Therefore, the Extended Infomax method suggested by Delorme and Makeig (2004) and Lee (1998) is applied according to its reliable performance to calculate independent components in EEG signals (Delorme et al. 2007). The EEG signals from 14 channels (14 electrodes) that record brain waves of different area of subjects' brain (Figure 2.1) were decomposed into 14 components (B in Figure 2.3). After decomposing the EEG signals into different components, scalp maps for each component can be drawn (C in Figure 2.3). Scalp maps of ICA components are investigated for each EEG dataset because EEG artifacts such as vertical eye movement, blinking, and muscular movement show a specific pattern in their power spectral density (PSD) activities (Delorme and Makeig 2004). Components that present muscular movement, blinking, and vertical eye movement will be detected using the ICA component patterns introduced for these artifacts by Delorme and Makeig (2004) After detecting and removing the components that represent artifacts of interest (D in Figure 2.3), the other non-artifactual components that represent the real brain waves were mixed to get clean EEG signals (E in Figure 2.3). In this chapter, components that represent artifacts were detected and removed off-line. The bad components were detected and removed manually by calculating the scalp maps of ICA components, then the bad components were detected by comparing the scalp map of all the component with the predefined maps for the components that present muscular movement, blinking, and vertical eye movement introduced by Delorme and Makeig (2004).

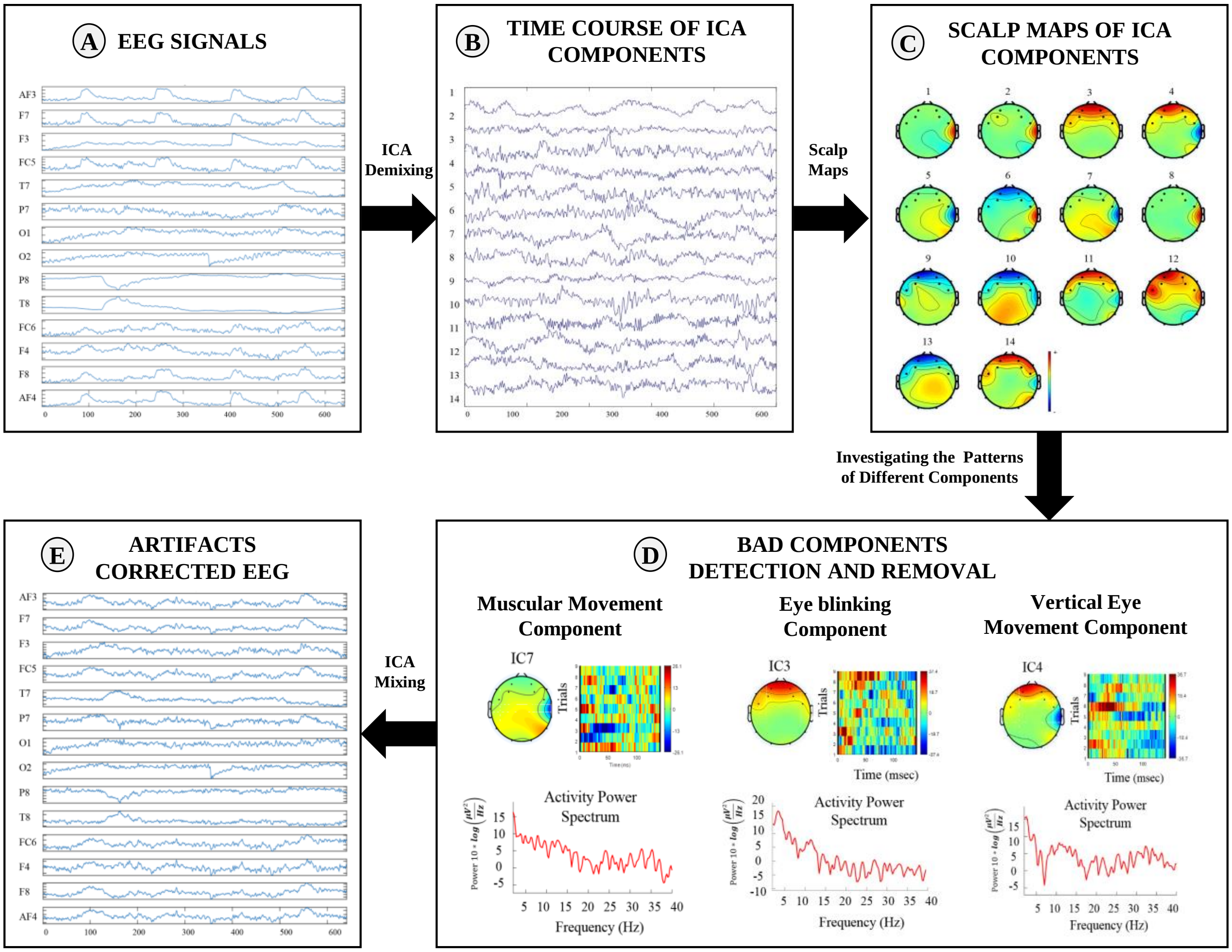

Figure 2.3. Schematic illustration of ICA calculation: (a) the time-series EEG data, captured by a wearable EEG device across 14 different electrodes placed at different area of the subjects brain; (b) time-series ICA components that unmixed from measured EEG signals; (c) scalp maps of ICA component that shows different components topographies; (d) three ICA components that show similar pattern in their PSD activity as artifacts of interest, these are the detected components representing muscular movement, eye blinking, and vertical eye movement; and (e) artifact-corrected EEG signals by mixing the clean components.

2.5.3 Power Spectra Analysis

The power spectral density (PSD) function shows the strength of energy variation as a function of frequency. In other words, it shows at which frequency the variations are strong and at which they are weak. The unit of PSD is energy per frequency, and the energy generated in a frequency range can be obtained by integrating PSD within that range. PSD is the average power distribution of frequency response of a random periodic signal (Stoica and Moses 1997). EEG signals recorded from the motor cortex area are used to validate the existence of neural signals in the recorded EEG. In this study, mean PSD in the beta frequency range is calculated for the electrodes near the motor cortex. As described before, the EEG device used in this study is capable of recording brain waves generated from different location of brains using 14 electrodes. Comparing the location of these 14 electrodes in the EEG device with the location of the electrodes in the international 10-20 system, which is a universally accepted system to define the location of scalp electrodes in the context of an EEG experiment (Herwig et al. 2003), the electrodes with the label name FC5 and FC6 locations represent the motor cortex activity (Jurcak et al. 2007). FC5 shows the activity of left motor cortex area while and FC6 does right motor cortex area activity (see Figure 2.1) while the subjects are working (active) and not working (inactive) (the experiment protocol in detail will be explained in the next section). The process to extract PSD from multi-channel signals (14 channels in this research) from different EEG electrodes (14 electrodes) is described as follows. After removing extrinsic and intrinsic artifacts as explained in previous sections, the cleaned 14-channel EEG signals were divided into epochs that represented a wide stationary signal. For the i*th* epoch, the 14-channel data at different instants t form a 14×T matrix, as follows:

$$S_i = [\, S_i(0), S_i(t=1), S_i(t=2), \ldots., S_j(i=T-1)] \qquad \text{i=1,…, N,} \qquad (5)$$

where T represents the number of dataset instants. A covariance matrix of the vectorized form of the i*th* epoch ($s_j = vec(S_j)$) was calculated using equation 6:

$R_i(\tau) = E[(s_i - \mu_i)(s_i - \mu_i)^T]$ i=1, … , N , $\tau = 0, \ldots, T-1$, (6)

where μ_i is the mean value of the ith epoch. After calculating the covariance matrix, the power spectral density matrix of the i*th* epoch signal at any frequency ω will be calculated using equation 7, as follows:

$P_i(\omega) = \sum_\tau e^{-j\omega\tau} R_i(\tau)$ i=1, … , N, (7)

where $P_i(\omega)$ is the power spectral density matrix of the i*th* epoch. Equation 7 is a calculation of the auto-correlation function of the EEG signals. In other words, the PSD is the Fourier transform of the auto-correlation function. The resulting dimension would be uV^2 for the power and uV^2/Hz for the power spectral density. EEG signals were analyzed off-line using a custom developed software based on the EEGLAB tool box (Delorme and Makeig 2004). A MATLAB version 8.1.0.604 program was used for all of the computations.

2.5.4 Beta Band Mean PSD and Statistical Analysis

After removing EEG artifacts, mean PSD of beta band is calculated by measuring the PSD on the frequency range 13 to 30 Hz. Mean beta PSD is measured for the electrodes located near the motor cortex area while the subjects are active and inactive by measuring the strength of energy variation as a function of beta frequency range. Activation of the motor cortex area of the brain is selected as the criterion to test the capability of the proposed framework in measuring brain waves infield. The beta frequency range is the major rhythm that appears while adults are active. The beta frequency range is selected since EEG in this frequency range can clearly show the activation of brain during a motor cortex activity (McFarland et al. 2000; Pfurtscheller and Neuper 1997).

After calculating beta band mean PSD among all the datasets, Wilcoxon signed-rank test analyses were used for values of PSD to compare these in inactive (e.g., none-working) and active (e.g., working) conditions. For each comparison among inactive and active conditions, Wilcoxon signed-rank test was conducted for mean power based on electrodes FC5 (left motor cortex area) and FC6 (right motor cortex area) and the means of FC5 and FC6. The alpha level for the Wilcoxon signed-rank test was set at 0.05. If the Wilcoxon signed-rank test result shows a significant difference between active and inactive conditions, it will confirm that the proposed framework can capture the activation of the motor cortex area of the brain and acquiring real brain waves of workers at the field.

2.6 Experimental Design

The EEG data were recorded for eight healthy male workers in the field. The field manager among volunteer workers recruited eight subjects after presenting the research objectives and steps. All subjects are males with at least 3 years of work experience, with 26 to 55 years of age (Table 2.1). All the data were collected from two sites, one from an on-site construction site in Detroit, and the other from an off-site shop (e.g., a HVAC/Sheet metal fabrication shop) in Wixom, MI, Michigan, during two weeks in 2016, the weeks beginning on March 18, 2016 and April 25, 2016. Data collection was approved by the University of Michigan Institutional Review Board. At the beginning of data collection, subjects were informed about the anonymity of data collection and participants' rights with the written consent form and they were asked to report if they have a history of mental health diseases. None of them had a history of epilepsy, learning disabilities, or attention deficit disorder that could affect their mental health. Then, participants were instructed to execute experimental tasks.

Table 2.1. Description of Subject Information.

Site	Subject	Age	Gender	Trade	Experience Level
On-site	1	55	Male	Carpenter	37
	2	45	Male	Labor	25
	3	37	Male	Labor	19
Off-site (Shop)	4	40	Male	Sheet metal worker	16
	5	38	Male	Sheet metal worker	18
	6	49	Male	Sheet metal worker	31
	7	26	Male	Sheet metal worker	3
	8	42	Male	Sheet metal worker	20

Emotiv EPOC+ was used to record subjects' brain waves in 14 channels (B and C in Figure 2.1). Emotiv EPOC+ has been introduced as an affordable off-the-shelf EEG device that is capable of recording EEG signals in a reasonable quality (Badcock et al. 2013; Trejo et al. 2015; Vokorokos et al. 2012). Figure 2.4 shows the EEG data collection at the construction site. Emotiv EPOC+ was paired with a nearby laptop wirelessly through a USB transceiver. Data was recorded with sequential sampling internally at 2,048 Hz, with a rate of 128 Hz deliverable. The data-collecting resolution was set at 14 bits with the connectivity at a 2.4 GHz band and a dynamic range of 8,400 µV (pp). To improve the contacts between electrodes and scalp, the felt pads used by the Emotiv EEG device were wetted with the solution suggested by the Emotiv.

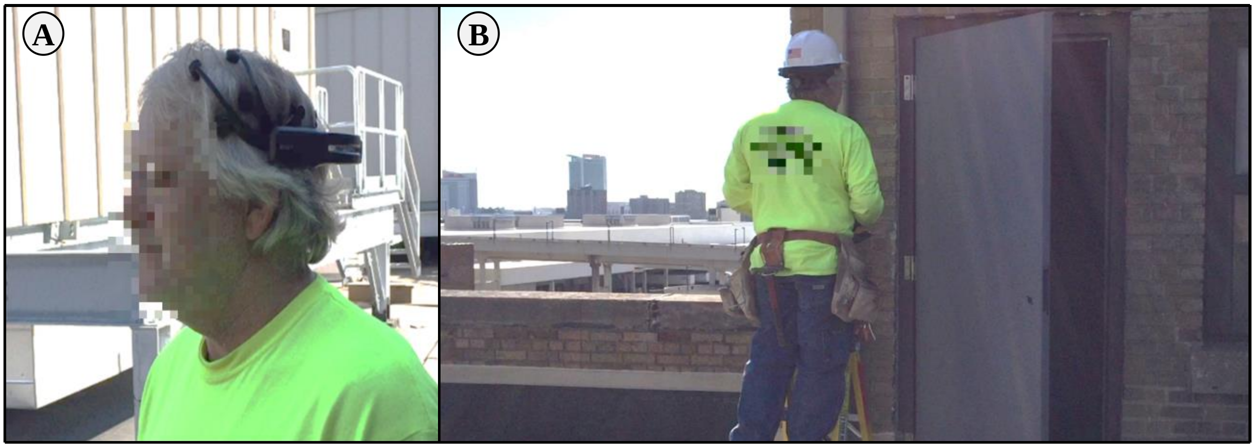

Figure 2.4. EEG data collection at the construction site: (a) placement of an EEG device; (b) integrating an EEG device and a safety hardhat.

Table 2.2 summarizes experimental tasks and protocols. During Tasks 1 and 2, subjects were asked to relax and think of nothing in particular. Then, subjects were asked to keep their eyes open and avoid blinking (Task 1) and to close their eyes (Task 2). During Task 3, subjects were told to keep blinking. Tasks 1, 2, and 3 were performed to recognize the typical pattern of artifacts from eye blinking and eye movement in the EEG signals so that these patterns can be used to develop ICA to remove intrinsic artifacts mentioned before. Task 4 is an inactive (i.e., none-working) motor cortex area task (idling) in which subjects were asked to assume a relatively stationary posture with no significant movements. Task 5 is active (i.e., working) motor cortex movement and subjects were asked to perform their normal work involving different body part movements. All the tasks were video-recorded for data labeling. Data pre-processing is necessary to synchronize different tasks with recorded EEG data. Recorded signals were labeled using the video, and 3,840 data points (30 seconds of each dataset) were extracted for analysis.

Table 2.2. Experimental setup and various experimental tasks.

Sites	Number of Subjects (Datasets)	Tasks
Construction Site	3	1. Eye Open (Stationary) 2. Eye Close (Stationary) 3. Eye Blinking (Stationary) 4. Inactive (Stationary) 5. Active (Working)
HVAC/Sheet metal fabrication shop	5	

2.7 Results

Table 2.3 shows the summary of mean PSD in the beta frequency range for different subjects across inactive and active working conditions (Tasks 4 and 5, respectively) after applying the proposed framework. All datasets (subjects) showed clear differences in the mean PSD of the beta frequency range between inactive and active conditions.

Table 2.3. Summary of beta mean power spectral density for different subjects among active and inactive conditions.

Subject	Condition	FC5 $(10 * log\left(\frac{\mu V^2}{Hz}\right))$	FC6 $(10 * log\left(\frac{\mu V^2}{Hz}\right))$	Average $(10 * log\left(\frac{\mu V^2}{Hz}\right))$
Subject 1	Inactive	0.48	4	2.59
	Active	3.64	9.87	7.79
Subject 2	Inactive	5.33	2.17	4.03
	Active	11.96	16.78	15.01
Subject 3	Inactive	-7.32	2.33	-0.23
	Active	2.57	5.82	4.49
Subject 4	Inactive	-2.07	0.25	-0.76
	Active	6.8	6.94	6.87
Subject 5	Inactive	0.23	0.91	0.58
	Active	7.75	6.14	7.02
Subject 6	Inactive	-0.5	0.83	0.21
	Active	26.27	29.32	28.06
Subject 7	Inactive	-0.23	2.83	1.56
	Active	9.08	9.41	9.25
Subject 8	Inactive	-7.46	1.49	-1.01
	Active	5.65	7.35	6.58

Table 2.4 summarizes mean and standard deviation (SD) of PSD for the beta frequency range power of FC5 (left motor cortex area) and FC6 (right motor cortex area) electrodes while subjects are in inactive and active conditions, and presents the results from the Wilcoxon signed-rank test analysis. The active condition (mean= 10.63, SD= 7.19) has higher beta frequency range power values than the inactive one (mean= 0.87, SD=1.63) in both FC5 and FC6. The p-values in both FC5 and FC6 are significantly lower than the alpha level, and the results confirm a significant difference in beta frequency range between inactive and active conditions for both electrodes (Figure 2.5).

Table 2.4. Summary results from the Wilcoxon signed-rank test analysis

Wilcoxon signed-rank test parameters	FC5 Electrode		FC6 Electrode		Mean FC5 and FC6	
	Inactive	Active	Inactive	Active	Inactive	Active
Mean	-1.44	9.21	1.85	11.45	0.87	10.63
SD	3.96	7.02	1.14	7.51	1.633	7.19
P(T<=t) two-tail	0.014		0.008		0.014	
Alpha	0.05		0.05		0.05	

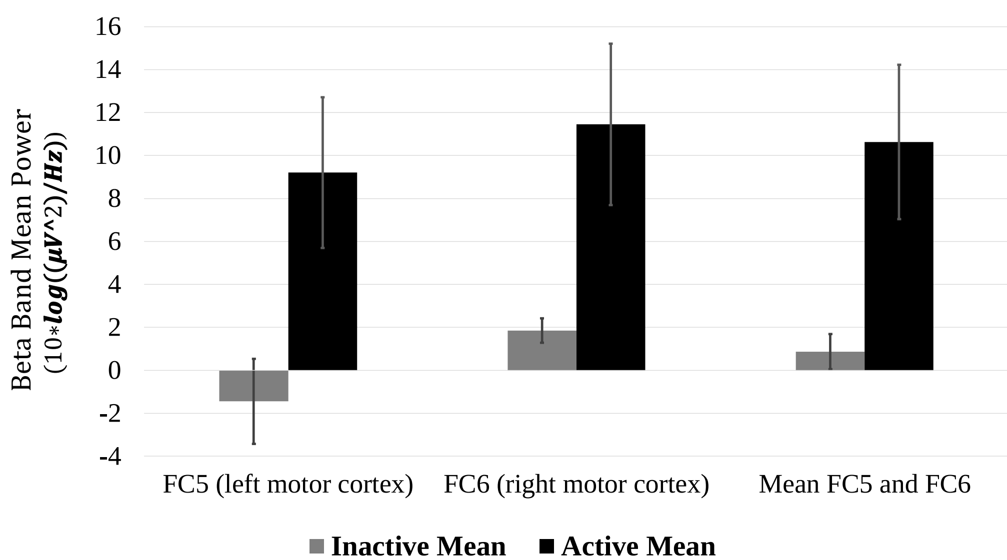

Figure 2.5. Mean and standard deviation beta frequency range power values of FC5 and FC6 electrodes.

To confirm the results, I further analyze a PSD graph, as shown in Figure 2.6 that is one case of PSD graphs for Subject #3. A higher value of the beta frequency range frequency (13–30 Hz) in an active condition is clearly visible than one in an inactive condition, which means that the motor cortex area of the subject's brain was clearly more activated while the subject was working comparing the stationary condition. In addition, a clear improvement in the EEG signal stability has been seen after applying the proposed signal-processing framework among all the 14 EEG channels (Figure 2.7).

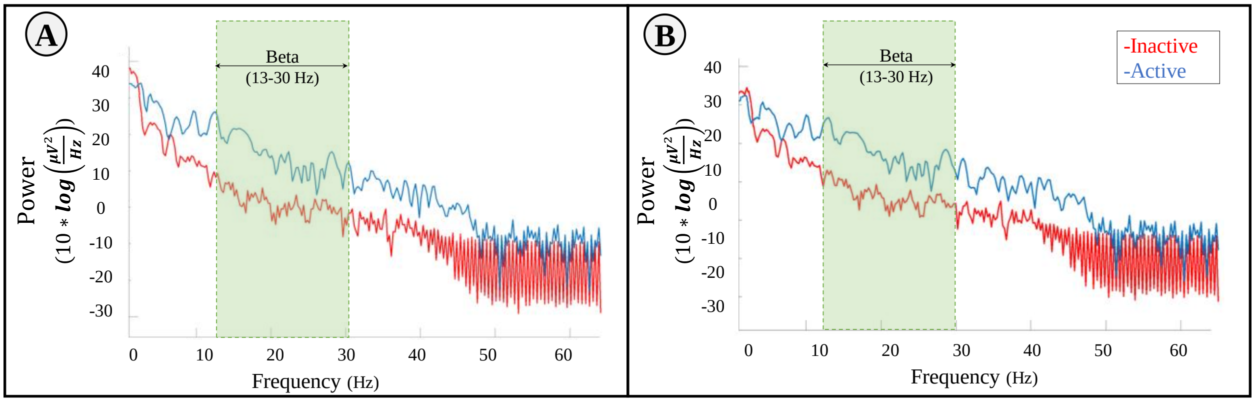

Figure 2.6. Representative PSD for subject #3: (a) PSD calculated based on electrode FC5; (b) PSD calculated based on electrode FC6.

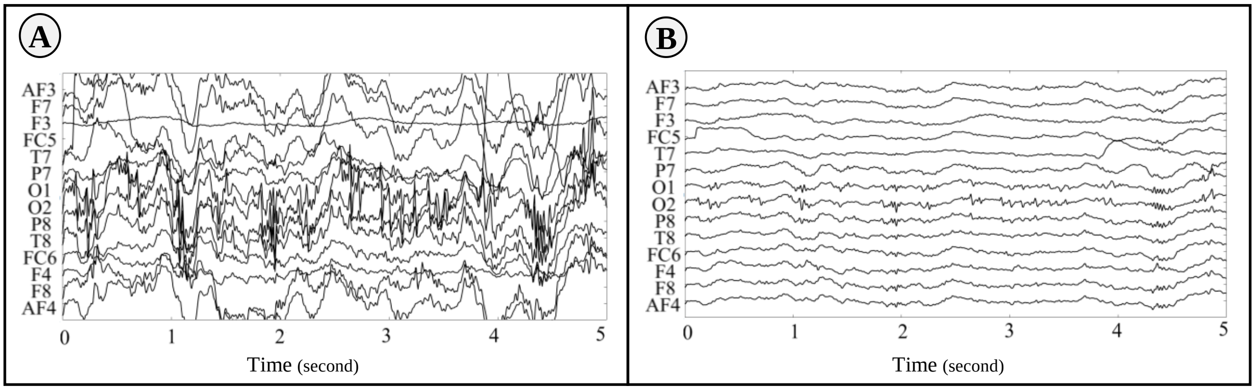

Figure 2.7. Representative EEG signals for subject #3: (a) raw EEG signals; (b) Processed EEG signals.

2.8 Discussion

From the results, the capability of the proposed signal-processing framework in acquiring high-quality EEG signals was demonstrated with significant differences in the mean PSD of the beta frequency range between inactive and active conditions. It is noteworthy that a large variability of beta frequency range power may be seen across different subjects. This variability has a lower range across the inactive condition (min= -1.01, max= 4.03) but has greater variability during the active condition (min= 4.49, max = 28.06). This divergence, especially through the active condition, can be related to different levels of motor cortex activation. In other words, some subjects had more bodily movements, which can cause higher activation levels in the motor cortex. For example, the mean PSD value of FC5 and FC6 electrodes in Subject #1's active condition was equal to 7.79. Subject #1 is a carpenter who was mostly working in a designated area during data collection without much moving around. On the other hand, Subject #2, who is a laborer doing the tasks with much movements, showed mean PSD value of 15.01 in an active condition, which is higher than the value of Subject #1. This variation among different subjects shows that the proposed framework not only helps to get clean EEG signals, but also has a potential to identify different level of brain activation. This highlights the capability of recording different brain wave patterns in the real construction sites. This also can explain the lower variability in the values during the inactive condition—in which all subjects had little body movement and stayed in a stationary posture with low variation of motor cortex activation.

One important concern in collecting the EEG signals in a construction field is integrating the EEG recording device with the safety hardhat that workers have to wear, because of a potential physical conflict between an EEG device and a hardhat. This may raise some problems such as affecting the contacts between the electrodes and scalp as well as the EEG device's wireless connection to the central computer. Thus, I compared the data recorded while subjects are wearing the EEG device alone and the data while EEG device are attached within the safety hardhat. Figure 2.8 compare the beta frequency range power values for three subjects while they were wearing hardhat attached within an EEG device and an EEG device alone. The result is very similar in both cases, which confirms attaching EEG within the hardhat does not affect the quality of EEG signals. When the wearable EEG device was secured with the safety hardhat, the sensors delivered better quality EEG signals with fewer signs of electrode drift and shifting, which was identified by the recorded signal patterns as well as the visualized information of the contact-quality level of each electrode provided by data receiving software (e.g., green signal representing high quality) of the EEG device. This can be explained as the result of the EEG device being secured with a safety hardhat. The hardhat provided constant pressure to the EEG electrodes, which could improve the contact of the electrodes with scalp. Also, attaching the EEG device within the safety hardhat didn't affect the wireless connection between EEG device and a laptop. In other words, attaching the EEG device within the hardhat can make the EEG device perform more like an EEG cap which is the best form among EEG recording devices.

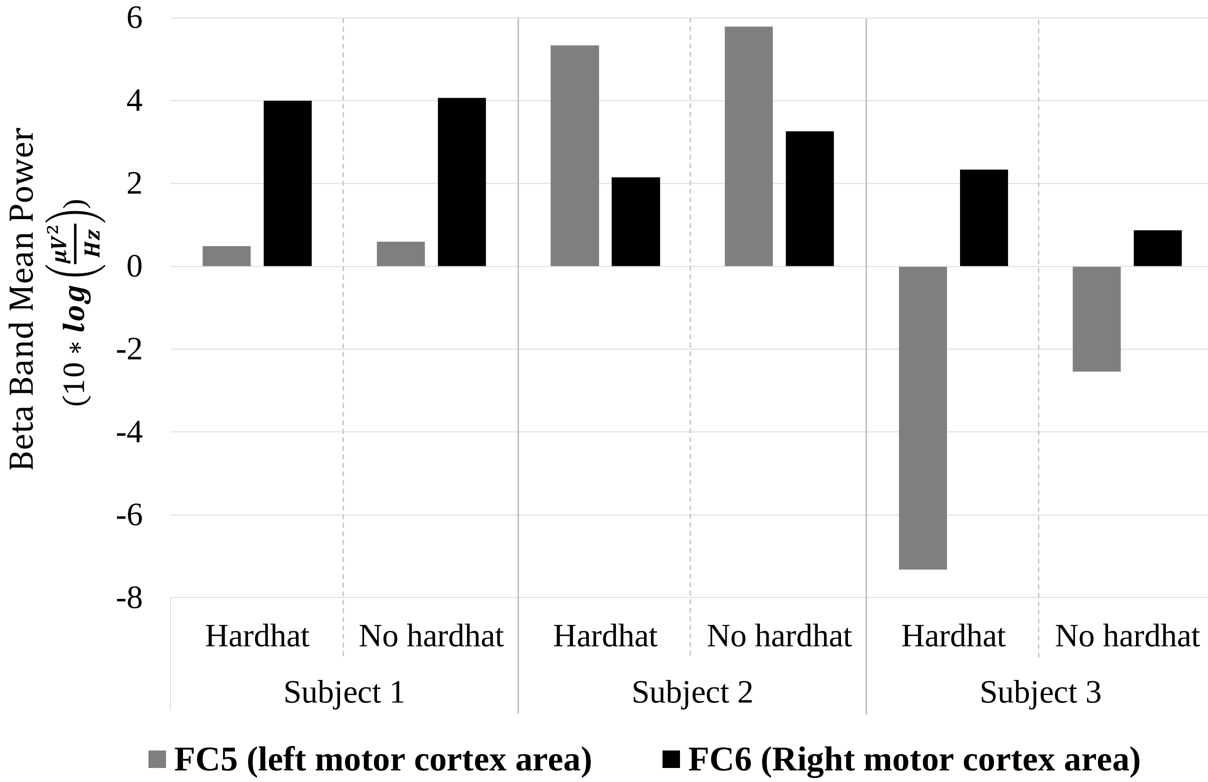

Figure 2.8. Comparing Mean beta frequency range power values of FC5 and FC6 electrodes while subjects wearing hardhat integrated with EEG device and EEG device alone.

In future research, quality EEG signals infield from the proposed signal processing framework will help to understand workers' brain activities which are related to psychosocial health problems such as workers' stress, emotional exhaustion, burnout, and mental fatigue. Also, by adopting current research efforts in the field of neural science and cognitive psychology to continuously measure human subjects' emotional status and stress level using EEG signals (Coan et al. 2006; Hou et al. 2015; Lopez-Duran et al. 2012), workers' emotional status and stress level can be monitored by continuously collecting workers' EEG data using a wearable EEG device. This research result can be used as a quantitative criterion to validate subjective and self-report methods suggested to measure construction workers' emotional status and stress level (Leung et al. 2010), which allows us to understand the relationship between workers' emotional status and stress level and their work performance. As a result, future research efforts to address the above issues will eventually contribute to the reduction of health problems of construction workers as well as improving their safety in the construction sites.

Toward such applications, several limitations still exist and need to be overcome. First, the components that represent artifacts were detected and removed off-line in this research. The bad components were detected and removed manually by calculating the scalp maps of ICA components, then the bad components was detected by comparing the scalp map of all the component with the predefined maps for the components that present muscular movement, blinking, and vertical eye movement introduced by Delorme and Makeig (2004). We suggest applying an automatic artifact removal algorithm suggested by LeVan et al. (2006) for future research direction that requires real-time detection of the bad ICA components. Second, the EEG sampling rate of this study was 128 Hz, which is reasonable for studying beta frequency range power. For any future research studying high mental activity or brain disorders, using a higher sampling rate is recommended to be able to study the gamma frequency range, which is higher than beta frequency range.

2.9 Conclusions

This study proposed a systematic signal-processing framework to remove artifacts from EEG signals that enables to obtain high-quality brain waves from real construction sites. This study validated the usefulness of the framework in capturing high-quality EEG data from a field study by using an off-the-shelf wearable EEG device. Specifically, the results garnered from eight workers showed a statistically significant difference between inactive and active conditions with regard to the PSD values of the beta frequency range in workers' EEG data from the electrodes located in the motor cortex area of the brain, which confirms the success in acquiring real brain waves.

The proposed framework is applicable to many cases where the EEG data is obtained from a wireless wearable EEG device in the field, by providing a standardized process of dealing with both intrinsic and extrinsic artifacts. Specifically, by addressing several issues in field EEG monitoring (e.g., significant artifacts from workers' movement, hardware limitations of a wearable EEG device), the major contribution of the proposed EEG signal-processing framework in this research is to overcome the difficulties in field application of existing EEG signal processing methods used in clinical domains which require subjects' stationary postures and exquisite EEG recording device.

Acquiring high-quality EEG signals at the field highlights numerous opportunities for using EEG recording devices on real construction sites. For instance, workers' psychosocial health problems that were listed above can be monitored. Measuring workers' psychosocial problems can greatly contribute to better understanding and management of workers' health and safety at construction sites. These may include the development of an EEG-based psychosocial monitoring system for workers' stress, emotional exhaustion, burnout, and mental fatigue. Considering that reasonable EEG signals can be acquired at real construction sites, future research can attempt to measure workers' characteristic psychosocial problems by using a wearable EEG device and applying the proposed signal-processing framework.

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Chapter 3:

Measurement of Workers' Emotional State Using A Wearable EEG during Construction Tasks[2]

3.1 Introduction

Despite advances in technology and automation, the construction industry remains a labor-intensive industry. Given the importance of workers to construction activities, workers' emotional states (e.g., pleasure, displeasure, excitement, and relaxation) have received a great deal of attention due to their impact on cognitive status (e.g., attention and motivation), decision-making and behaviors (e.g., risk-taking behaviors affecting unsafe actions), and mental and physical health (e.g., stress, sleep disorder, and headache) (Ashforth and Humphrey 1995; Schwarz 2000; Leung et al. 2014; Tixier et al. 2014). Such impacts consequently affect work performance such as safety, health, quality, and productivity (Ashforth and Humphrey 1995; Leung et al. 2016).

[2] This chapter is adapted from Hwang, S., Jebelli, H., Choi, B., Choi, M., and Lee, S. (2018) "Measuring Workers' Emotional State during Construction Tasks Using Wearable EEG." *Journal of Construction Engineering and Management*, 144(7), 04018050.

Despite the significance of workers' emotion in construction activities, there is a noticeable lack of research that investigates their emotions in the workplace. One of the main obstacles thwarting such an investigation is a lack of quantitative methods to measure emotions. Although various psychological instruments for measuring emotions have been widely used (Morris 1995; Wang and Cheong 2006; Leung et al. 2016), most of them are survey-based subjective self-assessment, which suffer from a possible bias. In addition, such survey-based methods can interfere with workers' ongoing work due to the time and effort required to answer the questions with care and precision. For this reason, they are deployed to construction sites on a limited basis, which makes it difficult to understand how workers' emotions vary while they are working.

To address such limitations, a number of studies have attempted to continuously and quantitatively measure human emotions by assessing human physiological responses (e.g., electro-dermal activity (EDA), heart rate (HR), blood volume pulse (BVP), and electroencephalogram (EEG)) because an individual's emotions are associated with his/her physiological activities (Takahashi et al. 2004; Chanel et al. 2011). Among them, EEG that captures brain waves has strength in measuring in emotions among others. EEG directly detects brain waves from the central nervous system activities (i.e., brain activities) while other responses (e.g., EDA, HR, and BVP) are originated from peripheral nervous system activities (Zhai et al. 2005; Chanel et al. 2011). Specifically, the central nervous system activities are related to diverse aspects of emotions (e.g., from displeasure to pleasure and from relaxation to excitement), but the peripheral nervous system activities are only associated with arousal and relaxation (Zhai et al. 2005; Chanel et al. 2011). Therefore, EEG can provide richer information on emotional states than others (Takahashi et al. 2004; Lee and Hsieh 2014; Liu and Sourina 2014; Hou et al. 2015).

Notwithstanding EEG's potentials described above, it has mostly been applied and tested in a controlled laboratory environment—not in the field like construction. Brain wave patterns from EEG sensors can be easily contaminated from diverse sources of signal noises (e.g., eye movement, respiration, and the use of muscles; Jung et al. 2000; Shao et al. 2009; Szafir and Signorile 2011; Urigüen and Garcia-Zapirain 2015), which are very common and severe at the construction site where workers move around a lot. Also, the hardware limitations of the traditional EEG devices used in a clinical setting (e.g., wired connections and exquisite equipment) makes it difficult to continuously and non-intrusively collect brain waves from workers engaged in their field job.

Recently, the advancement of wearable EEG sensors, which are portable, wireless, and affordable, has opened a new door toward the non-intrusive collection of workers' brain waves. However, these wearable EEG sensors are more vulnerable to EEG signal artifacts generated in the field than the ones used in a clinical setting because they typically have lower signal resolutions and signal-to-noise ratio (i.e., the level of a desired signal compared to the level of background noise). This low signal quality of wearable EEG sensors is the main obstacle to their use for field emotion measurement. To address an EEG artifact issue, I previously proposed and successfully tested an EEG signal processing framework to acquire high-quality EEG signals while workers perform real work tasks at the construction site using a wearable EEG sensor (Jebelli et al. 2017). Applying this EEG signal processing framework, I investigate the feasibility of measuring changes in workers' emotional states in this chapter. To do this, I first apply a bipolar dimensional emotion model (i.e., a valence-arousal model) to quantify workers' emotional state. A valence-arousal model represents an emotional state as two dimensions including a valence dimension from displeasure to pleasure and an arousal dimension from not aroused to excited state (Russell et al. 1989; Burkhardt 2001). Based on this model, workers' valence and arousal levels are measured using processed EEG signals collected during workers' ongoing tasks. Specifically, I apply an EEG-based valence-arousal calculation method that has been previously validated in a laboratory setting (i.e., a frontal EEG asymmetry method: Davidson et al. 1990; Blaiech et al. 2013). Then, the validity of the EEG-based emotion measurement is examined by comparing with cortisol levels obtained from workers' saliva samples, which have been accepted as a reliable physical measure of emotions (Brummett et al. 2012; Het et al. 2012). I also investigate workers' emotional states from several factors affecting emotions in the field, such as working hazards (e.g., hazardous work conditions such as working on the ladder and in a confined space) and a feeling of tiredness over time, which have been widely accepted to have a significant impact on emotions and common in construction projects (Berger 1996; Mignonac and Herrbach 2004).

3.2 Emotion and its importance in construction

Despite difficulty in defining and classifying emotions due to the complex nature and genesis of emotion (Ashforth and Humphrey 1995), it is generally accepted that an individual's appraisal of some external stimulus or event is the most important factor in determining his/her emotion (Lazarus 1982; Eysenck and Keane 2000). This cognitive appraisal implies that individuals primarily evaluate whether an environmental situation is positive (e.g., beneficial and desirable), negative (e.g., stressful, threatening, and dangerous), or irrelevant to one's well-being, and then evaluate the resources or their own ability to cope with the situation (Lazarus 1982; Eysenck and Keane 2000; Mignonac and Herrbach 2004).

Due to their complexity, many researchers have tried to classify emotions from a multi-dimensional perspective. Specifically, one's emotions can be classified from a dimensional perspective based on the valence-arousal-dominance (VAD) model (i.e., a valence dimension from displeasure to pleasure, an arousal dimension from not aroused to an excited state, and a dominance dimension from being in control to a feeling of being controlled by the emotion) (Mehrabian 1996). Nowadays, there is an agreement that the bipolar dimension of valence and arousal, as shown in Figure 3.1 (i.e., valence-arousal model), is enough to classify most emotional states (Russell et al. 1989; Burkhardt 2001). Given measured valence and arousal dimensions, emotional states (e.g., fear, happiness, and relaxation) can be defined by combining these two dimensions (e.g., happiness with a positive valence and a slightly positive arousal: Burkhardt 2001). By mapping emotions onto the space of bipolar dimensions, this model can also represent the intensity of emotion.

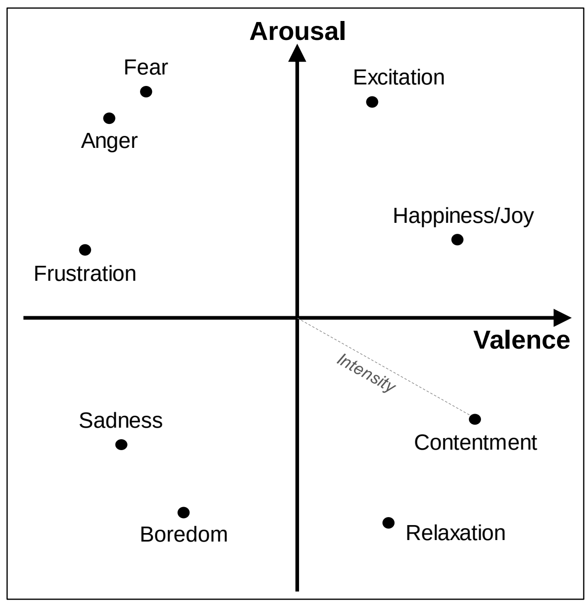

Figure 3.1. Valence-Arousal Model and Emotions

Taking into account the fact that an individual's appraisal of an external stimulus is the most important factor for his/her emotion, construction workers are frequently exposed to various external stimuli affecting emotions such as poor physical conditions (e.g., extreme outdoor temperatures, poor air quality, and excessive noise) and hazardous work conditions (e.g., working on the ladder, in confined space, and with dangerous machinery) while performing their tasks (Leung et al. 2012; Leung et al. 2016). Construction workers' emotions are also affected by their experience of demanding construction tasks (Leung et al. 2016). For example, stressful and dangerous situations as well as tiredness can cause negative valence (Berger 1996; Mignonac and Herrbach 2004). To sum up, construction workers experience various emotional responses in their workspace because they work under a continuously changing and complex environment that is even physically and psychologically demanding and hazardous (Leung et al. 2012 and 2014).

Given that workers' emotions during work have been linked with many organizational performances, it is important to understand their emotions at the workplace. Specifically, emotions strongly influence our cognitive process and decision-making abilities (Easterbrook 1959; Schwarz 2000; Bhandari et al. 2016). For example, high arousal can influence an individual's perception on the current situation by reducing the range of cues that a person uses which further affects one's subsequent behavior (Easterbrook 1959). The reduction on the range of perception leads to critical problems in construction sites where a failure in hazard perception can directly threaten workers' safety. Furthermore, existing experimental research supports that a person's emotions play an important role in determining whether decision processing will be either heuristic (i.e., high reliance on pre-existing knowledge structures) or systematic (i.e., analytic and cognitive processing with high attention to the relevant information in the present situation) which can change the outcome of decision making (e.g., risk-taking or protective behaviors) (Schwarz 2000; Kruglanski and Higgins 2013). Heuristic individual decision processing driven by emotions (e.g., low fear of skilled workers who are accustomed to dangerous work conditions) can also lead to unsafe behaviors. As such, understanding the impact of individual emotions on decision-making is particularly important in construction, where a worker is constantly engaged in making a series of task-related improvised decisions.

In addition, the continuous feeling of emotional stress (i.e., negative emotions) accounts for chronic fatigue, emotional drain, and a loss of devotion to job duties (Goliszek 1992; Leung et al. 2012). For construction workers, emotional stress causes workers to pay less attention on work tasks or ignore safety guidelines, which can lead to a serious accident at the site (Alexander and Klein 2001; Leung et al. 2012). Moreover, this emotional stress is closely associated with many physical symptoms, such as gastrointestinal disorders, sleep disorders, headaches, and others, which can also inversely and adversely affect mental health and emotions (Leung et al. 2016). Given that a construction workplace has many changing emotional contexts (i.e., emotion-related stimuli such as different work conditions and tiredness over time) that workers experience every day while significantly affecting their work performances (Allcorn 1994; Bensimon 1997), understanding emotions in the workplace provides meaningful insights for enhancing work performance.

Despite the contributions of these research efforts, they have inevitably taken into account only a part of a number of causes and effects of emotional changes in the workplace because the use of survey-based subjective measurement in these studies is hard to use continuously in the field, which limits continued field emotion studies and comprehensive understanding of workers' emotions in numerous situations. For a more in-depth understanding of workers' emotions, therefore, continuous and non-intrusive emotional state measurement in the field should take precedence, which is what this study aims to achieve.

3.3 Electroencephalogram (EEG)

As discussed earlier, electroencephalogram (EEG) has a great potential for continuous and quantitative emotional state measurement. EEG is the recording of the electrical signal along the scalp produced by the action of neurons within the brain, which can be measured using electrodes attached to the scalp (Khalil and Misulis 2006; Szafir and Signorile 2011). The activation of a central nervous system is thus manifested in the EEG signal. This brain activation can be understood by EEG rhythms including delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (> 30 Hz) frequency ranges (Blaiech et al. 2013; Borghini et al. 2014; Hou et al. 2015). Delta frequency range is predominant during deep sleep, while theta frequency range is related to drowsiness, creative inspiration, meditation, etc. Alpha frequency range is linked to relaxed states while beta frequency range is predominant during alert, active, busy states or anxious thinking and gamma frequency range is related with high mental activity and information processing (Buzsaki 2006; Szafir and Signorile 2011).

On the other hand, the location of the brain is associated with different functions of brain. For example, the frontal lobe of the brain is known as an emotion control center and is home to the personality, while also controlling voluntary movements. A parietal lobe takes care of processing of nerve impulses related to senses and language functions, while a temporal lobe is a primary organization of sensory input (Rusinov 2012). Therefore, all the EEG devices including wearable EEG sensors (A in Figure 3.2) have multiple electrodes that can be attached to different locations of the scalp (B in Figure 3.2) to capture diverse brain activations in different regions. For example, brain activation by changes in emotion are mostly captured from electrodes located in the frontal area (e.g., AF3. AF4, F3, and F4 in B of Figure 3.2).

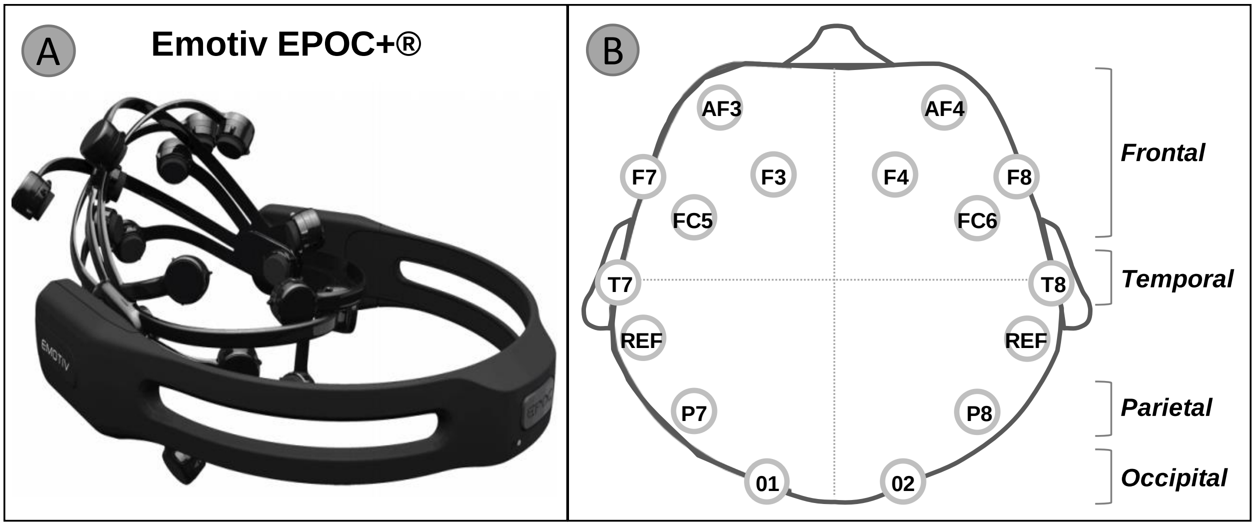

Figure 3.2. A Wearable EEG Sensor: (a) an Off-the-shelf Sensor; (b) Location of Electrodes

As such, EEG can provide plentiful information regarding brain activities related to perception, cognitive thinking, emotions, and others, from different EEG rhythms collected from different locations of brain. Focusing on such potential, I applied a wearable EEG sensor for field EEG monitoring to collect high-quality EEG signals by removing signal artifacts (Jebelli et al. 2017). Because the first step to identify brain activities is to procure high-quality EEG signals, which is particularly important in the context of a wearable EEG device, this previous study provides the necessary groundwork for this study. However, measuring emotions needs additional studies to interpret signal patterns through the use of relevant measurement methods and their validation, which this study tries to achieve. Chen et al. (2017) and Wang et al. (2017) also recently used a wearable EEG sensor to assess different levels of mental workload and attention of workers by showing different EEG signal patterns. The outcome of these research efforts can help to address psychological issues that regularly impact construction workers, especially those caused by burdensome mental workloads and attention. However, emotion is a different psychological aspect. While mental workloads and attention are more closely associated with cognitive thinking and can be understood by individual alertness or relaxation states, understanding emotions is a far more complex process due to the multifaceted characteristics (e.g., valence and arousal). Therefore, emotional states need to be measured from multi-dimensional perspectives, which is an objective of this study.

3.4 EEG-based emotion measurement process

In this section, I describe two important elements for field workers' emotion measurement using EEG signals collected from a wearable EEG sensor: removing field EEG signal artifacts and calculating emotional states based on the processed EEG signals.

3.4.1 Artifacts removal using the EEG signal processing framework proposed in Chapter 2

EEG signals can be highly contaminated by both extrinsic and intrinsic artifacts that obscure the signal of interest. Extrinsic artifacts are the noises generated mostly from an external source rather than human body physiology such as electrode popping, movement artifacts, environmental noise, and wiring noise in the EEG sensor. On the other hand, intrinsic artifacts are created within internal body changes. Eye movements and blinking and facial muscle movement are the most common source of intrinsic artifacts (Shao et al. 2009; Szafir and Signorile 2011; Urigüen and Garcia-Zapirain 2015). When subjects are relatively stationary, EEG artifacts (both extrinsic and intrinsic ones) are relatively small in scale, and can therefore be identified and corrected (Urigüen and Garcia-Zapirain 2015). However, construction workers in the field are frequently moving around, which makes the impact of both extrinsic and intrinsic artifacts on the EEG signals too significant. Even worse, EEG signals from a wearable EEG sensor are prone to much more extrinsic artifacts due to the low resolution (e.g., 128–256 Hz) from a wireless connection of such a sensor and the poorer attachment between electrodes and scalp than exquisite clinical EEG devices, all of which makes EEG's field use challenging.

In this regard, I proposed and tested an EEG signal processing framework, specifically designed for the field use of a wearable EEG sensor (Jebelli et al. 2017). This framework corrects both extrinsic and intrinsic artifacts from the raw EEG signals obtained from real construction sites thereby extracting only desired EEG signal (i.e., non-artifactual signal). It was demonstrated that this framework can acquire high-quality EEG signals while workers are performing their tasks. Therefore, this study applies this framework to the processing of raw EEG signals to be used to calculate field workers' emotional states.

In detail, Figure 3.3 illustrates this EEG signal processing framework (Jebelli et al. 2017). Firstly, appropriate filtering methods including a bandpass filter and a notch filter were suggested to remove the most common extrinsic artifacts from the EEG signals recorded from a wearable EEG. Among intrinsic EEG artifacts, muscle activity and eye movement artifacts are the most difficult to work with because their spectrum overlaps with an EEG activity (Brown 2000; Croft and Barry 2000). To deal with them, independent component analysis (ICA) method that can separate a signal into multiple components, is used to remove the artifactual components from the EEG signal (Comon 1994; Jung et al. 2000; Delorme and Makeig 2004; Chaumon et al. 2015). The ICA method was also used to remove eye movement and muscle activity artifacts from EEG signals (Jebelli et al. 2017).

