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Hand Motion Estimation by EMG Signals Using Linear Multiple Regression Models

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Abstract—**The purpose of this research is to construct an intelligent upper limb prosthesis control system that uses electromyogram (EMG) signals. The signal processing of EMG signals is performed using a linear multiple regression model that can learn parameters in a short time. Using this model, joint angles are predicted, and the motion pattern discrimination is conducted. Discriminated motions were grip, open, and chuck of a hand. Predicted joint angles were multi-finger angles corresponding to these three motions. In several experiments we proved the usefulness of processing EMG signals with a linear multiple regression model.**

I. Introduction

THE number of amputees is increasing in industrial or traffic accidents, although safety and accident prevention measures are being used. Since amputees use prostheses, such needs are increasing year after year. Electromyogram (EMG), a bioelectric signal produced when muscles are contracted, consists of the information of motions or forces. Since EMG signals can also be generated from the residual muscles of amputees, they are an effective control input for a prosthesis. Therefore, a myoelectric upper limb prosthesis is one of the most functional commercial prostheses. However, a commercial myoelectric upper limb prosthesis can only perform grasping motions and wrist rotation; since many myoelectric upper limb prostheses are moved by on/off controls, angle joints cannot be controlled. So, patients must pay much exercise caution when grasping objects.

Many researches on the multi-functionalization of myoelectric upper limb prostheses have been studied [1]–[7], and pattern recognition to discriminate the desired hand motions from EMG signals have been attempted. In these cases, artificial neural networks are commonly applied [4], [5]. Since EMG signals have nonlinear characteristics, it is reasonable to use artificial neural networks to make accurate nonlinear maps. However, a large amount of training time is necessary before actual use. In other researches, the separation of independent signals related to the movement of each finger was also studied using Independent Component Analysis [7], which is a statistical technique for the decomposition of a complex dataset into independent signals. Since it is assumed that the movement of each finger generates independent EMG signals, the electric signal measured on the skin surface is represented as a combination of EMG signals generated by each operation. However, since the technique is based on statistical theory, there is optionality of permutation and amplitude when a signal is separated. Therefore, since such post-processing as scaling, sorting, sign changing, offsetting, etc., is necessary, it is not practical. Many techniques using artificial neural networks for the prediction of joint angles have been proposed [8], [9].

The purpose of this research is to construct an intelligent upper limb prosthesis control system that uses EMG signals. The signal processing of EMG signals is performed using a linear multiple regression model that can learn parameters in a short time. Using this model, joint angles are predicted, and motion pattern discrimination is conducted. A linear multiple regression model provides less accuracy than a generally used artificial neural network, but accuracy is improved by the selection of suitable inputs and the generation of teacher signals. Discriminated motions were grip, open, and chuck of a hand. Predicted joint angles were multi-finger angles corresponding to these three motions. In several experiments we verify the usefulness of processing EMG signals with a linear multiple regression model.

II. Surface Electromyogram Signals

In this section, we discuss the generation mechanism of surface electromyogram signals. When the cell of a muscle is active, feeble electricity occurs in it. When muscular fiber (a muscular cell) receives a motor command signal from the upper motor center, action potential occurs, and tension occurs. When the tension, which occurred by the shrinkage of a lot of muscular fiber, accomplishes a unified exercise, it is called muscular strength. In this way when the exercise of a muscle occurs, we measure action potential because it always potential occurs by and can be used to analyze muscle activity itself. The technique to derive and record muscle action potential by various kinds of electrodes is called an electromyogram (EMG), which is already used in clinical medicine, sports engineering, rehabilitation, and virtual reality. There are two types of electrodes to measure EMG

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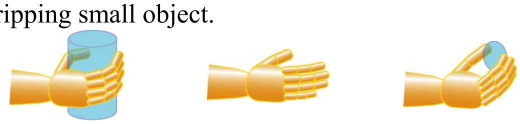
signals: needle and surface. When we want to measure the activity of a specific muscular fiber closely, needle is desirable. But in this research a non-aggression and a measurement stick an easy surface electrode on the skin surface and measure action potential. Because amplitude is generally 1–3 mV degrees and the surface EMG signal is very feeble, it is easily affected by noise. Therefore, we performed the measurements using a differential amplifier as an anti-noise measure. A differential amplifier uses two signal input terminals in addition to a terminal that ground. Because noise, which gets mixed into both signal terminals, is the problem, we can deny noise by amplifying the difference of two input signals and only measuring the signal ingredients.

