

Stiffness Perception using Transcutaneous Electrical Stimulation during Active and Passive Prosthetic Control

Luis Vargas, Helen Huang, Yong Zhu, and Xiaogang Hu

Abstract— Haptic feedback allows an individual to identify various object properties. In this preliminary study, we determined the performance of stiffness recognition using transcutaneous nerve stimulation when a prosthetic hand was moved passively or was controlled actively by the subjects. Using a 2x8 electrode grid placed along the subject's upper arm, electrical stimulation was delivered to evoke somatotopic sensation along their index finger. Stimulation intensity, i.e. sensation strength, was modulated using the fingertip forces from a sensorized prosthetic hand. Object stiffness was encoded based on the rate of change of the evoked sensation as the prosthesis grasped one of three objects of different stiffness levels. During active control, sensation was modulated in real time as recorded forces were converted to stimulation amplitudes. During passive control, prerecorded force traces were randomly selected from a pool. Our results showed that the accuracy of object stiffness recognition was similar in both active and passive conditions. A slightly lower accuracy was observed during active control in one subject, which indicated that the sensorimotor integration processes could affect haptic perception for some users.

I. INTRODUCTION

Haptic feedback is crucial to the understanding of various interactions with our surroundings. Without visual or auditory cues, object manipulation tasks can be performed through the exploitation of touch sensation [1]. Upper limb amputees lack this form of feedback resulting in limited dexterous control of their assistive devices [2], [3]. Reductions in device utility affects the user's confidence and satisfaction leading to device abandonment [3]. The delivery of sensory feedback describing grasp forces and/or joint angles improves task performance and promotes increased user confidence [4], [5].

A series of mechanoreceptors embedded in our skin allow neurologically intact individuals to sense various forms of tactile information [6]. Distinct receptors are responsible for classifying tactile cues based on the stimuli's frequency, intensity, and location. When grasping a deformable object, stiffness information can be characterized based on the rate of change of the force imposed onto the skin surface. Stiffness is a vital property that describes an object's resistance to a given force. Fine movements rely on the ability to perceive stiffness, especially when manipulating delicate objects. Unfortunately,

in the absence of tactile sensation, stiffness perception through visual cues can be unreliable [7].

Prior work has shown that stiffness information can be delivered using mechanical [8] or electrical stimulation [9]–[11]. In these cases, stiffness recognition is performed through the interpretation of modulated stimuli as it relates to the exerted forces from a prosthetic limb. For example, Raspopovic et al [10] utilized haptic sensations evoked using proximal peripheral nerve stimulation via an intrafascicular electrode in order to show that encoding stiffness as the rate of change of the stimulation intensity allowed for the recognition of various objects when paired with a prosthetic hand. Alternatively, D'Anna et al [9] evaluated the recognition accuracy when the subjects were not responsible for controlling the prosthetic limb. In this case, a similar encoding scheme was implemented; however, individuals were simply given prerecorded stimulation trains that corresponded to various prosthesis-object interactions. In comparison, active users have the potential to receive excess information through proprioceptive feedback during muscle activation, while passive prosthetic users benefit from the opportunity to focus on a single task. Both cases showed promising results, but the two approaches raise the question of whether the active or passive control condition of a prosthetic limb affects a user's stiffness perception accuracy.

Accordingly, the purpose of this study is to evaluate if and to what degree recognition accuracy is affected when a prosthetic hand is passively or actively articulated. Sensory feedback was delivered using transcutaneous electrical stimulation. Stimulation was delivered using a 2 x 8 electrode

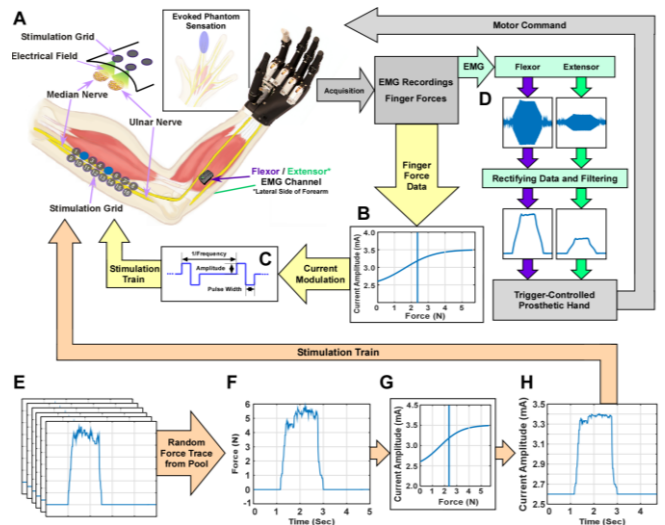


Figure 1. Diagram illustrating the placement of the 2x8 electrode grid and EMG channels (A). Flowchart describes how the prosthetic hand is articulated (D) and how stimulation amplitude is modulated during active control (B, C) and passive control (E-H).

