31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

Feasibility of Building Robust Surface Electromyography-based Hand Gesture Interfaces

Chen Xiang, Vuokko Lantz, Wang Kong-Qiao, Zhao Zhang-Yan, Zhang Xu, Yang Ji-Hai

***Abstract*—This study explored the feasibility of building robust surface electromyography (EMG)-based gesture interfaces starting from the definition of input command gestures. As a first step, an offline experimental scheme was carried out for extracting user-independent input command sets with high class separability, reliability and low individual variations from 23 classes of hand gestures. Then three types (same-user, multi-user and cross-user test) of online experiments were conducted to demonstrate the feasibility of building robust surface EMG-based interfaces with the hand gesture sets recommended by the offline experiments. The research results reported in this paper are useful for the development and popularization of surface EMG-based gesture interaction technology.**

***Index Terms*—Electromyography (EMG), hand gesture, pattern recognition, user interface**

I. Introduction

WHILE there are many technical advances and the state of the art reported in the research literature is promising, the development of surface EMG-based gesture interaction is progressing slowly. The distance from the current custom-built professional applications of surface EMG-based interaction technology to future commercial mass-market products is still significant [1]–[4].

Surface EMG-based gesture interaction is based on a fundamental assumption that the muscle activity patterns detected at certain measurement positions are repeatable for the selected gesture actions. However, there are many factors that affect the characteristics of surface EMG signals [5]–[7]. For instance, individual differences and electrode displacements on the skin surface can result in differences in surface EMG measurements of a particular person and gesture task made at different times. All these factors make it a challenging task to realize a robust surface EMG-based gesture interaction system.

The definition of a user-independent input command set is a key problem in the realization of a robust surface EMG-based interaction system. The major features of a user-independent input command set are high class separability between the gesture classes, low level of individual variations, and also high generality and repeatability of the surface EMG measurements. In other words, the surface EMG patterns of the gestures should be detected reliably and discriminated effectively using the same signal collection scheme and pattern recognition algorithm within and between the users. As a requisite for the implementation of a successful gesture-based user interface, the definition of input command gestures has not received enough attention. Reports that describe the user-independence of the input command gestures are hard to be found. Similarly, systematic studied on the feasibility of building a robust EMG-based interface cannot be found.

Different from previous studies which mainly focus on the pattern recognition algorithms, the novelty of this paper is to conduct a research on the feasibility of building robust surface EMG-based interface starting from the selection of input command gesture set. To reach the goal, a research scheme consisting of two types of experiments, i.e. offline and online experiments, was conducted. The motivation of the offline experiment was to identify user-independent input command sets suitable for surface EMG-based interaction. The online experiment was designed and conducted to demonstrate the feasibility of building robust surface EMG-based interfaces with the user-independent input command sets. The research results of this paper are meaningful for the development and popularization of surface EMG-based interaction technology. The target applications include various aspects in the field of myoelectric control, such as robotic control, prosthetics, and human- computer interaction etc.

II. Surface EMG Signals Pattern Recognition Method

The pattern recognition algorithm applied in our work consists of the detection of gesture action segments, feature extraction, and classification of hand gesture surface EMG signals. The segmentation algorithm is used for identifying the parts of the continuously measured surface EMG signal which corresponds to the gesture actions. A segmentation method based on a moving average algorithm [8] was used for searching the beginnings and ends of the gesturing action in our work.

Feature extraction algorithm compresses the surface EMG

Manuscript received April 3, 2009. This work was supported in part by National Nature Science Foundation of China (NSFC) under Grant 60703069, and National 863 plans projects under Grant 2009AA01Z322.

Chen Xiang is with the Electronic Science & Technology Dept. University of Science & Technology of China, PRC (phone: +86-551-3601811; fax: +86-551-3601806; e-mail: xch@ustc.edu.cn).

Vuokko Lantz is with Interaction & User Interfaces, Media CTR, Nokia Research Center, Helsinki, Finland (e-mail: vuokko.lantz@nokia.com).