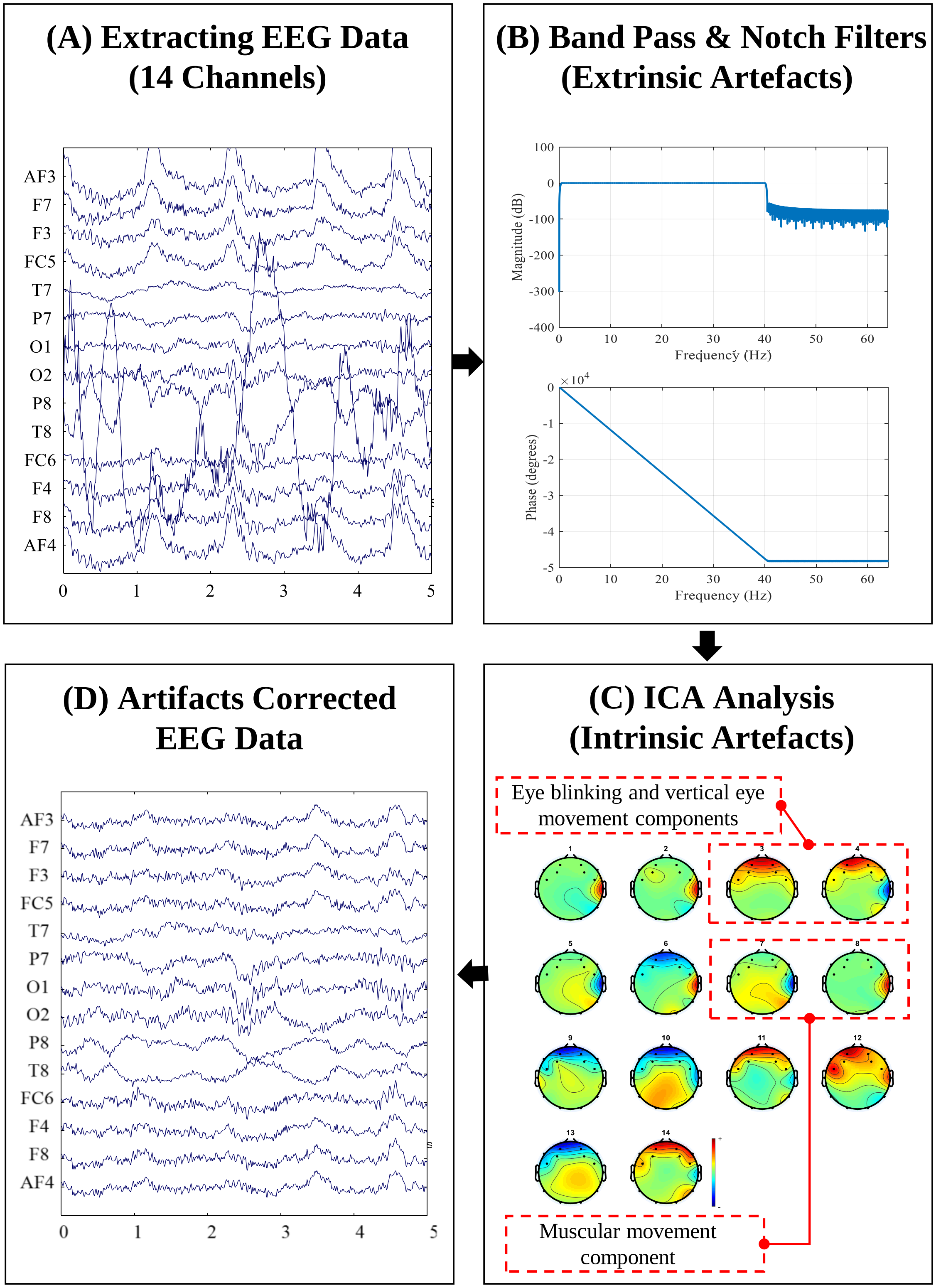

Figure 3.3. Illustration of EEG Artifacts Removal Process: (a) Raw EEG Data from 14 Channels; (b) Extrinsic Artifact Removal; (c) Intrinsic Artifact Removal; (d) Corrected EEG Data

3.4.2 Emotional state measurement using frontal EEG asymmetry calculation

EEG for brain signals has been effectively used to understand diverse levels of emotional states through significant correlation with EEG power (i.e., the amount of energy of the signal per unit time). Many individual-dependent emotion measurement algorithms using EEG are based upon the bipolar model of valence and arousal dimensions (Lewis et al. 2007; Winkler et al. 2010; Goodman et al. 2013; Liu and Sourina 2014). To measure valence and arousal levels and label emotions, features in EEG data need to be distinguished. Specifically, power spectrum features such as power spectral density (PSD) have been widely applied to the classification of valence and arousal levels according to the correlation with alpha (8–13 Hz) and/or beta (13–30 Hz) frequency ranges (Lewis et al. 2007; Blaiech et al. 2013; Hou et al. 2015). Other features such as statistical features (e.g., mean and variances) or fractal dimension features have also been used in previous research efforts (Takahashi et al. 2004; Liu and Sourina 2014; Hou et al. 2015).

Among many emotion measurement algorithms that use the above features, the frontal EEG asymmetry (FEA) method which is based on power spectrum features has been successfully applied to measure an individual's valence and arousal levels (Lewis et al. 2007; Winkler et al. 2010; Goodman et al. 2013; Allen and Reznik 2015). The FEA method captures both the left and right frontal activities of the frontal lobe of the brain which is known as an emotion control center (Rusinov 2012). A left frontal activity is usually associated with a positive or approach-related emotion whereas a right frontal activity indicates a negative or withdrawal-related emotion (Lewis et al. 2007; Winkler et al. 2010). In this regard, the FEA method shows the degree of activation of the left and right area by comparing the PSD in the alpha and beta frequency range between these two areas, in order to indicate a pleasure state (i.e., valence) of a person (Coan et al. 2006). In addition, the FEA method compares the power ratio of alpha and beta frequency ranges. Since the alpha frequency range is prominent in relaxed condition and beta frequency range is associated with an aroused state, this comparison indicates the excitation state (i.e., arousal) of a person.

Figure 3.4 represents the emotion measurement process using FEA calculation in this study. To measure valence and arousal, four channels in the frontal lobe area (i.e., electrodes AF3 and F3 in the left area and electrodes AF4 and F4 in the right area: see B of Figure 3.2) are used. After removing signal artifacts using the EEG signal processing framework (B in Figure 3.4), mean PSD of alpha and beta frequency range are calculated for these signals. PSD measures the average energy distribution as a function of frequency of a signal (C in Figure 3.4) (Stoica and Moses 1997). Here, the mean PSD is expressed as a logarithmic value (decibel) which can have either positive or negative value.

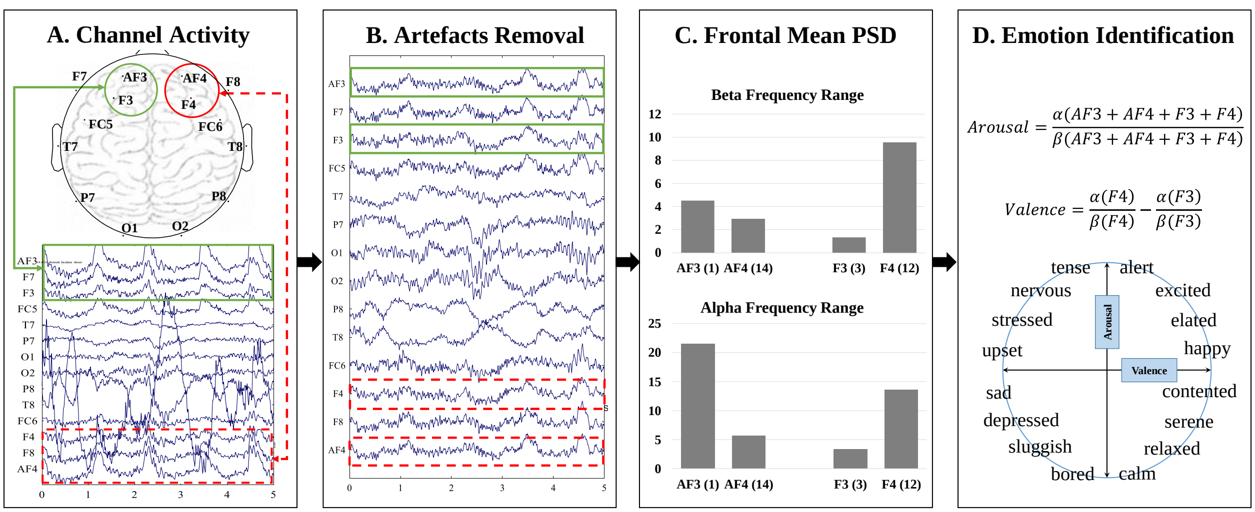

Figure 3.4. Emotion Measurement Process: (a) Collecting Time-Series EEG Data; (B) Removing Signal Artifacts in Time-Series EEG Data; (C) Measuring Mean PSD at the Frontal Area; (D) Calculating Valence and Arousal Levels Using the Frontal Area Mean PSD

Then, the valence and arousal dimensions of emotion are calculated using the mean PSD and the FEA indicators, based on the below Equations 1 and 2 (D in Figure 3.4: Davidson et al. 1990; Blaiech et al. 2013). Specifically, a positive valence is associated with relatively greater activation of the left frontal area whereas a negative valence is more related to relatively greater activation of the right frontal area. Equation 1 thus indicates a relative difference of activations between two areas to show the valence level. Although there is no pre-defined range of valence levels, more positive valence value means more pleasant emotion with more activation of a left area than a right one. On the other hand, Equation 2 indicates the arousal level by calculating the alpha/beta ratio (Lewis et al. 2007; Blaiech et al. 2013). Similarly, a greater arousal value indicates individual's more aroused emotional state:

$$Valence = \frac{\alpha(F4)}{\beta(F4)} - \frac{\alpha(F3)}{\beta(F3)} \qquad \text{(Equation 1)}$$

$$Arousal = \frac{\alpha(AF3+AF4+F3+F4)}{\beta(AF3+AF4+F3+F4)} \qquad \text{(Equation 2)}$$

Where α(i) and β(i) are correspond to the PSD of alpha and beta frequency range obtained from i-th channel of the EEG signal.

3.5 Field data collection

3.5.1 Overview

To test the feasibility of measuring construction workers' emotional states in the field using a wearable EEG sensor, I collected workers' EEG signals as well as their saliva samples for cortisol analysis from real construction sites. All the data including EEG data and cortisol samples were collected under different factors proven to affect emotions in the field, in order to confirm if workers' emotions measured from EEG signals vary by such factors.

In this study, the factors that I consider are work conditions with different hazard levels (e.g., less hazardous conditions like working at ground vs. more hazardous conditions like working on the ladder and in a confined space), and a different feeling of tiredness over time (e.g., less hours worked vs. more hours worked in a row), which have been widely accepted as significant factors affecting workers' emotions and prevalent at the worksite (Berger 1996; Mignonac and Herrbach 2004; Leung et al. 2016). To collect workers' EEG data, a wearable EEG sensor (see A in Figure 3.2) that has 14 channels (see B in Figure 3.2) and the 256 Hz sampling rate of each channel was attached to the inner side of a hardhat, as shown in A and B of Figure 3.5.

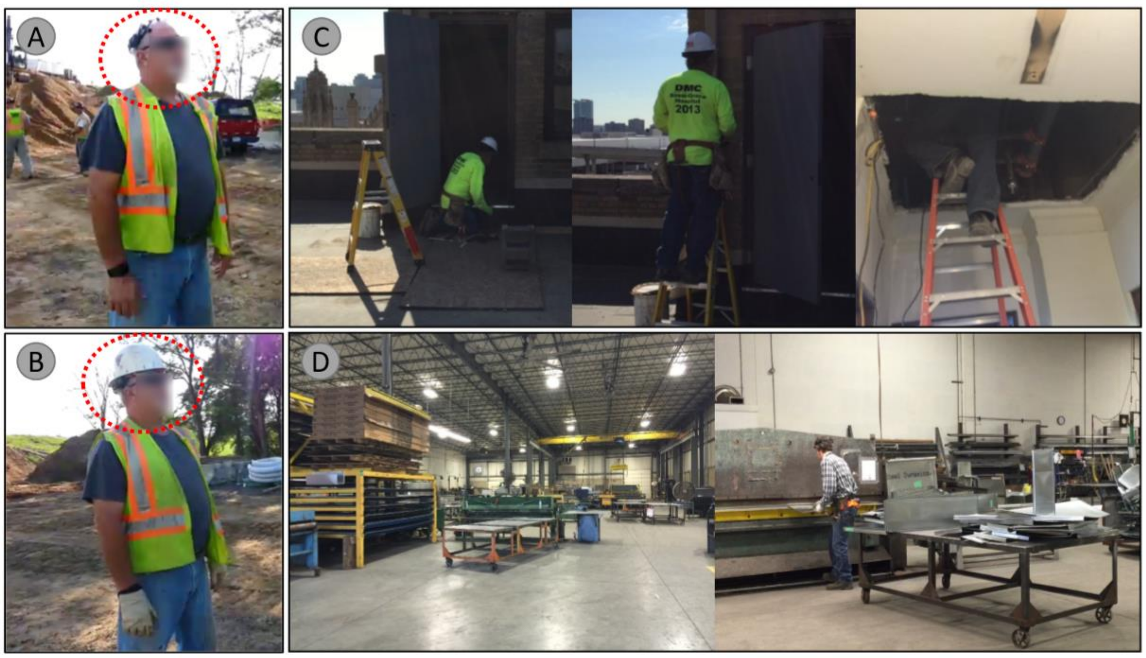

Figure 3.5. Subjects and Sites for Field EEG Data Collection: (a) A Subject Wearing an EEG Sensor; (b) A Subject Wearing an EEG Sensor with Hardhat; (c) On-site Work Conditions; (d) Off-site Shop Work Conditions Site information

For data collection, three worksites were approached: two on-sites including an office building renovation site in Detroit, Michigan (collected on March 18–25, 2016) and a hospital renovation site in Gary, Indiana (collected on February 22, 2017), and one off-site HVAC-sheet metal fabrication shop in Wixom, Michigan (collected on March 28–April 4, 2016). I chose two on-sites for an in-depth investigation of the effect of different work conditions on emotional states because the recruited workers on such sites were performing the same repetitive tasks in different conditions (e.g., working at ground, on the ladder, and in a confined space: see C in Figure 3.5). Additionally, I chose the off-site shop to investigate the effects of different amounts of working hours without resting (e.g., right after, one hour after, and two hours after the scheduled resting time) upon emotional states in an environment where recruited workers were performing the repetitive tasks at the same work location and environment (see D in Figure 3.5).

3.5.2 Participants and procedures

The EEG data were collected from ten healthy workers, including six workers (one carpenter, two electricians, and three laborers) on the two on-sites (i.e., three workers per each site) and four off-site sheet metal workers in the off-site shop. All subjects are Caucasian males between 26 to 55 years of age (see Table 3.1). Data collection was approved by the University of Michigan Institutional Review Board. The informed consent form was distributed to all the subjects before data collection in order for them to be informed about the anonymity of data collection and participants' rights. They were asked if they had any physical and physiological (e.g., headaches, breathing rapidly, feeling dizzy, and feeling fatigued), cognitive (e.g., difficulty in concentration and poor sleep quality), and emotional problems (e.g., feeling depressed, trapped, and cynical). None of them reported any such problems. I also assured each participant that they could stop participating in the data collection if they felt uncomfortable.

In the data collection, six subjects in the on-sites were asked to perform their work tasks with different work conditions including working at ground (Session #A1), working on the ladder

(Session #A2), and working in a confined and dimmed space (Session #A3). Also, while workers in the off-site shop performed their repetitive tasks, their EEG data were collected three times, 9:30AM, 10:30AM and 11:30AM. 9:30AM is the time when they came back from 30-minutes of scheduled resting time between 9:00AM–9:30AM and they continue to work without resting until 11:30AM (i.e., the time when they had a lunch). As such, these three sessions intend to capture workers' emotion right after the resting time (i.e., at 9:30AM; Session #B1), one-hour after the resting time (i.e., one hour's working; at 10:30AM; Session #B2), and two hours after the resting time (i.e., two hours' working; at 11:30AM; Session #B3). Each worker performed the same physical, everyday work tasks during all his/her sessions (e.g., labors performing cleaning tasks).

Before each session, at least 5 minutes of movement-artifacts-free EEG data were collected and used as a baseline to remove motion artifacts. During data collection, subjects were asked to remain still. Then, the EEG data during working were recorded more than 10 minutes.

To investigate the existence of additional significant changes in work conditions that could potentially affect subjects' emotional states (e.g., excessively loud noises) at the site, I video-recorded entire workspaces during the data collection. It is noteworthy that Subject #A-1 participated in only two sessions, neither of which was in a confined space, because there was no confined space in this subject's workspace. As a result, the total number of datasets were 29 as shown in Table 3.1.

On the other hand, an important concern on field data collection is subjects' bias like the Hawthorn effect because workers' awareness of being observed can modify their behavior. To minimize this bias, I first tried to avoid direct observation near the subjects as much as possible because wireless EEG data transfer of the sensor used in this study does not require continuous observations on subjects during the data collection. I also asked them not to deviate their routines of work while focusing on their work, by clearly informing them that their anonymity was guaranteed and all the collected data would never be used for any performance measurement.

I also collected subjects' cortisol samples after each session. Cortisol is known as a stress-related hormone and has been proven to have a relationship to emotions. Diffused from capillaries into tissues and found in body fluids, cortisol can be easily collected from saliva, urine, as well as hair (Levine et al. 2007; Russell et al. 2012). Salivary cortisol, is especially easy to collect, and related to acute body response to the stressors (Russell et al. 2012). Considering that a subject's salivary cortisol value (µg/ml) reflects his/her acute emotional state (e.g., emotions during the past half an hour or less) (Russell et al. 2012), each session was designed to perform half an hour or one hour later of the previous session to eliminate any residual emotion. As shown in Table 3.1, I collected 22 salivary cortisol samples for 22 sessions out of total 29 sessions for all the subjects. I could not collect two salivary cortisol samples from Subject #A-1's two sessions because of his reluctance to provide his cortisol samples. In addition, I decided to exclude five cortisol samples during the second sessions of five on-site subjects (Subjects # A-2–A-6) for this data analysis. This exclusion is due to the possibility that their cortisol values may reflect not only the second session but the first one. While these five on-subjects participated in this study, their second sessions were conducted less than 20 minutes after their first sessions due to their limited time for participating in data collection. All others followed the aforementioned protocol.

Table 3.1 Subject Information and Results: Valence and Arousal Levels and Cortisol Values

Workers	Subject #	Age	Gender	Session #*	EEG-based Valence Level*	EEG-based Arousal Level*	Cortisol [µg/dL] (%CV)**
[A] On-site workers	A-1 (Carpenter)	55	Male	A1: At ground	0.055	0.974	-
				A2: On the ladder	-3.239	1.594	-
	A-2 (Laborer)	45	Male	A1: At ground	0.566	2.215	0.17 (1.56%)
				A2: On the ladder	-2.291	-0.725	-
				A3: In confined space	-1.722	0.582	0.15 (5.13%)
	A-3 (Laborer)	37	Male	A1: At ground	5.472	5.748	0.19 (4.24%)
				A2: On the ladder	0.249	2.718	-
				A3: In confined space	-1.017	1.993	0.14 (7.19%)
	A-4 (Electrician)	35	Male	A1: At ground	4.786	-0.651	0.21 (8.00%)
				A2: On the ladder	-3.068	-1.467	-
				A3: In confined space	-8.197	-3.895	0.40 (7.48%)
	A-5 (Electrician)	27	Male	A1: At ground	-0.501	2.026	0.16 (2.77%)
				A2: On the ladder	-3.580	-0.557	-
				A3: In confined space	-0.824	1.878	0.16 (3.42%)
	A-6 (Laborer)	50	Male	A1: At ground	0.276	2.058	0.10 (10.81%)
				A2: On the ladder	-0.137	1.614	-
				A3: In confined space	-0.881	1.493	0.16 (10.28%)
[B] Off-site (shop) workers	B-1 (Sheet metal worker)	40	Male	B1: Right after rest	2.631	-1.005	0.31 (1.72%)
				B2: 1 hour after rest	-0.781	2.042	0.41 (3.32%)
				B3: 2 hours after rest	-2.409	1.789	0.58 (6.81%)
	B-2 (Sheet metal worker)	38	Male	B1: Right after rest	-2.010	3.046	0.08 (11.10%)
				B2: 1 hour after rest	3.488	4.649	0.10 (5.59%)
				B3: 2 hours after rest	-2.157	1.590	0.09 (4.83%)
	B-3 (Sheet metal worker)	49	Male	B1: Right after rest	2.915	-2.795	0.11 (0.97%)
				B2: 1 hour after rest	5.043	0.330	0.07 (9.04%)
				B3: 2 hours after rest	-0.089	1.666	0.29 (7.31%)
	B-4 (Sheet metal worker)	26	Male	B1: Right after rest	-0.864	-0.004	0.40 (0.93%)
				B2: 1 hour after rest	3.083	-2.954	0.11 (11.12%)
				B3: 2 hours after rest	-5.628	2.194	0.67 (2.06%)

Note: *Total # of sessions (datasets) = 29; **Total # of cortisol samples = 22

3.6 Results

Table 3.1 shows all the subjects' valence and arousal levels from EEG signals as well as their cortisol values. To analyze cortisol values, I used a commercially available assay kit that accurately measures hormones. The percentage coefficient of variation (%CV) is calculated, which is defined as the standard deviation of multiple measurements of each sample divided by the mean of them when the samples are run on multiple assays. Under 15%CV is generally acceptable for a reliable cortisol value measurement (Luecken and Gallo 2008).

3.6.1 Validation

As explained earlier, previous studies on EEG-based emotion measurement have mostly been conducted in a controlled laboratory environment using a controlled stimulus targeting a particular emotional state (e.g., visual stimulus such as a response to a horror movie or pictures: Lee and Hsieh 2014; Hou et al. 2015). Therefore, the reliability of EEG-based emotion measurement can be examined by comparing target emotional states (e.g., fear from a horror scene) and detected emotions by EEG signals. However, a major challenge of field emotion measurement in a naturalistic environment using EEG is that it is very difficult to introduce stimuli that can induce a particular emotional state. This makes it difficult to confirm whether the detected emotional state by EEG is valid or not.

An alternative is to use biochemical responses, particularly cortisol. Originally, cortisol has been used as a reliable marker to interpret stress because this stress-related hormone changes in response to stressors to cope with them (Levine et al. 2007; Russell et al. 2012; Sharma and Gedeon 2012; Hou et al. 2015). Given that one's emotional state is the most critical aspect of stress (particularly, emotional stress) (Hou et al. 2015), cortisol can provide meaningful information on emotional states. Specifically, previous studies have found the positive correlation of cortisol values with the degree of anger, anxiety, and depression (Vedhara et al. 2003; Brummett et al. 2012; Het et al. 2012). Such emotional states with high cortisol values (i.e., anger, anxiety, and depression), which are generally regarded as negative feelings, are very closely associated with negative valence levels even though arousal levels are either positive (e.g., angry with negative valence and positive arousal) or negative (e.g., depressed with negative valence and negative arousal), according to the valence-arousal model in Figure 3.1 (Russell et al. 1989; Burkhardt 2001). Therefore, significant negative correlations between valence levels and cortisol values can demonstrate the feasibility of this study's emotional state measurement.

Figure 3.6 shows the relationship between valence levels and cortisol values for 22 datasets. As shown in this figure, the Pearson product-moment correlation coefficients (r) and p-values are calculated between valence levels and cortisol values. A significant negative correlation is found between valence and cortisol ($r = -0.528$, $p < 0.01$). Here, a higher valence level indicates more positive and pleasant emotions (e.g., happiness, excitement, pleasure, or satisfaction) while a higher cortisol value means that an individual is more likely to have negative and unpleasant feelings of anger, anxiety, or depression. As a result, this negative correlation demonstrates the feasibility of measuring emotional state measurement in the field using a wearable EEG sensor.

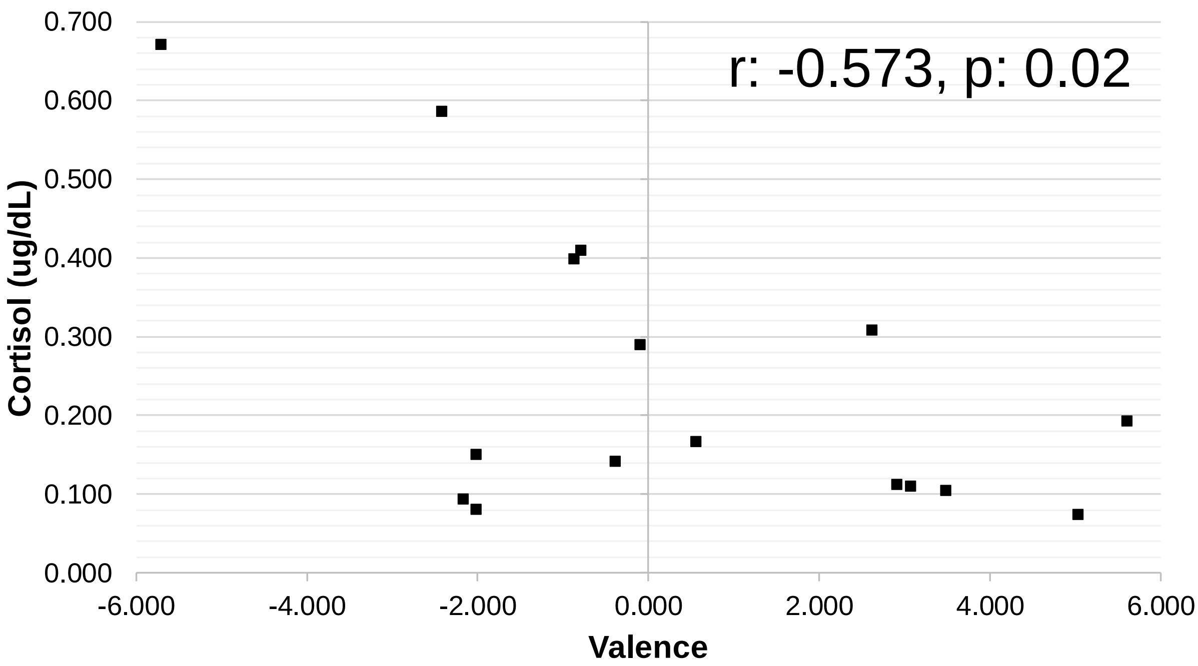

Figure 3.6. Emotional States of Valence and Cortisol Values

3.6.2 In-depth investigation of workers' emotions

Based on measured emotional states of workers using EEG, I performed an in-depth investigation of how workers' emotions change according to factors affecting emotions while working on construction sites. Firstly, Figure 3.7 summarizes the changes of both on-site and off-site workers' valence and arousal levels on average. Then, as shown in Figure 3.8, emotional states under different work conditions and feelings of tiredness after different working hours without resting can be inferred when average valence and arousal levels are located at the bipolar dimensions of emotions.

Workers show more positive emotions such as happiness, excitement, pleasure, or satisfaction in less stressful situations (e.g., working at ground and working one hour or less). On the other hand, workers can have negative emotions such as nervousness, stress, disappointment, irritation, and/or depression under more stressful situations (e.g., working on the ladder or in a confined space, and working two hours in a row). Such results correspond to many previous theoretical and empirical evidences that measure the effect of working hazards and a feeling of tiredness on emotions (Berger 1996; Mignonac and Herrbach 2004; Leung et al. 2016).

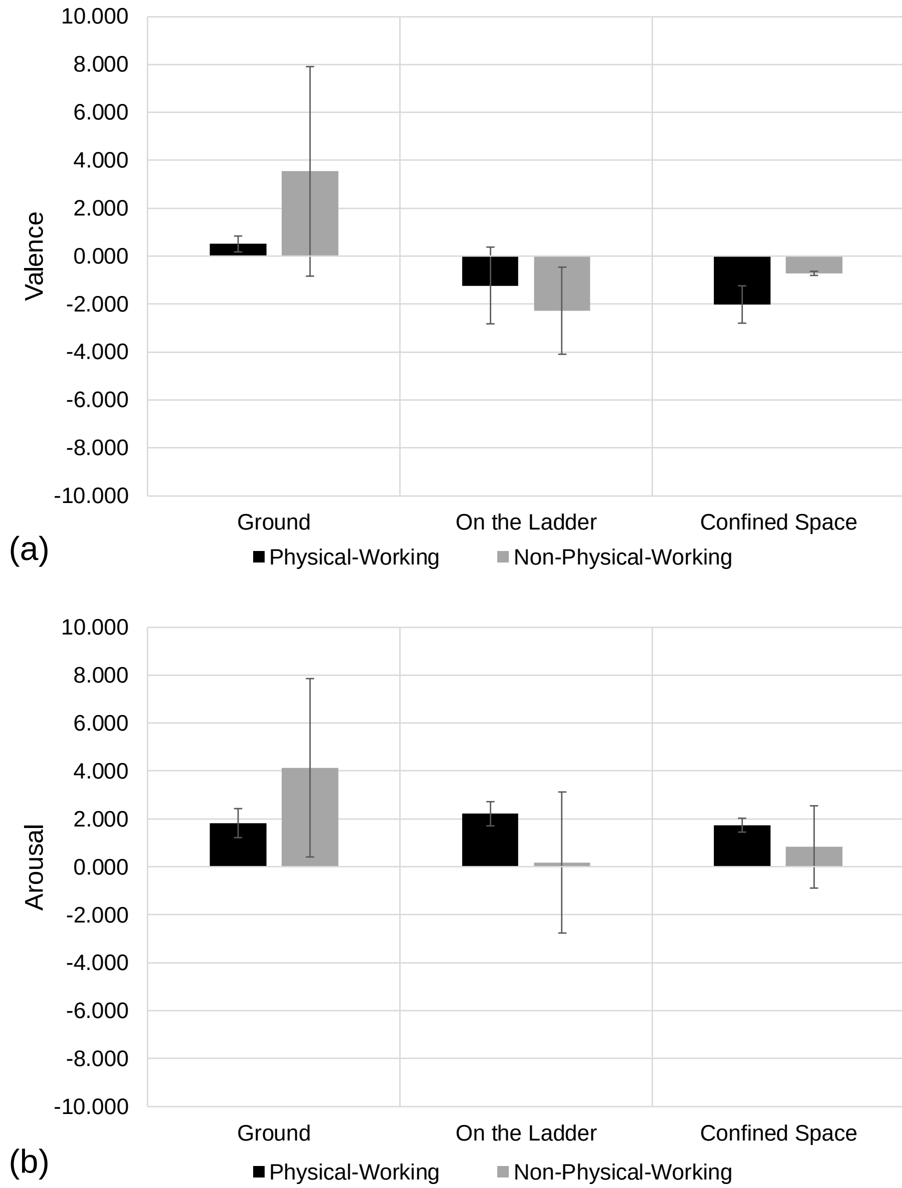

Figure 3.7. On-site Workers' Emotions in Different Work Conditions and Off-site (Shop) Workers' Emotions after the Different Amount of Working Hours: Valence and Arousal

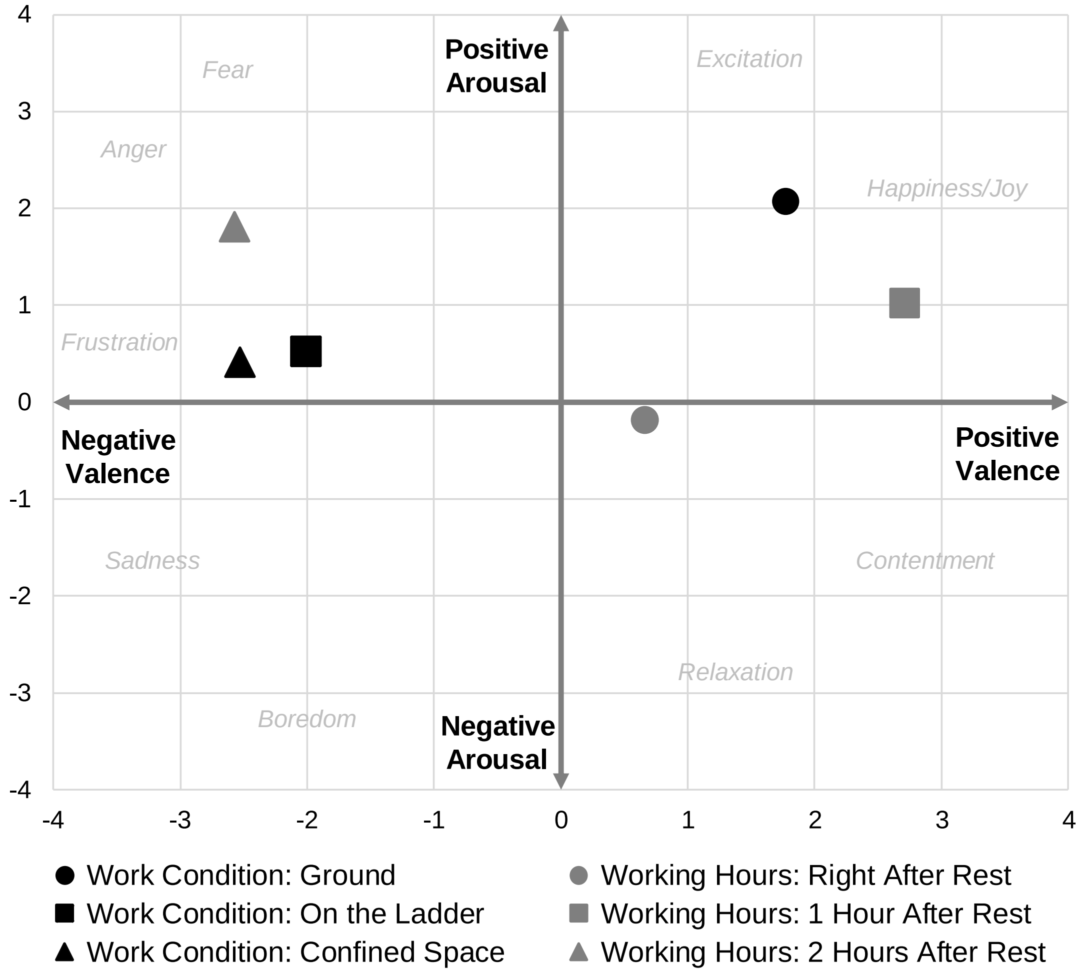

Figure 3.8. Workers' Bipolar Dimensions of Emotions While Working

Between two dimensions of emotions, workers' valence levels are more likely to be affected by work conditions and working hours (see Figure 7). On-site workers in less stressful work conditions (e.g., working at ground level) show positive valences (mean= 1.776, SD= 2.630), while those working in hazardous and stressful work conditions such as working on the ladder (mean= -2.011, SD= 1.660) and in confined spaces (mean= -2.528, SD= 3.189) show negative valences. Also, off-site workers' valence levels two hours after the scheduled resting time (i.e., the time when they continuously work during two hours without resting) are negative (mean= -2.571, SD= 2.288), while their valence levels are positive right after their scheduled resting time when they have access to refreshments (mean= 0.668, SD= 2.478). Their highest valence levels are found when workers perform their tasks one hour after the resting time (mean= 2.709, SD= 2.475). As such, it seems that such positive valences are linked to positive emotions (see Figure 3.8), even though the arousal level is either positive or negative unless it is an extreme value.

To confirm the result, I perform the Kruskal–Wallis test, which is a non-parametric one-way analysis of variance test used to assess whether different groups are same in some way, when the assumptions on the distribution of samples are not met with parametric tests (e.g., one-way ANOVA) (Hollander et al. 2013). Because of the small sample size, which makes it difficult to assume normal distribution of samples, the Kruskal–Wallis test is used. There are statistically significant differences of on-site workers' valence levels according to different work conditions (H= 9.093, p= 0.011) as well as off-site workers' valence levels according to different working hours (H= 6.500, p= 0.038) However, it is difficult to clearly infer an impact of work conditions on on-site workers' arousal levels (H= 2.587, p= 0.274) and an impact of working hours on off-site workers' arousal levels (H=1.192, p= 0.552). More detailed discussion on arousal measurement will be discussed in the next Discussion Section.

In addition, I further investigate the extrinsic effects of other factors possible to affect emotions (e.g., different ages and different work groups such as on-site workers and off-site workers). Firstly, the Spearman rank-order correlation, which is a non-parametric measure of association between two variables, is used to examine the effect of subjects' ages on emotions because assumptions required for the parametric test (e.g., normality assumption) could not be satisfied. The results show there is no significant correlation between age and two dimensions of emotions (i.e., valence and arousal). Second, I examine if working in the on-site and the off-site affects emotions because of observed significant differences in work cultures and work environments between on-site workers and off-site workers. The Kruskal–Wallis test is used to compare the effect of two groups on emotions, but no significant difference is found for both valence levels ($H= 0.567$, $p= 0.452$) and arousal levels ($H= 0.002$ $p= 0.965$).

3.7 Discussion

This study presented the potential of measuring and understanding construction workers' emotional changes during their ongoing work in the field using a wearable EEG sensor, by showing significant correlations between valence levels and cortisol values in Figure 3.6 and changes of emotions according to work conditions and working hours in Figure 3.8. Specifically, a worker's positive valence level leads to positive emotions under a less stressful situation (e.g., working at ground and working less than one hour). It is also clearly shown in Figure 3.8 that unsafe work conditions (e.g., on the ladder and in a confined space) and physically demanding working time (e.g., working two hours without resting) are likely to make workers fearful, frustrated, and/or depressed with negative valences. It is important to note that the reason for a positive valence level one hour after resting needs to be examined further, since it remains unclear whether a worker feels tired or not after continuous one-hour working. In this regard, Hwang and Lee (2017) investigated construction workers' physical demands from tasks and identified that off-site metal sheet workers' physical demands were not too high, which meant that they could be easily sustained over an hour. Moreover, I interviewed off-site subjects and found that they had a low-pressure schedule at the time of data collection with less physical demands than usual. Therefore, it was likely for off-site subjects not to feel tired until one hour after resting as indicated by their positive valence levels.

Between two dimensions of emotions, EEG's capability on measuring valence levels is particularly important because a valence level is a more critical dimension in classifying positive emotions (e.g., excitement, happiness, contentment, or satisfaction) and negative ones (e.g., fear, anger, frustration, or depression: see Figure 3.1). In addition, while other physiological responses except EEG, such as EDA, HR, and BVP, have a limited capability to measure valence levels (Takahashi et al. 2004; Zhai et al. 2005; Chanel et al. 2011), EEG, which can detect the central nervous system activities related to diverse aspects of emotions (e.g., from displeasure to pleasure and from relaxation to excitement), is a reliable means to measure valence levels (Lee and Hsieh 2014; Liu and Sourina 2014; Hou et al. 2015).

Additionally, such valence measurement is especially significant in construction workers. A positive valence level is associated with desired emotional states at the worksite that can lead to higher motivation, better attention, less stress, etc. even though arousal can be either positive or negative. Specifically, a slightly positive valence with a moderate level of arousal is closely associated with individuals' better attention and focus as well as higher productivity (Chickzentmihalyi et al 1990; Grimm et al. 2007). Moreover, a valence is more closely related to stress than arousal (i.e., low valence is linked to high stress: Hou et al. 2015). Thus, inducing a positive valence can lead to less mental stress while working thereby promoting their mental and emotional well-being. As shown in the results, workers' valence levels are more highly affected by diverse work conditions and the amount of working hours than an arousal during their ongoing work, which demonstrates that any corrective actions to working environment and way of working (e.g., modifying hazardous work conditions and frequent resting time) have a potential to induce desired valence levels at the worksite to promote workers' wellness and enhance work performance.

Despite EEG's promise in field emotion measurement, it is still challenging to clearly identify how work conditions and working hours affect workers' arousal levels. Previous studies have identified that many factors including slight physical movements, cognitive loads, or momentary distracting thoughts can cause sudden and significant arousal changes as much as a feeling of risks from hazardous work conditions and a feeling of tiredness do (Mignonac and Herrbach 2004; Pho et al. 2010; Brummett et al. 2012; Het et al. 2012; Picard et al. 2016). Because this study was conducted in a naturalistic working environment like real construction sites, it is almost impossible to completely control all the factors that could affect arousal levels even though I tried to control them (e.g., applying the same repetitive construction tasks). Nonetheless, the relationship between the individual arousal level and the brain activity recorded by the EEG has been well described in the previous literature (Makeig and Inlow 1993; Borghini et al 2014). Therefore, an attempt to measure both workers' valence and arousal levels in this study is a meaningful first step to better understand workers' emotional states in the field despite the difficulty of controlling many emotion-related factors in a naturalistic working environment.

Moreover, the research outcome in this study enable in-depth studies on how the emotions affect work performance such as safety, health, quality, and productivity. Such efforts will help to better understand which emotional states of workers are the most effective and need to be induced to achieve desired work performances, under the complex impacts of emotions on work performances (e.g., slightly positive emotions that lead to high motivations and productivity but extremely positive emotions that can cause high optimism and unsafe actions: Grimm et al. 2007).

3.8 Conclusions

This study investigated the feasibility of measuring construction workers' emotions in the field, based on two dimensions of emotions (i.e., valence and arousal levels) and using a wearable EEG sensor. The results confirmed that workers emotions can be reliably measured, particularly valence levels, which remain crucial to understanding workers' emotional states, through a comparison with physical markers (i.e., cortisol). The results also showed how workers' emotions change according to work conditions (e.g., less hazardous vs. more hazardous) and different amounts of working hours (e.g., less hours worked in a row vs. more hours worked in a row without resting).

Based on the contribution of I' previous study to collect high-quality EEG signals in the field (Jebelli et al. 2007), which provides the necessary groundwork, this study further interpreted EEG signals to measure emotional states and validated this measurement. As such, the major contribution of this study is to offer a means of reliable and continuous emotion measurement without interfering with their ongoing work using a wearable EEG sensor in the real worksite. The use of this measurement is expected to contribute to a more in-depth understanding of emotions in the demanding and hazardous construction site.

Despite the importance of both physical and psychological aspects of human workers in a labor-intensive construction industry, the body of knowledge of construction management regarding human aspects has relied more heavily on the physical realm. This imbalance is in part a consequence of a lack of field measurement of psychological states of workers. By enabling continuous, affordable, and reliable field emotion measurement, which is crucial to psychological aspects known to impact attention, motivation, decision-making, behaviors, physical and mental health and others, the outcome of this study will lead to a comprehensive study of both physical and psychological aspects of construction workers. Specifically, by studying how workers' emotions vary while working in real construction sites through continued emotion measurement while working, it can be understood which physical environments and physical works significantly impact workers' emotional states. For example, poor working conditions, which generate workers' significantly negative emotions, can be modified for a positive wellness culture in the workplace. In addition, such an understanding can provide an opportunity to find any significant relations between their emotions with work performance such as safety, health, and productivity in order to help improve human resource management in construction projects. Based on the identification of such relations, future research can also be extended to design a means to avoid significantly negative emotions and induce workers' desired emotional states at the demanding and hazardous construction site to promote mental and emotional well-being of workers and achieve desired work performances.

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Chapter 4:

Recognition of Workers' Stress Using an EEG at Construction Sites[3]

4.1 Introduction

To date, considerable attention on individuals' electroencephalogram (EEG) signals has been paid to measure and monitor workers' mental status in the clinical domain. EEG is a noninvasive measurement of the brain's electrical activity, which is generated by firing neurons in the brain (Jovanov et al. 2003; Szafir and Signorile 2011). EEG thus represents central nervous system activities along the scalp (Chen et al. 2015; Hosseini and Khalilzadeh 2010; Hou et al. 2015; Jovanov et al. 2003; Szafir and Signorile 2011). The advantage of EEG in recognizing individuals' stress is in that it can quantify stress from brain wave patterns by overcoming the possible biases of survey-based psychological stress measurement methods (Larson and Csikszentmihalyi 1983). Further, a recently available wireless and wearable EEG device can extend EEG's ability to non-intrusively assess the stress levels of construction field workers. If successfully applied in the field, continuous and affordable workers' stress recognition is enabled to overcome the limitations of

[3] Adapted from Jebelli, H., Hwang, S., and Lee, S. (2018) "EEG-based Workers' Stress Recognition at Construction Sites." *Automation in Construction*, 93, 315-324.

other cumbersome methods in field applications, which may interfere with workers' ongoing work tasks (e.g., measuring the stress-related hormonal responses such as cortisol that require cumbersome hormone sample collection: Vedhara et al. 2003).

Recently, several research efforts have enhanced the applicability of EEG devices on the construction site (Chen et al. 2015, 2017; Jebelli et al. 2017a, 2018b; a; Wang et al. 2017). For example, I' previous research proposed an advanced signal processing framework to acquire high-quality EEG signals from wearable EEG devices (Jebelli et al. 2017b). The use of this framework can overcome the major limitations associated with applying wearable EEG devices to field workers, including considerable signal noises (i.e., artifacts). In addition, other research efforts also reinforced the potential for a few features (e.g., valence, arousal, and EEG power) extracted from EEG signals to capture different brain wave patterns while workers were subjected to different stressors (Chen et al. 2017; Wang et al. 2017). The recognition of such patterns helps to understand workers' psychological states such as emotional states, attention levels, and mental workloads. Although these features can be used as informative signal features to understand the aforementioned psychological states, they are not enough when it comes to stress that is a very complex psychological state. In other words, an extensive range of EEG signal features is required to detect construction workers' stress due to complex EEG patterns from many different field stressors and among different subjects.

To address this issue, the objective of this chapter is to develop a procedure to automatically recognize workers' stress, which uses a comprehensive set of EEG signal features from the EEG signals acquired at real construction sites from a wearable EEG device. This automatic stress recognition is particularly important to detect and manage workers' excessive stress on construction sites where workers' stress levels can vary significantly according to with numerous field stressors that change over time. To achieve this research objective, I firstly collected real construction workers' EEG signals using a wearable EEG device while they were working at real construction sites. Workers' salivary cortisol levels, known as a stress hormone, were measured to label the tasks as low or high-stress. After removing EEG signals artifacts, relevant time and frequency domain features in EEG signals were calculated by applying fixed length and sliding windowing approaches. Then, several supervised learning algorithms were applied to select the best classifier to recognize worker's stress. Finally, by comparing the developed field stress recognition procedure with ones used in the clinical domains, the applicability of the developed procedure for construction workers' stress recognition will be demonstrated.

4.2 Stress and EEG

Despite different stress definitions, there is an area of agreement among these definitions; stress is the nonspecific reaction of the body and mind to changes in demands that affect human nervous system (Cohen et al. 1997). Stress interrupts the normal function of the human nervous system. The brain reacts to these distortions by releasing a series of chemical reaction (i.e., stress hormones) such as cortisol to retain the normal activity of nervous systems. Particularly, a change of currents during activation of the brain caused by stress produces a magnetic field, and this magnetic field over the scalp is measurable using EEG. Because EEG signals can provide rich information about individuals' mental status related stress, many attempts have been made to recognize and measure subjects' stress using EEG signals, mostly in the clinical domain. For instance, researchers in (Aftanas et al. 2004) showed the capability of EEG in differentiating different levels of arousal, which is defined as the state of being awoken and the degree of attention and closely associated with stress by changing under different stressors. (Kim et al. 2004) applied an audio and cognitive stimulus to recognize emotions related to stress (e.g., sadness, anger, and surprise) by applying a machine learning algorithm using subjects' EEG signals. They reported a prediction accuracy as good as 61.8%. The researchers in (Takahashi 2004) calculated six EEG features to classify five different emotions including stress and applied a Support Vector Machine (SVM), which resulted in the recognition rate of 41.7%. I in (Hosseini and Khalilzadeh 2010) used the induction visual images to generate two different levels of stress in a controlled environment such as calm-neutral and negatively-excited and obtained the accuracy of 78.3% using EEG signals with SVM classifier. The researchers in (Sani et al. 2014) reported the stress recognition accuracy of 83.33% using individuals' EEG signals. They applied a SVM to recognize the stressed subjects in a shelter center. I in (Jun and Smitha 2016) and (Hou et al. 2015) recognized individuals' stress while they induced mental stress by the Stroop color-word. They reported the prediction accuracies of 75% and 85.71%, respectively.

However, these research efforts have not been applied in the field. If applied using newly available wearable EEG devices, such stress recognition accuracies would not be guaranteed because of several hurdles in field application. These hurdles include low EEG signal quality caused by not only signal artifacts from workers' movements but also the poor spatial resolution (i.e., wearable EEG devices normally have 7-16 electrodes compared to 32-256 electrodes placed in wired EEG devices used in the clinical domain) and the low temporal resolution (i.e., wearable EEG devices data recording rate is in the range of 128-500 Hz compared to 2-100 kHz data recording range for the wired EEG devices used in the clinical domain) of wearable EEG devices. In addition, many stressors affecting stress in the real work environment requires the use of a more extensive range of signal features to recognize stress. All these challenges should be resolved before EEG signals are used to recognize construction workers' field stress.

4.3 EEG-based Field Stress Recognition Procedure

4.3.1 Overview

Figure 4.1 represents an overview of an EEG-based field stress recognition procedure developed in this study. It aims to achieve a similar accuracy of stress recognition in clinical domains overcoming all the hurdles discussed earlier. As the first step, EEG signals across 14 different channels were collected using an off-the-shelf wearable EEG device. Workers' EEG signals were labeled based on their stress-related hormone (A in Figure 4.1). Then, EEG signal artifacts were removed by applying an EEG signal processing framework signals suggested by I' previous work (Jebelli et al. 2017b) (B in Figure 4.1). After removing signal artifacts, EEG features in time and frequency domain were extracted (C in Figure 4.1). Features with the highest distinguishing power were selected among a comprehensive list of EEG features selected from the literature. Then, to select the best classifier to recognize workers' stress, the performance of several supervised learning algorithms were evaluated to recognize workers' stress (D in Figure 4.1). Details on each step will be described in the following sub-sections.

