Refined Myoelectric Control in Below-Elbow Amputees Using Artificial Neural Networks and a Data Glove

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Purpose: To develop a system for refined motor control of artificial hands based on multiple electromyographic (EMG) recordings, allowing multiple patterns of hand movements.

Methods: Five subjects with traumatic below-elbow amputations and 1 subject with a congenital below- elbow failure of formation performed 10 imaginary movements with their phantom hand while surface electrodes recorded the EMG data. In a training phase a data glove with 18 degrees of freedom was used for positional recording of movements in the contralateral healthy hand. These movements were performed at the same time as the imaginary movements in the phantom hand. An artificial neural network (ANN) then could be trained to associate the specific EMG patterns recorded from the amputation stump with the analogous specific hand movements synchronously performed in the healthy hand. The ability of the ANN to predict the 10 imaginary movements offline, when they were reflected in a virtual computer hand, was assessed and calculated.

Results: After the ANN was trained the subjects were able to perform and control 10 hand movements in the virtual computer hand. The subjects showed a median performance of 5 types of movement with a high correlation with the movement pattern of the data glove. The subjects seemed to relearn to execute motor commands rapidly that had been learned before the accident, independent of how old the injury was. The subject with congenital below-elbow failure of formation was able to perform and control several hand movements in the computer hand that cannot be performed in a myoelectric prosthesis (eg, opposition of the thumb).

Conclusions: With the combined use of an ANN and a data glove, acting in concert in a training phase, amputees rapidly can learn to execute several imaginary movements in a virtual computerized hand, this opens promising possibilities for motor control of future hand prostheses. (J Hand Surg 2005;30A:780–789. Copyright © 2005 by the American Society for Surgery of the Hand.)

Key words: Hand prosthesis, EMG recordings, ANN, virtual hands, myoelectric control, amputee.

Amputation of an arm may have an enormous impact on quality of life and activities of daily living for an amputee. A missing hand or upper limb has profound functional consequences and the incompleteness of the body often may constitute a considerable psychologic trauma.[1]

Although prosthetic hands may help to improve function and diminish disability, experience shows that the acceptance of such prostheses is surprisingly low—many patients reject the prostheses after 5 years.[2] Among several reasons for not using hand

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Table 1. Demographic Data

Subject	Age	Gender	Dominant Hand Amputated	Cause	Amputation Level	Time Since Amputation (y)	Type of Prosthesis Used
A	25	Male	Yes	Trauma	Wrist	1	Cosmetic/body powered
B	43	Male	No	Trauma	Forearm	12	Cosmetic
C	31	Male	Yes	Trauma	Forearm	4	Myoelectric
D	43	Male	No	Trauma	Wrist	20	Cosmetic
E	41	Male	No	Trauma	Forearm	4	Cosmetic
F	27	Female		Congenital	Forearm	-	Myoelectric

prostheses is their comparatively primitive function: on the basis of mass electromyographic (EMG) signals from extensor and flexor muscles in the remaining arm stump, the prosthetic hand can open and close; however, more complex grip functions including opposition of the thumb and movement of individual fingers are not possible in the commonly used types of prostheses. The lack of sensory feedback in commonly used prostheses is also an important reason for rejection.[3,4] Although a very simple function often may be sufficient as a support for the contralateral healthy hand, more degrees of freedom and the capacity for more complex grip functions would make prosthetic hands much more attractive for long-term use.

One main reason for the lack of development of more sophisticated hand prostheses is the lack of advanced control systems. It is well known that amputees can induce imaginary movements in their phantom hands, and that such imaginary movements are associated with activity in cortical motor areas that normally drive movements of the hand.[7] Thus there is a firm central nervous basis for generation of electrical signals to drive complex thought-controlled movements in an artificial hand. The large number of remaining muscles in an amputation stump hides a sleeping potential for the generation of specific patterns of EMG signals corresponding to complex hand movements.

