2010 IEEE International Conference on Robotics and Automation
Anchorage Convention District
May 3-8, 2010, Anchorage, Alaska, USA

Classification of Individual Finger Motions Hybridizing Electromyogram in Transient and Converged States

Genta Kondo, Ryu Kato, Hiroshi Yokoi, Tamio Arai

***Abstract*— To classify the five individual finger motions from an electromyogram (EMG) signal, a classification system that hybridizes EMG signals in both the transient and converged states of a motion is proposed. The classifications of finger motions are executed individually in each state by a well-established artificial neural network (ANN). Then, the outputs of the two classifiers are combined. The efficacy of the result is evaluated via a piano-tapping task, in which the subjects are instructed to tap a keyboard with each of their five fingers. We use this task to compare the proposed hybrid system and a conventional converged system that uses an EMG signal only in the converged state. For five of the six subjects, the accuracy ratio of finger motions was better in the proposed method: approximately 85% for each finger except the second. Further analysis suggests two remarkable advantages of the hybrid method: 1) the output of the ANN is more credible, and 2) finger motion in the transient state (i.e., the early phase) is more predictable.**

I. Introduction

MORE than 540,000 people in Japan have lost their hands [1]. An electromyogram (EMG) prosthetic hand is a robotic hand whose motion is controlled by an EMG signal, an electrical signal accompanying muscle contractions. Since the signal is easily measured on the skin surface of the forearm, an EMG prosthetic hand is a practical aid for people who have lost their hands. Currently, however, only simple motions are controllable by such a hand. For example, the most commercially prevailed EMG prosthetic hand is restricted to 1-DOF of hand motion: opening and closing [2]. Kato *et al.* have confirmed the control of 14 motions by an amputee, but these are wrist and hand motions [3]. Dexterous individual finger motions are currently unavailable in EMG prosthetic hands. The addition of finger motions would enhance the quality of life of physically disabled people. In order for them to participate in cultural events, such as playing sports or musical instruments, finger motions are essential. In this paper, we choose piano playing as an example of an activity that requires the control of all five fingers, and we propose a method to classify these motions from an EMG signal.

Several studies have been conducted to classify individual finger motions from an EMG signal, but practical hurdles remain. Tenore *et al.* classified 12 finger motions (flexion/extension of the five individual fingers and combinations of the third, fourth, and fifth fingers) [4]. However, 32 sensors were used to measure the EMG signals, which is not suitable for disabled people with a limited forearm area. Tsenov *et al.* classified 1 hand motion (grasping) and 3 finger motions (flexion of the first, second, and third fingers) using only 2 sensors, and confirmed 88% accuracy in an online test [5]. However, disabled people need active control of the fourth and fifth fingers. Instead of classifying the whole sequence of motions, Smith *et al.* classified the angle of the metacarpophalangeal joint in each finger and confirmed an average correlation coefficient of 0.91 between the actual joint angles and the classified joint angles [6]. However, they used a data glove to collect the learning data so this approach is not suitable for people who have lost their hands.

Compared with wrist and hand motions, the difficulty of classifying finger motions lies in the relatively low and unstable nature of the EMG signal. The muscles controlling finger motions are deep in the forearm, whereas the muscles controlling wrist and hand motions are in a superficial area [7]. Figure 1 shows the EMG signals accompanying two wrist motions (wrist flexion and wrist extension), and two finger motions (first-finger flexion and second-finger flexion) measured on the extensor and the flexor muscle of the forearm. The EMG signals of finger motions have relatively low magnitudes and attenuate easily. In other words, the

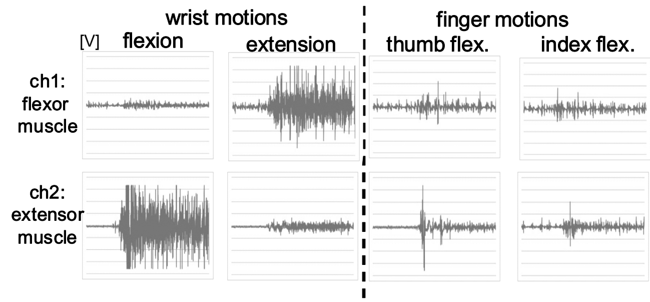


Fig. 1. EMG firing patterns of wrist and finger motions.

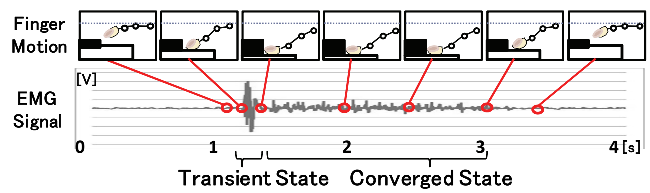


Fig. 2. Two states of EMG signals in one finger-motion sequence.

Genta Kondo (kondo@robot.t.u-tokyo.ac.jp) and Tamio Arai are with Department of Precision Engineering at The University of Tokyo, Tokyo, Japan.
Ryu Kato and Hiroshi Yoko are with Department of Mechanical Engineering and Intelligent Systems, The University of Electro-Communication, Tokyo, Japan.

firing patterns are similar among different motions.

