Subjective Costs of Movement:
Factors beyond Economy in Human Behavior

by

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Abstract

Humans generally tend not to spend more energy than necessary when they perform a task. However, subjective factors, such as the comfort associated with a movement, have a significant impact on how humans behave. Some studies have used constrained optimization to explain the decision making process for movement, the effect of ergonomic factors, or even diet choice. A task's goal represents a constraint on possible behavior, and the chosen, or optimal, behavior is determined to be that which minimizes some cost function. In biomechanics, researchers often assume costs related to energy or kinematic variability, which may miss some important subjective motivations for behavior. In this work, we leverage the optimization approach to predict and control behavior based on a more general subjective cost. However, we objectively quantify the subjective cost function in terms of mechanical work, which represents the trade-off in economy that subjective factors incur. More complete knowledge and the ability to control decisions for muscle use could benefit motor learning research, rehabilitation, and strength training.

We use an implicit approach to uncover the subjective costs associated with a number of exercise tasks. We alter task constraints, and their associated subjective costs, by unevenly weighting limb power toward a goal sum of this weighted power during exercise. The unknown subjective cost function may thus be characterized by sampling the preferred strategies for a range of different constraints. This method can be used to both characterize subjective costs of

exercise in terms of objective quantities such as work, and to provide a framework with which we may create tasks which direct effort toward specific limbs.

Results indicate that healthy subjects split effort between limbs based on more than economy alone. Factors of the exercise task, such as grip type, or reach length, can alter the subject's effort distribution toward greater use of arms or legs by about 15% of the mean net power performed. We found that implicit feedback could be used to unveil each subject's trade-off between mechanical power generated beyond the minimum required and factors beyond economy. The implicitly weighted feedback also allowed control of the distribution of effort to allow shifts in effort toward arms or legs up to 37% of the mean net power during an exercise task. We found that the feedback could be supplied in multiple ways. We tested the use of both implicit and explicit feedback provided either through visual feedback or by changing resistance in response to the combination of implicit weights and the subject's limb use. Subjects reduced error by 74% relative to their feedback goals and were able to perform simultaneous cognitive tasks 4.2% faster when they used implicit feedback to direct effort, rather than explicit feedback. Finally, subjective costs inform behavior outside of multi-limb exercise. In a drop landing experiment, subjects who dropped on cushioned surfaces performed up to 32% less excess work than those who landed on stiff surfaces, which allowed us to quantify the subjective cost of a more comfortable landing in terms of mechanical work.

Introduction

Humans make complex decisions on how to move their bodies when performing a task. The decision making process may be subconscious or active, but much of the time, people seek out the easiest way to accomplish their goals. For example, preferred step width while walking, and the way people swing their arms have been seen to coincide with the minimum expenditure of metabolic energy, compared with alternative widths or swing methods [1], [2]. However, there may be factors such as goal-setting [3], or the influence of fatigue [4], which are quite subjective and cause people to move in ways which are not economical. Moreover, subjective causes of uneconomical behavior are difficult to characterize. Qualitative surveys and scales are used to measure their influence [5], [6]. Unfortunately, comparisons or descriptions of the trade-offs between them are difficult without a common measure of them all. Here we describe a way to objectively quantify and compare between the factors that influence behavior. We use a constrained optimization approach to quantify the cost of subjective factors in terms of excess mechanical work and energy generated during exercise tasks. Similar approaches have been used previously in human factors research to explain choice of diet [7], or propose a method people use to choose when to use stairs vs. an escalator [8]. We aim to use the approach to allow prediction and control of behavior to encourage desired limb use for future application in areas such as strength training and motor rehabilitation, even if those factors are subjective or not directly related to energy expenditure. For example, patients in motor rehabilitation often suffer from weakened limbs due to illness or disease. Their preference for distribution of effort between limbs has been affected by their condition. They act according to many influences, including altered perceived exertion, lack of neurological control, and reduced physiological capacity. By measuring the effect of all of these factors on work output from the limbs, we may gain insight into how their effort has been influenced by their condition. We may even alter the rehabilitation exercises to better encourage use of the patient's weak limbs, such that the patient may regain strength and functional ability.

We first confirmed that behavior during the experimental recumbent stepping exercise was the result of decisions beyond the maximization of economy. Instead, we hypothesized that the nature of an exercise (e.g. related comfort, kinematics, or power requirements) may alter the effort distribution among limbs, away from the distribution that may result in the lowest energy expenditure. We compared metabolic rate with different distributions of effort between limbs. Then we measured mechanical power in each subject's preferred limb distribution for conditions which altered grip type, reach length, and power generation method. (Chapter 1).

Next, we offered an implicit approach to uncover the subjective cost function using a constrained optimization approach. Visual feedback was used to purposefully alter the work division among limbs toward a target distribution. The approach assigns weighted multiples of limb group power unevenly toward a goal of the sum of this weighted power from all the limbs. The more heavily weighted limb groups receive more credit toward the task's goal such that the use of these limbs reduces the actual overall required mechanical power. The weighting will alter the subject's sense of effort by incrementally changing the amount of extra power required to maintain their preferred, perhaps uneconomical, combination of limbs. We will thereby uncover a trade-off between the minimization of mechanical power and the subjective factors that enter into each person's decision making process on how to split effort between limbs. This function is quantified in terms of mechanical power, but will reflect all the factors that lead the subject to their choices (Chapter 2).

We compared our implicit feedback method against an equivalent form of explicit feedback. If successful, implicit weights could be used to steer effort toward specific limb groups, which could prove useful in motor rehabilitation. However, for our methods to be adopted, we would like to show that they have the potential to be as successful as traditional methods to encourage the use of targeted limbs, such as different forms of explicit feedback. Furthermore, we quantified additional benefits that implicit feedback affords, such as lower attentional demands and easier tracking of feedback goals. We compared each feedback mode's ability to predictably and consistently steer effort toward targeted limb groups, as well the interaction effects with simultaneous cognitive tasks (Chapter 3).

We may convey information about the implicit task constraints visually, or with altered resistance to motion. Tasks that alter resistance in response to implicit weights and the user's limb choice may be a simpler, and more direct form of feedback than visual feedback of summed weighted powers. We expect that lower amounts of resistance are preferred, even if we create weighted tasks in which lower resistance exercise is more costly in terms of required mechanical power. We tested whether preference for low resistance is able to alter effort distributions in exercise, with or without the aid of visual feedback (Chapter 4).

Uneconomic behavior extends beyond effort distributions in exercise. In other areas of biomechanics, people still base their behavior on more than just economy. For example, the desire for stability during walking or competitive drive during sporting events have been studied as possible motivators for uneconomical behavior [9], [10]. Uneconomical behavior in other activities, such as drop-landing, may provide people with non-work benefits such as comfort and injury prevention if they spend extra energy to cushion their drop. Stiff, straight-legged drops are the most economical, but may not be preferred because of their association with greater amounts of pain [11]. We expected that when the landing surface is cushioned, people will prefer to reduce the active muscle work they perform at collision, becoming more economical. The reduction of extra work subjects perform when they drop onto cushioned surfaces will allow us to indirectly measure the benefit the cushion provides and form predictions regarding the subject's future behavior (Chapter 5).

Our work here aims to yield a greater understanding of the interaction between difficult to measure subjective factors and human decision-making. Implicit feedback can be used in combination with constrained optimization approaches to motivate limb use in strength training or for patients in neuromotor rehabilitation. Such feedback may promote specific limb use without the need for explicit feedback and help alleviate burdens on the therapist and patient.

Chapter 1.

Condition-dependent Preferences for Power Distribution in Exercise May Allow for the Control of Effort among Limbs

Introduction

There is often a conflict between short and long term goals in exercise. In the long term, people wish to increase strength and coordination, but in the short term they are inclined to make the exercise feel easier. Athletes in training exercise to gain increased strength and coordination in the long-term, but their short-term desire for ease may lead to exercising with poor form, or for a shorter duration. Likewise, for patients in motor rehabilitation, the long-term goal is to recover strength lost due to injury or disease such as stroke or spinal cord injury. However, in the short term, patients may compensate for their weakness by finding ways to make the task less difficult. Unaffected limbs may perform the majority of the work necessary to fulfill a given task, which promotes learned disuse of the weakened side, and creates further asymmetry in strength [12]–[14]. Better rehabilitation may be possible if the short-term goal of ease could be aligned with the long-term goals of proper form and increased strength.

A person's sense of ease may be informed by a variety of factors. Humans often prefer to perform tasks, such as locomotion, in an energetically economical manner [1], [15]–[17]. However, there are many instances in which factors beyond economy influence how people complete a task and their sense of ease. Powerful incentives for changes in behavior include goal setting [18], anticipated duration and intensity of exercise [3], [19], [20], avoidance of pain [21], preference for stability while walking [9], and the effects of fatigue [4], [22]. These factors may have energetic components, but they do not always lead to the most economical movements. Therefore, it may be possible to use the non-energetic components of each factor to drive people to use specific limbs, although it may be less economical. The use of factors beyond economy to steer effort might be useful in rehabilitation. If patients can be compelled to use weaker limbs, they may increase strength and symmetry between their limbs. In turn, greater strength of affected limbs may reduce learned disuse, and lead to greater functional outcomes.

We explored three factors that we hypothesized would alter the effort distribution between limbs subjects choose in exercise. We used a recumbent stepping machine (NuStep, Ann Arbor, MI) to test how people distribute power among limbs under different conditions. Specifically, we examined the effects of grip type, kinematic configuration, and different power generation methods. There may be components of each condition that alter the economy of exercising with a given distribution. However, we also believe that factors beyond economy, such as comfort or habit, will inform each subject's choice for their distribution of effort. We expected that less comfortable grips with the hands will lead the subject to use their arms less. Likewise, we expected a change in the length of the machine's telescoping arms would alter how people directed their effort among limbs. This may be because muscle forces depend on their contractile velocities and length, which will be altered when reach is increased or decreased

[23]. There are also differences in economy depending on the spatial configuration and rate of power generation of the muscles [24]. However, in addition to energetic concerns, some configurations of the body may feel more or less comfortable or natural. Both energetic and subjective factors may play a role in how people decide to divide effort among their limbs. Finally, we expected that the way in which a subject generated power will alter their preferred distribution of effort. We found it reasonable to believe that the arms or legs may be better suited, or used more regularly, to generate power at increased speed or against a larger resistance. People may prefer to exercise in a manner consistent with their everyday experiences.

Consistent relationships may exist between the experimental variables and each subject's preferred distribution of effort. If so, an exercise task could be constructed to control how people distribute effort among their limbs. Such methods could be used in strength training or coordination tasks to encourage use of muscles in correct combinations to produce proper form. Exercise tasks could also be altered to promote specific effort distributions to help rehabilitate the weakened limbs of patients, directing more effort toward the limbs that need it most. Moreover, if the naturally preferred power distribution could be altered, target effort distributions could be driven spontaneously, without the need for explicit instruction or feedback. Therapists and trainers spend considerable time to reinforce exercise goals through verbal explicit feedback. Both could benefit from autonomous direction of effort toward limbs that require exercise.

Methods

We explored the relationships between exercise task modifications and limb effort distribution. We quantified limb effort with arms and legs power measurements as we varied the exercise task.

The recumbent stepper was instrumented to measure the distribution of work produced by the limbs (Figure 1.1 A). We provided visual feedback of the task's power goal and current performance with an LCD display (Figure 1.1 B). Individual limb power was calculated via measurements from custom load cells and gyroscopes. All information was recorded via a microcontroller (Arduino, Italy) sampling at around 60Hz.

We calculated the effort distribution as a function of each experimental factor to assess whether these factors could steer power generation toward the arms or legs. We reported power generation in each condition for all limbs. We also combined the powers of arms and legs, and then calculated arm use as the ratio of the net work performed by the arms (Figure 1.2). The ratio is a normalized quantity to allow direct comparison between conditions with different power outputs.

$$\text{Arm Power Ratio, } A = \frac{P_{arms}}{P_{arms}+P_{legs}} \qquad \text{(Equation 1.1)}$$

Six healthy adult subjects (4 male and 2 female, aged 21 ± 1.5 years (mean ± standard deviation)) participated in our study. We recorded anthropomorphic data including leg length (0.96 ± 0.069m) and body mass (69 ± 11kg). All subjects provided written informed consent according to University procedures.

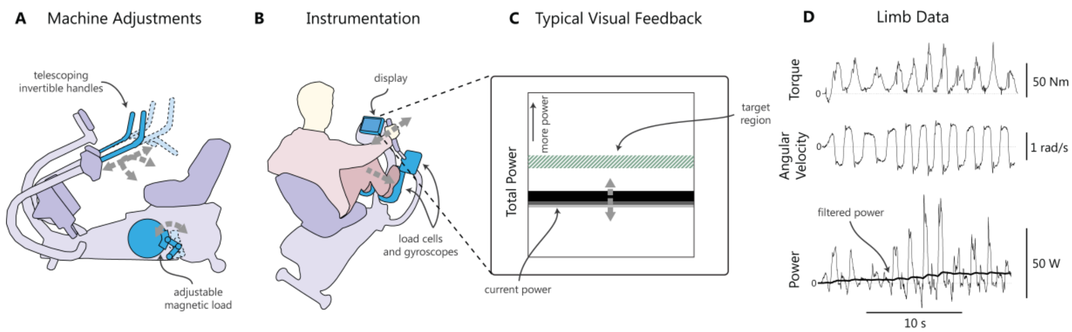

Figure 1.1: Experimental Setup

A: Adjustments of the NuStep exercise machine: The machine arms could be adjusted to be shorter or longer, or turned upside down. The magnetic load, which resists motion, could be increased or decreased. **B:** Instrumentation of the experimental hardware to measure power from each individual limb and provide visual feedback. **C:** Visual feedback provided for all experiments showing target power level and current contribution. **D:** Representative data collected at each individual limb. Torque was measured via load cells and knowledge of the kinematics of the machine. Angular velocity was measured via gyroscopes. The dot product of torque and angular velocity yielded power, which is cyclical in nature because of the stepping motion. A low-pass filter was applied to the power which yielded the current contribution.

First, we fit each subject to the machine and defined a consistent nominal seating position. We ensured that each subject could drive the machine through its entire range of motion without overextending their joints. We set the position of the NuStep's telescoping arms to a nominal position, which was determined using the subject's arm length after seat adjustment.

Next, we familiarized subjects to the visual feedback, which aided them to generate certain levels of power. The feedback presented a power goal, as well as the subject's current performance. Subjects received information about their current power generation from their arms and legs in the form of a moving power bar (Figure 1.1 C). Their goal was to raise the displayed power bar to a prescribed target level. They were to maintain the power at the target, while the instrumentation recorded the power from each of their individual limbs.

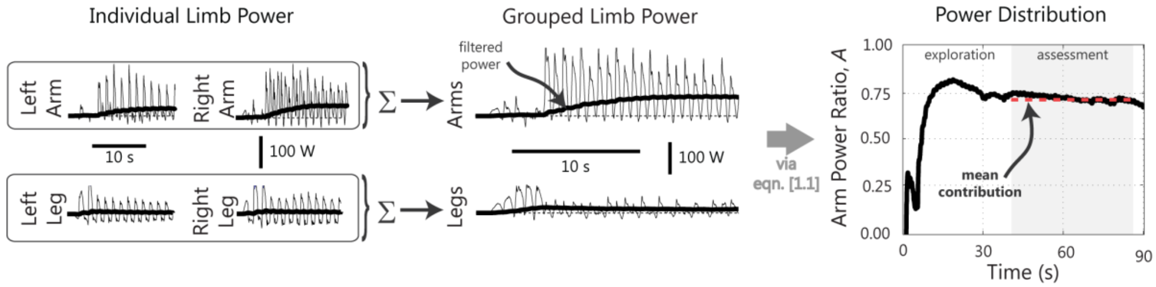

Figure 1.2: Individual and Grouped Limb Power Used to Calculate Power Distribution

Each individual limb power is combined into arm and leg grouped power. Next, the overall power distribution is calculated via the ratio of arm power to net power (Equation 1.1). Power is low-pass filtered to smooth cyclical data due to stepping during the exercise. For many of the conditions studied, the mean limb power and Arm Power Ratio is calculated over seconds 40-85.

We explored the metabolic cost of exercise on the NuStep. We measured each subject's metabolic rate during exercise on the NuStep with different combinations of arms and legs. We reported the result as the net metabolic rate beyond resting. Each subject generated approximately 70W of power with a variety of 5 different power distributions between arms and legs for 6 minutes.[1] Net metabolic rate was determined from oxygen and carbon dioxide measurements (CareFusion, San Diego, USA), and averaged for the last 3 minutes of collection to estimate steady state energy consumption. Net metabolic rate was non-dimensionalized for each subject using their mass, gravity, and leg length. The net metabolic cost for 70W of mechanical power was reported, linearly scaled from the amount of power the person actually generated. We reported arm and leg power for each condition. We further tested linear and quadratic fits which related the contribution from the arms to total power output

[1] The experiments were meant to be performed at constant power, but after further calibration, the power and distribution results were updated to reflect the more accurate final calibration. Actual powers are reported.

to net metabolic rate to determine if different power distributions resulted in different net metabolic cost.

After we determined the metabolic cost of exercise using the NuStep, we began exploration of the altered exercises. The experimental factors were as follows:

Grip Type

We changed the grip type used with the stepper's handles and measured differences in the preferred power distribution among limbs. We expected that each grip type would change how they used their arms during the exercise. Grip type should not significantly alter the amount of mechanical power required to fulfill the task goal as it does not change the dynamics of the exercise. However, each kind of grip will change the subject's level of comfort during exercise. We supplied four conditions in which the subjects performed the exercise. The subjects used the handles to push and pull, push and pull while the handles were upside-down, only push, and only push with their fists. While the subjects generated approximately 90W of power for 90 seconds, we measured individual limb use and reported arm and leg power, and the mean Arm Power Ratio over seconds 40-85. We used repeated measures analysis of variance (repeated measures ANOVA) to determine if there were significant differences between conditions. Where significant differences were found, we performed a set of paired t-tests under the Holm-Sidak step-down procedure to test for significant differences between individual pairs of conditions.

Reach

The distance the subject must extend their arms to reach the machine may also alter the preferred power distribution between their arms and legs. We adjusted the machine's telescoping arms to the nominal length as well as two lengths shorter and two lengths longer than the nominal position set at the beginning of the experiments. We set the lengths as a proportion of the subject's arm length (10% and 20% - which typically produced a range of about 0.3m from shortest to longest condition). We measured limb use for 90 seconds during a task in which the subject was guided by visual feedback to generate approximately 90W of power. The task was repeated, in random order, and included two trials of each reach length condition. We reported arm and leg power under each condition, and each subject's mean Arm Power Ratio over seconds 40-85. Linear and quadratic fits related reach length to Arm Power Ratio.

Power Generation

Finally, we tested whether different methods of power generation (via differences in speed and resistance) would alter preferred work distributions between arms and legs. We altered the amount of required power with accompanying changes in required speed of stepping or by changing resistance to motion. A third method consisted of generating constant power, in which we simultaneously increased resistance and decreased speed or vice versa. We measured arm and leg power, as well as the change in the mean Arm Power Ratio from the overall average Arm Power Ratio for each subject among all their trials for each task.[2] We created linear fits relating the three variables of speed, resistance, and power generation.

[2] Speed and power performance could not always be made constant under all conditions. Therefore, to isolate the change in arm contributions under mixed variable conditions, we performed post-processing to subtract the effect of the difference in speed or power from their nominal values. The population's fit for the constant resistance trend was used to calculate the adjustment in Arm Power Ratio reported in the constant speed and power trends.

For all statistical tests, the threshold for significance was set at $\alpha = 0.05$.

Results

Preferences for power distribution changed depending on a variety of factors. Metabolic rate during exercise was found to be similar across different levels of contribution from the arms, and yet subjects preferred to use their limbs in only a small range of arm contributions. Furthermore, our data ($N = 6$) suggest that limb power distribution was significantly affected by all of the experimental factors. Changes in grip type shifted up to 17.9% of the net work toward the legs. Changes in the reach length could steer 12.6% of the net work away from the arms when the machine arms set further away from the subject or close to the subject. Finally, power generation at different speeds or at different resistances shifted limb use away from the nominal distribution of limb work by up to 19.2% or 11.8% of the net work, respectively.

The net metabolic rate during exercise generally may be dependent on the distribution of effort among limbs. However, in our recumbent stepping exercise, we found no significant change in net metabolic rate across the tested distributions. Subjects used their arms to produce between 24% and 91% of 67.8 ± 10.6W of power during exercise (Figure 1.3). After normalization, all combinations of arms and legs had a similar metabolic rate (Quadratic fit, $p = 0.63$, 95% confidence interval (CI) for quadratic term including zero (-1.07e-5/2.39e-5), indicating we could not identify a minimum/maximum. Linear fit, $p = 0.56$, demonstrating no minimum of net metabolic rate using either all arms or all legs). However, when we examined data from trials with no constraint on effort

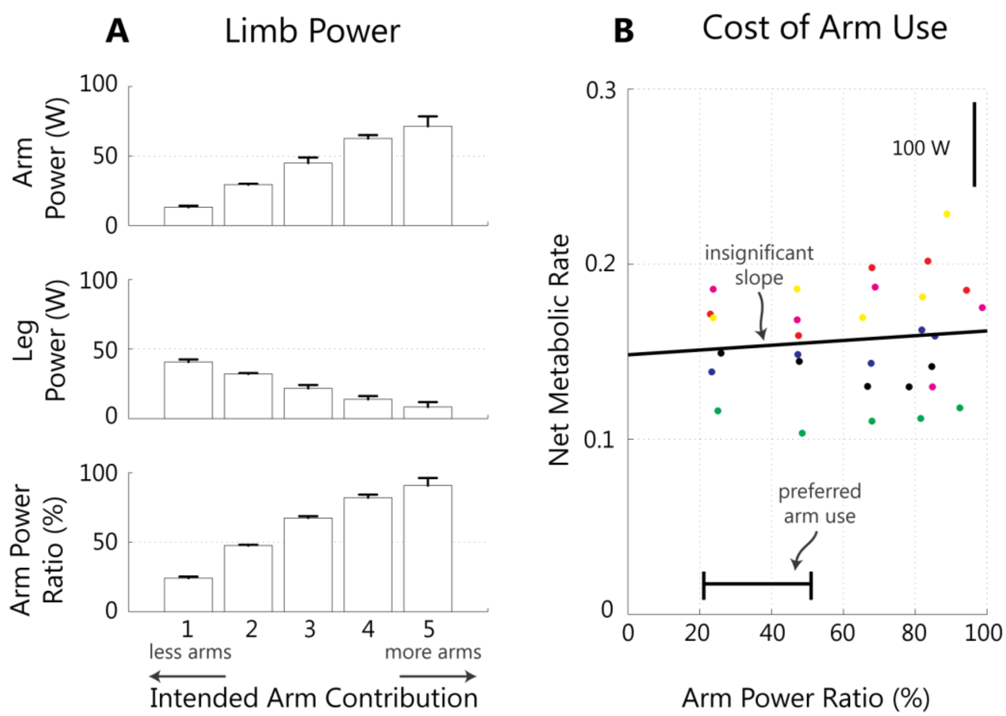

Figure 1.3: Limb Use and its Effect on Metabolic Rate

A: Limb power from arms and legs as a function of the intended arm contribution. **B:** Net metabolic work rate (beyond resting rate), normalized to 70W of mechanical power generation and non-dimensionalized with subject mass, leg length, and gravity. We found no trend in metabolic economy with respect to limb power distribution, implying that all combinations of arms and legs are equally metabolically costly for this exercise. However, subjects have a preferred arms contribution (preferred arm use during normal exercise indicated as standard deviation range).

distribution at similar power levels, we found that subjects prefer to exercise on the stepper using a mean arm contribution of 36.3% of net power and only vary with a standard deviation of 15.0%. Preferred distributions do not seem to be uniformly distributed, as we could have expected from equal net metabolic rate across all distributions of effort.

Grip Type

Grip type affected how subjects preferred to use their arms in exercise. When subjects changed their grip type, they displayed significant differences in the amount of power generated by the arms (repeated measures ANOVA, p = 1.8e-4) (Figure 1.4). Subjects generated 88.0 ± 6.2W of power across conditions.

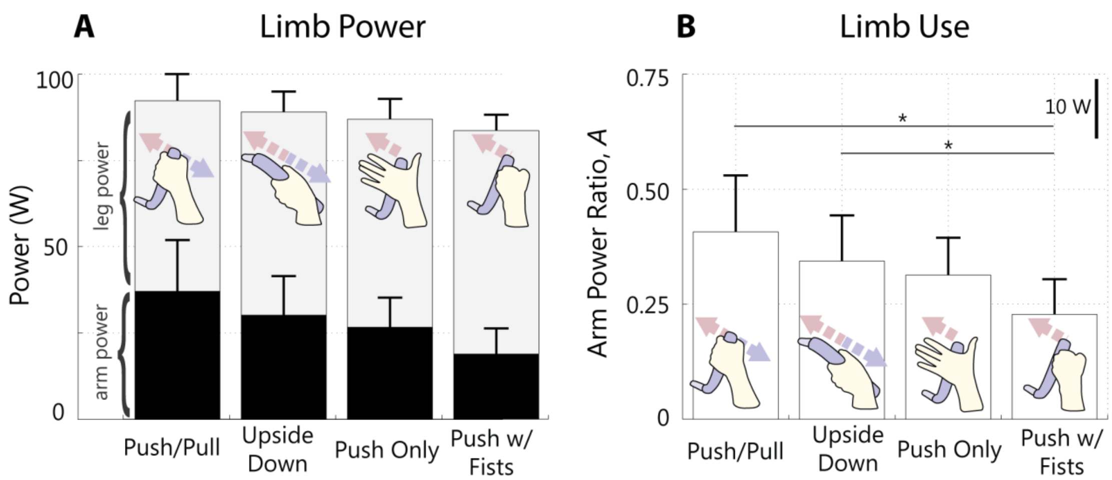

Figure 1.4: The Effect of Grip Type on Power Contributions

A: Arm and leg power for each of four grip types. **B:** The ratio of arm power to net power is reported for each configuration. Significant differences between grip types were found (* denotes significant differences between conditions, $p < 0.05$).

However, when subjects pushed on the machine's grips with fists, they produced significantly less arm power than when they were allowed to push and pull, either with the handles right side up or upside down. In trials in which subjects only pushed on the handles with their fists, we observed 15.8 ± 13.9W (Δ Arm Power Ratio, ΔA = 0.18 ± 0.16) less power with arms than in the nominal case (pushing and pulling with the handles right side up) (p = 0.0024). Subjects also performed 10.2 ± 8.7W (ΔA = 0.12 ± 0.10) less arms power pushing with fists than when the handles were upside down (p = 0.0019).

Reach

The distance between the subject and the machine arms affected their preferred power distribution. Subjects produced 91.0 ± 7.4W across conditions, but used their arms less with both a shorter and longer reach to the handles than in the nominal case (Figure 1.5). We modeled the overall relationship between reach length and Arm Power Ratio. The modeled trend consisted of a quadratic fit to the complete set of data (F-statistic of quadratic fit's p-value = 2.3e-4). The linear

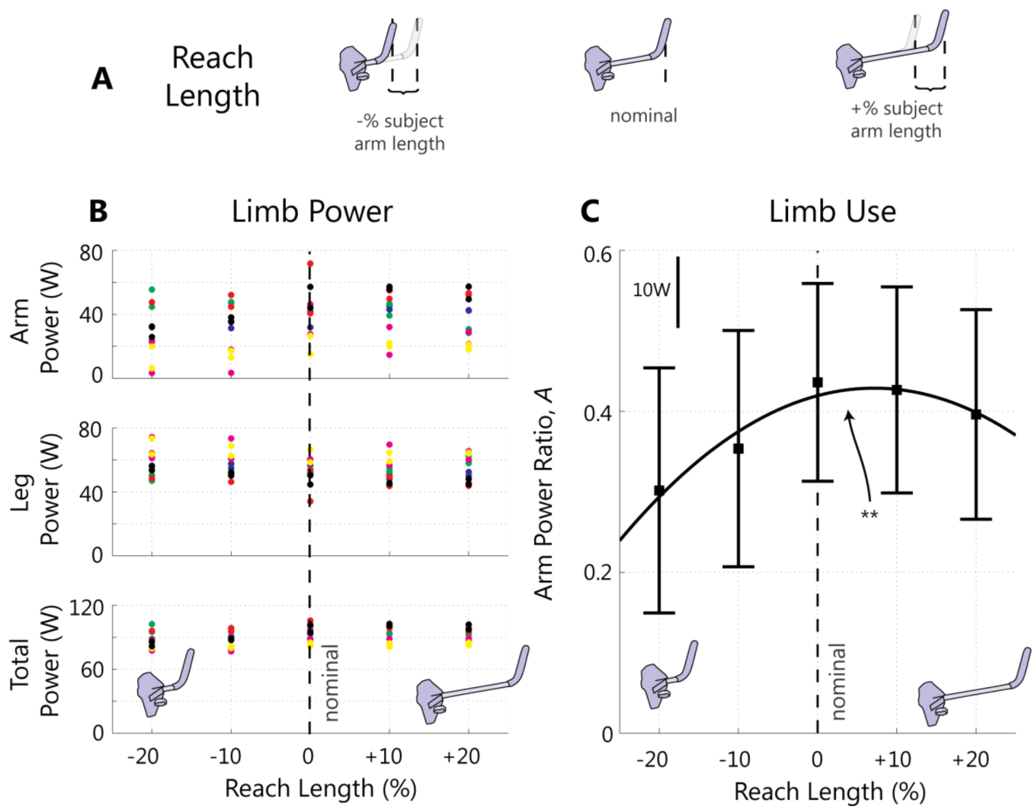

Figure 1.5: The Effect of Reach Length on Power Distribution

A: The machine's telescoping arms were lengthened and shortened from their nominal position. Reach length is defined by the difference from nominal, calculated via a percentage of the subject's arm length. **B:** For each reach length, arm, leg and total power is plotted. Each subject's data is indicated with a unique color. **C:** Finally, mean Arm Power Ratios for each reach length is plotted, along with the standard deviation. Arm use is reduced relative to the nominal length as the machine arms gets shorter or longer (** denotes p = 2.3e-4 for the F-statistic on the quadratic fit, indicating confidence that the fit has a maximum).

and quadratic terms have 95% confidence intervals excluding zero, indicating confidence that the fit has a maximum. Subjects reduced their arm power by 13.1W ± 13.7W (ΔA = 0.13 ± 0.13) when the machine arms were fully shorted relative to the nominal condition. Similarly, subjects reduced their arm power by 4.0W ± 10.9W (ΔA = 0.04 ± 0.09) when the machine arm length was fully lengthened.

