Classification of Combined Motions in Human Joints Through Learning of Individual Motions Based on Muscle Synergy Theory

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***Abstract*— This paper proposes a novel method of pattern classification for user motions to create input signals for human-machine interfaces from electromyograms (EMGs) based on muscle synergy theory. The method can be adopted to represent non-trained combined motions (e.g., wrist flexion during hand grasping) using a recurrent neural network by combining synergy patterns of EMG signals preprocessed by the network. This approach allows combined motions (i.e., unlearned motions) to be classified through learning of individual motions (such as hand grasping and wrist flexion) only, meaning that the number of motions can be increased without increasing the number of learning samples or the learning time needed to control devices such as prosthetic hands.**

The effectiveness of the proposed method was demonstrated through motion classification tests and prosthetic hand control experiments with six subjects (including a forearm amputee). The results showed that 18 motions (12 combined and 6 single) could be classified sufficiently with learning for just 6 single motions (average rate: 89.2 ± 6.33%), and the amputee was able to control a prosthetic hand using single and combined motions at will.

I. Introduction

Electromyograms (EMGs) reflect human motion intentions, and can be used to control a range of devices such as EMG-based prosthetic hands. Various related methods have been discussed in previous studies [1]–[4].

To enable estimation of human intentions and motions from EMG signals, it is necessary to model the relationships between each motion and samples of individual EMG signals. However, in the case of multiple motion estimation based on the idea of EMG pattern classification, large amounts of sample data and time are necessary to allow the learning of discriminators (such as neural networks) in accordance with the higher number of motions involved. The realization of EMG-based control for highly complex robot devices such as prosthetic hands with multiple degrees of freedom (DOFs) is exceptionally difficult due to the impracticality of measuring the large number of EMG signals corresponding to every possible motion generated by a human hand.

Human movement generation (i.e., the control of multiple joints and muscles with many DOFs) is quite a complex problem because the number of DOFs of the human body at the muscle level is in the order of 10^3 [5]. It is therefore considered that the human movement control system is realized based on a combination of multiple muscle synergies. Muscle synergy is defined by Sherrington as cooperative muscle activity [6], and some researchers have tried to extract muscle synergies from EMG signals. As an example, Bizzi et al. tried to extract multiple muscle synergies from time-series EMGs of a frog's leg, and reported that the measured EMGs could be reconstructed using a combination of the muscle synergies extracted [7]. However, the synergies identified focused only on measured EMGs, so cannot be used to estimate unknown motions.

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This paper proposes a novel pattern classification method that can be used to estimate unknown motion combinations by putting together the muscle synergies of a individual motion (e.g., a simple movement of the human hand such as wrist flexion or extension). This approach considers that each single-motion EMG signal reflects one muscle synergy. The muscle synergy is extracted from the individual motion's EMG pattern using a recurrent neural network, and unknown movements consisting of individual motions such as wrist extension with hand grasping (referred to as combined motions) are then estimated based on muscle synergy combinations. The combined motions can be estimated using only the single-motion EMG signals, and the number of motions in the problem of EMG pattern classification can be increased without a corresponding increase in the amount of sample data and learning time required.

This paper is organized as follows: in Sections II and III, the details of the muscle synergy theory and the proposed method are described. The validity of the proposed system is examined in Section IV, the conclusion is outlined in Section V, and future study plans are discussed to wrap up the paper.

II. Modeling of combined motions based on muscle synergy theory

Muscle synergies, which are coherent activations of groups of muscles in space or time, have been proposed as building blocks to simplify the construction of motor behavior [7]. The human body has an enormous number of DOFs, and it is exceptionally difficult to control the muscle units involved in achieving related movement; accordingly, the human brain lightens its huge calculation load by managing movements through muscle synergy combinations. If these muscle synergies can be extracted from EMG signals in accordance with human activity, it may be possible to ascertain the control mechanisms of complex movements with multiple DOFs.