In order to measure an EMG signal that can separate different finger motions, we focused on the transient state of motion. As shown in Fig. 2, we subdivided one motion sequence into two states, transient and converged. (The motion in Fig. 2 represents piano tapping.) In the transient state the posture of the hand or finger is being transformed; this occurs in the initial 200–300 ms of the motion. In the converged state, which follows the transient state, the posture is kept constant. The EMG signal has a higher magnitude in the transient state than in the converged state. In most studies, the converged-state EMG signal has been used for classification because of its stable and continuous (i.e., easy to measure) nature. However, Ito *et al.* confirmed that the both the transient-state and converged-state signals are able to classify 6 hand motions [8].

We propose a classification system that uses EMG signals in both the transient and converged states. The converged state is used to prevent the risk of a misclassification in the transient state persisting for the entire time period. The hybrid system is compared with a conventional converged system that uses only converged-state EMG signals. A piano-tapping task was conducted in both systems and the performances were compared.

II. Hybrid Classification System

A. Overview

Figure 3 shows an overview of the hybrid classification system. In general, the problem of classifying motions from EMG signals is defined as a problem of pattern recognition [9] and consists of two steps, feature extraction and motion classification.

In the feature-extraction step, features that are stable and separable among classifying motions are extracted from raw EMG signals. These features form a feature vector. Several features of EMG signals have been tested in preceding studies, such as time-domain features (e.g., zero crossing, IEMG, root mean square, and auto regression coefficients) and frequency-domain features (e.g., short time Fourier transform, wavelet transform, and wavelet packet transform) [10–12]. In the motion-classification step, the finger motion that most corresponds to the feature vector is determined by a classification function. Several classification functions have been examined in preceding studies (e.g., neural network, hidden Markov model, and heuristic fuzzy logic) [13–15].

In the hybrid classification system, the motion-classification step is executed by combining two subsystems whose system parameters are determined by EMG signals in the transient state and converged state respectively. We call the former subsystem the transient-classification system and the latter the converged-classification system. Both these systems output a set of probabilities for each targeted finger motion. In this paper, the outputs are denoted $[q_1, \dots, q_m]$ and $[p_1, \dots, p_m]$ respectively, where m is the number of finger motions and $p_i, q_i \in [0,1]$. The output of the hybrid system

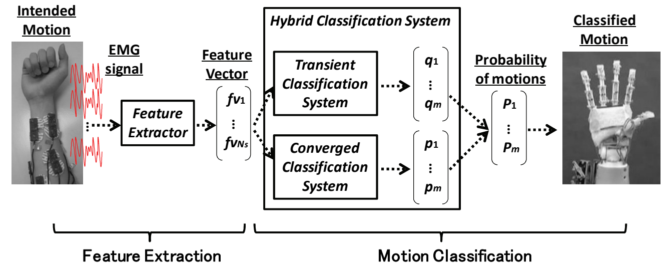


Fig. 3. Overview of the hybrid classification system.

denoted $[P_1, \dots, P_m]$ is calculated from these two outputs.

The transient-classification system is expected to be useful for classifying finger motions, because the EMG signal in the transient state is relatively higher and more separable than the EMG signal in the converged state. However, the transient-classification system alone is insufficient, because the EMG signal in the transient state attenuates quickly. One solution might be to maintain the output of the transient state until the transient state of the next finger motion, but this solution risks retaining a misclassified output throughout a motion. Therefore, we combine this approach with a conventional converged-classification system.

B. Converged-Classification System

The system parameters of the converged-classification system are determined by converged-state EMG signals. This system renews its output p_i continuously (i.e., every time the EMG signal is sampled from a sensor).

For components of the feature vector, integral EMG (IEMG), a typical time-domain feature is used. We did not use frequency-domain features because they are difficult to attain in the unstable transient state and have a high computational cost. The IEMG is defined to be the average absolute magnitude of the EMG signal in a certain time period. The IEMG at point n is given by

$$IEMG_s[n] = \frac{1}{\mathrm{T}} \sum_{k=n-\mathrm{T}+1}^{n} \left| EMG_s[k] - \overline{EMG_s} \right| \qquad (1)$$

where s=1,…, $\mathrm{N_s}$. $EMG_s[k]$ is the magnitude of the EMG signal at the sth sensor, , $\overline{EMG_s}$ is the average of $EMG_s[k]$ in time period T, and $\mathrm{N_s}$ is the number of sensors. The effect of averaging the EMG signal over time is to produce a stable and repeatable feature. Figure 4 shows the steps for converting the raw EMG into the IEMG.

