# Proceedins

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# An EMG-based Rehabilitation Aid for Prosthetic Control

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## Abstract

*This paper proposes a concept of an EMG-Based Rehabilitation Aid for prosthetic control and develops its prototype. The proposed system provides the EMG-based rehabilitation training for the physically handicapped in order to improve his or her muscle ability. Also the trainee can practice controlling a manipulator which is a part of this system using the EMG signal.*

*In the prototype system, three kinds of information are extracted from the measured EMG signal and used for rehabilitation training and prosthetic control. The EMG pattern discrimination method using the neural network is utilized as an essential technique of our system.*

## 1 Introduction

Precise and complex motions may be very difficult for the physically handicapped who have lost their manipulation capability of the upper limb by traffic accident, cerebral apoplexy, or other afflictions. Therefore, the development of prosthetic systems is necessary to support their daily life and enable them to achieve social integration.

Many prosthetic arms have been developed for amputees since the 1970's [1], [2], and many intelligent robots have been designed for power assistance, rehabilitation and other aids using modern techniques of robotics [3], [4].

In the prosthetic systems, an EMG signal has been often used as a manipulated signal in previous studies. The EMG signal accompanied by muscular contraction involves information on an operator's intended motion since every motion of a human operator is realized by muscular contraction controlled by the central nervous system (CNS). If the CNS and a part of the muscles which actuate the original limb still remain after amputation, the information on the operator's intended motion can be estimated through the EMG signals measured from his or her muscles. It is expected that a natural feeling of control similar to that of the original limb is realized using EMG signals. Graupe et al. reported on the discrimination of the EMG signal measured from one pair of electrodes using the autoregressive (AR) model [5]. Also, we have already proposed an EMG controlled robotic manipulator using neural networks and suggested its possible use as a human support robot [6], [7].

At present, however, most amputees do not use these EMG based prosthetic arms. The main reason for this situation may involve not only hardware problems such as heavy weight and motor noises, but also software problems such as the lack of training programs for operation and rehabilitation of muscle abilities of each user.

On the other hand, some investigations on biofeedback have been carried out in order to recover the patient's dysfunction. Biofeedback shows the information on the patient's body condition through visual and auditory senses and is used as a medical treatment for the handicapped. It is effective and essential for the muscular dystrophy patient, who cannot control the muscular contraction and cooperation voluntarily, to activate biofeedback using the information on his or her EMG signal [8]. The above mentioned facts indicate that the prosthetic system should be totally re-designed from the view point of not only hardware but software for rehabilitation training.

In this paper, the concept of an EMG-Based Rehabilitation Aid for prosthetic control is proposed and its prototype is developed. The proposed system can provide the EMG-based rehabilitation training for the physically handicapped in order to improve his or her muscle ability. Also the trainee can practice controlling a manipulator which is a part of this system using the EMG signal.

The paper is organized as follows: The components of the proposed system are described in Section 2. The rehabilitation training methods are explained in Section 3, and the experiments are conducted in Section 4. Finally, Section 5 concludes the paper.

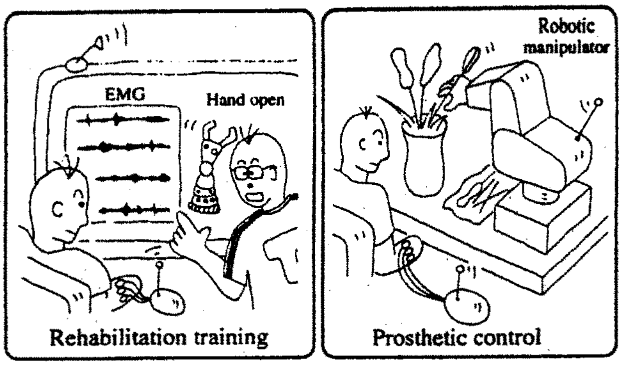



Figure 1: Concept of the EMG-Based Rehabilitation Aid.

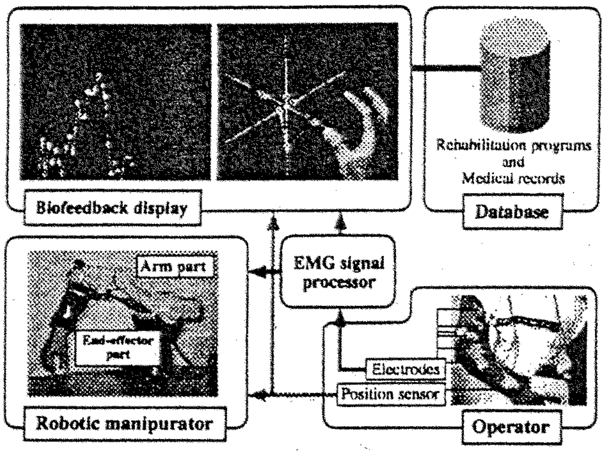



Figure 2: Components of the prototype system.