Bizzi *et al.* [7] assumed that time series EMG patterns generated from individual movements consist of specific muscle

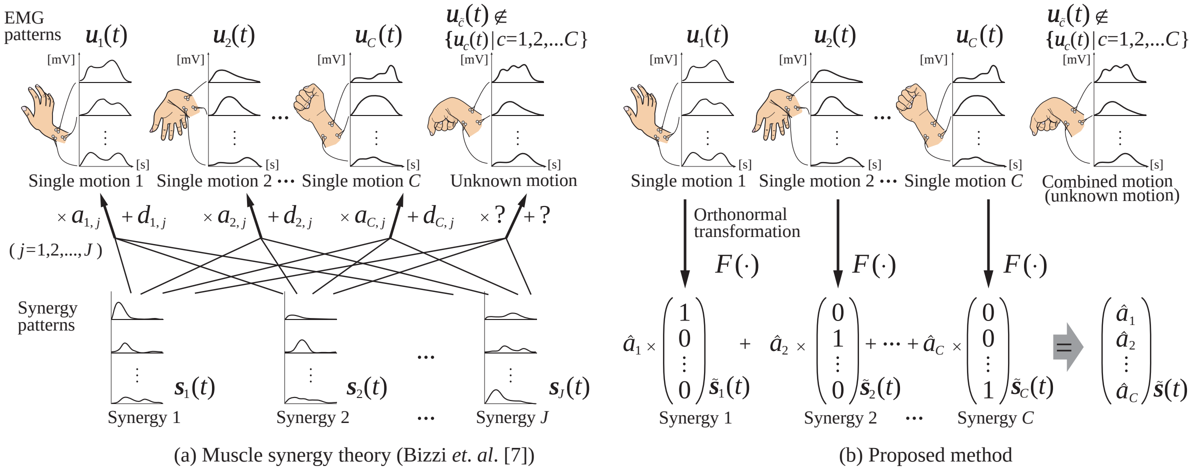

Fig. 1. Relationships between the muscle synergy theory of Bizzi *et al*. and the proposed method

synergy patterns, and defined EMG patterns as follows:

$$\boldsymbol{u}_c(t) = \sum_{j=1}^{J} a_{c,j}\boldsymbol{s}_j(t - d_{c,j}) \ , \qquad (1)$$

where $\boldsymbol{u}_c(t) \in \Re^L$ is an EMG pattern generated by an individual movement at a given time t, $\boldsymbol{s}_j(t) \in \Re^L$ $(j = 1, 2, \ldots, J)$ is the muscle synergy pattern, $a_{c,j}$ is the weight coefficient, $d_{c,j}$ is the delay, L is the number of channels and $c = 1, 2, \ldots, C$ is the motion number. Here, any $\boldsymbol{u}_c(t)$ can be expressed using muscle synergy patterns by searching for the $\boldsymbol{s}_j(t), a_{c,j}$ and $d_{c,j}$ with the minimum reconstruction error as

$$E^2 = \sum_{c=1}^{C}\sum_{t=1}^{T_c} \|\boldsymbol{u}_c(t) - \sum_{j=1}^{J} a_{c,j}\boldsymbol{s}_j(t - d_{c,j})\|^2 \ . \qquad (2)$$

It should be noted that the parameters $\boldsymbol{s}_j(t), a_{c,j}$ and $d_{c,j}$ are necessary to decide the new sample data $\boldsymbol{u}_c(t)$ using Bizzi's method. Accordingly, it is not possible to estimate the $\boldsymbol{u}_{\bar{c}}(t)(\notin \{\boldsymbol{u}_c(t)|c = 1, 2, \ldots, C\})$ of unknown motions using the calculated muscle synergy pattern $\boldsymbol{s}_j(t)$ (Fig. 1(a)).

In this paper, it is considered that unknown combined motions are expressed by the linear sum function of C basis vectors (which convert the muscle synergy pattern corresponding to C single motions into an orthonormal basis vector of C dimensions in vector space). First, the time series EMG $[\boldsymbol{u}(t), \boldsymbol{u}(t-1), \ldots, \boldsymbol{u}(t-n)] \in \Re^{L\times(n+1)}$ is converted as follows:

$$\tilde{\boldsymbol{s}}(t) = F(\boldsymbol{u}(t), \boldsymbol{u}(t-1), \cdots, \boldsymbol{u}(t-n)) \ . \qquad (3)$$

