An Improved Human-Robot Interface by Measurement of Muscle Stiffness

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Abstract—Human contact with haptic devices introduces instabilities due to human operators' attempts to stiffen their arm to stabilize the system. Controllers often cannot measure arm stiffness and do not typically account for this. A method to effectively adjust the controller of a robotic force assist device to compensate for changes in operator arm stiffness was established. It was expected to achieve reduced oscillations and increased performance than one with fixed gains. The results could be used to design human-robot interfaces for force assisting devices. The compensating system used EMG signals to measure muscle activity, then estimated the stiffness of the human's arm. This was used to adjust the parameters of a haptic device's impedance controller based on a threshold. The system was then implemented on a small haptic device to study the effects with a human subjects. EMG signals were experimentally validated as an effective prediction of the stiffness of an operator's arm. The system was assessed in terms of performance and was found to provide improved stability and demonstrated the potential for increased performance.

I. INTRODUCTION

Haptic devices require physical contact between the operator and the machine, using force feedback and creating a coupled system including the operator and the robot. This introduces inherent instabilities due to the typical response of human operators [1–4]. Instability in large haptically controlled force assisting devices which aid human operators in manipulating heavy or bulky loads can pose undesired risks to the load and the operator. Human operators often attempt to control oscillation by stiffening their arm, leading to a stiffer system with more instability. Controllers do not typically account for this, as the level of stiffness is often not directly measurable.

This research will design a control scheme that adjusts to changes in the way an operator grips a haptic controller to attempt to correct for this. It will adjust the control parameters based on the overall stiffness of the operator's arm, which is expected to achieve higher performance in robotic devices than a fixed control system. This study will consider the effects of such a system on haptic force assisting devices. The control scheme must acquire some metric to estimate the operator’s arm stiffness, and electromyogram (EMG) signals are expected to be suitable, as they provide information about the internal state of an operator’s muscles. This will be validated by testing if EMG signals can be used to accurately indicate the stiffness level of a human arm. It should then be possible to design a control scheme with increased stability and less oscillation. Such a control system is expected to increase the performance of an operator, and a human subject study will be completed to verify this.

II. BACKGROUND

Numerous studies have explored the stability of haptic controllers that an operator grips with their hand. Kazerouni 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 tuning the controller to be critically damped for the system, they were able to significantly reduce the instability of a haptic human-robot interface.

Colgate [5] established some conditions for stability of passive systems, and Hannaford [6] and Yokokohji [7] both used electrical analogue two port networks to analyze bilateral systems. Colgate [8] then extended this from the perspective of passivity, providing a foundation for analyzing the stability of devices such as the one to be designed here. He derived several criteria for ensuring the general stability of such systems. These results ensure that by using the impedance shaping method, an assistive system can be maintained as passive and therefore controllable by a human operator. For the system to be designed, the operator’s impedance changes when they stiffen their arm, thereby affecting the stability level of the system. Anderson [9] provided further passivity analysis of systems incorporating time delays.

Accomplishing the goals set out for this study requires understanding the mechanics of human arm muscles and how they relate to muscle stiffness. Subsequent to Bernstein’s discussion of human motor control [10], a variety of physiological studies have been done relating to muscle stiffness and methods for measuring it. Hatta, Sugi, and Tamura [11] 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 [12], 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 [13–17], 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. Osu, et al, discussed a methodology for evaluating joint stiffness using surface EMG measurements [18].

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, which complicates the analysis of the system as passive. If a high performance system begins to oscillate and becomes unstable, a human operator will naturally attempt to stiffen the arm grasping the control device by cocontracting. Based on the results 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 trade off between performance and stability by adjusting the control system. The operator’s act of cocontracting creates an inherently non-passive system, necessitating a system that can incorporate the human arm into the control dynamics, thereby masking the increased stiffness to achieve stable control. Therefore, the target design would consist of a system that could first read the muscle activity, possibly via 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.

III. DESIGN OF STIFFNESS ADJUSTING SYSTEM

A. Haptic Feedback Testbed Device

A simple 1-DOF device capable of producing haptic feedback via a force impeding or assisting the user was designed for use in testing. The design in Fig 1 was inspired by other haptic device designs [19–24], but with the specific goals of being low cost and versatile with a higher force capacity. Since it was to be used for human subject experiments, it was also designed with the safety of the operator in mind. A cable driven system allowed for amplification of the force generated by the motor while remaining compliant to the user’s applied force. The device was capable of generating a maximum force of approximately 100 N and gave a frequency response of up to 10 Hz. The device was controlled using a CompactRIO real-time controller and LabView software and uses an optical encoder and a six-axis force/torque sensor for feedback.

