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Investigation of the sensitivity of human arm to small interaction forces during physical human-robot interaction (pHRI)

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INVESTIGATION OF THE SENSITIVITY OF HUMAN ARM TO SMALL

INTERACTION FORCES DURING PHYSICAL HUMAN-ROBOT INTERACTION

(pHRI)

by

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ABSTRACT

Understanding the human motor control strategy during physical interaction tasks is crucial for developing future robots for physical human-robot interaction (pHRI). Effective pHRI depends on humans communicating their intentions for movement with robots. In physical human-human interaction (pHHI), small interaction forces are known to convey their intent between the partners. It is speculated that small interaction forces contain significant information to convey the movement intention of pHHI. However, the mechanism underlying this interaction strategy is largely unknown. Hence, the aim of this work was to investigate what affects humans' sensitivity to the interaction forces. The hypothesis was that small interaction forces are sensed through the movement of the arm and result in proprioceptive signals. A pHRI setup was used to provide small interaction forces to the seated participants' hands, and the participants were asked to identify the direction of the push while blindfolded. The result showed that participants' abilities to correctly report the direction of the small interaction force were lower with low interaction force and a high level of muscle contraction. In particular, the sensitivity to the interaction force direction increased with the radial displacement of the participant's hand from the initial position and when the misalignment of human arm movement with respect to the force direction was lower. The estimated stiffness of the arm varied with the level of muscle contraction and robot interaction force. These results suggested that humans' may benefit from a lower arm stiffness to detect small interaction forces. The outcomes of this work will help future researchers tailor the development of robotic systems for effective pHRI.

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NOMENCLATURE

Symbol	Description
pHHI	Physical Human-Human Interaction
pHRI	Physical Human-Robot Interaction

1. INTRODUCTION

1.1. OVERVIEW

Conventional robots were introduced for industrial purposes in 1980 and are used in different automation applications related to welding, painting, assembly, or production processes.[1-3] In medical applications, robots were first used in the year 1985.[4] The utilization and applications of robots have widely increased due to the technological development of robots and robotic systems.[5-7] In most applications, they are used as a preprogrammed systems to perform predefined tasks in a predictable environment.[8,9] They do not need continuous maintenance or operation from humans. Figure 1.1 shows a conventional robot that performs predefined tasks and an interactive robot that can help humans during their interaction tasks.

Figure 1.1. A conventional robot that performs predefined tasks and an interactive robot that can help humans during their interaction tasks.[10]

In some applications, there are cases where humans need to interact with robots continuously on a need basis, especially for neurological patients and blind people.[11-13] These people require support from human caregivers during their movement tasks because they cannot move with their own energy or visual feedback. However, the current and projected number of human caregivers is not enough to support those in need. Additionally, human caregivers need a significant amount of physical demands to provide support for neurological patients. They need specific training to serve and support elderly, neurological patients, and disabled people. To ensure a high-quality life for these people, the demand for nursing is increasing globally. The field of nursing was projected to increase approximately 15% from 2016 to 2020; that is higher than the scope of occupation.[14] Oftentimes, nurses must stretch, stand, run, bend, and lift when providing support to patients and elderly people. Consequently, human caregivers may suffer from muscle injuries or physical burnout on a regular basis.[15] A smaller number of available human workers, higher costs related to caregivers, and significant developments of robotic technologies accelerate the use and higher demand of humanlike interactive robots.[16,17] Hence, as an alternative, humanlike interactive robots can address the issue for aging and disabled people, including rehabilitation and physical therapy circumstances.[18-20] The expectation for robots is to provide support to disabled and healthy people to perform interaction tasks with humans such as guiding the elderly or patients to walk across a room at any time when a human caregiver is not available. Interactive robots can also help reduce human fatigue, augmentation of power, and improve the quality of life, particularly for elderly people.[21,22] In addition, exoskeleton-type robots can help patients suffering from stroke, paralysis, or Parkinson's disease to perform different types of tasks.[23,24] All these diseases are crucial for medical applications, hence interactive robots are significant to humans who need support from robots for their movement tasks. These tasks may be performed with proper safety measures and fewer physical demands using interactive robots.[25,26] Interactive robots may provide effective and intuitive interaction for tasks during physical human-robot interaction (pHRI) for healthcare, industrial applications, or entertainment.[27,28] Therefore, humanlike interactive robots have the potential to provide support and freedom in the applications of rehabilitation and physical therapy for neurological patients and elderly people.

The main factor for developing an interactive robot is to understand the movement intentions of humans that are mostly conveyed through physical couplings, such as human arm contact during effective physical human-robot interaction (pHRI).[29] The target users of these robots are elderly, disabled, and neurological patients who may need to convey their movement intentions without communicating verbally.[30,31] During non-verbal communication, humans may also expect safe and confident approaches that may be possible for human caregivers but may difficult for robot caregivers. In practice, humans are able to convey their movement intentions with another human through arm-to-arm contact during physical human-human interactions (pHHI). Hence, to develop an interactive robot, it is necessary to understand the underlying mechanism of conveying movement intentions between two humans where interaction forces are applied at the point of physical couplings, such as arm-to-arm contact. Indeed, these motor communications are generally conveyed through small interaction forces.[32,33] However, the encoded information for the interaction forces is not clear yet. Humans nonverbally communicate with other humans through physical arm contact and by the application of interaction forces during different interaction tasks, including walking, weight carrying, handshaking, etc. If a human can sense the direction of interaction force, then that human may convey the movement intentions even in an unknown environment. Therefore, the sensitivity of interaction forces at the physical coupling point is the driving factor for effective pHHI and pHRI. The higher the sensitivity of interaction force, the better a human can convey the movement intentions with another human or robot.[32]

To this end, the aim of this research project was to identify factors that can affect the sensitivity of small interaction forces. The goal was to identify modulation strategies for stiffness of the human arm for effective motor communication. The outcome of this research project will help to develop an effective interactive robot for natural, humanlike, and intuitive pHRI by identifying the relationship between human arm stiffness and small interaction forces.

1.2. PROBLEM STATEMENT

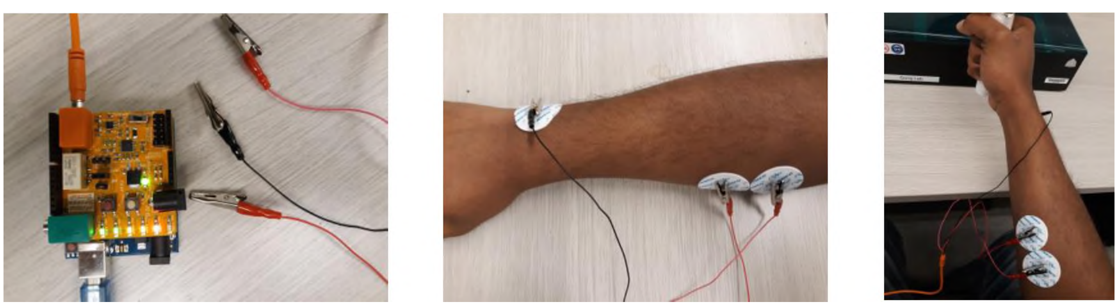
The main focus was to identify the factors that affect the sensitivity of a human arm to the applied interaction forces during effective pHRI. In this research, humans held the arm of a haptic robot, and the robot pushed in four different directions to provide interaction forces. Without visual feedback, human participants were asked to detect the direction of small interaction forces while maintaining a specific level of arm stiffness and arm posture. There was no verbal or any other communication from the environment, except the handholding of the robot arm with the human arm. How human participants then sensed the direction of applied small interaction forces was one of the main problem statements for this research.

It was assumed that the mechanoreceptors at the point of physical arm contact during human-robot or human-human interactions helped to sense the direction of small interaction forces. However, when high grip forces are required for stable physical arm contact between two humans or one human and a robot, mechanoreceptors may not sense the directions of small interaction forces. This is because, at higher grip forces, lower variations of small interaction forces could be below the specified range of the Weber fraction (<10%), which makes it difficult to sense the direction of the applied forces.[34] For this condition, factors that actually help humans identify the direction of small interaction forces were not identified, although they are crucial for effective pHRI. Generally, humans reduce their grip forces to improve their motor communication towards small interaction forces, while reducing their reliable arm contact with a human or a robot partner. Current research aims to find these factors necessary for small interaction to be effective and intuitive for human-robot interaction. In this research, humans followed the directions from small interaction forces provided by the robot arm. Hence, humans were followers, and robots led.

1.3. TECHNOLOGICAL FRAMEWORK

In this research, seated human participants held the robot arms and traversed a 2D motion trajectory through the application of small interaction forces. For physical interaction with a robot, the main factor is to make the robot-provided interaction force as human-like as possible. In this work, the interaction force was increased slowly to make it humanlike to avoid stretch reflex.[35]

To find the factors affecting small interaction forces, it was required to vary human arm stiffness or grip forces during human-human or human-robot arm contact interactions. As for lower arm stiffness, proprioceptors of human arm muscles and tendons may be used to identify the direction of small interaction forces through the kinematic displacements of the arm.[36] Low arm stiffness helps create sufficient arm movement allowing sufficient length changes to arm muscles or tendons above the specified range provided by Weber fraction. In this way, small interaction forces were sensed through the muscle spindle or Golgi tendon organs.[37] Therefore, to modulate the stiffness of the human arm and find the relationship with robot-provided small interaction forces, participants were asked to grip the haptic robot arm, while maintaining a specific level of maximum voluntary contraction (MVC) of arm muscles electromyography (EMG) signal. The maximum voluntary contraction (MVC) of forearm flexor muscles were measured using single-channel electromyography (Muscle SpikerShield Bundle model #V2.61, Backyard Brains, Inc. MI, USA). Figure 1.2 illustrates the experimental set-up of a single-channel muscle spiker shield bundle for measuring the maximum voluntary contraction (MVC) of forearm muscle groups. In addition, during the experiment, the human participants maintained a specific arm posture.



(a) (b) (c)

Figure 1.2. Experimental set-up of single-channel muscle spiker shield bundle for measuring the maximum voluntary contraction (MVC) of forearm muscle groups.

Human participants were verbally instructed to maintain two different levels (high: 70~80% and low: 0~20%) of maximum voluntary contraction (MVC) for the forearm flexor muscle group. In high-level maximum voluntary contraction (70~80%), participants were required to hold the haptic robot arm with a large handgrip force, so the electromyography (EMG) signal to the forearm flexor muscle group registered 70~80% on the computer screen. Participants could adjust the electromyography (EMG) signal for the level of maximum voluntary contraction (MVC) regarding the forearm flexor muscle group before starting a trial. However, participants had to maintain the required level of MVC, and the experiment team instructed them verbally if any modifications were needed. In contrast, for low-level maximum voluntary contractions (0~20%), participants held the haptic robot arm with a lower handgrip force, so the electromyography (EMG) signal of the forearm flexor muscle group registered 0~20% on the computer screen. The lower level of MVC was comfortable for humans, but higher levels of MVC may create muscle fatigue. As a consequence, there were no more than four consecutive higher levels (70~80%) MVC trials during the experiment where a ~1-minute mandatory break was provided.

In each trial, participants were not informed about the levels of interaction force intensity the robot applied. In this research, two different levels of interaction forces were applied by a haptic robot (Phantom Premium 1.5/6 DOF-HF, 3D Systems, Rock Hill, SC, USA). Participants were asked to identify the force directions (+Z: towards the participants, -Z: away from the participants. +X: right side of the participants, and –X: left side of the participants) without any visual feedback, and while maintaining the specific level of MVC and prescribed arm posture. They were allowed to provide their responses at any time during each ~5-seconds trial period for the application of robot interaction force. In this research, the responses were considered correct if participants were able to detect the exact direction of the applied force, considered incorrect if they made mistakes identifying the direction of the interaction force, and noted as no-response if they were not able to tell the direction of force or if they responded after ~5-seconds trial. In this way, each participant performed a total of 96 trials where there were 6 push interaction force trials in each of the four specified directions (+Z, -Z, +X,-X). Therefore, for 20 participants, there were a total of 1920 trials analyzed in the research to identify the factors affecting the small interaction forces. In addition, the maximum radial displacement of the human arm from the initial position and stiffness of the human arm was calculated from the robot-provided interaction forces. Finally, by analyzing participants' responses (correct, incorrect, no-response), maximum radial displacements, arm stiffness levels, and angular displacements between applied interaction forces and arm displacements from initial positions, factors affecting the sensitivity of small interaction forces were identified.

