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# Bio-mimetic Impedance Control of an EMG-controlled Prosthetic Hand

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**Abstract**

*This paper proposes a new control method of an externally powered prosthetic hand based on a skeletal muscle model. This method consists of two steps: In the first step, a joint of a prosthetic hand to be driven is selected based on the EMG pattern discrimination using a neural network. Then, muscular contraction levels of flexors and extensors are estimated using other neural networks and used for an impedance control of the prosthetic hand in the second step. In the experiments, natural feeling of the prosthetic control similar to that of a human arm is realized using the neural networks and the impedance control.*

**Key Words:** EMG signals, Prosthetic hand, Neural network, Impedance control.

## 1 Introduction

The number of people who have amputated their extremities by labor accidents, traffic accidents or other afflictions has been increasing with the years, although the importance of safety management and prevention of such accidents is fully recognized. Since precise and complex motions may be very difficult in their daily activities, development of prosthetic systems is necessary to support their daily activities and enable them to achieve social integration. Especially, artificial hand are required to be developed, since the role of "hand" is very important. If an externally powered prosthetic hand with natural feeling of control is developed, it seems to be useful. However, the control of such a hand is a difficult issue, which must be carefully designed consistent with amputee's remaining functions.

Many researchers have designed prosthetic limbs for amputees since its concept was proposed by Wiener in *Cybernetics* [1]. In the previous researches, electromyogram (EMG) has been often used as an interface tool of the prosthetic hands, because the EMG signals include information about operator's intended motion [2]-[8]. For example, the EMG-prosthetic hand made in USSR [2], the Waseda hand developed by Kato et al. [3], the Boston arm by MIT [4] and the Utha artificial arm by Jacobson et al. [5] are the pioneers in this field. Since the EMG signals also include information about force level and mechanical impedance properties of the limb motion, Akazawa et al. [6] estimated forces of flexors and extensors from the EMG signals, and proposed a scheme to use the EMG signals for control of a prosthetic hand. Also, Abul-haj and Hogan [8] proposed the prosthetic control based on an impedance model and analyzed its control characteristics.

Most of previous researches, however, used only the on/off control of prosthetic arms depending on results of EMG pattern discrimination [2], [3], [7], or controlled only a particular joint depending on torque estimated from the EMG signals [4], [5], [6], [8]. Multi-joint control of prosthetic arms considering variable viscoelasticity of flexors and extensors has not been realized yet.

This paper proposes a new control method of an externally powered multi-joint prosthetic hand, which considers muscular contraction levels of flexors and extensors using neural networks. This method can express difference between internal and external forces arising from the flexors and extensors, and all the joints can be controlled as an amputee intends. A natural feeling of control similar to that of the human arm can also be expected since the viscoelasticity of each joint is regulated using the EMG signals.

## 2 Bio-mimetic Control of Multi-Joint Motions

### 2.1 Control Strategy

Various human motions are generally realized by multiple skeletal muscles related to each joint. Therefore, the multi-joint motions may be controlled, if muscular contraction levels related to all joints can be estimated accurately from the EMG signals. However, if only the human wrist joint is considered, it has at least

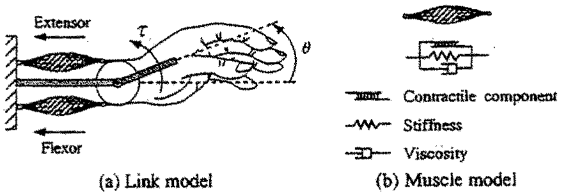


**Fig.1** Musculo-skeletal model of human wrist joint

three degrees of freedom and many muscles are related complicatedly. Moreover, the EMG signals measured on skin surface contain only information on muscles shallowly located in a human body, and the measured EMG signals have nonlinear and non-stationary characteristics. Therefore, the estimation of all forces and torques caused by the muscles is extremely difficult.

To overcome the difficulties, this paper proposed a new control method which consists of two steps: In the first step, the operator's intended motion is estimated from the surface EMG signals measured from the operator's skin, and then the joint of a prosthetic hand to be driven is selected. In the second step, muscular contraction levels of flexors and extensors are estimated, and the joint which is selected in the first step is controlled based on an impedance control method.

