Michigan Strength Augmenting Robotic Exoskeleton (M-STARX) Foot Sensor for State Classification

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Executive Summary

Powered exoskeletons are an important growing technology that can be used to augment users' physical abilities or provide gait rehabilitation/locomotion assistance. However, they require robust and responsive control algorithms that allow the exoskeleton to match a user's movement. The Michigan Strength Augmenting Robotic Exoskeleton (M-STARX) team requested that we develop a sensing system to be incorporated into their exoskeleton's foot to classify behavioral states: standing, walking, and running. This requires an original algorithm to process the raw data and output the behavioral state so the M-STARX team will be able to create responsive controls that mimic and assist the user's movement. For this project, we aim to achieve a 95% accuracy in state classification while maintaining a low manufacturing cost and easy integration with M-STARX's exoskeleton. Most of the specifications were determined based on the sponsor's budget and requests. The final design was an inertial measurement unit placed inside a 3D printed housing that transmits a signal of the accelerations and rotational velocities in the x, y, and z directions. The signal is then processed using a fourier decomposition to find the dominant frequency and magnitude. Then the algorithm determines the behavioral state based on thresholds for the signal frequency and magnitude. Verification and validation work was done using data collected by people incrementally going from standing to running then back down as well as moving at randomized speeds. The algorithm's classification was then compared to time stamped video data to verify the accuracy. It was able to achieve an 80% accuracy in state classification, but there is some future work that can be done to improve this. We concluded that increasing the sample rate or changing the high level algorithm into a neural network may be some ways to achieve the desired accuracy. Overall, the sensing system was able to achieve its goal of running in near real time (0.5 - 1.8 seconds delay) and classifying the behavioral state of the user.

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Project Introduction and Background

Exoskeletons are a field of technology that strives to push human boundaries and improve the quality of life of people. As shown in Figure 1, these devices augment the physical ability of the user and/or act as an assistive device generally by distributing loads and targeting joints.

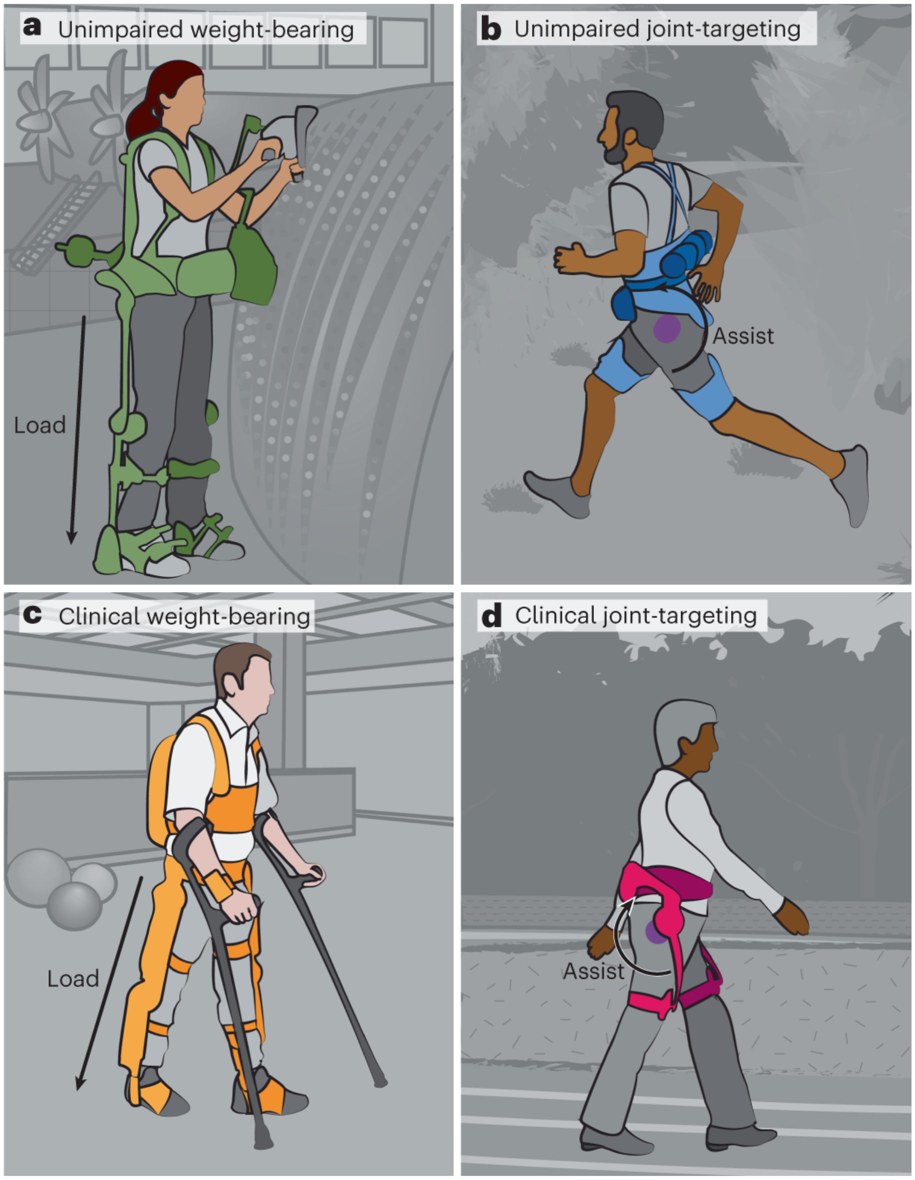

Figure 1. (a) Weight-bearing and joint-targeting (b) applications in unimpaired users. (c) Weight-bearing and joint-targeting (d) applications in clinical populations.[1]

Figure 2 on the next page provides specific examples of real-world applications of exoskeletons with images. There are many types of exoskeletons differentiated by factors such as target body part and intended usage.

[1] Siviy, C., Baker, L.M., Quinlivan, B.T. et al., "Opportunities and challenges in the development of exoskeletons for locomotor assistance", Nat. Biomed. Eng (2022). https://doi.org/10.1038/s41551-022-00984-1

Figure 2. Exoskeletons can be used by those who have difficulty walking (assistive device), first responders, the military, industry workers, and rehabilitation centers.[2,3,4,5,6]

For both augmentation and assistive uses, the exoskeleton helps combat fatigue by reducing the overall load the user bears. For the three applications shown in Figure 2 - first responders, military, and industrial - the exo helps them lift much more than they are normally capable of, which means many more people can be saved and labor-dependent productivity will increase. Despite the potential in how exoskeletons can improve society, this field is mostly limited to research purposes in labs as there are still many challenges blocking it from being widely available to the public. Exoskeletons can be expensive, heavy, have limited motion and power ranges, and are usually uncomfortable to wear. Our sponsor, the Michigan Strength Augmenting Robotic Exoskeleton (M-STARX) student engineering design team, aims to advance the field of powered exoskeleton technology to a practical and useful level by designing and building an exoskeleton that can help the user with everyday tasks and make a difference in the real world. In general, it is difficult to mimic natural human movement and having a robot predict a user's actions. A major hurdle in making exoskeletons a feasible technology is creating a robust and responsive control algorithm that can interpret what the user is doing and respond appropriately almost instantaneously. One of the sponsor's goals for the 2022-2023 academic year is to make improvements to the design and control algorithm of their Leg Exoskeleton by automatically identifying various behavior states to implement gait-specific assistive controls.

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[2] Lusardi R, Tomelleri S and Wherton J (2021) Living With Assistive Robotics: Exploring the Everyday Use of Exoskeleton for Persons With Spinal Cord Injury. Front. Med. Technol. 3:747632.

[3] Emergency Live. "Ambulance Professional Back Pain War: Technology, May You Help Me?" Emergency Live, 9 Sept. 2020.

[4] Gruss, Mike. "The Army Could Take a Run at Developing a Robotic 'Warrior Suit'." Defense News, Defense News, 19 Aug. 2022.

[5] "Exoskeletons: Next-Gen Mobility and Efficiency." The Timken Company, 27 Dec. 2022.

[6] "Exoskeleton Enables and Enhances Movement in Physical Therapy Patients." University Hospitals, University Hospitals, 25 Nov. 2020.

M-STARX is asking the ME 450 team to develop and manufacture a sensing system to be incorporated into the footplate of their exoskeleton that can be used to classify behavioral states including standing and different gait patterns - meaning walking, jogging, running. The team also needs to program the algorithm that can process the raw data and acquire relevant features from the sensing system. It should output the identified behavior state of the user and be able to provide the data in a readable format for the M-STARX team. The sponsor should then be able to integrate the final solution into the footplate of the M-STARX exoskeleton and implement responsive controls to best assist the user based on their movements. For integration, the sensing system will need to be able to physically attach to either the user or the exoskeleton itself while keeping within any design requirements and specifications. The system will also need to be able to connect to their power and processing system on their exoskeleton.

To understand the problem, the parts of the foot need to be broken down into a 2D system of points and angles. In Figure 3 below, the leg and foot can be broken down into several major points at the knee, ankle, toe, and heel. From this, the shank and foot angle from the figure can be derived as the angle between them and the horizontal and vertical axis respectively.

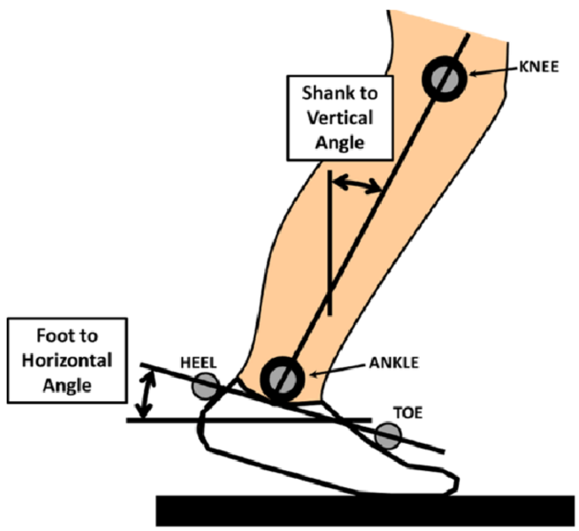


Figure 3. Important joints and angles of the leg. Foot angle and shank angle are in respect to the horizontal and vertical axis.[7]

Using IMUs will produce acceleration and angle data from the accelerometers and gyroscopes. We can use this data to determine positions of key points and the shank and foot angles. Using an Arduino, we can convert the data into a continuous signal for Matlab processing. The signals produced can be plotted as a time series graph like Figure 4, which can then be analyzed using prior knowledge about kinematic systems and linkages. This analysis will help us understand how each part of the gait cycle is mapped onto the signal data. Also, with our understanding of controls and dynamic systems, we can produce a model to better understand the expected response at each event in the gait cycle.

[7] Owen et al., Journal of Prosthetics and Orthotics, 2017

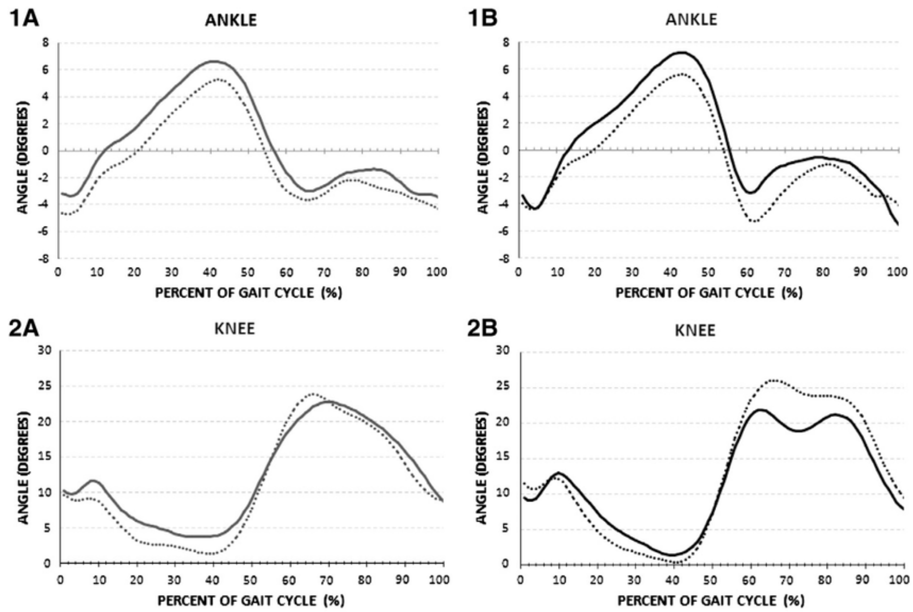


Figure 4. Ankle and knee angles with respect to the gait cycle. (A) refers to the comfortable speed and (B) represents faster speeds. Solid lines are experiments conducted with walking sticks, and dashed lines have no walking sticks.[8]

The models generated by the engineering fundamentals will help us make decisions on the algorithm thresholds. It will inform the algorithm on how to identify individual events and when the gait cycle changes from one stance to the next. This can also be used to assess whether the algorithm is working as intended. If the algorithm works, the part of the gait cycles it identifies should match the model. The mapping of the leg and foot motion can also act as a visual aid to check if both the model and algorithm are accurate.

