A Human-Assisting Manipulator Teleoperated by EMG Signals and Arm Motions

Osamu Fukuda, Toshio Tsuji, *Member, IEEE*, Makoto Kaneko, *Senior Member, IEEE*, and Akira Otsuka

***Abstract*—This paper proposes a human-assisting manipulator teleoperated by electromyographic (EMG) signals and arm motions. The proposed method can realize a new master–slave manipulator system that uses no mechanical master controller. A person whose forearm has been amputated can use this manipulator as a personal assistant for desktop work. The control system consists of a hand and wrist control part and an arm control part. The hand and wrist control part selects an active joint in the manipulator's end-effector and controls it based on EMG pattern discrimination. The arm control part measures the position of the operator's wrist joint or the amputated part using a three-dimensional position sensor, and the joint angles of the manipulator's arm, except for the end-effector part, are controlled according to this position, which, in turn, corresponds to the position of the manipulator's joint. These control parts enable the operator to control the manipulator intuitively. The distinctive feature of our system is to use a novel statistical neural network for EMG pattern discrimination. The system can adapt itself to changes of the EMG patterns according to the differences among individuals, different locations of the electrodes, and time variation caused by fatigue or sweat. Our experiments have shown that the developed system could learn and estimate the operator's intended motions with a high degree of accuracy using the EMG signals, and that the manipulator could be controlled smoothly. We also confirmed that our system could assist the amputee in performing desktop work.**

***Index Terms*—Adaptation, electromyographic (EMG) signals, human-assisting manipulator, neural network, pattern discrimination.**

I. Introduction

THE number of aged or physically handicapped people requiring someone's assistance in everyday life has been increasing in recent years. Furthermore, it is expected that robots will extend their usefulness to home and office environments to support daily activities. Under such situations, if the human operator's intention can be discerned from the electromyographic (EMG) signals, EMG signals may be used as a new interface tool for human-assisting robots and rehabilitation systems. The EMG signals contain a lot of important information such as muscle force, operator's intended motion, and muscle impedance. A physically handicapped person who has lost a part of his/her upper limb in a traffic accident or through other afflictions may sense a feeling of prosthetic control similar to that of the original limb using EMG signals if the central nervous system (CNS) and a part of the muscles that actuated the original limb remain after amputation.

EMG signals have often been used as control signals for prosthetic hands. However, these prosthetic hands are seldom used by the amputee for two main reasons. First, the hardware device has problems such as motor noise and excessive weight. Second, there is the problem of interfacing the human and the device. In most previous research, the accuracy of the discrimination was not sufficient to control the prosthetic hand smoothly.

In this paper, we propose and develop a new human-assisting manipulator system based on the EMG signals. We suppose that persons whose forearm has been amputated will use this system as a personal assistant for desktop work. The manipulator is compact and suitable for use in home environments. The prosthetic hand is used as the end-effector of the manipulator, and the arm part of the manipulator supports it instead of the amputee's upper limb. The prosthetic hand is detachable from the manipulator, and the amputee can attach it to his/her amputated part.

The proposed system uses EMG signals to realize a feeling of control similar to that of the human hand. In many cases, some part of the muscles near the amputated part remain after amputation, and the EMG signals measured from them can be used as a control signal for our proposed system. If the amputee cannot control the muscular contraction of muscles near the amputated part, it is also possible to use muscles in other parts. It is, however, very difficult to control all joints of the manipulator using only the EMG signals, so it is helpful to use the remaining arm motions to control the manipulator. Therefore, the proposed controller is divided into two parts: the hand and wrist control part that selects an active joint in the manipulator's end-effector part and controls it based on the EMG pattern discrimination; and the arm control part that controls joint angles of the manipulator's arm according to the amputee's remaining arm motions as measured by a three-dimensional (3-D) position sensor. Even if the amputee cannot move his/her amputated part very much, any slight motion can be amplified and used as the control signal. The 3-D position sensor may also be attached on the tip of an additional link fixed to the amputated part to extend the length of the amputated limb. The operator can control the manipulator naturally using the EMG signals and the arm motions.

The discrimination of EMG patterns with nonlinear and nonstationary characteristics is a key topic of this paper. In order to realize smooth motions of the manipulator, the system has

Manuscript received February 19, 2002; revised August 10, 2002. This paper was recommended for publication by Associate Editor J. Troccaz and Editor I. Walker upon evaluation of the reviewers' comments. This work was supported in part by the New Energy and Industrial Technology Development Organization (NEDO) of Japan, under the Industrial Technology Research Grant Program.

O. Fukuda is with the Research Institute for Human Science and Biomedical Engineering, National Institute of Advanced Industrial Science and Technology, Tsukuba 305-8564, Japan (e-mail: fukuda.o@aist.go.jp).

T. Tsuji and M. Kaneko are with the Department of Artificial Complex Systems Engineering, Hiroshima University, Higashi-Hiroshima 739-8527, Japan.

A. Otsuka is with the Department of Physical Therapy, Hiroshima Prefectural College of Health Sciences, Mihara 723-0053, Japan.

Digital Object Identifier 10.1109/TRA.2003.808873

to discriminate the EMG patterns with a high degree of accuracy. Moreover, we should adopt adaptive learning ability for robust discrimination against the differences among individuals, different locations of the electrodes, and time variations caused by fatigue or sweat. To achieve this, we use a novel statistical neural network called the log-linearized Gaussian mixture network (LLGMN) to discriminate EMG patterns; this is a distinctive feature of our system. We expect a high learning and discrimination ability as LLGMN is appropriate for discriminating EMG signals that have stochastic characteristics. Moreover, we propose a discrimination suspension rule and an online learning method to reliably discriminate EMG patterns while controlling the system for a couple of hours. These methods can reduce the discrimination errors. We also designed a method of regulating the learning time considering the practical usage of our system. We can thus reduce the mental stress of the operator waiting for the convergence of learning.

The paper is organized as follows. Related work is introduced in Section II, the components of the proposed system are explained in Section III, the experiments are reported in Section IV, and Section V concludes the paper.

II. Related Work

Up to the present, many researchers have investigated human-assisting robots and rehabilitation systems [1]. The studies in this field can be classified into two groups: the extension of human ability using the robot; and the rehabilitation or prostheses/orthoses for the physically handicapped based on the robotics. As examples of the former, Kazerooni [2] proposed "Extenders" as a class of robot manipulators that extend the strength of the human arm. Later, Salter [3] designed a continuous passive motion (CPM) device that gently bends and straightens an injured joint after surgery. Also, Krebs *et al.* [4] developed a training system for the upper limb movements through operating an end-effector of an impedance-controlled robot according to a target pattern, such as a circle, shown in the computer display. Wu *et al.* [5] proposed a neuromuscular-like control method, based on the spinal reflex, to develop a rehabilitation robot that assists the operator's limb motion.

Many researchers have also designed prosthetic hands for amputees since Wiener [6] proposed the concept of an EMG-controlled prosthetic hand. EMG signals have often been used as control signals for prosthetic hands, such as the Waseda hand [7], the Boston arm [8], and the Utah artificial arm [9], which are the pioneers in this field. Abboudi *et al.* [10] proposed a biomimetic controller for a multifinger prosthesis, and Kyberd *et al.* [11] developed a two-degree-of-freedom (DOF) hand prosthesis with hierarchical grip control. Since the EMG signals also include information about force level and mechanical impedance properties of the limb motion, Akazawa *et al.* [12] designed a signal processor for estimating force from the EMG signals, and Abul-haj and Hogan [13] analyzed the characteristics of the prosthetic control based on the impedance model. Also, Ito *et al.* [14] used amplitude information of this signal as the speed-control command of the prosthetic forearm. This prosthetic forearm was controlled with three levels of driving speeds.

Most previous research on prosthetic hands used on/off control based on EMG pattern discrimination or controlled only a particular joint, depending on torque estimated from the EMG signals. However, as the number of DOFs increased, it was difficult to discriminate the operator's intended motion with sufficiently high accuracy due to their nonlinear and nonstationary characteristics. Moreover, there is a problem that the EMG patterns are changed according to differences among individuals, different locations of the electrodes, and time variation caused by fatigue or sweat. We need a new discrimination method to control the various motions of a prosthetic hand required in daily activities.

Many studies on using EMG signal pattern discrimination to control prosthetic hands have been reported. During the first stage of this research, linear prediction models for EMG signals, such as the autoregressive (AR) model, were frequently used [15]–[19]. Graupe *et al.* [15] reported on discriminating EMG signal measured from one pair of electrodes using this model. However, it is very difficult to achieve high discrimination performance, especially for rapid movements, because of nonlinear characteristics and the large variability of the EMG signals.

Subsequent research has proposed several EMG pattern discrimination methods using neural networks [20]–[27]. The neural networks can acquire the nonlinear mapping of learning data. For example, Kelly *et al.* [20] proposed a pattern discrimination method combining the back propagation neural network (BPN) [28] and the Hopfield neural network. This method can acquire mapping from the EMG patterns measured from one pair of electrodes to four motions of elbow and wrist joints. Also, Hiraiwa *et al.* [21] used BPN to estimate five-finger motion. They reported that five-finger motion, joint torque, and angles were successfully estimated. Koike *et al.* [22] constructed a forward dynamics model of the human arm using EMG signals and arm trajectories. Their experiments estimated four joint angles, one at the elbow and three at the shoulder, from surface EMG signals of 12 flexor and extensor muscles during posture control in 3-D space. Farry *et al.* [23] proposed a method to remotely operate a robot hand by classifying the motions of the human hand from the frequency spectrum of EMG signals. Huang and Chen [24] constructed several feature vectors from the integral of the EMG, the zero-crossing and the variance of the EMG, and eight motions were classified using BPN. However, BPN, frequently used in previous research, cannot realize high learning and discrimination performance when the signal becomes more complex. For example, the EMG patterns differ considerably at the start and end of the motion even if they are within the same class. Also, they overlap each other when we discriminate many classes. Therefore, BPN needs a large amount of learning data and a great number of learning iterations.

