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Skill Assistance for Myoelectric Control Using an Event-Driven Task Model

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Abstract

Electromyogram (EMG) has been often used as a control signal for a prosthetic arm, which includes information on the operator's motor intentions and the mechanical impedance of joints. Most previous research adopted the control methods of the prosthetic arms based on the EMG pattern discrimination and/or the force estimation from the EMG signals, and did not utilize any knowledge on tasks performed by amputees such as a grasping-an-object and a soup-spooning task. In this paper, a new myoelectric control method is proposed using a statistically organized neural network and an event-driven task model. The task model is represented using a Petri net to describe the task dependent knowledge, which is used to modify the neural network's output. Experimental results show that the use of the task model significantly improves the accuracy of the EMG pattern discrimination.

1 Introduction

There are many people who have lost their extremities by industrial accidents, traffic accidents or other afflictions. Since it may be very difficult for them to perform precise and complicated work in their daily activities, development of human-assisting devices is very important and necessary to assist their daily activities and enable them to be engaged again in the production activity.

The electromyogram (EMG) is often used as an interface tool for a prosthetic hand. The EMG signal contains a lot of information such as human intended motions, muscle force, and joint impedance properties. Akazawa et al. [1] estimated forces of flexors and extensors from the EMG signals, and proposed a scheme to use the EMG signals for controlling a prosthetic hand. Ito et al. [2] used amplitude information of EMG signals like the speed control command of the prosthetic forearm. Also, Abul-haj and Hogan [3] proposed the control method of the prosthetic hand based on an impedance model and analyzed the control characteristics.

On the other hand, many studies of the EMG pattern discrimination have been carried out for prosthetic control. In the first stage of this research, linear prediction models for EMG signals were frequently used [4], [5]. However, it was very difficult to achieve high discrimination performance, especially for rapid movements, because of nonlinear characteristics and the large variability of the EMG signals. Under such situations, EMG pattern discrimination methods using neural networks have been proposed [6]-[8]. The neural networks can acquire the nonlinear mapping between the input patterns and the discriminating classes.

While BPN [9] is utilized in most previous studies, Tsuji et al. proposed the log-linearized Gaussian mixture network (LLGMN) [10] based on a log-linear model and a Gaussian mixture model. This network realized higher discrimination performance than that of BPN [11]. However, it is difficult to discriminate the mixed motion in which the hand motion and the wrist motion occur at the same time. Also, the EMG patterns are greatly changed depending on tasks and the operator's arm positions during daily activities, so that the discrimination performance decreases even if the operator is well trained and concentrates the EMG operation properly.

This paper proposes a new myoelectric control method, which combines an event-driven task model with the motion discrimination method by using LLGMN. Most tasks that are performed by a human operator are composed of a series of several motions, and they can be described using an event-driven model. In the proposed method, the operator's intended motion is discriminated by using LLGMN, and this discrimination result is modified according to the state in the event-driven task model. This method can be expected to achieve high discrimination performance based on the knowledge of the task,

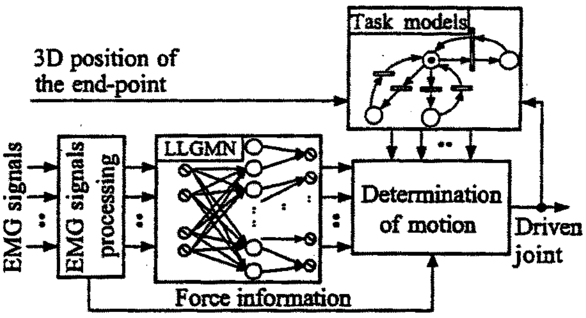


Figure 1: Structure of the proposed method.

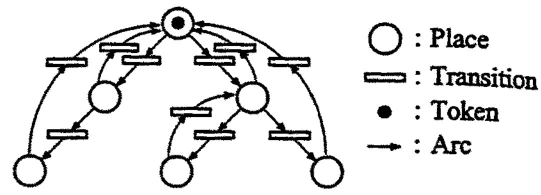


Figure 2: Task model represented by a Petri net.

even if the operator's arm position is changed or the discrimination of the LLGMN is ambiguous.