The sth component of the feature vector fv_s is normalized via

$$fv_s[n] = \frac{IEMG_s[n]}{\sum_{s=1}^{\mathrm{N_s}} IEMG_s[n]} \qquad (2)$$

As a classification function, the well-established three-layered artificial neural network (ANN) is used. As shown in Fig. 5, the input x_i^m and output y_i^m in the

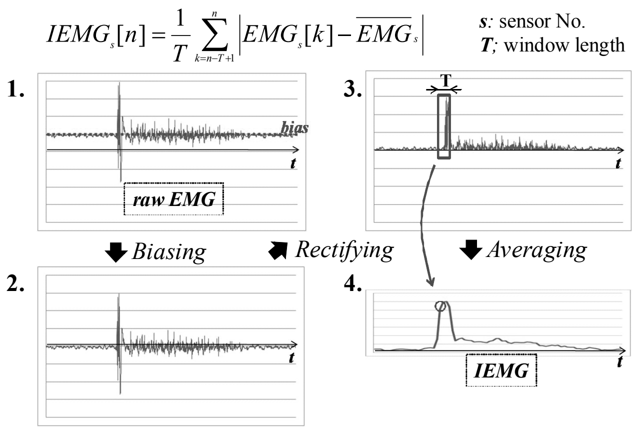


Fig. 4. Calculation of IEMG.

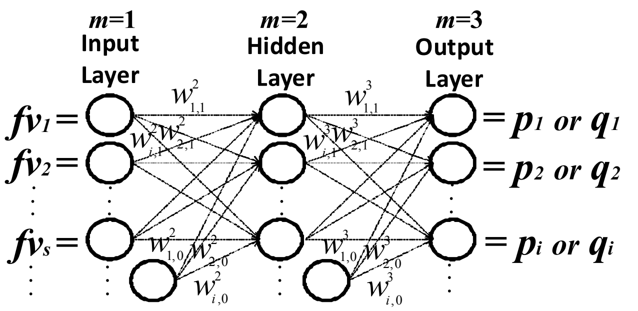


Fig. 5. Input and output of 3-layered ANN. Input is feature vector *fv* and outputs are probability of each classifying motion *p*,*q*.

*m*th layer are given as follows:

$$x_i^m = \sum_{j=0}^{\mathrm{N}_{m-1}} w_{ij}^m \cdot y_j^{m-1} \quad (3)$$

$$y_i^m = f(x_i^m) \quad (4)$$

$$f(x) = \frac{1}{1+\mathrm{e}^{-x}} \quad (5)$$

where m=2,3, and i=1, …, N_m. N_m is the number of neurons in the mth layer and w_{ij}^m is the weight between the jth neuron of the (m-1)th layer and the ith neuron of the mth layer. y_0^m is a bias neuron in each layer with a value of -1.

N_1 is the dimension of the feature vector and N_3 is the number of classifying motions. The value of y_i^3 is set between 0 and 1, which corresponds to the probability of the ith classifying motion (i.e., $x_i^1 = fv_i$, $y_i^3 = p_i$).

The back-propagation algorithm is used for learning. The weight w_{ij}^m [n] in the nth step is modified via

$$w_{ij}^m[n] = w_{ij}^m[n-1] - \eta\frac{\partial E}{\partial w_{ij}^m} \quad (6)$$

$$E = \sum_{i=1}^{\mathrm{N}_3}\left[\tilde{y}_i^k - y_i^3\right]^2 \quad (7)$$

where $\tilde{y}_i^k$ represents an output of learning data in k-th motion, E represents the performance function, η represents the learning ratio. Learning is terminated when either of following conditions is satisfied:

$$\mathrm{E} < \mathrm{TH_{error}} \quad (8a)$$
$$\mathrm{N_{learn}} > \mathrm{TH_{learn}} \quad (8b)$$

where $\mathrm{N_{learn}}$ is learning time, and $\mathrm{TH_{error}}$ and $\mathrm{TH_{learn}}$ are thresholds. $\{\tilde{y}_i^k\}$ is defined as follows.

$$\tilde{y}_i^k = \begin{cases} 1 & if\ i = k \\ 0 & otherwise \end{cases} \quad (9)$$

The probability of correct motion is set to 1, and the probabilities of other motions are set to 0.

C. Transient-Classification System

Here the feature vector and classification function are the same as for the converged-classification system. However, the output q_i is not renewed continuously; it is renewed at the starting point and maintained until the end point. As shown in Fig. 6, the transient-classification system has a function to detect from the behavior of the EMG signal the starting and end points of a finger motion.

To detect these points, we use a sensor-average of IEMG, $\overline{IEMG}$, given by

$$\overline{IEMG}[n] = \frac{1}{\mathrm{N_s}}\sum_{s=1}^{\mathrm{N_s}} IEMG_s[n] \quad (10)$$

Assuming an unimodal and repetitive nature of $\overline{IEMG}$ in the transient state of a finger motion, we define the starting point of the motion as the peak of $\overline{IEMG}$ that satisfies the following conditions:

$$\overline{IEMG}[n] > \mathrm{TH_{sta}} \quad (11a)$$
$$\overline{IEMG}[n] - \overline{IEMG}[n-1] < 0 \quad (11b)$$

$\mathrm{TH_{sta}}$ is a threshold to detect that $\overline{IEMG}$ has exceeded a certain magnitude. On the other hand, noticing that IEMG is highly correlated with a torque driven by muscle contraction [16], we define the end point of a motion as the point that the muscle contraction is released via

$$\overline{\mathrm{IEMG}}[n] < \mathrm{TH_{end}} \quad (12)$$

$\mathrm{TH_{end}}$ is a threshold to detect that $\overline{IEMG}$ has fallen below a certain magnitude. In Fig. 6, the starting and end points are depicted by circles and squares respectively.