The authors have, therefore, proposed a novel statistical neural network called the LLGMN [29], and used it to discriminate electroencephalograph (EEG) and EMG signals. LLGMN includes a preorganized structure and can model the complicated mapping between the input patterns and the discriminating classes, even for a small sample size. In contrast, BPN is trained by using only the learning sample data. This

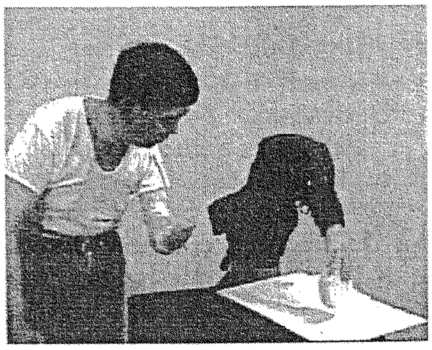


Fig. 1. Picture of the human-assisting manipulator.

network can acquire a Gaussian mixture model (GMM) [30], which is a kind of statistical model. The network outputs the *a posteriori* probability of each discriminating class. The authors conducted comparison experiments with maximum-likelihood neural networks [31], which are based on GMM. Numerical simulations and EEG discrimination results confirmed that LLGMN can achieve better discrimination than the previous statistical technique, even for a small sample size of the learning data [29]. The authors have also proposed the concept of a human-assisting manipulator using LLGMN, developed a prototype system, and conducted preliminary experiments on healthy subjects [32], [33].

III. System Components

This section presents the components of the proposed system. The developed manipulator, which consists of the prosthetic hand (Imasen Laboratory) [14] and the robot arm (Mitsubishi Electric Corporation), is shown in Fig. 1. It has 0.76 m radius of revolution and is suitable for use in home environments. The prosthetic hand is detachable from the manipulator, and an amputee can attach it instead to his/her amputated part. The robot arm supports the prosthetic hand and transports it to a position in the work space designated by the operator, although its structure does not match that of the human arm.

The manipulator has seven DOFs, as shown in Fig. 2. In this paper, the prosthetic hand and the J_4 joint are called the hand and wrist part, and the part from the first link to the third link is called the arm part. The joint angles (θ_1, θ_2, θ_3) of the arm part are defined as zero in the posture shown in Fig. 2(a). The relationship between the manipulator and the operator is shown in Fig. 2(c).

The prosthetic hand used in the hand and wrist part is shown in Fig. 3, and the specifications of the prosthetic hand and the robot arm are shown in Table I. The prosthetic hand is almost the same size as an adult's hand, and weighs about 1.0 kg. It is made from aluminum alloy and covered with a cosmetic glove. This glove has five fingers, and the four fingers from the index finger to the little finger are mechanically connected. This prosthetic hand has three DOF (J_5, J_6, J_7: supination/pronation, radial flexion/ulnar flexion, and hand grasp/hand open), and each joint is driven by an ultrasonic motor (SINSEI Corporation). The encoder attached at J_5 and potentiometers attached at J_6 and J_7 are installed as the angular sensor of each joint.

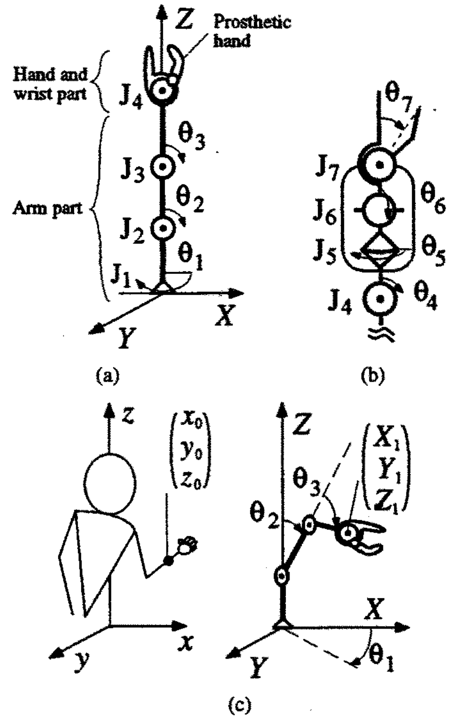


Fig. 2. Link model of the manipulator.

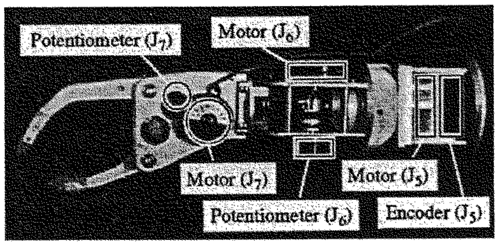


Fig. 3. Picture of the prosthetic hand.

The motor driving unit has voltage-controlled oscillators so that the driving speed of the ultrasonic motors can be regulated according to the voltage command. The ultrasonic motor has the advantages of light weight, high torque, and silent action. The motor noise of the prosthetic hand can, thus, be significantly reduced. Also, an ultrasonic motor can maintain its torque continuously against an environment, even when turned off. This is known as a self-locking characteristic.

The control system is shown in Fig. 4, which depicts the hand and wrist control part, the arm control part, and the feedback part. The hand and wrist control part determines the operator's intended motion based on EMG pattern discrimination and controls three joints (J_5, J_6, J_7) of the prosthetic hand and one joint (J_4) of the robot arm. The arm control part controls three joints (J_1, J_2, J_3) of the robot arm according to the operator's arm motions measured by a 3-D position sensor. The operator can execute the network learning easily because the system guides the operator through this procedure interactively via the display in the feedback part. During manipulator control, the feedback part displays information about the monitored EMG signals, the muscular contraction levels, the results of the EMG pattern discrimination and the graphical images of the manipulator. The control program is developed on a personal computer

TABLE I
SPECIFICATIONS (A) ROBOT ARM (B) PROSTHETIC HAND

Degree of freedom of motion	4	
Length	from J_1 to J_2	300[mm]
	from J_2 to J_3	250[mm]
	from J_3 to J_4	160[mm]
Motion range	J_1	-150° to +150°
	J_2	-10° to +120°
	J_3	0° to +110°
	J_4	-90° to +90°
Maximum speed	J_1	120° /[sec]
	J_2	72° /[sec]
	J_3	109° /[sec]
	J_4	100° /[sec]
Load capacity	1.2[kgf]	
Drive system	DC servo motor (J1 axis brake attached)	
Position sensing method	Absolute encoder	
Weight	Approx. 19[kgf]	

(a) Robot arm

Degree of freedom of motion	3	
Length	from J_4 to J_5	72[mm]
	from J_5 to J_6	135[mm]
	from J_6 to J_7	85[mm]
	hand	58[mm]
Motion range	J_5	-180° to +180°
	J_6	-30° to +30°
	J_7	0° to +120°
Maximum speed	J_5	135° /[sec]
	J_6	104° /[sec]
	J_7	46° /[sec]
Holding force	J_5	6.9[kg/cm]
	J_6	9.0[kg/cm]
	J_7	9.0[kg/cm]
Drive system	Ultrasonic motor	
Weight	Approx. 1.0[kgf]	

(b) Prosthetic hand

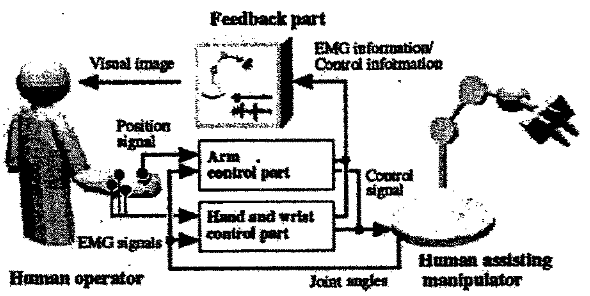


Fig. 4. Control system.

(Pentium 4, 1.8 GHz). It is also possible to implement the program on a single-board computer. We would like to develop a portable system. In this system, the learning period of the neural network may be extended, but it will be useful in practical applications. The details of each control part are explained in the following sections.

A. Hand and Wrist Control Part

EMG signals are used as the control signal to control the hand and wrist part. These signals are measured from the operator's forearm muscles when the operator imagines a desired motion (extension, flexion, ulnar flexion, radial flexion, supination, pronation, hand open, and hand grasp) and contracts his/her muscles. Fig. 5 shows the detailed structure of the hand and wrist control part, where three joint angles (θ_5, θ_6, θ_7) of the prosthetic hand and one joint angle (θ_4) of the robot arm are controlled. In this structure, the feature patterns are extracted from the measured EMG signals, and one driven joint is determined based on EMG pattern discrimination using LLGMN. The driving speed of the driven joint is controlled according to force information extracted from the EMG signals.

1) Preprocessing EMG Signals: First, the EMG signals measured from D pairs of electrodes (Web5000: NIHON KOHDEN Corporation) are digitized by an analog-to-digital (A/D) converter (sampling frequency, 1.0 kHz; quantization, 12 b) after being amplified (70 dB), rectified, and filtered through the Butterworth filter (cutoff frequency, f_c Hz; order, p). The nth sampled signals are defined as $\mathrm{EMG}_d(n)$ $(d = 1, \ldots, D)$.

To recognize the beginning and ending of the operator's motions, the square sum of $\mathrm{EMG}_d(n)$ is calculated as

$$s(n) = \sum_{d=1}^{D} \left(\mathrm{EMG}_d(n) - \overline{\mathrm{EMG}}_d^{st}\right)^2 \tag{1}$$

where $\overline{\mathrm{EMG}}_d^{st}$ is the mean value of $\mathrm{EMG}_d(n)$, which is measured while the arm is relaxed. When $s(n)$ exceeds the prespecified motion-appearance threshold, the motion is regarded as having been initiated.