Wang Kong-Qiao is with Visual Interaction Systems, Nokia Research Center, SRC Beijing, PRC (e-mail: kongqiao.wang@nokia.com)

Zhao Zhang-Yan, Zhang Xu, and Yang Ji-Hai are with the Electronic Science & Technology Dept. University of Science & Technology of China

TABLE I
BRIEF DESCRIPTIONS AND LABELING OF HAND GESTURES

Sorts	Gesture Name	Brief Description
Relaxation	RLXT	Relaxation
Wrist motions	FLWR	Flexion of Wrist
	EXWR	Extension of Wrist
	UFWR	Unlar Side Flexion of Wrist
	RFWR	Radial Side Flexion of Wrist
	WPRN	Wrist Pronation
	WSPN	Wrist Supination
Individual finger motions	EXTF	Extension of Thumb (I)
	EXIF	Extension of Index Finger (II)
	EXMF	Extension of Middle Finger (III)
	EXRF	Extension of Ring Finger (IV)
	EXLF	Extension of Little Finger (V)
	HOOK	"Hook" Gesture
Multi-finger motions	OKAY	"Okay" Gesture
	VCTR	"Victory" Gesture
	PINT	"Point" Gesture
	EXPM	Extension of Palm
	HDGP	Hand Grasp / Fist
	ASLC	Letter "C" in ASL[a] and CSL[b]
	ASLK	Letter "K" in ASL and CSL
	ASLM	Letter "M" in ASL and CSL
	ASLN	Letter "N" in ASL and CSL
	ASLY	Letter "Y" in ASL and CSL
	CSLT	Letter "T" in ASL and CSL

[a]ASL means American Sign Language, [b]CSL means Chinese Sign Language

TABLE II
SELECTED USER-INDEPENDENT HAND GESTURE SETS

	SN	Hand Gesture Tasks
5-task set	*1*	WPRN, HDGP, EXPM, EXWR, FLWR
	2	RFWR, HDGP, EXPM, EXWR, FLWR
	3	EXMF, HDGP, EXPM, EXWR, FLWR
	4	EXLF, HDGP, EXPM, EXWR, FLWR
	5	HOOK, HDGP, EXPM, EXWR, FLWR
6-task set	*6*	VCTR, WPRN, HDGP, EXPM, EXWR, FLWR
	7	EXTF, WPRN, HDGP, EXPM, EXWR, FLWR
	8	EXMF,WPRN HDGP, EXPM, EXWR, FLWR
	9	EXLF, RFWR, HDGP, EXPM, EXWR, FLWR
	10	EXMF, RFWR, HDGP, EXPM, EXWR, FLWR
8-task set	*11*	EXTF, EXLF, WSPN,WPRN, HDGP, EXPM, EXWR, FLWR

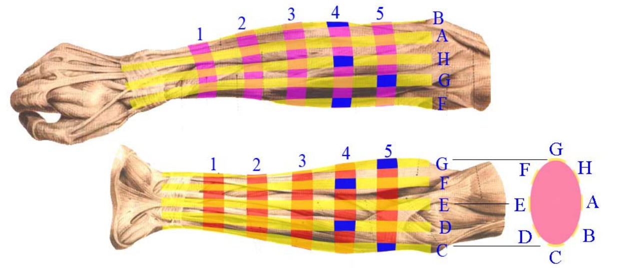

Fig. 1. Six-channel sensor placement scheme. The forearm was divided into five equal parts in longitudinal direction, and into eight parts in annular direction to determine electrode positions.

signal segments into feature vectors. The features should be designed so that they can emphasize the gesture class-specific characteristics of the surface EMG signal. Various time-domain, frequency-domain, and time-frequency surface EMG features have been used successfully for discriminating muscle contraction patterns [9], [10]. In our work, mean absolute values (MAV) and fourth-order autoregressive (AR) model coefficients, which are confirmed to be well suited to surface EMG signal modeling [11], were used in the formation of the feature vectors.

In classification phase, the classifier is trained with the feature vectors to distinguish the different gesture action from each other with high accuracy. Many kinds of classifiers such as classical linear classifier, neural network (NN), statistical, and fuzzy techniques have been used for the classification of gesture surface EMG features [12]–[13]. In this paper, Linear Bayes Normal Classifier (BayesNormal_1) [14] was adopted.

III. OFFLINE EXPERIMENTAL METHOD AND RESULTS

A. Surface EMG Data Collection

In total 23 hand gestures consisting of various wrist and fingers motions were defined and studied in this work. These gestures include 6 kinds of wrist motions, 6 kinds of individual finger motions, and 11 kinds of multi-finger motions, and are named after the four letters logograms of their English descriptions, as listed in Table I.

