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Exploration on the Feasibility of Building Muscle-Computer Interfaces using Neck and Shoulder Motions

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Abstract—**This paper investigates the feasibility of building muscle-computer interfaces starting from surface Electromyography (SEMG) -based neck and shoulder motion recognition. In order to reach the research goal, a real-time SEMG sensing, processing and classification system was developed firstly. Then two types of SEMG recognition experiments, namely user-specific and user-independent classification, were designed and conducted on seven kinds of neck and shoulder motions to explore the feasibility of using these motions as input commands of muscle-computer interfaces. In all 9 subjects took part in these experiments, 97.8% and 84.6% overall average recognition accuracies were obtained in user-specific and user-independent experiments respectively. The experimental results demonstrate that it is possible to build muscle-computer interfaces with neck and shoulder motions. In addition, the results of cross-time experiments designed to explore the relationship between training and accuracy in user-specific recognition indicate that users can interact accurately with computers using the defined motions only after four times training in different days.**

I. Introduction

Myoelectric control has fascinated many researchers for its applications range from rehabilitation to human computer interaction (HCI). In myoelectric control systems, a user's intension can be measured from Electromyography (EMG) signals in the form of muscular activities, using surface EMG sensors in a non-intrusive fashion [1]. Detected muscle activities are identified as motion commands which can be used for controlling externally powered devices [2]. EMG signal detecting and processing technologies provide us with the opportunity to interact directly with human muscular activities. Many previous works [2]–[4] have demonstrated the feasibility of muscle-computer interfaces (MuCIs) as an interaction method in which user inputs are gestures, such as finger, hand, wrist, and arm movements.

Due to the fact that the activation of neck, shoulder and back muscles can also control the orientation and posture of these body parts, it is possible to recognize neck and shoulder motions with EMG measurements. Most efforts at measuring surface EMG signals in neck and shoulder regions have focused on medical diagnoses [6], occupational rehabilitation [7], and industrial ergonomics [8]. However, few previous studies considered the EMG-based neck and shoulder motion recognition for MuCI applications. As a rare example in this field, Moon et al. [5] proposed a wearable EMG-based HCI for wheel-chair users with motor disabilities, in which users can express their control commands with three kinds of shoulder elevation.

In this study, we investigate the feasibility of building MuCIs starting from SEMG-based neck and shoulder motions recognition for healthy people in practical application. Section 2 introduces the approaches including the development of a real-time gesture recognition system, EMG signal acquisition and processing. Two types of SEMG recognition experiments, user-specific and user-independent classification, are conducted to recognize 7 kinds of neck and shoulder motions in section 3, and the experimental results for 9 subjects are given and discussed. We conclude the paper and point out our future research directions in the last section.

II. Methodology

A. System Architecture

All our experiments were implemented on the *EMG-based Real-time Gesture Recognition System*, which was established and updated from our pilot studies [9] for finger, hand, wrist, arm gestures, or neck and shoulder motions recognition using multi-channel surface EMG signals. Fig. 1 shows the system architecture including the hardware and software components. The operating principle of this system can be described as follows: First, the multi-channel EMG signals recorded on the activated muscles during motion performance are digitalized by an A/D converter for further processing on computer. Then, the computer discriminates the gesture with a SEMG pattern recognition algorithm consisting of data segmentation, feature extraction and classification. Finally, the classification results are shown on the graphic interface as visual feedback, and the recognized gesture can be translated into interaction commands.

B. EMG Signal Acquisition

1) Neck and Shoulder Motions: Taking into account the convenience of performance and natural senses in real application, seven kinds of neck and shoulder motions were selected as objects of the study. Fig. 2 shows the selected

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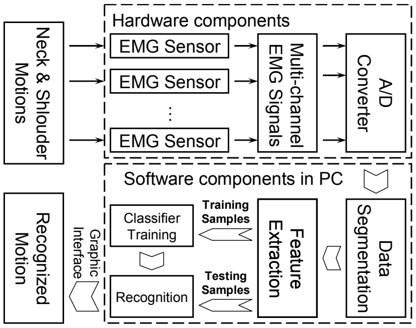

Fig. 1. The structure of neck and shoulder motion recognition system.

motions, which include two neck rotation motions (turn left or right), and five shoulder motions (upward or backward movement with left, right, or both left and right shoulders). The acceptance of these motions was also confirmed by the participants of the experiments.