B. EMG Measurement

To measure the level of cocontraction, EMG electrodes were located on two antagonistic muscle pairs: the biceps brachii (BB) and triceps brachii (TB) muscles in the upper arm and the flexor carpi ulnaris (FCU) and extensor carpi ulnaris (ECU) muscles in the forearm. These muscles were chosen because they are easily accessible for surface EMG measurements and are the primary muscle pairs controlling the elbow (E) and wrist (W) motion, respectively. [25,26]

The raw EMG signals were rectified, the DC component was removed, and the result was low pass filtered to 2 Hz to get the signal amplitude. The percent effort, $E_i^\% (t)$, was found using (1), where, for muscle $i$, $E_i^\% (t)$ is the processed signal and $E_i^{MVF}$ is the maximum voluntary force (MVF), found in advance when the subject generated their maximum possible force from an isometric contraction of the muscle. The cocontraction of the antagonistic pair for joint $j$, $C_j^\% (t)$, was calculated using (2).

$$E_i^\% (t) = \frac{E_i^\% (t)}{E_i^{MVF}}$$  \hspace{1cm} (1)

$$C_W(t) = \min E_{FCU}^\% (t), E_{ECU}^\% (t)$$

$$C_E(t) = \min E_{TB}^\% (t), E_{TB}^\% (t)$$  \hspace{1cm} (2)

C. Stiffness Classification

The noise in the EMG readings made a continuous stiffness scale difficult to implement, so a series of discrete levels was used to classify the operator’s arm stiffness. Testing indicated that a simple classification of the stiffness as high or low gave the best results. The stiffness was classified as high or low based on an adjustable threshold, $t_j$, for each pair of muscles as shown by (3). The thresholds could be adjusted to accommodate the variations of muscle activity levels of different operators.

$$S = \begin{cases} 
\text{high} & \text{if } C_W(t) \leq t_W \text{ and } C_E(t) \leq t_E \\
\text{low} & \text{if } C_W(t) > t_W \text{ or } C_E(t) > t_E 
\end{cases}$$  \hspace{1cm} (3)

To avoid excessive oscillation between states, the state only changed when the cocontraction level crossed the
threshold for some finite amount of time on the order of about 100 ms. The large amplification required to read EMG signals cause high levels of noise, necessitating filtering, which also helped with the former issue by adding to the required time that the percent activation must exceed the threshold before being classified.

D. Impedance Control

An impedance control scheme allows the system respond as if it had an arbitrary set of dynamic characteristics (mass \( m \), damping \( b \), and stiffness \( k \)), thus making control easier on the operator by masking the actual system dynamics. The outer force controller calculates the change in position, \( x_d \), for the model system under the applied force, which is then passed to the inner position control loop, which attempts to reach that position by sending an output signal, \( V \), to the motor controller [27,28]. (4) gives an impedance controller transfer function, where \( m \) and \( b \) are the mass and damping of the impedance model. No stiffness, \( k \), was included as this would cause the device to return to a neutral point when released, which was undesired. This is paired with a PD position controller with derivative and proportional gains, \( K_d \) and \( K_p \).

\[
\frac{X_d(s)}{F(s)} = \frac{1}{ms^2 + bs} \tag{4}
\]

E. Adjusting Controller

The impedance characteristics of the final system were chosen experimentally based on how a large force assisting device would move with zero stiffness and are given in Tbl I. Low arm stiffness, \( S = \text{low} \), should result in a system that moves quickly and easily with little resistance, so the mass, \( m_1 \), and damping, \( b_1 \), were set to be small. High stiffness, \( S = \text{high} \), should result in a system with less oscillation that is easier to hold steady, allowing the operator to more precisely control, so a higher damping, \( b_2 \), and mass, \( m_2 \), were used. A diagram of the complete system is shown in Fig 2.

IV. SYSTEM DEMONSTRATION

A. Human Contact Induced Instability

Using the haptic device it was possible to reproduce the conditions under which the system grew unstable as operator arm stiffness increased. Fig 3 plots the magnitude of device oscillation while the operator attempts to hold the device steady. The time delay for the force feedback and the stiffness of the operator’s arm were independently varied to characterize the stability of the device. As either variable increased, the magnitude of the uncontrollable oscillation grew, as indicated by the red shaded region in the upper right of the plot. With no time delay and minimal stiffness, the device was much more stable, as indicated by the dark blue region in the lower left near the origin. This shows that the increased stiffness and time delay combine to drive the system unstable.

