Targeted Muscle Reinnervation for Real-time Myoelectric Control of Multifunction Artificial Arms

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Context Improving the function of prosthetic arms remains a challenge, because access to the neural-control information for the arm is lost during amputation. A surgical technique called targeted muscle reinnervation (TMR) transfers residual arm nerves to alternative muscle sites. After reinnervation, these target muscles produce electromyogram (EMG) signals on the surface of the skin that can be measured and used to control prosthetic arms.

Objective To assess the performance of patients with upper-limb amputation who had undergone TMR surgery, using a pattern-recognition algorithm to decode EMG signals and control prosthetic-arm motions.

Design, Setting, and Participants Study conducted between January 2007 and January 2008 at the Rehabilitation Institute of Chicago among 5 patients with shoulder-disarticulation or transhumeral amputations who underwent TMR surgery between February 2002 and October 2006 and 5 control participants without amputation. Surface EMG signals were recorded from all participants and decoded using a pattern-recognition algorithm. The decoding program controlled the movement of a virtual prosthetic arm. All participants were instructed to perform various arm movements, and their abilities to control the virtual prosthetic arm were measured. In addition, TMR patients used the same control system to operate advanced arm prosthesis prototypes.

Main Outcome Measure Performance metrics measured during virtual arm movements included motion selection time, motion completion time, and motion completion ("success") rate.

Results The TMR patients were able to repeatedly perform 10 different elbow, wrist, and hand motions with the virtual prosthetic arm. For these patients, the mean motion selection and motion completion times for elbow and wrist movements were 0.22 seconds (SD, 0.06) and 1.29 seconds (SD, 0.15), respectively. These times were 0.06 seconds and 0.21 seconds longer than the mean times for control participants. For TMR patients, the mean motion selection and motion completion times for hand-grasp patterns were 0.38 seconds (SD, 0.12) and 1.54 seconds (SD, 0.27), respectively. These patients successfully completed a mean of 96.3% (SD, 3.8) of elbow and wrist movements and 86.9% (SD, 13.9) of hand movements within 5 seconds, compared with 100% (SD, 0) and 96.7% (SD, 4.7) completed by controls. Three of the patients were able to demonstrate the use of this control system in advanced prostheses, including motorized shoulders, elbows, wrists, and hands.

Conclusion These results suggest that reinnervated muscles can produce sufficient EMG information for real-time control of advanced artificial arms.

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The loss of one or both arms is a major disability that profoundly limits the everyday capabilities and interactions of individuals with upper-limb amputation. Currently available prostheses do not adequately restore the function of an individual's arm and hand. The most commonly used prostheses are body-powered. These devices capture remaining shoulder motion with a harness and transfer this movement through a cable to operate the hand, wrist, or elbow. With this control method, only 1 joint can be operated at a time. Myoelectric prostheses use the electromyogram (EMG) signals (the electrical signals generated during muscle contraction) from residual limb muscles to control motorized arm joints.

Current control strategies use the amplitudes of the EMG signals from 1 or 2 remaining muscles to sequentially operate each function in the prosthesis.[1] For example, the biceps and triceps muscles are used by an individual with transhumeral amputa-

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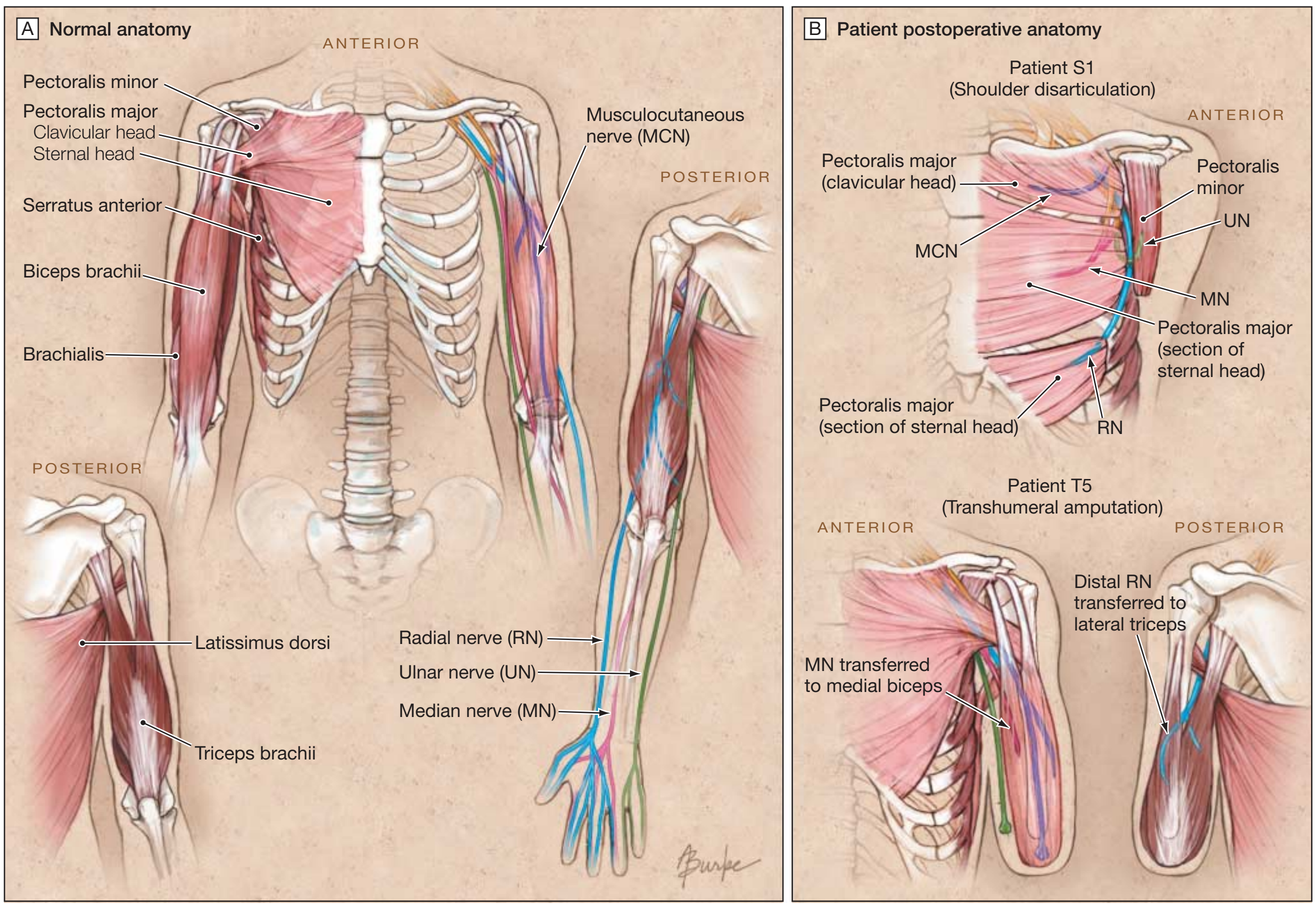
tion to control the elbow, wrist, and hand. The user must trigger a "mode switch" to sequentially select which of these devices is to be actuated. This type of operation is not intuitive, because the residual muscles control physiologically unrelated movements. The use of currently available arm prostheses is cumbersome and slow for individuals with transhumeral or shoulder-disarticulation amputations, whose disability is most severe.[2-8]

