Decoding a New Neural–Machine Interface for Control of Artificial Limbs

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Zhou P, Lowery MM, Englehart KB, Huang H, Li G, Hargrove L, Dewald JP, Kuiken TA. Decoding a new neural–machine interface for control of artificial limbs. J Neurophysiol 98: 2974–2982, 2007. First published August 29, 2007; doi:10.1152/jn.00178.2007. An analysis of the motor control information content made available with a neural–machine interface (NMI) in four subjects is presented in this study. We have developed a novel NMI—called targeted muscle reinnervation (TMR)—to improve the function of artificial arms for amputees. TMR involves transferring the residual amputated nerves to nonfunctional muscles in amputees. The reinnervated muscles act as biological amplifiers of motor commands in the amputated nerves and the surface electromyogram (EMG) can be used to enhance control of a robotic arm. Although initial clinical success with TMR has been promising, the number of degrees of freedom of the robotic arm that can be controlled has been limited by the number of reinnervated muscle sites. In this study we assess how much control information can be extracted from reinnervated muscles using high-density surface EMG electrode arrays to record surface EMG signals over the reinnervated muscles. We then applied pattern classification techniques to the surface EMG signals. High accuracy was achieved in the classification of 16 intended arm, hand, and finger/thumb movements. Preliminary analyses of the required number of EMG channels and computational demands demonstrate clinical feasibility of these methods. This study indicates that TMR combined with pattern-recognition techniques has the potential to further improve the function of prosthetic limbs. In addition, the results demonstrate that the central motor control system is capable of eliciting complex efferent commands for a missing limb, in the absence of peripheral feedback and without retraining of the pathways involved.

INTRODUCTION

Improving the control and function of artificial arms remains a great challenge, especially in the case of proximal amputations where the disability is greatest. Myoelectric control using a residual pair of agonist/antagonist muscles is the most common method for operating a motorized prosthesis (Parker and Scott 1986). With proximal amputation, the patient can control only one joint at a time and must switch back and forth to control multiple joints. This type of control is not intuitive, requires a great deal of conscious effort, and generally produces slow, clumsy movements. Attempts to retrain proximal muscles (e.g., shoulder or back muscles) or to extract control information from these remaining muscles with advanced signal processing techniques have had very limited success (Hudgins et al. 1993).

We have developed a new technique to improve the function of upper limb prostheses, termed targeted muscle reinnervation (TMR) (Kuiken 2003; Kuiken et al. 2004). TMR transfers residual nerves from an amputated limb onto alternative muscle groups that are not biomechanically functional due to the amputation. The target muscles are denervated before the nerve transfer. The reinnervated muscle then serves as a biological amplifier of the amputated nerve motor commands (Hofer and Loeb 1980). TMR thus provides physiologically appropriate surface electromyogram (EMG) control signals that are related to functions in the lost arm. TMR with multiple nerve transfers provides simultaneous, intuitive control of multiple degrees of freedom by the motoneuronal activity originally associated with the amputated muscles. Great success has been achieved in clinical practice for myoelectric prosthesis control. Using simple myoelectric control paradigms based on amplitude measurement of the EMG signal from each discrete target muscle region, our first four successful subjects have been able to, for the first time, control two degrees of freedom simultaneously using only EMG signals. Functional task performance has been measured by means of a box and block test and a clothes pin test. The subjects showed a 2.5- to 7-fold increase of speed. Subjectively, they reported significantly easier and more natural control of their prostheses (Kuiken et al. 2004, 2007; Lipschutz et al. 2005; to view video see www.ric.org/research/centers/necal/).

Targeted reinnervation presents a unique tool for neuroscientific study. The motor cortex dedicated to a limb is known to change after amputation (Pascual-Leone et al. 1996) and one might hypothesize that motor control pathways are permanently attenuated after long disuse in amputation or at least would require considerable training to evoke complex motor commands. TMR allows access to motor control outputs to assess the robustness of dormant central motor pathways.