1.4. HYPOTHESIS OF THIS RESEARCH

Considering the ongoing necessity to identify the factors affecting the sensitivity to small interaction forces and technological framework, the major hypotheses of this research were written as follows:

Hypothesis 1: Small interaction force is felt through the changes in the kinematic displacement of arm muscles and tendons.

Hypothesis 2: Alignment of the human arms with the direction of applied interaction forces may affect the accuracy of the direction of small interaction forces during pHHI and pHRI.

Hypothesis 3: Humans may decrease the stiffness of their arms to increase the sensitivity to small interaction forces.

PAPER

I. HUMAN ARM SENSITIVITY TO SMALL INTERACTION FORCES DEPENDS ON THE DISPLACEMENT OF THE ARM

ABSTRACT

Understanding the human motor control strategy during physical interaction tasks is crucial for developing future robots for physical human-robot interaction (pHRI). In physical human-human interaction (pHHI), small interaction forces are known to convey their intent between the partners for effective motor communication. The aim of this work is to investigate what affects the human's sensitivity to the externally applied interaction forces. The hypothesis is that the small interaction forces are sensed through the movement of the arm and the resulting proprioceptive signals. A pHRI setup was used to provide small interaction forces to the hand of seated participants in one of four directions, while the participants were asked to identify the direction of the push while blindfolded. The result shows that participants' ability to correctly report the direction of the interaction force was lower with low interaction force as well as with high muscle contraction. The sensitivity to the interaction force direction increased with the radial displacement of the participant's hand from the initial position and the further they moved the more correct their responses were. It was also observed that the estimated stiffness of the arm varies with the level of muscle contraction and robot interaction force.

1. INTRODUCTION

Beyond traditional robots that perform isolated tasks away from human operators,[1-4] future robots are expected to be physically closer to the users and perform interactive tasks.[5-8] In particular, robots that can physically interact with humans through direct contact have the potential to assist the human workforce in various scenarios, such as in healthcare, manufacturing, or education.[9-12] For example, the foreseen shortage of physical therapists and nurses amplifies the necessity for the development of effective and intuitive physical Human-Robot Interaction (pHRI). Robots may provide physical assistance to patients like human therapists would for effective movement assistance and rehabilitation.[10-15]

In order to advance pHRI, however, it is crucial to first understand the underlying mechanism of effective physical interaction from the perspective of human users.[16] Indeed, humans are experts of physical human-human interaction (pHHI) such as while hand-shaking,[17, 18] walking together,[16, 19, 20] or jointly carrying loads.[21, 22] In many pHHI tasks, humans coordinate their movements together, not through verbal communication or visual feedback, but through the interaction forces through their arms and hands.[20] This physical communication between partners can lead to improved performance in the absence of explicitly shared motor goals,[19, 23-27] a distinction of skill levels,[20] or roles,[28] or even motor adaptation.[29-31] These information-carrying interaction forces are typically 20N or less,[20, 32] are usually kept below 10N,[33, 34] and can sometimes be as low as 1N.[35] It would then be required of the humans in physical interaction tasks to be sensitive to the small changes in the interaction forces for better motor communication with the partner.

How, then, do human partners remain sensitive to small interaction forces during physical interaction tasks? One possibility is through the mechanoreceptors distributed at the site of the physical coupling, typically through holding of hands.[16, 19, 23, 25] However, these receptors may not be suitable for detecting subtle changes in the interaction forces due to the high preload of grip forces that is crucial to maintain a stable physical coupling.[36, 37] That is, the small changes in the interaction forces could be below the Weber fraction (< 10 %) of the pre-existing stimuli on the pressor receptors (grip force), making them unreliable for detecting interaction forces.[38, 39] Humans will have to loosen their grip for reliable motor communication at the cost of unreliable physical coupling.

Alternatively, proprioceptors on muscles, tendons, and joints may help detect the small interaction forces through the resulting kinematic displacements of the arm.[40, 41] The interaction force at the hand will create the corresponding movement of the upper and lower arm, which then creates length changes in the muscles and tendons that are sensed by muscle spindles and/or Golgi tendon organs (GTOs).[42, 43] In certain interaction tasks where there is little arm movement (such as in[20]), small movements can create muscle length changes above the Weber fraction. In this view, small changes in the interaction forces may be detected by the proprioceptors, as long as the arm stiffness is low enough to allow detectable movement in response to the small interaction force.

To this end, this work is aimed at investigating the physical interaction strategy in humans for effective motor communication through small interaction forces. In particular, this work investigates the effect of the state of the arm in the sensitivity to the information provided by the interaction force from an external source. The hypothesis is that humans are more sensitive to the direction of the subtle push on their palm when the arm is displaced more as a consequence of the push. Supporting observations will imply the presence of a specific pHHI/pHRI strategy that the humans may modulate their arm stiffness to improve sensitivity to small interaction forces.

2. MATERIALS AND METHODS

2.1. EXPERIMENTAL SETUP

20 healthy young adult subjects (19 males and 1 female), 18 to 35 years of age (22.1±4.025 years) without a self-reported history of neuromuscular injuries or disorders participated in this study. All participants reported themselves to be right-handed. The experimental protocol and procedure were approved and in accordance with relevant guidelines and regulations of the institutional review board (IRB) of the University of Missouri. All participants/subjects gave their written informed consent and were free to withdraw their participation at any time. The hypothesis and the experiment design are preregistered in the open science foundation (OSF: osf.io/qr785).

The experiment involved externally applied interaction forces to the hand of a seated participant as he/she relaxed or contracted their lower arm muscles. All participants were seated in a rigid chair to keep their back against the chair at all times. Shoulder straps were used to help maintain their posture as depicted in Figures 1(a) and 1(b).[44] Using their right hand, participants grabbed the handle of a haptic robot (Phantom Premium 1.5/6 DOF-HF, 3D Systems, Rock Hill, SC, USA) in front of them as shown in Figure 1(b). The right arm was posed such that the distance from their sternum to the right hand was approximately 30% of their arm length, with the shoulder abduction angle of ~71°, shoulder horizontal flexion of ~45°, elbow flexion angle of ~ 90°, and the forearm and wrist in its neutral position (~0°).[44, 45] The strength of the grip was inferred by the level of activity of the hand-grip muscles on the forearm[46-49] using single-channel electromyography (Muscle SpikerShield Bundle model #V2.61, Backyard Brains, Inc. MI, USA) above the forearm flexor muscle group. A high grip force was identified as 70-80% of the maximum voluntary contraction (MVC) of the forearm muscles, whereas a Low grip force was identified as 0~20% of MVC. Because the participants were asked to maintain their posture at all times, the contraction of the forearm flexor muscle groups was accompanied by a co-contraction of the whole forearm muscles.

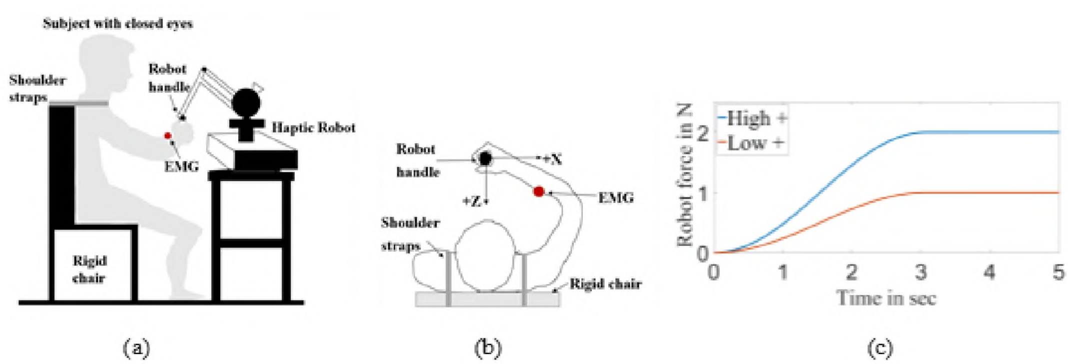


Figure 1. Seated human posture during the experiment with a haptic robot (a) experimental setup (b) top view of the experimental setup (c) applied robot interaction force profile for a trial of ~5 seconds.

A haptic robot was used to apply interaction force in two different magnitudes in one of four directions to a seated participant as shown in Figure 1. The robot applied a force that gradually increased from 0 → 1N (Low) or 0 → 2N (High) over a 5-second duration in such a way that the maximum level of interaction force was reached ~3 seconds (Figure 1(c)). The slow increase in the force was to avoid stretch reflex.[45] After ~3 sec the level of interaction force remained maximum constant value (2N or 1N) until ~5 sec when a single trial was ended as presented in Figure 1(c). Then, the level of interaction force remained constant until 5 seconds. The robot provided this force to the hand in one of the four directions on a horizontal plane (+X, -X, +Z, or -Z directions, Figure 1(b)). The direction of the interaction force was the target information that the robot provided to the human, whereas the level of the interaction force was the intensity of that information. The magnitude of the force was controlled in an open-loop manner where the appropriate motor torque profiles were commanded to the robot by the experimenter. The position of the robot handle (which is also the position of the participant's hand) was measured by the encoders of the robot joints.

2.2. EXPERIMENTAL PROTOCOL

The aim of this study was to find what affects the sensitivity of the interaction force during physical interactions in humans. In this experiment, participants were asked to identify if the direction of push as the robot provided the interaction force at the hands. Participants were blindfolded to encourage them to focus on the sensation at their hands to identify the direction of the push.

At each trial, the robot-provided interaction force was either high (2N) or low (1N), and the grip on the robot handle was either high (70~80% of MVC) or low (0~20% of MVC). It can be considered a low robot interaction force as RL, high robot interaction force as RH, low muscle contraction as ML, and high muscle contraction as MH. Therefore, there were four different conditions in the experiment such as high robot interaction force with high muscle contraction (RH*MH), high robot interaction force with low muscle contraction (RH*ML), low robot interaction force with high muscle contraction (RL*MH), and low robot interaction force with low muscle contraction (RL*ML).

Participants had no knowledge of the intensity setting of the interaction force in any particular trial. Each time the force was applied, participants were asked to identify whether the direction of the interaction force towards them (+Z), away from them (-Z), to their right (+X), or left (-X), while maintaining their pose. They were allowed to give the response at any time during the 5-second period of the force application. Participants' responses were recorded as correct, incorrect, or no-response, where they either declared that they could not identify the direction correctly or if they failed to provide a response within 5-seconds. For each of the four conditions (RH*MH, RH*ML, RL*MH, and RL*ML), there were 6 pushes in each of the four directions (+Z, -Z, +X, and –X), with a total of 96 trials in each experiment session. All 96 trials were equally randomized in the directions and intensity of the interaction forces as well as in the levels of muscle contraction. To avoid muscle fatigue, the randomized sequence of trials was checked to ensure that there were no more than four consecutive high-MVC trials. Also, mandatory ~1 min break were provided during the experiment. Each trial lasted approximately 10 seconds. In addition to the correctness of the response, the radial displacement of the hand as a result of the interaction force was recorded throughout the 5-seconds in all trials.

2.3. DATA PROCESSING AND ANALYSIS

For each trial, the measurement included the response (correct, incorrect, or no-response) and the maximum radial displacement.

$$R = \max(\sqrt{dx(t)^2 + dz(t)^2}),\ t = [0, 5] \tag{1}$$

Where dx and dz are the displacements of the handle in the X and Z directions with respect to its initial position at t = 0.

Human arm stiffness was also estimated in the experiment by considering the applied robot interaction force and the resulting hand displacement. While direct measurement of the interaction force was not available, the commanded robot interaction force was used as an approximation of the interaction force value, from which the 2-dimensional endpoint stiffness of the arm was estimated through the following procedure.[36, 50, 51]

The quasi-static stiffness of the arm is related to the interaction forces and the hand displacement such that

$$\begin{bmatrix} F_x \\ F_z \end{bmatrix} = \begin{bmatrix} K_{xx} & K_{xz} \\ K_{zx} & K_{zz} \end{bmatrix} \begin{bmatrix} dx(t) \\ dz(t) \end{bmatrix},\ t = 3 \text{ sec} \tag{2}$$

Where F_X and F_Z are the robot interaction force in the X and Z-direction; dx (t) and dz (t) are the displacements in X and Z, respectively, K_{XX}, K_{XZ}, K_{ZX}, and K_{ZZ} are the elements of the 2-dimensional stiffness matrix. To avoid dynamic effects, measurements at 3 seconds were used. Then, the stiffness elements K_{XX}, K_{XZ}, K_{ZX}, and K_{ZZ} were determined for each participant for each of the four conditions (RH*MH, RH*ML, RL*MH, and RL*ML) by using the linear least square regression method.

