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OPTIMALLY PLACED SURFACE EMG ELECTRODES ALLOW PEOPLE WITH UPPER-LIMB PROSTHESIS TO CONTROL MULTIPLE DEGREES OF FREEDOM

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ABSTRACT

The aim of this research is to better determine the optimal realistic number and placement of surface electromyographic (sEMG) electrodes to provide more accurate and intuitive control of upper-limb prostheses. sEMG is a non-invasive prosthesis control technique that can be used in place of intramuscular electromyography (iEMG) that requires an invasive procedure. The number of electrodes and their locations are often chosen semi-arbitrarily for use with computational control algorithms. Optimizing sEMG electrode number and location can provide improved control, perhaps approaching that of iEMG electrodes.

The sEMG data of 5 intact subjects controlling 8 degrees of freedom were gathered using 96 electrodes distributed evenly across the forearm. The Root Mean Square Error (RMSE) between the computer's prediction of the subject's movement and the computer's pre-programmed movement was computed and compared with an increasing number of electrodes. Spatial locations of useful sEMG information were analyzed using a data visualization technique called a heatmap.

Firstly, when the electrodes were placed optimally, approximately 50 electrodes were required for accurate control of the prosthesis, compared to the ~90 electrodes with inverse-optimal placement. Secondly, the data analysis showed that some electrodes out of total 96 were chosen more frequently than others, as among the best electrodes. Based on current results, approximately 50 best chosen electrodes placed in the respective areas on the arm are required to control 8 DOFs. This research will help the researchers to optimize sEMG control more effectively and thus provide more accurate control of myoelectric upper-limb prostheses.

INTRODUCTION

According to the National Center for Health Statistics, approximately 50,000 new amputations occur each year, twenty-five percent of which are upper limb [1]. Most people with upper-limb amputations are hesitant to get a functional prosthesis because of the expensive procedures [2]. The amputees who choose to get a functional prosthesis tend to abandon it due to several reasons, including lack of comfort, heavy weight leading to fatigue, and lack of function. Lack of function is a result of the non-intuitive control due to the limited number of degrees of freedom (DOFs). This limits the amputee's ability to perform activities of daily living (ADLs) that require various DOFs [3].

Each DOF activates different muscle(s) or groups of muscles that send electrical signals to the brain, indicating the person's desire to perform a certain movement [3]. Researchers have been able to extract these signals from the residual nerves or muscles of the amputee. This provides intuitive functional control to people with upper-limb amputations [4]. For advanced control, this approach has often used intramuscular electromyography (iEMG) recorded from surgically implanted electrodes. Although iEMG can provide accurate functional control over multiple DOFs, it requires invasive procedures that many amputees do not want to undergo [5]. A non-invasive alternative is surface electromyography (sEMG) that uses the electrodes placed on the arm surface to control the prosthesis. Although sEMG is in widespread clinical use for limited number of electrodes and DOFs [6], sEMG based prosthesis have not yet been found to provide intuitive control for multiple DOFs [7], [8]. The control of prostheses based on electromyography (EMG) depends on factors, including but not limited to the number and placement of the electrodes that record the signals. If placed optimally, sEMG electrodes might provide control similar to iEMG electrodes [9]. Because sEMG performance depends on electrodes, the ideal electrode count and their placement on the forearm are necessary parameters for better intuitive control of future functional prostheses [7], [9].

Increasing the number of electrodes facilitates more independent features to be recorded from the residual muscles in the amputated residual limb that enables intuitive amputee control over multiple DOFs [10]. A higher number of electrodes also improves the computational accuracy as it provides more combinations of electrodes for data analysis [11]. The different combinations, also called subsets, inform different electrode densities, that is, the spatial distribution of electrodes in an area [10]. This helps identify areas on the arm that provide the most useful movement signals to control various DOFs [12]. A definitive generic number and the specific placement for sEMG electrodes for optimal amputee control and functional performance remain unclear [5], [8].

The limitation of upper-limb prosthesis to control multiple DOFs was addressed by finding generalizable electrode count and placement on the amputee. We used an electrode sleeve with ninety-six electrodes that covered the entire forearm. The purpose of the sleeve was (a) the easy donning and doffing and (b) to restrict the electrodes from moving so that each electrode stays in the same position throughout the experiment. The number of electrodes used was much higher than the number typically used for sEMG controlled prosthesis [10]. With the high-count sleeve, we could thoroughly investigate the role that electrode count and placement played on prosthesis control. The number of electrodes needed for best control was determined by comparing prosthetic performance with increasing number of electrodes provided to the control algorithm. This facilitated direct assessment of prosthesis functional control with increasing electrode number. After modifying the pre-written computational algorithm, we analyzed the electrode channel selection patterns to inform better electrode count and placement for a universal approach to sEMG recording. Our results should guide future approaches to provide better functionally controlled upper-limb prosthesis, and hence increase acceptance rates for functional upper-limb prosthesis amongst the people with amputations.

BACKGROUND

12,500 upper-limb amputations are performed every year in the United States. This number is expected to double by the year 2050 [1], mainly due to the diabetes epidemic [12]. The major causes of upper-limb amputations include, but are not limited to accidents, tumors, infections, and congenital conditions [13]. Upper-limb amputations not only cause functional disabilities, but also impact the psychology of the individual, especially if they are due to a trauma [14], [15]. Most people with non-congenital upper-limb amputations feel the need to adopt a prosthesis [13]. People have exhibited psychological consequences after amputation due to a tragic event; having a prosthetic hand gives them some functional restoration that helps them recover psychologically [15].

There are different kinds of prostheses for different kinds of amputations. Upper-limb amputations can be (a) transradial, in which the amputation occurs somewhere below the elbow and above the wrist, (b) transhumeral, in which the amputation occurs somewhere above the forearm to the shoulder, (c) wrist disarticulation, in which the amputation occurs at the level of the wrist, (d) shoulder disarticulation, in which the amputation occurs at the level of the shoulder, or (e) hand amputation, in which the amputation occurs somewhere below the level of the wrist [12]. Transradial, wrist disarticulation, and hand amputations leave the extrinsic hand and wrist musculature behind that is used to control different DOFs [16], whereas transhumeral and shoulder disarticulation amputations do not [17]. Hence, people with amputations above the elbow require a more complex functional prosthesis than people with amputations below the elbow [12], [16], [17].

