34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

Prior Estimation of Motion Using Recursive Perceptron with sEMG: A Case of Wrist Angle

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***Abstract*— Muscle activity is followed by myoelectric potentials. Prior estimation of motion by surface electromyography can be utilized to assist the physically impaired people as well as surgeon. In this paper, we proposed a real-time method for the prior estimation of motion from surface electromyography, especially in the case of wrist angle. The method was based on the recursive processing of multi-layer perceptron, which is trained quickly. A single layer perceptron calculates quasi tensional force of muscles from surface electromyography. A three-layer perceptron calculates the wrist's change in angle. In order to estimate a variety of motions properly, the perceptron was designed to estimate motion in a short time period, e.g. 1ms. Recursive processing enables the method to estimate motion in the target time period, e.g. 50ms. The results of the experiments showed statistical significance for the precedence of estimated angle to the measured one.**

I. INTRODUCTION

THE signal of surface electromyography, sEMG, precedes motion in the human body[1]. Prior estimation of motion by sEMG can be utilized to assist the physically impaired people as well as surgeon. Prior estimation enables assisted motion for physically impaired people wearing powered suits. Prior estimation may also be used to prevent a surgeon from damaging important tissue, such as vessels and nerves. Machine learning could estimate or classify the motions of various people with training[2], [3], [4], [5]. A multi-layer perceptron offers the benefits of high calculation speeds compared to a support vector machine[8]. Previous studies of estimating joint angles using a machine learning with sEMG do not consider a mechanical response of the muscle fiber to the electrical signal[2], [3].

In this paper, we propose a real-time method for the prior estimation of motion by recursive multi-layer perceptron with sEMG. The proposed method is the case of the prior estimation of wrist angle. Finally, the possibility and accuracy of the prior estimation are validated.

II. METHOD FOR PRIOR ESTIMATION OF MOTION

The proposed method aims at estimating motion in advance of the actual motion. *Quasi tensional force*, which approximates the tensional force of a muscle[9] as described below, is estimated from sEMG. The wrist's change in angle is estimated from the quasi tensional force, wrist angle, and angular velocity. The features of the proposed method are as follows:

- *Initial weights based on the impulse response of muscle fibers.* Appropriate initial weights for the perceptron are necessary for stable and quick training. The initial weights used by the perceptron to estimate quasi tensional force are based on the impulse response of muscle fibers.
- *Recursive processing.* In order to estimate a variety of motions properly, the perceptron is designed to estimate motion in a short time period, e.g. 1ms. Recursive processing enables the method to estimate motion in the target time period, e.g. 50ms. Because of its simplicity, the model for a short time period responds to sEMG flexibly and requires only a short training time.

A. Perceptron for wrist angle

The amount of the wrist's change in angle at the forearm $\Delta\theta$ is determined by the current wrist angle θ, wrist angular velocity ω, and wrist torque τ. The wrist torque is determined by the developed tension of muscles and the current angle. The developed tension is determined by pseudo tensional force $\hat{F}$ and the amount of the muscle's change in length from the original length. Thus, the function is written:

$$\Delta\theta = f(\theta, \omega, \hat{F}) \tag{1}$$

Equation 1 is not easy to represent as a concrete equation. However, regression of the equation is possible using a multi-layer perceptron. Fig. 1 illustrates a view showing a multi-layer perceptron's estimation of the amount of a wrist's change in angle after minute time increments. The perceptron estimates the amount of wrist's change in angle at time $t+1$ by using the information obtained at time t.