A two-way measure of analysis of variance (ANOVA) was used to find the effect of the robot interaction force and muscle contractions on the measurement of the sensitivity of the interaction force direction. A generalized linear mixed-effects model was also used to analyze the data in a trial-by-trial manner, where the binomial outcome measure was whether participants responded correctly on that particular trial. For this, no-response was considered as an incorrect response. This analysis included fixed effects of robot interaction force, muscle contraction, motion direction (X/Z and +/-), and the logarithm of the maximum radial displacement on that particular trial, with a random intercept for participant and by-participant random slopes for muscle contraction. The maximum radial displacement was transformed to its logarithmic value due to the skewness and kurtosis of the raw data sets.

3. RESULTS

3.1. SENSITIVITY TO INTERACTION FORCES IS AFFECTED BY THE ROBOT FORCE AS WELL AS MUSCLE CONTRACTION LEVELS

Out of a total of 1920 trials among 20 participants, the number of correct responses was 1443 and the number of incorrect responses was 477 trials (including the number of no-response: 255).

Among the 4 possible combinations of conditions, the sensitivity to the interaction force direction was highest when the applied force was high and the muscle contraction was low (RH*ML, average 99.0%), and lowest in RL*MH (average 34.8%, Figure 2 (a)).

It was observed that with a low level of robot interaction force and low level of muscle contraction (RL*ML) condition, the percentage of correct responses was comparable (average 87.1%) with high robot interaction force and high muscle contraction (RH*MH, average 79.8%) condition, where in both RL*ML and RH*MH, the sensitivity was higher than in RL*MH and lower than in RH*ML. These trends were statistically significant where applying lower robot interaction force (RL*MH and RL*ML conditions) decreased the sensitivity by 11.88% ($p < 0.001$), whereas high muscle contraction (RH*MH and RL*MH conditions) decreased the sensitivity by 19.17% ($p < 0.001$, Figure 2 (b)). The combined effect of the low robot interaction force (RL) and the high muscle contraction (MH) was also significant, decreasing the sensitivity of the interaction force by an additional 33.13% ($p < 0.001$). These results are summarized in Table 1.

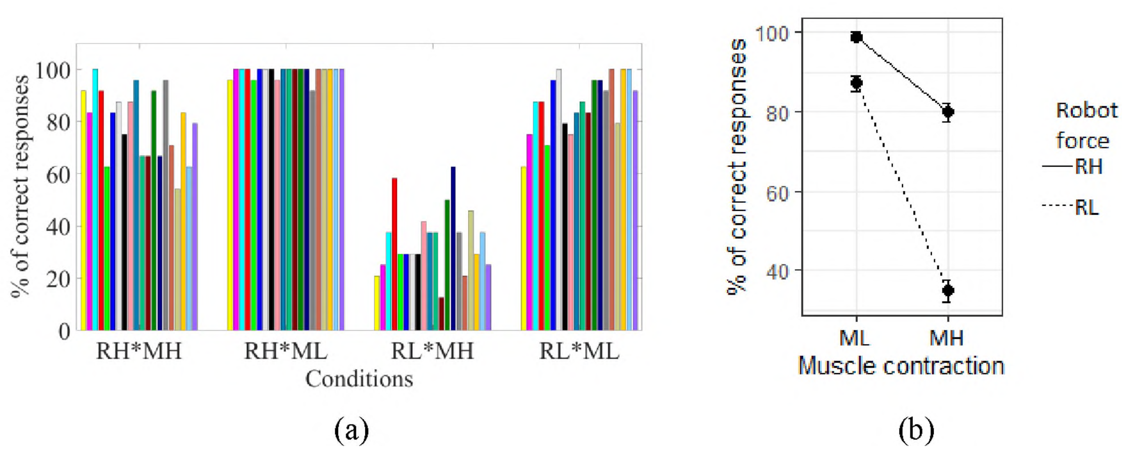


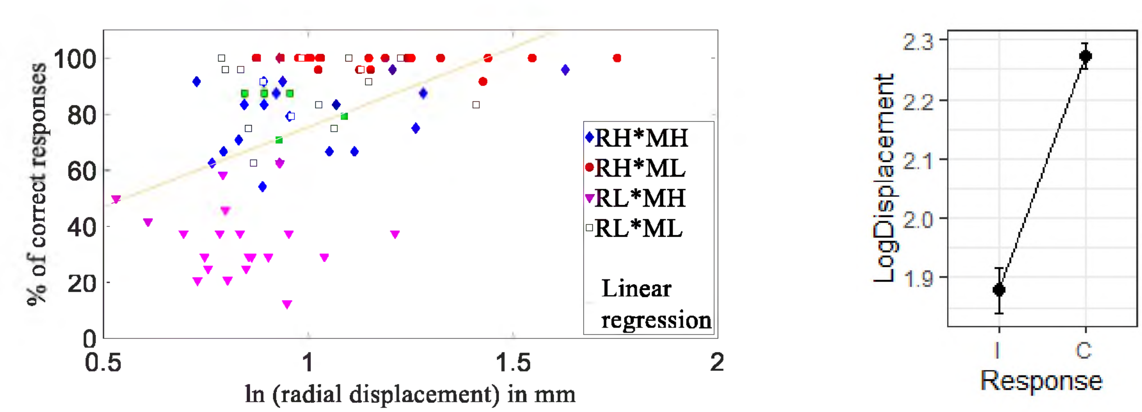
Figure 2. Percentage of correct responses varies with the level of muscle contraction where correctness was maximum (~100%) at high robot force with low muscle contraction (RH*ML) condition (a) experimental results (different colors represent different participants) (b) ANOVA analysis of the percentage of correct responses.

Table 1. Fixed effects of the percentage of correct responses using linear mixed model fit by REML and t-tests use Satterthwaite's method.

	Estimate	Std. Error	df	t value	Pr (>|t|)
Intercept	0.98958	0.02174	102.91522	45.512	< 2e-16 ***
RL	-0.11875	0.02848	137.00000	-4.170	5.38e-05 ***
MH	-0.19167	0.02848	137.00000	-6.730	4.25e-10 ***
RL*MH	-0.33125	0.04028	137.00000	-8.225	1.35e-13 ***

3.2. HIGH RADIAL DISPLACEMENT OF THE HAND INCREASES THE SENSITIVITY TO SMALL INTERACTION FORCES

The radial displacement of the hand from the center (initial position) in each trial was strongly correlated with the sensitivity of the interaction force direction (Figure 3(a)). The radial displacement was the highest during the RH*ML condition (red), during which the chance to make correct responses was also the highest. As the radial displacements are lower in RL*ML and RH*MH trials, the chance of correct responses was also lower. The radial displacement was the smallest in the RL*MH condition where the least correct responses were made. Linear regression showed a correlation of $R^2 = 0.228$ between the percentage of correct responses and the radial displacement in a logarithmic scale. In addition, the radial displacement was higher in trials with correct responses than in trials with incorrect responses after removing participant variability ($p < 0.001$, Figure 3(b)). Including participant variability, the logarithmic radial displacement of all trials with correct and incorrect responses was 2.270±0.430 mm (out of 1443 trials) and 1.876±0.302 mm (out of 477 trials), respectively. Paired sample t-test showed a difference of 0.40±0.26 mm with a large effect size (Cohen's D=1.54).



(a) (b)

Figure 3. (a) Percentage of correct responses increases with radial displacement from the initial position and was highest during high robot interaction force with low muscle contraction (RH*ML, red) condition, during which the radial displacement was also high. Linear regression fit gives R^2=0.228 (b) mean and standard deviation of logarithmic radial displacement of all correct response trials (C) was higher than incorrect response trials (I) ($p < 0.001$).

Then, a generalized linear mixed-effects model was used to analyze the items that affect the correctness of the response in a trial-by-trial manner, where the binomial outcome measure was whether participants responded correctly on that particular trial. We included fixed effects for robot interaction force, muscle contraction, the direction of the push from the robot (X/Z and +/-), and logarithmic radial displacement on that particular trial, with a random intercept for participants and by-participant random slopes for muscle contraction. Table 2 shows that the sensitivity to the direction of the force was reduced by low robot interaction force (RL, $p<0.001$), high muscle contraction (MH, $p<0.001$), and with Z-direction movement (DZ, $p<0.05$), as indicated by the negative estimates and the corresponding odds ratios below 1 (where {odd ratio} = exp (estimate)). The participants were 0.122 times more likely to be correct in RL trials than in RH trials, 0.058 times more likely to be correct in MH trials than in ML trials, and 0.766 times more likely to be correct in the Z direction movements than in the X direction. On the other hand, the sensitivity was increased by positive direction pushes (Dir+, in X+ or Z+ directions, $p<0.001$) and larger radial displacement (LogD, $p<0.02$), as indicated by the positive estimates and the corresponding odds ratios above 1. The participants were 1.678 times more likely to be correct in X+ or Z+ directions than in X- or Z- directions, and were 1.308 times more likely to be correct for a unit increase (1 mm) in the logarithmic radial displacement. The number of observations in this analysis was 1920 (20 participants x 96 trials).

Unlike the ANOVA analysis presented in Table 1, the interaction between the robot force and the muscle contraction was not significant in this analysis, suggesting that it may have been a statistical artifact caused by the ceiling effect of near-perfect accuracy in the RH*ML condition.

Table 2. Fixed effects of all parameters using generalized linear mixed model fit by maximum likelihood in a trial-by-trial manner.

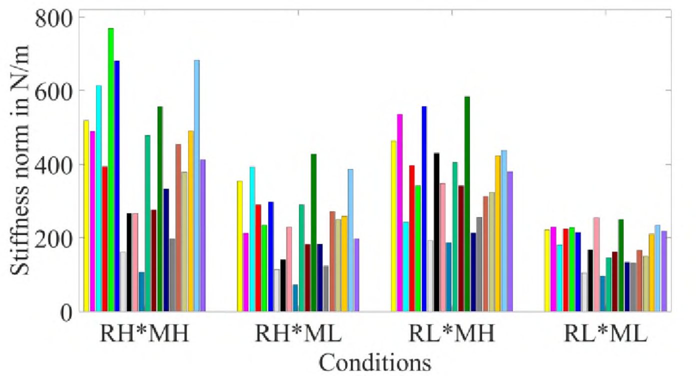
	Estimate	Std. Error	z value	Odds ratio	$\Pr(>\lvert z\rvert)$
(Intercept)	3.6454	0.4161	8.760		< 2e-16 ***
RL	-2.1046	0.1497	-14.055	0.12189	< 2e-16 ***

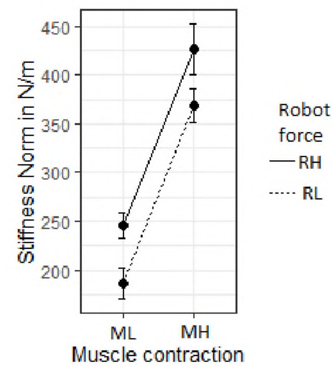
Table 2. Fixed effects of all parameters using generalized linear mixed model fit by maximum likelihood in a trial-by-trial manner (cont.).

MH	-2.8480	0.2985	-9.539	0.05796	< 2e-16 ***
Dir+	0.5178	0.1323	3.914	1.6783	9.07e-05 ***
DZ	-0.2666	0.1312	-2.032	0.76598	0.0421 *
LogD	0.2686	0.1138	2.361	1.308	0.0182 *

3.3. ESTIMATED ARM STIFFNESSES DEPEND ON BOTH ROBOT FORCE AND MUSCLE CONTRACTION LEVELS

The estimated arm stiffness was dependent on the experimental conditions (Figure 4(a)). The norms of the 2x2 stiffness matrices computed from the force-displacement relationship after 3 seconds were averaged across trials and participants for the four conditions. The average arm stiffness norm was the lowest in the RL*ML condition (167.13 N/m) and highest in the RH*MH condition (372.95 N/m), with intermediate values in RH*ML (225.07 N/m) and RL*MH conditions (314.57 N/m). The stiffness was higher in RH than in RL, and in MH than in ML. These trends were statistically significant ($p < 0.001$, Figure 4(b) and Table 3). The low robot interaction force (RL) reduced the arm stiffness norm by -58.47 N/m, whereas the high muscle contraction (MH) increased the arm stiffness norm by 181.56 N/m. The estimated 2x2 stiffness matrices are provided in Table 4, which shows the characteristics of typical arm stiffness matrices with low off-diagonal terms.[36, 50]





(a) (b)

Figure 4. Norm of the arm stiffness increases with the increase of muscle contraction and robot interaction force. The average stiffness was highest during high robot interaction force with high muscle contraction (RH*MH) condition (a) experimental results (different colors represent different participants) (b) ANOVA analysis of the stiffness norm.