Previous studies have shown the possibility of controlling the prosthesis by using multiple EMG recordings.[8–16] The number of electrode pairs in these studies was low (1–6 pairs), and therefore the number of predicted movements was limited. Electromyographic signals are attenuated by the tissue in the arm; beyond 2 to 3 cm from the electrode pair the signal will not be heard above the muscles located closer to the electrodes.[17] Therefore a matrix of electrode pairs enclosing the remainder of the lower arm can be used to optimize the accuracy in controlling the prosthesis. In this study we used 8 pairs of electrodes, which represents a step toward the vision of recording and using the entire amount of control information that is present in the remaining arm.

We recently described a principle for using complex patterns of EMG signals from the amputation stump to induce 7 different movements in a virtual computerized hand by the combined use of an artificial neural network (ANN) and a data glove on the healthy contralateral hand.[18] Here we use the same principle, in a refined form, on 6 upper-extremity amputees, the purpose being to present the concept that 10 different thought-controlled hand movements are driven by the use of multiple EMG recordings from the amputation stump, acting in concert with an ANN. The concept is based on a paradigm in which the ANN (during a training phase) learns to associate specific EMG patterns from the amputation stump with specific hand movements. In this study we show that the trained ANN, in a later phase, can perform these specific hand movements in an artificial hand, here represented by a virtual computer hand.

Subjects and Methods

Subjects

Five subjects with unilateral traumatic upper-extremity amputations participated in the study. The amputation level was at the wrist in 2 cases-and at various forearm levels in 4 cases. One additional person with a congenital below-elbow failure of formation participated. All subjects were accustomed prosthesis users. Table 1 shows the demographic data of the subjects.

Experimental Setup for Training of the Artificial Neural Network

During the experiments the test subjects were seated comfortably with both forearms resting in a neutral position on a table. Eight pairs of electrodes were attached to the forearm stump and the uninjured contralateral hand was equipped with a data glove. The subjects were instructed to perform 10 different

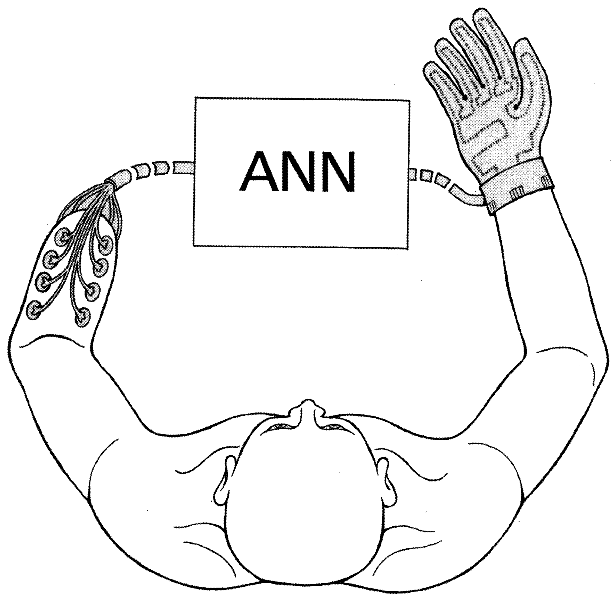

Figure 1. The recording set-up: the 8 electrodes are placed on the remaining forearm while a data glove is fitted onto the contralateral hand. The patient is viewed from above. During the recording the patient performed the same movements with both "hands" simultaneously.

movements with the uninjured hand and to perform the identical movements with the phantom hand simultaneously with the purpose of training the ANN to associate specific patterns of EMG signals from the forearm stump with specific hand movements (Fig. 1). The test subjects were informed about the different movements (Fig. 2) a few weeks ahead of the measurement session and were encouraged to prepare mentally for the experiment with a daily training session consisting of bilateral movements with the uninjured hand and the phantom hand simultaneously.