Although many studies on discrimination of motion from the EMG patterns have been reported so far[7][10][11], the method[12] proposed by Fukuda et al. is used for the first step. Also, many researchers have reported on the impedance control of the single-joint prosthetic arm using EMG signals[6][8][9]. We have already proposed the impedance control method of an externally powered prosthetic hand with three degrees of freedom based on the EMG signals[13]. However, this method did not consider difference between internal and external forces arising from the multiple muscles. If the internal and external forces are estimated separately from the flexors and the extensors, the joint control can be expected to be more natural and flexible. Especially, the stiffness control of the joint similar to that of the human arm may be realized using the internal force level.

### 2.2 Single Joint Model Considering Flexors and Extensors

Skillful motions performed by a human arm are realized by regulating its impedance property such as stiffness, viscosity, and inertia[14]. A natural feeling of control similar to that of the human arm can be expected, if the prosthetic control is performed on the basis of the impedance control with human arm impedance properties.

As shown in Fig. 1 (a), the characteristics of a joint motion can be represented by tension balance of flexors and extensors. Here, each tension of muscle $f_i$ is modeled as

$$f_i = f_{0i}(\alpha_i) - k_i(\alpha_i)x_i - b_i(\alpha_i)\dot{x}_i, \qquad (1)$$

where $\alpha_i$ $(0 \leq \alpha_i \leq 1)$ is the muscular contraction level; $f_{0i}$ is the maximum tension of muscle under isometric contraction in its natural length; and $x_i$, $k_i$, and $b_i$ are the displacement, stiffness, and viscosity, respectively. Also, the subscript $i \in \{f, e\}$ indicates flexors or extensors. Therefore, torque $\tau_f$ and $\tau_e$ generated by flexors and extensors are also described as

$$\tau_i = \tau_{0i}(\alpha_i) - K_i(\alpha_i)\theta - B_i(\alpha_i)\dot{\theta}, \qquad (2)$$

where $\tau_{0i}(\alpha_i)$, $K_i(\alpha_i)$, and $B_i(\alpha_i)$ are the joint torque in the natural muscle length, stiffness and viscosity, respectively; and $\theta$ is the joint angle. Thus, the equation of the wrist joint motion is represented as

$$\begin{aligned} I\ddot{\theta} &= \tau_f + \tau_e \\ &= \tau_0(\alpha_f, \alpha_e) - K(\alpha_f, \alpha_e)\theta - B(\alpha_f, \alpha_e)\dot{\theta}, \end{aligned} \qquad (3)$$

where $I$, $K(\alpha_f, \alpha_e)$, and $B(\alpha_f, \alpha_e)$ are the impedance parameters of the wrist joint such as the moment of inertia, joint stiffness and viscosity, respectively; and $\tau_0(\alpha_f, \alpha_e)$ is the joint torque in the muscle natural length. In order to control movements of the prosthetic hand based on (3), three problems must be solved: i) how to calculate muscle contraction levels $\alpha_f$, $\alpha_e$ of flexors and extensors during movements; ii) how to define $\tau_0(\alpha_f, \alpha_e)$; and iii) how to determine the parameters of $K(\alpha_f, \alpha_e)$ and $B(\alpha_f, \alpha_e)$.

In this paper, the EMG signals and neural networks are utilized for the first and second problems. Also, for the third one, the impedance parameters of wrist joint of intact subjects are measured experimentally[13].

## 3 Control System of the Prosthetic Hand

Figure 2 shows the control system of the prosthetic hand developed in this paper, which is based on the bio-mimetic impedance model explained in the previous section. This system estimates an operator's intended motion and selects a driven joint of the prosthetic hand. Then it calculates muscular contraction levels of flexors and extensors under the estimated motion. The prosthetic hand is controlled according to the muscle contraction levels based on the impedance control. It can be expected to realize smooth motion similar to that of the human hand.

This system consists of four parts: the feature extraction part, the determination part of the driven

