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An EMG Controlled Human Supporting Robot Using Neural Network

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Abstract

This paper discusses an EMG based control method of a robotic manipulator as an adaptive human supporting system, which consists of an arm control part, a hand and wrist control part and a graphical feedback display. The arm control part controls joint angles of the arm according to the position of the operator's wrist joint measured by a 3D position sensor. The hand and wrist control part selects an active joint out of four joint degrees of freedom and controls it using an impedance model based on the EMG signals. A distinctive feature of our method is to use a statistical neural network for EMG pattern discrimination. This network can adapt to changes of the EMG patterns according to differences among individuals, different locations of the electrodes, time variation caused by fatigue or sweat, and so on. It is shown from the experiments that the hand and wrist motions can be controlled based on the EMG signals sufficiently. It may be useful as an assistive device for a handicapped person.

1 Introduction

Many robots have been developed and used in factories, plants and extreme environments, so far. They support human workers and significantly reduce the risk of accidents. In future, the number of the aged and the physically handicapped requiring someone's help for everyday life will increase. It is expected that the robots extend their work space not only to manufactures and extreme environments, but also to home and office environments in order to support their daily activities. If the robot of high intelligence is developed for such people, it must be very useful [1].

Up to the present, some investigations concerning about human supporting robots and rehabilitation robots have been carried out [2]-[5]. The studies in this field can be classified into two groups: One is the extension of human ability using the robot, and the other is the rehabilitation or prostheses/orthoses for the physically handicapped based on the robotics. As examples of the former, Kazerooni [2] has proposed "Extenders" as a class of robot manipulators which extend the strength of the human arm. Al-Jarrah et al. [3] has reported on a human arm-manipulator coordination using a compliant control method. As the later, Salter [4] has designed a continuous passive motion (CPM) device, which gently bends and straightens an injured joint after surgery. Also, Ouerfelli et al. [5] have proposed to install a robotic manipulator driven by a pneumatic actuator in a wheelchair. However, there are few previous researches dealt with adaptive ability to changes of the operator's conditions, and many robotic orthoses have been designed customarily considering on the operator's individual dysfunction. Moreover, if the operator uses the robotic orthoses for many hours, the physical and mental stress of the operator may increase because of its heavy weight and volume.

Also, many researchers have designed prosthetic limbs for amputee since the 1960's. Especially, an EMG signal has been often used as a manipulated signal of prosthetic hands such as Waseda Hand [6] and Utha artificial arm [7], which are the pioneers in this field. The EMG signal includes information on not only operator's intended motion but also its force level and mechanical impedance property of his or her arm movements. For example, Akazawa et al. designed a signal processor for force estimation from the EMG signal [8], and Ito et al. [9] used an amplitude information of this signal as the speed control command of the prosthetic forearm. This prosthetic forearm was controlled with three levels of the driving speeds. Also, Abul-haj et al. [10] analyzed the characteristics of the prosthetic control based on the impedance model. Moreover, several EMG pattern classification methods using neural networks have been proposed for the prosthetic control [11]-[12]. Hiraiwa et al. [11] have used a back-propagation neural network for estimation of five