We have developed a new surgical technique, called targeted muscle reinnervation (TMR), to improve control of myoelectric prostheses.[9-14] With TMR, remaining arm nerves are transferred to residual chest or upper-arm muscles that are no longer biomechanically functional due to loss of the limb (FIGURE 1). Once reinnervated, these muscles serve as biological amplifiers of motor commands from the transferred arm nerves and provide physiologically appropriate EMG signals for control of the elbow, wrist, and hand. The TMR technique has been successfully performed in patients with transhumeral and shoulder-disarticulation amputations and has markedly improved their functional use of prostheses.[10,12,13] Using a simple control method based only on the amplitude of EMG signals from reinnervated muscles, patients who have undergone TMR surgery can intuitively and simultaneously control opening and closing of the hand as well as extension and flexion of the elbow.

Further investigation has shown that TMR provides a rich source of motor control information. Electrode arrays were used to record EMG signals as patients who had undergone TMR sur-

Figure 1. Normal Anatomy and Examples of Targeted Muscle Reinnervation (TMR)



The goal of TMR surgery is to create new surface electromyogram (EMG) signals that can be used to control a motorized prosthetic arm. This is accomplished by transferring arm nerves remaining after arm amputation to residual (target) chest or upper arm muscles. A, Normal muscular anatomy and innervation of the major muscles of the chest, shoulder, back, and arm. B, Examples of TMR surgery for patients with shoulder-disarticulation (S) and transhumeral (T) amputation. The surgical approach for each patient differs depending on the remaining anatomy after amputation. Nerves innervating target muscles are cut, and nerves from the amputated arm are transferred to these muscles. In patient S1, the pectoralis major muscle was divided into 3 functional regions (clavicular head and 2 sternal head sections), and the pectoralis minor was moved to the lateral chest wall to serve as another muscle region for the 4 major arm nerves. In patient T5, the median nerve was transferred to the medial biceps, leaving the lateral biceps to provide EMG signals for elbow flexion. The distal radial nerve was transferred to the lateral triceps muscle, leaving the long head of the triceps to provide EMG signals for elbow extension. (See Interactive figure.)

gery attempted 16 different motions involving the elbow, wrist, thumb, and fingers. The patterns produced by the combined EMG signals during the performance of different movements were used by a computer to create a "classifier." The classifier was then used to decipher which motion was being performed based on the current pattern of EMG signals. This strategy is called "pattern recognition." Analysis of the data revealed that the intended motions could be classified with a mean classification accuracy of 95%.[15,16] However, it is unknown whether reinnervated muscles can stably and accurately provide myoelectric signals for real-time control of multifunction prostheses. Real-time performance metrics are required to examine the clinical robustness and accuracy of myoelectric prosthetic control with TMR.

This study assessed the real-time control of multifunction prostheses based on TMR combined with a pattern-recognition algorithm. Performance metrics (motion selection time, motion completion time, and motion completion rate) were quantified by training and testing with a virtual multifunction prosthesis. This study also provided a qualitative assessment of ability to operate advanced experimental upper-limb prostheses.

METHODS

This study was conducted with 5 patients who had undergone TMR surgery 11 to 70 months prior to testing. For comparison, 5 control participants without amputation were also included. This study was approved by the Northwestern University institutional review board and conducted between January 2007 and January 2008 at the Rehabilitation Institute of Chicago. All participants provided written informed consent and provided permissions for publication of videos and photographs for scientific and educational purposes.

Five of the 6 individuals with shoulder-disarticulation or transhumeral amputation who had undergone TMR surgery in collaboration with the Rehabilitation Institute of Chicago agreed to participate in this study. Three of these participants had shoulder-disarticulation amputations. Patient S1 was a 54-year-old man who underwent bilateral shoulder-disarticulation amputations in May 2001 following high-voltage electrical injuries to both arms. During TMR surgery performed in February 2002, his residual musculocutaneous, median, radial, and ulnar nerves were transferred to the pectoralis major and pectoralis minor muscles (Figure 1B).[10,11,17] Patient S2 was a 24-year-old woman who underwent left shoulder-disarticulation (very short residual humerus) amputation in May 2005 following a motor vehicle collision. During TMR surgery performed in August 2005, the musculocutaneous, median, radial, and ulnar nerves were transferred to portions of the pectoralis major and serratus anterior muscles.[13] Patient S3 was a 37-year-old man who underwent right shoulder-disarticulation amputation in February 2005 following electrical burns. During TMR surgery, performed in July 2006, the musculocutaneous, median, radial, and ulnar nerves were transferred to the pectoralis major, pectoralis minor, and latissimus muscles.

Two patients with transhumeral amputations also participated in the study. Patient T4 was a 50-year-old man who underwent right transhumeral amputation in April 2004 following a motor vehicle collision. During TMR surgery performed in January 2005, the median nerve was transferred to the medial biceps, and the distal radial nerve was transferred to the brachialis muscle.[14] Patient T5 was a 38-year-old woman who underwent left transhumeral amputation in April 2006, also following a motor vehicle collision. During TMR surgery performed in October 2006, the median nerve was transferred to the medial biceps, and the distal radial nerve was transferred to the lateral triceps (Figure 1B).

For comparison, 5 healthy control participants without amputation (3 men and 2 women, aged 20 to 45 years) also participated in the study. These control participants were chosen to represent both sexes and had an age range similar to that of the TMR patients.

EMG Data Collection

For each patient who underwent TMR surgery, 12 self-adhesive bipolar EMG electrodes were placed on the skin over the reinnervated muscles. Four electrodes were placed at sites chosen previously through clinical evaluation to control the patients' prostheses.[10-12] The 8 additional sites were determined by an electrode-placement optimization algorithm,[16] which sought to maximize the classification accuracy for different movements. For control participants, 12 electrodes were used to record EMG signals from physiologically appropriate muscles in the arm and hand. One electrode was placed over the biceps muscle and a second over the triceps muscle; 6 were placed around the proximal forearm; 1 was placed on the dorsal side of the wrist; and 3 were placed on the hand (medial and lateral thenar eminence and hypothenar eminence). The EMG signals were amplified and band-pass filtered from 5 to 400 Hz. Data were sampled at 1 kHz by an analog-to-digital converter (USB-1616FS; Measurement Computing Corp, Norton, Massachusetts) and processed in real time on a desktop computer using Matlab version 7.3.0.267 (The Mathworks, Natick, Massachusetts).