Table 3. Fixed effects of stiffness norm using linear mixed model fit by REML and t-tests use Satterthwaite's method.

	Estimate	Std. Error	df	t value	Pr (>|t|)
Intercept	245.26	25.26	34.44	9.709	2.16e-11 ***
RL	-58.47	18.70	58.00	-3.127	0.00276 **
MH	181.56	18.70	58.00	9.709	9.16e-14 ***

Table 4. Estimated average stiffness values of all 20 participants.

Stiffness (N/m)	Conditions			
	RH*MH	RH*ML	RL*MH	RL*ML
K_{xx}	312.81	205.11	263.67	156.11

Table 4. Estimated average stiffness values of all 20 participants (cont.).

K_{XZ}	-8.36	-17.13	17.72	-8.02
K_{ZX}	21.86	-20.67	26.30	-10.93
K_{ZZ}	371.85	207.15	305.01	158.98

4. DISCUSSION

Forces applied to the hand may be sensed by the respective force sensors at the hand, such as the cutaneous pressure receptors on the palm. However, when the pressure on the palm is high due to a strong hand grip, the cutaneous pressure sensors on the skin may suffer from decreased sensitivity to small changes in the pressure, since our ability to detect a change in pressure (the Just Noticeable Difference, or JND) tends to be about 8-10% of the current stimulus intensity. This makes the detection of small interaction forces to be less effective through the pressure sensors on the hands in our MH conditions where the co-contraction of the forearm muscles increases the grip force. Indeed, the approximate grip force for the high muscle contraction (70-80% MVC) was 20-30N,[36,46,52,53] meaning that a 1N applied force is an increase of only 3-5%, likely below the threshold for detection. In contrast, during low muscle contraction (0~20% MVC) grip force was less than 5N, so 1N of applied force should be at least a 20% change. However, detecting a change in cutaneous pressure is not the only way to sense the applied force. As force is applied to the hand, the joints in the arms are displaced as a result, unless the human body is completely rigid which is impossible. This displacement is picked up by the proprioception on muscles and tendons (ex. the Golgi-tendon organs and/or the muscle spindle), which are known to sense kinematics. That is, forces at the hands may be sensed as the arm is displaced as a result, regardless of whether the applied force is above the detection threshold of the cutaneous pressure receptors. This is especially relevant in scenarios in which the handgrip must be tight to ensure the security of the mechanical coupling between the two partners (ex. providing balance assistance during walking).

Indeed, our experiment suggests that the participants may be utilizing these kinematic sensors as an effective force sensor. It was observed that the sensitivity of the interaction force direction was higher when the radial displacement/movement of human arms were larger. In addition, the sensitivity of the interaction force was higher when the muscle contraction was low that reduced the pressure on the palm. In this view, participants may have sensed the direction of the interaction force by sensing the displacement/movement of their arms and/or from the changes in the pressure on their palm when the grip was not tight (ML conditions). When the grip was very tight (MH), however, the hand-robot handle coupling between the human and the robot served mainly as a mechanical connection that allowed the interaction force to generate arm displacements which are eventually sensed by the proprioceptors. This view is consistent with the recent observation that the muscle spindles may encode forces during stretch.[54]

In this experiment, all participants were asked to sense the direction of interaction force through the senses in their arms and hands without any visual feedback. In all four combinations of conditions, the subject's arms were displaced from the initial position in X and Z-directions due to the applied interaction force from the robot handle. It was observed that human arm displacement was higher during low muscle contraction conditions (ML) in which the arms are estimated to be less stiff than in the high muscle contraction conditions (MH) as shown in Figure 4(b). This is consistent with the observation that the arm displacements were higher during ML than in MH conditions, as shown in Figure 3(a). The arm displacement was the smallest in the low robot interaction force and high muscle contraction (RL*MH) condition. The movement of human arms increased at a higher robot interaction force than low robot interaction force for the same level of muscle contraction

On the other hand, participants' ability to sense the interaction force direction was high when the arm displacement was also high - which occurred when the estimated arm stiffness was low. For example, the sensitivity of the direction of interaction force was higher in the RL*ML condition than the RL*MH condition. Hence, with the same level of robot interaction force in the same specific posture of the human arm, the sensitivity of the interaction force direction varied depending on the level of muscle contraction/stiffness/muscle activation level of the human arm. In addition, for the same specific posture, experimental trials where the arm was stiffer (less displacement) were less likely to be correct than trials with low arm stiffness (high displacement). Overall, human arm movement was related to the correctness of the interaction force/sensitivity of the interaction force direction. Hence, humans may benefit from lowering their arm stiffness as it would help them to increase the displacement of the arm, allowing even small interaction forces to be detected.

The estimated magnitudes (norms) of the 2x2 stiffness matrices are smaller when the robot force was low (RL) and higher in RH, despite the fact that the muscle contraction levels were kept similar, as shown in Figure 4(b) and Table 3 ($p<0.003$). A possible explanation for this phenomenon is that it is due to the well-known nonlinear force-displacement relationship of skeletal muscles. Given a nonlinear force-displacement curve originating from a specific level of muscle contraction and posture, the slope (stiffness) of the curve is high for high robot interaction force and low for lower robot interaction force. As a consequence, a linear approximation of the arm stiffness would be lower with low robot interaction force. That is, even if the participants did not modulate their muscle contraction level (%MVC), the arm stiffness may be estimated differently depending on the applied force level.

Nonetheless, there still is a possibility of voluntary modulations of the muscle contraction by the participant, due to the inherently variable muscle activity recordings that cannot completely rule out such cases. In this regard, a possible alternative explanation to the lower stiffness in RL conditions is that there may be an unmeasured lowering of muscle contraction in RL conditions, intentionally or otherwise, so as to be more sensitive to the low level of interaction force. This lowering of the arm stiffness may not have occurred as prominently in the RH conditions since the higher interaction forces are easier to detect even without lowering the arm stiffness to take advantage of the proprioception.

However, it is emphasized once again that a direct measure of the interaction force was not available in this research, and thus the reported arm stiffness is not a direct measurement. Therefore, further research is required to find the variation of endpoint stiffness with different levels of the interaction force.

Better pHRI may be possible by lowering the stiffness of the robot arm to mimic the characteristics of the human arms. Effective pHRI begins from a better understanding of how human participants communicate movement intentions with their partners through the physical coupling. It has been suggested that humans can effectively guide other humans by hand by using interaction forces to communicate intentions during walking,[16,19,20] handshaking,[17,18] etc. In this work, it was suggested that humans are more sensitive to the interaction forces when their arm stiffness is lower. Humans may expect their partner's arm stiffness to be lower because it is natural and advantageous for them to communicate through interaction forces. If so, in pHRI, the humans may also expect their robot partners to have a compliant, low-stiffness arm, rather than a stiff and sluggish arm. A low-stiffness robot arm may be regarded as more human-like.

There are a number of valuable additional benefits of a low-stiffness robot arm. For example, a soft, easy-to-manipulate robot arm is less likely to be a safety threat to a human partner and may help the subjective quality of the pHRI to improve. This may be especially important in healthcare applications where a robot may interact with frail populations. Also, to provide low stiffness, a robot arm may be designed using smaller actuators or power sources to reduce development cost and the overall size of the robot. Note, however, that robots do not require low stiffness for increased force sensitivity. Their sensors (electromechanical transducers) do not suffer from the same reduced sensitivity at a higher force that is common in human perception. Hence, if all the robot needs is to sense the interaction force from the human partner, its arm impedance is irrelevant. The low arm stiffness of the robot would be for the benefit of the human partner, and not as much for itself.

This work was mainly inspired by the necessity to implement intuitive and effective pHRI. It is suggested that low muscle contraction may help increase the sensitivity to the small interaction forces, which may contain movement intentions of the partner, by allowing higher arm displacements to occur. The results of this work imply that the lower robot arm stiffness or human arm muscle contraction may be the desired characteristics of pHRI and pHHI. The findings of this experiment can be used to guide the design of a robot for physical interaction tasks with a human.

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II. FACTORS AFFECTING THE SENSITIVITY TO SMALL INTERACTION FORCES IN HUMANS

ABSTRACT

Effective physical human-robot interaction (pHRI) depends on how humans can communicate their intentions for movement with others. While it is speculated that small interaction forces contain significant information to convey the specific movement intention of physical human-human interaction (pHHI), the underlying mechanism for humans to infer intention from such small forces is largely unknown. The hypothesis in this work is that the sensitivity to a small interaction force applied at the hand is affected by the movement of the arm that is affected by the arm stiffness. For this, a haptic robot was used to provide the endpoint interaction forces to the arm of seated human participants. They were asked to determine one of the four directions of the applied robot interaction force without visual feedback. Variations of levels of interaction force as well as arm muscle contraction were applied. The results imply that human's ability to identify and respond to the correct direction of small interaction forces was lower when the alignment of human arm movement with respect to the force direction was higher. In addition, the sensitivity to the direction of the small interaction force was high when the arm stiffness was low. It is also speculated that humans lower their arm stiffness to be more sensitive to smaller interaction forces. These results will help develop human-like pHRI systems for various applications.

1. INTRODUCTION

Conventional robots have been used in various application areas such as healthcare[1-3] and manufacturing.[4, 5] In most of these applications, robots perform only predefined tasks where they do not need to interact and follow human commands in a continuous fashion.[6] In contrast, interactive robots are expected to be used in physically closer applications to humans through direct arm contact. They are used to perform cooperative interaction tasks with humans,[6] such as in robot-assisted surgery or exoskeleton robots.[7, 8] Ongoing demand for quality nurses, therapists, and productivity in production increases the need for such human-like interactive robots. They have significant potential in nursing and patient care applications including rehabilitation, physical therapy, etc. Additionally, interactive robots may serve as full-time or temporary human caregivers for disabled elders and neurological patients.[8, 9]

Despite the technological advancement of robotics, for interactive robots to support human movement during human-like interaction tasks, there remain technological gaps for intuitive, safe, and effective physical human-robot interaction (pHRI). To develop a human-like interactive robot, it is necessary to first understand how humans physically interact with one another, to exchange their intentions and reactions through the physical coupling.[6] Indeed, humans are experts in physical interaction. Through non-verbal physical human-human interaction (pHHI), human dyads can improve their performance,[10,11] detect each other's roles,[11] and distinguish motor experience[13] through interaction forces only. These information-rich interaction forces are approximately 20N or less in magnitude,[13] and often even below 1N.[14] Therefore, the sensitivity of small changes of interaction forces is required for motor communication between human-human and human-robot dyads. Humans seem capable of decoding information from these small interaction forces.

Then, how do humans sense and interpret small interaction force during physically interactive tasks? A possibility is that humans detect small interaction forces through the mechanoreceptors at the skin of the hand.[6, 10, 11] However, these skin receptors may be ineffective to identify the subtle changes of the small interaction forces if the preload due to secure hand grip is much greater than the changes in the magnitudes of force.[15-17] Alternately, proprioceptors in the muscles and joints, such as muscle spindles or Golgi Tendon Organs, may detect arm movements as a result of small interaction force. As long as the arm stiffness is maintained low, small changes in force may generate sufficient arm movement that is detected by the proprioceptors and interpreted by the human.

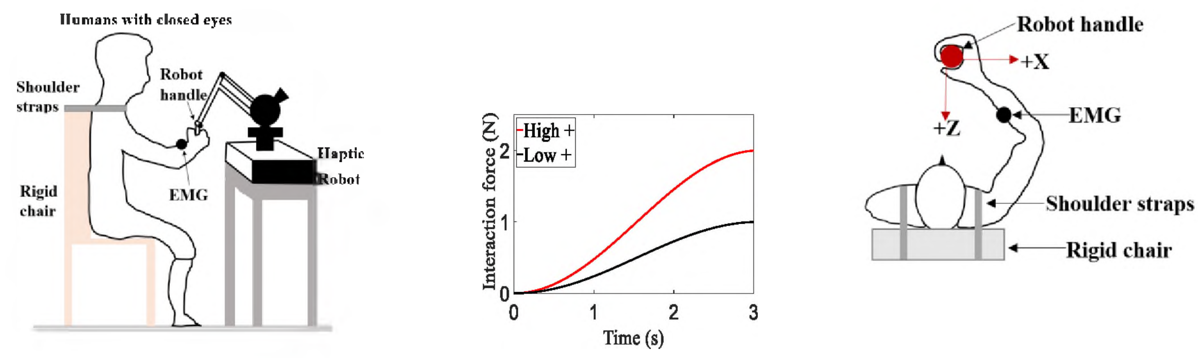
To this end, the aim of this paper is to investigate the factors that can affect the sensitivity to small interaction forces during pHRI. The hypothesis of this work is that a better sense of the small interaction force is obtained if the corresponding movement of the arm is aligned with the applied force. In addition, lower stiffness that is favorable for larger movement will improve the sensitivity to small forces.