If high-fidelity motor commands can be elicited, then it may be possible for TMR to make a much greater improvement in the control of artificial limbs. For example, we have used median nerve transfers to control only hand closing and have used distal radial nerve transfers to control only hand opening. However, in a normal body these nerves innervate dozens of muscles in the forearm and hand and control movement of all of the fingers, thumb, and wrist. We hypothesize that much more motor control information can be extracted to control wrist rotation, wrist flexion/extension, and possibly ulnar/
radial deviation. More dexterous hand operation may also be possible. For example, pattern recognition combined with TMR may allow a user to select different hand grasp patterns such as a three-jaw chuck, fine pinch, lateral pinch, or a power grasp. Although pattern-recognition control is still sequential, its intuitive nature would allow much easier and faster progression in the sequential control of multiple joints. This could greatly enhance the performance of artificial arms.

In this study we used high-density surface EMG recordings to investigate whether further control information can be extracted from TMR using postexperiment pattern-recognition and signal-processing techniques. The results of this study are expressed in terms of pattern classification accuracy. Although no actual real-time control is demonstrated in this study, our results demonstrate that TMR can provide a rich source of motor control information and this information in turn promises to dramatically improve artificial arm function for people with proximal arm amputations.

METHODS

Surgical descriptions

Targeted muscle reinnervation was performed with three different surgical methods based on the level of amputation, remaining muscle, and gender of the subject (Table 1). The essence of the technique is that nonfunctional residual muscles are denervated and the major residual nerves of the amputee are transferred to these target muscles. Four brachial plexus nerve transfers were performed on the left side of a 54-yr-old man with bilateral shoulder disarticulation (BSD) (Hijjawi et al. 2006; Kuiken et al. 2004) (Fig. 1) and a 23-yr-old woman with a very short transhumeral amputation (STH) (Fig. 2A) (Kuiken et al. 2007). TMR was performed on two men with long transhumeral amputations (LTH) ages 45 and 50 yr old; the median nerve was transferred to the medial head of the biceps and the distal radial nerve was transferred to the brachialis muscle (Fig. 2B). The lateral biceps and triceps remained intact for control of elbow flexion/extension.

**TABLE 1. Demographics of TMR subjects and timeline of experiments**

<table>
<thead>
<tr>
<th>Subject</th>
<th>Age at Time of Amputation</th>
<th>Gender</th>
<th>Mechanisms of Injury</th>
<th>Month After Injury TMR Surgery Performed</th>
<th>Month After Amputation EMG Experiment Performed</th>
</tr>
</thead>
<tbody>
<tr>
<td>BSD</td>
<td>54</td>
<td>Male</td>
<td>Electric burn</td>
<td>9</td>
<td>46, 57, and 61</td>
</tr>
<tr>
<td>STH</td>
<td>24</td>
<td>Female</td>
<td>Motorcycle</td>
<td>15</td>
<td>22 and 24</td>
</tr>
<tr>
<td>LTH1</td>
<td>45</td>
<td>Male</td>
<td>Automobile</td>
<td>12</td>
<td>41</td>
</tr>
<tr>
<td>LTH2</td>
<td>50</td>
<td>Male</td>
<td>Industrial trauma</td>
<td>8</td>
<td>18</td>
</tr>
</tbody>
</table>

**FIG. 1.** Schematic description of targeted muscle reinnervation technique in first human subject, a shoulder disarticulation amputee. Three arm nerves (in yellow) were transferred to 3 segments of the pectoralis major muscle. This reinnervated muscle then served as a biological amplifier of the residual nerve motor command signals. Surface EMG signals from these targeted muscle segments were then used to control a robotic arm. In this patient, the ulnar nerve transfer to the pectoralis minor muscle on the lateral chest wall (not shown in the figure) was unsuccessful, likely due to compromise of the pectoralis minor vascular supply.
hardware low-pass filter setting the -3-dB point at one fifth of the sampling rate (410 Hz).