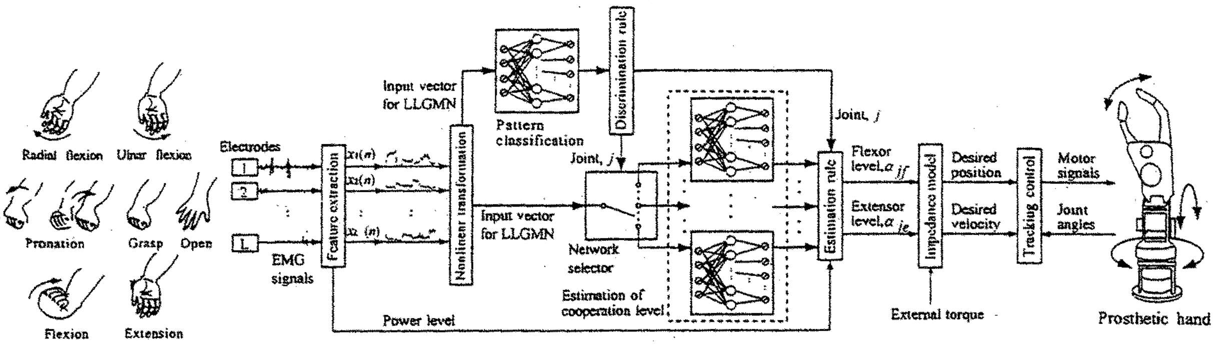


**Fig.2** Bio-mimetic control system of a prosthetic hand

joint, the estimation part of the muscular contraction levels, and the impedance control part. First, the EMG signals measured from electrodes are preprocessed, and its features are extracted for the determination of a driven joint and the estimation of muscle contraction levels. Then, the driven joint is determined by pattern discrimination using a neural network, and the cooperation ratio among several muscles are estimated from the EMG pattern using other neural networks. Also, the muscular contraction levels are calculated under the estimated cooperation ratio, and used as control signals of the prosthetic hand. The details of the signal processing and the prosthetic hand used in the developed system are explained in the following subsections.

### 3.1 Feature Extraction of the EMG Signals

First, the EMG signals measured from $L$ pairs of electrodes (Web5000: NIHON KOHDEN Corp.) are digitized by an A/D converter (sampling frequency, 1.0 [kHz]; and quantization, 12 [bits]) after they are amplified (70 [dB]), rectified and filtered out through the digital fourth order Butterworth filter (cut-off frequency, $f_c$ [Hz]). These sampled signals are defined as $E_l(n)$ $(l = 1, \cdots, L)$.

Next, the mean value $E_\mu(n)$ of all channels is calculated as

$$E_\mu(n) = \frac{1}{L}\sum_{l=1}^{L}(E_l(n) - E_l^{st}), \qquad (4)$$

where $E_l^{st}$ is the mean value of $E_l(n)$ which is measured while relaxing the arm. In this paper, $E_\mu(n)$ is used for the recognition of the beginning and ending of motions: When $E_\mu(n)$ is over the motion appearance threshold $E_d$, the motion is regarded as having occurred.

For the EMG pattern discrimination, $E_l(n)$ are normalized to make the sum of $L$ channels equal to 1.0:

$$x_l(n) = \frac{E_l(n) - E_l^{st}}{\sum_{l=1}^{L}(E_l(n) - E_l^{st})}. \qquad (5)$$

The neural network uses $x(n) = [x_1(n),\ x_2(n), \cdots, x_L(n)]^{\mathrm{T}} \in \Re^L$ as the input vector for the estimation of motion and torque.

### 3.2 Determination of the Driven Joint

For the estimation of operator's intended motion, the Log-Linearized Gaussian Mixture Network (LLGMN)[12] is used. The LLGMN is the three-layered network, and constructed based on the log-linearized Gaussian mixture model (GMM). This network can calculate the posteriori probabilities for the input pattern after the learning. In the proposed system, the driven joint $j$ is selected based on the output of the LLGMN.

### 3.3 Estimation of Muscular Contraction Level

In order to calculate the muscular contraction levels, the cooperation ratio $\beta_{jf}, \beta_{je}$ $(\forall j : \beta_{jf} + \beta_{je} = 1)$ between a group of flexors and a group of extensors for the $j$-th joint are estimated, and the gain $G(n)$ which translates the cooperation ratio $\beta_{jf}, \beta_{je}$ to the muscular contraction levels $\alpha_{jf},\ \alpha_{je}$ is also calculated. In this process, the LLGMN is also used for the estimation of the cooperation ratio among flexors and extensors based on the EMG pattern, the outputs of which are considered as the cooperation ratio of flexors and extensors. Note that if the estimated motion is considered as co-contraction in the determination process of the driven joint, the cooperation ratio are settled as $\beta_{jf} = \beta_{je} = 0.5$. This method can realize not the maintaining posture with variable viscoelasticity. In the above process, the EMG signals for learning data are sampled during the maintenance of each motion.

