Robust finger motion classification using frequency characteristics of surface electromyogram signals

Robust Finger Motion Classification using Frequency Characteristics of Surface Electromyogram Signals

Keisuke ISHIKAWA
School of Systems Information Science
Future University Hakodate
Email: g2110005@fun.ac.jp

Masashi TODA
Department of Media Architecture
Future University Hakodate
Email: toda@fun.ac.jp

Shigeru SAKURAZAWA
Department of Complex Systems
Future University Hakodate
Email: sakura@fun.ac.jp

Junichi AKITA
Department of technology
Kanazawa University
Email: akita@is.t.kanazawa-u.ac.jp

Kazuaki KONDO
Academic Center for Computing and Media Studies
Kyoto University
Email: kondo@media.kyoto-u.ac.jp

Yuichi NAKAMURA
Academic Center for Computing and Media Studies
Kyoto University
Email: yuichi@ccm.media.kyoto-u.ac.jp

Abstract—**Finger motion classification using surface electromyogram (EMG) signals is currently being applied to myoelectric prosthetic hands with methods of pattern classification. It can be used to classify motion with great accuracy under ideal circumstances. However, the precision of classification falling to change the quantity of EMG feature with muscle fatigue has been a problem. We addressed this problem in this study, which was aimed at robustly classifying finger motion against changes in EMG features with muscle fatigue. We tested the changes in EMG features before and after muscle fatigue and propose a robust feature that uses a methods of estimating tension in finger motion by taking muscle fatigue into consideration.**

Keywords-Surface-Electromyogram Signals (EMG); Finger Motion Classification; Frequency Characteristics; Tension Estimate;

I. INTRODUCTION

Users of the entry tools of wearable computers expect to use surface electromyogram (EMG) signals in the ubiquitous computer society. EMG is signal that cause muscle contractions in muscle fibers due to motion commands that occur in the brain.

EMG contains information on human motion. And it is possible to classify this motion with these signals. There has been much research on classifying motion and this has been applied interfaces such as those for myoelectric hands. Figure 1 shows a sample of an electromyogram signal waveform. Motion classification uses a highly-precision pattern analysis method in these signals. The three main advantages of an interface using EMG are that it 1) allows muscular tension to be estimated 2) enables undelayed input signals and 3) easily measurement. It can also solve problems with other methods such as those with acceleration sensors and motion-capture technology.

However, there is a problem in EMG changes over time in motion classification. EMG changes the nature of signals with muscle fatigue, removal of electrodes, and mastery of motion. The classification rate decreases over time because a traditional method is assumed where the feature space never changes and this is dependent on early-formed learning. Muscle fatigue particularly occurs often when EMG are applied. For example, false operation of a myoelectric hand is dangerous where a person has lost his hand. Muscle fatigue causes this in everyday life. In this study, we focused on muscle fatigue and propose a robust finger motion classification method doe to the muscle fatigue.

EMG signals change according to muscle fatigue. The integral quantity and frequency range are feature quantities that can be used to detect muscle fatigue from EMG signals [1]. The integral quantity increases linearly according to muscle fatigue and the frequency range shifts to low according to this fatigue. The shift to low frequencies can be attributed to the conduction rate of muscle fiber. When the muscle continually constricts, the extracellular concentration of potassium ions increases. The frequency shifts to low to change the extracellular electrical gradient under polarizing conditions. Increasing the integral quantity can be attributed to the increase in motor units. The contraction force of muscle fiber decreases because of fatigue. All motor units increase to mobilize new motor units to help this.

In this paper, we tested the change in the number of features before and after muscle fatigue and proposed a method of estimating the tension in finger motion considering muscle fatigue. Section 2 introduces studies related to methods if classifying motion using EMG and the relationship between EMG and muscle fatigue. Section 3 describes the proposed method of classification. Section 4 describes experiments we carried out with the proposed method. The paper is concluded in Section 5.