2 Discrimination method based on the event-driven task model

The structure of the proposed method is shown in **Fig.** 1. This consists of the EMG signal processing part, the neural network part, the task model part, and the motion determination part. First, in the EMG signal processing part, the EMG signals are preprocessed to extract the input pattern for the neural network part. Then, the neural network part outputs *a posteriori* probabilities of the operator's intended motion using LLGMN. The task model part includes a Petri net, which describes the task dependent knowledge, and outputs a modifying vector based on the state in this task model. Finally, the determination part determines the operator's intended motion based on the LLGMN's output and the modifying vector. The details of each part are explained in the following subsections.

2.1 EMG signal processing part

The EMG signals which are measured from L pairs of electrodes are amplified and digitized by an A/D converter. Then, they are rectified and filtered out through the second order Butterworth filter (cut-off frequency: f_c[Hz]), and re-sampled with a f_s[Hz] sampling frequency. These signals are defined as $E_l(n)$ $(l = 1, \cdots, L)$, and the mean value of all channels is calculated as

$$E_a(n) = \frac{1}{L}\sum_{l=1}^{L}(E_l(n) - E_l^{st}), \tag{1}$$

where E_l^{st} is the mean value of $E_l(n)$ while relaxing the muscles. $E_a(n)$ indicates the muscular contraction level. For the EMG pattern discrimination, the feature vector $x(n) = [x_1(n),\ x_2(n),\ \cdots,\ x_L(n)]^{\mathrm{T}} \in \Re^{\mathrm{L}}$ is calculated as

$$x_l(n) = \frac{E_l(n) - E_l^{st}}{LE_a(n)}. \tag{2}$$

Also, in order to recognize the beginning and ending of the operator's motions, the square sum $E_p(n)$ is calculated as

$$E_p(n) = \sum_{l=1}^{L}(E_l(n) - E_l^{st})^2. \tag{3}$$

2.2 Neural network part

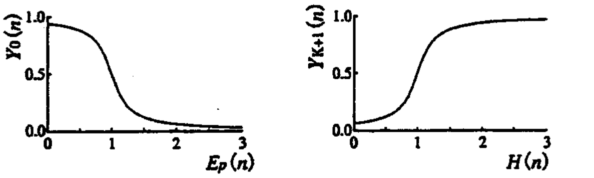
This part uses the log-linearized Gaussian mixture network (LLGMN) [10]. This network is a three-layered feedforward network based on a log-linear model and a Gaussian mixture model (GMM), and can model a probability density function of each discriminating class for the input patterns through the learning.

LLGMN receives the n-th input vector $x(n) = [x_1(n),\ x_2(n),\ \cdots,\ x_L(n)]^{\mathrm{T}} \in \Re^{\mathrm{L}}$ from the EMG signal processing part and outputs $Y(n) = [Y_1(n),\ Y_2(n),\ \cdots,\ Y_K(n)]^{\mathrm{T}} \in \Re^{\mathrm{K}}$ from the third layer. It should be noted that $Y_k(n)$ corresponds to *a posteriori* probability of the motion k which has initiated by the human operator [11].

2.3 Task model part

The task model part includes a number of the knowledge-based task models which are described by Petri nets [12]. This part estimates the operator's task state using the history of the discrimination results of LLGMN, and outputs the modifying vector according to the estimated state.

Let us imagine a "water-drinking" task. This task can be composed of the three states and the three motions: standby state → hand grasping → grasping-a-cup state → wrist rotation → drinking state → hand opening → standby state. The corresponding task model can be described by using the Petri net, which consists of the places, the transitions and the arcs, that denote the operator's task states, motions and flow of tasks, respectively. Thus, the task model $N = (P, T; F, M)$ can be described using



(a) Possibility of no motion (b) Possibility of motion suspension

Figure 3: Membership functions for no motion and motion suspension ($\alpha_1 = \alpha_2 = 5$, $\beta_1 = \beta_2 = 1$).

the sets of places $P = \{p_0, p_1, \cdots, p_P\}$, transitions $T = \{t_0, t_1, \cdots, t_T\}$, arcs $F \subseteq (P \times T) \cup (T \times P)$, and initial markings $M : P \to \mathbf{N} \cup \{\omega\}$ [12]. $\mathbf{N}$ and ω indicate the set of positive integer numbers and the infinitely. T and P indicate the number of transitions and places. In this paper, the initial marking $m_0 \in M$ is settled on the place p_0 which corresponds to the standby state.