Classifier Training and Testing

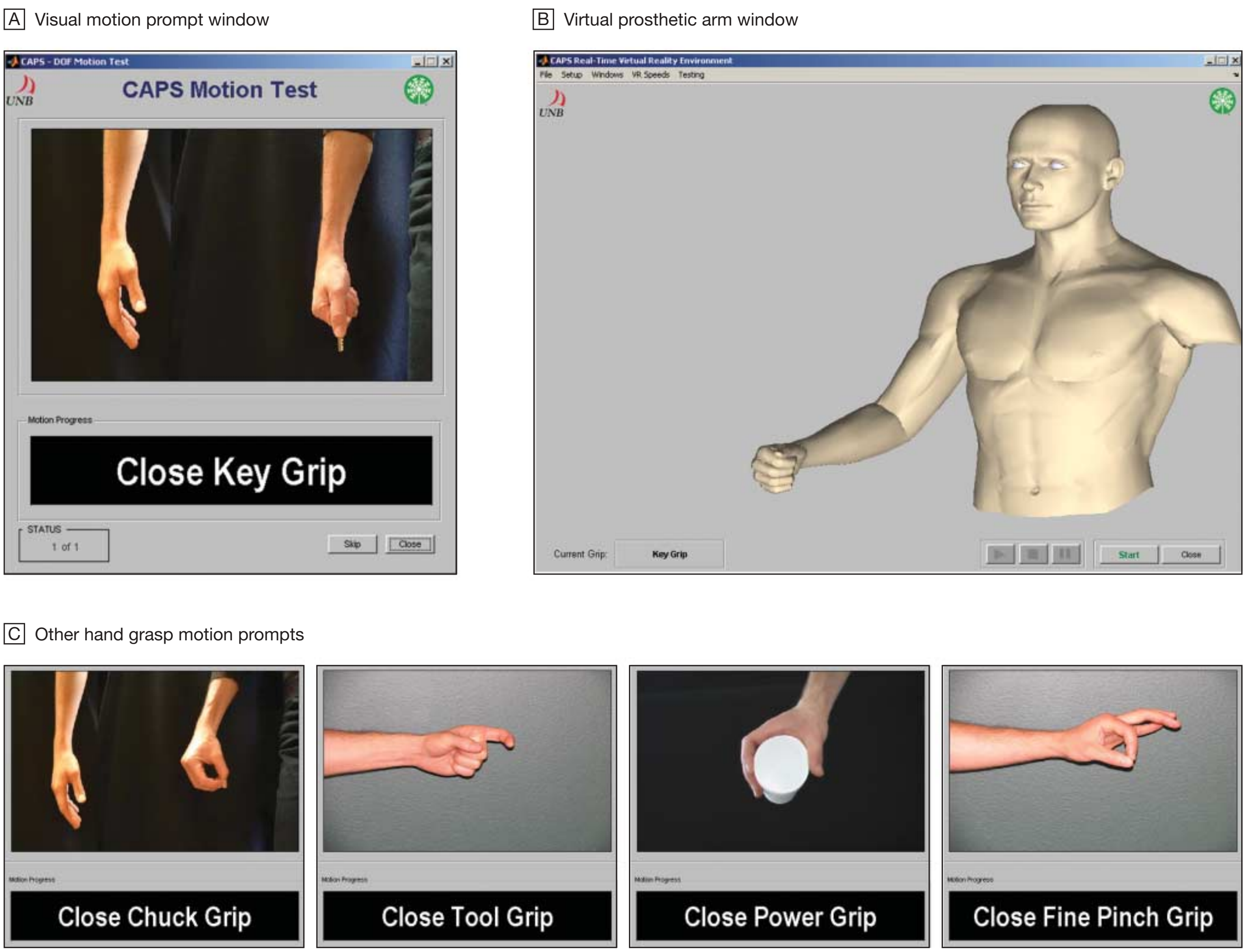
The 11 motion classes were elbow flexion, elbow extension, wrist flexion, wrist extension, wrist pronation, wrist supination, hand opening, 3 types of hand grasps, and no movement. Patients who had undergone TMR surgery were allowed to try 5 different hand-grasp patterns: 3-jaw chuck, fine pinch, key grip, power grip, and tool grip (FIGURE 2). Each patient chose 3 of these grips based on relative ease and reliability of control. For control participants, the 3 grasps were 3-jaw chuck, fine pinch, and tool grip; these were the 3 grasps most commonly chosen by the TMR patients.

Demonstrations of each movement were displayed in random order on a computer screen (Figure 2). For each movement, all participants were instructed to follow the demonstration of the movement and to perform the movement with a comfortable and consistent level of effort. The prompt was displayed with a countdown during the rest time between trials to give patients time to prepare.

Electromyogram data were collected in 8 consecutive trials. In each trial, each motion was repeated twice and held for 4 seconds, producing 8 seconds of EMG recordings per motion. There was a 3-second time interval between motions in the 4 even-numbered trials. A variable rest time of 0 to 3 seconds was used in the 4 odd-numbered trials in an attempt to keep the participants engaged and enhance the classifier's robustness. Electromyogram data from the 8 trials were split into 2 groups: the 4 odd-numbered trials were combined and used to create the classifier; the 4 even-numbered trials were combined and used to test the classifier.

The pattern-recognition algorithm used in this study was implemented as follows: EMG recordings were segmented into a series of 150-ms analysis windows with 50 ms of overlap, resulting in a new classification every 100 ms. Four time-domain features[3,15] were extracted from EMG signals in each analysis window. The combined features from the even-numbered trials were used to create a linear discriminant analysis classifier.[3,15,16,18] This classifier was then used to classify the combined features from the testing set. The classification accu-

Figure 2. Computer Interface Used in Classifier Training and Virtual Prosthesis Testing



Representative screen captures from the Control Algorithms for Prosthetics System (CAPS) (University of New Brunswick, Fredericton, New Brunswick, Canada/ Rehabilitation Institute of Chicago, Chicago, Illinois).

racy for each movement was the percentage of total analysis windows for that class that were correctly classified. The overall classification accuracy was the average of these values for all 11 movements. The linear discriminant analysis classifier was then used in real time to classify features extracted from real-time EMG signals, produce a new prediction of the motion class every 100 ms, and control a virtual-reality arm or a physical prosthesis, as described below. Computational time for each analysis window was less than 3 ms.