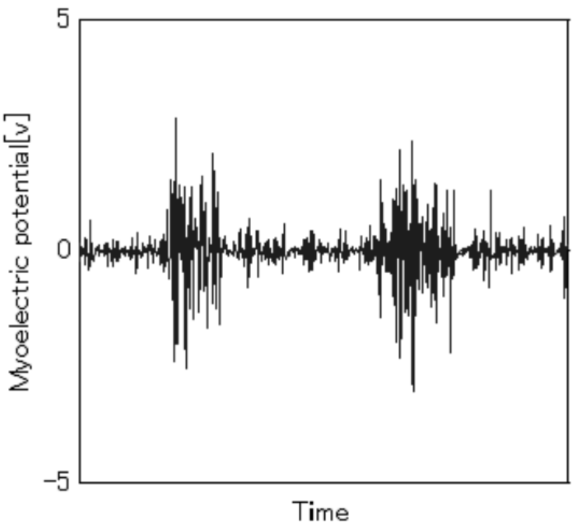

Figure 1. Example of a figure caption. (figure caption)

II. RELAYED STUDIES

A. Methods of estimating torque

There have been methods of recognizing muscle tension by using EMG. These methods need to accept target motion because the behavior of individual muscles changes. Elbow bending is simple motion and uses a simple muscle group. Koike proposed a method of estimation based on physiological data using neural networks [2]. Muscle tension in the lower limbs uses an analysis of walking motion and bicycling exercise. Tanaka estimated the muscle tension for walking using Electromyography-Assisted Optimization [3].

There has been research that has estimated muscle tension for finger motion. Okuno proposed a method of separately modeling the responses to tension and stretching and combining them [4]. Tsuchida's research cleared up the relation between the inner and outer muscle activities and the bending tension in finger motion [5]. These methods can be used where muscle activity is constant. However, there is a problem with not accepting changes in muscle conditions.

B. Relationship between classification and change over time

There has been some research on methods of classification that have taken changes over time into considering. Nishikawa proposed an on-line supervising mechanism for learning data in surface electromyogram motion classifiers [6]. Kiso proposed robust discrimination of motion based on human myoelectric potential by adaptive fuzzy inference by taking muscle fatigue [7]. However, there have been some problems with the results of classification because these methods have assumed continuity in classification results. The accuracy of classification decreases temporarily when redesigning the learning data after the number of features is changed. When muscle fatigue is rapidly reduced, the accuracy of classification decreases and does not accept continuity of motion. In this study, the method takes the characteristics EMG variation muscle fatigue into consideration.

III. MOTION ESTIMATED CONSIDERING MUSCLE FATIGUE

A. Muscle fatigue and EMG

EMG signals change according to muscle fatigue. The integral quantity and the frequency range are feature quantities which detect muscle fatigue from EMG signals. The integral quantity increases linearly according to muscle fatigue. This integral quantity feature is Average Rectified Value (ARV).

$$ARV(t) = \frac{1}{L}\sum_{t=0}^{l} | EMG(i) | \quad (1)$$

ARV is calculated with the mean value of the absolute EMG signal in the frame. The time change in ARV is obtained to calculate ARV while the frame is gradually sliding in terms of time. L is the number of samples in one frame. The frequency range shifts to low according to muscle fatigue. This frequency range feature is Mean Power Frequency (MPF).

$$MPF(t) = \frac{\sum fP(f,t)}{\sum P(f,n)} \quad (2)$$

The frequency spectrum of EMG is calculated by fast Fourier transform (FFT). The preprocessing algorithm is the Hamming window before applying the FFT processing. P(f) represents the power spectrum, f represents the frequency. MPF is calculated the centroid of frequency. If all spectrum change low frequency, MPF is smaller.

B. Tension estimate method

In this method, robust finger motion classification using MPF represent frequency characteristics. 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). The motion classification of 60[Hz] period is actualized while guaranteeing the number of samples which are necessary for feature extraction.

1) Conventional method

$$T(t) = aARV(t) \quad (3)$$

Motion torque in isometric contraction is linear to integral EMG and a is a constant [8]. It is calculated from ARV and the pressure sensor value by the least-squares method. However, the results of obtained with this method increase error according to muscle fatigue because ARV increases to the same torque. We propose a method of estimating muscle tension considering muscle fatigue using the MPF of frequency characteristics.