An example of the task model is shown in **Fig. 2.** In this figure, the place with the token denotes the standby state, and the branch subnets connecting this place represent the details of each task. For example, at meals, the series of motions such as "water-drinking" and "eating-with-chopsticks", are represented as the subnets. The tree structure of the task model is suitable for re-composing the subnet when the operator adds a new task.

In the task model part, according to the operator's task state, the modifying vector γ_m is selected and sent to the motion determination part:

$$\gamma_m = [\gamma_{m0}, \gamma_{m1}, \cdots, \gamma_{mK}, \gamma_{m(K+1)}]^{\mathrm{T}}, \quad (4)$$

where $m \in \{0, 1, 2, \cdots, P\}$ is the index of the place in the model; $\gamma_{m1}, \cdots, \gamma_{mK}$ indicate the modifying parameters for the motion k ($k = 1, 2, \cdots, K$); and γ_{m0} and $\gamma_{m(K+1)}$ indicate the modifying parameters for no motion and motion suspensions which are explained in the next subsection.

2.4 Motion determination part

In this part, the operator's intended motion is determined according to the outputs from the neural network part, the task model part and the squared sum $E_p(n)$ which is defined as Eq. (3). Here, the additional two motions, such as no motion and motion suspension, are defined.

The probability of no motion $Y_0(n)$ is defined using the following membership function:

$$Y_0(n) = -\frac{1}{\pi} \tan^{-1} \{\alpha_1(E_p(n) - \beta_1)\} + 0.5, \quad (5)$$

where $E_p(n)$ is the squared sum of the EMG signals defined as Eq. (3), and α_1, β_1 are positive constants. If the muscular contraction level $E_p(n)$ is close to 0, $Y_0(n)$ becomes close to 1. On the contrary, if $E_p(n)$ increases, $Y_0(n)$ decreases (**Fig.** 3(a)).

The probability of motion suspension $Y_{K+1}(n)$ is defined based on an entropy $H(n)$:

$$Y_{K+1}(n) = \frac{1}{\pi} \tan^{-1}\{\alpha_2(H(n) - \beta_2)\} + 0.5, \quad (6)$$

$$H(n) = -\sum_{k=1}^{K} Y_k(n) \log Y_k(n), \quad (7)$$

where α_2, β_2 are positive constants. The entropy is calculated using *conditional a posteriori* probabilities $Y_k(n)$ ($k = 1, 2, \cdots, K$) which are received from the neural network part. If the entropy $H(n)$ is close to 0, $Y_{K+1}(n)$ becomes close to 0. On the contrary, if $H(n)$ increases, this means that the network output is ambiguous, and $Y_{K+1}(n)$ is close to 1 (**Fig.** 3(b)). The probability of the motion suspension can be regarded as the index, which indicates reliability of the motion discrimination in the neural network part.

The probability $Z_k(n)$ ($k = 0, 1, \cdots, K, K+1$) is calculated using $Y_0(n)$, $Y_{K+1}(n)$ and *conditional a posteriori* probabilities $Y_k(n)(k = 1, 2, \cdots, K)$:

$$Z_k(n) = \quad (8)$$

$$\begin{cases} Y_k(n) & (k = 0) \\ (1 - Y_0(n))(1 - Y_{K+1}(n))Y_k(n) & (k = 1, .., K) \\ (1 - Y_0(n))Y_k(n) & (k = K+1). \end{cases}$$

Finally, the probability $Z_k(n)$ is weighted by the modifying vector γ_m,

$$O_k(n) = \frac{\gamma_{mk} Z_k(n)}{\sum_{j=1}^{K+1} \gamma_{mj} Z_j(n)}. \quad (9)$$

and the operator's intended motion, which corresponds to the greatest element, is selected as the determination result:

3 Experiments

3.1 Experimental system

We conducted the experiments using a human-assisting manipulator system which was developed by the authors [11]. In this system, the robotic manipulator (Move Master RM-501, Mitsubishi Electric Corp.) and the prosthetic forearm (Imasen lab.)