D. Hybridization of Two Systems

Combining the outputs of the transient and converged subsystems (p_i and q_i), the overall output of the hybrid classification system $[P_1, \ldots, P_m]$ is calculated by

$$P_i = \begin{cases} p_i \cdot q_i & while\ in\ finger\ motion \\ p_i & otherwise \end{cases} \tag{13}$$

Figure 6 shows the way that the outputs in each classification system or subsystem are renewed during the transition of finger motions.

Finally, from P_i, the classified motion M at the point n is determined by

$$M[n] = \begin{cases} i & if\ N_{\text{fired}} = 1 \\ M[n-1] & otherwise \end{cases} \tag{14}$$

where i=1,…,m. N_{fired} is the number of motions whose overall output P_i exceeds the threshold TH_{fired}. We installed a rejection function [3] to avoid the number of classified motions being zero or greater than one. The rejection function allows the system to renew M only if N_{fired} is 1. Otherwise, the system rejects the renewal and retains the previous classification. The rejection function makes a classified motion stable even if the pattern of the EMG signal does not strongly correspond to a particular finger motion.

III. Experiment

To evaluate the efficacy of the hybrid classification system, a piano-tapping task was tested on six physically unimpaired subjects (20 to 25 years old). This task was chosen because it uses each of the five finger motions. The test used both the hybrid system and a conventional converged-classification system, and the accuracy ratios of the two systems were compared.

A. *Piano-Tapping Task*

In the piano-tapping task we tested the classification of five piano-tapping motions made by individual fingers and a rest motion, shown in Fig. 7. As shown in Fig. 8, the subjects were required to match the classified motion of the system to the ideal motion shown on a monitor. The ideal finger motion was drawn in a bold line and the current classified motion was depicted as a circle. The subjects were instructed to keep the circle on the bold line as the time bar proceeded rightward. The length of one piano-tapping task was 20 s. During the task, the ideal motions shifted from the first finger to the second, third, fourth, and fifth, each motion lasting for 2 s and followed by 2 s of the rest motion. The subjects were told to keep their shoulder, elbow, and wrist stable.

The accuracy ratio of the ith finger motion r_i was calculated by

$$r_i = \frac{\text{N}^i_{\text{correct}}}{\text{N}^i_{\text{total}}} \tag{15}$$

where i=1,…, 5. $\text{N}^i_{\text{total}}$ is the number of sampling points while ith finger motion is instructed, and $\text{N}^i_{\text{correct}}$ is the number of points in $\text{N}^i_{\text{total}}$ which ith motion was classified correctly.

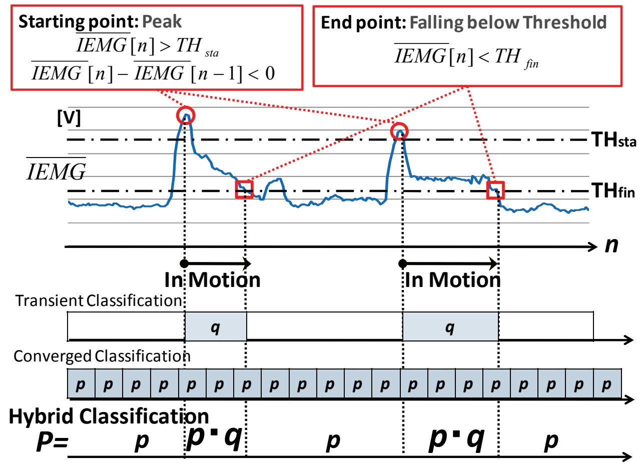


Fig. 6. Calculation of output of the hybrid classification system.

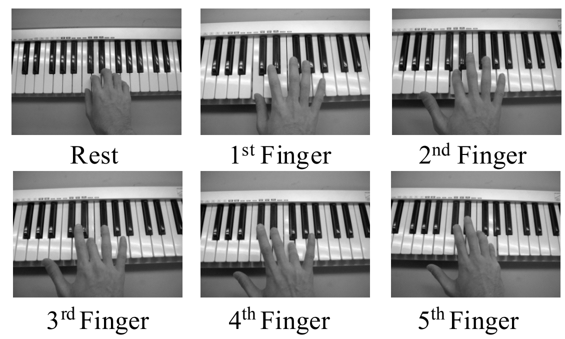


Fig. 7. Motions classified in piano-tapping task: Rest motion and five piano-tapping motions made by individual fingers.