Finally theoretical analysis can be done using training data from academic research literature. The training data can be used to validate the model and algorithm. Empirical testing can be done by attaching the IMU onto a person and walking on a treadmill. The results from the IMUs can be recorded and put through the algorithm to identify parts of the gait cycle while being visually compared to a video recording. If the results match what the video recording shows, it would validate the chosen algorithm and the parameters used.

Design Process

Choosing a design process that fits with our project is an important step to make a successful design. When choosing our design process, we discussed many factors and criteria that would need to be included in it. Since our project is more focused on due dates because we are in a class, a stage based approach was decided to be an important characteristic of the design. We also were not very familiar with the subject of the project, and so a problem based approach was chosen instead of a solution based approach. We were unaware of the specific steps that might be required to take during the design process, so we chose an abstract approach to be the most useful.[9] We are interviewing stakeholders who are knowledgeable in this field and then use that information to create an alpha design. Afterwards, we

[8] Polese et al., Clinical Biomechanics, 2011
[9] Pahl, G., et. al., "Engineering Design: A Systemic Approach", Springer, 2007.

would compare this to our requirements and specifications and then iterate with an updated design. We would then get feedback from the stakeholders about our updated design. This process met all the requirements we chose as well as including an iterative approach that will allow us to go back to other sections if we need to. We looked into many other designs as well to determine if they would be a better model, but they fell short of some of our requirements.[10] [11]

Benchmarking

Before diving any further into developing solutions and any testing, research was done to understand the overall problem and what research related to what the team is trying to achieve has already been done.

As specified in the problem definition, an important aspect in the creation of a sensing system is classifying behavioral states. The reason for the importance of these behavioral states is because an exoskeleton needs to conform to, assist, and enhance human motion. For an exoskeleton to function effectively, it needs to augment user motion and not hinder it. Gait allows us to understand how the human body moves and how we would like an exoskeleton to interact. Gait is a cyclical process that starts and ends from a single foot's heel contact. Stride is another word that is widely used in place of gait. This gait cycle can then be used to determine a person's walking speed and cadence (how quickly a full gait cycle can be completed). These values can then be used by the exoskeleton to augment or assist the gait cycle. This gait cycle can then be broken down further into more categories during the cycle to allow the exoskeleton to assist more accurately like in Figure 5 below.

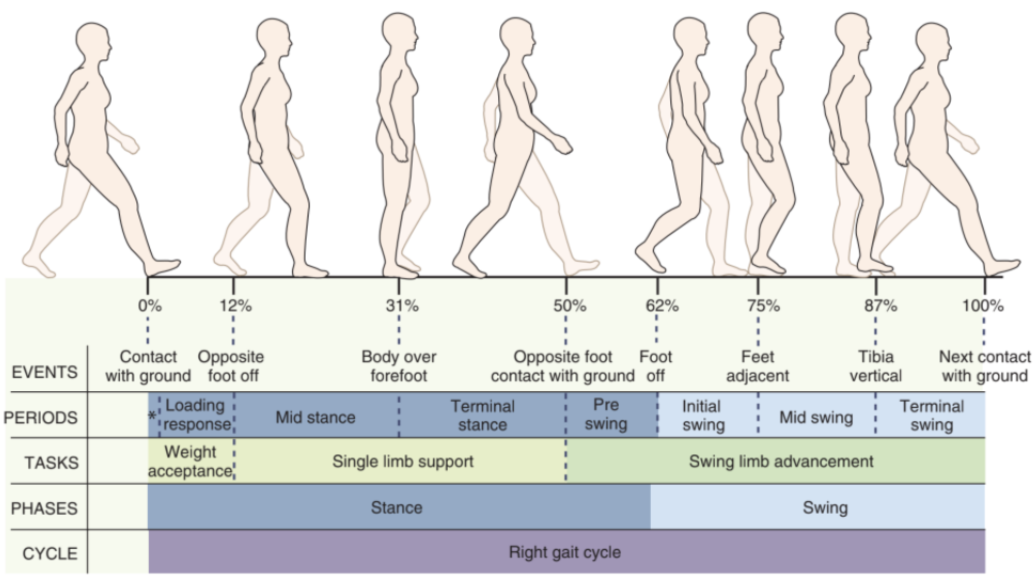


Figure 5. Important increments that model how the human gait cycle performs during the gait cycle.[12]

One type of sensor that has been used to understand this gait cycle are pressure sensors, which includes resistive, capacitive, and piezoelectric sensors. Figure 6 on the next page depicts how these pressure sensors measure the pressure caused by the user on their foot as they go through the gait cycle.

[10] Wynn, David, Clarkson, John, "Models of Designing", University of Cambridge, 2005.
[11] Ford Motor Company, Design Museum, http://www.crazyseoul.com/DM/FordPack.pdf.
[12] Neumann, Donald.A., "Kinesiology of the Musculoskeletal System: Foundations for Rehabilitation", Elsevier Inc., 2017.

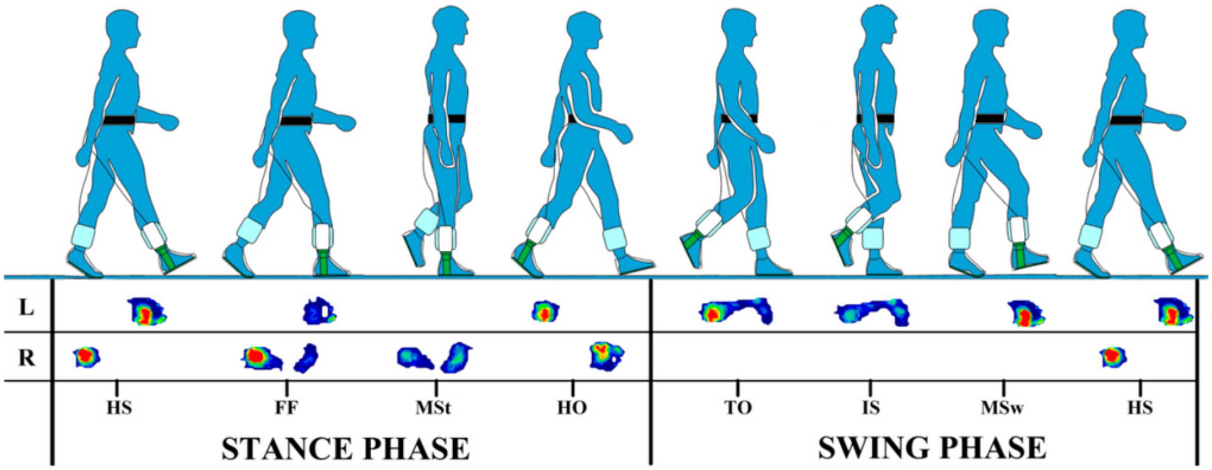


Figure 6. Pressure sensing map of the user during different events during the gait cycle where HS is heel strike, FF is foot flat, MSt is midstance, HO is heel off, TO is toe off, IS is initial swing, MSw is mid swing.[13]

These pressure distributions can then be used to define every part of the gait cycle and allow the team to create an algorithm that will predict user movement. However, an issue a foot pressure sensor has is defining gait in the user's different states or tasks. Various groups have designed algorithms that are able to learn what a human's gait cycle looks like and then understand the transition between the different tasks.[14] These attempts have yielded low success rates to define the transitions and are more successful at identifying discrete changes. Since the only information that the pressure sensor obtains occurs at specific moments throughout the gait cycle, it is not continuous and makes creating an algorithm that will interpret the data in a useful way difficult. Achieving an accurate representation of the user's movement through a pressure distribution only is difficult and has not yet been accomplished with a high success rate.

Another method for sensing a user's gait cycle that is becoming more common in research labs due to its usability is using an inertial measurement unit (IMU). An IMU consists of accelerometers, gyroscopes, and magnetometers. Using many of these components, the IMU can measure angular rate, acceleration, and magnetic field along three axes. The first two measurements are important to understanding the gait cycle because it allows us to see the change that the user's ankle makes as well as accelerations of the foot during the gait cycle. Using these measurements, we can also create an algorithm that will predict and augment the user's movement through the gait cycle. Researchers using this method used continuous parameterization that enabled the sensor to determine variation within a task and determined more of the task's specific features. The IMU continuously learned the phase, the phase rate, the ramp, and stride length. Using these parameters, the researchers created experimental data plots of the user's gait cycle as shown in Figure 7 on the next page.

[13] Wafai, Linah, et. al., "Identification of Foot Pathologies Based on Plantar Pressure Asymmetry", College of Engineering and Science, Victoria University, 2015.
[14] M. R. Tucker, et. al.,"Control strategies for active lower extremity prosthetics and orthotics: a review," J. neuroengineering and rehabilitation, vol. 12, no. 1, 2015.

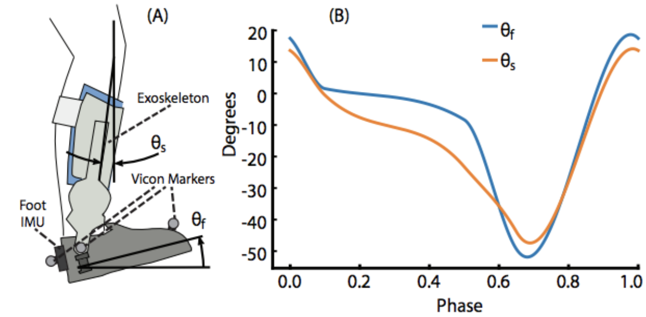
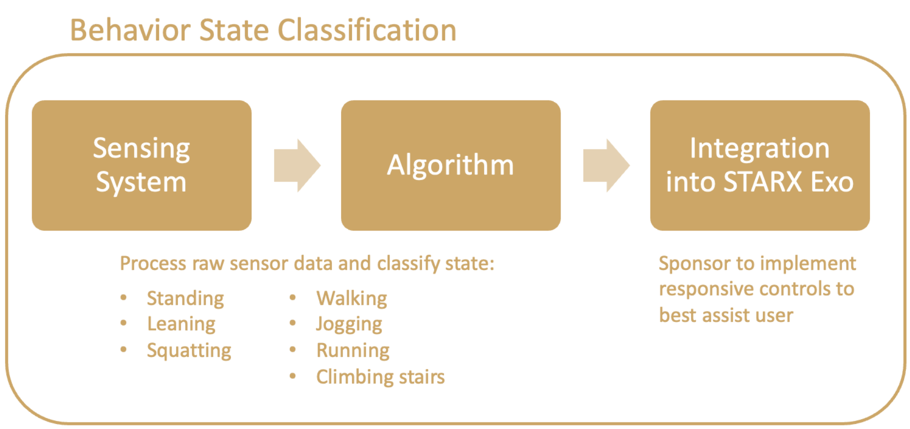


Figure 7. (A) Image of an IMU attached to heel of foot that can determine the shank angle (θ_s) and the foot angle (θ_f). (B) Model of degree vs phase of both the foot and shank.[15]

Both the pressure sensor and the IMU are useful tools in developing a way to sense user movement and gait. These methods will both require developing algorithms that will clearly define (discretely or continuously) different phases in the gait cycle. Pressure sensors have been used extensively for measuring gait cycles, but struggle when the user changes the gait cycle. IMU's use a different approach to determine gait and can be more accurate due to their continuous sensing approach. It will be important for us to test both these methods and determine which will be best for our purposes of designing a sensor for M-STARX.

Concept Generation

After doing benchmarking on the current products and research for foot sensors, each member of the team individually generated their own ideas for the design and then came together to generate new ideas based off of and organize our cumulative total of ideas. We used divergent thinking in developing these ideas and focused on thinking outside of the box to maximize the number of concepts. We categorized our concepts into three sub-sections: sensors, housing, and algorithms. The function decomposition in Figure 8 summarizes how each component plays into our behavior state classification solution. After the final step in our generation of concepts, we analyzed what we had come up with. Further information on all the different concepts that were generated for the parameters, sensors, and housing that were not mentioned can be found in the appendix.



[15] Medrano, Leo Roberto, et. al., "Real-Time Gait Phase and Task Estimation for Controlling a Powered Ankle Exoskeleton on Extremely Uneven Terrain", IEEE Transactions on Robotics, 2023.

Figure 8. Functional decomposition of problem statement and potential solution.

Sensor Concepts

Some of the main concepts that were generated for sensors were an IMU, force sensing resistor, step counter, weight sensor, and acoustic sensor. Each of these sensors would allow us to collect certain types of features that would then affect how well we could classify a user's behavioral state.

For our concept idea for IMU's, we thought that some of the parameters that would prove useful in our algorithm would be angle of the foot, angle of the shank, displacement, and acceleration. These parameters can be found throughout the gait cycle which will allow us to get even more data for classification. The IMU has a gyroscope and an accelerometer which allows us to find these parameters.