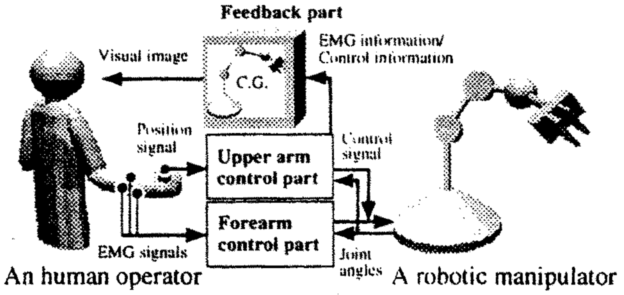


Figure 1: The EMG controlled robot

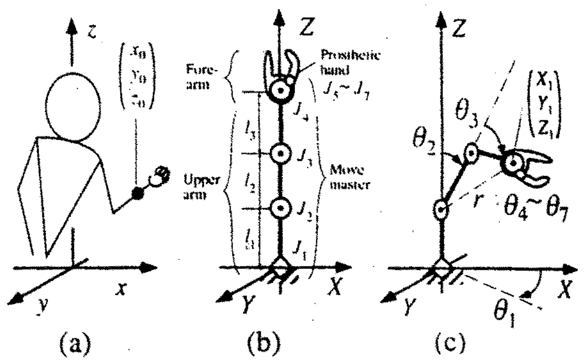


Figure 2: A link model of the robot

finger motions. Most of previous researches, however, used only the on/off control of the prosthetic arms depending on the results of the EMG pattern discrimination, or controlled only a particular joint depending on the torque estimated from the EMG signals.

On the other hand, Tsuji et al. have been studying on the estimation of impedance parameters from the EMG signals [13], [14], the motion discrimination using neural networks [15], and the EMG controlled human supporting robot [16]. The human supporting robot consists of an arm control part, a hand and wrist control part and a graphical feedback display. The arm control part controls the joint angles of the arm according to the position of the operator's wrist joint measured by a 3D position sensor. The hand and wrist control part selects an active joint from four joint degrees of freedom using the neural network. Also the graphical display provides visual information to the operator in order to help manipulator control. The system uses the neural network for EMG pattern discrimination, so that it 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. However, the on/off control was used depending on the EMG signals so that the manipulator motion was not natural, or rather artificial. Also, since the gripper of the manipulator was quite simple, the shape of the objects which could be grasped was restricted.

In this paper, the end-effector of the manipulator is newly developed using a prosthetic forearm driven by ultrasonic motors [9]. In order to realize the natural feeling of control similar to that of the human hand, the impedance model of human forearm is introduced to the control system. Also the force level during the motion is estimated from the EMG signals and used as the proportional control command to each joint.

2 EMG Controlled Human Supporting Robot

Figure 1 shows the components of the system which are the robotic manipulator, the upper arm/forearm control part and the feedback display. Move Master RM-501 (Mitsubishi Electric Corp.) and the prosthetic arm (Imasen lab.) are used as the arm and the end-effector of the manipulator. The size of the manipulator is compact, which has 60 centimeters of radius of revolution, and suitable for use in home environments. The prosthetic arm is detachable from the manipulator arm, so that it is possible for an amputee to attach it to his or her amputated part.

The manipulator has 7 d. o. f. shown in Fig. 2. In this paper, the part from the first link to the third link is called the upper arm part, and J_4 joint and the end-effector are called the forearm part. The joint angles $(\theta_1, \theta_2, \theta_3)$ of the upper arm part are defined as zero in the posture shown in Fig. 2 (b).

The control part consists of the upper arm control part and the forearm control part. The upper arm control part controls three joints (J_1, J_2, J_3) according to the position of the operator's wrist joint measured by a 3D position sensor, and the forearm control part controls one joint (J_4) of Move Master and three joints (J_5, J_6, J_7) of the prosthetic forearm according to EMG signals. The correspondence of the movement of the operator's upper limb with that of the manipulator enables the operator to control the manipulator intuitively. During the manipulator control, the 3D graphical image of the manipulator and information on the EMG signals extracted by the EMG signal processor are presented on the feedback display.

2.1 Upper Arm Control Part

In the upper arm control part, the 3D position sensor (ISOTRACK II : POLHEMUS, Inc.) is used as an input device. This device uses the electromagnetic fields to determine its 3D position. The static accuracy is ± 2.4 [mm] for x, y and z axes. It should be