Power Generation

Speed of stepping and resistance to motion during exercise influenced how

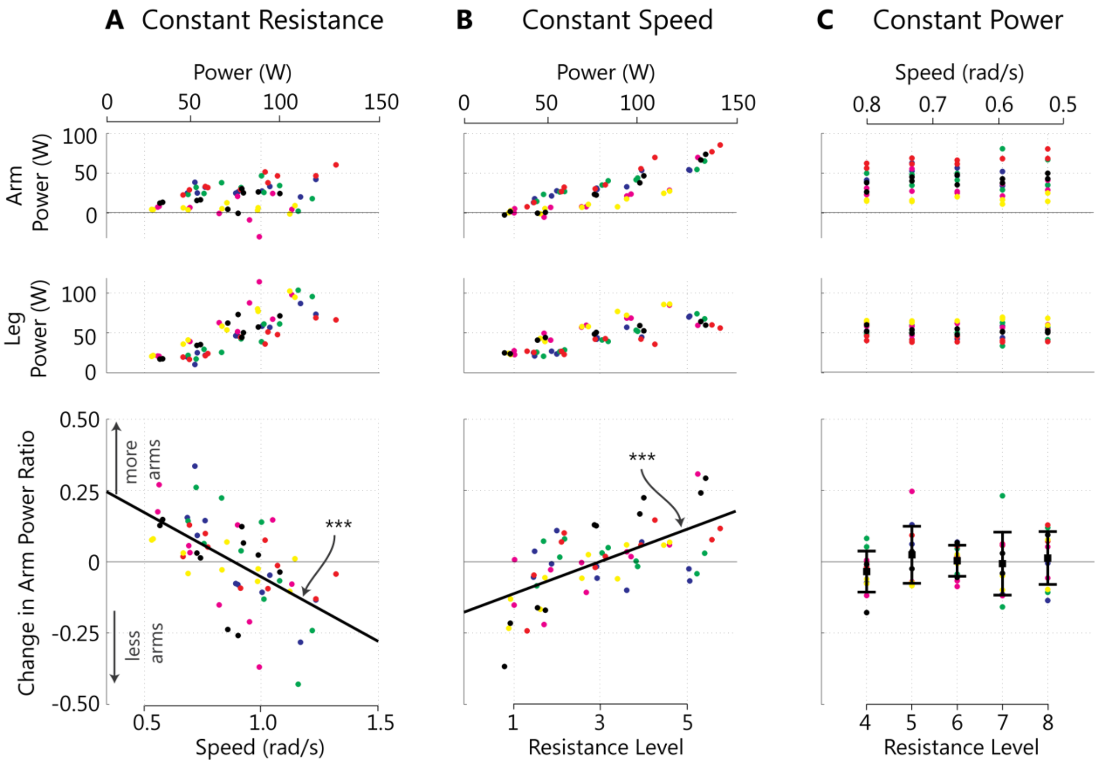

Figure 1.6**:** The Effect of Power Generation Method on Power Contributions

Arm and leg power, reported as a function of power generation method. In addition, we reported the change in the Arm Power Ratio as functions of speed, resistance and power level relative to the overall mean Arm Power Ratio for each method of power generation. The graphs show the isolated effects of each alternative. **A:** Arm and leg power as well as change in Arm Power Ratio as a function of speed. If subjects increase power generation by increasing speed, they direct more of the overall effort towards the legs at higher power outputs. **B:** Arm and leg power as well as change in Arm Power Ratio as a function of resistance level. If subjects maintain the same speed but produce more power by steeping against an increased internal resistance of the machine, they tend to increase the use of their arms as a percentage of the net work. **C:** Arm and leg power as well as change in Arm Power Ratio when resistance and speed are changed inversely to one another. If resistance is increased while speed is decreased to maintain constant power generation, there is no change in effort distribution as resistance increases. (***p < 0.0001)

subjects distributed effort among limbs. We found that subjects significantly increased arm use when they stepped more slowly against a constant resistive load, or when they generated more power by stepping against a high resistance level (Figure 1.6, A, B). However, when speed and resistance were varied inversely to one another, preserving constant power, subjects did not change their distribution of power (Figure 1.6, C).

Speed of stepping influenced preferred arms use. When internal resistance was fixed, increased power generation was achieved via increased stepping speed. In these conditions, subjects used their arms less when more power was required and used their arms more when less power was required (p = 6.1e-7). The trend indicated that at slow speeds, when subjects produced 25W of power, they would use their arms to generate 17.6% more net power than on average. At fast speeds, around 125W, subjects would use their arms to generate 19.2% less of the net power than average.

Differences in resistance to motion also altered each subject's preferred power distribution. When speed of stepping was constant, increased power was produced by stepping against a higher internal resistance of the machine. At higher resistances (higher power at constant speed), subjects tended to use their arms more, and at lower resistances (lower power), subjects used their arms less (p = 8.0e-8). The linear trend indicated that at low resistance (at 25W) subjects would use their arms to generate 11.8% less net power than their average contribution, while at high resistance (at 125W) subjects would use their arms to generate 11.8% more of the net power than average.

We found it interesting that when the amount of power was held constant, such that speed and resistance varied inversely to one another, no differences in the Arms Power Ratio were found (p = 0.43).

In terms of absolute work, power generation method influenced preferred limb use. When resistance was held constant, the amount of work performed by the arms generally increased as total power increased (p = 0.030). However, leg power increased to an even greater degree (p < 0.0001), such that the percentage of work done by the arms significantly decreased (as reported above). When speed was held constant, we noticed a similar finding. Both arm and leg power increased as total power generation increased (both $p < 0.0001$). However, arm power increased to a greater degree than that of legs, enough that, as a percentage, arms power significantly increased as a function of power generation (as reported above).

Discussion

We have shown there are numerous effective ways to redistribute effort between arms and legs. Furthermore, different proportions of effort between the arms and legs can be encouraged without modification of the exercise device.

We believe that subjects may allocate effort between limbs based on a desire to minimize an overall subjective cost associated with the task. Subjective cost includes a tendency to avoid expending more work or energy than is necessary to complete the task. However, there is the understanding that an individual's assessment of such costs is subjective, and that a variety of other costs such as comfort or goal-setting may also be important.

We may intuit some information about the subjective cost function. Consider a hypothetical subjective cost function that generally increases with the power from the arms and legs (Figure 1.7 A). We presume that there exist multiple combinations of arm and leg power that a person perceives as equally preferred. Because there may be factors other than mechanical power that contribute to a person's preference, these combinations might not be equal in mechanical power. For example, one may find it equally preferable to perform 25W of

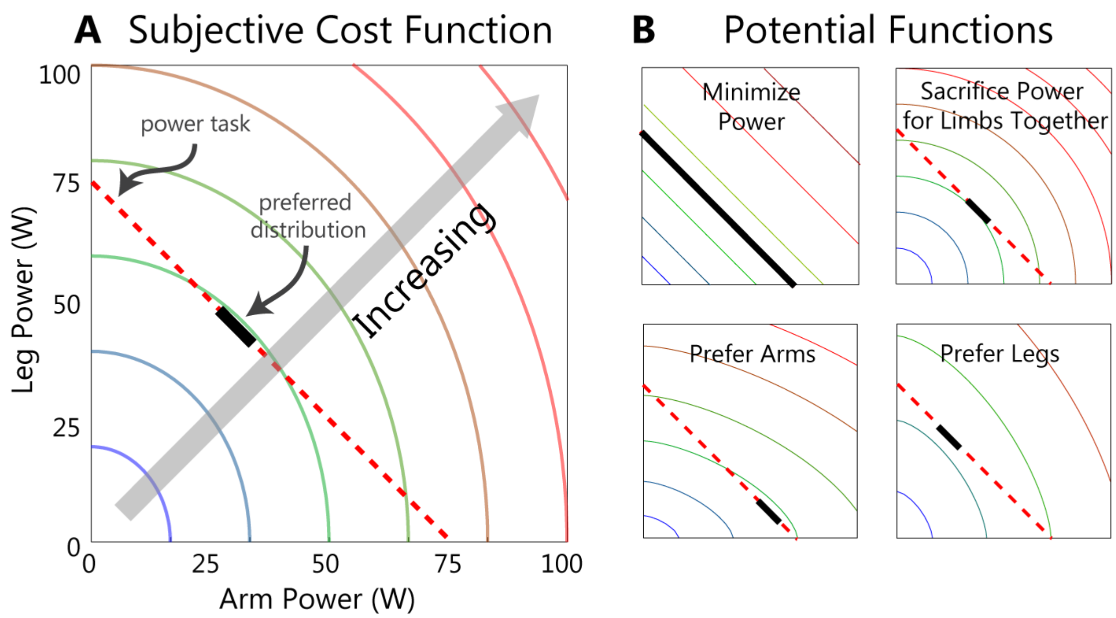

Figure 1.7: Potential Subjective Cost Functions

A: Hypothetical subjective indifference curves, as a function of power from the legs and arms. A power task may be viewed as a constraint line that may be achieved with some combination of arms and legs (denoted by dashed red line). Subjects are expected to prefer a limb combination (denoted by dark line segment) where the indifference curve is tangential to the task constraint, equivalent to minimizing their subjective cost. **B:** A number of potential Subjective Cost Functions for a given subject and condition. Each function yields a different preferred solution to the 75W power task. We may infer that changes to the exercise task may alter each subject's subjective cost associated with that task and individual. Completing the task will thereby lead to a difference in their chosen power distribution.

exercise with only the arms as it is to perform 30W with only the legs. We treat these as tasks of equal subjective cost (individual contours, termed Indifference Curves, in Figure 1.7 A). In terms of limb power, the subject's preferred task strategy may be interpreted as a constrained optimization problem. The preferred strategy is determined by the intersection of the task constraint (such as generating 75W of power) with the contour line of minimum subjective cost.

We hypothesize that people will prefer to perform different tasks with different proportions of limb power. Different kinds of tasks may alter the subjective effort associated with different combinations of limb power. Therefore, a unique Subjective Cost Function would exist for each pair of subject and task. For example, if subjects only chose to minimize their mechanical power output to satisfy the task, there would be no preference for power distribution between limbs and all combinations that satisfied the power task could be chosen arbitrarily (Figure 1.7 B, upper left). However, subjects could prefer to use limbs in combination because it felt more natural, or they could hope that by using their limbs in combination they could prevent fatigue. In this case, subjects may exhibit indifference curves which are associated with a larger amount of power if both limb groups are used in combination than when limb groups are used alone (Figure 1.7 B, upper right). Another possibility is that they could prefer the use of arms to generate power to a greater extent than the use of their legs. We found subjects had a bias toward the use of arms when greater power generation was required at constant speed. This would again skew the subjective cost indifference curves, and the resultant preferred distribution (Figure 1.7 B, lower left). Finally, the subjects may prefer to use their legs more than arms under certain conditions. We found this to be true when subjects gripped the machine with in uncomfortable ways, were required to reach very far or short distances, or had to generate more power at constant resistance. The bias toward leg use would again appear in the subject's Subjective Cost Function (Figure 1.7 B, lower right).

There also may be psychological reasons to split effort uneconomically. Probability matching is a generalizable suboptimal strategy in which choices are made in proportion to the choices' probability of success. If people wanted to maximize the expected value of their choices over time, they instead would learn to choose only the highest probability option [25], [26]. Similarly, in some exercises (e.g. arms and legs cycling ergometry), one might gain the greatest economic benefit by relying only on the more economical limb group to provide all the work [27]. It might even be expected that people would forgo the uneconomical group of limbs completely if they truly were to optimize for economy. In contrast to this expectation, limbs are often observed to be used in combination. The difference may be partially explained by the psychological factors that lead to such phenomena as probability matching. Perhaps if limb groups generate power in some proportion to their capacity, they may hold in reserve some energy for unknown future changes in power requirements or prevent fatigue over a long period of exercise. Quantification of effort distribution preferences may allow us to learn more about psychological motivations of behavior.

Another possible explanation for why people sometimes choose to distribute effort uneconomically involves the physiological capacity for the limbs to do mechanical work. If a single limb group was unable to provide the task's required power, the subject would be required to rely on the recruitment of additional muscle groups. It would not matter if they would enjoy a metabolic benefit when using only one group. Near maximal tasks could therefore necessitate an uneconomical division of power among limbs. Furthermore, it is possible that people do not suddenly change their behavior when maximal tasks are presented. Rather, they may scale their power output among limbs in some way according to the ultimate capacities of those limbs or the feeling of effort associated with limb work. In accordance with other research, we believe that the perception of effort scales with capacity for work from each limb group [28]–[30]. The impression of difficulty may play an important role in the division of effort among limbs.

As we consider applications to rehabilitation, we may not expect the factors studied here to affect patient populations in the same way or to the same degree as healthy subjects. We designed our exercise to avoid maximal capacity limits of the individual limbs, so we believe work capacity does not play a role in determining effort distributions in our experiment. However, for stroke patients, who often exhibit discrepancies between their left and right limbs, an inherent bias toward use of one side of their body or the other might be apparent. Similarly, spinal cord injury patients may have extreme weakness of their legs. Therefore, issues of capacity may begin to play a role.

Our results suggest that therapists could manipulate a patient's effort distribution through simple changes in exercise. Patient and therapist attention is valued at a premium during the rehabilitation of weakened limbs. Here we showed that there are many options available on common exercise machines to enable the shift of power output from one limb group to another spontaneously, without the need for explicit instruction. Such changes may outweigh the desire to act only in accordance to the maximization of economy of motion. Furthermore, implicit methods may help promote specific limb use without the need for explicit feedback and help alleviate the attentional burdens that exist for the therapist and patient.

Supplementary Material

Considerable research has explored the many factors that affect our metabolic costs, perception of effort, and mechanical work output. Many of these factors are seen to directly influence the preferred mechanical work distributions in multi-muscle activities.

The factors may explain some of the differences between demonstrated behavior and a simpler explanation, such as the behavior which would results from the

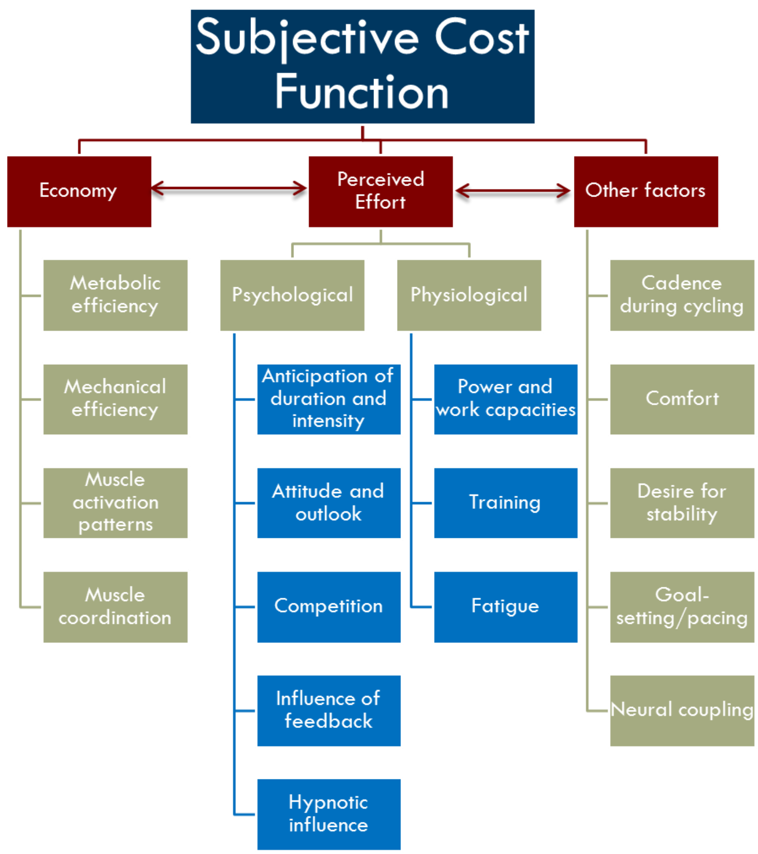

Figure 1.8: Subjective Cost Function

We propose that people make decisions for action based upon the minimization of a subjective cost function. In addition to economy, factors such as those associated with perceived exertion, and even more subjective factors such as mental state or goal setting can alter chosen behavior. Here is one possible categorization of some of these factors, which all are reflected in each person's Subjective Cost Function for a task.

maximization of economy. However, many factors interact and are not independent of one another. Therefore, economy often plays a role in our perception of effort, as well as comfort and fatigue, for example. Here we present some of the factors that have been studied.

<u>Factors which Affect Economy</u>:

Metabolic costs of limb use [27], [31]–[33], minimization of mechanical work used to explain walking and running [34]–[36], muscle activation [37], and muscle coordination [38]

<u>Factors which Affect Perceived Effort</u> (as developed by Borg [5]):

Anticipation of exercise duration and intensity [20], general attitude or outlook [39], competition [18], the influence of visual feedback [40], hypnotic perturbations of perceived effort [41], power and work capacities due to cardiac output [42], training [43], and fatigue [4], [22], [44]

<u>Other Factors which Affect Effort Distribution</u>:

Cycling at difference cadences [45], [46], comfort [11], desire for stability while walking [9], goal-setting/pacing [3], and neural coupling between limbs [47], [48]

Chapter 2.

A Reward System to Alter the Distribution of Effort in Multi-Limb Exercise

Abstract

It is unknown how an exercise can be constructed in which there exists an inherent motivation to use specific limb groups. Explicit feedback can be used to encourage specified limb use, but a person's natural tendency might be to use their limbs in a different distribution.

Here we demonstrate that implicitly weighting limb power contributions unevenly toward a scalar power task can affect healthy subjects' preferred effort distribution.

In an experimental study, limb group power was weighted unevenly, ranging between credit given only for arm power and credit given only for power from the legs. Under each condition we measured the amount of performed mechanical power from each of the subject's limbs. We found a consistent relationship between the amount of credit given to a limb group and that group's contribution towards the task. Its consistency allowed us to predict and alter their performed power distribution as a function of how much credit we gave to each limb group.

We believe that, in addition to healthy subjects, patients will also demonstrate a predictable relationship between the weighting of limb power and their performed power distribution. Such relationships could be used to steer motor rehabilitation patients toward exercising their weakened limbs to a predictable degree without the need for explicit instruction or guidance from the physical therapist.

Introduction

Rehabilitation is often employed to encourage exercise and strengthen weakened limbs. Persons with hemiparesis, partial paralysis from spinal cord injury, or other conditions may chronically prefer to use their unaffected limb, to the point that atrophy and learned disuse or nonuse occur [49]. One of the tasks of physical therapists and strength trainers is to discourage these tendencies, typically through resistance training performed on exercise machines. The therapist coaches the patient explicitly to encourage use of the patient's weakened limbs. Unfortunately, the therapist does not always have access to information about patient effort, and so proper coaching may be difficult. In addition, in some cases, physical interaction with the patient is required for the patient to complete the task, increasing the burden on the therapist, and adding to the cost and time involved with therapy.

One of the more successful ways to reduce reliance on the unaffected limb is the low-technology approach of constraint-induced therapy [50]. Restriction of the unaffected limb offers the patient little alternative but to practice with the affected limb. However, although highly effective, it may not be applicable for all patients. For example, some stroke patients with poor function may be unable to perform exercise without some assistance, which the unaffected side could provide. This is especially true for locomotor tasks, in which one leg cannot be substituted for both. The drawback is that, once the unaffected limbs are allowed to participate, they may again be favored to the exclusion of the affected limbs.

Some robotic interventions have been developed to lessen the assistance and feedback required from therapists. The Lokomat robot provides locomotor assistance by moving the patient's legs though a walking motion [51]. Similarly, the MIT Manus robot assists the patient's upper extremity through a reaching motion [52]. The remaining concern with such devices is that, with automated guidance or assistance, the patient may have little incentive to exert their own effort, which is the point of exercise [53][54]. Furthermore, robotic training often does not provide benefit beyond those which assure patient effort by the elimination of assistance, or training in which effort is required before robotic assistance is provided [55]. Perhaps outcomes could be improved if rehabilitation and exercise devices could be designed to encourage proper use of the affected limbs in addition to providing assistance.

Another manner of eliciting patient participation is by making the task self-driven [56]. However, there still remains the hurdle of giving a patient incentive to exercise a weakened limb, especially when only using stronger limbs may fulfill the exercise task.

Some recent technologies have been proposed to give greater feedback to the patients to enforce effort. Pedaling machines can provide explicit feedback about the contribution of each side of the body (Motomed, Germany). Walking assist robots can also provide the patient with explicit feedback regarding symmetry, limb motion, and effort [54]. Although these approaches are promising, a drawback of many feedback systems is the complexity of information presented to the patient [57][58][59]. Many patients may be cognitively taxed by a display of multiple graphs or other plots. Explicit feedback shows promise, but with the drawback of requiring attention.

The involvement of the affected limb might be encouraged without explicit feedback or as great of a cognitive burden if the task could be designed to take advantage of a patient's natural tendencies. The challenge is therefore to gain sufficient knowledge of a person's tendencies—their preference to use one group of limbs or another in combination—to permit their exploitation. In the present study, we attempt to quantify the tendencies of healthy adults performing a multi-limb, recumbent stepping exercise. We then test whether such quantification can predict the preferred contribution of a particular limb group when the task is implicitly biased to favor that group. Finally, we consider possible applications to rehabilitation.

We propose to reward the user with a variable weighting of limb group power contributions to create an implicit incentive for exercising designated limb groups. Humans often prefer behavior which is more economical, and therefore it may be possible to alter effort distributions toward a target if that target is made less effortful.

We will give more credit for work from some limbs than for the work from others during a work-based exercise task.

In essence, we suggest that a patient's bias in performance toward using one group of limbs over another stems from their chosen method feeling the easiest. There is already some evidence that effort can be directed by decreasing the magnitude of force necessary to complete an exercise task with the desired effort distribution [60]. Furthermore, humans may judge this force by means of their own subjective sense of effort, which scales with their force producing capabilities [61]. Therefore, there seems to be evidence that subjective impressions of biomechanical behavior influence the distribution of effort humans choose to accomplish a task. Here we manipulate one variable which influences ease, namely the power necessary to fulfill the task. Our aim is to use weighted tasks to quantify the subjects' sense of ease and then construct a task with proper feedback such that the easiest way to complete the task is with increased recruitment of their weakened limbs, or any other specific contribution goal.

Methods

We experimentally quantified how human subjects allocate power between limbs during multi-limb exercise, and how implicit uneven weighting of power from limb groups toward an exercise goal affects that allocation. Our subjects performed multi-limb exercise on a NuStep recumbent stepper machine (TRS 4000, NuStep, Inc., Ann Arbor, MI). While seated, the subject moves all four limbs against a single load (Figure 2.1 A). The NuStep is intended for self-driven rehabilitation exercises related to locomotion while allowing subjects to remain seated. We instrumented the machine to measure power from all four limbs, which could be weighted differently toward a weighted power target provided to the user via visual feedback. The power from either the legs vs. arms, or the left vs. right sides of the body, could thus be credited unevenly toward a task (Figure

2.1 C). The primary question was whether subjects would tend to alter the distribution of effort between limbs even if not explicitly informed about the weighting.

A separate experiment was conducted for each of two limb groupings. For the legs vs. arms study, 11 healthy adult subjects participated (6 male and 4 female, age 25.3 ± 7.1 years (mean ± standard deviation)). For the left vs. right side study, 10 healthy adult subjects participated (6 male and 3 female, age 21.9 ± 3.3 years). We recorded body mass (72 ± 13kg) for each subject, and all provided written informed consent according to University procedures. One subject in the legs vs. arms study was too weak to reach the weighted power target with their self-selected combination of arms and legs and so was excluded from further trials, and their data was deleted, leading to 10 data sets instead of 11. In addition, we experienced technical difficulties during one data collection in the left vs. right study and the subject could not return for another test, leading to 9 sets of data instead of 10.

The stepper machine was instrumented to measure mechanical power output from each limb (Figure 2.1 A). Customized load cells were installed in the handles (StrainSert, West Conshohocken, PA) and foot pedals (FlexiForce, South Boston, MA; Nintendo, Japan) to measure applied forces, and optical encoders were used to measure net motion. Subjects were instructed to maintain contact with the machine with all four limbs, even if they chose not to apply appreciable forces. Mechanical power for each limb was computed from the moment produced by the applied forces multiplied by the angular velocity. The summed power from all limbs was dissipated by the machine's internal resistance. The measurement of

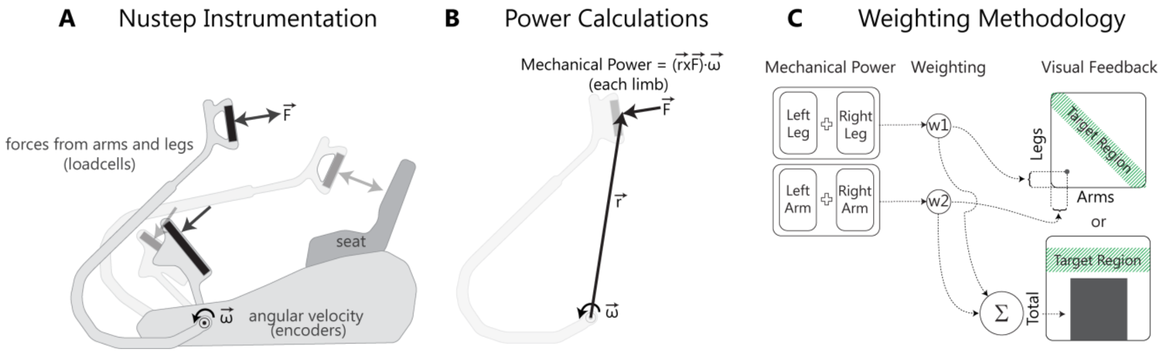

Figure 2.1: Experimental Setup

A: Force and angular velocity of the individual limbs are measured at each arm and leg. **B:** Limb power is calculated via the dot product of the moment exerted by each limb and the angular velocity. **C:** Limb group powers (legs and arms or left and right sides) are multiplied by a weighting factor and summed. The effect of the weighted sum is displayed to the subject as either individual limb group contributions relative to a target region (top), or their combined contribution towards a scalar target level of their summed weighted power (bottom). In either case, a moving average of the subject's current contribution is shown relative to their target region.

power from individual limbs is key to experimental testing of the conceptual approach, detailed as follows.

Conceptual Approach

We propose that users allocate effort between limbs based on the desire to minimize a subjective cost associated with the task. Subjective cost can be modeled as an objective function, as is typical of the optimization approach to motor control [62], [63]. A limitation of this approach is that there is usually incomplete knowledge regarding an individual's actual objective for a motor task, despite an experimenter's intended objective. In the context of neuromotor rehabilitation, we hypothesize that subjective cost includes a tendency to avoid expending more work or energy than is necessary to complete the task, but with the understanding that an individual's assessment of such costs is subjective, and that a variety of other costs may also be important. These may include cognitive load, physiological capacity for power generation, and even highly subjective factors such as comfort, habit, or goal-setting. Because the present task has explicit goals in terms of mechanical power, we will characterize subjective cost as a function of the power from the limb groups in question.