2. MATERIALS AND METHODS

2.1. EXPERIMENTAL SETUP

The hypothesis and experimental protocol of this research work are preregistered in the open science foundation (https://osf.io/qbmcx). 20 healthy young adults were recruited for this research (1 female, 22.1±4.0 years of age). All participants were right-handed and had no prior neurological disorders or diseases. The experimental protocol was approved by the institutional review board (IRB) of the University of Missouri. All subjects gave their written, informed consent.

The experiment involved a haptic robot (Phantom Premium 1.5/6 DOF-HF, 3D Systems, USA) that provided interaction forces to the arm of a seated participant while they held the robot handle as shown in Figure 1(a). Shoulder straps were used to maintain the back of the participants against the rigid chair throughout the experiment. All participants maintained a specific posture (distance between the sternum and right arm was ~30% of arm length, ~71^{o} shoulder abduction angle, 45^{o} shoulder horizontal flexion, 90^{o} elbow flexion, and forearm, wrist in their neutral 0^{o} position) during the experiment.[18] The level of forearm muscle contraction was measured using single-channel electromyography (Spikershield #V2.61, Backyard brains, MI, USA). The haptic robot applied two different levels of interaction force (low: $0 \rightarrow 1N$ and high: $0 \rightarrow 2N$) for ~5-seconds to the arm that increased gradually as shown in Figure 1(b). Between ~3 to ~5-seconds the levels of forces were kept constant at their maximum values (1N or 2N). The gradual increase of interaction force was intended to avoid stretch reflexes The robot provided the interaction forces in four different directions (+Z, -Z, +X,-X) as shown in Figure 1(c).



(a) (b) (c)

Figure 1. (a) Experimental setup (b) force profile for high (2N) and low (1N) robot interaction force up to 3 sec (c) top view of experimental setup.

2.2. EXPERIMENTAL PROTOCOL

All participants maintained the specific right arm posture with their eyes closed. Two different levels of interaction force (high: 2N, low: 1N) were applied to the participants' hands while they maintained one of two levels of forearm muscle contraction (high: 70-80% MVC, low: 0-20% MVC), constituting four different experimental conditions (HH- high force high muscle contraction, HL- high force low muscle contraction, LH- low force high muscle contraction, and LL- low force low muscle contraction). Each participant performed a total of 96 trials that consisted of 24 trials of each of the four conditions (HH, HL, LH, and LL). For each condition, the force was applied 6 times in each of the four orthogonal directions (+X, -X, +Z, or -Z).

2.3. DATA PROCESSING AND ANALYSIS

In addition to the participant's responses, the setup also measured the alignment of arm movement with the directions (+X and +Z, Figure 2(a)) of robot interaction force.

$$\theta = \tan^{-1}\left(\frac{|dz(t)|}{|dx(t)|}\right) \tag{1}$$

$$\theta = \tan^{-1}\left(\frac{|dx(t)|}{|dz(t)|}\right) \tag{2}$$

where, dz and dx are the displacements of the robot handle from the initial position (t=0) in the Z and X directions at the point where radial displacement for a trial (0-5 seconds) was maximum that can be calculated using dx and dz.

$$R = \max\left(\sqrt{dx(t)^2 + dz(t)^2}\right), t = [0, 5] \tag{3}$$

In this experiment, arm stiffness was also estimated from the interaction forces that is commanded to the robot and the arm (robot handle) displacements. The two-dimensional stiffness was calculated by the following equation.[19]

$$\begin{bmatrix} F_x \\ F_z \end{bmatrix} = \begin{bmatrix} K_{xx} & K_{xz} \\ K_{zx} & K_{zz} \end{bmatrix} \begin{bmatrix} dx(t) \\ dz(t) \end{bmatrix} \tag{4}$$

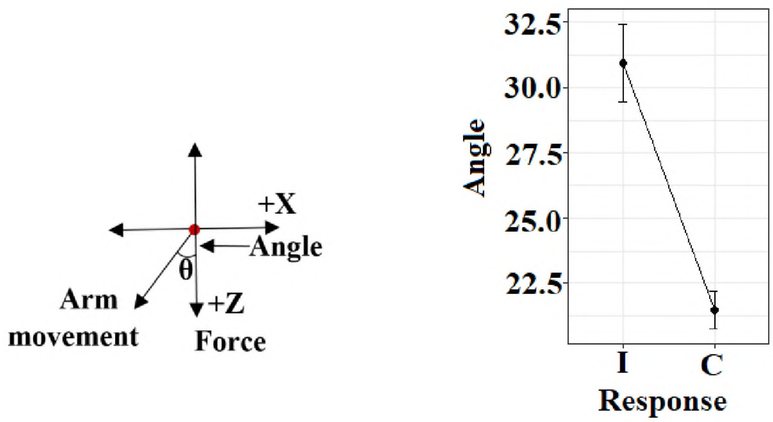
where F_X and F_Z are the robot commanded interaction forces in the X and Z-direction, K_{XX}, K_{XZ}, K_{ZX}, and K_{ZZ} are the elements of the 2-dimensional stiffness matrix. The stiffness elements and stiffness norm were calculated using a linear least square regression model. To overcome dynamic effects, stiffness was measured at 3 seconds for the high and low levels of forces. For comparing the stiffness at 1N, the stiffness was also measured at 1.5 seconds during the high-force trials.

For statistical analysis, a generalized linear mixed model was used to find the data in trial-by-trial manner, where correct and incorrect responses were the binomial outcomes where no-response was considered as an incorrect response. This analysis included the fixed effects of the alignment of arm movement to the force (angle). Two-way analysis of variance (ANOVA) was used to find the effect of low robot interaction force and high muscle contraction on the stiffness norm.

3. RESULTS

3.1. THE ALIGNMENT OF ARM MOVEMENTS TO INTERACTION FORCES AFFECT THE SENSITIVITY

Among 1443 correct trials and 477 incorrect trials where 255 trials were no-response for all participants, the sensitivity to small interaction forces was high when the misalignment of arm movement with the force direction was low (Figure 2(b)). The highest sensitivity was observed when the arm movement was exactly along the direction of the applied robot interaction force. These trends were statistically significant ($p<0.05$). The linear mixed-effects model of the angles showed that the sensitivity to small interaction forces was decreased by the increase of misalignment of arm movement (negative estimate,-0.06442). The odds ratio (0.937) was found to be less than 1, which indicates that subjects were 0.937 times as likely to be correct for a 10° increase of the misalignment angle.



(a) (b)

Figure 2. (a) Representation of arm alignment (angle) with the direction of interaction force (b) correct responses had a lower average angle with the direction of applied robot interaction force than incorrect responses (ANOVA analysis).

3.2. HIGHER ARM STIFFNESS DECREASES SENSITIVITY TO SMALL INTERACTION FORCES

The human arm stiffness norm for the high and low levels of interaction force was correlated with the sensitivity to the force direction (Figure 3). Linear regression for the trials with a high level of interaction force (2N) showed a correlation of R^2=0.2470 between the percentage of correct responses and the stiffness norm where forearm muscle contraction varied between high (H: 70-80 %MVC) and low (L: 0-20 %MVC). Similarly, linear regression of small interaction force (1N) provided a correlation of R^2=0.50. However, the coefficients (slope) of linear regression for high interaction force was -0.03942, while it was -0.1606 for small robot interaction force, which indicates that the reduction of sensitivity with the increase of stiffness norm was more pronounced for smaller interaction forces.

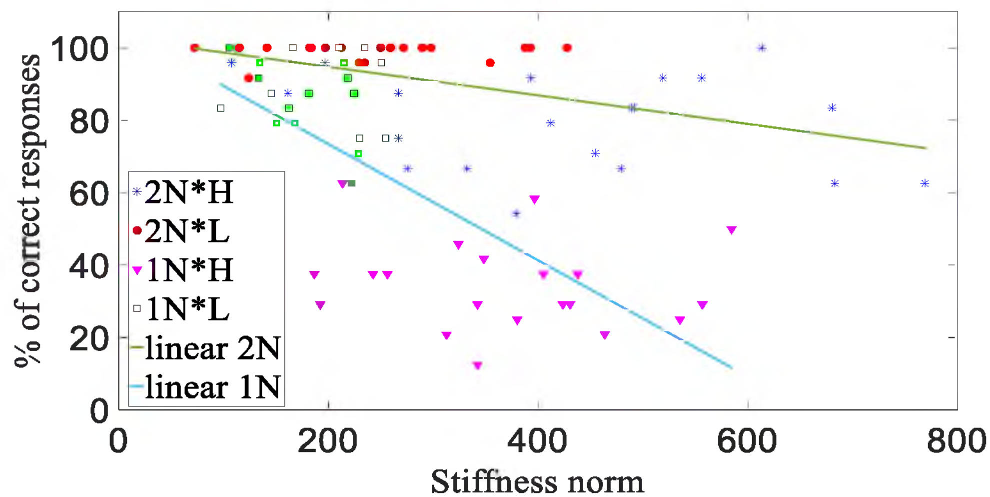
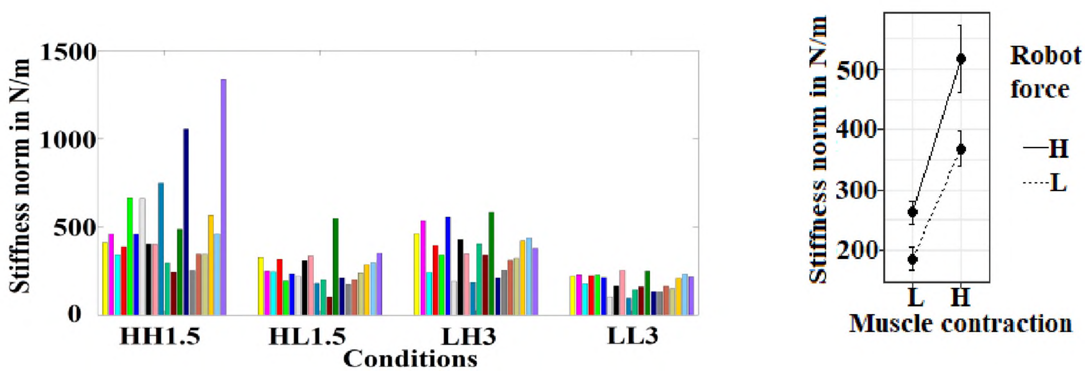


Figure 3. Percentage of correct responses increases with the decrease of stiffness norm of human arm during pHRI (slope and R^2 values for high force (2N) was -0.03942 and 0.2470, for low force (1N) they were -0.1606 and 0.50 respectively).

3.3. ARM STIFFNESS IS LOW AT LOWER INTERACTION FORCE

The estimated stiffness of human arm varied with the level of interaction force despite the instructions to the participants to maintain a constant level of muscle contraction (%MVC) (Figure 4). The stiffness norm (2N) was calculated from the force-displacement relationship at t=3 seconds as well as t=1.5 seconds, while only at 3 seconds for the small interaction force (1N), since after 1.5 seconds in the high force trial, the magnitude of force was equal (1N) to the small interaction force trial (1N) at 3 seconds. All the stiffness values were averaged across all participants and trials for all four conditions.

It was observed that all the subjects were stiffer in the Z direction than X-direction force as $K_{zz} > K_{xx}$ for all the four conditions (Table 1, 399.01 N/m>346.93 N/m, 211.82 N/m>204.29 N/m, 305.01 N/m>263.67 N/m, and 158.98 N/m>156.11 N/m). Also, stiffness at 2N force at 3 and 1.5 seconds trials were comparable with each other (Table 1, HL=205.11 N/m= ~204.29 N/m), while higher for 1N at 3 seconds trial (Table 1, 312.81 N/m >263.67 N/m, 371.85 N/m >305.01 N/m, 207.15 N/m > 158.98 N/m). These trends were statistically significant ($p<0.001$, Figure 4(b)). It was also observed that the stiffness norm was higher for high robot interaction force, while lower for a lower level of interaction force, regardless of the level of muscle contraction (Figure 4(b)).



(a) (b)

Figure 4. (a) Human arm stiffness is high for high interaction force (2N) and low for lower interaction force (1N) trial for the same level of muscle contraction (different color denotes different subjects) (b) ANOVA analysis of stiffness norm for high and low level of interaction force.