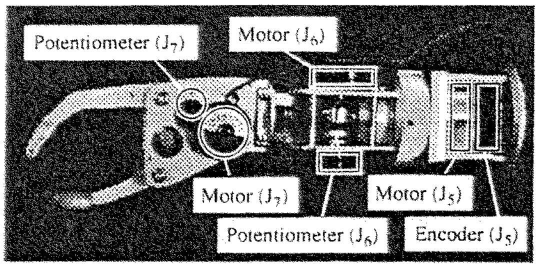


Figure 3: Picture of the end-effector

Table 1: Specifications of the end-effector

Joint	Motion	Movable range	Holding torque	Gear ratio
J_5	Spination / pronation	$0 \sim 360^\circ$	0.68 Nm	5.8
J_6	Radial flexion / ulnar flexion	$0 \sim 60^\circ$	0.88 Nm	7.5
J_7	Grasp / open	$0 \sim 120^\circ$	0.88 Nm	30.1

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 of 60 [Hz]. Then, the desired values of joint angles of the upper arm $(\theta_1, \theta_2, \theta_3)$ are calculated and the corresponding joints are controlled by the PID control method.

2.2 Forearm Control Part

The picture of the prosthetic forearm used as the end-effector is shown in Fig. 3 and its specifications are shown in Table 1. It is almost the same size as an adult's hand, and the weight is about 1 [kg]. This prosthetic forearm has 3 d. o. f. (J_5, J_6, J_7: forearm spination and pronation, wrist radial flexion and ulnar flexion, hand grasp and open), and each joint is driven by an ultrasonic motor (SINSEI Corp.). The encoder attached at J_5 and potentiometers attached at J_6 and J_7 are installed as the angular sensor of each joint. The motor driving unit has a voltage controlled oscillators so that the driving speed of the ultrasonic motors can be regulated according to the voltage command.

The ultrasonic motor has several advantages, such as light weight, high torque and silent motion. For example, the motor noise of the prosthetic hand can be significantly reduced. Also, the ultrasonic motor has the capability of maintaining the torque continuously against an environment even under the power-off. This characteristic is well known as the self-locking one.

Figure 4 shows the structure of the forearm control part, where four joint angles $(\theta_4, \cdots, \theta_7)$ of the manipulator are controlled. This part estimates the operator's intended motion and its force level based on the measured EMG signals. For EMG pattern discrimination, the log-linearized Gaussian mixture network (LLGMN) [17] is used. The network can calculate the posteriori probability of each motion.

2.2.1 EMG Feature Extraction

First, the EMG signals measured from L pairs of electrodes (NIHON KOHDEN Corp.) are digitized by an A/D converter (sampling frequency, 1 [KHz]; and quantization, 12 [bits]) after they are amplified (70 [dB]), rectified and filtered out through the second-order Butterworth filter UAF42 (BURR-BROWN Corp., cut-off frequency : f_{cut} [Hz]). These measured signals are defined as $EMG_i(n)$ $(i = 1, \cdots, L)$. Next, $EMG_i(n)$ $(i = 1, \cdots, L)$ are normalized to make the sum of L channels equal 1:

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

where EMG_i^{st} is the mean value of $EMG_i(n)$ which is measured while relaxing the arm. The LLGMN uses the n-th input vector $\boldsymbol{x}(n) = [x_1(n), x_2(2), \cdots, x_L(n)]^T \in \Re^L$ for EMG pattern discrimination. In this paper, we assume that the amplitude level of the EMG signal changes in proportion to muscle force, and the system uses the EMG amplitude information for forearm control. The force information $F_{EMG}(n)$ for the n-th input vector is defined as

$$F_{EMG}(n) = \frac{1}{L}\sum_{i=1}^{L}\frac{EMG_i(n) - EMG_i^{st}}{EMG_i^{max} - EMG_i^{st}}, \qquad (2)$$

where EMG_i^{max} is the mean value of $EMG_i(n)$ which are measured while keeping the maximum voluntary contraction.