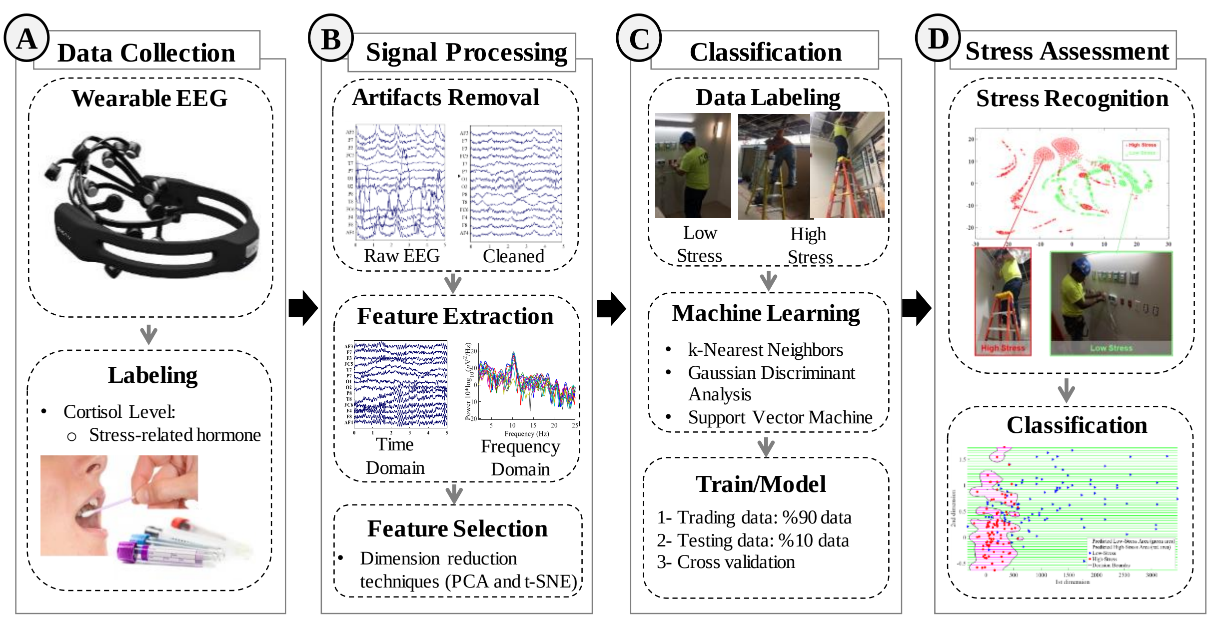

Figure 4.1 An Overview of Field Stress Recognition Procedure

4.3.2 EEG preprocessing and artifacts removal

Although the EEG device is designed to record brain activity, it also records electrical activity arising from other sources than the brain (Urigüen and Garcia-Zapirain 2015). As mentioned in Section 2, EEG signals contain a significant amount of extrinsic and intrinsic artifacts, which obscure the brain waves. The signal artifacts are significantly greater when acquiring EEG signals from construction workers at actual construction sites, due to workers' extensive movements and existing different environmental factors (e.g., construction equipment's noise). To solve this issue, I previously proposed and validated a signal processing framework suggested (Jebelli et al. 2017b) to remove EEG signal artifacts thereby acquiring high-quality EEG signals at construction sites.

Below is a summary of artificial removal steps in this framework, and more information can be found in (Jebelli et al. 2017b). Usually, extrinsic artifacts (e.g., electrode popping, movement artifacts, environmental noise, and wiring noise in the EEG sensor) have different frequencies with brain waves. Therefore, filtering the frequencies out of the range of EEG signals will remove most of the extrinsic artifacts. A bandpass filter with a higher cutoff frequency of 64 Hz and a lower cutoff of 0.5 Hz was used to remove most of the present extrinsic artifacts that cause slow and rapid changes in the EEG signals. The lower cutoff frequency criterion to design the bandpass filter was based on the frequency range of the rhythmic brain potentials detected with surface electrodes placed on the head (e.g., Delta waves 0.5–4 Hz, Theta waves 4–7.5 Hz, Alpha waves 7.5–13 Hz, Low beta waves 13–15 Hz, Beta waves 15–20 Hz, High beta waves 20–38 Hz, and Gamma waves 38–higher Hz) and the higher cutoff frequency was selected considering the EEG data recording rate (128 Hz) and Nyquist frequency, which is the highest frequency that we can expect to be present in the sampled data considering the recording rate. Nyquist frequency is equal to the half of the sampling rate (64Hz in this research). Also, a notch filter, which filters out a very narrow band of frequencies from a signal (Ferree et al. 2001), was used to remove the ambient electrodes' wire noise that comes from the power line interference signal (e.g., 60 Hz). Unlike extrinsic signal artifacts, intrinsic signal artifacts are within the same frequency range as the EEG signals. To eliminate intrinsic artifacts, an independent component analysis (ICA) was applied to detect the artifactual components (e.g., eye movement, blinking, and muscle artifacts) existing in EEG recording signals (Jebelli et al. 2017b). ICA method can isolate EEG intrinsic artifacts from the original EEG without losing EEG signal (Jung et al. 2000) by identifying the artifactual EEG components in the EEG and subtracting the components that are associated to intrinsic artifacts to achieve a clean EEG signal. ICA method has been commonly used in EEG research in the clinical domain to detect and remove intrinsic EEG artifacts (Delorme and Makeig 2004; Makeig et al. 1996; Reddy and Narava 2013; Vigário 1997; Zhukov et al. 2000). More detailed explanations about the pattern of artifactual components recorded by a wearable EEG device at actual construction sites is provided in Chapter 2 (Jebelli et al. 2017b).

4.3.3 EEG signals feature extraction and selection

The next step is to select useful features that can be used to recognize stress. In most of the machine learning algorithms, selection of relevant features is of critical importance because it affects not only the accuracy of classification but also the computational cost of classification algorithms. A feature is an informative and measurable property of the detected signals. According to the literature, there are two well-known feature selection methods: a correlation-based method and a wrapper method (Dash and Liu 1997; Hall et al. 2000). Correlation-based methods select the most useful features by ranking them with correlation coefficients. Wrapper methods assess subsets of features according to their usefulness to a given predictor (Guyon and Elisseeff 2003). Wrapper methods make various subsets of features and run learning algorithms, and the feature subsets that provide the best accuracy will be considered as the relevant features. Wrapper methods are not very practical to be used on a large number of features due to high computational cost. When dealing with EEG signals, there are a large number of features both in time and frequency domains. Learning on all the possible subsets combination and comparing the accuracy requires a high computational cost and time. Unlike wrapper methods, correlation-based methods filter out the features that have the least effect on the classification. So in this chapter, I first applied the correlation-based method to filter out the features with least correlation to the prediction accuracy. Then, I examined the optimal feature subsets that maximize classification accuracy by applying a wrapper method. 540 features were derived from 14 EEG channels (40 features for each EEG channel) from the existing literature in time and frequency domains. Among all those features, 224 features were selected using correlation-based methods. Considering the overall prediction accuracy and computational cost and time, the top 80 features (Table 4.1) that resulted in the greatest prediction accuracies were selected after applying a wrapper based methods on the selected 224 features.

Table 4.1 Time and frequency domains features, extracted from EEG signals

	Features	Equation	Explanation
Time domain	Cumulative maximum	$Cmax_{ij} = \max(EEG_{1:i,j})$	Maximum amplitude of channel j up to sample i
	Cumulative minimum	$Cmax_{ij} = \min(EEG_{1:i,j})$	Minimum amplitude of channel j up to sample i
	Mean value	$\text{MAV}_j = \frac{\sum_{i=1}^{N} EEG_{ij}}{N}$	Average absolute value of amplitude among different channels
	Median value	$Med_j = sort(EEG)_{\frac{N+1}{2},j}$	Median of the signal among different EEG channels
	Smallest window elements	$Min_j = \min_i EEG_{ij}$	Minimum amplitude among different channels
	Moving median with window size k	$MovMed_{i,j} = Median(EEG_{i:i+k-1,j})$	Median of the signal of channel j in a widow with size k samples
	Maximum-to-minimum difference	$MaxMin_j = \max_i EEG_{ij} - \min_i EEG_{ij}$	Difference between maximum and minimum of the EEG signals amplitude among different EEG channels
	Root-mean-square level	$\text{RMS}_j = \sqrt{\frac{\sum_{i=1}^{N} {EEG_{ij}}^2}{N}}$	Norm 2 of the EEG signals divided by the square root of the number of samples among different EEG channels
	Peak-magnitude-to-RMS ratio	$\text{PRMS}_j = \frac{\left\|\left\|EEG_{:,j}\right\|\right\|_\infty}{\sqrt{\frac{\sum_{i=1}^{N}\left\|EEG_{ij}\right\|^2}{N}}}$	Maximum of the EEG signal amplitude divided by the RMS_j
	Root-sum-of-squares level	$\text{RSS}_j = \sqrt{\sum_{i=1}^{N}\left\|EEG_{ij}\right\|^2}$	Norm of the EEG signals among different channels in each window
	Standard deviation	$\text{STD}_j = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N} {EEG_{ij}}^2}$	Deviation of EEG signals among different channels in each window
	Variance	$\text{VAR}_j = \frac{1}{N-1}\sum_{i=1}^{N} {EEG_{ij}}^2$	Variance of the signal EEG amplitude among different channels
	Peak	$Pk_j = \max_i EEG_{i,j}$	Maximum value of EEG amplitude among different channels in time domain
	Peak location	$LPk_j = \arg\max_i EEG_{i,j}$	Location of maximum EEG amplitude among channels
	Peak to Peak	$PP_j = LPk_j - \arg\max_{i,i\neq LPk_j} EEG_{i,j}$	Time between EEG signal peaks between the various windows
	Kurtosis	$k_j = \frac{\frac{1}{N}\sum_i\left(EEG_{ij} - \text{MAV}_j\right)^4}{\left(\frac{1}{N}\sum_i\left(EEG_{ij} - \text{MAV}_j\right)^2\right)^2}$	Shows the sharpness of EEG signals peak
	Total zero cross number	$ZCN_j = \left\|\{i \mid EEG_{i,j} = 0\}\right\|$	Number of points where the sign of EEG amplitude changes

Table 4.1 (continued)

	Features	Equation	Explanation
Frequency Domain	Alpha mean power	$\alpha_j = power(EEG_{:,j}, f \in [8Hz, 15Hz])$	Power of the EEG signal in channel j in frequency domain in the interval $[[8Hz, 15Hz]]$
	Beta mean power	$\beta_j = power(EEG_{:,j}, f \in [16Hz, 31Hz])$	Power of the signal in Beta interval
	Delta mean power	$\delta_j = power(EEG_{:,j}, f \in [0Hz, 4Hz])$	Power of the signal in Delta interval
	Theta mean power	$\theta_j = power(EEG_{:,j}, f \in [4Hz, 7Hz])$	Power of the signal in Theta interval
	Valence	$V = \frac{\alpha(F4)}{\beta(F4)} - \frac{\alpha(F3)}{\beta(F3)}$	Level of happiness
	Arousal	$A = \frac{\alpha(AF3 + AF4 + F3 + F4)}{\beta(AF3 + AF4 + F3 + F4)}$	Level of excitement
	Median frequency	$power\left(EEG_{:,j}, f \in \left[0Hz, MEDF_j\right]\right) = power\left(EEG_{:,j}, f \in \left[MEDF_j, 64Hz\right]\right)$	Half of the signal power of channel j is distributed in the frequencies less than $MEDF_j$

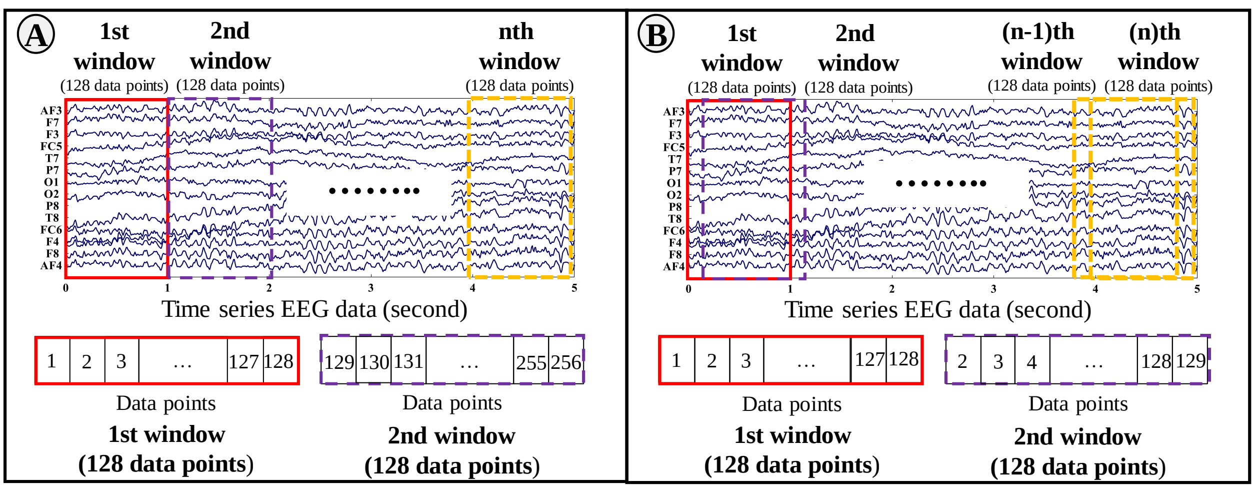

Figure 4.2 EEG windowing approaches: (a) fixed windowing approach; (b) sliding windowing approach

4.3.4 EEG classification

In this chapter, different supervised machine learning algorithms are thoroughly tested using fixed and sliding windowing approaches. The tested algorithms included *k*-Nearest Neighbors (*k*-NN), Gaussian Discriminant Analysis (GDA), Support Vector Machine (SVM) with different similarity functions (linear, Gaussian, cubic, and quadratic). Additionally, I explored the Hidden Markov Models (HMM), decision tree, and Logistic Regression approaches for classification. However, their preliminary results were discouragingly lackluster and were not pursued further. 10-fold cross validation was utilized for the selected classifiers to validate obtained classification accuracies; classification was performed ten times using 90% of data for training and 10% of data for testing each time.

4.3.4.1 K-Nearest Neighbors (k-NN)

k-NN is a memory-based algorithm, which utilizes the entire database for prediction, based on a similarity measure in the instance space (Altman 1992). Memory-based algorithms find a set of nearby data points in the instance space with similar features, known as neighbors (Daelemans and Van den Bosch 2005). To predict the label of a new data point, a group of nearby neighbors referred to as the neighborhood is formed. k-NN is based on the assumption that the nearby data points in the instance space have the same class (Beyer et al. 1999).

When a new unlabeled data $X_i \in R^d$ arrives, k-NN measures the distance, $d_E(X_i, Z_j)$, between the unlabeled target data points $\{X_1, X_2, X_3, \dots, X_m\}$, $i = 1,2, \dots, m$ and labeled training data points $\{Z_1, Z_2, Z_3, \dots, Z_n\}$, $j = 1,2, \dots, n$. Where n is the size of training data set and m is the number of unlabeled data points.

$$d_E(X_i, Z_j) = \|X_i - Z_j\|_2 = \sqrt{(\sum_{l=1}^{d}(x_i{}^l - z_j{}^l)^2)} \quad \text{(Equation 1)}$$

After calculating the distance between unlabeled data points and training data points, the subset of k nearest neighbors to the unlabeled data point is defined as $\theta_k(X_i)$ where $\theta_k(X_i) = \{\theta_1, \theta_2, \theta_3, \dots, \theta_k\} \subseteq \{Z_1, Z_2, Z_3, \dots, Z_n\}$ and the class label for θ_l, l=1,2,3,…,k defined as $L(\theta_l)$ and is derived from Equation 2.

$$L(\theta_l) = y \; where \; y \in \{+1 \; (high \; stress), -1 (low \; stress)\} \quad (2)$$

Finally, the predicted label for X_i is defined as the majority labels of $\theta_k(X_i)$ using Equation 3.

$$L(X_i) = \begin{cases} +1 \; high \; stress \; if \; |A_{+1}| \geq |A_{-1}| \\ -1 \; low \; stress \; if \; |A_{+1}| < |A_{-1}| \end{cases} \quad (3)$$

Where A_{+1} is the set of the neighbor data points labeled as +1 (high stress), and A_{-1} is set of the neighbor data points labeled as -1 (low stress). In this research, the performance of *k*-NN algorithm was optimized by selecting the smallest *k* (*k*=100) given the highest prediction accuracy. Euclidean distance metric was chosen to measure the distance between unlabeled target data points X_i and labeled training data points Z_j.

4.3.4.2 Gaussian Discriminant Analysis (GDA)

GDA is a generative machine learning method that predicts the unlabeled data by modeling a Bernoulli probability for two classes of data (-1 indicating low stress and +1 shows high stress) using Equations 4 and 5.

$$P(x|y=-1) = N(\mu_{-1}, \Sigma) = \frac{1}{(2\pi)^{\frac{n}{2}}(|\Sigma|)^{\frac{1}{2}}} \exp(\frac{1}{2}(x-\mu_{-1})^T\Sigma^{-1}(x-\mu_{-1})) \quad (4)$$

$$P(x|y=+1) = N(\mu_{+1}, \Sigma) = \frac{1}{(2\pi)^{\frac{n}{2}}(|\Sigma|)^{\frac{1}{2}}} \exp(\frac{1}{2}(x-\mu_{+1})^T\Sigma^{-1}(x-\mu_{+1})) \quad (5)$$

where x_i is training data points and y_i is the labels, $\mu_{-1} \; and \; \mu_{+1}$ are different classes mean values, and Σ is the covariance of $N(\mu, \Sigma)$. GDA expresses the joint likelihood of a set of data $i = 1,2, \ldots, n$ using Equation 6.

$$l(\phi, \mu_{-1}, \mu_{+1}, \Sigma) = \prod_{i=1}^{n} P(x_i, y_i) = \prod_{i=1}^{n} P(x_i|y_i)P(y_i) \quad (6)$$

where x_i is the features for i*th* data point and y_i represents data point class and $\phi = \frac{\sum_{i=1}^{n} y_i}{n}$ is the parameter of Bernoulli distribution. Finally, the predicted label for X_i defined as the maximize conditional probability of labels given data point x using Equation 7.

$$L(X_i) = argmax_{k=1,\dots,m} P(y|x) = argmax\ \left(\frac{P(x|y)p(y)}{p(x)}\right) = argmax\ (P(x|y)p(y)) ==$$

$$\begin{cases} +1\ high\ stress\ if\ P(y=1|x) > P(y=-1|x) \\ -1\ low\ stress\ if\ P(y=1|x) < P(y=-1|x) \end{cases} \quad (7)$$

4.3.4.3 Support vector machine (SVM)

SVM is a supervised learning method frequently used in machine learning and data mining (Burges 1998). SVM has been introduced as an appropriate classifier for physiology data class actions (Liu et al. 2005). SVM creates hyperplanes that separate data points of a binary classification problem. SVM applies an iterative learning process to converge into an optimal hyperplane that maximizes the margin between data points of two classes by minimizing following objective function.

$$\min_{w,b,\xi} \frac{1}{2}||w||^2 + \frac{C}{n}\sum_{i=1}^{n} \xi_i \quad for\ i = 1, \dots, N \quad (8)$$

where $C > 0$ is a user specified tuning parameter, and n is the number of training data points. In linear SVM, the separating hyperplane $\mathcal{H}$ is defined as $\mathcal{H} = W^T X = \{x| < w, x > +b = 0\}$ where *w* is a normal vector and $w \in R^m$, $b \in R$ and <.,.> denoting the inner product. Linear-SVM solve the objective function (Equation 8) by considering following constrains $[y_i(< w, x > +b) \geq 1 - \xi_i\ , i = 1, \dots, n\ , \xi_i \geq 0]$.

If the data points are not separable using linear SVM, a non-linear SVM employs a transfer function $\phi(X)$, which maps the data point x_i of data space to a feature space *H* where the separable hyperplane can be defined. Non linear-SVM uses a mapping function $\phi(X)$ to create a *m*-dimensional feature space from a *n*-dimensional input data, in which *m* is greater than *n*. In other words, SVM maps data into a richer feature space, which allows for a definition of the hyperplane that separates the data points that are not easily separable in the input data dimension. Non-linear SVM solves the objective function (Equation 8) by considering the following constraints [s.t$y_i\left(\sum_{j=1}^{m} w_i\, \phi_j(X_i) + w_0\right) \geq 1 - \xi_i,\ i = 1, \dots, n,\ \xi_i \geq 0$], where y_i represent class labels, *w* is the weigh vector, $\phi(X_i)$ is the mapping function, ξ_i is a nonnegative slack variable that generalized the classifier with soft margins, w_0 is constant that captures offset of data points, and N is training data points number.

In this chapter, I examine both linear and non-linear SVMs. Three different mapping functions, including cubic polynomial: $K(x_i, x_j) = (1 + x_i{}^T x_j)^3$, quadratic polynomial: $K(x_i, x_j) = (1 + x_i{}^T x_j)^4$, and Gaussian radial basis function: $K(x_i, x_j) = \exp(\frac{-\|x_i - x_i\|^2}{2\sigma^2})$, were selected for non-linear SVM. After determining $\mathcal{H}$ using Equation 8 by selecting appropriate mapping function, unlabeled data class will be decided using decision function.

$$L(x_i) = sign\ (W^T \phi(x_i)) = \begin{cases} +1\ high\ stress \\ -1\ low\ stress \end{cases} \qquad (9)$$

4.4 Field Construction Workers' EEG Data Acquisition

To examine the performance of the developed field stress recognition procedure, I collected EEG signals from three real construction sites: an office building renovation site in Detroit, Michigan (collected on March 18–25, 2016); a hospital renovation site in Gary, Indiana (obtained on February 22, 2017); and one off-site HVAC-sheet metal fabrication shop in Wixom, Michigan (collected on March 28–April 4, 2016) using an off-the-shelf wearable EEG device. The data collection protocol was approved by the University of Michigan Institutional Review Board (IRB Approval no. HUM00102068).

4.4.1 Subjects and data acquisition process

EEG signals were obtained from 11 male workers. Subjects reported no history of epilepsy, learning disabilities, and mental disorders. Seven subjects working at on-site construction sites were asked to perform the same repetitive tasks in three different conditions with varying levels of operating hazards (i.e., working on the ground, at the top of a ladder, and in a confined space), as shown in A of Figure 4.3. Four subjects working in an off-site fabrication shop were asked to perform their daily tasks at different times with a varied number of working hours after resting (i.e., right after, and one or two hours after the scheduled resting time), which could yield different stress levels, as shown in B of Figure 4.3. I' previous study showed that workers feel more negative emotions while working at the top of a ladder/in a confined space and continuous working without taking an enough break than working on the ground and working after having enough break time (Hwang et al. 2018).

Using an off-the-shelf wearable EEG device (e.g., Emotiv EPOC+ that this study used as denoted by C in Figure 4.3), workers' brain waves from 14 channels (D in Figure 4.3) were captured. Data was with a rate of 128 Hz deliverable. The data-collecting resolution was set at 14 bits with the connectivity at a 2.4 GHz band and a dynamic range of 8,400 μV (pp). Data collection was approved by the University of Michigan's Institutional Review Board. Before starting the data collection sessions, subjects were informed of the purpose of this study and provided with a comprehensive explanation of the data collection process.

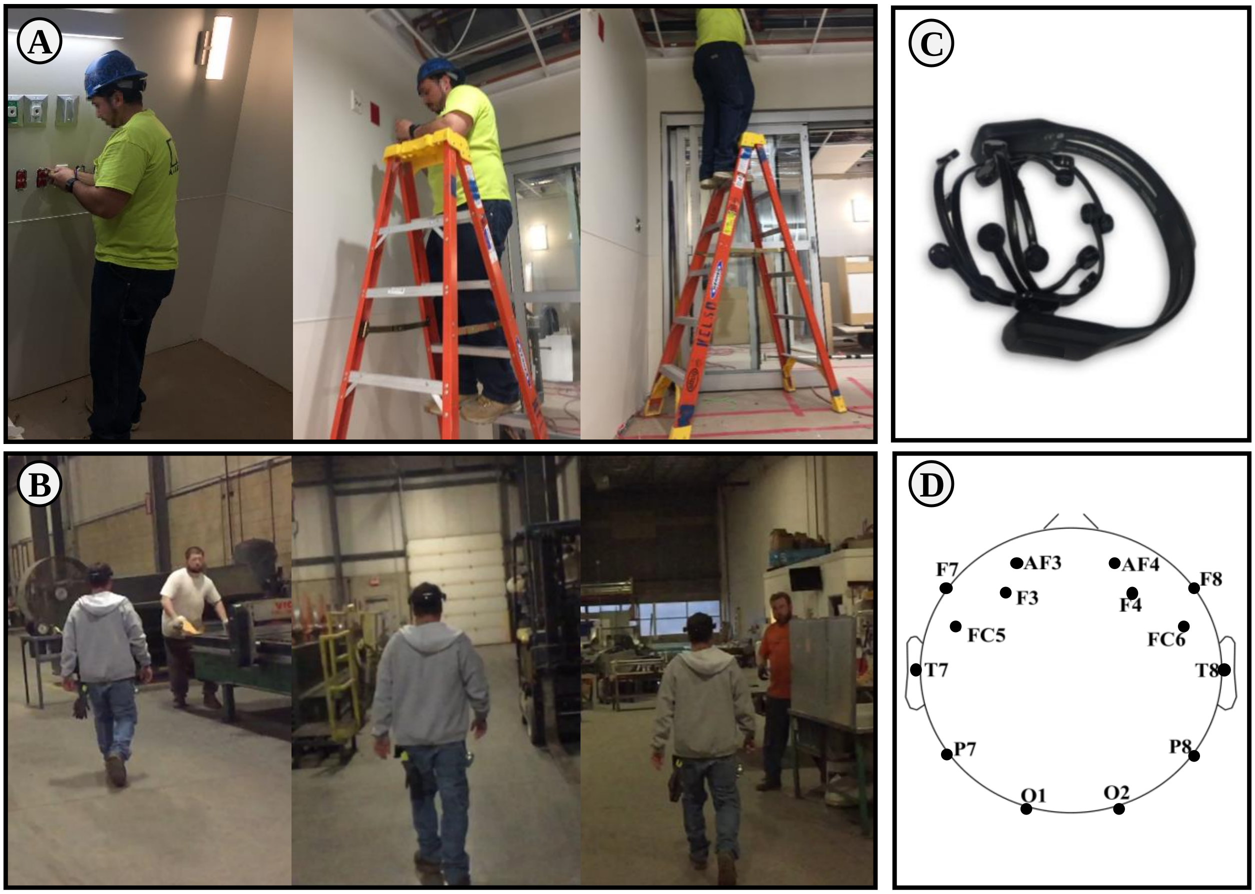

Figure 4.3 EEG data collection in-field; (a) working in a construction site with different work conditions; (b) working in an off-site shop while subjects work different amounts of working hours; (c) wearable EEG headset (Emotiv EPOC+); (d) location of EEG electrodes

4.4.2 Data labeling

In order to select the appropriate labels for data (i.e., low stress and high stress), I selected two job site stressors: working hazards and tiredness. Working in hazardous conditions (e.g., working at the top of a ladder and working in a confined space) and feelings of tiredness over time (e.g., continuous work without taking a break time) adversely affects workers' stress levels (Berger 1996; Leung et al. 2016; Mignonac and Herrbach 2004). These tasks were labeled as the tasks with higher-level stress. On the other hand, working on the ground level and working right after taking a short break time were labeled as low stress tasks.

In addition to these assumptions, I screened subjects' stress by measuring their cortisol levels to confirm these assumptions. To screen the data and select the most appropriate datasets to train and test the field stress recognition procedure, I measured subjects' cortisol levels obtained from their saliva samples after each session. A higher cortisol level indicates a higher stress level (Levine et al. 2007). Out of 11 subjects, we selected 7 who had significantly higher cortisol levels while working in hazardous conditions and working in a row without resting. Table 4.2 shows demographic characteristics of the selected seven subjects. Table 4.3 summarized the cortisol level, data size, and assigned labels to different datasets. One notable point is that there is not a significant change in the cortisol level of Subject 2, who works in a shop, while working right after the rest (cortisol level is 0.08 µg/dL) and 1 hour after the rest (cortisol level is 0.10 µg/dL). However, this subject asked to stop the experiment because of the high occupational stress this subject perceived after 1 hour of the break time, so that we assigned a high stress label for this data.

Table 4.2 Subjects sample information (n=7).

Statistical Parameters	Age (years)	Height (ft.-in.)	Weight (lb)	Working Experience (years)
Mean	37.9	5 10	202.3	16.4
SD	8.8	0 4	30.4	9.8
Min value	26.0	5 3	151.0	3.0
Max value	50.0	6 3	235.0	31.0

Table 4.3 Overview of participants' data size, cortisol level, and label.

Site	Subject	Session#	Work Conditions	Cortisol [µg/dL] (%CV*)	Data size [128 data/second]	Label
On-site	1	1	At ground	0.21 (8.00%)	76800	Low Stress
		2	At the top of a ladder and in confined space	0.4 (7.48%)	76800	High Stress
	2	1	At ground	0.16 (2.77%)	76800	Low Stress
		2	At the top of a ladder and in confined space	0.36 (4.12%)	76800	High Stress
	3	1	At ground	0.10 (10.81%)	76800	Low Stress
		2	At the top of a ladder and in confined space	0.16 (10.28%)	76800	High Stress
Off-site (Shop)	1	1	Right after rest	0.30 (1.72%)	61440	Low Stress
		2	1 hour after rest	0.40 (3.32%)	61440	High Stress
	2	1	Right after rest	0.08 (11.09%)	61440	Low Stress
		2	1 hour after rest	0.10 (5.59%)	61440	High Stress
	3	1	Right after rest	0.11 (0.96%)	61440	Low Stress
		2	2 hours after rest	0.28 (7.30%)	61440	High Stress
	4	1	Right after rest	0.39 (0.93%)	61440	Low Stress
		2	2 hours after rest	0.67 (2.05%)	61440	High Stress

Note: *CV= Percentage coefficient of variation of cortisol levels, CV lower than 15% is known as a reliable cortisol measurement.

4.5 Results

I applied the proposed field stress recognition procedure on the data collected from real construction sites after randomly dividing 90% of the data into training and 10% into testing data. Table 4.4 shows the classification accuracies among all the tested methods based on the fixed and sliding window approaches. The classification accuracies were calculated as the proportion of the correctly predicted results (both true high stress and low stress) among the total number of the tested data point. Gaussian SVM, which used the fixed window approach to extract the features as learning inputs, showed the highest prediction accuracy of 80.32% among the tested supervised learning methods.

Table 4.4 Classification accuracies of each tested algorithm.

Algorithm	Classification accuracy (%)	
	Fixed Window	Sliding Window
k-NN	65.80	61.12
GDA	74.92	69.98
Linear SVM	75.9	69.54
Cubic SVM	77.71	65.25
Quadratic SVM	69.62	63.24
Gaussian SVM	80.32	72.15

A comparison of different windowing methods revealed that fixed window size showed better prediction accuracy among all the classification algorithms. Visualization of the trained SVMs provides us with intuition about the classification's performance. Figure 4.4 visualizes the decision boundaries and the performance of various classification methods of a randomly selected subset of data after applying a dimension reduction algorithm (principal component analysis method (PCA)) to reduce the dimensions of the feature vector to two dimensions. The first PCA component captures the highest amount of the variance in the feature vector. The second PCA component is orthogonal to the first principal component to capture the variance in the feature vector that is not captured by the first principal component. We normalized all the features before applying the PCA. Therefore, the results are all dimensionless. In Figure 4.4, the light-gray background shows the area that is predicted by the classifier to be low-stress and the dark-gray background shows the area predicted to be high-stress. Gray triangle and white circle points show the actual labels of the data points. As shown in Figure 4.4, Gaussian SVM shows the best distinction between low and high stress data points and better prediction performance compared with other algorithms.

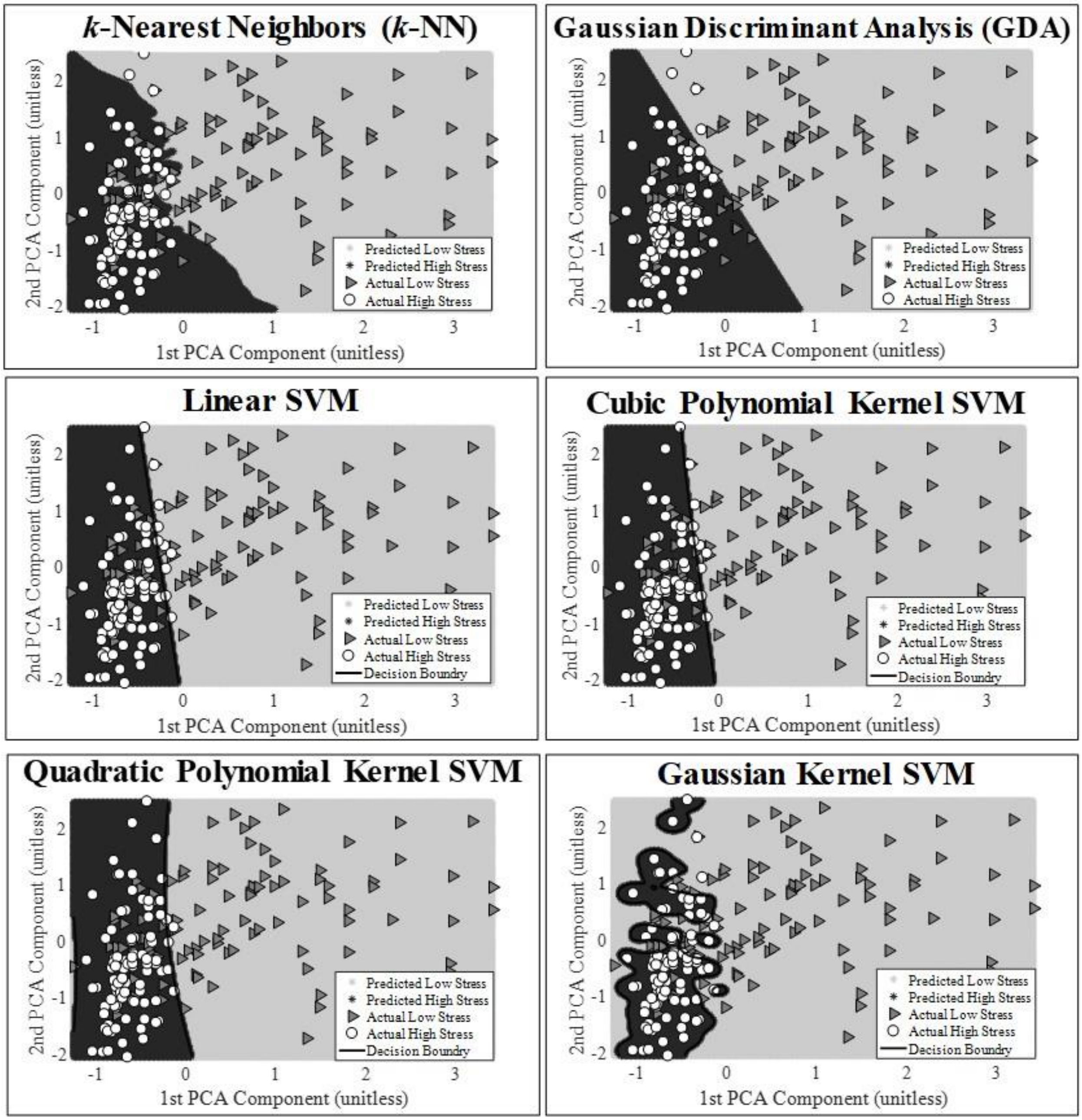

Figure 4.4 Hyperplanes and decision boundaries by applying different classifications

4.6 Discussion

The results show the capability of the proposed procedure in field recognition of construction workers' stress while working at real construction sites using EEG signals recorded from a wearable EEG device. The results of the proposed procedure are competitive with other stress recognition algorithms with a binary labeling setting in the clinical domain that are using a wired-EEG device in the controlled environment while their subjects were in stationary conditions with the minimal body movements: 85.60% in (Al-Shargie et al. 2017); 87.30% in (Al-shargie et al. 2015); 80.43% in (Jie et al. 2014); and 77.90% in (Shen et al. 2007). For instance, the researchers in (Al-shargie et al. 2015) recorded the brain waves of 12 healthy male subjects using an exquisite and wired EEG device. They recognized subjects' stress while subjects were under the stress of solving arithmetic problems. Subjects were asked to minimize their head movement during the data collection to minimize EEG signal artifacts. They reached the average classification accuracy of 87.30% by applying a SVM. Compared with the existing stress recognition procedures, the proposed stress recognition in this research provides a promising result considering that acquiring and processing the EEG signal was challenging from significantly moving subjects during the field data collection using a wearable EEG.

Among all tested classifiers used in the field stress recognition procedure, SVM showed higher prediction accuracy; this can be related to the high performance of SVM to deal with overfitting by tolerating some misclassifications on the training dataset. In recognizing stress using EEG signals, due to the number of EEG channels and the complexity of EEG signals, I need to have a large number of features to recognize stress appropriately. As such, the increasing number of features increases the probability of overfitting in training process. SVMs algorithms tend to be resistant to the overfitting problem. This is because SVM is optimizing its parameters over the training process to prevent the overfitting problem (Cawley and Talbot 2010). To decrease the probability of overfitting, SVM derives a generalization error bound, which depends on the SVM margin and is independent of the outliers and the dimensionality of feature space. As a result, it is expected that SVM will demonstrate reliability when dealing with large dimensions feature space data such as EEG signals.

Conversely, *k*-NN showed the lowest prediction accuracy among all the selected methods; this might be related to the inductive bias of *k*-NN method. *k*-NN inductive bias corresponds to the underlying assumption of *k*-NN method that classifies each instance data point *i* as the class label of the majority of other *k* neighboring instances by measuring Euclidean distance. This causes a practical problem while dealing with EEG signals that require measuring a large number of signal features among different channels to represent signals patterns adequately. *k*-NN algorithm measures the distance between instances based on all features of the instance and considers the same weight for all the features; this becomes problematic for some data windows that only a small subset of the entire feature set is the discriminative features. Also, the *k*-NN performance is sensitive to noisy features. Although we removed a large number of signal artifacts, however, it is not possible to remove all the artifacts from EEG recording and EEG signals usually known as noisy signals, and there are some sources of noise that are unavoidable.

Upon further investigation of the misclassified labels, I noticed that 71% of the misplaced labels occurred among low-stress level detection. In other words, the classification accuracy is consistently better for high-stress detection rather than low-stress detection. This can be explained by the better performance of selected stressors to elicit high stress (e.g., working at the top of a ladder in a confined space) comparing with the stressor that has been chosen to cause low-stress conditions (e.g., working on the ground).

One unanticipated finding was that the applying sliding windowing method to extract EEG features led to a lower stress recognition prediction accuracy compared to fixed windowing approach among all the selected method. Applying the sliding windowing approach to extract EEG features increases the size of the training set and may smooth specific features, as well as provide consistent feature mapping inputs between training and testing steps. On the other hand, it may increase the computational cost and time as well as decrease the testing accuracy as the results of overfitting during the training process. Also, considering that sequential EEG signals have different levels, applying this technique will increase the likelihood of mislabeling EEG signals.

Several limitations still exist and need to be addressed in the future research. Different subjects show different brain wave patterns while facing the same stressors. These various patterns among different subjects adversely affect the performance of the proposed stress recognition procedure due to the static nature of the supervised learning algorithms used in the proposed procedure. To further improve the stress recognition accuracy, I suggest applying multi-subjects/tasks learning algorithms, which optimize classifier parameters for different tasks and subjects.

In addition, the recognition of varying stress levels will help to enhance the suggested procedure in this research. Although the Gaussian SVM classifier proposed in this research separated data into two classes (low stress and high stress), recognition of more classes can be done in future research by plugging in voting algorithms to the proposed procedure in this research (Hsu and Lin 2002).

4.7 Conclusions

This study developed and examined a field procedure to recognize construction worker's stress at real construction sites by applying supervised learning algorithms stress using a broad range of

EEG signal features. To select the best classifier in this procedure, this study examined the performance of several supervised learning algorithms in recognizing worker's stress from EEG signals collected at the real construction site using an off-the-shelf wearable EEG device. Notably, based on the results garnered from seven workers and among all tested classifiers, Gaussian SVM, which relies on a fixed windowing approach has the highest stress recognition accuracy. This accuracy of recognizing field workers' stress level in a real construction site is very promising given the competitive accuracy of stress recognition in clinical domains where extricate and wired EEG devices were used and stressors were controlled in a laboratory setting. The proposed field stress recognition procedure can be used as a mean toward affordable and continuous monitoring of workers stress under various stressors in construction sites, which can contribute to workers' stress management. It is noteworthy to mention that despite the large size of datasets (952,320 data points in total) and applying a validation step (10-fold cross-validation), the data was collected from seven subjects. To confirm the performance of the proposed framework in recognizing the stress level of workers with various trades, it is recommended that future studies further examine the performance of the proposed framework using a bigger sample size collected from more workers.

4.8 References

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Chapter 5:

A Continuously Updated, Computationally Efficient, Stress-Recognition Framework Using EEG by Applying Online, Multi-Task Learning Algorithms (OMTL) [4]

5.1 Introduction

Occupational stress is defined as the harmful physical and emotional responses that happen when the requirements of the job are greater than workers' capacity (Sauter et al. 1999). Numerous statistics and studies show that occupational stress has become the major source of stress in the U. S. (Sauter et al. 1999), in which 32% of workers reported extreme stress at work. Excessive job stress can have a detrimental impact on workers' performance (e.g., productivity, safety, health and well-being) (Leung et al. 2008). In addition, recognizing workers' stress has been known as one of the main challenges in the area of human factor research (Aricò et al. 2017a; Graziani et al. 2016).

[4] This chapter is adapted from Jebelli, H., Khalili, M, and Lee, S. (2018) "A Continuously Updated, Computationally Efficient Stress Recognition Framework Using Electroencephalogram (EEG) by Applying Online Multi-Task Learning Algorithms (OMTL)." *IEEE journal of biomedical and health informatics*, Sep (18).

A number of studies have been carried out to assess individuals' stress by employing subjective assessment of stress (e.g., stress questionnaires (Bashir and Ismail Ramay 2010; Kawakami et al. 1995; Mucci et al. 2015). Though these studies were successful in capturing signs of stress over a long period, they interfere with time-sensitive tasks since workers have to stop their ongoing work to answer questionnaires. Alternatively, when workers are asked to complete the questionnaires after the work is completed, the method of capture is subject to high biases since they rely on the reconstruction of feelings in the past. (Leung et al. 2016; Morris 1995; Tsutsumi et al. 2018).

Several neuroimaging approaches, e.g., magnetic resonance imaging (MRI), functional MRI (fMRI), positron-emission tomography (PET), single-photon-emission computed tomography (SPECT), and functional near-infrared spectroscopy (fNIRS), have been used to determine the effects of psychological stress on neural activity of the brain (Al-Shargie et al. 2017; Bremner et al. 1995, 2003; Rauch et al. 2000; Wang et al. 2005). Despite the potential of these methods to identify individuals who are at risk to develop stress-related disorders (Dedovic et al. 2009), these methods are not designed to assess individual's stress continuously.

A promising alternative to measuring stress is to utilize physiological responses. When individuals experience stressful conditions, the autonomic nervous system is activated, thus causing an imbalance between the sympathetic and parasympathetic systems. As such, physiological responses that are related to the nervous systems, such as electroencephalography (EEG), electrodermal activity (EDA), and photoplethysmograph (PPG), could be indicative of workers' stress. Among different physiological responses, electroencephalography (EEG), which is a method to collect electrical activity of the brain along the scalp and transmit them to an amplifier, can provide rich and reliable information on the factors that cause stress. Electrical activity of the central nervous system elicited by stressors can be characterized by the EEG signals (Hou et al. 2015b; Matthews 2000; Sharma and Gedeon 2012). Particularly, continuous recording of EEG signals on a near real-time basis can greatly contribute to an understanding of field workers' stress patterns because EEG signals are rapidly (millisecond by millisecond) responding to many different stressors (Ranabir and Reetu 2011). Therefore, EEG can be very useful in studying field stressors, developing online physiological monitoring systems, and passive brain-computer interfaces in the field (Aricò et al. 2017b; Ortiz-Rosario and Adeli 2013) compared with other physiological responses (e.g., PPG, EDA, blood pressure-volume) that have a time lag (Jebelli et al. 2018a).

Previous EEG studies attempted to assess individuals' stress by studying the changes in the patterns of their brainwaves while individuals were exposed to various stressors, mostly when subjects were in a stationary position in a controlled laboratory (Al-shargie et al. 2015; Al-Shargie et al. 2017; Jie et al. 2014; Shen et al. 2008). Such conditions might be problematic due to the difficulty of simulating all the actual real job sites stressors in a controlled environment when it comes to stress in the field. Also, the current stress recognition frameworks define one single classifier to recognize individuals' brainwave patterns under various stressors using batch-learning algorithms (e.g., supervised learning methods). Applying one single classifier to recognize different subjects' brainwaves increases the prediction error due to the fact that the same stressor may not have the same effect on different individuals' brainwaves. Another limitation of current stress recognition algorithms is that the prediction usually happens in an offline setting, which requires storing all the data to update the classifier. This will dramatically increase computational time and memory usage if someone wants to update the classifier once new data arrives. Therefore, there is a limitation in the efficient recognition of multiple subjects' stress, particularly while they are facing various stressors at actual job sites.

To address these gaps, this study proposes a new stress recognition framework featured with continuous updates of stress classifier, which can be gradually extended to stress recognition for new stressful situations that are beyond the range of pre-defined brainwave patterns for stress. In addition, the framework can train a specific classifier for each subject and consider the interaction between different classifiers to train a new EEG dataset. As a result, it is expected that the stress recognition accuracy and precision would be higher as compared to previous EEG-based stress recognition frameworks that considered a classifier for the entire dataset (Al-shargie et al. 2015; Al-Shargie et al. 2017; Jebelli et al. 2018b; c; Jie et al. 2014; Shen et al. 2007). Furthermore, since the proposed framework recognizes stress in near real-time it may be advantageous to be used on actual job sites, not only in a controlled environment. Also, there is no need to store the previous data and update the classifier on the entire dataset. This will significantly lower the computational time and memory usage compared with previous batch learning based stress recognition frameworks. The proposed framework applies Online Multi-Task Learning (OMTL) algorithms to recognize the pattern of subjects' brainwaves under stressful conditions in near real-time using a broad range of EEG signal features. The proposed framework optimizes OMTL parameters (e.g., learning rate and epoch) based on EEG data. Therefore, OMTL can make a new decision to identify stressful situations when new EEG dataset from different subjects or the same subject under different stressor is available.

To examine the performance and to show the versatility of the proposed framework, I applied this framework to two different datasets. The first dataset is a Dataset for Emotion Analysis Using Physiological Signals (DEAP) (Koelstra et al. 2012). DEAP recorded EEG signals from 32 subjects in a controlled laboratory environment using a traditional wired EEG device. The second dataset is collected by me from real construction workers using a wearable EEG headset while workers were working under different conditions and facing various stressors on real construction sites. It is expected that this research will help to not only assess individuals' stress in near real-time in the controlled environment, but also recognize workers' stress while working on real job sites.

5.2 EEG-based stress recognition

Due to the rich information provided by EEG signals about the central nervous system activities, there is a considerable amount of attention to recognize individuals' stress using EEG signals (Hou et al. 2015a; Liu and Sourina 2014). In order to recognize different brainwave patterns under various stressors, previous researchers extracted and calculated different EEG signal features in time and frequency domain (Blaiech et al. 2013; Frantzidis et al. 2008; Huang et al. 2012; Jirayucharoensak et al. 2014; Khosrowabadi et al. 2014; Liu et al. 2013; Oude Bos 2006). The EEG signal features in these domains showed a high potential to distinguish different EEG signal patterns while individuals facing different stressors (Davidson et al. 1990; Li and Lu 2009; Louwerse and Hutchinson 2012; Xu and Plataniotis 2012). As a result, various time-domain signal analysis methods (Cherubino et al. 2016; Mehrkanoon et al. 2014) and different machine learning methods such as neural nets (Huang et al. 2012) and supervised learning algorithms (Hou et al. 2015b; Jebelli et al. 2018b; c; Khosrowabadi et al. 2014; Li and Lu 2009) have been applied to automatically recognize individuals' stress. Some studies found that the use of neuroanatomical observations, such as frontal area asymmetry metrics (Allen and Reznik 2015; Goodman et al. 2013; Lewis et al. 2007; Winkler et al. 2010), improves the stress recognition accuracy in addition to the time and frequency domain features (Petrantonakis and Hadjileontiadis 2012). However, most of the current research on EEG-based stress recognition is based on the EEG recorded from wired EEG devices while subjects are in the stationary postures. So, the performance of these methods has not been examined to recognize workers' stress in actual job sites, where EEG should be recorded using a wearable EEG headset in which the quality of acquired EEG is lower compared to wire EEG devices because of the lower data recording rate and less dense electrode arrays of EEG device. Also, virtual stimuli (e.g., watching a different type of musical videos) were used as the stressors to induce different levels of stress in the controlled environment. Therefore, the performance of these frameworks remains unclear while dealing with real stressors at actual job sites.

Recently, a few researchers have attempted to study the performance of wearable EEG device to assess workers' mental status (e.g., emotions, stress, and mental tasks) (Chen et al. 2015, 2016; Hwang et al. 2018; Jebelli et al. 2017a, 2018b; d). Their research efforts showed the capability of time domain, frequency domain, and related neuroanatomical features (e.g., valence and arousal) in measuring workers' emotions and stress while working in different conditions. Chapter 2 examined the capability of a wearable EEG headset to assess valence and arousal, two important neuroanatomical related features. These studies reinforced the feasibility of a few EEG-based features (e.g., EEG power, valence, and arousal levels) to distinguish various brain wave patterns while workers' worker in different conditions (e.g., different work environment). Use of these features helps to better understand workers' mental status such as attention levels, emotional states, and mental workload. However, they are not enough to find the complex patterns of the brain waves while workers expose to different stressors. To this end, I' earlier work (Jebelli et al. 2018b) developed a framework to recognize construction workers' stress using an off-the-shelf wearable EEG device by applying signal processing techniques (e.g., filtering methods and independent component analysis) and various supervised learning algorithms (e.g., k-Nearest Neighbors, Gaussian Discriminant Analysis, and Support Vector Machine). Although this framework resulted in a high-stress recognition prediction accuracy as good as 81%, the prediction is in an offline setting. Monitoring workers' stress in the offline setting can provide worthwhile information regarding detecting stressors in the job sites. However, this may not be capable of identifying workers' stresses under numerous stressful situations in a naturalistic environment. In other words, it is simply impossible to identify stress if the EEG patterns in a certain stress have not been observed and learned. In addition, this may not be used to monitor workers' stress in a near real-time basis. Supervised learning classification algorithms are not suitable to be used in near real-time due to high computational cost and time of these methods in an online setting.

