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An EMG Controlled Robotic Manipulator Using Neural Networks

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Abstract

This paper proposes an adaptive human-robot interface using a statistical neural network which consists of a forearm controller and an upper arm controller. The forearm controller selects an active joint out of three joint degrees of freedom and controls its driving speed or grip force according to EMG signals measured from a human operator. The upper arm controller controls the joint angle of the upper arm according to the position of the operator's wrist joint as measured by a 3D position sensor. Experiments have shown that the EMG patterns during forearm and hand movements can be classified with high accuracy using our network to be of use as an assistive device for a handicapped person.

1 Introduction

Many robots have been developed for and used in both manufacturing and extreme environments. They support the human workers and significantly reduce the risk of accidents, fatigue and stress to them. In future, the number of aged people and handicapped people requiring support in their daily life and at their workplace will increase. It is expected that robots will extend their usefulness beyond manufacturing and extreme environments, to the home environment providing support in our daily life and help in our daily routines.

For example, it is very difficult for some handicapped people, including traffic accident victims and those suffering cerebral apoplexy and so on, to do precise and complex activities by themselves. It is particularly impossible for a bedridden patient to actively take part in daily life. If a robot is developed with high intelligence and support capability, it cannot fail to be useful.

An effective human support requires complete identification of the operator's conditions. Needless to say, essential functions of adaptability and safety are required, because an operator's physical ability and dysfunction differ among individuals and change during the rehabilitation training or the effect of the aging process. In this paper, a new human-friendly intelligent robot which can adapt to these difference among individuals and also between operator's physical abilities is discussed.

Up to the present, some investigation of human support robots and rehabilitation robots have been carried out. Kazerooni [1] proposed "extenders" as a class of robot manipulators which extend the strength of the human arm. In his paper, the stability of the system consisting of a human operator, the extender and the object being manipulated is analyzed. On the other hand, Nagai et al. [2] and Sakaki et al. [3] designed a robotic orthosis for expanding the manipulation capability of the human limbs. These robotic orthosises are being developed for rehabilitation of the disabled who have lost a part of their manipulation capability of the upper or lower limb. Noritsugu et al. [4] developed a rubber artificial muscle actuator and applied a two degrees of freedom manipulator driven with this actuator to the rehabilitation robot for the exercise of the restoration of function. A rubber artificial muscle is compliant and safe for a human in the contacting operation.

However, most of the previous researches on the human support robot did not deal with the adaptation to the operator's conditions, so many robotic orthosis were custom designed taking the operator's individual dysfunction into consideration. Moreover, if the operator uses robotic orthosis for many hours, the physical and mental stress of the operator may increase because of its heavy weight and volume. It is also impossible for the operator to control the robot at a distance from him.

In recent years, the bioelectric signals such as an electroencephalogram (EEG) and an electromyogram (EMG) have been tried as an interface tool for virtual reality and teleoperation devices, and as a communication tool for the handicapped person [5]-[9]. For example, if an operator's intended motion can be estimated from the EMG pattern, a natural feeling of control

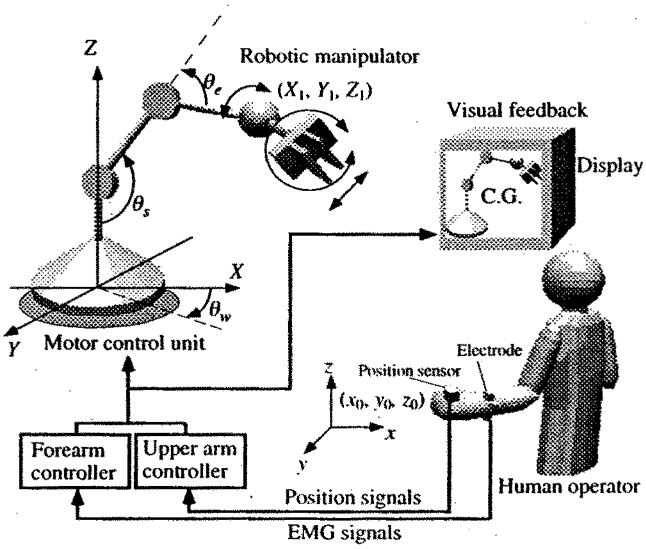


Figure 1: The overview of the control system

similar to that of the natural limb may be realized. We have already reported the pattern discrimination of the bioelectric signals using neural networks, and suggested its possible use as a human interface tool [7]-[9].

