Personalized Protocol to Select Usable Movements for Myoelectric Pattern Recognition

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Abstract— **Although pattern recognition studies have classified for upper limb movements, there is remaining issues for multi-finger movements. Depending on the user's characteristic, usable movements for pattern recognition might be different. In addition, different finger movements might show similar surface electromyography (sEMG) from forearm and wrist. Therefore, we present a personalized protocol to select usable movements for each subject. Firstly, all movements were sorted into k classes using a k-means clustering method. Secondly, the movement, which showed different sEMG features for trials, was removed. 20 healthy subjects performed the 64 finger movements and 4 wrist movements. We found that the maximum number of classes (>95%) is different depending on the individual and location of electrodes; 18.5±3.0 on forearm and wrist, 11.7±1.9 on forearm, and 8.9±1.7 on wrist. The large standard deviation supports the personalized protocol for each subject in both locations.**

Keywords— **Surface electromyography, movement selection, pattern recognition.**

I. INTRODUCTION

Surface electromyography (sEMG) based pattern recognition has been widely studied because of the merits it offers as an control input for many applications such as prosthetics, exoskeletons, robotics, etc [1]. For the control of upper limb movement, the features extracted from sEMG have been used to classify several classes of the forearm, wrist, and hand movement. However, systems with sEMG-based control were not popularly used in the commercial market because there remains several issues to overcome, such as electrode shift, force change, variation of limb position, and time-varying signal characteristics [2].

In addition, the personal characteristics of muscle structure and degree of freedom for target movements are also important for myoelectric pattern recognition. In particular cases for finger movements, the classification of finger movements is more challenging than other forearm movements because sEMG signals related to finger movements are smaller in amplitude, and the muscles responsible for finger movements are, in general, located in the intermediate and deep layers of the forearm [3].

Many groups tried to classify predefined finger movements using different features and classification methods [4]–[9]. For example, Al-Timemy *et al.* [8] classified 15 classes of different finger movements using sEMG electrodes placed on the forearm. They achieved an accuracy over 98% when tested on healthy subjects. However, previous studies only investigated predefined movements and did not take into account the different characteristics existing among individuals.

sEMG characteristics can vary among individuals and some finger movements are distinct amid individuals depending on their muscle structure. Depending on the user's muscle structure, some finger movements can be challenging to perform. Generally, the movements of the thumb and index finger are more independent compared to the other three fingers [10]. Consequently, producing several hand gestures that involve the coupled fingers can cause discomfort depending on the user. Therefore, a personalized approach is necessary to identify the finger movements available as input commands.

We propose a personalized protocol to select usable movements among 64 finger movements and 4 wrist movements by processing sEMG signals for each individual. The proposed method aims to identify usable movements as input commands and to then evaluate the classification accuracy. A *k-means* clustering method was used to sort all movements into *k* classes based on the characteristic of sEMG features and a number of k was changed from 2 to 68. Experiments were performed by 20 healthy volunteers with a total of 18 sEMG electrodes: 11 electrodes on the forearm and 7 electrodes on the wrist.

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II. Materials and Methods

A. Experimental setup

The sEMG signals were acquired using 18 bipolar electrode sensors (DE-2.1 sensor; Delsys Inc., USA) and were amplified by a factor of 1,000 using BagnoliTM systems (Delsys Inc., USA). The sEMG signals were sampled at 1 kHz and were band pass filtered using an FIR filter with a frequency range between 20 and 450 Hz. The electrodes were attached on the right forearm and wrist of the subjects. The electrodes were placed into two rows around the circumference of the wrist region proximally near the head of the ulna (7 electrodes) and the thickest region of the upper forearm (11 electrodes), as shown in Fig. 1.

B. Experimental Procedures

20 healthy volunteers (12 males and 8 females, 25.2±2.5 years old, right-handed persons), who had no previous experience with the following pattern recognition experiment, were recruited. The protocol (KH2010-25) was approved by the Institutional Review Board at KAIST. Written informed consent and assent were obtained from all subjects.

The subjects were asked to sit comfortably on a chair and to place their right elbow on the chair armrest. The subjects placed their hand so that the thumb pointed upwards and the little finger pointed downwards as if handshaking.