The subjects were asked to imagine and actuate 16 different movements involving the amputated limb. These movements were chosen to involve all aspects of arm function that might be incorporated in advanced upper limb prostheses. The subjects were instructed to follow a video demonstration of each movement displayed on a monitor and attempt the movement with a comfortable consistent effort. The subjects did not practice the movements before or during the experiments. Each trial consisted of 11 repetitions of one type of movement. After an initial video demonstration of a movement, the subjects were then asked to repeat the movement 10 times along with the video demonstration. For each repetition of a movement, the subjects were asked to exert a comfortable level of contraction at a medium force that was held for about 4–5 s. To avoid muscle fatigue, the subjects were allowed to rest for 5 s between each repetition and for 3 min between each trial. All data were analyzed off-line, after the experiments.

\textbf{Signal processing}

The surface EMG signals were first processed with a fifth-order Butterworth high-pass filter at 5 Hz to remove the movement artifact and then down-sampled to 1 kHz. The majority of the noise contaminating the EMG signal from the reinnervated muscles is the electrocardiogram (ECG) artifact. We have investigated the effects of the ECG artifact on the accuracy of a pattern-classification–based scheme for myoelectric control of powered prostheses. It was found that ECG interference, at levels typically encountered in a clinical measurement, has little effect on classification accuracy. Therefore in this study, the ECG artifact was not removed from the EMG signals before classification.

A suitable segmentation of contraction/no contraction epochs was determined manually for each movement. A channel with clear EMG activity and quiescent baseline in between was chosen as shown in Fig. 4. An EMG amplitude threshold detection scheme was performed on this channel to select the muscle contraction period and segment the data. This segmentation was applied to all channels for the trial. Ideally, an automatic, amplitude-based threshold algorithm would be used to segment the data; however, in some recording sessions, subjects produced antagonist muscle activity on returning from the actuated movement to the neutral position. When using an automatic threshold algorithm, these data would be incorrectly labeled as belonging to the agonist class and would not allow for proper pattern-recognition training. To avoid mislabeling antagonist muscle activity as the actuated class, we used the manual segmentation method and...
carefully checked the segmentation process using the video as a reference.

Pattern recognition was then performed on analysis windows that were 256 ms in duration. This may be considered the maximum practical record length for real-time operation; data buffering for longer would introduce a noticeable delay (the processing delay is negligible). For each analysis window, a feature set was computed and then provided to the pattern classifier. Overlapping analysis windows (Englehart and Hudgins 2003) were used to maximize the continuous stream of data and to produce a decision stream that was as dense as possible, with regard to the available computing capacity (Englehart and Hudgins 2003). Here, 256-ms windows were advanced by 64 ms, producing an overlap of 192 ms. The overlapping windowing scheme was applied to the training data (the first half of the active data) to obtain more training examples. Thus on average about 400 windows were obtained from the five repetitions lasting several seconds each. Disjoint analysis windows (i.e., nonoverlapping) from the second half of the active data were used as a test set to evaluate the classifier’s accuracy. The five test repetitions thus produced about 100 seconds each. Disjoint analysis windows (i.e., nonoverlapping) from the second half of the active data were used as a test set to evaluate the classifier’s accuracy. The five test repetitions thus produced about 100

The number of zero crossings is a simple frequency measure of segments in the record. In our application, a segment corresponds to the length of the waveform over the segment. This is simply the cumulative number of zero crossings produced by low-level noise. Given two consecutive samples, the zero-crossing count is incremented if

\[ x_k > 0 \land x_{k+1} < 0 \]  

The number of slope sign changes is a feature that may provide information on the waveform complexity in each segment. This is simply the cumulative number of slope sign changes, the threshold \( \epsilon \) was set to 2.5% of the full-scale range, after amplification.