## 2 EMG-Based Rehabilitation Aid

Figure 1 shows the concept of the EMG-Based Rehabilitation Aid (EBRA). The proposed system provides EMG-based rehabilitation training for the physically handicapped in order to improve his or her muscle ability. The delicate muscle activities can be observed clearly using the EMG signal measured from the surface electrodes, so that an effective rehabilitation training can be carried out for the trainee who has a serious dysfunction of the limbs. Also, this rehabilitation training can be applied to manipulation training of the EMG-controlled robotic manipulator. This training is executed according to the therapist's diagnosis or the computer program.

After the training, the trainee can control the manipulator placed on the table using the EMG signal. The manipulator is compact and suitable for use in the home environment, so that physical and mental stress may not increase even if the trainee uses it for a long time.

Figure 2 shows the components of the developed prototype system which consists of the EMG signal processor, the biofeedback display, the database for rehabilitation training and the robotic manipulator. The EMG signal processor extracts the information of the measured EMG signals, and discriminates the trainee's intended motion. During the rehabilitation training, the biofeedback display provides information on the current status of the muscles to the trainee in order to improve his or her physical strength. The rehabilitation programs and medical records are put together into the database. Also, the robotic manipulator is controlled according to the discrimination result. The details of each technique are described in the following subsections.

### 2.1 EMG signal processor

The Structure of the EMG signal processor is shown in Fig. 3. This processor is the essential part of the proposed system. This processor extracts three kinds of information of the measured EMG signals, and discriminates the trainee's intended motion. These information and discrimination results are used for the rehabilitation training and manipulator control.

#### 2.1.1 Extraction of motion information from EMG signal

During the training, three kinds of information are extracted from the measured EMG signal in order to examine the trainee's muscle activity. The first is force information. In this paper, we assume that the amplitude level of the EMG signal changes in proportion to muscle force, and the system uses the amplitude of EMG as the force information. The second is cooperation information of the EMG signals measured from multiple electrodes. Most of human motions are realized by cooperation of multiple muscles. Therefore, in order to increase the motion control ability of the trainee, the cooperation of muscles should be trained using this information. The third is the information of the beginning of the motions. For smooth motions, it is important not only to control the muscular strength and the cooperation of muscles but also to control the timing of the muscular contraction.

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, 500 [Hz]; and

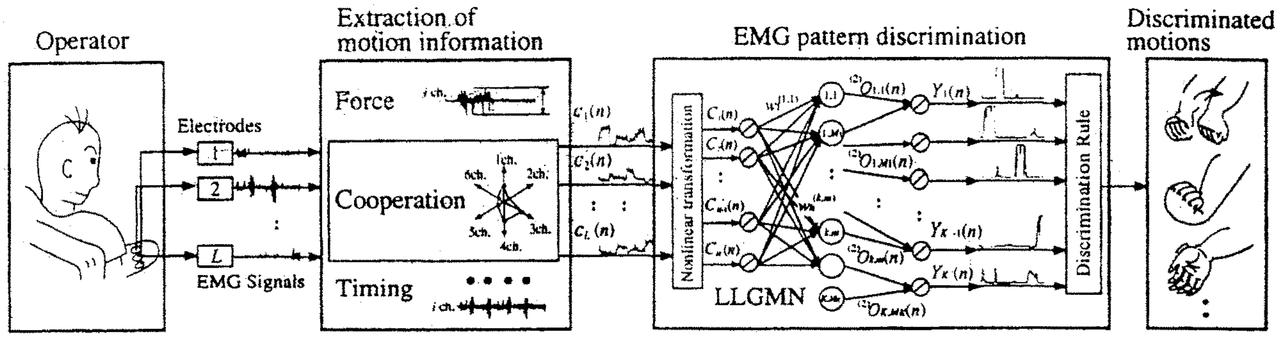


Figure 3: Structure of the EMG signal processor.

quantization, 12 [bits]). This sampled signal is defined as $f_i(t)$ $(i = 1, \cdots, L)$, and used as the force information. The beginnings of the motions can be recognized using this signal. Then $f_i(t)$ is normalized every $T = 10$ samples (0.02 [s]) to make the sum of $L$ channels equal 1:

$$c_i(n) = \frac{\sum\limits_{t=n-T+1}^{n} (f_i(t) - f_i^{st})}{\sum\limits_{i'=1}^{L} \sum\limits_{t=n-T+1}^{n} (f_{i'}(t) - f_{i'}^{st})}, \qquad (1)$$

where $f_i^{st}$ is the mean value of $f_i(t)$ while relaxing the arm. $c(n) = [c_1(n), c_2(2), \cdots, c_L(n)]^{\mathrm{T}} \in \Re^L$ expresses the cooperation information of muscles, and is used as the feature input vector of the LLGMN.