For our concept idea for force sensing resistors, we thought that using pressure as parameter for state classification would be effective. Every time each foot touches the ground, pressure is applied at different locations which can be measured. Force sensing resistors are pressure sensors and we would have multiple at different locations to get a pressure map of the foot.

For our concept idea for a step counter, we would use a sensor that would be able to tell when contact is made by each foot. This would allow us to identify the beginning and end of the gait cycle.

For our concept idea for a weight sensor, we would be able to determine the force that the foot makes with the ground. This would allow us to determine different stages of the gait cycle based on how much force is applied by a person on the ground based on their weight.

Finally, for our concept for an acoustic sensor, we would measure the sound that the foot makes as it touches the ground. In this way, we would classify stages in the gait cycle based on how much sound is made by the foot at each stage (i.e. running should create a larger sound due to the impact of the foot and occur more frequently than walking).

Housing Concepts

Developing the housing involved two considerations: placement of the sensor(s) (i.e. ensure the necessary data for state classification is collected) and increasing the robustness of the system (i.e. eliminating any unintended movement and protecting the sensor from any damage). Some of the main concepts that were generated for housing were putting sensors on the bottom of the foot, on the top of the foot, and on the ankle.

For our concept of having the sensor on the bottom of the foot, since a lot happens with the foot as it touches the ground, a foot sensor on the bottom of the foot would give us a lot of options for collecting data.

For our concept of having a foot sensor on top of the foot, we wanted to protect a sensor that we might use from getting damaged, which putting it on top of the foot would ensure.

Finally, for our concept of putting the foot sensor on the ankle, this would enable us to get data for both the foot and the leg. This could be useful for getting even more data to help classify the events in the gait cycle.

Algorithm Concepts

Some of the main concepts that were generated for algorithms were thresholding, machine learning, neural network, k–nearest neighbor, and logistic regression. For our concept idea for thresholding, we would have the algorithm be able to define what the exact parameter values were for each specific stage/event during the gait cycle. These parameter values would have a certain tolerance assigned to them at each stage to account for unforeseen fluctuations. Using these defined thresholds, the algorithm would be able to determine at what stage the user is in. The process the algorithm would undergo for thresholding is called a decision tree. We would have 'if' statements that would check whether the parameters at an instance of time would fit into different thresholds. Then if certain parameters fit, we would have the algorithm tell us at what stage of the gait cycle the user was in.

For our concept idea for machine learning, we thought of using a support vector machine. This method uses some of the same ideas as thresholding, but enables the parameter domains to which it chooses the classification to be less static. The algorithm is able to adapt/learn where this classification is located in reality based on its iteration process. This would allow us to get very accurate results.[16]

For our concept of a neural network, we would develop an algorithm that is able to think like a human and adapt to changes. This is another machine learning classification method and would allow our algorithm to be able to comprehend complex data sets.

For our concept of k-nearest neighbors (K-NN), we would compare points that are near each other. Then, based on a defined allowable distance, it would determine the highest repeatability for each stage of classification to determine the important events in the gait cycle.

Finally, for our concept for logistic regression, we would develop an algorithm that would be able to find a linear model for the gait cycle. The algorithm would make a prediction as to what it thinks the data will do based on previous data and then iterate based on the accuracy of its prediction until it reaches sufficient accuracies.[17]

Design Context

Figure 9 on the next page identifies the stakeholders for the project including primary (those directly affected by our work), secondary (those indirectly affected by our project), and tertiary (those who are only remotely influenced by the project), and classified them according to the legend.

[16] Suthaharan, Shan, "Machine Learning Models and Algorithms for Big Data Classification", Springer, 2016.
[17] Ghalyan, M F, et. al., "Human Gait Cycle Classification Improvements Using Median and Root Mean Square Filters Based on EMG Signals", IOP Conf. Series: Materials Science and Engineering, 2021.

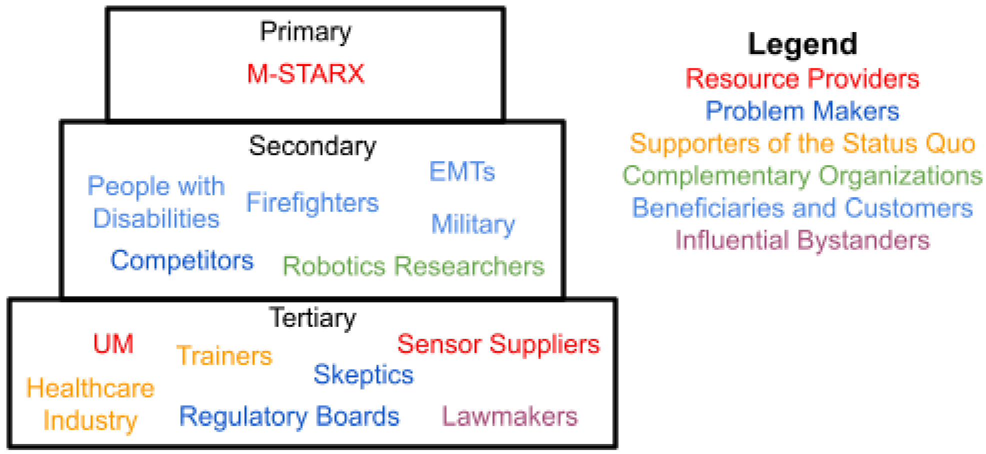


Figure 9. Graphic describing who the primary, secondary and tertiary stakeholders are and color coded based on what type of stakeholder each one is based upon the legend.

Our resource providers include M-STARX, the University of Michigan (UM), and commercial sensor suppliers. UM is supplying us with the $400 budget, M-STARX is supplying us with dimensions and consultation, and commercial sensor suppliers are supplying us with the necessary sensors. Our problem makers include competitors, regulatory boards, and skeptics. The competitors for our design are other college exoskeleton teams such as the MSU STARX team. Regulatory boards may oppose our design if the design is unsafe and don't meet standards. The only standards we found that would be applicable to our product pertained to recommended testing procedures for exoskeletons as opposed to their design. ASTM F3443 − 20 outlines procedures for safely testing the load-bearing capabilities of exoskeletons, ASTM F3444/F3444M − 20 specifies the standard practice for training users in operating exoskeletons, and ASTM F3528 − 21 details testing procedures for exoskeletons.[18] [19] [20] While these standards will be important to evaluating our designs once we have a completed system to test, they do not contain information of much use in guiding our design at this stage.

Skeptics may oppose our design because they do not believe foot sensors or exoskeletons will ever work and therefore will oppose the research due to the cost. The supporters of the status quo include trainers and the healthcare industry. Trainers would prefer not to have to learn how to train people who use exoskeletons to assist their movement. They would have to learn how exoskeletons work and it would be easier if they did not have to. The healthcare industry would also prefer to keep their current practices to make profit rather than allowing people to recover faster and leaving their facilities earlier. Our complementary organizations are researchers. Professors and other researchers will work with us and are allied with us to determine how to classify gait cycles. The beneficiaries and customers of our project are people with disabilities, EMTs, firefighters, and the military. All of these people/organizations would benefit from our project either in an assistive or augmentative way. One group of influential bystanders of our project are lawmakers. Lawmakers would be impacted if exoskeletons were made on the commercial market. Since our project is designed to help exoskeletons achieve this goal, lawmakers would be impacted as they would have to deal with new laws that will be created for the exoskeletons. It is important to note as well that some of these stakeholders may overlap into the other classifications.

[18] Standard Test Method for Exoskeleton Use: Gait, ASTM F3528 − 21.

[19] Standard Practice for Training Exoskeleton Users, ASTM F3444/F3444M − 20.

[20] Standard Practice for Load Handling When Using an Exoskeleton, ASTM F3443 − 20.

We believe that the positive impact of our project can extend to the M-STARX team who will have more development done toward their exoskeleton, as well as the intended users of said exoskeletons. Beyond the beneficiaries, we want to ensure that people downstream of our project are not negatively affected by our design decisions. Those who are training users to operate exoskeletons, for example, should ideally not be burdened by designs that require special or counterintuitive operating techniques to use.

After considering our stakeholders, their interests, and how they might be affected by our design, we made a map of some key stakeholders' inputs to and outputs from our work, shown in Figure 10.

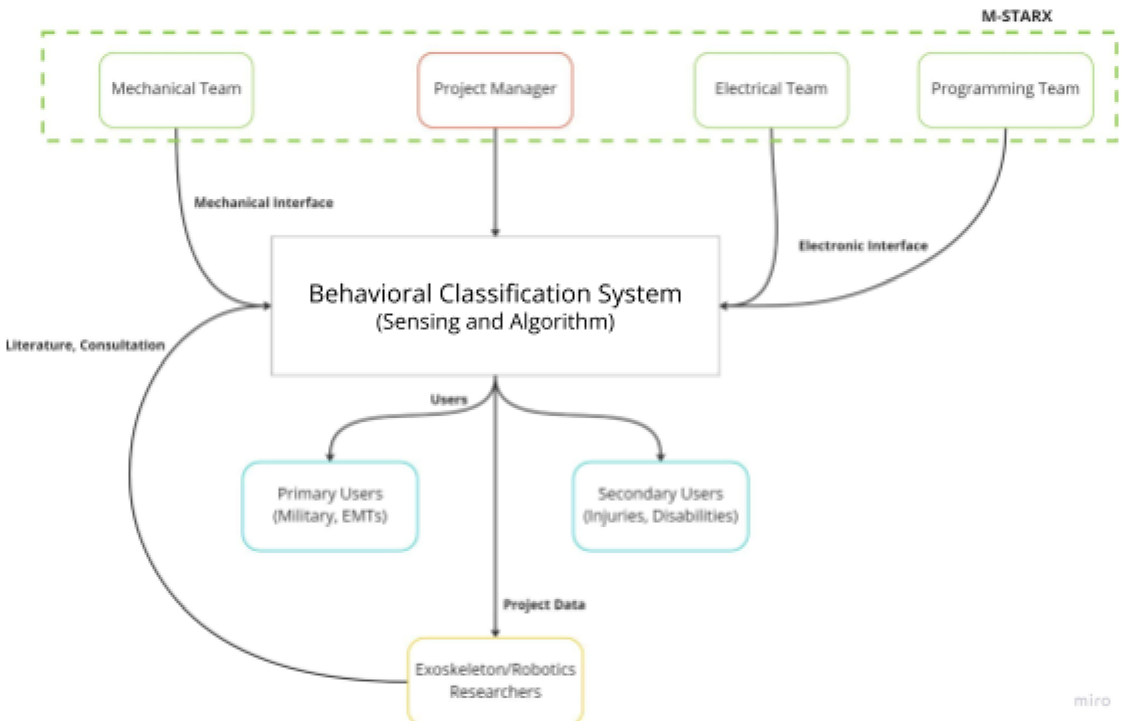


Figure 10. Stakeholder map detailing the main inputs and outputs from our project. The stakeholders in the green dotted square include the M-STARX team. The colors associated with the main primary stakeholder, other primary stakeholders, secondary stakeholders, and tertiary stakeholder are red, green, blue, and yellow consecutively.

We've met with a few of these stakeholders already, including M-STARX's project manager and lead engineers, as well as Elliot Rouse, a UM professor researching assistive exoskeletons. Professor Rouse has shared with the team what research on gait classification their lab has already conducted, which has better guided the direction of this project after reconsidering what is feasible and has already been tried. From these meetings, we've been able to better understand our user requirements and translate them into specifications, as well as get a better idea of how technologies similar to ours are being implemented in the status quo and how we might be able to solve a problem as complex as gait identification within the time and resource constraints of ME 450.

Exoskeleton technology is currently a widely researched area of robotics and assistive devices. As such, despite the fact that our primary stakeholders are members of the M-STARX team, the development of our project can have more far reaching implications for exoskeleton research applications. Commercially available exoskeletons are expensive enough to put them out of reach of most people, bringing down the cost of one of their key components may improve their affordability and accessibility. With many exoskeletal assistive devices on the market being priced from $40,000 to $80,000, we want to ensure that our project ameliorates the problem instead of entrenching it.[21] For instance, current approaches to gait identification usually use expensive pressure mapping insoles or myography techniques that track muscle forces.[22] These custom insoles have a significant mark-up due to the customization involved in creating such personalized devices.

Developing a more affordable alternative to these sensor schemes by limiting the scope of our sensor performance to stay within our cost constraints could create a solution which works for the purposes of many research labs while driving down development costs. Keeping costs down would allow M-STARX to buy or manufacture sensors in the future after the lifespan of the sensor has passed. This cost-conscious approach could also yield benefits that extend beyond research.

The intellectual property the team creates will ultimately be owned by the university for the M-STARX team. Because we are ourselves a university entity being a team of UM students, we have not yet encountered any hurdles to our work as a result of intellectual property concerns. Indeed, working within university organizations has given us the opportunity to reach out to multiple researchers at UM and obtain valuable technical information to aid our research, like communicating with PhD student Christopher Nesler about his work in foot pressure sensors. With this context in mind our team does not believe that intellectual property restrictions will put any barriers in the way of our project.