Here, $\tilde{\boldsymbol{s}}(t) = [\tilde{s}_1(t), \cdots, \tilde{s}_C(t)]^{\mathrm{T}} \in \Re^C$, $\sum_{j=1}^{C} \tilde{s}_j(t) = 1$, and the function $F(\cdot)$ converts the jth single motion $[\boldsymbol{u}_j(t), \boldsymbol{u}_j(t-1), \cdots, \boldsymbol{u}_j(t-n)] \in \Re^{L\times(n+1)}$ into unit vector $\tilde{\boldsymbol{s}}_j(t) = F(\boldsymbol{u}_j(t), \boldsymbol{u}_j(t-1), \cdots, \boldsymbol{u}_j(t-n)) \in \Re^C$ (where the jth element is equal to 1). Based on the above method, the combined motions' EMG $\tilde{\boldsymbol{s}}(t)$ can be expressed using $\tilde{\boldsymbol{s}}_j(t)$ as follows:

$$\tilde{\boldsymbol{s}}(t) = \sum_{j=1}^{C} \hat{a}_j \tilde{\boldsymbol{s}}_j(t) \ , \qquad (4)$$

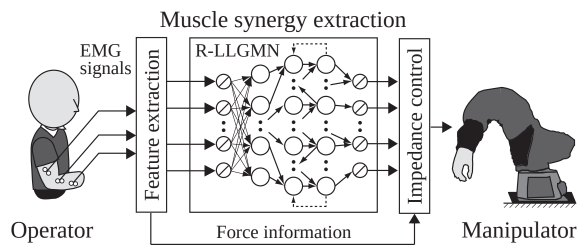

Fig. 2. Overview of the proposed pattern classification method for combined motions with a prosthetic arm

where $\hat{a}_j$ is the combination ratio of each single motion. Since $\tilde{\boldsymbol{s}}_j(t)$ is an orthonormal system, $\tilde{\boldsymbol{s}}(t)$ is expressed as

$$\tilde{\boldsymbol{s}}(t) = [\hat{a}_1, ..., \hat{a}_j, ..., \hat{a}_C]^{\mathrm{T}} \ . \qquad (5)$$

Thus, if the function $F(\cdot)$ is found from the time series EMG of the single motions, the combination ratio $\hat{a}_j$ of each single motion can be calculated by converting the combined motions' EMG into $\tilde{\boldsymbol{s}}(t)$ (Fig. 1(b)). This paper outlines the proposal of a construction method for the function $F(\cdot)$ using a recurrent neural network, and the following section describes efforts to control a prosthetic hand based on muscle synergy theory.

III. Combined Motion Classification for Prosthetic Hand Control

The concept of the proposed combined motion classification method for controlling a prosthetic hand is shown in Fig. 2. The details of each part are outlined in the following subsections.

A. EMG measurement and feature extraction

First, EMG signals measured from L pairs of electrodes are digitized using an A/D converter (sampling frequency: f_s [Hz]), and are rectified and filtered out through a second-order Butterworth filter (cut-off frequency: f_c [Hz]) for each channel. These sampled time-series EMG signals are

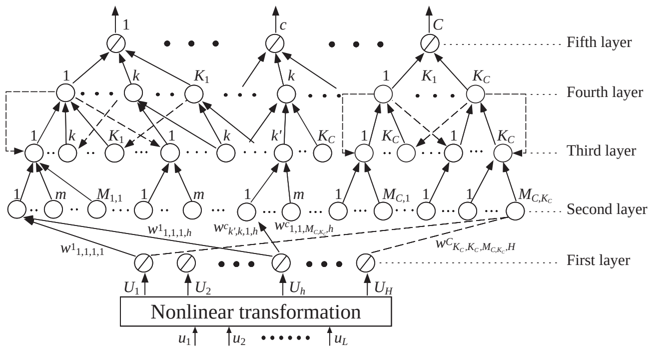

Fig. 3. Structure of the R-LLGMN [8]

defined as $EMG_l(t)$ $(l = 1, \cdots, L)$. The force information $F_{\mathrm{EMG}}(t)$ of the user is then computed as follows:

$$F_{\mathrm{EMG}}(t) = \frac{1}{L}\sum_{l=1}^{L} \frac{\left|EMG_l(t) - \overline{EMG_l^{st}}\right|}{EMG_l^{max} - \overline{EMG_l^{st}}} \tag{6}$$

where $\overline{EMG_l}^{st}$ is the mean value of $EMG_l(t)$ in a state of muscle relaxation and EMG_l^{max} is the maximum voluntary contraction. When $F_{\mathrm{EMG}}(t)$ is greater than the threshold F_{th}, motion is judged to have occurred.

