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Finger Motion Classification Using Surface-electromyogram Signals

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***Abstract*—The finger movement has the information about force, speed to bend and the combination of fingers. If these information is estimated, the many degrees of freedom interface can apply it. In this study, we aimed for the many degrees of freedom finger movement classification. We tried each fingers classification and the estimate of the flexural finger force using surface-electromyogram signals. In the technique, amount of characteristic are a cepstral coefficient of EMG signals and an integral calculus EMG signals. A support vector machine performs learning and classtification. Therefore, I propose the classification technique and inspected a classification each finger and the combination of fingers by offline data handling using surface EMG signals.**

***Keywords*-Surface-Electromyogram Signals(EMG); Finger Motion Classification; Support Vector Machines(SVM);**

I. Introduction

Entry tools of wearable computer expects to use surface-electromyogram signals (EMG) in the ubiquitous computer society. As a result of development of Internet and the computer technology, the computer becomes indispensable for our life. Therefore, recording and taking desired information anytime or anywhere, instantly is demanded. Entry tools that require the use of hands, such as the mouse and the keyboard, are dangerous when we use the computer while walking. Using EMG, we get the hand motion information by placing the hand over the electrode. The hand motion information from EMG results in the application of a new human interface. We propose the wearable computer entry device using EMG.

Surface-electromyogram signals are signals causing muscle contraction on muscle fiber by movement command occurred in a brain. The animals such as human beings hold a great deal of muscle fiber and carry out various activities by contraction each muscle fiber in various pattern. The human movement has the information about force, speed, the combination of fingers. If these information is estimated from surface-electromyogram signals, the many degrees of application can apply it. Application using electromyogram signals was centered on the medical application such as artificial hand. But the intuitive interface for everyday use become an active area of research because it is not necessary to learn how to use so that a controller uses own body. The advantage of the interface using surface-electromyogram is 1) allowing estimate of muscular tension 2) available information if muscle consist 3) undelayed input signals 4) measuring easily.

The hand finger is used for job the most and has complicated movement in movement of the person. Extracting the movement, the research which applies to human interface and finds out traditional technical skill etc is advanced. Until recently, extraction of movement is done with dynamic picture image processing and motion capture and the data glove. The delay is caused in the entry device because they measure data after the movement. In addition, dynamic picture image processing and motion capture are limited the measurement place because the measurement equipment is large. The data glove becomes obstacle of operation because the measurement equipment is putted the hand using for the work. In this research, we focus attention on surface-electromyogram signals which can solve those problems. Estimation of the hand finger operation is expected many degree of freedom to apply myoelectroric hand and entry to the computer and gesture recognition.

Purpose of this research is estimate of the finger movement many degree of freedom from surface-electromyogram signals. It is necessary to establish the hardware of electromyographic measure and the software which removes the control signal from electromyogram signals. The latter must estimate the hand finger movement. Pattern recognition was used mainly to achieve it. The reason uses pattern recognition is described below.

・can classify the numbers of more movements than the electrodes

・can decrease the burden of training by adapting to an individual variation of electromyogram signal

・can estimate steady the movements from electromyogram signal fluctuate each the movement in an individual

Various pattern recognition techniques were used for the motion estimate. There are researches which used primary pattern recognition technique such as linear discriminant analysis[1] and learned nonlinear map between electromyogram pattern and the motion with neural net[2]. On the other hands, there is support vector machine(SVM) which is relatively new pattern recognition technique was proposed to the nineties. The features of SVM is described below.

・guarantee general optimal solution

・provide better classification performance to unseen pattern

・easy to search of hyper parameter

・have a low calculation amount about classification

・have the algorithm study efficiently

SVM becomes obvious availability in bioinformatics[3] and image processing[4], text classification[5]. High classification rate is obtained in case of the motion classification uses electromyogram signals. Yoshikawa's study[6] try real time hand motion classification with SVM and comparison of classification efficiency of other pattern recognition technique. Motions of classification are six motion to wrist extension, wrist flexion, grasp, open, pronation of forearm, supinaton of forearm. But, we propose SVM availability to hand finger motion of many degrees of freedom is not clear because the motion in that study are small in number and unnatural. In this paper we present many degree of freedom hand finger motion classification technique using surface-electromyogram and do classification experimentation five finger and combination pattern of all fingers.

