ESTABLISHING BIONIC PROSTHETIC CONTROL IN INDIVIDUALS RECEIVING TARGETED MUSCLE REINNERVATION FOR PAIN PREVENTION

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ABSTRACT

Targeted muscle reinnervation for the prevention of neuromas and phantom pain (N-TMR) is rapidly emerging as standard surgical intervention. The efficacy of N-TMR for pain treatment and the low complexity of the nerve redirection procedure at the time of amputation have been a key aspect of its widespread adoption. However, N-TMR was not developed for prosthetic control. Unlike the original prosthetic-focused targeted muscle reinnervation surgeries, N-TMR often redirected nerves to less accessible muscles. Therefore, using surface electromyography to measure the activity of the deeper reinnervated muscles for prosthetic control is very difficult especially since muscle orientation, signal separation, and electrical crosstalk are also not considered during N-TMR surgery. To address these limitations, we investigated the feasibility of applying sonomyography, a prosthesis control technique that is capable of measuring reinnervated muscle activity across the depths of the residuum. We applied ultrasound imaging techniques paired with image processing and machine learning algorithms to classify patterns of muscle activity according to the motor intentions of participants' missing limbs. In two participants with transhumeral amputation and N-TMR surgery we demonstrated that 4-6 functionally relevant missing hand and wrist movements could be classified with 82% to nearly 100% accuracy. We suggest that like the original prosthetic-focused targeted muscle reinnervation surgeries, N-TMR provides opportunities to establish bionic interfaces with advanced prostheses. We see a significant opportunity to improve prosthetic motor outcomes for the growing number of individuals with high-level amputations that are receiving this procedure for pain prevention.

INTRODUCTION

Mechatronic upper limb prostheses have become exceptionally sophisticated. Control of these advanced systems has evolved to leverage surgical, engineering, and neuroscientific approaches that detect users' intentions directly from their motor nervous systems [1], [2]. Here, Targeted Muscle Reinnervation (TMR) has demonstrated significant potential as a long-term, real-world nerve machine interface for individuals with high level upper limb amputations [3], [4]. By redirecting severed nerves, the patient's intentions to move their missing limb are amplified by the residual muscles and can be used to establish a bionic link to control their prosthesis. However, like almost all bionic control interfaces, to ensure the best functional outcomes, TMR requires a large interdisciplinary team to plan and execute the surgical procedure prior to therapy and prosthesis fitting. TMR is most often performed as a secondary surgery and relevant factors related to prosthetic control inform surgical decisions. For example, the muscles to be reinnervated are carefully chosen and may be first denervated from native nerves, surgically modified, and/or moved to ensure that electromyographic (EMG) signals will be robust and that crosstalk is minimized when operating prostheses [5], [6]. As the degree of surgical planning and technical complexity is high, most individuals with high-level amputations do not have access to this procedure and the functional benefits it may provide.

A variant of TMR surgery is rapidly gaining widespread clinical acceptance. Unlike prosthesis-focused TMR, targeted muscle reinnervation for the prevention of nerve-related amputation pain (N-TMR) is a less complex intervention to manage the disorganized nerve growth after amputation. N-TMR helps prevent phantom and nerve-related pain by redirecting severed nerves to the closest appropriate muscle nerve branches [7]–[9]. N-TMR does not typically require large interdisciplinary teams and at some institutes it is being offered as standard-of-care at the time of primary amputation surgery. Although only recently emerging, the effectiveness in pain prevention and low surgical complexity have resulted in the number of individuals with N-TMR vastly expanding. However, N-TMR was not designed for bionic control of prostheses and current EMG control interfaces can be challenged to effectively measure the activity of reinnervated muscles. This is because surgical consideration is not given to muscle orientation, separation, or the prevention of EMG signal crosstalk; and importantly, EMG sensors remain on the skin's surface while the reinnervated muscles are often located deeper in the residuum.

Sonomyography is an emerging prosthetic control technique that derives control signals from muscle activity across the depths of the residuum [10]–[12]. Although this robust control technique was established in non-TMR amputee populations, it has tremendous potential in unlocking bionic control for the growing population of individuals receiving N-TMR surgeries. Sonomyography uses a small ultrasound transducer positioned on the residual limb to image the muscle deformations that occur below the surface of the skin. Image processing and machine learning algorithms are applied in real-time to capture patterns of muscle deformation, classify them according to the user's motor intentions, and actuate the corresponding prosthetic movements. Sonomyography holds multiple potential benefits including the accurate detection of minuet muscle deformations throughout the residuum, capturing continuously variable activity to proportionally command prosthetic movements, and improved signal to noise ratios when compared to traditional EMG approaches [12], [13].