Waveform length is a feature that provides information on the waveform in each segment. This is simply the cumulative length of the waveform over the segment, defined as

\[ L_0 = \sum_{i=1}^{I} |x_k| \]  

where \( \Delta x_i = x_k - x_{k-1} \). The resultant values indicate a measure of waveform amplitude, frequency, and duration.

Graupe et al. (1982) showed that for stationary Gaussian statistics, the EMG signal can be modeled as a linear autoregressive (AR) time series

\[ x_k = \sum_{i=0}^{p} a_i x_{k-i} + e_k \]  

where \( a_i \) represents AR coefficients, \( p \) is the model order, and \( e_k \) is the residual white noise. It has been shown that the EMG spectrum changes with muscle contraction state, resulting in a change in AR coefficients. Therefore by monitoring the AR coefficients, one can estimate the muscle contraction state. In this study, a six-order AR model and RMS amplitude of the segment were used to build the feature set.

For each analysis window, a feature set was extracted on each channel, producing an m-dimensional feature vector \( (m = 4 \text{ for TD feature sets}; m = 7 \text{ for AR + RMS feature sets}). After concatenating the feature sets of all the channels, the final feature set vector \([m \times n]-dimensional, where n is the number of channels] was provided to the classifier. A linear discriminant analysis (LDA) classifier (Tou and Gonzalez 1974) was used for classification of different movements. More complex and potentially more powerful classifiers may be constructed, but it has been shown in previous work (Hargrove et al. 2007) that the LDA classifier does not compromise classification accuracy. Compared with other classifiers, the LDA classifier is also much simpler to implement and much faster to train.

Bipolar electrode configurations have a more focal recording area, are spatially selective with respect to muscle fiber direction, and are more clinically relevant than monopolar recordings. Therefore the pattern-recognition analyses were also performed using bipolar electrode configurations. In the transhumeral subjects the bipolar electrodes were aligned with the humerus and the dominant muscle fiber direction. In the BSD and short transhumeral subjects the pectoral muscle fibers run in different directions; thus an analysis of bipolar spatial orientation was performed with vertical, horizontal, and diagonal directions.

Channel selection

The high-density surface EMG recording was used to evaluate how much control information one can extract with the maximum possible number of EMG signals from the TMR sources. However, it is impractical to use the high-density surface EMG as a source for real-time control. Therefore a preliminary study seeking a practical number of electrodes was conducted. In this study, a straightforward sequential feedforward selection (SFS) algorithm was used (Somol et al. 1999), which iteratively added the most informative channels, as determined by empirical classification performance. In the first iteration, each channel was used, independently, to train and subsequently test classification performance. The channel producing the highest classification accuracy was chosen as the first “optimal” channel. For the next iteration, the first optimal channel was paired with each of the other channels to form a two-channel EMG data set for classification. The pair of EMG channels generating the highest classification accuracy was considered the “optimal” two-channel subset. This procedure was repeated until the number of “optimal” electrodes cumulated to a desired number of EMG channels.
RESULTS

The spatial EMG activity for each movement was characterized by contour plots or color maps where the root mean square (RMS) value of each channel’s EMG was represented by different colors, interpolating the EMG amplitude between electrode sites. With each intended arm movement, the intensity of the surface EMG signal above the reinnervated muscles had a distinct and repeatable pattern. Figure 5 shows an example of the spatial EMG activity for six movements characterized with contour plots in the BSD subject. It is worth noting that for several movements such as thumb adduction, wrist pronation, and elbow flexion, the maximum EMG amplitude focuses on a similar location. This suggests that the conventional control (i.e., solely based on EMG amplitude) is not suitable for control of these movements. Pattern-recognition–based control is needed in a case such as this.

