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EMG-based Human-Robot Interface for Rehabilitation Aid

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Abstract

This paper proposes the concept of a human-robot interface as rehabilitation aid and develops the prototype system. The prototype system aims to be used as a controller for the robotic manipulator and as rehabilitation system for the handicapped person. In order to adapt the system to the characteristics of the operator's electromyogram (EMG) signal, the EMG pattern discrimination method using the neural network is utilized as an essential technique of our system. In the experiments, it can be seen that the robotic manipulator can be controlled with high accuracy using the operator's EMG signal, and that the adaptive learning of the neural network improves the discrimination ability of the EMG signal. The rehabilitation program and biofeedback are also discussed.

1 Introduction

Precise and complex motions may be very difficult for handicapped people who have lost their manipulation capability of the upper limb by traffic accident, cerebral apoplexy, or other afflictions. For these people, various interface systems and prosthetics have been proposed in order 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 intelligent robots are being designed for power assistance, rehabilitation and other aid using modern techniques of robotics, such as sensor technology and control method [3]. For example, Wu proposed neuromuscular-like control based on muscle-reflex to develop rehabilitation robot which assists the operator's limb motion [4].

In order to design the human-robot interface, a bioelectric signal was used as a manipulated variable in several previous studies. For example, the EMG 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/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]. On the other hand, a back propagation neural network was used by Hiraiwa et al. to predict two Japanese syllables. In their research, the non-averaged single trial multichannel EEG data recorded prior to the utterance was used [6]. Also, we have already proposed an EMG controlled robotic manipulator using neural networks and suggested its possible use as a human support robot [7].

At present, however, the problem of designing these interfaces has not yet been solved because most amputees do not use these EMG based interfaces, prosthetic arms, rehabilitation robots or other aids. 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 easy operation and rehabilitation training.

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 person. It is effective and essential for the muscular dystrophy patient, who can not control the muscular contraction and cooperation voluntarily, to activate biofeedback using the information on his/her EMG signal [8]. The above mentioned facts indicate that the design of the human-robot interface requires the total re-design of the system including not only the hardware but software for easy operation and rehabilitation training.

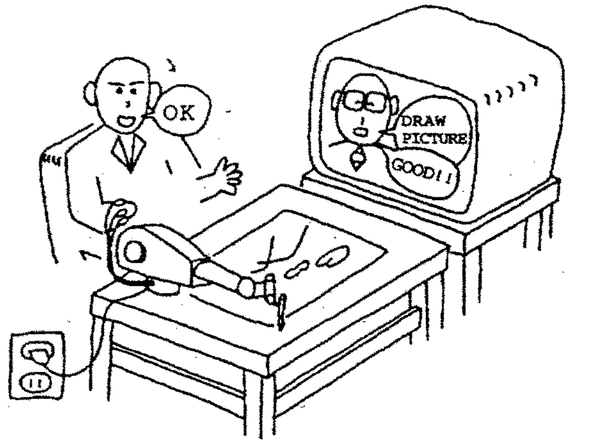

Figure 1: Concept of the EMG-based human-robot interface for rehabilitation aid.

In this paper, the concept of a new human-robot interface for rehabilitation aid is proposed and the prototype system is developed. The prototype system aims to be used as a controller of the robotic manipulator and as rehabilitation system for the handicapped person. This system can adapt itself to the operator's characteristics using the neural network.

This paper is organized as follows : The concept and structure of the proposed interface is described in Section 1 and 2. The EMG signal processor, robotic manipulator and rehabilitation training method are explained in detail in Section 3, 4 and 5, respectively. The experiments are conducted in Section 6. Finally, Section 7 concludes the paper.

2 EMG-based human-robot interface

Figure 1 shows the concept of the EMG-based human-robot interface for rehabilitation aid. This system has two functions. The first is a control function of the robotic manipulator. The operator can control the manipulator placed on the table using his/her 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 operator uses it for a long time. The other is the manipulation and rehabilitation training function for the handicapped person. The handicapped person can improve his/her physical strength through voluntary or interactive training using this system.