$EMG_l(t)$ is then normalized to make the sum of L channels equal to 1 using the following equation:

$$\begin{aligned} u_l(t) \;\; &= \;\; \frac{\left|EMG_l(t) - \overline{EMG_l}^{st}\right|}{EMG_l^{max} - \overline{EMG_l}^{st}} \\ &\quad \times \sum_{l=1}^{L} \frac{EMG_l^{max} - \overline{EMG_l}^{st}}{\left|EMG_l(t) - \overline{EMG_l}^{st}\right|} \end{aligned} \tag{7}$$

$\boldsymbol{u}(t) = [u_1(t), u_2(t), \cdots, u_L(t)]^{\mathrm{T}} \in \Re^L$ is utilized to estimate user motion.

B. Muscle synergy extraction

The recurrent log-linearized Gaussian mixture network (R-LLGMN) proposed by Tsuji *et al.* [8] is used for muscle synergy extraction, and its network structure is shown in Fig. 3. It is composed of a Gaussian mixture model (GMM) and a hidden Markov model (HMM), and copes with the time-varying characteristics of input signals. Learning the relationships between the user's EMG patterns and each single motion using the R-LLGMN makes it possible to estimate the function $F(\cdot)$ from the user's EMGs for muscle synergy extraction.

First, the input vector $\boldsymbol{u}(t)(t = 1, 2, \cdots, T_d; T_d$ is the time length of the input vector) is processed through non-linear computation using the following equation:

$$\begin{aligned} \boldsymbol{U}(t) \;\; = \;\; & [1, \boldsymbol{u}(t)^{\mathrm{T}}, u_1(t)^2, u_1(t)u_2(t), \cdots, \\ & u_1(t)u_L(t), u_2(t)^2, u_2(t)u_3(t), \\ & \cdots, u_2(t)u_L(t), \cdots, u_L(t)^2]^{\mathrm{T}} \ . \end{aligned} \tag{8}$$

$\boldsymbol{U}(t)$ is a newly input vector at a given time t. The first layer consist of of $H = 1 + L(L+3)/2$ units corresponding to the dimension of $\boldsymbol{U}(t)$ and the identity function is used for activation of each unit.

Unit $\{c, k, k', m\}$ $(c = 1, \cdots, C;\ k, k' = 1, \cdots, K_c;\ m = 1, \cdots, M_{c,k})$ in the second layer receives the output of the first layer ${}^{(1)}O_h(t)$ corresponding to $U_h(t)$ $(h = 1, 2, \cdots, H)$ weighted by the coefficient $w^c_{k',k,m,h}$. The relationship between the input and the output in the fourth layer is defined as

$${}^{(2)}I^c_{k',k,m}(t) = \sum_{h=1}^{H} {}^{(1)}O_h(t) w^c_{k',k,m,h} \ \ , \tag{9}$$

$${}^{(2)}O^c_{k',k,m}(t) = \exp\Big({}^{(2)}I^c_{k',k,m}(t)\Big) \ \ , \tag{10}$$

where K_c is the number of states, and $M_{c,k}$ is the number of components of the Gaussian mixture distribution in class c and state k.

The input into a unit $\{c, k, k'\}$ in the third layer integrates the output of units $\{c, k, k', m\}$ $(m = 1, \cdots, M_{c,k})$ in the second layer, and the output of the fourth layer is also fed back to the third layer. These are expressed as follows:

$${}^{(3)}I^c_{k',k}(t) = \sum_{m=1}^{M_{c,k}} {}^{(2)}O^c_{k',k,m}(t) \ \ , \tag{11}$$

$${}^{(3)}O^c_{k',k}(t) = {}^{(4)}O^c_{k'}(t-1) {}^{(3)}I^c_{k',k}(t) \ \ , \tag{12}$$

where ${}^{(4)}O^c_{k'}(0) = 1.0$ is for the initial state.

The relationship in the fourth layer is defined as

$${}^{(4)}I^c_k(t) = \sum_{k'=1}^{K_c} {}^{(3)}O^c_{k',k}(t) \tag{13}$$

$${}^{(4)}O^c_k(t) = \frac{{}^{(4)}I^c_k(t)}{\sum_{c'=1}^{C}\sum_{k'=1}^{K_{c'}} {}^{(4)}I^{c'}_{k'}(t)} \ \ . \tag{14}$$

Finally, unit c in the fifth layer integrates the outputs of K_c units $\{c, k\}$ $(k = 1, \ldots, K_c)$ in the fourth layer. The relationship in the fifth layer is defined as

$${}^{(5)}I^c(t) = \sum_{k=1}^{K_c} {}^{(4)}O^c_k(t) \tag{15}$$

$${}^{(5)}O^c(t) = {}^{(5)}I^c(t) \ \ . \tag{16}$$

In R-LLGMN, the calculations in the third and fourth layers are associated with the feedback connections. A time-varying relation of each pattern can therefore be used as input data, and it is possible to discriminate for multivariate time series signals using the NN [8].