5.3 Online Multi-Task Learning (OMTL)

Batch-learning techniques (e.g., k-Nearest Neighbors, Gaussian Discriminant Analysis, and Support Vector Machine) train a classifier using the entire dataset considering data labels regardless of the origin of data points. Unlike these techniques where a single classifier is defined over the whole dataset, Online Multi-Task Learning (OMTL) updates the optimal classifiers when new data is arriving (Saha et al. 2011). In OMTL, different data sources (e.g., different subjects and tasks) were named as tasks. OMTL simultaneously learns the task interactions and the classification/regression parameters among different data points across various tasks. OMTL jointly learns the related tasks and achieves generalization over all tasks (Heskes 2000). The main advantages of OMTL compared with the batch learning is that the classification can be learned from different tasks, not only the input data points in an online setting (Pratt and Jennings 1996). By sharing common feature settings like parameters of Gaussian processes (Lawrence and Platt 2004), prior distribution of Bayesian models (Yu et al. 2002, 2004), or neural structures (Baxter and others 2000), OMTL reduces the risk of overfitting by providing a generalized model of a group of similar tasks.

Since the performance of the OMTL depends highly on the similarity between tasks, it is essential to define a proper metric for measuring task relationships. Several methods and algorithms have been proposed to measure the task relationships. A task-clustering algorithm that applied K-Nearest Neighbors was introduced by (Thrun and O'Sullivan 1996). In (Bakker and Heskes 2003), researchers applied a common prior density function, forming a mixture distribution in the hierarchical model. In (Cavallanti et al. 2010), researchers have used K perceptrons, also known as K binary classifiers and Cav-OMTL, to learn K tasks as a fixed-task relational matrix. In (Dekel et al. 2007), multi-task problems were solved by applying a global loss function across tasks, compared to the learning options where the presentation of relatedness is restrictive and inflexible. In (Saha et al. 2011), researchers proposed an OMTL algorithm to learn the relationships adaptively from real-time streaming datasets and tested this approach on a spam emails classification dataset. In (Saha et al. 2011), researchers applied linear classifiers to the data from K different tasks to learn K weight vectors and a task-relatedness matrix at the same time. The learning of task relationships was framed as a Bregman divergence-minimization problem of a positive definite matrix. They selected the most informative examples and learned the relatedness matrix adaptively. Their mechanism of OMTL, while using an adaptive task relationship, outperformed existing online multitask learning algorithms such as Cav-OMTL (Cavallanti et al. 2010) in both flexibility and accuracy.

Considering multitask aspect of OMTL, it is expected that OMTL performs better on EEG-based stress recognition compared to batch learning algorithms. OMTL considers the interaction between different data that comes from different subjects, which helps to train a more efficient classifier for each subject and therefore, leads to better overall prediction accuracy. Besides, the online training and prediction aspect of OMTL makes the EEG-based stress recognition possible in near real-time. This will expand the application of the stress recognition outside the controlled lab environment, where the reconstruction of all actual job stressors is not possible. To examine the performance of OMTL algorithms, I adjust their parameter (e.g., Epoch) on the EEG datasets and apply them to recognize individuals' stress.

5.4 Method and Framework Development

I propose an adaptive stress recognition framework to capture the brainwave patterns of different subjects while working under various stressors in near real-time. The proposed framework predicts the label of new upcoming data in an online setting to improve stress recognition accuracy in case of new stressful situations. As the first step, the framework applies different artifacts removal methods to remove EEG signal artifacts. Then, a broad range of EEG signals features were extracted to examine the EEG signal patterns in various conditions. As the last step, the Epoch parameter of different OMTL algorithms were adjusted based on EEG datasets and these algorithms were applied to classify individuals' stress. Figure 5.1 shows the overall framework to assess different workers stress while working in different conditions in near real-time. Proposed framework in this research was modeled using a custom developed software in MATLAB. A MATLAB version 8.1.0.604 program was used for all of the computations.

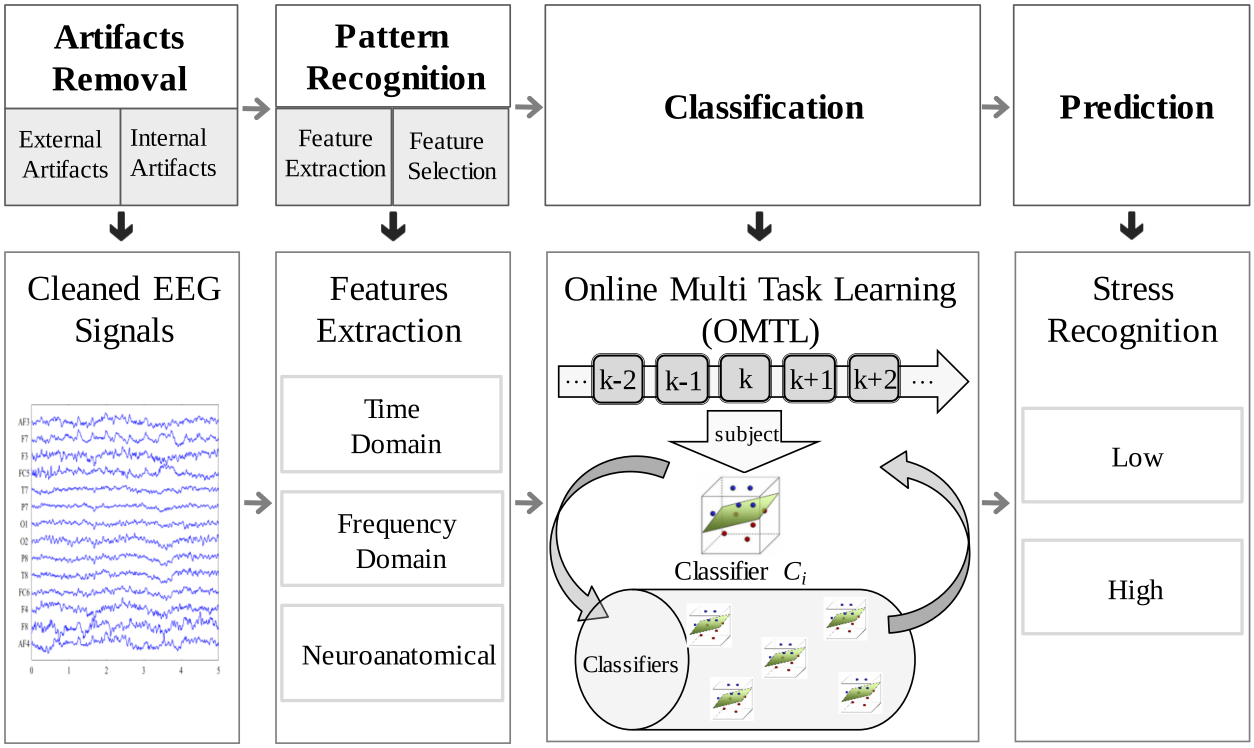

Figure 5.1 An overview of real-time stress recognition framework.

5.4.1 EEG Signal Artifacts Removal

EEG records the electrical activity of the brain at the scalp, and ranges from 20 to 200 µV (Novák et al. 2004). EEG is highly subject to different sources and forms of noise (Urigüen and Garcia-Zapirain 2015). EEG contains signal noises and artifacts mostly from two sources: intrinsic signal artifacts and extrinsic signal artifacts. The intrinsic signal artifact is defined as the signal noise that comes from the body itself such as eye blinking, vertical eye movements, and facial muscle movements. On the other hand, the extrinsic signal artifact comes from external factors (e.g., drift in the electrodes, body movement artifacts, and environment noises) or the device itself (e.g., wire's line noise). Before analyzing EEG signals, it is necessary to remove signal artifacts. This chapter is not intended to offer a comprehensive explanation of the EEG preprocessing and artifacts removal process. In this chapter, I applied the EEG signal processing framework explained in chapter 2. Below is a summary of artifacts removal procedures. Proposed EEG artifacts removal procedure is capable of reducing both intrinsic (e.g., eye movement, eye blinking, and facial muscle noises) and extrinsic (e.g., device wiring artifacts, electrode popping, movement artifacts, and environmental noise) EEG signal artifacts. First, to remove extrinsic signal artifacts, a bandpass filter (higher cutoff frequency of 64 Hz and a lower cutoff of 0.5 Hz) was applied to reduce the artifacts that cause slow and rapid changes in the EEG. Also, a notch filter was applied to filter out ambient electrodes' wire noise at 60 Hz. To reduce intrinsic signal artifacts, an independent component analysis (ICA) was applied to decompose raw EEG signals into different components and therefore identify the artifactual components (e.g., eye movement, blinking, and muscle artifacts). To calculate different components in EEG signals the Extended Infomax method was applied to decompose the original EEG recording across 14 different electrodes into 14 components (Delorme and Makeig 2004; Lee 1998). Then, three components that represented the most common intrinsic signal artifacts (i.e., eye movement, eye blinking, and facial muscle noises) were removed. More detailed information about the artifacts removal process in the field is provided in Chapter 2 (Jebelli et al. 2017b). A custom developed software based on the EEGLAB toolbox (Delorme and Makeig 2004) was used for ICA analysis. Figure 5.2 presents the raw EEG signals across 14 different electrodes before and after applying this EEG signal processing framework (Jebelli et al. 2017b).

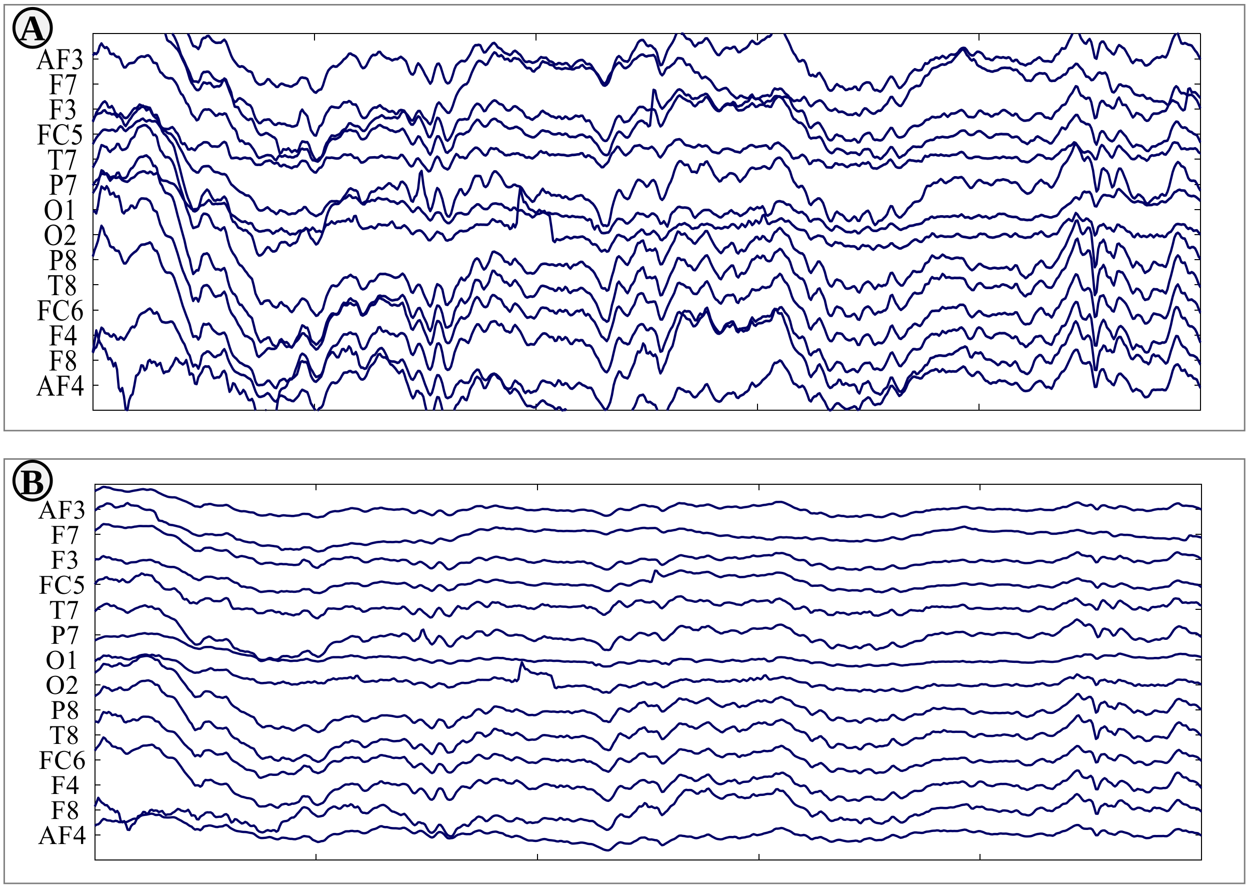

Figure 5.2 Artifacts removal: (a) Raw EEG, and; (b) Filtered EEG.

5.4.2 Feature Extraction and Selection

In order to characterize the EEG signal patterns while subjects' were faced with different stressors, extracting the relevant features is required. An EEG feature is a measurable characteristic of the EEG signals in a specific number of data points called a window. To determine the optimal window size to train and test the classifiers, I varied the window size between 0.5 (64 data points) and 10 seconds (1280 data points) by 0.5-second step (64 data points). The window size of 1-second (equal to 128 data points) was determined as the optimal window size and was selected as the window size to extract appropriate features in this chapter. This chapter attempts to calculate three categories of EEG features: time domain features, frequency domain features, and neuroanatomical features. After extracting a broad range of EEG signal features in these three categories, the framework applies two feature selection algorithms (i.e., a correlation based method and a wrapper method (Dash and Liu 1997)) to select the most relevant features.

5.4.2.1 Time Domain Features

EEG recording devices capture the original EEG signals as time-series data in a time domain. Time domain features are amplitude related (Teplan 2002). Time domain features provide rich temporal details on the EEG signals. I previously explored a broad range of EEG signal features in the time domain in order to determine the most appropriate time domain features to recognize individuals' stress (Jebelli et al. 2018b). According to Chapter 4, the selected features in the time domain are as following: EEG signal mean amplitude value, standard deviation, peak, cumulative maximum, cumulative minimum, median amplitude value, smallest element in each window, moving median within each window, maximum to minimum difference, root mean square level, peak magnitude to RMS ratio, root sum of squares level, total zero cross number, kurtosis, peak location, and peak to peak are the features that were extracted and selected on time-series EEG signals among different channels to recognize subjects' stress.

5.4.2.2 Frequency Domain Features

Frequency is the measure of the number of occurrence of an event in specified time. EEG is a non-stationary signal and captures various events that take place at the same time. If the signal is represented only by its time domain feature, the different events that are occurring at the same time cannot be captured. In order to obtain information about these events, I considered frequency domain features as well. Previous researchers have found individuals' EEG signal frequency domain features are significantly correlated with their stress level (Hosseini and Khalilzadeh 2010; Khosrowabadi et al. 2011; Lim and Chia 2015). I' earlier work (Jebelli et al. 2018b) examined a wide range of EEG features in the frequency domain; the researchers found that frequency domain features are capable of distinguishing individuals' brainwaves while working under different stressors. The selected frequency domain features and their computational procedure be explained as follows:

1. Delta mean power: it is defined as the power of the EEG signal in the frequency domain in the interval [[0.5Hz,4Hz]] across different channels and can be calculated as in (1). $\delta = power(EEG, f \in [0.5Hz, 4Hz])$ (1)
2. Theta mean power: it is defined as the power of the EEG signal in the frequency domain in the interval [[4Hz,7Hz]] across different channels and can be calculated as in (2). $\theta = power(EEG, f \in [4Hz, 8Hz])$ (2)
3. Alpha mean power: it is defined as the power of the EEG signal in the frequency domain in the interval [[8Hz,13Hz]] across different channels and can be calculated as in (3). $\alpha = power(EEG, f \in [8Hz, 13Hz])$ (3)
4. Beta mean power: is defined as the power of the EEG signal in the frequency domain in the interval [[13Hz,30Hz]] across different channels and can be calculated as in (4). $\beta = power(EEG, f \in [13Hz, 30Hz])$ (4)
5. Median frequency power: is defined as the frequency power in which half of the signal power is distributed in the lower frequencies than this frequency across different channels and can be calculated as in (5). $MEDF = power\left(EEG, f \in \left[0Hz, MEDF_j\right]\right) = power(EEG, f \in [MEDF, 64Hz])$ (5)

5.4.2.3 Neuroanatomical Features: Frontal EEG Asymmetry

In addition to time and frequency domain features, many individual-dependent emotion measurement algorithms found that frontal EEG asymmetry-based features were advantageous to recognize individuals' various emotions including stress (Goodman et al. 2013; Lewis et al. 2007; Liu and Sourina 2014; Winkler et al. 2010). Frontal EEG asymmetry (FEA) has been considered one of the most important neuroanatomical features that can represent individuals' mental status (e.g., emotions, and stress) (Allen and Reznik 2015; Winkler et al. 2010). FEA measures the dissimilarity in EEG signal power between right and left electrodes located in the frontal area of the brain (Allen and Reznik 2015). Valence and arousal are two important parameters that are highly associated with an individual's emotional states (Bradley and Lang 1994). Arousal refers to a physiological activity dimension, ranging from quiet to active mood (Russell 1980). Arousal is linked to the excitement level of individuals (Coan and Allen 2003). Valence refers to another physiological activity dimension orthogonal to arousal, ranging from misery to pleasant (Russell et al. 1989). Equations (6) and (7) are used to calculate the arousal and valence features based on EEG.

$$Arousal = \frac{\alpha(AF3 + AF4 + F3 + F4)}{\beta(AF3 + AF4 + F3 + F4)} \tag{6}$$

$$Valence = \frac{\alpha(F4)}{\beta F4} - \frac{\alpha(F3)}{\beta(F3)} \tag{7}$$

where α(i) and β(i) correspond to the power of alpha and beta frequency band obtained from i-th channel of the EEG signal.

5.4.3 Near Real-Time Classification

In order to recognize individuals' stress in near real-time, this chapter examines the performance of several OMTL algorithms with an adaptive task relationship matrix as a means to predict workers' stress at the job site in near real-time. I applied three OMTL algorithms, which allowed to train and update classifiers using the correlation of the tasks through the time in an online setting. To compare the performance of the suggested OMTL algorithms, I compared their performance with a traditional OMTL algorithm called Cav-OMTL. To compare the computational cost and time, I also compared the suggested OMTL algorithms with a batch learning method in an online setting. In this chapter, K denotes the number of tasks (different subjects and different stressful situations), and $\boldsymbol{w}_i$ is the weight vector of a classifier of task i. OMTL algorithms first train a classifier i independently from other tasks. Then, OMTL attempts to discover the correlation between task i and other tasks, OMTL use the information from previously trained tasks to train a classifier for the new task j. OMTL aims to train classifiers of different tasks by considering their correlations (Xue et al. 2007). The correlation between different tasks defined by a matrix called as interaction matrix in this chapter. Table 5.1 shows different algorithms that were tested in this chapter.

Table 5.1 Algorithms to recognize individual's stress in the real-time

Algorithms	Classifier	Interaction Matrix (IM)
Batch learning	SVM	No IM
OMTL with a Fixed Task Relationship	Cav-OMTL	Fix IM
OMTL with Adaptive Task Relationship Matrix	OMTL-Covariance	Equation (10)
	OMTL-LogDet	Equation (11)
	OMTL-Vonneumann	Equation (12)

5.4.3.1 Batch Learning Algorithm in the Online Setting

To compare the performance of OMTL algorithm with offline machine learning algorithms, I applied a batch learning method in the online setting. Batch learning algorithms require access to a considerable amount of data points and labels (for a training process) to find the optimal classifier. Previous research efforts examined the performance of different batch learning algorithms to recognize individuals' stress (Hou et al. 2015a; Shen et al. 2008; Trejo et al. 2015). Non-linear Support Vector Machine (SVM) demonstrated the best performance in recognizing individuals' stress using their EEG signals comparing to other batch learning methods among a large number of batch learning algorithms (Jebelli et al. 2018b; c). SVM is an offline method for the binary classification. SVM estimates a hyperplane in a m-dimentional space for separating data points. If the data points are not linearly separable, non-linear SVM algorithm can be used for classifying data points. SVM algorithm finds the weight vector ($\boldsymbol{w}$) of the optimal classifier using $(\boldsymbol{x}_1, y_1), \cdots, (\boldsymbol{x}_n, y_n)$ which are the available training data points from different subjects. After finding the optimal classifier parameter $\boldsymbol{w}$, the estimated label of data point $\boldsymbol{x}$ is given by (8).

$$L(\boldsymbol{x}) = \begin{cases} 1 \; if \; \boldsymbol{w}^T\boldsymbol{x} \geq 0 \\ -1 \; if \; \boldsymbol{w}^T\boldsymbol{x} < 0 \end{cases} \tag{8}$$

In this chapter, I applied a nonlinear-SVM with the Gaussian kernel in an online setting. The optimal values of kernel parameter (σ) and the regularization parameter of the SVM (C) were determined by examining the changes of the cross-validation accuracy as a function of these parameters ($optimal\ \sigma = 5.2$ and $optimal\ C = 1.2$). Table 5.2 shows the developed algorithm to apply SVM in the online setting.

Table 5.2 Batch learning algorithm in an online setting

Algorithm
1. Initialize $\boldsymbol{w} = \boldsymbol{0}_{1\times m}$ and $t = 1$, $s = 1$
2. Receive and estimate the label of $\boldsymbol{x}_t$: $L(\boldsymbol{x}_t) = Sign(\boldsymbol{w}^T\boldsymbol{x}_t)$
3. If true label y_t is available receive y_t and store $\boldsymbol{x}_t, y_t$ $\boldsymbol{z}_s \leftarrow \boldsymbol{x}_t$ $l_s \leftarrow y_t$ else $t = t + 1$ and go to 2
4. Find optimal SVM classifier weight $\boldsymbol{w}_{new}$ using $(\boldsymbol{z}_1, l_1) \cdots (\boldsymbol{z}_s, l_s)$
5. $s = s + 1$ and $\boldsymbol{w} \leftarrow \boldsymbol{w}_{new}$ and go to 2
6. $t = t + 1$ and go to 2

5.4.3.2 Online Multi-Task Learning with a Fixed Task Relationship Matrix (Cav-OMTL)

Cav-OMTL is a traditional Online Multitask Learning algorithm developed by researchers in (Cavallanti et al. 2010). Cav-OMTL showed high performance in classifying different tasks in an online setting (Cavallanti et al. 2010). Therefore, I chose Cav-OMTL as a baseline algorithm to assess the performance of proposed OMTL algorithms in this framework. Table 5.3 summarizes Cav-OMTL updating process. In Cav-OMTL $A \in R^{K\times K}$ denotes task relationship matrix, which tells us how different task are related to each other.

Table 5.3 Cav-OMTL Algorithm

Algorithm
1. Initialize A and $\boldsymbol{w}_0 = \boldsymbol{0}_{1\times Km}$ and $s = 0$ and $t = 0$
2. Estimate the label of $\boldsymbol{x}_t$: $L(\boldsymbol{x}_t, k_t) = Sign\left(\boldsymbol{w}_{s,k_t}^T \boldsymbol{x}_t\right)$
3. If true label y_t is available receive y_t else $t = t + 1$ and go to 2
4. If $L(\boldsymbol{x}_t, k_t) \neq y_t$; $s = s + 1$ Update $\boldsymbol{w}_s$: $\boldsymbol{w}_{s,i} = \boldsymbol{w}_{s-1,i} + y_t A_{i,k_t}^{-1} \boldsymbol{x}_t$ $\forall i \in \{1,2,\cdots,K\}$
5. $t = t + 1$ and go to 2

5.4.3.3 Online Multi-Task Learning with Adaptive Task Relationship Matrix (OMTL)

OMTL is an online multitask learning platform with an adaptive task relationship matrix (Saha et al. 2011). OMTL simultaneously updates classification parameters including weight vector ($\boldsymbol{w}_s$) and task relationship matrix (A_s). Table 5.4 shows the proposed OMTL algorithm in this chapter. In OMTL, $\boldsymbol{x}_t \in R^m$ denote data point at time t streaming from subject k_t where $k_t \in \{ 1, 2, \cdots, K \}$. Label of $\boldsymbol{x}_t$ is denoted by y_t. If the label $y_t \in \{-1(low\ stress), +1(high\ stress)\}$ is known, algorithm take into account data point $(\boldsymbol{x}_t, y_t)$ for updating the classifier of task k_t as well as classifiers of other tasks. $\boldsymbol{w}_s = [\boldsymbol{w}_{s,1}, \boldsymbol{w}_{s,2}, \cdots, \boldsymbol{w}_{s,K}]$ defines as the weight vector for all tasks where s is the number of updates and $\boldsymbol{w}_{s,i}$ is the weight classifier of task i. Therefore, estimated label of $\boldsymbol{x}_t$ after s times of updating classifier can be calculated as follow using (9).

$$L(\boldsymbol{x}_t, k_t) = Sign\left(\boldsymbol{w}_{s,k_t}^T \boldsymbol{x}_t\right) = \begin{cases} 1\ if\ \boldsymbol{w}_{s,k_t}^T \boldsymbol{x}_t \geq 0 \\ -1\ if\ \boldsymbol{w}_{s,k_t}^T \boldsymbol{x}_t < 0 \end{cases} \tag{9}$$

Table 5.4 OMTL Algorithm

Algorithm
1. Initialize $A_s = \frac{1}{K} I_{K\times K}$ and $w_0 = 0_{1\times Km}$ and $s = 0$ and $t = 0$ and $l = 0$
2. Estimate the label of x_t: $L(x_t, k_t) = Sign\left(w_{s,k_t}^T x_t\right)$
3. If true label y_t is available receive y_t else $t = t + 1$ and go to 2
4. If $L(x_t, k_t) \neq y_t$
a. $s = s + 1$
b. Update w_s: $w_{s,i} = w_{s-1,i} + y_t A_{i,k_t}^{-1} x_t \ \ \forall i \in \{1,2,\cdots,K\}$
c. If $l \leq Epoch$
i. Update A_s using (10), (11), and (12)
ii. $\boldsymbol{l = l + 1}$
5. $\boldsymbol{t = t + 1}$ and go to 2

In OMTL algorithm, l counts the number of labeled data and Epoch is a parameter that determines the required portion of the dataset and the number of iterations to update the relationship matrix. A_s denotes the task relationship matrix after s times of update. The updating process of the relationship matrix significantly affects the performance of OMTL. In order to optimize the performance of the proposed framework in this chapter, I examined various OMTL algorithms with different methods to update task relationship matrix. I considered the following three updating rules in this research:

1. Covariance update rule: $A_s = Cov(W_{s-1})$ (10)

2. LogDet update rule: $A_s = \left(A_{s-1}^{-1} + \eta\ (W^T{}_{s-1} W_{s-1})\right)^{-1}$ (11)

3. Von-neumann update rule: $A_s = \exp(\log(A_{s-1}) - \eta\ \mathrm{W}_{s-1}^{\mathrm{T}} W_{s-1})$ (12)

Where $W_s \in R^{m\times K}$ is weight matrix whose i^{th} column is a weight vector $\boldsymbol{w}_{s,i}$. Notice that the covariance of a matrix $M \in R^{m\times K}$ is given by, $Cov(M) = \frac{1}{m-1}\sum_{i=1}^{m}\left(M_{i,:} - \mu\right)^T (M_{i,:} - \mu)$, where $M_{i,:}$ is the i^{th} row of the matrix M and $\mu = \frac{1}{m}\sum_{i=1}^{m} M_{i,:}$. η is called learning rate and is a user specific parameter. Notice that $\log M$ and $\exp M$ of an arbitrary matrix $M \in R^{K\times K}$ is given by,

$\log M = U^T \log \Lambda\, U$ and $\exp(M) = U^T \exp \Lambda\, U$, where $M = U^T \Lambda U$ is the eigenvalue decomposition of M and $\log \Lambda$ is a diagonal matrix whose i^{th}diagonal item is $\log \lambda_i$ where λ_i is the i^{th} eigenvalue of M. Similarly, $\exp \Lambda$ is a diagonal matrix whose i^{th}diagonal item is $\exp \lambda_i$.

5.5 Datasets

I tested two EEG datasets to show the versatility of the proposed framework on predicting individuals' stress both in a controlled laboratory setting while acquiring brainwaves using a traditional wired-EEG and at actual job sites while recording workers' brainwaves using a wearable EEG device.

5.5.1 Database for Emotion Analysis Using Physiological Signals (DEAP)

The Database for Emotion Analysis using Physiological signals (DEAP) was used to examine the performance of the proposed stress recognition framework. DEAP is presented in (Koelstra et al. 2012) , dataset for the EEG signals that are collected in a controlled laboratory setting using a wired-EEG device with 32 active AgCl electrodes (international 10/20system positions). DEAP recorded EEG signals of 32 subjects at a sampling rate of 512 Hz while subjects were watching 40 music videos. DEAP's participants rated each video regarding the levels of arousal, valence, like/dislike, dominance, and familiarity. In this chapter, I used DEAP's subjective rating to label signals as high stress and low-stress conditions. According to a bipolar dimensional emotion model (Russell et al. 1989). Data was labeled as high stress when subjects reported positive (high) arousal level and negative (low) valence level (1,966,080 data points). On the other hand, data was labeled as low stress when subjects perceived positive (high) arousal and positive (high) valence (1,966,080 data points). In order to examine the performance of the proposed online stress recognition framework in this research, I assumed that all the subjects' brainwaves were recording and streaming simultaneously in real-time.

5.5.2 Construction Workers' EEG Dataset

In addition to DEAP dataset, I collected EEG signals using a wearable EEG device from three real construction sites, which is reported in the previous chapter. The EEG signals were collected from 7 healthy workers (Age: 37.9±8.8 years; height: 5' 10''±4'' weight: 202.3±30.4 lb.; work experience: 16.4±9.8 years). Subjects were selected randomly from a group of workers with no history of depression and anxiety. In addition, workers reported no sign of physical and physiological disorders at the time of data collection. Workers were given enough time to experience the EEG headset. Also, EEG signals were collected at least two hours after workers started their work to eliminate possible individual biases from varying baseline stress levels among different subjects. Workers were given enough time to experience the EEG headset. Also, EEG signals were collected at least two hours after workers started their work to eliminate possible individual biases from varying baseline stress levels among different subjects. Workers' brainwaves across 14 channels were recorded using a wearable EEG headset. As showed by A in Figure 5.3, Emotiv EPOC+ was selected to collect workers EEG in the field because this device fits into workers safety hard hat, it is an affordable device, and previous researchers confirmed the quality of EEG recording using this device (Barham et al. 2017; Jebelli et al. 2017b; Kotowski et al. 2018). Considering the EEG signal's rhythmic frequencies and Nyquist frequency, I set the recording frequency to 128 HZ. Nyquist frequency is the minimum signal-recording rate, which should be selected as the sampling rate to collect signals without introducing errors (Eyer and Bartholdi 1999). Considering the capabilities of the wearable EEG headset, the data-collecting resolution was set at the maximum value equal to 14 bits with the connectivity at a 2.4 GHz band. Other settings were the defaults of the wearable EEG headset, a dynamic range of 8,400 μV (pp), bandwidth of 0.16 – 43Hz. In order to assess subjects' stress levels and label the signals, subjects' cortisol samples were collected from their saliva after each session (A in Figure 5.3). Cortisol is a known stress hormone; it has been proven to higher cortisol is associated with higher stress.

Working in the field with different hazard levels (working at the top of a ladder and in a confined space as shown in B in Figure 5.3), and working with varying levels of tiredness were (C in Figure 5.3) selected as the factors that affect workers stress. According to the literature, these factors adversely affects workers' stress (Berger 1996; Hwang et al. 2018; Jebelli et al. 2018b; Leung et al. 2016; Mignonac and Herrbach 2004). To confirm the resolution of prior stress experience, subjects were given enough break time prior to starting a new session. At the beginning of each session, subjects confirmed the resolution of prior stress experience as resolved. All the data collection session happened between 9:00AM–11:30 AM. I labeled working on the ground level and working right after taking a short break time as low stress tasks (476,160 data points). On the other hand, working at the top of a ladder, working in a confined space, and continuous working for at least two hours without taking a break time were labeled as high stress level tasks (476,160 data points). To confirm these assumptions, subjects' stress levels were assessed at the end of each session using their cortisol level. To confirm the reliability of the saliva analyses, the coefficient of variation (CV) was calculated. CV lower than 15% is known as a reliable cortisol measurement (Levine et al. 2007). According to a Wilcoxon signed-rank test there was a significant difference in subjects' cortisol level while working in low and high stress level conditions (p-value= 0.0156 less than significant level of 0.05). Furthermore, to confirm the feasibility of the subjects' cortisol levels to measure their stress, I performed a Pearson correlation between the workers' cortisol values and their valence levels. Valence level was selected to perform the correlation test, since according to the valence-arousal model proposed in (Burkhardt 2001; Russell et al. 1989) significant correlations between valence and cortisol levels confirms the potential of EEG for identifying an individual's emotions (i.e., stress level). This finding is consistent with the findings in Chapter 3. It is noteworthy to mention that to generalize the correlation between workers' cortisol level and their valence levels while working in different conditions, future research should consider using a bigger sample size collected from more workers. Table 5.5 shows an overview of each participant's data size, cortisol level, and label. Data collection was approved by the University of Michigan Institutional Review Board.

Table 5.5 Overview of participant's data size, control level, and label.

Subject	Session #	Work Conditions	Cortisol Level [μg/dL] (%CV[1])	Data size [data points]	Label
1	1	G[2]	0.21 (8.00%)	76800	L[5]
	2	TL[3] and/or CS[4]	0.4 (7.48%)	76800	H[6]
2	1	G	0.16 (2.77%)	76800	L
	2	TL and/or CS	0.36 (4.12%)	76800	H
3	1	G	0.10 (10.81%)	76800	L
	2	TL and/or CS	0.16 (10.28%)	76800	H
4	1	RB	0.30 (1.72%)	61440	L
	2	AB	0.40 (3.32%)	61440	H
5	1	RB	0.08 (11.09%)	61440	L
	2	AB	0.10 (5.59%)	61440	H
6	1	RB	0.11 (0.96%)	61440	L
	2	AB	0.28 (7.30%)	61440	H
7	1	RB	0.39 (0.93%)	61440	L
	2	AB	0.67 (2.05%)	61440	H

Notes: [1]CV= percentage coefficient of variation of cortisol levels, [2]G= working on ground level, [3]TL= working at top of a ladder, 4CS= working in a confined space, [5]L= low stress, [6]H= high stress.

Figure 5.3 Construction workers' dataset data collection: (a) Wearable EEG headset, location of electrodes, and salivary cortisol sample collection kit; (b) Working in the work area with different hazard levels; (c) working with different level of tiredness.

5.6 Results

5.6.1 Performance of the Selected Features

Figure 5.4 visualizes features extracted from a construction workers' EEG dataset. For visualization purposes, the feature vectors are reduced to two and three dimensions using t-

Distributed Stochastic Neighbor Embedding (t-SNE). T-SNE is a non-linear dimensionality reduction method developed to visualize high-dimensional data [64]. Despite the limitations of high-dimensional data visualization, a clear distinction can be seen between high stress and low-stress conditions. Much of the seemingly overlapped actions in Figure 5.4 are in fact separated within the hidden dimensions. This provides preliminary evidence that the selected features are capable of distinguishing and detecting low-stress and high-stress conditions. Considering this initial separation, I' investigated the performance of different OMTL algorithms to recognize subjects' stress in the near real-time

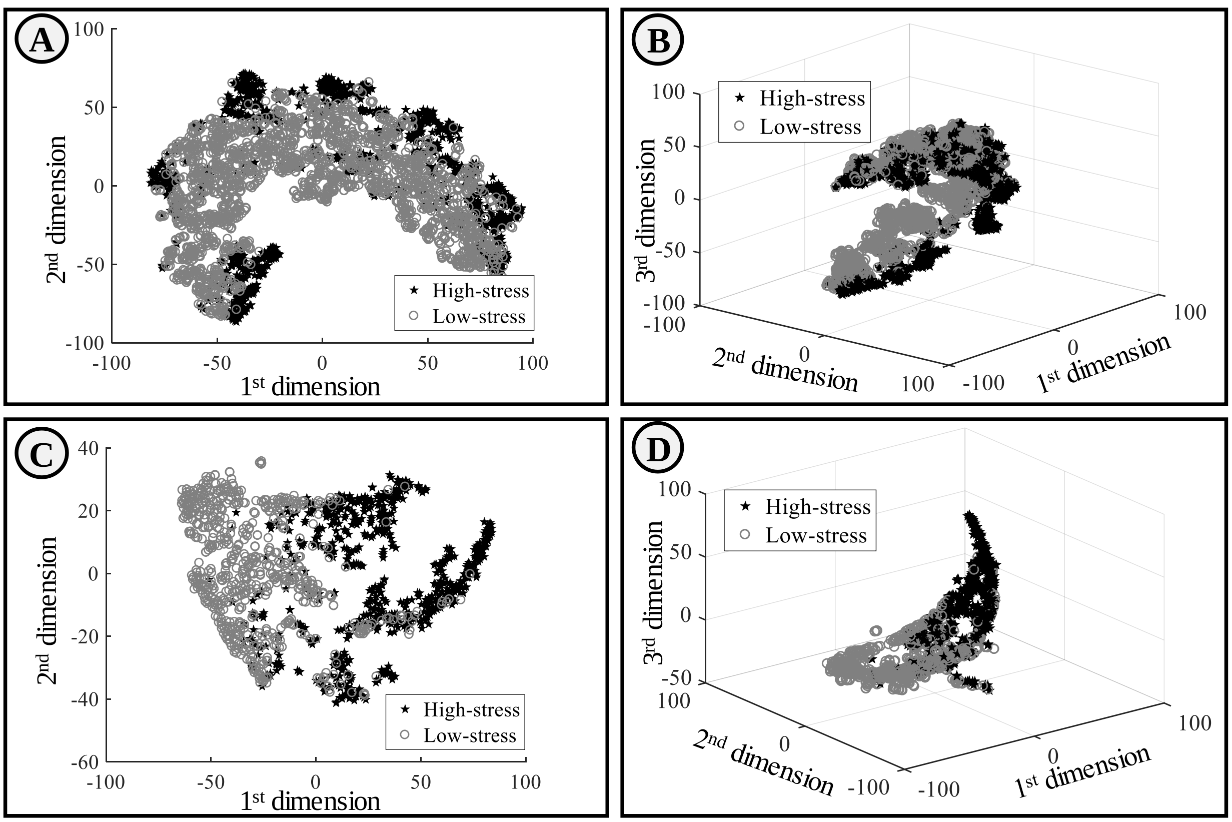

Figure 5.4 Visualization of EEG features: (a) DEAP dataset features reduced into two dimensions; (b) DEAP dataset features reduced into three dimensions; (c) Construction workers dataset features reduced into two dimensions; (d) Construction workers dataset features reduced into three dimensions.

5.6.2 Error Rates

According to the results, the batch-learning method in an online setting showed the lowest prediction accuracy on both DEAP dataset (average prediction accuracy, 59.82%) and construction workers' dataset (average prediction accuracy, 66.28%). OMTL-VonNeumann demonstrated the best prediction accuracy on both DEAP dataset (average prediction accuracy, 71.14%) and construction workers' dataset (average prediction accuracy, dataset 77.61%). Moreover, for both datasets, the OMTL-VonNeuman seems the most stable algorithm, with the lowest standard deviation when permuting data, and the smallest number of outliers. The averages, standard deviations, median value, interquartile range, and outliers of the prediction accuracy from 20 random permutations over different algorithms are reported in Figure 5.5. Table 5.6 shows the confusion matrices of the best classifier, OMTL-VonNeumann, on DEAP dataset and construction workers' dataset.

Table 5.6 Overview of confusion matrices of the OMTL-VonNeumann

Construction Workers' EEG Dataset			
	Low stress	High stress	Recall
Low stress	0.407	0.112	0.784
High stress	0.117	0.363	0.756
Precision	0.776	0.764	Accuracy: 0.776
DEAP Dataset			
	Low stress	High stress	Recall
Low stress	0.379	0.144	0.725
High stress	0.146	0.332	0.695
Precision	0.722	0.698	Accuracy: 0.711

5.6.3 OMTL Parameter

Figure 5.6 shows the performance of different OMTL algorithms vs. Epoch selection. All OMTL algorithms show that there has been a sharp rise in the prediction accuracy by increasing Epoch from 5 percent to 20 percent across all three OMTL algorithms on both datasets. According to Figure 5.6, the maximum prediction accuracy of all three OMTL algorithms happens while Epoch is selected in the range of 0.65 to 0.75. A comparison of the two datasets suggests that selecting Epoch parameter in the range of 0.65 to 0.75 would yield optimum prediction accuracy and is preferable in terms of time complexity since a large Epoch will result in higher computational time. In addition, the results show the optimal learning rates of $\eta = 3.9069 \times 10^{-13}$ for OMTL Covariance, $\eta = 1.1514 \times 10^{-13}$ for OMTL LogDet, and $\eta = 1.3257 \times 10^{-12}$ for OMTL VonNeumann.

5.6.4 Computational Complexity

To assess the computational complexity of proposed OMTL algorithms, the computational time and cost (memory usage) of different algorithms were compared. As shown in Figure 5.7, a traditional batch learning algorithms in an online setting led to significantly higher computational time and memory usage compared with the proposed OMTL algorithms. All of the proposed OMTL algorithms present low computational complexity (average computational time equal to 1 second and average memory usage equal to 10^4 Bytes). No significant differences were found in computational cost and time among different OMTL algorithms.

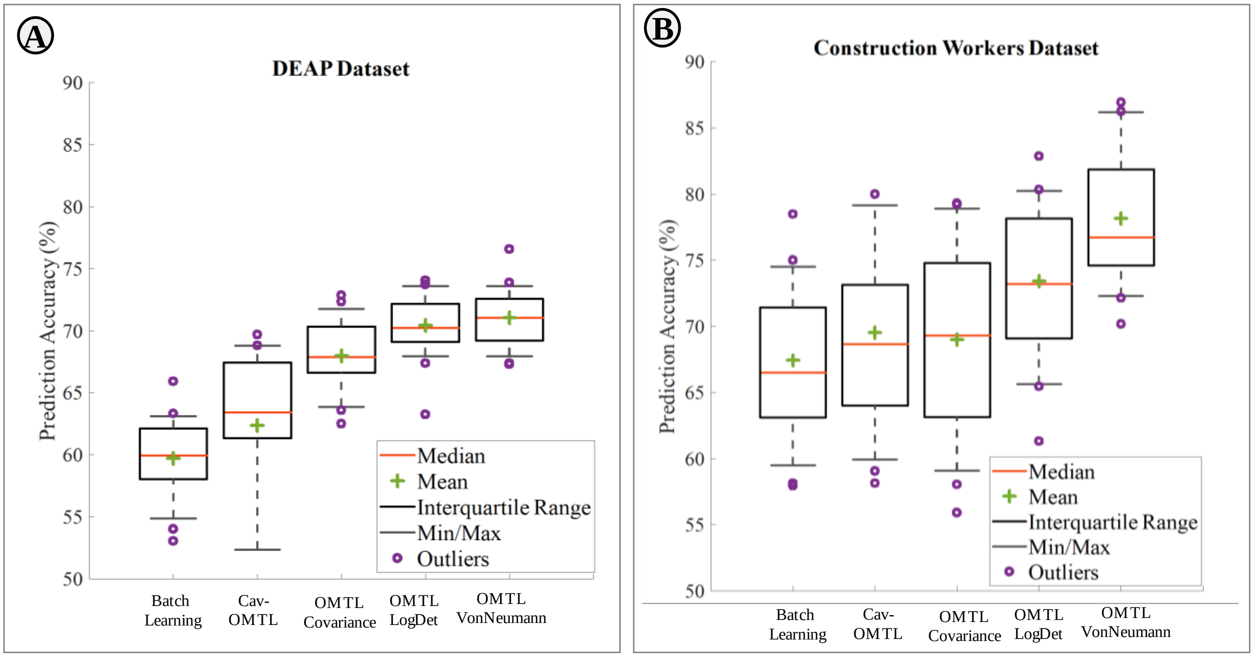

Figure 5.5 Prediction accuracy among different algorithms: (a) DEAP Dataset; (b) Construction workers dataset

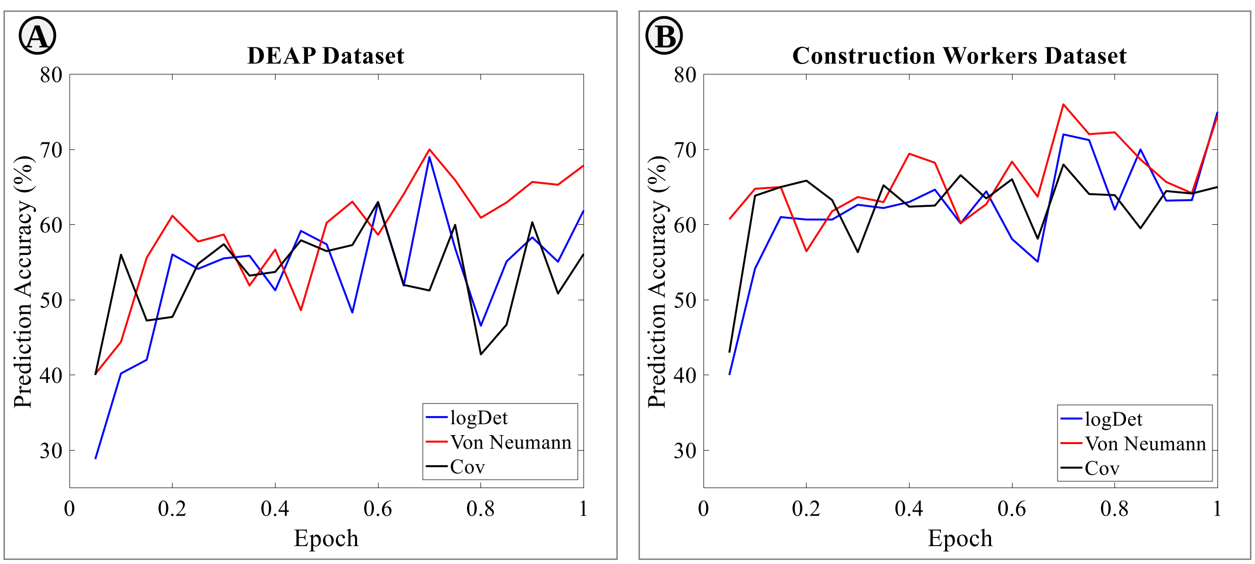

Figure 5.6 OMTL algorithms prediction accuracy vs. Epoch parameter selection

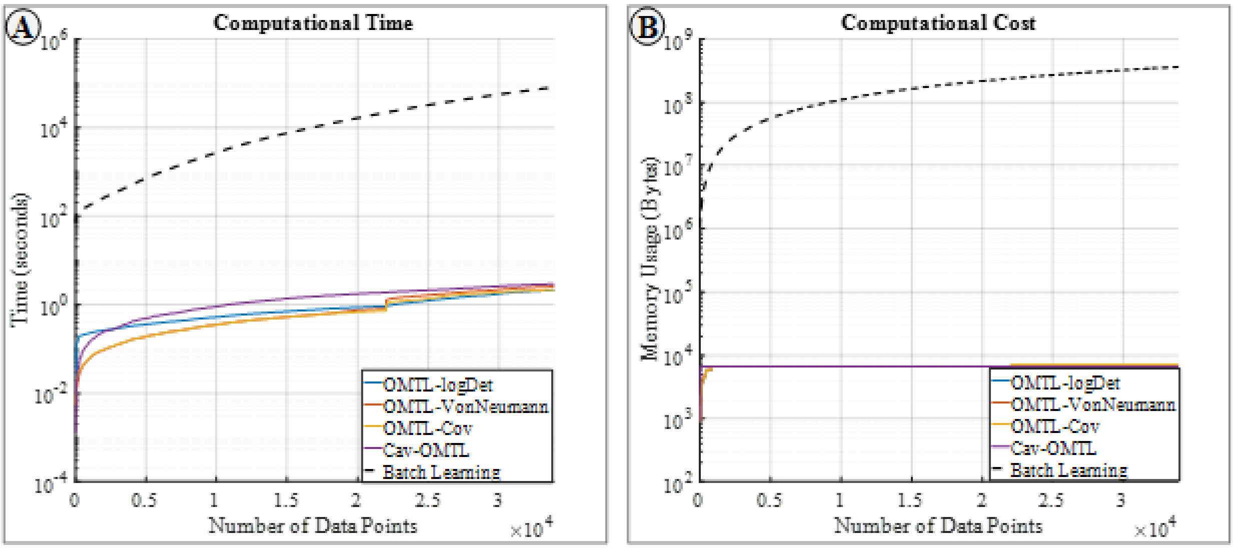

Figure 5.7 Different algorithms computational complexity; (a) Computational time, (b) Memory usage.

5.7 Discussion

The performance of the proposed framework was examined on the EEG signals acquired from controlled and real job site conditions. This study showed the potential of the proposed framework to be used in practice to recognize workers' stress in the job sites (e.g., construction, mining, and manufacturing) in near real-time. The results suggest the higher performance (higher prediction accuracy and lower computational cost) of the proposed OMTL algorithms comparing with the traditional OMTL algorithms (Cav-OMTL), and batch learning algorithm in the online setting. The results of the proposed procedure are competitive with other stress recognition algorithms with a binary labeling setting in the clinical domain that are using a wired-EEG device in the controlled environment while their subjects were in stationary conditions with the minimal body movements: 85.60% in (Al-Shargie et al. 2017); 87.30% in (Al-shargie et al. 2015); 80.43% in (Jie et al. 2014); and 77.90% in .