Figure 2 shows the structure of the developed prototype system which consists of the EMG signal processor, robotic manipulator, rehabilitation program and biofeedback. The EMG signal processor discriminates the operator's intended motion and force information from his/her EMG signal. Then, the robotic manipulator is controlled according to this discrimination result. Also, rehabilitation program and biofeedback are provided to the operator in order to improve his/her physical strength. The statistical neural network is incorporated into the EMG signal processor so that the system can adapt itself to the characteristics of the operator. The details of each technique are described in the following sections.

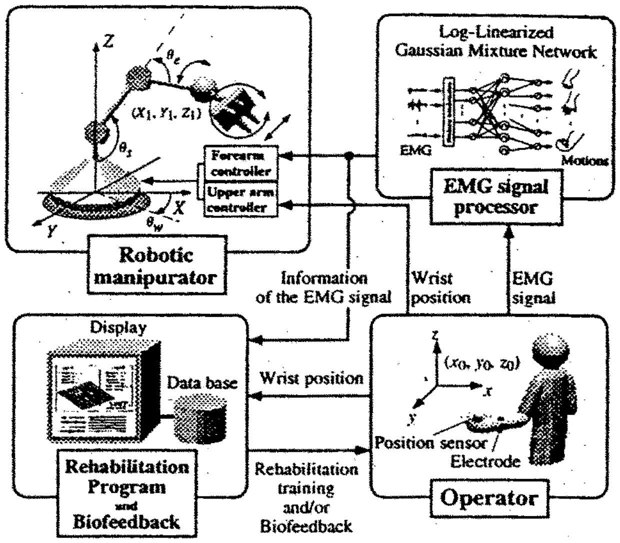

Figure 2: Structure of the prototype system.

3 EMG signal processor

The EMG signal processor is the essential part of the proposed system. This processor extracts a feature pattern and amplitude information on the EMG signals measured from the electrodes, then discriminates the operator's intended motion and force information. This discrimination result is used for the manipulator control and rehabilitation training. In this 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 operator'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 operator's EMG pattern and 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

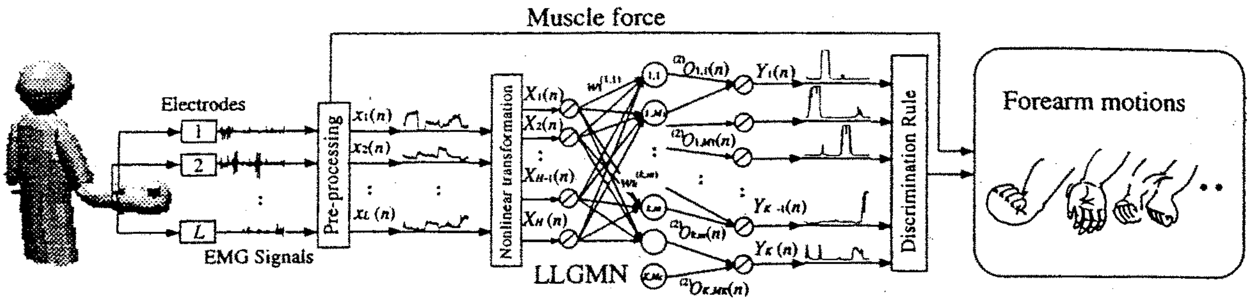

Figure 3: Structure of the EMG signal processor.

the number of the electrodes, and kinds of the operator's motions can be settled arbitrarily.

3.1 Discrimination of the EMG signal

The Structure of the EMG signal processor is shown in Fig. 3. First, the EMG signal measured from L pairs of electrodes (NIHON KOHDEN Corp.) is digitized by an A/D converter (sampling frequency, 200 [Hz]; and quantization, 12 [bits]) , and it is rectified and filtered out through the first-order Butterworth filter (Cut-off frequency : 1 [Hz]). These measured signals, defined as $EMG_i(t)$ $(i = 1, \cdots, L)$, are normalized every $T = 10$ samples (0.05 [s]) to make the sum of L channels equal 1:

$$x_i(n) = \frac{\sum_{t=n-T+1}^{n} (EMG_i(t) - EMG_i^{st})}{\sum_{i'=1}^{L} \sum_{t=n-T+1}^{n} (EMG_{i'}(t) - EMG_{i'}^{st})} \quad (i = 1, \cdots, L), \qquad (1)$$

where EMG_i^{st} is the mean value of $EMG_i(t)$ while relaxing the arm. The LLGMN uses $x_i(n)$ $(i = 1, \cdots, L)$ as an element of the n-th input vector $x(n) \in \Re^L$ for the pattern discrimination.