Virtual Prosthesis Control

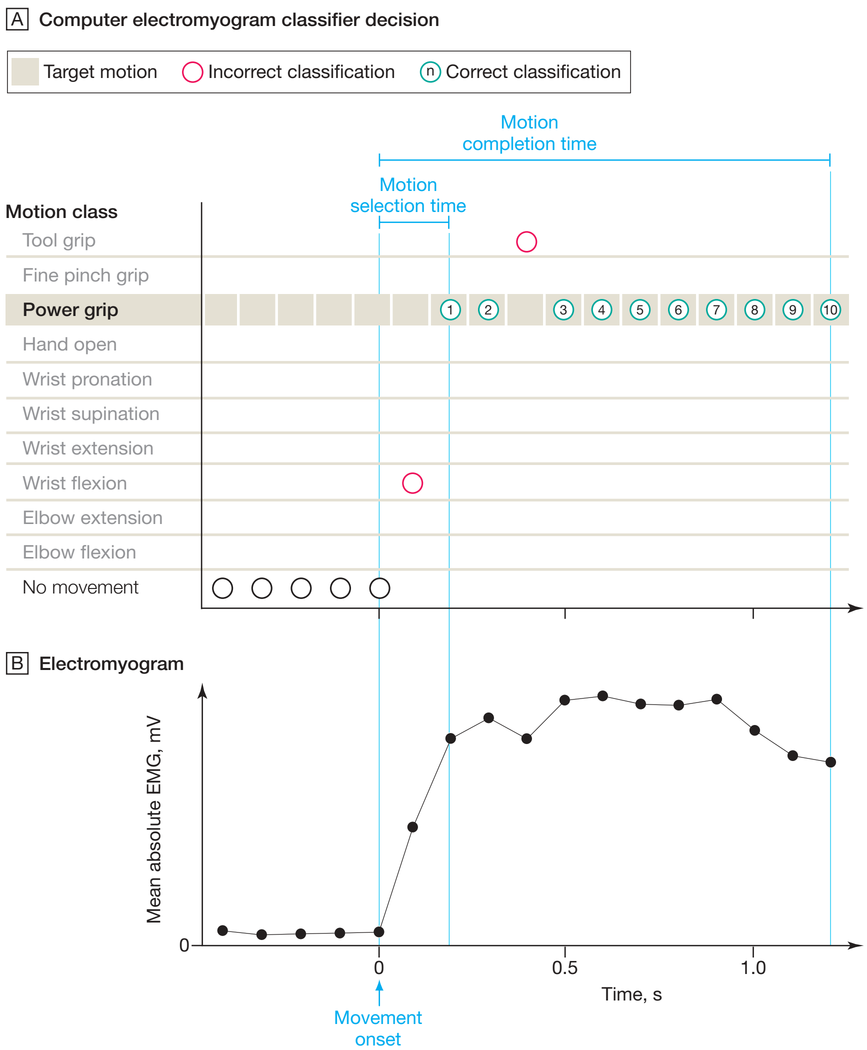
Experiments with a virtual prosthesis were performed immediately after classifier training. All participants were instructed to follow visual prompts for each movement, and a virtual arm that responded to the classifier output was displayed on the screen (Figure 2). Once the participants correctly selected the desired movement, they were asked to maintain it until the virtual arm completed the movement. The time of movement onset was identified as the time of the last "no movement" classification (FIGURE 3). Each of the 10 motions was randomly presented 3 times in a trial, and the trials were repeated 6 times for a total of 180 movements (72 hand-grasp motions and 108 elbow and wrist motions). These data were used to evaluate the speed and consistency of control using real-time pattern recognition.

The performance metrics used to assess virtual prosthesis control were motion selection time, motion completion time, and motion completion ("success") rate. The motion selection time was the time taken to correctly select a target motion and was defined as the time from movement onset to the first correct classification (Figure 3). This quantity measures how quickly motor commands can be translated into correct motion predictions.

The motion completion time was defined as the time from movement onset to the 10th correct classification (which represented the full range of motion for any movement) (Figure 3). The fastest possible speed to complete any motion was 1 second, corresponding to 10 consecutive correct classifications, with new classifications occurring every 100 ms. If the correct class was not selected within a 5-second time limit, the movement was considered a failure.

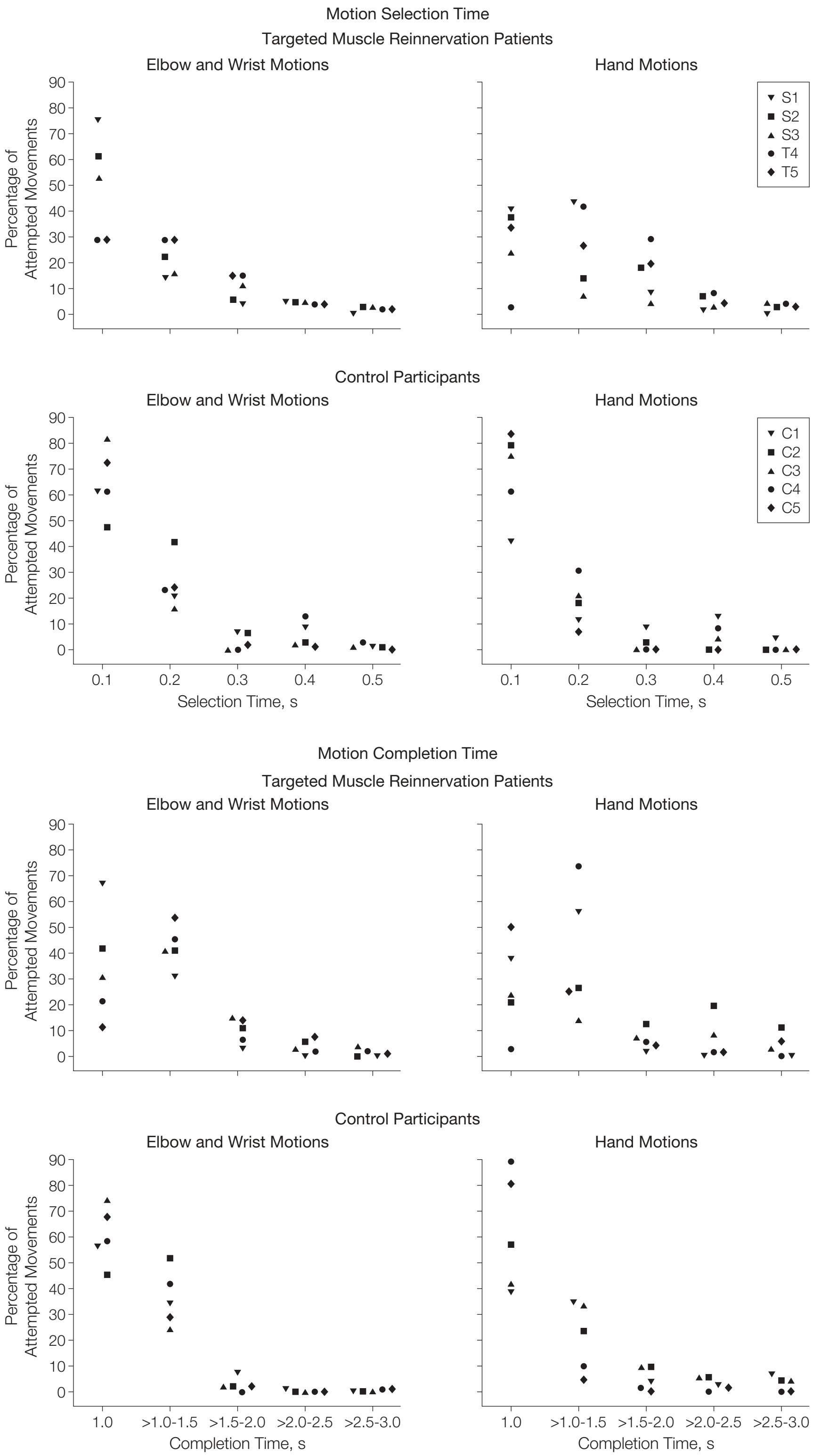
The motion completion rate was the percentage of successfully completed motions out of the total attempted motions (72 attempted motions for the hand, 108 attempted motions for the elbow and wrist) within the time limit. Because the motion selection and motion completion data for each participant were highly skewed, the median