Next, to extract the EMG pattern, $\mathrm{EMG}_d(n)$ are normalized to make the sum of D channels equal 1.0

$$x_d(n) = \frac{\mathrm{EMG}_d(n) - \overline{\mathrm{EMG}}_d^{st}}{\sum\limits_{d'=1}^{D} \left(\mathrm{EMG}_{d'}(n) - \overline{\mathrm{EMG}}_{d'}^{st}\right)}, \qquad d = 1, \ldots, D. \tag{2}$$

This is necessary to extend the EMG pattern independent of the amplitude of the EMG signals that highly depend on the force level. Thus, the input vector $x(n) = [x_1(n), x_2(n), \ldots, x_D(n)]^T \in \Re^D$ is extracted and used as the nth pattern vector for LLGMN.

Also, $\sigma_k(n)$ is defined as

$$\sigma_k(n) = \frac{1}{D} \sum_{d=1}^{D} \frac{\mathrm{EMG}_d(n) - \overline{\mathrm{EMG}}_d^{st}}{\overline{\mathrm{EMG}}_{d,k}^{\max} - \overline{\mathrm{EMG}}_d^{st}} \tag{3}$$

where $\overline{\mathrm{EMG}}_{d,k}^{\max}$ is the mean value of $\mathrm{EMG}_d(n)$ while keeping the maximum voluntary contraction (MVC) for motion $k (k = 1, \ldots, K)$. $\sigma_k(n)$ is considered to be information about the force level $(0 \leq \sigma_k(n) \leq 1)$ for motion k. The speed of the driven joint corresponding to a determined motion is controlled according to this value.

2) EMG Pattern Discrimination: The EMG signals are the sum of the spike potential generated in the muscle fibers. Their generation intervals are not constant, and differ greatly in each fiber. It is quite difficult to model these signals using a simple equation. Therefore, in our approach, these patterns are regarded as stochastic patterns, and an LLGMN [29] is used to discriminate EMG patterns. This network is constructed based on a pat-

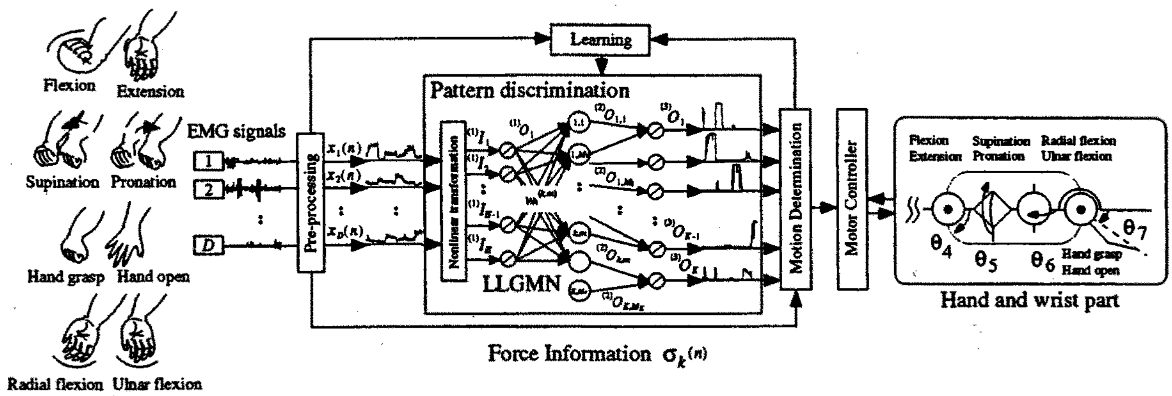


Fig. 5. Hand and wrist control part.

TABLE II
STRUCTURE OF LLGMN

The 1st layer	Number of units	H
	Input	$^{(1)}I_h(n)$
	Output	$^{(1)}O_h(n)$
	I/O function	Identity function
The 2nd layer	Number of units	$\sum_{k=1}^{K} M_k$
	Input	$^{(2)}I_{k,m}(n)=\sum_{h=1}^{H} {}^{(1)}O_h(n) w_h^{(k,m)}$
	Output	$^{(2)}O_{k,m}(n)$
	I/O function	Gereralized sigmoid function [see (7)]
The 3rd layer	Number of units	K
	Input	$^{(3)}I_k(n)=\sum_{m=1}^{M_k} {}^{(2)}O_{k,m}(n)$
	Output	$^{(3)}O_k(n)$
	I/O function	Identity function
Weight coeficients from 1st layer to 2nd layer		$w_h^{(k,m)}$
Weight coeficients from 2nd layer to 3nd layer		1

tern discrimination using the GMM [30], which is a kind of statistical model, and exhibits a high learning and discrimination ability.

Table II describes the LLGMN parameters. First, the input vector $x(n) \in \Re^D$ is preprocessed and converted into the modified input vector $^{(1)}I(n) \in \Re^H$ as follows:

$$^{(1)}I(n) = \Big[1, x(n)^T, x_1(n)^2, x_1(n)x_2(n), \ldots, x_1(n)x_D(n), x_2(n)^2, x_2(n)x_3(n), \ldots, x_2(n)x_D(n), \ldots, x_D(n)^2\Big]^T. \tag{4}$$

This nonlinear transformation is needed to represent the probability density function (pdf) corresponding to each component of the GMM as a linear combination of the new input vector $^{(1)}I(n)$. The first layer consists of $H = 1 + D(D+3)/2$ units corresponding to the dimension of $^{(1)}I(n)$, and the identity function is used for an activation function of each unit. The output $^{(1)}O_h$ of the unit h in the first layer is defined as

$$^{(1)}O_h(n) = {}^{(1)}I_h(n). \tag{5}$$

The second layer consists of the same number of units as the total number of components of GMM. Each unit of the second layer receives the output of the first layer weighted by the coefficient $w_h^{(k,m)}$ and outputs the *a 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

$$^{(2)}I_{k,m}(n) = \sum_{h=1}^{H} {}^{(1)}O_h(n) w_h^{(k,m)} \tag{6}$$

$$^{(2)}O_{k,m}(n) = \frac{1}{\sum_{k'=1}^{K} \sum_{m'=1}^{M_{k'}} \exp\left[{}^{(2)}I_{k',m'}(n) - {}^{(2)}I_{k,m}(n)\right]}. \tag{7}$$

The parameter M_k in LLGMN indicates the number of the Gaussian components that construct GMM. In GMM, the pdf of the sample data is approximated by summing up the Gaussian components. The modeling ability generally increases as the number of components increases, although the learning procedure requires many learning iterations. The weight coefficients of LLGMN originally correspond to the statistical parameters in GMM, and have several statistical constraints (e.g., $1 \geq$ probability ≥ 0, standard deviation ≥ 0). These constraints may cause difficulty in the learning procedure, so we defined new weight coefficients $w_h^{(k,m)}$ as the difference from $w_h^{(K,M_K)}$ and ignored these statistical constraints. The weight coefficients $w_h^{(K,M_K)}$, $(h = 1, \ldots, H)$ are set to zero for this reason [29]. It should be noted that (7) can be considered as a kind of generalized sigmoid function. The third layer consists of K units corresponding to the number of hand and wrist motions, and outputs the *a posteriori* probability of the motion $k (k = 1, \ldots, K)$. The relationship between the input and the output is defined as

$$^{(3)}I_k(n) = \sum_{m=1}^{M_k} {}^{(2)}O_{k,m}(n) \tag{8}$$

$$^{(3)}O_k(n) = {}^{(3)}I_k(n). \tag{9}$$

It should be noted that, in LLGMN defined above, GMM can be acquired through only the learning of the weight coefficient $w_h^{(k,m)}$.

3) Motion Control: The motion of the hand and wrist part is determined and controlled based on the outputs of LLGMN, which indicates the *a posteriori* probabilities of the corresponding motions, so that the operator's intended motion can be discriminated according to Bayes' decision rule. At the same time, we calculate the entropy $E(n)$, defined as

$$E(n) = -\sum_{k=1}^{K} {}^{(3)}O_k(n) \log {}^{(3)}O_k(n) \tag{10}$$

to achieve reliable discrimination and use it for a discrimination-suspension rule [33], because the entropy indicates, or may be interpreted as, the risk of incorrect discrimination. For example, if the entropy exceeds the prespecified discrimination threshold E_d, the discrimination and motor control should be suspended, since large entropy means that the network output is ambiguous. Thus, this rule should reduce the possible incorrect discriminations.

Finally, if the square sum of $\mathrm{EMG}_d(n)$ defined as (1) exceeds the prespecified motion appearance threshold and the entropy $E(n)$ is below the prespecified discrimination threshold E_d, the driven joint is determined and controlled based on the result of the EMG pattern discrimination. The driving speed is controlled proportionally to the force level $\sigma_k(n)$ defined as (3).

4) Learning: We use offline and online learning methods to discriminate the EMG pattern with a high degree of accuracy. Before starting the manipulation, LLGMN must learn in the offline learning method to adapt itself to the differences among individuals and different locations of the electrodes. The electrodes do not have to be placed on specific muscles. Furthermore, the operator does not need physiological knowledge for electrode placement, because LLGMN learns the mapping between the input pattern and the hand and wrist motions. A one-arm amputee can place the electrodes by himself, but a person with both arms amputated will require assistance. We conducted the experiments with several electrode placement patterns and confirmed discrimination robustness to different electrode locations [25], [26]. The network learning takes about ten seconds using a personal computer (Pentium 4, 1.8 GHz), and 3 min is enough to place the electrodes on the operator's arm. During manipulation, the online learning method is used because the EMG properties are gradually changed due to muscle fatigue, sweat, and changing electrode characteristics. Online learning plays an important role when the operator uses the manipulator for a couple of hours.