II. SYSTEM DESCRIPTION

It is difficult to classify unprocessed EMG data because EMG is complex and irregular waveform. It is general to classify processed signals. Whole classification technique is shown in Figure 1. First, Surface-electromyogram(later EMG) is measured from the forearm, and Integral EMG (later IEMG) form on the basis of integral calculus of EMG. Next, feature vector make from EMG and IEMG. Feature vector constitutes from the cepstrum coefficient of EMG and IEMG. The cepstrum coefficient shows the envelope form of the spectrum of EMG. IEMG which show the amplitude of EMG. Discriminant function is calculated from the study data which gives motion class with SVM. Feature vector is classified on the basis of discriminant function, and motion class is given.

A. *Feature extraction*

Feature vector makes the feature quantity in frame. The frame is shifted with frame length 64[ms](128 samples) during frame period 16 [ms](32 samples). Because, the motion classification of 60[Hz] period is actualized while guaranteeing the number of samples which are necessary for feature extraction. EMG is done window processing by hamming window.

Feature vector is two feature quantity which are extracted Average IEMG feature and cepstrum coefficient feature in frame. Two feature quantities is describe below.

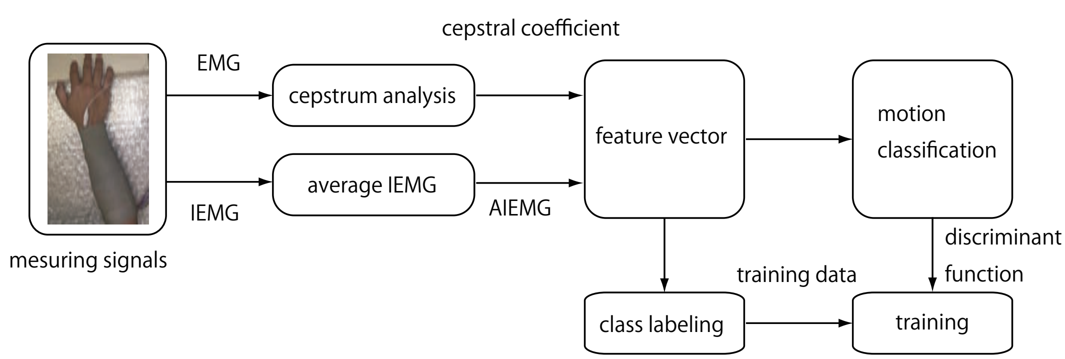

Figure 1. system flow

1) AIEMG:

$$AIEMG_l(p) = \frac{1}{N} \sum_{n=0}^{N-1} IEMG_l(n) \quad (1)$$

AIEMG feature is IEMG time average in frame, and represent ENG amplitude value. $IEMG_l(n)$ is IEMG sample of n point in l frame. N is number of sample in one frame. L is number of electrodes.

2) CC: The frequency component of the signal is the important component in motion classification using EMG. Action potential of the motion unit which the minimum unit of EMG is the electric potential like only barely several milli-seconds the pulse is not continued. Because surface EMG is measured with surface electrodes is the signal adds countlessly, surface EMG becomes the electric potential like the noise which occurs continually. Hence, it is the signal add variety wavelength and frequency and phase AC signal while time change. Small frequency component which is computed with simple fourier transform is almost unrelated information. Therefore, we use cepstrum coefficient can outline it.

Cepstrum coefficient is obtained by cepstrum analysis for EMG in frame. $EMG_l(n)$ is EMG sample of n point in l frame. $X_l\ k(n)$ given with fourier transform becomes

$$X_l^k(p) = \sum_{n=0}^{N-1} EMG_l(n) e^{-j2\pi kn/N} \quad (2)$$

Cepstrum coefficient follows that

$$CC_l^n(p) = \frac{1}{N} \sum_{n=0}^{N-1} log|X_l^k(p)| e^{j2\pi kn/N} \quad (3)$$

Cepstrum analysis can separate envelope shape and microscopic structure of the spectrum. Low dimensional coefficient denote envelope shape and High dimensional coefficient denote microscopic structure. In this method, suppose that CC feature is envelope shape.