Current functional upper-limb prostheses for beyond cosmetic purposes are either body-powered (BP), myoelectric (MYO), or a hybrid combination of the two [18], [19]. BP prostheses are unintuitively controlled using other body parts such as the shoulder [18]. These prostheses use cables to control the prosthetic hand that allow the user to switch between pre-set drips [19]. Most people with upper-limb amputations opt-in for BP prostheses because they are less expensive, lighter, easier to use, and more robust than MYO prostheses [19], [20]. MYO prostheses have the potential to be more robust and can control various DOFs intuitively, because they use biological signals from the residual muscles [21]. The biological signals that control the arm are still physiologically active and can be exploited from the residual limb of people with amputations below the elbow, that is, people with transradial, wrist disarticulation, and hand amputations [16], [22]. This helps drive an intuitive prosthesis control similar to the ability of the native hand [22].

Non-invasive prostheses provide an important advantage because patients abandon their prostheses, in large part, due to discomfort, and non-invasive prostheses cause less discomfort than invasive prostheses [20], [23]. Despite the current advantages of BP prostheses over MYO prostheses, their rejection rates are similar to each other [3], [24]. Rejection rate depends on various factors such as function and comfort [20]. In a recent study, BP prostheses had 80% rejection rate due to reasons including, but not limited to, slow movement and ineffective intuitive control. MYO prostheses had 75% rejection rate due to insufficient movements of hand, fingers, and wrist, not allowing them to perform various ADLs [25]. In another study, 26% of the participants rejected the

BP prostheses and 23% rejected the MYO prostheses, due to similar reasons as the previous study [3].

ADLs require different movements and hence different DOFs. Each DOF activates different muscle groups in the residual arm [24]. Current myoelectric prostheses in the market may control as little as 2 DOFs, whereas the intact human hand performs up to 16 DOFs in daily life [26]. Additionally, for more DOFs, the user must switch controlling between different DOFs as needed [24]. Previous studies show that there are specific areas on the forearm for different DOFs [27]. The DOFs that the prostheses users, especially transradial amputees, desire are wrist flexion, wrist extension, pronation, supination, and hand open/close [28]. Because the current prostheses do not allow simultaneous control over multiple DOFs, people with amputations do not have intuitive control and this makes it difficult for them to perform ADLs. Intuitive control is an essential user need for the upper-limb prostheses [29].

The popular approach to achieve intuitive control is EMG that extracts the biological signals from the residual muscles, either invasively via iEMG or non-invasively via sEMG [8]. iEMG is gathered from surgically implanted electrodes whereas sEMG is gathered from the electrodes placed on a sleeve via a one-on-one association of surface electrodes with the action potentials of each motor neuron [4], [8]. Although iEMG electrodes provide more stable control and have functional advantages over non-invasive sEMG electrodes [5], most people with amputations do not wish to undergo additional surgeries for electrode placement and interfacing because of the psychological trauma they have already gone through [15]. Additionally, most commercial upper-limb prostheses are not configured to utilize high numbers of EMG recordings.

Multi-DOF sEMG-based prostheses require machine learning techniques or other algorithms that can power simultaneous control over multiple movements, as different movements result in different EMG patterns due to activation of different muscle groups [10], [26]. As sEMG records local field potentials generated from functional muscles near the residual limb, summated electrical activity is sampled from muscles beyond those directly beneath the electrode [30]. sEMG collection of muscle activity from non-associated muscle systems produces unnecessary sources of noise that interfere with patient control of the upper limb prosthesis [8]. The interfering signals arise the normal biological process of activation of other muscles around the muscle that has electrodes placed directly on it [4]. Functional prosthetic control for given DOFs is improved by involving only those muscles that activate specific sEMG electrodes. This drives the motivation to understand how sEMG electrode locations and numbers produce this optimal control without engaging distracting neuromuscular features [8].

The sEMG control method usually involves (a) record EMG signals from the subject's intended movement, (b) preprocessing the signal to reduce noise captured during the experiment, (c) extracting unique information related to the movement, and (d) translating the extracted information into a physical movement that will move the prosthesis [31]. Currently, there are problems in recording accurate EMG signals pertaining to the user's intended movement due to the subject's motion or movement of the electrodes placed on the subject's arm [32]. It has been found that if more electrodes are placed on the arm, electrode shift causes less difference in the user's intended movement accuracy [33].

Ultimately, prosthetic performance depends on various attributes including, but not limited to, function and comfort. Amputees tend to reject the prostheses after a short time of usage due to lack of function and discomfort [34]. This research addresses the function aspect of the prostheses and aims towards improving their intuitive control. This is done by looking at the important areas of the arm responsible for multiple DOFs. Placing electrodes in these important areas will allow intuitive control of those DOFs. Identifying the areas will also lead to a generic number of electrodes required for the intuitive control.

METHODS

Materials

Table I: Materials Used for Gathering Data

Description	Use
Black neoprene sleeve with 96 electrodes	Used to gather data from an intact subject residual limb engaged with prosthesis.
Ripple Neuro Grapevine Neural Interface Processor (NIP)	Used to process electromyography signals from the arm to display them on the decode interface
3 grapevine 32-channel Socket Connectors	Used to connect electrodes on the sleeve to NIP

A. The Apparatus

The wearable sleeve with 96 electrodes embedded in it (Fig. 1) was connected to the EMG channel of the NIP using the 3 socket connectors. The NIP was connected to a computer running the motor-decode routine that decoded the electrical signals from the subject's arm muscles into EMG signals using a modified Kalman Filter (mKF), a computational control algorithm used to decode motor intent of the nerves by matching the EMG signals with pre-programmed movements [35].