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grid placed along the medial side of the upper arm. By selecting distinct electrode pairs, different set of axons in the median and ulnar were activated producing somatotopic sensations at distinct regions across the hand [12], [13]. In addition, amplitude-modulated sensations can be perceived and used to discriminate various object properties, such as stiffness, shape, and surface topology, during passive control [14], [15]. Building on this approach, myoelectric control was implemented to introduce active control of a prosthesis. The sensorized prosthetic hand interacted with objects of varying stiffnesses. Recorded fingertip forces were translated to stimulation amplitudes that evoked sensation along the subject's index finger. Stiffness recognition trials were performed using one of three prosthetic articulation speeds during both active and passive control. Based on the initial data, future comparisons can help evaluate the sensorimotor integration processes involved in prosthetic control individually, i.e. motor/sensory modules, in the hopes of improving prosthetic dexterity.

II. METHODS

A. Subjects

We tested three neurologically intact subjects (3 Male, 24-30 years of age). Each subject gave informed consent via protocols approved by the Institutional Review Board of the University of North Carolina at Chapel Hill.

TABLE I. ELECTRODE PAIRS AND SENSATIONS ELICITED

Subject	Electrode Pair	Elicited Sensation Region	Sensory Threshold (mA)	Motor Threshold (mA)
1	4-6	Index & Thumb	2.6	3.5
2	4-12	Index, Middle, & Ring	2.0	2.5
3	3-6	Index & Middle	4.1	4.6

B. Experimental Setup

Subjects were sat with one arm placed on a table in front of them. Using alcohol pads, the medial side of their upper arm was cleaned. A 2x8 electrode grid was placed along the vector connecting the medial epicondyle of the humerus and the center of the axilla (Figure 1A). This location was selected due to its superficial access to the median and ulnar nerves. To maintain electrode-skin contact, a custom vice was used to apply mild inward pressure. By selecting different electrode pairs, unique electric fields are generated resulting in the activation of different sets of axons innervating distinct regions of the hand.

Custom MATLAB (MathWorks Inc) interfaces were used to control a switch matrix (Agilent Technologies) and stimulator (Multichannel Systems). The switch matrix chose electrode pairs by linking one of 16 Ag/AgCl gel-based electrodes (1 cm in diameter) to the stimulator's anode and cathode channels. The stimulator delivered charge-balanced, biphasic, square waves (Figure 1C) with a fixed pulse width and frequency of 200 μ s and 150 Hz, respectively [12]–[14].

Current amplitude was modulated using force recordings from a prosthetic hand. A force sensor (SingleTact) was fixed on the prosthesis' index fingertip (iLimb, Ossur) to record pinch grasps forces. Forces exerted were converted to current amplitudes using a subject-specific sigmoid function (Figure

1B). The sigmoid function is constructed using an allowable stimulation range, minimum and maximum force, and a steepness value [14], [15]. For each subject, the sensory threshold and just below the motor threshold were used as the stimulation range. Using current steps of 0.1 mA, the sensory and motor thresholds were found when finger sensation or finger motion first occurred, respectively. (Table 1)

Using a wireless acquisition system (Delsys Trigno, MA), two electromyography (EMG) electrodes, placed on the medial and lateral side of the subject's forearm, recorded the muscle activation of the flexor and extensor muscles of the finger, respectively. The EMG was processed in real-time to control the prosthetic's index finger. Using a 200-ms window with 100-ms overlap, the level of activation was extracted from the rectified and filtered signal. The differential between the EMG signals determined the direction (rest, close, or open) in which the prosthesis articulated using one of three set speeds.

To encode object stiffness, the rate of change of the index force/sensation corresponded to the object's stiffnesses. Three

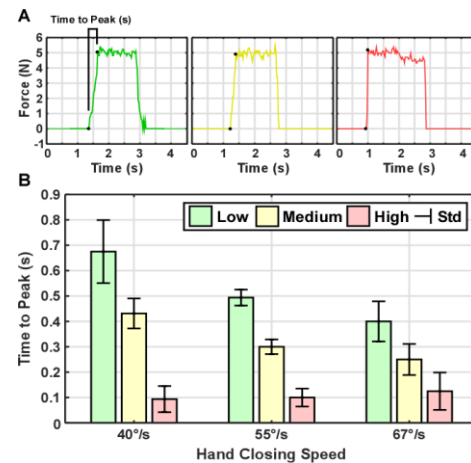


Figure 2. Example force traces (A) recorded as the prosthetic hand grasped the low (green), medium (yellow), and high (red) stiffness object using the highest hand closing speed. The average and std of the time to peak for each combination of speed and object stiffness is shown as well (B).