A series of pattern-recognition analyses were performed on data windows using a time domain (TD) feature set, and the combination of autoregressive (AR) coefficients and the RMS of the signal as a feature set. The analysis was conducted using a monopolar electrode configuration and three bipolar electrode configurations in transversal, longitudinal, and diagonal directions, respectively. Classification accuracy for the 16 intended movements was high using all of the surface EMG recordings from the reinnervated muscles. Table 2 shows class-to-class results from a typical experiment; examination of the specific movements revealed only a few movements that had accuracies ≤95%. Table 3 summarizes the average classification performance for all 16 movements in the four subjects. The classification accuracy for the 16 intended distal arm movements using surface EMG recordings from the reinnervated muscles was high in all subjects. With the monopolar channels the average overall classification accuracy was 90.5 ± 6.3% for TD feature sets and 90.0 ± 7.3% for AR + RMS feature sets. Using bipolar electrode configurations consistently improved the accuracy of classification to an average of 96.0 ± 3.9% with TD and 95.0 ± 5.2% with AR + RMS features. Across all subjects, there was no notable difference in the accuracy of the TD versus the AR + RMS feature sets.

Analyses were performed using bipolar electrodes aligned in transversal, longitudinal, and diagonal directions to determine whether there might be an optimal angle with respect to the underlying muscle fiber direction. There was no appreciable difference in classification accuracy with the three bipolar electrode orientations (<2.5% difference in accuracy in any given experiment). Consistent levels of accuracy were observed in the repeated experiments of two subjects. High accuracy was found when experiments were conducted as long as 5 yr after injury and 4 yr after targeted reinnervation surgery.

There were no pronounced patterns of error between subjects. Errors occurred in all movement classes with the majority of error related to fine finger and thumb movements. The best performance was seen in a long transhumeral amputation subject (LTH2). Examination of his averaged class-to-class results revealed only one movement had accuracy <99%; classification of index finger extension was only 77%. It was confused exclusively with fingers 3–5 extension and accounted for 88% of all errors in this experiment. The classification accuracy was notably lower in the female subject with the high transhumeral amputation compared with the other three subjects. We suspect that the decreased performance is due to breast tissue attenuating the surface EMG from the median nerve to sternal pectoral muscle transfer.

The preliminary channel reduction analysis indicated that a greatly reduced number of EMG electrodes could be used while maintaining high classification accuracy. As shown in Fig. 6, five to nine bipolar electrodes still allowed classification accuracy within 5% of each subject’s maximum accuracy using all possible electrode combinations in these four subjects. Only four to seven optimally placed bipolar electrodes were required to maintain 90% of the maximum accuracy.

The pattern-recognition methods used in this investigation are computationally efficient; a speed benchmark was described previously (Englehart and Hudgins 2003) in which a 1-GHz Pentium III–based workstation requires roughly 4 ms to process each EMG channel. Improvements in coding efficiency and processor speed currently place this delay at <0.25
Targeted muscle reinnervation is a new neural–machine interface that uses residual muscles as biological amplifiers of amputated arm nerve motor commands. Initial clinical successes with TMR using simple signal processing methods based on EMG amplitude measurement (i.e., direct control) have been very promising. However, only a single independent EMG signal can generally be acquired from each nerve transfer and the motor control information of nerve is mixed in the reinnervated target muscle. Two independent antagonist EMG signals are needed to control each degree of freedom in the TMR prosthesis. This has limited the technique to provide control of two simultaneous degrees of freedom with TMR: 1) hand open/close and 2) elbow flexion/extension. Other arm movements, like wrist flexion/extension and rotation, have been controlled with shoulder switches—a fairly unintuitive and cumbersome method of operation.

In the current study we have demonstrated that by applying pattern-recognition techniques with TMR, substantially more motor control commands can be extracted from the reinnervated muscles. Using pattern-recognition techniques on high-density surface EMG recordings allowed very high accuracy in predicting the intended 16 movements (i.e., 8 degrees of freedom) of the targeted reinnervation subjects. The median and distal radial nerve transfers best highlight the difference between direct control and pattern-recognition control. With direct control the muscle segments reinnervated by the median and distal radial nerve operated only hand opening and closing. Using pattern recognition, information was extracted about the subject’s desire to perform wrist flexion, wrist extension, wrist rotation, and separately move the thumb, index finger, or digits 3–5. This demonstrates a great potential to provide intuitive control of more articulate artificial arms and further improve function for people with amputations.