The R-LLGMN can model the *a posteriori probability* of each single motion through learning (which means setting of the weight coefficient between the first and second layers). The network outputs the *a posteriori probability* ${}^{(5)}O^c(t)$ of each class from the input vector $\boldsymbol{U}(t)$ at given time t through calculation for each layer. The output ${}^{(5)}O^c(t)$ is defined by the element of muscle synergy corresponding to single motion c as $\tilde{s_c}(t)$.

For R-LLGMN learning, only the normalized EMG of each single motion $\boldsymbol{u}(t)$ is used, and the number of learning data for each class is M. Accordingly, the total number of learning data is $(N = M \times C)$. Here, a set of vector streams $\boldsymbol{u}(t)^{(n)}(t = 1, 2, \cdots, T_l)$ is given for training of the R-LLGMN with teacher vector $\boldsymbol{Y}^{(n)} = [Y_1^{(n)}, \cdots, Y_c^{(n)}, \cdots, Y_C^{(n)}]^{\mathrm{T}}$ $(n = 1, \ldots, N)$. Here, if the vector stream $\boldsymbol{u}(t)^{(n)}$ is set for class c, then $Y_c^{(n)} = 1$ and $Y_{\hat{c}}^{(n)} = 0$ $(\hat{c} \neq c)$ for all the other classes in this subset. In this paper, the energy function for the network is defined as

$$J = \sum_{n=1}^{N} J_n = -\sum_{n=1}^{N} \sum_{c=1}^{C} Y_c^n \log {}^{(5)}O^c(T)^{(n)} \quad , \qquad (17)$$

where ${}^{(5)}O^c(T)^{(n)}$ is the *a posteriori probability* at a given time T for time series patterns. The learning process is to minimize J, that is, to maximize the likelihood. Because of the recurrent connection in R-LLGMN, the backpropagation-through-time (BPTT) algorithm is used.

When the time series EMG vector $\boldsymbol{u}(t)$ of a single motion is newly input to the learned R-LLGMN, the network outputs the unit vector. Thus, the conversion of Eq. 3 can be realized using the R-LLGMN, and the muscle synergy pattern of each single motion can be extracted from the EMG pattern as an orthonormal basis vector.

C. Prosthetic hand control

The prosthetic hand developed by Fukuda *et al* [4] is controlled based on human hand impedance characteristics [9] and muscle synergy $\tilde{\boldsymbol{s}}(t)$ extracted from EMG patterns. This paper first defines the equation of motion for a manipulator with Q links defined as follows based on human hand impedance characteristics:

$$\boldsymbol{M}(\theta)\ddot{\boldsymbol{\theta}} + \boldsymbol{H}(\dot{\boldsymbol{\theta}}, \boldsymbol{\theta}) + \boldsymbol{G}(\boldsymbol{\theta}) = \boldsymbol{\tau} \ , \qquad (18)$$

$$\boldsymbol{\tau} = \boldsymbol{K}(\alpha)(\boldsymbol{\theta}^* - \boldsymbol{\theta}) - \boldsymbol{B}(\alpha)\dot{\boldsymbol{\theta}} \quad . \qquad (19)$$

Here, $\boldsymbol{\theta} = [\theta_1, \theta_2, \ldots, \theta_Q]^{\mathrm{T}} \in \Re^Q$ is the joint angle of the manipulator, $\boldsymbol{M}(\theta) \in \Re^{Q\times Q}$ is the inertial matrix, $\boldsymbol{H}(\dot{\boldsymbol{\theta}},\boldsymbol{\theta}) \in \Re^Q$ represents terms of centrifugal and Coriolis force, respectively, $\boldsymbol{G}(\boldsymbol{\theta}) \in \Re^Q$ is the term of gravity, and $\boldsymbol{\tau} \in \Re^Q$ is the joint torque vector. Also, $\boldsymbol{K}(\alpha)$, $\boldsymbol{B}(\alpha) \in \Re^{Q\times Q}$ are diagonal matrices with viscoelastic elements $K_q(\alpha), B_q(\alpha)$ $(q = 1, 2, \cdots, Q)$, and are defined as