2) Proposed method

$$T(t) = f(x)ARV(t) \tag{4}$$

$$f(x) = mx + n \tag{5}$$

$$x = MPF(t) \tag{6}$$

The conventional method in the proposed approach is extended for equation 4. f(x) changes according to muscle fatigue. Slope f(x) is designed to decrease according to fatigue. f(x) establishes the relation represented by MPF and is derived in equations 5 and 6. We found x was a linear MPF linearly from a preliminary experiment and this will hereinafter be described in detail after this. Constant numbers m and n can be calculated from the EMG data before and after muscle fatigue using the least squares method.

$$T(t) = mARV(t)MPF(t) + nARV(t) \tag{7}$$

Tension can be calculated as described above considering the muscle fatigue. Tension can be estimated from m and n if the position of the electrode does not change.

C. Estimation of Flow

Here, we explain the estimation of flow with the proposed and conventional methods. We will describe how to estimate flow with the conventional method. The constants a and b in Equation 3 are determined using least-squares estimates of torque values obtained from pressure sensors and the ARV data range of the first set. Only the state before muscle fatigue was learned.

We will describe how to estimate flow with the proposed method, where there are two phases for learning and estimation. Constants m and n are calculated from the data of muscle fatigue process in the learning phase. Tension is calculated in the estimate phase from ARV and MPF based on constants, which are calculated in the learning phase.

In the learning phase, constants m and n are calculated from the EMG data on the muscle fatigue process. The data are the separated frames of 1000 points. The slope value is calculated by using another set using the least squares method, which is the same as that with the conventional method. f(x) is determined in other set as the slope changes only by using the least squares method. f(x) decreases according to fatigue. f(x) has a relation represented by MPF. MPF is used as the average of each set. Figure 2 shows a sample of the scatter plot for MPF and f(x). The constants m and n are calculated from these values using the least squares method. In the estimate phase, tension is calculated from ARV and MPF based on constants that are calculated in the learning phase. ARV is not specially treated. It is difficult to calculate a unique MPF through time because the EMG wave-form is complex. Consequently, MPF is used as a smoothing technique at 1000 points so that there is no change over time.

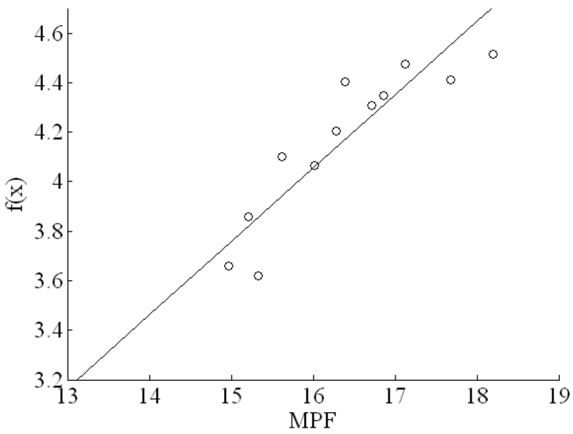

Figure 2. Relationship between MPF and f(x)

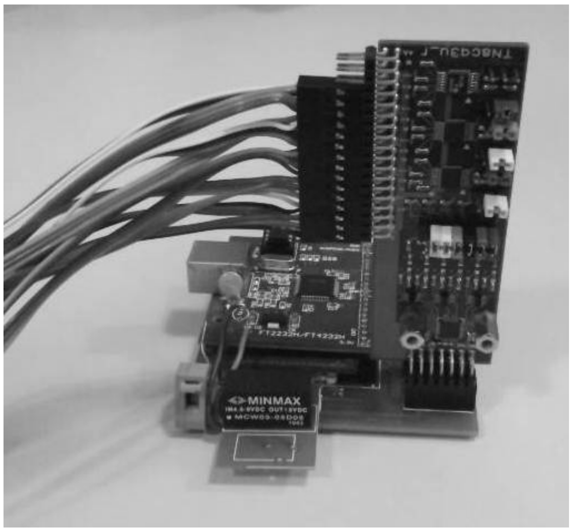

Figure 3. EMG measurement system

IV. EXPERIMENT AND EVALUATION

We carried out experiments to classify finger motion using EMG to test availability proposed method. The male subject aged 23 and was right-handed.

A. Measurement signals

Figure 3 shows the hardware we used to measure EMG. They were measured with an easily-removable surface electrode. We used a bipolar-lead electrocardiogram to place the electrode a wide area on the forearm because a single-lead electrocardiogram would have caused large amount of noise.