Each finger has three possible states: flexion, extension, and rest, allowing a total of 64 combinations of finger movements. We asked the subjects to perform 64 finger movements and 4 wrist movements. There were several movements that were uncomfortable or challenging to perform depending on the subjects because of the muscle anatomy of the human hand. We asked the subjects to perform the movements as naturally as possible. In addition to the 64 finger movements, 4 wrist movements, flexion, extension, radial deviation, and ulnar deviation were performed. Therefore, a total of 68 movements were performed for single trial.

A binary number system is implemented for simplicity. The binary number 1” indicates flexion or extension and 0” indicates rest. The first digit of the binary number represents the little finger, the fifth digit represents the thumb and the intermediate digits represent the ring, middle, and index fingers. The order of flexion or extension movement is incremented by one. For example, 00011” (4th movement) represents the flexion of the ring and little fingers and the rest of the thumb, index, and middle fingers. And then 00100” (5th movement) represents the flexion of the middle finger and the rest of the others. All 32 possible flexion

Fig. 1. 18 sEMG channel locations for forearm (11 electrodes) and for wrist (7 electrodes).

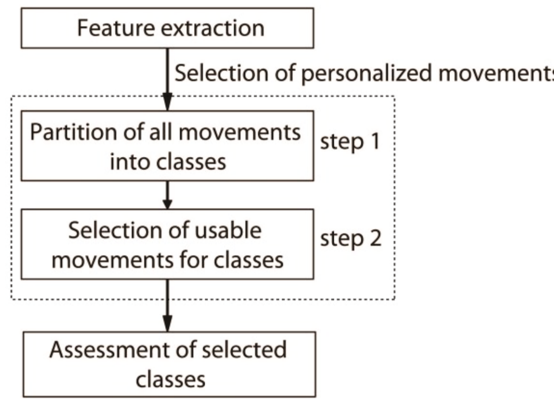

Fig. 2. Proposed protocol to select usable movements for classes.

movements are performed and then the 32 extension movements are carried out in the same manner.

The subjects maintained a rest posture (no movement), which is defined as the state when the amplitudes of the sEMG signals from all channels are not activated. Subjects were then asked to produce each movement for 4.5 s which was followed by a 1.5 s resting period, namely, each movement took 6.0 s for all 68 movements during a single trial. Subjects performed a total of 680 movements during 10 trials. They produced movements with a moderate and constant force. To avoid fatigue, two minutes of rest was provided after each trial.

C. Personalized protocol to select usable movements

1) Feature extraction

In Fig. 2, the time-domain features were extracted every 50 ms, during the time interval between 1.8 s to 4.3 s of each movement with a time window of 200 ms in duration. Features were normalized with the maximum values from each channel of each trial. 3 time-domain features: the mean absolute value (MAV), waveform length (WL), and Willison amplitude (WAMP) were calculated [1].

2) Selection of personalized movements

The purpose of selecting usable movements for each subject is to find applicable movements among all possible movements and to arrange them into classes. There are

Table 1 Selected movements for 15 classes in FW location (S03 and S15)

Class	S03	S15
1st	1 33	1 33
2nd	2 6 22 26 30	2
3rd	3 4 11 12 19 20 27 28 45	15
4th	5 17 21	**16 24**
5th	9 25 34 48	23
6th	**16 24**	32
7th	35 43	34
8th	36 37 40	35 39
9th	38 46	41 42
10th	41	43 44
11th	49 57	49 57 58
12th	51 54 59	65
13th	52 56 63 64	66
14th	66 67	67
15th	68	68

some movements that are challenging to perform, making them difficult to be repeated, and some movements that share similar sEMG characteristics, making them difficult to differentiate from one another during pattern recognition.

Step 1) Partition of all movements into classes

All movements in the odd number trials were sorted into distinct classes using the *k*-means clustering method. The *k*-means clustering method was used to partition movements into $N_{k\text{-}means}$ (number of *k*-means) classes in which each movement belongs to the class with the nearest mean. In this paper, a *class* is a collection of movements sharing similar sEMG features, namely, the movements in the same class indicate that they share similar sEMG features and can be used as the same input command. However, in some cases, the same movements may not be in the same class because the sEMG characteristics could vary over trials.

