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A Human Supporting Manipulator Using Neural Network and Its Clinical Application for Forearm Amputation

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Abstract

This paper proposes a training system based on EMG signals for prosthetic control and the development of its prototype. This system aims to enhance three kinds of control ability: muscular contraction, cooperation among several muscles, and the timing of EMG generation. For the EMG signal processing, a statistical neural network is used, which can adapt itself to changes of the EMG patterns according to the differences among individuals, the different locations of the electrodes, the time variation caused by fatigue or sweat, and so on. During the training, information on the EMG signals is displayed in the feedback monitor in order to support the training. The experiments have been conducted using the prototype system. The subject is a 51 year-old man who has had an amputated forearm since he was 18 years old. As the results of training for five days, the ability to manipulate the EMG signal of the subject has been enhanced and the effectiveness of this system is shown.

1 Introduction

Most handicapped people who have an amputated upper limb use a prosthetic arm for a daily life. Until now, many researchers have proposed the control method of it using EMG signals. Waseda hand [1], Boston arm (MIT) [2] and Utha artificial arm (USU) [3] were the pioneers in this study. The EMG signals accompanied by muscular contraction involve much useful information, such as the operator's intended motion, force level, and the mechanical impedance parameters of his or her limb. If the muscle which actuated the original limb still remains after amputation, the information on the intended motion can be estimated through the EMG signals measured from them. It is expected that a natural feeling of control similar to that of the original limb is realized using EMG signals.

Recently, the motion discrimination method which used neural networks has been reported [4]-[8]. A system which uses a neural network can adapt itself to changes in the EMG signals, in accordance with the difference among individuals, different locations of the electrodes, time variation caused by fatigue or sweat, and so on. The authors also have been studying the motion discrimination using neural networks, the EMG controlled prosthetic arm, and the human supporting manipulator [6]-[8].

Although the technology for the prosthetic arm which uses the EMG signals has been developing gradually, the EMG-controlled prosthetic limb are seldom used by the handicapped. There are two main reasons for this situation: One is problems with the hardware device, such as heavy weight and loud motor noises. The second problem deals with operator issues, such as the physical strength, the lack of control experience and training. It is necessary for handicapped people to be provided with rehabilitation and manipulation training based on the EMG signals.

Many studies about rehabilitation systems for the handicapped using robotic and mechatronic technology have been carried out [9]. The "Kokoro web" which is the web site of the IBM Corp. introduces many kinds of hardware/software for various dysfunctions [10]. Tremendous potential exists in such approaches because the personal computer and Internet service have become very popular.

On the other hand, a few education/training systems for prosthetic control have been reported, although they are necessary in order to realize the prosthetic arm which has introduced advanced technology. Dupont and Morin developed the control training system for the prosthetic hand [11]. This system simulates the EMG-controlled prosthetic hand and shows its computer graphic model on a display. However, it provides only the opening and closing training of the prosthetic hand. Also, Kawamura Corp. developed

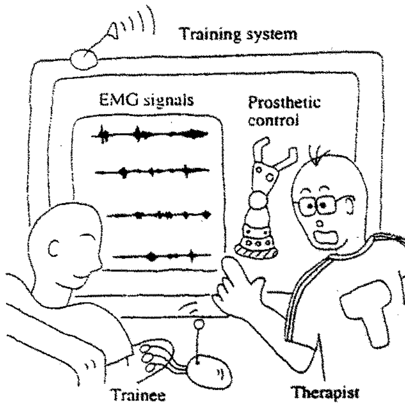


Figure 1: Concept of the proposed system

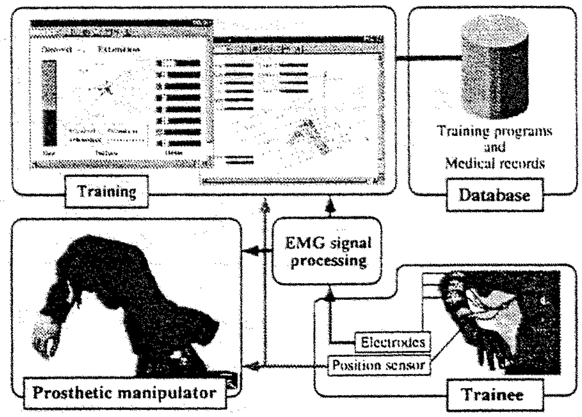


Figure 2: Components of the prototype system

the feedback equipment (Myotrainer) using the EMG signals in order to support the selection of electrode locations and gain regulation of the EMG amplifier. However, it is difficult for this equipment to be used for rehabilitation training because its function is quite simple.