We wish to determine the characteristics of our subjects' subjective functions. Consider a hypothetical subjective cost function that generally increases with the power from the arms and legs (Figure 2.2 A). We presume that there exist multiple combinations of arm and leg power that a person perceives as equally preferred. Because there may be factors other than mechanical power that contribute to a person's preference, these combinations might not be equal in mechanical power. For example, one may find it equally preferable to perform 25W of exercise with the arms alone as to perform 30W with the legs alone. We treat these as tasks of equal subjective cost (individual contours in Figure 2.2 A). The nature of the subjective cost function may be revealed, in part, through observations of the limb combinations a subject prefers as a function of task conditions. Unequal task weightings may be applied to the limbs, so that the limbs contribute differently toward a goal amount of weighted power which is presented to the use via visual feedback. We called the weighted sum of power the subject's Performance, which is calculated as follows:

$$\text{Performance, } P = (2 - |\lambda|)\left((1-\lambda)P_{legs/left} + (1+\lambda)P_{arms/right}\right)$$

(Equation 2.1)

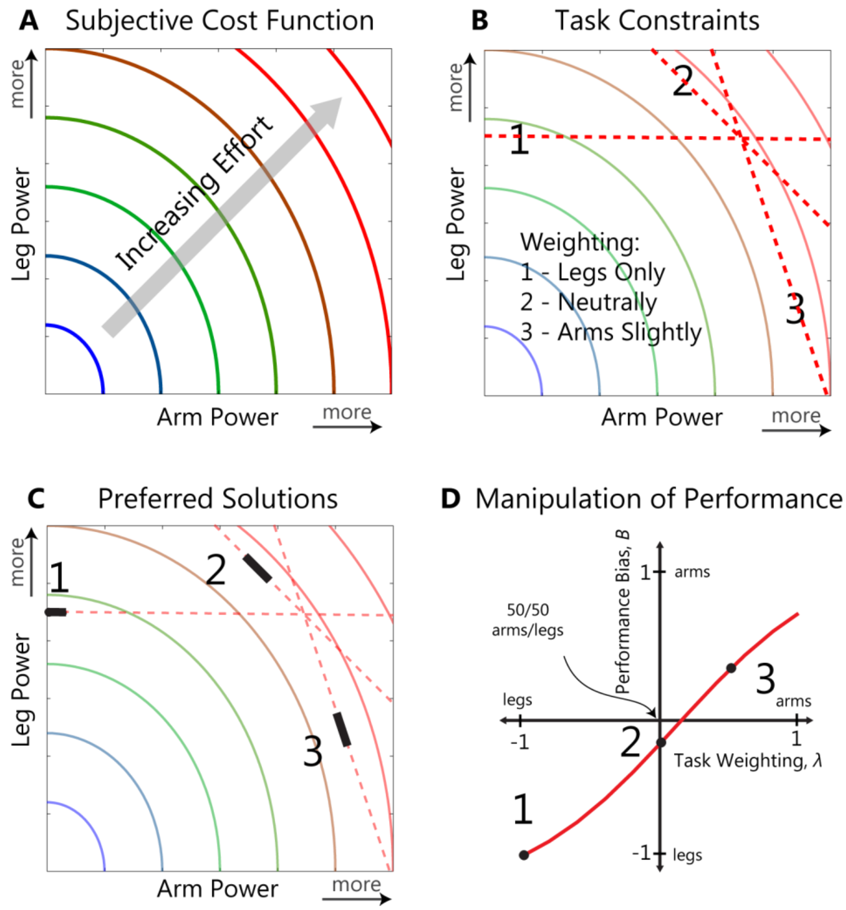

Figure 2.2: Relationship between Subjective Cost and Manipulation of Performance

A: Hypothetical subjective indifference curves, as a function of power from the legs and arms. **B:** A weighted task may be viewed as a constraint line that may be achieved with many combinations of arm and leg power. Three possible tasks are shown, weighting the legs only, legs and arms equally, and arms slightly toward a scalar amount of Performance. **C:** Subjects are expected to prefer a limb combination (denoted by dark line segments) for each task where the indifference curve is tangential to the task constraint, equivalent to minimizing their subjective cost associated with the task. **D:** Preferences are expressed in terms of the subject's limb use at each preferred distribution for each Task Weighting (x-axis). Limb use is reported as a Performance Bias, *B*, which represents the amount of power coming from each limb group, varying from using the legs to generate 100% of the net power (*B* = -1), to using the arms to generate 100% of the net power (*B* = 1).

where *P* is the total weighted power, and λ is a Task Weighting to give limbs unequal contributions toward a goal amount of *P*. A value of λ = -1 corresponds to weighting the legs (or left side) alone, λ = 1 to the arms (right side) alone, and λ = 0 to equal weighting, such that *P* is the same as actual total mechanical power. Each value for λ is thus a task that a user would be expected to perform with a different combination of limbs. A task constraint is set to match a target amount of Performance (Figure 2.2 B). Different combinations of limb powers will satisfy the constraint, but these are limited by Equation 2.1. For practical reasons, we chose to express the target visually as a zone within 15% of the goal level:

$$\text{Target Region, } P_{Vis} = P_{Goal} \pm 15\% \qquad \text{(Equation 2.2)}$$

In terms of limb power, the subject's preferred task strategy may be interpreted as a constrained optimization problem. The preferred strategy is determined by the intersection of the task constraint with the contour line of minimum subjective cost (Figure 2.2 C). The unknown subjective cost function may thus be characterized by sampling the preferred strategies for a range of task weightings λ. In addition, the preferred strategy itself may be summarized by a Performance Bias parameter, *B*, which expresses the amount of leg/arm, or left/right side, power relative to net power. It is computed from the user's actual power contributions according to:

$$\text{Performance Bias, } B = 2\left(\frac{P_{arm/right}}{P_{arm/right} + P_{leg/left}}\right) - 1 \qquad \text{(Equation 2.3)}$$

Here, a *B* value of -1 corresponds to using the legs or left side to generate 100% of the net power, and 1 corresponds to the arms or right side generating 100% of the net power. We show the relationship between the Performance Bias and the Task Weighting as the Manipulation of Performance Function (Figure 2.2 D).

We hypothesize that people will prefer to perform different tasks with different proportions of limb power, dependent on the task weighting. Even if a biased weighting is not indicated explicitly, a tendency to seek lower subjective cost is expected to cause a change in Performance Bias, away from their neutrally weighted Performance Bias. A subject's decision on how to distribute effort for different tasks is reflected in the shape of the Subjective Cost Function's contours, or indifference curves (Figure 2.2, power combinations along a contour are equally preferable). The shape of the indifference curves can be used to demonstrate a trade-off between multiple variables that all have an effect on choice or preference. Applications of indifference curves, though predominantly used in economics, have started to be used to describe behavioral decision-making [8].

Experimental Protocol

Each experiment consisted of a Familiarization period followed by an Experimental period. Familiarization was intended to allow subjects to gain an understanding of the task and explore a range of different limb combinations that would satisfy the task constraint. In the subsequent Experimental period, we randomly assigned Task Weightings, λ, unknown to the subject, and measured their preferred Performance Bias, *B*.

During Familiarization, we presented subjects with explicit visual feedback of the instantaneous weighted power from each limb pair (Figure 2.3 A). This was displayed as a dot cursor (smoothed with a moving average) plotted on a two-dimensional field with the leg and arm (or left and right) power as the two axes. We displayed a target zone for the cursor and asked the subjects to explore different combinations of limb power to locate their cursor in different areas of the target region. This allowed the subject to experience a nearly full range of

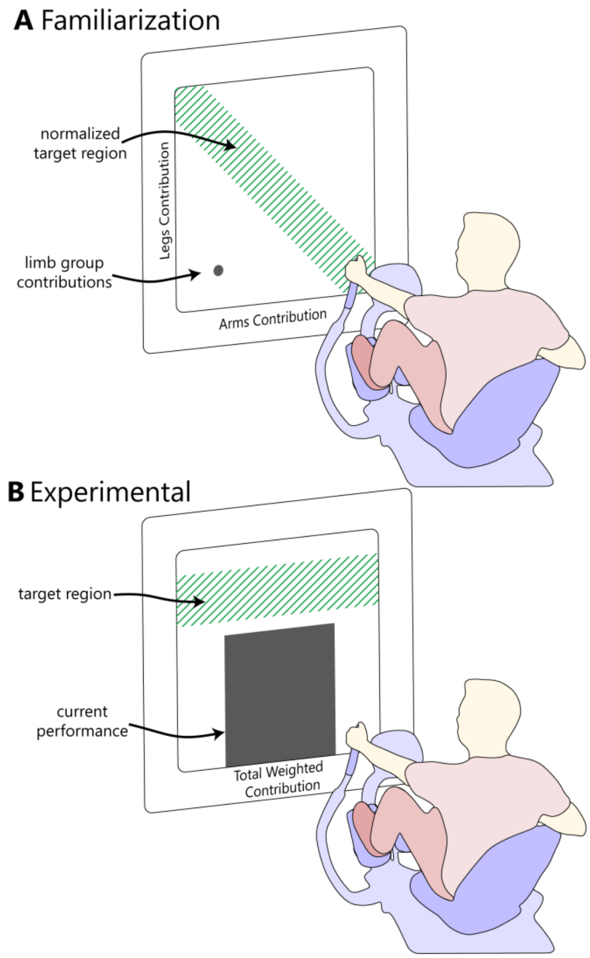

Figure 2.3: Explicit and Implicit Feedback

A: Familiarization (Explicit): Different task constraints favoring one group of limbs or another are normalized and explored. Weighted arm power is displayed as the x-coordinate of the moving dot cursor, and weighted leg power is displayed as the y-coordinate. The task constraint is normalized to be viewed as a diagonal region in all conditions. **B:** Experimental (Implicit): Weighted limb contributions are summed to create a single-goal task to assess each subject's choice for limb power distribution for each condition.

power distributions and experience how the multi-limb task goal could be accomplished using different appropriate combinations of limb power.

Next, the Experimental portion determined each subject's preferred distribution of effort during implicitly weighted tasks. A moving average of their Performance, P (Equation 2.1), was displayed in real time on a bar graph meter, along with a visual target, P_{Vis}, which indicated the level of Performance to be achieved (Figure

2.3 B). The Task Weighting was varied with each condition, and subjects were asked to achieve the target level without knowledge of the weighting. We measured Performance Bias for each task (Equation 2.3). For example, one task might weigh the legs alone (λ = -1) toward subject Performance, and the subject might respond by biasing their effort toward the legs (Performance Bias, B = -1) or by using arms and legs equally (B = 0).

The Experimental sessions consisted of a period of Exploration and Assessment (Figure 2.4). In Exploration, subjects were encouraged to explore different combinations of limbs on their own, though now without knowledge of the weighting or explicit information about the weighted sum of their limb power. When they were confident about the limb combination they most preferred to satisfy the task, they signaled to the experimenter and Assessment began. In Assessment, the subject honed their preferred limb distribution under each condition as data was recorded. The experiment consisted of two sets of 11 trials with Task Weightings, λ, distributed in the range -1 to +1, conducted in random order, again unknown to subjects. We collected data during Assessment over a brief period of at least 15 - 30 seconds. Subjects typically reached a steady state distribution of effort within this time frame. Each trial was followed by a brief rest, with a longer rest between sets.

The effort levels were determined as follows: For male subjects, the target level was equivalent to 100W of mechanical power for equally weighted trials ($\lambda = 0$). Female subjects were given a target 40% lower to account for typical strength differences between genders. Subjects were generally able to conduct repeated trials at these target levels, except for one subject who, as previously noted,

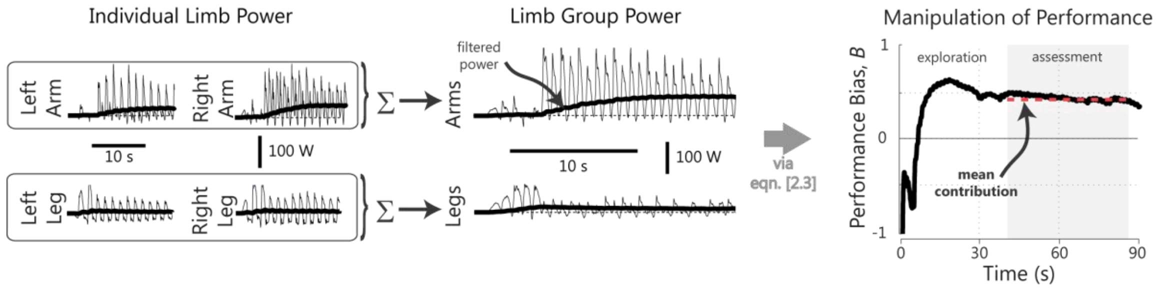

Figure 2.4: Combination of Limb Power to Yield Performance Bias

Each individual limb power is combined into arm and leg grouped power. Next, the overall power distribution is calculated via the ratio of arm power to net power scaled to range from -1 to 1 (Equation 2.3). Power is low-pass filtered to smooth cyclical data due to stepping during the exercise.

became fatigued early in the experiment, and whose participation was terminated and whose data were excluded from the analysis.

Data Analysis

We characterized Performance Bias, *B*, across Task Weightings, λ, as a logistic function of according to:

$$\text{Manipulation of Performance, } B(\lambda) = B_1 + \frac{B_2 - B_1}{1 + e^{-\sigma(\lambda - \Lambda^*)}} \qquad \text{(Equation 2.4)}$$

This curve has asymptotes at the two extremes of limb use preference, and changes monotonically between the extremes (Figure 2.2 D). The parameter Λ^* describes the weighting at which there is the greatest change in $B(\lambda)$. It reflects a horizontal shift in the curve, and indicates a non-neutral Performance Bias at a neutral Task Weighting. Values greater than 0 indicate an inherent preference for legs or the left side, and values less than 0 indicate that, under a neutral Task Weighting, subjects will generate more power with their arms or right side. The parameters B_1 and B_2 are the lower and upper asymptotes, respectively. They represent the limits to which subjects are willing to generate more of the net power with a single limb group. Finally, the parameter σ characterizes the sharpness of the curve, where larger values tend toward the creation of a step function. A sharper curve indicates a more sudden transition from use of one pair of the limbs to the other as a function of Task Weighting.

We reported the limb power performed for each condition and fit the parameters for the Manipulation of Performance function for the population and individuals. Statistical comparisons were made between the fit parameters and meaningful values using their confidence intervals (for the population) or a one-sample Student's t-test (for individuals). The legs/left asymptote, B_1, was compared to -1, which would indicate that the legs or left side performed 100% of the net power. The arms/right asymptote, B_2, was compared to +1, which would indicate that the arms or right side performed 100% of the net power. The parameter Λ^* was compared to 0, which would indicate an equal division of power between limb groups at a neutral Task Weighting. For t-tests, the significance threshold was set at $\alpha = 0.05$.

We also estimated the Subjective Cost Function for the studied population numerically from the Manipulation of Performance fits. We derived contour shapes according to performed power and individual limb contributions at each Task Weighting. Each Task Weighting equates to a task constraint with a specified slope for the Subjective Cost Function. We also know from optimization that the Subjective Cost Function will have an identical slope when minimized at the solution. The Performance Bias equates to a specific point on that constraint. By smoothly sampling the Performance Bias at each Task Weighting, we can derive slopes of the Subjective Cost Function to create an entire contour at a designated amount of weighted power, or on a unique indifference curve. The goal amount of Performance can be scaled higher or lower to estimate neighboring indifference curves.

The derivation of the Subjective Cost function from the Manipulation of Performance function enforces equivalences between the shape parameters of the two functions (Figure 2.5). The shape of the contour is the same at each indifference curve because we have not characterized the parameters of the Manipulation of Performance Function independently for different Performance levels.

Finally, a validation of the Manipulation of Performance Function fit was made for each individual subject. We fit a Manipulation to Performance trend to a subset of each subject's data. The data were chosen such that the data would span the range of the Task Weighting, and consist of 75% of the trials. We reserved 25% as validation data to test the predictive power of the individual fits. We reported each curve fit result with median R^2 values and ranges—one for the fit data, and another for the same curve fit's prediction of the validation data.

Results

We found that Task Weightings had a systematic effect on each subject's limb use during exercise. Tasks weighted toward a particular limb pair generally resulted in greater use of those limbs (Figure 2.6).

All Subjects

To summarize the overall subject pool, a single Manipulation of Performance Function was fit to all of the subject data for each study (parameter values in

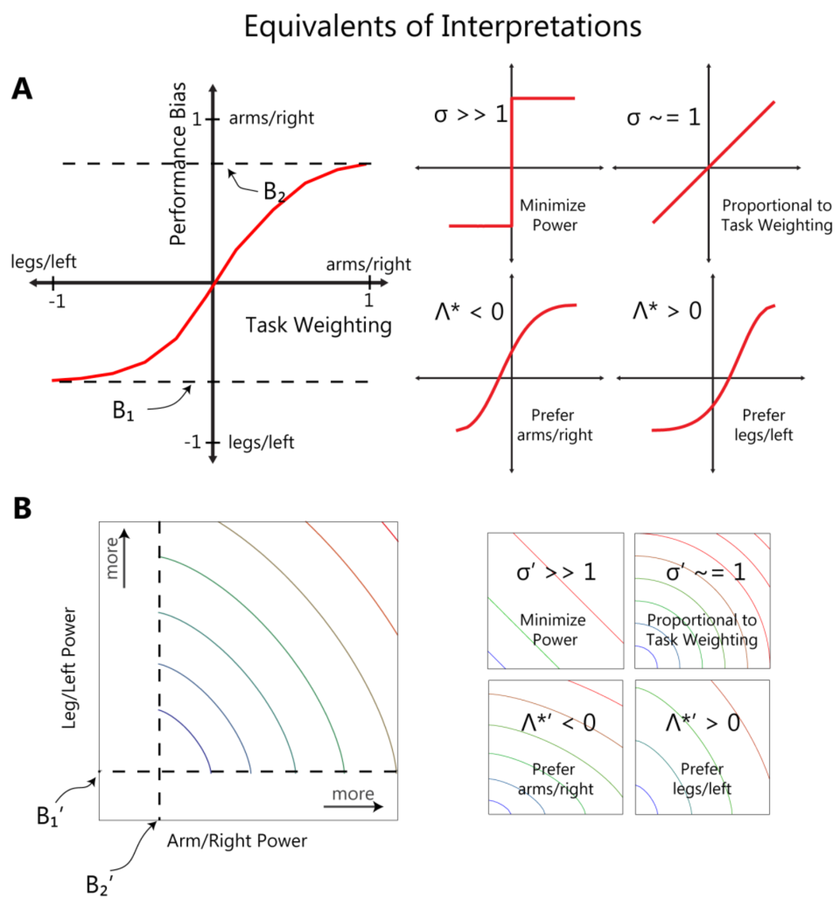

Figure 2.5: Equivalents of Interpretations

We may estimate the shape of the Subjective Cost Function's contours numerically from knowledge of the logistic trade-off between Task Weighting and Performance Bias. **A:** Manipulation of Performance Function – Each of the parameters in Equation 2.4 relate to a graphical and physiological interpretation of the curve. Here, each parameter is shown with its associated influence on the logistic curve's shape. **B:** Subjective Cost Function – The logistic curve includes information about limb group power and Task Weighting which will uniquely define the shape of the Subjective Cost Function's contours. Here we show the effect that each of the parameters in Equation 2.4 (indicated with primes) have on the shape of the contours, thereby drawing equivalence between the two interpretations of the data.

Table 2.1). The overall fit of Performance Bias vs. Task Weighting confirms the consistency and repeatability of inter-subject performance (R^2 = 0.80 for legs vs. arms and R^2 = 0.79 for left vs. right, Figure 2.7).

The population preferred to use the legs significantly more than arms under the neutral weighting condition (57% vs. 43%, from Λ^* = 0.12, 95% confidence

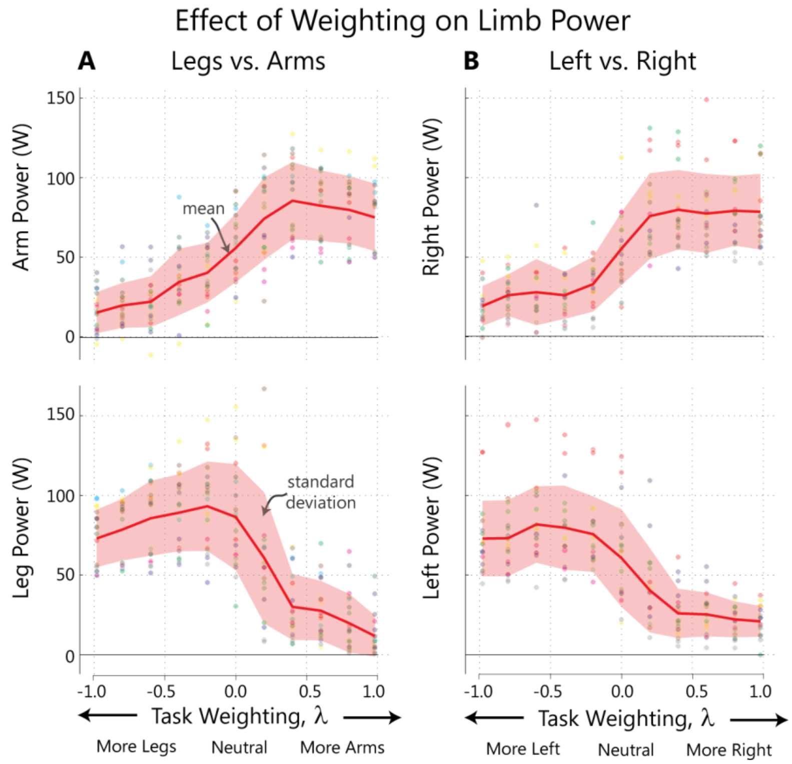

Figure 2.6: Limb Group Power Generated across Task Weightings

Individual limb group power vs. Task Weighting. The mean is indicated with a red line and the shaded region is the standard deviation of limb group power at each weighting. The more heavily weighted limb group is used more than the less weighted limb group.

interval (CI): 0.05/0.20). There was no significant bias away from neutral in the left vs. right experiment (Λ^* = 0.02, CI: -0.03/0.07).

At extreme task weightings, which rewarded individual limb groups alone, subjects generally tended to perform a non-zero amount of power with the other group of limbs, (legs vs. arms: B_1 = -0.65, CI: -0.74/-0.57, B_2 = 0.74, CI: 0.62/0.86, and left vs. right sides: B_1 = -0.54, CI: -0.61/-0.47, and B_2 = 0.55, CI: 0.48/0.61). The population also exhibited a smoother shift in preference for legs/arms (σ = 4.43, CI: 3.05/5.82) than for left/right limbs (σ = 8.31, CI: 5.07/11.54).

		Manipulation of Performance for Population			
parameter		B_1	B_2	σ	Λ^*
description		legs/left asymptote	arms/right asymptote	step/line trade-off	Inherent bias
Legs vs. Arms	value	-0.65	0.74	4.4	0.12
	95% CI	-0.74/-0.57	0.62/0.86	3.1/5.8	0.05/0.20
Left vs. Right	value	-0.54	0.55	8.3	0.02
	95% CI	-0.61/-0.47	0.48/0.61	5.1/11.6	-0.03/0.07

Table 2.1: Manipulation of Performance Results for Population
Parameters of the fit for the population in the form of Equation 2.4. Table includes best-fit values and 95% confidence intervals (CI).

We also used the population's Manipulation of Performance Function to numerically generate contour curves for both the legs vs. arms and the left vs. right side study (Figure 2.8).

Individual Subjects

Each subject exhibited a unique limb preference curve. To illustrate the variation between subjects, representative individual preferences are shown in Figure 2.9. Results are first presented for the legs vs. arms trials, followed by left vs. right.

We found logistic curves to fit the individual data reasonably well (Figure 2.9 - fit of form Equation 2.4 to all data for each individual subject: median R^2 = 0.89 for legs vs. arms study and R^2 = 0.86 for the left vs. right study). The range of limb use was typically close to the possible extremes, but usually not with the exclusion of any limb group. For example, when the task only credited power from the legs (λ = -1), subjects tended to strongly prefer the legs, but with some remaining contribution from the arms (median B_1 = -0.65, comparison: B_1 > -1, p

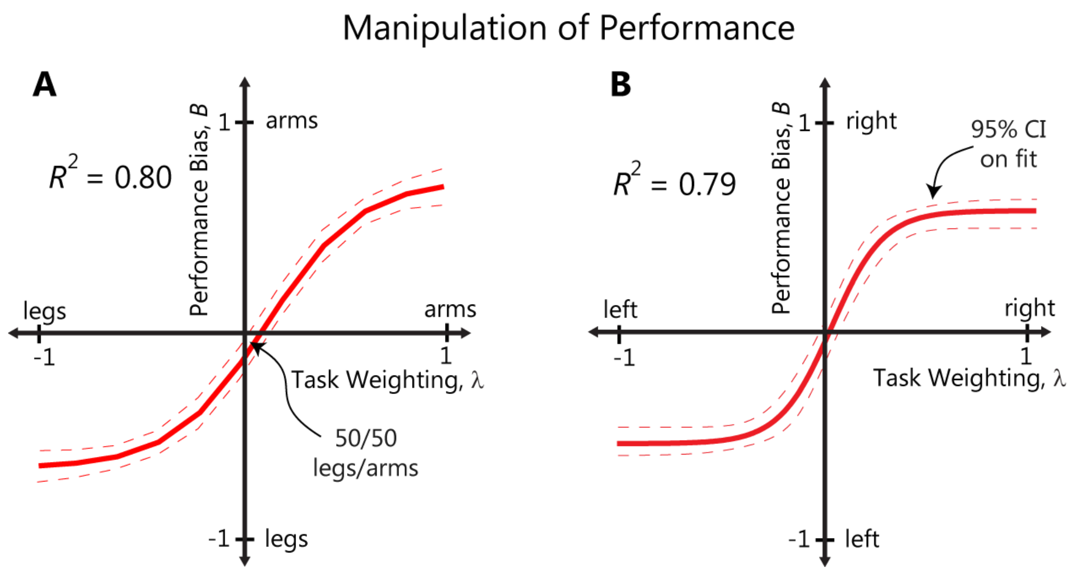

Figure 2.7: Manipulation of Performance Functions for All Subjects

Plotted is the Performance Bias vs. Task Weighting for the population studied in both legs vs. arms and left vs. right studies. The data is fit with generalized logistic functions in the form of Equation 2.4. **A:** Relationship between Task Weighting and Performance Bias for legs vs. arms grouping. **B:** Relationship between Task Weighting and Performance Bias for left vs. right grouping. Solids lines are a fit to data from all subjects. Dotted lines represent 95% confidence intervals on fit parameters.

= 6.6e-4). For pure arms weighting (λ = 1), subjects still performed some work with the legs (B_2 = 0.80, $B_2 < 1$, p = 0.047). For the left vs. right task, subjects again chose to maintain some power production by the unweighted limb-group (B_1 = -0.57, $B_1 > -1$, p = 1.1e-4 and B_2 = 0.61, $B_2 < 1$, p = 0.013) (Table 2.2).

Subject power distribution preference typically did not exhibit a linear dependence on task weighting, displaying a more sigmoidal relationship with weight. The parameter σ describes that dependence, with a value of σ = 1 denoting a linear increase with λ, and σ values tending toward infinity denoting a step-like change in limb use. The observed median of σ = 5.5 for the legs vs. arms study indicates a relatively gradual, sigmoidal dependence. For the left vs. right study, the median σ = 8.3 indicates a similarly sigmoidal trade-off.

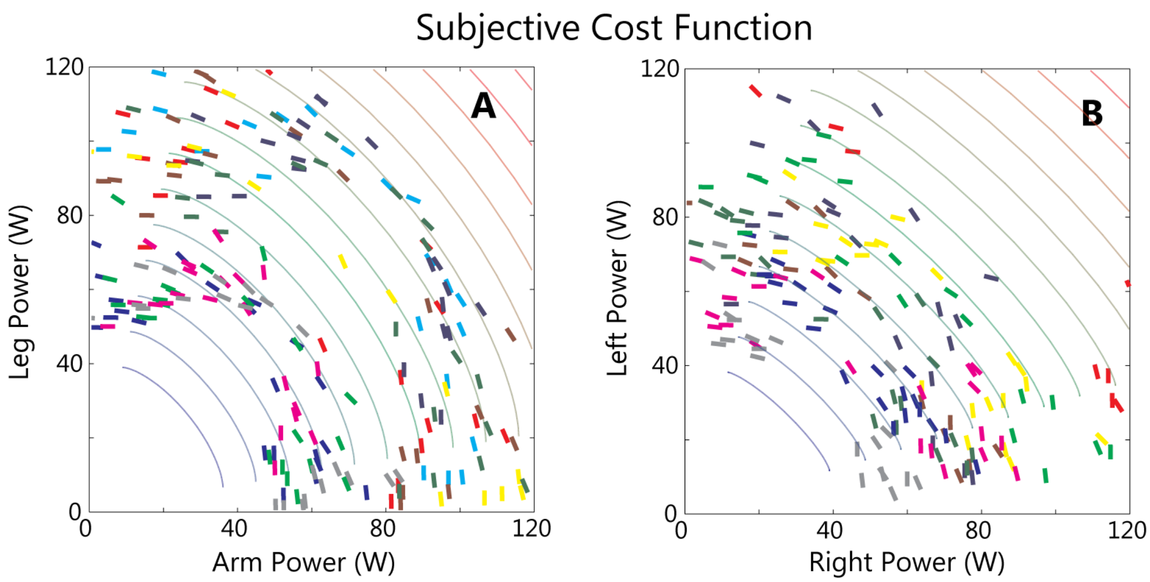

Figure 2.8: Estimated Subjective Cost Functions for All Subjects

A: Estimated Subjective Cost trade-off between arms and legs. **B:** Estimated Subjective Cost trade-off between left and right sides. Individual subjects are shown with unique colors.