Then, the input vector $x(n) \in \Re^L$ is preprocessed and converted into the modified input vector $X(n) \in \Re^H$ as follows:

$$\begin{aligned} X(n) = & [1, x(n)^{\mathrm{T}}, x_1(n)^2, x_1(n)x_2(n), \cdots, \\ & x_1(n)x_L(n), x_2(n)^2, x_2(n)x_3(n), \\ & \cdots, x_2(n)x_L(n), \cdots, x_L(n)^2]^{\mathrm{T}}. \end{aligned} \qquad (2)$$

The first layer consists of $H = 1 + L(L+3)/2$ units corresponding to the dimension of $X(n)$, 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

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

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

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 forearm motion is decided according to the Bayes' rule. During the operation, also the amplitude information on the EMG signals, which is the sum of the squared $x_i(n) (i = 1, \cdots L)$, is used in order to recognize the beginning of the forearm motions and select the driving speed or grip force out of four possible levels (0.1, 0.2, 0.3, 0.4[m/sec] or 0.0, 20.0, 70.0, 120.0[N]).

3.2 Adaptive learning

The human-robot interface requires the adaptation to the human operator, because the EMG signal patterns are different among individuals, and 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, off-line and on-line learning procedures are carried out using the LLGMN.

Now, let us consider the learning with the teacher vector $T(n) = (T_1(n), \cdots, T_k(n), \cdots, T_K(n))^{\mathrm{T}}$ for the n-th input vector $x(n)$. The teacher signal is used $T_k(n) = 1$ for the particular class k and $T_k(n) = 0$ for all the other classes. As an energy function J for the network, we use

$$J = -\sum_{n=1}^{N}\sum_{k=1}^{K} T_k(n)\log Y_k(n), \tag{7}$$

and the learning is performed to minimize this, that is, to maximize the likelihood function.

Here the dynamics of a terminal attractor [10] is incorporated into the learning rule in order to regulate the convergence time. The concept of the terminal attractor (TA) is invented on the basis of the idea that the state of the dynamic system converges to the equilibrium point in a finite time, if the Lipschitz conditions are violated at the equilibrium point. The convergence time is always less than the prespecified upper limit so that the mental stress of the operator waiting for the convergence of learning may be reduced.

Before starting the use of the proposed system, the EMG pattern vectors $x(n)$ for forearm motions of the operator are measured during motions, which are used for the off-line learning. Then the operator controls the manipulator for many hours, it is necessary to consider the variations of EMG properties resulting from muscle fatigue, sweating and the change of electrode characteristics. Therefore, it is required to find an on-line learning method adaptable to these variations, in order to discriminate the EMG pattern successively at all times.

The problem is that we cannot ascertain whether the estimated motion coincided with the amputee's intended one while controlling the manipulator. Thus we cannot directly find the desired output, that is, the teacher signal. Therefore, we utilize the entropy $H(n)$ defined as

$$H(n) = -\sum_{k=1}^{K} Y_k(n)\log_2 Y_k(n). \tag{8}$$

If the entropy $H(n)$ of the output of the LLGMN for the EMG pattern $x(n)$ is less than the threshold of the on-line learning θ_o, a pair of $x(n)$ and the output motion is added to the set of the learning data, and the oldest of the stored learning data is deleted. Then, the network weights are updated using the new set of the learning data. In the case where the energy function J does not decrease during the first ten iterations of the learning procedure, the weights are not updated to avoid incorrect learning [7].

The human-robot interface has to be reliable for human use. Therefore, in order to reduce the ill-discrimination, the entropy is used also 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 θ_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.

4 EMG controlled robotic manipulator

The robotic manipulator (Move Master RM-501 : Mitsubishi electric, Corp.) has three degrees of freedom both in the forearm and the upper arm. The control system consists of the forearm controller and the upper arm controller. The forearm controller uses the information on the EMG signals of an operator through the EMG signal processor, and the upper arm controller uses the position of a 3D sensor attached to the operator.