2) Six-channel EMG Sensor Placement: In our experiments, six-channel surface EMG signals were measured by Delsys Myomoniter IV wireless sensor system with inbuilt band-pass filters (20-1000 Hz) and amplifier (60dB) in each channel. Two silver bar-shaped electrodes, with a 10mm x 1mm contact dimension and 10mm electrode-to-electrode spacing, are embedded in each sensor. The EMG signal streams are digitalized by NI PCI-6010 16-ch D/A card (PCI slot) with the sampling rate 1 kHz.

The six-channel EMG sensor positions are shown in Fig. 3: CH1 and CH2 are placed on the left and right region of the neck respectively for detecting the activities of left and right *Sternocleidomastoideus*; CH3 and CH4 are situated at left and right shoulder to detect the activities of *Levator Scapulae*; CH5 and CH6 are mainly used for detecting the activities of the muscles on back, for example, the *Upper Trapezius*.

C. EMG Signal processing

In this sub-section, the SEMG pattern recognition algorithms, from data segmentation to classification, are introduced.

1) Data Segmentation: In order to recognize neck and shoulder motions effectively, the active segments corresponding to neck or shoulder movements in multi-channel EMG signal stream need to be captured automatically. A data segmentation method based on moving average algorithm and thresholding was designed to search the start and end points of each active segment [10]. First, the system calculates the average value of the six-channel EMG signals. Then, the moving average algorithm is applied with a window size of 60 points (60ms) on the squared average EMG stream. Next, a threshold is used for segmentation. The active segment begins when the moving averaged stream is above a given threshold and continues until all sample points in a 50ms time period are below the threshold. According to general knowledge on normal motions, a length eligible range (about 100-800ms) was defined. The active segments whose time lengths were out of this range were discarded as noises. Fig. 4 shows typical SEMG signal patterns of the 7 defined

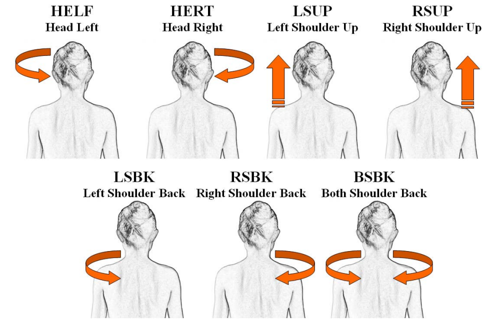

Fig. 2. Seven kinds of defined neck and shoulder motions.

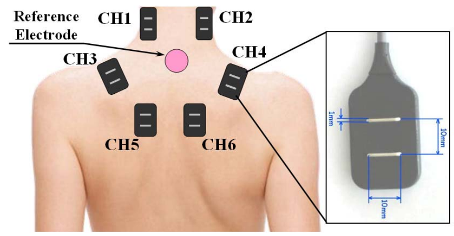

Fig. 3. Six-channel EMG sensor placemen.

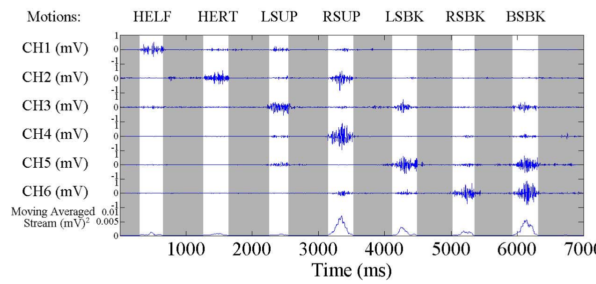

Fig. 4. Illustration of data segmentation and typical signal patterns for each motion.

motions. The active segments are marked with white bars.

2) Feature Extraction: In order to recognize neck or shoulder motions effectively, distinctive features that represent the specific motion pattern have to be extracted from the raw SEMG data. Various kinds of EMG features based on time and spectral statistics are used for myoelectric control in the literature. Our pilot study [10] demonstrated that the Mean Absolute Value (MAV) and Auto-Regressive (AR) model coefficients are well suited to SEMG pattern classification with high test-retest repeatability. Therefore, the MAV and third-order AR model coefficients of each channel were computed and used to form feature vector in our system. Hence, each active segment of six-channel EMG signals was converted into a 24-dimensional feature vector.