Figure 3. Example of Electromyogram (EMG) Pattern Classification and Virtual Prosthetic Arm Performance Metrics



Example of the time course of EMG pattern classifications in response to the prompt to perform a power grip motion. The classifier made a motion prediction every 100 ms (A, circles). The participant starts from a "no movement" rest state, indicated by the low amplitude of the mean absolute EMG level (B). As the participant attempts the movement, the EMG signal increases, and the classification decision changes. In this example, 2 incorrect classification decisions (red circles) are made before the 10 correct decisions (green circles) are completed. Motion selection time is defined as the time from the last "no movement" classification to the first correct classification of the intended motion. Motion completion time is defined as the time from the last "no movement" classification until the 10th correct classification of the intended motion.

Figure 4. Motion Selection and Motion Completion Times



Calculated from all completed movements, with a limit of 5 seconds. S1-S3 indicates patients with shoulder-disarticulation amputation; T4 and T5, patients with transhumeral amputation; C1-C5, controls.

value for all 6 arm movements (elbow and wrist) and all 4 hand movements (hand open and 3 hand grasps) were calculated for each participant, and these values were averaged across the 5 patients who had undergone TMR and the 5 control participants.

Preliminary research demonstrated that hand-grasp patterns were more difficult to perform than elbow and wrist movements. Therefore, the control scheme for hand grasps was modified. A hand grasp could only be selected when the hand was fully open. Once a grasp was selected, any hand-grasp pattern would close the hand in the initially selected grasp. However, if the initial hand-grasp pattern selected was incorrect, the patient would have to fully open the hand and try again.

Physical Prosthesis Control

Three of the patients who had undergone TMR surgery were able to test advanced upper arm prosthesis prototypes developed under the Defense Advanced Research Project Agency's Revolutionizing Prosthetics program. Video of this initial testing is presented in the Multimedia feature.

The Johns Hopkins University Applied Physics Laboratory and collaborators developed a prosthetic arm with 7 degrees of freedom that was tested with patient S1 in January 2007. Patient S1 controlled flexion and extension of the motorized shoulder by using residual shoulder motion to operate a mechanical rocker switch. A motorized humeral rotator was controlled with EMG signals from the residual deltoid and latissimus dorsi muscles. Powered elbow flexion/extension, wrist pronation/supination, wrist flexion/extension, and a hand that allowed 3-jaw chuck and lateral pinch grip were controlled with EMG signals from reinnervated muscles and the pattern recognition algorithm.

DEKA Integrated Solutions Corporation and collaborators developed a prosthetic arm system with 10 degrees of freedom that was tested with patients S1, S2, and T5 in May, June, and July 2007, respectively. A shoulder controller operated with residual shoulder movement allowed patients with shoulder-disarticulation amputation to simultaneously operate shoulder flexion/extension and abduction/adduction. Humeral rotation was controlled with EMG signals from the latissimus dorsi and deltoid muscles. The powered elbow, wrist, and hand were controlled with pattern recognition of EMG signals recorded over reinnervated muscles. For patient T5, the humeral rotator was controlled with a switch, while the elbow, wrist, and hand were controlled with pattern recognition of EMG signals recorded over reinnervated muscles. The DEKA hand had multiple motors and was able to form a variety of hand-grasp patterns, including those shown in Figure 2.

Surface electrodes were either self-adhesive or built into the patients' prosthetic sockets. The arm systems were trained at the beginning of each session with a short pattern-recognition protocol similar to the one described above. Training and testing with the prostheses occurred over a 2-week period for each patient. Sessions generally lasted 2 to 3 hours, with one session in the morning and one in the afternoon.

RESULTS

Virtual Prosthesis Testing

The mean classification accuracy was 88% (SD, 7%) for patients who had undergone TMR surgery and 97% (SD, 2%) for control participants.

The majority of movements were selected quickly, with motion selection times less than 0.3 seconds (FIGURE 4). The mean motion selection times for elbow and wrist movements (elbow flexion/extension, wrist rotation, and wrist flexion/extension) were 0.22 seconds (SD, 0.06) for TMR patients and 0.16 seconds (SD, 0.03) for control participants (TABLE). The mean motion completion rate for elbow and wrist movements was high (96.3% [SD, 3.8%] for TMR patients and 100% [SD, 0%] for control participants). For TMR patients, the selection of the appropriate hand-grasp patterns took longer and had, on average, a 9.4% lower success rate than wrist and elbow movements (Table). For control participants, the mean motion selection time for hand grasps was similar to that of elbow and wrist movements (Table). The motion completion rate for hand grasps was slightly (3.3%) lower (Table).

Table. Performance Metrics for Virtual Prosthesis Testing Protocol With a 5.0-Second Time Limit

Performance Metric	Mean (SD): TMR Patients (n = 5)	Mean (SD): Control Participants (n = 5)
Motion selection time, s		
Elbow and wrist[a]	0.22 (0.06)	0.16 (0.03)
Hand grasp[b]	0.38 (0.12)	0.17 (0.09)
Motion completion time, s		
Elbow and wrist[a]	1.29 (0.15)	1.08 (0.05)
Hand grasp[b]	1.54 (0.27)	1.26 (0.18)
Motion completion rate, %		
Elbow and wrist[a]	96.3 (3.8)	100 (0)
Hand grasp[b]	86.9 (13.9)	96.7 (4.7)

Abbreviation: TMR, targeted muscle reinnervation.
[a] For 108 attempted elbow and wrist movements.
[b] For 72 attempted hand grasps.

The movements performed by TMR patients as well as control participants were also completed quickly, consistent with the high classification rates (Figure 4). The fastest possible motion completion time was 1 second, representing perfect classification of the intended movement. The mean motion completion times for elbow and wrist movements were 1.29 seconds (SD, 0.15) for TMR patients and 1.08 seconds (SD, 0.05) for control participants. For both groups, hand grasps took longer to complete than arm movements; the mean motion completion times for hand grasps were 1.54 seconds (SD, 0.27) for TMR patients and 1.26 seconds (SD, 0.18) for control participants.