Table 1. Overall human arm stiffness during higher (2N) and lower levels of force (1N).

Stiffness (N/m)	Condition 1		Condition 2		Condition 3	
	Time 3 sec and force 2N		Time 1.5 sec and force 2N		Time 3 sec and force 1N	
	HH	HL	HH	HL	LH	LL
K_{xx}	312.81	205.11	346.93	204.29	263.67	156.11
K_{xz}	-8.36	-17.13	7.17	-10.29	17.72	-8.02
K_{zx}	21.86	-20.67	3.95	-15.93	26.30	-10.93
K_{zz}	371.85	207.15	399.01	211.82	305.01	158.98

Table 2. Fixed effects of stiffness norm during linear mixed model.

	Estimate	Std. Error	df	t value	Pr (>|t|)
Intercept	280.81	30.72	69.20	9.141	1.61e-13 ***
Robot_low	-112.47	33.89	58.00	-3.32	0.00157 **

For the same 1 N of force, the average stiffness norm was higher (399.6 N/m) for HH at 1.5 sec than for LH at 3 seconds (314.57 N/m). Similarly, the average stiffness norm was higher (221.71 N/m) for HL at 1.5 sec, compared to the LL condition (167.13 N/m) at 3 sec. All these trends were statistically significant (Table 2, $p<0.001$). Conditions with smaller interaction force decreased the stiffness norm by 112.47 N/m although participants maintained the same level of muscle contraction (Table 2).

4. DISCUSSION

Humans may sense the direction of interaction force through the cutaneous pressure receptors of their palms during pHHI and pHRI. However, the results in this work suggest that higher alignment of arm movement to the direction of force increases the sensitivity of small interaction force, despite the fact that the force direction does not change and the pressure receptors could have detected the direction of force. This suggests that accurate arm movement direction, and not force direction, is important in detecting the direction of the push or pull with small forces. This further implies that the proprioceptors that detect the arm movement, such as the Golgi tendon organs or muscle spindles, may be more suitable for detecting small interaction forces than the pressure receptors at the hand. This is especially true when the grip force dominates the preloaded pressure on the cutaneous sensors,[17] as can be seen by the reduced sensitivity during high muscle contraction trials in which the grip forces are higher.

For proprioceptors to detect the force, however, sufficient arm movement should be generated at the direction of the force. At higher arm stiffness, the displacement or movement of the arm may be insufficient and thus reduce the sensitivity to small interaction forces. The results in Figure 3 illustrates this interpretation that, in addition to reducing the efficacy of the cutaneous sensors by increasing the preload, high muscle contraction also leads to higher arm stiffness that will also reduce the efficacy of the proprioceptors.

A notable observation was that the arm stiffness was higher when the applied force was high (2N), even though the muscle contraction remained similar. A possible explanation is that higher force created faster and larger movements which results in larger stiffness due to stretch reflex as well as the non-linear force-to-length relationship of the muscles. Alternatively, humans may have reduced their arm stiffness, perhaps unconsciously, to better sense the direction of small interaction force (1N). The muscle contraction measure may not have captured this due to inherently noisy signals. Further investigation on this phenomenon may benefit from more accurate measurement of muscle activities as well as a direct measure of the interaction force.

5. CONCLUSIONS

This research work was motivated by the need to develop an effective human-like interactive robot. It is suggested that low arm stiffness with better alignment of arm movement with the direction of force may help improve physical communication through small interaction force during pHRI.

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SECTION

2. CONCLUSIONS AND RECOMMENDATIONS

2.1. CONCLUSIONS

This research investigated the factors that affect physical interactions between two humans or one human and another robot. The work was completed because of the necessity for developing a humanlike interactive robot that can be used for different interaction tasks with humans. To identify and analyse the factors, a physical human-robot interaction (pHRI) experiment was developed and the resultant information was utilized to program an interactive robot. In the developed pHRI system, humans held the arm of a haptic robot that guided humans in different prescribed directions. The data from the developed pHRI experiment, such as applied robot interaction force, maximum radial displacement of the arm, level of maximum voluntary contraction (MVC) of forearm muscle, human arm stiffness, and the alignment of human arm movement with the direction of applied interaction forces were used to identify the sensitivity of human arm to small interaction forces. In this experiment, the commanded haptic robot interaction force was used as an approximation of the interaction force, and an electromyography (EMG) system was used to find the level of MVC of the forearm muscle. The experimental data was then used to investigate the research hypotheses of this work and conclusions were drawn accordingly.

Hypothesis 1 states that a small interaction force is felt through the changes in the kinematic displacement of arm muscles and tendons. This was supported.

The results of this research showed that the sensitivity of small interaction forces was highest when the radial displacement of the hand from the initial position was also the highest. This was obtained at higher (2 N) robot interaction forces and low muscle contraction (RH*ML) conditions. Additionally, on a logarithmic scale, a linear regression R^2=0.228 implied that the sensitivity of small interaction forces depends on maximum radial displacement from the initial (center) position. However, the sensitivity of the interaction force direction was higher when the muscle contractions were low, and that decreased the pressure on the palm. From this perspective, participants may have sensed the direction of the interaction force by sensing the displacement of their arms and/or from the changes in the pressure on their palm when the grip was not tight (low muscle contraction conditions). When the grip was very tight (high muscle contraction conditions, 70-80% MVC), the hand-robot handle coupling between the human and the robot served mainly as a mechanical connection that allowed the interaction forces to generate arm displacements that were eventually sensed by the proprioceptors. Additionally, this hypothesis was supported because low arm stiffness can be used to increase the kinematic displacement of arm muscles, joints, and tendons, and that can be sensed by proprioceptors, including Golgi-tendon organs. In this research, participants utilized these kinematic sensors as an effective interaction force sensor to sense the direction of small interaction forces. Hence, higher arm stiffness can make the detection of small interaction forces less effective through the pressure sensors on the hands, but they may be sensed through the kinematic sensors in human arms.

Hypothesis 2 states that the alignment of the human arms with the direction of applied interaction forces may affect the accuracy of the direction of small interaction forces during pHHI and pHRI. This hypothesis was supported.

The results of this research supported the third hypothesis including the alignment of the human arm with the direction of applied interaction forces that significantly affected the sensitivity to small interaction forces during pHRI. This finding suggested that the appropriate direction for the movement of the human arm was significant to sense the direction of applied small interaction forces. This hypothesis also strengthened the first hypothesis regarding the proprioceptors (Golgi tendons) that helped detecting the arm movements, and they may be more effective for sensing small interaction forces than pressure receptors in the human arm. This is true when humans hold robot arms with high grip forces.

Hypothesis 3 states that humans may decrease the stiffness of their arms to increase the sensitivity to small interaction forces. This was also supported.

The results of this research implied that lower arm stiffness is an effective way to sense the direction of small interaction forces, even when humans hold robot arms with a high grip force. It was obtained that 2x2 stiffness norms were low for low robot interaction forces, and it was high for high robot interaction forces. Although, the level of muscle contraction was the same. This may be due to humans intentionally reducing their arm stiffnesses during small interaction forces making them more sensitive to the low levels of robot-provided interaction forces. However, lowering of the arm stiffness may not have occurred as prominently in the high robot interaction force conditions because the higher interaction forces were easier to detect even without lowering the arm stiffness to take advantage of the proprioception. Humans may have intentionally reduced their arm stiffnesses to increase sensitivity to small interaction forces when their arm grip forces and pressures on the palms, were high enough that the cutaneous pressure sensors on the skin suffered from reduced sensitivity to small changes in the pressure. This happens because humans' abilities to detect a change in pressure are low at about 8-10% of the current stimulus intensity. Additionally, lower robot arm stiffness may be better for effective and intuitive pHRI as when there was no visual feedback for heightened humans' sensitivities to small interaction forces when compared to higher arm stiffnesses. This experiment finding help design an interactive robot to mimic the characteristics of human arms.

2.2. RECOMMENDATIONS

The research showed several different aspects, factors, hypotheses, and scientific answers regarding the sensitivity of small interaction force through human arms during physical interactions with haptic robots. However, there are scopes to expand upon for future research.

In this research, there was no direct measurement of robot interaction forces. The commanded robot interaction force was considered as the approximation of the prescribed interaction force value. As a consequence, the calculated stiffness was also not a direct measurement of human arm stiffness. Hence, a direct measurement setup through a force sensor could be added for further research. This could be added at the interaction point between the human arm and the robot handle. In this way, the variation of human arm stiffness can be obtained for different levels of interaction forces.

Another consideration for future research is to a use multi-channel high-resolution electromyography (EMG) system for different upper arm muscles throughout the experiment. In the experiment, the strengths of the grips and levels of maximum voluntary contractions (MVC) were measured by the activity levels of the hand-grip muscles on the forearm using single-channel electromyography for the muscle spikershield bundles (model #V2.61, Backyard Brains, Inc. MI, USA) above the forearm flexor muscle groups. By using a multi-channel electromyography (EMG) system, the strength of shoulder, bicep, tricep, and wrist muscles can be measured. Only the levels of maximum voluntary contraction (MVC) were used in this study to identify the sensitivity of small interaction forces at two different stiffnesses for the human arms, and no direct results were calculated regarding these levels of MVC.

APPENDIX A.

PARTICIPANT INFORMATION

PARTICIPANT INFORMATION

Table A.1. Details of the Participants.

Participant	Participant Code	Gender	Age*	Length of arm (inch)	Prior Neurological Disorder
1	P01	M	18	35	N/A
2	P02	M	22	36	N/A
3	P03	M	18	36	N/A
4	P04	M	27	35	N/A
5	P05	M	18	33	N/A
6	P06	M	19	36	N/A
7	P07	M	19	35	N/A
8	P08	M	24	34	N/A
9	P09	M	28	35	N/A
10	P10	M	20	36	N/A
11	P11	M	29	36	N/A
12	P12	M	27	34	N/A
13	P13	M	19	35	N/A
14	P14	M	22	37	N/A
15	P15	F	24	36	N/A
16	P16	M	20	36	N/A
17	P17	M	23	37	N/A
18	P18	M	29	33	N/A

Table A.1. Details of the Participants (cont.).

19	P19	M	18	36	N/A
20	P20	M	18	35	N/A

*Age on the date of the experiment

APPENDIX B.

SEQUENTIAL INSTRUCTIONS FOR THE EXPERIMENTER

SEQUENTIAL INSTRUCTIONS FOR THE EXPERIMENTER

1. Prior to participant's arrival

- Turn on Phantom motors.
- Power on the electromyography equipment.
- Setup and open the Visual Studio and Arduino software

2. As soon as the participant enters the lab

- Check the participant's body temperature using an infrared thermometer.
- Ask participants to clean their hands with soap from the sink in the lab and use sanitizer.
- Ask the experimenter and the participants to wear face coverings throughout the experiment.
- Proceed once all sanitation practices are completed.

3. Start of the experiment

- Provide participants with consent forms and demonstration of the experiment, give verbal instructions, and take queries if any.
- Measure the arm length of the participant using a measuring tape.
- Sit in front of the haptic robot experimental set up on a chair.
- Perform conventional skin preparation techniques before applying disposable dual electrodes to the skin. For example, remove extra hair of hand on electromyography (EMG) electrode sites, and use non-alcoholic wipes.

- Set the electrode of the electromyography equipment on the participant's arm muscle.
- Verify the MVC level from the computer screen by contracting the arm muscles.
- Ask participants to keep their backs against the chair at all times. Shoulder straps may be used to help maintain their posture.
- Ask the participant to hold the end effector of the haptic robot.
- Set different arm and haptic robot posture angles using a goniometer.
- Set the required distance of participant's right hand from the sternum.

4. During each trial of the experiment

- Maintain handgrip and arm muscles stiffness with high (70~80%) or low (0~20%) level of MVC for each trial of the experiment.
- Ask participants to close their eyes and maintain the same arm and haptic robot posture during each trial of the experiment without reacting with perturbation force.
- Ask participants to tighten or loosen their grips for each trial.
- Require participants to keep the tightness of the grip consistent for ~10 seconds.
- Tell participants to say "GO" to start the trial, from which time participants feel the robot slowly push them in a direction for 3 seconds.
- Ask participants to tell the sensed direction of interaction force at any time during the ~5-seconds trial. After ~5-seconds of trial, responses were noted as no-response for the sensitivity of small interaction force.

5. At the end of each trial of the experiment

- Ask the participants about the direction of interaction force after each trial of the experiment.
- Save the participant's response to each trial with the corresponding datasheet and trial number.
- Check all the postures for the next trial.
- Change the level of MVC with the same body postures and repeat a total of 96 trials for the experiment with different body postures and directions of interaction forces.
- Ask participants to clean their hands once again before leaving the laboratory.
- Save and close all the software windows.
- Secure the consent form and the datasheet with remarks and experimental information for future uses.