3) Classification: Linear Discriminant Classifiers (LDC) [10] were adopted for feature classification in our system due to their low computational complexity and stable recognition performance in practical application. The classification software was designed with two functional modes: training and testing. In the training mode, feature vectors of each class were recorded and saved in a database as training data samples. While in testing mode, the system loaded the training data samples to train classifiers, and the well-trained classifiers were then used for the recognition of new motions.

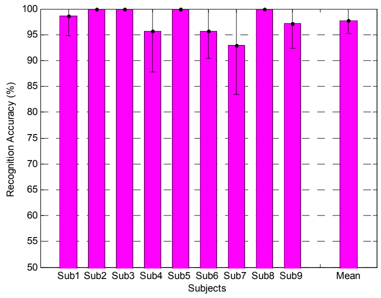

Fig. 5. User-specific classification accuracies of 7 kinds of neck and shoulder motions.

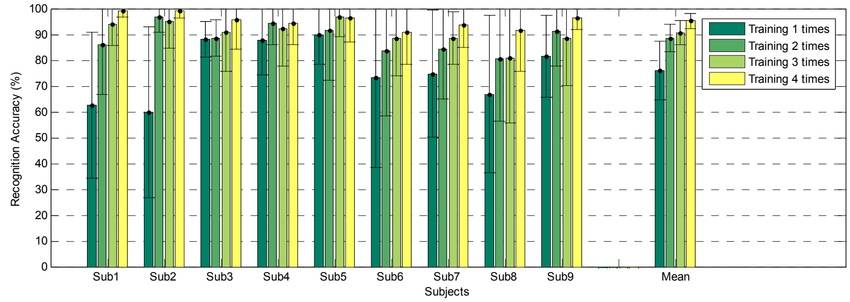

Fig. 6. User-specific cross-time classification accuracies of 7 kinds of neck and shoulder motions.

III. Experiments and Results

A. Experimental Settings

Nine subjects, 5 males and 4 females, aged from 21 to 27, participated into the neck and shoulder motion recognition experiments. They all are healthy and have no history of neuromuscular or joint diseases and were informed of the associated risks and benefits specific to the study.

The experiments consisted of two testing scenarios: user-specific and user-independent classification. In user-specific classification, training data and testing data were different but from the same user. Classifiers were trained and tested independently on data from each user. Each of the 9 subjects was required to participate into experiments for more than five times (five days, one experimental session per day). In each session, subjects performed the defined 7 kinds of neck and shoulder motion in a sequence with 20 repetitions per motion, and recorded the SEMG signals as training data samples firstly. Then they performed 20 testing samples per motion for classification and the results were recorded for later analysis. In the first session, the system loaded the data recorded in the current session to train the classifiers. From the second to the fifth sessions, the classifiers utilized in *i*-th session were trained with data samples collected in the 1st to (*i-1*) th sessions, in order to evaluate the test-retest repeatability of system in cross-time classification.

In user-independent classification, the training data from one set of users were mixed together to train classifiers, which then were applied to recognize motions performed by another user [3]. As a preliminary exploration of this scenario, we conducted a nine-fold cross-validation using "Leave One Out" method. The training data from eight subjects in all five sessions were loaded together to train classifiers, and the remaining subject performed motions to test the system. The experiment was proposed to evaluate the generality of EMG-based neck and shoulder motion recognition.

B. Experimental results and analysis

1) User-specific Experiments: In the first session of user-specific experiments, a new classifier of system was created for each user. Every user had to test the system immediately after their training samples had been recorded and used for the training of the classifiers. The average

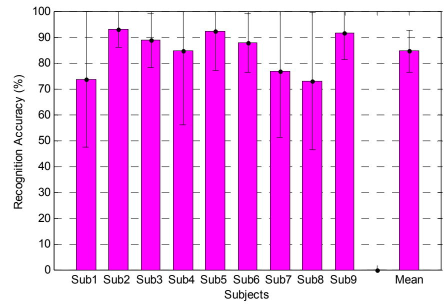

Fig. 7. User-independent classification accuracies of 7 kinds of neck and shoulder motions.

classification accuracies of the 7 kinds of neck and shoulder motions for each subject are shown in Fig. 5 for each subject separately. The mean classification accuracy for all the subjects reached 97.8% (SD: 2.6%) average accuracy. These satisfying results demonstrate the feasibility of building user-specific MuCIs with neck and shoulder motions.