Ten healthy subjects (5 males, 5 females), with an age range from 20 to 26 years, were recruited for the data collection. Among the ten subjects, two females and two males are members of the research group and had received some training before data collection. The other six subjects were recruited from the university and did not receive any relative training beforehand. These subjects have no history of neuromuscular or joint diseases and were informed of the associated risks and benefits specific to the study. Subjects signed an informed consent form prior to data collection.

DELSYS Myomonitor IV EMG system was used for the signal acquisition. Six sensor positions (4B, 4D, 4F, 4H, 5C, and 5G shown in Fig. 1. in blue blocks) on the back of the forearm were used for capturing hand gestures for they covered nearly all the main muscles involved in the defined hand gesture tasks. Surface EMG data samples were collected from each subject on five days in a four-week time period. Two separate measurement sessions were performed per day and each task was repeated 20 times per session. The interval time between two sessions was over four hours to ensure that subjects had enough time to rest and recover. Sensors were removed when a session was finished and re-installed before the next session. Thus natural sensor displacements and skin condition variations occurred between measurement sessions.

B. Three Types of Offline Hand Gesture Pattern Recognition Schemes

Same-user experiment. Training data and test data consisted of different gesture samples but were collected from the same subject.

Multi-user experiment. Data from all ten subjects were used for training a common classifier which was then used for classifying gesture action samples from these same users.

Cross-user experiment. Data from four well-trained subjects were used for training a classifier, and the well-trained classifier was then used for recognizing hand gestures of the six other untrained subjects.

These three types of offline experiments were carried out orderly. Only those hand gesture sets which yielded good recognition rates in the previous experiment were taken into consideration in the next experiment. Hand gesture sets which got excellent recognition results in all the three experiments were considered to be user-independent and were recommended to be used in general surface EMG-based user interfaces. For ensuring the reliability of the experimental results, the same-user and multi-user experiments were implemented with training data from the first three collection days and test data from the fourth and fifth day. The cross-user experiments were implemented with training data and test data from all five days but from different subjects.

C. *Offline Experimental results*

Three kinds of offline surface EMG pattern recognition experiments with all 5-task, 6-task and 8-task sets of 23 defined hand gestures were conducted. Based on these results, in total 11 hand gesture sets (see Table II), including six 5-task sets, four 6-task sets, and one 8-task set were considered to be user-independent and recommendable as input command sets for surface EMG-based user interfaces. Fig. 2 shows the average recognition rates for these selected user-independent hand gesture sets in three types of offline hand gesture recognition experiments. The x-coordinate denotes the serial number (SN) of the hand gesture set (see Table II) and the y-axis represents the recognition rates (true positive values) in percentages. Results were averaged across subjects and all hand gestures within each set. The recognition rates are given in the form of mean ± standard deviation. Markers show the mean values and the height of the error bars above and below the mean values is the standard deviation.

Following observations can be made from Fig. 2: 1) The average recognition rates for the 11 gesture sets were 89.6%-94.3% in the same-user experiment. Because the pattern recognition experiments were carried out with data from ten subjects within a four-week time period, the generality and repeatability of these hand gesture sets were affirmed. 2) The average recognition rates were 86.4%-94.3% in the multi-user experiment and 76.7%-90.2% in the cross-user experiment. These results demonstrate the user-independence of these selected hand gesture sets. However, there were significant standard deviations in the cross-user experiment results. In the data analysis, we found out that gesture class separability was poor for three untrained subjects and good for the other three.

IV. Online Test Experimental Method and Results

As an example, one of the 6-task hand gesture sets and the 8-task set (No.7 set and No. 11 set in Table II) were selected for online test, and all test experiments were conducted on a real-time surface EMG-based gesture recognition platform. More details can be found about the platform in our previous publication.

Twenty subjects (10 males, 10 females) with age ranges from 20 to 36 were recruited for same-user online test experiments. To ensure the generality and robustness of classifiers, each subject took part in firstly 8 data collection sessions (in 4 days) designed for collecting the training data. Then each subject finished 2 test trials in 2 different days. Subject performed 20 actions per task in each trial, and the well-trained classifier was used for classification.

The first step of multi-user & cross-user test experiments was to establish a classifier. The classifier was trained using surface EMG data from ten well-trained subjects who performed excellently in the same-user test experiment. We call these subjects whose surface EMG data were used to train the classifier template subjects. To establish a robust hand gesture classifier insensitive to time variations and sensor displacements, data from ten trials in same-user online test experiment was used to train the classifier. In multi-user test experiments, 10 template subjects took part in online test. In cross-user test experiments, 50 non-template subjects (40 males, 10 females, with ages from 21 to 63) took part in online test. The requirements and the procedure to select the test subjects were the same as for the offline experiments. Each subject was tested ten times on five different days with 20 actions per task per trial in the two kinds of online test experiment.