stiffness-varied cubes were used, which included a soft foam (1.7 N/mm), a stiff foam (2.9 N/mm), and a wooden block. During active control, the prosthesis' hand closing speed was set to either 40, 55, or 67 degrees per second, which is relatively fast for most object exploration task. This was determined through preliminary testing. The prosthesis can articulate at speeds between 20 and 80 degrees per second; however, at lower speeds the peak force attainable when grasping the three objects varied greatly due to observed prosthetic limitations. If these conditions were kept, subjects could feasibly recognize the stiffness level simply based on peak force exerted. Alternatively, if speeds were any higher, the recorded forces would exceed the force range most utilized by neurologically intact individuals during activities of daily living [16]. Moreover, to minimize the variability in peak forces exerted, a maximum force level of 5 N was utilized for the sigmoid transfer function.

To evaluate the recognition accuracy during passive control, prosthesis-object interactions were prerecorded. The force traces were saved among a pool for each condition and

then drawn from at random during the study. (Figure 1) Force recordings were repeated 5 times for each combination of object stiffness and speed to account for any variability in the system. Example traces for the highest speed and the average time to peak across all conditions are shown in Figure 2.

C. Procedures

The experiment began by searching through the electrode grid for a pair that produced sensation along the subject's index finger. The selected pair was then coupled to the index finger's force sensor or recordings in order to modulate stimulation intensity during active and passive control, respectively. Each subject's selected electrode pair and its sensation region is described in Table 1.

The main experiment was broken into two experimental blocks based on whether passive or active control was being implemented. Each subject was visually and auditorily blinded

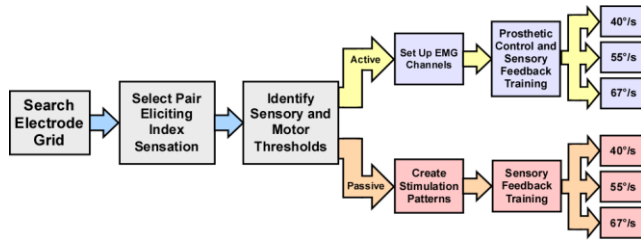


Figure 3. Flowchart illustrating the experimental protocol

throughout the study. During passive control, three sub-blocks tested the subject's ability to recognize an object's stiffness using each hand closing speed. The three sub-blocks consisted of 4 trials per object resulting in 36 total trials. Each trial required subjects to report the stiffness perceived based on a random force trace delivered. During active control, 36 trials across three sub-blocks were again performed; however, subjects now were responsible for manually articulating the prosthesis through flexion and extension of the wrist. Prior to the start of the active trials, subjects were given 5 minutes to practice articulating the prosthesis. During each trial, subjects were instructed to grasp an object using the prosthesis and report its perceived stiffness. The order of the blocks and speeds were randomized across subjects. Reinforcement learning was utilized before the start of each sub-block. Subjects were given 10-15 trials where they would attempt to identify the object's stiffness. This was the only time subjects were given feedback about their response. A flowchart describing the experimental protocols is shown in Figure 3.

III. RESULTS

We evaluated each subjects' ability to recognize an object's

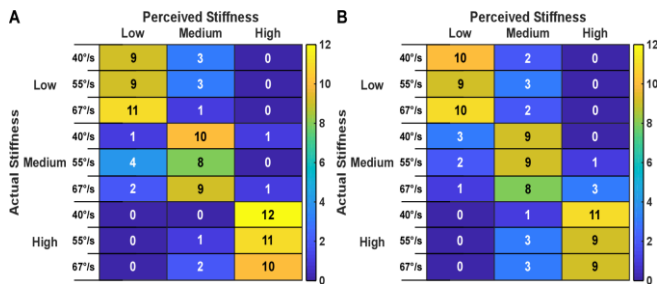


Figure 4. Confusion matrices illustrating the perceived stiffness when a given ground truth and hand closing speed is employed during passive (A) and active control (B).

stiffness during both active and passive control. Figure 4 shows two confusion matrixes that each compare the actual and perceived object stiffness across all subjects. Each row within a given stiffness level corresponds to individual hand closing speeds. The confusion matrices detail the type of recognition errors that occurred. Specifically, the majority of recognition errors for both active and passive control arose from trials where subjects reported an object as being one stiffness level higher or lower than the actual. In other words, no subject had issues discriminating between the stiffest and the least stiff object at any of the hand closing speeds. Additionally, the results suggest that as the speed increases the number of errors and the distribution of the errors appear to increase as well. Misidentification between the medium and high stiffness objects occur more frequently as higher speeds are implemented for both control schemes.

