Final Report: Measurement of Human Muscle Stiffness and Its Application to Effective Human-Robot Interface Design

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Abstract

The ultimate goal of this research was to establish a method to effectively adjust the control scheme of a robotic assist device based on arm stiffness measurements of an operator. This controller was expected to achieve higher performance in assist devices than other methods such as fixed gain controllers. The necessary steps for this were 1) to develop a wearable device for the measurement of biosignals related to muscle activity level such as electromyogram (EMG) as well as a haptic feedback device to be used in testing, 2) to develop a method to extract the changes in muscle stiffness from biosignals, 3) to develop a method to adjust the controller gains of a lift device based on the muscle stiffness information, and 4) to investigate the association between human stiffness and system performance limit. The results could be used to design and control various human-machine interfaces in assembly lines. Investigation of key human characteristics and their role in machine controls would lead to achieving effective

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human machine interface designs. The design of the EMG measurement and haptic feedback device are discussed, and an experiment was performed to investigate the relationship between EMG signals and human arm stiffness. It was determined that EMG signals can provide an effective prediction of the stiffness of an operator's arm, which can then be used to adjust such a control system. A system that used a simple threshold classifier to estimate stiffness was implemented that would adjust the impedance characteristics of an impedance controller. An experiment was then performed to assess the change in performance of the new system. It was found that the new system provided improved stability.

1 Introduction

Human-robotic interaction has become a rapidly expanding field, with many people researching new and innovative ways for people to control robots. Haptics is a popular control method, as it has been found that touch is a very intuitive way for controlling a robotic device. Force feedback and haptic controllers are now common in areas from gaming to industrial machines. Haptic devices require physical contact between the operator and the machine, introducing feedback and creating a coupled system. This has been shown to introduce inherent instabilities due to the typical response of human operators [1, 2, 3, 4]. To attempt to correct for the negative effects of feedback, this study will design a control scheme that adjusts to changes in the way an operator grips a haptic controller.

Adjusting the control scheme of the robot will be accomplished by tuning the control gains based on the overall stiffness of the operator's arm. This gain adjustment is expected to achieve higher performance in robotic devices than fixed control gains. For the purposes of this study, only industrial lifting devices will be considered.

There are four ultimate goals of this research. First, it will develop a wearable device for the measurement of biosignals related to muscle activity level, such as electromyogram (EMG). Second, it will be necessary to develop a method to extract the changes in muscle stiffness from these biosignals. Third, a method to adjust the controller gains of a lift device based on the calculated muscle stiffness will be developed. Fourth, it will investigate the association between human stiffness and any system performance limits and evaluate the effectiveness of the final system. The results could be used in the design and control of various human-machine interfaces, both in assembly lines and in other areas of robotics. Investigation of key human characteristics and their role in machine controls would help to achieve effective human machine interface designs.

Since the level of stiffness is not directly measurable in typical control situations, the control scheme must acquire some analogous or correlated metric. Electromyogram (EMG) signals are expected to be a promising alternative. Unfortunately, the relationship between EMG signals and arm end point stiffness has not been thoroughly studied, and there is little literature discussing it. Therefore, this research must determine if EMG signals can be used to accurately indicate the stiffness level of a human arm, and if such a control system effectively improves the performance. It is expected that as a human operator varies the end point stiffness of his or her arm, the EMG signal will show a correlation such that it can be used as a predictor for arm stiffness. By then using this, it should be possible to design a control scheme with increased stability and less oscillation.

2 Background

Numerous studies have explored the stability of haptic controllers that an operator grips with their hand. Kazerooni and Snyder [1] demonstrated the inherent instability induced by a human operator in a haptic hand controller. They developed an impedance controller using the force the operator was applying to the controller. However, they found that for stability, it was necessary to have some compliance in either the human arm or the control device.

Duchaine and Gosselin [2] furthered this study using Lyapunov Theory. They developed a more detailed model of both the robot and human arm characteristics, then defined a thorough description of the stability region of the system. They then performed an experiment with human operators to validate their theory. By modeling the stiffness in both the robot and the human, and then finding the control system was critically damped for the system, they were able to significantly reduce the instability of a haptic human-robot interface.

Both of these prior studies illustrated how trade-offs must be made to find a well suited control system. A high performance system must have some compliance in the system to avoid instability, whereas a stable system that will operate well under stiff conditions will yield comparatively lower performance. Unfortunately, the natural human response to an unstable system is counter to this. If a high performance system begins to oscillate and become unstable, a human operator will naturally attempt to stiffen the arm grasping the control device. Based on the results of both of these previous studies, this would make the system more unstable, worsening the oscillations. However, by monitoring the stiffness of the operator's arm, it would be possible to dynamically vary the tradeoff between performance and stability by adjusting the control system.

Accomplishing the goals set out for this study requires understanding the mechanics of human arm muscles and how they relate to muscle stiffness. A variety of physiological studies have been done relating to muscle stiffness and methods for measuring it. Hatta, Sugi, and Tamura [5] performed tests using frog muscles to determine the relationship between contraction and changes in muscle stiffness. Using ultrasonic waves to measure the stiffness of a muscle, they induced a contraction and recorded the corresponding change in stiffness. They found that stiffness increases with contraction, and that the change in stiffness is larger for larger contractions. They then suggested some physiological reasoning for this. However, as shown by Monroy, Lappin, and Nishikawa [6], muscles exhibit a time history that must be considered.

Other studies have extended this work to muscles in the body. Each joint is moved by at least two muscles that pull in opposite directions, known as antagonistic muscles. It has been shown that an antagonistic pair contracting together, called cocontraction, is indicative of a higher joint stiffness [7, 8, 9, 10, 11], since the cocontraction of an antagonistic pair would result in no motion, but more force on the joint. Therefore, by detecting the cocontraction of a pair of antagonistic muscles, or multiple pairs for accuracy, it would be possible to estimate the stiffness of an operator's arm.

Based on these prior studies, the target design would consist of a system that could first read the EMG signals of various arm muscles and determine the magnitude of cocontraction, and then convert that into an estimate of arm stiffness. It would then calculate an appropriate adjustment to the robot control system to ensure stability.