APPENDIX C.

VERBAL INSTRUCTIONS TO THE PARTICIPANTS

VERBAL INSTRUCTIONS TO THE PARTICIPANTS

Describing the two maximum voluntary contractions (MVC) in the experiment

- **High level of MVC (70~80%)**

  This was the instance when the participants gripped the haptic robot end effector (the end part of the haptic robot arm that interacts with humans) with higher forces. Participants had to hold the haptic robot end-effector with a large handgrip force by contracting wrist extensors and flexor muscles. They applied large grip forces so that the maximum voluntary contraction (MVC) level of the wrist extensor and flexor muscle groups were 70~80% (higher grip force) on the computer screen. Participants could adjust their muscle's MVC levels by expanding or contracting their wrists and flexor muscles using higher or lower grip forces and then the experimenter observed the muscles electromyography (EMG) signal displays on a computer screen. Additionally, under these conditions, participants had to stiffen their upper arm muscles by contracting the biceps and triceps muscles in such a way that the MVC levels for both muscle sets were 70~80% (High stiffness).

- **Low level of MVC (0~20%)**

  Under these conditions, participants had to hold the end effector of the haptic robot with small comfortable grip forces using wrist extensor and flexor muscle groups. The levels of maximum voluntary contraction (MVC) for wrist extensor and flexor muscle groups were approximately

0~20% (lower grip force). In addition, for these conditions' participants had to loosen their upper arm bicep, and tricep muscles in such ways that the MVC levels for both muscle groups were approximately 0~20% (low stiffness).

Instructions for the experiment with a demonstration

- Participants maintain the distance from the arm to the sternum and maintain robot posture throughout the ~5-seconds trial.
- Participants maintain the levels of maximum voluntary contraction (MVC) within ranges throughout the ~5-seconds trials. For example, maintain 70~80% MVC for a higher level of MVC and 0~20% MVC for a lower level of MVC.
- Participants must always close their eyes and keep their backs against the chair using shoulder straps without reacting with perturbation force.
- Participants will say "GO", and from that point, the experimenter starts the trial.
- Each trial ends in ~5-seconds from the point, participants say "GO".

APPENDIX D.

EXCERPT C++ CODE FOR THE OPERATION OF THE HAPTIC ROBOT

EXCERPT C++ CODE FOR THE OPERATION OF THE HAPTIC ROBOT

The code can be found in the Visual Studio file FrictionlessSphere_VS2010, which is located at C:\OpenHaptics\Developer\3.4.0\Virtual Objects\All Virtual Objects\All Virtual Objects in the computer labeled R04SONGYUN at room 203 in the Department of Mechanical and Aerospace Engineering at Missouri University of Science and Technology.

```
// Force on the haptic robot arm
float bx;                    //Fixed Robot Interaction Force in X Direction
float by;                    //Fixed Robot Interaction Force in Y Direction
float bz;                    //Fixed Robot Interaction Force in Z Direction
//2N push in Z direction
if (timer <= 320)     //First ~3 seconds
{bx = 0;
by = 0;
bz = ((-1.0) *cos(2 * 3.141592*0.2*timer*0.0078125) + 1.0);
else if (timer > 320 && timer <=520)   //Next ~3 seconds to ~5 seconds
{ bx = 0;
by = 0;
bz = 2.0;}
//2N pull in Z direction
if (timer <= 320)  //First ~3 seconds
```

```
{bx = 0;
by = 0;
bz = -((-1.0)*cos(2 * 3.141592*0.2*timer*0.0078125) + 1.0);
else if (timer > 320 && timer <=520)   //Next ~3 seconds to ~5 seconds
{bx = 0;
by = 0;
bz = -2.0;}
//2N push in X direction
if (timer <= 320)     //First ~3 seconds
{bx = ((-1.0) *cos(2 * 3.141592*0.2*timer*0.0078125) + 1.0);
by = 0;
bz = 0;
else if (timer > 320 && timer <=520)   //Next ~3 seconds to ~5 seconds
{bx = 2.0;
by = 0;
bz = 0;}
//2N pull in X direction
if (timer <= 320)  //First ~3 seconds
{bx = -((-1.0)*cos(2 * 3.141592*0.2*timer*0.0078125) + 1.0);
by = 0;
bz = 0;
else if (timer > 320 && timer <=520)   //Next ~3 seconds to ~5 seconds
{bx = -2.0;
```

```
by = 0;

bz = 0;}

//1N push in Z direction

if (timer <= 320)      //First ~3 seconds

{bx = 0;

by = 0;

bz = ((-0.5) *cos (2 * 3.141592*0.2*timer*0.0078125) + 0.5);

else if (timer > 320 && timer <=520)   //Next ~3 seconds to ~5 seconds

{bx = 0;

by = 0;

bz = 1.0;}

//1N pull in Z direction

if (timer <= 320)  //First ~3 seconds

{bx = 0;

by = 0;

bz = -((-0.5) *cos (2 * 3.141592*0.2*timer*0.0078125) + 0.5);

else if (timer > 320 && timer <=520)   //Next ~3 seconds to ~5 seconds

{bx = 0;

by = 0;

bz = -1.0;}

//1N push in X direction

if (timer <= 320)      //First ~3 seconds

{bx = ((-0.5) *cos (2 * 3.141592*0.2*timer*0.0078125) + 0.5);
```

```
by = 0;

bz = 0;

else if (timer > 320 && timer <=520)   //Next ~3 seconds to ~5 seconds

{bx = 1.0.

by = 0;

bz = 0;}

//1N pull in X direction

if (timer <= 320)  //First ~3 seconds

{bx = -((-0.5) *cos (2 * 3.141592*0.2*timer*0.0078125) + 0.5);

by = 0;

bz = 0;

else if (timer > 320 && timer <=520)   //Next ~3 seconds to ~5 seconds

{bx = -1.0.

by = 0;

bz = 0;}
```

APPENDIX E.

ARDUINO CODE FOR MAXIMUM VOLUNTARY CONTRACTION (MVC) OF ELECTROMYOGRAPHY (EMG)

```
#define NUM_LED 6                    // sets the maximum numbers of LEDs
#define MIN 0                        // minimum posible reading tweak this value
#define MAX 100                      // maximum posible reading tweak this value
const int numReadings = 10;          // value to determine the size of the readings array
int reading[numReadings];            // variable to store the read value reading
int k= 0;                            // the index of the current reading
int total = 0;                       // the running total
int average = 0;                     // the average
byte litLeds = 0;                    //variable to store the read value
byte leds [] = {8, 9, 10, 11, 12, 13};
void setup () {
Serial.begin(9600);                         //begin serial communications
for (int i = 0; i < NUM_LED; i++) {         //initialize LEDs as outputs
   pinMode(leds[i], OUTPUT);}               // configure LED as output
for (int i = 0; i < numReadings; i++) {     // initialize all the readings to 0
   reading[i] = 0;}}
void loop () {
total = total - reading[k];                 // subtract the last reading
reading[k] = analogRead(A0) ;               // read from the sensor
total = total + reading[k];                 // add the reading to the total
k = k + 1;                                  // advance to the next position in the array
if (k >= numReadings) {
k = 0;}
```

```
average = total /numReadings;                    // calculate the average
for (int j = 0; j < NUM_LED; j++) {              //write all LEDs Low i.e. Off
digitalWrite(leds[j], LOW);}
Serial.print("EMG Signal: \t ");
Serial.print(average);                           //send average to serial connection
Serial.print(" \t ")
average = constrain (average, MIN, MAX);   //constrain average value within 0 to MAX
int average1 =map (average, MIN, MAX, 0,100);
Serial.print("value of EMG Signal: \t ");
Serial.print(average1);
Serial.print(" \t ");
litLeds = map (average, MIN, MAX, 0, NUM_LED);       //Re-maps of values
for (int k = 0; k < litLeds; k++) {
digitalWrite(leds[k], HIGH);}                    //write all LEDs high i.e. On
Serial.print("Light Up LED: \t ");
Serial.println(litLeds);                   //last value must be followed by a carriage return
delay (10);                                //delay time
```

APPENDIX F.

MATLAB CODE FOR THE ANALYSIS OF STIFFNESS

```
close all;

clear all;

%Excel read

filename='Calculation file 1.xlsx';

Sheet=2;                    %Sheet 2

M7=xlsread (filename, Sheet);

count7=M7 ( : , 4);          %time

distance_x7=M7 ( : , 5);     %distance in X-direction

distance_z7=M7 ( : , 7);     %distance in Z-direction

force_x7=M7 ( : , 8);        %robot interaction force in X-direction

force_z7=M7 ( : , 10);       %robot interaction force in Z-direction

Fx7=force_x7 (end, end);   %robot interaction force in X-direction at the end of 5 sec

Fz7=force_z7 (end, end);   %robot interaction force in Z-direction at the end of 5 sec

%Average values of displacements

dx =mean (distance_x7);

dz =mean (distance_z7);

% Displacement matrix A

A= [dx*10^-3; dz*10^-3];

%Force matrix B and C

B= Fx7;

C= Fz7;

%Unknown values of stiffness in B=AX

k= [inv (A'*A)*A'*B; inv (A'*A)*A'*C]
```

APPENDIX G.

SAMPLE EXPERIMENTAL DATA

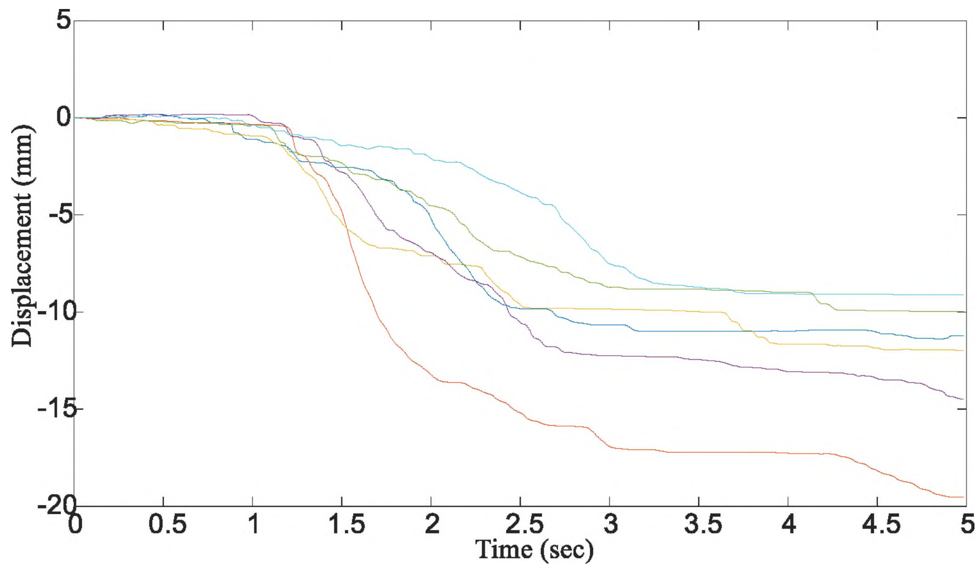

Figure G.1. Displacement trajectory in the X-direction with respect to time for the application of 2N force in –X-direction with a higher level of maximum voluntary contraction (MVC) (participant 7).

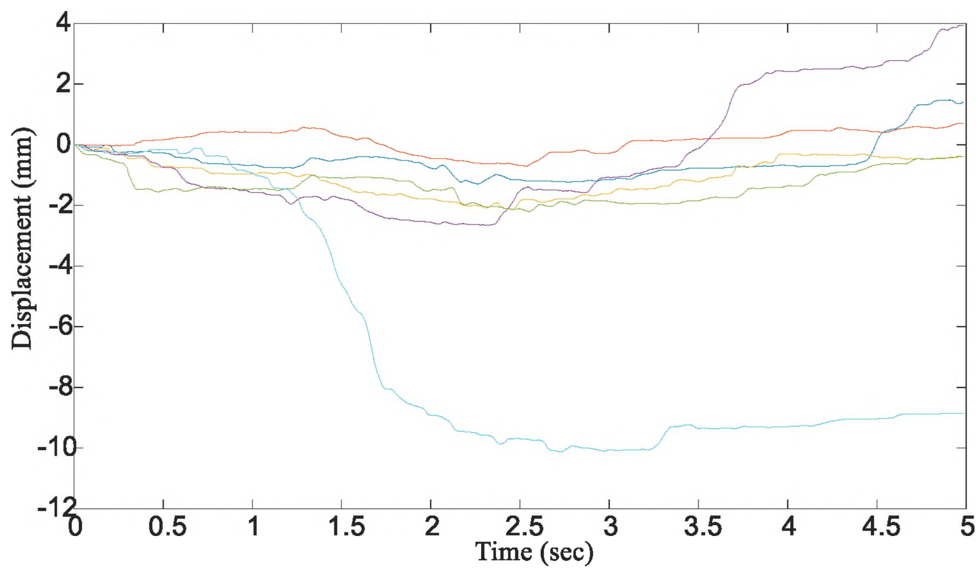

Figure G.2. Displacement trajectory in the Z-direction with respect to time for the application of 2N force in –X-direction with a higher level of maximum voluntary contraction (MVC) (participant 7).