Step 2) Selection of usable movements for classes

It is necessary to remove the outlying movements, which were not able to be sorted into a certain class repeatedly. If the number of movements in each class was larger than a $threshold_1$ (τ_1), the corresponding movement was saved or otherwise eliminated. The selected classes will then be used to build a classifier and assess the classification performance in the next section.

Step 1) and step 2) were repeated under several conditions of $N_{k\text{-}means}$ and τ_1. To investigate the effect of $N_{k\text{-}means}$, step 1 was tested for all possible values of $N_{k\text{-}means}$ ranging from 2 to 68 (number of all movements). In order to determine the appropriate values of τ_1, step2 was carried out for 3 different values. The values chosen for τ_1 were 3, 4, and 5 because the number of trials for the selection processes was 5, a half of all trials. To guarantee that a single movement was always included in one class, the minimum number τ_1 was 3 and was increased to 5. The entire process consisting of two steps above was carried out under 67×3=201 conditions iteratively.

To investigate the effects of electrode location, 3 locations were used such as the first forearm + wrist (FW) location with 18 electrodes, the forearm (F) location with 11 electrodes, and the wrist (W) location with 7 electrodes.

3) Assessment of selected classes.

An artificial neural network (ANN) with multilayer per-

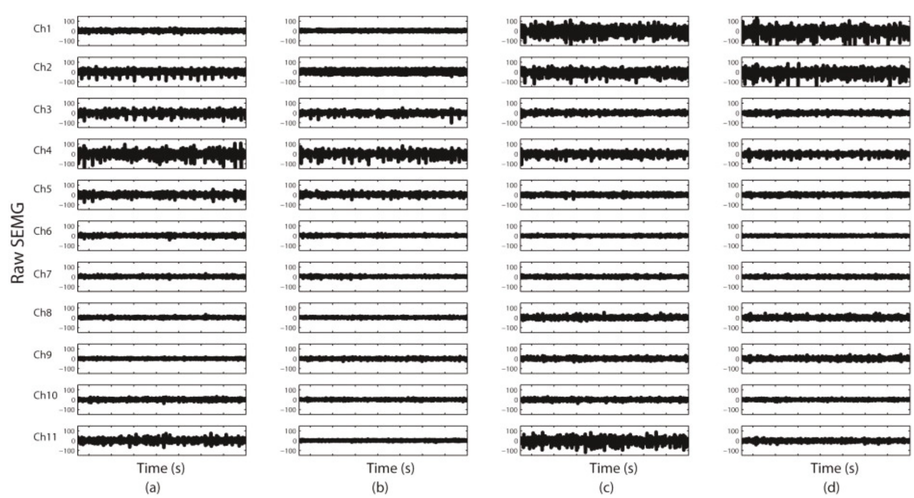

Fig. 3. Raw SEMGs of ch1 - ch11 on forearm for (a) 16th movement and (b) 24th movement for S03, (c) 16th movement and (d) 24th movement for S15. 16th movement is index, middle, ring, and little finger flexion. 24th movement is thumb, middle, ring, and little finger flexion.