$$K_q(\alpha) = k_{q,1}\alpha^{k_{q,2}} + k_{q,3} \quad , \qquad (20)$$

$$B_q(\alpha) = b_{q,1}\alpha^{b_{q,2}} + b_{q,3} \quad . \qquad (21)$$

Here, q is the joint number in the manipulator, and α $(0 \leq \alpha \leq 1)$ describes the muscle activation level defined as follows using force information F_{EMG}:

$$\alpha = \frac{F_{\mathrm{EMG}}}{\sum_{j=1}^{C} F_{\mathrm{EMG}}^{j} \hat{a}_j} \ . \qquad (22)$$

Here, $F^j{}_{\mathrm{EMG}}$ identifies the value of F_{EMG} with the maximum voluntary muscle contraction. $\boldsymbol{\theta}^* = [\theta_1^*, \theta_2^*, \cdots, \theta_Q^*]^{\mathrm{T}}$ is the equilibrium joint vector, and is defined using the combination ratio $\hat{a}_j$ of a single motion corresponding to joint q as

$$\theta_q^* = \begin{cases} \theta_q^{max} & (\hat{a}_j \geq a_{th}^{max}) \\ \hat{a}_j(\theta_q^{max} - \theta_q) & (a_{th}^{min} \leq \hat{a}_j < a_{th}^{max}) \\ \theta_q & (\hat{a}_j < a_{th}^{min}) \end{cases} \ , \qquad (23)$$

where a_{th}^{max} is the threshold of the combination ratio corresponding to the maximum joint angle, a_{th}^{min} is the dead-zone threshold, θ_q^{max} describes the equilibrium angle of the manipulator joint, and θ_q is the individual joint angle of the manipulator. θ_q changes with the combination ratio $\hat{a}_j$ as shown in Eq. 23, and torque τ_q is then generated from the user's EMG pattern for control of the manipulator.

IV. EXPERIMENTS

To verify the validity of the proposed method, classification experiments for user motion and control experiments with a prosthetic hand were conducted using muscle synergy theory. In these experiments, the sampling frequency of EMG measurement was $f_s = 1$ [kHz], and the cut-off frequency of the low-pass filter was $f_c = 1$ [Hz].

A. Classification experiments for combined motions

1) Methods: Pattern classification experiments on single and combined motions using muscle synergy calculated from user's EMG signals were conducted to confirm the conversion ability of the function $F(\cdot)$ using the R-LLGMN. The user's motions were determined using the basis pattern $\hat{\boldsymbol{s}}^{(g)} = [\hat{s}_1^{(g)}, \cdots, \hat{s}_C^{(g)}]^{\mathrm{T}}(g = 1, \cdots, G)$, where G is the number of all motions including single and combined motions. Here, $\hat{\boldsymbol{s}}^{(g)}$ is defined as a unit vector in which the corresponding element is 1 for the case of single motions, and is also a vector in which the corresponding elements are $\frac{1}{N_s}$ for the case of combined motions consisting of N_s single motions. The distance $\frac{1}{N_s}$ between $\tilde{\boldsymbol{s}}(t)$ and $\hat{\boldsymbol{s}}^{(g)}$ is then calculated using Eq. 24, and the motion g with minimum distance $d_g(t)$ is determined as the user's intended motion:

$$d_g(t) = \sqrt{\sum_{j=1}^{C} (\tilde{s}_j(t) - \hat{s}_j^{(g)})^2} \quad (g = 1, \cdots, G) \ . \qquad (24)$$

In the experiments, six pairs of electrodes were attached to the user's arm (ch. 1: extensor carpi ulnaris; ch. 2: brachioradialis; ch. 3: extensor carpi radialis; ch. 4: flexor carpi radialis; ch. 5: brachialis; and ch. 6: biceps brachii) for EMG signal measurement. The number of learning data M was 1, the threshold of the force information F_{th} was 0.18, and T_l and T_d were 20 [ms] and 6 [ms], respectively.