The upper arm controller controls a joint angle of the upper arm according to the position of the operator'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 accuracy is $\pm$ 2.4 [mm] for the x, y or z position. It should be noted that this device allows the operator to take an arbitrary position having no occlusion problem. The operator's wrist position is measured with the sampling frequency 5 [Hz], and the joint angles of the manipulator are calculated using this position. The correspondence of the operator's wrist position with the manipulator's one enables the operator to control the manipulator intuitively[7].

The forearm controller controls forearm motions, its driving speed and grip force according to the information on the EMG signals.

5 Rehabilitation training and biofeedback

The handicapped person can improve his/her physical strength through voluntary and interactive training. When the operator goes into training, the amplitude information on the EMG signals, feature patterns and discrimination results of the EMG signal processor are shown as the biofeedback. The 3D computer graphics of the virtual manipulator is also provided

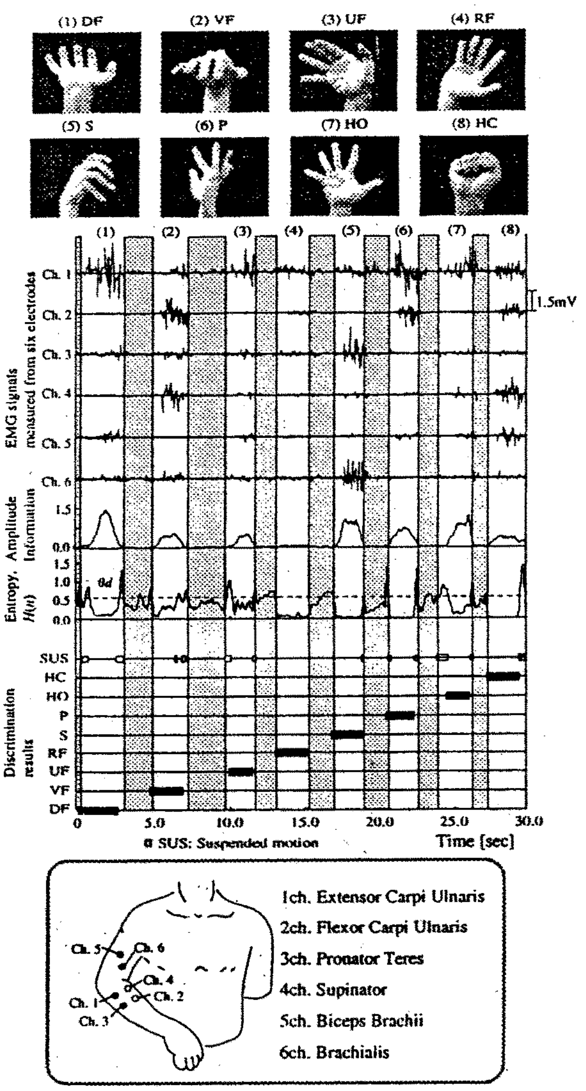

Figure 4: An example of the robot control.

during the manipulation training. Even if the operator does not use the real manipulator, the manipulation training can be simulated using the virtual manipulator on the display. Moreover, the tests for physical strength are prepared in order to examine the improvement of the operator's physical ability through training. These processes are performed by the operator's intention or the therapist's diagnosis at any time. The results of the test are put together into a database. The rehabilitation program can then be modified by the therapist's diagnosis based on this database.

6 Experiments

6.1 Example of the robot control

We have conducted experiments to demonstrate and verify the proposed method. Six pairs of surface

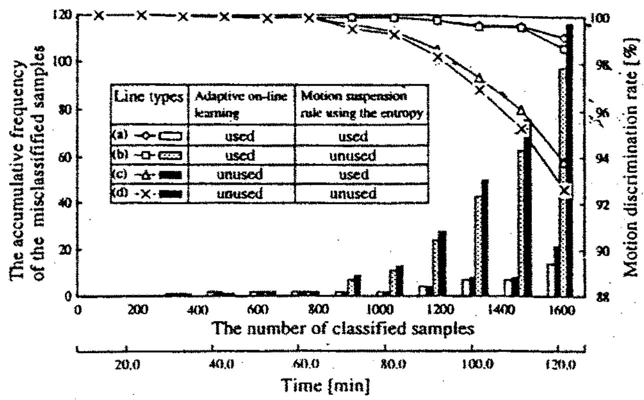

Figure 5: Improvements of motion discrimination rates by the on-line adaptive learning.

electrodes ($L = 6$) were attached to the forearm and upper arm of the subject. The subject is a university student (Male, age 27, normal). The determination threshold and the online learning threshold were settled as $\theta_d = 0.55, \theta_o = 2.0$, and the number of the learning data was $N = 80$ (8 motions, 10 for each motion).