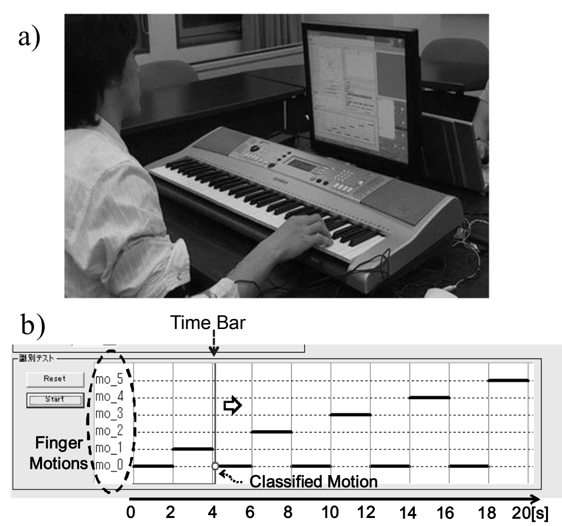


Fig. 8. Piano-tapping task: a) Overview. b) Instruction on display (mo_0=rest, mo_1=first finger, mo_2=second finger, mo_3=third finger, mo_4=fourth finger, mo_5=fifth finger).

The ANN parameters (i.e., weights) were determined by collecting learning data individually for each subject. The number of learning sample-points was 3 per motion in the transient state and 10 per motion in the converged state. In the transient state, the IEMG was extracted at the starting point of a finger motion and then twice more. In the converged state, 10 serial IEMGs were extracted 1 s after the starting point of a motion.

The test was performed first in the converged system and then in the hybrid system. In each system, the task was repeated 10 times. The first 5 trials allowed the subject to become familiar with the system, since skill acquisition is one of the principal factors that determines performance [17]. The data from the next 5 trials were analyzed.

B. Condition

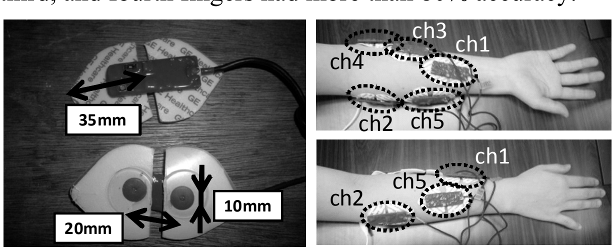
As shown in Fig. 9, EMG signals were measured on 5 points on the subject's forearm using differential-amplifying active EMG sensors. A notch filter with a cutoff frequency of 50 Hz and an amplifier of ±9 [V] were equipped with the sensor. The arrangement of the EMG sensors followed the approach of Itoh *et al.* [18] as shown in Fig. 9. The amplified EMG was input to the computer (CF-W8, Panasonic) by an AD converter (AD12-8(PM), Contec) at 1600 samples/s with 12-bit resolution.

The time period to calculate the IEMG was T=160 ms. The numbers of neurons in each ANN layer were N_1=5, N_2=10, and N_3=6. The learning ratio was η=0.1 The thresholds of learning termination were TH_{learn} =30,000 and TH_{error}=0.001. The threshold in the rejection function to count the number of activated motions was TH_{fired}=0.5. The thresholds for detecting the starting point (TH_{sta}) and the end point (TH_{end}) of a finger motion were manually adjusted for each subject.

C. Result

Table 1 shows the accuracy ratio attained by the hybrid classification system. The value in parentheses is the increase from the conventional converged-classification system. (▲ indicates negative.) An increase in the overall accuracy ratio using the proposed system was confirmed in 5 of the 6 subjects and for these subjects the ratios exceeded 85%. The accuracy ratios of all the individual finger motions except the second were also above 85% for the 5 subjects.

To evaluate the effect of the transient signal-classification system, we investigated the accuracy of its output as shown in Fig. 10. The output was considered "correct" when N_{fire}=1 and the activated neuron corresponded to the intended motion, "wrong" when N_{fire}=1 and the activated neuron did not correspond to the intended motion, and "rejected" when N_{fire}=0 or N_{fire}>1. The data in the figure are averaged over subjects C, D, and E. The overall accuracy was 68%. The first, third, and fourth fingers had more than 80% accuracy.



ch1: flexor pollicis longus
ch2: extensor carpi ulnaris
ch3: palmaris longus
ch4: extensor carpi ulnaris
ch5: extensor dindicis

Fig. 9. Size and arrangement of EMG sensors.

TABLE I

ACCURACY RATIO IN PIANO-TAPPING TASK

	1st finger	2nd finger	3rd finger	4th finger	5th finger	overall
subjectA	93(20)%	98(9)%	96(32)%	95(4)%	92(7)%	95(15)%
subjectB	100(5)%	90(11)%	97(1)%	100(6)%	100(0)%	97(4)%
subjectC	96(76)%	76(▲8)%	88(30)%	90(33)%	97(24)%	89(31)%
subjectD	93(10)%	55(18)%	91(6)%	99(10)%	90(9)%	86(11)%
subjectE	90(▲2)%	65(▲27)%	96(48)%	98(4)%	100(5)%	90(6)%
subjectF	80(3)%	34(▲21)%	31(6)%	57(▲6)%	54(14)%	52(▲1)%

Accuracy ratios of the hybrid classification system for 6 subjects. Increases from conventional converged-classification system are in parentheses. Negative values are shown by ▲.

