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Combined Use of sEMG and Accelerometer in Hand Motion Classification Considering Forearm Rotation*

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Abstract— **Hand motion classification using surface electromyography (sEMG) has been widely studied for its applications in upper-limb prosthesis and human-machine interface etc. Pattern-recognition based control methods have many advantages, and the reported classification accuracy can meet the requirements of practical applications. However, the pattern instability of sEMG in actual use limited their real implementations, and limb position variations may be one of the potential factors.**

In this paper, we give a pilot study of the reverse effect of forearm rotations on hand motion classification, and the results show that the forearm rotations can substantially degrade the classifier's performance: the average intra-position error is only 2.4%, but the average interposition classification error is as high as 44.0%.

To solve this problem, we use an extra accelerometer to estimate the forearm rotation angles, and the best combination of sEMG data and accelerometer outputs can reduce the average classification error to 3.3%.

I. Introduction

Surface electromyography (sEMG) has been widely used in power prosthetic control for decades [1], and also been used as a new type of human-machine interface these years [2]. However, present applications of sEMG can only control a limited number of degrees of freedom (DOFs), and pattern-recognition based methods are promising to produce natural and multiple DOFs control for users [1].

Most of the present researches about sEMG classification focused on various techniques of preprocessing, feature extraction, and different kinds of classifiers to reach higher classification accuracies [3]–[6]. The up-to-date classifiers can achieve an accuracy as high as 98% [7], which can fully meet the needs of practical applications. However, there are few successful commercial use of pattern-recognition based myoelectric prosthesis because of the pattern instability in actual use [1]. The nonideal conditions in clinical implementations may lead to inconsistencies with the reported classification accuracy under controlled conditions. To bridge the gap between research and clinical practice, some researchers began to investigate the potential causes and solutions of failed use of pattern-recognition control method [8]–[11].

E. Scheme *et al.* [9] first studied the reverse effects of limb position on pattern recognition based myoelectric control, and the results showed that, limb position variations in sEMG training and testing led to a substantial decrease of the classification accuracy. In this paper, they considered 8 limb positions and the mean interposition error was as high as 35.0%, while the mean intra-position classification error was only 6.9%. To resolve the limb position effects in myoelectric pattern recognition, Anders Fougner *et al.* [10] added two accelerometers which were placed on the forearm and upper arm respectively, and reduced the average classification error from 18% to 5%.

However, the above researches only considered the large motions of the upper body or the whole upper limb, such as torso horizontal [9], straight arm hanging straight, straight arm reaching up 45° [10] *etc.* Actually, most of the hand motions are controlled by small and closely spaced muscles on the forearm, and the sEMG pattern changes caused by the forearm movements may be the most contributions to the large classification errors.

Typical forearm rotations like pronation and supination are commonly used in daily life, which can change the palm orientation when the hands perform different motions. Some researchers considered the forearm supination and pronation as two hand motions to design pattern classifiers [11]–[13]. Actually, forearm rotations turn the hands to rotate, and hand motions (hand close, wrist flexion, etc.) can still perform as the forearm rotates at different positions. For sEMG use, when the forearm rotates, the related muscles also move, and the relative shift between surface electrodes and target muscles may change the sEMG patterns [13], [14], and degrade pattern recognition performance.

In this paper, we conducted a pilot research focused on the reverse effects caused by the forearm rotations. In order to solve this problem, we used an accelerometer to sense the forearm rotations, and a best combination of accelerometer outputs and sEMG features was proved to be able to achieve a robust and high classification accuracy system.

II. Experiment

A. Data Acquisition

The accelerometer outputs and sEMG data corresponding to 7 classes of hand motions were collected from 6 healthy subjects (5 male, 1 female; 24-28 years old).