The mean motion completion rates within a 3-second time limit were 94.1% (of 108 elbow and wrist movements) and 80.3% (of 72 hand grasps) for TMR patients and 99.6% (of 108 elbow and wrist movements) and 93.6% (of 72 hand grasps) for control participants (FIGURE 5). The motion completion rate for hand grasps was lower for 2 of the 5 TMR patients. The motion completion rate increased as the time limit was increased up to approximately 2 seconds and then began to plateau; the maximum motion completion rate was generally reached by 6 seconds.

Real-Time Control of Advanced Prosthetic Arm Systems

Building on the virtual-arm training experience, 3 patients who had undergone TMR surgery were able to demonstrate control of physical arm systems (Multimedia feature). All 3 patients were able to perform basic operations using pattern-recognition control on the first day of testing. Over a 2-week trial period, their proficiency improved with practice, systems debugging, and minor systems improvements.

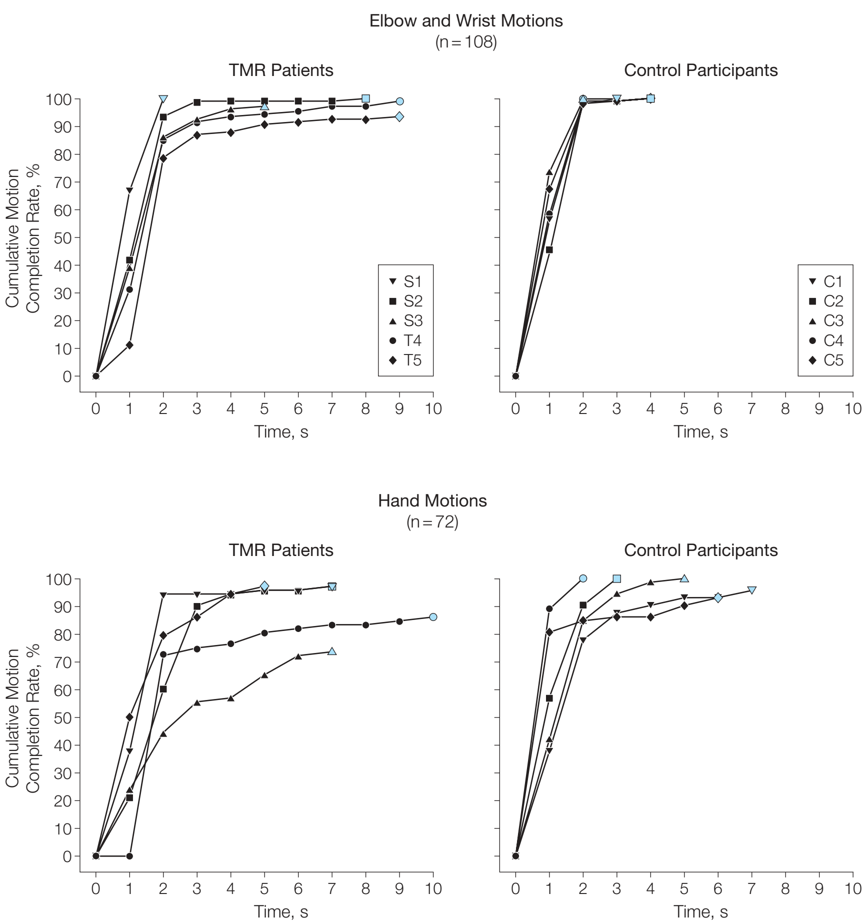
The patients were able to operate all functions of the prosthetic arm prototypes. Control of arm and hand movements using pattern-recognition of EMG signals from reinnervated muscles provided the ability for intuitive, sequential control of the elbow, wrist, and hand. The patients with shoulder-disarticulation amputation were able to simultaneously operate the shoulder and arm. Patients generally performed 1 motion at a time and would occasionally operate 2 joints simultaneously for reaching tasks.

The joints on these prostheses were capable of relatively high speeds. The speed range was customized to each patient, because the patients preferred to operate the arms at slower speeds to allow more accurate control. This control is demonstrated by patient S1 catching checkers rolling across a table, patient S2 stirring a spoon in a cup, and patient T5 moving small blocks (Multimedia feature).

The powered-shoulder systems markedly increased the work space of the prostheses. Motorized shoulder flexion allowed the patients with shoulder-disarticulation amputation to reach above their heads. Motorized shoulder flexion also allowed these patients to have a deeper work space, as demonstrated by patient S2 performing reaching motions over a table (FIGURE 6). Humeral rotation and shoulder abduction widened the work space for all patients and facilitated reaching to the midline for bimanual tasks. The powered wrist served mostly to preposition a functional wrist angle and facilitate better hand operation. The increased number of powered joints also allowed more precise orientation of the hand in space. For example, a ring could be moved across a geometric wire (Figure 6B).

Many different hand grasps were possible with the DEKA arm system; patients were able to attempt 3-jaw chuck, lateral pinch, fine pinch, power grasp, and tool grip. Patients varied in their abilities to control different grasps: one patient could reliably control 4 hand-grasp patterns, another could control up to 3, and the third could reliably control 2. Training with a smaller number of hand grasps improved performance. Choosing different hand-grasp patterns was also more difficult than operating the wrist or elbow motions, consistent with the virtual data presented above. The different grasps facilitated different functional activities. For example, the power grip allowed a firm grasp of a hammer, and the fine pinch enabled picking up small objects (Figure 6A).

Figure 5. Motion Completion Rates



Data markers shown in blue indicate maximal completion rate achieved by each individual. TMR indicates targeted muscle reinnervation. S1-S3 indicates patients with shoulder-disarticulation amputation; T4 and T5, patients with transhumeral amputation; C1-C5, controls.

COMMENT

This study presents experiments on real-time control of highly articulated artificial arms in patients with targeted muscle reinnervation—a novel neural-machine interface. In this study, we demonstrated that a pattern-recognition algorithm can be used to decode surface EMG data from reinnervated muscles and provide intuitive control of powered elbows, wrists, and hands.

The quantification of outcomes is always a challenge with respect to arm function. Studies of EMG pattern recognition generally report classification accuracies found with able-bodied participants. The accuracies are generally in the range of 90% to 100% regardless of the classification algorithm chosen, demonstrating a ceiling effect. However, classification accuracy is a limited metric of control function. For instance, Lock et al were unable to demonstrate a high correlation between pattern classification accuracy and simple performance testing.[19] In our study, classification accuracy for patients who had undergone TMR surgery was lower than that for control participants. The values measured here were similar to previously reported data from our laboratory and from other investigations using pattern recognition of EMG signals to classify intended movements.[16,20,21] However, classification accuracy is not a dynamic estimation of performance but rather only the averaged accuracy of being able to hold a motion for several seconds.