Higher prediction accuracy of the proposed OMTL algorithms compared to Cav-OMTL was achieved since the Cav-OMTL approach seems restrictive in two respects. First, Cav-OMTL does not have any information about a priori relationship. Second, Cav-OMTL assumes that all the tasks are positively correlated. Therefore, a fixed interaction matrix may not always be the right choice considering the variation of EEG signal patterns among different individuals and tasks. In addition, a comparison of the three OMTL algorithms reveals that OMTL-Covariance led to the lowest stress recognition accuracy. The covariance update rule is an intuitive method and is not based on a divergent function. Therefore, one possible explanation for the lower performance of the covariance-based OMTL is the lack of a divergent function in the updating process. A divergence function can decrease the risk of overfitting while finding the interaction matrix and training the classifier. According to the results, OMTL-VonNeumann algorithms led to higher performance compared with OMTL-LogDet. It seems possible that this result is due to the exponential and logarithmic updating process of the interaction matrix, which may deal better with the EEG signal outliers.

The traditional batch learning method in an online setting resulted in the lowest prediction accuracy. A possible explanation for this result may be the lack of adequate information to train batch leaning classifiers while dealing with EEG signals streaming from different subjects. The batch learning method is not a multi-task classifier and assigns the same classifier to different subjects and tasks. Assigning the same classifier to the different subject may decrease the stress recognition accuracy since EEG pattern varying among different individuals.

Increasing the Epoch value led to a gradual improvement in prediction accuracy among all OMTL algorithms. This was consistent with the conclusion of previous works that stated an increase in Epoch value resulted in higher prediction accuracy (Saha et al. 2011). It can be concluded that an Epoch equal to 0.65-0.75 was a preferable setting regarding both accuracy and time complexity for the EEG datasets.

Batch learning methods in the online setting results in dramatically higher computational time and memory cost compare with OMTL algorithms. A possible explanation for this might be that batch learning method requires storing all the data points to be able to update the classifier while receiving new data points. This caused data storage capacity to dramatically increase after each iteration. Because the data storage capacity is limited, the number of updates that the algorithm can perform is also limited, and it wouldn't be practical to update the classifier in the long run. To clarify this further, assume that data points $(\boldsymbol{x}_1, y_1), \cdots, (\boldsymbol{x}_n, y_n)$ are available and weight vector $\boldsymbol{w}$ has been found using a batch learning algorithm (e.g., SVM) in the online setting. For using SVM in an online setting the model has to save all the data points after finding the classifier. Then wait until the arrival of a new data point with its label $(\boldsymbol{x}_{n+1}, y_{n+1})$. After arriving new data point, SVM in online setting finds new weight vector $\boldsymbol{w}_{new}$ using data points $(\boldsymbol{x}_1, y_1), \cdots, (\boldsymbol{x}_{n+1}, y_{n+1})$ and saves $(\boldsymbol{x}_1, y_1), \cdots, (\boldsymbol{x}_{n+1}, y_{n+1})$ for the future updates. However, OMTL algorithms modify classifier parameters $\boldsymbol{w}$ without saving previous data points when the new data point $(\boldsymbol{x}_{n+1}, y_{n+1})$ arrives. OMTL algorithms have the advantage to find new weight vector $(\boldsymbol{w}_{new})$ only by using $(\boldsymbol{x}_{n+1}, y_{n+1})$ and old weight vector $\boldsymbol{w}$**.** Therefore, OMTL algorithms remove the data points after updating the classifier as they do not need old training data points for the future updates.

One unanticipated finding was the lower prediction accuracy of the DEAP dataset compared to the construction workers' dataset. Considering the higher EEG recording quality in the DEAP dataset compared to construction workers' dataset, it was expected that the DEAP dataset would lead to a higher classification accuracy. One possible explanation for this result is the selected stressors to induce stress in the tested datasets; real job sites stressors have been used to induce stress in construction workers' dataset (e.g., working at the top of a ladder in a confined space) in contrast, virtual stimuli (e.g., watching different type of musical videos) was selected as the stressor in DEAP dataset. Previous researchers are questioning the possibility of the virtual stimuli (e.g., watching the video, and listening to music) to induce stress response (Inducing Anxiety through Video Material), the results of this study can imply that stressors in actual jobs site induce higher stress to compare to a virtual stimulus such as watching the video. One other reason for the lower classification accuracy of the suggested framework on the DEAP dataset can be related to the labeling process. In the DEAP dataset, a subjective survey was used to label the individual's stress. However, in the construction workers' dataset, I labeled the data by measuring individuals' stress hormone (i.e., cortisol level). There exists higher uncertainty while labeling the data using subjective methods as compared with labeling based on stress hormone.

It is noteworthy to mention in this chapter an ICA method was implemented to remove intrinsic signal artifacts. To avoid the problem of mutual contamination between different components and losing non-noisy components (Urigüen and Garcia-Zapirain 2015), only the three most common intrinsic signal artifacts were removed. In order to be able to remove more intrinsic signal artifacts, it is recommended that more workers brain waves across more channels need to be collected in future research. Furthermore, in order to decrease the computational time of the preprocessing and artifacts removal steps, it is recommended that future studies consider replacing the ICA method with other artifacts removal algorithms with lower computational time (e.g., a regression-based method for intrinsic artifacts removal proposed in (Di Flumeri et al. 2016)).

There is one caveat worth noting regarding the present study. In this chapter, OMTL algorithms were applied to the binary labels and individuals' stress was labeled as low-stress and high-stress. Future studies will need to be undertaken to take different stress levels into account. In addition, future research can apply the proposed stress recognition framework toward in-depth understanding of the effect of the individual factors (e.g., ages, work experiences, and physical health status) and organizational factors (e.g., trades, crews, and projects) on workers' stress using a larger number of subjects. In addition, future research should modify the proposed stress-recognition algorithm based on existing methods in the literature (Khalili et al. 2017a; b; c, 2018b; a; Zhang et al. 2018a; b) to address security and privacy concerns.

5.8 Conclusion

This study applied different signal processing and machine-learning techniques to develop an EEG-based stress recognition framework, which considers changes in brainwave patterns among different subjects and continuously updates the classifier in an online setting with a low computational cost and memory usage. This study takes into account two EEG datasets to examine the performance of proposed stress recognition framework both in a controlled environment using a traditional EEG device, and in actual job sites, using EEG signals collected from an of the shelf wearable EEG device. This study showed the advantage of the proposed OMTL algorithms compared with traditional methods (i.e., a batch learning algorithm in an online setting) by comparing the prediction accuracy, computational cost, and time of the proposed framework with traditional frameworks. According to the results, the proposed OMTL algorithms achieved a higher prediction accuracy, while lowering computational cost and time.

The present study contributes to the recognition of individuals' stress in near real-time either in a controlled laboratory environment using traditional wired EEG caps or at an actual job site using a wearable EEG headset. This highlights the potential for numerous additional opportunities for using a wireless EEG recording device as a non-invasive method to continuously detect the stressful moments in various stressful occupations (e.g., firefighter, construction workers, etc.) where it is not practical to train a stress recognition algorithm for all the possible stressors. Early detection of the stressors can greatly contribute to manage individuals' stress, to prevent psychosocial health problems, and to improve well-being. For instance, construction workers' excessive stress can have detrimental impacts on work performance including productivity, safety, and health (Leung et al. 2008, 2015). The proposed framework can be used to measure and characterize construction workers' stress levels in the field in order to reduce workers' injuries, accidents, and errors and to enhance productivity and worker satisfaction.

5.9 References

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Chapter 6:

Wristband-Type Wearable Biosensor to Assess Construction Workers' Mental Stress[5]

6.1 Introduction

The construction industry is one of the largest industries in the U.S. It employs around 6.5 million people (CPWR 2018). In this mega-industry, 68% of its workers are suffering from excessive stress (Campbell 2006) due to extended exposure to stressful site situations such as poor and hazardous work environments and task complexity. Further, construction has approximately 200,000 cases of worker injuries and illnesses. This amounted to about 80,000 cases of days away from work in 2016 (BLS 2017). In addition, it has been widely recognized that physical and psychological stress is strongly associated with workers' safety behavior (Leung et al. 2015), which contributes to 80-90% of accidents (Heinrich et al. 1980; Lingard and Rowlinson 2005). Furthermore, many studies have demonstrated that occupational injuries and illness lead to additional stress, anxiety, or depression (Jacobsen et al. 2013). It has also been reported that construction workers are 1.7 times more likely than those in other industries to suffer from

[5] This chapter is adapted from Jebelli, H., Choi, B. and Lee, S. (2019) "Application of Wearable Biosensors to Construction Sites. Part I: Assessing Workers' Stress." *Journal of Construction Engineering and Management* (under review).

emotional and mental disorders (Petersen and Zwerling 1998). Workers in the field reported having higher levels of burnout and chronic health problems compared with those in the head or corporate offices of the same organizations (Lingard and Francis 2004). Despite the importance of assessing worker stress and mitigating job stressors, excessive stress among construction workers has received relatively little attention. Therefore, it is essential to measure and characterize workers' stress in the field, which can ultimately lead to reduced injuries, accidents, and errors and can also improve workers' productivity and job satisfaction.

Stress is defined as the body's response to a psychological barrier (e.g., environmental conditions and excessive job demand) (Selye 1956). A number of studies have attempted to assess individual stress by evaluating individuals' psychological and physiological responses to various stressors. Specifically, a number of instruments for subjective estimations of stress (e.g., International Survey of Stress) have been used to measure the individual's perceived stress (Abbe et al. 2011; Bowen et al. 2013; Goldenhar et al. 2003; Gutierrez and Ostermann 1999; Leung et al. 2010; Love et al. 2009; Seo and Lee 2010). However, these methods are subjective and rely on imprecise memory and reconstructions of the past (Larson and Csikszentmihalyi 1983).

In contrast, physiological measures for biochemical responses (e.g., stress hormones) have been used widely in the clinical domain as reliable markers for monitoring stress levels. Stress-related hormones (e.g., cortisol and glucocorticoids) change in response to stressors , so tracking the changes in these hormones provides meaningful insight of individuals' stress (Levine et al. 2007; Ranabir and Reetu 2011; Russell et al. 2012; Sharma and Gedeon 2012). Despite the validity of this approach, this method is not viable for continuous stress monitoring because measuring stress-related hormones requires the collection of serum, saliva, urine, or hair samples. Given dynamic changes in work environments, continuous monitoring of stress is particularly meaningful in construction sites. Furthermore, analyzing collected samples require laboratory processing, which is difficult to apply in the field.

To address this problem, this study aims to develop a framework for the noninvasive and non-subjective assessment of worker stress using signals collected from a wristband type biosensor. To achieve this objective, workers' physiological signals were collected using a wristband type biosensor. After reducing signal artifacts, a broad range of measurable properties and characteristics of signals (i.e., features) were extracted in time domain (e.g., heart rate, inter-beat-interval, heart rate reserve, electrodermal level, electrodermal response etc.) and frequency domain (e.g., mean frequency, power spectral density, peak power, etc.). Then, a machine learning model is trained to recognize worker stress. Workers stress-related hormone (cortisol) levels were measured using their saliva samples to label data as low, moderate or high stress levels. Recognizing stress levels in the field will lead to the early detection of stressors, which will enhance construction-site safety and worker health and productivity.

6.2 Field Stress Recognition

6.2.1 Overview

Figure 6.1 presents an overview of the proposed framework using physiological signals from a wristband type biosensor to recognize stress in the field. This framework is designed to recognize worker stress continuously without interrupting ongoing tasks. As the first step, the authors collected three physiological signals including PPG, EDA, and ST, using a wristband type biosensor. These signals were labeled low, moderate, and high stress based on workers stress hormone (i.e., cortisol) levels. After removing artifacts and enhancing the quality of the signals, the authors extracted patterns and characteristics of physiological signals by selecting different signal features. Then, by applying a supervised-learning algorithm (e.g., Gaussian SVM), a machine-learning model was developed to predict workers stress by examining the changes in the pattern of physiological signals. More detail on each step is provided in the following sections.

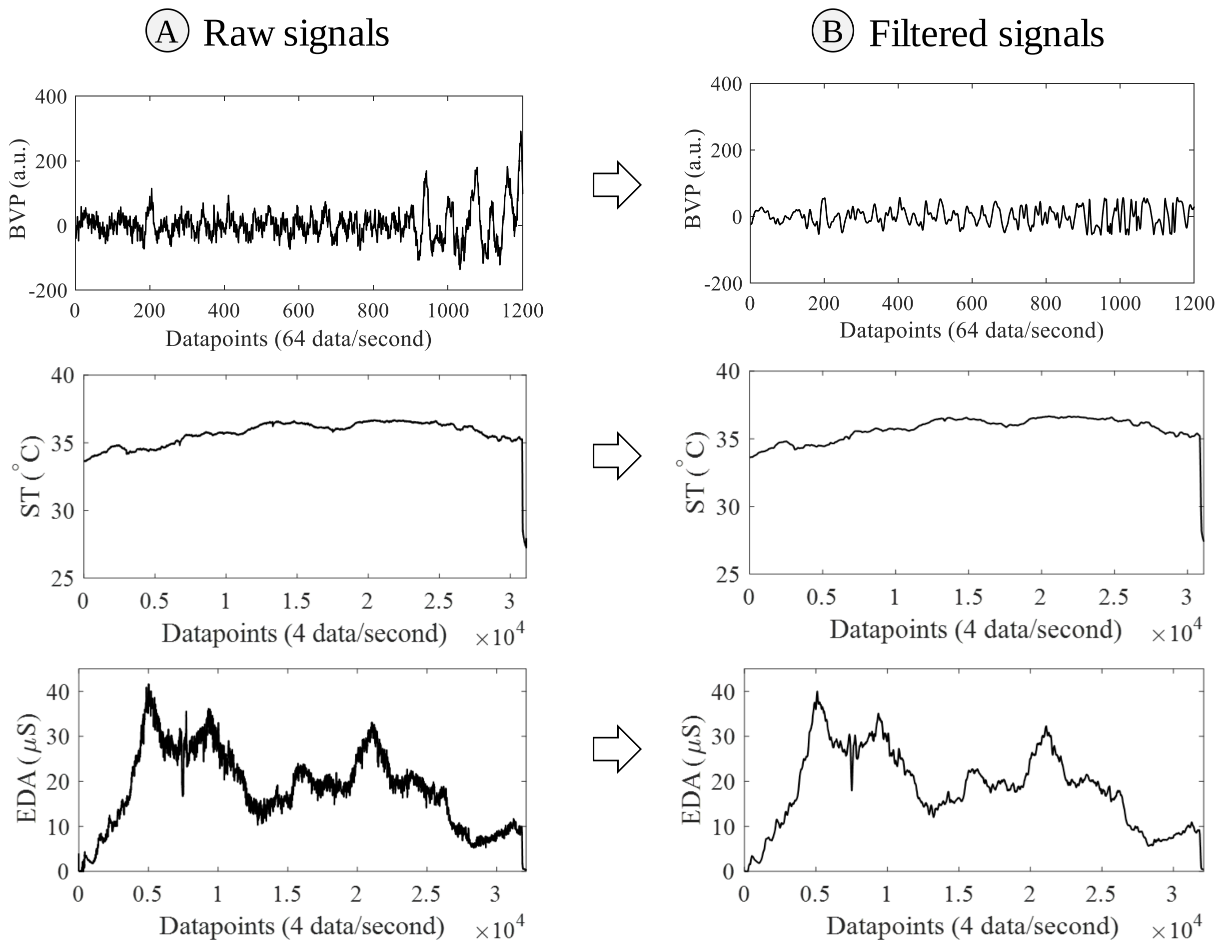


Figure 6.1 Raw (A) and filtered (B) physiological signals

6.2.2 Capturing High-Quality Physiological Signals: Artifacts Removal

As discussed earlier, the signals recorded using a wearable sensor include a large number of artifacts and noises coming from body and sensor movements, muscle activities and the device power line (Dosinas et al. 2017; Jebelli et al. 2018a; Lee and Chung 2009; Pantelopoulos and

Bourbakis 2010). To reduce these artifacts, the authors applied several filtering and outlier removal methods such as Hampel, low pass, and bandpass filters.

The typical frequency of PPG signals is between 0.5 and 5 Hz (Bagha and Shaw 2011). So, a bandpass filter with a low cut-off frequency of 0.5 Hz and higher cut of the frequency of 5 Hz was designed to filter out the non-PPG component of the signal. EDA takes place in the low frequencies, within 0-0.05 Hz (Electrodermal Level [EDL]) and 0.05-1.5 Hz (Electrodermal Response [EDR]) (Braithwaite et al. 2013). Therefore, the authors applied a low pass filter with a cutoff frequency of 1.5 Hz to remove non-EDA signal components from the recorded signal. In addition, a notch filter centered on the power-line frequency was applied to attenuate power-line interference in the recorded signals. Furthermore, to remove the outliers from the physiological signals, a Hampel filter was applied according to a method proposed by (Allen 2009) to remove the spikes and replace them with a median value of the neighboring signals. A in Figure 6.2 shows the raw physiological signals that were collected at real construction sites. After applying the artifact-removal steps, the authors achieved higher quality physiological signals, shown in B in Figure 6.2.

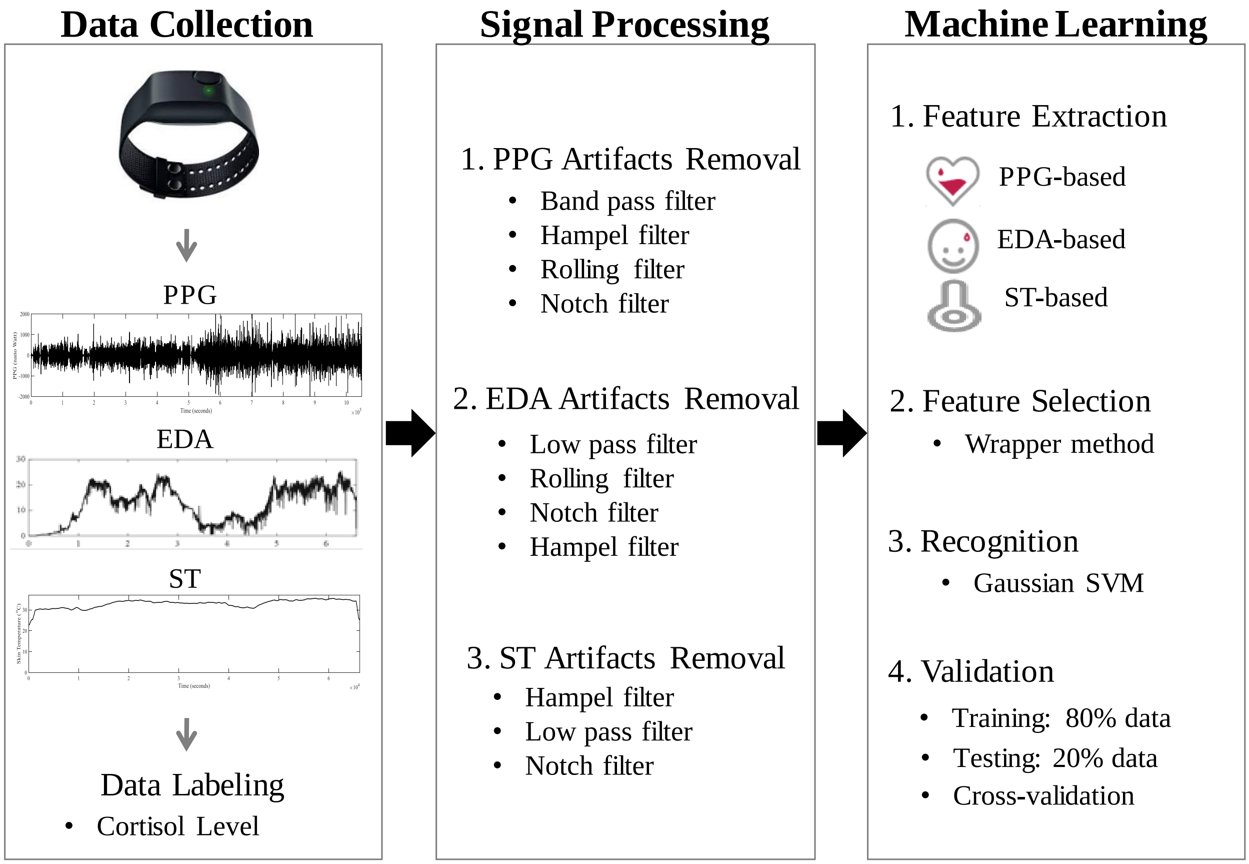


Figure 6.2 An Overview of Proposed Framework to Recognize Worker Stress using Physiological Signals Acquired from a Wristband Type Biosensor

6.2.3 Physiological Signals Pattern Recognition: Feature Extraction and Selection

After reducing signal artifacts, the authors extracted a broad range of measurable properties of physiological signals (or features) in time and frequency domains. The extracted features from PPG signals included statistical metrics in the time domain (e.g., cumulative maximum, cumulative minimum, mean value, variance, median value, smallest window elements, maximum-to-minimum difference, root-mean-squares level, peak-magnitude-to-RMS ratio, root-sum-of-squares level, standard deviation, peak, peak location, peak to peak, kurtosis, and total zero cross number), PPG statistical metrics in the frequency domain (e.g., median frequency, mean frequency, power spectral density, mean power of low-frequency band [0.5-1 Hz], mean power of high-frequency band [4-5 Hz], peak power of low-frequency band [0.5-1 Hz], peak power of high-frequency band [4-5 Hz]), heart rate (HR), inter-beat-interval (IBI), heart rate variability (HRV), and percentage heart rate reserve (%HRR). In addition to the extracted features from PPG, several features extracted from the EDA signal, included EDA statistical metrics in the time domain (e.g., cumulative maximum, cumulative minimum, mean value, variance, median value, smallest window elements, maximum-to-minimum difference, root-mean-squares level, peak-magnitude-to-RMS ratio, root-sum-of-squares level, standard deviation, peak, peak location, peak to peak, kurtosis, and total zero cross number), EDA statistical metrics in the frequency domain (e.g., median frequency, mean frequency, power spectral density, and peak power), electrodermal level (EDL), and electrodermal response (EDR). Furthermore, the extracted features from ST signals in time and frequency domain included the average of skin temperature, variation of the skin-temperature amplitude, and the rate of changes in skin-temperate signal amplitude in each window were extracted from the ST signal. Table 6.1 summarizes the extracted features from the physiological signals.

Table 6.1 Time and frequency domains features extracted from physiological signals.

	Features	Explanation
PPG	Statistical metrics in the time domain	Cumulative maximum, cumulative minimum, mean value, variance, median value, smallest window elements, maximum-to-minimum difference, root-mean-square (RMS) level, peak-magnitude-to-RMS ratio, root-sum-of-squares level, standard deviation, variance, peak, peak location, peak to peak, kurtosis, total zero cross number
	Statistical metrics in the frequency domain	Median frequency, mean frequency, power spectral density, mean power of low-frequency band (0.5-1.00 Hz), mean power of the high-frequency band (4.00-5.00 Hz), peak power of low-frequency band (0.5-1.00 Hz), peak power of high-frequency band (4.00-5.00 Hz)
	Heart Rate (HR)	Number of heartbeats per minutes
	Inter-Beat Interval (IBI)	Time intervals between heartbeats
	Heart Rate Variability (HRV)	Variation in time intervals between heartbeats
	Heart Rate Reserve (HRR)	Difference between resting heart rate and maximum heart rate
EDA	Statistical metrics in the time domain	Cumulative maximum, cumulative minimum, mean value, variance, median value, smallest window elements, maximum-to-minimum difference, root-mean-square (RMS) level, peak-magnitude-to-RMS ratio, root-sum-of-squares level, standard deviation, variance, peak, peak location, peak to peak, kurtosis, total zero cross number
	Statistical metrics in the frequency domain	Median frequency, mean frequency, power spectral density, peak power
	Electrodermal Level (EDL)	Tonic changing component of the EDA
	Electrodermal Response (EDR)	Phasic short-term component of the EDA
ST	Statistical metrics in the time domain	Average of skin temperature, Variation of the ST amplitude, The rate of changes in ST amplitude in each window
	Statistical metrics in the frequency domain	Median frequency, mean frequency, Power Spectra Density, Peak Power

To capture the patterns of the physiological signal with high granularity, a wristband type sensor uses a relatively high frequency to record the physiological signals (PPG at 64 Hz, EDA at 4 Hz, and ST at 4Hz). Therefore, calculation of a feature over a single physiological signal may not be informative enough. To address this problem, the authors calculated features over a block of continuous reading referred to as a window. To determine the optimal window size within which to recognize worker stress, the authors applied a cross-validation method concerning prediction accuracy and tested window sizes of 1 to 20 seconds, increased by a 1-second step.

After extracting a broad range of features from signals, selection of the most relevant features is the crucial next step. This selection process not only affects the recognition accuracy of the model (Hall 1999) but the computational cost and time of the framework (Koller and Sahami 1996; Zhu et al. 2007 p.). In addition, considering the noise of the physiological signals acquired in the field, using fewer features will reduce the risk of model overfit, if the right subset of features is chosen. To do so, the authors applied a backward-elimination wrapper method (Kohavi and John 1997). This method selects the top features by removing the least significant feature at each iteration with regard to the prediction accuracy (Guyon and Elisseeff 2003; Mao 2004). The authors repeat this process until no significant improvement is observed upon removing the next feature (less than 0.5%).

6.2.4 Stress Recognition Model: Classification and Validation

To select the most appropriate supervised learning algorithm an initial analysis was conducted on 25 percent of the data and the performance of various supervised learning algorithms (e.g., k-nearest neighbor, multi-layer perceptron, decision tree, and multi-class support vector machine) to recognize workers stress was examined. According to the results of a preliminary analysis, the authors selected a nonlinear SVM with a Gaussian kernel function (Hearst et al. 1998) to gauge worker stress based on physiological signals. Non-linear SVM is a deterministic machine-learning algorithm used to find a separating hyperplane plane for a dataset that is not linearly separable. It does so by solving the following optimization problem in Equation 1 (Mohri et al. 2012).

$$\min_{w,b,\xi} \frac{1}{2} ||\boldsymbol{w}||^2 + \frac{C}{n} \sum_{i=1}^{n} \xi_i$$

$$\text{s.t., } y_i(\boldsymbol{w}^T \Phi(\boldsymbol{x}_i) + b) \geq 1 - \xi_i \,, i = 1, \ldots, n \qquad (1)$$

$$\xi_i \geq 0 \,, i = 1, \ldots, n$$

Where $\Phi(.)$ is a transform kernel function that enriches the dimension of feature space, $\boldsymbol{x_1}, \boldsymbol{x_2}, \cdots, \boldsymbol{x_n}$ are the training data points, and $\boldsymbol{y_1}, \boldsymbol{y_2}, \cdots, \boldsymbol{y_n}$ are the labels, $\boldsymbol{w}\ and\ \boldsymbol{b}$ are the classifier parameters, $\boldsymbol{C}$ is the user-specified tuning parameters, which helps diminish the effect of the outliers on the training classifier, and $\boldsymbol{\xi_i}$ is the slack variable that determines the soft-margin hyperplane classifier.

To find the optimal kernel function on physiological signals, the authors explored the performance of a number of kernel functions (e.g., trivial, quadratic, polynomial, and radial basis function kernels) for nonlinear SVM. After the initial results, a radial-basis function kernel that led to the best classification performance was chosen. By applying a radial-basis function kernel (Gaussian kernel), the selected features from the physiological signals were transformed to a higher-dimension domain. Then, optimal SVM parameters (e.g., $\boldsymbol{w}$ and b) were calculated by iteratively solving equation 1. After training our SVM algorithm and determining the optimal $\boldsymbol{w}$ and $\boldsymbol{b}$ values, the algorithm will predict the label of unbaled data point $\boldsymbol{z}$ using equation 2.

$$L(\boldsymbol{z}) = \begin{cases} 1\ if\ \boldsymbol{w}^T \Phi(\boldsymbol{u}) + b \geq 0 \\ -1\ if\ \boldsymbol{w}^T \Phi(\boldsymbol{u}) + b < 0 \end{cases} \qquad (2)$$

To train the model where more than two labels occurred (various levels of stress), a Multiclass SVM, a more general form of SVM, was applied. Multiclass SVM trains multiple one-versus-rest classifiers and defines multiple optimum-separating hyperplanes for each pair of labels (Hsu and Lin 2002). A custom software written in MATLAB (version 8.1.0.604, The Math Works Inc., USA) is used for all calculation steps.

6.3 Field Data Collection

6.3.1 Subjects and Data Collection Procedure

To examine the performance of the proposed framework, the authors visited two construction sites – an indoor construction site in Gary, Indiana, and an outdoor site in Cincinnati, Ohio. Ten healthy, able-bodied construction workers participated in this study (four working indoor and six outdoor). Subjects were selected from a wide range of ages (23 to 50 years old), work experience (1 to 25 years), trades (two carpenters, two electricians, two ironworkers, two plumbers, and two concrete workers) and working environments (indoor and outdoor). Subjects reported no disabilities or clinical conditions that could affect their work performance. Table 6.2 summarizes subjects' demographic information. The data collection procedure was approved by the Institutional Review Board (IRB) at the University of Michigan.

Table 6.2 Description of Subject Information and Collected Data.

Subject Index	Age (years)	Height (cm)	Weight (kg)	Working Experience (years)	Trade	Environment
S1	50	186	98	25	Carpenter	Indoor Construction Site
S2	38	189	81	12	Carpenter	
S3	27	183	99	5	Electrician	
S4	35	183	109	13	Electrician	
S5	43	180	84	20	Ironworker	Outdoor Construction Site
S6	23	183	117	1	Ironworker	
S7	28	175	90	1	Plumber	
S8	40	172	65	18	Plumber	
S9	29	183	90	10	Concrete labor	
S10	37	165	83	2	Concrete labor	

Workers' physiological signals were collected using an off-the-shelf wristband type biosensor (e.g., E4 wristband manufactured by Empatica Inc, Cambridge, MA, U.S.A.), which included a PPG sensor, an EDA sensor, and an infrared thermopile (A in Figure 6.3). The PPG sensor was set to acquire signals with a sampling rate of 64 Hz and an output resolution of 09 nW/Digit. The EDA sensor was set to collect the electrical properties of the skin with 4 Hz sampling frequency, 900 pSiemens resolution and the range of 0.01-10 µSiemens. An infrared thermopile measures skin temperature with a sampling rate of 4 Hz and accuracy of ±0.02 °C within normal skin temperature. Subjects were asked to wear the sensor above their dominant hand, except for one whose dominant hand was fully tattooed, which might have affected data-collection quality. Before starting the data collection, subjects learned the objectives of this research. All were provided with a comprehensive explanation of the data-collection steps. 1.5 hours per subject were collected under three different conditions, which induced different levels of stress. In the first condition, physiological signals were collected during break time or immediately afterward (B in Figure 6.3). In the second condition, subjects were asked to work at the top of a ladder (C in Figure 6.3). In the third condition, subjects were asked to perform same tasks that they performed during the second condition, but at the top of a ladder and in a confined space (D in Figure 6.3).

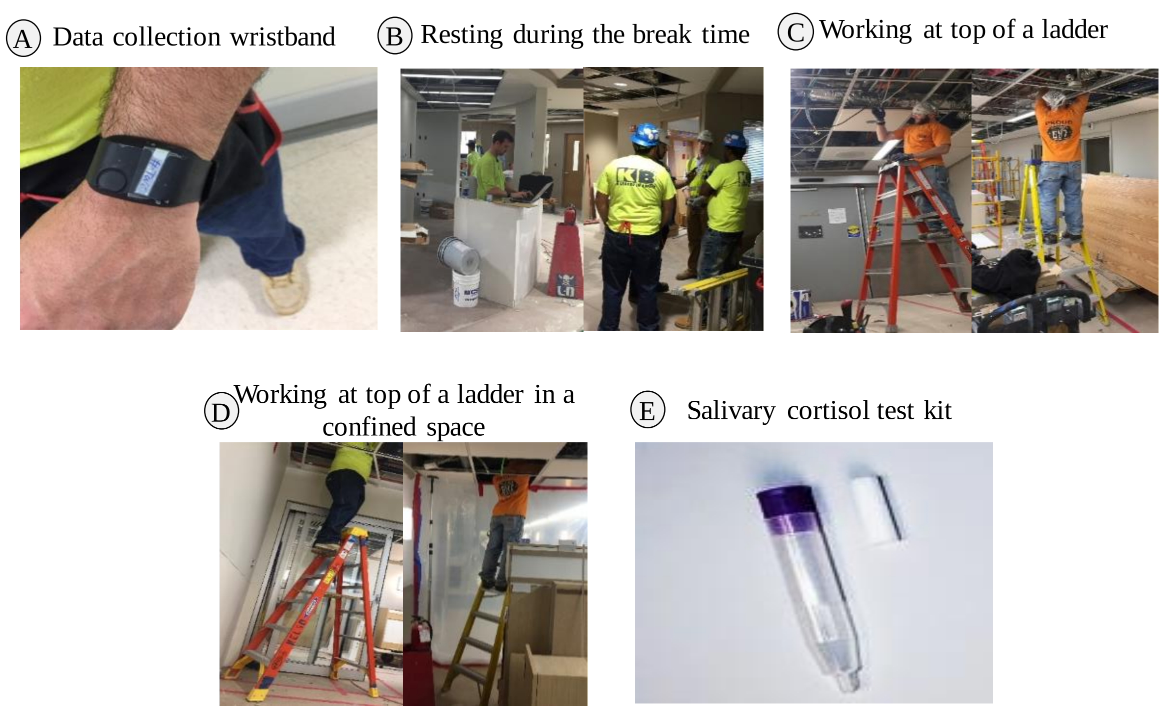


Figure 6.3 An Physiological signals collection in the field.

6.3.2 Data Labeling: Cortisol Level as a Baseline to Assess Worker Stress

To label subjects' physiological signals, it was hypothesized that worker stress level is low while they are on break, moderate while they are at the top of a ladder, and high while working at the top of a ladder in a confined space. To examine the labeling hypothesis, subjects' cortisol levels were measured while working under different conditions. Cortisol is known as a stress hormone and is highly associated with an individual's stress (Levine et al. 2007; Vedhara et al. 2003). The authors collected subjects' saliva samples (E in Figure 6.3). Then, these saliva samples were sent to a laboratory to analyze for cortisol level. The authors conducted a Wilcoxon signed-ranked test to examine whether there is a significant difference in subjects' cortisol levels while they were performing different tasks. According to a Wilcoxon signed-rank test, there is a significant difference in subjects' cortisol levels across low, moderate and high mental-stress tasks (p-value=0.01); as well as between low and moderate (p-value=0.03) and moderate and high stress levels (significance level=0.05). The results of the Wilcoxon signed-rank tests statistically support the labeling hypothesis (i.e., worker stress level is low while they are on break, moderate while they are at the top of a ladder, and high while working at the top of a ladder in a confined space). Figure 6.4 shows cortisol levels in three different working conditions.

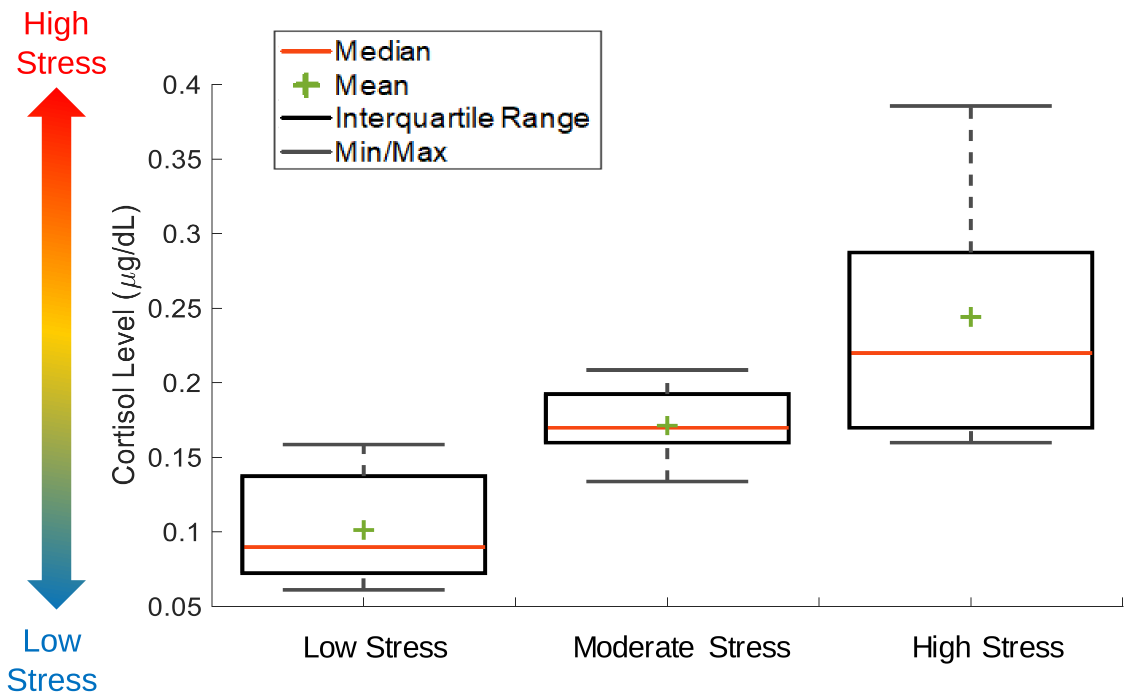
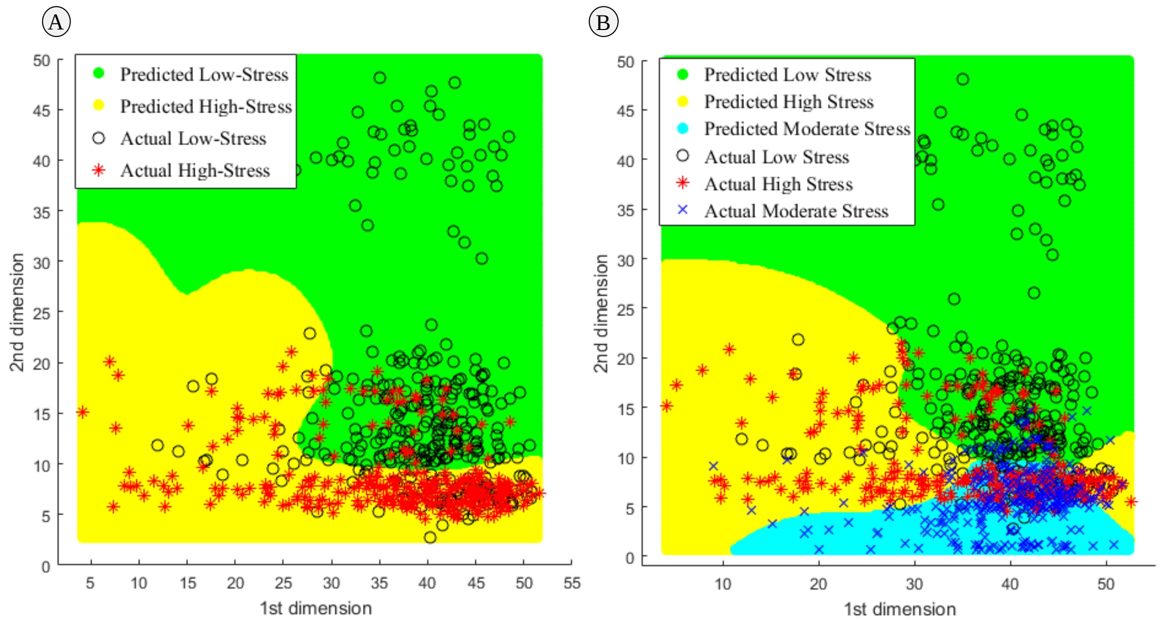


Figure 6.4 Subjects' cortisol level under different conditions.

6.4 Results

The authors applied the proposed framework to data collected from the construction sites. Figure 6.5 shows the performance of the Gaussian kernel SVM in two dimensions for two and three classes. A in Figure 6.5 shows the performance of the classifier for distinguishing low and high stress levels after excluding data points that were corresponded to moderate stress. A randomly selected subset of data after applying a principal component analysis (PCA) method, a dimensionality reduction algorithm, to reduce the feature vector to two dimensions. These two unit-less dimensions are the components of a linear mapping of the entire feature vector and represent the highest variation of the entire dataset. B in Figure 6.5 represents the performance of the classifier for distinguishing low, moderate, and high stress levels. The background illustrates the area predicted by our classifier. The points show the actual labels of the different data points based on their cortisol level. According to the results, the proposed framework led to a prediction accuracy of 84.48% for distinguishing between low and high stress levels and 73.28% distinguishing among low, medium, and high stress levels.



Low and High Mental Stress Recognition: 84.48%

Low, Moderate, and High Mental Stress Recognition: 73.28%

Figure 6.5 Stress-recognition classification performance in two dimensions.

To further investigate the performance of the proposed stress-recognition framework, the confusion matrices for distinguishing two classes (low and high stress) and three classes (low, moderate, and high stress) are shown in Tables 3 and 4. Each row of confusion matrix represents the predicted label of each class, while each column corresponds to true condition (actual label). Sensitivity signifies the proportion of correct predictions of the total number of positive instances (number of true positive/total number of positive samples). On the other hand, specificity illustrates the framework’s ability to correctly predict the true negative rate (number of true negatives/total number of actual negatives). The results of the confusion matrices indicate the high performance of proposed stress recognition for different levels.

Table 6.3 Confusion matrices for distinguishing low and high stress levels.

Stress Levels	**Low**	**High**	**Sensitivity**
Low	0.45	0.09	0.83
High	0.07	0.39	0.88
Specificity	0.87	0.81	Accuracy: 0.84

Table 6.4 Confusion matrices for distinguishing low, moderate, and high stress levels.

Stress Levels	**Low**	**Moderate**	**High**	**Sensitivity**
Low	0.26	0.05	0.02	0.79
Moderate	0.07	0.24	0.07	0.63
High	0.03	0.04	0.21	0.75
Specificity	0.73	0.73	0.70	Accuracy: 0.73

6.5 Discussions

The present study developed and validated a framework to recognize worker stress using a noninvasive wristband type biosensor. The performance of the proposed framework is examined using the data collected from actual construction sites. To examine the performance of different physiological signals in recognizing worker stress, the authors trained and tested four different Gaussian kernel SVMs and each time removed the features of one physiological signal. The results of this study present the potential of wristband type biosensors to measure workers' stress during their on-going work by providing reasonable accuracy on the stress recognition as shown in Table 6.3 and Table 6.4. Since a wristband type biosensor can continuously collect the physiological data over 12 hours without interrupting workers' ongoing work, the framework proposed in this study allows us for noninvasive, continuous, and objective monitoring of worker stress in construction sites. Compared to the current approaches to measure worker stress (e.g., survey and stress hormone), the continuous monitoring will provide an in-depth understanding of various stressors in construction projects by analyzing the changes in workers' stress during their work.

In Figure 6.6, a comparison of four models reveals that the ST-based metrics weren't among the features selected to recognize worker stress. In other words, results indicated that ST is not an appropriate physiological signal with which to recognize stress. This finding is in agreement with (Vinkers et al. 2013) a finding that showed that peripheral body temperature measured from wrist skin is not significantly affected in response to stress. Turning now to the most useful feature, it can be seen that removing EDA-based features significantly reduced the performance of the framework. This finding is consistent with those of other studies suggest that together EDA provides essential information for the model to predict individual stress (Barreto et al. 2007; Masood et al. 2012; Rigas et al. 2008).

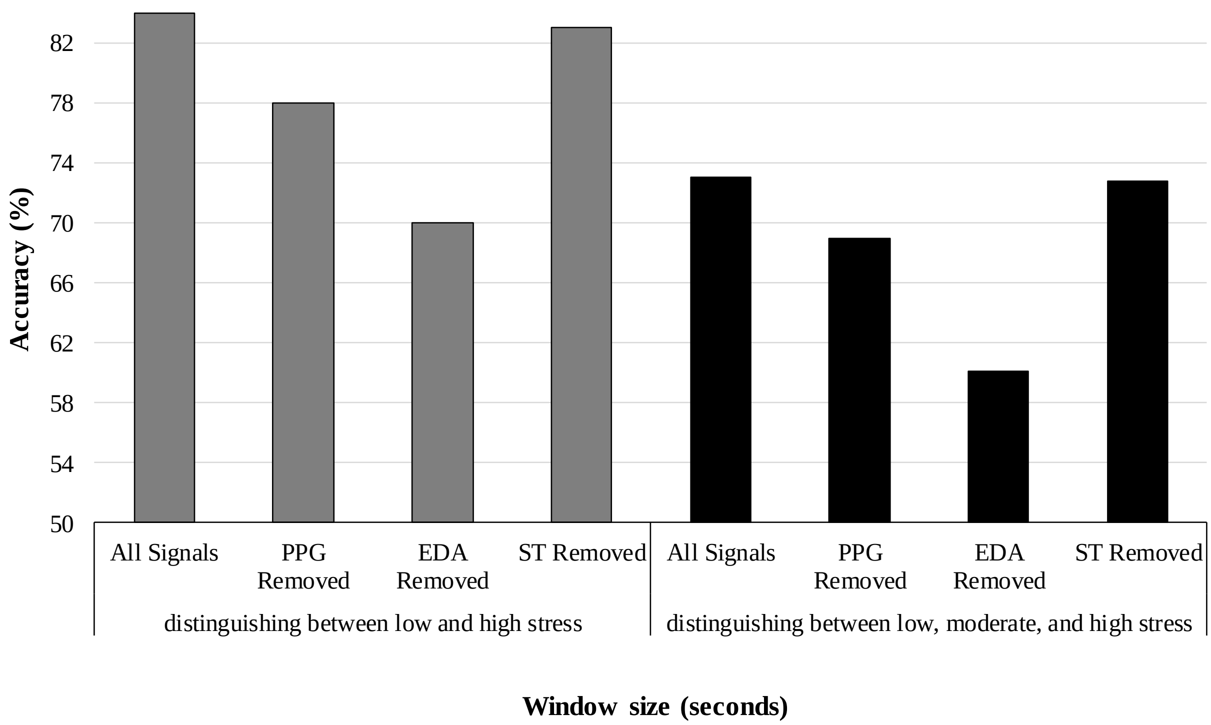


Figure 6.6 Stress-recognition classification performance using different physiological signals.

The authors further examined the performance of the proposed framework with regard to the window size used to extract physiological signal features. For distinguishing between low and high stress levels, the results reveal that the stress-prediction accuracy increased by 9.25% when window size increased from 5 to 6 seconds. The changes in prediction accuracy have a small variation in the region of 6 to 10 seconds. The optimal window size that led to the highest prediction accuracy was 7 seconds. By increasing the window size to greater than 10 seconds, a gradual decrease of prediction accuracy was observed. The same trend is true for identifying low, medium, and high stress levels. Figure 6.7 shows the accuracy of the classifier with different window sizes.

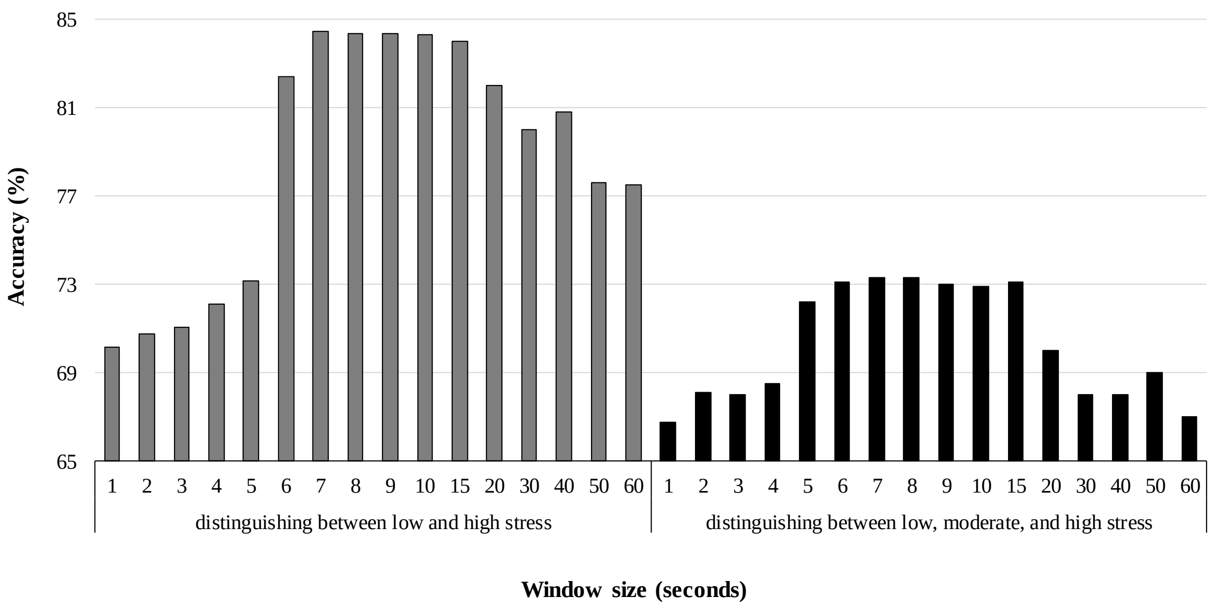


Figure 6.7 The accuracy of classifications with varying window sizes.

Upon further investigation of the predicted classes among different subjects, the authors noticed the highest number of high stress level data points was predicted for subjects 6 and 7. Subject 6 was an ironworker, and subject 7 was a plumber; both worked in an outdoor environment. This finding may be explained by the fact that these subjects were relatively younger compared with other subjects with low work experience (1 year). This finding agrees with Humpel and Caputi (2001), who showed that there is a significant correlation between levels of work stress and years of experience. This finding shows the potential of the proposed physiological signal-based stress recognition framework to identify workers stress with different characteristics (e.g., years of work experience, age, trades, etc.).

A few studies, including the authors' previous studies attempted to recognize workers mental status by analyzing the pattern of Electroencephalography (EEG) (Chen et al. 2017a; b; Hwang et al. 2018b; Jebelli et al. 2018c; b). EEG measures the electrical activity of the brain recorded from the scalp by EEG electrodes placed on the scalp. EEG capture the action potential of the neurons in the brain, which are associated with individual stress (Hosseini and Khalilzadeh 2010; Lopez-Duran et al. 2012; Seo and Lee 2010). The results of the current study outperform prior studies that have recognized workers' stress by examining patterns of EEG while exposed to various stressors e. A possible explanation for this result may be the higher quality of physiological signals collected from a wristband type sensor compared with the brainwaves collected from a wearable EEG headset. Despite all physiological signals being subject to extrinsic signal artifacts (e.g., device wire noise, environmental noise, etc.), in addition to these extrinsic signal artifacts, EEG signals are sensitive to intrinsic signal artifacts (e.g., vertical eye movement, eye blinking, etc.) (Jebelli et al. 2017). Another reason EEG-based stress recognition has led to lower stress recognition accuracy is that collecting physiological signals with a wristband type sensor is more convenient; therefore, the size of the training dataset for examining the performance of the proposed framework was significantly larger compared with the dataset used for examining the performance of the EEG-based stress recognition in the authors' earlier work (Jebelli et al. 2018b; c; d; e).