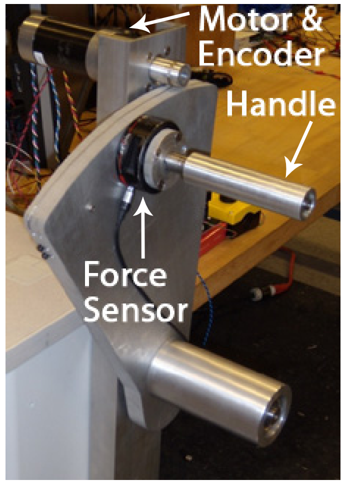

Figure 1: One Degree of Freedom Haptic Feedback Device

3 Hardware Design

3.1 One Degree of Freedom Haptic Feedback Device

As a test bed for the control system to be designed and as an instrument for conducting the experiments necessary to investigate the relationship between EMG signals and human arm stiffness, a simple one degree of freedom device was designed that was capable of producing haptic feedback via a force either impeding or assisting the user's motion. The design, shown in Figure 1, was inspired by devices such as Phantom haptic feedback devices and other haptic paddle designs [12, 13, 14, 15, 16], but with the specific goals of being low cost and versatile with a higher force capacity. Since it was to be used for human participant experiments, it was also designed with the safety of the operator in mind. Using a cable driven system allows for amplification of the force generated by the motor while remaining compliant to the user's applied force. The device has maximum generated force at the handle of approximately 100 N and a frequency response of up to 10 Hz. The control of the device was implemented using a CompactRIO real-time controller and LabView software, and uses an optical encoder and six axis force and torque sensor for feedback

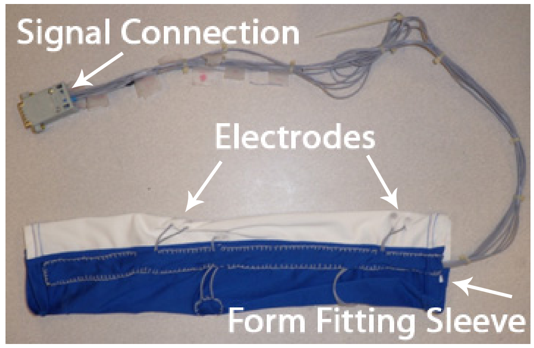

Figure 2: Wearable EMG Measurement Device

3.2 Wearable EMG Measurement Device

The wearable device was created to measure EMG signals from the arm. The device consisted of an elastic sleeve with embedded EMG electrodes, shown in Figure 2. The sleeve is designed to allow the device to be taken on and off quickly, as well as fitting a wide range of arm sizes. Electrode pairs were located on two antagonistic muscle pairs, with the first being the biceps brachii (BB) and triceps brachii (TB) and the second being the flexor carpi ulnaris (FCU) and extensor carpi ulnaris (ECU). These muscles were chosen because they are easily accessible for surface EMG measurements and are the primary muscle pairs controlling the elbow and wrist motion, respectively. Electrodes were placed with a center to center spacing of approximately 10 mm, and a ninth electrode was located on the elbow as a ground. For each muscle the signal was processed by first removing the DC component and taking the absolute value of the signal. Then each signal was low pass filtered with a cutoff frequency of 2 Hz. To calculate the percent effort of each muscle, the signal was compared to the maximum amplitude of a signal processed as described above when the subject generated their maximum voluntary force from an isometric contraction of the same muscle. A measure of the cocontraction for each antagonistic muscle pair was then determined by taking the minimum percent effort of the pair.

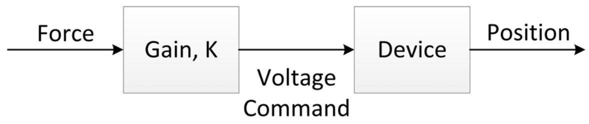

Figure 3: Control System to Provide Force Assistance

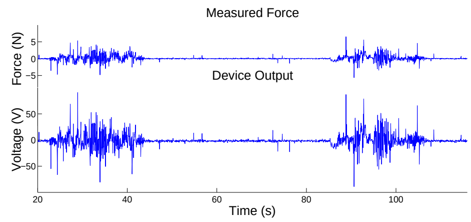

Figure 4: Demonstration of Increase in Instability with Increase of Stiffness

3.3 Instability Induced by Human Arm End Point Stiffness

Using the one degree of freedom haptic feedback device it was possible to reproduce the conditions under which the system grows unstable with increased operator arm stiffness. The device was programmed with a force assisting controller similar to that used in large lifting devices, as shown in Figure 3. This controller scales the force applied to the device as read by the force sensor on the handle by a gain, then provides it to the motor as the input. This causes the motor to generate a force in the same direction as the operator, thereby assisting the operator. Figure 4 shows a plot of both the force recorded by the device and the motor output of the device. Increased operator arm stiffness results in a higher frequency force signal with higher magnitude. This then created more oscillation in the device, which grew to a noticeable size, making it difficult or impossible for the operator to hold the device still and stabilize it.

4 EMG Signals as Indication of Arm Stiffness

4.1 Experimental Procedure

4.1.1 Concept

Human muscles are a complicated system, and it is extremely difficult to create an analytical model of them. However, prior work [2, 4] has modeled it as a spring-damper system with a single stiffness and single damping value (The damping is occasionally omitted). Using such a model, designing an experiment to test the correlation between EMG signal and stiffness can be simplified. If the position of the base of a spring is fixed and the position of the other end and the applied force is known, then the stiffness of the spring can be calculated. Treating the arm as a spring leads to two values that must be measured to calculate the stiffness of the arm. If these two values can be controlled, then the only measured value is the EMG signal.

Based on this analysis, an experiment was designed with a minimum number of variables. By having a participant hold the handle of the haptic feedback device shown in Figure 1, it was possible to control the position and force at the end point of the arm, leading to two independent experimental variables. The stiffness, which was the actual desired independent variable, was then directly calculated from these values. This left the EMG signal for each muscle, which were read using the sleeve shown in Figure 2 as the only dependent variables. It was expected that the EMG signals and stiffness value would covary throughout the experiment, so the experiment was designed attempt to verify this as exhaustively as possible so that the results could be generalized properly. Therefore, the experiment was run at a variety of stiffness values, leading to the requirement that both force and position be set to multiple levels. The force was be tested at twenty different levels up to approximately 100 N, with three different levels for position: one with the arm in a neutral position, one with the arm slightly more out stretched, and one with arm slightly more bent.