User Requirements and Engineering Specifications

Meetings with the sponsor enabled the team to develop a list of requirements and targets that the final solution will need to meet. The user requirements and engineering specifications resulting from these discussions are summarized in Table 1 below.

Table 1. Problem requirements and quantified specification targets determined after multiple discussions with the sponsor and research. Accuracy and Low Cost are the most important according to the sponsor. The Flexibility specifications were found through research.[23]

User Requirements	Engineering Specifications
Accuracy	95% accuracy in classifying behavior state
Dimensions	≤ 3” thick Accommodates 5th-95th percentile American shoe sizes
Flexibility	Allow the user’s foot to have a dorsiflexion of ~12° and a plantarflexion of ~20°
Foot Support	Withstand heel-fall forces from a user weighing up to 250 lbs at a running pace (10 mph)
Integration	Allow a user to wear their own shoe
Light Weight	Increased per-step energy cost ≤ 16% ⇒ ≤ 1 lb per plate
Low Cost	≤ $400 / 2 plates
Safety	Ensure no risk of injury to user by eliminating sharp edges and exposed wires

Importance

[21] Limakatso, Katleho, “Exoskeletons: Costs and Where to Buy One”, Health News, January 2023.
[22] Prasanth, Hali, et al., “Wearable Sensor-Based Real-Time Gait Detection: A Systematic Review”, National Library of Medicine, 2021.
[23] Neumann, Donald.A., “Kinesiology of the Musculoskeletal System: Foundations for Rehabilitation”, Elsevier Inc., 2017.

As our solution moved more towards a software and algorithm-based approach throughout this project, the necessary requirements and specifications shifted to those shown below in Table 2. These are more focused on what was actually considered in our design after eliminating now-irrelevant requirements like Dimensions and Foot Support. This table also includes a brief description of the validation and verification results of each requirement after corresponding checks discussed later in the *Verification and Validation Approach* section.

Table 2. Final algorithmic solution-oriented requirements and specifications.

User Requirements	Priority	Engineering Specifications	Validation and Verification Results
Accuracy	High	95% accuracy in classifying behavioral state (standing, walking, and running)	80% accuracy
Low Cost	High	≤ $400 total	BOM, $17.98 spent
Processing Speed	Medium	≤ 1.5 second delay	Confirmed
Integration	Low	Compatible with M-STARX Exoskeleton	No hardware issues

The main requirements the sponsor has conveyed to the team to be the most important remains a high classification accuracy and low cost solution. These are important as high accuracy signifies the solution is working properly and a low cost ensures the team can recreate it in the future without having to worry about it affecting the budget. There were two more requirements such as making sure it had a moderately fast processing speed so it could run in near real-time, and that it can be integrated in the M-STARX exoskeleton. The processing speed requirement is only of medium importance because we do not expect to make large calculations and hit computing limits. The integration requirement is just to make sure that the hardware of the system can actually be used without affecting the rest of the exoskeleton, and that the software can be used with the rest of the exoskeleton code.

Concept Selection Process

Preliminary gut checking done by the team eliminated some of the generated concepts just based on personal experience and knowledge (e.g. tracking radioactive decay with a radiation sensor is very problematic). The curated list of requirements and specifications after discussions with the sponsor and Professor Rouse made up the criteria the team used to evaluate the remaining concepts. Parameters, sensors, and housing were each evaluated separately. The weights assigned to each requirement was determined through team discussion and in consideration of the sponsor's priorities.

The top scoring concepts from the three categories were then assembled into various combinations to evaluate full solutions. The system combinations were formed based on the compatibility of the different components (e.g. using resistance as the parameter will require the FSR (an IMU cannot be used), which then limits the housing options to an insole or other concepts related to an underlying plate). A portion of this Pugh chart is shown in Figure 11 on the next page, with the IMU scoring the highest in combination with linear and angular speed calculations and placing the sensor on the ankle or top of the foot.

Parameters

Requirement	Weight	Neural Network	Image / Computer Vision Processing	Pressure/Force Map	Shank/Toe/Heel Angle Calculation	Thresholding w/ Timings	Position Change (x/z)	Linear and Angular Speed Calculation	Contact/ Timing	Stance State	Resistance
Accuracy	5	1	0	0	-1	-1	-1	1	-1	-1	0
Ease of Use	2	-1	1	1	0	1	1	1	1	0	1
Processing Speed	3	0	-1	1	0	1	0	1	1	1	1
Total	**-**	**3**	**-1**	**5**	**-5**	**0**	**-3**	**10**	**0**	**-2**	**5**

Sensors

Requirement	Weight	IMU	FSR	Weight	Motion Capture	Manual/Camera	Lidar/Laser	Capacitive	Piezoelectric	Acoustic	Deformable Material (Gel/Water/Foam)
Size	4	1	1	1	0	0	0	1	1	1	-1
Safety	2	1	1	1	1	1	1	1	1	1	0
Durability	3	1	-1	-1	1	1	0	-1	-1	0	-1
Ease of Use	1	1	1	1	0	-1	-1	1	1	-1	1
Cost	5	1	1	1	0	0	-1	-1	1	1	1
Accuracy	5	1	1	1	-1	0	-1	0	0	-1	0
Total	**-**	**20**	**14**	**14**	**0**	**4**	**-9**	**-1**	**9**	**5**	**-1**

Housing

Requirement	Weight	Elastic Material	Manual Adjustment	Gaps/Hollow	Exo-Foot	Flexible/Hinge	Snap Sensors	Springs	Insole	Metal Plate	Acrylic
Durability	1	-1	1	1	1	1	0	0	1	1	1
Integration	1	1	1	1	0	0	1	1	1	1	1
Comfort/Flexibility	3	1	0	1	-1	1	1	1	1	0	0
Cost	5	0	1	1	0	1	0	1	1	1	1
Weight	4	1	0	1	-1	1	1	0	1	-1	1
Total	**-**	**7**	**7**	**14**	**-6**	**13**	**8**	**9**	**14**	**3**	**11**

System Combinations

Parameter	Linear and Angular Speed Calculation	Linear and Angular Speed Calculation	Linear and Angular Speed Calculation	Linear and Angular Speed Calculation	Neural Network	Threshold w/ Timings	Threshold w/ Timings	Resistance	Pressure/ Force Map	Resistance
Sensor	IMU	IMU	IMU	IMU	IMU	IMU	Step Counter	FSR	FSR	FSR
Housing	Sensor on Ankle	Sensor on Top	Elastic Material	Manual Adjustment	Sensor on Ankle	Sensor on Ankle	Sensor on Ankle	Insole	Insole	Flexible/Hinge
Total	**44**	**44**	**37**	**37**	**37**	**34**	**34**	**33**	**33**	**32**

Figure 11. A portion of the Pugh chart used to evaluate the concepts with final scores for system combinations.

The process for choosing an algorithm was based on a separate evaluation of the pros and cons of each of the algorithms discussed earlier: thresholding, ML, neural network, K-NN, and logistic regression. Thresholding will be the easiest to build through experimentation and observation of the IMU signals to define thresholds for different behavioral states, but it may not be able to classify the same states between users with very different gaits as the thresholds may not encapsulate the full signal or portions of the gaits. This would mean the algorithm would have to be calibrated to every person to ensure the accuracy of the device. ML can resolve this by identifying trends and patterns to automatically build on itself to handle varieties of data, but it is more difficult to program given our team's unfamiliarity with the field and would require much more time.[24] The other algorithms are similar in that they are built off ML, which itself is a very broad umbrella term - neural networks being a high-level unsupervised version of ML. K-NN is a supervised ML system, so it would be more intuitive and easy to understand while still being able to evolve on its own. However, it is constrained by the number of variables it can handle and the need for tagged historical data, which we would need to collect for each behavior state (Professor Rouse's research only used walking data).[25] Logistic regression is not very appropriate for the functionality that we desire as, although it is efficient to train and very fast at classifying unknown records, it is binary and constructs linear boundaries under the assumption of linearity between the dependent and independent variables.[26]

Overall, all of these algorithms incorporate thresholding and modeling the system at some level, so we plan to focus first on the simplest method of thresholding in the essence of time. Once the thresholding algorithm is completed with relatively accurate results, we will try to enhance the overall processing and accuracy (especially between different users) by implementing machine learning (potentially a neural network) if there is enough time before the Design Expo.

[24] Prasanna. "Advantages and Disadvantages of Machine Learning: Pros and Cons of Machine Learning, Drawbacks and Benefits.", 2022.
[25] Genesis, "Pros and Cons of K-Nearest Neighbors." *From The GENESIS*, 25 Sept. 2018.
[26] "Advantages and Disadvantages of Logistic Regression." *GeeksforGeeks*, GeeksforGeeks, 10 Jan. 2023.

Alpha Design and Initial Testing

Moving forward with the IMU system as the selected concept, the team carried out some initial testing and generated an alpha design. First, we purchased several IMUs to begin collecting data and building the algorithm and housing. Specifically, the MPU-6050 is a Micro-Electro-Mechanical Systems (MEMS) with both a 3-axis accelerometer and a 3-axis gyroscope (it also has a built-in temperature sensor that we will likely not use). This sensor will allow us to measure acceleration, velocity, orientation, displacement and many other motion-related parameters of a system or object. Figure 12 shows what the sensor looks like as well as its coordinate system. It is low cost and we were able to easily acquire several for future testing where we have two IMUs on the user's foot or if any are damaged during the process.

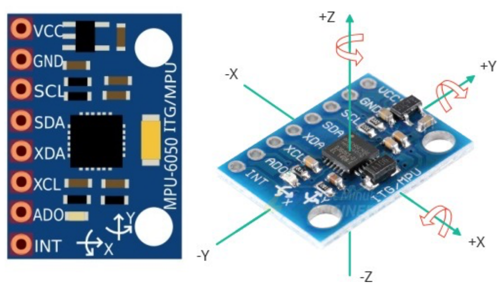


Figure 12. The acquired IMU (MPU-6050) is very low cost and easily available. The accelerometer and gyroscope can detect in three dimensions - as shown in the right diagram.[27] [28]

We determined that the simplest way to acquire the data from the sensor was through Arduino. The work space provided to us from the ME Department has the necessary hardware available - including an Arduino Uno, breadboards, and jump wires. Figure 13 below shows the setup we used for initial testing. Tape was used so that we could quickly piece together the IMU and breadboard holding the IMU as a single unit and then attach the entire system to one of our team member's pant legs. The Arduino board was also connected to a laptop that was pulled along as the user walked. We plan to implement the algorithm and power connections of our sensing system into the backpack of the M-STARX exoskeleton

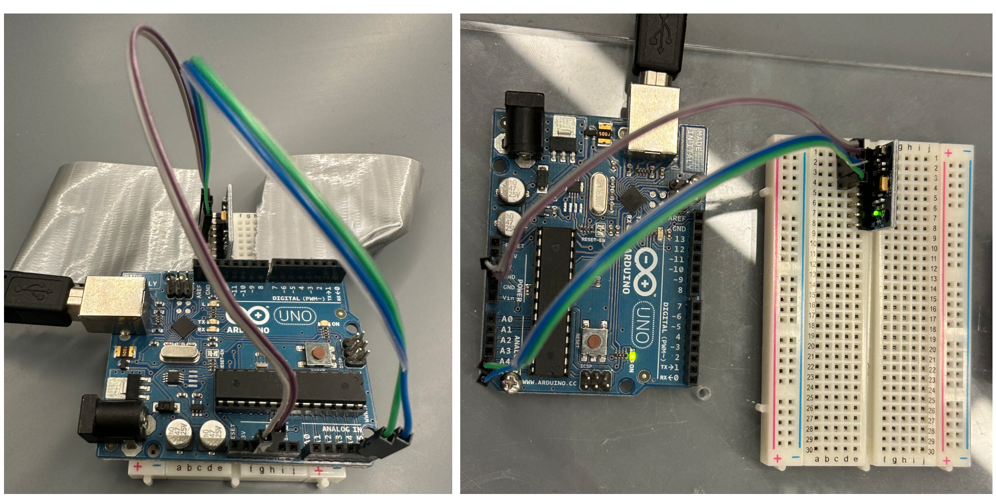


Figure 13. Hardware setup used for initial testing. The IMU was connected to the Arduino with a breadboard and jump cables for better stability as the cables did not have a robust connection to the IMU pins.