#### 2.1.2 EMG pattern discrimination

In the proposed system, the trainee's intended motions are discriminated using the feature input vector $c(n)$, and the discrimination results are used for rehabilitation and manipulation training. In the EMG signal processor, the log-linearized Gaussian mixture network (LLGMN) proposed by Tsuji et al. [9] is used for the EMG pattern discrimination. The LLGMN can acquire the Log-Linearized Gaussian Mixture Model through the learning, and calculate the posteriori probability of the trainee's motion based on this model. In 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 pattern and the corresponding motion. The LLGMN can adapt itself to changes of the EMG patterns according to the difference among individuals, different locations of the electrodes, time variation caused by fatigue or sweat, and so on. Also the number of the electrodes and the trainee's motions can be settled arbitrarily.

First, the input vector $c(n) \in \Re^L$ is preprocessed and converted into the modified input vector $C(n) \in \Re^H$ as follows:

$$\begin{aligned} C(n) &= [1, c(n)^{\mathrm{T}}, c_1(n)^2, c_1(n)c_2(n), \cdots, \\ &\quad c_1(n)c_L(n), c_2(n)^2, c_2(n)c_3(n), \\ &\quad \cdots, c_2(n)c_L(n), \cdots, c_L(n)^2]^{\mathrm{T}}. \end{aligned} \qquad (2)$$

The first layer of the LLGMN consists of $H = 1 + L(L+3)/2$ units corresponding to the dimension of $C(n)$, and the identity function is used for an output function of each unit. The second layer consists of the same number of units as the total number of the components used in the Gaussian Mixture Model [9]. Each unit receives the output of the first layer weighted by the coefficient $w_h^{(k,m)}$ and outputs the posteriori probability of each component. The input to the unit $\{k, m\}$ in the second layer, ${}^{(2)}I_{k,m}(n)$, and the output, ${}^{(2)}O_{k,m}(n)$, are defined as

$${}^{(2)}I_{k,m}(n) = \sum_{h=1}^{H} {}^{(1)}O_h(n) w_h^{(k,m)}, \qquad (3)$$

$${}^{(2)}O_{k,m}(n) = \frac{1}{\sum\limits_{k'=1}^{K} \sum\limits_{m'=1}^{M_{k'}} \exp[{}^{(2)}I_{k',m'}(n) - {}^{(2)}I_{k,m}(n)]}, \qquad (4)$$

where $w_h^{(K,M_k)} = 0$ $(h = 1, \cdots, H)$. It should be noted that (4) can be considered as a kind of generalized sigmoid function. The third layer consists of $K$ units corresponding to the number of motions and outputs the posteriori probability of the motion $k$ ($k = 1, \cdots, K$). The unit $k$ integrates the outputs of $M_k$ units $\{k, m\}$ ($m = 1, \cdots, M_k$) in the second layer. The relationship between the input and the output is defined as

$$
\begin{aligned}
{}^{(3)}I_k(n) &= \sum_{m=1}^{M_k} {}^{(2)}O_{k,m}(n), &(5)\\
Y_k(n) &= {}^{(3)}I_k(n). &(6)
\end{aligned}
$$

Finally, in the discrimination part, the trainee's intended motion is determined according to Bayes' rule. During the operation, the sum of the squared $f_i(t)$ is used in order to recognize the beginning of the motions and regulate the driving speed or grip force of the manipulator.

The proposed system requires the adaptation to the trainee, because the EMG signal patterns are different among individuals and change depending on the electrical impedance of the skin, electrode locations, and time variation caused by fatigue or sweat, and so on. In order to adapt to the change of the characteristics of EMG signals, before starting the use of the proposed system, the EMG pattern vectors $c(n)$ for forearm motions of the trainee are measured. These measurements are used for the learning, and learning procedures are carried out using the LLGMN [7]. It should be noted that the dynamics of a terminal attractor [10] is incorporated into the learning rule in order to regulate the convergence time. 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 may be reduced.

The proposed system has to be reliable for human use. Therefore, in order to reduce the ill-discrimination, we calculate the entropy $H(n)$ defined as

$$H(n) = -\sum_{k=1}^{K} Y_k(n) \log_2 Y_k(n), \qquad (7)$$

and use it for a motion suspension rule, because the entropy indicates, or may be interpreted as, a risk of ill-discrimination. For example, if the entropy is over the determination threshold $\theta_d$, the determination should be suspended since large entropy means that the network output is ambiguous. Thus, possible ill-discriminations are expected to be reduced.