Four pre-amplified sEMG sensors (part #243 by Noraxon) were used to collect sEMG signals at four equally spaced spots around the forearm. For each channel, two Ag/AgCl electrodes were placed along the forearm, with a distance of about 1.5cm between them and another reference electrode was placed near the elbow. Besides, we chose a 3-axis analog

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accelerometer (ADXL335B by ADI) to record accelerations on each axis, and fixed it on the back of the forearm with its Z axis pointing above, and X axis along the forearm. Fig. 1 shows the configuration details.

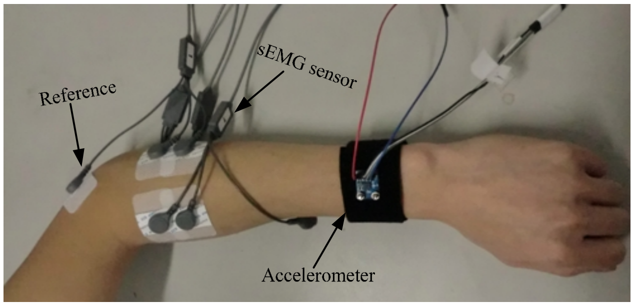

Fig. 1. Placement of the accelerometer and electrodes.

All sEMG channels were pre-amplified 500 times and low-pass filtered at 500Hz. The accelerometer was configured to have a sensitivity of 300mV/g at a range of 3.6g, where g represents the gravitational acceleration. Both the sEMG and accelerometer outputs were recorded using a NI DAQ Card (USB6211) at a sample rate of 2kHz.

In order to study the influences of forearm rotations on hand motion classification, we selected 3 typical forearm rotary positions: supination, pronation and a neutral rotation of 90° as illustrated in Fig. 2.

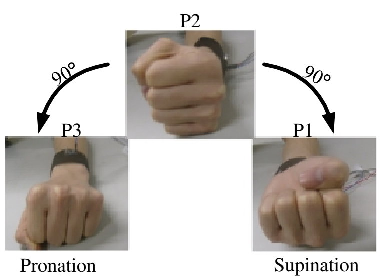

Fig. 2. Forearm rotary positions.

Seven classes of representative hand motions (C1-C7) were selected as shown in the Fig.3.

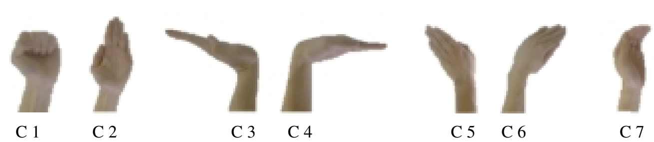

Fig. 3. Hand motion classes. (C1: Hand close C2: Hand open C3: Wrist extension C4: Wrist flexion C5: Ulnar deviation C6: Radial deviation C7: Hand at rest)

Under each forearm position, the subjects performed 7 classes of hand motions. Each motion was repeated 10 times, during which each contraction was sustained for 3 seconds and then rested for 3 seconds before subsequent contractions to avoid fatigue. During the experiment, the subjects sat at the table, with elbows laid on the table to avoid the influences of large body movements.

B. *Feature Extraction and Preprocessing*

Many sEMG features like time domain (TD) feature [3], autoregressive (AR) coefficients [6], the wavelet packet transform [7] have been widely studied in hand motion classification. TD feature was adopted here for its simple implementation and good performance in combined use with most classifiers [15]. Four TD features (mean absolute value, zero crossings, slope sign changes and waveform length) of each channel were computed within a 200ms sliding window, and 3 axis outputs of the accelerometer were simply averaged for further use. Please refer to [3] for more details about TD feature extraction.

The raw features usually need to be preprocessed before classifier training, and 16 features of 4 channels were too many for the following computation. Principal Component Analysis (PCA) has been used in many papers and proved to be effective in sEMG classification [12]. Using PCA, the raw features are projected onto directions of principal components, which have orders of their importance in classification, and formed new features. On one hand, some features may make little contribution to classification, and a lower feature space dimension is necessary for embedded implementations. On the other hand, the less important features may have some relations with noises, and should be discarded to improve the robustness of the system [12]. In our research, we use PCA to reduce the features number from 16 to 11 without sacrificing accuracy.