The expectation was that it would not matter what the individual combinations of force and position were, as stiffness was the main value that is of interest. However, the human arm is not necessarily a linear system, and it is possible that human muscles could exhibit other, more difficult to account for, tendencies, such as hysteresis. Therefore, force and position were considered as independent variables, with stiffness as a calculated intermediate

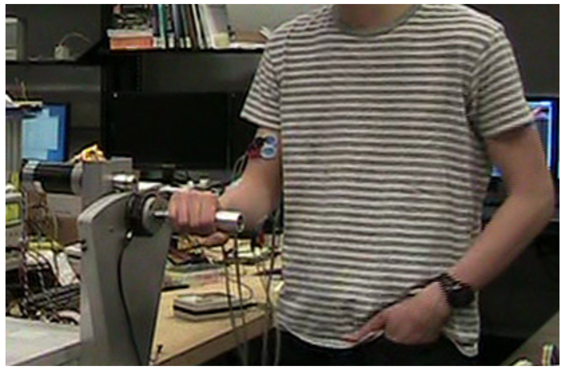

Figure 5: A Participant Performing the Experiment

variable. The most exhaustive design that fully crossed the levels of force and position was used, leading to sixty cases. In addition, each person's size and strength varies significantly, introducing extraneous variables that complicate comparisons between individuals. For this reason, each experiment participant was be asked to perform multiple trials of the experiment, covering all of the sixty cases. This was feasible, as each case will only took between 5 and 10 seconds to perform. It was expected that each participant's results would follow the same general trend.

4.1.2 Method

Each participant stood aside the one-degree-of-freedom haptic feedback device such that, when the device's handle was at its neutral position, the participant's arm was comfortably held out with the elbow slightly bent and the forearm parallel to the floor, as shown in Figure 5. For each case, the participant was asked to hold the haptic feedback device stationary in the given position. After some amount of time, the device applied a force against the user, which required the user to stiffen their arm to continue to hold the device in place. During this time, an arm band was continuously measuring the participant's EMG signals for each of the four muscles. Learning effects associated with the task were expected to not be significant, as there was no procedure the participant must become accustomed to or apparatus they must figure out how to use. The data was then analyzed to look for correlations between stiffness and EMG signal. This experiment was performed following an approved Institutional Review Board protocol.

4.1.3 Analysis

Once the experiment was completed, a multiple regression/correlation (MRC) technique was used on the data to look for a relationship between the measured cocontraction values and the arm stiffness calculated from the measured position deviation and applied force on the device. This analysis was done based on the methods described by Cohen [17]. To validate the use of cocontraction, another MRC was calculated that used all four EMG signals as predictors instead of the two cocontractions. Finally, to measure the influence of device position and force strength on the relationship, the nominal values of device position and generated force were included in the regression. For each regression performed using the MRC technique, the value of the multiple correlation coefficient, R^2, and of the zero-order correlation coefficients for each predictor, r_i^2's, were found. R^2 indicated the quality of the fit, while each r_i^2 shows how much of the variance of the predicted variable can be attributed to each predictor variable. The results were expected to indicate a statistically significant relationship between cocontraction and stiffness along with a comparable relationship between EMG signals and stiffness, and that neither position nor device force were significant contributors to the variance of stiffness. The data from all participants was anonymized and processed using MATLAB software, while SPSS and G*Power 3.1 [18] were used for statistical analysis.

The number of participants in a human subjects experiment is generally chosen based on the desired power of the resulting statistical analysis. The power, an indication of the probability of Type I or Type II errors in the statistical analysis, should be close to 1, and is often chosen to be 0.95, leaving a 5% chance of statistical errors. However, this experiment collected a very large amount of data, and this power value is generally only accepted for up to about 200 data points. In an effort to simplify the resulting analysis, each trial was filtered and reduced to 10 points, which was enough to ensure that the main effects of the signal were preserved with minimal information loss while also reducing the noise. This resulted in 600 data points per subject, well in excess of the 200 stated previously. Therefore, a desired power value much closer to 1 was chosen. Using a desired power of 0.9999 required approximately 1,500 data points, which resulted in a 1 in approximately 10,000 chance of a Type I or Type II error. This required at least three participants to obtain the desired power. A total of four trials of the experiment were completed, resulting in roughly 2,000 data points. All participants were male

Table 1: Variance Partitioning for Cocontraction

Variable	r_i^2
Cocontraction (elbow)	11.7%
Cocontraction (wrist)	11.1%
Nom Angle	0.2%
Nom Force	28.7%

Table 2: Variance Partitioning for EMG

Variable	r_i^2
EMG (BB)	11.6%
EMG (TB)	16.0%
EMG (ECU)	8.0%
EMG (FCU)	12.9%
Nom Angle	0.2%
Nom Force	28.7%

and ranging in age from 20 to 26. Due to the limits of the force sensor on the device, trials with very high forces could not be accurately read, reducing the number of usable data points to approximately 1,200, resulting in an actual power of 0.9976 and a required critical F of 4.69 for statistical significance of the regression.

4.2 Results

The MRC method is based on a linear least squares fit of data. The models calculated from a basic linear fit provided an R^2 value of 0.173 for the cocontraction/stiffness relationship and 0.201 for the EMG/stiffness relationship, indicating the relationship poorly represented the data. Since the fundamental form of the relationship between muscle activity and arm stiffness is unknown, a variety of data transformations were tested, including exponential and logarithmic transformations. It was found that a logarithmic transformation of the EMG and cocontraction data provided the best fit.