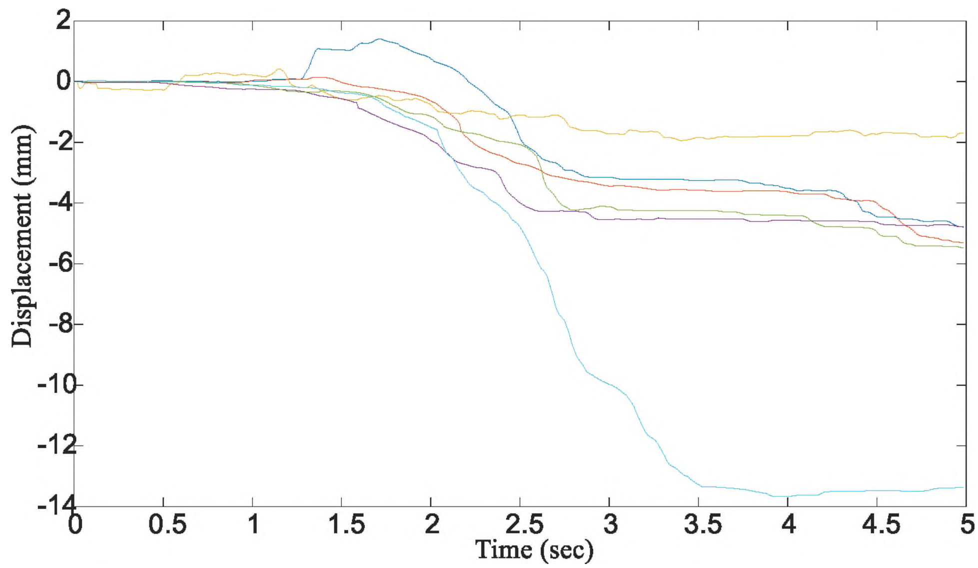

Figure G.3. Displacement trajectory in the X-direction with respect to time for the application of 2N force in +Z-direction with a lower level of maximum voluntary contraction (MVC) (participant 7).

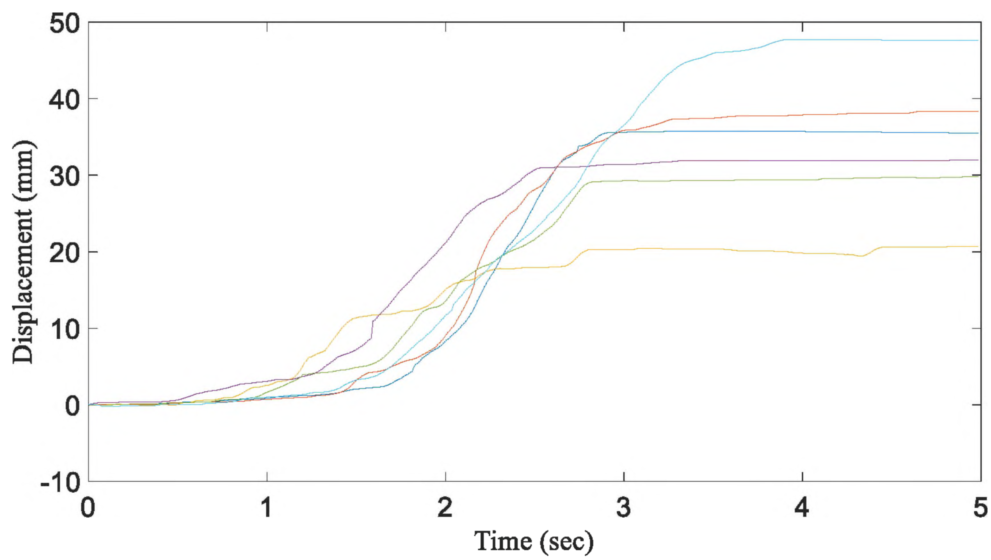

Figure G.4. Displacement trajectory in the Z-direction with respect to time for the application of 2N force in +Z-direction with a lower level of maximum voluntary contraction (MVC) (participant 7).

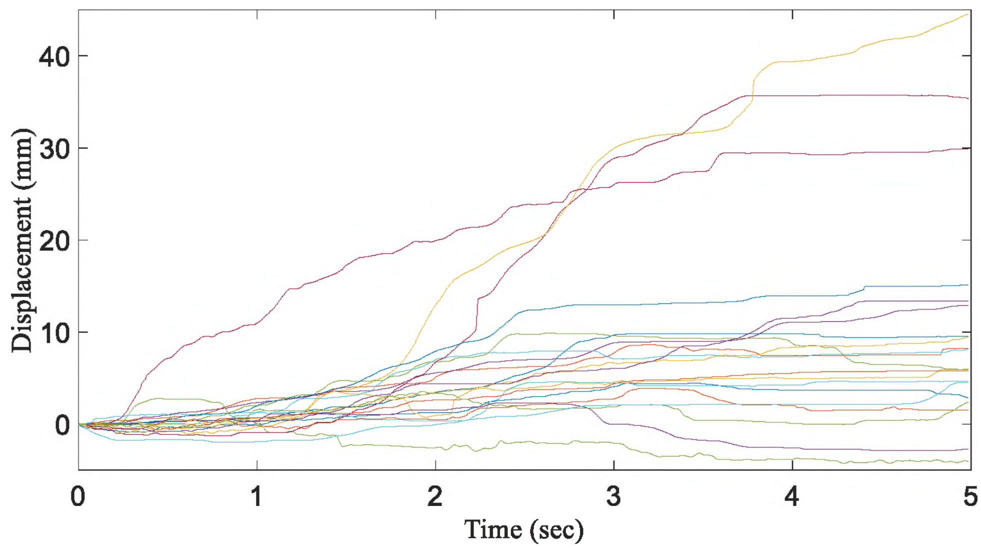

Figure G.5. Displacement trajectory in the Z-direction with respect to time for the application of 2N force in +Z-direction with a higher level of maximum voluntary contraction (MVC) (Different colors present different participants with a total of 20 participants).

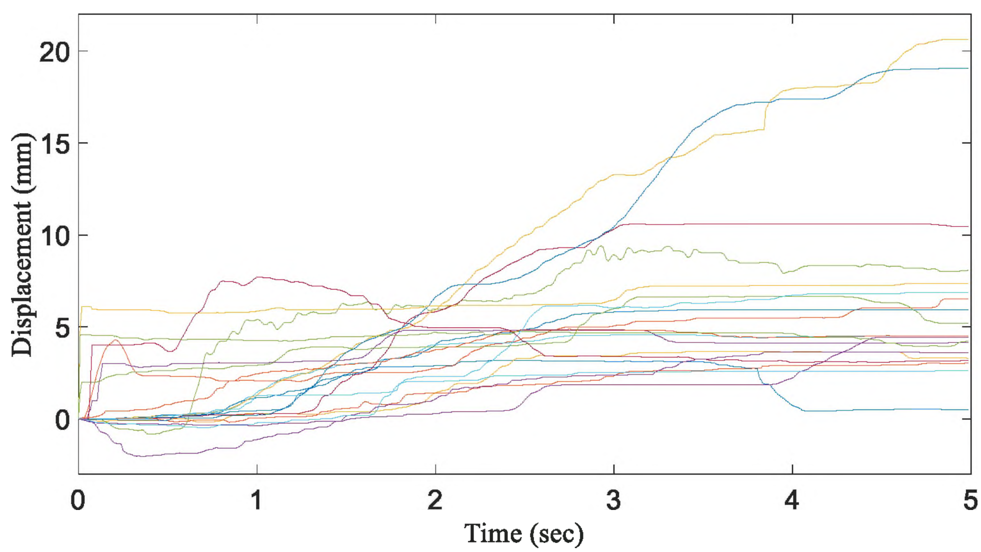

Figure G.6. Displacement trajectory in the X-direction with respect to time for the application of 1N force in +X-direction with a lower level of maximum voluntary contraction (MVC) (Different colors present different participants with a total of 20 participants).

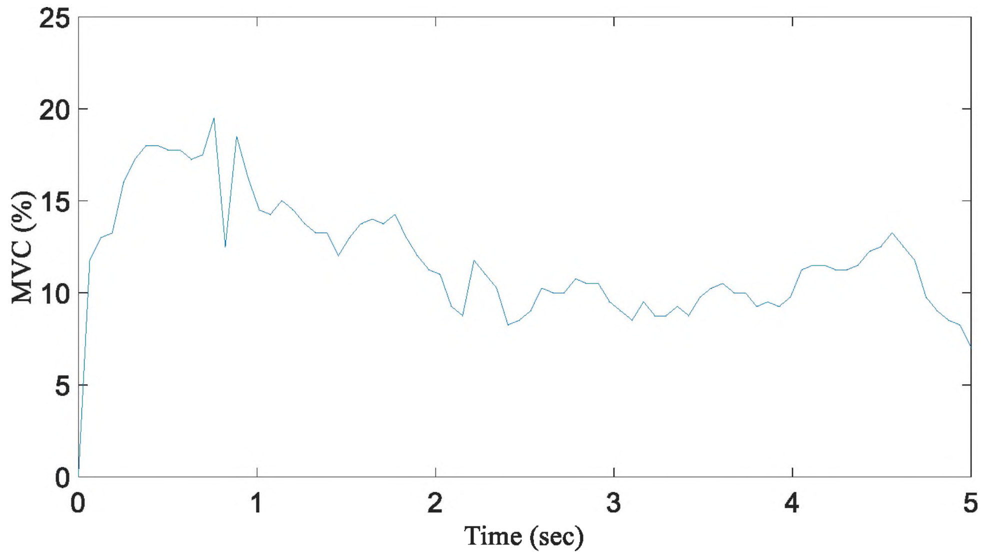

Figure G.7. Trajectory of average lower level of maximum voluntary contraction (MVC) with respect to time for participant 3.

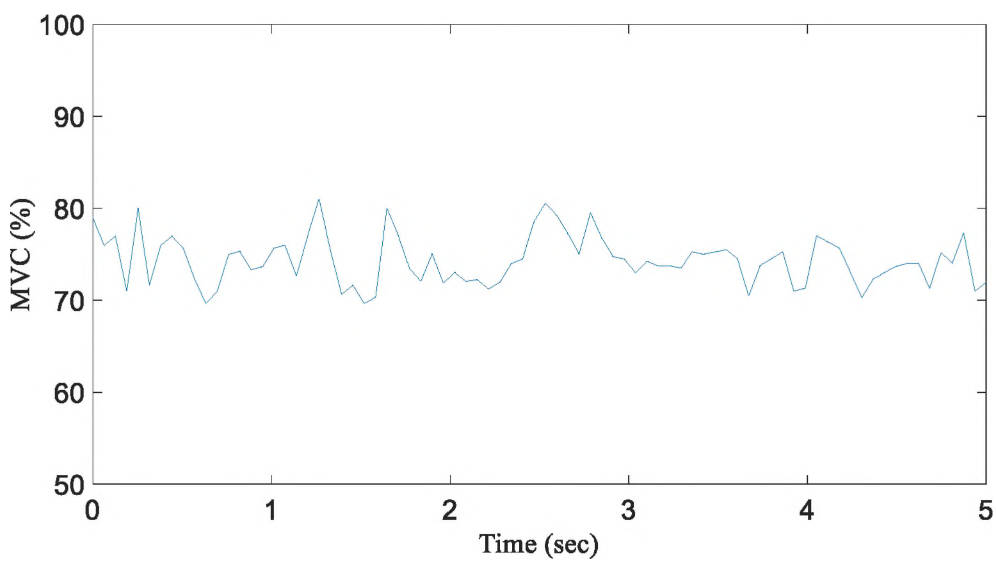

Figure G.8. Trajectory of average higher level of maximum voluntary contraction (MVC) with respect to time for participant 3.

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VITA

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