[27] Nasir,"Introduction to MPU6050.", The Engineering Projects, 2019.
[28] Last Minute Engineers, "In-Depth: Interface MPU6050 Accelerometer & Gyroscope Sensor with Arduino.", 2022

All of the acquired IMU signals as the user walks on level ground was displayed using the Arduino Serial Plotter in almost real time (with only a delay of 5 ms). Figure 14 is an annotated version of a snapshot of the raw signal output from Arduino. Focusing on the signal with the most obvious trend, the angular velocity in the z-direction, *gz* (pitch), corresponds accurately to the angular change of the user's ankle as they walk. Following the coordinate system of the IMU, *gz* increases positively as the ankle leans forward and then rotates negatively for a longer period of time as the step is taken. It then increases again and plateaus as the foot is planted after the step (flat-foot). The signal repeats immediately as the user continues walking. The acceleration in the x- and y-directions, *ax* and *ay*, were also identified to follow this same pattern - although with less obvious changes in amplitude. The other four parameters will likely not be used for now as the acceleration in the z-direction, *az*, and angular velocity in the x- and y-directions, *gx* (roll) and *gy* (yaw), provide information on the side-to-side movement of the foot and we want to focus on forward movement in the beginning stages of our algorithm. These three could become useful when trying to identify leaning or other behavior states we are not covering. Temperature, *temp*, is not needed in general because we only care about movement in this design (one of the parameters eliminated during concept generation).

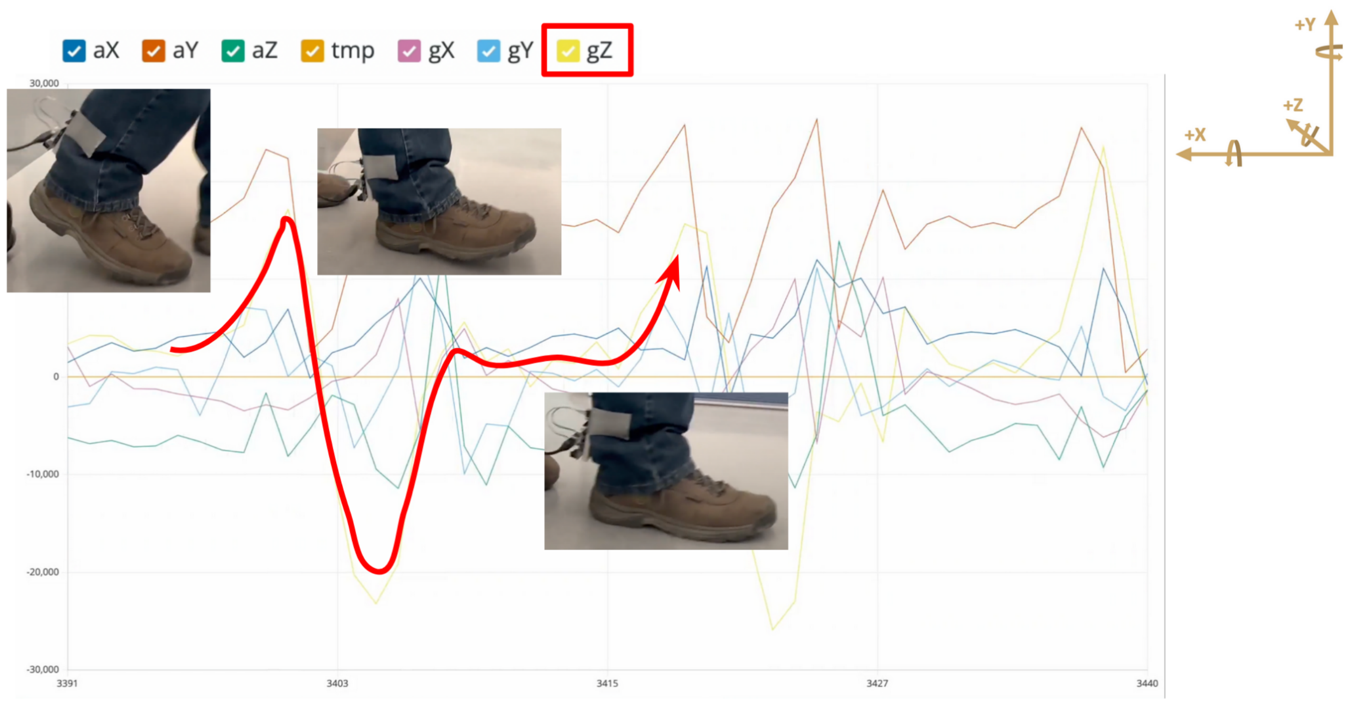


Figure 14. Angular velocity in the z-direction has a signal that clearly indicates the trend of walking.

To further enhance the accuracy of our algorithm, we are also working on adding motion tracking to the videos we have recorded of walking with the IMU to get accurate angular and directional changes to better identify our thresholds. We will also need to manufacture a more robust housing piece to better capture the user's movement and eliminate noise. Figure 15 on the next page is a CAD model of our initial design for the system. The plan is to place the IMU and Arduino board in a protective housing that will be then strapped on to the user's ankle. We hope to replicate this at the front of the foot as well for the system to be able to classify behavioral states even more accurately.

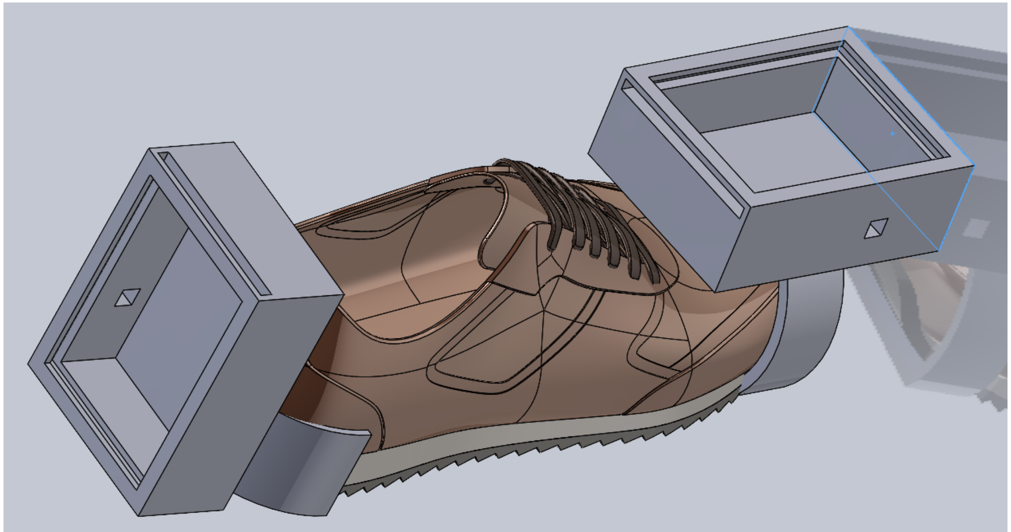


Figure 15. Housing for the Arduino board and IMU that will be attached to the user with a strap.

Our CAD model in Figure 15 shows our initial design concept for the housing. We intend to have straps attaching an IMU to the top of the foot/shoe as well as an IMU attached to the heel. The next section discusses in more detail the reasoning behind this design and why we believe it will be a better design than just one IMU.

Engineering Analysis

To test our system and algorithm, we conducted experiments using the following process. We attached the IMU to the ankle of a user and collected data of acceleration along the x, y, and z axis while they were walking, jogging, and running. The roll, pitch and yaw of the system was also recorded during these tests. We tested on treadmill with 0 incline to ensure this would be a basis for our algorithm's threshold values. We considered incline to be outside the scope of this project. After collecting data from those behavioral states, we then began to collect data as a person was transitioning from one behavioral state to another. This allowed us to better understand and refine the threshold values to determine when a state changes from one to another. Each of these experiments were recorded with a camera to provide visual verification if our system's output matched the behavioral state in the video.

Problem Domain Analysis

Designing a sensing and classification system for an exoskeleton is a complex and challenging problem. There are multiple factors that play into how well the system interacts with the rest of the exoskeleton and user. By far and large, the main issue when developing a sensing and classification system is that it needs to accurately understand what the user is doing at the moment. It needs to correctly classify the behavioral state 95% of the time. Assessing the engineering specification of accuracy is difficult because we may not always understand why the behavioral state was incorrectly classified. There are multiple inputs that the algorithm uses to identify the correct state so when improving the accuracy, we would need to investigate each individual input.

To meet the accuracy specification, we are using a thresholding algorithm to determine the person's gait and the behavioral state. The algorithm will depend on a large amount of data to fine tune and adjust the thresholds. These adjustments to the thresholds will increase the accuracy in determining each event in the stances of the gait. Some critical decisions to consider for the future will be how close to real time the algorithm will operate. Even though the data may be inputted in real time, the algorithm will need to aggregate data points together to be able to produce an accurate result.

When solving this, the main technical skills used would be working with Arduino and Matlab code. Experience and previous knowledge in designing a thresholding algorithm will be important in developing the actual code. Currently the knowledge we lack is in determining the factors that go into classifying the behavioral state. However, this will be supplemented by literature from previous researchers who worked on gait analysis and predictive algorithms for exoskeletons as we continue our own research. This will also be the case for when we want to build further on the algorithm by developing it into a neural network that can self-learn and be more accurate for our sponsors to use.

By the end of the semester, the goal of this project is to produce a wearable device with IMU sensors that will transmit data and output the current action of the person (standing, walking, jogging, or running). The physical prototype will be developed during the second half of the semester to be used for recording data.

Final Design

Moving forward with the alpha design, Figure 16 shows both the CAD and build models of the sensor housing hardware. Foam, a zip tie, and a buckled belt strap are used to keep the IMU stable while strapped to the user as they move.

Figure 16. *(Left)* Sensor housing CAD model. *(Right)* Full housing setup to stabilize IMU and strap to the user.

Figure 17 on the next page shows the entire housing and electrical components of the sensing system. The IMU pins were soldered to the wires of an insulated cable that connects to the Arduino. In addition, heat shrink and electrical tape were used to eliminate any exposed wire. This cable is long enough to lead from the sensing system on the user's ankle to the M-STARX exoskeleton backpack that houses all of their controls. For now, we have built two sensing setups, but we have been only using one as it has proven to provide enough data for state classification so far. Further testing with the second unit on the user's toe will be carried out to determine if there is any significant benefit.

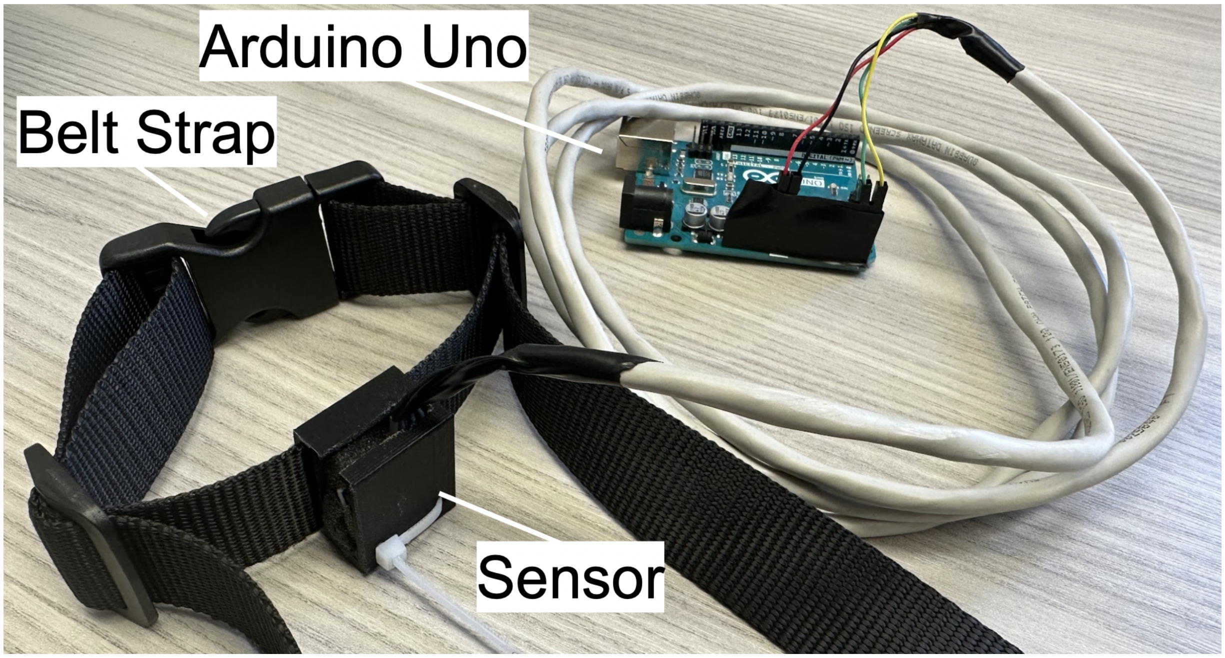


Figure 17. Full sensing system including IMU, housing, and Arduino for data acquisition to be processed by algorithm.

The full setup strapped onto the user and connected to a laptop can be seen in Figure 18. This was the setup used for testing as the team still needs to integrate the system with the M-STARX exoskeleton. A diagram of the IMU orientation when strapped to the user is also provided.

Figure 18. *(Left)* Data collection setup. *(Right)* Coordinate system of IMU sensor in relation to the user.