On the other hand, the gain $G(n)$ is calculated using amplitude information of the EMG signals as follows:

$$G(n) = \max\{\frac{E_\mu(n) - E_d}{\sum_{i\in\{f,e\}} E_{ji}^{\max}\beta_{ji} - E_d}, 0\}, \quad (6)$$

where $E_{ji}^{\max}$ $(i \in \{f, e\})$ are the maximum value of $E_\mu(n)$ in the flexion motion and the extension motion of the joint $j$, which are measured before the prosthetic control. Therefore, muscular contraction levels $\alpha_{jf}$, $\alpha_{je}$ are described as

$$\alpha_{ji} = G(n)\beta_{ji}, \quad (7)$$

where $i \in \{f, e\}$. Note that if $E_\mu(n)$ is less than the threshold $E_d$, the gain $G(n)$ equals to zero. This means no motion has occurred. Conversely, if $E_\mu(n)$ is over the threshold $E_d$, $G(n)$ can be regarded as the ratio to the maximum muscular contraction level.

### 3.4 Impedance Control

The estimation method of the muscular contraction levels $\alpha_{jf}$, $\alpha_{je}$ has been explained as mentioned above. Then, the joint torque $\tau_j(\alpha_{jf}, \alpha_{je})$ in (3) must be calculated. In this paper, it is assumed that the joint torques caused by the muscular contraction of flexors and extensors have almost the same properties.

Under this assumption, the joint torque $\tau_j(\alpha_{jf}, \alpha_{je})$ is approximated as

$$\tau_{0j}(\alpha_{jf}, \alpha_{je}) \approx g_j(\alpha_{jf} - \alpha_{je}), \quad (8)$$

where $g_j$ is a constant which means the maximum joint torque with the natural muscular length. On the other hand, we also approximate the relationships between muscular contraction levels and impedance properties such as stiffness and viscosity around the joint as follows:

$$K(\alpha_f, \alpha_e) = k_1\alpha_f^{p_1} + k_2\alpha_e^{p_2} + k_3, \quad (9)$$

$$B(\alpha_f, \alpha_e) = b_1\alpha_f^{q_1} + b_2\alpha_e^{q_2} + b_3, \quad (10)$$

where $k_s$, $b_s$ $(s = 1, 2, 3)$, $p_t$, $q_t$ $(t = 1, 2)$ are constants; and $k_3$, $b_3$ correspond to the viscoelasticity during relaxing the arm.

Using the above equations, the desired joint angles can be calculated numerically using the dynamic equation (3) considering changes of the EMG signals. Figure 3 shows the impedance control system used in this paper. After the impedance filter part receives $\alpha_f$ and $\alpha_e$, the desired joint angles are calculated. Then, they are used in the tracking control part shown in Fig. 3, where $K_p$, $K_i$ and $K_v$ are the gain parameters for the PID control[13]. This method can be expected

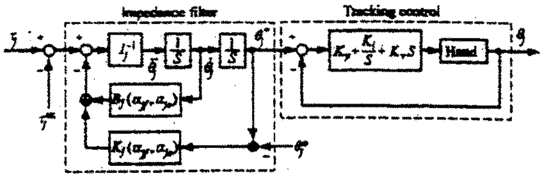


Fig.3 Impedance control system

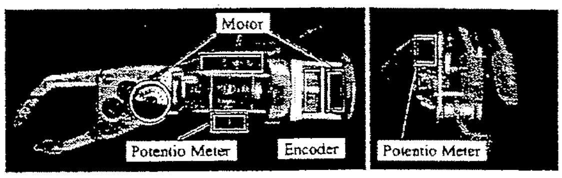


Fig.4 Prosthetic forearm

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. Also, the hand can react to the external force using the force sensor.

### 3.5 Prosthetic Hand

The photograph of the prosthetic hand developed in this paper is shown in Fig. 4. It is almost the same size as an adult's hand, and the weight is about 1.0 [kg]. This prosthetic hand has three degrees of freedom (Supination/Pronation, Radial flexion/Ulnar flexion, Grasp/Open), and each joint is driven by an ultrasonic motor (SINSEI Corp.)[7]. An encoder or a potentiometer is installed as an angular sensor of each joint as shown in Fig. 4.

## 4 Experiments

### 4.1 Determination of Impedance Parameters

The impedance control is one of the effective techniques in order to realize natural feeling of the prosthetic control similar to that of a human hand. However, it is difficult to set the parameters appropriately. Therefore preliminary experiments are carried out in order to estimate the impedance parameters of human wrist joint.