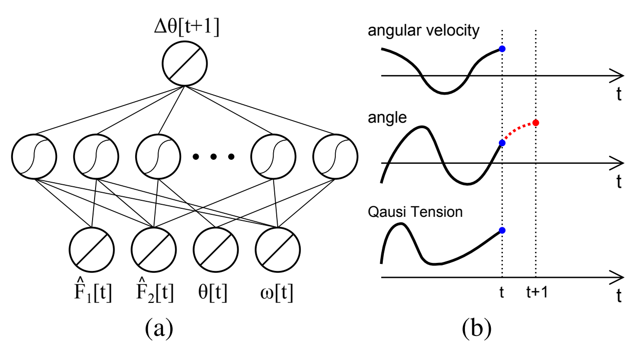

Fig. 1. Perceptron to estimate a wrist's angular change

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The training of the perceptron is carried out by inputting quasi tensional force estimated from sEMG, wrist angle, and wrist angular velocity at time t and using the amount of angular change from time t to $t+1$ as a teacher signal. At the training stage, regression is established with high precision without pre-estimation.

B. Perceptron for quasi tensional force

sEMG can be assumed to represent an impulse, because sEMG has a short response period compared to the tensional force of a muscle fiber. The impulse response of a muscle fiber is written in the following equation[7]:

$$F(t) = F_0 \frac{t}{T} e^{-\frac{t}{T}} \tag{2}$$

where t is elapsed time from the impulse, T is the time from the impulse to the maximum tensional force, $F(t)$ is the tensional force of a muscle fiber at time t, and F_0 is a constant specific to a muscle fiber. T varies from 20 to 120msec according to the type of motor unit[9]. T is shorter when the fiber is fast muscle, while T is longer when the fiber is slow muscle. In order to estimate quasi tensional force accurately, the activity of the whole muscle have to be estimated.

The perceptron for estimating tensional force is illustrated in Fig. 2. This perceptron is a single-layer perceptron with input and output layers.

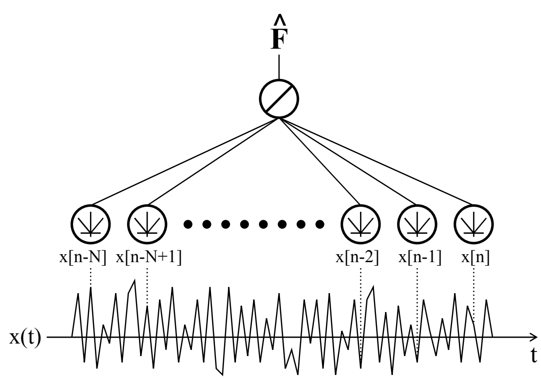


Fig. 2. Perceptron for estimating tensional force

The input data for the perceptron is the time-series absolute value of sEMG in the period since previous sampling time N. Quasi tensional force $\hat{F}$ is written:

$$\hat{F} = \sum_{i=0}^{N} w_i^{(1)} |x[n-i]| \tag{3}$$

where discrete sEMG at sampling time n is $x[n]$, and the weight of sEMG at sampling time $n-i$ is $w_i^{(1)}$. The initial weights of the links are derived from Equation 2, because the response can be approximated by Equation 2. If the sampling frequency is set to f, the weight $w_i^{(1)}$ is set as,

$$w_i^{(1)} = \frac{i}{Tf} e^{-\frac{i}{Tf}} \tag{4}$$

The quasi tensional force is regularized from 0 to 1 by dividing the subtraction of force in the resting state from the maximum force.

C. Whole perceptron for motion estimation

Fig. 3 illustrates the four-layer perceptron developed for motion estimation, which consists of the perceptrons for quasi tensional force and wrist angle. The perceptrons are trained by backward propagation of errors.