Method for Simultaneous Electromyographic and Hand Position Recordings

Electromyographic recordings were based on 8 pairs of bipolar wet gel electrodes with a diameter of 1 cm and a center to center distance of 2 cm within each electrode pair. Electromyographic amplifiers were used with a bandwidth of 0.2 to 2 kHz. Six of the electrodes were placed on the volar–ulnar side of the forearm and the remaining 2 electrodes were placed on the dorsal side. The considerable differences between the configurations of the arm stumps in length and diameter did of course influence the placement of the electrodes. Some of the electrodes were moved thereafter, if it was necessary and possible, to avoid redundant muscle measurements. For the subject with the shortest remaining forearm (8 cm), however, the electrodes nearly covered the stump. The general purpose of the electrode placement was to achieve recordings from as many different muscles as possible. All subjects provided informed consent and the study was approved by the Ethical Committee of the University of Lund, Sweden.

A glove (CyberGlove; Virtual Technologies, Inc., Palo Alto, CA) with 18 degrees of freedom was used to record the hand positions from the opposite healthy hand. The joint angles measured were as follows: finger abduction (3 sensors); metacarpophalangeal and proximal interphalangeal joints of the fingers (8 sensors); thumb abduction, thumb opposition, thumb metacarpophalangeal and interphalangeal joints, and wrist flexion/extension (1 sensor); ulnar/radial wrist action (1 sensor); and palm arch (1 sensor). The hand positions were recorded continously and simultaneously with multiple EMG recordings. Ten different movements were selected to be investigated including active movements of individual fingers, the thumb, and the wrist (Fig. 2). For instance a movement of the index finger consisted of flexion, holding the flexed movement for 2 to 4 seconds, and then returning to the rest position. Movement M1, flexion of the small and ring fingers, were grouped together because individual control of these fingers is difficult. Three thumb movements were included: opposition, adduction, and flexion of the distal phalanx (movements M4, M9, M10). Because of limitations of the data glove the rotation of the lower arm and ulnar/radial deviation of the wrist

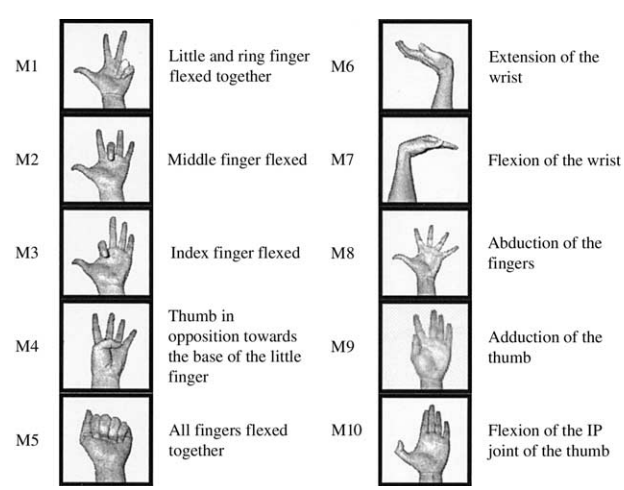

Figure 2. The performed movements during the recording session. Each movement began from a resting position, open palm and with relaxed muscles. A movement then was performed until the end position was reached. The end position was held actively for 1 to 3 seconds before returning to the rest position.