Figure 5 shows the experimental results which indicates the relationship between the muscular contraction levels and measured impedance parameters $K_j$, $B_j$[13]. In this figure, $\alpha_f$, $\alpha_e$ $(0 \le \alpha_f, \alpha_e \le 1)$ indicate the muscular contraction levels estimated from the EMG signals. The EMG signals are measured from four pairs of electrodes located to flexors or extensors: 1ch. Flexor Carpi Radialis, 2ch. Flexor Carpi Ulnaris, 3ch. Exten Carpi Radialis, 4ch. Brachioradialis. Then, they are rectified, filtered out and normalized by the EMG signals during the maximum volun-

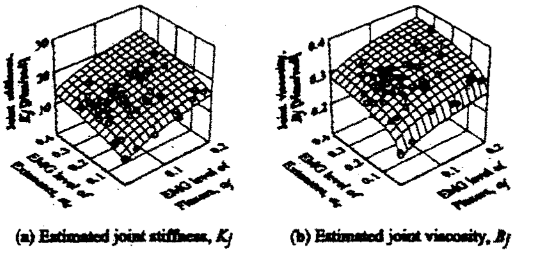


**Fig.5** 3D plots of the estimated impedance parameters of human wrist joint

**Table 1** Viscoelastic parameters used in Eqs. (9) and (10)

| | $k_1$ | $k_2$ | $k_3$ | $p_1$ | $p_2$ | $b_1$ | $b_2$ | $b_3$ | $q_1$ | $q_2$ |
|---|---|---|---|---|---|---|---|---|---|---|
| $j=1$ | 23.7 | 16.0 | 0.56 | 0.37 | 0.71 | 0.46 | 0.04 | 0.097 | 0.54 | 0.60 |
| $j=2$ | 20.0 | 20.0 | 0.60 | 0.50 | 0.50 | 0.30 | 0.30 | 0.220 | 0.5 | 0.5 |
| $j=3$ | 0.80 | 0.80 | 0.30 | 0.6 | 0.6 | 0.08 | 0.08 | 0.009 | 0.3 | 0.3 |

$k_1$, $k_2$, $k_3$: [Nm/rad]
$b_1$, $b_2$, $b_3$: [Nms/rad]

tary contraction. The plotted data are the measured values, and the fitting surface indicates the approximated value based on the equations (9) and (10). It can be seen from the experimental results that stiffness $K_j$ and viscosity $B_j$ are changed according to the muscle contraction: Especially, $K_j$ and $B_j$ increase as the muscle contraction levels become high. In the experiments of prosthetic control, parameters of (9) and (10) are settled as shown in Table 1 based on Fig. 5, where $j$ indicates the joint number: 1. Flexion/Extension, 2, Supination/Pronation, 3. Grasp/Open.

### 4.2 Impedance Control

Here, in order to examine the validity of the impedance parameter, the motions of the subject's wrist joint and manipulator's one were compared. The subject was a fully functional (male, age 25) and he was executed the wrist flexion and extension. Then the wrist joint angle and the EMG signals were measured from the subject as shown in Fig. 6. The muscle contraction levels $\alpha_{jf}, \alpha_{je}$ were calculated from the EMG signals using the proposed method, and the desired joint angle $\theta_1^*$ (see Fig. 6) was calculated according to the muscle contraction level and the motion equation of the wrist joint with the variable viscoelasticity (Eqs. (3), (8), (9) and (10)). In the experiment, four electrodes ($L=4$: 1ch. Flexor Carpi Radialis, 2ch. Flexor Carpi Ulnaris, 3ch. Exten Carpi Radialis, 4ch. Brachioradialis) were used and two motions (Flexion/Extension) were discriminated using the neural network. The cut-off frequency of the digital Butterworth filter were settled as $f_c = 1.0$ [Hz], number of the components in hidden layer was settled