Figure 5 illustrates the recognition accuracies and standard error across subjects when utilizing each of the three hand closing speeds. For the individual recognition accuracies, the order of the circles in the legend indicate which datapoints correspond to which subject with subject 1 being purple, subject 2 being green, and subject 3 being orange. The results showed that subjects could identify a given object stiffness during both control schemes at all three speeds. Specifically, the closing speeds of 40, 55, and 67 degrees per second resulted in an accuracy and standard error of $86.1\% \pm 4.8\%$, $77.8\% \pm 4.8\%$, and $83.3\% \pm 14.4\%$, respectively, during passive control. Alternatively, during active control, the recognition accuracies were slightly lower resulting in accuracies and standard errors of $83.3\% \pm 8.3\%$, $75.0\% \pm 8.3\%$, and $75.0\% \pm 8.3\%$, respectively. When evaluating across hand closing speeds, active control showed a drop in accuracy as the speed increased from 40 to 55 degrees per second; however, no change was observed when assessing the highest two speeds.

IV. DISCUSSION

This preliminary study sought to evaluate if stiffness perception varies across active and passive prosthetic control schemes. Amplitude-modulated haptic feedback localized along the index finger was delivered using transcutaneous electrical stimulation. Active control was implemented using two channels of EMG that triggered the movement of the prosthesis' index finger using a set speed. Stimulation for passive control was delivered using prerecorded force traces

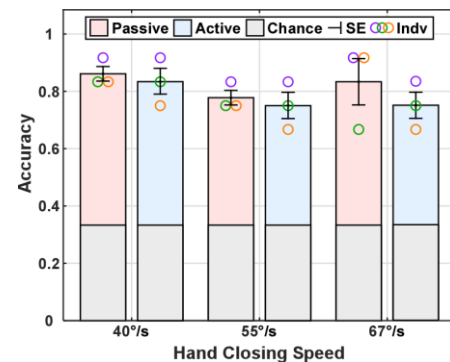


Figure 5. Bar graph illustrating the accuracy and standard error during each combination of hand closing speed and control scheme.

that corresponded to each combination of hand speed and object stiffness. Our results showed that both control schemes allowed subjects to correctly identify the stiffness of the object being grasped. Slightly lower accuracies reported in one subject (denoted by red circle) for the active condition suggest that factors, such as the need to focus on two tasks, could have potentially affected some subject's recognition performance. This result indicates the need to further evaluate the motor and sensory pathways of current human-machine interfaces independently using evaluations of both passive and active control, or open-/closed-loop systems.

Our results demonstrated that stiffness could be recognized using both control scheme at all hand closing speeds. This suggest that nerve stimulation delivered in this manner provided subjects with sufficient information to make appropriate recognitions. Our results did, however, show that across hand closing speeds and control schemes there was a reduction in recognition accuracy. Overall, increasing hand closing speed appeared to reduce accuracy, which intuitively makes sense given the reductions in average time to peak. Regarding decreased accuracy between active and passive, subjects were naïve to prosthetic control and the sensory feedback module indicating that this could have been a factor. Extended training could alleviate current differences, but further evaluations are required.

Sensation intensity was performed using amplitude modulated stimulation. Our results indicate that the subject with the largest stimulation range appeared to discern stiffness better. This is likely due to their ability to distinguish more distinct stimulation, i.e sensation, levels. Subjects with lower stimulation ranges could potentially benefit from altering the stimulation wave delivered. Reducing the pulse width of the delivered biphasic square trains decreases the injected charge and could potentially increase the range between the sensory and motor threshold. Although this is supported mathematically, this claim should be tested. Alternatively, cathode-first biphasic stimulation trains and/or the inclusion of an interphasic delay could potentially improve upon the delivered stimuli [17]. Stimulation delivered in a more biomimetic manner may improve the amount of transferable information as well [18].

Three limitations of the current study include the lack of amputee subject, sample size, and the use of a simple trigger-based myoelectric control scheme. First, prior work has shown that stimulation delivered to neurologically intact individuals and amputees result in similarly elicited haptic perceptions [12]. This suggests that a portrayal of amputee behavior may be represented through the results from intact participants. Secondly, this study was meant to be conducted as a preliminary evaluation. Future work will be expanded to include a larger population. Lastly, the use of a rather simple control scheme allowed us to mitigate many of the variability in exerted force present during active control ensuring that stiffness was determined solely based on the rate of change of the evoked stimuli. By utilizing set articulation speeds, direct comparisons could be made between active and passive control schemes. Although accuracies were similar, slight differences suggest that other factors may affect sensory perception. Realistically, many current prostheses are operated using more complex controllers that relate muscle

activation to a finger position or velocity. Users of these devices could potentially receive more information pertaining to hand state through proprioception; however, cognitive burden is likely to increase as well. As control schemes become more complex, the benefit of testing sensory feedback in active and passive formats are further increased through the ability to detect potential issues residing in the motor and sensory pathways of human-machine interfaces.

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