This paper proposes a concept of a training system based on the EMG signals for prosthetic control and development of its prototype. In this system, the information on the EMG signals is displayed in the feedback monitor in order to support the training. Also the prosthetic manipulator [8] is incorporated into the system and used for the control training. The trainee may improve his or her ability of the EMG generation and the manipulation of the prosthetic arm through this training.

2 EMG based training system

Figure 1 shows the concept of the system. A number of electrodes are attached to a trainee, and the information on the EMG signals measured from them is shown on the display. The training program is developed based on the personal computer, thus it enables the trainee to perform the interactive training at home. An example of the training supported by a therapist is shown in Fig. 1.

The system consists of the EMG signal processing part, the training part, the database part and the prosthetic manipulator part as shown in Fig. 2. The EMG signal processing part extracts the information on the muscle activity from the measured signals and discriminates the intended motion from them. The trainee performs the rehabilitation training based on this information. The results of the training are recorded in the database part. After the training, it is expected that the trainee can control the prosthetic manipulator using his or her EMG signals [8], where the end-effector and the wrist joint of the manipulator are controlled using the EMG signals.

2.1 EMG signal processing part

The structure of the EMG signal processor is shown in Fig. 3. This extracts the EMG information and discriminates the trainee's intended motions.

2.1.1 Extraction of the EMG information

Here, three kinds of EMG information are extracted. The first is the information on muscular contraction. In this paper, the EMG signals are rectified and filtered out through the analogue electric circuit, and the amplitude level of these signals are used as the muscular contraction information. The second is information on cooperation among several muscles. This is necessary for training because most human motions are realized by cooperation of several muscles. The third is information on the timing of the EMG generation. To perform several motions smoothly, this information is important. These three types of information are used for the training.

First, the EMG signals measured from L pairs of electrodes (Web5000: NIHON KOHDEN Corp.) are rectified and filtered out through the second-order Butterworth filter (cut-off frequency : 1 [Hz], UAF42, BURR-BROWN Corp.), and they are digitized by an A/D converter (sampling frequency, 60 [Hz]; and quantization, 12 [bits]). These sampled signals are defined as $EMG_i(n)$ $(i = 1, \cdots, L)$, and the following equation is calculated:

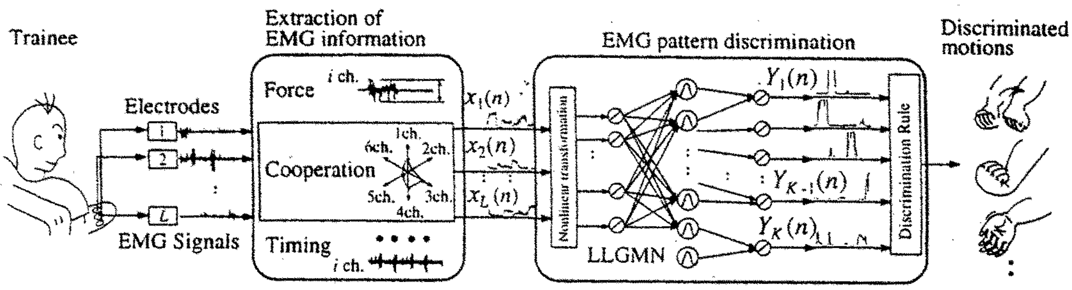


Figure 3: Structure of the EMG signal processor

$$\alpha_k(n) = \frac{1}{L}\sum_{i=1}^{L}\frac{EMG_i(n) - EMG_i^{st}}{EMG_{k,i}^{max} - EMG_i^{st}}, \quad (1)$$

where EMG_i^{st}, $EMG_{k,i}^{max}$ are the mean values of $EMG_i(n)$ while relaxing the arm and keeping the maximum voluntary contraction (MVC), respectively. The $\alpha_k(n)$ indicates the ratio of the muscular contraction level when performing the motion k to the MVC. This ratio is defined as the information of the muscular contraction level.