Figure 4 shows the discrimination results by the EMG signal processor. In the figure, the motion pictures, EMG signals, amplitude information of the EMG signal, entropy $H(n)$ and the discrimination results are shown. It can be seen that the EMG patterns are discriminated with high accuracy. The ill-discrimination can be reduced using the motion suspension rule. These figures indicate that the operator can control the manipulator successfully using the proposed system.

6.2 Effect of the adaptive on-line learning

Next, we examined the effect of the motion suspension rule and the on-line learning on discrimination ability in the EMG signal processor. The operator was asked to continue to perform eight kinds of motions for about 120 minutes, and the discrimination rates were calculated every 10 minutes. The operator was not informed of the discrimination result.

The time histories of discrimination rates and the accumulative frequency of the misclassification data in the forearm control unit are shown in Fig. 5. The discrimination rates of the line (d) which did not use the motion suspension rule and the on-line learning decrease depending on time, because of the time variation of the EMG pattern caused by fatigue or sweat. The lines (b) and (c) indicate that the motion suspension rule reduces the ill-discrimination. Especially, the discrimination rate of the line (a) which uses both the

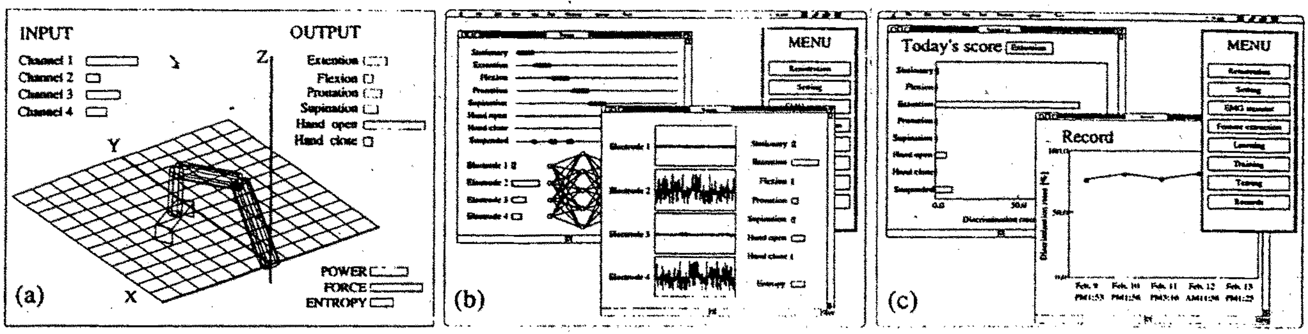

Figure 6: An example of the biofeedback during the rehabilitation training.

motion suspension rule and the on-line learning keeps considerably high classification rate during the whole time the operator was controlling the manipulator.

6.3 Example of the rehabilitation training and biofeedback

Figure 6 shows the example of the biofeedback display during the rehabilitation training. In Fig. 6(a), the 3D computer graphics of the virtual manipulator, the feature pattern, amplitude information and discrimination results of the measured EMG signal are shown. This screen image is updated every 200[msec]. The central window in Fig. 6(b) shows the measured EMG signal data for 5.0[sec]. Also, the time series of the discrimination results for these signals is displayed in the left window. In Fig. 6(c), the central window shows the records for the past five times and the left window shows the correct discrimination rate for the test of the flexion motion. In addition, the training menu is shown in the right window.

7 Conclusion

This paper proposes the concept of a human-robot interface as rehabilitation aid and develops the prototype system. The prototype system has two functions : to be used as a controller of the robotic manipulator and as rehabilitation system for the handicapped person. In the experiments, it is seen that the robotic manipulator can be controlled with high accuracy via the operator's EMG signal, and that the adaptive learning of the neural network improves the discrimination ability of the EMG signal. The rehabilitation program and biofeedback are also discussed.

Future research will be directed at developing techniques to improve the rehabilitation program and biofeedback method. We would further like to extend the usefulness of our human-robot interface using the internet protocol.

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