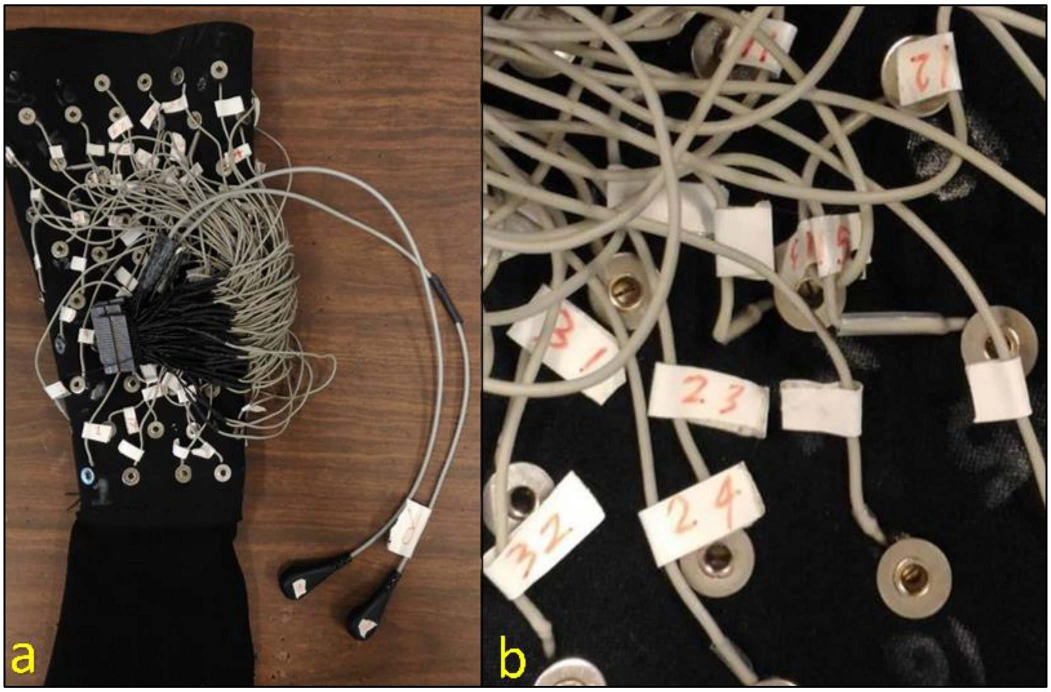

Fig. 1. a) Wearable sleeve with 96 active embedded electrodes, 1 reference electrode, and 1 ground electrode to record EMG signals from intact subjects. b) A zoomed-in picture of the same sleeve showing that each electrode is numbered to facilitate referencing and identification.

B. Prosthesis Control Paradigm

The 96 electrodes on the wearable sleeve gathered sEMG signals at 1 kHz through the 512-channel Grapevine System (Ripple Neuro LLC, Salt Lake City, Utah). These signals were then filtered through low pass (375 Hz, second-order Butterworth), high pass (12 Hz, sixth-order Butterworth), and 60/120/180 notch filters. A 300-ms mean absolute window moving at 30 Hz was then used to calculate the recordings from the 96 electrodes. This was used as an input to the motor decode algorithm. EMG features and kinematics were used to fit weights of a Kalman Filter, which was used for prosthesis control. The Kalman Filter, commonly used for prosthesis control in research, predicted the user's motor intent when given new EMG signals. This drove the prosthesis to the user's intended position.

C. Training and Testing the Decode Algorithm

EMG signals were recorded from 5 intact subjects at different times. The subjects mimicked 8 pre-programmed DOFs (Table 2). Each DOF was repeated 10 times in order to train and better test the algorithm. Two movements associated with each DOF resulted in 160 (8 x 2 x 10) total movements per subject. Out of these 160, 80 movements were used to train the motor-decode algorithm and the remaining 80 were used to test it. The control algorithm used the training data to predict the user's motor intent and actuate the prosthesis.

Table II: Description of the Degrees of Freedom (DOF) tested

DOF #	DOF Description
1	Thumb: Flexion/Extension
2	Index Finger: Flexion/Extension
3	Middle Finger: Flexion/Extension
4	Ring Finger: Flexion/Extension
5	Pinky: Flexion/Extension
6	Thumb: Abduction/Adduction
7	Wrist: Flexion/Extension
8	Wrist: Pronation/Supination

D. Techniques used for Data Analysis

a. Heatmap

To analyze signals for spatial density of information, a Gram-Schmidt orthogonalization algorithm was used. This helped find spatial locations of useful sEMG information. This information was analyzed using a data visualization technique called a heatmap that uses the intensity of colors to depict the frequency of a parameter (Fig. 3). In this case, the parameter was the number of times an electrode was ‘chosen.’ Each electrode was ‘chosen’ by the Gram-Schmidt orthogonalization algorithm based on the uniqueness of the signals from them. The information from the heatmap was used to provide electrodes to the motor-decode algorithm in both decreasing (optimal) and increasing (inverse-optimal) orders of signal uniqueness.

b. <u>Root Mean Square Error (RMSE)</u>

RMSE was used as a parameter to access the prosthesis control. It was the difference between perfect pre-programmed kinematic movement from a computer software that the subject was mimicking and the computer’s attempt to replicate that kinematics using the EMG signal. To calculate the mean movement RMSE, the intended movement RMSE and crosstalk RMSE were calculated first.

i. <u>Intended Movement RMSE</u>

Intended movement RMSE is the difference between the pre-programmed virtual movement and the computer’s attempt at predicting the user’s movement (Fig. 2). It was calculated using MATLAB’s in-built as well as user-defined functions.

ii. <u>Crosstalk RMSE</u>

Crosstalk RMSE is the unintended movement RMSE and refers to the difference between the pre-programmed virtual movement and the unintended movement that the computer predicted but the user did not instruct (or presumably intend) to do (Fig. 2). It was also calculated using

MATLAB’s in-built as well as user-defined functions.

iii. Mean RMSE

The mean movement RMSE refers to the average of the intended movement and crosstalk RMSEs. It was also calculated similarly using MATLAB.

The mean RMSE between the intended and unintended movements described above was calculated with increasing number of activated electrodes presented to the control algorithm. The idea behind increasing the electrodes one-by-one was to see how RMSE, that is, how prosthesis control is affected with more electrodes versus fewer electrodes. The mean RMSE was calculated for both the optimal as well as the inverse-optimal placement of electrodes (Fig. 4).

For the optimal placement, the electrode with the most unique signals was provided to the motor-decode algorithm first and the electrode with the least unique signals was provided at the last. For the inverse-optimal placement, the electrode with least unique signals was provided to the algorithm first and the electrode with the most unique signals was provided at the last. This was done to mimic the worst-case scenario of poor placement of electrodes. Comparing the optimal and inverse-optimal placements helped establish if it is useful to have an optimal number of electrodes or not. The p-value was calculated from a two-tailed and a left-tailed t-test at 0.05 significance level to verify the results.