Next, $EMG_i(n)$ are normalized to make the sum of L channels equal 1:

$$x_i(n) = \frac{EMG_i(n) - EMG_i^{st}}{\sum_{i'=1}^{L}(EMG_{i'}(n) - EMG_{i'}^{st})}. \quad (2)$$

$x_i(n)$ indicates the ratio of the muscle activation under the kth electrode to the sum of all muscle activation. The feature vector $\boldsymbol{x}(n) = [x_1(n), x_2(2), \cdots, x_L(n)]^T \in \Re^L$ is defined as the cooperation information and used for the input vector of the neural network in order to discriminate the trainee's intended motion.

Also, the square sum of the EMG signals is calculated as follows:

$$s(n) = \sum_{i=1}^{L}(EMG_i(n) - EMG_i^{st})^2. \quad (3)$$

This value is used for the detection of a motion: When $s(n)$ is over the prespecified threshold, it is determined that a motion has occurred.

2.1.2 EMG pattern discrimination[9]

Next, the log-linearized Gaussian mixture network (LLGMN) proposed by Tsuji et al. [13] is used for the EMG pattern discrimination. The LLGMN can acquire the log-linearized Gaussian mixture model through learning and calculate the posteriori probability of the trainee's intended motion based on this model. The probability density function is expressed by the weighted sum of the Gaussian components. It enables the LLGMN to learn the complicated mapping between the trainee's EMG patterns and motions.

Before starting the use of the proposed system, the EMG pattern vectors $\boldsymbol{x}(n)$ are measured and used for the learning. It should be noted that the dynamics of a terminal attractor is incorporated into the learning rule in order to regulate the convergence time [8]. The convergence time is always less than the prespecified upper limit so that the mental stress of the trainee waiting for the convergence of learning can be reduced.

The unit of the third layer outputs the posteriori probability of each motion. The trainee's intended motion can be determined according to Bayes' rule. Also, in order to reduce ill-discrimination, the entropy $H(n)$ is calculated and used for a motion suspension rule [7]. The entropy indicates, or may be interpreted as, a risk of ill-discrimination. The possible ill-discriminations are expected to be reduced using this rule.

2.2 Training part

In order to improve the muscle ability of the trainee, the training programs using the EMG signals are prepared. The training is composed of three types: (1) muscular contraction, (2) cooperation among several muscles, and (3) timing of EMG generation. Each training has two modes: One is a voluntary mode in which the training is executed freely depending on the intention of the trainee, and the other an instruction mode in which the system instructs the trainee to execute the desired task. In both modes, the interactive training can be performed much like a computer game. The parameters such as the number of motions, the difficulty of task, and the training time can be changed according to the dysfunction.

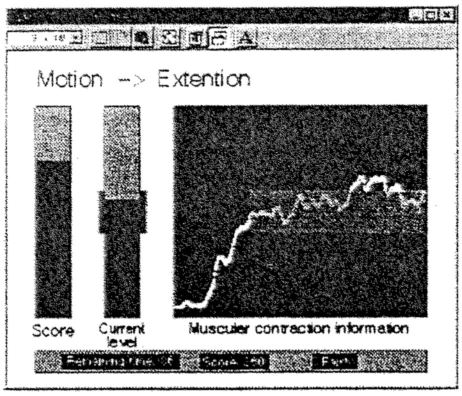


Figure 4: Feedback display for the muscular contraction training

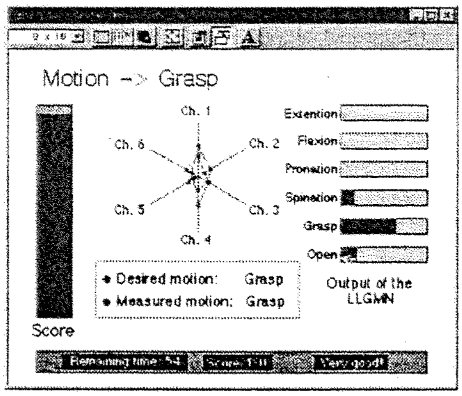


Figure 5: Feedback display for the cooperation training

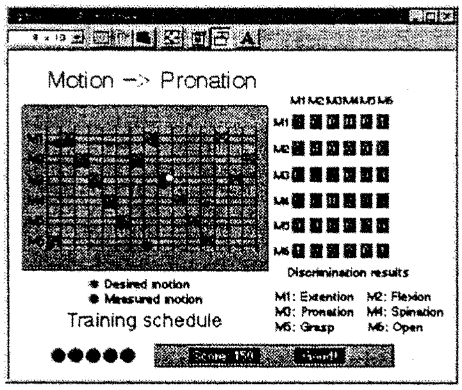


Figure 6: Feedback display for the timing training

2.2.1 Muscular contraction training

In this training, the trainee tries to regulate the muscular contraction level while monitoring the information $\alpha_k(t)$ which is extracted in the EMG signal processor. During a trial, the system instructs the trainee to keep ascertain muscular contraction level and evaluates its achievement. The muscular ability of the trainee can be improved through this training.