Finally, in the legs vs. arms study, subjects demonstrated an inherent bias toward legs, whereas they demonstrated no significant bias under the unweighted condition between the left and right sides. The parameter Λ^* had a median value of 0.16 ($\Lambda^* \neq 0$, p = 0.012) for the legs vs. arms study, indicating a significant bias toward using the legs under a neutral Task Weighting. In the left vs. right study, Λ^* had a median value of 0.0055 ($\Lambda^* \neq 0$, p = 0.21), showing no significance difference.

We also performed a test of the consistency of limb preference within subjects. Fits for each subject, in the form of Equation 2.4, were created using 75% of their data, spanning the range of Task Weightings. The remaining 25% of their data was withheld from fitting as validation data. We tested how well the validation data conformed to the fits to the fit data. For the legs vs. arms study (N = 10), the fit data fits yielded a median R^2 = 0.90 (ranging from 0.79 to 0.96). We used the same fits on the independent validation data, which resulted in a median R^2 =

		Manipulation of Performance for Individual Fits			
parameter		B_1	B_2	σ	Λ^*
description		legs/left asymptote	arms/right asymptote	step/line trade-off	Inherent bias
Legs vs. Arms	median value	-0.65	0.80	5.5	0.16
	comparison	> -1	< 1	---	Different than 0
	p-value	6.6e-4	0.047	---	0.012
Left vs. Right	median value	-0.57	0.61	8.3	0.0055
	comparison	> -1	< 1	---	Different than 0
	p-value	1.1e-4	0.013	---	0.21

Table 2.2: Manipulation of Performance Results for Individual Fits
Parameters of individual fits in the form of Equation 2.4. Median values and statistical comparison values are reported. Significance of comparisons with inter-subject fit parameters is indicated with one sample t-test p-values.

0.83 (ranging from 0.23 to 0.97). For the left vs. right comparison (N = 9), the fits on fit data yielded a median R^2 = 0.92 (ranging from 0.76 to 0.97), and the validation data yielded a median R^2 = 0.84 (ranging from -0.14 to 0.92; see Figure 2.9). The results suggested a reasonable degree of repeatability and robustness within subjects, albeit for a small number of outliers.

Discussion

We had hypothesized that humans have a tendency to prefer movements that minimize a subjective cost, quantifiable in terms of mechanical work. The hypothesis implies that implicit weighting of limb powers toward a goal amount of weighted limb power could alter the preferred limb contributions by altering the subjective cost associated with each weighting and distribution. Furthermore, we may induce these effects without the need for explicit feedback to the subject

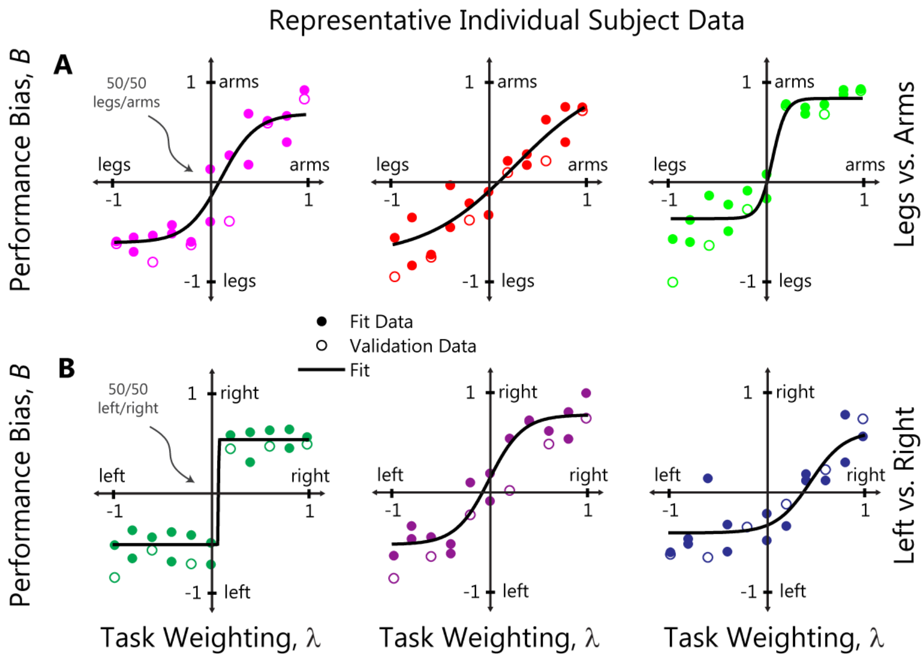

Figure 2.9: Representative Individual Subject Data and Fits

Performance Bias vs. Task Weighting relationship from representative subjects in the form of Equation 2.4. Logistic curves (solid lines) were fit to a portion of the data (Fit Data, filled circles). The remainder of the data was reserved and used to test the predictive ability of the fit (Validation Data, unfilled circles). **A:** Representative legs vs. arms study subjects – Median R^2 for validation data for all subjects was 0.83. **B:** Representative left limbs vs. right limbs study subjects. Median R^2 for validation data for all subjects was 0.84

about weightings. Our results show that subjects biased their use of limbs in accordance with these expectations.

The subjects did not arrive at the limb distributions reported immediately, but only after some exploration with different limb distributions that allow subjects to judge which they preferred. Most subjects explored each task for up to one minute before settling upon their preferred limb distribution. We suspect that determining preference is a physiological process that occurs continually. However, the consistency of our repeated trials suggests that continued refinement would have had little effect.

We found it curious that subjects tended to use all limbs, even if one pair was not weighted at all toward the task goal. In fact, subjects sometimes performed 20-40W of unnecessary power to preserve using the limbs together. This may have been a consequence of our requirement that subjects maintain contact between all four limbs and the machine. Subjects might have found it difficult to produce zero force with the non-weighted limbs, and would have chosen to remove those limbs from the exercise machine entirely, given the choice. But there are also other possible explanations. There may exist neural coupling between limbs, meaning that movements of one limb group may necessarily activate the muscles of another [47]. Or, it may be helpful to use both sides of the body to prevent twisting of one's torso, which may occur if the limbs on one side were used much more than the other. Maintaining control over posture with some additional effort may be important to the subject, even if the extra work appears not to contribute to their primary task goal.

Expected fatigue and the capacity for power generation or work of limbs may also play a role in how subjects determine their effort distribution. Subjects may use combinations of limbs to reduce the possibility for fatigue which may reduce their ability to complete a future task that might demand more of only one limb group. Distribution of the workload among the limbs may serve to ensure that the subject will be able to complete future tasks, despite the fact that in the current task, concentrated effort would make the task easier. Finally, it may seem unnatural to only use one group of limbs if the subject expects the task to require all their limbs. Expectations about the nature of the task, or the subject's previous experience under similar circumstances could influence their preferred strategy.

In possible applications to rehabilitation, our intention with implicit feedback is to increase strength by recruiting weak limbs for a greater period of time and to a greater degree. We do not assume that better symmetry induced from training will persist after exercise or that after-effects of altered symmetry are necessary to achieve functional benefits or increased strength. Our method therefore contrasts with some others which attempt to instill a learned effect which will persist after training has stopped or via error augmentation [64]–[67]. We do not claim or dispute that such learning occurs, but rather only rely on subjects acting in accordance to preferences they already had to benefit from the strength training implicit feedback may encourage.

At this point, our implicit feedback relies on visual feedback to the user. A visual display is somewhat abstract compared to the normal force and proprioceptive feedback humans regularly use to inform many of their behaviors during everyday activities. We used visual feedback for its straightforward implementation, but an alternative approach might be to adjust the physical resistance felt by the user in response to their limb use and our implicit weightings. One could imagine a system in which resistance to motion could be decreased when subjects use the more heavily weighted limbs, but the same speed of stepping is required to match their exercise goal. Lower effort via changes in resistance could thus provide an incentive toward the use of specific limbs, similar to those found in this study. We suspect that more natural feedback could perhaps reduce the cognitive demand of the task.

It remains uncertain what actually determines a person's subjective cost function. Our experiment revealed the preferred power distribution as a function of Task Weighting, which may be interpreted as the intersection of a subjective indifference curve with an applied task constraint. The composition of many such intersections revealed an image of indifference curves (Figure 2.8). Unfortunately, we lack the ability to assign values to these contours. We presume that subjective cost depends on a variety of factors, such as metabolic energy expenditure, limitations on muscle strength or previous training [68], and even less measurable effects such as discomfort and fatigue [4], [11], [22]. There is even evidence that expectations of an exercise's duration or intensity can alter perceived exertion [69]. Further experiments targeted at such factors might provide more specific insight regarding subjective cost.

The methods to quantify subjective preferences examined here may be used to motivate limb use generally in strength training or for patients in neuromotor rehabilitation. As an extension of this work, it may even be possible to control the kinematics of certain movements via similar mechanisms to help with coordination tasks. Correct form could be mapped to lower subjective costs via similar implicit feedback, and therefore become controlled by lowering the subjective cost associated with correct movements. Implicit feedback may reduce the vigilance and attention required of athletic trainers and physical therapists when they provide explicit feedback in a wide range of possible applications.

Chapter 3.

Implicit Vs. Explicit Feedback: A Comparison of Methods to Redistribute Effort during Multi-Limb Exercise

Introduction

It often takes great concentration and effort to exercise with the proper form or strengthen muscles. In rehabilitation in particular, the therapist directs the patient to use the limbs weakened due to injury or disease, despite the time and attention it takes to reinforce the behavior. Patients who have suffer from stroke or spinal cord injury may instead prefer to compensate with their strong limbs because it feels less difficult. In traditional therapy patients must pay attention to the therapist's cues to correct their behavior and achieve improvement. Their attention might already be strained due to limitations arising from brain injury [57], [70], or through the process of aging. Lower cognitive function is related to poorer functional performance [71], such that if the patient's cognitive abilities are overextended or they become confused by elaborate feedback, there may be delays in recovery. Furthermore, explicit feedback from the therapist or exercise machine may interfere with the subconscious adaptation of limb use [58], [59]. It might be better to steer patient effort implicitly, and leverage patient preferences to alter their work distribution without the need for constant explicit reinforcement. Implicit feedback could potentially reduce the demands on the therapist and patient if an exercise could be made in which the subject's desire for ease was aligned with increased work from particular limbs.

We propose to implicitly weigh power contributions from the arms and legs of healthy subjects unevenly toward a scalar goal of this weighted power to encourage the use of the more heavily weighted limb group [similar in method to Chapter 2]. We hypothesize that humans determine their preferred distribution of limb effort based, in part, on relative ease, and will use the combination of limbs which satisfy their exercise goal with the least effort. We intend to compare this implicit strategy with an analogous explicit feedback mode to determine the effect of the feedback on limb distribution preference and cognitive ability. If healthy subjects demonstrate less interference between exercise performance and cognitive performance with the use of implicit feedback, then patients, with their more limited and variable ability levels, may also benefit from the same approach.

Methods

We performed an experiment to compare subject limb use when they used implicit and explicit feedback to match power and symmetry goals during multi-limb exercise. We also compared cognitive demand of the two modes of feedback. We determined if implicit feedback had less of an effect on the ability to perform a secondary math-based cognitive task than explicit feedback. Conversely, we explored how the cognitive task would affect each subject's ability to use implicit or explicit feedback to match their exercise goals.

Twelve healthy adult subjects participated (8 male and 4 female, age 21.8 ± 2.5 years (mean ± standard deviation)). We recorded body mass (68 ± 14kg) for each subject, and all provided written informed consent according to University procedures.

A recumbent stepper (NuStep, Ann Arbor, MI) machine was instrumented to allow measurement of the subject's power distribution among limbs (Figure 3.1 A). We presented visual feedback to the user about their performance and exercise goals via an LCD display (Figure 3.1 B). Individual limb power was calculated with force and motion measurements. Force was measured with custom load cells at each hand and foot. Gyroscopes were used to measure angular velocity. We used the forces and the machine's kinematics to calculate the moments generated from each limb about the exercise machine's axis of rotation. Then we calculated each individual limb's instantaneous power with the dot product of the moments and the angular velocity (Figure 3.1 C).

Subjects were first *familiarized* with the feedback modes, the exercise, and cognitive task. Then we *characterized* the effect of the implicit weightings on limb use during the exercise. Finally, we performed an experiment in which three implicit weightings or explicit symmetry and power targets were given to alter subject effort distribution toward arms or legs at a certain level of mechanical power. For each condition given, subjects first *explored* the task with different combinations of arms and legs to feel the differences. Then we *assessed* their preferred limb distribution as a function of each condition. The feedback was constructed as follows:

Implicit Feedback

Implicit feedback unequally weighted power contributions toward a scalar task goal in an attempt to alter their preferred effort distribution. Visual feedback

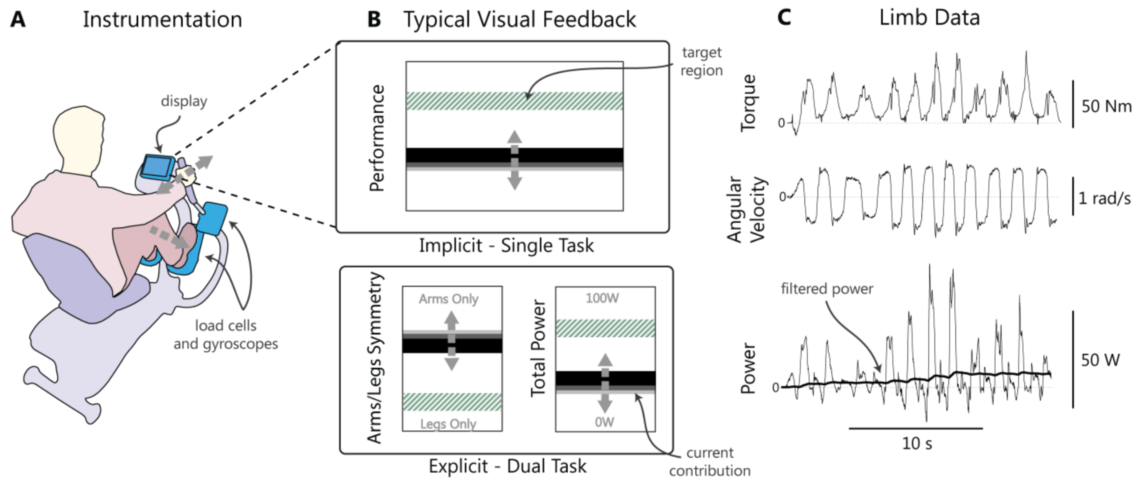

Figure 3.1: Visual Feedback and Measured Data during Experiment

A: Instrumentation of the experimental hardware to measure power from each individual limb and provide visual feedback. **B:** Visual feedback provided for implicit and explicit tasks. Performance in power, symmetry, or summed weighted power is displayed as a moving bar. Target amounts of each of these quantities are shown as target zones. **C:** Representative data collected at each individual limb. Torque is measured via load cells and knowledge of the kinematics of the machine. Angular velocity is measured via gyroscopes. The dot product of torque and angular velocity yield power, which is cyclical in nature due to the stepping motion. A low-pass filter is applied to the raw powers to smooth their signal during processing.

showed subjects a single bar graph, with a target level, and a moving bar which represented their current performance (Figure 3.1B upper). Subjects were given a Performance score, which was a function of weighted power from the limbs according to:

$$\text{Performance, } P = \frac{(2-|\lambda|)}{2}\Big((1-\lambda)P_{legs} + (1+\lambda)P_{arms}\Big) \qquad \text{(Equation 3.1)}$$

where *P* is the credited amount of weighted power. Performance is filtered and displayed to the subject. The parameter λ is a Task Weighting which gives limbs unequal credit toward a target level of Performance. A value of λ = -1 corresponds to crediting the legs alone, λ = 1 to the arms alone, and λ = 0 to equal credit. Unequal weightings imply that the subject may satisfy their exercise goal with less power from the more heavily weighted limb group than with the lesser weighted limb group. Lower overall power may make the task less difficult and may simultaneously promote greater use of the more heavily weighted limb group. Implicit weightings may thereby provide an incentive for increased use of targeted limb groups. If subjects shift effort when we apply weightings, we may set power and symmetry goals for the subject implicitly as a function of the provided Task Weighting, without the need to explicitly display both goals separately.

Explicit Feedback

Explicit feedback consisted of two bar graphs showing limb power and symmetry targets individually (Figure 3.1 B, lower). The subjects are shown their current symmetry and power and corresponding target levels, but now as two separate graphs. With explicit feedback, the subject cannot use different combinations of arms and legs to fulfill the task, and their targets reflect a single combination of arm and leg power.

Task goals expressed in terms of power from the arms and legs for implicit and explicit feedback and typical subject power trajectories during a trial can be seen in Figure 3.2.

Protocol

We first familiarized the subjects with the implicit weighting feedback. The feedback was verbally explained to them during a number of trials. Then, the subject would match a target amount of Performance using implicit feedback. Subjects were told the Task Weighting for each trial as they tried to match their implicit goal. Knowledge of the weighting allowed the subjects to explore the effort associated with different power distributions under each condition.

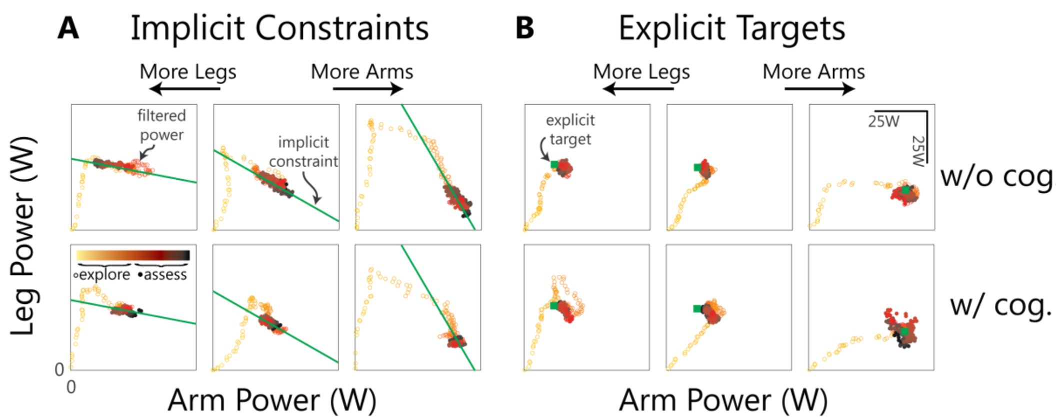

Figure 3.2: Representative Performance during Different Trial Types

Arm and leg power throughout the course of representative trials, including implicit and explicit tasks with and without the presence of a secondary cognitive task. **A:** Implicit Constraints: A target level of Current Performance can be achieved via different combinations of arm and leg power. The combinations constrain distributions that fulfill the task along a line in the space of arm and leg power. **B:** Explicit symmetry and power targets equate to a single point in the space of arm and leg power. Only a single combination of arm and leg power can satisfy the task goal.

After familiarization, we characterized subject preferences with a number of implicit weightings. The subjects were presented with tasks with implicit Task Weightings of λ = -0.68, -0.28, and +0.26[3]. The Task Weightings were unknown to the subject, though they understood some weighting might be present. The subject was instructed to reach the target level for that trial, which could range from 30-60W of actual power, depending on the weighting and the subject's limb distribution. The three weighted conditions were repeated three times, in an order unknown to the subjects. The same Task Weightings would be used for future implicit trials, and the subject's mean symmetry and power levels during

[3] Original Task Weightings were λ = -0.5, 0.0, and +0.5. However, further calibration of our sensor information changed the effective Task Weightings to those reported in the text. We do not believe the difference should change the trends or significance of our results, as the weightings chosen are somewhat arbitrary. They were chosen only to weigh the contributions differently in each condition. Any set of weightings, sufficiently far apart, should lead to similar trends.

the last two characterization trials of each weighting were used as targets for the explicit tasks.

Next we presented experimental trials with either implicit or explicit feedback, for which we attempted to alter the distribution of effort of the subject toward target power and symmetry levels. The trials consisted of a work task at a level of 40 units of Performance, *P*, for implicit tasks or corresponding symmetry and power targets from the characterization for the explicit trials. Each type of trial lasted 90 seconds. The trials were presented in groups of three implicit, then three explicit trials. In each group, all three limb distribution targets were given, either implicitly using weightings, or explicitly with two different visual targets for symmetry and power.

Finally, we explored the effects of a cognitive task on the exercise task, and vice versa. The implicit and explicit tasks outlined above were performed with and without a secondary cognitive task for each of the three implicit weightings and explicit targets. After 6 trials without the cognitive task, 6 additional trials were given with a secondary cognitive task which consisted of counting backwards alternately by 7 and 6 aloud from a random 3-digit number. Both sets with and without cognitive trials were repeated for a total of 24 trials.

Analysis

Subject performance was characterized in terms of limb use, ability to match their feedback targets, and the variability of their performance. Limb use was expressed in terms of power from the limbs, as well as the ratio of arm power to net power, according to:

$$\text{Arm Power Ratio, } A = \frac{P_{arms}}{P_{arms}+P_{legs}} \qquad \text{(Equation 3.2)}$$

The subjects were instructed to explore different combinations of arms and legs to find the combination they most preferred. Subjects most often displayed steady-state effort distributions about half way through the trial (Figure 3.3). Data from seconds 40-85 of the trial were used to calculate steady-state results. Therefore, we termed the first part of the trials *exploration*, and the second part *assessment*. The Arm Power Ratio under various implicit and explicit targets was compared with Student's t-tests.

Next we described how well subjects matched their feedback goals, and the variability of their performance (Figure 3.4). We first calculated the difference between the subject's performance and their implicit or explicit target(s). For the implicit task, the feedback error was measured as the distance, in watts, between their mean arm and leg power during assessment and the closest combination of power that satisfied the task of form Equation 3.1 (Figure 3.4 A, perpendicular distance). For the explicit task, their feedback error was calculated as the distance between their performed mean arm and leg power during assessment and the powers necessary to satisfy the explicit target for both symmetry and total power (Figure 3.4 B, absolute distance). The errors were compared with Student's t-test for significant differences between implicit and explicit trials with and without the presence of a secondary cognitive task.

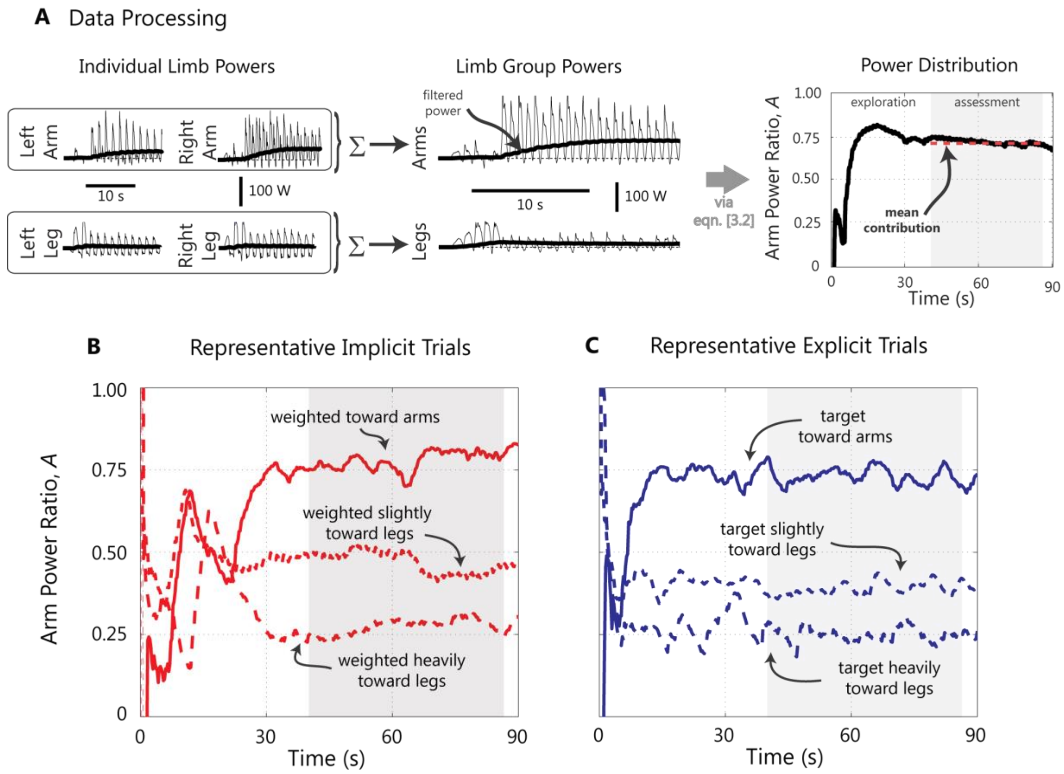

Figure 3.3: Representative Transient Response for Implicit and Explicit Tasks

A: Each individual limb power is combined into arm and leg grouped power. Next, the overall power distribution is calculated via the ratio of arm power to net power (Equation 3.2). Power is low-pass filtered to smooth cyclical data due to stepping during the exercise. Mean limb contributions and the Arm Power Ratio are calculated over seconds 40-85 (shaded assessment area). **B:** Arm Power Ratio for three representative trials with different implicit weightings. After some exploration, subjects approach their preferred power distributions, which are different, depending on the implicit weighting. **C:** Arm Power Ratio for three representative trials with different explicit targets. Subjects approach their targets more quickly when using explicit feedback, at the expense of having to fulfill two simultaneous tasks.

We performed analyses using linear algebra techniques to characterize steady-state variability for implicit and explicit trials. We used Eigen-decomposition of the covariance matrices of each subject's power data throughout the time course of the assessment period to measure the ratio of leg and arm power responsible for the most variability (the two Eigen-vectors, or the direction of greatest variability and direction perpendicular to it).

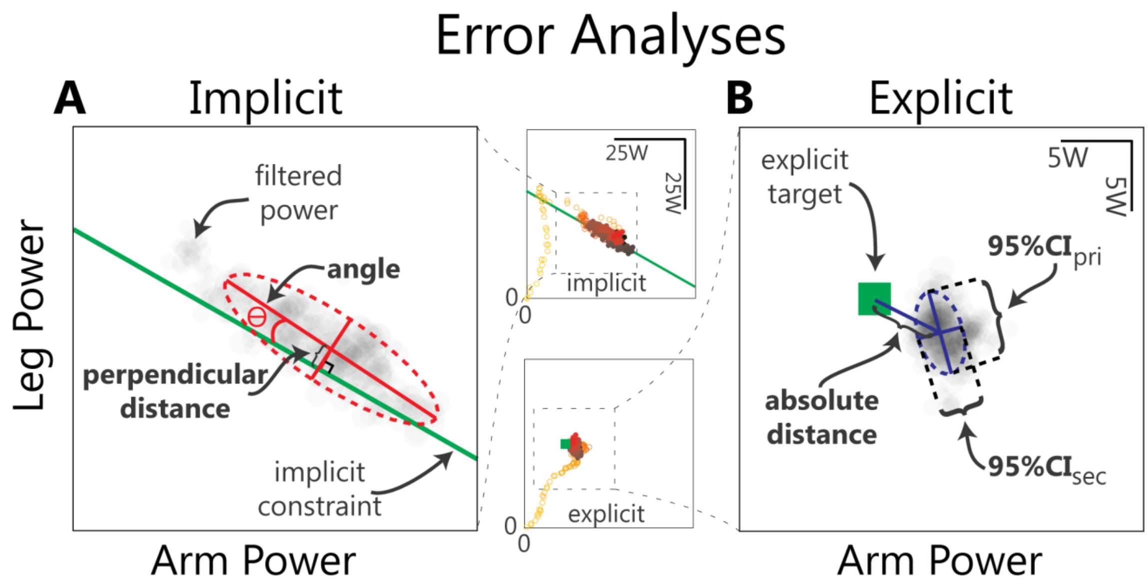

Figure 3.4: Error Analyses for Implicit and Explicit Trials

The filtered arm and leg power during the assessment period of each trial was used to analyze performance. For all trials, we calculated the 95% confidence interval for the variability in the primary and secondary directions of variability (95%CI$_{pri}$ and 95%CI$_{sec}$) and the trace of the covariance matrix, which represents the overall variability of the data. **A:** During implicit trials, performance error was defined as the perpendicular distance between the mean arm and leg power during the assessment period for each subject, and the subject's implicit constraint. We also quantified how close the axis of primary variability aligned with the task constraint in terms of the cosine of the angle between them. **B:** For explicit trials, in addition to measures of variability, we defined performance error to be the absolute distance between mean power during assessment and the subject's explicit target power.

We also reported information about the magnitude of variability. Each Eigen-vector (primary and secondary directions of variability) has an associated Eigen-value, which is a scalar value defined as the variance of the data in the direction of the Eigen-vector. We report the span of 4 standard deviations (4 times the square root of the Eigen-value) around the mean power (roughly 95% confidence interval (95%CI) in the direction of variability). The 95%CI is in units of watts, and is reported for both the primary axis of variability, and the orthogonal secondary direction of variability. To assess the overall variability, we also calculated the trace of the covariance matrix, which is the sum of the diagonal terms. It should be noted that the trace of the covariance matrix is identical to the trace of the diagonal, Eigen-decomposed matrix, or of the covariance matrix of the data expressed in any set of orthonormal basis-vectors with the same scale. Therefore, it represents an absolute measure of the variability of the data, independent of how it is oriented. The trace and variabilities in the primary and secondary directions between implicit and explicit conditions were compared with Student's paired t-tests.