This paper proposes an EMG based control method of a robotic manipulator as an adaptive human support system. A distinctive feature of our method is to use a statistical neural network for EMG pattern discrimination. This network can acquire the stochastic representation of measured EMG patterns through learning, based on the log-linearized Gaussian mixture model, so that it can adapt 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. Experiments have shown that the EMG patterns during forearm and hand movements can be discriminated with high accuracy using our method.

2 The Structure of the EMG Controlled Robotic Manipulator

An overview of the robot system is shown in Fig. 1. 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, the upper arm controller and the graphic feedback display. The forearm controller controls six forearm motions (flexion, extention, pronation, supination, hand grasping, hand opening), its driving speed and grip force according to the EMG signals. The upper arm controller controls a joint angle of the upper arm according to the position of the operator's wrist joint measured by a 3D position sensor. Also the graphic display provides visual information via a 3D graphic interface to the operator in order to help manipulator control.

This system uses the EMG signals and the position of the 3D sensor which corresponds to the manipulator's wrist position as the control input, so that it enables the operator to control the manipulator naturally. The size of the manipulator is compact with 60 centimeters radius of revolution, and is suitable for use in the home environment. The operator can control the manipulator using visual information via a 3D graphic interface, even if it is placed out of view.

2.1 Upper Arm Control Unit

In the upper arm control unit, the 3D position sensor (ISOTRACK II : POLHEMUS, Inc.) is used as an input device. This device uses the information of the electromagnetic fields to determine its 3D position. The static accuracy is ± 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.

Let us now consider the control method of the manipulator with the control input (x_0, y_0, z_0) corresponding to the operator's wrist position. The manipulator's wrist position (X_1, Y_1, Z_1) is defined as

$$\begin{pmatrix} X_1 \\ Y_1 \\ Z_1 \end{pmatrix} = c \begin{pmatrix} x_0 \\ y_0 \\ z_0 \end{pmatrix} \tag{1}$$

where $c = \text{diag.}[c_x, c_y, c_z]$ is the gain matrix. The sensitivity of the manipulator's motion to the operator's motion can be regulated using this matrix. Then, each joint angle of the upper arm shown in Fig.1 is calculated. The waist angle θ_w is given as

$$\theta_w = \tan^{-1}\left(\frac{Y_1}{X_1}\right), \tag{2}$$

and the length r between the wrist joint and the shoulder joint can be expressed as

$$r = \sqrt{X_1^2 + Y_1^2 + (Z_1 - l_1)^2}. \tag{3}$$

Then, the elbow and shoulder angles θ_e, θ_s can be calculated:

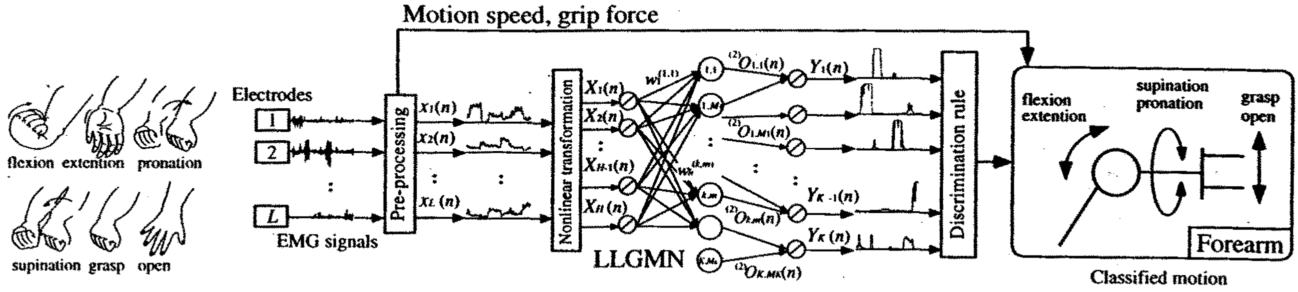


Figure 2: The Forearm Control Unit

$$\theta_e = \cos^{-1}\left(\frac{l_2^2 + l_3^2 - r^2}{2l_2\, l_3}\right) - \pi, \tag{4}$$

$$\begin{aligned}\theta_s &= \sin^{-1}\left(\frac{Z_1 - l_1}{r}\right) \\ &+ \cos^{-1}\left(\frac{l_2^2 + r^2 - l_3^2}{2l_2 r}\right) + \frac{\pi}{2}.\end{aligned} \tag{5}$$

According to these joint angles $\theta_w, \theta_e, \theta_s$, the manipulator is controlled by the point to point control method. The positioning accuracy is ± 0.5 [mm] for the desired position.