Figure 4 is an example of the screen image immediately after the trial. The desired motion "Extension" is shown on the top of the screen, and the time history of the information $\alpha_k(t)$ is shown on the right half. The band-shape area indicates the range of the desired contraction level: the trainee tries to keep $\alpha_k(t)$ in this range during a trial. The duration of one trial is about 10 seconds. The first several seconds are for preparation and the remainder is for evaluation. The left bars show the score and the current value of $\alpha_k(t)$. The ratio of "the total time which the contraction level $\alpha_k(t)$ was kept in the desired range" to "the evaluation time" is used to define the score for the trial, where the maximum value is 100. Also, the remaining time and the total score are displayed on the bottom of the screen.

2.2.2 Cooperation training

The trainee has to use several muscles in order to perform the desired motion in this training. Before the training, the cooperation information $x(n)$ is extracted from the trainee, then the LLGMN is trained to learn the mapping between $x(n)$ and the trainee's motions. During trials, the system instructs the trainee to perform the desired motion and calculates the cooperation information $x(n)$. The ability to control several muscles is evaluated from the discrimination results of the LLGMN.

Figure 5 shows an example of the screen image. The desired motion and the cooperation information are displayed at the top and the center of the screen, respectively. As the cooperation information, two patterns are shown: One is measured in real time, and the other measured before training. The trainee has to control muscles to make these cooperation patterns equal. The bars on the right are the output of the LLGMN corresponding to the posteriori probability of each motion. The intended motion (Grasp) is successfully discriminated in this case and displayed under the cooperation information. The left bar shows the score.

2.2.3 Timing training

The trainee tries to perform the desired motion with right timing. The smoothness of swiching the motions may be improved through this training. During the training, the system instructs the desired mo-

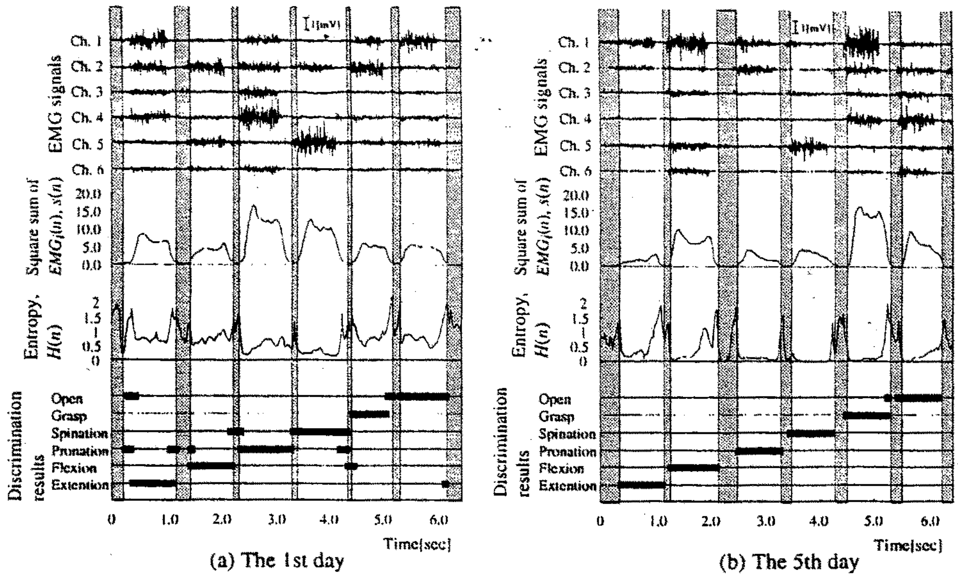


Figure 7: Changes of EMG signals during the training

tion and its timing, and discriminates the intended motion from the measured pattern $x(n)$ using the trained LLGMN. The ability of timing control is evaluated from the discrimination result.