C. *Classifier Design and Training Methods*

Many modern classification methods like Linear Discriminant Analysis (LDA), artificial neural networks, Gaussian mixture models, and hidden Markov models have been investigated in sEMG classifications, but there are no big differences in their classification performances [16]. Among all these classifiers, LDA is a very simple method to find a linear combination of features which separates two or more classes. In this experiment we chose LDA classifier as it was widely used and has been proved to be suitable for sEMG classification and work well with TD features [15].

In the experiment, we designed 3 different training modes:

1) Only sEMG samples were used and 3 LDA classifiers was trained under each single forearm position. In order to study the effects of forearm rotations on classification, these 3 classifiers were then tested using sEMG samples of all forearm positions.
2) A LDA classifier was trained and tested using all sEMG samples of 3 forearm positions.
3) The accelerometer outputs were used for classification in combination with sEMG TD features.

In mode (3), we first used the accelerometer outputs to estimate the forearm rotary angles, and then used the angles to train the classifier in mode (2) as an extra feature. This method was different from the one used in paper [10], where all the accelerometer outputs and sEMG features were concatenated to form feature vectors. Our usage of the accelerometer only added 1 feature, and less computation than the latter method.

The accelerometer can measure the linear accelerations on each axis, while the components of gravitational field vector g exist all the time. In the absence of linear accelerations or the linear accelerations are negligible compared with gravitational acceleration like the situations in our experiment, the accelerometer outputs are only the components of g on the corresponding axis, which can be used to determine the accelerometer rotary angles.

According to the principle of spatial transformation [17], the coordinate representation of g in the accelerometer reference frame is:

$$\begin{pmatrix} g_x \\ g_y \\ g_z \end{pmatrix} = \mathbf{R}_x(\phi)\mathbf{R}_y(\theta)\mathbf{R}_z(\psi)\begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$$
$$= \begin{pmatrix} -\sin\theta \\ \cos\theta\sin\phi \\ \cos\theta\cos\phi \end{pmatrix} \quad (1)$$

The vector $(0, 0, 1)^T$ in (1) is the coordinate representation of g in gravitational frame, and R is the rotation matrix of each axis, with parameters of roll angle ϕ , pitch angle θ and yaw angle ψ.

The orientation angles are dependent on the order in which the rotations are applied, and we adopt the commonly used aerospace sequence of yaw then pitch and finally a roll rotation. In our experiment, the X axis was configured along the forearm, so the forearm rotary angle is the roll angle ϕ.

It's easy to calculate ϕ from (1):

$$\phi = Atan2(g_y, g_z) \quad (2)$$

where $Atan2$ is a four-quadrant inverse tangent function, and the results of ϕ can vary between $-180°$ and $180°$.

III. Results

At first, only sEMG samples were used, and 3 different classifiers were trained under 3 forearm rotatory position respectively, but tested using sEMG samples from all positions.

The interposition errors are averaged across all subjects and motions, and the results are shown in Fig.4. The vertical axis denotes the different training positions and the horizontal axis denotes the test positions. The entries in the main diagonal represent the intra-position classification errors, while the off-diagonal elements represent the interposition errors.

Training Position \ Test Position	P1	P2	P3
P1	3.1	39.8	47.5
P2	40.4	2.8	50.7
P3	41.9	30.1	1.4

Fig. 4. Interposition classification errors (in %), averaged across all subjects and motions.

The average intra-position classification error was 2.4%, whereas the average interposition error was 44.0%. This large classification performance degradation makes the commonly used single-position training method failed to be used in practical applications.

In order to decrease the inter-position errors caused by forearm rotations, the forearm positions needed to be included in the classification. Three methods were compared in the experiment:

- A new classifier was trained using data from all forearm positions, and the underlying position information in the samples were expected to produce a good overall performance.
- The estimated forearm rotation angle using accelerometer outputs were used as an extra feature to train a LDA classifier with sEMG data from all forearm positions.
- 3 accelerometer outputs were used directly with sEMG samples of all positions to train a new classifier.