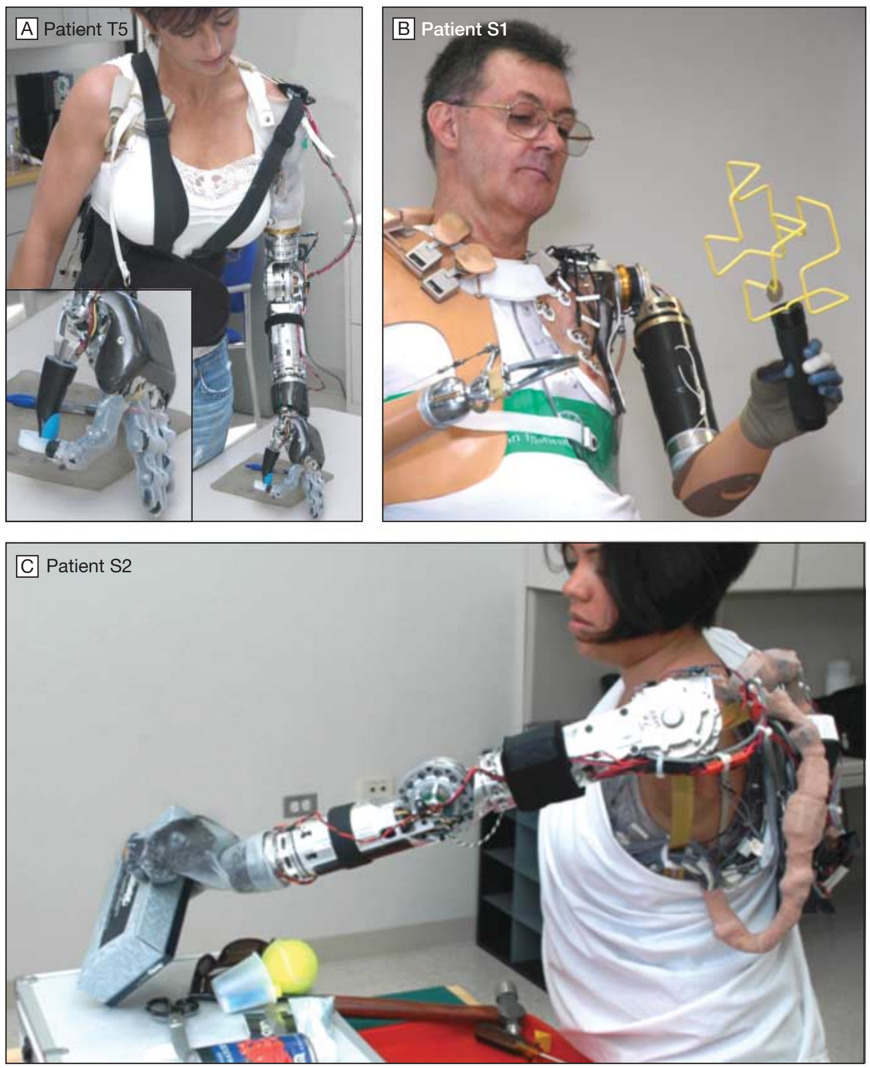
In this study, we developed a protocol to assess the control of a virtual arm. We believe that this protocol is more challenging and allows measurement of more insightful performance parameters. The data from control participants performing the same tests are presented as a reference and represent the performance possible with a more complete EMG data set. Our protocol allows the quantification of several key performance metrics. The motion selection time is the speed at which the user can access a function in the prosthesis. Faster is clearly better, but what is good enough? Farrell et al found that participants did not appreciate a time delay of less than 100 ms,[22] and others have advocated that a delay of up to 300 to 400 ms is acceptable.[20,21,23] Thus the motion selection times of TMR patients for arm function are quite good (≤220 ms), and the motion selection time for hand grasps is perhaps marginal at 380 ms. It should be noted that this delay is not due to computational processing, which takes only a few milliseconds. The motion selection time delay is intrinsic to EMG control, because it represents the need for sufficient data to accumulate before an accurate decision can be made.

The motion completion time is a measure of speed of use. We set a normalized gain so that a task could be completed in 1 second, which correlates to a reasonable speed for prosthesis function of 90°/s to 120°/s. Here we see that the TMR patients did quite well compared with the control participants. Perhaps the most important metric was the motion completion rate, which represents a measure of robustness. A very high success rate is needed to allow adequate function and prevent user frustration. One patient had excellent completion rates of 99% for the elbow and wrist and 96% for the hand grasps; this was comparable to the rates for the control participants. Two other patients had difficulty performing multiple hand-grasping functions. In general, the success rates for elbow and wrist functions were high, but the success rates for controlling multiple hand grasps were much lower, demonstrating that this is more challenging for some individuals.

Quantifying operation of a virtual arm allowed measurement of some useful metrics in the laboratory. However, the ultimate goal is for amputees to operate more dexterous prosthetic arms. Controlling a real prosthesis introduces many practical challenges, such as stability of EMG signal recording, interference from muscles controlling remaining joints, and the effects of tissue loading and arm dynamics.[24]

As part of this program of the Defense Advanced Research Projects Agency, we had the opportunity to conduct initial testing of advanced prosthetic arms with 3 patients in our study. The arms were operated using practical control schemes, including pattern recognition control using EMG signals from reinnervated muscles, conventional myoelectric technology, and custom powered-shoulder controllers. Each patient was able to gain some mastery of the systems in the first day of testing. Within 2 weeks they were all able to demonstrate encouraging control of these complex devices.

Figure 6. Examples of Patients Using Experimental Advanced Prosthetic Arm Systems



A, Patient T5 shown picking up a plastic bottle cap with a fine pinch grip. B, Patient S1 shown moving a ring across a geometric wire. C, Patient S2 shown reaching out to set down a tissue box. Patient T5 has a transhumeral amputation; patients S1 and S2 have shoulder-disarticulation amputations. (See Multimedia feature.)

Our training and testing periods were brief. Improvement in control and function would be expected with more practice. Simultaneous operation of all shoulder motions and 1 arm movement was demonstrated. However, patients would use simultaneous operation of only 2 joints for reaching tasks and usually operated only 1 motion at a time. This is likely owing to the cognitive burden of operating such a complex device.

The lack of sensory feedback is an obstacle for controlling such complex devices. Patients currently must rely on visual feedback. Improved sensory feedback, especially proprioception, will be critical to the long-term goal of neural integration and more natural control of complex prosthetic arms.