The yellow markers seen in Figure 18 were used for motion capture analysis in *Kinovea* software. This analysis collects kinematic data on speed that could be used to further define our behavioral states. We are focusing on general gait classification instead of transition phases or specific events within a gait, so the motion capture video is currently being used for demonstration purposes only. This generalization of the gaits also applies to the data collected from the IMU. As seen in Figure 19 on the next page, when comparing the raw signals from standing, walking, and jogging against each other, the angular velocity in the y-direction provides the most distinguishing pattern between the three gaits.

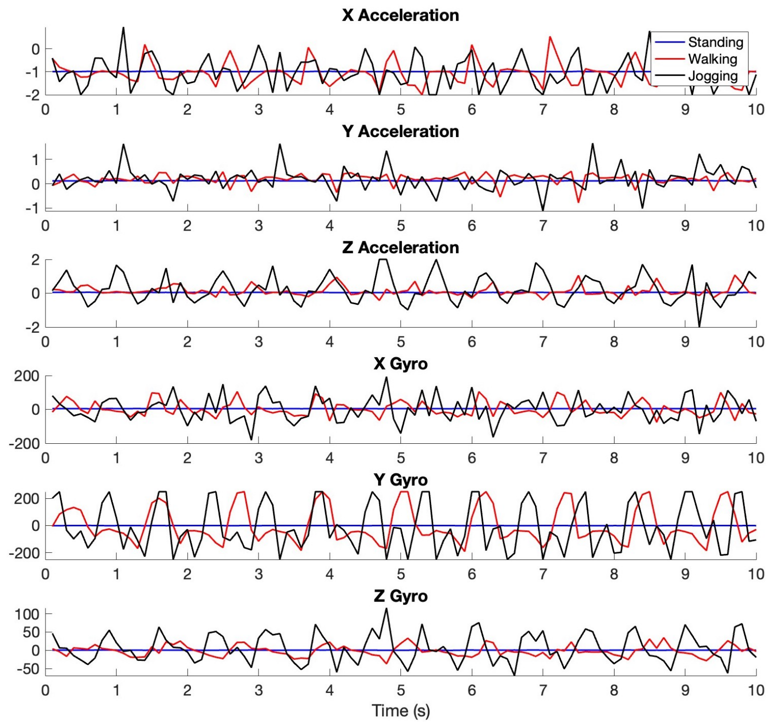


Figure 19. Side-by-side comparison of raw standing, walking, and jogging signals from IMU. Data from y-directional angular velocity provides the clearest signal for distinguishing between gaits.

Zooming more into the y-directional angular velocity of a walking signal in Figure 20, the stride can be broken down into the two phases of swing and stance as described in Figures 5 and 6. Four events labeled as Heel Off, Swing, Heel Down, and Flat Foot are also included. This repeating pattern is also reflected in the jogging and running signals the team has collected.

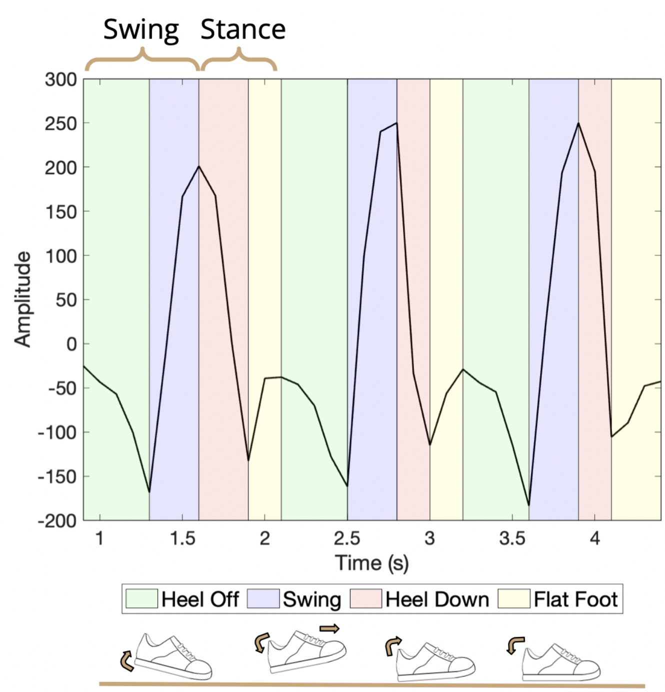


Figure 20. Gait phase and event breakdown of y-directional angular velocity signal collected from walking displays the repeating and easily-identifiable pattern in the human stride.

This sinusoidal pattern of the y-direction gyroscope presented an opportunity for a simple method for developing our algorithm: differentiating gait based on the frequency of the signal. We decided to perform Fourier decompositions on the incoming signals, which converts the signal from the time domain to the frequency domain and identifies a periodic signal's sinusoidal components as shown in Figure 21 below. Like the motion capture data, the full accelerometer and gyroscope data collected could be potentially used to further narrow down on specific gait events, transition phases, and other behavioral states, but, for the purposes of this project and what the sponsor wants, we will focus on this Fourier method.

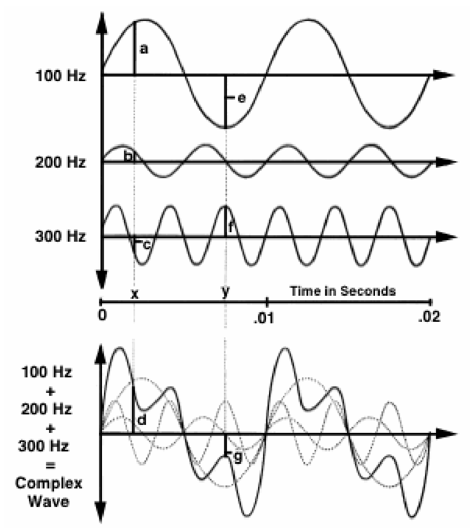


Figure 21. Fourier Decomposition Conceptual Diagram[29]

Our Fourier decomposition uses a fast Fourier transform (FFT) method to determine both the magnitude and frequency of the highest amplitude sinusoid comprising the signal. An FFT is run every time a datapoint is collected from the IMU. While some of our initial algorithm prototypes only ran an FFT on a prerecorded subset of data across its entire recording interval, we realized that this method would be infeasible for real-time gait identification. Our new algorithm architecture uses data framing to decide the intervals on which to run FFTs, allowing gait identification in real-time. When the algorithm starts, an FFT is run on the first incoming data point from the IMU. When the second data point is recorded, an FFT is run on the first two data points. When the third datapoint is received, an FFT is run on the first three data points, so on and so forth until a transition between gaits is detected.

When a transition between gaits is detected, the algorithm starts from scratch and only runs FFTs on data points received after the transition. This cycle continues, effectively containing Fourier transforms to dynamically sized frames of data in order to identify data as it is received in real-time. In the Simulink model shown in Figure 22 on the next page, the "read" block determines the data framing based on inputs from the "transition" block which identifies gait transitions, then sends this data to the "fourier"

[29] Wormus, Robert, and Wayne Staab. "Fourier Analysis and Its Role in Hearing Aids." *Hearing Health & Technology Matters*, HHTM, 24 Feb. 2022.

block which runs the FFT on the appropriate data frame. From this FFT, maximum magnitude and dominant frequency data are extracted and inputted to a stateflow model in which the heart of our algorithm lies.

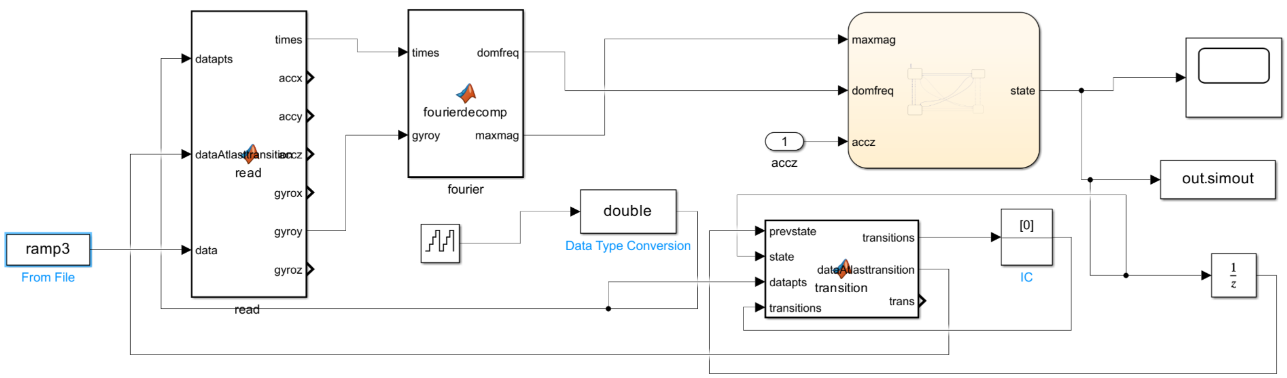


Figure 22. The Simulink model bins the incoming IMU data to process it and direct it to the stateflow model.

Our stateflow model in Figure 23 compares incoming data from the FFT to fixed thresholds for maximum magnitude and dominant frequency to determine the gait between standing, walking, jogging, and running. In the figure below, the plot on the right shows the algorithm running on a user who is walking. Notice that because of the data framing, the algorithm initially identifies the user to be standing, outputting a zero. It takes five data points, a delay of half a second, for the algorithm to take enough data to correctly identify that the user is walking and output a one. This test was used as an initial verification of our algorithmic architecture's ability to identify gait in real time.

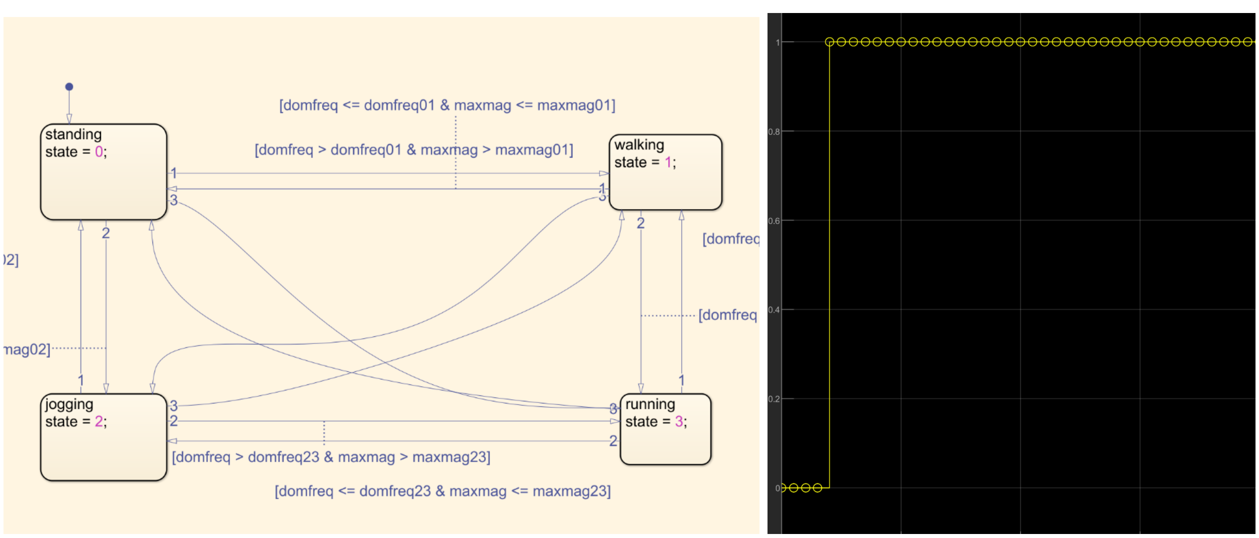


Figure 23. (*Left*) Stateflow model of the different behavioral states. (*Right*) Identification delay plot.

Verification and Validation Approach

For us to verify that our algorithm meets the 95% accuracy level of correctly classifying gait cycles, we plan to test the algorithm on multiple people of varying heights. This will ensure that the algorithm thresholds can either be easily modified based on user height or can fit any user height. We may not have enough time to test more than a few people with the time left for the project, so our algorithm may be confined to users of similar heights. We have training data to help us narrow down what our thresholds might be. This data does not encompass all types of people who might use the exoskeleton, but will allow our algorithm to be much more accurate.

To further determine the accuracy of our algorithm, we plan to use specific speeds where the user makes the transitions between walking and running. Then by running on a treadmill at those specific speeds, we can check to see if our algorithm is accurately classifying the gait cycles. The transition speed between walking to jogging/running is approximately 2 m/s.[30] We plan to test this transition speed and test if it can distinguish between variations of the speed to determine walking and jogging/running.

Using a treadmill, we collected data from members of this project team. This was done to mark the speeds during the verification test and standardize the conditions. Each trial consisted of collecting 4 minutes of data. The first trial began with a standing start then moving at set speeds that increased from 0.9-2.7 m/s with 30 seconds at each set speed. Then the speeds were decreased back down to standing at the same rate. The second trial was collected with randomized speeds at every interval. This data collection was performed by all members on the team to then be validated versus the actual behavioral states based on timestamps.