2.2.2 EMG Pattern discrimination

In the proposed system, the LLGMN is used for the EMG pattern discrimination. First, the input vector $\boldsymbol{x}(n) \in \Re^L$ is preprocessed and converted into the modified input vector $\boldsymbol{X}(n) \in \Re^H$ as follows:

$$\begin{aligned}\boldsymbol{X}(n) &= [1, \boldsymbol{x}(n)^T, x_1(n)^2, x_1(n)x_2(n), \cdots, \\ &\quad x_1(n)x_L(n), x_2(n)^2, x_2(n)x_3(n), \\ &\quad \cdots, x_2(n)x_L(n), \cdots, x_L(n)^2]^T. \qquad (3)\end{aligned}$$

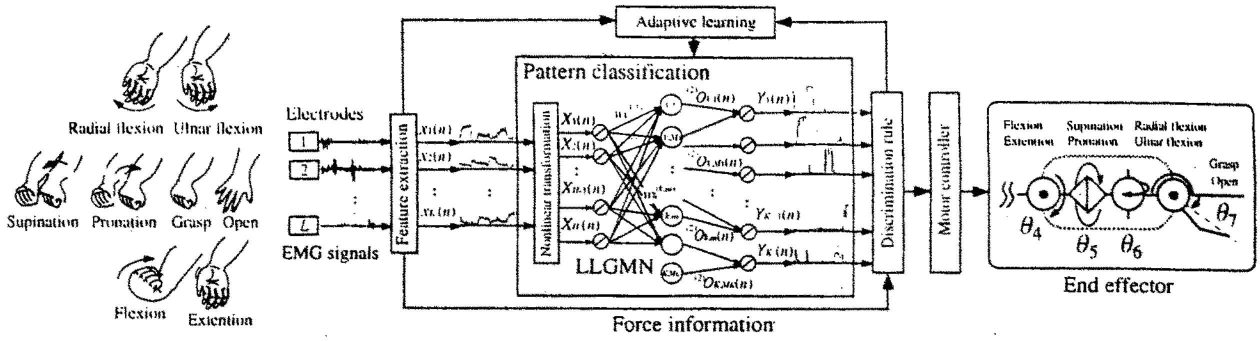


Figure 4: Forearm control part

The first layer consists of $H = 1 + L(L+3)/2$ units corresponding to the dimension of $\boldsymbol{X}(n)$, and the identity function is used for an activation function of each unit. Each unit of the second layer 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

$$ {}^{(2)}I_{k,m}(n) = \sum_{h=1}^{H} {}^{(1)}O_h(n) w_h^{(k,m)}, \tag{4} $$

$$ {}^{(2)}O_{k,m}(n) = \frac{\exp[{}^{(2)}I_{k,m}(n)]}{\sum_{k'=1}^{K} \sum_{m'=1}^{M_{k'}} \exp[{}^{(2)}I_{k',m'}(n)]}, \tag{5} $$

where $w_h^{(K,M_K)} = 0$ $(h = 1, \cdots, H)$. 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 relationship between the input and the output is defined as

$$ {}^{(3)}I_k(n) = \sum_{m=1}^{M_k} {}^{(2)}O_{k,m}(n), \tag{6} $$

$$ Y_k(n) = {}^{(3)}I_k(n). \tag{7} $$

The system should be adaptable to any changes of the conditions, because the EMG signal patterns are different among individuals and change depending on the electrical impedance of the skin, electrode locations, and so on [16]. Before starting the operation, the LLGMN has to learn the EMG pattern vectors $\boldsymbol{x}(n)$ for K forearm motions which are measured while keeping each motion. It should be noted that the dynamics of a terminal attractor 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 operator waiting for the convergence of learning may be reduced. Also, the on-line learning can be carried out in order to adapt the variations of EMG properties resulting from muscle fatigue and sweat.

2.2.3 Discrimination Rule

Any human supporting robot has to be absolutely safe for human. In order to reduce a risk of misoperation, the discrimination is performed using the entropy of the LLGMN outputs and force information $F_{EMG}(n)$. Since the third layer of the LLGMN outputs the posteriori probability of each motion k, the entropy is calculated as

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

The entropy indicates, or may be interpreted as, a risk of ill-discrimination. If the entropy is over the determination threshold H_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 H_d, the Bayes decision rule is used to determine the specific class. Thus, possible ill-discrimination can be reduced [16].