Figure 4. Conductive fabric supporter

Figure 5. Position of electrode placed on subject's forarm

The electromyogram measured at the electrode was increased with an amplifier. Measured data were taken from samples with a sampling frequency of 2000 [Hz] and a quantization bit rate of 16 [bit]..

1) noise abatement regulation

There is a variety of noise in our living environment, which causes alternating current sources and electromagnetic waves from mobile phones and PCs. We needed to use a shielded room to reduce these noise in an experiment. However, we needed to creat an experimental environment in which noise could be easily reduced ubiquitously because working in a shielded room is not practical in everyday use. As a result, we used a conductive cloth that created an environment like that in a shielded room [8]. Figure 4 has a photgraph of the conductive cloth.

B. Experimental environment

The target motion was three types of powers of the same motion to reduce problems in this experiment. The motion was index finger flection Specifically for sustained isometric contraction. The subject performed a task in the experiment of sitting on a chair next to a desk with a pressure sensor between his index finger and the desk. He could provide the intended tensional force while watching the sensor value. One channel was used for the electrodes, which were attached to the subject's forearm, as can be seen in Figure 5.

We measured Maximal Voluntary Contraction (MVC) with the pressure sensor before the experiment. Three types of power is 30%, 40% and 50%MVC that took into consideration range of motion were performed that resulted in muscle fatigue and that easily changed the features. One set was maintained for 3 seconds according 30%, 40% and 50%MVC in 12 sets when measuring the data.

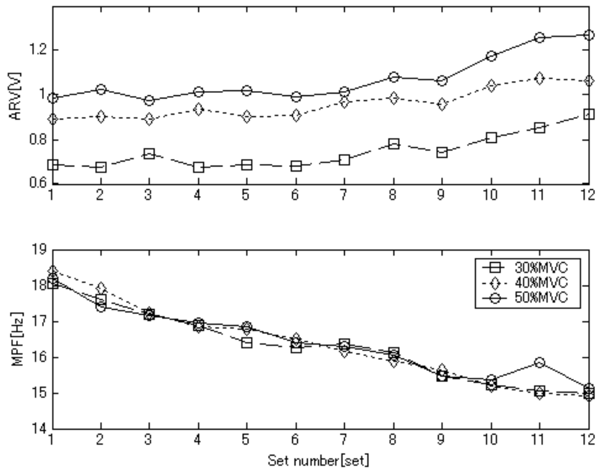

Figure 6. Each set mean of ARV and MPF

Calibration was performed to match EMG waveforms and pressure sensor waveforms. The EMG waveforms were measured faster than the pressure sensor waveforms. The calibration was performed in three sets to force changes in the 50 % MVC from 0 % MVC before the experiment. We determined the correlation between the ARV of EMG waveforms and waveform of pressure sensors. The pressure sensor had the least delay in waveforms. Figure 7 shows the measured data after calibration.

C. Change in features to muscle fatigues

Figure 6 plots the means of ARV and MPF in the set. The ARV increases and the MPF decreases with the increasing degree of the set. The ARV increased according to the increase in the percent of MVC. The MPF does not change. This is because it is possible to detect muscle fatigue using MPF.

D. Estimation Result of proposed method

We propose evaluating the accuracy with which tension can be estimated considering muscle fatigue. The significance of the proposed method was found by comparing actual tension obtained from a pressure sensor using the proposed approach and a conventional method..

Figure 8 above shows the results obtained from estimation with the conventional method. It is clear that highly accurate results can be estimated before muscle fatigue occurs. However, the data estimated after muscle fatigue occurs have a high error rate. The bottom of Figure 8 shows the results obtained from estimation using the proposed method. It is clear that very accurate results can be estimated before and after muscle fatigue occurs.

We compared the error value calculated as the difference between the actual torque to assess the accuracy of the proposed and the traditional method. Figure 9 plots the results. The error values represent the mean of each set. The error value for the conventional method increased from the sixth set. The error value for the proposed method does not increase.