Finally, for implicit trials, we described the orientation of maximum variability relative to the implicit constraint. Specifically, we report the absolute value of the cosine of the angle between the axis of primary variability and the implicit constraint. This value can range between 0 and 1, where 0 corresponds to an orthogonal orientation and 1 indicates that the axis of primary variability is parallel to the implicit constraint. The measure should reflect how much the subjects exploited the degree of freedom the implicit constraint afforded them. Their performance was not penalized in any way if they varied arm and leg power along this constraint to match their target. If the orientation of the variability was at a random orientation to the implicit constraint, we would expect a mean value of the cosine of this angle to be the cosine of 45 degrees, or roughly 0.707. Therefore, we expect that if subjects exploited the use of this degree of freedom, the cosine of the angle will be significantly greater than 0.707. We made the comparison with a one-sample t-test.

We also compared the speed and accuracy of the mental math performed by the subjects for the secondary cognitive task during both implicit and explicit tasks. We measured the number of subtractions performed by the subject during the trial, as well as the number of mistakes they made. To achieve a baseline level of mental math ability at the time of testing, we performed the cognitive task without the primary exercise task. Paired t-tests were used to compare the number of subtractions performed and the number of errors made under baseline and simultaneous, implicit, and explicit tasks. The threshold for significance for all tests was set at $\alpha = 0.05$.

Results

Results ($N = 12$) shows that subjects altered their effort distribution among limbs as a result of both implicit and explicit feedback about power and symmetry goals. Subjects changed their preferred distribution by an average of about 20.0% of the net power toward either the arms or legs away from their power distribution in the central condition (Figures 3.5, 3.6). Moreover, trials with implicit feedback resulted in less feedback error than with explicit feedback, though with more variability. However, much of the variability in implicit trials occurred along the implicit constraint's degree of freedom. Finally, subjects were slower at the secondary cognitive task using explicit feedback than with implicit feedback.

Subjects matched distribution targets about 24% of net power away from their central preferred distribution toward arms or legs, under the implicit weightings tested without the presence of the cognitive task (Figures 3.5 A, & 3.6 A). Subjects directed 6.35 ± 7.7W (mean ± standard deviation) more power toward their legs, away from their preferred distribution under the central weighting, when leg power contributions were heavily weighted. The change is equivalent to a change in their Arm Power Ratio of 0.13 ± 0.16 (comparison against the central weighting, p = 4.9e-4). Subjects also significantly directed 16.6 ± 9.2W (ΔA = 0.35 ± 0.20, p = 7.4e-9) toward the arms when that limb group was heavily weighted.

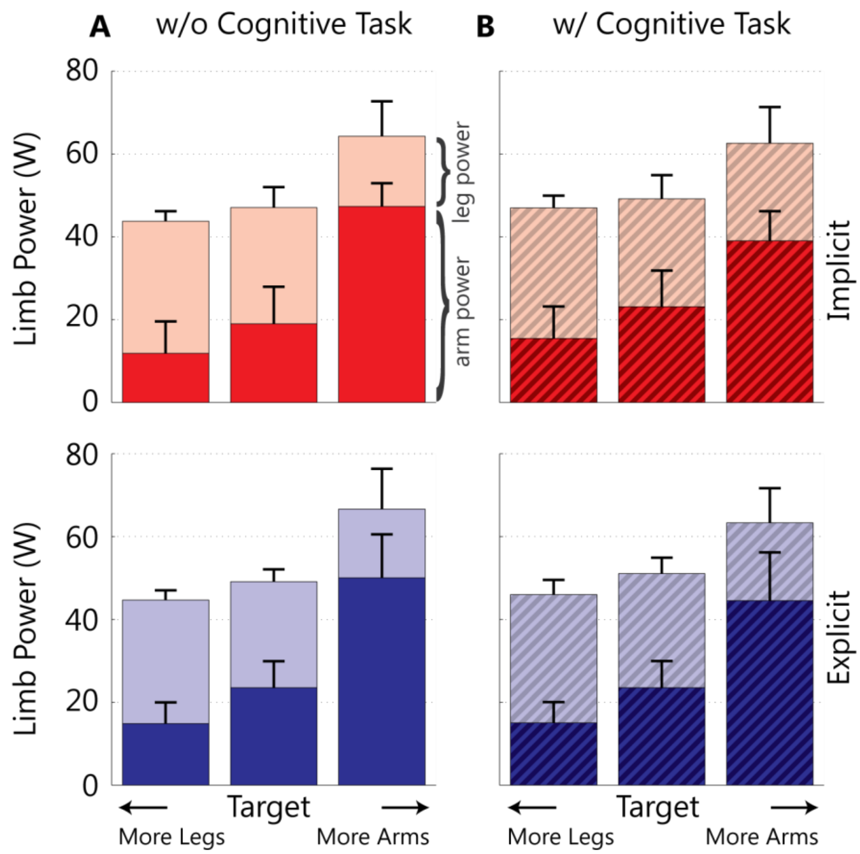

Figure 3.5: Normal vs. Divided Attention Limb Power

A: Arm and leg power for each implicit and explicit targets, without performing the secondary cognitive task. **B:** Arm and leg power for each implicit and explicit targets, while performing the secondary cognitive task. Subjects significantly altered their effort distributions when they used implicit and explicit feedback to target specific limbs.

With explicit targets, subjects matched distribution targets about 21% of net power away from their central preferred distribution with no concurrent cognitive task. Subjects directed 7.2 ± 4.2W (ΔA = 0.15 ± 0.08, p = 1.5e-8) toward the legs, or 13.6 ± 9.0W (ΔA = 0.28 ± 0.18, p = 1.5e-8) toward the arms away from their distribution with the central target.

With the addition of the cognitive task, subjects demonstrated a reduced distribution range with the same implicit weightings or explicit targets. Furthermore, variability in the distributions increased. Still, subjects produced

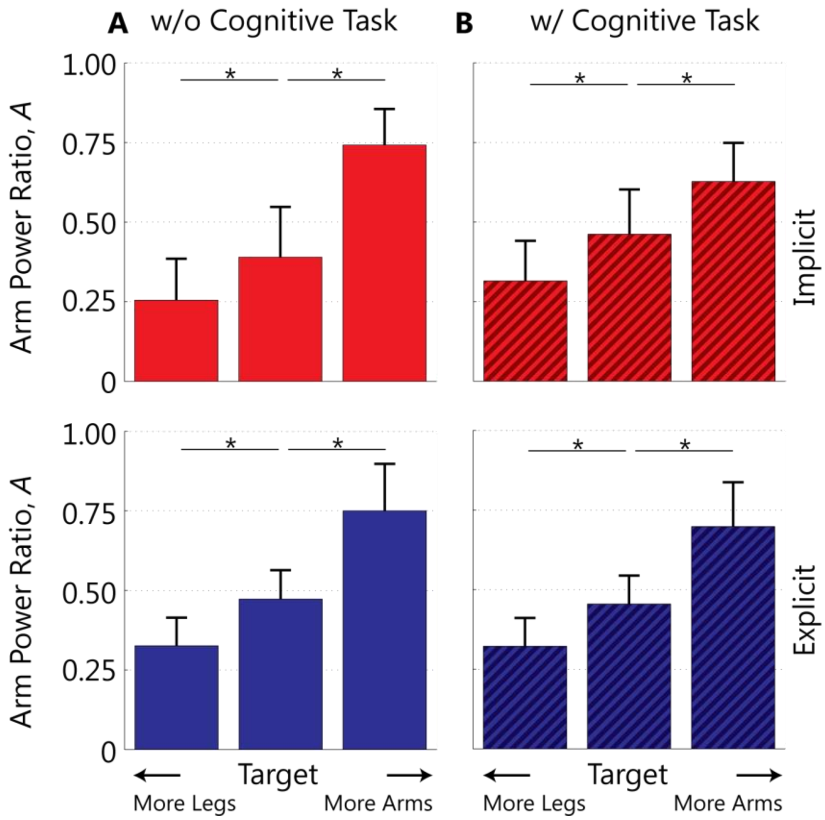

Figure 3.6: Normal vs. Divided Attention Power Distributions

A: Arm Power Ratio under different implicit and explicit task targets, without performing the secondary cognitive task. **B:** Arm contributions under different implicit and explicit task targets while performing the secondary cognitive task. Subjects significantly altered their effort distributions with arm or leg targets when they used both implicit and explicit feedback (* denotes significant differences in paired t-tests, $p < 0.05$).

more power with the arms or legs, depending on the target, by an average of about 16% or 19% of mean net power, for implicit or explicit trials respectively (Figures 3.5 B, & 3.6 B). Subjects significantly directed 7.2 ± 6.9W (ΔA = 0.15 ± 0.14, p = 3.1e-5) toward the legs, or 8.1 ± 9.0W (ΔA = 0.17 ± 0.18, p = 2.0e-4) toward the arms, away from their central preferred distributions for implicit tasks. When subjects used explicit feedback to match symmetry and power goals directly, they directed 6.8 ± 4.0W (ΔA = 0.13 ± 0.08, p = 2.3e-8) toward the legs, or 12.4 ± 9.1W (ΔA = 0.24 ± 0.18, p = 3.1e-5) toward the arms, away from their central preferred distribution.

measure	**Feedback Error**	**Trace**	**95%CI$_{pri}$**	**95%CI$_{sec}$**	**Cosine Angle**
(units)	(W)	(W^2)	(W)	(W)	(0-1)
Implicit w/o Cog.	1.1 ± 1.1	15.6 ± 16.2	6.7 ± 3.5	2.1 ± 0.8	0.92 ± 0.16
Implicit w/ Cog.	2.7 ± 2.7	26.5 ± 29.7	8.6 ± 5.2	2.4 ± 0.9	0.87 ± 0.21
Explicit w/o Cog.	4.3 ±1.7	7.1 ± 5.3	4.5 ±1.8	2.2 ±0.7	n/a
Explicit w/ Cog.	5.7 ±3.5	17.7 ±17.1	7.1 ±3.4	2.6 ±1.3	n/a

Table 3.1**:** Error Analyses for Implicit and Explicit Trials

Both implicit and explicit feedback helped subjects to alter their effort distribution toward arms or legs. However, feedback error was greater with explicit feedback (Table 3.1). The mean implicit error (perpendicular distance) without the addition of the cognitive task was 1.1 ± 1.1W (Table 3.1). Explicit error (absolute distance) without the cognitive task was 4.3 ± 1.7W, significantly greater than the implicit case (p = 5.8e-21).

Explicit feedback error was also greater than implicit feedback with the addition of the secondary cognitive task. Now, the mean subject feedback error for trials using implicit feedback was 2.7 ± 2.7W, a significant increase from implicit trials without the cognitive test (p = 2.2e-8). Trials that provided explicit feedback during the cognitive task also had a significantly higher associated mean error of 5.7 ± 3.5W (p = 8.0e-4) than without the cognitive task present. However, the mean error in explicit trials was also significantly greater than in the trials using implicit feedback when both had the concurrent cognitive task (p = 2.6e-11).

Explicit trials were generally less variable than implicit trials. The trace computed for explicit trials was significantly less than the trace of the power data during implicit trials (p = 2.8e-5 w/o cog., p = 0.038 w/ cog.). Furthermore, variability in the primary direction of variability is greater for implicit trials than those trials which use explicit feedback (p = 1.5e-6 w/o cog., p = 0.036 w/ cog.). However, variability during implicit trials is not significantly greater in the secondary direction of variability (p = 0.47 w/o cog., p = 0.14 w/ cog.). We believe this is important, as we also found that the primary direction of variability in the implicit trials was quite well aligned with the implicit constraint. The absolute value of the cosine of the angle between the primary direction of variability and the implicit constraint was found to be significantly greater than 0.707 (one-sample t-test, p = 6.4e-18. w/o cog., p = 1.1e-8 w/ cog.), which indicates that the variability of implicit trials was more aligned with the constraint than could be the outcome of random chance. Variability parallel with the constraint is un-penalized variability which does not result in greater visual feedback error for implicit trials. That means that implicit trials result in less penalized variability, in addition to the lower mean error as described above.

Next we compared the effects of using implicit and explicit feedback on the secondary cognitive task. Generally, the use of explicit feedback did not result in an increased error rate of the mental arithmetic greater than the rate during implicit trials. However, subjects did perform fewer mental calculations while using the explicit feedback. Subjects who performed the cognitive task performed an average of 27.6 ± 6.3 mental calculations over the 90 seconds of the trial. In that list, subjects made an average of 3.5 ± 2.2 errors. The number of errors did not significantly change when the exercise task was introduced (p = 0.55 and p = 0.58 for implicit and explicit trial errors vs. baseline errors, respectively). Furthermore, the number of errors between explicit and implicit trials were not significantly different (p = 0.73). Subjects did perform the cognitive task more slowly when the primary exercise task was reintroduced (Figure 3.7). Implicit trials resulted in 22.4 ± 5.7 mental calculations, and explicit

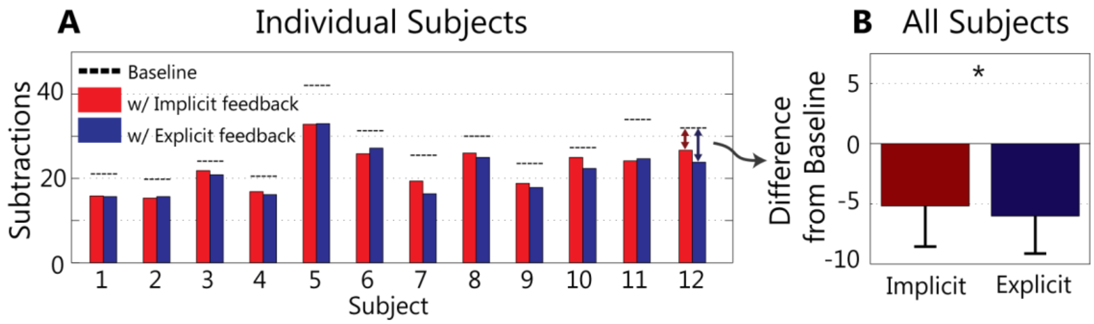

Figure 3.7: Performance of the Secondary Cognitive Task

A: Mean performance of cognitive task for each subject. **B:** The number of subtractions performed in the secondary cognitive task relative to the baseline for all trials. Baseline calculations were performed at rest without the primary task of matching implicit or explicit exercise goals. Subjects made fewer subtractions during trials with explicit feedback (*$p < 0.05$).

trials resulted in 21.5 ± 5.7 calculations being reported. Both results were significantly shorter than the baseline performance (p = 1.3e-20 for implicit trials and p = 7.6e-26 for explicit trials). Furthermore, the number of subtractions subjects performed while using implicit feedback was 0.83 calculations (3.7%) longer than when they used explicit feedback (p = 0.042). The explicit feedback slowed down calculation 16.1% more than implicit feedback did relative to their difference from baseline.

Discussion

Both implicit and explicit feedback can be used to steer effort in a multi-limb exercise. However, our subjects demonstrated that implicit feedback may be an appropriate alternative to explicit strategies if there exist concerns about attentional constraints, or the difficulty of the exercise task. Not only were subjects able to perform more mental math when using the implicit feedback alternative, but they did so with less error matching their visual feedback target and without sacrificing the range of possible power distributions attainable with the feedback. We thought it may be of little surprise that an implicit exercise, in which the subject must match only one goal, would incur less error than in the explicit, dual-goal, task. However, the implicit feedback was still able to encourage greater use of targeted limb groups, and so there may be little reason to complicate the feedback with another simultaneous task goal.

We found some evidence for strategies learned over time, or habitually, which subjects used to perform our feedback tasks. We expected that for explicit tasks, variability in the power from the arms and legs would no specific coupling. Therefore, we would expect, on average, a 45 degree angle between the primary axis of variability and any other vector. However, analysis of the explicit trials with the presence of the cognitive task showed the orientation of the variability may not have always been random. The variability of these trials was actually somewhat aligned with the previous trial's implicit constraint. The absolute value of the cosine of the angle between the explicit trial's primary axis of variability and the implicit constraint of the previous trial had a value significantly greater than 0.707 (cosine of 45 degrees) (cosine of angle = 0.82, greater than 0.707, one-sample t-test, p-value = 4.7e-6). We found it curious that people varied in their power distribution along a similar limb combination as they had previously experienced as not penalized. With explicit feedback they gained no advantage by varying power in this way, and were indeed penalized the same as if they varied away from their goal in any other direction. Therefore, one possible explanation for the behavior is that subjects learned the combination of limbs to use without penalty during implicit trials, and this effect carried over for the explicit trials. Alternatively, another possible explanation is that people naturally vary power generation with a combination of limbs that resemble the direction of the implicit constraints used here. However, we noticed the effect was only present in explicit trials with the secondary cognitive task, and not in those trials with the explicit exercise task alone. Perhaps the cognitive task distracted our subjects to allow any learned or subconscious strategy to have a greater effect than when the subjects could concentrate on the exercise alone. Further study should be done to determine if there is an underlying mechanism for unconscious variation with the observed combination of arms and legs, or if the effect is learned.

There were a number of limitations to this study. One limitation was the relatively small range of induced limb power distributions. Although the feedback tested here induced shifts in effort of only 15-20% of net power, these results do not necessarily represent a limitation on the magnitude of the shift. Previous work has shown that a greater range of limb distributions is possible with higher magnitude implicit weighting biases [Chapter 2]. However, there are observed limits to how much subjects will use arms or legs in exclusion of the other group. A strong preference exists to use limbs in combination for this particular exercise task.

Another limitation to this study was the limited effect of the exercise task on performance of the cognitive task. The exercise task might not have been challenging enough to cause a large effect on each subject's ability to perform mental math.

Implicit feedback did not induce the precision of explicit feedback in terms of guiding subjects to match specific symmetry or power goals. However, if we consider applications to neuromotor rehabilitation, the therapist is often more concerned with the patient's increased limb use than an exact distribution of limb power. Strength training rehabilitation for target limbs has shown promise of increasing functional performance [72], [73] and improvement of coordination and control [74], [75]. If implicit feedback is able to steer effort toward a group of limbs that need it, it may not be important to match any specific power distribution.

Implicit task weightings may provide a simple alternative to explicit strategies to encourage use of specific limb groups during exercise. Implicit tasks may also have potential in rehabilitation applications where they may require less patient attention and be easier to perform than explicit feedback.

Chapter 4.

Preference for Low Resistance Can Be Used to Control Power Distribution among Limbs during Exercise

Introduction

Humans often prefer to perform tasks in ways that reduce energy expenditure [1], [15] or feel less difficult [19], [45], [61]. As a result, if given the choice to use limbs in different combinations toward satisfying a task's goal, people may produce more of the work with the limb group that makes the task feel easier to complete. This is especially true in rehabilitation, where limbs weakened due to injury or disease tend to be used less, or differently, than the unaffected limbs. The difference can be partially explained by decreased strength [13], [73], decreased capacity for work, or an increased sensitivity to fatigue [76] of the affected limbs. Patients may also have difficulty controlling movement [75], [77]. More generally, humans are thought to maximize subjective utility to choose how to behave [78]. This utility decreases as the subjective costs of ease and other factors such as control ability of the task increase. We may therefore view the way in which humans choose to allocate effort among their limbs as a minimization of a subjective cost of the performance of a given task [Chapter 2].

To determine if people minimize some subjective cost consistently when they decide how to accomplish a task, we introduced an exercise in which we unevenly weight limb power contributions toward a scalar goal amount of this weighted power. Effectively, the weightings make it possible to reduce the overall work required for the subject to satisfy their exercise goal if they favor the more heavily weighted limb group. Skinner and Kuo have shown that subjects respond to weighted power tasks with altered effort distributions, in part to reduce the work required to match their goal, but they also demonstrate a willingness to generate more power than necessary to satisfy more subjective objectives [Chapter 2]. Furthermore, subjects do not need knowledge of the specific weighting or the distribution of their limb power desired by the experimenter. Thus, we may leverage the subject's natural inclinations for ease as well as other subjective quantities to provide a useful tool to implicitly control the effort distribution to the subject's or patient's advantage.

Feedback is necessary to indicate the achievement of specific weighted power goals. Visual feedback can be used to allow the subjects to track their performance relative to a task goal. The feedback allows the subjects to judge their sense of effort in response to different power distributions that satisfy the task. In previous work, subjects generally chose power distributions that reduced the mechanical power necessary to achieve the task goal [Chapter 2, 3]. The reduction in work enabled a subject to pedal the experimental equipment, a recumbent stepper, more slowly. In other words, the preference for lower power production was coupled to any preference for lower speeds.

Alternatively, information about limb use could be communicated via a change in the resistance to motion of the exercise machine. Resistance could be decreased if the subject used the heavily weighted limb group more, in addition to the reduction in the total power necessary to match their visual feedback goal.

Furthermore, there may be inherent preferences for different levels of resistance, independent of preference for low power, which may be used to alter the power distribution during exercise.

In this work, we hypothesize that humans will demonstrate preferences for lower power and resistance that will allow for the manipulation of their distribution of effort between limb groups. We expect that preferences will be consistent with our general hypothesis that humans commonly search out less effortful methods by which to satisfy a given task, and so shall generally self-select limb use distributions that result in lower power generation, when possible. We also believe that subjects will prefer lower resistances if they perform self-paced exercise with no visual feedback or power requirements. If preferences for low resistance exist, independently of power requirements, exploitation of these preferences could steer effort toward targeted limb groups without the need for visual feedback. Changes in resistance can be felt directly by a user, and therefore would not require visual feedback to inform the subject of their power distribution. Self-selected exercise intensities have been shown to increase compliance in strength-training programs while subjects maintain adequate amounts of exercise for a number of target populations [79]–[83]. Therefore, the ability to steer effort without strict guidelines on power or the need for visual feedback may be beneficial.

Methods

We experimentally quantified how human subjects divided power between limbs during multi-limb exercise, and how implicit weighting of limb powers affects that distribution. Furthermore, we compared a task in which weighting power contributions from arms and legs changed the speed (and thereby power) necessary to complete the task with one that altered the required power via a change in resistance. Both tasks used visual feedback to display performance and task goals to the subject. We went further to compare the use of visual feedback with a set of self-paced trials. These trials were given without visual feedback, but still included changes in resistance to movement dependent on the subject's power distribution among their limbs and the task weighting. However, the exercise did not have specific goals about power generation or speed.

Fifteen healthy adult subjects participated: 9 male and 6 female, age 24.6 ± 4.36 years (mean ± standard deviation). All subjects provided written informed consent according to University procedures.

For the multi-limb exercise task, we instrumented a NuStep recumbent stepper machine (TRS 4000, NuStep, Inc., Ann Arbor, MI), to measure individual limb power and adjust resistance to motion (Figure 4.1 A). We provided visual feedback about their task and performance with a display screen (Figure 4.1 B). A seated subject moved all four limbs against a variable load and power was calculated via custom load-cells and gyroscopes. We calculated individual limb power via the dot product of measured torque and angular velocity. A low-pass filter smoothed the cyclic power caused by the stepping motion (Figure 4.1 C).

Our experiment included a familiarization phase, followed by an experimental phase. Before data was recorded, familiarization introduced subjects to the feedback. Familiarization was intended to allow subjects to gain knowledge of the effect of the weightings, which we term Task Weightings. We introduced a number of the weights to the subject and instructed them to explore a range of

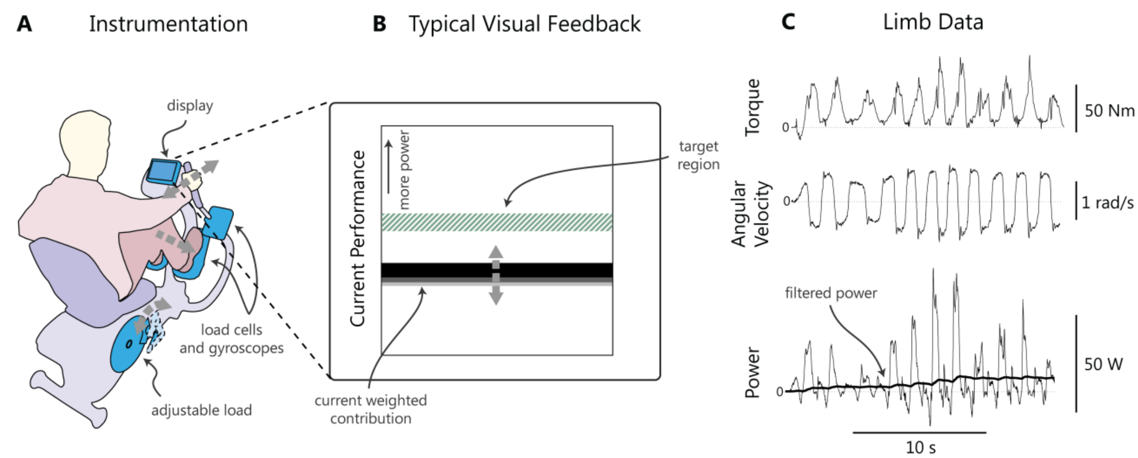

Figure 4.1: Experimental Setup

A: The NuStep recumbent stepper was instrumented to measure the power generated at each individual limb. The machine resists motion via an adjustable load. Finally, information about the task and performance can be displayed to the user on an LCD screen. **B:** The exercise task consists of reaching a target level of weighted power (Current Performance). The target and the subject's current weighted contribution are displayed. **C:** Load-cells measure force, which is used in combination with machine dimensions to calculate torque. In addition we measure angular velocity via gyroscopes and calculate the dot product of these two measurements to yield an individual limb's power. A low-pass filter is applied to the power calculation to smooth the cyclical signal.

different limb combinations that would satisfy the current task's feedback goal. The subject could therefore feel the different required power from arms and legs necessary to fulfill the task under different implicit Task Weightings.

In the subsequent experimental phase, we determined each subject's preferred distribution of effort during implicitly weighted tasks. We randomly assigned Task Weightings, unknown to the subject, and measured their preferred Performance Bias. The weighting was varied with each condition, and subjects were asked to achieve a specified amount of weighted power without knowing the implicit weight.

The experiment was performed with visual feedback only (Visual Feedback Trials), visual feedback with continually altered resistance (Resistance Trials), and also without visual feedback but with changes in resistance (Self-paced Trials). The task consisted of generating a goal amount of weighted power for both the Visual Feedback and the Resistance Trials. Note that visual feedback was still necessary for the Resistance Trials to control for the subject's level of weighted power. We brought back a portion of the same subject pool (N = 5) for additional tests of trials which altered resistance without visual feedback. Subjects were aware that changes in their distribution of effort would affect the resistance felt, but were only told to exercise at comfortable levels, allowing the subject to choose the power, speed and distribution of power among limbs.

Subjects generated power with their arms and legs to match an exercise task goal. Task Weightings allowed arms and legs to contribute toward the exercise goal according to:

$$\text{Performance, } P = \frac{(2-|\lambda|)}{2}\left((1-\lambda)P_{legs} + (1+\lambda)P_{arms}\right) \qquad \text{(Equation 4.1)}$$

where a goal amount of Performance, *P* (target region in Figure 4.1 A), can be set, and λ is a Task Weighting which gives arms or legs unequal contributions toward the task goal. A value of λ = -1 corresponds to giving credit for power from the legs alone, λ = 1 to the arms alone, and λ = 0 to equal weighting. The more the subject uses the more heavily weighted limb group, the less mechanical power is necessary to satisfy a goal amount of their Performance. Each value for λ is thus a task that a user would be expected to perform with a different combination of power from their limb groups. The nominal *P*, under a neutral weighting (λ = 0), was set to be equivalent to 40W of mechanical power.

We created two measures to summarize limb use under different weighted conditions (Figure 4.2). Preferred limb use was summarized by a Performance Bias parameter, *B*, which expressed the amount of net power generated by the arms and legs. It was computed according to:

$$\text{Performance Bias, } B = 2\left(\frac{P_{arms}}{P_{arms}+P_{legs}}\right) - 1 \qquad \text{(Equation 4.2)}$$

Here, a *B* value of -1 corresponds to producing 100% of net power with the legs, and 1 with producing 100% of net power with the arms. Note that it is possible to produce values of *B* greater than 1 and less than -1 if significant negative power is generated with one limb group (e.g. -5W with legs and 25W with arms would result in a *B* of 1.5). At other points we wished to simply quantify the ratio of the arm power to net power. It was computed similarly to Equation 4.2:

$$\text{Arm Power Ratio, } A = \frac{P_{arms}}{P_{arms}+P_{legs}} \qquad \text{(Equation 4.3)}$$

Subjects first explored different combinations of limbs to find their preferred distribution, which we termed the Exploration period. Then, in an Assessment period, we measured the subject's power generation and calculated their mean distribution. We characterized the relationship between implicit weights and mean limb use with a logistic curve fit. The curve described the Performance Bias as a function of Task Weightings. This curve has asymptotes at two extremes, and changes monotonically between the two with task weighting:

$$\text{Manipulation of Performance, } B(\lambda) = B_1 + \frac{B_2 - B_1}{1+e^{-\sigma(\lambda-\Lambda^*)}} \qquad \text{(Equation 4.4)}$$

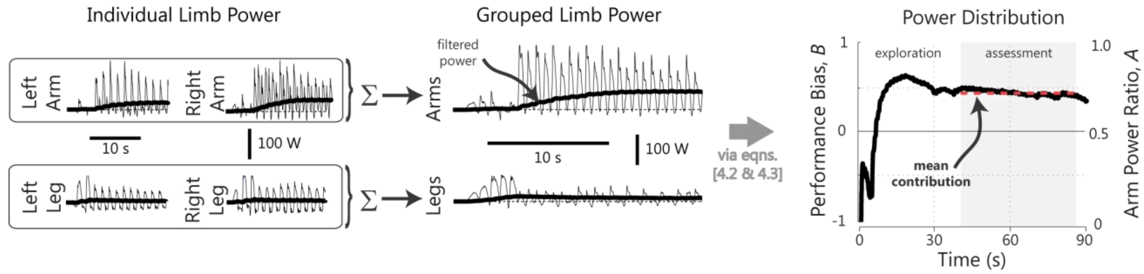

Figure 4.2: Combination of Limb Power to Yield Outcome Measures

Individual limb power is combined into arm and leg power. Next, the overall power distribution is calculated via the ratio of arm power to net power that is either scaled to range from -1 to 1 (Performance Bias, Equation 4.2), or unscaled (Arm Power Ratio, Equation 4.3). Power is low-pass filtered to smooth cyclical data due to stepping during the exercise.

where B_1 and B_2 are respectively lower and upper asymptotes. Parameter σ characterizes the sharpness of the curve, where larger values tend toward a step function, and A^* is the weighting which results in the largest change in limb use (effectively a shift in the curve left or right). Shifts of the curve left or right result in an unequal reported distribution of effort at the neutral weighting bias, which indicates the subject's preference for arms or legs with a neutral weighting.