III. Motion Discrimination

With multiple regression models, we generate a signal that has positive value when a certain motion is performed (called motion signal hereafter) from EMG signals to discriminate motions. We model every motion and discriminate motion by motion signals, which are output values. When a certain motion is performed, a motion signal assumes that the motion will become the greatest discrimination result. In this research, three motions ("grip," "open," and "chuck"), as shown in Fig. 1, were recognized. The grip motion is suitable for grabbing pillars and spherical objects, and the chuck motion is suitable for gripping small object.



Motion 1 (Grip) Motion 2 (Open) Motion 3 (Chuck)

Fig. 1. Hand Motions

A. Motion Discrimination Model

It is assumed that the signal corresponding to each motion i is generated by the following linear multiple regression model from measured EMG signals,

$$y_i = a_{i0} + \sum_{l=1}^{d} a_{il} emg_l \quad , \tag{1}$$

where y_i expresses the signal corresponding to motion i, l expresses the number of channels of measured EMG signals, and a is a partial regression coefficient. This is presumed by the least squares method using a target signal-generating method described later.

B. Generation Method of a Target Signal

A target signal is needed when presuming a coefficient by the least squares method. The generation of target signal yt_k is described as follows. Each motion is performed once, and sum S of the EMG signals of each channel is calculated. It is assumed that there are d channels of the EMG signal measured and m motions are operated.

$$S = \sum_{l=1}^{d} emg_l \quad , \tag{2}$$

Since the EMG signal produces a peak whenever a motion is operated, S produces m peaks. The k-th peak corresponds to the motion performed to the k-th. The target signal corresponding to motion k is calculated as follows:

$$yt_k = \begin{cases} S & (i = k) \\ -S & (i \neq k) \end{cases} , \tag{3}$$

where i (i = 1,$\cdots$, k, $\cdots$, m) expresses the number of peaks. When a corresponding motion is performed, the target signal takes a positive value, and it takes a negative value when the other motion is performed. Fig. 2 shows an application example of this technique in the case of d =4, m =3. Because both EMG and teaching signals are together in real time and can be measured; we can update partial regression coefficients at any time.

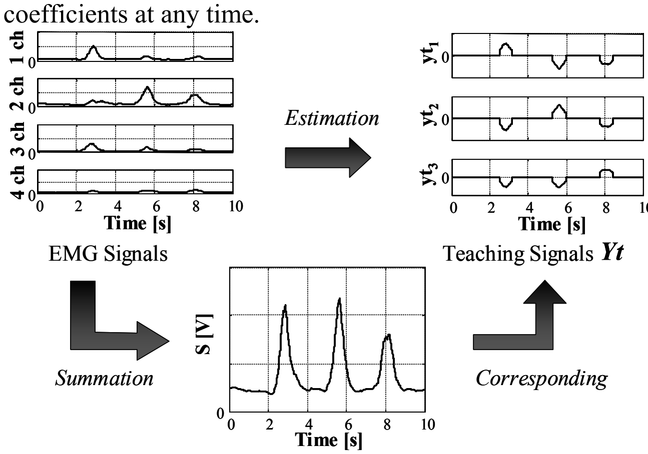


Fig. 2. The Generation Method of the Teaching Signals

IV. Joint Angle Estimation

A. Joint Angle Estimation Model

It is assumed that the angle of the finger joint is the alignment sum of the present joint angle and motion signals. We consider the linear multiple regression model shown below,

$$\theta_{ref}(T) = \sum_{i=1}^{m} A_i ym_i + B\theta_{ref}(T-1) + C \quad , \tag{4}$$

where A, B, and C are partial regression coefficients. Motion signals and the joint angle are measured simultaneously and are presumed by the least squares method. In the model, θ_{ref} is the desired value of the finger joint angle. When learning partial regression coefficients, $\theta_{ref}(T)$ is the joint angle, and $\theta_{ref}(T\text{-}1)$ is the joint angle measured before one sample. We presume that $\theta_{ref}(T)$ is set to $\theta_{ref}(T\text{-}1)$ in the following sample when this model is used after learning.

B. Learning Method

When learning the partial regression coefficients of models, we have to give real joint angles as teacher signals. We considered a method to measure joint angle with position measurement devices such as potentiometer, but chose a method to give teacher signals without measuring real joint angles.