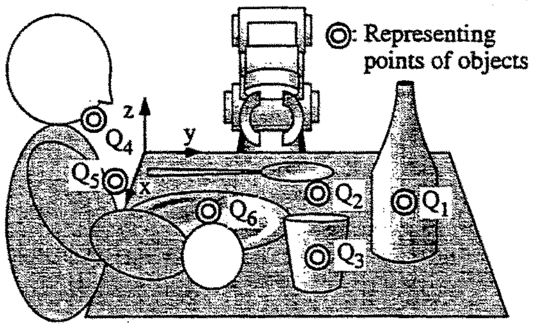


Figure 4: Experimental setup for meal assistance.

[2] are used as the arm and end-effector parts, respectively. The prosthetic forearm is driven by an ultrasonic motor (SINSHEI Corp.) to reduce a motor noize. The joint angles of the prosthetic forearm are controlled by the joint impedance control method based on the motion determination result and the muscular contraction level $E_a(n)$ [13]. This method can realize smooth motions similar to that of the human arm. The robotic manipulator is controlled by the 3D position sensor (ISOTRACK II: POLHEMUS Inc.). The joint angles of the arm part are controlled by the PID control method according to the operator's wrist position measured by this sensor. The correspondence of the movement of the operator's wrist joint with the end-effector part enables the operator to control the manipulator system intuitively. The prosthetic forearm has 3 d. o. f. and six motions (hand grasping, hand opening, pronation, supination, extension, flexion: $K = 6$). These motions are discriminated in the experiments. The EMG signals are measured from six pairs of electrodes ($L = 6$): Four pairs of electrodes are attached to the forearm and two pairs at the upper arm. The cut-off frequency of the Butterworth filter and the re-sampling frequency in the EMG signal processing part is settled as $f_c = 1.0$[Hz] and $f_s = 27$[Hz]. LL-GMN is well learned before the operation [10], [11], [13].

3.2 Experimental conditions

In the experiments, five subjects performed the manipulator control using the proposed method. Subjects A, B had enough experience of EMG manipulation, while Subjects C, D, E were not familiar with EMG manipulation. Subjects were asked to perform a "having-a-meal" task which composed of three subtasks (pouring water into a cup from a bottle, drinking a cup of water, spooning and eating soup). The experimental setup is shown in Fig. 4. The subjects were asked to perform the following motions:

Table 1: Places and transitions.

Places		Transitions	
p_0	Standby	t_0	Opening
p_1	Grasping a bottle	t_1	Grasping in Q_1
p_2	Pouring	t_2	Supinating in Q_2
p_3	Grasping a cup	t_3	Grasping in Q_3
p_4	Drinking water	t_4	Pronating in Q_4
p_5	Grasping a spoon	t_5	Grasping in Q_5
p_6	Spooning up	t_6	Supinating in Q_6
p_7	Eating soup	t_7	Pronating in Q_4

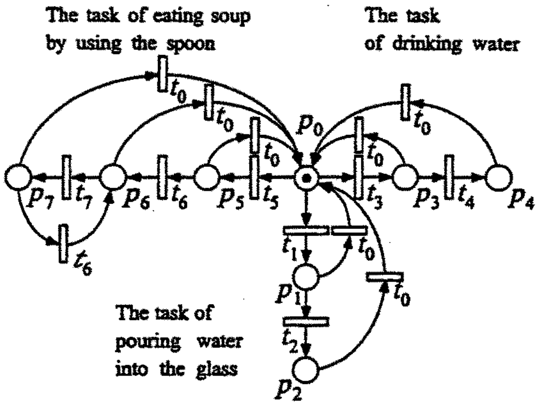


Figure 5: Task model for having a meal.

(1) Grasping the bottle using the manipulator.