In the offline learning method, we use the EMG pattern vector $x(i)$ and the teacher vector $T(i) = (T_1(i), \ldots, T_k(i), \ldots, T_K(i))^T$ $(i = 1, 2, \ldots, N)$ for the ith learning sample data, where N is the number of samples. The EMG patterns are measured for each motion. The teacher signal is $T_k(i) = 1$ for the particular class k, and $T_k(i) = 0$ is used for all the other classes. Here, $k = 1, 2, \ldots, K$ corresponds to the hand and wrist motions. As the energy function J for the network, we use

$$J = -\sum_{i=1}^{N} \sum_{k=1}^{K} T_k(i) \log {}^{(3)}O_k(i) \tag{11}$$

and the learning is performed to minimize this energy function (i.e., to maximize the likelihood function).

The newly extracted learning samples, which are pairs of the input pattern vectors and the discrimination results while controlling the manipulator, are used for the online learning method. However, the problem is that we cannot ascertain whether the discriminated motion coincided with the amputee's intended one. Thus, we cannot directly find the desired output, that is, the teacher signal. To solve this problem, we also calculate the entropy $E(n)$, and the new learning samples are automatically provided based on this value [33]. If the entropy $E(n)$ of the output of LLGMN for the EMG pattern $x(n)$ is less than the online learning threshold E_o, the reliability of the discrimination result seems to be high. Therefore, $x(n)$ and the discrimination result are added to the learning data set, and the oldest of the stored learning data is deleted. The network weights are then updated using the new learning data set. If 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. In the online learning procedure, the weight coefficients of the network are modified gradually so that the discrimination does not degrade rapidly. However, this method may not be effective when the EMG pattern is changed significantly and rapidly. If discrimination performance begins to decrease gradually, the operator can use the offline learning mode again.

For practical applications of the proposed system, we must take into account the convergence time of network learning. This paper proposes a method to regulate this time. In this learning method, the energy function always converges stably to the equilibrium point in finite time. The equilibrium point is a kind of terminal attractor discovered by Zak [34]. Using this method, the convergence time of learning is always less than the prespecified upper limit, so that we may reduce the mental stress of the operator waiting for the convergence of learning.

Weight $w_h^{(k,m)}$ is considered as a time-dependent continuous variable. In the proposed method, its time derivative is defined as

$$\dot{w}_h^{(k,m)} = -\eta\gamma \frac{\partial J}{\partial w_h^{(k,m)}} \tag{12}$$

$$\gamma = \frac{J^\beta}{\sum_{h=1}^{H} \sum_{k=1}^{K} \sum_{m=1}^{M_k} \left(\frac{\partial J}{\partial w_h^{(k,m)}} \right)^2} \tag{13}$$

where $\eta > 0$ is a positive learning rate and β $(0 < \beta < 1)$ is a constant. The time derivative of the energy function J can be calculated as

$$\dot{J} = \sum_{h=1}^{H} \sum_{k=1}^{K} \sum_{m=1}^{M_k} \left(\frac{\partial J}{\partial w_h^{(k,m)}} \dot{w}_h^{(k,m)} \right) = -\eta J^\beta \leq 0. \tag{14}$$

From (14), it can be seen that J is a monotonically nonincreasing function and always converges stably to the equilibrium point (the global minimum or a local minimum). In this case, the convergence time can be calculated as

$$t_f = \int_0^{t_f} dt = \int_{J_o}^{J_f} \frac{dJ}{\dot{J}} = \frac{J_0^{1-\beta} - J_f^{1-\beta}}{\eta(1-\beta)} \leq \frac{J_0^{1-\beta}}{\eta(1-\beta)} \tag{15}$$

where J_0 is an initial value of the energy function J calculated using initial weights, and J_f is a final value of J at the equilibrium point. For $J_f = 0$, the equal sign of (15) is held. Thus, the convergence time can be specified by learning rate η. In contrast, for $J_f \neq 0$, the convergence time is always less than the upper limit of (15). In this paper, the learning is performed by a discrete form of (16) derived from (12)

$$w_h^{(k,m)}(t+\Delta t) = w_h^{(k,m)}(t) + \frac{\Delta t}{2}\left(\dot{w}_h^{(k,m)}(t) + \dot{w}_h^{(k,m)}(t+\Delta t)\right) \quad (16)$$

where Δt denotes the sampling time. The total number of learning iterations becomes $t_f/\Delta t$, and the computation time, in turn, depends on this number.

B. Arm Control Part

The arm control part uses a 3-D position sensor (ISOTRACK II; POLHEMUS, Inc.) as an input device for the control signal. The size of the sensor control unit is 28.9(W)×28.1(L)×9.2(H) cm, and sufficiently portable to use beside the manipulator. If an amputee attaches the prosthetic hand, which is detached from the manipulator, to his/her amputated part, the arm control part is not needed and the system can be more portable.

The 3-D position sensor uses electromagnetic fields to determine its 3-D position. The static accuracy is ±2.4 mm for the x, y, and z axes. It should be noted that this device allows the operator to take an arbitrary position having no occlusion problem. The operator's wrist position $(x_0, y_0, z_0)^T$ is measured with the sampling frequency of 60 Hz. The desired position of the J_4 joint $(X_1, Y_1, Z_1)^T$ (see Fig. 2) is calculated as

$$\begin{pmatrix} X_1 \\ Y_1 \\ Z_1 \end{pmatrix} = \mathbf{c} \begin{pmatrix} x_0 \\ y_0 \\ z_0 \end{pmatrix}. \quad (17)$$

where $\mathbf{c} = \mathrm{diag}\,[c_x, c_y, c_z]$ is the gain matrix. The sensitivity of the manipulator's motion to the operator's motion can be regulated using this matrix. The desired values of joint angles of the robot arm (θ_1, θ_2, θ_3) are then calculated according to this position, and the corresponding joints are controlled by the proportional-integral-derivative (PID) control method. The correspondence of the movement of the operator's wrist joint with that of the manipulator's joint enables the operator to control the manipulator intuitively.

IV. Experiments

We conducted experiments with the developed manipulator system on eight subjects. Subjects A and B were 51- and 43-year-old men whose forearms were amputated when they were 18 and 41 years old, and they had never used EMG-controlled devices. Subjects C–H were fully functional, from 21- to 31-year-old men. Rehabilitation training is beneficial before manipulation when the amputee's muscle force declines with long lapses of time after amputation. For this purpose, Subject A was trained using an EMG-based training system for prosthetic control [35], [36]. This system seeks to enhance three kinds of muscle abilities: cooperation among several muscles, timing of EMG generation, and muscular contraction. We first performed control experiments on the hand and wrist part, and examined the effect of online learning while the subject controlled this part for a couple of hours. We then performed experiments on manipulator control using the EMG signals and the 3-D position sensor. Finally, to improve the feeling of control in the hand and wrist part, we tried to control the joint angles based on the joint impedance model of the human forearm.

In the experiments, we used six electrodes ($D = 6$: ch. 1 Flexor Carpi Radialis; ch. 2 Flexor Carpi Ulnaris; ch. 3 Pronator Teres; ch. 4 Supinator; ch. 5 Biceps Brachii; ch. 6 Brachialis). If the subject was an amputee, we placed four electrodes (ch. 1–4) on the muscles near the amputated part, and two electrodes on the upper arm muscles (ch. 5 Biceps Brachii, ch. 6 Triceps Brachii). The sampling frequency for controlling the arm part and hand and wrist part were 60 and 100 Hz, respectively. The cutoff frequency and the order of the Butterworth filter in the preprocessing part were determined as $f_c = 1.0$ Hz and $p = 2$. The discrimination suspension and the online learning thresholds were determined by trial and error, considering the results of our previous research [25], [26]. The LLGMN structure was determined based on the number of electrodes, the Gaussian components, and the desired motions. Gaussian components were used to approximate the pdf of the sample data. The numbers of components and learning samples were specified as one and 20 for each motion, which were adequate for achieving high-discrimination performance.

A. Discrimination Ability of the Hand and Wrist Motions

First, we examined the EMG pattern discrimination ability. In the experiments, we used the discrimination suspension rule and the online learning method, and determined the thresholds as $E_d = 0.55$, $E_o = 2.0$. There were $N = 160$ (eight motions, 20 for each motion) learning data inputs. Fig. 6 shows an example of the discrimination results for Subject C. The subject performed eight motions ($K = 8$; (E) extension, (F) flexion, (UF) ulnar flexion, (RF) radial flexion, (S) supination, (P) pronation, (HO) hand open, and (HG) hand grasp) for about 30 s. The figure shows the motion photos, EMG signals, force level $\sigma_k(n)$, the entropy $E(n)$, and the discrimination results. Darkened areas indicate no motion because the square sum of $\mathrm{EMG}_d(n)$, which was defined as (1), was below the prespecified threshold. We achieved quite high discrimination accuracy, although we observed several suspended discriminations and incorrect discriminations at the beginning and ending of the motion. The incorrect discriminations can be reduced using the discrimination suspension rule.