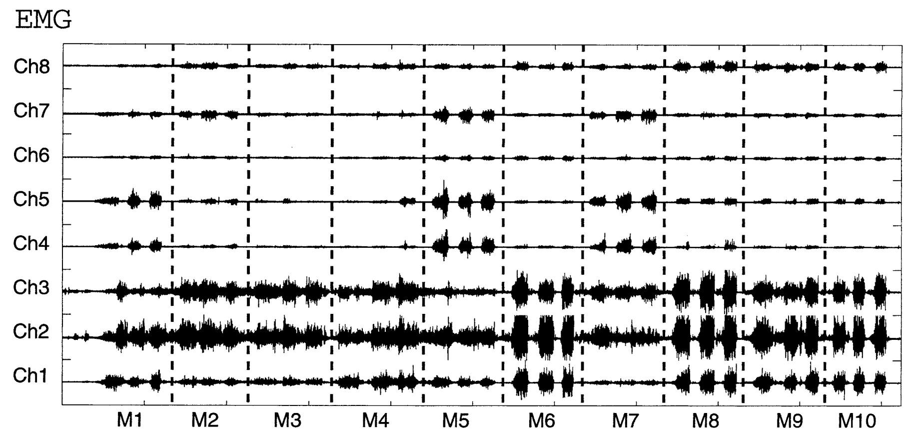

Figure 3. Typical recording from patient A. Eight EMG channels were recorded while the patients performed 10 different movements (movements M1–M10, see Fig. 2) each repeated 3 times. The EMG channels Ch2 and Ch3 show activity even when the subject should be relaxed, unlike the other subjects.

were excluded. Abduction of the fingers (movement M8), however, was possible to record with the data glove and was included in the study.

The test subjects did not see the computer screen during the recordings. Thus the movements with the phantom hand only were imagined by the subject. The first 3 to 4 recordings were performed to train the subject on performing the movements. After the subjects were familiar with the recording procedure, 5 to 7 recordings, recorded in a sequence, were performed and used to calculate the performance of the control system. Each recording session consisted of the movements shown in Figure 2 performed consecutively. Every unique movement was repeated 3 times on command. A typical recording session is shown in Figure 3. The EMG recording shown in Figure 3 had an approximate duration of 2 minutes and 40 seconds. It is possible to see some resemblance among the same movements and some differences between different movements (eg, movements M1, M2). The technical aspects of this new learning set- up, composed with the use of ANNs purposed to improve the control system for a multifunction prosthesis, are described in detail in a previous report.[18]

The Artificial Neural Network

The ANN we used is a tree-structured neural network[19] with properties resembling local approximation with lazy learning.[20] The recorded data, the filtered EMG, and the joint angles are stored in a tree structure. To retrieve the prediction the new unknown EMG is presented and compared with the stored data for each level of the tree. For each level a decision is performed to decrease the number of possible predictions and because only a fraction of the stored data is searched the algorithm is very fast. Similar tree-structured networks have been reported.[21–23] The first recording in the sequence for each subject was used to train the ANN, and the following recordings were used to calculate the performance of the control system and the subject. Thus 120 to 180 individual movements and 12 to 18 minutes of concentrated recordings from each subject were used to calculate the performance. When the ANN was trained the multiple EMG recordings were fed to the ANN together with the glove data. The ANN thus learned to associate EMG patterns with hand movements (Fig. 4, left side). After the ANN was trained it used only the EMG to generate control signals, in this case to a virtual hand (Fig. 4, performance section). The predictions from the ANN were continuous.

To evaluate the ANN's prediction of the 18 joints in the data glove 10 groups of prototypes of hand movements were created from the glove training dataset (Fig. 4, right side). The groups of prototypes corresponded with the movements in Figure 2. Note that the size of each prototype group consisted of several hand positions and the number of positions for each group depended on the size of the training dataset. The start and stop of each movement was better evaluated this way (the prototypes were created for evaluation statistics only). The prediction from the ANN (the position of the 18 joints) then was matched mathematically against the prototypes by using the Euclidean distance and the best-fit prototype was identified. The selected prototype thereafter was compared with the expected movement and the accuracy (% correct match) thus could be computed