6.6 Conclusions

This study set out to develop and validate a framework with which to recognize construction workers' stress using physiological signals collected from a wristband type biosensor by applying a supervised learning algorithm. The performance of the proposed framework was examined using physiological signals collected from ten construction workers in the field. A stress prediction accuracy of 84.48% was achieved for distinguishing low and high stress levels, as well as an accuracy of 73.28 % for distinguishing low, moderate, and high stress levels.

6.7 References

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Chapter 7:

Wristband-Type Wearable Biosensor to Assess Construction Workers' Physical Demand[6]

7.1 Introduction

Construction is a $1,006.1 billion industry in the United States, employing 11 million workers (CPWR 2018). Construction is very labor intensive, including physically demanding and repetitive manual tasks (Ng and Tang 2010). Nearly 40% of the U.S. construction workforce experiences severe fatigue, which could result in devastating impacts on worker safety, productivity, and general well-being (Ricci et al. 2007). Because of long working hours, unpleasant working conditions, and heavy workloads, the adverse effects of fatigue can be exacerbated (Abdelhamid and Everett 2002; Hallowell and others 2010; Sluiter 2006; Toole 2005). Therefore, a large number of construction workers suffer from significant levels of fatigue that can increase error rates and cause unsafe actions (Sluiter 2006). Excessive fatigue may also cause work-related

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musculoskeletal disorders (WMSDs) and productivity loss (Hallowell and others 2010; Sluiter 2006; Toole 2005).

Fatigue has been defined as a decline in the ability of a person to maintain his or her normal level of performance (Edwards 1981). This definition is more complicated due to the various physiological (e.g., muscle contractile process that happens in muscle fibers) and psychological (e.g., neuromuscular fatigue process that happens in motor cortex area of the brain) phenomena contributing to it. During physical activities, fatigue is associated mainly with the intensity of tasks, measured as physical demands (Frone and Tidwell 2015). To prevent the potential risks of physical fatigue, evaluating the level and duration of high physical demands resulting from planned tasks should take precedence. As such, there has been significant research to assess worker fatigue prior to work through the development of subjective fatigue assessments to measure perceived fatigue levels (Arellano et al. 2015; Borghini et al. 2014; Debnath et al. 2015; Dittner et al. 2004; Fang et al. 2015; Lu et al. 2017; Zhang et al. 2015), empirical assessments (e.g., regression equations) and theoretical models of endurance using physiological or mechanical mechanisms (e.g., mathematical equations) along with simulation-based assessment of workers' fatigue under varying degrees of work intensity (Abdous et al. 2018; Garcia 2018; Liu et al. 2002; Ma et al. 2009; Perez et al. 2014; Seo et al. 2015, 2016; Xia and Law 2008).

However, any subjective assessment of worker fatigue has two important limitations for the field. First, these methods rely on workers' internal perception and their previous experience and are subject to strong biases. Second, stopping workers during their tasks to have them fill out fatigue questionnaires interrupts their work. On the other hand, the empirical estimation and theoretical models of worker fatigue do not have the limitations of subjective methods. However, they are limited to individual factors (the body's capabilities, age, experience, varying trades, etc.)

and site conditions (temperature, humidity, differences from indoor to outdoor, etc.) that can affect workers' physical demands. Each worker is unique with different personal characteristics (e.g., age, experience, physiological characteristics, gender, etc.) and therefore workers do not respond the same to a certain task. For instance, the same tasks that require a low physical demand for one worker may cause a higher physical demand for another worker, or even for the same worker in a different environment (Gatti et al. 2014; Hwang and Lee 2017; Mohamed and Alginahi 2009). As such, in order to appropriately assess each worker's physical demands, rather than how much the task physically demands, to what extent the worker responds to the task is more important and indeed, accurately reflect the required physical demands for the worker.

To address these limitations, quite recently, a few researchers have been trying to assess worker physical demands by examining the changes in physiological signals under various conditions (Aryal et al. 2017; Hwang and Lee 2017). Aryal et al. (2017) showed the potential for skin temperature and heart rate in measuring physical fatigue under room temperature in a laboratory setting. Hwang and Lee (2017) recorded heart rate with a smartwatch and showed the potential of measuring the percentage of heart-rate reserve (%HRR), a metric calculated from the heart rate, to distinguish different levels of physical demand. Although the heart rate, skin temperature, and percentage of HRR confirmed the potential of physiological signals to determine individual physical demand for relatively a long period of time from days to weeks, they are not enough when it comes to continuous physical demand identification of workers with different characteristics (e.g., work experience, physical and mental health status) while performing several tasks in short time interval in the field. A range of physiological signals is necessary to identify physical demand due to changes in physiological signals among different subjects performing tasks under different conditions.

To address this problem, this chapter aims to develop and validate an automatic and noninvasive method for continuous monitoring and recognition of physical demand during on-site work. To accomplish this, a machine-learning model is trained on various physiological signals, such as photoplethysmogram (PPG), electrodermal activity (EDA), and skin temperature (ST), to recognize physical demand. The physiological signals were acquired using a wearable, wristband-type biosensor that is capable of acquiring a wide range on physiological signals simultaneously without interrupting worker ongoing task. The signal quality was improved by reducing signal artifacts with various filtering methods (e.g., bandpass, rolling, notch, and Hampel filter). To recognize the changes in physiological signals at various construction sites, a broad range of features in physiological signals were extracted in the time domain and frequency domain. Then, a Gaussian kernel support vector machine (SVM) is applied to train the machine-learning model. Worker energy expenditure (EE), which represents the rate of energy required to carry out a physical activity (Westerterp 2013), was used as a baseline to label different tasks for different workers as low, moderate or high physical-intensity activities.

7.2 Method

7.2.1 Data collection procedure and working conditions

To measure workers' physical demand in the field based on physiological signals from a wristband-type biosensor, I conducted a field data collection. Workers' physiological signals were collected from 10 workers at two construction sites, including four workers (two carpenters and two electricians) working at an indoor construction site in Gary, Indiana, and six (two ironworkers, two plumbers, and two concrete workers) at an outdoor construction site in Cincinnati, Ohio. Data collection was approved by the University of Michigan's Institutional Review Board. All subjects were informed about the data-collection procedures, and they were given enough time to get familiar with the wristband-type biosensor before data collection. The subjects were told they could stop being a part of the data collection without offering an explanation. Also, they were informed that data collected did not contain personal information and will not be shared with their companies. None of the subjects reported any physical or physiological problems that would affect their work performance. Table 1 summarizes demographic information on the subjects.

Table 7.1 Description of subject information.

	Age (years)	Height (cm)	Weight (kg)	Working Experience (years)
Mean	35	179.9	91.6	10.7
SD	7.8	6.8	14.1	8
Min value	23	165	65	1
Max value	50	189	117	25

As shown in A in Figure 7.1, an off-the-shelf wearable biosensor (E4 wristband of Empatica Inc, Cambridge, MA, USA) was used to collect workers' PPG, EDA, and ST signals. These were obtained simultaneously at the highest recording rate (PPG at 64 Hz; EDA and ST at 4Hz) and highest resolution the biosensor could record (PPG at 09 nW/Digit, EDA at 900 pSiemens, and ST at 0.02 °C). Subjects were asked to perform daily tasks on a site while wearing a wristband-type biosensor. A member of the research team recorded their activities over a four-hour session. Subjects were video-recorded over a continuous session using a GoPro Hero+ camera (GoPro, Inc., San Mateo, CA, USA). The camera angle was chosen to provide a subject's full body motion from a third-view perspective, allowing detection of various body-part movement and type of activity (A in Figure 7.1). Common low-intensity activities were included but were not limited to standing and talking or performing light tasks with minimal body movement (B in Figure 7.1). Examples of common medium-intensity activities included but were not limited to: cleaning the construction site, finding tools, handling light material, and measuring and cutting sheets (C in Figure 7.1).

Examples of common high-intensity activities included handling plasterboard, installing drywall, and moving heavy material (D in Figure 7.1). Data labeling will be discussed in more detail in the next section.

Figure 7.1 Physiological signal collection in the field to recognize worker physical demand.

7.2.2 Workers' Physical Demand Labeling

Energy expenditure is defined as the required amount of energy the body needs to carry out a given activity (Klaman et al. 2000). It is associated with individual physical activity and demand levels (Dannecker et al. 2013; Pinheiro Volp et al. 2011; Plasqui et al. 2005). To understand the patterns of physiological signals among subjects who experienced different levels of physical demand, it is essential to provide data (physiological signals) with a known level of physical demand (labels). Therefore, to label subjects' physical demand, I measured worker energy expenditure while subjects were performing various tasks. To calculate energy expenditure, I used an energy expenditure prediction program (EEPP), a tool developed by the University of Michigan at the

Center for Ergonomics at the University of Michigan College of Engineering (available at: https://c4e.engin.umich.edu/tools-services/eepp-software) to estimate the energy expenditure rates for different tasks based on industrial ergonomics (Alexander 1986; Section and Group 1986) and work physiology (Bink 1962; Bonjer 1962). EEPP estimates metabolic energy expenditure rates for complex tasks by breaking them down into a number of simple activities and integrating the energy required of each of them. EEPP has been used widely in various domains to evaluate physical workload for different tasks and to gauge the physical demand of subjects (Çakıt 2016; Chagnon 2017; Martin et al. 2018; Waters et al. 1998).

I video recorded workers' activities, then simulated each while performing different tasks in EEPP. After that, the energy expenditure rate for different tasks (EEactive) was calculated in kcal/min. Resting energy expenditure (EErest) was calculated for each subject using EEPP based on workers' personal characteristics (e.g., gender, height, weight, and physical form). Based on the subjects' energy expenditure, physical activity was measured using the metabolic equivalent of task (MET), the ratio of energy expenditure during an activity to resting energy expenditure (MET= EEactive/EErest). MET is the energy required of a given physical activity. Based on the MET for different workers and tasks, workers' activities were sorted into three classes of activity: low intensity (MET < 3), moderate intensity ($3 <$ MET < 6), and high intensity (MET > 6) (U.S. Department of Health and Human Services 2008). Low-intensity activities included standing and talking with others during break and performing light tasks with minimal body movements (B in Figure 7.1). Medium-intensity activities included cleaning the construction site, finding tools, handling light material, and measuring and cutting sheets (C in Figure 7.1). High-intensity activities included handling the plasterboard, installing drywall, and moving heavy material (D in Figure 7.1). Figure 7.2 shows the subjects' physical activity levels performing different tasks in these classes. Wilcoxon-signed rank tests confirmed there is a significant difference in the subjects' levels of physical activity among three different classes (p-value=0.015 between low and moderate, and p-value=0.020 between moderate- and high physical-intensity activities; significance level=0.05).

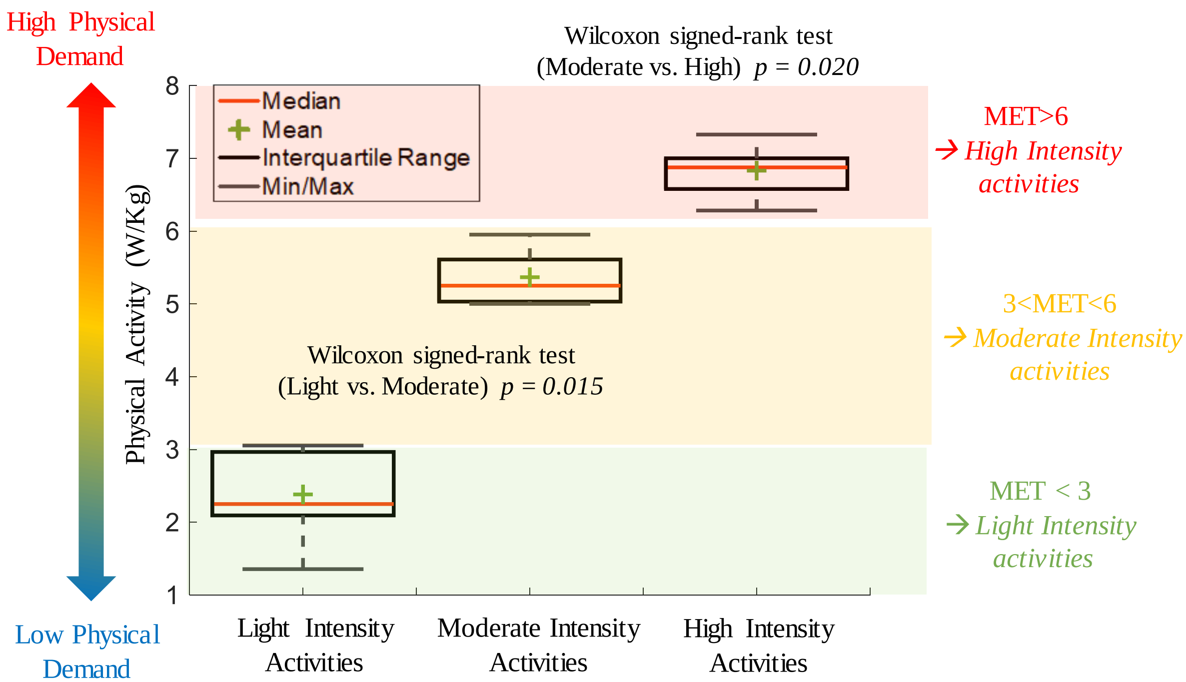

Figure 7.2 Subjects' physical activity levels under different conditions.

7.2.3 Physiological Signals Analysis

Figure 7.3 shows an overview of the procedure to recognize worker physical demand based on physiological signals collected from a wristband-type biosensor. After such signals were collected, physiological signal artifacts were reduced by applying various filtering methods. After that, a range of physiological-signal features was extracted in the time and frequency domains. At the end, a supervised-learning algorithm (Gaussian kernel SVM) was trained to recognize worker physical demand. Detailed explanations of each step are provided in the following sections.

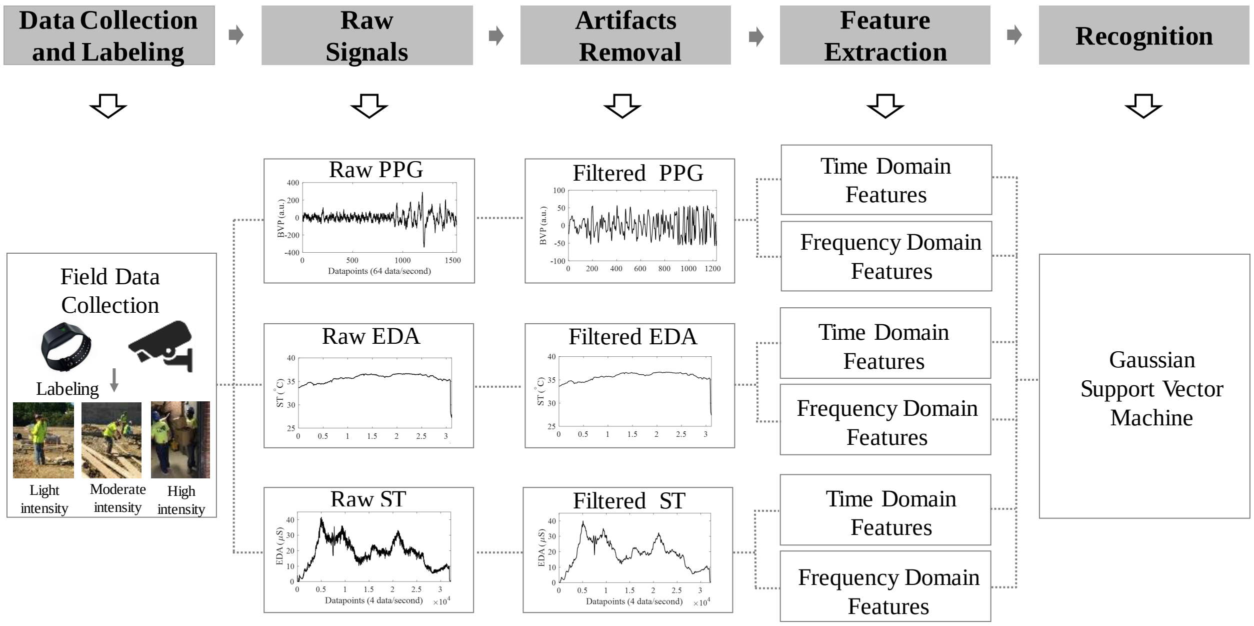

Figure 7.3 An overview of physical demand levels based identification of physiological signals.

7.2.3.1 Artifacts Removal

An essential step before analyzing biosignals, particularly collected from the field, is reducing signal artifacts (Jebelli et al. 2017, 2018c; Jebelli and Lee 2018). Although a wristband-type biosensor is designed to capture various biosignals, it also captures a significant amount of unwanted and unknown signals (e.g., noises from body and sensor movements, its power-line, and environmental noise) that disturb the signal of interest (Jebelli et al. 2018a; Mishra and Singla 2013; Sweeney et al. 2012). To reduce these artifacts, I applied various filtering and outlier removal methods, outlined in Table 2. Details of the artifacts-removal process can be found in chapter 6.

Table 7.2 Filters applied to reduce noise and artifacts from physiological signals.

Physiological Signal	Desired Signal Frequency Range	Filtering Methods	Filter Design
PPG	0.5 to 5 Hz	Bandpass	the low cut-off frequency of 0.5 Hz and higher cut of the frequency of 5 Hz
		Hampel	An outlier detection procedure design based on the PPG signal medial value from the moving data widow described in (Davies and Gather 1993)
		Notch	at 60-Hz
EDA	0-0.1.5 Hz	Low pass	the low cut-off frequency of 1.5 Hz
		Hampel	An outlier detection procedure design based on the EDA signal medial value from the moving data widow described in (Davies and Gather 1993)
		Notch	at 60-Hz
ST	>0.05Hz	Highpass	the high cut-off frequency of 0.05 Hz
		Hampel	An outlier detection procedure design based on the ST signal medial value from the moving data widow described in (Davies and Gather 1993)
		Notch	at 60-Hz

7.2.3.2 Feature Extraction and Selection

After reducing signal artifacts, I extracted various features from physiological metrics to assess physical demand. A feature is defined as a measurable attribute of the input variable (Guyon and Elisseeff 2006). In this study, the input variables are different physiological signals, and features are the metrics that represent the patterns of physiological signals. To study the patterns of physiological signals while subjects were performing different tasks that require various physical demand levels, I extracted both time and frequency domains features. Time domain features are mostly statistical metrics related to signal amplitude. Time domain features provide rich temporal detail on the physiological signals (Jebelli et al. 2018b; Jerritta et al. 2011; Kim et al. 2004; Tkach et al. 2010). However, if the signal is represented only by its time domain features, different events occurring at the same time cannot be captured. In order to obtain these events, I considered frequency domain features as well. After extracting a range of features, I applied a wrapper method (Kohavi and John 1997) to select features pertinent to physical demand. The wrapper method runs the learning algorithms on various subsets of features and selected one that led to the highest prediction accuracy. The features that resulted in the highest prediction accuracies were selected after applying a wrapper-based method. Selection of the relevant features are essential not only because they affect the time and cost of the model's prediction of physical demand (Kira and Rendell 1992a), but they also improve its accuracy (Kira and Rendell 1992b). Table 7.3 shows features extracted and selected from physiological signals in time and frequency domains.

Table 7.3 Algorithms to recognize individual’s stress in the real-time

Domain	Signal	Metrics
Time Domain	PPG	Heart Rate (HR)*, Inter-beat-Interval (IBI), Heart Rate Variability (HRV)*, and Heart Rate Reserve (HRR)*, Cumulative Maximum, Cumulative Minimum, Mean Value*, Variance*, Median Value, Smallest window elements, Maximum-to-minimum difference, Root-mean-square level, Peak-magnitude-to-RMS ratio, Root-sum-of-squares level, Variance*, Peak*, Peak location, Peak to Peak, Kurtosis, Total zero cross number.
	EDA	Electrodermal Level (EDL)*, Electrodermal Response (EDR), Cumulative maximum, Cumulative minimum, Mean value*, Variance, Median value, Smallest window elements, Maximum-to-minimum difference, Root-mean-square level, Peak-magnitude-to-RMS ratio, Root-sum-of-squares level, Standard deviation, Variance, Peak, Peak location, Peak to Peak, Kurtosis, Total zero cross number
	ST	Average of skin temperature*, Variation of the ST amplitude*, The rate of changes in ST amplitude in each window*
Frequency Domain	PPG	Median frequency*, mean frequency*, Power Spectra Density*, Mean Power of Low-Frequency Band (0.5-1.00 Hz)*, Mean Power of the High-Frequency band (4.00-5.00 Hz)*, Peak Power of Low-Frequency Band (0.5-1.00 Hz), Peak Power of High-Frequency band (4.00-5.00 Hz)
	EDA	Median frequency, mean frequency*, Power Spectra Density, Peak Power
	ST	Median frequency*, mean frequency, Power Spectra Density, Peak Power

*Selected features after applying a feature selection method (wrapper method).

7.2.3.3 Supervised Learning-based Classification

After extracting a broad range of physiological-signal features and selecting the most relevant from the 40 hours of signals that were collected from 10 workers, a total of 9,216,000 data points. I applied various supervised-learning algorithms (e.g., k-nearest neighbor, multi-layer perceptron, decision tree, linear-support vector machine, non-linear-support vector machine with different kernel functions); all of the algorithms have been used widely in the clinical domain to assess individual physical status (Boostani and Moradi 2003; Patel et al. 2011; Su et al. 2007; Subasi and Kiymik 2010; Tapia et al. 2007; Wu et al. 2012). After an initial analysis, Gaussian kernel SVM led to the optimal classification performance of a 90% testing accuracy, compared with other supervised learning algorithms: 76% for k-NN; 71% for GDA; 81% for Linear SVM; 83% for Cubic SVM; and 84 % for Quadratic SVM. SVM separates data points of different classes by creating a hyperplane to maximize the margins between different classes (Burges 1998; Hearst et al. 1998). Initially, SVM is a binary (two-class) classifier. The typical technique for multi-class classification problem is to build a SVM classifier for any pair of the labels and select a class which is chosen by the majority of classifiers (Franc and Hlavác 2002). The two-class SVM is found by soliciting the optimization problem, $\min_{w,b,\xi} \frac{1}{2}||\boldsymbol{w}||^2 + \frac{C}{n}\sum_{i=1}^{n} \xi_i$, s.t., $y_i(\boldsymbol{w}^T \boldsymbol{x}_i + b) \geq 1 - \xi_i\, , i = 1, \ldots, n \;\; and \; \xi_i \geq 0\, , i = 1, \ldots, n$. Where $(\boldsymbol{x}_1, y_1), (\boldsymbol{x}_2, y_2), \cdots, (\boldsymbol{x}_n, y_n)$ are the training data points and C is the user-specified tuning parameters that moderate the effect of the outliers on the training classifier. ξ_i is defined as the slack variable that determines the soft-margin hyperplane classifier. If the solution to the above optimization problem is (w^*, b^*), then linear SVM classifier is $f(x) = (\boldsymbol{w}^*)^T x + b^*$. In some cases, due to the complexity of the signal patterns, an optimum separable hyperplane in linear space cannot be formed. To solve this problem, a non-linear SVM maps the feature vector to a richer feature space using a mapping function (Cristianini et al. 2000;

Scholkopf and Smola 2001). If the mapping function is denoted by $\phi(x)$, kernel function $K(x, x')$ is defined by $K(x, x') = <\phi(x), \phi(x')> = \phi(x)^T\phi(x')$. After examining various kernel functions – such as the polynomial kernel, Gaussian radial basis function (RBF), Laplace RBF kernel, hyperbolic tangent kernel, sigmoid kernel, Bessel function of the first kernel, ANOVA radial-basis kernel, linear-splines kernel in one-dimension– a Gaussian radial-basis-function (RBF) kernel was selected as the optimal function. A Gaussian radial basis function (RBF) kernel is defined $K(x, x') = \exp(-\frac{||x-x\prime||^2}{2\sigma^2})$ where σ is a free parameter and was carefully chosen to maximize the accuracy. To validate the model, a 10-fold cross-validation was used to examine the predictive performance of the model on a new dataset. Each subjects' dataset was performed to one of the 10-folds. Therefore, a 10-fold per-subject, cross-validation was used to confirm that the proposed model generalizes well to other subjects. To ensure the framework was independent of the data order, the data is permuted over each run, that is, uses a different subject each time.

7.3 Results

7.3.1 Classifying Low- and High-Physical Demand Levels

To examine the performance of the proposed procedure in recognizing workers' physical demands in the field, I applied the proposed procedure to the physiological signal dataset. To distinguish two levels of physical demands (low and high), the proposed framework led to a prediction accuracy of 90 percent. A in Figure 7.4 shows the performance of the framework in two dimensions after applying a principal-component analysis to cut the feature vector into two unitless dimensions. In this figure, the background shows the area that is predicted by the trained Gaussian kernel SVM and the data points. It illustrates the actual labels (low- or high-physical demand) of the data points. To examine the performance of the framework so as to recognize all relevant levels of physical demand within the dataset, the confusion matrix set up to recognize low and high physical demand is shown in B in Figure 7.4. According to the results, the framework achieved a sensitivity of 86% and precision of 93% to recognize high physical demand and 87% sensitivity and 94% precision to recognize low physical demand.

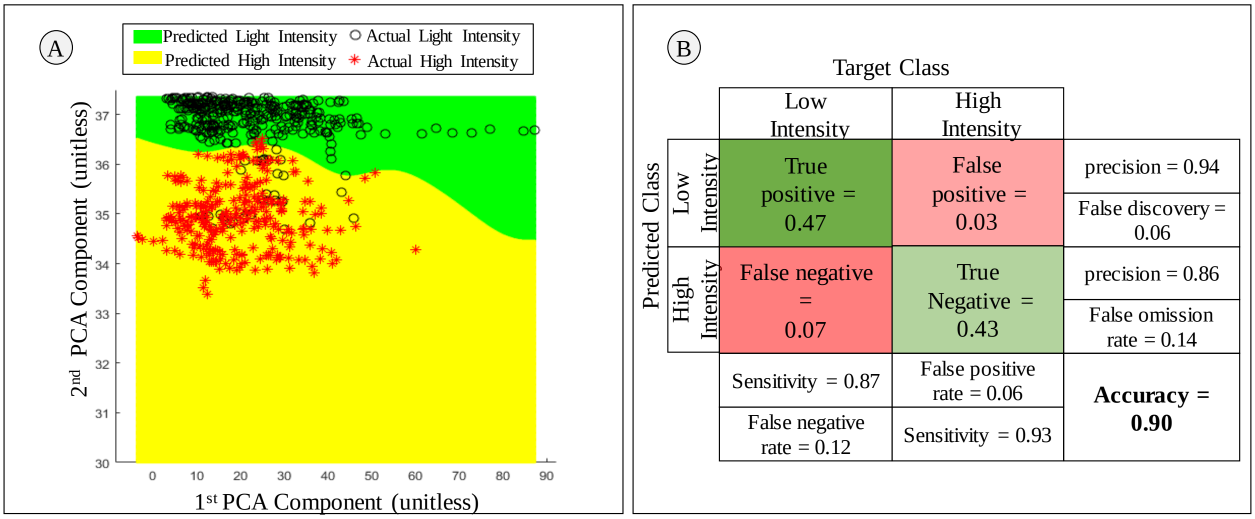

Figure 7.4 Performance of the proposed physiological signal-based, physical-demand recognition to classify low and high physical demand. (a) Visualization of the classifier; (b) confusion matrix

7.3.2 Classifying Low- and High-Physical Demand Levels

To examine the effectiveness of the proposed procedure so as to recognize different levels of physical demand, a multi-class SVM was trained by labeling worker activities into three classes (low, moderate, and high-intensity activities). The prediction accuracy of the proposed framework to classify these three categories was 87% (A in Figure 7.5). B in Figure 7.5 shows the confusion matrix of the model predicting low, moderate, and high physical demand. According to the result, the framework achieved 93% sensitivity and 82% precision to recognize high physical demand, 79% sensitivity and 87% precision to recognize moderate physical demand, and 88% sensitivity and 93% precision to recognize high physical demand.

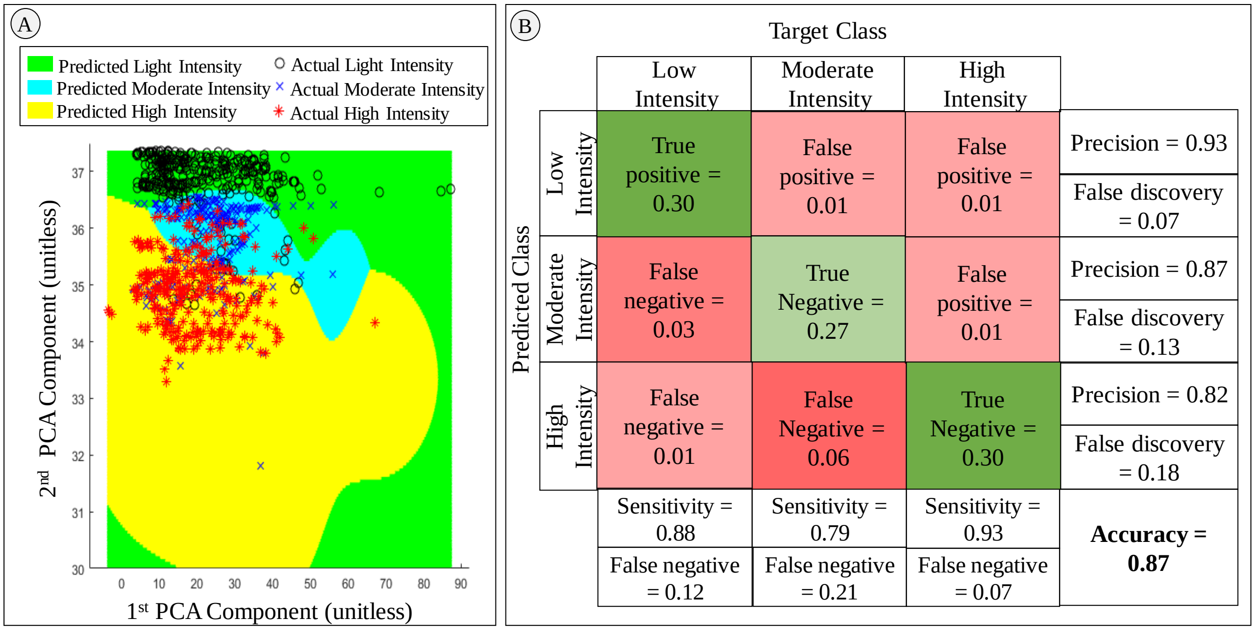

Figure 7.5 Performance of the proposed physiological signal-based physical demand recognition to classify low and high physical demand. (a) Visualization of the classifier; (b) confusion matrix

7.3.3 Optimal Window Size

To capture the patterns of physiological signals, the signals were divided into segments of data that refer to the window. To determine the impact of the window size on classification accuracy, I trained and tested different Gaussian kernel SVMs and varied the window size each time. Figure 7.6 shows the accuracy of the classifier with different window sizes. According to the results, the optimal window size was 30 seconds for distinguishing between low and high physical demand and 35 seconds for distinguishing between low, moderate, and high physical demand. As pointed out in chapter 6, the optimal window size with which to recognize worker mental stress, based on their physiological signals, is 7 seconds. Comparing the results shows that a longer period is needed to recognize physical demand.

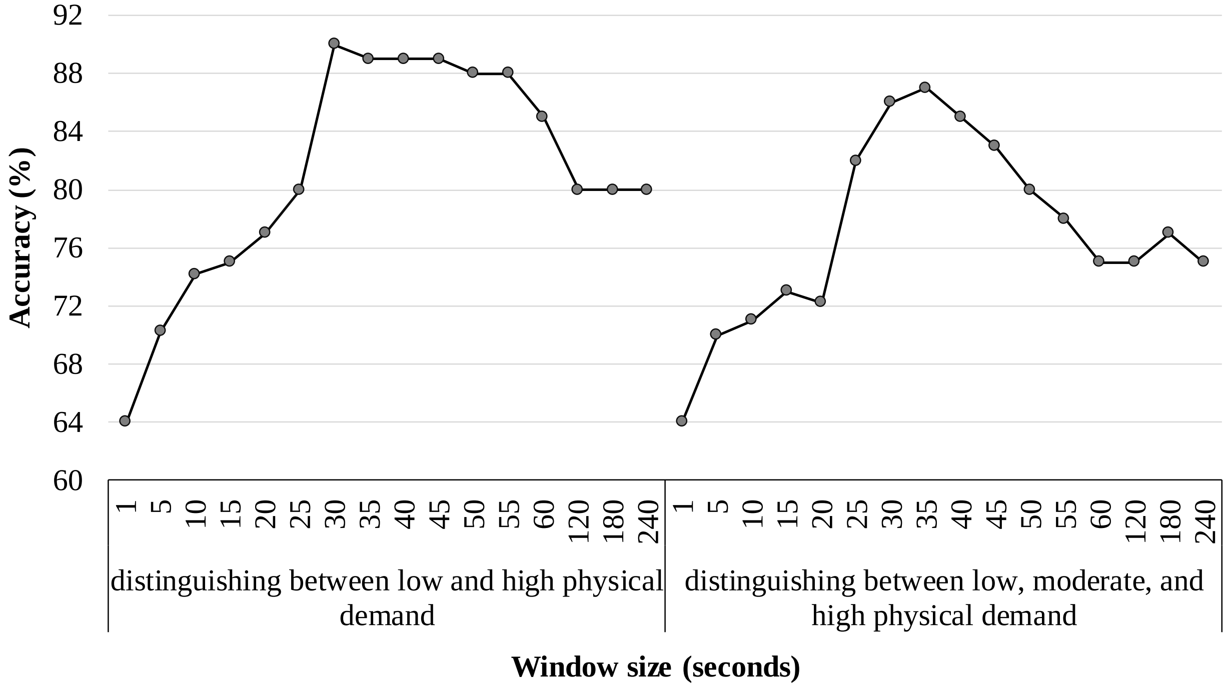

Figure 7.6 The accuracy of physical-demand recognition with varying window sizes.

7.4 Discussions

The results of this study confirmed the potential of the proposed procedure for assessing physical demand in the field. These results can be compared to the findings of those of (Aryal et al. 2017), who achieved a recognition accuracy of 80.60%, the highest, to classify fatigue levels using heart rate and skin temperature in a lab environment, not at real sites. There are several possible explanations for the higher classification accuracy of the proposed procedure. One might be the type of the data that was used to train a machine-learning model. Aryal et al. (2017) used a limited number of features, mostly in the time domain extracted from skin temperature and heart-rate data, to train a model. However, in this study, I extracted a broad range of features from EDA, PPG, and ST signals. In addition, in the current study I considered frequency domain features (median frequency, mean frequency, power-spectral density, and peak power) on top of time-domain features. Frequency-domain features provide essential information on the patterns of physiological signals (Kim et al. 2004), which will lead to an improvement in the prediction accuracy of the classifier. Besides the number and types of the extracted features, it is noteworthy that the proposed framework applied a feature-selection algorithm to select the most relevant features. Another possible explanation for better performance of the proposed framework may be due to the labeling process. Aryal et al. (2017) used a questionnaire (Borg's RPE) to assess fatigue level. Subjective assessment of fatigue level was limited by personal sensations and affected by previous experience (Breukink et al. 1998; Minton and Stone 2008). In this study, physical demand was gauged using an energy-expenditure prediction (EEPP). Labeling worker activity based on their energy expenditure reduces the risk of mislabeling the data and improved the prediction accuracy of the model.

Four different Gaussian kernel SVMs were trained to examine the importance of different physiological signals to identify physical demand levels, and each time features of one physiological signal were excluded. According to the results, the features that were extracted from the EDA signal were not among the top features to recognize physical demand. In other words, the results showed that EDA might not be an appropriate physiological signal for physical demand. There are two possible explanations. First, EDA measurement depends on the activity of the eccrine glands (Krapohl and Shaw 2015). Eccrine glands can be activated by the sympathetic part of the autonomic nervous system, which are mainly influenced by mental stress (Dawson et al. 2007). The second possible explanation is that while one primary function of sweat glands is thermoregulation, keeping the body within a specific temperature range during physical activity, sweat glands in wrist skin are less involved in thermoregulation than in stress-related responses (Sano et al. 2014). According to Figure 7.7, a significant drop in the prediction accuracy of the model comes from eliminating the PPG- and ST-based parameters to assess workers' physical demands. These results are consistent with those of other studies and suggest that that skin temperature and cardiac activity can be related to various levels of physical activity (van Marken Lichtenbelt et al. 2006; Mikus et al. 2012).

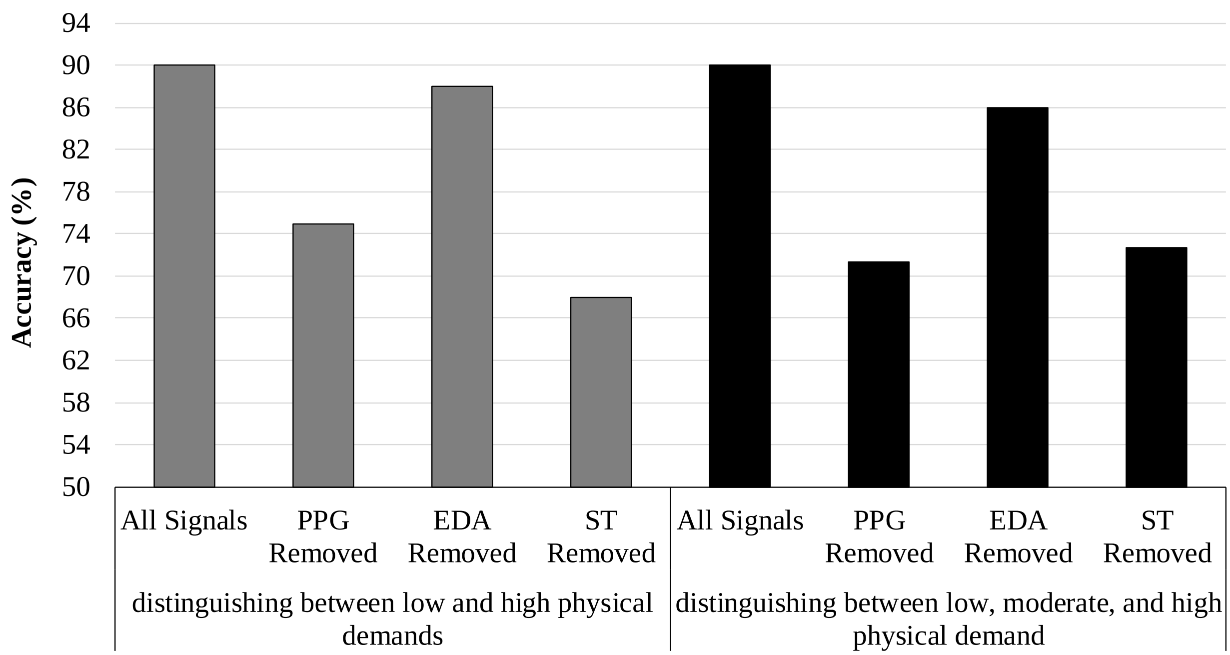

Figure 7.7 Classification of performance of physical-demand recognition using different physiological signals.

As an example of implementation of the proposed framework in the field, I examined the variations in high physical demand among different subjects to assess the effect of worker characteristics (in particular, trades and experience) and job environment (indoor or outdoor) on physical demand. Figure 7.8 shows the percentages of data points predicted as high physical demand for different trades. Comparing the percentage of high physical demand of different trades, it can be seen that among all five trades, the ironworkers and concrete laborers were the trades with the highest percentage of high physical demand. This finding was expected due to the working demands of ironworkers and concrete laborers, who frequently have to use muscles to lift, push, pull, or carry heavy objects. A comparison of the percentage of high physical demand levels of experienced workers (more than five years of work experience) and non-experienced group (less than five years of work experience) reveals that experienced workers have a lower percentage of high physical demand. The finding is consistent with findings of Madeleine and Madsen (2009), which showed more time and body movement are needed for a worker with less experience to perform a task. In addition, Lee et al. (2014) confirmed that novices and experienced workers adapt to high physical demanding activities differently.

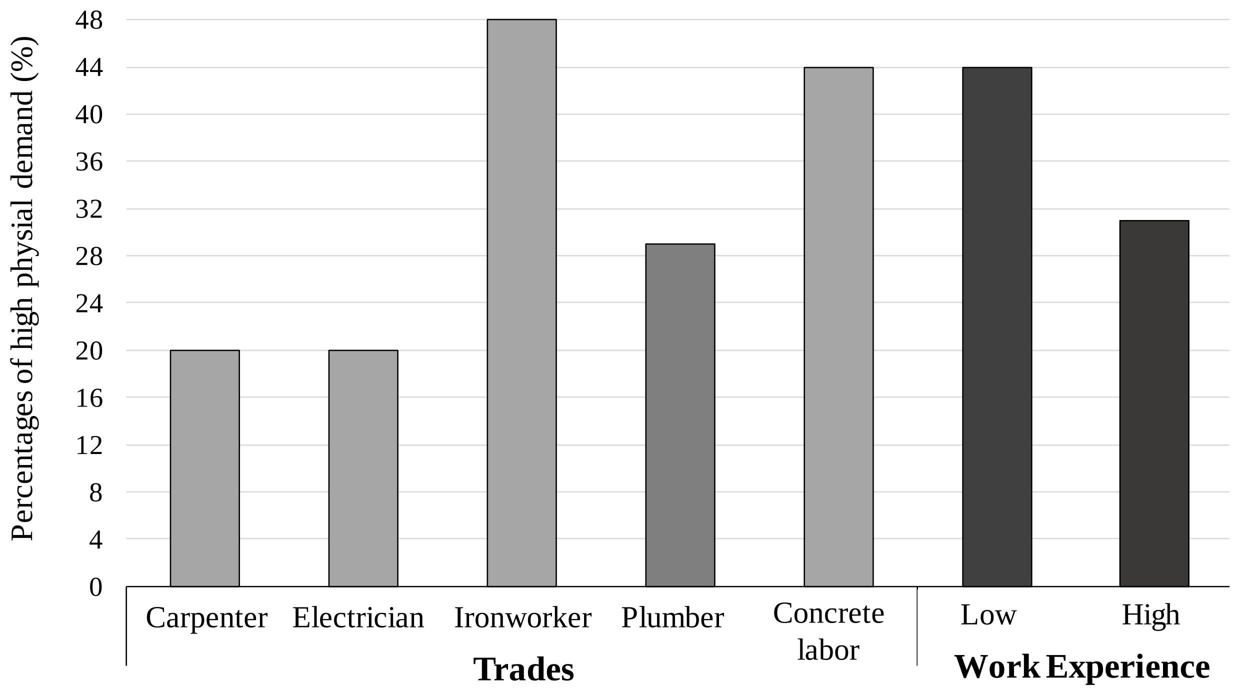

Figure 7.8 The percentages of data points predicted as high physical demand in different trades and in non-experienced and experienced workers.

Although this study has successfully demonstrated the application of the proposed framework to the physical demands of workers with different characteristics (e.g., years of work experience and trades), the reader should bear in mind that the primary objective of this chapter was to develop a physical demand identification framework, not provide a detailed investigation of changes in workers' physical demands while they perform different tasks. As such, future research should perform a more detailed comparison of different trades using a more extensive database. The present study, along with chapter 6, confirmed the potential of physiological signals from a wristband-type biosensor to identify worker stress and physical-demand levels. However, more research on this topic needs to be undertaken before the association between worker physical and mental stress is more clearly understood. In addition, it is expected that future research will reach a higher physical- demand prediction accuracy by training the proposed framework on a dataset with a larger number of subjects with more diverse personal characteristics (e.g., age, work experience, and physical health), as well as considering organizational factors (e.g., crew, trade, and site conditions). Further research should investigate the performance of deep learning-based algorithms for improving the prediction accuracy of physiological signal-based recognition of physical demand. In future research, the use of an enhanced feature vector could be a means of achieving higher prediction accuracy.

7.5 Conclusions

The purpose of this study was to develop an automatic framework that could recognize construction workers' physical demand levels using physiological signals from a wristband-type biosensor while performing various tasks at construction sites. To examine the performance of the proposed framework, 40 hours of physiological signals were collected from 10 construction workers at two sites. This study has shown that the framework achieves an accuracy of 90% for physical demand recognition in distinguishing low and high levels, and an accuracy of 87% for distinguishing low, moderate, and high levels. Chapter 6 examines the potential of physiological signals collected from a wristband-type biosensor to assess worker mental stress. Taken together, these results indicate the potential physiological signals collected from a wristband-type to assess worker stress and physical demand levels. The proposed physiological signals-based physical demand recognition framework has the following two major contributions: (1) considering workers' personal characteristics to identify their physical demand and (2) providing a method for continuous and noninvasive measurement of workers physical demands that can be used in the field. The proposed framework can be used as a means for early detection of stressors in the field, which will result in safer construction sites and healthier and more productive workers. It is recommended that further research should be undertaken to examine more closely the links between stress and physical demand.

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Chapter 8:

Conclusions

8.1 Summary

Construction is one of the most stressful occupations because it involves physiologically and psychologically demanding tasks performed in a hazardous environment. High occupational stress significantly affects one's cognitive state, e.g., affecting attention and motivation, decision making, and risky or risk-avoidance behaviors. Such outcomes increase the likelihood of errors, incidents, and injuries, and are linked to stagnant and decreased productivity. Various survey instruments for measuring workers' subjective assessments of mental and physical stress have been used, e.g., a perceived stress scale and a fatigue severity scale. Using these methods, we can document the subjects' overall stress. However, they have several key limitations. They are subjective, invasive, and cannot be used for continuous stress monitoring.

To address these problems, this research aims to promote safe construction sites and healthy and productive workers by developing measurable frameworks for continuous monitoring of workers' mental and physical stress using noninvasive, low-cost, wearable biosensors. Considering this research goal, this research had five objectives: (1) to achieve high-quality physiological signals in the field; (2) to develop and validate a bipolar emotion model to quantify workers' emotional states; (3) to develop a procedure to automatically recognize workers' stress in construction sites using EEG signals; (4) to develop and validate an EEG-based, stress-recognition framework that takes into account each subject's brainwave patterns to train the stress-recognition classifier and continuously update this classifier based on new input signals in near real-time; and (5) to develop a framework for worker's mental stress and physical-demand recognition using physiological signals collected from a wristband type biosensor. To achieve these objectives, this research focuses on evaluating the psychological and physical well-being of construction workers through the application of novel signal-processing, machine-learning, and computational methods for exploring and analyzing physiological signal patterns in the field by conducting three inter-related studies, summarized below:

8.1.1 Capturing high-quality physiological signals in the field:

Chapter 2 introduced a signal-processing framework that reduces interference by movements and environmental factors, as well as a worker's physiological processes and physical activities, e.g., eye movement, blinking, and facial muscle activity. Filtering methods, e.g., bandpass filter, Hampel filter, and rolling filter, were used to removed extrinsic artifacts, while intrinsic artifacts were removed using an independent component analysis (ICA). This framework is validated by examining whether the brain activation (particularly by body movements) can be identified using the processed EEG signal applied to eight field workers' under working (i.e., active) and non-working (i.e., inactive) conditions. Specifically, mean power spectral density (PSD) of the EEG beta frequency range is calculated from electrodes near the motor cortex of the brain that controls voluntary movements. A significant difference in mean PSD in the beta frequency range between active and inactive conditions demonstrates that the processed EEG signal, based on the proposed framework, captures brain activation. The results show the potential of the proposed signal-processing framework to monitor workers' brain-wave patterns in the field with a wearable EEG device, which opens the door to assessing workers' psychosocial status in construction so that any psychosocial problems of workers can be investigated. This framework allowed us to achieve high-quality physiological signals from wearable, wireless biosensors in the field. After testing it on workers at four different sites, the performance of the proposed frameworks was confirmed to produce high-quality signals, even in noisy environments.

8.1.2 Assessing workers' mental status in the field based on their EEG signals

Chapters 3 – 5 developed a framework to recognize worker stress in an offline setting and in real time by applying multiple advanced signal-processing and machine-learning algorithms. Chapter 4 devised a way to apply supervised learning techniques, e.g., K-nearest neighbors, Gaussian discriminant analysis, and Support Vector Machines, to recognize worker stress facing various stressors in the field in the offline setting. Chapter 5 adapted online multi-task learning (OMTL) to interpret EEG data to measure stress in real time and for new stressful conditions. OMTL does not rely on predefined datasets or situations but adapts to new data in real time. For analyzing worker EEG activity, especially when their jobs put them in unexpected scenarios in real time, this is crucial. To examine these frameworks, brain waves of 11 workers were collected at four construction sites using an off-the-shelf wearable EEG. The results indicated that the proposed framework could identify stressful responses to workplace stimuli within an accuracy of 80.32% in offline, and 77.61% in real-time, settings. These results are competitive with other stress-recognition algorithms, even those in the clinical domain, that use a wired EEG device in a controlled environment. Chapters 3 – 5 contribute to the body of knowledge on in-depth studies for understanding workers' mental status in the field by providing a means to continuously and non-intrusively measure workers' emotions and stress while they are working. The proposed stress-recognition framework continuously updates its classifier and therefore contributes to stress recognition for new stressful situations beyond the range of pre-defined conditions in near real-time, both in a controlled lab environment and at real job sites. In addition, the results demonstrate that the proposed field-stress recognition procedure can be used for the early detection of workers' stress, which can contribute to improving workers' safety, health, wellbeing, and productivity.