The cocontraction/stiffness relationship utilizing a logarithmic transformation of the data achieved an R^2 value of 0.338. Table 1 lists how the

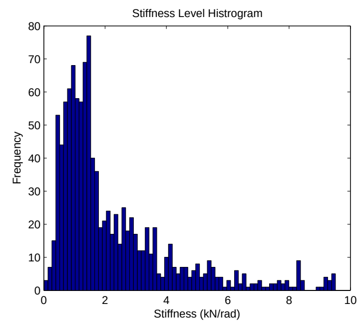

Figure 6: Histogram of All Measured Stiffness Levels

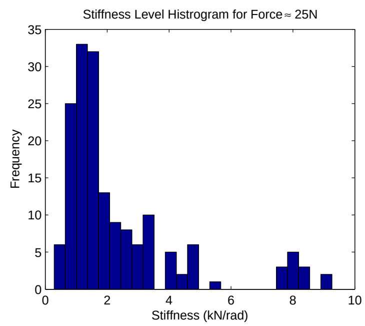

Figure 7: Histogram of Measured Stiffness Levels for a Single Force Level

variance of the stiffness was partitioned amongst the various predictor variables, indicating the degree to which each predictor contributed to the change in the stiffness. The regression resulted in a statistical F value of 75.8, which exceeded of the value required for statistical significance. The EMG/stiffness relationship with a similar transformation resulted in an R^2 value of 0.377. The corresponding partitioning of the variance of the stiffness is shown in Table 2. The second regression resulted in an F value of 59.8, also in excess of the critical F value for statistical significance.

4.3 Discussion

The results presented above indicate that a statistically significant relationship does exist that allows the use of measured EMG signals as a predictor of the operator's arm stiffness. However, the fit using the calculated measure of cocontraction actually provided a poorer fit than using the raw EMG data.

While the correlation is still significant and usable, this indicates that the level of cocontraction may be better represented by something more than just the level of contraction that both muscles of an antagonistic pair have met or exceeded. As expected, changing the starting position of the device's handle had little effect on the stiffness of the operator's arm, as indicated by the 0.2% of the variance that this variable accounts for. However, the nominal force of each trial had a much larger effect on the regression than anticipated. Based on these results, it should be possible to use EMG readings to design a control system that can account for the stiffness of the operator's arm. However, more research will have to be done to determine the ideal indicator to use for cocontraction.

Further analysis of the collected data indicates that the operator's strategy for choosing the appropriate stiffness level for a given situation is not straightforward. It would be expected for a person to choose a stiffness level that is just high enough for the applied force, however, the data show that this is not the case, as the stiffness level for a given applied force is inconsistent. Figure 6 shows a histogram of the stiffness of all data points. The plot shows that points are neither uniformly nor normally distributed, but instead tend towards the shape of a Poisson distribution. In addition, Figure 7 shows the stiffness level for all trials at the middle force level. While the strategy that a human uses to choose the appropriate stiffness level is unknown, it is clearly more complicated than just balancing the applied force with minimum effort.

4.4 Conclusions

This study intended to investigate the relationship between EMG measurements and human arm stiffness. It is known that muscle cocontraction increases with increased joint stiffness, and it is desired to design a robot control system that can adjust based on operator arm end point stiffness. Therefore, using EMG measurements as a gauge of muscle activity and cocontraction level, it should be possible to obtain an estimate of arm end point stiffness. However, the validity of this relationship had not previously been demonstrated. After performing an experiment where a participant was asking to stiffen their arm in response to a force applied at their hand, a regression was obtained based on EMG signals as predictors of arm end point stiffness. The data showed that the correlation is statistically significant, making it possible to use EMG signals in this way. While the calculated cocontraction level was sufficient, the raw EMG signals provided a better indication. It was also seen that the operator's chosen stiffness level was not necessarily the minimum required to perform the task, and that perhaps there are other factors that effect this choice.

5 Controller Design

After establishing the system for measuring arm stiffness, it was necessary to design the compensating controller. This consisted of two parts: a method for classifying operator arm stiffness into discrete levels and a method for adjusting the robot controller based on these levels.

5.1 Classifying Operator Arm Stiffness

The system first measured the operator's muscle activity using the reusable sleeve, and then calculated the cocontraction for both the forearm and upper arm. It next needed a way to determine how the resulting stiffness level should be classified. Due to the noise in the EMG readings, it was decided that a series of discrete levels would be used. Attempting to use a continuous scale resulted in a controller that was constantly changing, making it very difficult to use. After some testing, it was found that a simple classification of the stiffness as high or low gave the best results. More levels may be possible by using a more accurate and less noisy EMG measurement system.

The next task was to determine the best method to use for classifying the stiffness into the high and low categories. Multiple methods were considered. An Artificial Neural Network (ANN) and a Support Vector Machine (SVM) were both considered, as they are commonly used classifiers. They are both learning methods that can adapt over time to changing conditions and are driven by complex systems of nonlinear equations. However, due to time constraints, these methods could not be thoroughly explored, so a simpler method was chosen that classified the stiffness as high or low based on an adjustable threshold for each pair of muscles. These thresholds could be adjusted to accommodate the variations of muscle activity levels of different operators.

With a threshold based system, there are a few characteristics that must be considered. The first is the chance for oscillation across the threshold, leading to a system that is constantly switching between high and low states.

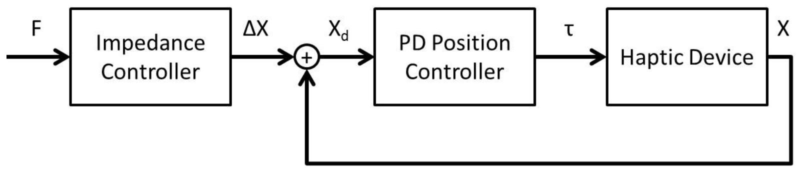

Figure 8: Block Diagram of an Impedance Controller

To compensate for this, the system required that the cocontraction level crossed the threshold for some finite amount of time before changing the classification. Another concern was the noise in the EMG measurements. Due to the extremely small voltages being measured and the large amplification required to read them, the signals can be extremely noisy. To make the signals usable, they had to be filtered, as described in the section regarding the reusable sleeve. This also helped with the former issue, as the filter added to the required time that the signal must exceed the threshold before being classified.