### 2.2 Biofeedback display for rehabilitation training

The trainee can improve his or her physical strength through voluntary and interactive training. During the training, the information on the EMG signals extracted by the EMG signal processor is presented through the biofeedback. The 3D computer graphics of the virtual manipulator is provided and used for the control training. The score and messages which depend on the accomplishment of the training are shown on the biofeedback display. Also, the tests for muscular strength are prepared in order to examine the improvement of the trainee's physical ability through training. These processes are performed according to the trainee's intention or the therapist's diagnosis, and the results of the tests are put together into a database. The rehabilitation program can then be modified by the therapist's diagnosis based on this database.

### 2.3 EMG controlled robotic manipulator

The robotic manipulator consist of the arm part (Move Master RM-501 : Mitsubishi electric, Corp.) and the end-effector part (Imasen lab.) [11], and has three degrees of freedom in each part. The arm part is controlled according to the position of the trainee's wrist joint measured by the 3D position sensor (ISOTRACK II : POLHEMUS, Inc.). This device uses the information on the electromagnetic fields to determine its 3D position. The static measurement accuracy is $\pm$ 2.4 [mm] for the x, y or z coordinates. This device allows the trainee to take an arbitrary position having no occlusion problem. The trainee's wrist position is measured with the sampling frequency 50 [Hz], and the joint angles of the arm part are calculated using this position. The correspondence of the trainee's wrist position with the arm's enables the trainee to control the manipulator intuitively [7]. The end-effector part is controlled according to the information on the EMG signals. Its driving speed and grip force depend on the squared sum of $f_i(t)$.

## 3 Rehabilitation training

Rehabilitation training adopted in the proposed system is composed of four training as explained in the following subsections. First three training are corresponding to three kinds of information extracted from the EMG signal, and the last one is for controlling the EMG-based robotic manipulator.

### 3.1 Force control training

In this training, the trainee controls the muscular contraction level based on the force information, $f_i(t)$, extracted from the measured EMG signal.

At the beginning of the training, the trainee's maximum voluntary muscle force is examined. Then the maximum amplitude of the desired signal is determined on the basis of this value. The trainee controls

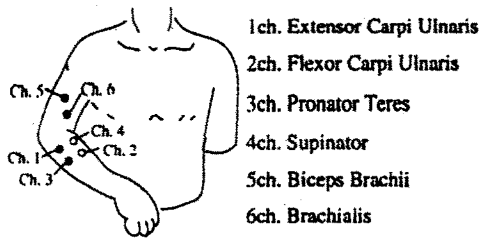



Figure 4: Electrode locations.

his or her EMG signal in such a way that the extracted force from the EMG follows the desired signal.

## 3.2 Cooperation training

The trainee's intended motions are realized by cooperation of muscles. In this cooperation training, the trainee practices controlling the contraction level of each muscle in order to realize the desired motions.

Before the training, a set of the desired motions are selected, and the corresponding cooperation patterns of the EMG signals measured by the multiple electrodes are sampled and learned using the LLGMN. After learning, the trainee is instructed to perform one of the desired motions, then the measured cooperation information $c(n)$ are discriminated using the LLGMN. The cooperation ability of the trainee's muscles can be evaluated by the pattern discrimination results. During the training, the measured cooperation information $c(n)$ and the discriminated motion are presented on the display as the biofeedback with the desired motion and the corresponding desired cooperation pattern.

The desired motions usually correspond to the functions of the prosthetic hands. However, it may be very difficult for the trainee who has a serious dysfunction of his or her limbs to perform all the motions. In this case, a few possible motions are selected by the therapist, and the number of the motions is gradually increased according to the results of training.

## 3.3 Timing control training

For smooth motions, it is also important to control the timing of the muscular contraction. Timing control training is carried out in order to practice controlling the timing of the muscular contraction.

During the training, the diagram of the time course of the desired forces or the desired motions is shown on the biofeedback display. The trainee is instructed to control his or her muscular contraction according to the pre-specified timing shown in this diagram. Note that the beginning of the muscle contraction is determined using the threshold of the squared sum of the force information $f_i(t)$.