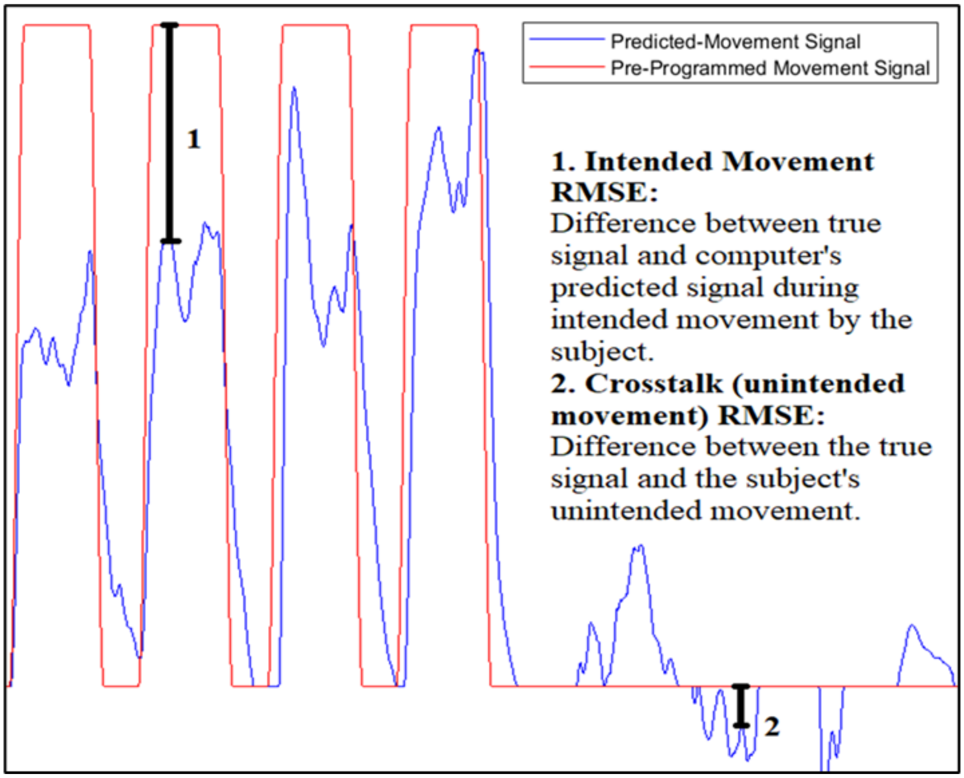

Fig. 2. EMG signal for one DOF (middle finger flexion and extension) illustrating intended movement RMSE and crosstalk RMSE. The red signal represents the computer's pre-programmed movement, and the blue signal represents the computer's prediction of the subject's movement. The positive blue signal represents the computer's prediction of the subject's intended movement and the negative blue signal represents the computer's prediction of the subject's unintended movement during the study experiment.

RESULTS

A. Heatmap

The heatmap had 96 boxes corresponding to the 96 electrodes on the wearable sleeve. All the boxes had different color intensities, that is, the electrodes had different probabilities of getting ‘chosen.’ ‘Chosen’ refers to the electrodes with the most unique EMG signal. The uniqueness depends on the quality of the signal and is decided by the Gram-Schmidt orthogonalization algorithm. The more chosen electrodes correspond to darker color intensity on the heatmap (Fig. 3). The color intensity of the heatmap in Fig. 3 shows that some electrodes were chosen more frequently compared with the others, across data from 5 subjects. For instance, the boxes on the lower right-hand corner of the heatmap are darker in color than the boxes on the upper left-hand corner.

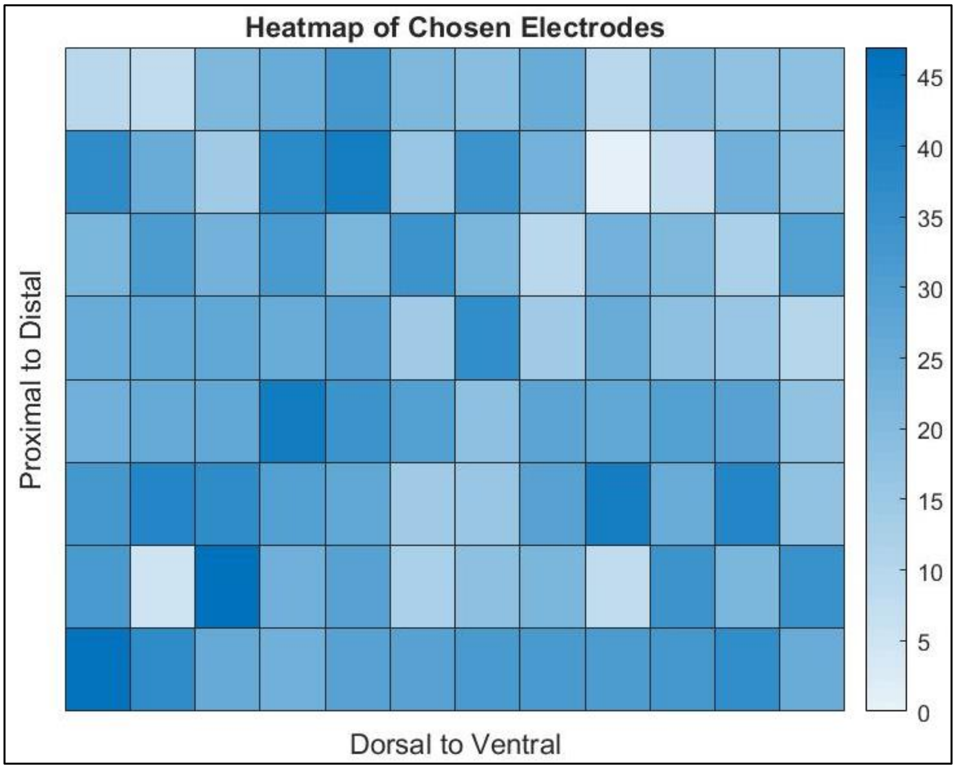

Fig. 3. Heatmap for activation frequency for 96 electrodes on the muscle sleeve. The x and left y axes depict the direction of the placement of electrodes on the sleeve: dorsal to ventral and distal to proximal, respectively. The right y-axis shows the color bar from lighter to darker color reflecting ascending frequency of electrodes. Each box represents one electrode on the 96-electrode wearable sleeve, with color intensity depicting the number of times each electrode was chosen across the data from 5 subjects based on signal uniqueness calculated by the Gram-Schmidt algorithm. The darker boxes represent electrodes with more useful information compared to the lighter boxes. For example, the boxes in the lower right-hand corner are darker than the boxes in the upper-left hand corner.