5.2 Adjusting Controller

Many haptic devices use an impedance control scheme, as it allows the robot to make the system respond as if it had an arbitrary set of dynamic characteristics (mass, damping, and stiffness). This makes control easier on the operator, because the actual system dynamics are masked by those set in the controller. A diagram of a simple impedance controller is shown in Figure 8. The input to the system is the force applied to the device handle. The outer force control loop then calculates the change in position that a system with the desired impedance characteristics would exhibit under this loading over a signal controller time step. This change is then added to the device's current position and given to the inner position control loop, which attempts to reach that position. This process is repeated each time step, resulting in a system that moves in the same manner as an actual system with the same dynamics as the programmed impedance characteristics.

For the purposes of the system to be designed here, the impedance characteristics were chosen based on how a large lifting robot would move. Stiffness was set to zero, as a non-zero stiffness would cause the robot to return to the same position every time the handle was released. For the case where arm stiffness was low, the mass and damping were set to be small, allowing the

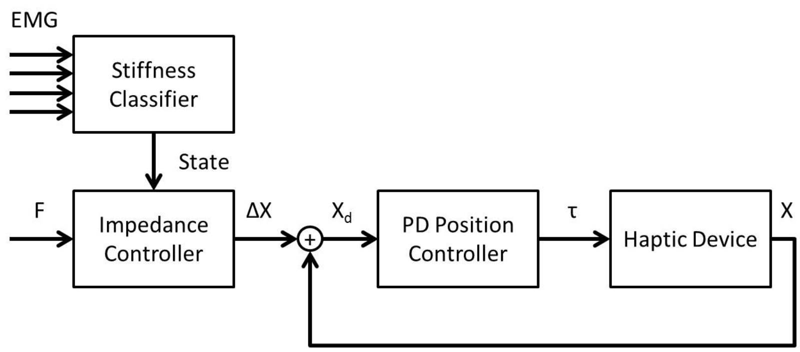

Figure 9: Block Diagram of the Complete Control System

system to move quickly and easily with little resistance. However, when the stiffness was high, these values were increased. The higher damping reduced oscillations in the system, while the higher mass made the system easier to hold steady, allowing the operator to more precisely control it. A diagram of the complete system is shown in Figure 9.

5.3 Demonstration

Figures 10 and 11 demonstrate the use of the designed system. In both figures, the left graph shows the motion of the device using a standard impedance controller, whereas the right graph shows the same motion with the new system with the yellow highlight indicating the system has detected higher operator arm stiffness. In the former figure, the haptic device was moved through a trajectory and held still at certain points. The graph showing the compensating controller illustrates the increased stability and smoother motion without sacrificing the ability to move the handle rapidly over long distances. The latter figure shows the device being held against a rigid surface. Without compensation, the device oscillates rapidly under the stiff conditions. However, with the compensation, the device can be easily held against the rigid surface. To further demonstrate this improvement, Figure 12 shows the frequency spectrum of both signals. The range between 10 and 15 Hertz shows a clear decrease in the magnitude of oscillations with the compensation on.

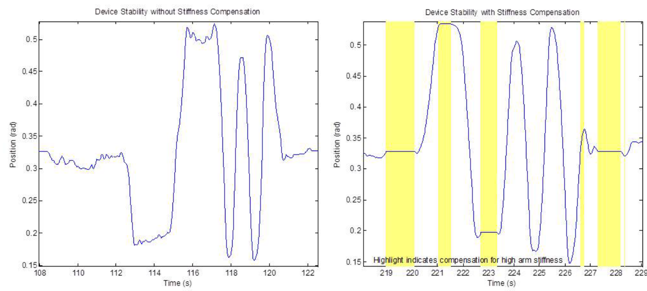

Figure 10: Movement Through a Trajectory with the Compensation Off (Left) and On (Right)

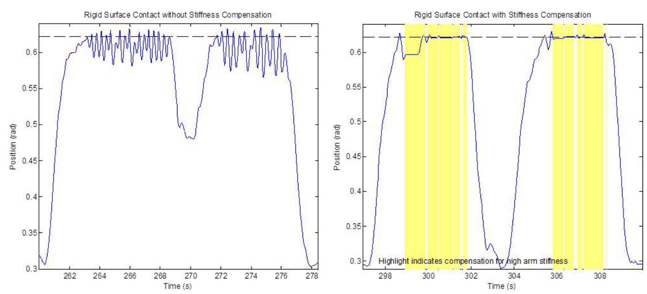

Figure 11: Contact with a Rigid Surface with the Compensation Off (Left) and On (Right)

6 Evaluation of System Performance

6.1 Experimental Procedure

6.1.1 Concept

With the final working system completed, it was necessary to perform a series of tests to evaluate the performance of the new system as compared to some baseline. For comparison, a standard impedance controller was used as the baseline. This controller used the same parameters as the low stiffness case for the compensating controller. For simplicity, tests performed with the compensating controller will be referred to as tests with the controller on, while tests with the basic impedance controller will be referred to as tests with the controller off.

It was desired to design an experiment that could test two aspects of the

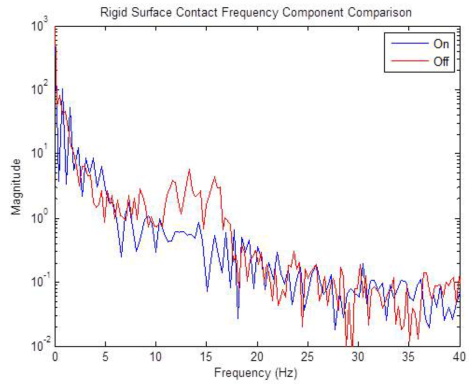

Figure 12: Frequency Spectrum Comparison of Contact with a Rigid Surface with the Compensation Off (Red) and On (Blue)

system: 1) the effects on stability in a stiff situation and 2) the effects on operator performance in a typical usage scenario. For the first case, the best situation would be one that typically is unstable for impedance controllers. This way, any increase in stability with the controller on could be measured. To do this, the case where the handle of the haptic device was held against a rigid surface was chosen. In a typical impedance controller without a high damping coefficient, the device would contact the rigid surface, then bounce back due to the force of impact. With an operator attempting to hold it against the surface, the device would bounce repeatedly and the system would be unstable. It was expected that with the controller on, the operator would stiffen their arm to attempt to hold the device steady against the rigid surface, thereby causing an increase in the damping coefficient and making the system more stable. For this experiment, all variables, such as the position of the rigid wall, were held constant, with the only independent variable being whether the controller was on or off. The position of the device was then recorded over time. To measure the stability of the system, the RMS of the distance of the handle from the rigid wall was calculated for the duration that the operator was attempting to hold the device against the surface.