2.2 Forearm Control Unit

Figure 2 shows the structure of the forearm control unit. This unit controls the forearm motion and the driving speed or grip force according to the EMG pattern discrimination using the neural network.

In this control unit, the log-linearized Gaussian mixture network (LLGMN) proposed by Tsuji et al. [10] is used for EMG pattern discrimination. Note that the log-linearized Gaussian mixture structure is incorporated in this network through learning, thus enabling network to calculate the posteriori probability of each class.

2.2.1 Feature Extraction

First, the EMG signal measured from L pairs of electrodes (Imasen lab.) is digitized by an A/D converter (sampling frequency, 200 [Hz]; and quantization, 12 [bits]) after that it is amplified (70[dB]), rectified and filtered out through the first-order Butterworth filter (UAF42 : BURR-BROWN Corp., 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 [sec]) to make the sum of L channels equal 1:

$$x_i(n) = \frac{\sum_{t=n-T+1}^{n} (EMG_i(t) - EMG_i^{st})}{\sum_{i'=1}^{L} \sum_{t=n-T+1}^{n} (EMG_{i'}(t) - EMG_{i'}^{st})} \quad (i = 1, \cdots, L), \tag{6}$$

where EMG_i^{st} is the mean value of the $EMG_i(t)$ while relaxing the arm. The LLGMN uses this element $x_i(n)(i = 1, \cdots, L)$ of the n-th input vector $\boldsymbol{x}(n) \in \Re^L$ for the pattern discrimination. Also, in order to recognize the beginning of the forearm motions and control the driving speed or grip force, $Power_{emg}(n)$ and $Force_{emg}(n)$ are calculated as

$$Power_{emg}(n) = \frac{1}{T} \sum_{t=n-T+1}^{n} \sum_{i=1}^{L} (EMG_i(t) - EMG_i^{st})^2, \tag{7}$$

$$Force_{emg}(n) = \frac{1}{TL} \sum_{t=n-T+1}^{n} \sum_{i=1}^{L} \frac{EMG_i(t) - EMG_i^{st}}{EMG_i^{max} - EMG_i^{st}}, \tag{8}$$

where EMG_i^{max} is the mean value of the $EMG_i(t)$ during the maximum voluntary contraction. If $Power_{emg}(n)$ is over the motion threshold θ_m, the input vector $\boldsymbol{x}(n)$ is discriminated, and the driving speed or grip force is selected 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]) according to the $Force_{emg}(n)$.

2.2.2 EMG Pattern discrimination

First, the input vector $\boldsymbol{x} \in \Re^L$ is preprocessed and converted into the modified input vector $\boldsymbol{X} \in \Re^H$ as follows:

$$\begin{aligned} \boldsymbol{X}(n) &= [1, \boldsymbol{x}(n)^{\mathrm{T}}, x_1(n)^2, x_1(n)x_2(n), \cdots, \\ &\quad x_1(n)x_L(n), x_2(n)^2, x_2(n)x_3(n), \\ &\quad \cdots, x_2(n)x_L(n), \cdots, x_L(n)^2]^{\mathrm{T}}. \end{aligned} \tag{9}$$

The first layer consists of $H = 1 + L(L+3)/2$ units corresponding to the dimension of $\boldsymbol{X}$, 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. 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

$${}^{(2)}I_{k,m}(n) = \sum_{h=1}^{H} {}^{(1)}O_h(n) w_h^{(k,m)}, \tag{10}$$

$${}^{(2)}O_{k,m}(n) = \frac{\exp[{}^{(2)}I_{k,m}(n)]}{\sum_{k'=1}^{K} \sum_{m'=1}^{M_{k'}} \exp[{}^{(2)}I_{k',m'}(n)]}, \tag{11}$$

where $w_h^{(K,M_k)} = 0$ $(h = 1, \cdots, H)$. It should be noted that (11) can be considered as a kind of generalized sigmoid function. Finally, the third layer consists of K units corresponding to the number of classes and outputs the posteriori probability of the class 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