B. Root Mean Square Error: Prosthesis Function

The mean RMSE, which is the mean of movement and crosstalk RMSE, decreased gradually as the number of electrodes presented to the motor-decode algorithm increased. The RMSE for optimal placement of electrodes begins at 0.42 at 8 electrodes, decreases to 0.32 at 18 electrodes, and to 0.172 at 50 electrodes. The RMSE value for optimal placement reached a constant magnitude after approximately 50 electrodes.

Although, the mean RMSE decreased with increasing number of electrodes for both optimal and non-optimal placement, it dropped to a constant magnitude of 0.172 at approximately 50 chosen electrodes with optimal placement. On the other hand, the mean RMSE also dropped to the same value but at approximately 90 chosen electrodes for non-optimal placement of electrodes (Fig. 4). The difference between the two RMSEs is the highest initially between approximately 8-20 electrodes. The difference decreases past that range.

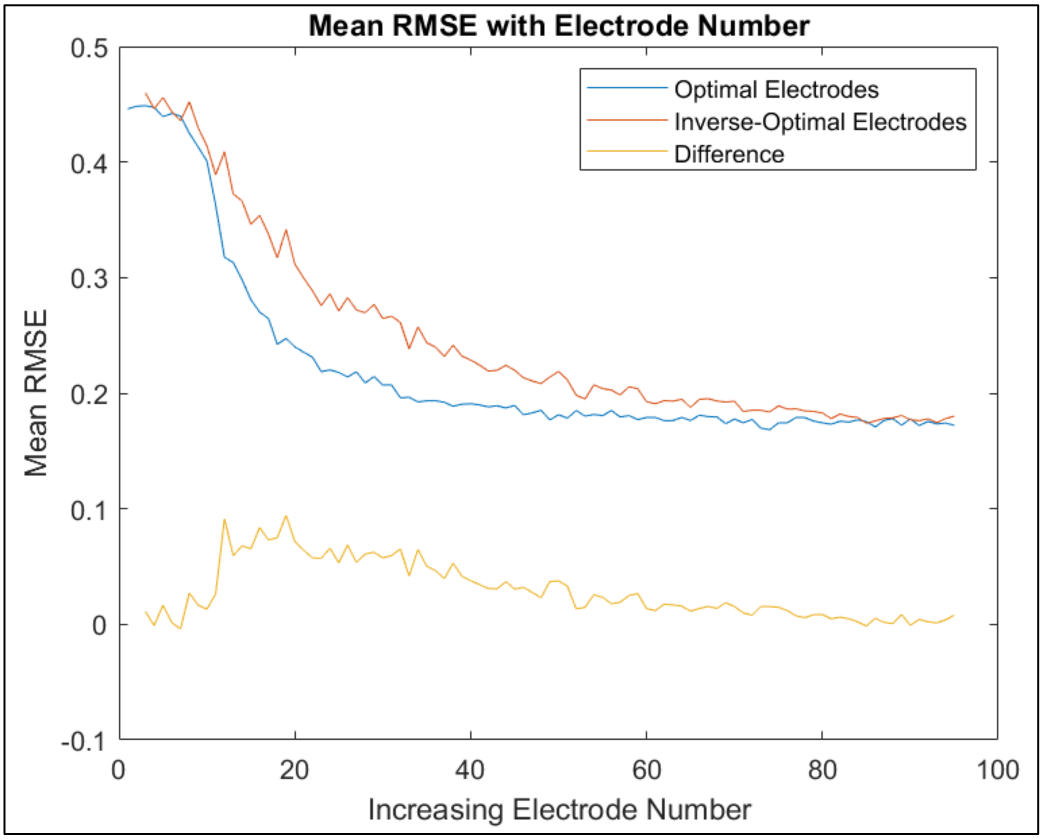

Fig. 4. Comparison of RMSE between mean of intended and unintended movement with increasing number of electrodes provided to the control algorithm based on their uniqueness (from the heatmap). The mean RMSE decreases for both optimal and inverse-optimal placement as the number of electrodes increase. It drops down from 0.45 with 1 electrode to 0.172 at 50 electrodes for optimal placement whereas it reached the same value of 0.172 at 90 electrodes for inverse-optimal placement. The difference between the two was the highest initially, between 8-20 electrodes and it decreased gradually past that range.

C. <u>EMG Signal for a single DOF</u>

The EMG signal for a single DOF (Fig. 5) shows that the computer's prediction of the subject's intended movement improves as the number of electrodes increase. The computer's prediction, which is translatable to the movement of the prosthesis, is better at 96 electrodes compared to 15 electrodes as seen in Fig. 5.