B. SVM

$$f(x) = sign\left(\sum_{i=1}^{D} \lambda_i y_i K(x_i, x) + b\right) \quad (4)$$

$$K(x_i, x) = exp(-\gamma ||x_i - x||^2) \quad (5)$$

Support vector machine is the method make the pattern discriminant function of two class by separating the space with hyperplane. Let y_i be the class label for training data x_i. Let λ_i be Lagrange's undetermined multipliers. Let b be bias term. Let $K(x_i, x)$ be the kernel function and use Radial basis function kernel. Using a kernel function, nonlinear curve become linearly separable to mapping to hyperplane.

Furthermore, to give the discriminant function, we desire λ maximize convex quadratic program with large margin. The nonzero desired λ_i is called a support vector. Because the discriminant function construct a few support vector, it is evaluated a few amount of calculation.

III. MUSCULAR AND SKELETAL SYSTEM

A. hand skeleton

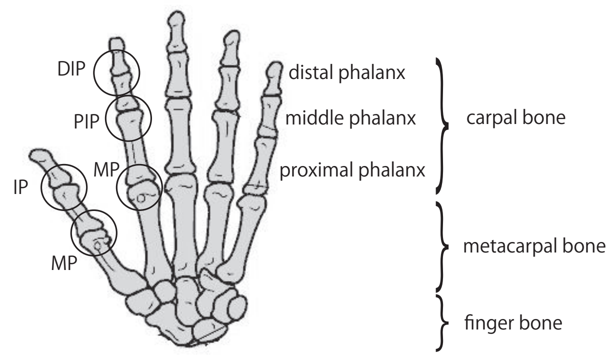

Figure 2. hand skeleton

The bone of the hand consists of 3 groups of carpal bone, metacarpal bone and finger bone as pictured in the figure 2. There are 14 tubuliform bones which support 5 fingers in one hand. Thumb has two bones and 2-5th finger has each three bones. It is called proximal phalanx, middle phalanx and distal phalanx from proximity, the thumb don't have middle phalanx. In this paper, each joint of 2-5th finger is called MP(metacarpal-phalangeal joint), IP(Proximal inter-phalangeal joint), DIP(distal interphalangeal joint) from proximal. In the thumb it is called MP(Metacarpal-phalangeal joint), IP(Interphalangeal joint) from proximal.

B. muscle related finger motion

Proposition technique classify finger motion according electromyogram input of a muscle which relates to finger motion. The muscle is seen mainly in the forearm and the hand. But, when application to interface and actual motion is considered, the muscle in the hand disturbs those. The classification is done with only the input of EMG from the muscle of the forearm. Figure 3 show the muscle of the forearm.

Forearm has multilayer structure that muscle overlap intricately. Flexor digitorum superficialis muscle, flexor digitorum profundus muscle and flexor pollicis muscle is the muscle directly control the finger motion. Flexor digitorum

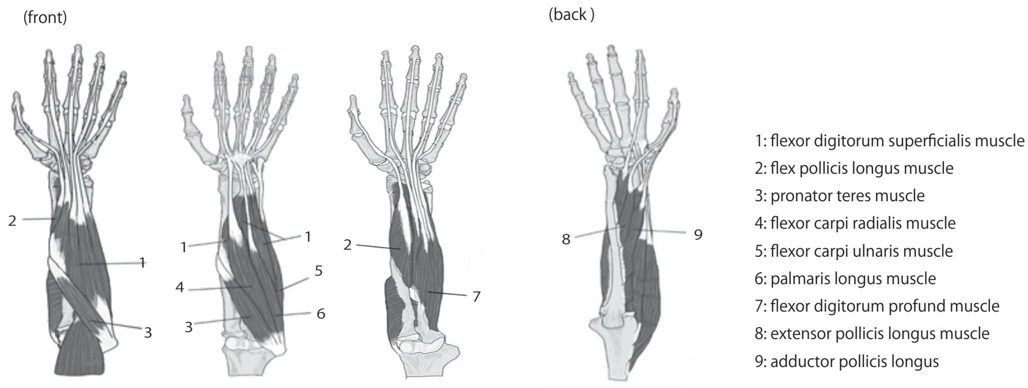

Figure 3. hand skeleton

super ficialis muscular tendon stops 2-5th finger middle phalanx. The muscle controls flexion of 2-5th finger PIP. Flexor digitorum profundus musclar tendon stops 2-5th finger distal phalanx. The tendon passes the respective wrist bone trunk and reaches distal phalanx through between the flexor digitorum superficialis musclar tendon split. The muscle controls flexion of 2-5th finger DIP. Flexor pollicis longus muscle stops distal phalanx of thumb and controls floxion of IP.