At first we control a robot hand as reference signals with chirp signals, as shown in the next expression.

$$\theta_t(t) = -A\cos\{2\pi[(f_2 - f_1)t/\Delta t + f_1]t\} + A \quad . \tag{5}$$

For this reference signal, amplitude is A, and the frequency changes in Δt from f_1 to f_2 in time. The subject carries out a similar activity while watching the motion of a robot hand. With reference signals to a robot hand of this time as teacher signals, we use the value of the encoder installed to each joint of a robot hand for sample data for learning explanation variables. Fig. 3 shows a scene of learning. Because motion signals and the angle of a robot hand are together in real time and can be measured, we can update partial regression coefficients at any time.

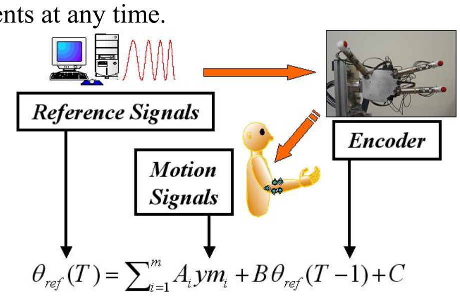


Fig. 3. Data Collection for Training the Model

V. Experiment

A. Experimental Equipment

In this controlled experiment, a PC (Pentium IV, 2.8 GHz, 1 GB) served as the workstation. The control system was designed using MATLAB/Simulink. DS1005 (Power PC 800 MHz, dSPACE) was applied for DSP, A/D, and D/A conversions. The experimental system is shown in Fig. 4. We used the Gifu Hand III [10], which has three fingers, as the multi-fingered robot hand. Fingers are attached in the positions of a human thumb (Thumb), the index finger (Finger 1), and the third finger (Finger 2). Table I shows the desired values of the joint angles corresponding to each motion.

EMG amplifiers (EMG-025, Harada Hyper Precision Inc.) were used to measure EMG signals, which were amplified 500 times (54 dB). Disposable electrodes built into the preamplifier were employed. Four channels of the EMG signals were measured, and the electrodes were arranged around the forearm electrode arrangement did not follow a strict pattern.

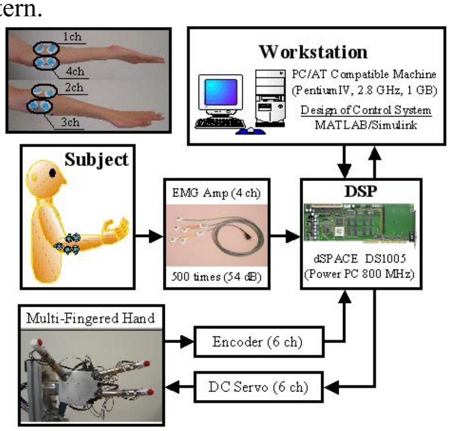


Fig. 4. Component of the System

TABLE I
Joint Angles Corresponding to Each Motion [Deg]

		Motion		
		Grip	Open	Chuck
Thumb	CM	45	0	40
	MP	45	0	30
Finger 1, 2	MP	60	0	80
	PIP	60	0	30

B. Experimental Method

The subject performed a motion discrimination experiment and a joint angle slaved tracking experiment. Three motions are discriminated by the motion discrimination experiment. For display static or the dynamic target angle and joint angle of a robot hand on a monitor, the subject makes a motion that follows the targeted value and verifies the slaved tracking precision of a joint angle by a joint angle slaved tracking experiment.

C. Experimental Results and Discussion

In both experiments, we confirmed that our method updated partial regression coefficients of a model at the time of learning at any time.

First, we show the result of the motion discrimination experiment. After learning, we directed the subject to repeatedly perform "grip," "open," and "chuck motions". Fig. 5 shows the amplitude of EMG signals, which did rectification / smoothing. Fig. 6 shows motion signals. In this example, subject performs "grip motion" in about 0.8–1.5 seconds, 5.5–6.5 seconds, "open motion" in about 2.1–3 seconds, 7–8 seconds, and "chuck motion" in about 3.7–4.4 seconds, 8.6–9 seconds. Also, ym_1 corresponds to "grip motion," ym_2 corresponds to "open motion" and ym_3 corresponds to "chuck motion" in Fig. 6. When the subject performed the corresponding motions, motion signals take positive values, and they take negative values when the other motions are performed. Therefore, we chose the greatest value and show results that discriminate the three motions in Fig. 7. From the above, we demonstrated that the discrimination of "grip," "open," and "chuck motions" was possible.