Next, we performed experiments to compare LLGMN and the common BPN network. Table III presents the discrimination results for five subjects, including the two amputees. Subjects B–E executed all eight motions, but Subject A executed six motions, excluding UF (ulnar flexion) and RF (radial flexion) because he could not imagine them. We calculated the mean values and standard deviations for ten randomly chosen initial weights. During the experiment, we did not use the discrimination suspension rule or the online learning method. The discrimination rates of BPN decreased in some motions, and the standard deviations were greater than those of LLGMN. However, LLGMN realized quite high discrimination accuracy for all subjects. The

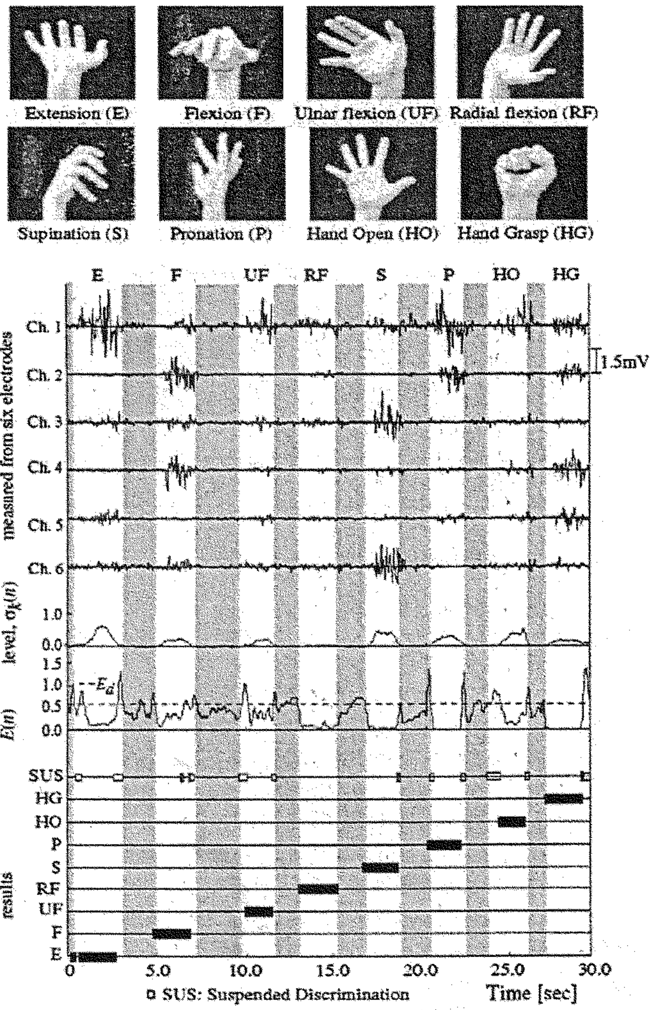


Fig. 6. Example of the hand and wrist control using the EMG signals: the subject executed eight hand and wrist motions for about 30 s. The darkened areas indicate no motions because the square sum of $\mathrm{EMG}_d(n)$, which was defined as (1), was below the prespecified threshold. "SUS" in the discrimination results indicates the suspended discrimination where $E(n)$ exceeds the prespecified threshold E_d.

TABLE III
DISCRIMINATION RESULTS IN HAND AND WRIST PART

Subjects	Methods	E	F	UF	RF	S	P	HO	HG	Total (%)
A	LLGMN Mean±SD(%)	100.0 ±0.0	100.0 ±0.0	—	—	95.0 ±0.0	98.7 ±1.3	100.0 ±0.0	100.0 ±0.0	98.9 ±0.2
	BPNN Mean±SD(%)	73.4 ±38.1	3.9 ±8.2	—	—	99.1 ±2.0	84.0 ±28.8	80.7 ±10.7	99.5 ±1.7	73.4 ±7.9
B	LLGMN Mean±SD(%)	100.0 ±0.0	100.0 ±0.0	96.5 ±0.4	100.0 ±0.0	100.0 ±0.0	82.8 ±1.1	100.0 ±0.0	100.0 ±0.0	97.1 ±0.2
	BPNN Mean±SD(%)	29.0 ±41.8	4.8 ±8.3	66.2 ±44.0	96.3 ±7.7	97.7 ±7.3	89.4 ±14.2	97.0 ±5.1	100.0 ±0.0	72.6 ±7.8
C	LLGMN Mean±SD(%)	98.9 ±2.3	100.0 ±0.0	100.0 ±0.0	95.9 ±3.0	100.0 ±0.0	100.0 ±0.0	88.9 ±3.3	100.0 ±0.0	97.9 ±0.6
	BPNN Mean±SD(%)	100.0 ±0.0	96.5 ±5.1	81.5 ±24.1	98.0 ±3.2	60.1 ±45.3	100.0 ±0.0	59.9 ±36.5	87.4 ±29.7	85.4 ±6.2
D	LLGMN Mean±SD(%)	79.6 ±1.1	97.2 ±3.2	94.3 ±0.1	100.0 ±0.0	100.0 ±0.0	100.0 ±0.0	96.3 ±7.7	98.4 ±0.0	95.4 ±1.1
	BPNN Mean±SD(%)	0.0 ±0.0	0.0 ±0.0	100.0 ±0.0	100.0 ±0.0	21.0 ±35.2	100.0 ±0.0	89.3 ±19.0	100.0 ±0.0	63.8 ±4.9
E	LLGMN Mean±SD(%)	100.0 ±0.0	96.1 ±0.1	100.0 ±0.0	81.0 ±0.2	100.0 ±0.0	100.0 ±0.0	100.0 ±0.0	99.5 ±0.2	96.8 ±0.1
	BPNN Mean±SD(%)	64.8 ±44.4	61.0 ±44.2	80.0 ±42.2	72.9 ±21.2	100.0 ±0.0	96.3 ±11.7	1.2 ±3.8	79.3 ±27.2	69.4 ±9.0

Motions: Extension (E), Flexion (F), Ulnar Flexion (UF), Radial Flexion (RF), Supination (S), Pronation (P), Hand Open (HO), Hand Grasp (HG)

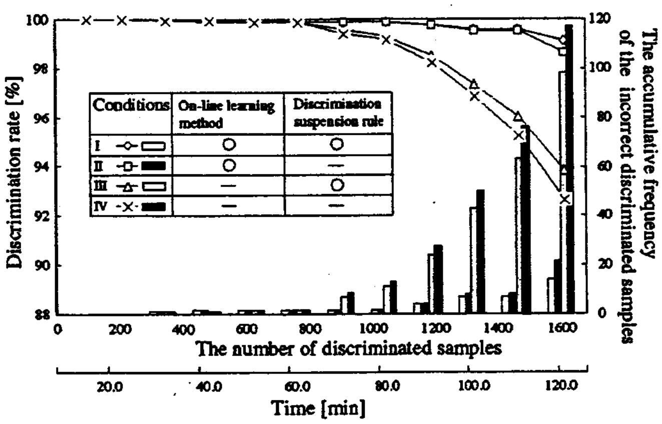


Fig. 7. Effect of the online learning method on the motion-discrimination ability while controlling the hand and wrist part for 120 min.

subjects could, thus, control the hand and wrist part successfully based on EMG pattern discrimination using LLGMN.

B. Effect of Online Learning

We next examined the effect of the discrimination suspension rule and the online learning method on discrimination performance under the following experimental conditions.

- I) The discrimination suspension rule and online learning method were used.
- II) Only the online learning method was used.
- III) Only the discrimination suspension rule was used.
- IV) Neither the discrimination suspension rule nor the online learning method were used.

Subject C, who had enough manipulation experience, was asked to continue to perform eight motions ($K = 8$; (E) extension, (F) flexion, (UF) ulnar flexion, (RF) radial flexion, (S) supination, (P) pronation, (HO) hand open, and (HG) hand grasp) for 120 min. This task was very exhausting as 1600 forearm motions had to be executed. The number of learning data was $N = 160$. The discrimination suspension threshold and the online learning thresholds were determined to be $E_d = 0.55$, $E_o = 2.0$, respectively. The discrimination rates were calculated every 10 min. Cases in which the system did not recognize any motions were counted as incorrect discriminations. During the experiment, the subject was not informed of the discrimination results.

The time histories of discrimination rates and the accumulative frequency of the incorrect discrimination data are shown in Fig. 7. The discrimination rate of condition IV, which did not use the discrimination suspension rule and the online learning method, decreased over time, possibly because of variations of the EMG pattern potentially caused by fatigue and/or sweat. Notably, the discrimination rate of condition I, which used both the discrimination suspension rule and the online learning method, maintained the highest discrimination rate during the experiment. Finally, only 16 incorrect discriminations were observed through 1600 trials.

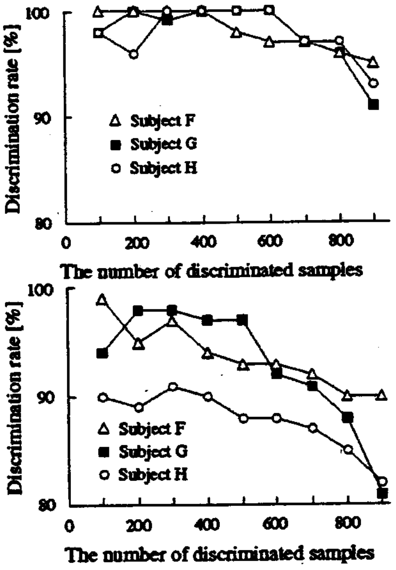


Fig. 8. Changes of discrimination accuracy for three subjects under conditions I and IV, where the discrimination suspension rule and the online learning method were used or not used.

We examined these effects for three other subjects (F–H) who were not familiar with the manipulation. There were six motions; UF (ulnar flexion) and RF (radial flexion) were not included because this experiment was the first time subjects G and H experienced controlling the manipulator. The number of learning data was $N = 120$, and the discrimination suspension and the online learning thresholds were determined as $E_d = 0.47$, $E_o = 1.7$, respectively. The subjects executed the exhausting work, executing 900 hand and wrist motions, and were not informed of the discrimination results. The experimental conditions were I and IV, and the discrimination rates in every 100 trials are plotted as shown in Fig. 8. Cases in which the system did not recognize any motions were counted as incorrect discriminations. The length of the experiments of subjects was 41.3 min for F, 64.4 min for G, and 75.6 min for H. Each subject achieved high discrimination performance in the beginning of the experiments. Especially, the high discrimination performance could be realized in condition I by using the discrimination suspension rule and the online learning method. For condition IV, the discrimination rates tended to decrease with time. In contrast, the discrimination rates for condition I remained relatively high during the experiment. Only $5 \sim 9$ incorrect discriminations were observed after 900 trials. The proposed method can adapt to the changes of the EMG pattern caused by fatigue or sweat.

C. Manipulator Control Using the 3-D Position Sensor

Previous experiments demonstrated the ability of the proposed method to discriminate hand and wrist motions using the EMG signals with high accuracy. However, it is very difficult to control all joints of the manipulator using only the EMG signals, so it is helpful to use the remaining arm motions to control the manipulator. Therefore, our system utilizes the information of the 3-D position sensor for the manipulator's arm control. This sensor was attached to the subject's wrist joint, and enabled the operator to control the manipulator's arm part intuitively.