For the second case, a test was designed that could mimic a real-world usage scenario using the hardware designed and discussed above. The large lifting robots that this system was designed for are typically used to move objects from one point to another. Therefore, a computer simulation show-

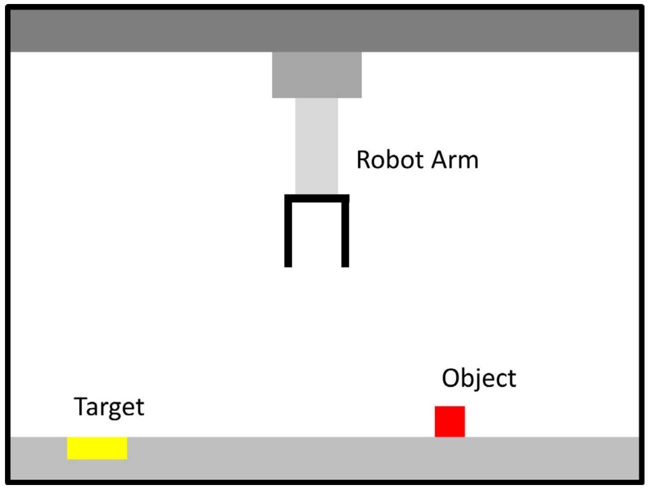

Figure 13: The Simulated Lifting Device

ing a lifting arm whose position was controlled with the haptic device was developed. An operator could then use the device to move the arm, then press a button to lower the arm and pick up an object. Again using the device, they could move the arm to a target, and again push the button to put the object down. Figure 13 shows the simulation. For this task, there were two independent variables: the state of the controller and the distance from the object's initial location to the target. Performance is an inherently subjective quantity that can be difficult to measure. When operating a machine in a factory or assembly line, the goal is to produce as many products of as high a quality as possible. Therefore, operators would be expected to perform their job both quickly and accurately. To this end, the measures of performance used in this experiment were placement speed and precision. It was expected that this experiment would demonstrate an increase in speed and accuracy with the controller on.

For this experiment, the results were analyzed using the ANOVA method to look for statistically significant differences between the two controller states.

6.1.2 Method

Each participant in this study was oriented with the EMG measurement system and haptic device before performing the experiment. They then had the

EMG measurement system connected to their right arm and stood aside the device in a similar posture to the previous experiment. They were then given the opportunity to use the device unconstrained, but with the compensating controller off, few two to three minutes, allowing each participant to become accustomed to it. This, along with other measures outlined below, minimized any learning effects that might be present in the experiment.

Once the subject was comfortable with the set up, the first task was presented and explained. They were asked to place the handle of the device against a rigid surface and hold it in contact with the surface for five seconds, after which time the experimenter would instruct them to move the handle away from the surface. They were then asked to repeat this several times. This was to be done both with the controller on and off. Since the controller must be tuned to each individual separately, a series of trials were first completed in which the experimenter adjusted the cocontraction threshold accordingly, which also helped to minimize learning effects in the task. This resulted in each participant performing between 4 and 8 trials of the task, of which only 2 were used for data collection (The one with the controller off and the one with the controller on and properly tuned).

After completing the first task, the second task was presented. The simulation was explained and the goal of picking up the object and placing it as closely to the center of the target as possible was demonstrated. Participants were allowed to pick up the object and place it multiple times until they were satisfied with its location. The participant was then given a few minutes of free time to use the device and become accustomed to the simulation. During this time, no data was recorded. When the participant felt comfortable with the system, the actual experimental trials were started. A similar tuning method was used as before to ensure that the thresholds were appropriate to each participant, as well as to minimize any learning effects. The participant performed the task several times for each trial, with only two of the trials used for data analysis. Both tasks of this experiment were performed following an approved Institutional Review Board protocol.

6.1.3 Analysis

After completing the experiment, the data was analyzed using an ANOVA analysis to look for statistically significant differences between the case where the controller was on and the case where the controller was off. This analysis was performed for both tasks. The data from all participants was anonymized and processed using MATLAB software, while SPSS and G*Power 3.1 [18] were used for statistical analysis.

A power analysis was performed beforehand to again calculate the required number of participants. However, since each participant would contribute only a small number of data points compared to the previous experiment, it was unlikely that more than 200 points would be collected for either task. Therefore, a more typical expected power of 0.95 was chosen. This required a minimum of 16 participants to obtain statistically significant results. To be conservative, the experiment aimed to gather 20 participants. In total, 21 participants were involved in the experiment. Due to software errors, one participant's results were unusable, leaving 20 participants, resulting in an actual power of 0.965 and a required critical F of 1.29 for statistical significance. Of the 20 people involved, 12 were male and 8 were female, with ages ranging from 19 to 37.

6.2 Results

6.2.1 Stability Task

The first task resulted in 80 data points, 4 per participant (2 with the controller on, 2 with the controller off). Figure 14 shows the distribution of the RMS data for this task. As demonstrated by Figure 15, the points with the controller on have a lower average RMS with a smaller variance. The ANOVA analysis results in an F value of 55.726, exceeding the critical F value of 1.29, demonstrating that this result is statistically significant.

6.2.2 Performance Task

Unfortunately, the data from the performance task provided no statistically significant result. However, numerous helpful observations were made during the experiment, and trends were observed for participants individually, as illustrated in the Discussion section below.