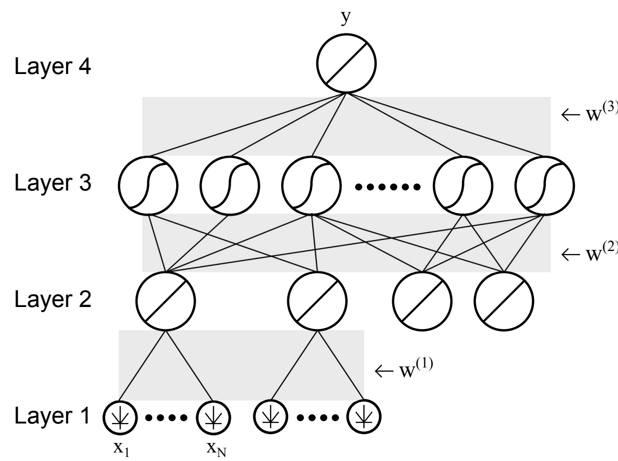


Fig. 3. Four-layer perceptron to estimate motion

The first layer is the input layer of the perceptron for quasi tensional force. The second layer is the input layer of the perceptron for wrist angle, which is the output layer of the perceptron for quasi tensional force on the other hand. The third layer is an intermediate layer and the forth layer is the output layer of the whole perceptron. $w_{hi}^{(1)}$, $w_{ij}^{(2)}$, and $w_j^{(3)}$ are the weights between the first and second, second and third, and third and forth layers, respectively. The output of the perceptron and training signals, which are measured data, are represented as y and r, respectively. x_{hi} is the sEMG signal. $\hat{F}_i$ is the quasi tensional force calculated by Equation 3. The input and output of layer L are represented as $a^{(L)}$, and $z^{(L)}$, respectively. Error is evaluated by the regularized error function $\overline{E}(\mathbf{w})$ as shown in Equation 5.

$$\overline{E}(\mathbf{w}) = E(\mathbf{w}) + \frac{\lambda}{2} \mathbf{w}^T \mathbf{w} \tag{5}$$

where $\lambda (> 0)$ is a damping coefficient and $\mathbf{w}$ is the vector of weights. The derivation of the error function by $w_j^{(3)}$ is solved analytically as follows:

$$\frac{\partial \overline{E}}{\partial w_j^{(3)}} = (y-r) z_j^{(3)} + \lambda w_j^{(3)} \tag{6}$$

The derivation of the error function by $w_{ij}^{(2)}$ is

$$\frac{\partial \overline{E}}{\partial w_{ij}^{(2)}} = \hat{F}_i \frac{\partial h(a_j^{(3)})}{\partial a_j^{(3)}} w_j^{(3)} (y-r) + \lambda w_{ij}^{(2)} \tag{7}$$

where the function h is an activation function, such as logistic sigmoid function. The derivation of the error function by $w_{hi}^{(1)}$ is solved by back-propagation as follows:

$$\frac{\partial \overline{E}}{\partial w_{hi}^{(1)}} = |x_h|(y-r)\sum_{j} w_{ij}^{(2)} w_j^{(3)} \frac{\partial h(a_j^{(3)})}{\partial a_j^{(3)}} + \lambda w_{hi}^{(1)} \quad (8)$$

D. Recursive processing for prior estimation

In the training stage, the perceptrons for quasi tensional force and wrist angle are trained to estimate the amount of angular change after 1 sample time. The precedence time from the current to the target time is represented by T. The prior estimation of wrist angle is conducted by recursive estimation using the trained perceptron. As shown in Fig. 4, the state at $t+1$ is estimated by using the state at t, and the state at $t+2$ is estimated by using the estimated state at $t+1$. Finally, the state at $t+T$ is estimated.