In the training, the time schedule of the desired motions is displayed as shown in Fig. 6. The trainee must execute the motions according to this schedule. The five indicator lamps located near the bottom left-hand corner light up in the order from left to right, and the motion discrimination is carried out when the one furthest right lights up. A series of the desired motions and the discrimination results are plotted side by side in the time schedule, and the numbers of its accumulation are shown in the right table. The score increases when the discrimination result agrees with the desired motion. The total score and the comment from the system are displayed at the bottom of the screen.

3 Experiments

The experiments were conducted for 5 days using the prototype system. The subject was a 51 year-old man whose forearm was amputated when he was 18 years old. He has never used the EMG controlled hand and usually uses a cosmetic hand. The training time takes about 1.5 hours for each day, and a physical therapist supports the training. Six pairs of electrodes were used: Four pairs of electrodes are attached to the forearm and two pairs at the upper arm. Their locations are identical throughout the entire period of the experiment. On the last day, the trainee tried to control the prosthetic manipulator.

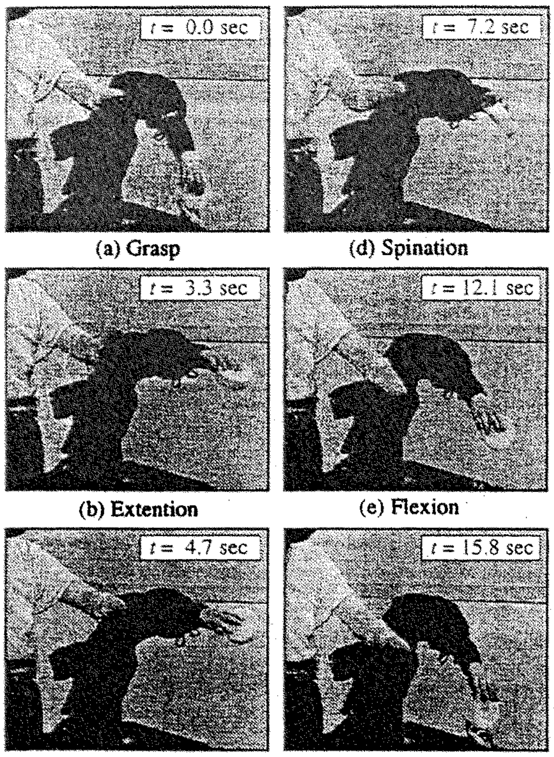
3.1 Changes of the EMG signals

The changes of the EMG signals are examined during 5 days. The examples of the EMG signals are shown in Fig. 7, where the signals were measured just after the training on (a) the first day and (b) the fifth day. In the figures, the EMG signals, the square sum of $EMG_i(n)$, the Entropy $H(n)$ and the discrimination results are shown, while the trainee performed 6 motions continuously. The discrimination results are improved through the training. The entropy $H(n)$ in Fig. 7(b) is smaller than the one in (a). This means that the discrimination becomes clear.

The amplitude level of the EMG signals are also changed. Especially, the channels 1, 2 and 4 extracted from the forearm shows considerable changes. It can be seen that the discrimination ability of the trainee was improved during the training.

3.2 Example of the manipulator control

The control experiment of the prosthetic manipulator was conducted on the last day. Figure 8 shows a series of the photos during the experiment. The trainee received the object from the therapist (Fig. 8(a)), then he performed some motions ((b)-(e)) and returned it again ((f)). No ill-discrimination were observed, and all motions were performed smoothly. It



(a) Grasp (d) Spination

(b) Extention (e) Flexion

(c) Pronation (f) Open

Figure 8: The EMG controlled manipulator used by an amputee

took about 16 [sec], and the time is noted on each picture. The experimental results certify that the control ability of the trainee improved through the use of this system.

4 Conclusion

This paper proposes a concept of a training system based on the EMG signals for prosthetic control and the development of its prototype. This system aims to enhance the trainee's ability to control his or her EMG signals. The experiments have been conducted using the prototype system. As the results of training for five days, the ability of the subject to control the EMG signals has been enhanced, and the effectiveness of this system is shown. In the future, we wish to conduct the experiment with many subjects in order to make the effectiveness and the problems of this system clear.

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