$${}^{(3)}I_k(n) = \sum_{m=1}^{M_k} {}^{(2)}O_{k,m}(n), \tag{12}$$

$$Y_k(n) = {}^{(3)}I_k(n). \tag{13}$$

Now, let us consider the learning with the teacher vector $\boldsymbol{T}(n) = (T_1(n), \cdots, T_k(n), \cdots, T_K(n))^{\mathrm{T}}$ for the n-th input vector $\boldsymbol{x}(n)$. 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

$$J = -\sum_{n=1}^{N} \sum_{k=1}^{K} T_k(n) \log Y_k(n), \tag{14}$$

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

Here the dynamics of a terminal attractor [11] 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 robot, the EMG pattern vectors $\boldsymbol{x}(n)$ for six forearm motions (flexion, extention, pronation, supination, hand grasping, hand opening) of the operator are measured during motions, which are used for off-line learning. Also, on-line learning is carried out in order to adapt to the changes of the EMG patterns according to the time variation caused by fatigue or sweat, and so on.

2.2.3 Discrimination Logic of Forearm Motion Using Entropy

The human support robot has to be safe for human use. Therefore, in order to reduce the ill-discrimination, the entropy of the network output is defined and used for the motion suspension rule. The third layer of the LLGMN outputs the posteriori probability of each class k $(k = 1, \cdots, K)$, so that the entropy is calculated from this posteriori probability,

$$H(n) = -\sum_{k=1}^{K} Y_k(n) \log_2 Y_k(n), \tag{15}$$

and the discrimination is performed using this entropy [7]. 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. On the other hand, if the entropy is less than θ_d, the Bayes decision rule is used to determine the specific class. Thus, possible ill-discriminations are expected to be reduced.

2.2.4 On-line Adaptive Learning

When the operator controls the manipulator for many hours, it is necessary to consider the variations of

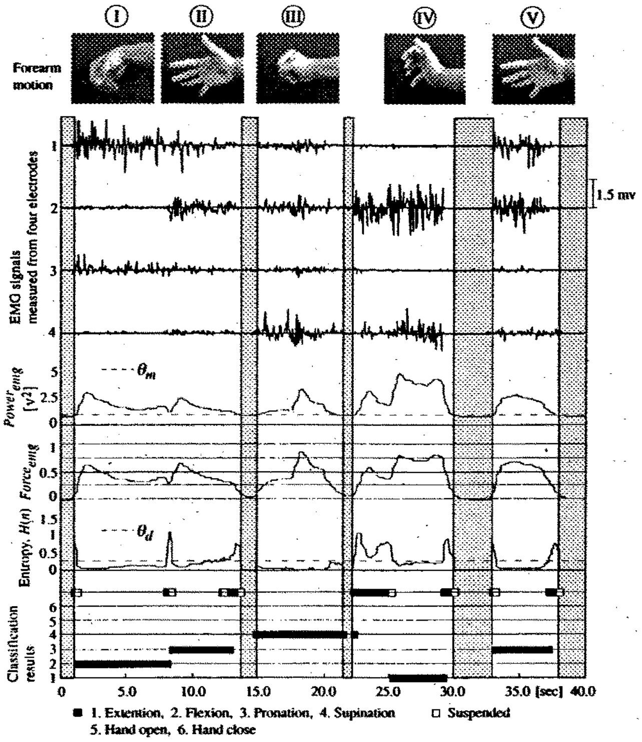


Figure 3: An example of the EMG pattern discrimination results by the forearm control unit

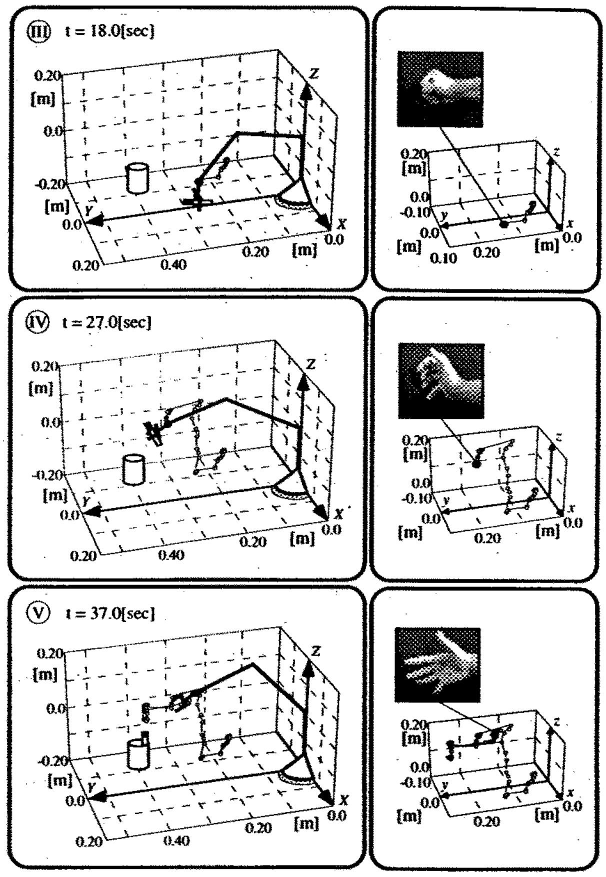
EMG properties resulting from muscle fatigue, sweating and the change of electrode characteristics. Therefore, it is required to find an on-line learning method adaptable to these variations, in order to discriminate the EMG pattern successively at all times.