We also explored subject limb use over the time course of each trial (Figure 4.3). Over the course of each trial, subjects explored different combinations of limb use to experience the subjective costs associated with each task (Figure 4.3 A). Subjects were allowed to alter their preferred power distribution at any time, but usually found a steady-state distribution after about 30-45 seconds. After exploration, subjects would choose their preferred power distribution. We computed the time course of their Arm Power Ratio and deviations from steady-state (calculated as the mean of seconds 40-85, known as the Assessment period) (Figure 4.3 B). Over all trials for each subject, we calculated an exponential fit to all absolute deviations from steady-state for Visual Feedback and Resistance trials starting after the first 5 seconds (Figure 4.3 C). The exponential curve describes

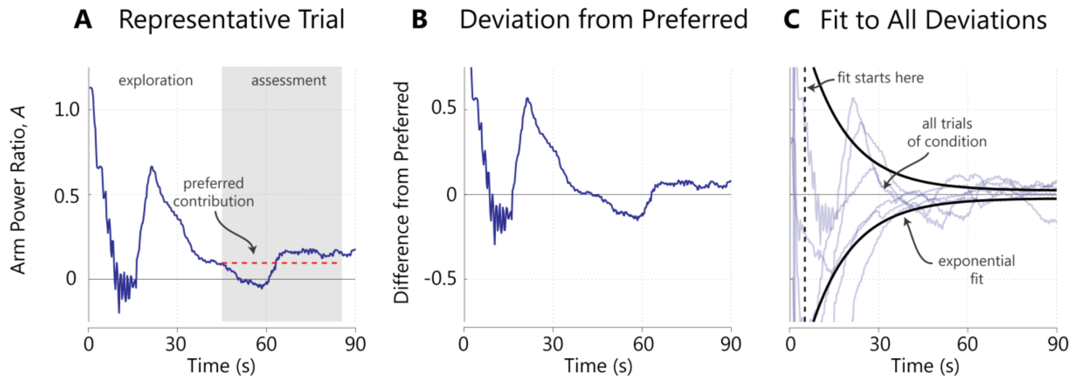

Figure 4.3: Representative Time Series Results

A: Over the length of the trial, the subject's power distribution is calculated in terms of the ratio of arm power to net power (Equation 4.3). The subject's "preferred contribution" is calculated as the mean Arm Power Ratio over roughly the second half of the trial. **B:** Deviations from the subject's preferred contribution in terms of Arm Power Ratio **C:** An exponential function is fit to each subject's complete data set of deviations away from their preferred arm power ratio. The fit describes the rate at which the subject approaches their preferred Arm Power Ratio, and the variability about this preference. The fit's parameters for each subject can be compared between Visual Feedback Trials and Resistance Trials.

the rate at which subjects made their choice for their effort distribution, and the level of variability at that choice, on average. We reported the time constant and asymptote of the fits for each subject's Visual Feedback Trials and compared them to the fitted parameters for the Resistance Trials. The time constant describes the rate at which the preferred contribution was approached, and the asymptote describes the amount of steady-state variability.

We provided three methods to convey information about the implicit weights to the subjects, and also tested if subjects would alter their power distribution away from their preferred distribution with no visual feedback. The study consisted of 6 Visual Feedback Trials, 14 Resistance Trials, and 6 Self-paced Trials. Within a set of trials, each individual trial was 90 seconds long, with Task Weightings, λ, distributed in the range -1 to +1. Each weighting was given in random order, again unknown to subjects. Each trial was followed by a brief rest, with longer rests if requested by the subject to avoid fatigue. The Visual Feedback Trials and

Resistance Trials were grouped into blocks, and these blocks were presented in alternating order with each additional subject. The self-paced trials were given on a follow-up day for a subset of the subjects (N = 5 of 15). All statistical comparisons used Student's paired t-test unless otherwise noted. The threshold for significance was set at $\alpha = 0.05$.

Results

We found that implicit tasks which used visual feedback or changed resistance to motion in response to the subject's effort distribution had a systematic effect on limb use during exercise. Tasks weighted toward a particular limb pair generally resulted in a greater preference for those limbs. In the absence of visual feedback, subjects still demonstrated a preference for low resistance, which allowed altered power distributions among arms and legs through changes in resistance as a function of limb use and Task Weighting.

For Resistance Trials, there existed a consistent and repeatable overall trend in Performance Bias vs. Task Weighting. However, there was significant variability in the Performance Bias at each individual weighting. We investigated limb group power and the source of this variability across Task Weightings (Figure 4.4). We found high variability was associated with the less heavily weighted limb group. More heavily weighted limbs were used more and with less variability than those limbs which received less credit toward the subject's Performance goal. We believe this is a favorable source of variability, as the limbs targeted to receive more exercise do so more consistently.

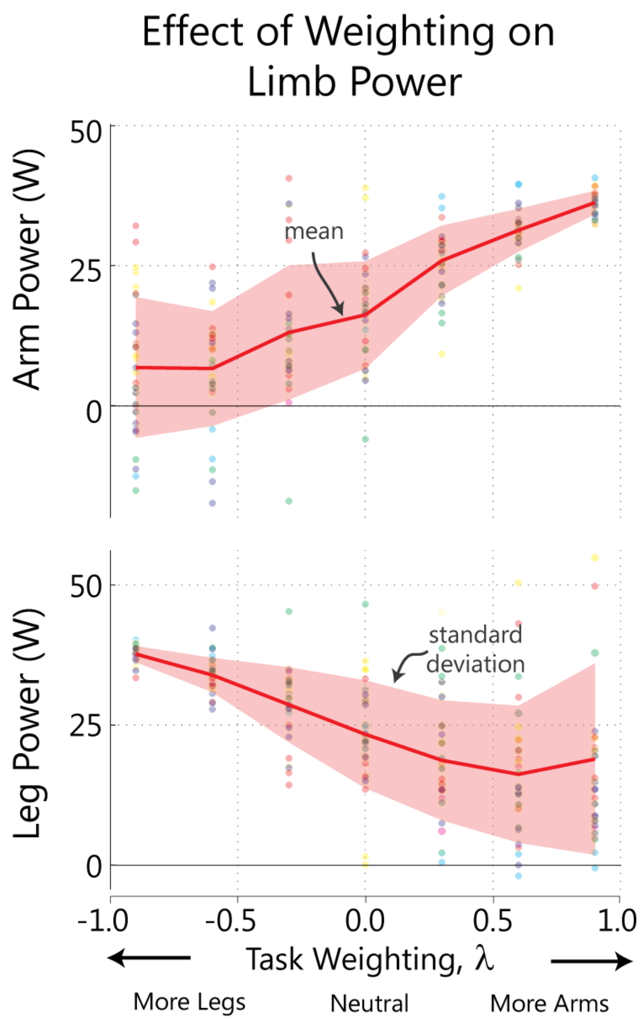

Figure 4.4: Limb Power as a Function of Task Weighting for Resistance Trials

Individual limb group power vs. Task Weighting. The mean is indicated with the solid line. The shaded region is the standard deviation of limb group power at each weighting. The more heavily weighted limb group is used more and with less variability than the less weighted limb group.

Resistance Trials and Visual Feedback Trials resulted in similar effort distributions and variability (Figure 4.5). We analyzed the subset of the Resistance Trials data which used the same weightings as the Visual Feedback Trials to compare between the modalities (λ = -0.6, 0.0, and 0.6). The Visual Feedback data collected here serves as a benchmark against a previous study's findings that concluded visual feedback of Performance and target levels of weighted power

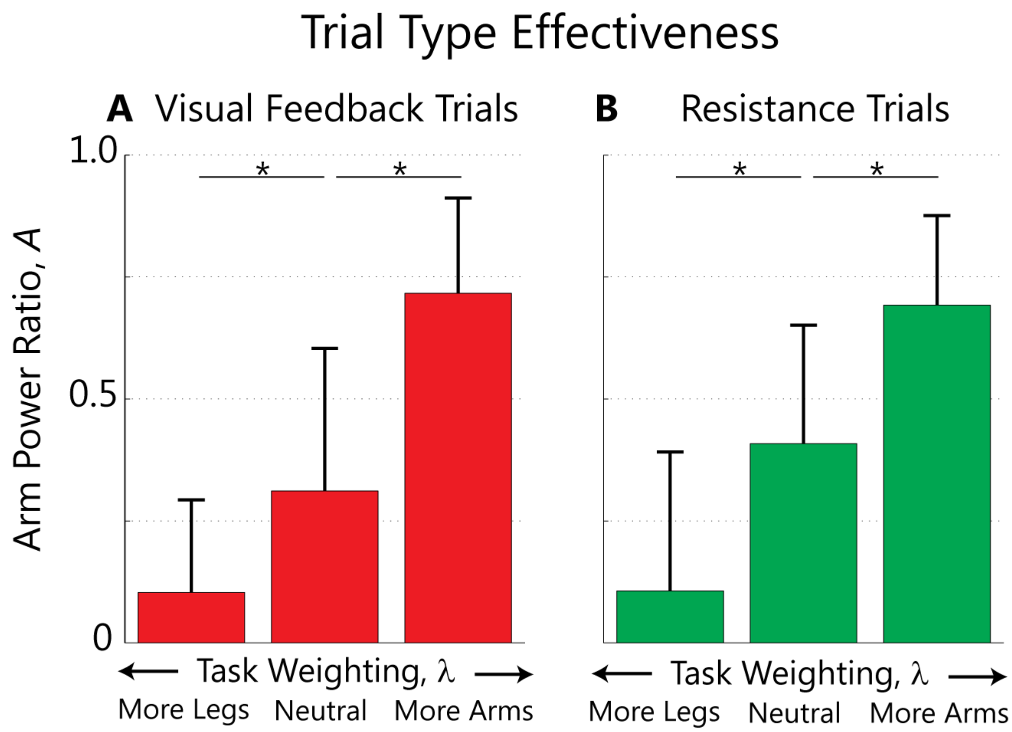

Figure 4.5: Visual Feedback vs. Resistance Trial Results

Three weighting conditions were given to subjects using either Visual Feedback or via changes in resistance (Resistance Trials). Mean Arm Power Ratios were calculated for the last half of each trial. Significant differences exist for both Visual Feedback Trials and Resistance Trials for conditions weighted away from neutral (* denotes significance, p < 0.05).

enables subjects to steer limb group power toward heavier weighted limb groups [Chapter 2]. In the current study, tasks that gave more credit for arms or legs resulted in greater use of that limb group, respectively (Performance Bias under conditions λ = -0.6 and λ = 0.6 vs. λ = 0.0; Visual Feedback Trials: p = 1.2e-5 and p = 6.9e-7, respectively; Resistance Trials: p = 3.5e-6 and p = 4.9e-7, respectively). Furthermore, subjects demonstrated similar distributions, independent of trial modality (Performance Bias at λ = -0.6, λ = 0.6, and λ = 0.0 for Resistance vs. Visual Feedback Trials, all p > 0.10). However, variability when using Visual Feedback for the leg biased trials (λ = -0.6) was significantly lower than the corresponding Resistance Trials (F-tests comparing Performance Bias variability between Visual Feedback Trials and Resistance Trials for λ = -0.6, p = 0.033).

Visual Feedback Trials and Resistance Trials demonstrated similar temporal characteristics as well (Table 4.1). We again used the same subset of Resistance Trials and all Visual Feedback Trials. We compared the time course of each subject's effort distribution against their steady-state choice with an exponential fit. Subjects in both forms of trial approached their choice for limb group distribution steadily and similarly. Subjects reached a distribution within 10% of their steady-state distribution in 47.5 seconds and 45.8 seconds on average for Visual Feedback Trials and Resistance Trials, respectively. Each fit's time constant, which represent speed of progress toward steady-state, were similar for each trial type's fit: 0.064 ± 0.031 (mean ± standard deviation) for the Visual Feedback Trials and 0.057 ± 0.024 for those trials also using changes in resistance, showing no significant difference (p = 0.54). The asymptote of each fit reflects variability about the preferred contribution, away from the calculated steady-state distribution. The asymptote for the exponential fit was an Arm Power Ratio equal to 0.015 ± 0.078 for the visual feedback trials, and 0.029 ± 0.022 for resistance trials, again with no significant difference (p = 0.62).

Analysis of the complete set of resistance trials data revealed that each subject

Measure	**Time Constant**	**Asymptote**
Units		*(A)*
Visual Feedback Trials	0.064 ± 0.031	0.015 ± 0.078
Resistance Trials	0.057 ± 0.024	0.029 ± 0.022
Different? (p-value)	0.54	0.62

Table 4.1: Comparison of Visual Trials and Resistance Trials Temporal Characteristics

Exponentials were fit to the Arm Power Ratio over time for each kind of trial. Each fit's parameters were reported, along with a comparison of the parameters between the two types of trial.

exhibited a unique limb preference curve. To illustrate the variations between subjects, a representative 6 of the 15 individual preference curves of form Equation 4.4 are shown in Figure 4.6. Although individual subjects displayed quite different trends in performance in reaction to the weighting, they shared some key characteristics. We believe the most important is that all subjects displayed an increasing relationship between Task Weighting and Performance Bias. No subject consistently used a limb group more if they received less credit for power from that limb group toward their Performance goal, and no subject demonstrated complete insensitivity to the Task Weighting. Another shared

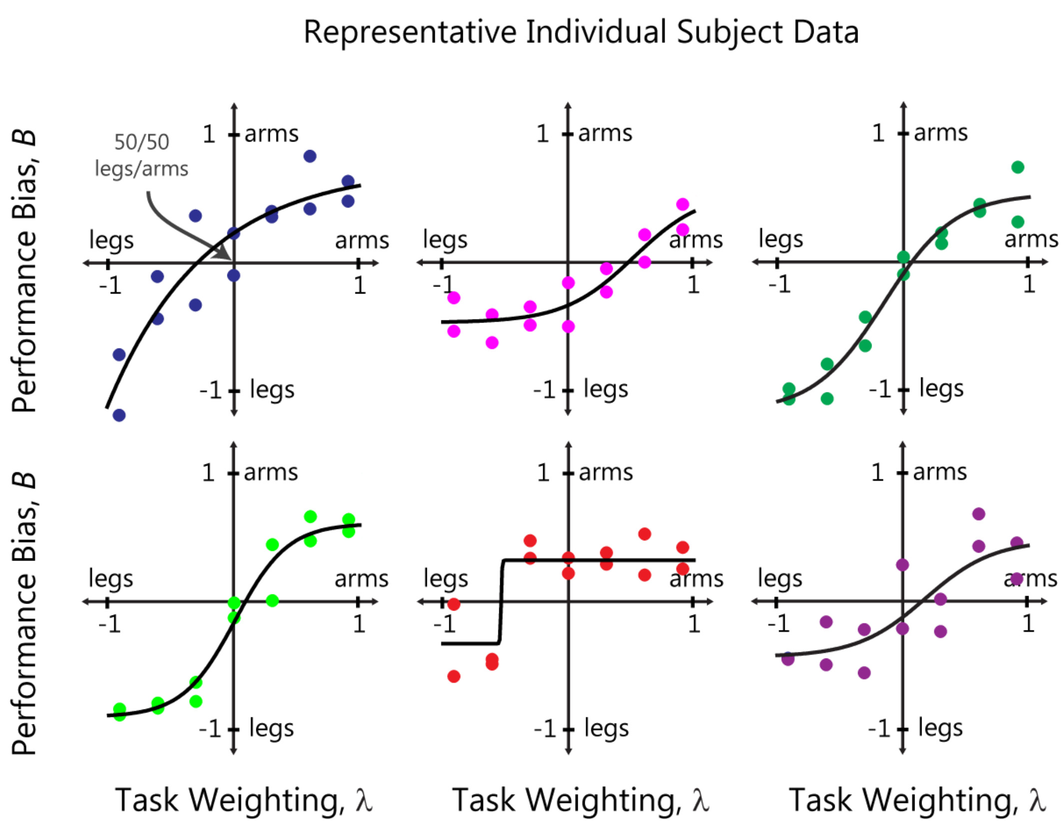

Figure 4.6: Representative Individual Results

Six of the 15 individual fits of form (Equation 4.3) for Resistance Trials. The Task Weighting, λ, credits the power generation of limb groups unevenly, ranging from only giving credit for the power generated by the arms (λ = 1) toward the exercise task, to only giving credit for power from the legs (λ = -1). The Performance Bias, *B*, quantifies the amount of limb group use in relation to the total net power. *B* = 1 indicates the arms produced 100% of the net power, and *B* = -1 indicates that the arms produced 0% of the net power. Median R^2 for individual fits was 0.86.

characteristic was the relative consistency of intra-subject data. For each subject, individual trials did not stray far from the trend line for that subject's complete data set (median R^2 of all individual subjects' fits: 0.86).

To summarize the overall trend for Resistance Trials, a single limb preference curve of form Equation 4.4 was fit to all of the subject data (Figure 4.7). The overall fit of Performance Bias vs. Task Weighting confirms the consistency and repeatability of intersubject performance. The lower and upper asymptotes of the logistic fit were B_1 = 0.03 95% confidence interval (CI): -0.11/0.17, and B_2 =0.74 CI: 0.63/0.85, which indicate the limits to which subjects altered their use of arms and legs. The data indicate subjects were much more willing to forego use of their arms and complete the task almost completely with their legs than vice versa. The average arm use at the weighting which almost exclusively credited

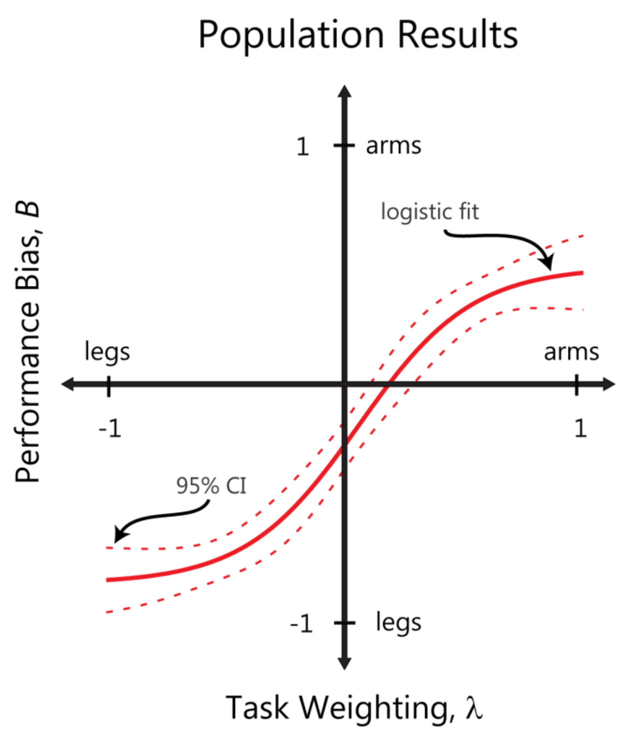

Figure 4.7: Manipulation of Performance Function for All Subjects

Performance Bias vs. Task Weighting. A single fit of form (Equation 4.3) is applied to all subject data. The 95% confidence interval (95% CI) of the fit's parameters is plotted as a dotted line.

power from the legs was 6.9% of net power (3.1W of a mean of 44.8W). However, when the weighting heavily biased arm power, subjects still preferred to use their legs to produce 29.4% (13.1W of a mean of 44.5W) of the net power, on average. The population also preferred to use the legs more than arms under the neutral weighting condition, though with enough variability throughout the population that the result was not significant (59.2% vs. 40.8%, reflected by the parameter Λ^* = -0.07 CI: -0.23/0.09).

According to (Equation 4.1) the power required to satisfy the task could always be minimized by using only those limbs receiving a heavier weighting, no matter how much the weighting was biased. Still, subjects preferred to alter their power distributions more in proportion with the weighting (smoothness of the curve reflected by the parameter σ = 3.67 CI: 1.30/6.04). Subjects' willingness to produce more power than necessary hints at costs, beyond mechanical power, associated with performing the task that may influence how the subjects split their effort.

Subjects demonstrated a similar preference in Self-paced Trials to alter their preferred limb use away from their nominal unweighted Arm Power Ratio. Uneven weightings now changed the resistance to motion of the machine, but there was no visual feedback provided. Subjects freely chose power, distribution of effort, and the speed at which to exercise. Still, subjects decided to generate 50.2 ± 13.8W of power during the trials.

Under uneven weightings, subjects directed effort toward those limbs whose use would result in reduced resistance to movement. Similar to Resistance Trials, subjects in Self-Paced Trials chose power distributions under uneven weightings significantly away from those chosen distribution with a neutral weighting (λ = -0.9 and λ = 0.9 vs. λ = 0 were significantly different, p = 0.035 and p = 1.8e-4, respectively) (Figure 4.8). Lower resistance to motion was generally preferred in the population, despite the absence of a specific required amount of weighted power. When use of legs reduced the resistance to motion (condition: λ = -0.9), subjects chose to use the legs to supply 84.0% (42.4W of the mean 50.4W) of net power. When arms were weighted more heavily (condition: λ = 0.9), subjects used them to produce 72.1% (41.9W of the mean 58.1W) of net power. Subjects always had the choice not to alter their limb distribution toward target limbs, which would result in increased resistance to motion, but would not require them to generate any additional power, since their effort was self-paced. Subjects could have chosen to simply slow down if they desired lower power output.

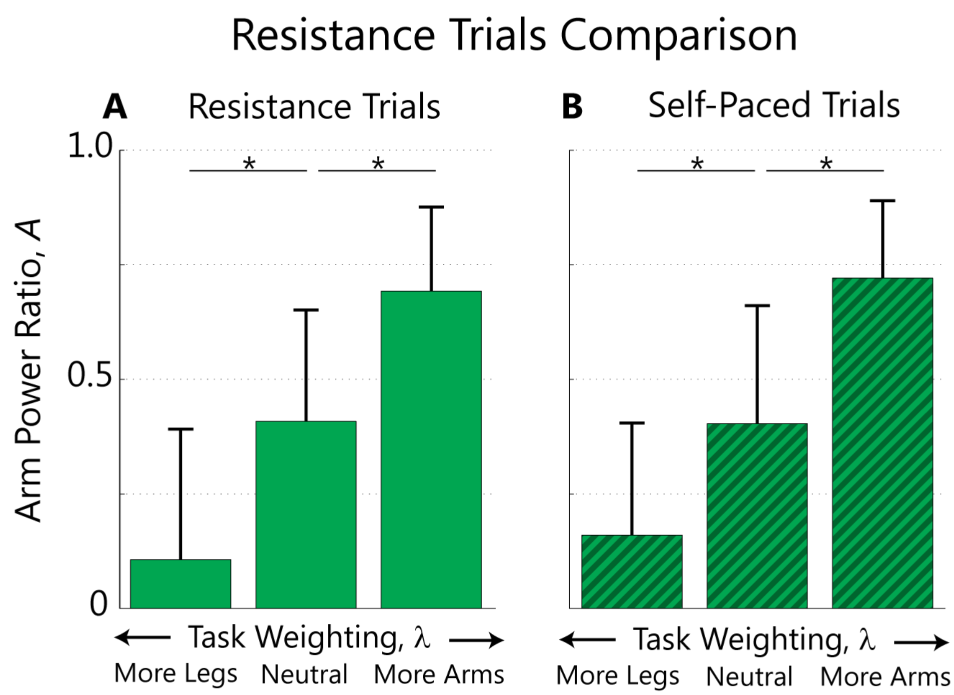

Figure 4.8: Self-paced Power Distributions Resistance Trials with and without Visual Feedback

Arm Power Ratio as a function of Task Weighting. **A:** Arm Power Ratio for Resistance Trials with three different Task Weightings. **B:** Arm Power Ratio for Self-Paced Trials under the same Task Weightings. Subjects significantly alter their power distribution for weightings that give more credit for arms or legs relative to the neutral performance for both Resistance Trials and Self-Paced Trials (*denotes p < 0.05).

Finally, we compared limb use between Resistance trials that still had visual feedback, with Self-Paced trials where no visual feedback was present. Despite the lack of constraints on speed or power performed, power distributions in the Self-paced Trials were quite similar to those in the Resistance Trials. Subjects displayed similar Performance Biases and variabilities in both kinds of trial (Table 4.2 – unable to find significant differences between trial types).

Discussion

Visual feedback, with or without the addition of proprioceptive feedback via changes in resistance, can be used to alter limb power distributions. Furthermore, even without any visual feedback, subjects displayed a preference for low resistance, which can be coupled to specific limb use to encourage greater recruitment of those limbs.

There may exist in this study evidence for self-imposed regulation of exercise under self-selected conditions. For the Self-paced Trials, in which there was no visual feedback, subjects self-selected speed, power, and resistance in a fairly consistent manner. It may be interesting to investigate whether subjects regulate

Task Weighting (λ)	Performance Bias		Different? (p-value)
	Self-paced (30 trials)	Resistance (90 trials)	
-0.9	-0.68 ± 0.49	-0.86 ± 0.60	0.391
0.0	-0.19 ± 0.51	-0.18 ± 0.49	0.957
0.9	0.44 ± 0.34	0.41 ± 0.35	0.810

Table 4.2: Comparison of Resistance and Self-paced Trials
Performance Biases for different Task Weightings in Self-Paced and Resistance trials. Biases reported in terms of mean ± standard deviation. A 2-sample t-test between Self-Paced and Resistance Trials tested if the two modes of trial result in different Performance Biases. We found no differences in effect between the two modes of exercise.

one or more of these factors when they are free to control all three. Subjects reported that although they chose to endure some minimal resistance such that the exercise was challenging, they would not naturally choose a higher resistance. Two subjects noted that they wanted to choose a speed to reach a comfortable pace, and then choose a preferred balance of resistance and power distribution by altering their power distribution among limbs. It was mentioned that, at high resistances, the exercise was closer to the level of exertion (albeit self-imposed) of weight-lifting, and dissimilar to aerobic exercise, which was preferred on this machine.

During trials with visual feedback, subjects displayed a tendency to avoid power generation in excess of the required amount necessary to complete the task. However, an individual's assessment of effort is subjective. A variety of other costs may also be important that cause subjects to choose distributions of effort which result in non-minimal power. These may include cognitive loads associated with conscious splitting of effort among limbs [Chapter 3], force magnitudes and physiological capacity for generating power in individual limbs [24], and even highly subjective factors such as comfort and stability [9], [11]. These subjective factors manifest in the shape of the trade-off between Task Weighting and Performance Bias. If subjects chose the combination of limbs that resulted in the minimal amount of mechanical power required for the task, they would only use the more heavily weighted limbs. Using only the more heavily weighted group minimizes the power necessary to satisfy the task constraint of form Equation 4.1. The result of this pure minimization would be a step function in the Manipulation of Performance curve (Figure 4.7) and a large σ in the fit of form Equation 4.4. Instead, subjects chose to produce significant power from both limb groups for many of the weightings. Therefore, they assumed a cost, in terms of mechanical power (difference from the minimum), which they were willing to spend in exchange for the perceived benefits of other factors. The ability to indirectly measure the effect of subjective factors using mechanical power may prove useful for the prediction and control of exercise and behavior in general.

Limitations on the study include time delays in the visual feedback due to filtering cyclical powers, and also delays changing resistance, due to the amount of time needed for the servo to physically change position.

It is possible implicit weighting of limb contributions may be used to the benefit of targeted strength training, or to promote the use of weakened limbs in rehabilitation. Growing evidence suggests that strength training in rehabilitation can be of benefit without detrimental effects on control, and that preferences for high force output under higher loads may be one way to increase the recruitment of weakened limbs [84]. Even though there are a number of ways to use implicit weights with or without feedback, we have demonstrated that uneven weighting power contributions toward a scalar amount of weighted power or lower resistance to motion can successfully alter effort distributions.

Supplementary Material

Subjective Cost Function

Similarly to Chapter 2, we can estimate the population's Subjective Cost Function from their Manipulation of Performance Function (Figure 4.9). In contrast with previous studies, the power required from each subject here was kept close to 35W via the difference between equations 2.1 and 4.1, which denote the task constraint. Therefore, we sampled the function in a smaller range of powers, which may yield a better estimate of its shape in that region, but makes us less confident about its shape along different indifference contours.