Figure5 depicts the classification of 7 classes using 3 methods and the errors are averaged across all subjects.

The average classification error using only sEMG data is 4.5%, and the average error using extended features of sEMG and rotation angle is 3.3%, while the average error using sEMG and 3 raw accelerometer outputs is 4.1%. This result means the inter-position error is efficiently reduced by the best combined use of sEMG and accelerometer. The average classification errors of C1 are higher than other motions, mostly because the subjects didn't perform uniform strength during different hand close contractions.

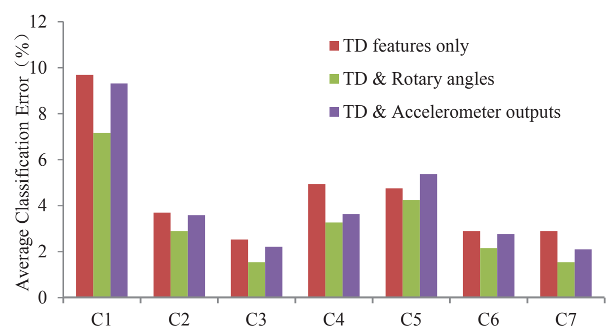

Fig. 5. Classification error of each motion using different features averaged across all subjects.

In the experiment, we also tried a two-stage classification method like the one used in [10]. We first trained a forearm position classifier using the the estimated angles, and then selected the corresponding single-position trained sEMG classifier. The result showed that, 3 forearm rotary positions could be classified 100% using the accelerometer samples, and we could achieve a lower classification error of 2.4% as in the single-position conditions. However, this method is not appropriate for practical use, where more than 3 forearm positions should be considered and more classifiers are needed to be trained.

IV. Discussion

As the results show, LDA and TD features of 4 sEMG channels worked well, and could reach an average accuracy of 97.6% in 7 hand motion classifications. The supplement of preprocessing techniques like PCA makes it easy to be implemented in embedded systems.

The large interposition classification error caused by forearm rotations reveals that the classifiers trained under a special forearm position can hardly recognize the same hand motion under a different forearm position. As referred in the introduction, pattern-recognition based myoelectric hands are less prevalent in practical applications just because the pattern instability, and our results show that forearm rotation may be one of the potential causes.

In clinical sEMG collection procedures, there are some recommendations about the sEMG sensor location and orientation on the muscle [18]. These recommendations are expected to be good for getting stable signals, and decreasing the risk of crosstalk. However, for sEMG hand motion classification, relative movements of muscles and the sensors during the experiment are inevitable, therefore a robust sEMG post-processing is more important.

Actually, when we rotate the forearm, the related muscles also rotate, while the electrodes placed on the skin of the forearm move little, resulting in a relative shift of electrodes and targeted muscles, which may cause the sEMG feature space change. Some previous researches have proved that relative shift may influence the classification results [13], [14], and the situation in forearm rotations is more serious. In this paper, we selected 3 typical forearm positions for the comparison convenience, whereas more positions need to be considered in actual use when collecting sEMG samples, and it's easy to record the forearm positions using accelerometers. At the same time, multiple sEMG channels are needed, which can guarantee collections of sEMG under different forearm rotary positions.

Accelerometers have been widely used in body position detection, like walking pattern analysis [19], hand gesture recognition [20] and so on. However, accelerometer cannot accurately sense the body position when an additional linear acceleration exists. In clinical implementations of sEMG classifications, inertial measurement unit (IMU) is a better choice, which usually include a triaxial gyroscope, a triaxial accelerometer, and a triaxial magnetometer [21].

Our experiment has proved the large influence of forearm rotations on sEMG hand motion classification, and previous researches like [9]–[11] revealed that large limb position variations relative to the body matter as well. However, these papers did not exclude the forearm rotations in their experiments, which may be one of the biggest contributions to the classification error. Therefore, in our future work, we will compare the accurate contributions caused by forearm rotations and large upper limb motions.

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