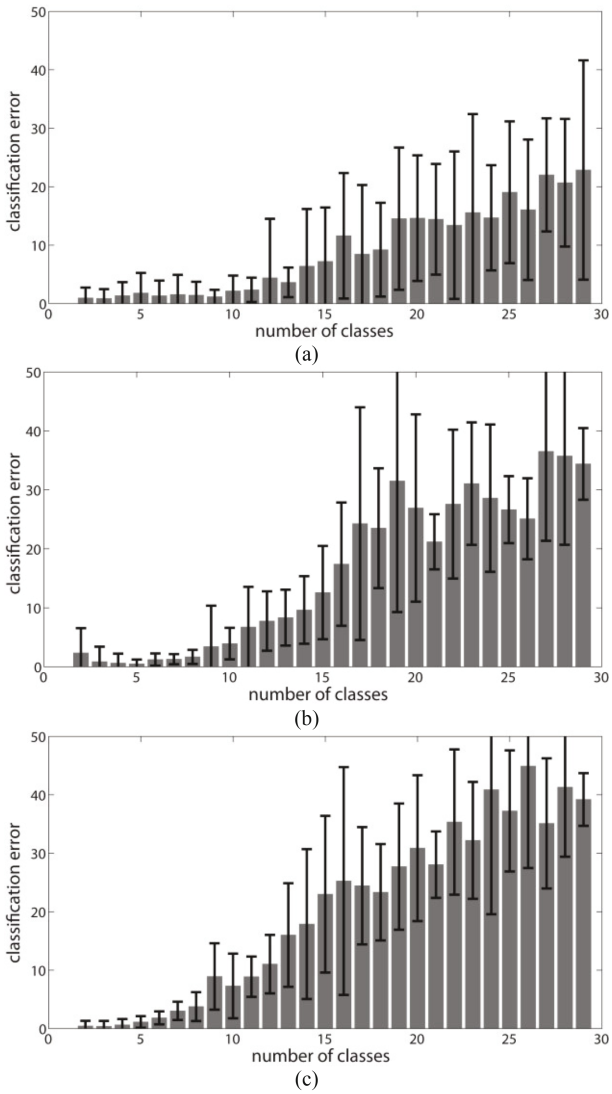

Fig. 4. Average errors of 20 subjects for (a) forearm and wrist location, (b) forearm location, and (c) wrist location.

ceptrons, which is one of the most popular machine learning-based classification and regression algorithm, was used for classification [11]. The odd number trials were used as the training set to optimize the ANN model parameters and the even number trials were used as the test set [7], [8]. The classification was performed when N_c ranged between 2 and 29 because we achieved a meaningless accuracy when N_c was larger than 30. The lowest error was found for each N_c and was used for the result analysis.

III. RESULTS AND DISCUSSION

A. Selected movements for classes

Among 68 movements, usable movements for 15 classes were different depending on sEMG features of each subject. For example, Table 1 shows the selected movements for 15 classes of two subjects in FW location. The each class was composed of more than one movement. Two subjects (S03 and S15) had a same class, which was composed of 16th movement and 24th movement. For each subject, both movements showed same features based on raw sEMG (ch1~ch11 on forearm) as shown in Fig. 3. When some movements had similar sEMG features, corresponding movements were used for same input commands. However, both movements showed different features between both subjects despite of same movements (16th and 24th movements). In addition, the total number of movements in 15 classes was less than the number of all movements (68) in both subjects. In order words, the movements, which showed different sEMG features in trials, were removed from classes.

B. Classification performance in 3 locations

Fig. 4 shows the average errors for each class (2-29) in FW, F, and W locations. As the number of classes increased, the errors increased in all locations. The maximum number of classes less than 5% error was 13 classes for forearm and wrist location, 10 for forearm location, and 8 for wrist location. Based on the user's requirements such as classification error and number of electrodes, user can select the location of electrodes.

The maximum number of classes with less than 5% error on each subject was 18.5±3.0 for FW, 11.7±1.9 for F, and 8.9±1.7 for W. FW outperformed F and W (p-value < 0.05). F also outperformed W (p-value < 0.05). The p-values were calculated from the one-way analysis of variance (ANOVA). The standard deviation of maximum number of classes in different electrode locations was attributed to the sEMG features from each movement and in same location was attributed to how well each subject moved their fingers repeatedly.

IV. CONCLUSIONS

We proposed the personalized protocol to use the applicable movements for pattern recognition. The sEMG features from the 11 electrodes on forearm and 7 electrodes on wrist were used to analyze whether movements are usable.

The proposed protocol selected the movements for classes among all candidate movements, before a classification process. We used the k-means clustering method to sort all movements into classes and removed unrepeatable movements based on threshold value. The selected movements for each number of classes were different on each subject. The maximum number of classes with less than 5% error on each subject was 18.5±3.0 for FW, 11.7±1.9 for F, and 8.9±1.7 for W. The outcome of this study can be used to select usable movements for myoelectric pattern recognition.

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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