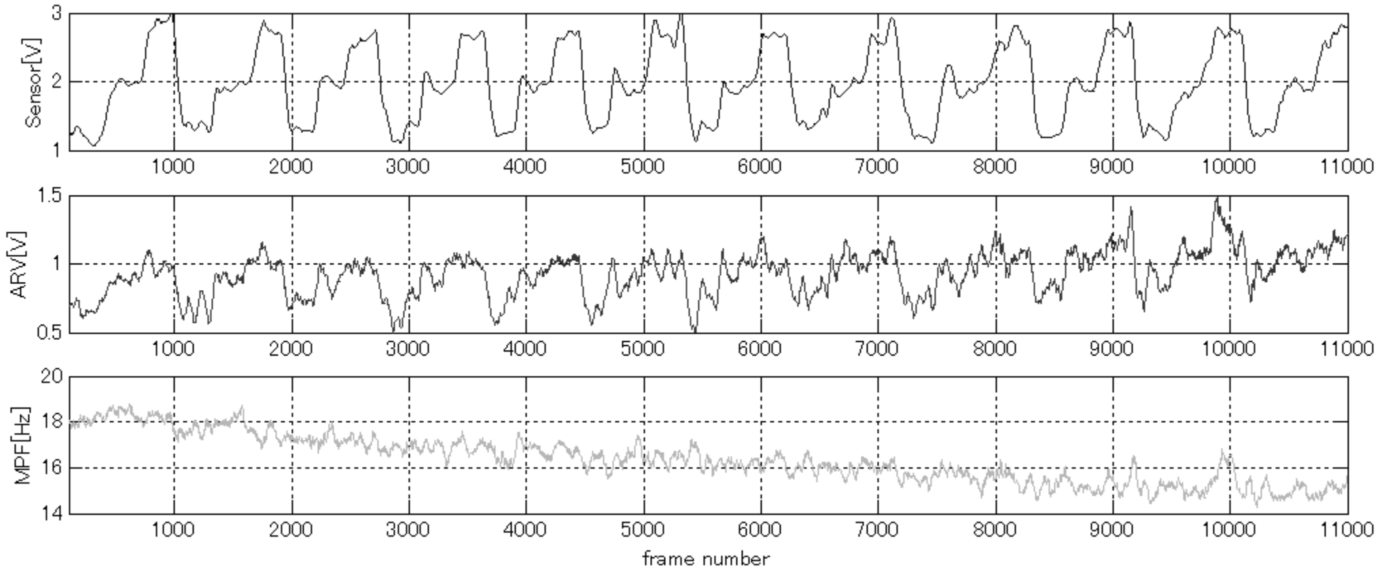

Figure 7. Sample of measured data

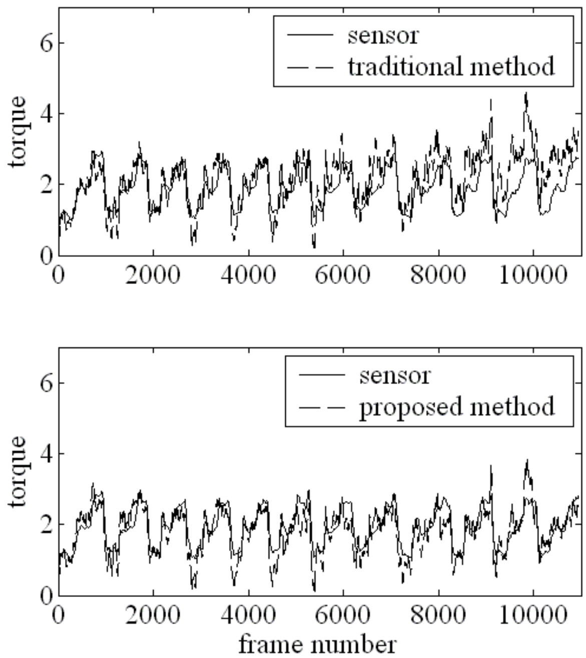

Figure 8. Results of estimating tension in muscle fatigue environment

E. Discussion

It is possible to accurately estimate results even when muscle fatigue occurs using this method. Its main problem is the need to calculate a constant with muscle fatigue EMG before tension is estimated. Once the state to muscle fatigue is not only time consuming, but imposes restriction on finger movement. We need to calculate the constant by estimating the change in MPF and f(x) in the early stages.