(2) Moving the bottle over the cup, and pouring some water (supinating wrist joint).

(3) Putting the bottle on the table.

(4) Grasping the cup, and moving it near the mouth.

(5) Drinking water (pronating wrist joint).

(6) Putting the cup on the table.

(7) Handing the spoon to the manipulator in front of the subject's chest.

(8) Moving the spoon over the soup plate.

(9) Spooning soup (supinating wrist joint).

(10) Moving spoon near the mouth, and eating soup (pronating wrist joint).

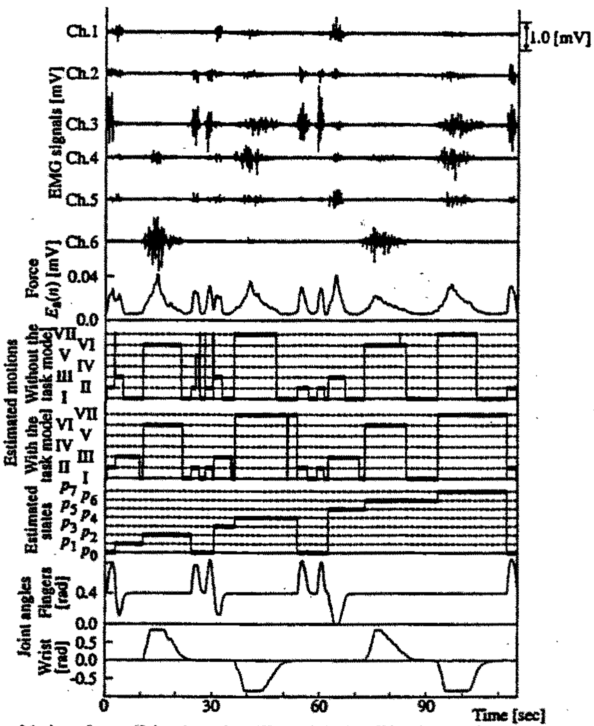
(11) Handing the spoon to the subject in front of his chest.

The eight motions, eight states and the task model are shown in **Table** 1 and **Fig.** 5. In this task, position information of the end-effector part was added as the condition of each transition in the task model to utilize the knowledge depending on the position. For example, the system should know that the spooning task is expected when the manipulator moves over the soup plate with spoon. Six regions were defined, which were the sphere with the centers Q_i $(i = 1, 2, \cdots, 6)$ and the radius r_i $(i = 1, 2, \cdots, 6)$. The centers Q_i of regions are shown in **Fig.** 4, which are corresponding to the bottle (Q_1), the region over the cup (Q_2), the cup (Q_3), the regions in front of operator's mouth (Q_4) and chest (Q_5), the soup plate (Q_6), respectively. The radius of each regions were $r_1 = 0.08[m]$, $r_2 = 0.08[m]$, $r_3 = 0.08[m]$, $r_4 = 0.08[m]$, $r_5 = 0.08[m]$, $r_6 = 0.08[m]$. The modifying vectors were defined to give a priority to the motions, e.g., the grasping and supination motions for using the bottle task, the grasping and pronation motions for using the cup task, the grasping, pronation and supination motions for spooning task. These parameters were chosen through the trial and error.

3.3 Experimental results

An example of the measured signals during the manipulation is shown in **Fig.** 6. This figure shows: the EMG signals, the estimated muscle force $E_a(n)$, the estimated motions with the task model and without the task model, the task states estimated in the task model part, and the joint angles of the prosthetic hand. In the results without the task model, incorrect discrimination was observed during the manipulation of the bottle and the cup. On the contrary, using the task model, incorrect discrimination decreased and robustness of the motion discrimination was improved.

Table 2 shows the mean values and the standard deviations of the discrimination results. Each subject performed the having-a-meal task for five times. **Table** 2(a) shows the results with the task model, and (b) the one without the task model. If $O_0(n) \leq 0.4$, the system recognized that the motion had occurred. On the contrary, if $O_0(n) > 0.4$, the system recognized no motion. The discrimination rates were calculated during the manipulation except for the standby state. The inappropriate motions (e.g., hand opening motion when the operator was grasping a bottle) were counted as the incorrect discrimination. It can be seen that the proposed method can achieve high discrimination performance. Effect of the task model is confirmed during the grasping a cup or a bottle task. These tasks were required the posture changes of the subject's upper limb.