Then, in order to recognize the beginning of the motions, the force information $F_{EMG}(n)$ is compared with the motion appearance threshold F_k $(k = 1, \cdots, K)$. If $F_{EMG}(n)$ is over the threshold F_k, the joint torque $\tilde{\tau}_k(n)$ of the estimated motion is calculated as

$$ \tilde{\tau}_k(n) = \begin{cases} G_k(F_{EMG}(n) - F_k) & (F_{EMG}(n) \geq F_k) \\ 0 & (F_{EMG}(n) < F_k), \end{cases} \tag{9} $$

Table 2: Parameters of the impedance model used in the experiments

Joint, j	Motion(k)	K_j [Nm/rad]	B_j [Nms/rad]	I_j [kgm^2]	τ_j [Nm]
J_4	Flexion(1) / extention(2)	6.0	0.1	0.004	$+\tilde{\tau}_1$ / $-\tilde{\tau}_2$
J_5	Spination(3) / pronation(4)	4.0	0.1	0.002	$+\tilde{\tau}_3$ / $-\tilde{\tau}_4$
J_7	Grasp(5) / open(6)	4.0	0.2	0.001	$+\tilde{\tau}_5$ / $-\tilde{\tau}_6$

where G_k is the gain parameter which transforms the force information to the joint driving torque. The joint torque is equal to 0 if the force information $F_{EMG}(n)$ is less than F_k.

2.2.4 Motor Control Part

The skillful motion performed by the human forearm and hand is realized regulating its impedance property such as stiffness, viscosity, and inertia. A natural feeling of control similar to that of the human arm can be expected, if the robot control is performed on the basis of the impedance control with human arm impedance properties [14].

Let us consider the incorporation of the impedance model into the control system of the prosthetic forearm. Here, the dynamic equation of the j-th joint of human forearm is defined as

$$I_j \ddot{\theta}_j = \tau_j - K_j \theta_j - B_j \dot{\theta}_j, \tag{10}$$

where I_j, K_j, B_j are the inertia, stiffness, viscosity, respectively; τ_j is the joint torque; and θ_j is the angle of the j-th joint.

In the motor control part, the manipulator's forearm is controlled based on this equation. The j-th joint angle $\theta_j(n)$ can be measured by the angular sensors, and $\dot{\theta}_j(n)$ can be calculated by the numerical differentiation of $\theta_j(n)$. Also the joint torque $\tau_j(n)$ which derived from $\tilde{\tau}_k(n)$ is estimated from the EMG signals (9), so that the right side of (10) can be calculated. Therefore, the desired joint angles of the forearm are calculated by integrating (10) numerically. The joint angles are controlled using the PID control method.

This method can be expected to realize a natural feeling of control similar to that of the original limb, if the impedance parameters are set to the similar values to the human arm. In future, we would like to use an impedance model which is experimentally derived from human arm movements, where the viscoelasticity changes depending on the EMG signals [14].

3 Experiments

We have conducted experiments to demonstrate and verify the proposed system. Six forearm motions