Table III and Table IV give the online test results for 6-task and 8-task sets, respectively, and recognition rates were averaged across all subjects for each task. We can observe that same-user experiments got excellent average recognition rates (97.4% for 6-task set, and 94.6% for 8-task set) with small standard deviation. At the same time, multi-user experiments also got excellent average recognition rates (94.7% for 6-task set, and 89.5% for 8-task set), and cross-user test got 90.7% and 81.3% average recognition rates, respectively.

V. Discussion and Conclusion

To identify user-independent hand gestures with low level of individual differences, three kinds of offline pattern recognition experiments were designed to explore the effects of detection time, sensor displacements and individual differences on the repeatability and user-independence of hand gesture surface EMG measurements. In the offline same-user experiments, we found that most of the 5-task, 6-task and 8-task sets of the 23 defined hand gestures can be classified accurately. This result demonstrates that the between-day differences are modest compared to the overall class separability of these hand gesture tasks. Thus it is easy to build a well performing user-specific surface EMG-based interface with these hand gesture sets. This experimental result is in accordance with the previous research findings in the field of surface EMG-based gesture recognition.

In multi-user and cross-user experiments, 11 different hand gesture sets consisting altogether of 12 hand gesture tasks

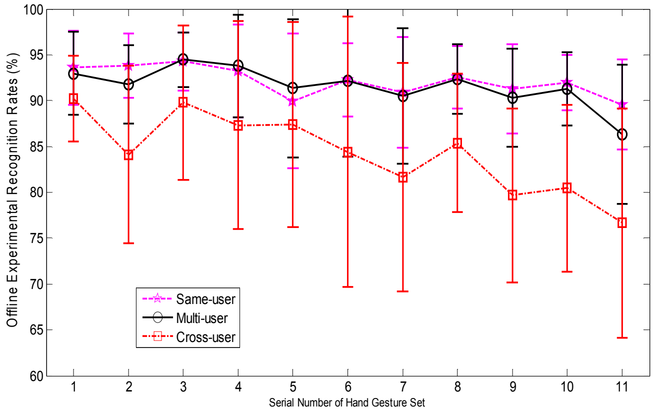

Fig. 2. Offline pattern recognition results for 11 selected user-independent hand gesture sets.

TABLE III
ONLINE TEST RESULTS FOR 6-TASK SET

Task	Same-user		Multi-user		Cross-user	
	Mean(%)	Std(%)	Mean(%)	Std(%)	Mean(%)	Std(%)
FLWR	98.6	4.1	99.4	1.8	90.4	19.6
EXWR	95.3	8.7	90	12.8	87.6	17.7
HDGP	96.9	5.7	81.3	33.3	85.1	21.3
EXPM	97.5	6.7	99.4	1.8	96.8	7.5
WPRN	98.6	2.9	100	0	91.8	14.4
EXTF	97.5	6.2	98.1	5.3	92.4	18.7
AVR	**97.4**	**1.23**	**94.7**	**9.2**	**90.7**	**16.5**

TABLE IV
ONLINE TEST RESULTS FOR 8-TASK SET

Task	Same-user		Multi-user		Cross-user	
	Mean(%)	Std(%)	Mean(%)	Std(%)	Mean(%)	Std(%)
FLWR	97	6.6	95	8.0	89.2	21.7
EXWR	95	10	93.8	8.8	82	25.6
HDGP	95.3	9.5	84.4	34.6	69	37.4
EXPM	95.3	13.9	100	0	97.2	6.1
WPRN	96.8	6.7	80	35.2	83.2	23.7
WSPN	92.8	10.8	86.3	31.6	76	31.6
EXTF	93.3	8.0	95	7.1	77.4	35.5
EXLF	91.3	16.9	81.3	29.4	76	35.5
AVR	**94.6**	**1.98**	**89.5**	**19.3**	**81.3**	**27.1**

were classified with good recognition rates (see Fig. 2). This result shows that some hand gesture tasks, such as HDGP, EXPM, EXWR and FLWR, can be distinguished very reliably from other tasks. So the surface EMG measurements of these tasks have small between-day and between-subject differences and good class separability. These gestures are considered to be well suited for user-independent EMG-based interfaces. On the other hand, we found that some tasks, especially six sign language tasks (ASLC, ASLK, ASLM, ASLN, ASLY, and CSLT), were difficult to discriminate. This result shows that there are large between-subject differences for these hand gesture tasks, and advanced pattern recognition approaches are needed for classifying them.