8.1.3 Assessing workers' mental and physical stress using other physiological signals collected from a wristband-type biosensor

Chapters 6 and 7 develop a framework for continuous and automatic measurement of worker mental stress and physical demand by examining the changes in workers' physiological signals collected from a wristband biosensor. These frameworks apply various filtering methods to reduce physiological signal noises and extract the patterns of physiological signals as workers experience various stress levels. Then, the frameworks learn these patterns by applying a supervised-learning algorithm. To examine the performance of the proposed framework, physiological signals were collected from 10 construction workers in the field. The proposed framework resulted in a stress-prediction accuracy of 84.48% distinguishing between low and high stress levels, 73.28% distinguishing among low, medium, and high stress levels and a physical-demand prediction accuracy of 90% recognizing low and high physical-intensity levels and 87% for low, moderate, and high physical-intensity levels. The results confirmed the potential of the proposed framework for assessing workers' stress and physical demand in the field. This study contributes to the body of knowledge on the in-depth understanding of construction workers' stress and physical demand on construction sites by developing a noninvasive means for continuous monitoring and assessing workers' stress using a convenient wristband biosensor. The proposed stress-recognition framework is expected to enhance workers' health, safety, and productivity through early detection of occupational stressors on actual sites.

8.2 Contribution and Potential Applications

The results of this study contributes significantly to the current body of the literature. First, it confirms the potential of using physiological signals of construction workers acquired from off-the-shelf, wearable biosensors to gauge worker's mental and physical stress. Second, the findings from this study provides new insights on construction worker safety and health through the noninvasive monitoring of worker stress. Furthermore, this study has practical implications as well. For instance, the proposed stress-recognition framework can be integrated with a collective sensing approach for the automatic and early detection of the stressors at construction sites. Also, findings from this study pave new directions for better management of different tasks. For example, by monitoring multiple workers' stress levels in the field, tasks with a high potential for stress can be detected and eventually corrected. Another practical application of the proposed frameworks in this dissertation is for the continuous monitoring of individual workers' mental and physical status and provide informative feedback (using their smartphone, smartwatch, or wearable sensor) when they are experiencing high mental or physical stress. Thereby, this research can contribute to enhancing worker health, safety, and productivity.

8.3 Directions for Future Research

This dissertation proposed frameworks to acquire high-quality physiological signals using wearable biosensors at construction sites and to recognize workers' mental and physical status in the field. However, future research will be required to improve these frameworks and to explore other possibilities in greater details. It is expected that this dissertation will open several future research directions, as discussed below.

8.3.1 Further improving the quality of the physiological signal at construction sites.

This dissertation dealt with several intrinsic (e.g., vertical eye movement, eye blinking) and extrinsic (e.g., movement, respiration, and use of muscles) signal artifacts that adversely affect the quality of the signal. However, future research is needed in this area to further improve the quality of physiological signals recorded in the field. For instance, it is recommended that future researchers apply a Dependent Component Analysis (DPA) method to find the correlation between various intrinsic signal artifacts in EEG recording. Moreover, as shown in Figure 8.1, there other sources of signal artifacts (e.g., respiration artifacts) that need to be considered when acquiring physiological signals. Therefore, further research should be pursued to investigate the effects of other intrinsic and extrinsic signal artifacts on physiological signals.

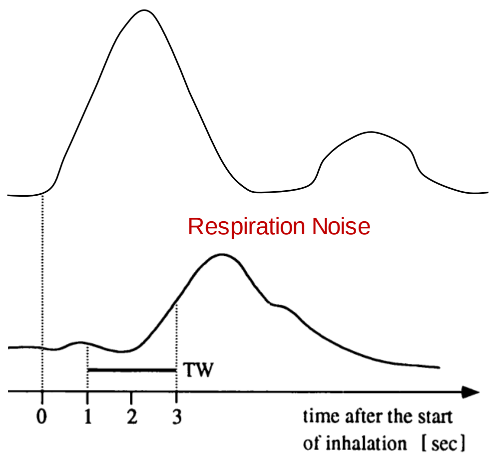

Figure 8.1 The effects of respiration noise on EDA recording, adapted from (Boucsein 2012)

8.3.2 Further improving the classification accuracy

Future studies could improve the classification accuracy of the proposed frameworks by advancing the feature engineering step. For instance, future studies can examine the performance of more efficient feature extraction methods (e.g., autoencoder) to learn the patterns of physiological signals when subjects are exposed to stressors. In addition, there is abundant room for further progress in determining the performance of the proposed stress recognition framework by integrating EEG and other physiological signals collected from a wristband-type biosensor (e.g., PPG, EDA, and ST).

8.3.3 Exploring the effects of individual and organizational factors on workers' mental and physical stress.

Continuous measurement of workers' mental and physical stress in the field can provide ample opportunities to reveal how workers' mental and physical status varies in the workplace. Specifically, the future research directions can be extended to in-depth investigations of how other individual factors (e.g., age, training and experience, and physical health status) and organizational factors (e.g., trades, crews, and projects) affect workers' mental and physical states with the larger number of subjects. It has been widely studied that combined effects of factors affecting human psychological states can be not merely additive, but also synergistic (i.e., more than additive) or antagonistic (i.e., less than additive) (Evans and English 2002; Sexton and Hattis 2007). Under numerous factors affecting emotions pervasive in construction sites, the interaction effects of such factors on emotions can be further studied in the field. In addition, continued measurement of emotions is expected to gradually minimize subjects' bias, like the Hawthorne effect, if subjects become accustomed to the long-term measurement, which helps to overcome subjects' possible bias caused by single emotional state measurement in this study. Also, future research should further examine the potential of the proposed stress-recognition frameworks to distinguish occupational stress and personal stress.

8.3.4 Linking the changes in the physiological signals to occupational health and job

This dissertation formed a basis for understanding workers' mental and physical status under various conditions based on their physiological signals. However, further efforts are needed to link the changes in these signals with job hazards. To what extent are changes in these signals related to occupational hazards? What is the relationship between physical and mental status? What about dehydration and heat stress? How can these sensors work together as a unit to detect and localize occupational and health hazards and inform workers and infrastructure users?

8.4 Concluding Remark

In summary, this dissertation involves quantifying workers' physiological signal responses to stressors on site. It is expected that a better understanding of the causes of mental and physical stress contributes critically to enhancing the safety of construction sites and improving worker health and productivity.

APPENDICES

Appendix A – EEG-based Workers' Stress Recognition by Applying Neural Network[7]

A.1. Overview

A large number of construction workers are struggling with high stress associated with their perilous job sites. Excessive occupational stress can cause serious job difficulties by negatively impacting workers' productivity, safety, and health. The first step to decrease the adverse outcomes of this work-related stress is to measure workers' stress and detect the factors causing stress among workers. Various self-assessment instruments (e.g., a stress assessment questionnaire) have been used to assess workers' perceived stress. However, these methods are compromised by several drawbacks that limit their use in the field. Firstly, these methods interrupt workers ongoing tasks. Secondly, these methods are subject to a high degree of bias, which can lead to inconsistent results. I' earlier work attempted to address the limitations of these subjective methods by applying different machine learning methods (e.g., Supervised Learning algorithms) to identify the pattern of workers' brain waves that is acquired from a wearable Electroencephalography (EEG) device,

[7] This appendix is adapted from Jebelli, H., Khalili, M., and Lee, S. (2019) "Mobile EEG-based Workers' Stress Recognition by Applying Neural Network." *In Advances in Informatics and Computing in Civil and Construction Engineering*, Springer, 173-180.

while exposed to different stressors. This research thus attempts to improve the stress recognition accuracy of the previous algorithms by developing an EEG-based stress recognition framework by applying two Learning Neural Networks (DNN) structures: a convolutional learning neural network (CNN) and a Fully Connected Neural Network. Results of the optimum DNN configuration yielded a maximum of 86.62% accuracy using EEG signals in recognizing workers' stress, which is at least six percent more accurate when compared with previous handcraft feature-based stress recognition methods. Detecting workers' stress with a high accuracy in the field will lead to enhancing workers' safety, productivity, and health by early detection and mitigation of stressors at construction sites.

A.2. Introduction

With 68% of construction workers suffering from high mental stress as a result of working in the industry, construction work is one of the most stressful occupations (Campbell 2006). Workplace stress is strongly associated with workers' productivity, health, and safety behavior (Leung et al. 2015). Therefore, it is critical to measure and characterize construction workers' stress levels in the field, which can not only reduce their injuries, accidents, and errors but also improve their productivity and job satisfaction.

Various instruments to measure workers' stress have been used, but they either rely on imprecise memory and reconstruction of feelings in the past (e.g., stress assessment questionnaires) (Mucci et al. 2015) or interfere with workers' ongoing work (e.g., biochemical measurement), which limits their use in the field. One of the most reliable ways to assess stress is to examine the reflection of various stressors on brain activity (Al-shargie et al. 2015; Goodman et al. 2013). To measure this reflection, an Electroencephalogram (EEG) has frequently been used in clinical diagnosis and biomedical research (Al-shargie et al. 2015; Al-Shargie et al. 2017; Goodman et al.

2013; Hou et al. 2015). In spite of the fact that EEG holds promise as a means to assess individuals' stress in the clinical domain, using traditional EEG devices to assess construction workers' EEG signals while working on a construction site is impractical due to the wired connections and complicated settings of these devices.

Due to recent technological advancements, wearable and wireless biosensors are readily available and have demonstrated a great potential to be used at construction sites to improve workers' safety (Choi et al. 2019; Fardhosseini et al. n.d.; Fardhosseini and Esmaeili 2016; Habibnezhad et al. 2016; Lucky Agung Pratama et al. 2018; Ryu et al. 2018) , well-being, and health (Baghdadi et al. 2018; Hwang et al. 2016, 2018; Jebelli et al. 2014, 2015, 2016, 2017a, 2018b, d, a; c; Kim et al. 2018; Nouredanesh et al. 2016; Yang et al. 2015). Wearable technology offers a less invasive method for assessing construction workers' stress using their EEG signals, which remain independent of workers' imprecise memories. Quite recently, I' applied different signal processing and machine-learning techniques (e.g., Supervised Learning algorithms) to recognize construction workers' stress by extracting a handcraft feature from EEG (Jebelli et al. 2018c). This research seeks to improve the stress recognition accuracy of the current frameworks by proposing a Deep Learning based stress recognition. In this research, I examine two classes of Neural Network (NN) architectures models. First, a convolutional neural network (CNN) was trained to recognize workers stress based on their EEG signals. CNN was selected due to its high performance in Deep Learning based classification task. Then, I developed a Fully Connected Neural Network, based on the EEG signals that were collected at real construction sites.

To examine the performance of the proposed Deep Learning based stress recognition framework, I collected EEG signals from 10 construction workers while performing different tasks in the field. Workers' stress-related hormone (cortisol), which is a reliable method to assess human stress (Levine et al. 2007), was measured using a saliva sample. Workers' cortisol level was used to label different construction tasks as low or high stress. Recognizing workers' stress with high accuracy is expected to improve the conditions of construction sites and workers' well-being through the detection and mitigation of the stressors at construction sites.

A.3. EEG-based Stress Recognition by Applying Learning

Figure A.1 illustrates the overview of the proposed framework to recognize workers' stress using their brain waves. As the first step, the workers' brain waves were collected from 14 different locations of their scalp using a wearable EEG headset, which was fit into their safety hard hat. As mentioned earlier, workers' cortisol level was measured as a ground truth to be used to label workers' stress. Then, as the second step, a signal processing framework that was proposed in Chapter 2 was applied to enhance the quality of the EEG signal by reducing signal noises and artifacts. As the last step, two DNN structures (a Fully Connected Neural Network and a Convolutional Neural Network) were applied to recognize workers' stress.

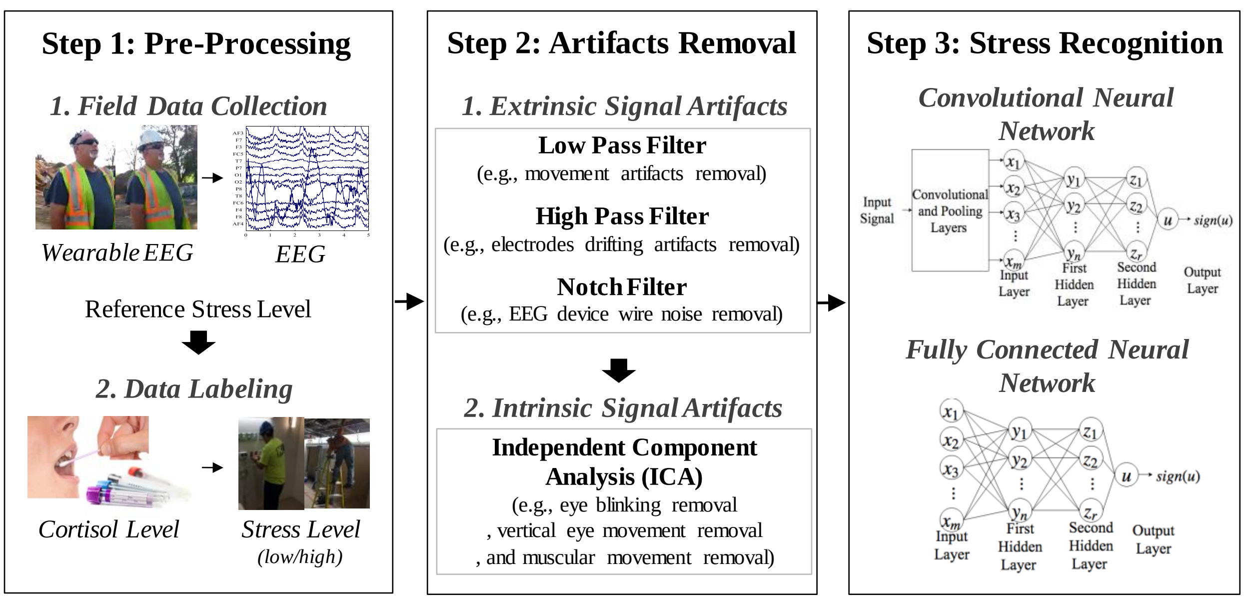

Figure A.2 The Overview of a Neural Network (DNN)-based stress recognition framework using the EEG signals collected in the field.

A.3.1 EEG Signal Pre-processing: Artifacts Removal

A large number of external and internal sources can contaminate the quality of EEG signals (Urigüen and Garcia-Zapirain 2015). In this regard, EEG signal artifacts can be divided into two groups: intrinsic signals artifacts, that come from the body itself (e.g., vertical eye movement, eye blinking) (Urigüen and Garcia-Zapirain 2015), and extrinsic signal artifacts, that come from external factors (e.g., movement, respiration, and use of muscles) (Jung et al. 1997; Kar et al. 2010; Shao et al. 2009). EEG signal artifacts are more significant while collecting data at construction sites, due to the noisy sites environment and frequent body movement of the workers. Therefore, it is essential to reduce EEG signal artifacts before analyzing data. To reduce EEG signal artifacts, I previously developed an EEG signal processing framework, which acquires high-quality EEG signals by removing the most common EEG signal artifacts from the EEG recorded using a wearable EEG device at the construction site (Jebelli et al. 2017b). The proposed framework in I' former work, reduces both extrinsic and intrinsic artifacts in EEG signals. To reduce extrinsic artifacts from the EEG signals recorded in the real construction sites a 60 Hz low-pass filter, a 0.5 Hz high-pass filter, and a notch filter with the cutoff frequency of 60 Hz were applied. To reduce intrinsic artifacts, I applied an independent component analysis (ICA). ICA is a computational method that has been commonly used in EEG research to remove intrinsic signal artifacts (Delorme and Makeig 2004; Vigário 1997; Zhukov et al. 2000). ICA detects and removes the artifactual components from the EEG signal (Comon 1994) by separating the original signal into multiple components (Jung et al. 1997).

A.3.2 Fully Connected Neural Network

A Fully Connected Neural networks can be interpreted as a complex function which gets an input data, $x = [x_1, x_2, \cdots, x_m]$ (e.g., EEG signals across different channels) and predicts the label of the data as an output (e.g., different stress levels). Network layers and neurons make the structure of a Fully Connected Neural networks. The first hidden layer comprises of n neurons and n hidden variables $(y_1, y_2, \cdots, y_n)$. Each edge between neuron x_i and y_j is associated with a weight value represented by α_{ij}. The hidden variables $(y_1, y_2, \cdots, y_n)$ are calculated based on equation 1.

$$y_j = f\left(\sum_{i=1}^{m} \alpha_{ij} x_i\right) j = 1,2, \cdots, n, i = 1,2, \cdots, m \quad (1)$$

Where $f(.)$ is an arbitrary function and usually is taken to be the sigmoid function. Similarly, the second hidden layer has r neurons and r hidden variables $(z_1, z_2, \cdots, z_r)$. Let β_{ij} denote the weight value between neuron y_i and z_j. Then, hidden variables of the second hidden layer are calculated using equation 2.

$$z_j = f\left(\sum_{i=1}^{n} \beta_{ij} y_i\right) j = 1,2, \cdots, r \quad (2)$$

Finally, the output u, which represents the predicted label (low or high stress) is calculated using equation 4.

$$u = f\left(\sum_{i=1}^{r} \gamma_i z_i\right) \quad (3)$$

Where, γ_i is the weight value of neuron z_i and output u. After observing output u, if $u \geq 0$, we predict the label of the input data as 1 (high stress), otherwise the predicted label is -1 (low stress). In other words, the predicted label is $sign(u)$. For training a neural network, I applied a backpropagation algorithm (Hecht-Nielsen 1992) to find optimal weight values α_{ij} and β_{ij} and γ_i based on the training data. Fully Connected Neural Network in this research was modeled off-line using a custom developed software based on the Neural Network Toolbox provided by MATLAB. A MATLAB version 8.1.0.604 program was used for all of the computations.

A.3.3 Convolutional Neural Network

In addition to a Fully Connected Neural Network, I explored the capability of a Convolutional Neural Networks (CNN) to recognize workers' stress using their EEG signals. Convolutional and pooling layers are two essential types of layers that create the structure of a CNN. Convolutional layers extract the patterns of different blocks of the data around each window of the input signal. Then, pooling layers aim to reduce the risk of model overfitting and the computational cost and time of the model by decreasing the spatial size of the output of convolutional layers. Each convolution layer calculates the convolution of its input with a bunch of filters. Each filter defined as a $p \times q$ matrix. The convolution between input signal I and filter F is calculated using equation 4.

$$O[m,n] = (I * F)[m,n] = \sum_{i=1}^{p} \sum_{j=1}^{q} I[m-i, n-j] \cdot F[i,j] \quad (4)$$

Where, O is the convolution of I and F. I is the input signals (different EEG channels) and F is a filter. Notice that if $m - i \leq 0$ or $n - j \leq 0$, then $I[m-i, n-j] = 0$.

To learn complex EEG signal patterns, four blocks of the consecutive convolutional and pooling layers were used. Then, to classify the learned patterns, a softmax layer was added after convolutional and pooling layers. A fully connected network was used as the classification layer. The fully connected neural network tries to find the best classifier using extracted features by convolutional and pooling layers. In other words, convolutional and pooling layers helps classifier to extract features from neighboring pixels. On the contrary, the softmax layer considers input data (all EGG channels) without emphasis on the patterns existing among neighbor pixels and data points. Figure A.2 shows the architecture of the developed CNN in this research. The network was modeled off-line using a custom developed software based on an open source library (Keras-toolbox) provided by Python. A Python version 2.7.11 program was used for all of the computations.

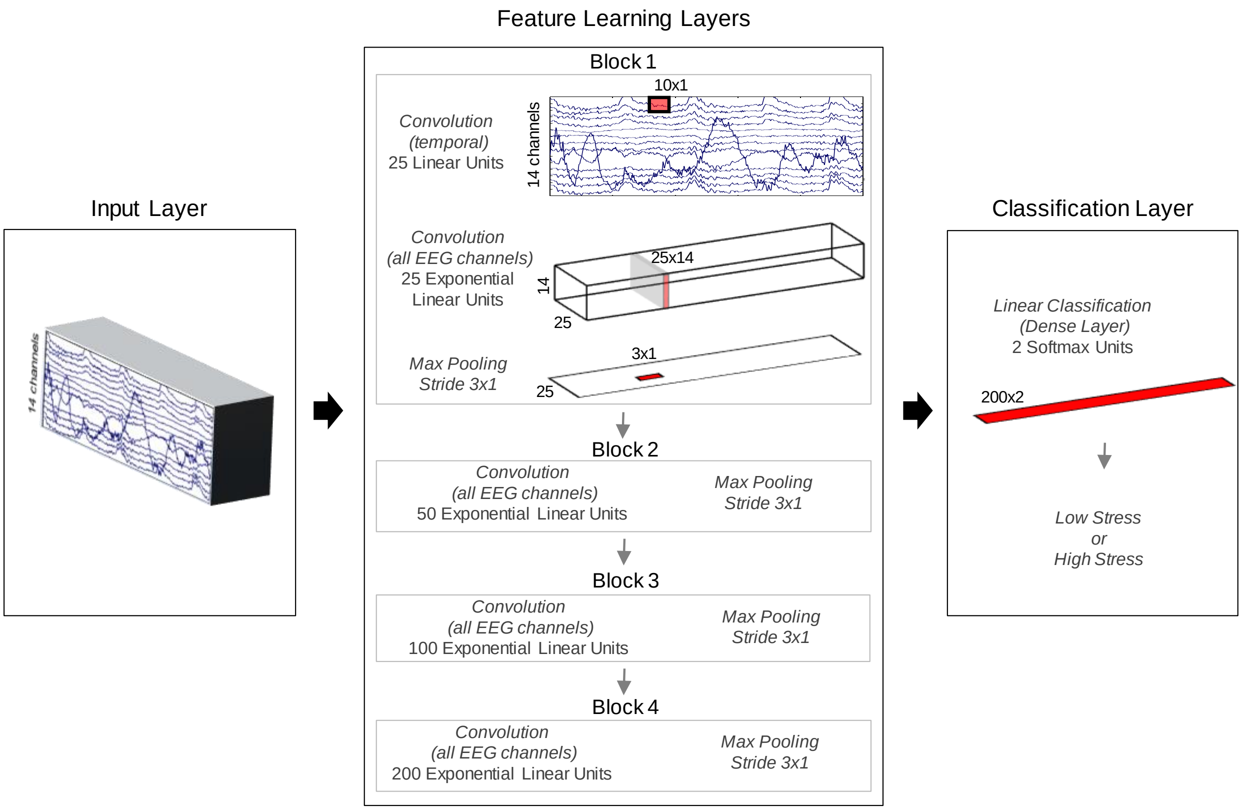

Figure A.3 Convolutional Neural Network Architecture to Recognize Construction Workers' Stress Level based on Their EEG Signals.

A.4. Experimental Setting

To examine the performance of the proposed Learning-based stress recognition framework to recognize workers' stress while exposed to different stressors at actual construction sites, I' visited four different construction sites and recorded 10 construction workers' brain waves using a wearable EEG headset. Subjects reported no mental disorders or history of epilepsy that could affect their brain waves. Subjects' were asked to perform same tasks under low stress conditions (e.g., working on the ground level and working right after taking a break) (A in Figure A.3) and high stress conditions (e.g., working at the top of a ladder, working in confined space, and continuous work without taking a break) (B in Figure A.3). Before starting the data collection, all the subjects were informed of the purpose and procedure of the data collection. Workers' brain waves were collected across 14 different channels using a wearable EEG headset (C in Figure A.3). The data collection rate was set at 128 data per second, with the recording resolution of 14 bits with the connectivity at a 2.4 GHz band a dynamic range of 8,400 µV (peak to peak). Subjects' actual stress was determined by measuring their cortisol level. Cortisol is known as stress hormone and is highly associated with subjects' stress (Russell et al. 2012). In this study subjects' cortisol level was measured using the saliva sample (D in Figure A.3). Subjects' cortisol level was used as a baseline to label their stress level as low or high while working in different conditions.

Figure A.4 EEG data collection in field: (a) Low stress experimental tasks (e.g., working on the ground level and working right after break); (b) High stress experimental tasks (e.g., working at top of a ladder, working in a confined space, and working in dangerous environment); (c) Wearable EEG headset fit into worker's safety hardhat; (d) Salivary cortisol samples kit.

A.5. Results and Findings

I applied two proposed learning neural network on the data collected at actual construction sites. The result of this study shows that the proposed Fully Connected Neural Network led to an overall prediction accuracy of 86.62%. On the other hand, the Convolutional Neural Network model led to an overall prediction accuracy of 64.20%.

Figure A.4 shows the stress recognition accuracy of the model under different network structures (different number of layers and neuron in the model). According to A in Figure A.4, a network with two hidden layers is preferable and will lead to the highest prediction accuracy and lowest computation cost as well. The result of optimizing the number of neurons in each layer show that selection of 83 neurons in the first layer and 23 neurons in the second layer will lead to the optimum network structure (B in Figure A.4).

The present finding is promising, considering that highest EEG-based stress recognition prediction accuracy using supervised learning algorithms is around 80.00% by applying Gaussian Kernel Support Vector Machine (SVM) (Jebelli et al. 2018c). Also, the proposed learning-based stress recognition does not have the limitation of supervised learning algorithms (e.g., SVM and logistic regression), which are fundamentally a binary classifier and have not been standardized for dealing with multi-class problems, to identify multiclass classification (identifying different stress levels).

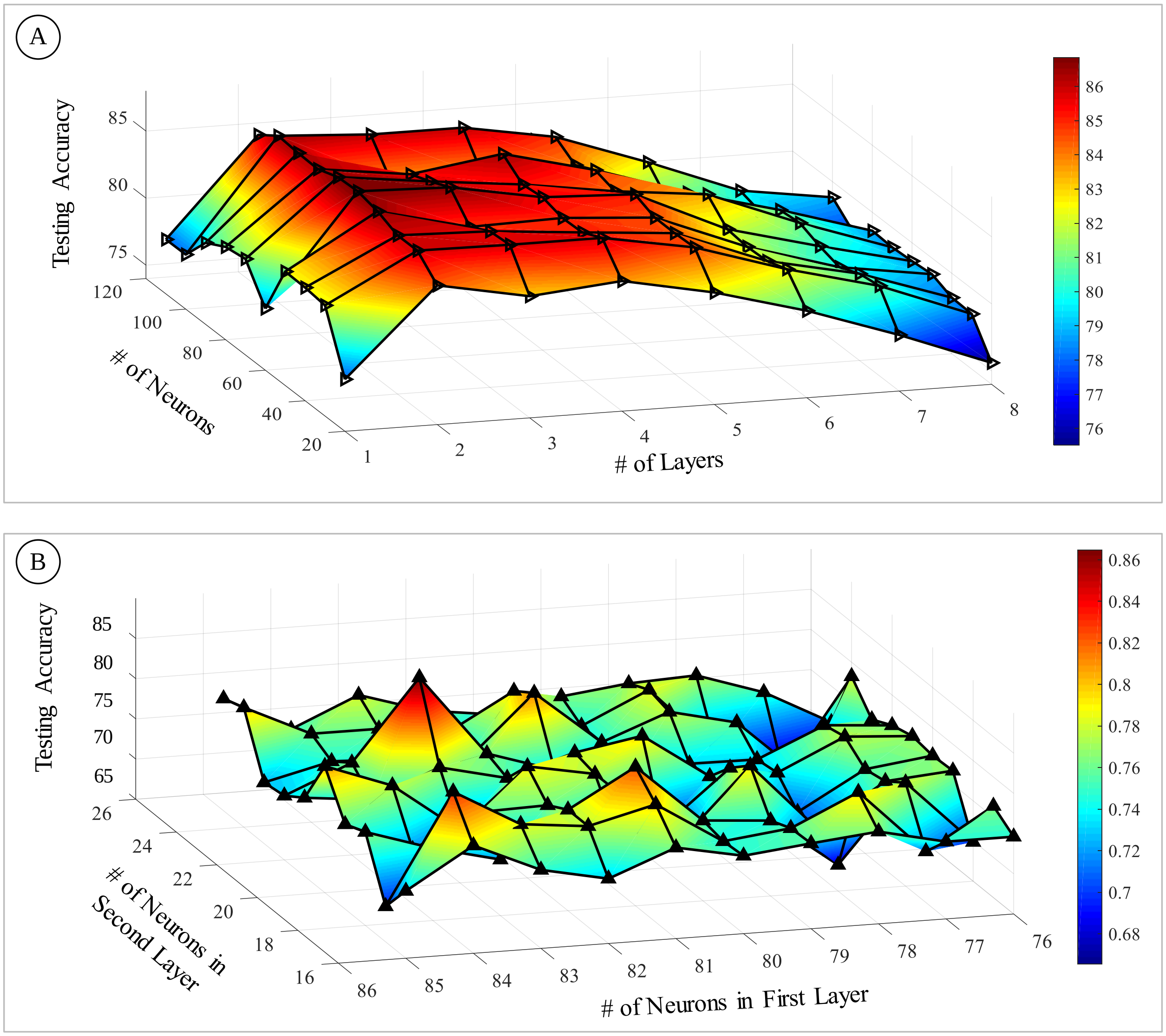

Figure A.5 Optimizing the architecture of Fully Connected Neural Network: (a) optimizing the number of layers in the network; (b) optimizing the number of neurons in each layer

To further investigate the classification performance, the confusion matrices for training and testing steps of the proposed network are shown in Table A.1. In this table, each row represents actual labels (stress level) while each column corresponds to predicted labels. In addition to classifier accuracy, Table A.1 shows two critical parameters to further examine the performance of the classifier; accuracy and recall. Precision is defined as the ratio of the number of correct prediction to the total number of instances classified as positive (high stress) or negative (low stress). The recall represents the ratio of the number of correct predictions (correct high or low stress) to the total number of instances (total high stress or low stress). Both “high stress” and “low stress” labels achieved relatively high recall and precision, which shows the high performance of the performance in detecting both low stress and high stress conditions.

Table A.1 Confusion matrices of training and testing steps.

Training	Low Stress	High Stress	Recall
Low Stress	2670	320	0.893
High Stress	270	2740	0.91
Precision	0.90	0.89	Accuracy: 0.90
Testing	Low Stress	High Stress	Recall
Low Stress	580	70	0.89
High Stress	100	540	0.84
Precision	0.85	0.88	Accuracy: 0.87

A.6. Conclusion

This study was undertaken to develop an EEG-based stress recognition framework by applying deep learning algorithms to recognize construction workers’ stress while performing different tasks at actual construction sites. This study showed the capability of a Fully Connected Neural Network to recognize workers stress with high accuracy. According to the results, the optimum network configuration to recognize construction workers’ stress requires two hidden layers, 83 neurons in the first hidden layer and 23 neurons in the second hidden layer. Also, the proposed DNN based stress recognition eased the need for feature extraction and feature engineering, one the most time-consuming steps in the Supervised Learning algorithms. Besides, multi DNN based stress recognition is expected to be the ultimate classifier to recognize workers’ stress with high accuracy, particularly while dealing with different levels of stress, where most of the supervised learning algorithms are limited to a binary classification setting. This study will serve as a basis for future studies to accurately identify different workers' stress levels using their brain waves in the field.

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Appendix B – Wearable Electromyography (EMG) to Assess Workers' Local Muscle Fatigue8

B.1. Overview

Due to the labor-intensive nature of construction tasks, a large number of construction workers frequently suffer from excessive muscle fatigue. Workers' muscle fatigue can adversely affect their productivity, safety, and well-being. Several attempts have been made to assess workers' fatigue using subjective methods (e.g., fatigue questionnaire). Despite, the success of subjective methods in assessing workers' fatigue in a long period, these methods have limited utility on construction sites. For instance, these methods interrupt workers' ongoing tasks. These methods are also subject to high biases. To address these issues, this study aims to examine the feasibility of a wearable Electromyography (EMG) sensor to measure the electrical impulses produced by workers' muscles as a means to continuously evaluate workers muscle fatigue without interfering with their ongoing tasks. EMG signals were acquired from eight subjects while lifting a concrete block using their upper limbs (i.e., elbow and shoulder muscles). As the first step, filtering methods

[8] This appendix is adapted from Jebelli, H. and Lee, S. (2019) "Feasibility of Wearable Electromyography (EMG) to Assess Construction Workers' Muscle Fatigue." In Advances in Informatics and Computing in Civil and Construction Engineering, Springer, 181-187.

(e.g., bandpass filter, rolling filter, and Hampel filter) were applied to reduce EMG signal artifacts. After removing signal artifacts, to examine the potential of EMG in measuring workers' muscle fatigue, various EMG signal metrics were calculated in time domain (e.g., Signal Mean Absolute Value (MAV) and Root Mean Square (RMS)) and frequency domain (e.g., Median Frequency (MDF) and Mean Frequency (MEF)) . Subjects' perceived muscle exertion (Borg CR-10 scale) was used as a baseline to compare the muscle exertion identified by EMG signals. Results show a significant difference in EMG parameters while subjects were exerting different fatigue levels. Results confirm the feasibility of the wearable EMG to evaluate workers' muscle fatigue as means for assessing their physical stress on construction sites.

B.2. Introduction

Construction is one of the most labor-intensive occupations in which workers are repetitively performing physically demanding tasks (Ng and Tang 2010). As a result, construction workers often suffer from a significant level of muscle fatigue that adversely affects their productivity, safety, and health (Kajimoto 2008). Workers' fatigue has been introduced as one of the major factors that increase workers' error rate and lead to unsafe work actions (Slack et al. 2009). Also, Workers' fatigue adversely affects their alertness, reaction time, mental acuity and disposition (Bowen et al. 2013). For these reasons, it is essential to mitigate the factors and tasks associated with workers' muscle exertion. The first step toward mitigating fatigue in the workplace is to evaluate muscle exertion. Evaluating the level of workers' muscle fatigue in planned tasks before engaging in these tasks can greatly contribute to identifying the tasks that may lead to muscle exertion. Then, adjusting the scheduled tasks and actions before severe fatigue takes place will enhance workers' safety, productivity, and well-being.

Previous research efforts have attempted to assess workers' muscle fatigue using subjective assessment (e.g., fatigue questionnaires) (Conrad and Kellar-Guenther 2006; Sadeghniiat-Haghighi and Yazdi 2015). However, interrupting workers' ongoing work to complete questionnaires interferes with time-sensitive tasks. Also, such methods are subjective and therefore include high biases. In addition to subjective assessment of physical fatigue, theoretical models of physiological or mechanical mechanisms (e.g., mathematical models) have been developed to assess workers' muscle fatigue (Liu et al. 2002; Ma et al. 2009). Despite their potential to evaluate workers' muscle fatigue, these mathematical models are limited in the context of construction tasks that have time-varying force exertions and irregular pauses and short breaks (Ma et al. 2009). Therefore, there is a definite need for a measurable and noninvasive method that can continuously measure construction workers' muscle fatigue.

In recent decades, one well-known method for measuring human beings' muscle fatigue is the use of electromyography (EMG), which is the measurement of the electrical impulses produced by the muscle during its contraction (Reaz et al. 2006). The EMG signal has been used widely in the clinical domain for the diagnosis of muscle fatigue (Cifrek et al. 2009; Katsis et al. 2004; McDonald et al. 2017) and nerve disorders (Okazaki et al. 2017; Visser et al. 2008). However, the EMG signal acquired in the clinical domain is based on invasive methods, either by inserting a needle directly into the muscle through the skin or by measuring surface EMG using wired electrodes placed on the skin. Despite the high quality of the EMG signals recorded using these methods, the use of these methods to measure muscle activity is impractical at construction sites due to their invasive experimental settings. However, with recent advancement in sensing technologies, wearable and portable sensors are available and contributed to enhancing job site conditions (Baghdadi et al. 2018; Hwang et al. 2016, 2018; Jebelli et al. 2014, 2015, 2016, 2017a;

b, 2018b, d, a; c; Kim et al. 2018; Nouredanesh and Tung 2015; Yang et al. 2015). In this regard, a wearable EMG can open a new door toward a noninvasive and continuous measurement of workers' muscle activity.

Despite the potential of a wearable EMG to collect workers' muscle activity while performing different tasks, the feasibility of a wearable EMG to measure workers' muscle fatigue has not been tested. To address this issue, this study tests the feasibility of a wearable Electromyography (EMG) sensor to measure the electrical impulses produced by workers' muscles as a means of continuously evaluating their muscle exertion and recovery without interfering with their ongoing tasks. To this end, we conducted an experiment to collect EMG signals of eight subjects' upper limb muscles (e.g., bicep and shoulder muscle) while they were experiencing different fatigue levels. We applied various filtering methods (e.g., a bandpass filter, a rolling filter, and a Hampel filter) to reduce EMG signal artifacts. Then the feasibility of a wearable EMG in distinguishing different levels of muscle fatigue was examined by comparing various metrics (e.g., signal Mean Absolute Value (MAV), Root Mean Square (RMS), Mean Frequency (MNF), and Median Frequency (MDF)) that were calculated based on the EMG signal. The Borg Rate of Perceived Exertion (RPE) scale, which is a well-known method to evaluate perceived muscle exertion, was used as a baseline to measure subjects' muscle fatigue level. Lastly, the feasibility of a wearable EMG sensor in measuring workers' muscle fatigue was examined by comparing the EMG-based metrics for different levels of muscle exertion.

B.3. Surface EMG to Measure Workers' Muscle Fatigue

Surface Electromyography (EMG) is a noninvasive method that provides useful information about the early manifestation of muscle fatigue by measuring the electrical activity of the muscle (Reaz et al. 2006). Even though raw EMG signals offers valuable information about the muscle activity, these signals need to be processed to measure muscle fatigue level. EMG signals are informative only if they can be quantified. Several studies have illustrated that there exists a significant relationship between EMG parameters (e.g., mean signal amplitude, root mean square, signal variance, mean power frequency, and median power frequency) and muscle fatigue (Cifrek et al. 2009; De Luca 1993; Katsis et al. 2004; McDonald et al. 2017).

In this section, we explain two essential steps to examine the feasibility of measuring construction workers' muscle fatigue using a wearable EMG sensor. Before analyzing the signal, one essential step is to reduce signal noises and signal artifacts. After reducing signal artifacts, to examine the feasibility of a wearable EMG to distinguish different muscle fatigue levels, we extracted different metrics based on the EMG signals.

B.4. Artifacts Removal

EMG signal quality can be adversely affected by different sources and forms of signal artifacts. The recorded EMG signal contains a component that shows the electrical response of the muscle activity (desired signal) as well as various noise components that come from sources other than muscle activity (undesired signals) (Reaz et al. 2006). Ambient noise, motion artifacts, electrical noise from power lines, and inherent instability of the EMG signal are main noise sources (De Luca et al. 2010; Nouredanesh et al. 2016). We applied different filtering methods (e.g., a bandpass filter, a rolling filter, a Hampel filter and a notch filter) to remove noises from the EMG signals. To remove ambient noise that comes from external electromagnetic sources (e.g., device wire noise), we applied a notch filter with a cutoff frequency of 60 Hz, which was recommended by previous researchers as an appropriate cutoff frequency to remove this type of noise (Hogan 1976). To remove signal outliers a Hampel filter was applied, Hampel filter has been introduced as a useful method to remove EMG signal outliers (Marateb et al. 2012). A bandpass filter with the lower cutoff frequency of (0.5 HZ) and higher cutoff frequency of 250 Hz was applied to reduce other external signal artifacts (e.g., motion artifacts, ambient noise, and inherent instability of the EMG signals) (Merletti and Di Torino 1999). To smooth the signal and to avoid aliasing in the data, a rolling filter was applied (De Luca et al. 2010). Figure 9.5 shows the raw EMG signals and the filtered EMG signals.

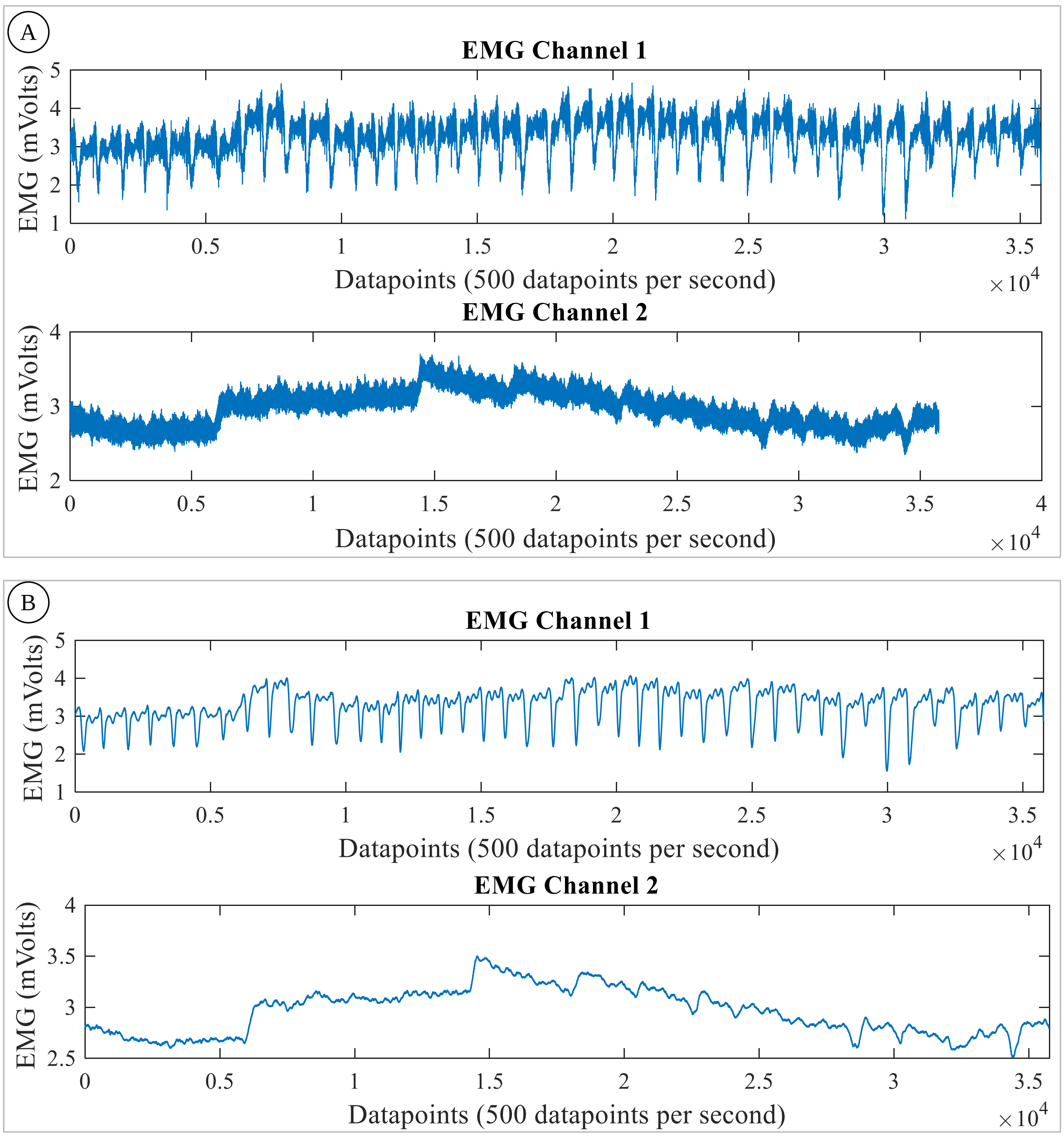

Figure B.1 EMG signal artifacts removal: (a) Raw EMG signals recorded from a worker's bicep muscle (Channel 1) and shoulder muscle (Channel 2); (b) Filtered EMG signals

B.5. EMG-based Metrics

Signal Mean Absolute Value (MAV), Root Mean Square (RMS), Mean Frequency (MEF), and Median Frequency (MDF) were calculated as the metrics to examine the potential of EMG in measuring workers' muscle fatigue. All of these metrics have been used widely in the clinical domain to assess muscle fatigue. EMG amplitude related parameters in the time domain (e.g., MAV and RMS) have been introduced as the informative metrics to evaluate muscle fatigue and estimate the endurance time (McCrary et al. 2017; Tkach et al. 2010). In addition, to the parameters that are calculated in the time domain, previous researchers found that changes in EMG signal patterns in frequency domain also are significantly associated with a decline in muscle force from the fresh state and therefore, it has a high potential to be used to measure muscle fatigue (Mannion et al. 1996; McDonald et al. 2017). Table B.1 shows the extracted parameters based on EMG signal in time and frequency domains. In this research, we extracted different EMG signal parameters from a block of 500 consecutive data point (1 second) since A single EMG data point is not informative to Due to the high temporal resolution of EMG recording (500 data point in a second).

Table B.1 Extracted EMG signal metrics in time and frequency domain.

Domain	Parameters	Equation	Explanation
Time Domain	Mean Absolute Value (MAV)	$MAV = \frac{\sum_{i=1}^{N} \lvert EMG_i \rvert}{N}$	Average absolute value of EMG amplitude
	Root Mean Square Level (RMS)	$RMS = \sqrt{\frac{\sum_{i=1}^{N} EMG^2}{N}}$	Norm 2 of the EMG amplitude divided by the square root of the number of samples
Frequency Domain	Average Frequency (MEF)	$power(EMG, f \in [0Hz, 250Hz])$	Power of the EMG the signal in the frequency domain in the interval $[[0Hz, 250Hz]]$
	Median Frequency (MDF)	$power(EMG, f \in [0Hz, MDF]) = power(EMG, f \in [MDF, 250Hz])$	Half of the signal power is distributed in the frequencies less than MDF

B.6. Experimental Setting

To examine the feasibility of the EMG-based parameters in measuring workers' muscle fatigue, we conducted an experiment and measured the electrical activity of eight healthy subjects while performing tasks with different fatigue level. Subjects were asked to use their upper limbs (i.e., elbow and shoulder muscles) and perform two tasks. In Task 1, subjects were asked to use their shoulder muscle (shoulder flexions from 0° to 120°) to lift a concrete brick that weighed 30 percent of their maximum shoulder muscle strength (a in Figure B.1). In Task 2, subjects were asked to lift a concert brick that weighted 30 percent of their maximum bicep muscle strength using their bicep muscle (b in Figure B.1). Subjects' maximum muscle strength of elbow and shoulder muscle was measured using a hand-held manual muscle tester (e.g., JTECH Commander Muscle Tester). Also, subjects were asked to maintain a constant lifting speed to prevent accelerations in lifting and to minimize variations in forces during different tasks.

EMG signals were acquired from subjects' bicep and shoulder muscles across two channels using a wearable EMG device (C and D in Figure B.2). EMG electrodes were placed parallel with the muscle fiber between the motor point and the tendinous insertion, near the center of the muscle. A reference electrode was placed far away from the bicep and shoulder muscles at an electrically neutral point of the body (E in Figure B.2). The Borg Rate of Perceived Exertion scale (Borg 1982), which assesses perceived exertion of the subjects was used as a baseline to assess subjects' perceived exertion (Borg 1982). Subjects were asked to rate their upper body muscles (shoulder muscle in Task 1 and bicep muscle in Task 9.2) fatigue level every 15 seconds. According to subjects' perceived exertion, the recorded EMG signals were divided into: Low Fatigue Level (RPE scale between 0 to 2), Moderate Fatigue Level (RPE scale between 3 to 4), High Fatigue Level (RPE scale between 5 to 7), and Extremely High Fatigue Level (RPE scale between 8 to 10) (Borg 1982).

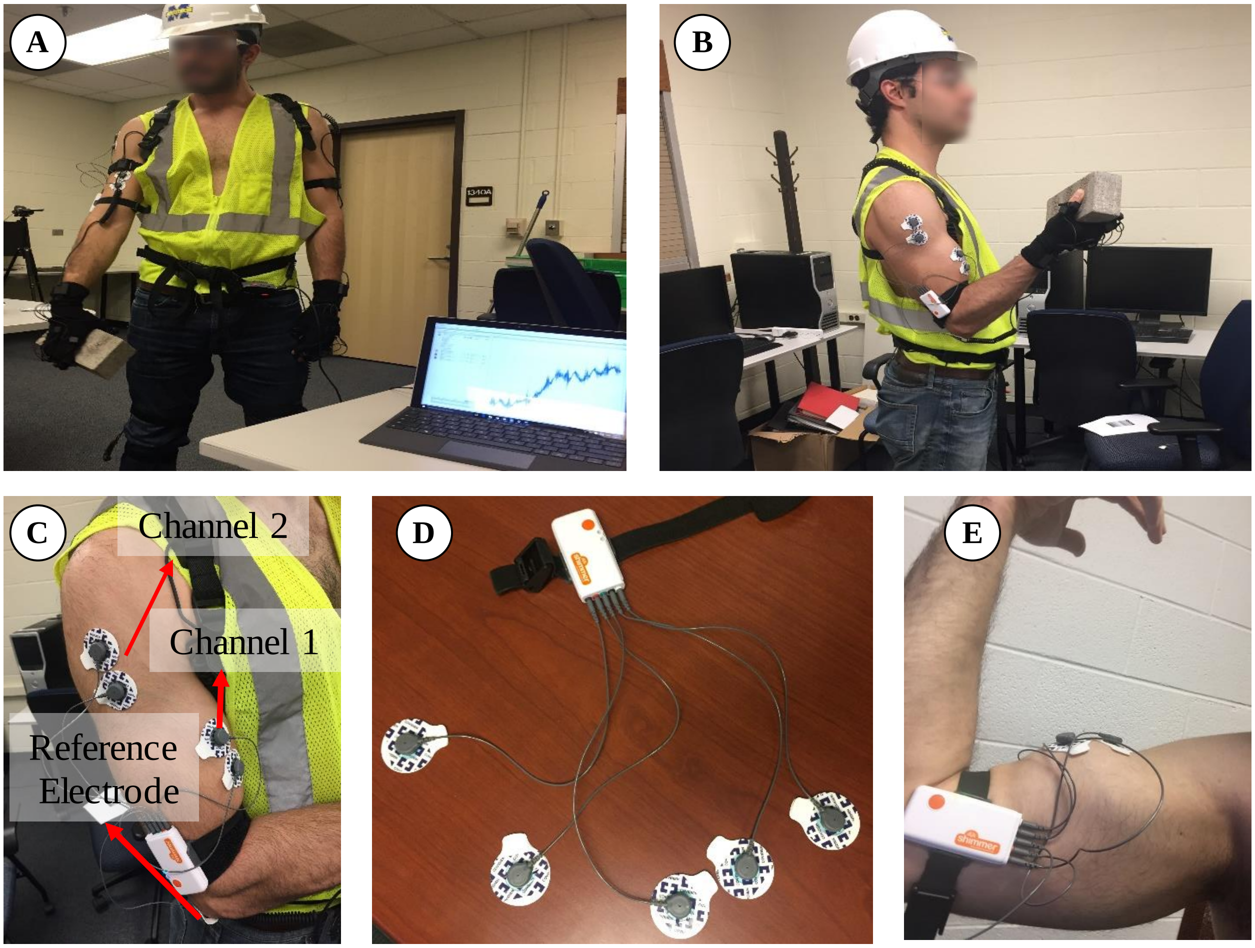

Figure B.2 EMG signal artifacts removal: (a) Raw EMG signals recorded from a worker's bicep muscle (Channel 1) and shoulder muscle (Channel 2); (b) Filtered EMG signals

B.7. Results and Findings

Figure B.3 and B.4 show the calculated EMG-based metrics values for bicep and shoulder muscles while subjects' were performed the experiment tasks under different fatigue levels. Results indicated a clear difference in MAB, RMS, MEF and MDF values while subjects were perceiving different fatigue levels for both bicep and shoulder muscles. Results show higher MAB, RMS values while subjects experienced higher muscle fatigue level (higher Borg scale rate) compared to the situation with less muscle fatigue (lower Borg scale rate). Higher MAB and RMS values show higher muscle exertion (Dideriksen et al. 2010). This confirms the feasibility of the extracted metrics in the time domain to measure workers' upper limb muscle fatigue.