These early trials demonstrate the feasibility of using TMR to control complex multifunction prostheses. Additional research and development need to be conducted before field trials can be performed. Improving EMG signal recording repeatability and stability are required to minimize or eliminate daily classifier training. Work is ongoing to develop more robust surface EMG recording systems and prosthetic interfaces. Implantable EMG systems eliminate some of the surface EMG recording problems and may provide more stable systems.[25] Adaptive pattern-recognition algorithms also may improve the stability of control with extended use. Various existing hierarchical control schemes may be more robust for some patients; customization of control hierarchy is an accepted practice in modern prosthetics.

The prosthetic arms tested in this study performed very well as early prototypes. Further improvements are needed and have been planned, including reducing the size and weight and increasing the robustness of these advanced prostheses.

Author Contributions: Drs Kuiken and Li had full access to all the data in the study and take equal responsibility for the integrity of the data and the accuracy of the data analysis.
Study concept and design: Kuiken, Li, Lock, Lipschutz, Miller, Stubblefield, Englehart.
Acquisition of data: Li, Lock, Lipschutz, Miller, Stubblefield.
Analysis and interpretation of data: Li, Kuiken, Lock.
Drafting of the manuscript: Kuiken, Li.
Critical revision of the manuscript for important intellectual content: Kuiken, Li, Lock, Lipschutz, Miller, Stubblefield, Englehart.
Statistic analysis: Li.
Obtained funding: Kuiken.
Administrative, technical, or material support: Kuiken, Li, Lock.
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REFERENCES

1. Sears HH. Trends in upper-extremity prosthetics development. In: Bowker HK, Michael JW, eds. *Altas of Limb Prosthetics: Surgical, Prosthetic, and Rehabilitation Principles.* 2nd ed. Rosemont, IL: American Academy of Orthopedic Surgeons; 1992.
2. Parker PA, Scott RN. Myoelectric control of prostheses. *Crit Rev Biomed Eng*. 1986;13(4):283-310.
3. Hudgins B, Parker P, Scott RN. A new strategy for multifunction myoelectric control. *IEEE Trans Biomed Eng*. 1993;40(1):82-94.
4. Huang Y, Englehart KB, Hudgins B, Chan ADC. A Gaussian mixture model based classification scheme for myoelectric control of powered upper limb prostheses. *IEEE Trans Biomed Eng*. 2005;52(11):1801-1811.
5. Ajiboye AB, Weir RF. A heuristic fuzzy logic approach to EMG pattern recognition for multifunctional prosthesis control. *IEEE Trans Neural Syst Rehabil Eng*. 2005;13(3):280-291.
6. Edell DJ. A peripheral-nerve information transducer for amputees: long-term multichannel recordings from rabbit peripheral nerves. *IEEE Trans Biomed Eng*. 1986;33(2):203-214.
7. Strange KD, Hoffer JA. Restoration of use of paralyzed limb muscles using sensory nerve signals for state control of fes-assisted walking. *IEEE Trans Rehabil Eng*. 1999;7(3):289-300.
8. Branner A, Stein RB, Fernandez E, Aoyagi Y, Normann RA. Long-term stimulation and recording with a penetrating microelectrode array in cat sciatic nerve. *IEEE Trans Biomed Eng*. 2004;51(1):146-157.
9. Kuiken TA. Consideration of nerve-muscle grafts to improve the control of artificial arms. *Technol Disabil*. 2003;15:105-111.
10. Kuiken TA, Dumanian GA, Lipschutz RD, Miller LA, Stubblefield KA. The use of targeted muscle reinnervation for improved myoelectric prosthesis control in a bilateral shoulder disarticulation amputee. *Prosthet Orthot Int*. 2004;28(3):245-253.
11. Hijjawi JB, Kuiken TA, Lipschutz RD, Miller LA, Stubblefield KA, Dumanian GA. Improved myoelectric prosthesis control accomplished using multiple nerve transfers. *Plast Reconstr Surg*. 2006;118(7):1573-1578.
12. Kuiken T. Targeted reinnervation for improved prosthetic function. *Phys Med Rehabil Clin N Am*. 2006;17(1):1-13.
13. Kuiken TA, Miller LA, Lipschutz RD, et al. Targeted reinnervation for enhanced prosthetic arm function in a woman with a proximal amputation: a case study. *Lancet*. 2007;369(9559):371-380.
14. O'Shaughnessy KD, Dumanian GA, Lipschutz RD, Miller LA, Stubblefield KA, Kuiken TA. Targeted reinnervation to improve prosthesis control in transhumeral amputees: a report of three cases. *J Bone Joint Surg Am*. 2008;90(2):393-400.
15. Zhou P, Lowery M, Englehart K, Hargrove L, Dewald JPA, Kuiken TA. Decoding a new neural-machine interface for control of artificial limbs. *J Neurophysiol*. 2007;98(5):2974-2982.
16. Huang H, Zhou P, Li G, Kuiken TA. An analysis of EMG electrode configuration for targeted muscle reinnervation based neural machine interface. *IEEE Trans Neural Syst Rehabil Eng*. 2008;16(1):37-45.
17. Kuiken TA, Marasco PD, Lock BA, et al. Redirection of cutaneous sensation from the hand to the chest skin of human amputees with targeted reinnervation. *Proc Natl Acad Sci U S A*. 2007;104(50):20061-20066.
18. Duda RO, Hart PE, Stork D. *Pattern Classification.* 2nd ed. Hoboken, NJ: John Wiley & Sons; 2000.
19. Lock BA, Englehart K, Hudgins B. Real-time myoelectric control in a virtual environment to relate usability vs. accuracy. Presented at: Myoelectric Controls Symposium; August 15-19, 2005; Fredericton, New Brunswick, Canada.
20. Englehart K, Hudgins B. A robust, real-time control scheme for multifunction myoelectric control. *IEEE Trans Biomed Eng*. 2003;50(7):848-854.
21. Englehart K, Hudgins B, Chan AD. Continuous multifunction myoelectric control using pattern recognition. *Technol Disabil*. 2003;15(2):95-103.
22. Farrel TR. *Multifunctional Prosthesis Control: The Effect of Targeting Surface vs. Intramuscular Electrodes on Classification Accuracy, and Effect of Controller Delay on Prothesis Performance* [dissertation]. Evanston, IL: Northwestern University; 2007.
23. Hefftner G, Zucchini W, Jaros GG. The electromyogram (EMG) as a control signal for functional neuromuscular stimulation, I: autoregressive modeling as a means of EMG signature discrimination. *IEEE Trans Biomed Eng*. 1988;35(4):230-237.
24. Farina D. Interpretation of the surface electromyogram in dynamic contractions. *Exerc Sport Sci Rev*. 2006;34(3):121-127.
25. Weir REF, Troyk PR, DeMichele G, Kuiken TA. Implantable myoelectric sensors (imes) for upper-extremity prosthesis control: preliminary work. Presented at: Proceedings of the 25th Silver Anniversary International Conference of the IEEE Engineering in Medicine and Biology Society (EMBS); September 17-21, 2003; Cancun, Mexico.