Motions: I, rest; II, hand opening; III, hand closing; IV, wrist extenion; V, wrist flexion; VI, pronation; VII, supination

States: P_0, standby; P_1, grasping a bottle; P_2, pouring; P_3, grasping a cup; P_4, drinking water; P_5, grasping a spoon; P_6, spooning; P_7, eating soup

***Figure 6:** An example of the EMG pattern discrimination for a having-a-meal task (Subject A)*

4 Conclusion

This paper proposed a new myoelectric control method for human assisting devices such as prosthetic hands and manipulators. This method combined the task model with the neural network to improve reliability of the prosthetic control. In this method, the discrimination results of the neural network are modified using the knowledge of the task model. The high discrimination performance can be expected for the unstable EMG patterns caused by the changes of the operator's posture and the environments. The results obtained in this paper were summarized as follows:

(1) The tasks which were very difficult to perform using the previous method, such as a "Putting-a-building block" task and a "having-a meal" task, can be successfully performed using the proposed method.

(2) The discrimination accuracy was improved using the modifying vectors in the task model part.

(3) The manipulation using the proposed method

Table 2: Classification rates for motions included in the task

(a) The proposed method using the task model

Motions	Subject A (%)	Subject B (%)	Subject C (%)	Subject D (%)	Subject E (%)
Grasping a bottle	98.8 ± 0.8	92.1 ± 7.3	89.8 ± 10.2	94.0 ± 3.7	96.0 ± 3.7
Pouring	99.4 ± 0.4	91.9 ± 7.9	97.0 ± 3.6	97.0 ± 2.8	96.4 ± 4.2
Graspping a cup	92.6 ± 8.6	97.2 ± 2.5	94.5 ± 6.7	80.1 ± 12.7	92.1 ± 7.0
Drinking water	91.1 ± 6.5	95.4 ± 4.2	96.3 ± 4.8	81.1 ± 8.6	94.8 ± 8.7
Graspping a spoon	97.1 ± 2.6	92.4 ± 11.5	95.5 ± 3.6	96.2 ± 3.2	86.5 ± 5.9
Spooning up	97.9 ± 1.8	96.7 ± 1.4	98.9 ± 1.2	97.7 ± 1.7	90.6 ± 4.3
Eating soup	95.5 ± 3.5	92.6 ± 4.7	98.7 ± 1.0	88.6 ± 9.1	98.1 ± 1.6

(b) The previous method not using the task model

Motions	Subject A (%)	Subject B (%)	Subject C (%)	Subject D (%)	Subject E (%)
Graspping a bottle	51.3 ± 16.6	88.2 ± 8.6	81.9 ± 9.8	74.4 ± 13.7	93.1 ± 3.5
Pouring	94.3 ± 1.9	83.8 ± 10.5	90.8 ± 9.8	78.0 ± 5.0	54.7 ± 17.3
Graspping a cup	47.4 ± 22.3	93.7 ± 3.8	85.4 ± 9.2	64.5 ± 10.2	88.5 ± 6.0
Drinking water	79.3 ± 4.0	81.3 ± 12.4	66.0 ± 24.2	61.3 ± 9.8	83.9 ± 22.9
Graspping a spoon	59.9 ± 11.2	87.6 ± 11.2	80.3 ± 9.6	60.5 ± 14.6	83.1 ± 6.9
Spooning up	87.2 ± 6.2	68.2 ± 15.2	94.3 ± 4.3	64.5 ± 8.2	59.4 ± 9.7
Eating soup	73.8 ± 11.7	75.7 ± 9.3	77.1 ± 13.0	76.4 ± 16.8	78.9 ± 29.2

does not need excessive experience and concentration.

In the future research, we would like to develop a method to adjust the parameters automatically in the task model part by learning, and extend the proposed skill assist method to a dual-arm manipulator system.

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