The subjects were five healthy males (A–D: 24 years old; E: 22 years old). The total number of motions in the discrimination was $G = 18$, and six single motions ($C = 6$; 1: hand opening; 2: hand grasping; 3: wrist extension; 4: wrist flexion; 5: pronation; and 6: supination) and twelve combined motions ($N_s = 2$; 7: opening and pronation; 8:

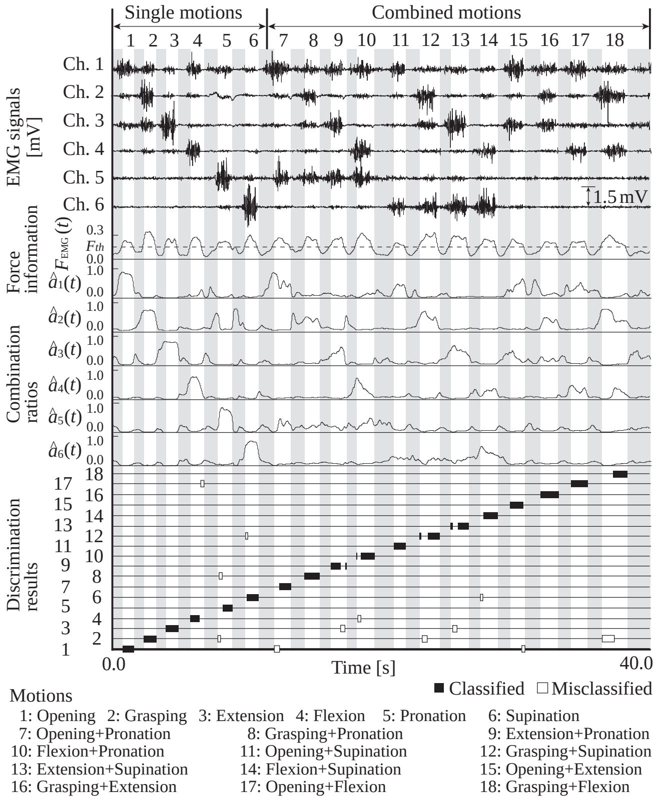

Fig. 4. Example of discrimination results with Subject A

grasping and pronation; 9: extension and pronation; 10: flexion and pronation; 11: opening and supination; 12: grasping and supination; 13: extension and supination; 14: flexion and supination; 15: opening and extension; 16: grasping and extension; 17: opening and flexion; and 18: grasping and flexion) were focused on for the discrimination. It should be noted that some combinations are impossible, such as simultaneous hand opening and grasping, and wrist flexion and extension.

2) Results: An example of the experimental results from Subject A is shown in Fig. 4. The figure plots EMG signals, force information, combination ratios and discrimination results. The non-shaded area indicates the time during which $F_{EMG}(t)$ was greater than F_{th}. The figure shows that single motions (as learned by the R-LLGMN) can be classified accurately. However, it is confirmed that some misclassification of combined motions (i.e., unknown ones) occurred. This result is mainly due to two factors: the R-LLGMN learned only the EMGs of single motions, and one of the EMG patterns of single motions was generated first while combined motions were being performed.

Figure 5 compares the results of the proposed method and the conventional method with learning and discrimination for all motions (18, including combined motions). It shows the average discrimination rates with all subjects. Here, T_l and T_d are defined as 1, and the other conditions are the same as those of the proposed method.

Although only six motions were learned in the proposed

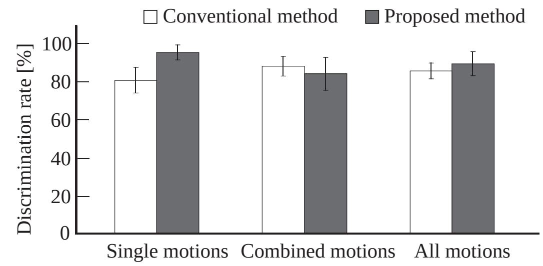

Fig. 5. Comparison of discrimination rates using the proposed and conventional methods

TABLE I
Impedance parameters used in the experiments

Joint, q	Motion (j)	$k_{q,1}$ [Nm / rad]	$k_{q,2}$	$k_{q,3}$ [Nm / rad]
1	Opening (1) / Grasping (2)	0.90	0.6	0.3
2	Extension (3) / Flexion (4)	32.8	0.6	3.2

approach, the figure shows that both the proposed and conventional methods have the same classification ability for all motions. The discrimination ratios of all motions for each method were $85.5 \pm 4.14\%$ (conventional) and $89.2 \pm 6.33\%$ (proposed). These results lead us to conclude that the proposed method can be used to classify unknown combined motions by implementing learning for the EMGs of single motions.