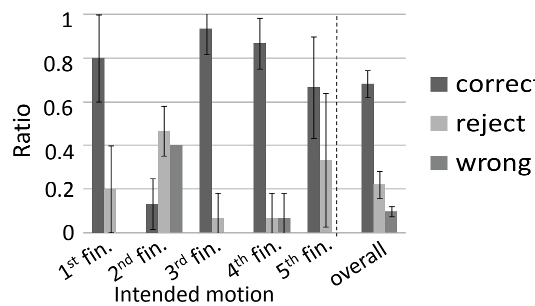


Fig. 10. Accuracy of the transient classification.

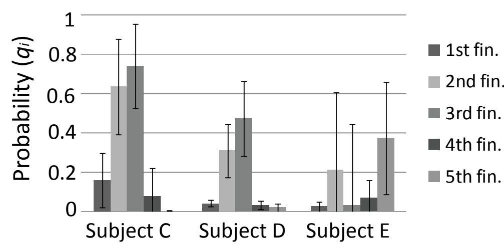


Fig. 11. Probability (q_i) output when second-finger motion is the ideal motion.

The second finger had less than 20% accuracy, which explains its relatively low accuracy ratio in the piano-tapping task. As which finger was the second finger misclassified? Figure 11 shows the probability of each motion q_i attained when second-finger motion was the ideal motion. Although the trends differed among the subjects, the probability of the third (subject C, D) or fifth (subject E) finger exceeded the probability of the second finger.

Figure 12 shows the transition of the probability of each finger motion output by ANN in the hybrid and converged classification systems. The transition for the hybrid system is depicted as a solid line, and the transition for the converged system is depicted as a dotted line. The motions are indicated in bold at the bottom of the figure. The credibility of the probabilities is greater in the hybrid system, in that the value increases only when the corresponding finger motion is indicated (i.e., its value stays low when other motions are indicated). Here an increase in the credibility of the output is confirmed as an effect of the hybrid classification system. The effect is particularly obvious for the first and fifth fingers for subject C, the fifth finger for subject D, and the first, third,

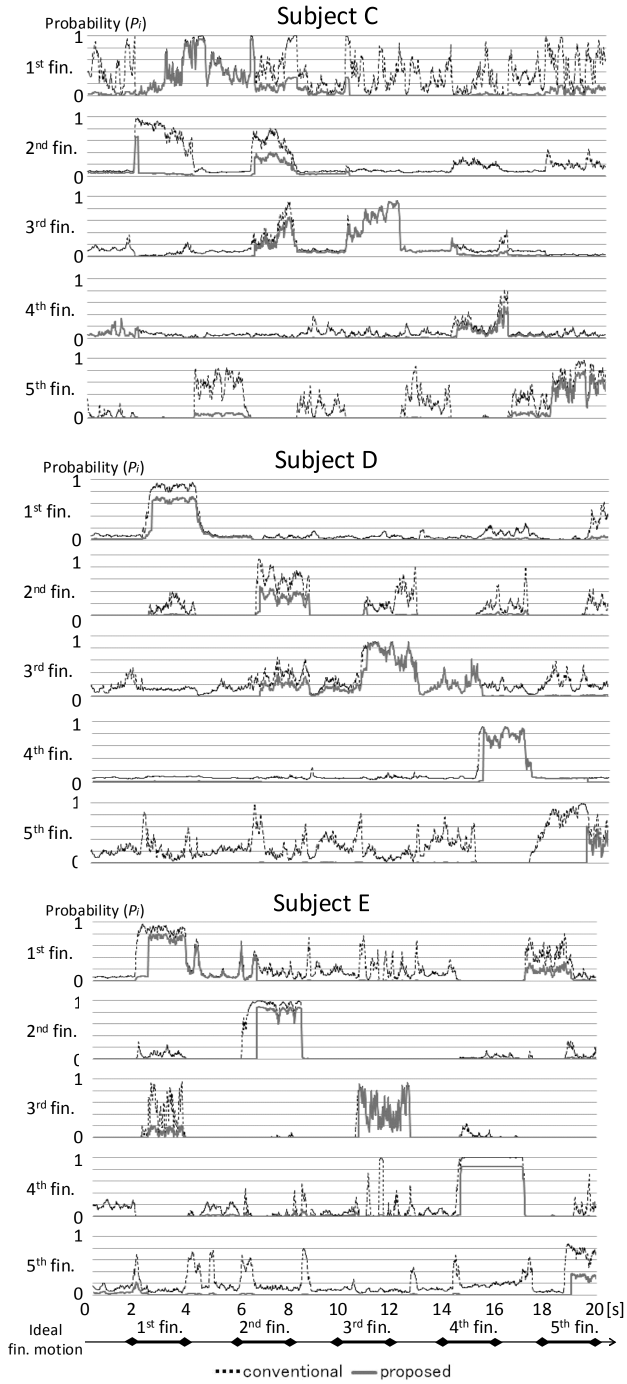


Fig. 12. Transition of probability (P_i) of proposed and conventional systems for piano-tapping task.

and fifth fingers for subject E. In addition, the high misclassification ratio of the second finger is also explained in this figure. Although the output of the second finger increased when the second finger was indicated, the output of the third finger increased more for subjects C and D.