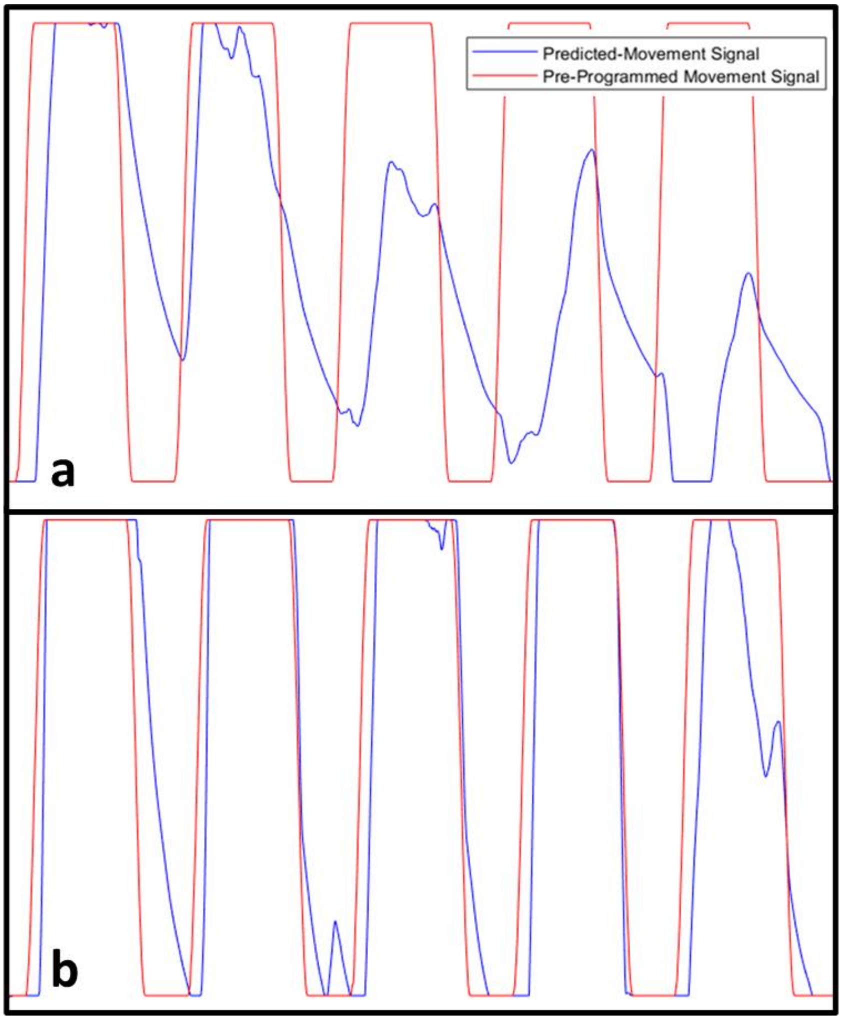

Fig. 5. Two EMG signals (a & b) for a single DOF (Middle Finger Flexion and Extension) with (a) 15 electrodes and (b) 96 electrodes. The red signal represents the computer's pre-programmed movement, and the blue signal represents the computer's prediction of the subject's intended movement. The computer's prediction of the subject's intended movement improves with more number of electrodes as the blue signal is mimicking the red signal more at (b) 96 electrodes vs at (a) 15 electrodes.

D. Statistical Analysis

A two-tailed t-test gave a p-value of $0.04 < 0.05$ implying the difference between optimal and inverse-optimal placement of electrodes. A left-tailed t-test at the same significance level gave a p-value of $0.02 < 0.05$, thus, indicating that the mean RMSE with optimal placement is less than the mean RMSE with inverse-optimal placement. The mean RMSE ± SEM with optimal electrode placement was 0.153 +/- 0.009. This was significantly less than the mean RMSE ± SEM of 0.246 +/- 0.009 with non-optimal electrode placement.

DISCUSSION

Current upper-limb prostheses in the market have a low acceptance rate in good part because they do not provide effective intuitive control to the user. Advanced EMG-based prostheses have the potential to provide intuitive control. The aim of this research was to find an optimal number of sEMG electrodes and their placement across the forearm for an improved functional control of the surface EMG (sEMG) based upper-limb prostheses. We found that placing electrodes according to the spatial information from the heatmap decreases RMSE between the computer's prediction of the subject's intended movement and the computer's pre-programmed movement. This allows better control of the prosthesis by allowing the user to intuitively control multiple degrees of freedom (DOFs) and hence, perform activities of daily living (ADLs) with ease.

The heatmap (Fig. 3) displays spatial distribution of useful information across the 96 electrodes. The color intensity represents the selection tendency of an electrode across the data from 5 subjects. The electrodes are 'chosen' by the Gram-Schmidt orthogonalization algorithm based on signal uniqueness. Darker color intensity implies that the electrode was 'chosen' more times compared to the electrodes corresponding to the lighter intensity boxes. More 'chosen' electrode is more useful compared to others as it records useful EMG signals from the muscle groups underneath it. Each box in Fig. 3 represents each of the 96 electrodes on the muscle sleeve and the difference in color intensity of each box shows that the useful information is not distributed uniformly across the forearm, specifically for the DOFs that the subjects mimicked. As the boxes in the lower right-hand corner have a darker color intensity compared to the boxes in the upper left-hand corner, it implies that the electrodes corresponding to the former are placed in more important areas of the forearm, where more unique signals to control various DOFs can be found. The information from the heatmap can be used to place ‘n’ number of electrodes in the most important areas on the forearm. The heatmap, thus, informs about the electrodes placed in more important areas than others to control the DOFs the subjects mimicked in our studies. With this information, we can find accurate placement positions for the ‘n’ number of electrodes for accurate intuitive functional control of the prosthesis.

The electrodes incorporated into the control algorithm in both the decreasing as well as increasing order of their selection tendency based on the heatmap (Fig. 3) showed a decrease in RMSE as the number of electrodes increased (Fig. 4). This is also shown by Fig. 5 where the EMG signal for computer’s prediction of the subject’s movement is improved at the number of electrodes go from 15 (Fig. 5a) to 96 (Fig. 5 b) The electrodes that were placed optimally, that is, in decreasing order of selection tendency, showed a sharper decrease in RMSE (blue line in Fig. 4) compared with the inverse-optimal placement of electrodes (orange line in Fig. 4). This shows that fewer electrodes are needed to control the prosthesis if they are placed optimally. The plot in Fig. 4 also shows that with optimal placement, the RMSE levels out at approximately 50 electrodes, but with inverse-optimal placement, it does not reach the same value until approximately 90 electrodes. These results indicate that ~30 fewer electrodes are required when using optimal placement over inverse-optimal placement. The difference between the optimal and inverse-optimal placement RMSE is the highest between 10-20 electrodes, which implies that it is most important to place the electrodes optimally when using any number of electrodes between this range. If not placed optimally between this range, say at 15 electrodes, one may not get an accurate control of the prosthesis because the RMSE value will be much higher at this point than if placed optimally. On the contrary, if placed inverse-optimally at 8 electrodes, which is the commonly used number of electrodes by researchers working with sEMG based upper-limb prosthesis, there is not much difference in the RMSE between optimal and inverse-optimal. This implies that at 8 electrodes, one cannot achieve accurate control of the prosthesis, even with optimal placement. Given the results in Fig. 4, if the electrodes are placed optimally between 10-50 electrodes, the prosthesis control will be better than inverse-optimal placement, as the RMSE stops changing after 50 electrodes, when placed optimally. This shows that with optimal placement of electrodes based on signal uniqueness, we need 50 electrodes, much fewer than 90 electrodes with inverse-optimal placement, to achieve accurate prosthesis control for 8 DOFs.

The upper-limb myoelectric (MYO) prostheses have high rejection rates. One of the main reasons is the cost and the ineffective intuitive control [13]. The MYO prosthesis can be intuitively controlled with EMG signals from the forearm [9]. These can be controlled either with intramuscular electromyography (iEMG) or sEMG. iEMG prostheses are expensive and requires an invasive surgery [5]. MYO prostheses based on the non-invasive sEMG are not clinically viable yet as their functional control is limited and has not been fully exploited [8]. Researchers have found that sEMG based prostheses have the potential to function the same way as iEMG based prostheses if studied [5].