Beginning and end of the muscle are not only bones but also nearby fascia and tendon. These also control flexion of the finger indirectly. It is called muscular connection, and it is said that the tension due to the muscle contraction of one side infect other muscle in the its case - namely, the muscle can also control the finger motion indirectly. Table 1 shows muscular connection to flecor digitorum superficialis muscle, flexor digitorum profundus muscle and flexor pollicis muscle.

Table I
MUSCULAR CONNECTION

flexor digitorum superficialis muscle	pronator teres muscle biceps brachii muscle flexor carpi ulnaris muscle flexor carpi radialis muscle Palmaris longus muscle
flexor digitorum profundus muscle	biceps brachii muscle flexor carpi ulnaris muscle extensor pollicis longus muscle adductor pollicis longus flexor pollicis longus muscle
flexor pollicis longus muscle	flexor digitorum profundus muscle

IV. EXPERIMENT AND EVALUATION

To substantiate availability proposed method, we performed two types of finger motion classification experiments using EMG. A subject is right-handed man in his twenties.

A. experiment environment

EMG measured with easily-removable surface electrode. To place the electrode a wide area on the forearm, we use bipolar-lead electrocardiogram because single-lead electrocardiogram causes large noise. The electromyogram measured at electrode is increased by the amplifier. Measured data is recorded by POWERLAB and taken a sample by sampling frequency 2000[Hz], quantization bit rate 16[bit].

1) noise abatement regulation : There is a variety of a noise in our living environment. The noise cause a alternating current source and the electromagnetic wave from mobile phone and PC. To reduce these noise in an experiment, we use a shield room. But, we need to make the experiment environment easily reduced noise everywhere because a work in a shield room is not practical for everyday use. Accordingly, we use the conductive cloth[7] that make the environment like a shield room. Figure 4 show the conductive cloth.

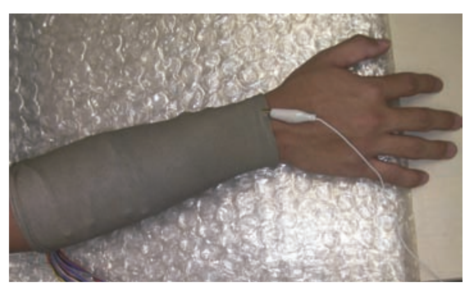

Figure 4. conductive cloth

2) experiment system: The system character extraction is written in the visual C++(Microsoft Corporation). The training / classification algorithm of SVM is used SVM library LIVSVM[8]. The program is executed by personal computer(CPU : Core 2 Duo 2.4[Hz], OS : Windows Vista, memory : 2[G byte]).

B. Experiment 1: classification each finger

We verify the classification precision of each finger on this method. In one trial, the subject infect 30 times of 6 sets according thumb, index finger, center finger, ring finger, little finger in 60 seconds. The subject push the desk with each finger from state of neutral rank, pull out power and reset to neutral rank and do the following operation. The motion class is made from the pressure sensor. The motion interval is predicted on the basis of the survey value which is measured with the pressure sensor. Feature vector is given identical motion class in the motion interval. The feature vector is called the training data. Motion class is 6 types of neutral, thumb, index, center, ring, little. Training data of two trials is used SVM training. The neutral class is larger than other class, and so the neutral class data reduce one-tenth. Position of electrode is determined on the basis of the anatomy knowledge explained in chapter 3. Figure 5 shows position of electrode.