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's signal. Therefore, we utilize the entropy $H(n)$ defined as equation (15).

If the entropy $H(n)$ of the output of the LLGMN for the EMG pattern $\boldsymbol{x}(n)$ is less than the threshold of the on-line learning θ_o, a pair of $\boldsymbol{x}(n)$ 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].

3 Experiments

3.1 Forearm Control Using EMG Signals



(a) Manipulator (b) Human operator

Figure 4: The trajectory of the wrist joint of the human operator and the stick pictures of the manipulator

We have conducted experiments to demonstrate and verify the proposed method. Four pairs of surface electrodes ($L = 4$) were attached to the forearm, 7 cm from the elbow joint. The motion discrimination threshold, the determination threshold and the on-line learning threshold were settled as $\theta_m = \theta_d = \theta_o = 1.0$ respectively, and the number of the learning data was $N = 120$ (20 for each motion). The gain of the control input were settled as $c_x = c_y = c_z = 2.0$.

In the experiments, we used a task that the manipulator took the pen lying on the desk to the pencil jar. The operator controlled the forearm and upper arm of the manipulator using the EMG signals and the 3D position of his wrist joint. Figure 3 shows the discrimination results in the forearm control unit. The EMG signals were discriminated while controlling the manipulator for about 40 seconds. In the figure, the motion pictures, EMG signals, $Power_{emg}(n)$,

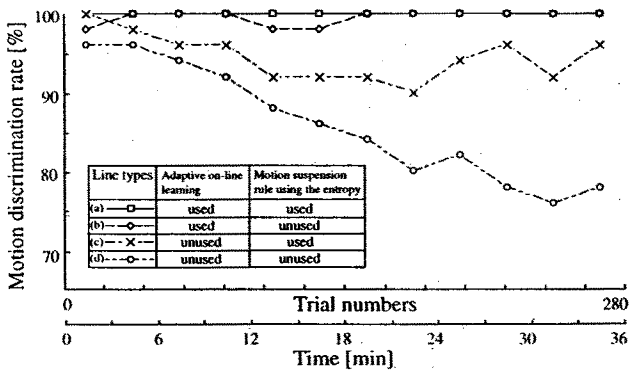


Figure 5: Improvements of motion discrimination rates by the on-line adaptive learning

$Force_{emg}(n)$, 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 determination threshold θ_d.

Next, Fig. 4 (a) shows the stick pictures of the manipulator and (b) shows the trajectory of the wrist joint of the human operator which is measured from the 3D position sensor, while controlling the manipulator. The number (III, IV, V) of the motion pictures in Fig. 4 are corresponding to the ones in Fig. 3. These figures indicate that the operator can control the manipulator successfully using the proposed method.

Finally, we examined the effect of the motion suspension rule and the on-line learning on discrimination ability in the forearm control unit. The operator was asked to continue to perform six kinds of motions for about 36 minutes, and the discrimination rates were calculated every 3 minutes. The operator was not informed of the discrimination result.

The time histories of discrimination rates 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), (c) indicate that the motion suspension rule reduces the ill-discrimination. Especially, the discrimination rate of the line (a) which uses both the motion suspension rule and the on-line learning keeps 100% of the classification rate during the whole time the operator was controlling the manipulator.

4 Conclusion

In this paper, the EMG based control method of a robotic manipulator as an adaptive human supporting system is proposed. In the experiments, the EMG pattern during forearm and hand movements can be discriminated with high accuracy using the proposed method.

Future research will be directed at developing techniques to improve the adaptive human support robot system, which includes the use of the impedance information based on the EMG signals.

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