The objective of this case series was to investigate the degree and accuracy to which sonomyography techniques could be applied to detect missing hand and wrist motor-intentions from the reinnervated muscles of two individuals with transhumeral amputation and N-TMR surgery. We hypothesized that attempting missing limb movements would generate distinct patterns of muscle deformations in the reinnervated musculature, and the combination of ultrasound imaging and machine learning could accurately predict the user's motor intentions from this muscle activity.

METHODS

Two participants with transhumeral amputations and N-TMR surgery were recruited. Protocols were approved by UC Davis' Intuitional Review Board and subjects provided written informed consent prior to participation.

Par-1 was a 52-year-old female with left transhumeral amputation and N-TMR surgery. She did not regularly wear a prosthesis, and it had been 6 months since her N-TMR surgery at the time of testing. Her median, ulnar, and radial nerves were all transferred to her left pectoralis major muscle branch. She reported experiencing a phantom hand that was telescoped at the end of her residual limb and described very minor phantom pains. She also reported being able to visualize moving her missing fingers.

Par-2 was a 40-year-old male with left transhumeral amputation and N-TMR surgery. He did not regularly wear a prosthesis and it had been almost 18 months since his N-TMR surgery at the time of testing. His median and ulnar nerves were transferred to his pectoralis minor muscle branch, and his radial and musculocutaneous nerves to the serratus anterior muscle branch. He reported feeling a phantom limb with minor to moderate phantom pain experienced as tingling, shocks, tightness, or itching.

Data Collection

Participants were seated with their residual limb at their side. A Terason 3200T uSmart Ultrasound system with a 16HL7 linear array transducer (Teratech Corp) was used to capture muscle deformations with an imaging depth set to 4 cm [12]. The transducer was affixed to the reinnervated pectoral areas of each participant using a custom bracket and medical bandages at the location of maximum tissue displacement; determined by motoring the ultrasound screen and asking participants to freely attempt moving their missing hands. Once affixed, participants were asked to attempt a series of functionally relevant missing-hand and -wrist movements which included power grasp, pinch grasp, key grip, digit 2 extension (pointing), wrist rotation, and wrist flexion or extension [14]. Each movement was repeated 10 times. Patients were encouraged to mirror their intended motion with their unaffected limb and were able to view a live feed of the ultrasound images to assist with motor visualizations. Ultrasound video data was sampled at 30Hz, labelled, and stored for post hoc classification analysis.

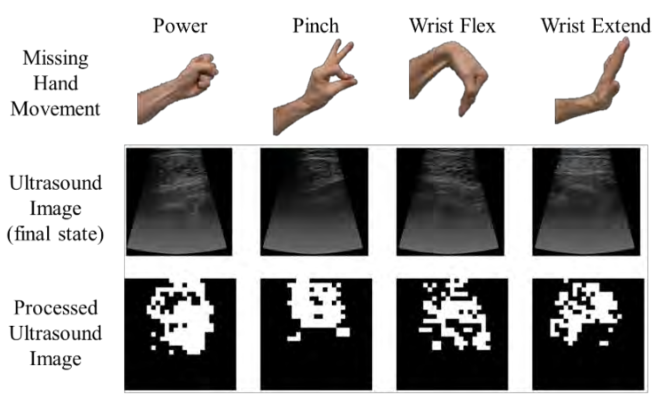

Figure 1: Ultrasound image processing procedure

Data Analysis

Raw ultrasound video data were captured at a 1920x1080 pixel resolution. Video frames were post-processed which included cropping and down sampling to a 128x128 image by averaging neighbouring pixels. Thresholding was performed such that pixels became black or white creating a binary image resembling a QR code (Figure 1) [10]. To classify missing hand movements, we first identified the frames depicting the final movement position for each repetition of each missing hand and wrist movement. As ultrasound recordings ended with the patient at their final movement state, the Pearson correlation distance from the first frame to all following frames was used to estimate when the final state was first achieved. These identified frames were then used as feature vectors for a K nearest neighbour (KNN) machine learning algorithm to determine which grasps produced distinct and separable tissue deformation states. To quantify the accuracy to which hand and wrist movements could be predicted using the KNN classifier, a leave-one-out cross validation of the dataset was performed [15].

RESULTS

Par-1 completed all 6 hand and wrist movements. They did not report any difficulties in visualizing these missing limb movement and there was no apparent muscle spasms or fatigue effects observed during data collection. Classification accuracies for each movement ranged from 89.5% through 96.8% (Figure 2).

Although Par-2 was able to visualize and attempt moving their missing hand into a variety of positions, they reported this task physically and mentally challenging. As a result, each time they attempted to move their missing limb, they required time to concentrate and often intensely contracted their residual muscles. They were able to complete data collection for 4 hand and wrist movements (pinch, power, wrist flexion, and wrist extension) prior to muscle fatigue, spasms, and testing duration forcing the termination of the experiment. Three movements were classified with greater than 99.9% accuracy and pinch grip was able to be classified with 82.0% accuracy (Figure 2).