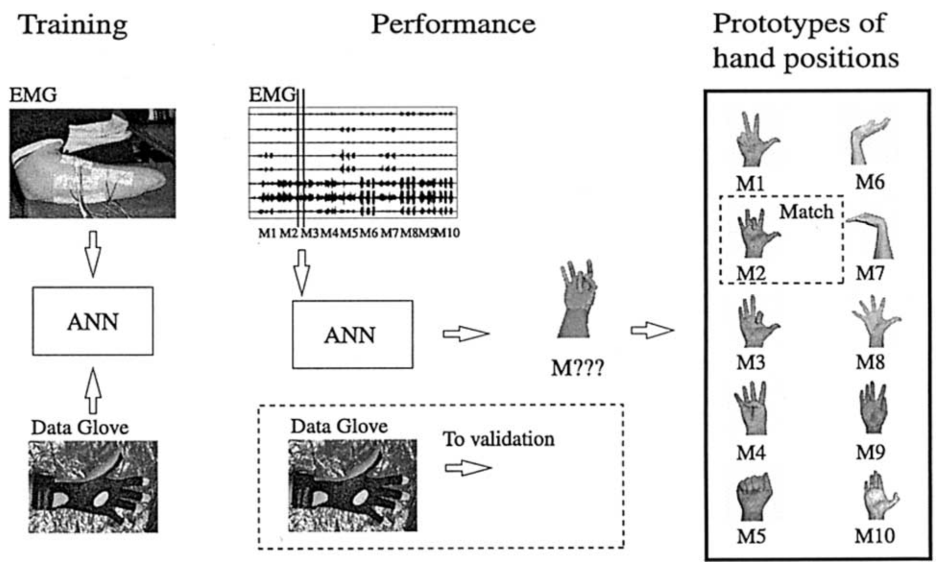

Figure 4. Example of the phases in the system to match the final movement with the intended movement. In the training phase the multiple EMG was fed to the ANN together with the position of the healthy hand. In the performance phase the ANN predicts the hand position only from the EMG, and the hand position from the healthy hand is recorded for error evaluation. For calculation of the accuracy of the prediction the predicted positions were compared with 10 prototype hand positions. The closest match was selected as the predicted movement and compared with the recorded hand position.

by counting the correct number of movements and dividing the sum with the total number of performed movements. The accuracy of the mean performance and the performance from the best session were calculated, and finally the precision of the reference glove was calculated.

Results

The individual results for each patient are shown in Figure 5. The level of accuracy (percent) is represented by the y-axis and the x-axis denotes which movement is addressed (Fig. 2). The 3 calculations are separated in Figure 5. Because of the limitations of the data glove and the variability among the subjects to control the healthy hand, the precision of the data glove is lower in some cases. The best session is the recorded session with the highest percentage of correct movements 10 movements repeated 3 times) (Fig. 3). The best session was performed at the end of the experiment for each subject or among the last sessions. The number of totally correct (100% accuracy) movements performed in this session was 3, 8, 6, 6, and 4 for subject A through E, respectively. The subject with congenital failure of formation (subject F) performed 5 different types of movements. The accuracy of the best session implies that a specific movement could be classified as totally correct or false for all repetitions within a recording session. This could be seen for some of the subjects for whom each type of movement was classified as either 100% correct or 100% incorrect. The ANN mean prediction accuracy is based on 15, 18, 12, 15, 12, and 18 repetitions for each movement for through subjects. A, F, respectively. Three repetitions of each movement thus were used to train the ANN. Subject B and D had the highest accuracy with over 90% accuracy in 6 individual movements. Subject B's best session consisted of 27 of 30 correct executed movements. The 3 error movements wereas follows: thumb opposition classified as thumb adduction, thumb opposition delayed in time (classified as too late), and a wrist flexion with too short a duration. Subject F (congenital failure of formation) and subject A had the least accurate mean performances. Although subject A seemed to be less successful regarding accurate control, he displayed a clear correlation for all types of movements that were performed.

The abduction of the finger movement M8 was predicted with a high accuracy (>90%) in the best session by 2 of traumatically amputated subjects but also by the congenital failure-of-formation subject. The EMG activity for movement M8 was the strongest response or was equally are strong as the wrist movements M6 and M7 for all subjects (based on the root mean square value of the EMG). The most similar movement to the abduction of the fingers, by examining the EMG response pattern, was flexion of the wrist, movement M6, for all subjects. Wrist ex-