Figure 13 plots the transition of the accuracy ratio every 200 ms during a finger motion. The accuracy ratio is averaged over all motions. The transition in the hybrid classification system is depicted as a solid line and the transition in the converged-classification system is depicted as a dotted line. The higher accuracy ratio in the hybrid classification system

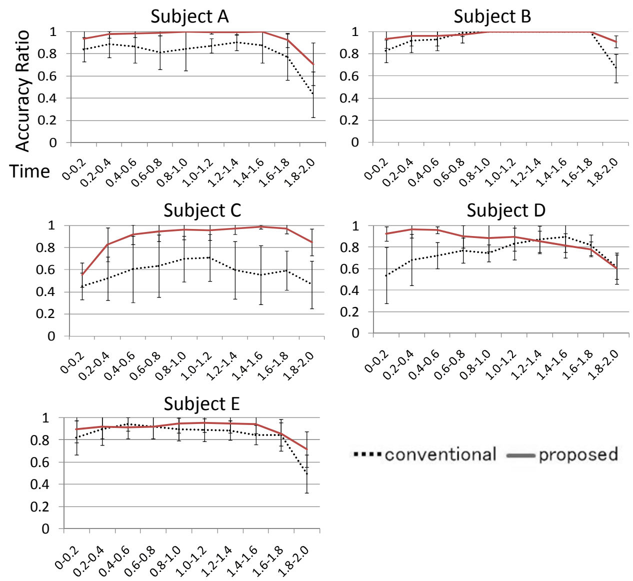


Fig. 13. Transition of accuracy ratio every 200 ms.

was confirmed throughout the period, except for a short period for subject D. Especially for subjects B, D, and E, a large increase is confirmed in the first 200 ms of a motion; this corresponds to the transient state. Here, an increase in the accuracy ratio of the transient state is suggested as another effect of the hybrid classification system.

IV. Discussion

The results of the piano-tapping task suggest the efficacy of the hybrid classification system. However, we should note that several practical problems remain unsolved.

First, the differences between performing in a virtual simulation and in a real situation (i.e., tapping a piano using an EMG prosthetic hand) must be taken into account. The piano-tapping task will be more difficult in the real world because: 1) high joint torque is required to press a keyboard; 2) haptic and proprioceptive feedbacks are necessary for users to recognize a prosthetic hand posture; 3) the overall computational cost must be low to avoid a delay between the user's intention and the actual motion of the prosthetic hand.

Secondly, the proposed method has to be examined on physically disabled people. Although disabled people can control the hand and wrist motions of an EMG prosthetic hand [3], finger motions will be more challenging since fingers are controlled by relatively small muscles. Moreover, especially for people who have congenitally lost their hands, it is extremely difficult to conceive an image of a finger motion. Therefore, the largest hurdle for users of EMG prosthetic hands will be to acquire the ability to deliberately generate the EMG patterns corresponding to each finger motion.

Thirdly, the constraints imposed on a subject's joints must be removed for daily use of a prosthetic hand. In the experiment, shoulder, elbow, and wrist were instructed to be kept stable, but a DOF of these joints is fundamental for daily activity. Therefore, we must develop methods to measure the

EMG signal corresponding to finger motions independently of the posture of other parts of the body.

Moreover, the second finger has to be classified accurately. To solve this problem, either the feature vector or the classification function must be improved. For the feature vector, a component representing a dynamic feature (e.g., the gradient of IEMG) instead of the static IEMG may be more separable for motions in the transient state. For the classification function, a stochastic classification assuming asymmetric prior probabilities (instead of treating the five finger motions equally) may reduce the misclassification rate of the second finger. A hierarchical classification based on similarities among the targeted motions may also be useful.

Lastly, the adaptability of the proposed method for fast transition of finger motions must be tested. The experiment in this paper had a rest interval of 2 s between two finger motions. The firing patterns of the EMG signal may change when a finger motion is directly transformed from the previous motion.

V. Conclusion

A classification system hybridizing EMG signals in both the transient and converged states of a motion has been proposed to classify the five individual finger motions. From the piano-tapping task, the hybrid system has been demonstrated to have a higher accuracy ratio than the conventional converged system that uses only converged-state EMG signals. The advantages of the hybrid system are twofold. First, the credibility of the probabilities output by ANN increases (i.e., the probability of a particular motion increased only when that motion was intended). Secondly, a motion is more predictable from an early phase. However, a high misclassification rate of the second finger has also been confirmed.