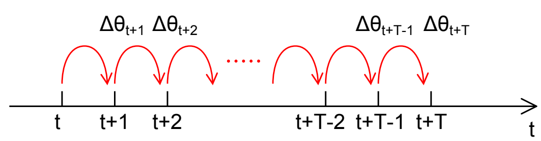


Fig. 4. Recursive estimation

TABLE I

SPECIFICATION OF THE SYSTEM

Amplifier	
Manufacture	Digitex Lab.
Model	BA1104-CM
Gain	60dB
High-path filter	300Hz
Time constant	0.03sec
common mode rejection ratio	$\geq 90dB$
Noise	$\leq 10\mu$Vpp
Head amplifier	
Manufacture	Digitex Lab.
Model	BA-U411
Gain	20dB
Input impedance	$\geq 10M\Omega$
Electrodes	
Manufacture	Nihon-denko
Model	J-vitrode
Input impedance	$\leq 3k\Omega$
A/D converter	
Manufacture	Contec Co., Ltd.
Model	AIO-163202FX-USB
Resolution	16bit
Conversion speed	2μsec/ch
3D Pointer	
Manufacture	SensAble Technologies, Inc
Model	PHANTOM Omni
Resolution	0.055mm
Max. sampling freq.	1kHz
Computer	
CPU	Intel Core2 Duo E7500 2.93GHz
Main memory	2GB

III. EXPERIMENTAL SETUP

A. System

The system consists of the parts that measure sEMG, the parts that measure wrist angle, and a computer. sEMG is measured by an amplifier with electrodes (BA1104-CM, TEAC)[6] and is acquired in the computer through an A/D converter (AIO-163202FX-USB, Contec). Joint angle is measured by a 3D pointer (PHANToM Omni, SensAble). Fig. 5 shows the measurement system. Table I shows the specification of the system.

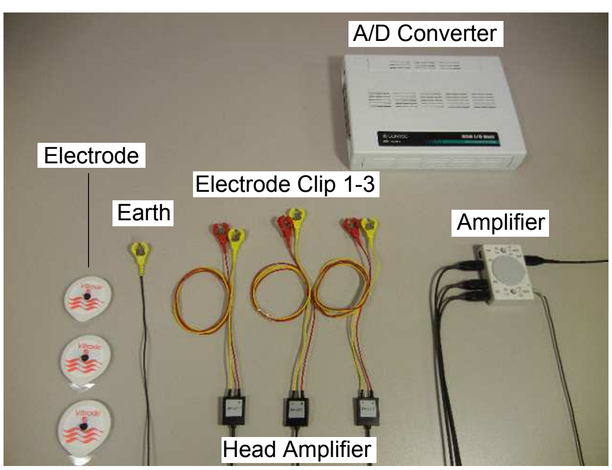
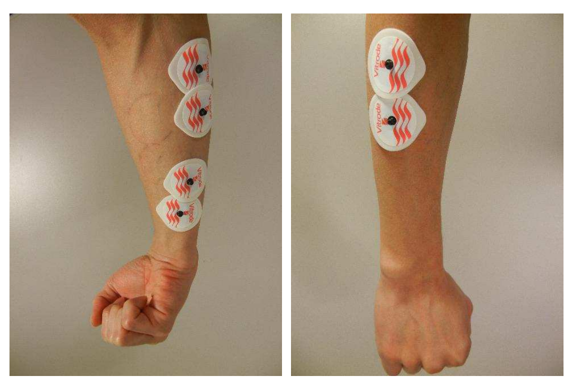


Fig. 5. sEMG measurement system

B. Condition

In the experiment, sEMG of superficial flexor muscle of fingers and ulnar flexor muscle of wrist were measured as palmer flexion with consideration of the order of contribution of muscles for flexion.

Fig. 6 shows the electrodes attached to the right hand. Fig. 6(a) shows the electrodes used to measure the superficial flexor muscle of the fingers and the ulnar flexor muscle of the wrist. Fig. 6(b) shows the electrodes used to measure the common digital extensor muscle. The ground electrode was attached to the ulnae of the right elbow.



(a) (b)

Fig. 6. Attached place of measurement electrodes

Table II shows the parameters used by the perceptron to estimate quasi tensional force. Estimation was carried out by using time-series sEMG data with 400 sampling points, which were obtained 400msec before. The initial values of the weights of the link were set to 50msec for T and 1000Hz for f in Equation 4.