B. An example of prosthetic hand manipulation

Experiments involving prosthetic hand control using the proposed classification method were conducted. The subject was a forearm amputee (49 years old), and EMG signals were measured from four pairs of electrodes attached to the forearm (ch. 1: extensor carpi ulnaris; ch. 2: brachioradialis; ch. 3: extensor carpi radialis; and ch. 4: flexor carpi radialis). The total number of discriminated motions G was eight, consisting of four single motions ($C = 4$; 1: hand opening; 2: hand grasping; 3: wrist extension; and 4: wrist flexion) and four combined motions ($N_s = 2$; 5: opening and extension; 6: grasping and extension; 7: opening and flexion; and 8: grasping and flexion). The other conditions were as outlined in IV-A. In the experiments, two DOFs of the prosthetic hand (opening/grasping and extension/flexion) were controlled using the motions discriminated under the proposed method ($Q = 2$). $K_q(\alpha)$ is defined as shown in Table I, and $B_q(\alpha) = 0$.

Figure 6 shows the operation of the prosthetic hand in each time period, and Fig. 7 shows an example of the experimental results with EMG signals, force information, muscle activation levels, combination ratios and the joint angle of the prosthetic hand. The non-shaded area indicates the time during which $F_{EMG}(t)$ was greater than F_{th}. The figure shows that the user could voluntarily control single and combined motions at will. The discrimination rate in this experiment was 98.8%. Thus, the results show that

(a) Opening

(b) Grasping

(c) Extension

(d) Flexion

(e) Opening and extension

(f) Grasping and extension

(g) Opening and flexion

(h) Grasping and flexion

Fig. 6. An amputee controlling the manipulator

the proposed method can be used to control a prosthetic hand with unknown combined motions estimated from single motions.

V. Conclusions

This paper proposes a method by which unknown combined motions can be classified at the same time based on muscle synergy theory and used as part of a base control method for a prosthetic hand. In the experiments performed, muscle synergy patterns were extracted from five subjects, and twelve unknown combined motions were discriminated through learning for six single motions. The discrimination rates of each motion were $95.2 \pm 3.91\%$ (single motions), $84.0 \pm 8.6\%$ (combined motions) and $89.2 \pm 6.33\%$ (all motions), thereby clarifying that the proposed method can be used to classify unknown motions. We also confirmed that the amputee could voluntarily control combined motions for prosthetic hand operation based on this technique.

The classification accuracy of the proposed method is highly influenced by individual parameters such as F_{th} and T_l. In future work, we plan to investigate a way of determining each parameter in the proposed method. We also aim to develop a system to enable training for EMG pattern generation, as EMG signals change according to the subject's condition, posture and task performance.

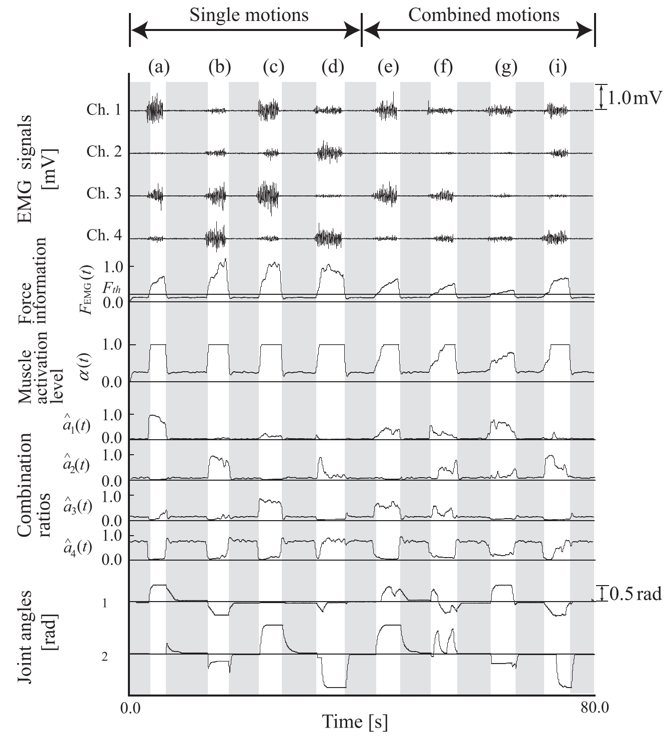

Fig. 7. Example of experimental results for manipulator control

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