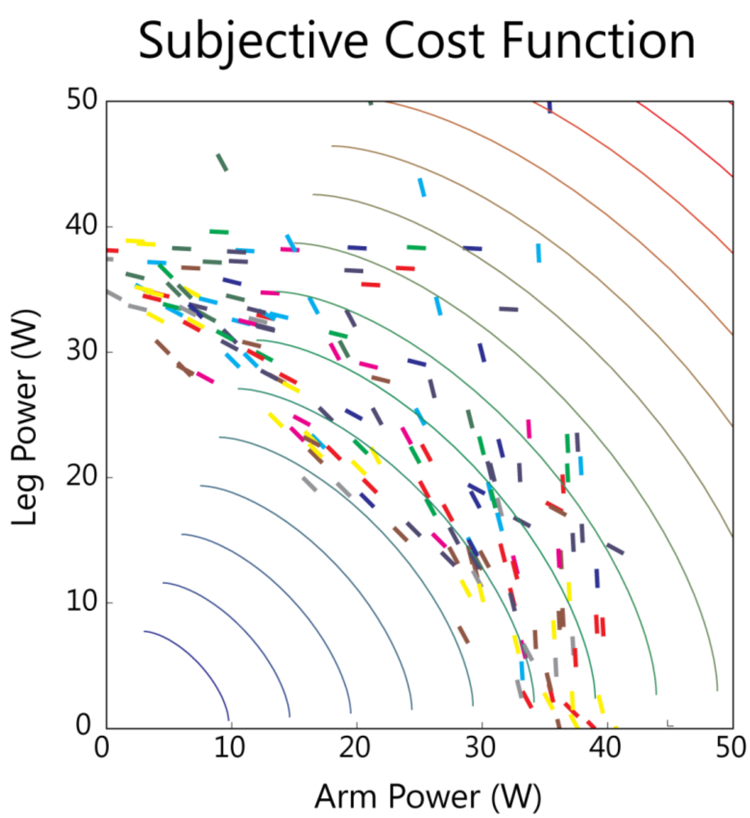

Figure 4.9: Subjective Effort Function for All Subjects

Contours of equal subjective effort, expressed as combinations of arm and leg power. Contours are derived from the Manipulation of Performance trade-off.

Setting Resistance

In this study's experiments, the resistance changed such that if the subject used the more heavily weighted limb group, the resistance would be lowered, and vice versa. We attempted to create equivalence between Resistance trials and Visual Feedback trials. Under either scenario, depending on the weighting, the subject enjoyed a benefit in terms of reduced required power if they used the more heavily weighted limbs, or suffered a penalty, in terms of increased required power, when they instead used the lesser weighted limbs. We attempted to make the penalty or benefit equal in terms of power for the two kinds of trial if the subject displayed the same distribution of power between limbs.

The primary source of power dissipation in the NuStep machine is via an eddy-current damper attached to an internal flywheel. Although there may be other sources of loss (friction, etc.), we assume them to be small as compared to the magnetic damping. We instrumented the damper to increase or decrease resistance via changes in overlap between the magnet and flywheel, operated by a servo.

We first calibrated the relationship between power measured at the individual limbs, the speed of the flywheel, and servo-controlled resistance. In one model, the power dissipation of eddy current resistance is proportional to the squares of the amount of overlap between the flywheel and magnet, and the flywheel's speed.[4] Our calibration function was therefore:

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[4] Adapted from Wikipedia: Eddy Current 2013

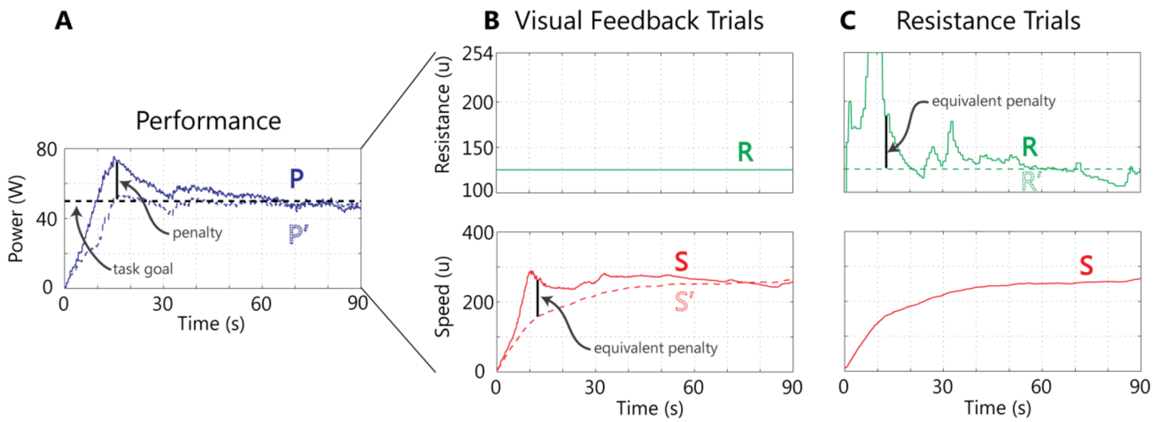

Figure 4.10: Resistance Calibration

A: Performance for a given task, in terms of the power actually generated (*P*) (Equation 4.5), and the current Performance (*P'*) (Equation 4.6). The difference between *P* and *P'* represents a penalty, in terms of power beyond the required power for the task. The subject would not need to generate this extra power to satisfy the exercise task if they only used the more heavily weighted limbs. **B:** In visual feedback trials, resistance is fixed and the subject must change speed to satisfy the task goal. They are equivalently only being rewarded for *S'* (The amount of speed that would equate to *P'* amount of real power). **C** For the resistance trials, the resistance is set such that their speed will be the same as their rewarded speed if resistance was a constant value (*S* for resistance trials is equal to *S'* for visual feedback trials–calculated via Equation 4.4). The equivalence results in equal penalties in terms of actual power, which is in terms of either speed or resistance—not a combination of the two.

$$P(r,v) = (\alpha_0 r + \alpha_1)^2(\alpha_2 v + \alpha_3)^2 \qquad \text{(Equation 4.4)}$$

Where *P* is the total power measured at the individual limbs, *v* is the speed of the internal flywheel, *r* is the resistance level, and alphas are constants to be determined. Total mechanical power is expressed as:

$$P = P_{legs} + P_{arms} \qquad \text{(Equation 4.5)}$$

And the weighted power awarded to the subject via the implicit feedback is:

$$\text{Current Perfromance,} \quad P' = \frac{(2-|\lambda|)}{2}\Big((1-\lambda)P_{legs} + (1+\lambda)P_{arms}\Big) \qquad \text{(Equation 4.6)}$$

The reward or penalty that arises from using certain limb combinations is the difference between the actual power generated, P, and the weighted power, P' (Penalty in Figure 4.9). We used the combination of Equations 4.4-4.6 to equate a resistance that would provide the same penalty as the difference in speed would create with identical subject performance.

Chapter 5.

Why Make More Work for Yourself? Factors beyond Economy of Movement in Drop Landing

Abstract

Humans can choose to perform a task in many different ways [85], yet often adopt movements that reduce muscle work [1], [16]. Sometimes, people may prefer to reduce metabolic energy expenditure via decreases in muscle force or increases in the time of activation, even if achieving no mechanical work benefit [86] [24]. In drop-landings specifically, researchers have noticed different landing strategies and associated energetics between males and females [87] and amateur and professional gymnasts [88], [89] which may indicate additional goals beyond energetic minimization. Minimization of overall muscle activation has been suggested to more accurately replicate experimentally derived mechanics than maximization of economy, which may even result in *increased* metabolic cost [37]. People may prefer to sacrifice economy to avoid subjective costs, such as discomfort [21], [90], [91]. Here we measure how people land on cushioned and non-cushioned surfaces to investigate a proposed trade-off between economy and other subjective factors.

Introduction

Despite a common desire in people to minimize extraneous effort, some activities encourage uneconomical behavior. In drop-landings, humans perform extra mechanical work beyond the minimum amount required. If humans landed with stiff straight legs and no bending at the hips, soft tissues such as cartilage and fat stores would dissipate the energy imparted by gravity during the drop passively, and the amount of work necessary to stop their descent would be minimized [21]. Instead, humans perform active muscle work to lower and raise their center of mass (COM) upon landing in such a way that they stop their fall more slowly than if they landed with straight legs.

There should be some perceived benefit to landing less stiffly since it requires extra work and sacrifices economy of movement. Devita et al. propose that humans may value reduced impact stresses, which are lowered during landing with bent knees as the muscles actively absorb more of the body's kinetic energy [92]. Or, as Minetti et al. discuss, it may be important in some circumstances to increase the height at which it is safe to drop [93]. It would be extremely painful, and potentially harmful, for people to land on straight stiff legs during many forms of locomotion. When people land on surfaces of different compliance, they bend their knees to maintain an overall constant effective stiffness of the legs/surface system [94][95]. Subjects that land on stiffer surfaces tend to produce lower peak forces and longer landing times than on softer surfaces [96]. Perhaps these results demonstrate a trade-off between compliance for safety, and landing with straight legs to increase economy. It is possible that humans could save energy via dissipation of energy with cushioned materials to create a more comfortable landing, and make landing with straighter legs more preferable.

In this study, we determined how subjective costs affect the mechanical work associated with impact during drop-landings. We hypothesized there may be a trade-off between the influence of apparently more major behavioral determinants, such as economy, and more subjective factors, such as comfort or stability. The trade-off may be thought of as an exchange rate between the two determinants. Changes in mechanical work under different conditions may indirectly characterize this exchange-rate and predict the mechanical work costs of the subjective influences in movement, similar to the work of Zelik, et al. [11].

Methods

We measured the work associated with a number of drop landing tasks onto different amounts of foam. We compared the mechanical work performed with the minimum amount of work necessary to land in order to characterize the influence of the foam's subjective influences on economy.

Eight healthy adult subjects participated in this study (6 male and 2 female, age 21 ± 0.9 years (mean ± standard deviation)). We recorded anthropomorphic data including leg length (0.93 ± 0.056m) and body mass (71 ± 15kg). Each subject provided written informed consent according to University procedures.

Subjects performed a series of drop-landings onto different thicknesses of foam over in-ground force plates (AMTI, Watertown, MA) (Figure 5.1). Each trial consisted of drop-landing on zero to four layers of foam. The landing surface had 0-4 layers of 2" (0.051m) foam or a bare landing surface (force plates alone). Subjects stood at the edge of a raised platform in an upright position. They were instructed to drop from their initial height and land as they preferred. Then they were to return to the upright posture they had at the beginning. Eight drops were performed per condition. Subjects were instructed to cross their arms during the drop. Crossed arms helped to reduce work peripheral to their center-of-mass (COM). Conditions were presented in random order.

We measured mechanical work associated with each drop and compared work beyond the minimum required for each foam condition. We measured ground reaction forces (GRFs) from in-ground force plates to describe each landing (Figure 5.4). We analyzed the vertical forces to measure COM velocity, position, and work rates. We divided forces by subject mass and subtracted the acceleration of gravity to calculate COM acceleration. We then integrated COM acceleration to yield vertical COM velocity, with the integration constant determined according to a final velocity of zero. Vertical COM position relative to the final position was calculated by integrating the COM velocity, and work rate was calculated by taking the dot product of the original vertical GRF and the COM velocity. Finally, negative and positive work is calculated by integrating the work rate over the course of the landing. We defined Collision Work to be the negative work and Recovery Work to be the positive work performed during landing. Recovery work is mostly performed in order to raise the COM of the subject to achieve their starting posture from its lowest height. Landing was said to begin when the vertical force was above 1% of body weight, which we termed touchdown. Landing was said to end when a moving average of the vertical work rate over 20ms measured less than 30W, or approximately 1% of peak work rates.

We attempted to maintain the same drop height across subjects and conditions to fix the minimum amount of work necessary to stop the fall for each subject.

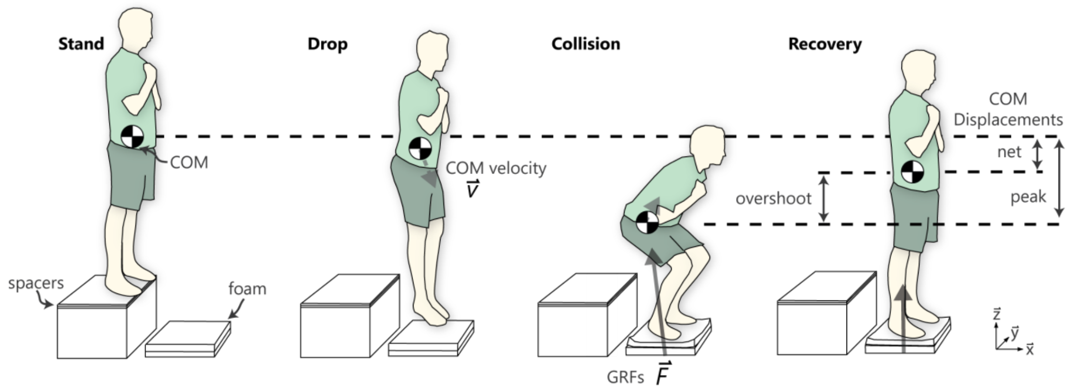

Figure 5.1: Drop-landing Protocol

Subjects stand at a height of roughly 0.4m above their landing level, with arms crossed. They are instructed to drop onto the foam and return to their original standing posture. Drops are performed on 0 to 4 layers of foam. Force plates measure the ground reaction forces (GRFs), which are used to calculate center-of-mass (COM) velocity and drop displacements (net, peak and overshoot) and work. Overshoot displacement is defined as the difference between the lowest position of the COM and the final COM position after landing.

The subject's gravitational potential energy on the drop platform is changed into kinetic energy during the drop. The person and landing surface must perform, at minimum, negative work equal to this amount of kinetic energy to come to rest, which is also equal to their original gravitational potential energy. The subject is free to perform additional positive and negative work beyond that which is necessary, although there will be no net work beyond the minimum negative work if the subject's final velocity is zero. Therefore, work beyond the minimum negative work required to stop the fall may be considered excess work. To achieve a fixed drop height, we added spacers to the drop platform to accommodate the variable depth to which subjects sank into different thicknesses of foam. We measured each subject's height on different layers of foam to determine their distance off the ground. We then added this thickness to the drop platform via spacers to fix the drop height. A number of spacers came in three thicknesses of 0.012m, 0.073m, or 0.155m. We chose the combination of spacers that best matched the offset in height caused by different layers of foam. The offset was typically 0.30-0.35m.

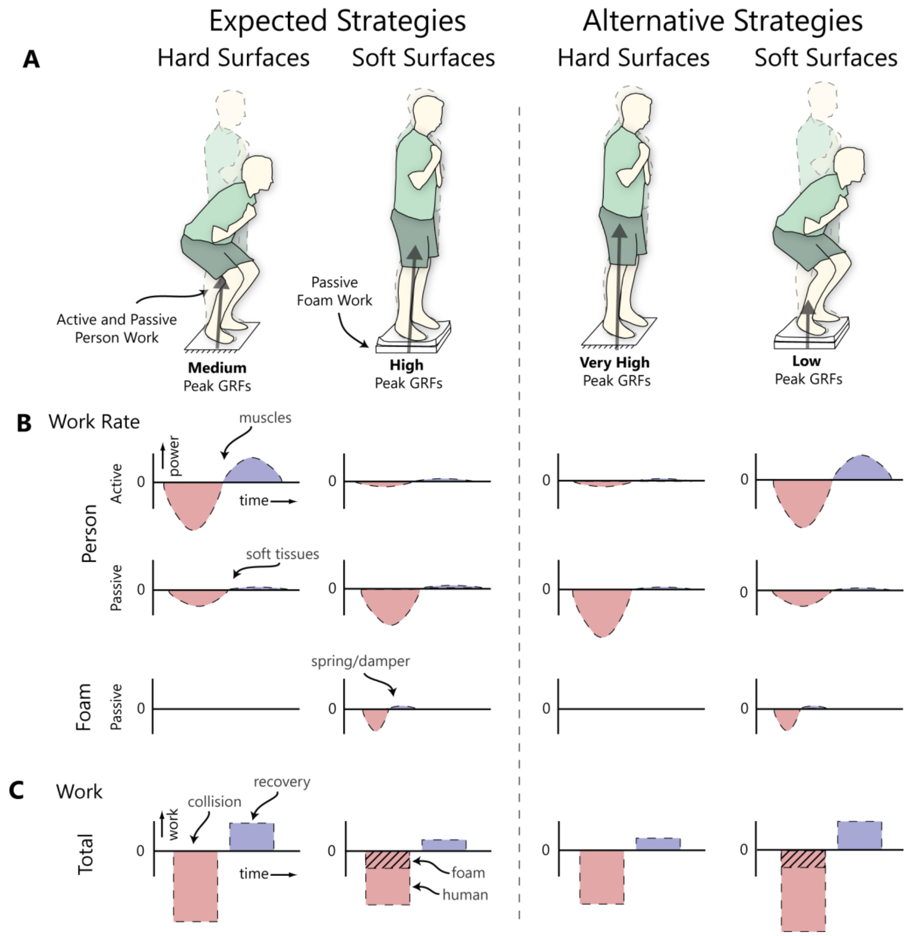

Figure 5.2: Possible Drop-landing Strategies

A: Subjects may demonstrate a number of landing strategies on bare ground and foam. The subject may change how much they lower and raise their center of mass (COM) depending on the surface. Their chosen strategy results in different contributions from muscles, soft tissues and the landing surface toward stopping the fall. **B:** Work rates from the person and landing surface, including those of the active muscle, passive soft tissues, and the passive spring/damper of the foam. **C:** Total positive and negative work during landing.

In accordance with the work of Butler and others, we expected that subjects would choose to lower and raise their COM to maintain equivalent overall compliance over many of the conditions, as it may help to reduce potentially damaging impact forces and cushion the subject's landing, despite costing more energy [92], [97] (Figure 5.2). For hard surfaces, with little foam, we expected that subjects will lower their COM beyond their final COM position to increase the time of collision and reduce forces. On softer surfaces, we expected them to land with less COM displacement beyond their final COM position. Alternatively, subjects may land stiffly on hard surfaces and allow soft tissues to dissipate energy or they may continue to lower their COM beyond their final position on soft surfaces.

We characterized the action of the foam independently from the experimental procedure similarly to Pain et al. [98]. We also determined typical kinetics and kinematics for the different thicknesses of foam from motion capture and force measurements of a small number of tests (Figure 5.3). The measurements allowed us to estimate contributions from the foam to the landing work of the subjects in our experiment. We found the foam to have a spring constant of ~1400Nm^{-1} and a damping coefficient of ~120Nsm^{-1} when operating in its linear region.

We compared a kinetics and kinematics of the subject during landing for each of the five foam conditions. We measured Recovery Work during landing, which is the positive work performed throughout landing by the COM. We believe that positive work is primarily due to muscles actively raising the COM from its lowest position to the final standing position. We also defined a measure of excess COM movement, which we called Overshoot, as the difference between the lowest and final position of the COM (Figure 5.1). If the subject landed with maximum economy (stiff straight landing), COM overshoot and Recovery Work would be zero. Therefore, Recovery Work represents the amount of extra mechanical work subjects are willing to produce in response to different landing conditions. COM Overshoot could reflect flexed ankle, knees and hips, which would lower their COM position. Force, velocity, position, work rate and work were non-dimensionalized with body mass, leg length, and gravity to yield unit-less measures. Unit-less measures allowed for comparison between subjects of

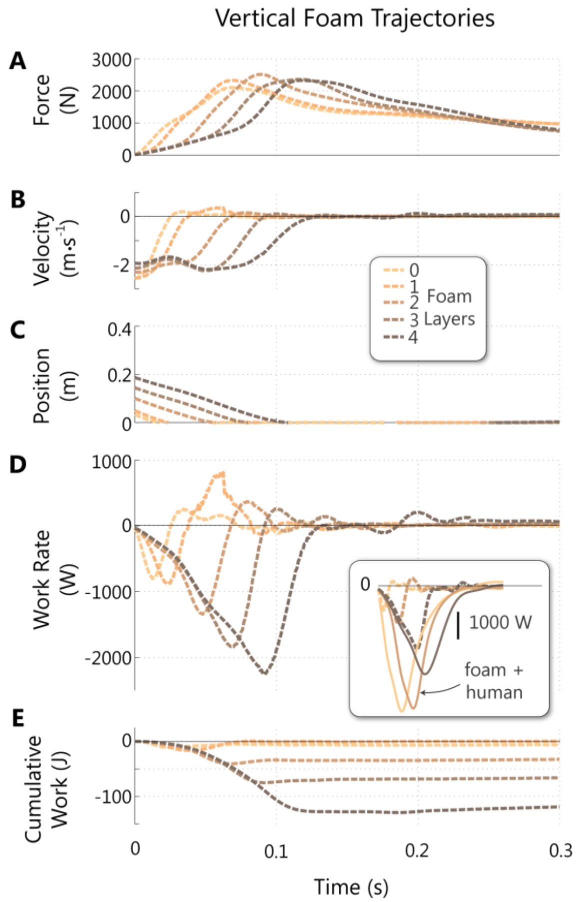

Figure 5.3: Time Series of Vertical Trajectories of Foam

Force, velocity, position, work rate and work quantities estimated for different thicknesses of foam. **A:** Measured vertical force over the course of a few typical landings. **B:** Estimated velocity of the top surface of the foam during landing. **C:** Estimated position of the top of the foam while landing. **D:** Work rate calculated as the foam's velocity multiplied by the force it conveys to the ground. A few conditions are compared to typical overall work rates of the foam and human drop combined. **E:** Cumulative work over the course of a drop. Foam work appears for a relatively short period of time during landing. The complete time course is used in later analysis of subject forces and work.

different sizes. For the five conditions, we compared outcome measures with repeated measures analysis of variance (repeated measures ANOVA). Where significant differences were found, we performed a set of paired t-tests under the Holm-Sidak step-down procedure to test for significant differences between individual pairs of conditions. Linear regression was used to describe trends throughout the entire population over all conditions. The threshold for significance was set at α = 0.05.

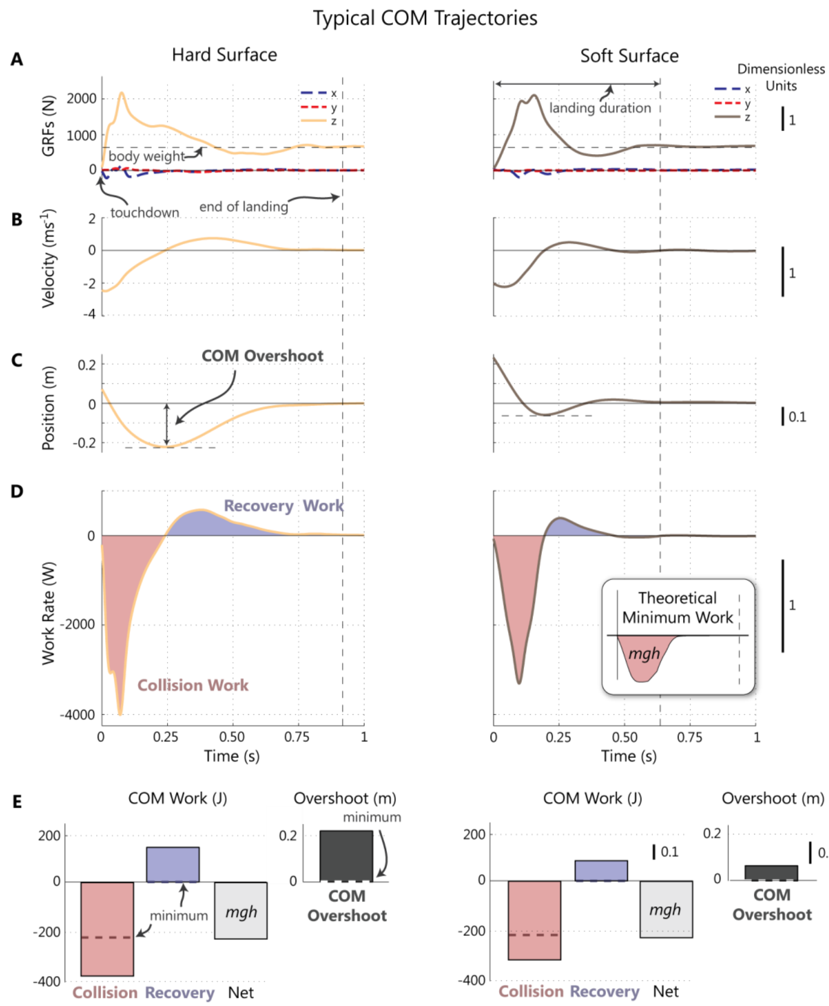

Figure 5.4:Typical COM Trajectories

Measured and calculated traces for two typical landings, one on a hard surface (0 layers of foam), and another on a soft surface (4 layers of foam). **A:** Ground reaction forces (GRFs) from an in-ground force plate during landing. **B:** Vertical COM velocity was calculated from the vertical GRF, accounting for gravity and zero final velocity after landing. **C:** Velocity was integrated to yield position. The difference between the lowest COM position and the final position was termed COM Overshoot. **D:** We calculated the work rate as the dot product of COM force and COM velocity. **E:** We integrated work rate to calculate COM work for the drop. Negative work is termed Collision work and positive work is termed Recovery work. Measurements were non-dimensionalized using body mass, leg length, and gravity to compare between subjects.

Results

We found that subjects reduced their COM Overshoot and performed less Recovery Work on cushioned surfaces than on bare ground. Furthermore, subjects displayed a longer onset to peak force production when landing on foam (Figures 5.5 & 5.6).

The calculated drop height did not differ between foam conditions (Figure 5.6 A, p = 0.77). The mean estimated drop height was 0.41 ± 0.008m (mean ± standard deviation).

Peak forces and time until peak force performed by subjects changed as a

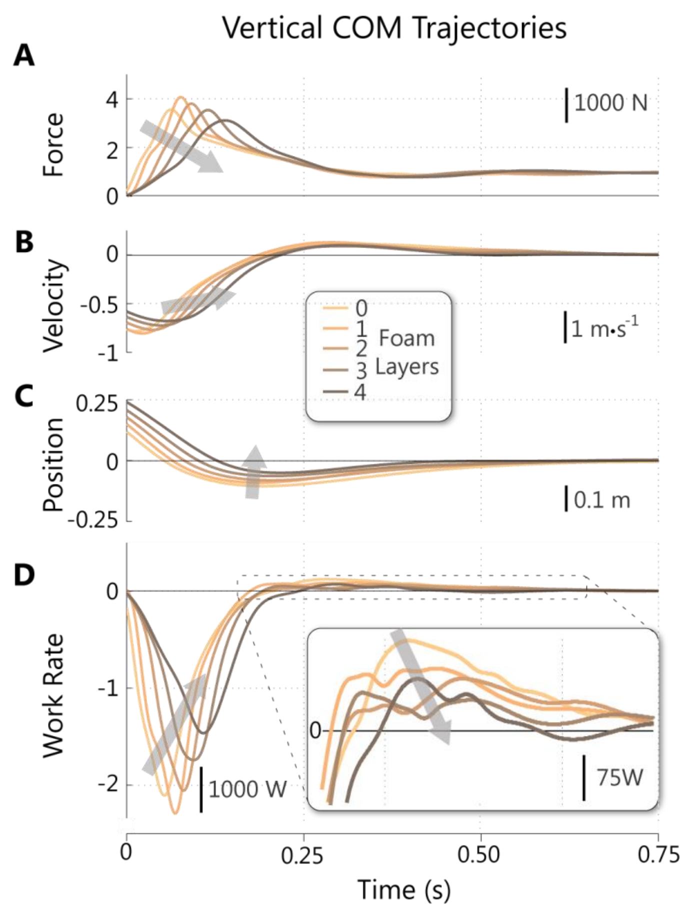

Figure 5.5: Mean Forces, Kinematics, and Work Rate for all Conditions

Force, velocity, position, and work quantities for different thickness of foam. **A:** The mean vertical force throughout landing for each condition. **B:** The COM vertical velocity throughout landing for each condition. **C:** Vertical COM position throughout landing. **D:** Calculated mean vertical work rate trajectories for each condition. Quantities were non-dimensionalized with body mass, leg length, and gravity to compare between subjects.