TABLE II

PARAMETERS OF QUASI TENSIONAL FORCE

Type of perceptron	Single-layer
Amount of input nodes	400
Amount of output nodes	1
Activation function	Logistic sigmoid function
Error function	Regularized error sum of squares
Damping coefficient	10^{-6}
Learning rate	0.01
Coefficient of inertia	0.3

IV. RESULTS AND DISCUSSION

A. Evaluation of training

Table III shows the average absolute error and standard deviation of the estimated wrist angle compared with the measured wrist angle for 5,000 sampling points over the course of 5 seconds.

TABLE III

ERROR OF ESTIMATED WRIST ANGLE

Average of absolute error[rad]	0.019
Average of absolute error[deg]	1.085
Standard deviation of absolute error[rad]	0.022
Standard deviation of absolute error[deg]	1.236

B. Evaluation of pre-estimation

Prior estimation of wrist angle is carried out after five minutes of training. Fig. 7 shows estimated wrist angle after 50msec in real-time. The cross correlation between estimated and measured wrist angles were calculated. Fig. 8 shows the cross correlation between estimated and measured wrist angles. The average and standard deviation of the peak of precedence in 22 measurements were 106.7 and 16.7msec, respectively. The results showed statistical significance for the precedence of estimated angle to the measured one. The reason why the average precedence was more than 50msec is that sEMG signals from some muscle fibers precede tensional forces by more than 50msec.

V. CONCLUSION

In this paper, a method for prior estimation of wrist's change in angle using sEMG and a multi-layer perceptron model was proposed. The part for estimating quasi tensional force enabled the estimation of quasi tensional force with high accuracy. The cross correlation between measured and estimated the wrist angle using the proposed method showed statistical significance for the precedence of estimated angle to the measured one. The evaluation of the efficiency in training and the development of a navigation system using the proposed prior estimation method are future works.

VI. ACKNOWLEDGMENTS

This study was partly supported by the Global COE Program "*in silico* medicine" at Osaka University.

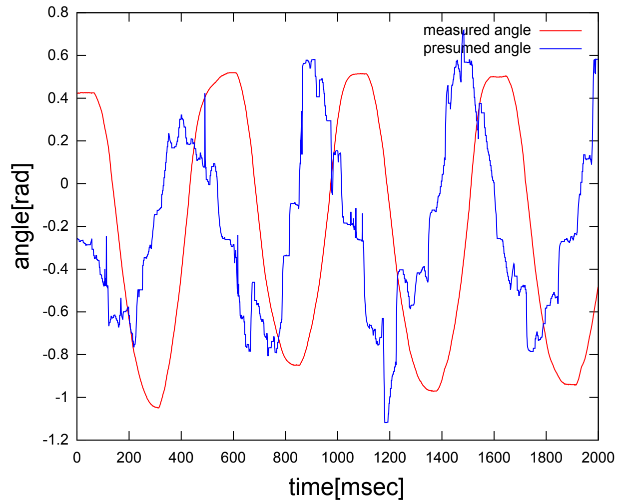


Fig. 7. Pre-estimation of wrist angle

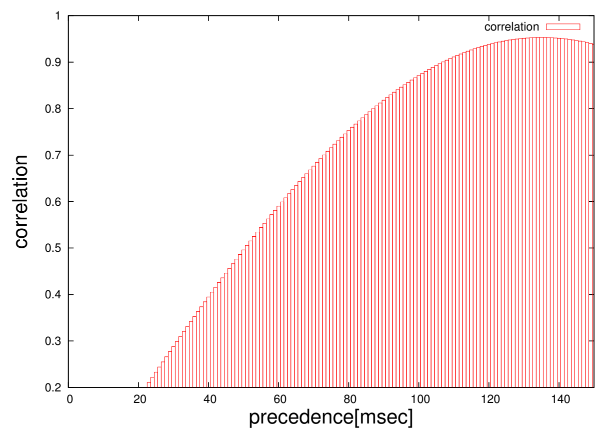


Fig. 8. Cross-correlation between pre-estimated and measured wrist angles

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