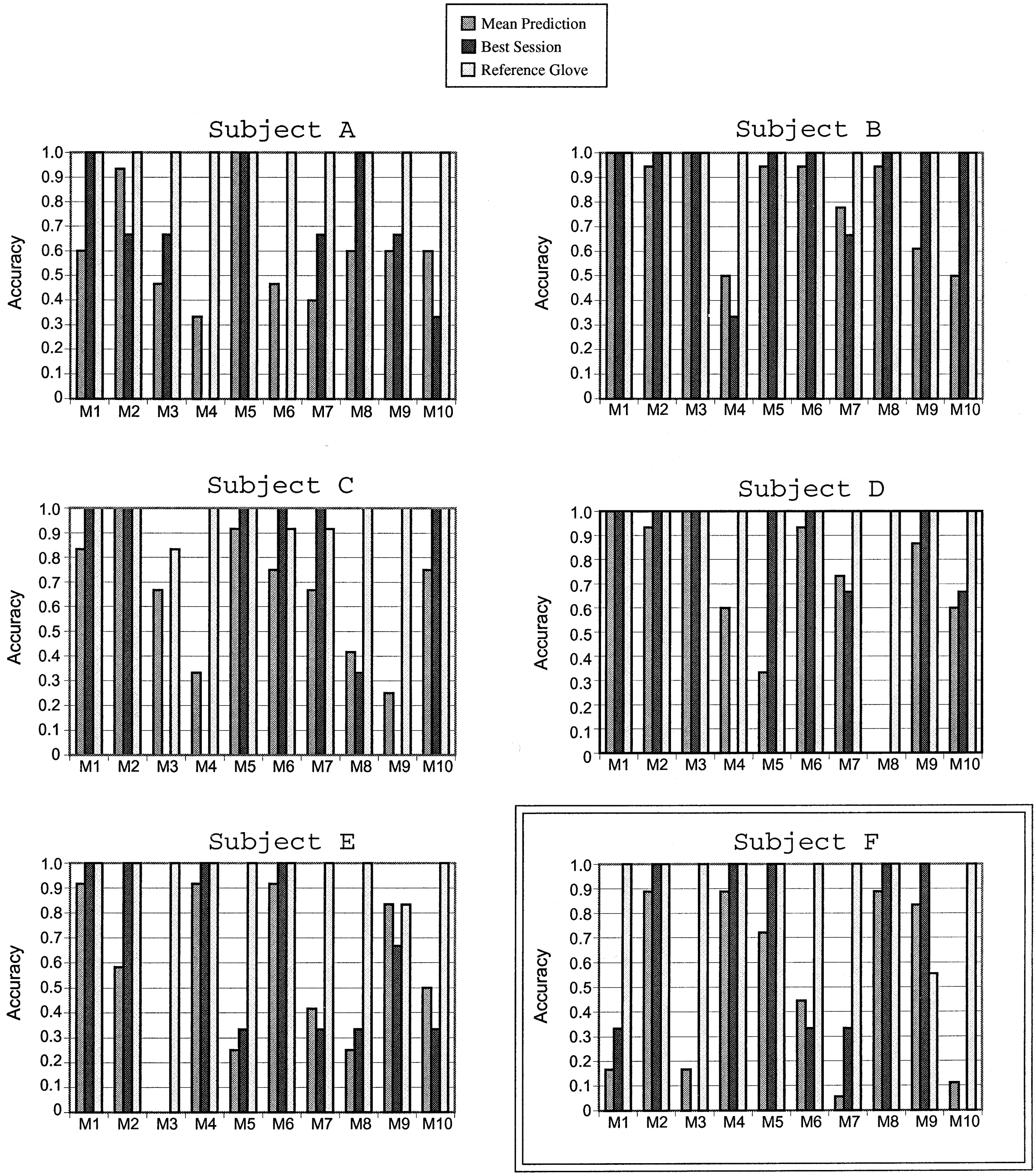

Figure 5. The results for the individual subjects are shown in the diagrams for the different movements. The amputees are indexed as subject A through E, whereas subject F has the congenital failure of formation and is marked with a rectangle around the diagram. The x-axis represents the 10 movements shown in Figure 2, whereas the y-axis denotes the prediction accuracy. Three boxes are presented for each movements corresponding to the following: (1) the mean prediction, (2) the best recording session, and (3) the reference data glove. Note that the data glove results are not always 100% accurate. Subject A had the least accurate performance but all 10 predicted movements had significant correlation to correct movement. Subject B on the other hand performed best in the studied group with a mean performance of 6 movements with greater than 90% accuracy. The best recording session for subject B was almost flawless.