For the development of an EMG prosthetic hand with dexterous finger motions, the hybrid classification system must overcome several problems: 1) installation in real apparatus (i.e., the prosthetic hand), 2) application to physically disabled people, 3) reduction of constraints on proximal joints, 4) accurate classification accuracy of the second finger, and 5) reduction of interval for the transition of two motions. Nevertheless, this paper has made progress toward the ultimate goal by demonstrating an improvement in the classification accuracy when the EMG signal in the transient state is taken into account.

Acknowledgment

This study is the result of “Brain Machine Interface Development” carried out under the Strategic Research Program for Brain Sciences by the Ministry of Education, Culture, Sports, Science and Technology of Japan.

References

[1] Cabinet Office Japan, “Annual Report on Government Measures for Persons with disabilities”, 2008, Available: http://www8.cao.go.jp/shougai/english/annualreport/2008/index-pdf.html

[2] Sensor Hand Technical Information Booklet, Otto Bock Co., Ltd, 2001, Available: http://www.healthcare.ottobock.com/.

[3] R. Kato, H. Yokoi, T. Arai, “Competitive learning method for robust EMG-to-motion classifier”, Intelligent Autonomous Systems, vol. 9, IOS Press, pp.956-953, 2005.

[4] F. Tenore, A. Ramos, A. Fahmy, S. Acharya, R. Etienne-Cummings, N.V. Thakor, “Towards the Control of Individual Fingers of a Prosthetic Hand Using Surface EMG Signals”, Proceedings of the 29th Annual International Conference of IEEE EMBS, pp.6145-6148,2007.

[5] G. Tsenov, A.H. Zeghbib, F. Palis, N. Shoylev, V. Mladenov, “Neural Networks for Online Classification of Hand and Finger Movements Using Surface EMG signals”, Proceedings of the 8th Seminar on Neural Network Applications in Electrical Engineering, pp.167-171, 2006.

[6] R.J. Smith, F. Tenore, D. Huberdeau, R Etienne-Cummings, N.V. Thakor, “Continuous Decoding of Finger Position from Surface EMG Signals for the Control of Powered Prostheses”, Proceedings of the 30th Annual International Conference of IEEE EMBS, pp.197-200, 2008.

[7] F.H. Netter, “Atlas of Human Anatomy”, 4th ed., Saunders, 2006

[8] K. Ito, M. Tsukamoto, T. Kondo, “Discrimination of Intended Movements based on Nonstationary EMG for A Prosthetic Hand Control”, Proceedings of the 3rd International Symposium on Communications, Control and Signal Processing, pp.14-19, 2008

[9] C.M Bishop, “Pattern Recognition and Machine Learning (Information Science and Statistics)”, 1st ed. Springer, 2008.

[10] K.Englehart, B. Hudgins, P.A. Parker, M. Stevenson, “Classification of the myoelectric signal using time-frequency based representations”, Medical Engineering & Physics Vol.21, pp.431-438, 1999.

[11] A. Khadivi, K. Nazarpour, H. S. Zadeh, “SEMG classification for upper-limb prosthesis control using higher order statistics”, Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing, Vol.5, pp.385-388, 2005.

[12] M.Khezri, M. Jahed, N. Sadati, “Neuro-Fuzzy Surface EMG Pattern Recognition For Multifunctional Hand Prosthesis Control”, IEEE International Symposium on Industrial Electronics, pp. 269-274, 2007.

[13] O. Fukuda, T. Tsuji, H. Shigeyoshi, M. Kaneko, “An EMG controlled human supporting robot using neural network”, International Conference on Intelligent Robots and Systems, vol.3, pp.1586-1591, 1999.

[14] A. Chan, K. Englehart, “Continuous myoelectric control for powered prostheses using hidden Markov models”, IEEE Transactions on Biomedical Engineering, Vol.52, Issue.1, pp.121-124, 2005.

[15] A.B. Ajiboye, R.F. Weir, ”A heuristic fuzzy logic approach to EMG pattern recognition for multifunctional prosthesis control”, IEEE Transactions on Neural Systems and Rehabilitation Engineering, Vol. 13, Issue. 3, pp.280-191, 2005

[16] K. Akazawa, T. E. Milner, R. B. Stein, “Modulation of reflex EMG and stiffness in response to stretch of human finger muscle”, Journal of Neurophysiology vol.49, pp.16-27, 1983.

[17] K. Kita, R. Kato, H. Yokoi, T. Arai, ”Analysis of skill acquisition process: A case study of arm reaching task”, Selected Papers from 9th International Conference on Intelligent Autonomous Systems, Vol. 57, Issue .2, pp. 167-171, 2009

[18] Y. Itoh, H. Uematsu, F. Nogata, T. Nemoto, A. Inamori, K.Koide, H. Matsuura, “Finger curvature movement recognition interface technique using SEMG signals”, Journal of Achievement in Materials and Manufacturing Engineering Vol.23, Issue.2, pp.43-46, 2007