In the results presented above, the classifiers were trained and tested on data from the same session with a fixed-placement of EMG sensors. In user-specific cross-time classification, the classifiers were trained on data from previous multiple sessions and testing samples were further performed by subject to evaluate the system performance. The average recognition accuracies of the classifiers trained with data mixed from the first 1, 2, 3, and 4 sessions, are shown in Fig. 6.

Our experimental results of cross-time classification gave a brief insight into the relationship between the number of training sessions and classification accuracies. The recognition results show that the more training sessions for the system, the more accurate recognition performance it can be expected to achieve. When the classifiers were trained on data from only the first session, the average recognition rates are from 62.69% to 89.69% for nine subjects. And when training data samples were from four sessions, the recognition rates are all above 90% (Mean: 95.2%, SD: 2.9%). We believe that this phenomenon is mainly attributed to two factors. One is the SEMG differences caused by physiological changes between days for each subject, and the other is the sensor displacements between the different experimental sessions. Because the characteristics of SEMG signals are very sensitive to sensor placement, the sensor displacement is regarded as the dominant factor which affects the classification accuracy. In the second session, with training data only from the first session, the sensor displacements could result in low recognition accuracies. When the system was trained with data from multiple sessions, which could cover most of the possible sensor displacements, the classifiers became more robust and less sensitive to sensor displacements, and the classification accuracies were thus improved significantly. We concluded that a relatively effective choice of number of training sessions is four, because when the number reached four in our experiments, for most of the subjects, the recognition results improved significantly and were very close to those results with training and testing data from the same session.

2) User-independent Experiments: To extend the user-specific classification results, we explored the feasibility to realize the cross-user system. Each of 9 subjects was required to do additional testing experiment with cross-validation in which the training datasets of remaining eight subjects from all five sessions were mixed together. Fig. 7 shows user-independent classification results. The classification accuracies for nine subjects range from 73.56% (SD: 26.21%) for Sub1 to 93.07% (SD: 7.19%) for Sub2 with the mean rate 84.6% (SD: 8.1%). It is not unexpected that the recognition rates in user-independent classification are lower than that in user-specific classification.

Due to the individual differences of biosignals, there exist great challenges to establish user-independent EMG-based recognition and interaction systems. Although previous researchers have realized various outstanding prototypes with MuCIs, few studies on user-independent classification have been reported and the limited testing results are not satisfying. T.S. Saponas et al. [3] explore the feasibility of MuCIs using forearm EMG to classify five kinds of finger "Lift" gestures at an average of 57% accuracy in user-independent experiments. J. Kim et al. [4] developed an EMG-based controlling interface to navigate an RC car with only four kinds of wrist gestures. A remarkable average rate of 93.17% could be achieved in user-independent classification, after the participants spend a long time practicing to perform the gestures with a sufficiently low variation. We did not do any optimization in subjects practice schemes or experimental design according to the gender, height, weight or degree of muscle strength in this study. We believe that the user-independent classification performance could be improved if the factors mentioned above are considered. Anyway, our present experimental results also demonstrated that it's possible to build user-independent MuCIs.

IV. Conclusion and Future Work

To investigate the feasibility of building muscle-computer interfaces with neck and shoulder motions, a real-time SEMG sensing, processing, and classification system was developed and two types of SEMG recognition experiments were designed and conducted on 7 different motions. The experimental results of user-specific, cross-time and user-independent classification demonstrate that neck and shoulder motions can be distinguished accurately based on SEMG signals from different views. So it is feasible to build MuCIs using neck and shoulder motions as input command for control of computers, mobile phones and other consumer electronics. Especially from cross-time experimental results, we concluded that the MuCIs can overcome the effects of sensor displacements when the classifier is trained with data collected in four collection sessions hold on different days. This conclusion means that user can interact directly with the interfaces after a few prior training sessions.

However, as we expect MuCIs should be utilized by healthy people in actual applications, MuCIs with neck and shoulder motions are faced with challenges. For instance, since common end-users will not be expert to configure EMG sensor placement [3], the sensors should be embedded in special necklace or clothes for easy wear. Additionally, motionless neck and shoulder motions to be preferred as isometric contractions are unnoticeable and thus provide a method to control computer quietly and in subtle manner in special circumstances such as subway or conference. Our future work will focus on the realization of natural, convenient and wearable MuCIs using various body gestures.

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