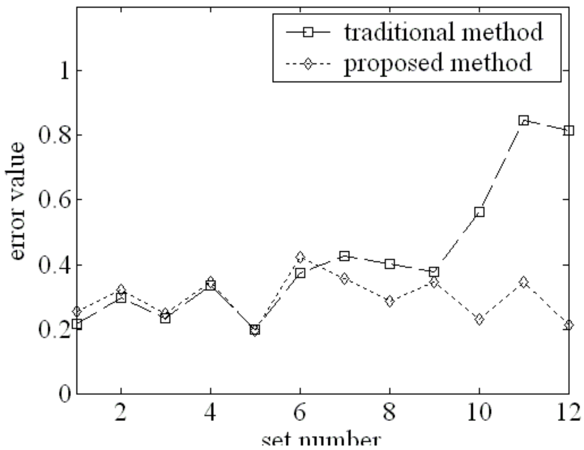

Figure 9. Error rate in muscle fatigue environment

V. CONCLUSION AND FUTURE WORK

In this paper, we tested changes in the number of features before and after muscle fatigue and proposed a method of estimating the tension in finger motion considering the muscle fatigue. The main characteristics detected in muscle fatigue were the integral EMG and frequency range. The integral EMG increased linearly with muscle fatigue. The power spectrum of EMG frequency band shifted to low frequencies.

It is possible to robustly estimate tension considering muscle fatigue by using a model of the transition fatigue using ARV and MPF. As a result of the experiment, we found it was possible to accurately estimate muscle fatigue using this method even before it occurs.

In future work, we need to calculate the constant while estimating the change in MPF and f(x) in the early stages. We also plan to extend the present method to more than one finger. We may be able to configure the number of robust feature in muscle fatigue with this indicator. We think that our method of classifying finger motion has great potential in the future.

REFERENCES

[1] Tohru Kiryu, "Viewing local muscle fatigue from surface electromyogram", Journal of the Society of Biomechanisms, Vol.21, no.2, pp.75-80, 1997-05-01

[2] Yasuharu Kike, Kiyoshi Honda, Makoto Hirayama, Hiroaki Gomi, Bateson Eric Vatikiotis, Kawato Mitsuo,"Estimation of Isometric Torques from Surface Electromyography Using a Neural Network Model", The Journal of the Institute of Electronics, Vol.2, no.6, pp.1270-1279, 1993.

[3] Yuya Tanaka, Yoshihiro Ehara, Kazuki Mizusawa, Katsuya Furukawa,"Validity of Muscle Forces Predicted by Electromyography-Assisted Optimization", The Japanese journal of ergonomics, Vol.46, no.3, pp.215-222, 2010.

[4] Ryuhei Okuno, Masaki Yoshida, Kenzo Akazawa, "Formulation of Tension Response during Human Thumb Muscle Extension for a Prosthetic Hand Controller", Transactions of the Japanese Society for Medical and Biological Engineering, Vol.43, no.1, pp.133-139, 2005.

[5] Naomi Tsuchida, Mineo Oyama, Yutaka Maki, Takae Yoshizu, "Relationship between bending strength and finger flexor muscle activity in the flexor digitorum profundus and superficialis finger flexion movement", The Journal of Japanese Society for Surgery of the Hand, Vol.25, no.5, pp.611-615, 2009.

[6] Daisuke Nishikawa, Wenwi Yu, Hiroshi Yokoi, Yukinori Kakazu, "On-Line Supervising Mechaniam for Learning Data in Surface Electromyogram Motion Classifiers", The Journal of the Institute of Electronics, Vol.D-II, no.12, pp.2634-2643, 2001.

[7] Atsushi Kiso, Hirokazu Seki,"Discrimination of Human Forearm Motions on the Basis of Myoelectric Signals by Using Adaptive Fuzzy Inference System", Transaction of the Institute of Electrical Engineers of Japan, Publication of Fundamentals and Materials Society, Vol.130, No.11, pp.1272-1278, 2010-11-01

[8] Toru Shintani, Junichi Akita, Shigeru Sakurazawa, Masashi Toda, "Presice Multi-channel Electromyography Measurement System Using Shield and Power Supply Function of Conductive Wear", Transactions of Information Processing Society of Japan, Vol.48, No.12, pp.3784-3792, 2007-12-15.