tension in subjects B and E had similarities to the EMG response pattern with the abduction of the fingers, movement M8. Moreover several of the subjects had overlap in the prediction of wrist extension and abduction of the fingers. Two other movements that had some overlap among the subjects were wrist flexion and flexion of all fingers, movements M5 and M7. The 3 thumb movements (movements M4, M9, M10) had more or less overlap in classification, depending on the subject, for the studied group. Subject C and D would, in these recordings, have the most benefits from merging the 3 thumb movements M4, M9, and M10 into 1 remaining thumb movement. The accuracy after the merge would be 86% and 100%, respectively. By merging different types of movements together one can reduce the number of movements that it is possible to perform with the control system, but the remaining types of movements are classified better. Subject E had better discrimination for thumb movements compared with the 2 former subjects, C and D, and achieved 100% accuracy for 2 types of thumb movements (ie, merging movements M9 and M10). The person with congenital failure of formation (subject F) had trouble separating the fingers. Movements M1 and M3 therefore were classified mostly as movement M2. The thumb movements, however, were controlled accurately by the subject with congenital failure of formation.

Discussion

In our study we trained the ANN by using 10 different movements performed in the phantom hand simultaneously with identical movements in the contralateral healthy hand, wearing an 18 degree of freedom data glove. In this way the ANN could learn to associate specific EMG patterns with specific hand movements. After training of the ANN all subjects could control advanced movements of an 18 degree of freedom virtual hand. The degree of accuracy in the performance of the movements varied among the subjects, but our results may change the perspective of future functional hand prostheses.

There are a number of internal and external possible explanations for the variance among the subjects. For instance the length of the time period after amputation might be expected to influence the ability of the subject to initiate and control advanced movement patterns in the remaining forearm muscles. This study indicates, however, that subjects with old amputations do not perform with less precision than subjects with more recent amputations. Another factor could be the length of the remaining forearm—in this study the length varied from a few centimeters to a totally present forearm. Among other important factors was the placement of the electrodes. If no electrode pairs were located in a zone close to important muscles involved in a specific movement then that movement could be expected to have lower accuracy. There is, however, a possibility that the movement still could be predicted with high precision (see the Results section for the prediction of abduction of all fingers, movement M8). Multiple muscles normally are activated for individual hand movements; therefore there is always some EMG pattern present to be recognized. The precision of the prediction thus will depend on the uniqueness of that pattern and the correlation to the intended movement.

Another source of error was the tissue volume of the forearm. The tissue attenuates the signals, and patients with a larger forearm circumference thus would be expected to have comparable lower accuracy. Moreover myoelectric users learn to produce strong EMG patterns in wrist flexor and extensor muscles. Thus the muscles under the electrodes of the prosthesis strengthen whereas muscles used for other movements before amputation are less active or inactive. The myoelectric prosthesis users (subject C and the subject with congenital failure of formation) have a very uneven EMG response in which the trained muscles become dominant. This might be a disadvantage when reproducing the motor commands to an artificial hand.

An important issue was the placement of the electrodes. The configuration of the amputation stumps varied widely. It was therefore impossible to standardize the localization of the electrodes between the subjects. The optimization of the electrode localization was accomplished by minimizing the cross-talk visually. A better result could be expected if the prediction is used to relocate electrodes for better control[15] (eg, if the performance of a specific movement is not acceptable the electrodes for the targeted muscles could be relocated). Rapid retraining of the ANN also can solve the problems with displacement of electrodes. The control system developed in our concept is designed for recalibration within minutes. This could mean a quick recalibration with this system every time a future prosthesis is applied to the arm. Implanted electrodes in the forearm may solve many of the problems because recordings could be performed from deep as well as superficial muscles; isolation effects from adjacent tissues could be avoided and the signal-to-noise ratio could be reduced.