The sEMG prostheses control depends on the electrodes placed on the arm, the same way as it depends on implanted electrodes in iEMG controlled prostheses [5]. Previous studies [10], [22], [36] have found that increasing the number of electrodes improves the prosthesis control which is also shown by our results. As the number of electrodes increased (Fig. 4), the RMSE value dropped indicating less difference between the computer's prediction of the subject's intended movement and the computer's pre-programmed kinematics. This implied an improvement in the functional control of the prosthesis.

Up until now, the researchers studying sEMG based upper-limb prostheses have usually used up to 8 electrodes to enable the prostheses to control the DOFs similar to iEMG based prostheses [5], [22], [25], [37]. Intuitive control of the prosthesis improves as the electrodes are increased in number [38] which is in accordance with our results. Ryser et al. used 8 electrodes and showed 94% accuracy of three DOFs among healthy subjects [25]. Akhtar et al. used 6-8 sEMG electrodes embedded into a prosthetic socket to allow the subjects to control five DOFs [39]. Farina et al. used 50 electrodes on the upper arm and 50 on the lower [8]. Although this resulted in 89.1% accuracy of nine DOFs, the average performance accuracy was lower than Ryer et al. and Akhtar et al. studies. A higher number of electrodes than usually used with the sEMG based upper-limb prostheses showed that there are different regions across the forearm that have more useful information than others to control various DOFs performed in daily lives [10]. If the electrodes are placed in the areas of useful information across the forearm, the RMSE decreases significantly [13]. The decreased RMSE shows improved prosthesis function to control multiple DOFs. Our results echoed the same: if the electrodes are placed optimally, we need far fewer electrodes to achieve accurate prosthesis control compared to random placement.

One limitation of this research is the small number of subjects. Collecting EMG data from more subjects can help solidify the current results. Future work related to this topic includes gathering additional data with more subjects and analyzing RMSE trend for each DOF separately. This analysis will provide a more accurate and generic number and placement of electrodes for controlling multiple DOFs. The additional data could also be used to study muscle fatigue from the heavy weight of the prosthesis, another reason behind people with amputations not wanting the prostheses. Analyzing the impact of fatigue over time and accounting for it in the motor-decode algorithm may help improve the performance of the upper-limb prostheses further. Another aspect of this work can be to make a new wearable sleeve with a new arrangement of electrodes based on the results from the heatmap. The electrodes that are in close proximity to each other and have approximately the same number of unique signals can be substituted with one electrode placed at the center point of those electrodes. This sleeve can then be tested for functional control to see if it provides the similar accuracy in intuitive control.

This work will improve the functional control of the surface EMG based upper-limb myoelectric prostheses. Improved functional control will provide intuitive control to the user. This will allow the user to perform the 8 DOFs we used in this study intuitively, without having to switch between different DOFs. The user will be able to use the prostheses like a native hand and perform various activities of daily living with ease and comfort. This work can help in psychological as well as emotional recovery process of the people with upper-limb amputations who are suffering from post-traumatic stress due to their accident that caused the amputation.

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REFERENCES

[1] C. O'Neill, "An advanced, low-cost prosthetic arm," *SENSORS, 2014 IEEE*, Valencia, Spain, 2014, pp. 494-498.

[2] F. Cordella et al., "Literature review on needs of upper limb prosthesis users," *Front. Neurosci.*, vol. 10, no. 209, May 2016.

[3] E. A. Biddiss and T. T. Chau, "Upper limb prosthesis use and abandonment: A survey of the last 25 years," *Prosthet. Orthot. Int.*, vol. 31, no. 3, pp. 236–257, Sept. 2007.

[4] S. Wendelken et al., "Restoration of motor control and proprioceptive and cutaneous sensation in humans with prior upper-limb amputation via multiple Utah Slanted Electrode Arrays (USEAs) implanted in residual peripheral arm nerves," *J Neuroeng Rehabilit.*, vol.14, no. 1, Nov. 2014.

[5] L. J. Hargrove, K. Englehart, and B. Hudgins, "A comparison of surface and intramuscular myoelectric signal classification," in *IEEE Trans on Biomed Eng.*, vol. 54, no. 5, pp. 847–853, May 2007.

[6] A. Sturma, L. A. Hruby, C. Prahm, J. A. Mayer, and O. C. Aszmann, "Rehabilitation of upper extremity nerve injuries using surface EMG biofeedback: Protocols for clinical application," *Front. Neurosci.*, vol. 12, Dec. 2018.

[7] I. Campanini, C. D. Klug, W. Z. Rymer, and R. Merletti, "Surface EMG in clinical assessment and neurorehabilitation: Barriers limiting its use," *Front. Neurol.*, vol. 11, Sept. 2020.

[8] D. Farina et al., "The extraction of neural information from the surface EMG for the control of upper-limb prostheses: Emerging avenues and challenges," in *IEEE Trans Neural Syst Rehabilit Eng.*, vol. 22, no. 4, pp. 797–809, Jul. 2014.

[9] O. W. Samuel *et al*., “Intelligent EMG pattern recognition control method for upper-limb multifunctional prostheses: advances, current challenges, and future prospects,” in *IEEE Access*, vol. 7, pp. 10150-10165, 2019.

[10] T. S. Davis et al., “Restoring motor control and sensory feedback in people with upper extremity amputations using arrays of 96 microelectrodes implanted in the median and ulnar nerves,” *J Neural Eng.*, vol. 13, no. 3, Jun. 2016.

[11] A. Boschmann and M. Platzner, “Reducing classification accuracy degradation of pattern recognition based myoelectric control caused by electrode shift using a high density electrode array,” in *2012 Annual Intl Conf of the IEEE EMBS*, pp. 4324-4327.

[12] P. Maduri P and H. Akhondi, “Upper Limb Amputation,” in *StatPearls Treasure Island (FL)*, Jan. 2021.

[13] L. Resnik, “Advanced Upper Limb Prosthetic Devices: Implications for Upper Limb Prosthetic Rehabilitation,” *Archives of Phy Med Rehabilit*, vol. 93, no. 4, pp. 710-717, Apr. 2012.

[14] I. Dudkiewicz et al., “Evaluation of prosthetic usage in upper limb amputees,” *Disabil Rehabilit.*, vol. 26, no.1, pp. 60-63, Jul. 2004.