To simulate the real life use situations and to collect representative gesture samples, surface EMG data for offline analysis in this paper was collected in open environment. We designed flexible wearable electrode belts to reduce the time-cost in placing sensors, and the sensor placement was adaptive without strict adjustment for the locations of electrode. So the selected hand gesture sets should be robust enough for user-independent interfaces and the reported recognition results can be considered to be realistic. Results of the online experiments demonstrated even further the feasibility of building user-specific, multi-user, and user-independent surface EMG-based interfaces with these recommended hand gesture sets. With the proposed user-independent hand gesture sets and by training the classifier with gesture data collected from some well-trained users, a new user can interact with the system without training the recognition system with his/her own gesture samples first. The promising research results reported here can hopefully drive the development of user-independent surface EMG-base interaction systems forwards.

ACKNOWLEDGMENT

The authors would like to acknowledge all the volunteers for their help to take part in the data collection experiments.

REFERENCES

[1] J.-U Chu, I. Moon, and M.-S. Mun, A Real-Time EMG Pattern Recognition System Based on Linear-Nonlinear Feature Projection for a Multifunction Myoelectric Hand," *IEEE Trans. Biomed. Eng.* vol. 53(11), pp. 2232-2239, Nov. 2006.

[2] P. Shenoy, K. J. Miller, B. Crawford, R. P. N. Rao, "Online Electromyographic Control of a Robotic Prosthesis," *IEEE Trans. Biomed. Eng.* vol.55(3), pp. 1128-1135, Mar. 2008

[3] E. Costanza, A. Perdomo, S. A. Inverso, and R. Allen, "EMG as a Subtle Input Interface for Mobile Computing", in *Proc. 6th int. Symp. MobileHCI 2004,* LNCS, Springer, vol. 3160, pp. 426-430, Sep. 2004.

[4] M. A. Oskoei and H. Hu, "Myoelectric control systems—A survey," *Biomed. Signal Process. & Control*. vol. 4(1), pp. 275–294, Oct. 2007.

[5] L Hargrove, K Englehart, B Hudgins, "The effect of electrode displacements on pattern recognition based myoelectric control," in *Proc. 28th IEEE EMBS Annu. Int. Conf.* New York City, USA, Aug 30-Sept 3, 2006

[6] C. De Luca, "Surface electromyography detection and recording," In Neuromuscular Research Center, Boston University. 1997.

[7] P. Konrad, "The ABC of EMG," Version 1.0, Powered by: Noraxon INC. USA. April, 2005.

[8] X. Chen, X. Zhang, Z.Y. Zhao, J. H. Yang, V. Lantz, K. Q. Wang, "Hand gesture recognition research based on sEMG sensors and 2D-accelerometers," in *Proc. 11th IEEE Int. Symp. Wearable Computers, pp:1–4,* Oct. 2007

[9] S. Du, "Feature Extraction for Classification of Prehensile Electromyography Patterns", Master's thesis, San Diego State University, USA, 2003.

[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(6-7), pp: 431-438, Jul. 1999.

[11] X. Hu, V. Nenov, "Multivariate AR modeling of electromyography for the classification of upper arm movements," *Clinical Neurophysiology,* vol. 115(6), pp. 1276-1287, 2004.

[12] A. B Ajiboye, R. F. Weir, "A Heuristic Fuzzy Logic Approach to EMG Pattern Recognition for Multifunctional Prosthesis Control," *IEEE Trans. Neural Systems & Rehabilitation Engineering*, vol. 13(3), pp. 280-291, 2005.

[13] Y. Huang, K.B. Englehart, B. Hudgins, A.D.C. Chan, "A Gaussian Mixture Model Based Classification Scheme for Myoelectric Control of Powered Upper Limb Prostheses," *IEEE Trans. Biomed. Eng.* vol. 52(11), pp. 1801-1811, Nov. 2005.

[14] Z.Q. Bian, G.X. Zhang, "Pattern Recognition (In Chinese)," 2nd ed. Beijing: Tsinghua University Press, 2002