The control of the virtual hand was performed off-line and no feedback was given to the subjects during the experiments. Real-time feedback from a prosthesis or a virtual hand would render better possibilities for the patient to use the plasticity and learning capability of the human brain,[8,24–27] perhaps achieving better results already during the experimental session. The best session, as mentioned in the Results section, indicated that a type of movement quite often was classified as totally correct or incorrect in the same recording session. This could be explaned in that no feedback was given and thus the same type of movement could be performed with a variation of force that varied between the recording sessions. Artificial sensory feedback could be useful to enhance the motor control.[5,6]

Two of the 5 traumatic amputated subjects performed with 100% accuracy in abduction of the fingers in their best session movement M8. Considering that no intrinsic muscles were present the outcome probably could be explained by secondary, yet unique, activity in the forearm to stabilize the hand. For myoelectric control purposes this shows the possibility of controlling movements for which the actual muscles normally performing the movements are absent.

An amputation always is followed-up by extensive functional reorganization of the brain cortex. Studies on various types of experimental animals such as rats,[38,39] racoons,[32] and monkeys,[28–30,34–37] as well as humans[31,33,40,41] have shown that de-afferentiation results in a rapid reorganization of the cortical hand/arm map so that adjacent cortical territories expand into the former hand/arm territory.[28–41]

These events may occur rapidly (within 24 hours) after amputation[42] and may result in strange sensory phenomena. For instance touching the face of the amputee may induce sensations in the missing limb[26,27,42,43] as a result of the face representation expanding into the former arm territory in the somatosensory cortex, probably as a result of unmasking of existing synaptic connections between these cortical areas.[44]

The cortical functional reorganization that follows amputation, however, is a reversible phenomenon,[45] an important observation when considering possible critical time windows after amputation when the learning process of the motor control of a prosthesis is optimal. The cortical response of an amputee after receiving a hand transplant has been studied recently.[45–47] In these studies the motor cortex representation of the hand, as assessed by the use of functional magnetic resonance imaging techniques before surgery and at various intervals after surgery, was regained at 3 to 6 months after transplantation. The same type of cortical reorganization also might occur with the use of a myoelectric prosthesis because in such cases involvement of the motor cortex also is required.

The interval from traumatic amputation to our clinical trial with the use of ANN and the data glove varied from 1 to 20 years. We found that the time elapsed since amputation did not seem to influence the ability of the 5 amputees to generate selected movements in the virtual hand. The capacity to induce multiple movements in the virtual hand even after 20 years indicated strongly that the adult brain rapidly can relearn and undergo plastic changes to initiate movements that had not been performed for a long period of time. It is likely that sleeping motor cortical areas were awakened, and the involvement of adjacent cortical areas also may be of importance as described in motor relearning after brain lesions.[25,48] We feel that the synchronous and bilateral hand movements may play an important role in this training process.

The subject with congenital failure of formation (subject F) is of special interest because several hand movements that had never been executed before could be induced in the virtual hand after a short training session. This means that this patient, at the age of 27, still was capable of mobilizing areas in the motor brain cortex to induce these movements. It is known that patients with congenital failure of formation can induce imaginary movements in their missing hands and that such procedures are associated with activity in the motor cortex.[7] One possibility is that sleeping motor areas, present since birth, are awakened and brought into action. Another explanation is that adjacent cortical areas are recruited into new functions induced by training. Recruitment of new cortical areas for regaining new motor functions have been described previously after, for example, rehabilitation after stroke,[25,48] tetraplegia,[49] and after transfer of the ulnar nerve to the femoral and gluteal muscles in paraplegia.[50] In our study the relearning was a very rapid process, requiring only minutes of training, indicating unmasking of existing synapses[26,27,40,51] rather than the creation of new synaptic connections.

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