Figure 24 below shows an example of the verification process. We collected the y gyroscope signal data which is compared to the current speed of the treadmill and the behavioral state predicted by the algorithm. We found the raw data corresponded well with the raw signal. The speed changes were found through manual time-stamping and had some slight variable alignment.

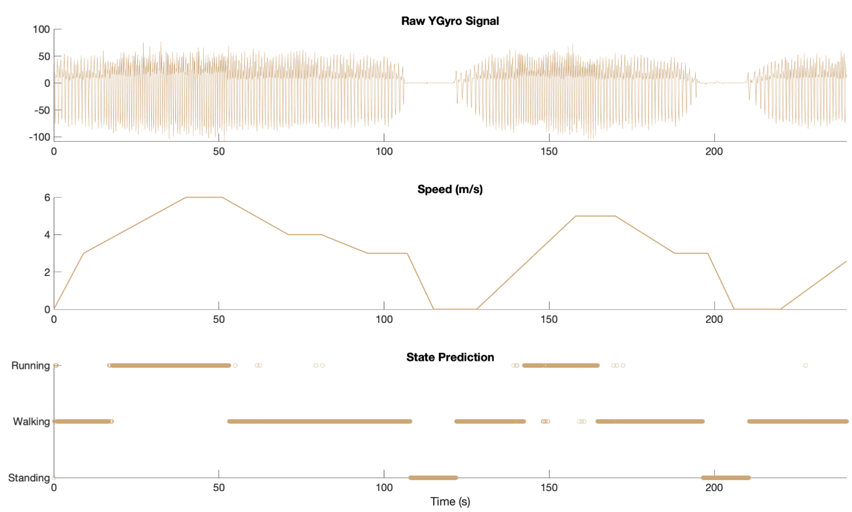


Figure 24. Plot of raw gyroscope data for y axis (top graph), the speed of the treadmill over time (middle graph), and the behavioral state prediction from the algorithm (bottom graph).

In Figure 25 on the next page, we then compare the state prediction versus the actual state. The evaluated algorithm accuracy is found by comparing predicted state and actual state. In the graph, the gold data represents the algorithm's prediction and the blue represents the actual state. The accuracy of

[30] Rotstein et al., "Preferred Transition Speed between Walking and Running: Effects of Training Status", American College of Sports Medicine, 2005.

the algorithm was determined to be 80.0%, including during transitions between states. This value shows how well the algorithm can accurately predict a user's movement through different gait patterns. This value may be inaccurate due to the linear ramps that were assumed with the speed causing variable alignment.

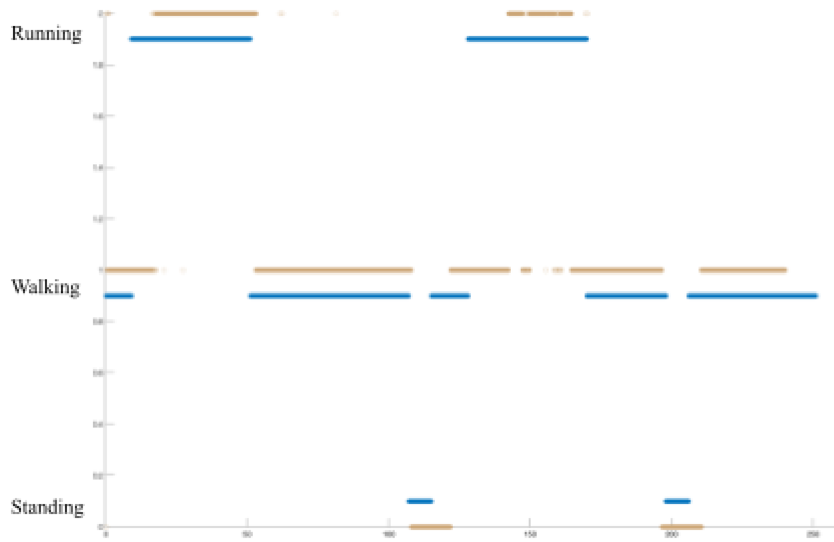


Figure 25. Plot of the algorithm state prediction compared to the actual states determined by speed and time stamped data.

For the verification of our algorithm, we confirmed with our sponsor whether or not our design solved the problem they had.

Discussion and Design Critiques

Overall, our solution proved to be successful in determining the behavior state of our tested users. There is definitely more work that can be done to improve the accuracy of the algorithm as we did not achieve the goal of a 95% accuracy - discussed later in the *Recommendations and Future Work* section. Table 3 below summarizes the strengths and weaknesses of our final solution.

Table 3. The final solutions accomplished the basic goals and needs of the team and our sponsor, but more work needs to be done to improve on the overall accuracy of the state identification capability.

Strengths	Weaknesses
Simple Physical Design	Inaccurate Phase Determination
Accurate Cycle Determination	Low Sample Size
Real-Time Capability	Cannot identify jogging from running

The main challenge in this project was collecting data and fine tuning the thresholding algorithm. This was a challenge because it required that the data collected is in a controlled environment and has multiple people to test the algorithm against multiple different gaits. By testing against a lot of different walking patterns, we could validate whether our algorithm is accurate enough to meet the specifications. Since people have different heights and maybe even the way they walk, this would cause the frequency we determine for each of them to vary. People can get exhausted which would also cause a change in the frequency we would determine for the gait cycle. This would cause the algorithm to have to adjust to fit these different frequencies and may cause the algorithm to not be able to determine walking, jogging, running, etc. We planned to have multiple people test the design to determine if this will be a problem and hopefully adjust our algorithm to fit people of varying gaits. In the end, we only tested on our team members, so the sample size used is relatively small.

A challenge the team determined was distinguishing between jogging and running. Jogging and running look very similar and are even too difficult to distinguish mathematically.[31] It may not be possible for us to distinguish them without a pressure sensor or other methods.[32] We believe adding another IMU to the other foot may allow us to calculate the flight phase or the phase where both feet are in the air. Since the flight phase is different between jogging and running, we would be able to distinguish between jogging and running.

The final problem we had to overcome was having wires that were too long. Since our sponsor would like to integrate our design into their exoskeleton, they will need wires that can extend from the IMU on the foot to the backpack controller they have on the user. Since the wire will have to be long to reach the backpack, this can cause the signal from the IMU to deteriorate and give us sporadic data. To fix this problem, we are very limited. We can add buffers along the wire to ensure the signal integrity, but this method is very time consuming and does not always work. Signal integrity may be a problem with the arduino and we could fix it by streaming the arduino through a separate board that has better signal control. So far, we have not experienced this issue, but it is possible that it is an underlying cause of our lowered accuracy that needs to be looked into.

As we were not able to connect our solution to the working M-STARX exoskeleton and controls system to check compatibility and long-term usage, we have to hand it over to the M-STARX team to test and fix since it is a problem that takes more time than we had investigate

Reflection

Our design impacts the world in many different ways. One of these impacts that our design makes is with public health, safety, and welfare. Our design will be handed off to the M-STARX University of Michigan project team who are making exoskeletons to augment a user's movement. With our design integrating into their exoskeleton, they will be able to more efficiently accomplish this task. Further development and research of exoskeletons can not only help augment people, but will help assist users as well. This will allow the public to use these exoskeletons in everyday life. It will help police officers, the military, the elderly, and many more.

Another way our design will impact the world is in the global marketplace. Since our design will make exoskeletons more efficient, other designs will not be able to compete. This will affect the marketplace since one exoskeleton will outclass the others. It will not affect prices too much though since our design is so inexpensive.

[31] Everett et al., "Lower Limb Position During Treadmill Jogging and Fast Running in Microgravity", Aviation, Space, and Environmental Medicine, 2009.

[32] Mann et al., "Comparative electromyography of the lower extremity in jogging, running, and sprinting", American Journal of Sports Medicine, 1986.

The social and economic impacts of our design associated with manufacture, use, and/or disposal of the design will be minimal. Since our design is so simple to manufacture in terms of price, material, and labor, it will not impact either the environment or economy that much. The impact due to the disposal of our design will also be minimal due to the same reasons.

A tool we used to characterize the potential societal impacts of our design was our stakeholder map (Figure 10). We determined that our stakeholders would have societal impacts from our design are the military, EMTs, disabled, and injured users. All of these groups would be either assisted or augmented by our design and exoskeletons in general.

Some of the differences and similarities between the team members that influenced the approaches the team took throughout the project were from the differences in backgrounds. Some of these background differences could be caused due to the differences in classes taken, cultural differences, or even personality differences. This may have caused different individuals on our team to have different ideas or ways to approach problems. The final design may have been impacted by these differences.

An ethical consideration our team faced was what our design may be used for or by after we hand it off to the M-STARX project team. We questioned whether it would be our fault if someone was injured due to incorrect implementation of our design. We hope our design will be useful and those that integrate our design will be ethical in their decision making.

Recommendations and Future Work

Although the sensing system and algorithm are working and can be implemented immediately into the M-STARX exoskeleton, there can be future work done to this project to improve the accuracy and provide more information about the user's movement. Accuracy should be the main focus of future work as this project did not reach the intended goal of 95% accuracy. In the discussion, we saw that the accuracy fell short because of two main issues, transition times and blipping. On a system level approach, we could consider using machine learning to better identify when a person switches states which would reduce the transition times. If it can better understand the transition states, it can also potentially reduce the amount of blipping. An alternative method to improving accuracy would be to increase the sampling rate of the IMU and collect more data from a larger sample size. This method would create more data points closer to real time for the algorithm to process so the transition times would be shorter. Also, more data from a larger sample size can set better thresholds for the system which should help reduce blipping.

Another problem we foresaw during prototyping was IMU drift. This causes the values of the data to be inaccurate as the gyroscope may still move even when the foot has stopped. This causes a problem if we would like our algorithm to be extremely accurate and to define different phases of the gait cycle. A potential solution to this problem would be a correction value or a filter to adjust the values due to the drift. We did not end up seeing too much of a problem because of this, but a filter could still help clean up the data to make it easier for the algorithm to differentiate noisy signals from the various states.

Other recommendations we considered for this project would be to design built-in exoskeleton hardware for the sensing system. This would make it easier to put all the hardware components in one central location and have everything integrated. There could also be more work done into identifying gait events in the user. By using multiple IMU's or considering other data collected, you could potentially identify important gait events like heel strike or toe off. It may not be important now, but in the future it may be beneficial to control algorithms if there was more information available.

Conclusions

Exoskeletons are complex technologies that have applications in many industries, but require information and data to help it assist and emulate human motion. In this project, we aimed to develop a sensing system and algorithm to determine the exoskeleton user's behavioral state of standing, walking, or running. We were able to create a 3D printed housing to hold the IMU and collect signals about a person's foot's acceleration and angular velocity data in the x, y, and z directions. The y gyroscope data best resembled the cyclic pattern of the gait cycle so we used that for our algorithm processing. We applied a fourier decomposition on the signal to determine the dominant magnitude and frequency for which we could then set thresholds based on testing and training data. This algorithm was then verified through testing using a treadmill and then compared to time stamped video data. It was only able to achieve 80% accuracy despite a goal of 95% accuracy. Although it falls short of the goal, there are some recommendations that we considered that can help increase the accuracy and reduce the errors we saw.

Acknowledgements

We would like to thank our sponsor M-STARX, Professor K Alex Shorter, Professor Elliott Rouse, Gabriel Antoniak, the University of Michigan Mechanical Engineering Department, and all persons involved in ME 450 for their support throughout this project.

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Appendices.

A. Tables of Additional Concepts Generated
B. Build Design Build of Materials
C. Manufacturing/Fabrication Plan
D. Team Biographies

Appendix A. Tables of Additional Concepts Generated

Table A1. All other parameter ideas from concept generation not mentioned in the paper.

Concept	Description
Pressure/Force	Measure the pressure or force that each part of the foot causes with contact with the ground
Resistance	Measure the resistance of a wire or other device that changes resistance as the foot makes contact
Muscle/Brain Signal	Measure the muscle signals to determine how the body/leg is moving
Center of Mass	Measure the center of mass of the body to develop a map over time of the center of mass of the user
Displacement/Velocity/ Acceleration	Measure the kinematic values of the foot as it moves through the gait cycle (x/z directions)
Magnetic Field	Measure the magnetic field that each of the feet make when having magnets placed on them
Light	Use light to determine where the feet are located
Moment	Measure the moment that the foot is making
Balance	Measure where the balance of the user is to determine how they are shifting from foot to foot
Tension	Measure how much tension is caused by something external to the user or the muscle
Angle	Measure the angle changes that the foot/leg makes (foot/shank)
Temperature	Measure the temperature distribution the feet make with the ground

Table A2. All other sensor ideas from concept generation not mentioned in the paper.