6.3 Discussion

6.3.1 Stability Task

As the figures in the Results section clearly show, the compensating controller made the device significantly more stable, decreasing the magnitude

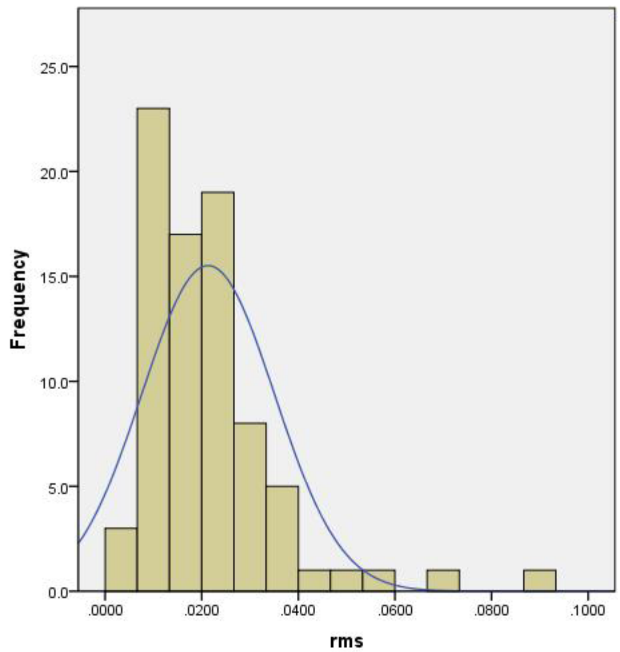

Figure 14: Histogram of the Recorded RMS for All Participants

of oscillations. On average, the magnitude was decreased by more than 50%, with the best case showing a decrease of 75%. Figure 16 shows the average RMS of controller off case for each participant, normalized by that participant's controller on RMs. Most participants showed oscillation magnitudes of less than half the controller off case.

6.3.2 Performance Task

The results of the performance task are less straightforward than those of the stability task. The main reason for this lies in the variation of each person's execution of the task. All participants were given the same instructions to "place the object as close to the center of the target as possible." However, each participant interpreted these instructions somewhat differently and executed the task to different tolerances. While some participants simply placed the object quickly as best as they could, others felt the need to more carefully position the object before placing it down. This difference made comparing speed and accuracy between subjects very difficult. Therefore, a less rigorous analysis was done looking at each participant individually. This provided

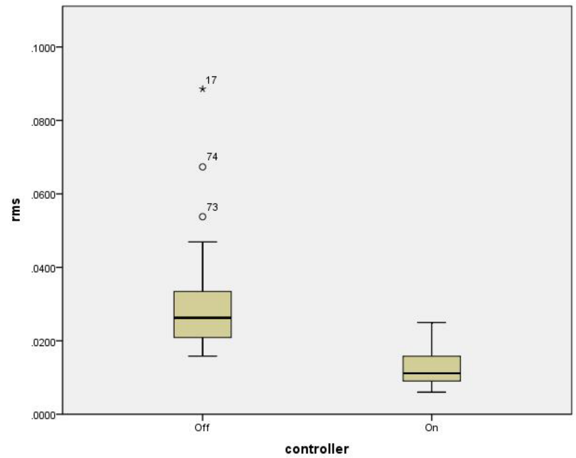

Figure 15: Comparison of Mean and Variance of RMS Points for Each Controller State

only 10 data points per analysis, less than the amount required by the power analysis for statistical significance, but showed helpful trends in the data.

For each trial, the speed and accuracy of object placement were calculated. Since participants were allowed to re-place the object multiple times, two measurements of each were determined: for the initial placement and for the best placement. Speed was calculated from the distance the object was moved over the time from when the simulated robot gripped the object to the when it released the object, while accuracy was calculated by taking the distance from the center of the target to the center of the object. For the majority of participants, an increase in speed and decrease in distance from target was observed. Tables 3 and 4 show the results for participant 11, whose results were typical. While no statistical significance can be proven, the speed generally increases for the cases with the controller on, while the distance to the target generally decreases. In one trial, the participant was able to place the object exactly on the target. Some participants showed somewhat more noticeable increases in performance, while a few showed little to no performance gain. However, the results listed here were the most common.

Also, some empirical observations were made that support this. Several participants noted when the compensating controller was turned off how the device became more difficult to stabilize. One participant observed that the

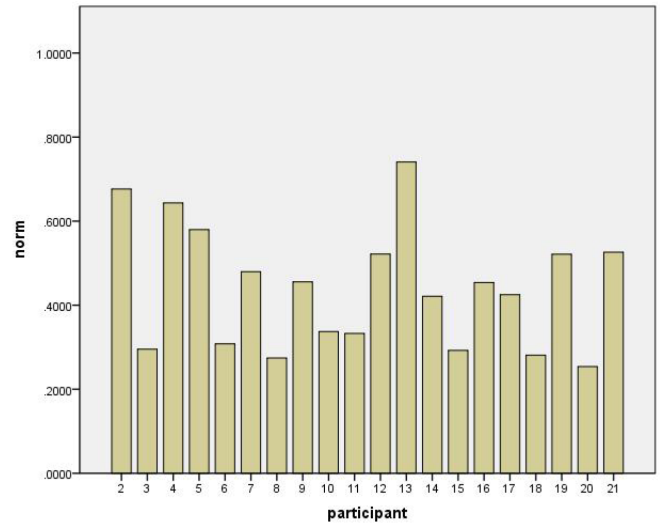

Figure 16: Controller On Average RMS as Fraction of Controller Off Average RMS

experiment "was getting harder" after this occurred. Another participant commented regarding the case where the controller was on that the device was "moving more smoothly." In general, most participants could noticeably tell the difference between the two cases. Therefore, while statistically the difference is not significant, the visible trends and operator observations show that the improvement is evident.

6.4 Conclusions

This study intended to show that the compensating controller provided improved stability and increased performance over a standard impedance controller. It demonstrated with statistical significance the increase in stability in stiff situations. While the performance increase was not able to be verified statistically, the collected data did show trends of faster and more accurate task completion. Ultimately, the system proved to be an improvement over an impedance controller that did not compensate for operator arm stiffness.