B. Improvement with Compensating System

In Fig 4 and Fig 5, the top graph shows the motion of the device using a standard impedance controller, and the bottom graph shows the same motion with the new system, with the yellow highlight indicating the system has detected higher operator arm stiffness and is compensating for it. First, the haptic device was moved through an arbitrary 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. Next, the device was 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.
V. EMG SIGNALS AS INDICATION OF ARM STIFFNESS

A. Experimental Procedure

1) Concept: Human muscles can be modeled with a spring-damper system, and some have also omitted damping [2,4]. To experimentally validate the use of EMG signals, the stiffness, $k_b$, can be calculated from (5) if the base of a spring was fixed and the position, $x_e$ and applied force, $f_c$, of the end were known. By controlling these values, only the EMG signal must be measured. The assumed linearity is valid for consistent posture and low velocities [29,30].

$$f_c = k_b x_e$$

(5)

Participants held the handle of the device while the position and force were controlled, and stiffness was calculated from by recording their difference from the control inputs. The EMG signals were also recorded. It was expected that the EMG signals and stiffness value would covary throughout the experiment. To achieve a variety of stiffness levels, the force was tested at twenty levels evenly spaced from 5 N to 100 N, and the handle position at three levels of $-20^\circ$, $0^\circ$, and $20^\circ$. A fully crossed experiment was used, leading to sixty cases.

Individual combinations of force and position were not expected to influence the results significantly, but stiffness was. Possible errors could arise since each person’s size and strength varied, introducing extraneous variables, so each participant was be asked to perform multiple trials of the experiment. Deviations from the assumed linearity could also introduce errors.

2) Method: For each case, they were asked to hold the device stationary in the given position, as shown in Fig 6. It applied a force required them to stiffen their arm to continue to hold the device in place while the EMG signals were recorded. Learning effects were expected to be insignificant. Only data from the first 200-300 ms of each trial was used to avoid measuring any voluntary applied force from the operator. The data was analyzed to look for correlations between stiffness and EMG signal. This experiment was performed following an approved Institutional Review Board (IRB) protocol.

3) Analysis: A multiple regression/correlation (MRC) technique was used as in Cohen [31] to look for a relationship between the cocontraction and stiffness. Another MRC was calculated using all four EMG signals as predictors instead of the two cocontractions for completeness. The nominal values of device position and generated force were included to measure their influence on the relationship. The values of the multiple correlation coefficient, $R^2$, (indicating the quality of the fit) and the zero-order correlation coefficients for each predictor, $r^2$s, (indicating predictor i’s influence on the predicted variable’s variance) were found. The results were expected to indicate a statistically significant relationship between cocontraction and stiffness and comparable results between EMG signals and stiffness, with no significant contribution to the variance of stiffness from position or force. The data from all participants was anonymized and processed using MATLAB software, while SPSS and G*Power 3.1 [32] were used for statistical analysis.

The number of participants was chosen based on the desired power, $1 - \beta$, of the resulting statistical analysis, which indicates the chance of statistical errors, $\beta$. While $1 - \beta = 0.95$ is typical, experiments collecting in excess of 200 points require a higher value. Using $1 - \beta = 0.9976$ proved sufficient for the data collected, requiring four trials, resulting in roughly 1,200 data points, and giving a required critical $F = 4.69$ for statistical significance of the regression. All participants were male and ranging in age from 20 to 26.

B. Results

The MRC method, based on a linear least squares fit of data, provided $R^2 = 0.173$ for the cocontraction/stiffness relationship and $R^2 = 0.201$ for the EMG/stiffness relationship, indicating the a poor representation of the data. The fundamental form of the relationship between muscle activity and arm stiffness was unknown, so data transformations such exponential and logarithmic were tested, with logarithmic providing the best fit.

The cocontraction/stiffness relationship utilizing a logarithmic transformation achieved $R^2 = 0.338$. Tbl II lists the variance of the stiffness partitioned amongst the predictor variables, indicating the degree to which each predictor contributed to a change in stiffness. The regression resulted in $F = 75.8$. The EMG/stiffness relationship with a similar transformation resulted in $R^2 = 0.377$ and $F = 59.8$, and the corresponding partitioning of the variance of the stiffness is shown in Tbl III. Both regressions were statistically significant.

C. Discussion

A statistically significant relationship existed that allowed the use of measured EMG signals as a predictor of the operator’s arm stiffness. The fit using the cocontraction provided a slightly poorer fit than the raw EMG data, indicating that further analysis should be done about how to characterize

![Fig. 6. A participant performing the experiment](image.png)

![Fig. 7. The simulated lifting device](image.png)

TABLE II

<table>
<thead>
<tr>
<th>Variable</th>
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<td>Cocon (elbow)</td>
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<td>11.1%</td>
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<tr>
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cocontraction from muscle activity. The starting position of the device accounted for only 0.2% of the variance, as expected. However, the nominal force of each trial had a much larger effect on the regression than anticipated. These results demonstrate the viability of using EMG signals in the controller design.