In similar experiments using the forearm of able-bodied individuals to simulate control of transradial amputees similar levels of classification accuracy to those observed here were found (95–97%) (Chu et al. 2006; Huang et al. 2005), allowing the subject proportional, sequential control of a virtual hand and wrist in real time. These studies in able-bodied subjects demonstrate that pattern-recognition algorithms can successfully be used to provide intuitive control of artificial limbs and proportional control of movement. However, neither of these studies included articulations of the thumb, index finger, and fingers 3–5 as performed by the TMR users. Presumably, this would be a very difficult task using only signals from the extrinsic muscles; TMR users have a distinct advantage as they possess sites containing activity corresponding to the intrinsic muscles of the hand.

TMR provides a rich source of additional control data that are physiologically related to the missing limb. The high classification accuracy was consistent within subjects, demonstrating good repeatability. It was also high between subjects who had different surgical procedures and had different remaining posttraumatic anatomy and geometry of their target muscle, demonstrating that the surgical concept can be applied to a broad array of injury levels. The lowest accuracy was
TABLE 3. Pattern recognition results in amputee subjects

<table>
<thead>
<tr>
<th>Subject</th>
<th>Monopolar</th>
<th></th>
<th>Bipolar</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>TD</td>
<td>AR + RMS</td>
<td>TD</td>
<td>AR + RMS</td>
</tr>
<tr>
<td>BSD**</td>
<td>94.1 ± 0.2</td>
<td>92.3 ± 2.7</td>
<td>98.4 ± 0.7</td>
<td>97.8 ± 1.1</td>
</tr>
<tr>
<td>STH**</td>
<td>81.1 ± 3.5</td>
<td>79.5 ± 6.5</td>
<td>90.3 ± 2.9</td>
<td>87.6 ± 2.9</td>
</tr>
<tr>
<td>LTH1</td>
<td>94.2</td>
<td>92.0</td>
<td>97.1</td>
<td>95.5</td>
</tr>
<tr>
<td>LTH2</td>
<td>92.4</td>
<td>96.2</td>
<td>98.3</td>
<td>99.2</td>
</tr>
<tr>
<td>Average</td>
<td>90.5 ± 6.3</td>
<td>90.0 ± 7.3</td>
<td>96.0 ± 3.9</td>
<td>95.0 ± 5.2</td>
</tr>
</tbody>
</table>

Values are means ± SD, expressed as percentages. Time domain (TD) feature set and a combination of autoregressive features and the root mean square (AR + RMS) feature sets were used. *Average of three experiments. **Average of two experiments. For both, three different bipolar electrode configurations were used for each experiment.

The ability to proportionally control velocity or force of prosthetic components significantly enhances function. In these experiments, subjects were asked to maintain a moderate constant force, and feedback regarding the level of contraction was not provided; thus the results do not specifically address whether proportional control is possible in TMR subjects using pattern-recognition techniques. On inspection of the data of this study, it is evident that the contraction levels do indeed vary substantially, suggesting that proportional control is indeed possible. Also, proportional control has been demonstrated by our subjects using amplitude-based EMG control with their prostheses (Kuiken et al., 2004, 2007). Further experiments are necessary to determine the dynamic range of contraction levels that is possible, without significantly degrading classifier performance.

Direct comparisons between different NMI approaches are difficult. For amputees, direct peripheral nerve recording and stimulation have been investigated using nerve-cuff electrodes, sieve electrodes, and penetrating arrays (Branner et al., 2004; Crampon et al., 2002; Stieglitz et al., 2002), although no clinically viable systems have been developed. Targeted reinnervation is clearly a practical approach in that no implanted devices are required to record the motor control, as opposed to brain–machine interfaces using cortical implants and peripheral nerve recording systems. The fidelity of motor control data extracted with TMR is high; clinically we can simultaneously control 2 degrees of freedom very well and this study indicates the potential to have much more refined control in the wrist, hand, and even fingers.