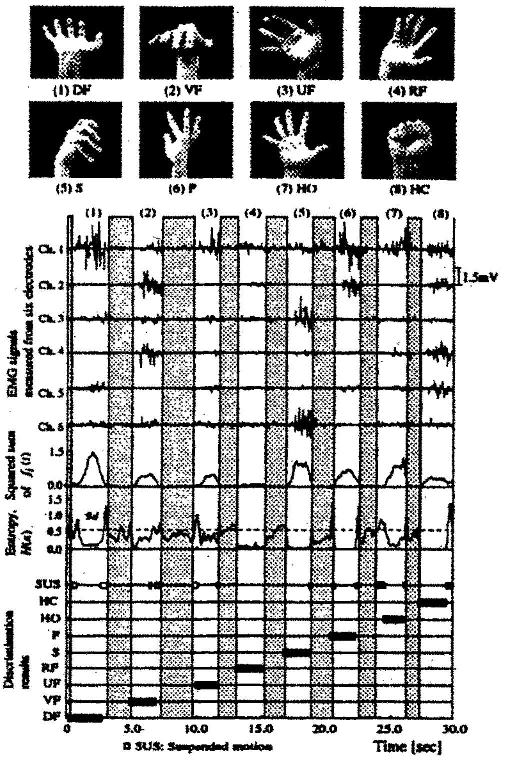



Figure 5: An example of the robot control.

## 3.4 Virtual manipulator control training

To master the manipulation of the EMG-based robotic manipulator is one of the most important goals of the proposed training system. If the trainee can control the manipulator as he or she wants, the manipulator is very useful in order to support his or her daily life.

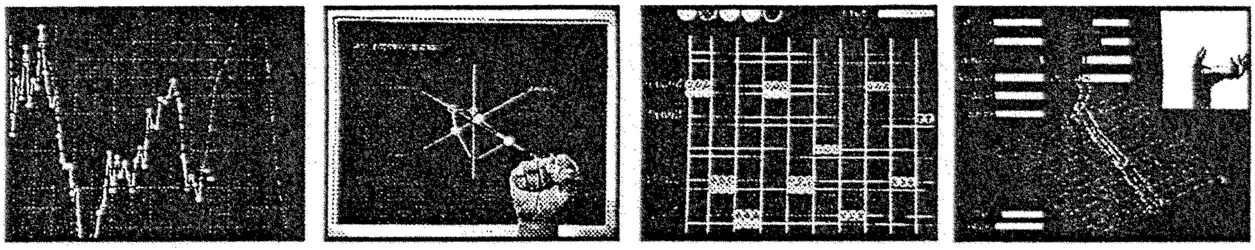
However, it is not safe for inexperienced trainees to perform the manipulation training for a real manipulator system, so the proposed system provides the training using a virtual manipulator which is constructed by 3D computer graphics.

During the manipulation training, the 3D image of the manipulator and the EMG information such as force and cooperation are shown on the biofeedback display.

# 4 Experiments

## 4.1 Example of the prosthetic control

We have conducted experiments to demonstrate and verify the proposed method. Six pairs of surface electrodes ($L = 6$) were attached to the forearm and upper arm of the subject as shown in Fig. 4. The



(a) Force training (b) Cooperation training (c) Training diagram (d) Virtual manipulator

Figure 6: Examples of the biofeedback training.

subject is a student: Male, age 27, normal. The determination threshold was settled as $\theta_d = 0.55$, and the number of the learning data was $N = 80$ (8 motions, 10 data for each motion).

Figure 5 shows the discrimination results by the EMG signal processor. In the figure, the motion pictures, EMG signals, squared sum of $f_i(t)$ for all channels, entropy $H(n)$ and the discrimination results are shown. In this experiment, the EMG patterns are discriminated with high accuracy, and the ill-discrimination can be avoided using the motion suspension rule.

## 4.2 Example of the biofeedback training

Figure 6 shows examples of the biofeedback during the rehabilitation training.

Figure 6 (a) is a biofeedback display during the force control training. In this figure, both the desired and current force information, $f_i(t)$, are shown. During the cooperation training, the radar chart of the cooperation information is presented as shown in Fig. 6 (b). In this case, six pairs of electrodes are used, and the muscle contraction level of each muscle is indicated in each axis. The training diagram which indicates the desired motion and timing of its execution is shown in Fig. 6 (c). The trainee tries to perform the desired motion according to the pre-specified timing shown in this diagram. Also, in Fig. 6 (d), the 3D computer graphic virtual manipulator is shown. This screen image is updated every 200 [msec].

# 5 Conclusion

This paper has proposed the concept of the EMG-Based Rehabilitation Aid for prosthetic control and developed the prototype. The proposed system provides the EMG-based rehabilitation training for the physically handicapped in order to improve his or her muscle ability.

Future research will be directed at conducting an experiment for an amputee using the proposed system. Also we would further like to extend the usefulness of our system using Internet protocol.

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