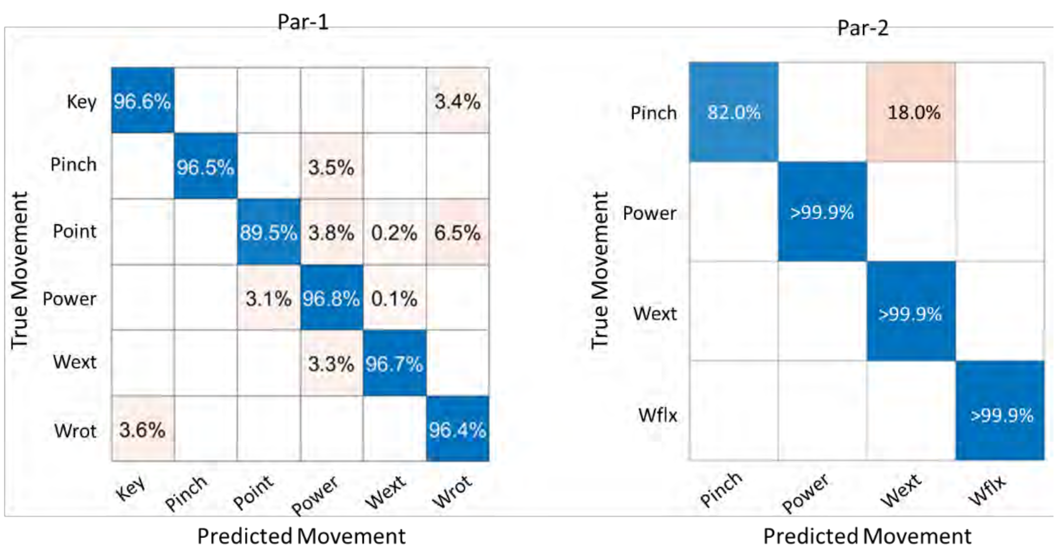

Figure 2: Classification accuracy. Diagonal elements show the accuracy of our algorithms in predicting a missing limb movement from muscle deformation patterns, and the off-diagonal elements represent the likelihood of misclassification. Wext- wrist extension, Wflx- wrist flexion, Wrot- wrist rotation.

DISCUSSION

This work supports that individuals who have received N-TMR have untapped potential to establish bionic links with their prostheses. We found that detectable patterns of reinnervated muscle activity existed with attempts to move the missing limb and this activity could be used to reliably infer missing-limb motor intentions. This was true even for Par-2 who has not used his reinnervated muscles to control a prosthesis, nor his once-intact limb for nearly 18 months. Although he was challenged by the experimental tasks, and muscle fatigue impacted his ability to complete testing, he still produced data that was consistent and accurately classifiable across 4 missing limb movements. We suggest that the effects of fatigue and the ability to visualize and perform missing had movements may improve with training. Further investigation is warranted to better understand how learning and therapeutic approaches may be applied to maximize the accuracy and dexterity that sonomyography may offer individuals with N-TMR.

These data are also compelling given the nature of the nerve reassignments. Par-2 had his median and ulnar nerves transferred to the pectoralis minor muscle branch. The pectorals minor is a deeper muscle covered by the more superficial pectoralis major. It was this region of his chest where the ultrasound transducer was located. The fact that our approaches captured and classified reinnervated muscle activity in this area demonstrates the utility of sonomyography and its ability to measure contraction patterns throughout the depths of the residuum. Further, Par-1 had 3 individual nerves (median, ulnar, radial) all transferred to a single muscle branch (pectorals major). Attempts to move the missing hand/wrist into functionally relevant configurations still generated unique patterns of muscle activity despite the reinnervation of only a single motor branch. An advantage of Sonomyography is the ability of a single sensor and machine learning algorithms to detect even minuet differences across contraction patterns which is emphasized by these findings.

As N-TMR continues to grow as an adopted standard for the prevention of neuromas and phantom pain, so too will the opportunity for patients to reap the benefits of advanced prosthesis control strategies. This work provides evidence that like those who received prosthetic-focused TMR, patients with N-TMR can establish bionic control over their prostheses, they just need to provide the appropriate muscle measurement interfaces. Ultrasound technology continues to be miniaturized, and now battery-powered handheld systems are commercially available making them feasible to incorporate in prostheses. Further, wearable prosthesis-focused sonomyography systems are currently undergoing commercial development. Taken together, this may allow the expansion of N-TMR beyond an effective intervention for pain prevention to include the benefits associated with neural-control of advanced prostheses.

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