VI. EVALUATION OF SYSTEM PERFORMANCE

A. Experimental Procedure

1) Concept: Evaluation of the compensating controller required testing the effects on both stability in a stiff situation and operator performance in a typical usage scenario.

Holding a device against a rigid surface is a typically unstable situation for impedance controllers, as the device bounces back from contacting the rigid surface due to the force of impact. It was expected that the operator would stiffen their arm to hold the device steady against the surface, so the damping coefficient would increase when the compensation was on, stabilizing the system when needed. The position of the surface was held constant and the compensation state was varied, while the device position was recorded over time. To measure the stability of the system, the root-mean-square error (RMSE) of the distance to the surface was calculated for the duration the operator was attempting to hold the device against the surface, which was expected to be minimal for a goal of maintaining contact with the surface.

Participants then performed a pick-and-place task by using the haptic device to control a simulated lifting arm shown in Fig 7, where the state of the controller and the distance of the object’s initial location to the target were varied. Performance was measured by finding the speed and accuracy of the operator’s object placement. It was expected that this experiment would show an improvement in both with the compensation on.

2) Method: Each participant was oriented with the EMG measurement system and haptic device before performing the experiment. After having the EMG measurement system connected, they were allowed to use the device unconstrained for two to three minutes and become accustomed to it, but with the compensation off, which helped minimize learning effects that might be present. Participants were asked to place the handle of the device against the rigid surface and hold it in contact for five seconds. This was repeated several times with the compensation both on and off. Participants were then introduced to the simulation and given the goal of picking up the object and placing it as close to the center of the target as possible. The participant also repeated this several times with the compensation both on and off. The experiment followed an approved IRB protocol.

3) Analysis: An ANOVA analysis was performed for both tasks after the data from all participants was anonymized. Processing was done using MATLAB software, while SPSS and G*Power 3.1 [32] were used for statistical analysis.

Using $1 - \beta = 0.95$, a minimum of 16 participants was required for statistically significant results. The experiment included 20 participants, with 12 males and 8 females ranging from age 19 to 37, resulting in an 1 − $\beta = 0.965$ and a required critical $F = 1.29$ for statistical significance.

B. Results

The rigid surface task resulted in 80 data points (2 compensation on and 2 compensation off per subject). As demonstrated by Fig 8, the participants were able to reduce their average RMSE with the compensation on. The ANOVA analysis resulted in $F = 55.72$ and $p \leq 0.05$, demonstrating statistical significance. No statistical significance was found for the simulation, but helpful observations were made during the experiment, and trends were observed for participants individually.

C. Discussion

The compensating controller provided significantly increased stability during rigid surface contact, decreasing the magnitude of oscillations. On average, the magnitude was decreased by more than 50%, with the best case showing a decrease of 75%, as demonstrated in Fig 9. Most participants showed an RMSE of less than half the compensation off case.

Statistical significance was not obtained for the simulation due to the large variations in each person’s strategy for execution of the task, making comparing speed and accuracy between subjects difficult. Future experiments can more thoroughly control experiment parameters, such as velocity or force, for better results. However trends in the data showed most participants took less time to place the object and had less error with the compensation on. Fig 10 and Fig 11 show the results for a participant whose results were typical, supporting increased performance. Most participants noticed the difference, with one participant observing that the experiment “was getting harder” when the compensation was off and another participant commenting “moving more smoothly” when the compensation was on.
VII. CONCLUSIONS

The designed system could estimate a robot operator’s arm stiffness and compensate for increases by damping out undesired oscillations. To accomplish this, EMG sensors measured activity in two antagonistic muscle pairs and calculated the cocontraction level for each, classifying it as high or low based on a threshold. An impedance controller that was adjusted to increase damping and make the system response smoother when the stiffness level was high was implemented on a haptic feedback testbed device. The correlation between EMG measurements and arm stiffness was tested and found statistically significant, supporting the use of EMG signals. Another experiment yielded statistically significant results showing increased stability and illustrated trends showing increased performance.

Several enhancements could be made in to improve these results. EMG signals were used, less noisy alternatives would be beneficial. Advances in muscle cocontraction research may also provide improved stiffness identification. Additional information about the operator, such as pose, would help to better identify high stiffness. These improvements could allow the use of a continuously adjusting controller rather than one using discrete states. Further testing in more controlled scenarios, on a variety of devices, and with varying operator postures would strengthen these results.

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REFERENCES