In addition, there was a clear difference in the metrics that were calculated in the frequency domain (MEF and MDF) among different fatigue levels. The results of this study are in accordance with the previous studies in the clinical domains that stated a lower MEF and MDF values shows greater muscle fatigue level (Allison and Fujiwara 2002). Furthermore, the values of MEF and MDF are consistent, and both illustrated that subjects' experience higher muscle fatigue while they keep lifting the concert bricks continuously. In comparison of time and frequency domain metrics, the metrics that were calculated in the frequency domain led to a higher performance in distinguishing different levels of fatigue; this can be related to less sensitivity of these metrics to the signal noise as well as data aliasing (Watanabe and Akima 2010).

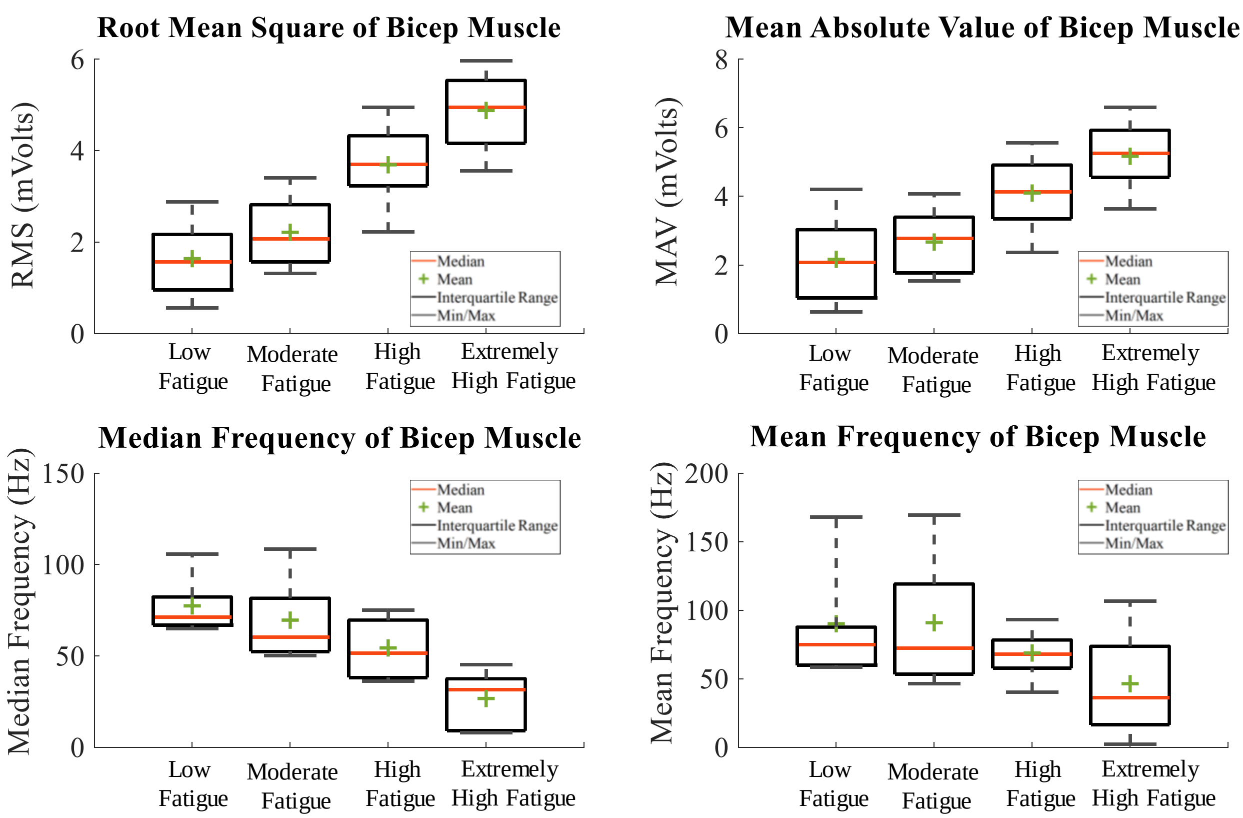

Figure B.3 The values of MAV, RMS, MEF, and MDF for bicep muscle.

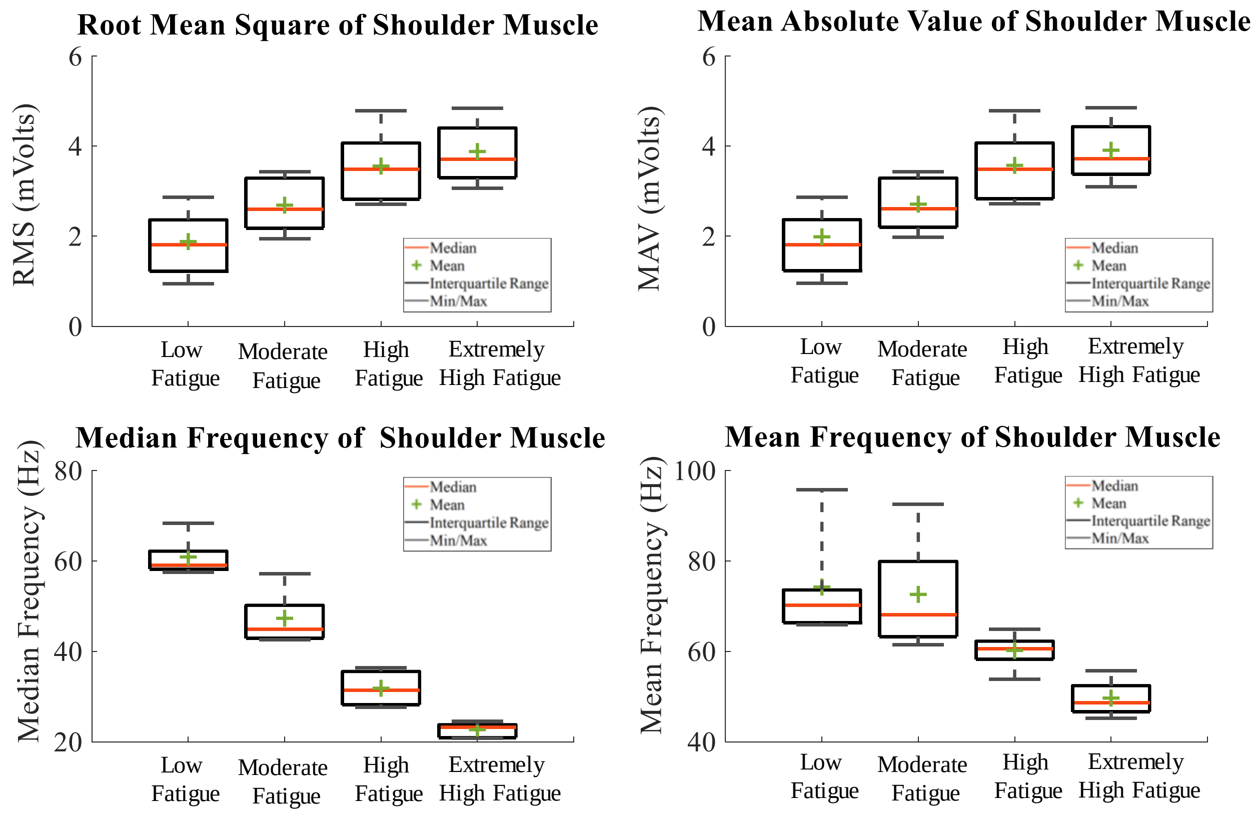

Figure B.4 The values of MAV, RMS, MEF, and MDF for shoulder muscle.

B.8. Conclusion

The present study was designed to determine the feasibility of a wearable EMG sensor to measure construction workers' upper limb muscle fatigue. The results of this study show the feasibility of the wearable EMG to evaluate workers' muscle fatigue, which can result in measuring physical stress at construction sites. The results showed that higher muscle fatigue level leads to higher MAB and RMS values and Lower MEF and MDF values. These finding may be used to improve construction workers' productivity, safety, and well-being by developing an automatic and mountainous framework to measure workers' muscle fatigue based on their EMG signal. It is recommended that further research be undertaken to validate the use of current metrics in this study in measuring construction workers' fatigue through additional experiments with a larger number of subjects on different muscle groups.

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Appendix C – Physiology-based Dynamic Muscle Fatigue Model for Construction Tasks[9]

C.1. Introduction

Construction is labor intensive, involving repetitive material or tool handling tasks that are physically demanding (Ng and Tang 2010). Many construction workers thus suffer from a significant level of muscle fatigue that can cause diverse detrimental impacts on their safety, health, and productivity. Specifically, it is widely recognized that excessive muscle fatigue can result in more than an increase of human errors and unsafe acts; it also decreases the quality of work and worker satisfaction (Eklund 1997; Huang and Hinze 2006; Kajimoto 2007; Slack et al. 2009; Bowen et al. 2017). Also, in the long term, work-related musculoskeletal disorders (WMSDs) and chronic fatigue have been reported as an adverse health outcome from consistent and excessive muscle fatigue (Bültmann et al., 2002; Åkerstedt et al. 2004; Iridiastadi & Nussbaum 2006; Shen et al. 2006; Ricci et al. 2007; Pierce 2016).

[9] This appendix is adapted from Jebelli, H., Seo, J., Hwang, S., and Lee, S. (2018) "Physiology-based Dynamic Muscle Fatigue Model for Upper Limbs during Construction Tasks." *International Journal of Industrial Ergonomics* (in review).

In this regard, evaluating the level of muscle fatigue in planned tasks (i.e., prior to work) can greatly contribute to workers' safety and health by taking proper preventive actions before severe fatigue takes place. Focusing on this research need, considerable research efforts have previously tried to estimate individual muscle fatigue using surveys, instruments, and mathematical models (Studer et al. 1999; Iridiastadi and Nussbaum 2006; Xia and Frew Law 2008; Ma et al. 2009; Debold 2012; Karatzaferi and Chase 2013). Although they contributed to quantifying human muscle fatigue based on laboratory experiments or an in-depth examination of mechanical and metabolic mechanisms related to muscle fatigue during muscle contraction, they do not take into account irregularly varying muscle activation as well as fatigue recovery from frequent idling/resting periods during a task. They are therefore especially limited in the context of construction tasks that involve varying force exertion levels and intermittent idling/resting periods.

In an effort to address these issues, this study proposes a novel physiology-based muscle fatigue model that takes into account the fundamental fatigue process in a human body. It estimates the level of muscle fatigue over time by representing and quantifying physiological mechanisms of dynamic muscle fatigue generation and recovery during construction tasks. Specifically, a System Dynamics (SD) model, which is a differential equation-based continuous simulation, is used to represent localized muscle responses to fatigue over time caused by varying workloads of construction tasks. In this study, the modeling focus is the upper limbs including elbows and shoulders because upper limbs are less fatigue resistant than lower limbs (Van Hall et al. 2003; Smoliga 2007), and many construction tasks include high levels of material and tool handling that uses upper limbs. To develop the model, the fatigue responses of upper limbs are modeled based on fundamental mechanisms of the accumulation and clearance of intramuscular metabolites during physical exertion and the effects of the metabolites on muscle contractile processes. To refine and validate the model, we will use laboratory experimental data from real construction workers who heavily use their upper limbs. Specifically, parameters for elbow and shoulder muscle fatigue models are firstly determined using a part of experimental data. Then, we validate developed models (i.e., elbow and shoulder models) by comparing the output of the developed model with remaining experimental data.

C.2. Importance and Challenge of Evaluating Localized Muscle Fatigue in Construction

Occupational fatigue is one of the most common workplace hazards, which may lead to workers' safety and health issues (Sadeghniiat-Haghighi and Yazdi 2015). In particular, workers performing demanding physical activities normally suffer from physical fatigue. From a physiological perspective, physical fatigue is associated with impaired muscle function, such as an inability of the muscles to maintain the required level of force (Edwards 1981), a reduction in force-generating capacity of the muscles (Chalder et al. 1993) or a decrease in muscle capacity to perform physical activities (Friedman et al. 2007). That is why physical fatigue has been often denoted by 'muscle fatigue' (Abd-Elfattah et al. 2015). Workers' muscle fatigue can cause more devastating impacts on construction due to its involvement of heavy workloads, awkward working postures, or prolonged working hours (Abdelhamid and Everett 2002; Sluiter et al. 2003; Toole 2005; Hallowell 2010). For instance, WMSDs in construction yield 34.6% of all non-fatal occupational injuries and illness (BLS 2016) and 29% of compensation claims (Albers et al. 2006). Thus, managing workers' muscle fatigue is extremely important to improve workers' safety and health in construction.

As the first step to manage workers' muscle fatigue, identifying physically demanding tasks by fatigue measurement is of importance. Previous research efforts on fatigue measurement in occupational settings have focused on post-work evaluation because of the difficulty of muscle fatigue measurement during performing tasks. One of the widely used methods for real-time measurement is surface electromyography (sEMG), which estimates the level of fatigue by analyzing the EMG signals from surface electrodes on muscles (Vøllestad 1997). However, attaching surface electrodes on muscles could interfere with ongoing work, and the misplacement of electrodes due to workers' movement may hinder the use of sEMG in occupational settings. Post-work evaluation of fatigue measurement relies on subjective survey or quantification by using fatigue scales and questionnaires (Sadeghniiat-Haghighi and Yazdi 2015). These methods are useful to identify specific tasks and causes of muscle fatigue in a given workplace setting. However, the use of these methods is still challenging in construction as construction tasks are not standardized, and thus physical demands from work could vary depending on projects. As a result, problematic tasks could be different from one project to another. To address this issue, Seo et al. (2016) emphasized the need for evaluating muscle fatigue prior to work for construction tasks. They proposed a simulation-based approach to predict muscle fatigue from the planned construction operations. Considering varying work demands from construction tasks, effective strategies to manage muscle fatigue can be devised from its evaluation prior to work, which can include redesigning workplaces and tasks, ensuring proper workload distribution based on each individual's capacity, and providing proper work/rest schedules (Seo et al. 2016).

There have been significant research efforts to quantitatively assess muscle fatigue prior to work, through a model-based estimation (Vøllestad 1997; Perez et al. 2014). Existing muscle fatigue models can be classified into empirical and theoretical models (Xia and Frey Law 2008).

Empirical models have estimated endurance times under diverse work intensities using regression equations that were derived from laboratory experiments. However, these models are applicable only to specific conditions where the models were developed, such as static exertions (i.e., isometric muscle contraction) (Sato et al. 1984; Manenica 1986; Rohmert et al. 1986; Rose et al. 1992; Rose et al. 2000), intermittent static exertions (Hagberg 1981; Iridiastadi and Nussbaum 2006), or dynamic force exertions with cyclic changes (i.e., continuous isotonic contraction) (Hagberg 1981) at a specific body segment. Therefore, they are not flexible enough to represent the dynamics of muscle fatigue (e.g., irregularly varying muscle activation and contraction) that result from diverse construction tasks. On the other hand, theoretical muscle fatigue models that mathematically represent physiological or mechanical mechanisms of fatigue can be applicable to more complex tasks (Liu et al. 2002; Xia and Frey Law 2008; Ma et al. 2009). However, these models are limited in the feasibility of their application to real conditions because of limited use of the model (e.g., only for static exertion) (Liu et al. 2002), complex data input (e.g., joint torque, angle, and velocity) (Xia and Frey Law 2008), and lack of consideration of recovery from fatigue and validation (Ma et al. 2009). As a result, they are also not suitable for representing the dynamics of localized muscle fatigue that involve varying force exertion levels and intermittent idling/rest periods, which are prevalent in construction tasks. To better estimate muscle fatigue in dynamic occupational tasks, a new modeling approach, particularly the representation of the dynamics of muscle fatigue from a physiological perspective, is thus needed to incorporate mechanisms of muscle fatigue generation and recovery over time during construction tasks with varying physical demands, which is the aim of this study. By doing so, the proposed modeling approach in this study can be used for better understanding of workers' physiological muscle responses to diverse construction tasks thereby measuring workers' muscle fatigue prior to work.

C.3. Development of System Dynamics-based Muscle Fatigue Model

Based on the fundamental muscle fatigue mechanisms specified in the literature, this study models dynamic muscle fatigue mechanisms using System Dynamics (SD). An SD model can provide an analytic solution for complex, nonlinear, and dynamic systems by understanding interactions among system variables (Sterman 2000; Williams 2002). As a result, SD has been applied to understand complex physiological and biological systems (e.g., energy metabolism) in the human body, where interactions among different variables (e.g., fatigue substances and the level of muscle exertion) are important (Abdel-Hamid 2002; Homer et al. 2006; Karanfil and Barlas 2008; Owen and Griffiths 2013; Tedeschi et al. 2013). SD can thus be very effective on representing physiological responses of dynamic muscle fatigue generation and recovery in the human body that continuously interact with one another forming feedbacks (i.e., an output of a system passes back through as an input cyclically). Since SD consists of a causal loop diagram based on a cause-and-effect relationship among variables and a stock-and-flow diagram based on multiple differential equations, SD enables not only to continuously capture the level of the physiological variables (e.g., fatigue substance and the level of muscle exertion) over time but also to understand the core process on how these variables change. Focusing on these capabilities of SD, the proposed model aims to represent dynamic feedback processes of muscle fatigue generation and recovery. Also, the model aims to evaluate the level of muscle fatigue by predicting both reduced muscle capacity due to the accumulation of fatigue substances and endurance time during diverse and varying workloads such as construction tasks.

Figure C.1 shows a core structure of the dynamic muscle fatigue model. This model aims to simulate the underlying mechanism of how the muscle forces are reduced as muscles become fatigued as well as how the muscle forces recover over time during idling or resting (i.e., muscle fatigue generation and recovery mechanisms). In particular, this model focuses on metabolic muscle fatigue due to the accumulation of metabolic by-products that has been known as a major cause of muscle fatigue during intense exercise (Layzer 1990). Physically demanding tasks with heavy workloads that exceed the aerobic capacity of the muscles cause the accumulation of intramuscular metabolites (e.g., inorganic acids and phosphate) in an anaerobic state that reduces muscle force production in muscle fibers (Kent-Braun 1999; Cairns 2006). As a response of forceful exertion, the cardiovascular system increases heart rates to deliver blood to the exercising muscles, not only providing oxygen and substrates, but also removing metabolites (Christensen 1986). As a result, metabolic concentrations diffused out of the muscle, returning muscle force to normal (Layzer 1990).

In a muscle fatigue generation and recovery process, the proposed model represents a muscle fatigue from accumulation and diffusion of intramuscular metabolites as a stock (a box variable in Figure C.1), called 'Fatigue in pH.' The changes in the amount of 'Fatigue in pH' are influenced by 'Fatigue Production Rate' (inflow into the stock in Figure C.1) and 'Fatigue Diffusion Rate' (outflow of the stock in Figure C.1) during force exertions and idling/resting periods reflecting the metabolic mechanisms of muscle fatigue. The level of muscle fatigue from accumulated fatigue substances is represented as potential of hydrogen (pH) in the model as fatigue substances has linear relationship with change of pH. Usually, the acidosis in human muscle fibers without fatigue is pH 7.0 and the largest acidosis level when fully fatigued is around pH 6.2 (Cairns 2006). Thus, the value of 'Fatigue in pH' ranges from 7.0 (no fatigued) to 6.2 (fully fatigued) in the model. On the other hand, this 'Fatigue in pH' would determine the decline or recovery of worker's maximum ability for muscles to contract, which is represented as 'Exertable Maximum Force' (A in Figure C.1). The value of 'Exertable Maximum Force' is a percentage of an individual's maximum voluntary contraction (MVC) of muscles (i.e., %MVC).

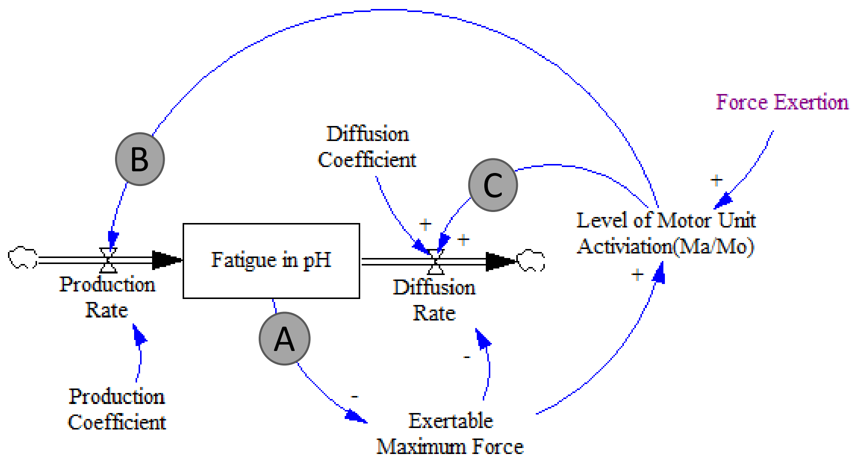

Figure C.1 SD-based Muscle Fatigue Model

During the work tasks, the high level of work intensity (i.e., 'Force Exertion' which is the input value representing workloads in the model) increases the level of muscle contraction, which can be represented as the number of motor units to be activated (M_A) among total available motor units (M_0) (i.e., 'Level of Motor Unit Activation (M_A/ M_0)') (Xia and Frey Law 2008). It is known that the rate of accumulation of fatigue (i.e., 'Production Rate') is linearly correlated with the intensity of force exertions (i.e., 'Force Exertion') and the level of motor unit activation (Sjøgaard et al. 1988), through increase of an anaerobic breakdown of glycogen by activated motor units (B in Figure C.1) (Westerblad et al. 2002). During idling/resting periods, fatigue substances diffuse out of the muscle by changing the level of 'Fatigue in pH', contributing to the recovery from muscle fatigue (C in Figure C.1). It was found that reduced muscle strength can be recovered in 5–10 minutes up to about 90%MVC while more than 30 minutes are additionally required to be fully recovered (Lind 1959). Also, the recovery rate under 90%MVC is about 16 times higher than the rate over 90%MVC (Seo et al. 2016). Based on this evidence, the production and diffusion of 'Fatigue in pH' can be expressed by the following equations:

$$Fatigue\ in\ pH(t) = \int_0^t [Production\ Rate(s) - Diffusion\ Rate(s)]ds \quad (pH{:}\ 7.0\ - 6.2) \qquad (1)$$

$$Production\ Rate(t) = \ Motor\ Unit\ Activation\ Level\ (Ma/Mo)(t) * Production\ Coefficient \qquad (2)$$

$$\begin{aligned} &Diffusion\ Rate(t)\ (when\ Level\ of\ Motor\ Unit\ Activation\ (Ma/Mo) = 0) = \\ &Diffusion\ Coefficient\ \ (Exertable\ Maximum\ Force\ (\%MVC) < 0.9) \\ &Diffusion\ Coefficient/16\ \ (Exertable\ Maximum\ Force\ (\%MVC) > 0.9) \end{aligned} \qquad (3)$$

It is noteworthy that 'Production Coefficient' and 'Diffusion Coefficient' have not been fully identified. To address this issue, empirical data from laboratory experiment will be used to calibrate coefficients, which will be described later. In this model, a major input variable is 'Force Exertion' that represents the individual physical demands of tasks from workloads with a variable unit of %MVC (i.e., percentage of individual's maximum voluntary contraction (MVC)), while a major output variable is 'Exertable Maximum Force' that represents resultant change in muscle strength from fatigue with a variable unit of %MVC (Vøllestad 1997). In the model, the level of 'Exertable Maximum Force' from muscle fatigue is determined by empirical evidence from previous research (A in Figure C.1 and Equation 4: Cairns 2006), which found a relationship between the level of intramuscular pH and peak tetanic force of body parts (i.e., exertable maximum force):

$$\begin{aligned} &Exertable\ Maximum\ Force = \\ &\quad - 1.333 + 0.333 * Fatigue\ Substance\ \ (pH)\ (pH > 6.7) \\ &\quad - 19.2 + 3 * Fatigue\ Substance\ (pH)\ \ (pH > 6.6) \\ &\quad - 9.3 + 1.5 * Fatigue\ Substance\ (pH)\ \ (pH > 6.2) \end{aligned} \qquad (4)$$

Based on the identified exertable maximum force of body parts, muscles' maximum endurance time (MET), which is related to the fatigue failure (i.e., the accidental failure of muscle contraction), can be predicted based on a workers' muscle capability. Specifically, as shown in Figure C.2, MET is determined as the simulation time when muscle capability (i.e., 'Exertable Maximum Force' in Figure C.1) is lower than physical demands of tasks (i.e., 'Force Exertion' in Figure C.1). The developed model, which provides a comprehensive understanding of muscle fatigue, can also provide recognition of muscle endurance time related to fatigue failure in demanding construction work. In addition, the use of diverse dynamic input values for work intensity ('Force Exertion' in Figure C.1) enables the model to represent a worker's muscle fatigue according to varying forces and intermittent idling/resting periods, which are very common in construction tasks.

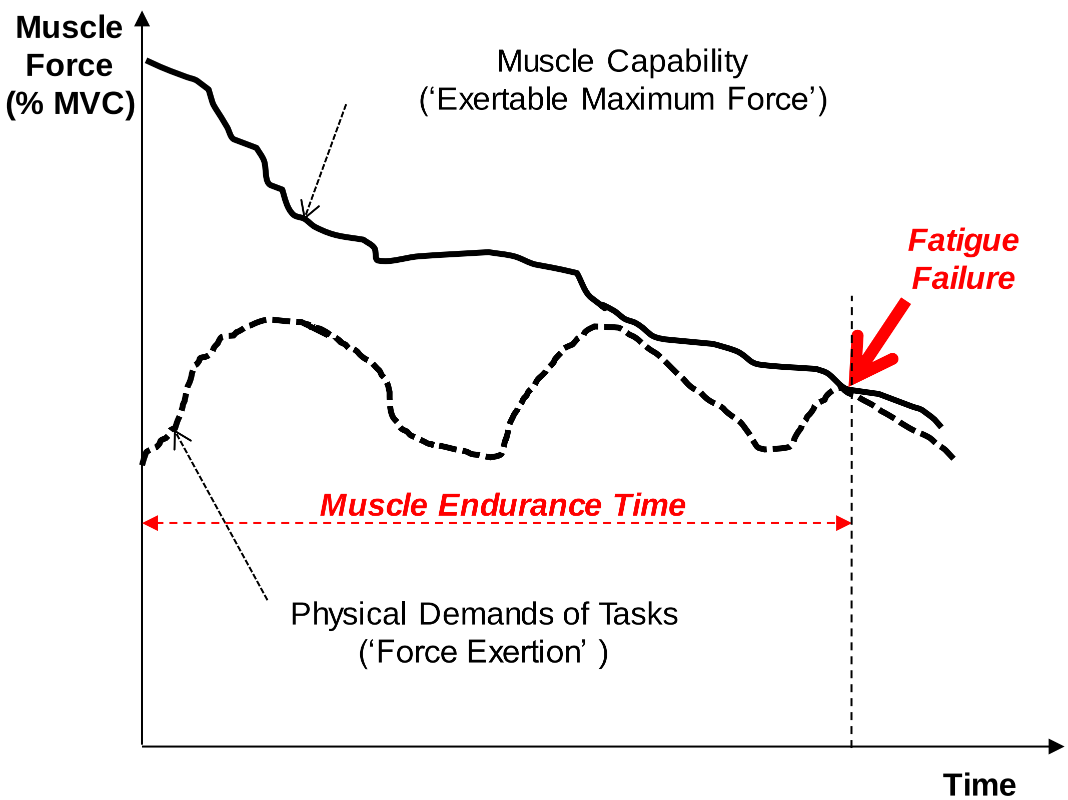

Figure C.2 SD-based Muscle Fatigue Model

C.4. Laboratory Experiment

To refine and validate the dynamic fatigue model developed for upper limbs, we performed laboratory experiments. Specifically, the extent to which subjects' physical capacities (i.e., muscle strength and endurance time) of upper limbs (i.e., elbow and shoulder) can vary by muscle fatigue generation and recovery is a major concern. Since the allowable physical limits have been well established for each demographic category (e.g., gender, age, height, and weight) (Chaffin et al. 2006), the experiments will focus on change in allowable endurance and strength induced by varying workloads (e.g., varying forces and intermittent rest periods).

To do this, we recruited 15 healthy subjects within ages between 22 and 35 years (see Table C.1). For this study, we recruited only male subjects because most of production work in construction is performed by male workers. Data collection was approved by the University of Michigan Institutional Review Board. The informed consent form was distributed to all the subjects before data collection in order for them to be informed about the anonymity of data collection and participants' rights. As shown in Table C.2, each subject performed six endurance tasks (i.e., two protocols for elbow and shoulder tasks and three tasks per each elbow or shoulder protocol) with randomly assigned task orders. All tasks were performed for elbow and shoulder flexions from 0° to 120°. Before performing each task, the subject's maximum muscle strength of elbow and shoulder flexion was measured using an off-the-shelf hand-held manual muscle tester (e.g., JTECH Commander Muscle Tester) following the procedure described by Hagberg (1981) and Mital et al. (2000). In addition, they were asked to maintain a constant lifting speed (i.e., two seconds for each lifting cycle) to minimize variations in forces due to accelerations. During six tasks, endurance time for each task was measured when the subject could not maintain the force level.

Table C.1 Description of Subject Information

Subject #	Age	Weight (kg)	Height (cm)	Maximum Muscle Strength	
				Elbow (N)	Shoulder (N)
1	25	75	180	221	159
2	28	70	178	135	120
3	35	80	180	127	106
4	30	70	170	140	119
5	25	65	173	111	88
6	22	65	170	102	90
7	28	70	178	116	111
8	27	80	180	137	102
9	24	98	170	128	98
10	27	75	179	120	89
11	30	70	177	165	111
12	37	86	168	210	151
13	32	70	175	118	67
14	30	55	160	83	89
15	27	89	192	196	178
Mean	28.46	74.50	175.33	140.59	112.00
SD	3.89	10.38	7.08	40.08	30.12
Min	22	55	160	83	67
Max	37	98	192	221	178
Median	28	70	177	128	106

Table C.2 Experimental Protocols

Protocols	Tasks*	Purposes
Protocol #1: Elbow Tasks	Task#1: Continuous lifting a 2.72kg (6lb) block	Parameter setting
	Task#2: Continuous lifting a 5.44kg (12lb) block	Parameter setting
	Task#3: Mixing 3 cycles of lifting a 2.72kg (6lb) block and 3 cycles of lifting a 5.44kg (12lb) block (a few seconds of resting when changing blocks)	Validation
Protocol #2: Shoulder Tasks	Task#1: Continuous lifting a 2.72kg (6lb) block	Parameter setting
	Task#2: Continuous lifting a 5.44kg (12lb) block	Parameter setting
	Task#3: Mixing 3 cycles of lifting a 2.72kg (6lb) block and 3 cycles of lifting a 5.44kg (12lb) block (a few seconds of resting when changing blocks)	Validation

** Each lifting cycle for all the tasks is two seconds*

Figure C.3 Laboratory Experiments: (a) Protocol #1 for Elbow; and (b) Protocol #2 for Shoulder

In detail, both elbow tasks (i.e., Protocol #1) and shoulder tasks (i.e., Protocol #2) as shown in Figure C.3 consist of three tasks including continuous lifting a 2.72kg (6lb) block (Task #1), continuous lifting a 5.44kg (12lb) block (Task #2), and mixing 3 cycles of lifting a 2.72kg (6lb) block and 3 cycles of lifting a 5.44kg (12lb) block (Task #3). In Task #3, a few seconds of pauses exist when subjects change the block. Task #1 (15–40%MVC of force exertion among different subjects) and #2 (30–80%MVC of force exertion among different subjects) are designed to determine model parameters (e.g., Production and Diffusion Coefficients) to reflect diverse levels of force exertions while Task # 3 that includes varying forces and short breaks is designed to validate the dynamic muscle fatigue generation and recovery model. Table C.3 shows the results (i.e., muscles' maximum endurance time: MET) for all experimental tasks. All loaded weights are considered relatively based on the subjects' maximum muscle strength and measured as a ratio, which is defined as %MVC. For example, if the subject's maximum muscle strength to lift using their arm is 267N, then 2.72kg (6lb) weight, which is 26.7N, would be 10%MVC. Since the individual difference on muscle capability will significantly affect the time to fatigue, the use of relative ratio considering individual capability is better on estimating fatigue than the use of absolute value of weight. Also, the previous studies measured the time for fatigue when a subject voluntarily gives up their loaded weight, and such time was defined as a maximum endurance time (MET). %MVC and MET have been widely used in numerous muscle fatigue estimation models.

Table C.3 Experimental Results

Protocol	Subject	Task #1		Task #2		Task #3	
		Force Exertion (%MVC)	MET* (Min.)	Force Exertion (%MVC)	MET* (Min.)	Force Exertion (%MVC)	MET* (Min.)
#1: Elbow	#1	12%	6.0	24%	1.9	12–24%	6.3
	#2	20%	4.5	40%	1.5	20–40%	2.5
	#3	21%	3.6	42%	1.1	21–42%	2.3
	#4	19%	5.5	38%	1.5	19–38%	3.3
	#5	24%	2.0	48%	1.0	24–48%	1.4
	#6	26%	3.3	52%	1.0	26–52%	1.5
	#7	23%	2.1	46%	0.8	23–46%	1.5
	#8	20%	3.3	40%	0.9	20–40%	2.1
	#9	21%	4.7	42%	1.0	21–42%	2.1
	#10	22%	2.4	44%	1.0	22–44%	1.8
	#11	16%	5.0	32%	1.8	16–32%	2.1
	#12	13%	5.3	26%	2.5	13–26%	4.8
	#13	23%	2.7	46%	1.1	23–46%	1.3
	#14	32%	1.9	64%	0.8	32–64%	0.9
	#15	14%	7.5	28%	2.3	14–28%	3.5
#1: Shoulder	#1	17%	3.3	34%	2.0	17–34%	2.2
	#2	22%	1.2	44%	0.7	22–44%	1.3
	#3	25%	0.9	50%	0.8	25–50%	1.0
	#4	22%	3.1	44%	0.8	22–44%	2.5
	#5	30%	1.0	60%	0.6	30–60%	1.0
	#6	29%	2.8	58%	1.3	29–58%	1.7
	#7	24%	1.2	48%	0.8	24–48%	1.2
	#8	26%	1.1	52%	0.7	26–52%	1.3
	#9	27%	0.8	54%	0.7	27–54%	1.1
	#10	30%	0.8	60%	0.5	30–60%	0.9
	#11	24%	2.3	48%	2.3	24–48%	2.0
	#12	18%	3.0	36%	3.0	18–36%	3.6
	#13	40%	0.6	80%	0.3	40–80%	0.8
	#14	30%	2.1	60%	1.0	30–60%	1.7
	#15	15%	4.4	30%	4.4	15–30%	2.5

C.5. Model Calibration and Validation

As mentioned earlier, quantitative equations between physiological variables in the developed model need to be further refined (e.g., Production and Diffusion Coefficients in the model). This is because previous models for muscle fatigue have produced variable results (Hagberg 1981; Sato et al. 1984; Manenica1986; Rose et al. 1992, 2000; Ma et al. 2009; Seo et al. 2016), which makes it difficult to determine accurate single values of coefficients. Also, according to differences of muscle fiber composition in body parts thereby varying fatigue substance accumulation and diffusion rates of body parts (Van Hall et al. 2003), model parameters for elbow and shoulder tasks need to be customized.

To do this, we firstly pre-defined the range of the Production Coefficient and the Diffusion Coefficient to -0.008 ~ -0.018 and -0.0004 ~ 0.0005, respectively, by comparing the model's results and various previous models (Hagberg 1981; Sato et al. 1984; Manenica1986; Rose et al. 1992, 2000; Ma et al. 2009; Seo et al. 2016). Then, based on experiment data in Tasks #1 and #2 for both elbow and shoulder tasks, we finally set the exact values of the Production Coefficient and the Diffusion Coefficient so that results (i.e., METs from diverse force exertion levels) between the proposed model and the experiment is the most similar as shown in Figure C.4. For this comparison, normalized root mean square deviation (NRMSD) and Pearson product-moment correlation coefficients (r) are used because of their wide usage (Ma et al. 2009; Ji et al. 2014). As shown in Figure C.4, the coefficients for the elbow and shoulder models, which produce the most similar behaviors between the model behavior and the experimental data (i.e., the lowest NRMSD and the highest correlation coefficients), are determined as -0.014 of Production Coefficient and -0.0005 of Diffusion Coefficient for the elbow model (Figure C.4a), and -0.018 of Production Coefficient and -0.0005 of Diffusion Coefficient for the shoulder model (Figure C.4b).

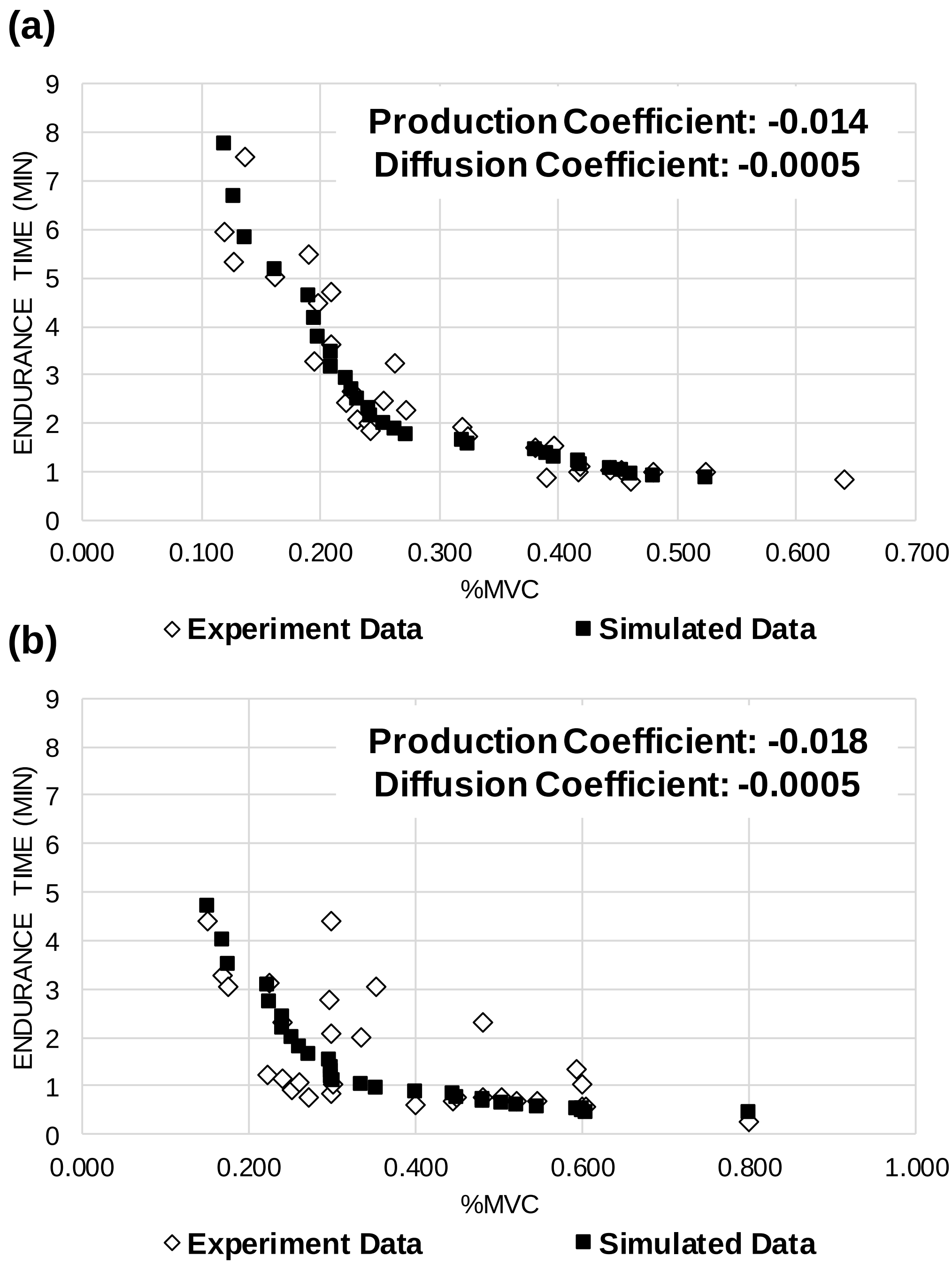

Figure C.4 Model Parameter Setting: (a) Elbow Model; and (b) Shoulder Model

Using the refined elbow and shoulder models, we tested the developed models (both elbow and shoulder models) by comparing the models' results with the experiment data of Task #3. Task #3 is very useful for validating the developed dynamic muscle fatigue generation and recovery model because this task includes varying forces and intermittent pauses. Figure C.5 shows validation results when incorporating input values of varying workloads in Task #3 into both the elbow and shoulder models. Validation will be achieved by means of statistical comparison using NRMSDs and the Pearson product-moment correlation coefficients (r) between both METs from the proposed model and the experiment data.

As shown in Figure C.5a, NRMSDs between METs measured from the model and the experiment shows 0.136. It is widely accepted that NRMSDs of less than 0.2 are considered acceptable and less than 0.1 can denote excellence (Hargreaves et al. 2013; Ji et al. 2014). Also, the Pearson product-moment correlation coefficients (r) and p-values are calculated between METs of the model and the experiment data, and a significant correlation is found (r:= 0.933, $p < 0.001$). For the shoulder model in Figure C.5b, a significant correlation between METs of the model and the experiment is also found (r: 0.700, p: 0.004). However, NRMSDs is a little bit higher than the above thresholds (MRMSDs for the shoulder model: 0.247). One notable point is that estimating shoulder muscle fatigue is more difficult than elbow's one because the anatomical structure of shoulder is much more complex than one in the elbow and hand (Ma et al. 2009), which can be an evidence of highly variable experiment data of shoulder tasks and would be the major cause of higher NRMSDs than expected (see Figure C.4b and Figure C.5b). Taking into account such a reason, both the developed elbow and shoulder models are useful to not only understand muscle fatigue generation and the recovery process but also to estimate the muscle fatigue level and muscles' endurance time from construction tasks with varying workloads.

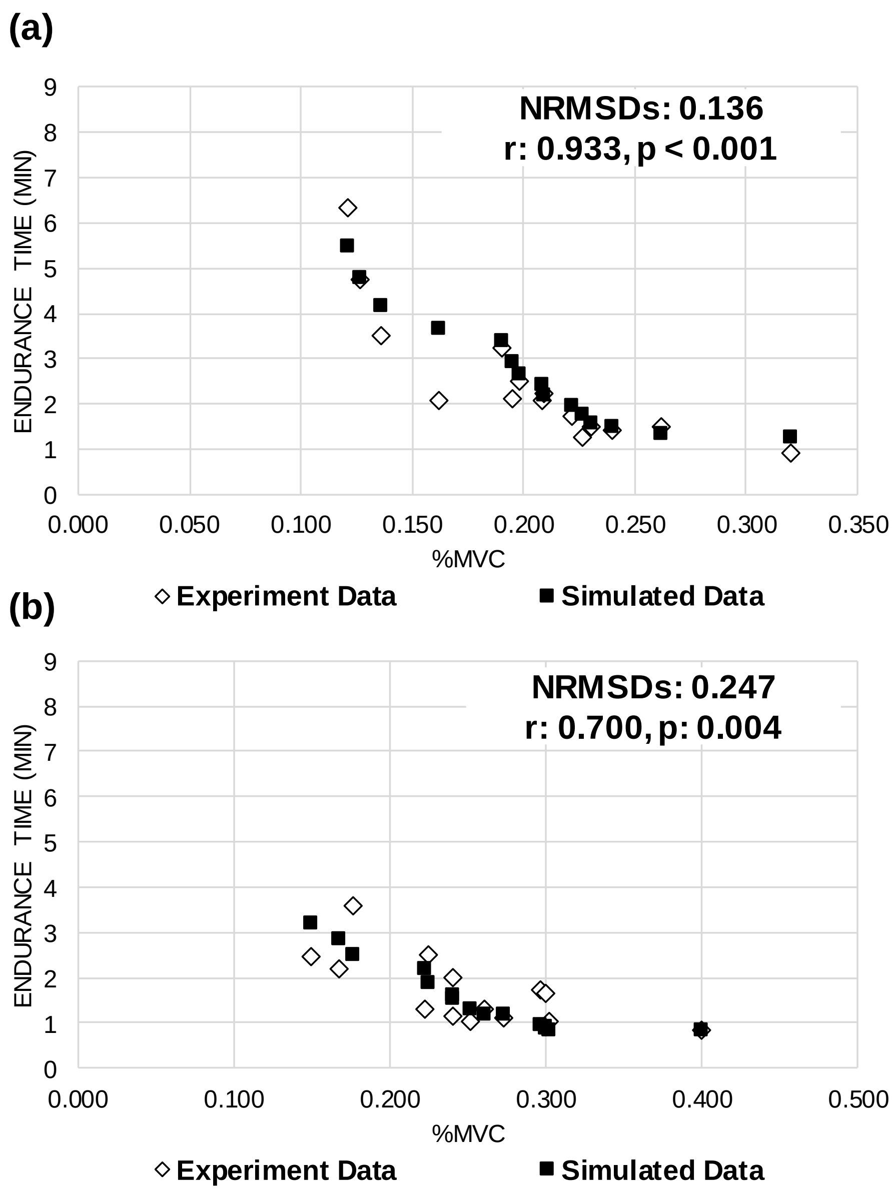

Figure C.5 Model Parameter Setting: (a) Elbow Model; and (b) Shoulder Model

C.6. Discussion

Understanding fatigue generation and its underlying mechanism are challenging because various physiological variables in fatigue generation and recovery are closely interrelated (e.g., feedback process) as well as these variables are dynamic (i.e., change over time). By modeling the relationships among such variables using the causal-loop-diagram and stock-and-flow diagram in

SD based on the fundamental physiological mechanism, the proposed model enables us to understand dynamic muscle fatigue mechanisms. Also, by determining quantitative equations using experiment data, the model also enables reliable estimation of the level of workers' muscle fatigue in occupational settings prior to work. Most existing models provide the level of muscle fatigue only as a form of an endurance time (i.e., MET), which can be inefficient in understanding how this value is produced during the construction works. On the other hand, the developed model based on causal relationship among variables shows the process of muscle fatigue generation and recovery that can vary according to different workloads and idling/resting time during tasks. This understanding is beneficial for construction managers to design work guidelines for diverse construction tasks with varying force exertions as well as intermittent rest periods which are very common in construction tasks, in order to encourage a proper way of work manners. Specifically, various appropriate interventions to manage excessive muscle fatigue can be introduced by the simulation results, which include ensuring proper workload distribution based on each individual's capacity, and providing proper work/rest schedules, and education and training workers how to deal with expected fatigue prior to work. These managerial efforts can be helpful in minimizing workers' muscle fatigue without sacrificing productivity. In addition, the efforts to reduce workers' muscle fatigue can enhance work performance with regard to health and safety.

Further, the model can be applied to real-world construction work with accurate input values of actual workloads (%MVC) of diverse construction tasks. In this case, diverse biomechanical analysis tools (e.g., 3D SSPP) can be integrated to measure varying physical demands of a certain body part from workloads and then convert them into %MVC (i.e., 'Force Exertion ' in Figure 1) based on each subject's physical capability (Garg et al. 1980; Chaffin et al. 2006). The use of more accurate input for actual workloads in diverse construction tasks enhance the applicability of the developed model in practice, in order to improve work performance with regard to health and safety of workers and consequently sustained long-term productivity.

Since it is recognized that metabolic factors contribute about 80% of muscle fatigue (Kent-Braun 1999), this research mainly focuses on metabolic mechanisms in muscle fatigue, especially anaerobic metabolism for physically demanding construction work. Further, additional contributors can be considered and added into the core structures of the model. For example, the central fatigue (i.e., central nervous system fatigue), which is caused by an impaired central nervous system (e.g., brain and spinal cord), neurochemical changes (e.g., serotonin and dopamine), or lack of motivation during prolonged exercise, can be incorporated even though its underlying mechanisms of central fatigue and its effectiveness is still controversial. In addition, the model can be customized for other body parts (e.g., back and hip) because muscle endurance varies with the fiber type composition of the muscle groups according to the metabolic differences between fibers. Based on such physiological differences between body parts, this further customization can be applied to the developed model by adjusting model parameters (e.g., 'Production Coefficient' or "Diffusion Coefficient' of fatigue in Figure 1).

C.7. Conclusion

We proposed the SD model to estimate the level of workers' muscle fatigue prior to work and understand its underlying mechanisms in occupational settings for construction tasks. Through model refinement and validation through a laboratory experiment, we demonstrated the applicability of the proposed model to evaluate workers' muscle fatigue under construction tasks with varying workloads prior to work. With the comprehensive understanding of the physiological mechanisms of muscle fatigue, the proposed model is expected to provide a test tool for estimating a worker's muscle fatigue level under heavy and varying workloads. This estimation can help to design appropriate interventions (e.g., redesign work schedule or proper workload distribution) prior to work execution, and thus can reduce undesirable results from muscle fatigue. Further, the physiology-based muscle fatigue modeling approach advanced in this research can be extended to other major body parts (e.g., back and lower limbs) and light work (i.e., aerobic) as well as diverse injury-prone construction tasks, which will be highly impactful for creating proper preventive actions before serious fatigue takes place.

C.8. References

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