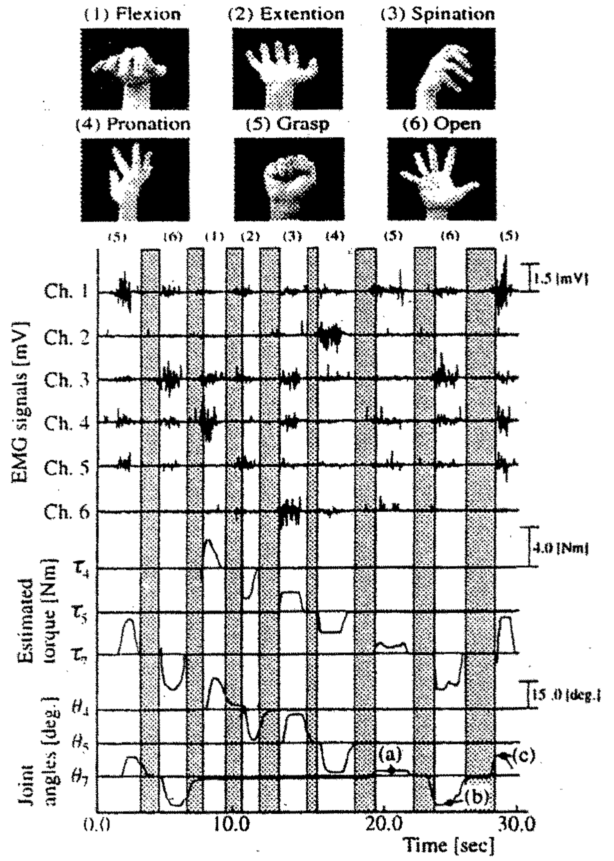
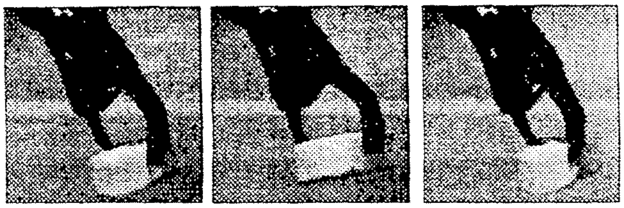


Figure 5: An example of the forearm control based on the EMG signals

(J_4: flexion and extention, J_5: spination and pronation, J_7: grasp and open) are controlled using the EMG signals. Six pairs of surface electrodes ($L = 6$) were attached to the forearm and upper arm of the subject who is a university student (male, age 23, healthy). The determination threshold H_d and the motion appearance thresholds F_k ($k = 1, \cdots, 6$) were settled as $H_d = 0.25, F_1 = 0.69, F_2 = 0.42, F_3 = 0.46, F_4 = 0.63, F_5 = 0.64, F_6 = 0.62$, and the number of the learning data was $N = 120$ (6 motions, 20 for each motion). Also the cut-off frequency of the Butterworth filter is settled as $f_{cut} = 1.0$ [Hz] and the conversion gains G_k ($k = 1, \cdots, 6$) of the force information $F_{EMG}(n)$ to joint torque τ_k are $G_1 = G_2 = 0.30, G_3 = G_4 = 0.20, G_5 = G_6 = 0.36$. The impedance parameters and the relationship between $\tilde{\tau}_k$ and τ_j are shown in Table 2. The sampling frequency for the control of the forearm is 100 [Hz], and the 4th-order Runge-Kutta method is used as the numerical integration (10).

Figure 5 shows an example of the forearm control



(a) (b) (c)

Figure 6: Pictures of the end-effector controlled by the EMG signals

based on the EMG signals. The EMG signals are discriminated for about 30 seconds. In the figure, the EMG signals, the estimated joint torques τ_j, and joint angles θ_j are shown. It can be seen that the operator can control the manipulator successfully using the EMG signals.

Finally, Fig. 6 shows motion pictures during the manipulation. These pictures show three kinds of hand motions which correspond to the points (a), (b), (c) marked in Fig. 5. The joint angles are controlled according to the joint torques estimated from the EMG signals successfully.

4 Conclusion

The EMG controlled robotic manipulator has been developed as an adaptive human supporting system. In this paper, the end-effector of the manipulator was newly designed using the prosthetic forearm driven by the ultrasonic motors. Also the impedance model was introduced to the control system in order to realize the natural feeling of control similar to that of the human arm. In the experiments, it can be seen that the operator can control the manipulator successfully using the EMG signal.

In the future, we would further like to attach some force sensors to the manipulator in order to control motions reacted to external force. Also we wish to conduct experiments with many subjects in order to make clear the effectiveness and the problems of this system.

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