Fig. 9(a)–(c) shows the control examples for subjects A and C. In the experiments, all signal processing, such as preprocessing the EMG signals, EMG pattern discrimination, motion control, and online learning, is done in real time, whereas it takes a relatively long period of time for the amputee to execute even a simple task because the operator's control ability depends highly on the level of disablement and the experience of the EMG operation. In many cases, however, this time period can be shortened considerably through the rehabilitation training. The developed system's advantage is in assisting the disabled with their daily activities, even if it takes a long period of time.

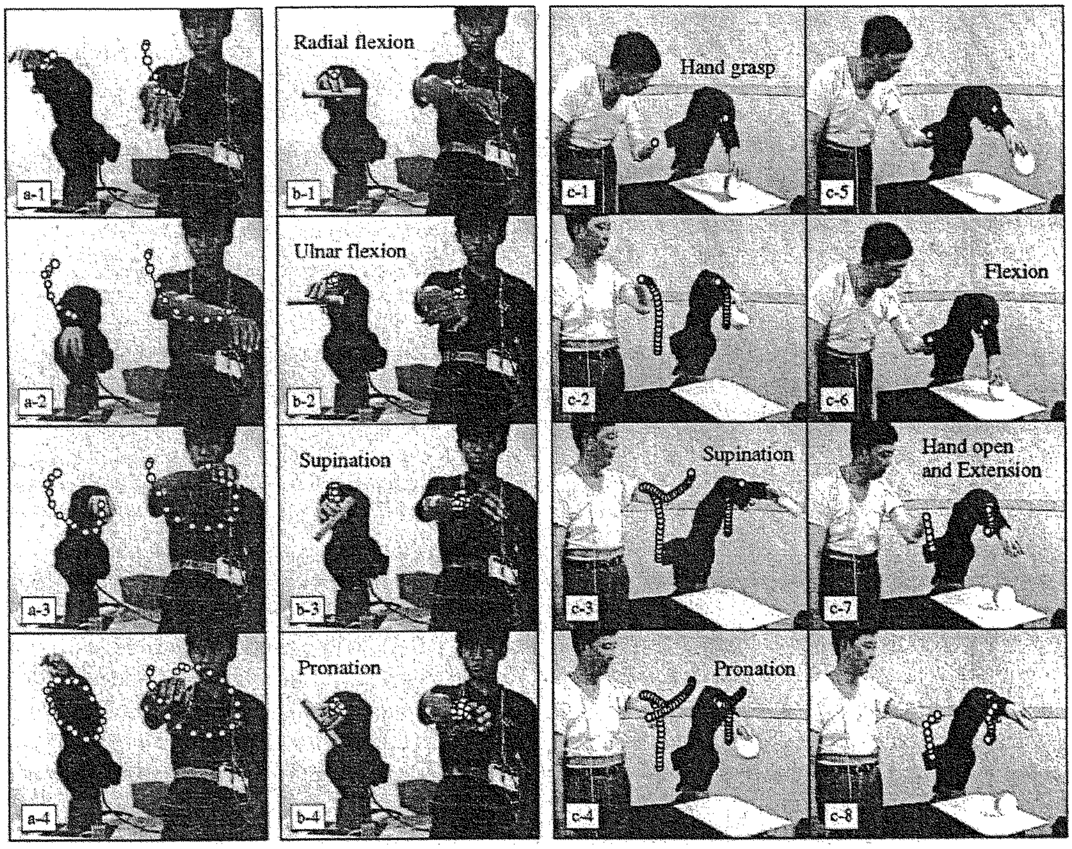
The plotted data (○) tracked the trajectory of the wrist joint of the operator and J_4 joint of the manipulator every 0.1 s. The gain matrix $c = \mathrm{diag}\,[c_x, c_y, c_z]$ was specified as $c_x = c_z = 1.0$, $c_y = 0.5$ for the fully functional subject and $c_x = c_y = c_z = 0.6$ for the amputee subject. The manipulator and the operator have the same orientations for comparing their motions. Most gain parameters were assigned low values considering the movable range.

In Fig. 9(a), Subject C controlled the arm part using the 3-D position sensor. The joint angles of the arm part were controlled according to the subject's wrist position, which, in turn, corresponds to the position of the manipulator's J_4 joint. The manipulator's motion was delayed a little from the subject's motion, primarily due to the phase lag of the Butterworth filter used to smooth the EMG signal in the preprocessing. Also, the motion appearance threshold is specified as a large value so that the sensitivity decreases. The discrimination is executed every 10 ms, and there is no time delay. The operator has no significant problem controlling the manipulator at normal speed. The feedback gains of the PID control were determined as $K_P = 5.0$, $K_V = 0.8$, and $K_I = 2.0$ to ensure safety. These values were specified by trial and error. Also, in Fig. 9(b), the hand and wrist part was controlled using the EMG signals while keeping the arm in the same position. In Fig. 9(c), Subject A executed a pick-and-place task using his EMG signals and remaining arm motions. He picked up the object from the table, performed some motions, and then set it on the table again. No incorrect discriminations were observed, and all motions were performed smoothly.

D. Control Based on the Joint Impedance Model

In the previous experiments, the driving speed of the hand and wrist part was controlled proportionally to the force level $\sigma_k(n)$ defined as (3). The operator could control the manipulator intuitively and perform some simple tasks based on this method. However, it is more realistic to control the hand and wrist part based on the joint torque, which is calculated from the force level $\sigma_k(n)$ and joint impedance properties, because the skillful motions of the human arm are realized by regulating them. Motions similar to those of the human arm may be realized if the joint impedance model of the human arm is introduced into the control system and the arm is controlled by the estimated torque.

Several studies on the wrist joint impedance of the human arm, such as stiffness, viscosity, and inertia, have been carried out [37]–[42]. These were conducted primarily in the physiological field to examine the kinetic characteristics of human



(a) Arm control (b) Hand and wrist control (c) A pick-and-place task

Fig. 9. Motion photos while controlling the manipulator. Subject C (fully functional) and A (amputee) performed the manipulation using their EMG signals and arm motions.

movements. For example, Akazawa *et al.* [37] reported on the relation between the stiffness of the Flexor pollicis longus and the myotatic reflex. Gielen and Houk [38] discovered that changes in the wrist joint viscosity depended on its angular velocity. Sinkjær and Hayashi [39] examined the changes in wrist joint stiffness by intercepting the reflection system. Furthermore, Abul-haj and Hogan [13] utilized the joint impedance model for prosthetic control and tried to realize control feelings similar to those of the human hand. Tsuji [40] and Tsuji *et al.* [41] have also been studying how to estimate joint impedance parameters from EMG signals.

Let us consider control based on the joint impedance model of the human forearm. For example, the dynamic equation of the jth joint in the hand and wrist part is defined as

$$I_j\ddot{\theta}_j + B_j\dot{\theta}_j + K_j(\theta_j - \theta_j^o) = \tau_j^{ex} \tag{18}$$

where I_j, B_j, and K_j are the inertia, the viscosity, and the stiffness, and τ_j^{ex} and θ_j are the external torque and the measured angles of the jth joint. The equilibrium angle (virtual trajectory) of jth joint is calculated as

$$\theta_j^o = \frac{\sigma_k(n)\tau_k^{\max}}{K_j} \tag{19}$$

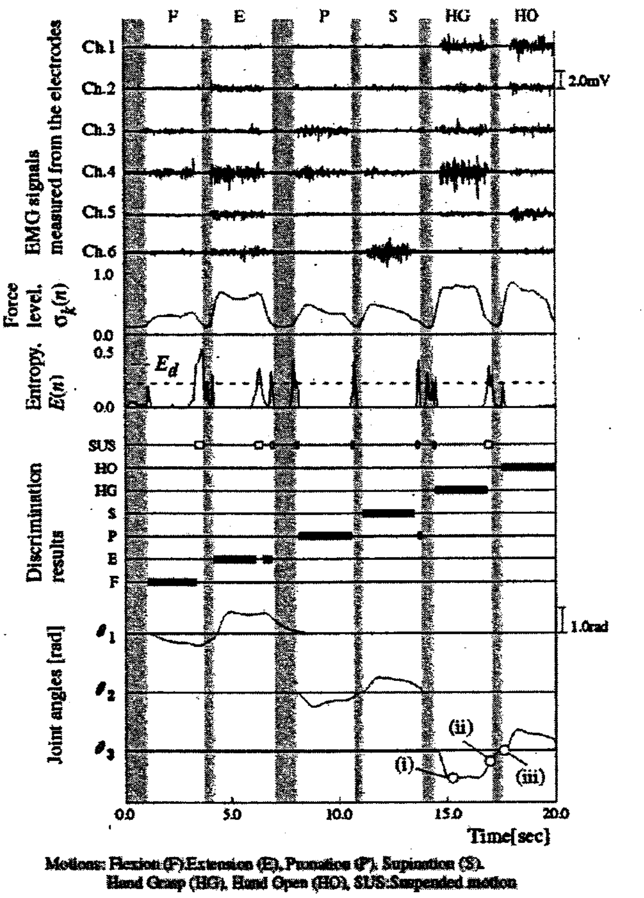
where $\tau_k^{\max}$ is the maximal torque for the motion k.