Neural plasticity

It is known that the motor cortex dedicated to an amputated limb changes after amputation and one might hypothesize that the unused motor control abilities are lost with time (Pascual-Leone et al., 1996). This work demonstrates that the central motor control system is capable of eliciting complex efferent neural commands for a missing limb without any training to awaken these pathways. The time of complete nonuse for these central pathways was at >18 mo (time from amputation to reinnervation and fitting of a TMR prosthesis) and high recognition rates of finger and thumb movements could be found over 5 yr after amputation. This unique experimental model indicates and adds evidence that motor command pathways are very enduring.

It has long been known that, peripherally, regenerating motor axons can cross-reinnervate a foreign muscle (Kuiken et al., 1995; Weiss and Hoag, 1946). TMR utilizes this principle...
to an extreme. Very large nerves that normally innervate dozens of different muscles functionally reinnervated the target muscles. A broad spectrum of motor units had to be present in these relatively small reinnervated muscle segments to allow identification of different finger, thumb, wrist, and elbow movements. These motor units were recruited relatively easily because the subjects were instructed to perform the specific movements at moderate force levels in a relaxed manner, not a vigorous contraction that would activate motor units with high recruitment thresholds. Furthermore, there was evidence of organization in the reinnervating process as seen in the contour maps of Fig. 3. In our BSD subject, his thumb abductors reinnervated a separate muscle area than the other median nerve flexion muscles. This adds to the growing evidence that there is functional organization of the proximal brachial plexus nerves (Stewart 2003).

Future developments for improved control of multiarticular prosthetic devices

This work demonstrates the potential for further improving the control of more advanced, highly articulated prosthetic arms. More research is needed to implement a practical system, including minimizing electrode numbers, determining acceptable locations, and dealing with the challenges of recording EMG signals in a dynamic environment. There are many other paths that could lead to increased control with TMR. Refinements in surgical technique may allow for the creation of more independent EMG control signals. If there is somatotopic organization to nerves, then different fascicles of a nerve may have different motor functions. Separating the fascicles of nerves and transferring each to separate muscle regions may provide more spatial separation and an increased number of functionally independent muscle regions. For example, if the fascicles that went to the triceps could be separated from the rest of the radial nerve in a shoulder disarticulation amputee, then two independent reinnervated muscle regions could be formed with distinctly separate functions.

There are additional computational approaches that may also allow improved simultaneous control of prostheses. Although pattern classification as used in this analysis precludes simultaneous control of multiple joints, a hybrid approach of using pattern-recognition techniques in conjunction with traditional direct control is promising. For example, the amplitude of the EMG from muscle areas reinnervated by the musculocutaneous nerve and radial nerve may be used to directly control elbow function, whereas median and radial nerve areas may be used concurrently to operate the wrist and hand with pattern recognition. Using parallel pattern-recognition techniques on different muscle regions may also enable simultaneous control of more movements in an intuitive manner. Also, the LDA classifier used in this study is but one of many possible tools; other decoding schemes may yield better performance. Other computational approaches include source separation techniques, such as blind source separation (Farina et al. 2004), or traditional “inverse model” approaches as used in cardiac physiology (Li et al. 2003) and neurophysiology (Ilmoniemi et al. 1985).

Finally, accessing EMG signals under subcutaneous fat, breast tissue, or from deeper muscle regions remains a challenge with surface EMG. An implanted myoelectric sensor system (IMES) (Loeb et al. 2001; Lowery et al. 2006) could ameliorate many problems such as signal attenuation by subcutaneous fat, cross talk, movement artifact, and skin impedance variation. It would bypass the skin interface, provide access to deeper tissues, and allow recording from more focal areas of target muscle. This may allow for more stable EMG recording and higher discrimination of signal content, making the motor control information more consistent and the classification algorithms more robust.

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