Next are the results of joint angle slaved tracking experiments. We set the static targeted value (CM joint of Thumb: 15, 30°) and the dynamic targeted value (CM joint of Thumb: amplitude 22.5° grip motion, 20° chuck motion. The chirp signal changes frequency from 0.1 to 0.2 Hz in 20 seconds in time). Figs. 8 and 9 show an example of a result, which was estimated as a targeted value with average slaved tracking error E to show the difference of operation angle in the next expression,

$$E = \sum_{T=Ns}^{Ne} \left|\theta_{ref}(T) - \theta_{enc}(T)\right| \Big/ (Ne - Ns + 1) \quad , \tag{6}$$

where θ_{ref}, θ_{enc} express the target angle and the angle of a robot hand and Ns, Ne express a sample number at the time of error evaluation start and a sample number at the time of the end, respectively. We verified precision after the subject arrived at the targeted value of the static targeted value. As a result, average slaved tracking error was delivered within less than 2°, and precision was very good and could be followed. The average slaved tracking error was delivered within less than 5° with the dynamic targeted value. Slaved tracking errors increased with the dynamic targeted value in comparison with the static targeted value, but an orbit tendency of the operation angle agrees with the targeted value. Indication delay of a monitor is considered to cause the error increase.

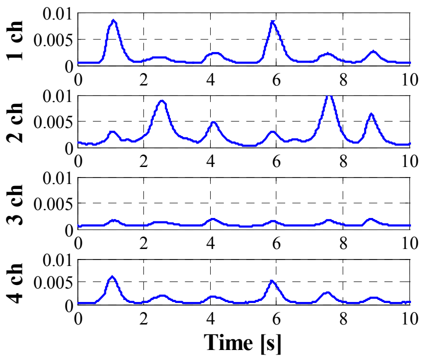


Fig. 5. EMG Signals

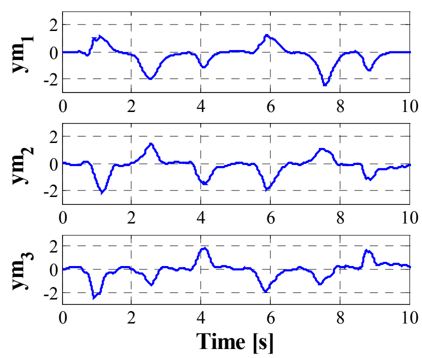
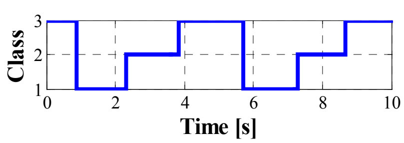


Fig. 6. Motion Signals



Class 1: Grip, Class 2: Open, Class 3: Chuck

Fig. 7. Discrimination Result

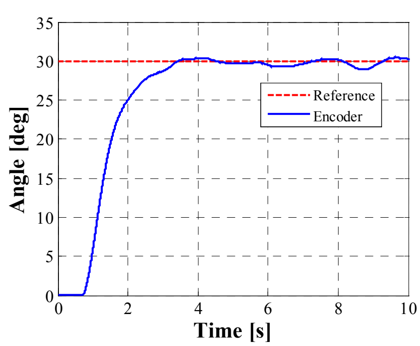


Fig. 8. Trajectory of Tracking the Static Target

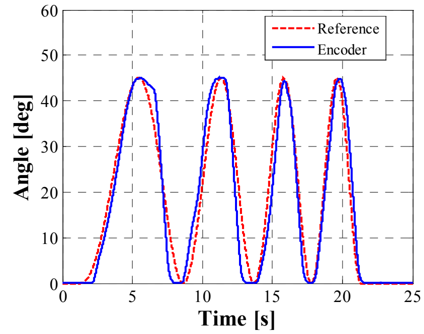


Fig. 9. Trajectory of Tracking the Dynamic Target

VI. CONCLUSION

In this research, we aimed to construct an intelligent upper limb prosthesis control system for which we used electromyogram signals and suggested a technique to discriminate motion and estimate joint angles. After verifying it, we reached the following conclusions.

1) The discrimination of grip, open, and chuck motions of a hand is possible by the suggested techniques.
2) The estimation of finger joint angles of a hand is possible by the suggested techniques.
3) We demonstrated that we could make a signal processing model in a short time by using multiple regression analysis.

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