Table 3: Speed of Simulation Trials (pixels/s) (Participant 11)

	Off	On
	22.71	32.38
	27.36	40.38
	33.46	43.78
	51.46	47.16
	60.67	100.42
Avg:	39.13	52.83

Table 4: Distance to Target for Simulation Trials (pixels) (Participant 11)

	Off	On
	2	0
	3	1
	4	2
	5	3
	6	10
Avg:	4	3

7 Concluding Remarks

A system was designed that could estimate a robot operator's arm stiffness and compensate for situations with higher stiffness by damping out unwanted oscillations. To accomplish this, a wearable and reusable sleeve was developed that incorporated EMG sensors to measure muscle activity. This sleeve measured the activity of two antagonistic pair of muscles that are the dominant pairs for the wrist and elbow. The system then calculated the level of cocontraction for each pair, and classified it as either high or low by whether it exceeded a set threshold. An impedance controller was implemented on a haptic feedback device designed for the purpose. When either joint's stiffness was determined to be high, the impedance controller's parameters were adjusted to increase damping and make the system response smoother.

A series of experiments were performed to support this work. In the first, the correlation between EMG measurements and arm stiffness was tested. It was found that a statistically significant correlation did exist, support this research's use of EMG signals as indicators of arm stiffness to be classified. In the second, the performance of the system was tested. Statistically significant results showed that the designed system increased device stability in stiff situations. While the measures of performance did not demonstrate a statistically significant result, it did illustrate trends that showed increased speed and accuracy of operation using the compensating controller.

Some further enhancements to the system could be made in the future. It may be possible to implement a more advanced classifier, such as an ANN or SVN, that would more accurately classify arm stiffness. This could allow for a system that better adapts to variations in operators or a system that can classify stiffness more accurately than the designed two state classifier. Also, the system would benefit significantly from the design of a wireless transmitter, making the system more practical to implement in real world scenarios. A better estimate of the system's performance improvements could be obtained by testing it on a larger device more analogous to the lifting robots it was designed for. Finally, with more time, a more rigorous theoretical analysis can be performed to provide a better indication of the system's stability and the range of operating parameters under which it is advantageous to use.

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References

[1] H. Kazerooni and T. J. Snyder, "Case study on haptic devices: Human-induced instability in powered hand controllers," *Journal of Guidance Control Dynamics*, vol. 18, pp. 108–113, Jan. 1995.

[2] V. Duchaine and C. M. Gosselin, "Investigation of human-robot interaction stability using lyapunov theory," in *Proc. IEEE Int. Conf. Robotics and Automation ICRA 2008*, pp. 2189–2194, 2008.

[3] E. Colgate and N. Hogan, "An analysis of contact instability in terms of passive physical equivalents," in *Robotics and Automation, 1989. Proceedings., 1989 IEEE International Conference on*, pp. 404 –409 vol.1, May 1989.

[4] T. Tsumugiwa, Y. Fuchikami, A. Kamiyoshi, R. Yokogawa, and K. Yoshida, "Stability analysis for impedance control of robot in human-robot cooperative task system," *Journal of Advanced Mechanical Design, Systems, and Manufacturing*, vol. 1, no. 1, pp. 113–121, 2007.

[5] I. Hatta, H. Sugi, and Y. Tamura, "Stiffness changes in frog skeletal muscle during contraction recorded using ultrasonic waves.," *The Journal of Physiology*, vol. 403, no. 1, pp. 193–209, 1988.

[6] J. A. Monroy, A. K. Lappin, and K. C. Nishikawa, "Elastic properties of active muscle-on the rebound?," *Exercise and Sport Sciences Reviews*, vol. 35, no. 4, pp. –, 2007.

[7] S. J. Serres and T. E. Milner, "Wrist muscle activation patterns and stiffness associated with stable and unstable mechanical loads," *Experimental Brain Research*, vol. 86, pp. 451–458, 1991. 10.1007/BF00228972.

[8] J. Nielsen, T. Sinkjr, E. Toft, and Y. Kagamihara, "Segmental reflexes and ankle joint stiffness during co-contraction of antagonistic ankle muscles in man," *Experimental Brain Research*, vol. 102, pp. 350–358, 1994. 10.1007/BF00227521.

[9] T. E. Milner, C. Cloutier, A. B. Leger, and D. W. Franklin, "Inability to activate muscles maximally during cocontraction and the effect on joint stiffness," *Experimental Brain Research*, vol. 107, pp. 293–305, 1995. 10.1007/BF00230049.

[10] J. H. van Dien, I. Kingma, and J. van der Bug, "Evidence for a role of antagonistic cocontraction in controlling trunk stiffness during lifting," *Journal of Biomechanics*, vol. 36, pp. 1829–1836, Dec. 2003.

[11] P. J. Lee, E. L. Rogers, and K. P. Granata, "Active trunk stiffness increases with co-contraction," *Journal of Electromyography and Kinesiology*, vol. 16, pp. 51–57, Feb. 2006.

[12] C. Richard, A. M. Okamura, and M. R. Cutkosky, "Getting a feel for dynamics: using haptic interface kits for teaching dynamics and controls," in *1997 ASME IMECE 6th Annual Symposium on Haptic Interfaces*, 1997.

[13] D. I. Grow, L. N. Verner, and A. M. Okamura, "Educational haptics," in *AAAI 2007 Spring Symposia - Robots and Robot Venues: Resources for AI Education*, 2007.

[14] C. Wong and A. M. Okamura, "The snaptic paddle: A modular haptic device," in *First Joint Eurohaptics Conference and Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems (World Haptics)*, 2005.

[15] K. Bowen and M. K. O'Malley, "Adaptation of haptic interfaces for a labview-based system dynamics course," in *14th Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems*, 2006.

[16] R. B. Gillespie, M. Hoffman, and J. Freudenberg, "Haptic interface for hands-on instruction in system dynamics and embedded control," in *IEEE Virtual Reality Conference*, 2003.

[17] J. Cohen, P. Cohen, S. G. West, and L. S. Aiken, *Applied multiple regression/correlation analysis for the behavioral sciences*. L. Erlbaum Associates, 3rd ed., 2003.

[18] F. Faul, E. Erdfelder, A.-G. Lang, and A. Buchner, "G*power 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences.," *Behavior Research Methods*, vol. 39, no. 2, pp. 175–191, 2007.