TABLE IV
PARAMETERS OF IMPEDANCE MODEL USED IN EXPERIMENTS

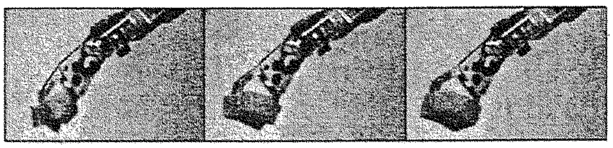
Joints	Motions(k)	K_j [Nm/rad]	B_j [Nms/rad]	I_j [kgm^2]	τ_k^{max} [Nm]
J_4	Flexion (1) / Extension (2)	6.0	0.1	0.004	0.30 (k = 1, 2)
J_5	Pronation (3) / Supination (4)	4.0	0.1	0.002	0.20 (k = 3, 4)
J_7	Grasp (5) / Open (6)	4.0	0.2	0.001	0.36 (k = 5, 6)

This impedance model functions as a kind of the filter so that the joint angles are controlled smoothly even if the system fails to discriminate the motion with complete accuracy. In the proposed method, the joint angle and velocity are calculated by integrating (18) numerically. The joint angle then tracks them using the PID control method. If the numerical calculation is executed in a sufficiently short time and the PID controller controls the joint angles with a high degree of accuracy, this method can be regarded to be the same as the conventional impedance control method.

We conducted an experiment in order to examine the ability of the joint impedance control defined above. As the first step of this trial, we determined the parameters in Table IV, although they may change depending on the joint angles, the muscular contraction levels, and other factors. These values were specified by trial and error considering the results in our previous research [40], [41]. Subject C executed six forearm motions (K = 6: 1. flexion, 2. extension, 3. pronation, 4. supination, 5. hand grasp, 6. hand open), and six electrodes (D = 6: ch.



(a)



(i) (ii) (iii)

(b)

Fig. 10. Example of the joint impedance control. The subject executed six hand and wrist motions for about 20 s. The darkened areas indicate no motions because the square sum of $\mathrm{EMG}_d(n)$, which was defined as (1), was below the prespecified threshold.

1 Flexor Carpi Radialis, ch. 2 Triceps Brachii, ch. 3 Extensor Carpi Radialis, ch. 4 Biceps Brachii, ch. 5 Brachioradialis, ch. 6 Flexor Carpi Ulnaris) were used.

Fig. 10 shows an example of the joint impedance control for about 20 s. Fig. 10(a) shows the EMG signals, force level $\sigma_k(n)$, the entropy $E(n)$, the discrimination results, and joint angles θ_j. The darkened areas indicate no motion because the square sum of $\mathrm{EMG}_d(n)$, which was defined as (1), was below the prespecified threshold. It can be seen that the operator could successfully control the joint angles based on the joint impedance model. During the manipulation, all motions were performed very smoothly. The motion photographs are presented in Fig. 10(b) and show three hand positions corresponding to the different joint angles marked (i), (ii), and (iii) in Fig. 10(a). Hand and wrist motions similar to those of the human arm were realized using the control method based on the joint impedance model.

However, we cannot clarify whether speed control or impedance control is better, because it depends heavily on the operator's disabled limb and control ability. We should thus select the control method according to the operator's control ability and the objective task.

V. Conclusion

This paper proposed and developed a new human-assisting manipulator system. The distinctive feature of our system is that it uses a novel statistical neural network, called LLGMN, to discriminate the EMG pattern. LLGMN includes a preorganized structure and can model the complicated mapping between the input pattern and the discrimination classes even for a small sample size. Furthermore, the weight coefficients of LLGMN are not statistically constrained and are mutually independent, so that LLGMN achieved higher discrimination performance than the conventional statistical technique. In contrast, BPN, which was frequently used in previous research on EMG-controlled prosthetic hands, is trained by using only a large amount of learning data, and cannot achieve high discrimination performance. Also, the discrimination suspension method and an online learning method can be designed using the LLGMN's outputs, which indicates the *a posteriori* probabilities of the corresponding motions. We conducted experiments using the developed system for eight subjects, including two amputees. The results obtained in the experiments are summarized below.

- The operator's intended motions could be discriminated from the EMG patterns accurately enough using LLGMN.
- The system maintained highly accurate motion discrimination using the discrimination suspension rule and the online learning method, even if the operator used the manipulator continuously for a couple of hours.
- The operator could control the human-assisting manipulator intuitively using his/her EMG signals and arm motions measured by the 3-D position sensor.
- Motions similar to those of the human arm were realized based on the joint impedance-control method using the joint torque calculated from the EMG signals.

In our future research, we would like to try to perform a "having-a-meal" task using the developed system. However, it will be difficult to directly extend the proposed method in this paper, since the operator will have to concentrate heavily on the EMG operation. A new control strategy may be necessary to improve the control of the developed system. Therefore, we are trying to introduce task models, such as a grasping an object and spooning soup, into the system [43]. Based on this technique, an amputee may realize various tasks by selecting a simple command using the EMG signals. Also, we would like to examine the relationship between the joint impedance parameters of the human arm and the muscular contraction level, and introduce this regulation mechanism into the control system to realize more a natural feeling of the prosthetic control.

Acknowledgment

The authors would like to thank H. Sako and K. Fujita for participation in the experiments.

REFERENCES

[1] W. A. Gruver, "Intelligent robotics in manufacturing, service, and rehabilitation: An overview," *IEEE Trans. Ind. Electron.*, vol. 41, pp. 4–11, Feb. 1994.

[2] H. Kazerooni, "Human-robot interaction via the transfer of power and information signals," *IEEE Trans Syst., Man, Cybern.*, vol. 20, pp. 450–463, Feb. 1990.

[3] R. B. Salter, "Clinical application of basic research on continuous passive motion for disorders and injury of synovial joints. A preliminary report of a feasibility study," *J. Orthop. Res.*, no. 1, pp. 325–342, 1984.

[4] H. I. Krebs, N. Hogan, M. L. Aisen, and B. T. Volpe, "Application of robotics and automation technology in neuro-rehabilitation," in *Proc. Japan/USA Symp. Flexible Automation*, vol. 1, 1996, pp. 269–275.

[5] C. H. Wu, S. L. Chang, and D. T. Lee, "A study of neuromuscular-like control in rehabilitation robot," in *Proc. IEEE Int. Conf. Robotics and Automation*, 1996, pp. 1178–1183.

[6] N. Wiener, *CYBERNETICS or Control and Communication in the Animal and the Machine*. Cambridge, MA: MIT Press, 1948.

[7] I. Kato, E. Okazaki, H. Kikuchi, and K. Iwanami, "Electropneumatically controlled hand prosthesis using pattern recognition of myo-electric signals," in *Dig. 7th ICMBE*, 1967, pp. 367–367.

[8] R. B. Jerard, T. W. Williams, and C. W. Ohlenbusch, "Practical design of an EMG controlled above elbow prosthesis," in *Proc. Conf. Engineering Devices for Rehabilitation*, Boston, MA, 1974, pp. 73–73.

[9] S. C. Jacobson, D. F. Knutti, R. T. Johnson, and H. H. Sears, "Development of the Utah artificial arm," *IEEE Trans. Biomed. Eng.*, vol. BME-29, pp. 249–269, Apr. 1982.

[10] R. L. Abboudi, C. A. Glass, N. A. Newby, J. A. Flint, and W. Craelius, "A biomimetic controller for a multifinger prosthesis," *IEEE Trans. Rehab. Eng.*, vol. 7, pp. 121–129, June 1999.

[11] P. J. Kyberd, O. E. Holland, P. H. Chappell, S. Smith, R. Tregidgo, P. J. Bagwell, and M. Snaith, "Marcus: A two degree of freedom hand prosthesis with hierarchical grip control," *IEEE Trans. Rehab. Eng.*, vol. 3, pp. 70–76, Mar. 1995.

[12] K. Akazawa, H. Takizawa, Y. Hayashi, and K. Fujii, "Development of control system and myoelectric signal processor for biomimetic prosthetic hand," *Biomechanism 9*, pp. 43–53, 1988.

[13] C. J. Abul-haj and N. Hogan, "Functional assessment of control systems for cybernetic elbow prostheses—Part I, Part II," *IEEE Trans. Biomed. Eng.*, vol. 37, pp. 1025–1047, Nov. 1990.

[14] K. Ito, T. Tsuji, A. Kato, and M. Ito, "An EMG-controlled prosthetic forearm in three degrees of freedom using ultrasonic motors," in *Proc. Annu. Int. Conf. IEEE Engineering in Medicine and Biology Soc.*, vol. 14, 1992, pp. 1487–1488.

[15] D. Graupe, J. Magnussen, and A. A. M. Beex, "A microprocessor system for multifunctional control of upper limb prostheses via myoelectric signal identification," *IEEE Trans. Automat. Contr.*, vol. AC-23, pp. 538–544, Aug. 1978.

[16] S. Lee and G. N. Saridis, "The control of a prosthetic arm by EMG pattern recognition," *IEEE Trans. Automat. Contr.*, vol. AC-29, pp. 290–302, Apr. 1984.

[17] P. C. Doershuk, D. E. Gustafson, and A. S. Willsky, "Upper extremity limb function discrimination using EMG signal analysis," *IEEE Trans. Biomed. Eng.*, vol. BME-30, pp. 18–29, Jan. 1983.

[18] T. Tsuji, K. Ito, and M. Nagamachi, "A limb-function discrimination method using EMG signals for the control of multifunctional powered prostheses," *Trans. Inst. Electron., Inform. Commun. Eng.*, vol. J70-D, no. 1, pp. 207–215, 1987.

[19] R. J. Triolo and G. D. Moskowitz, "The theoretical development of a multichannel time-series myoprocessor for simultaneous limb function detection and muscle force estimation," *IEEE Trans. Biomed. Eng.*, vol. 36, pp. 1004–1017, Oct. 1989.

[20] M. F. Kelly, P. A. Parker, and R. N. Scott, "The application of neural networks to myoelectric signal analysis: A preliminary study," *IEEE Trans. Biomed. Eng.*, vol. 37, pp. 221–230, Mar. 1990.

[21] A. Hiraiwa, K. Shimohara, and Y. Tokunaga, "EMG pattern analysis and classification by neural network," in *Proc. IEEE Int. Conf. Systems, Man, Cybernetics*, 1989, pp. 1113–1115.