Concept	Description
Spring System	Measure the displacement in the springs when they are attached to the foot
Leveler	Use an object that moves as the person moves and can determine the angle by how much it moves
Roller Blades	Instead of walking, use roller blades and can measure the rotational/angular speeds of the wheels
Visual/Camera	Use camera and motion tracking system to determine gait
Walking on Gel	Able to sense when gel is displaced and can find out the length of the gait cycle
Capacitive	Pressure sensor that measures the voltage across the capacitive plates as they are compressed by the feet
Piezoelectric	Pressure sensor that measure the current created by a material that creates a current when compressed
Rope-Pulley System	Rope connected to each foot that is connected to pulley that tries to pull in the rope and then can measure the force as the legs pull the rope
Temperature/Heat	Measure a heat map of the foot as it presses on the ground/shoe
Radioactive Material	Radioactive material on the foot and can measure the gamma rays
Manual	Just manually push a button to determine when each foot makes contact with the ground
LIDAR	Use lasers on foot to measure the distance the feet are from the ground

Table A3. All other housing ideas from concept generation not mentioned in the paper.

Concept	Description
Manual Adjustment	Have the user of the exo manually adjust using an adjustable strap, shoe, etc.
Elastic Form Fit	Have a material that is elastic and will stretch and come back to fit around users foot
Insole	Have something to be inserted into shoe
Metal Plate	Simple metal plates that the user can fit their feet on
Acrylic Box	A box that will fit around the foot and contain all the necessary sensors
Multiple Plate Sizes	Variations of plates to fit different feet sizes
Springs	Springs that will house the feet and allow
Solar Powered	Solar panels that will charge the sensors/batteries
Wind Powered	Fans that will charge the sensors/batteries
Gaps/Hollow	Hollow plate to minimize weight
Extend Exo to Foot	Sensors attached to extended exo to the foot
Flexible/Hinge	Flexible housing using hinge for the toes or some other type to allow for easier maneuverability

Appendix B. Build Design Bill of Materials

Many of the supplies used in this project were sourced from the University, so estimated costs and potential sources are listed as well in Table B1 below. See the notes and Appendix C for more details on quantities of each component used in the design. Many of the parts can be purchased from other sources than the ones listed, so this BOM provides more of an idea of how our team accomplished our prototyping than a more formal and exhaustive list. The total actually spent was $17.98. The estimated cost of the entire project was $127.03.

Table B1. Bill of Materials of all components used in final design of sensing system.

Name	Cost	Source	Notes
0.5" Polyethylene Foam	$7.99	University / Amazon	Cut to shape
3x Hi-Letgo MPU-6050	$9.99	Amazon	Used only one in solution
4" Zip Ties	$6.99	University / Amazon	Optional (only need one)
6 Yd Buckles & Strap	$11.99	Amazon	Cut to length
2.0 A/B USB Cable	$7.60	University / Arduino	For uploading code and testing
Arduino Uno	$27.60	University / Arduino	Can switch to a newer model
Cable Pins	$7.88	University / Amazon	Need four connectors
Ethernet Cable	$16.99	University / Amazon	At least 4 wires and 4 ft long
FDM 3D Print	$30.00	University (LBME)	Cost roughly approximated

Appendix C. Manufacturing/Fabrication Plan

These are instructions on how to manufacture the hardware components of the sensing system solution broken into two main parts: preparing the sensor and the housing of the sensor. Note that some of the figures and overall descriptions have already been shown/discussed in earlier sections of the report (e.g. the *Alpha Design and Initial Testing* and *Final Design* sections).

Sensor Setup

Ideally, locate a long insulated cable (ours was about 4 ft long, should go from user's ankle to their mid back without issue) with four internal wires with male pin connectors (see Figure C1) attached. The pins should fit into an Arduino pin without risk of coming loose. If such a cable cannot be found, one can be made using an ethernet cable, exposing the wires (cutting off any extra wires if necessary), and crimping on pin connectors using wire strippers and pliers.

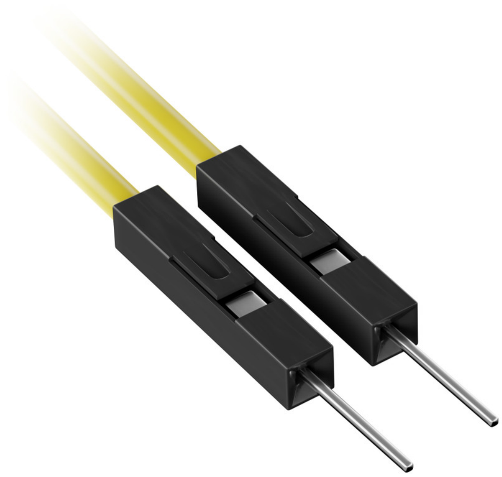


Figure C1. Male pin connectors for reference.

The IMU used in this project is the Hi-Letgo MPU-6050 as seen in Figure C2. If not already done, solder the short end of the bent pins to the sensor. The other end of the cable from earlier should have four exposed wires that need to be soldered on the IMU VCC, Ground (GND), Serial Clock (SCL), and Serial Data (SDA) pins. Make sure to use heat shrink to fully secure the connection and for safety.

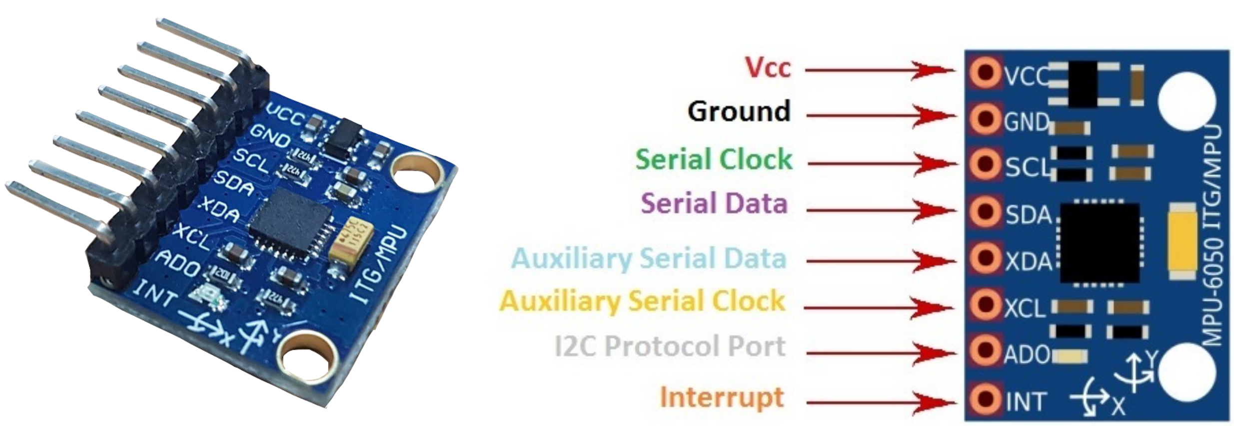


Figure C2. (*Left*) MPU-6050 IMU with attached pins. (*Right*) Pinout diagram.

Housing

We 3D printed the CAD model seen in Figure C3 (contact sponsor for file) using the UltiMaker S5. The part was printed with polylactic acid (PLA), and the supports with polyvinyl alcohol (PVA).

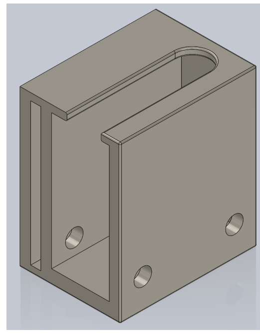


Figure C3. Sensor housing CAD model.

Foam (and optionally a zip tie) was used to keep the sensor in place when placed into the housing. The sensor should be oriented such that it follows the ankle component shown in Figure C4. A belt strap was looped through the designated slot in the housing. The length is customizable to a user's ankle.

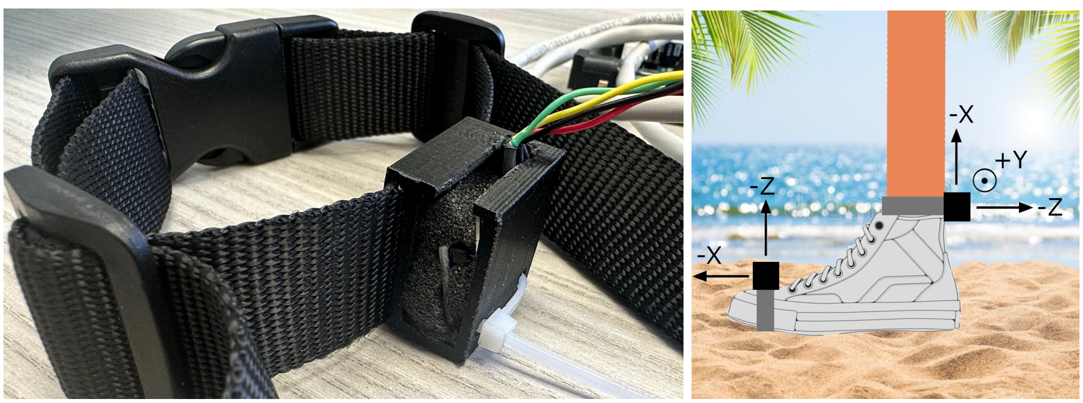


Figure C4. Sensor orientation and placement in the housing and on the user.

Finally, the sensor can be connected to the Arduino board: VCC → 5V, GND → GND, SCL → A5, and SDA → A4. Electrical tape was used to further secure the wire connections as seen in Figure C5.

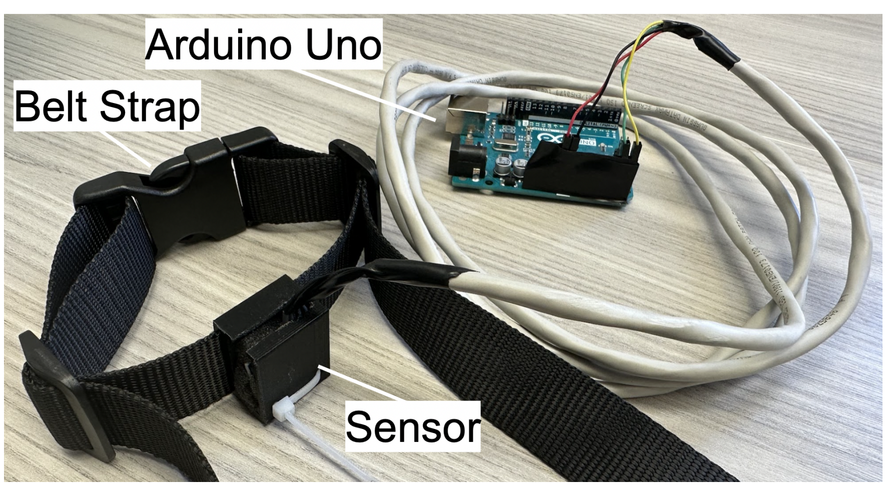


Figure C5. Complete sensing system hardware.

Appendix D. Team Biographies

Andrew Estey

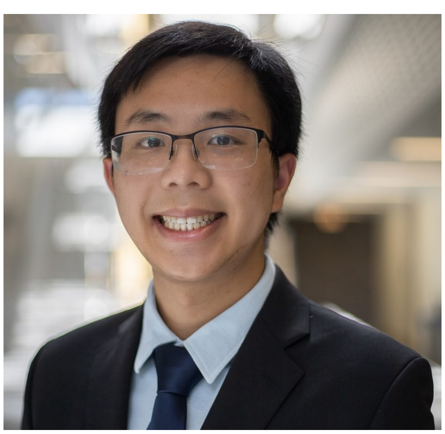
I'm a senior studying ME and I graduate in the Winter 2023 semester. Mechanical Engineering has always interested me because I like World War 2 history and the military vehicle advancements made during the time. I am currently interning at the US Army Corps of Engineers assisting their hydrographic survey crew. My hobbies include board games, soccer, and backpack camping.

Kayra Ilkbahar

I'm a senior studying ME with minors in electrical engineering and math, and I'll be continuing my studies at MIT in the Fall. I grew up in the San Francisco Bay Area and decided to study mechanical engineering because of my interest in machine design. Outside of my studies, I'm the mechanical systems lead for the solar car team and do dynamics and systems engineering for automotive applications. My research interests include mechatronics, manufacturing technology, dynamic systems, and controls. My hobbies and interests include cars, guitars, food, and outdoorsmanship.

Mandy Mai

I'm a senior studying Biomedical and Mechanical Engineering graduating in April 2023. I plan on going into industry post-graduation and am interested in working on medical devices, manufacturing, and product design. As I'm from NYC, NY, I'm hoping to end up on the East Coast eventually. Outside of classes, I'm the President of the Society of Asian Scientists and Engineers (SASE), a former member of the Michigan All-Girl Cheer Team (MAGC), and involved in the Michigan Strength Augmenting Robotic Exoskeleton (M-STARX) student design team. My interests include traveling, arts & crafts, and binging TV shows.



Keith Wong

I'm a senior studying Mechanical Engineering and graduating in the winter semester of 2023. On campus, I am a part of the Michigan Strength Augmenting Robotic Exoskeleton team as the business team lead. Outside of academics, I enjoy playing board games and racquetball.