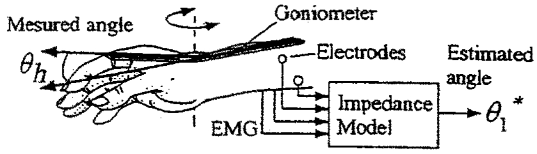


**Fig.6** Estimation of the joint angle from EMG signals based on bio-mimetic impedance model

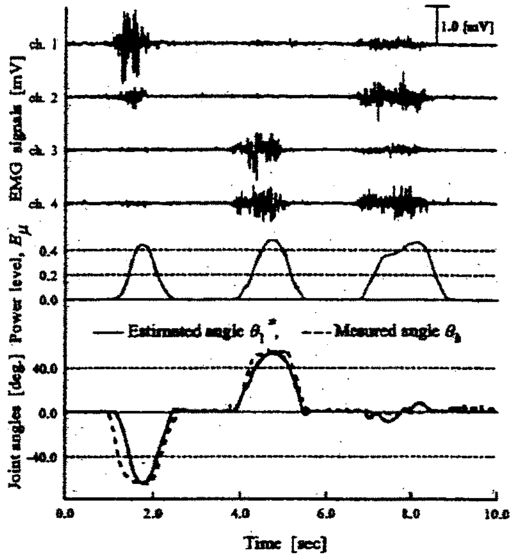


**Fig.7** Comparison between the estimated and measured angles of the wrist joint

as $M=2$, and the motion appearance threshold was settled as $E_d = 0.51$. Fig. 7 shows the experimental result. The wrist joint angle of the manipulator almost agrees with the one of the subject. Moreover, the maintenance of the posture under muscle co-contraction was realized. It can be seen that the joint angles of the prosthetic hand can be controlled using the EMG signals.

### 4.3 Prosthetic Control

Control experiments of the prosthetic hand based on the EMG signal were carried out in order to verify the proposed method using the estimated muscular contraction levels of flexors and extensors. The subject was an amputee (male, age 43) whose forearm was amputated when he was 41 years old. He was never used the EMG controlled hand and usually uses a cosmetic hand. The experimental conditions are almost the same as previous experiments. Eight electrodes ($L=8$) were used, and the sampling frequency was settled as 100 [Hz]. Figure 8 is one of the experimental results, which shows the desired motion, the EMG signals of 8 channels, power level $E_\mu$, discriminated driven joints $j$ where N. M. indicates the no motion,

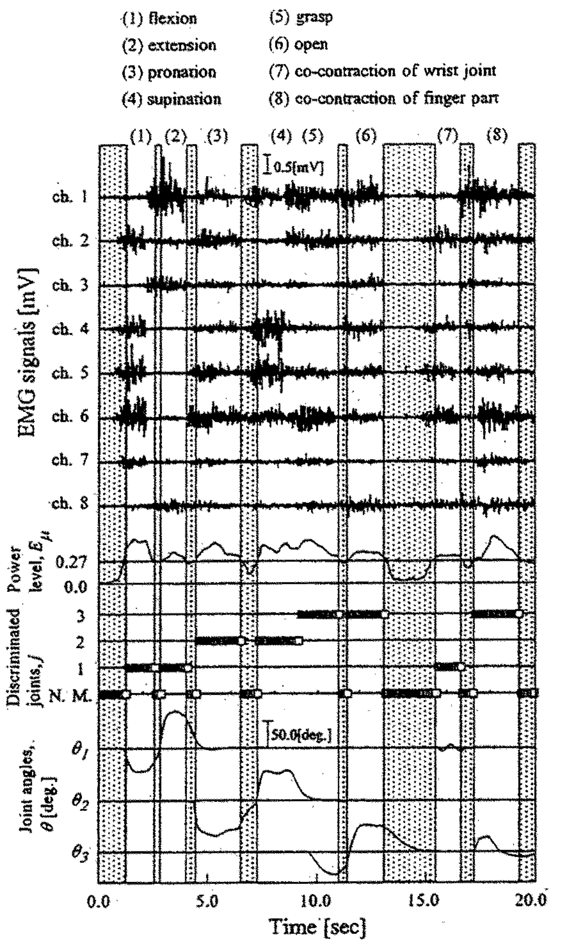


**Fig.8** An example of experimental results

and the desired joint angles $\theta_1, \theta_2, \theta_3$ calculated using the impedance model. The joint angles of the prosthetic hand can be controlled using the EMG signals. Especially, the co-contraction of flexors and extensors can be expressed sufficiently: The change of the joint angles are small although the power level $E_\mu$ is increased during (7) and (8) in Fig. 8.

## 5 Conclusion

This paper proposed the prosthetic control method considering flexors and extensors in order to construct the multi-joint prosthetic system and to realize natural feeling of its control. In the experiments, the natural feeling of the prosthetic control similar to that of the human hand were realized using the neural networks and the bio-mimetic impedance control method.

In the future, we would like to improve the estimation accuracy of the cooperation ratio of multiple muscles, and re-construct the system which realizes more natural feelings of control.

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