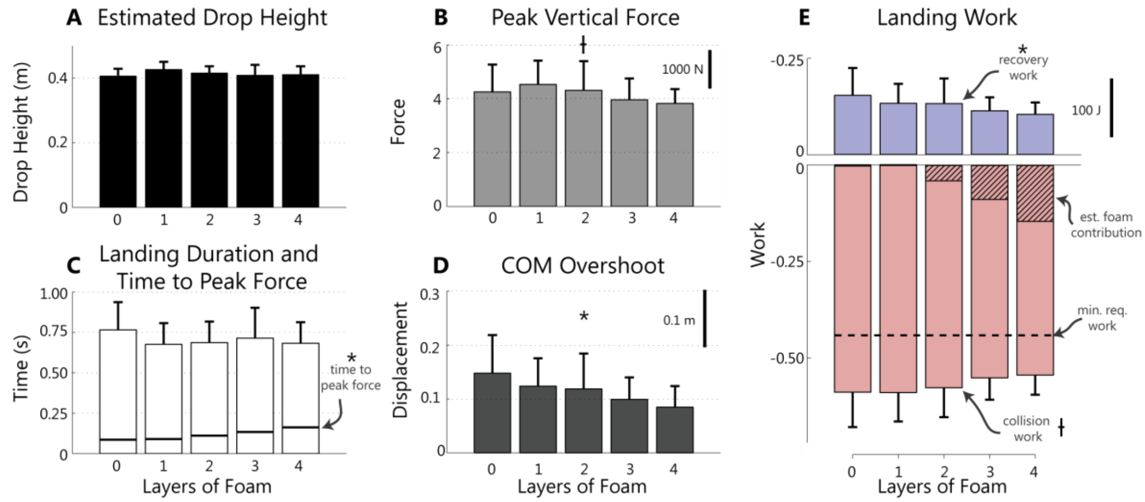

Figure 5.6: Mean Summary Measures of Drop Landings for all Conditions

Force, distance, and work for landing on zero to four layers of foam. **A:** Estimated drop heights calculated from the net work performed by the subject in each condition. **B:** Peak vertical ground reaction force landing on 0 to 4 layers of foam. **C:** Landing duration and time to peak force after touchdown. **D:** The center of mass (COM) overshoot below the final measured COM position. **E:** The mean positive and negative works subjects performed during landing. Hatched bars represent estimated contributions to work from the foam. Measurements were non-dimensionalized with body mass, leg length, and gravity to compare between subjects. * denotes significant linear regression results, ł denotes significant repeated measures ANOVA difference between conditions, $p < 0.05$.

function of the number of layers of foam, whereas overall landing duration did not change (Figure 5.6 B, C). Subjects displayed mean peak forces during landing that ranged from 1880N to 3970N. Significant differences were found between conditions (repeated measures ANOVA, $p = 0.0087$), although peak forces did not change monotonically as foam thickness increased (linear regression, $p = 0.15$). The time from touch-down until peak force varied from 0.05s to 0.23s with a mean and standard deviation for the bare ground condition of 0.09 ± 0.03s and time until peak force in the 4 layers of foam condition of 0.16 ± 0.03s. Time to peak force increased with increasing layers of foam across all subjects (linear regression: $p = 2.7\text{e-}7$). In contrast, overall landing time did not appear to differ between conditions (Repeated measures ANOVA: $p = 0.07$), and was, on average, 0.71 ± 0.04s.

Subjects landed with reduced COM Overshoot magnitudes as foam thickness increased (Figure 5.6 D, linear regression: $p = 0.015$). Calculated COM position at the lowest point during landing ranged from 0.048m to 0.30m below their final calculated COM position. The overshoot was 0.15 ± 0.070m on bare ground and 0.085 ± 0.040m on 4 layers of foam. The difference between subjects' COM overshoot on bare-ground and on four layers of foam was an average of 0.078m, which was 46% of their mean overshoot on bare ground. Still, all trials resulted in non-zero overshoots. The minimal overshoot was 0.047m, which was still 61% of that subject's maximum overshoot. In fact, the subject with the largest reduction in COM overshoot still displayed a 0.163m overshoot under the most cushioned condition.

Subjects changed the amount of negative (Collision) and positive (Recovery) work they performed in different conditions (Figure 5.6 E). Subjects performed -374.3 ± 13.8J of negative work during landing, but there existed significant differences between conditions ($p = 0.0048$). However, Collision work did not change linearly as a function of condition ($p = 0.11$). Subjects performed 100.6 ± 46.7J of Recovery work on bare-ground conditions, and 68.4 ± 20.2J on 4 layers of foam. An overall linear trend was found, in which the population produced less positive work landing on greater amounts of foam ($p = 0.046$).

We analyzed individual performed work to investigate differences between subjects. Individual subjects also regularly performed less COM positive work landing on four layers of foam compared to landing on the force plates alone (Figure 5.7). Linear regression fits to each subject's Recovery Work data included an offset and a slope, which indicate the amount of positive work performed during the landing with no foam, and the change in that work as foam was

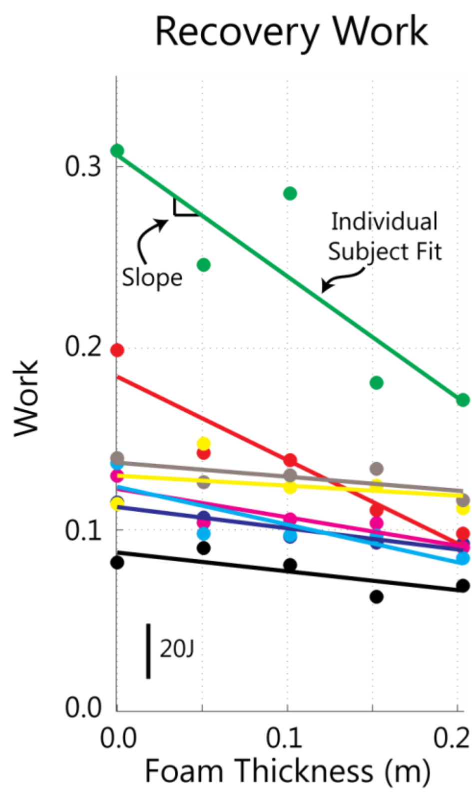

Figure 5.7: Individual Subjects' Recovery Works

Recovery Work (positive work) for landing on different thicknesses of foam. Each subject's dotted trials are fit with a solid line using linear regression. Recovery Work was non-dimensionalized with subject mass, leg length, and gravity.

added, respectively. All subject fits had negative slopes, which, as a group, indicated a significant reduction in the amount of Recovery Work performed when landing on greater thicknesses of foam (p = 0.019). However, the subjects varied in the amount of Recovery work they produced. In the conditions studied, the population produced an average of 32.3J (32.1%) less Recovery Work when they dropped onto the most cushioned surface than when they dropped onto the bare force plates. Furthermore, each subject performed non-zero Recovery Work during all landings. Even in the most cushioned condition, subjects performed, on average, 68.4J more Recovery Work than the 0J required, and no subject performed less than 34.9J of Recovery Work in any condition.

Discussion

We attribute unrequired work the subjects performed while drop landing to subjective factors such as comfort. Subjective factors are not directly measureable. However, we quantified unrequired work performed by the subjects as they lowered and raised their center of mass on various cushioned surfaces. Our results suggest that subjects land uneconomically on uncushioned surfaces because economical landing would be uncomfortable. Therefore, quantification of the work cost of the subjective factor of comfort may be measured and predicted.

We do not believe that subjects would choose a landing strategy to maximize energetic economy with additional layers of foam. Although subjects generated less positive work when foam was added to the landing surface, all subjects in all conditions still demonstrated positive work of at least 34.9J. A cushioned landing platform may reduce some aspects of the subjective cost of landing, such as pain [99]. However, as the stack of foam grows thicker, it is possible the cost of maintaining stability increases, which may again cause excess work to be produced to create a more stable landing [9], [100]–[102]. There may also be a minimal amount of energy that subjects will produce in return for the greater kinematic control afforded when their legs are bent [103].

The relationship between Recovery Work and foam thickness suggests a quantifiable tradeoff between work and other subjective factors that govern movement. It is difficult to isolate subjective factors experimentally, especially since many are not well defined. However, we may still describe their collective cost in terms of mechanical work. Indeed, in this experiment, the slope of Recovery Work vs. foam thickness describes the rate at which economy can be increased as a function of the subjective aspects of adding foam to the landing area, including comfort, stability, and any other factor not based on economy.

The relationship between foam thickness and peak force is complex. Our results show an initial increase in peak forces generated by subjects landing on one layer of foam versus landing on bare ground. However, peak forces then tend to decrease as additional layers of foam are added. The initial increase in peak force is consistent with some findings regarding barefoot running vs. running with sneakers [104]. Impact forces have been found by some researchers to be lower for barefoot running, in contrast with higher forces with cushioned, shod running. This may provide evidence that cushion may increase loading in the knees and other joints, possibly causing increased rates of injury. Our data do not contest their results. However, since peak forces begin to decrease when even greater cushion is provided on the landing surface, our data indicated that the relationship between forces and cushion is not linear, and may deserve more attention.

Subjects displayed varied sensitivity to any economical benefit provided by additional foam on the landing surface. Based on the trend-line fits to their individual data, one subject only produced an average of 7.8J (6.3%) less positive work on four layers of foam relative to bare ground while another subject reduced their performed Recovery Work by 85.4J (45.3%). We found that two subjects, who were less economical than the rest in the bare ground condition, experienced the largest reduction of Recovery Work. It may be that subjects who are more practiced in drop landing, or have higher pain thresholds are more likely to drop economically, expending less Recovery Work. Those less practiced, or with lower pain thresholds, could possibly benefit to a greater extent when cushion is added to soften their collisions.

There are a number of limitations to this study. One limitation is that our analysis of energetics solely uses mechanical energy of the center of mass. Metabolic energy expenditure may inform our decisions for changing our behavior to a greater degree than mechanical work, as it captures more of the physiological energetic expense of using our bodies to accomplish tasks. However, metabolic measurements require long term activities that primarily use aerobic pathways. For short term activities, mechanical work still may be a better measurement.

Another limitation is our lack of kinematic data. Without information about limb segments, we are unable to assign responsibility for the mechanical work measured to specific joints, such as the knee or ankle, although we do believe bending at these joints is most responsible for the COM Overshoot and positive work reported. Kinematic data and inverse dynamics analysis for drop landing do exist in other works. Such work can provide information about individual body segment contributions, such as the attribution of increased energy absorption by the hips and knees for soft landings whereas ankles provide more energy absorption during stiff landings [92]. However, our experiment was designed to capture the general tradeoff between work and subjective factors. Still, kinematic data would allow us to examine the relationship between the work of individual muscle groups and subjective factors.

Our results may have implications for tasks beyond drop-landings. Collisions also occur when we walk or run, as well as when we hop or jump. Straight legged locomotion could reduce the costs associated with walking and running [105],

[106], if only the associated subjective non-energetic costs were made low enough to make more economical locomotion preferable.

Here we were able to leverage the relationship between mechanical work and subjective costs to encourage more or less economical drop-landing. We may describe and predict many trade-offs indirectly through measurement of mechanical work. We have shown that, in some cases, it is possible to save energy through passive dissipation. Knowledge of the trade-offs between subjective factors and mechanical work can therefore be used to shape our behavior.

Discussion and Conclusions

People sometimes choose to spend more energy than necessary performing tasks, in terms of metabolic cost or mechanical work,. We hypothesized people are willing to expend extra energy to gain advantages in other, more subjective areas, such as the reduction of pain, or the prevention of fatigue.

We believe that our methods to determine the costs of subjective factors, as well as the application of these methods to areas such as rehabilitation, pose potential opportunities for future research and commercial endeavors. A great deal of research currently available is concerned with either quantified performance, in terms of biomechanical factors such as work, joint forces, metabolic cost, etc., or is confined to subjective experiences and perceptions. We aimed to combine the biomechanics field's use of constrained optimization to predict behavior with the ability of psychophysics and ergonomics to sometimes provide a more complete representation of human motivations. Our research will be successful if the methods described here can be used to form a lasting bridge between these two areas of study.

Each of the experiments aimed to uncover some of the energy costs of performing a task in the manner preferred by the subjects. Most of the experiments dealt with exercise on a recumbent stepper because of its applicability to rehabilitation. However, we attempted to broaden the scope of our hypothesis and our approach by examining drop-landing as well. Our set of experiments is not intended to limit the breadth of potential application areas, and is only meant to represent a small sample of the types of human movement that could be studied in a similar manner.

Of course, our approach is still limited, and a number of weaknesses have surfaced as we have continued the assessment of our methods. One of the greatest weaknesses of our work is that we did not explore alternative approaches to uncovering subjective costs. We chose to derive costs of subjective factors in terms of mechanical work and metabolic cost. We chose energy costs as they are present in all activities and are quite influential in their determination of behavior. However, there are alternatives. The use of some attributes of movement, such as muscle forces or muscle activation, may offer more complete understanding of the internal trade-offs a person can exploit when choosing how to move their body. Instead, we used a variable extrinsic to the body to describe why people choose to move as they do. Measurements of the body's impact on the environment necessarily hide many motivations for peoples' behavior from our scientific view. For example, there were minimal kinematic constraints on each subject's body. They could manipulate the metabolic cost of exercise by moving their torso or by creating lengthening contractions of the muscles around the shoulder, elbow, hip or knee. These movements might be variable among subjects and enable benefits such as bodily stability or other factors that would lead to changes in their work output or metabolic cost. Unfortunately, we did not measure them. The closer we get measuring the internal physiology of the human body, the more we will be able to develop a comprehensive understanding of the strategies and tactics people employ when they decide how to behave.

Another limitation to our work is that we performed no explicit modelling of the perceptual or subjective components that in some part led to the behavior we observed. We made no claims about what, exactly, people valued, or in what combination. We were intentionally vague as to what we meant by *comfort, stability*, and so on. Therefore, we have gained minimal new knowledge about these perceptual qualities, and do not have information about how they interact. Instead, we only know their effect as a whole. Specifically, we only know how much energy people spend during a few specific tasks in return for the effects of a group of hypothesized subjective factors. For a complete bridge between quantitative biomechanics methods and subjective perception frameworks to be built, additional research will have to be performed to strengthen the connection.

Still, we believe the simplicity of our general approach offers an advantage beyond the traditional explanations of human task performance, such as optimizing biomechanical variables. The idea of an umbrella cost function that serves as the aggregate of all individual subjective costs allows a more direct approach to quantifying preference. We measure the output we wish to control and then observe the effect on that output which arises from underlying subjective factors and energetic considerations directly. We can thereby control behavior with a minimal set of underlying assumptions. We have sacrificed comprehensive understanding for completeness and directness of application.

We conducted experiments to determine methods to quantify and control behavior via knowledge of subjective factors and their associated energetic costs. We were able to show that our experimental apparatus, the NuStep recumbent stepper, was chosen appropriately to conduct experiments aimed at describing the influence on behavior of subjective factors. Subjects that exercised on the NuStep altered their distribution of effort between arms and legs based on grip type, machine arm length, and the method with which they generated power. Limb distribution was variable despite the variation not providing any reduction in the necessary mechanical work required for the task.

We then introduced a method of implicit feedback to quantify the energy cost of preferred limb use, as well as steer effort toward specific limb groups. We weighted limb power contributions unequally toward a goal amount of the summed contribution. The achievement of the goal was performed with a preferred distribution of limb effort, which may or may not have been identical to the minimum power solution. We thereby developed a predictable relationship between the weighting and the preferred limb power distribution, as well as knowledge of the energetic costs associated with the desired distribution.

The feedback was tested against another form of feedback which was supposed to simulate the explicit information supplied by a therapist during motor rehabilitation. Our implicit approach demonstrated its potential to be just as effective in steering effort toward target limbs, as well as the possibility that implicit feedback is less cognitively taxing than its explicit alternative.

Visual feedback, no matter how intuitive, is still more demanding than if effort could be controlled without the need for visual information to be communicated. We found in our subjects a preference for low resistance. Low resistance could be experimentally associated with the use of target limbs, thereby eliminating the need for visual feedback completely, while still being able to adequately steer effort.

Finally, we extended our experimentation to other areas of biomechanics—specifically, the landing phase of a person's drop from a height. We found that in this activity, subjects were willing to spend extra energy beyond the minimum required to gain the perceptual benefit of a more comfortable landing.

All of these experiments are attempts to uncover the methods by which humans make choices for behavior. The decision process may not be known to the subject, and it may be subconsciously driven. Still, we were able to show that these decisions for action may be predictable, as long as we can capture the effect the process has on the quantifiable performance variables of a task. If we can measure the costs of non-work factors in terms of work, we can form a more complete picture of human decision-making.

Appendix

A copy of the NuStep instrumentation was created and installed in the MedRehab clinic, a rehabilitation clinic run by the University of Michigan. The patients there were exposed to various forms of feedback we had created. We have not yet performed studies which test our primary hypotheses on patient populations. However, we collected data during the various patients' normal use of the machine while they used simplified forms of the visual feedback to monitor limb power output, symmetry, or while they recorded their effort but did not choose to pay attention to the information on the screen. Patients seen in the clinic using our instrumentation include those who have suffered a stroke, were recovering from orthopedic surgery, suffered from various infections of the limbs, or simply had lower back pain which required physical therapy. The following figures illustrate some of our observations and thoughts on the data we collected. None were collected in a controlled environment, or with specific scientific aims. Still, we could not find many publications with information about individual limb use of patient populations. Therefore, the results may still be of interest, both in terms of demonstrated capability of our instrumentation and by pointing toward possible directions for future research.

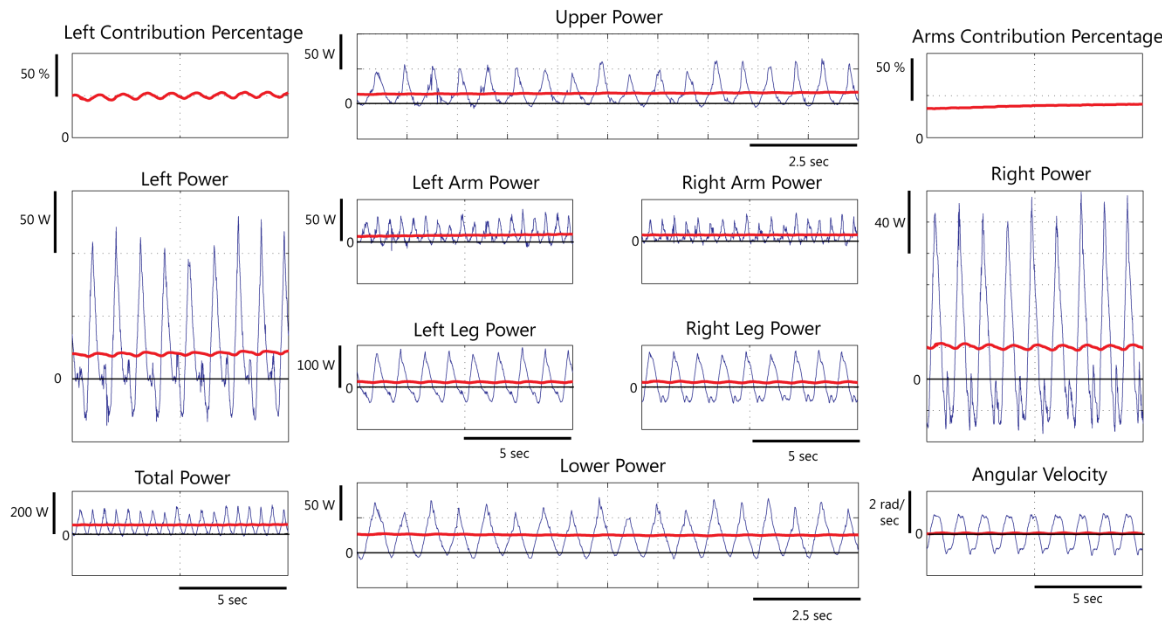

Figure App.1: Quantification of patient effort

Power trajectories for individual limbs, limb groups, and other measures from a characteristic subject for a portion of the duration of exercise. Each individual limb's power output may be graphed vs. time to display temporal characteristics (center four graphs). Furthermore, individual limbs can be grouped into limb pairs or other groups (e.g. left or right limb combination graphed at left and right, upper or lower limb combination graphed above and below). We also plotted limb contributions from the left side or arms relative to the total power, in terms of a percentage (top corners). Finally, we plotted total power output from all limbs and the angular velocity of the stepper machine's telescoping arms (bottom corners). All quantities are cyclical from the nature of the NuStep exercise. Therefore, the continuous trajectories are smoothed with a low pass filter.

Little data could be found in the literature relating patient condition and rehabilitation routines to individual limb use. Although our dataset is small, we have begun to see the promise of considering this level of description of patient exercise.

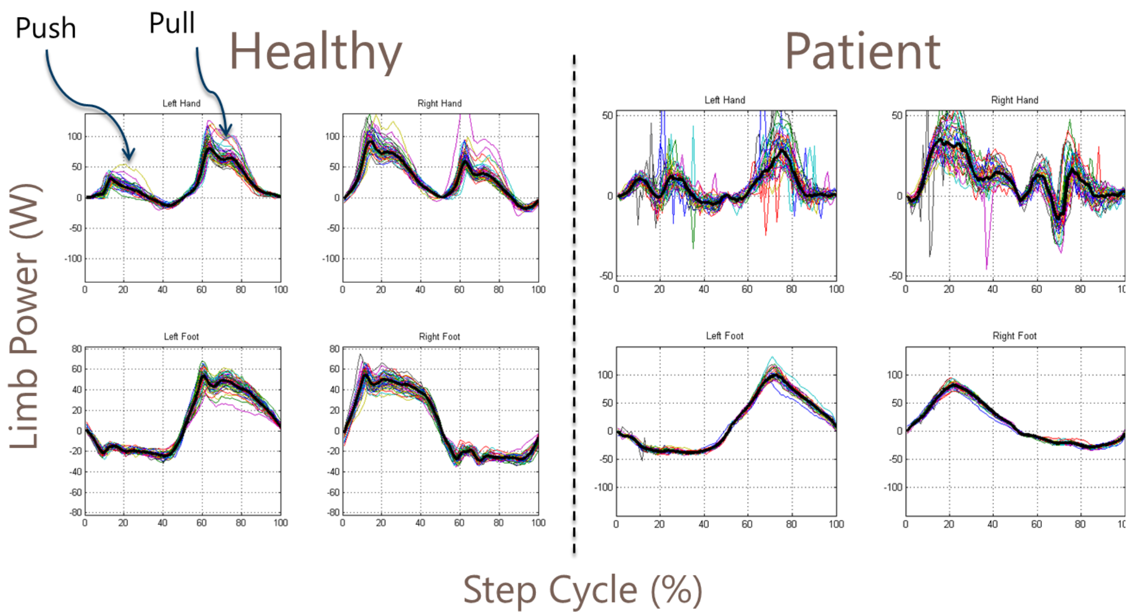

Figure App.2: Time-course of power output from individual limbs: Healthy vs. Patient

Power trajectories from each limb from a characteristic healthy subject and from a patient. Exercise on the NuStep is cyclical. Power output during each cycle is scaled to be equal in duration and superimposed for each limb (thin lines). The median trace of all cycles is shown as the thick line.

The healthy subject displayed limited variability in power output for each cycle in each limb. They were able to produce positive power output while both pushing and pulling with their arms, and sustained extended bouts of positive power output with each leg. On the other hand, the patient produced substantially less power output from the arms, and with greater variability. Furthermore, they were unable to continue to produce power with their legs after reaching a momentary peak in power output.

Analysis of time-series data of individual limb power output from patients may demonstrate significant potential to allow for the fuller understanding of the dynamics that arise as a result of a disease.

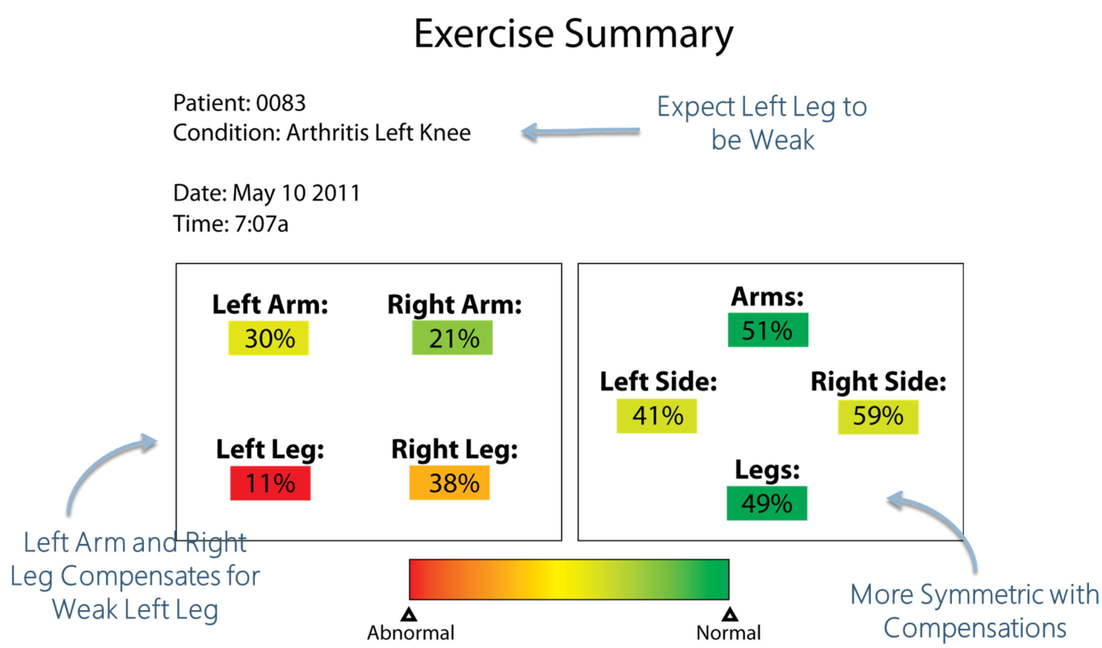

Figure App.3: Illustration of compensation mechanisms

A summary of average power contributions from each limb during one session of exercise on the NuStep (in terms of percentage of total power). The patient was recovering from arthritis of the left knee. One may expect them to display a weakness of their left leg. Weaknesses are difficult to detect visually by the therapist, but the therapist may sometimes deduce lower power output by the resulting asymmetry in the patient's posture and movement which results from the weakness.

In the figure we can see that symmetry between arms and legs is quite good, and asymmetry between left and right sides is not very dramatic. The therapist may not be able to see any abnormality from observing the patient. However, the general balance is only possible because the compensations made by the left arm and the right leg. They produce more power than normal to reduce the asymmetries caused by the weak left leg. This may be beneficial to the patient to reduce abnormal twisting of the torso during exercise, but it may hide the weakness from the therapist. Feedback of the power generation from each limb is able to uncover and display these hidden compensation mechanisms, potentially allowing for more appropriate and effective rehabilitation.

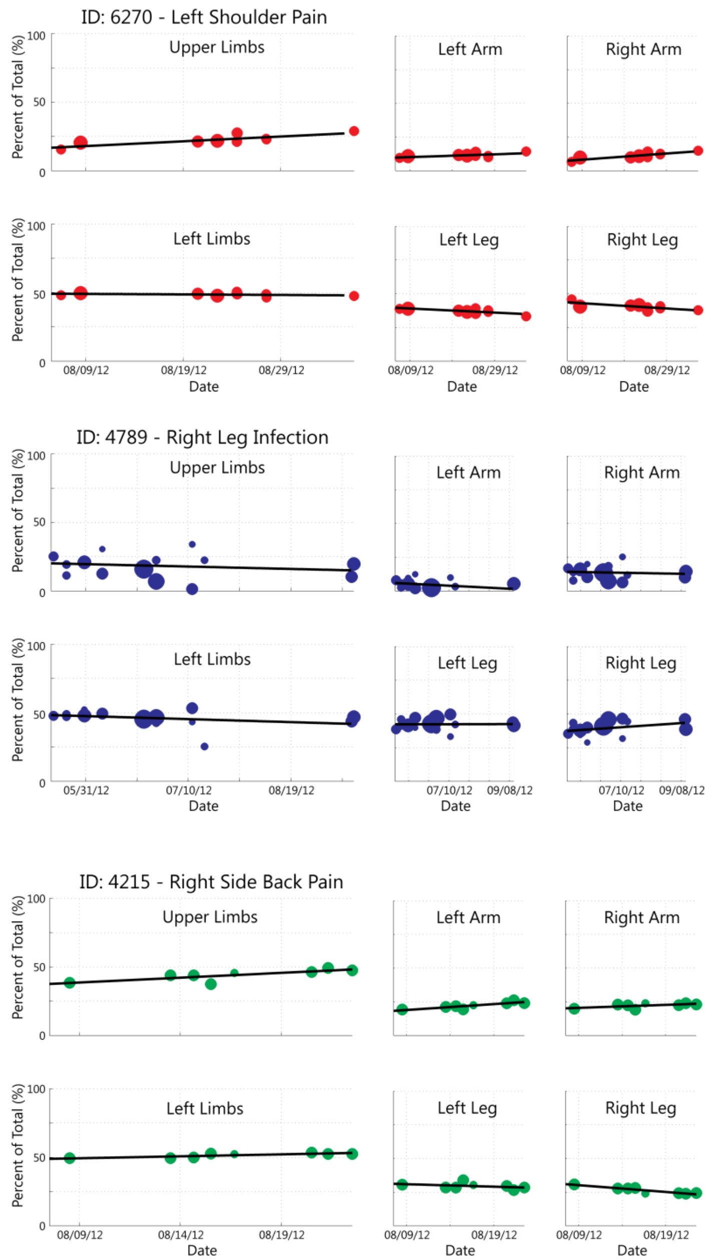

Figure App.4: Longitudinal tracking of multiple patients' limb use

Summary data for three patients (each their own color) over a time period of one half to three months. Each dot represents the average power contribution (percent of total power) over a single exercise session. The size of dot is proportional to the duration of the session.

A number of patients routinely used our instrumentation, and we were able to track their use over multiple sessions. This kind of data allows us to judge patient consistency, correlate their power output to their condition, and track their progress over time. We believe that this type of data analysis could be of great use to track the benefit of rehabilitation and inform its process.

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