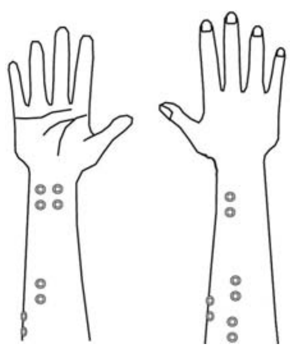

Figure 5. electrodes

Table 2 show the result of classification. The correct classification probability is 98 % at neutral, 61 % at center finger, 80 % at other finger. But, the incorrect classification probability to neutral is high and the incorrect classification probability to other finger is low.

Table II
RESULT OF CLASSIFICATION EACH FINGER

		estimate class					
		neutral	thumb	index	center	ring	little
Actual class	neutral	98.6	0.6	0.2	0.1	0.2	0.4
	thumb	20.9	77.7	0.0	1.4	0.7	0.0
	index	11.7	0.1	83.7	3.6	0.0	0.4
	center	22.7	3.3	0.7	61.4	7.7	4.2
	ring	8.7	0.4	0	5.6	81.9	3.5
	little	15.7	0.0	0.0	5.5	5.7	73.1

C. Experiment 2: classification combination pattern of all fingers

We verify the classification precision of combination pattern of all fingers on the this method. The motion class is made from the pressure sensor. Motion class is 32 types of the combnation. Considering classification class increase, number of position of electrode increase 3ch over experiment 1.

Table 3 shows result of classification. 1 denote thumb, 2 denote index finger, 3 denote center finger, 4 denote ring finger, 5 denote little finger. 12 denote the combination of thumb and index, 1234 denote the combination of thumb, index, center, ring. Total classification probability is 57.3%. The classification precision vary in whole. Beside, many incorrect classification is the classification to motion involve same finger for example combination of index and center to index, center and ring.

Table III
RESULT OF CLASSIFICATION COMBINARION OF ALL FINGERS

sub	1	2	3	4	5
	60.3	46.4	57.6	75.6	51.4

	12	13	14	15	23	24	25	34	35	45
	65.4	49.9	65.6	67.8	62.9	62	43.2	76.2	55.4	63.9

	123	124	125	134	135	145	234	235	245	345
	60.9	67.3	70.5	54	60.8	66.6	60.8	41	64.7	36

	1234	1235	1245	1345	2345	12345	total
	71.9	30.1	57.5	46.5	39	47.6	57.3

V. DISCUSSION

From the result of experiment, this chapter show consideration of effectiveness of proposition system.

A. Experiment 1: classification each finger

Classification ratio is high through the whole. The incorrect classification to neutral is many, but the incorrect classification to other motion is low. The incorrect classification to neutral show there is many classification to the both ends of motion section. Because, EMG wave shape provide the value of the both ends is smaller than the value of center. Beside, this is due to the short motion interval. When the classification result of the both ends is neutral, the beginning input to application delays. So, we must improve it.

B. Experiment 2: classification combination pattern of all fingers

Many incorrect classification results are classification to the combination involve same finger. Because, we presume that saparable EMG pattern cannot be detected to be the same muscle controlling each finger. The muscle in a forearm is three laminar structure - shallow layer, middle layer and deep layer. The muscle that controls the finger motion places deep layer which is difficult to measure with surface electrode. So that, we think that the finger motion classification is difficult with only simple signal processing and a pattern recognition. We expect the problem is soleved due to the limit of the classification extent giving various constraint. The various constraint is described as follows.

・the constraint of the application function

・the constraint of motion history, focusing on motional continuity

・the constraint of physiological information to range of joint movement

VI. CONCLUSION AND FUTURE WORK

This paper presented two type of motion classification experiment for many degrees of freedom finger motion classification with support vector machine. The system has character extractions are cepstrum coefficient and average integral EMG, and do discriminative learning with SVM. In each finger classification experiment, the incorrect classification to neutral is many, but the incorrect classification to other motion is low. Proposition technique precision can do the each finger motion classification well. In all combination patterns of fingers experiment, the incorrect classification to the motion the same finger is included is many. Proposition technique precision cannot do all combination patterns of fingers classification well.

It is necessary to classify the finger motion in the expansion of EMG application. But, the experiment showed because muscle of the forearm is complex in structure, the complicate motion classification using EMG is difficult. Future work should investigate application function using EMG and motion history of finger motional continuity and physiological information to range of joint movement. It remains possible that these information limit the search range. We will propose the technique and the application which consider them.

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