[15] G. Pomares, H. Coudane, F. Dap, and G. Dautel, “Psychological effects of traumatic upper-limb amputations,” *Orthop & Traumatol: Surg & Res*., vol. 106, no. 2, pp. 297-300, Apr. 2020.

[16] A. H. Al-Timemy, R. N. Khushaba, G. Bugmann, and J. Escudero, “Improving the Performance Against Force Variation of EMG Controlled Multifunctional Upper-Limb Prostheses for Transradial Amputees,” in *IEEE Trans on Neural Syst & Rehabilit Eng.*, vol. 24, no. 6, pp. 650-661, Jun. 2016.

[17] C. Toledo, L. Leija, R. Munoz, A. Vera, and A. Ramirez, "Upper limb prostheses for amputations above elbow: A review," in *2009 Pan American Health Care Exchanges*, Mexico City, Mexico, pp. 104-108.

[18] L. Haverkate, G. Smith, and D. H. Plettenburg, "Assessment of body-powered upper limb prostheses by able-bodied subjects, using the Box and Blocks Test and the Nine-Hole Peg Test," *Prosthet Orthot Int.*, vol. 40, no. 1, Feb. 2016.

[19] J. Uellendahl, "Myoelectric versus body-powered upper-limb prostheses: A clinical perspective," *Prosthet and Orthot*., vol. 29, no. 4S, pp. 25-29, Oct. 2017.

[20] S. L. Carey, D. J. Lura, and M. J. Highsmith, "Differences in myoelectric and body-powered upper-limb prostheses: Systematic literature review," *J Rehabilit Res Dev*., vol. 52, no. 3, pp. 247-262, 2015.

[21] C. Igual, L.A. Pardo, J. M. Hahne, and J. Igual, "Myoelectric control for upper limb prostheses," *Electronics*, vol. 8, no. 11, 2019.

[22] E. Scheme and K. Englehart, "Electromyogram pattern recognition for control of powered upper-limb prostheses: state of the art and challenges for clinical use," *J Rehabilit Res Dev.,* vol. 48, no. 6, pp. 643+, 2011.

[23] S. Muceli and D. Farina, "Simultaneous and proportional estimation of hand kinematics from EMG during mirrored movements at multiple degrees-of-freedom," in *IEEE Trans on Neural Syst Rehabilit Eng.*, vol. 20, no. 3, pp. 371-378, May 2012.

[24] E. A. Biddiss, D. Beaton, and T. Chau, "Consumer design priorities for upper limb prosthetics," *Disabil & Rehabilit: Assist Technol*., vol. 2, no. 6, pp. 346-357, 2007.

[25] F. Ryser, T. Bützer, J. P. Held, O. Lambercy, and R. Gassert, "Fully embedded myoelectric control for a wearable robotic hand orthosis," in *IEEE Int. Conf. Rehabilit.*

Robot., pp. 615–621, 2017.

[26] D. Riet, R. Stopforth, G. Bright, and O. Diegel, "An overview and comparison of upper limb prosthetics," in *2013 Africon*, Pointe aux Piments, Mauritius, pp. 1-8.

[27] M. Gazzoni et al., "Quantifying forearm muscle activity during wrist and finger movements by means of multi-channel electromyography," *PLoS One*. vol. 9, no. 10, Oct. 2014.

[28] N. Jiang, H. Rehbaum, I. Vujaklija, B. Graimann, and D. Farina, "Intuitive, online, simultaneous, and proportional myoelectric control over two degrees-of-freedom in upper limb amputees," in *IEEE Trans Neural Syst Rehabilit Eng.*, vol. 22, no. 3, pp. 501-510, Aug. 2013.

[29] F. Montagnani, M. Controzzi, and C. Cipriani, "Exploiting arm posture synergies in activities of daily living to control the wrist rotation in upper limb prostheses: A feasibility study," *Annu Int Conf IEEE Eng Med Biol Soc. 2015*, pp. 2462-5.

[30] S. Amsüss et al., "Self-correcting pattern recognition system of surface EMG signals for upper limb prosthesis control," in *IEEE Trans Biomed Eng.*, vol. 61, no. 4, pp. 1167-1176, Apr. 2014.

[31] O. W. Samuel et al., "Intelligent EMG pattern recognition control method for upper-limb multifunctional prostheses: advances, current challenges, and future prospects," in *IEEE Access*, vol. 7, pp. 10150-10165, 2019.

[32] M. R. Masters, R. J. Smith, A. B. Soares, and N. V. Thakor, "Towards better understanding and reducing the effect of limb position on myoelectric upper-limb prostheses," in *Annu Int Conf IEEE Eng Med Biol Soc*, Chicago, IL, USA, 2014, pp. 2577-2580.

[33] I. Kyranou, S. Vijayakumar, and M. Erden, “Causes of performance degradation in non-invasive electromyographic pattern recognition in upper-limb prostheses,” *Front. Neuronbot*., vol. 12, Sept. 2018.

[34] J. T. Belter and A. M. Dollar, “Performance characteristics of anthropomorphic prosthetic hands,” in *2011 IEEE Int Conf Rehabilit Robot.*, Jun. 2011.

[35] G. A. Clark et al., “Using multiple high-count electrode arrays in human median and ulnar nerves to restore sensorimotor function after previous transradial amputation of the hand,” in *2014 36th Annu Int Conf IEEE Eng Med Biol Soc*., Chicago, IL, pp. 1977-80.

[36] D. Farina and S. Amsüss, “Reflections on the present and future of upper limb prostheses,” *Expert Rev Med Devices*, vol. 13, no. 4, pp. 321-324, Mar. 2016.

[37] M. Atzori, H. Muller, and M. Baechler, “Recognition of hand movements in a trans-radial amputated subject by sEMG,” in *IEEE Int. Conf. Rehabilit Robot*., pp. 1–5, 2013.

[38] M. González-Izal, A. Malanda, E. Gorostiaga, and M. Izquierdo, “Electromyographic models to assess muscle fatigue,” *J Electromyogr Kinesiol.*, vol. 22, no. 4, pp. 501–512, Aug. 2012.

[39] A. Akhtar et al., “A low-cost, open-source, compliant hand for enabling sensorimotor control for people with transradial amputations,” in *Proc Annu Int Conf IEEE EMBS*, pp. 4642–4645, Oct. 2016.