[22] Y. Koike and M. Kawato, "Estimation of arm posture in 3-D space from surface EMG signals using a neural network model," *Trans. Inst. Electron., Inform., Commun. Eng.*, vol. J77-D-II, no. 1, pp. 193–203, Jan. 1994.

[23] K. A. Farry, I. D. Walker, and R. G. Baraniuk, "Myoelectric teleoperation of a complex robotic hand," *IEEE Trans. Robot. Automat.*, vol. 12, pp. 775–787, Oct. 1996.

[24] H.-P. Huang and C.-Y. Chen, "Development of a myoelectric discrimination system for a multidegree prosthetic hand," in *Proc. IEEE Int. Conf. Robotics and Automation*, 1999, pp. 2392–2397.

[25] T. Tsuji, H. Ichinobe, K. Ito, and M. Nagamachi, "Discrimination of forearm motions from EMG signals by error back propagation typed neural network using entropy," *Trans. Soc. Instrum. Contr. Eng.*, vol. 29, no. 10, pp. 1213–1220, 1993.

[26] T. Tsuji, O. Fukuda, M. Kaneko, and K. Ito, "Pattern classification of time-series EMG signals using neural networks," *Int. J. Adaptive Control and Signal Processing*, vol. 14, pp. 829–848, 2000.

[27] O. Fukuda, T. Tsuji, and M. Kaneko, "Pattern classification of EMG signals using neural networks during a series of motions," *Trans. Inst. Elect. Eng. Japan*, vol. 117-C, no. 10, pp. 1490–1497, 1997.

[28] D. E. Rumelhart, J. L. McClelland, and R. J. Williams, "Learning internal representations by error propagation," *Parallel Distrib. Processing*, vol. I, pp. 318–362, 1986.

[29] T. Tsuji, O. Fukuda, H. Ichinobe, and M. Kaneko, "A log-linearized Gaussian mixture network and its application to EEG pattern classification," *IEEE Trans. Syst., Man, Cybern. C*, vol. 29, pp. 60–72, Feb. 1999.

[30] H. G. C. Tråvén, "A neural network approach to statistical pattern classification by semiparametric estimation of probability density functions," *IEEE Trans. Neural Networks*, vol. 2, pp. 366–377, May 1991.

[31] L. I. Perlovsky and M. M. Manus, "Maximum-likelihood neural networks for sensor fusion and adaptive classification," *Neural Networks*, vol. 4, pp. 89–102, 1991.

[32] O. Fukuda, T. Tsuji, and M. Kaneko, "An EMG-controlled robotic manipulator using neural networks," in *Proc. IEEE Int. Workshop on Robot and Human Communication*, 1997, pp. 442–447.

[33] ——, "A human-supporting manipulator based on manual control using EMG signals," *J. Robot. Soc. Japan*, vol. 18, no. 3, pp. 79–86, 2000.

[34] M. Zak, "Terminal attractors for addressable memory in neural networks," *Phys. Lett. A*, vol. 133, pp. 218–222, 1988.

[35] O. Fukuda, T. Tsuji, A. Otsuka, and M. Kaneko, "EMG-based human-robot interface for rehabilitation aid," in *Proc. IEEE Int. Conf. Robotics and Automation*, vol. 4, 1998, pp. 3492–3497.

[36] O. Fukuda, T. Tsuji, and M. Kaneko, "A human-supporting manipulator using neural network and its clinical application for forearm amputation," in *Proc. IEEE Int. Conf. Knowledge-Based Intelligent Information Engineering Systems*, 1999, pp. 129–134.

[37] K. Akazawa, T. E. Milner, and R. B. Stein, "Modulation of reflex EMG and stiffness in response to stretch of human finger muscle," *J. Neurophysiology*, vol. 49, pp. 16–27, 1983.

[38] C. C. A. M. Gielen and J. C. Houk, "Nonlinear viscosity of human wrist," *J. Neurophysiology*, vol. 52, pp. 553–569, 1994.

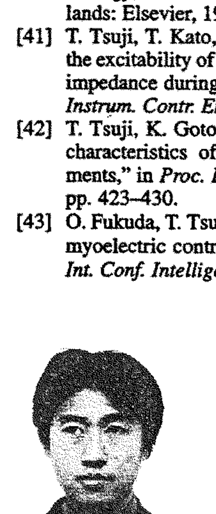
[39] T. Sinkjær and R. Hayashi, "Regulation of wrist stiffness by the stretch reflex," *J. Biomech.*, vol. 22, pp. 1133–1140, 1989.

[40] T. Tsuji, "Human arm impedance in multijoint movements," in *Self-Organization, Computational Maps and Motor Control Advances in Psychology*, P. Morasso and V. Sanguineti, Eds. Amsterdam, The Netherlands: Elsevier, 1997, vol. 119, pp. 357–382.

[41] T. Tsuji, T. Kato, T. Shibata, and M. Kaneko, "The relations between the excitability of the stretch reflex system and changes in the wrist joint impedance during isometric muscle contraction in human," *Trans. Soc. Instrum. Contr. Eng.*, vol. 34, no. 11, pp. 1698–1705, 1998.

[42] T. Tsuji, K. Goto, M. Moritani, M. Kaneko, and P. Morasso, "Spatial characteristics of human hand impedance in multijoint arm movements," in *Proc. IEEE Int. Conf. Intelligent Robots and Systems*, 1994, pp. 423–430.

[43] O. Fukuda, T. Tsuji, K. Takahashi, and M. Kaneko, "Skill assistance for myoelectric control using an event-driven task model," in *Proc. IEEE Int. Conf. Intelligent Robots and Systems*, 2002, pp. 1445–1450.



Osamu Fukuda was born in Fukuoka, Japan, on September 30, 1969. He received the B.E. degree in mechanical engineering from the Kyushu Institute of Technology, Kitakyushu, Japan, in 1993, and the M.E. and Ph. D. degrees in information engineering from Hiroshima University, Higashi-Hiroshima, Japan, in 1997 and 2000, respectively.

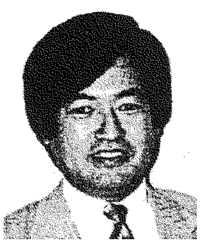
From 1997 to 1999, he was a Research Fellow of the Japan Society for the Promotion of Science. He joined the Mechanical Engineering Laboratory, Agency of Industrial Science and Technology, Ministry of International Trade and Industry, Japan, in 2000. Since 2001, he has been a member of the Assistive Device Technology Group, Research Institute for Human Science and Biomedical Engineering, National Institute of Advanced Industrial Science and Technology, Tsukuba, Japan. His main research interests are in human interface and the neural network.

Dr. Fukuda is a member of the Japan Society of Mechanical Engineers and the Robotics Society of Japan.

Toshio Tsuji (A'88–M'99) was born in Kyoto, Japan, on December 25, 1959. He received the B.E. degree in industrial engineering in 1982, and the M.E. and Doctor of Engineering degrees in systems engineering in 1985 and 1989, all from Hiroshima University, Higashi-Hiroshima, Japan.

He was a Research Associate from 1985 to 1994, and an Associate Professor, from 1994 to 2002, in the Faculty of Engineering at Hiroshima University. He was a Visiting Professor at the University of Genova, Genova, Italy for one year from 1992 to 1993. He is currently a Professor in the Department of Artificial Complex Systems Engineering, Hiroshima University. He has been interested in various aspects of motor control in robot and human movements. His current research interests have focused on the control of EMG-controlled prostheses, and computational neural sciences, in particular, biological motor control.

Dr. Tsuji is a member of the Japan Society of Mechanical Engineers, Robotics Society of Japan, and Japanese Society of Instrumentation and Control Engineers.



Makoto Kaneko (A'84–M'87–SM'00) received the B.S. degree in mechanical engineering from Kyushu Institute of Technology, Iizuka, Japan, in 1976, and the M.S. and Ph.D. degrees in mechanical engineering from Tokyo University, Tokyo, Japan, in 1978 and 1981, respectively.

From 1981 to 1990, he was a researcher with the Mechanical Engineering Laboratory (MEL), Ministry of International Trade and Industry (MITI), Tsukuba Science City, Japan. From 1988 to 1989, he was a Postdoctoral Fellow with the Technical University of Darmstadt, Darmstadt, Germany. From 1990 to 1993, he was an Associate Professor with the Department of Computer Science and System Engineering, Kyushu Institute of Technology. Since October 1993, he has been with Hiroshima University, Higashi-Hiroshima, Japan, as a Professor in the Graduate School of Engineering. His research interests include tactile-based active sensing, grasping strategy, and medical robotics.

Dr. Kaneko received eight academic awards, including the Humboldt Research Award, IEEE ICRA Best Manipulation Award, and IEEE IASTP Outstanding Paper Award. He served as a Technical Editor of the IEEE TRANSACTIONS ON ROBOTICS AND AUTOMATION from 1990 to 1994. He is a member of the IEEE Robotics and Automation, Systems, Man, and Cybernetics, and Industrial Electronics Societies.

Akira Otsuka was born in Ehime, Japan, on April 17, 1949. He received the certificate in physical therapy in 1972, the B.A. degree in social welfare in 1983 from Bukkyo University, Bukkyo, Japan, and the Doctor of Engineering degree in systems engineering in 2002 from Hiroshima University, Higashi-Hiroshima, Japan.

He was a practicing Physical Therapist from 1972 to 1991 and the Head of the Physical Therapy Department at Aino Gakuin from 1991 to 1995. He is currently a Professor in the Department of Physical Therapy, Hiroshima Prefectural College of Health Sciences, Mihara, Japan. He has been interested in and actively engaged in many facets of the human control of upper extremity prostheses and of patients with neuromuscular skeletal disorders. His current research interests are centered on internally-powered hand prostheses and "barrier-free" access projects for those with disabilities.

Dr. Otsuka is a member of the Japanese Physical Therapy Association and the International Society for Prosthetics and Orthotics.