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Evaluation of EMG Feature Extraction for Classification of Exercises in Preventing Falls in the Elderly

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Abstract

Falls are among the most common causes of injuries in elderly people. In order to prevent falls, one of the most effective and easy ways is home-based regular exercise, which consists of simple movements and do not require weights. To develop exercise recognition system based on surface electromyography (EMG) signals, the first and the most important step is an extraction of the efficient features. A main advantage of the system is an ability to monitor the performance of the defined exercises with the particular muscles. This research was aimed to address this challenge by investigating the class separability performance of frequency-domain EMG features during exercises in elderly people, and identifying the suitable feature sets that would provide the effective pattern recognition. Eleven features were evaluated by using a statistical criterion method, and tested with EMG data recorded from ten elderly subjects on four muscles during employing seven exercises. Frequency ratio and mean frequency showed the best class separation performance of all studied features for the posterior and the front thigh muscles respectively, whereas the third spectral moment produced the best classification performance for the muscles located in the lower leg. The combination of such features is recommended to further improve the performance of the exercise recognition system in the elderly.

Keywords: electromyography signal, fall prevention, feature selection, pattern recognition, RES index

1. Introduction

Falls are among the most common causes of injuries in elderly people [1]. In order to prevent falls, one of the most effective and easy ways is home-based regular exercise [2], which consists of simple movements and do not require weights. To promote the daily-life exercises in elderly people, the research proposed the exercise recognition system based on surface electromyography (EMG) signals. A main advantage of this system is an ability to monitor the performance of the defined exercises with particular muscle groups [3]. In addition, the system can be used to control the computer game or toy robot in order to communicate with elderly persons [4-5].

In the EMG-based pattern recognition system, the first and the most important step is an extraction of the efficient features [6-7]. Because, the EMG data do not contain only the useful information but also include a variety of noises or interferences [8]. This may lead to difficulty in the analysis of EMG data. This research was aimed to address this challenge by investigating the class separability performance of frequency-domain EMG features during balance and strength exercises in the elderly, and identifying the suitable feature sets that would provide the effective EMG pattern recognition. To our best knowledge, the evaluation of frequency-domain EMG features of classifying exercises in preventing falls in elderly persons has never been studied before [9-10].

2. Experiments and Data Acquisition

EMG data used in the signal analysis were recorded from ten elderly subjects during seven exercises on four specific muscles. The seven balance and strength exercises recommended from two physiotherapists respond to the important lower-limb muscle groups consisting (1) standing hip flexion with the right leg, (2) standing hip flexion with the left leg, (3) half squats, (4) wall push-off with chair, (5) standing toe raises, (6) standing heel raises, and (7) pulling stomach in. More details about these exercises were described in the next subsection.

Four representative muscles on the right leg are (1) the biceps femoris, (2) the vastus medialis, (3) the gastrocnemius and (4) the tibialis anterior, as shown in Fig. 1. The bipolar Ag/AgCl surface electrodes (Kendal ARBO, H124SG) were used for each muscle and an Ag-AgCl Red-Dot surface electrode (3M, 2237) was placed on the wrist to provide a common ground. The measurement device was set a band-pass filter with a 10-500 Hz bandwidth and an amplifier with a 1000x. In addition, EMG data were sampled by using an analog-to-digital converter (NI, USB-6009), and the sampling frequency was set at 1024 Hz with a resolution of 14 bits.

Each participant was asked to perform seven exercises as mentioned above for three seconds (3072 samples). However, the recording length was set at 4000 samples because elderly subjects cannot provide the accurate exercise within three seconds for all trials. Each exercise was repeated for three times. In order to avoid any effect of muscle fatigue on the measurements, a resting time of at least five minutes was taken between each trial. In total, 30 datasets were collected for each exercise from ten subjects.

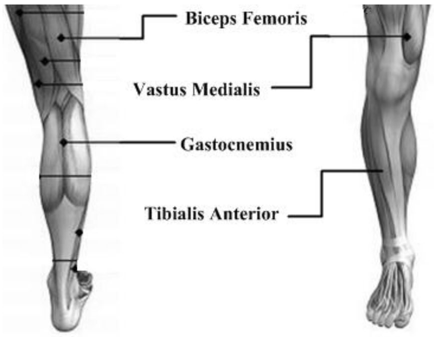


Figure 1. The muscle locations for four muscles.

2.1 Balance and Strength Exercises

In preparation stage, the subject firstly stands behind a chair with feet one foot apart and uses it for support. Next, the subject places both hands on the chair backrest. This preparation procedure was for the first three exercises and also the fifth and the sixth exercises. For the seventh exercise, the subject stands with feet together and both arms at side. However, for the fourth exercise, the subject sits on the chair with keeping the back straight and looking straight ahead, while places the feet against the wall, about one foot from a wall by bending the knee. The following is the description of the execution stage. It should be noted that each exercise was performed within three seconds.

E1) Standing hip flexion with the right leg: The subject lifts right leg off the floor by bending the knee toward chest, no more than 90 degrees, while standing on left leg. After that the subject returns his/her leg to the preparation position to complete one round.

E2) Standing hip flexion with the left leg: This exercise is similar to the first exercise but the subject lifts the left leg and stands on the right leg instead.

E3) Half squats: The subject bends his/her knees, no more than 90 degrees, and holds for a second. After that the subject returns his/her knees to the preparation position to complete one round.

E4) Wall push-off with chair: The subject pushes off the wall until his/her legs are in an outstretched position and holds for a second, and returns to the preparation position to complete one round.

E5) Standing toe raises: The subject rises up onto his/her heels as lifting both toes off the ground and holds for a second, and then returns to the start position to complete one round.

E6) Standing heel raises: The subject rises up onto his/her toes as lifting both heels off the ground and hold for a second, and then returns to the start position to complete one round.

E7) Pulling stomach in: The subject breathes in and slowly pulls his/her stomach in, and holds for a second. Then, the subject breathes out and slowly pushes his/her stomach out.

The procedure of seven exercises is respectively shown in Fig. 2(a) through Fig. 2(g). All exercises were employed in order to improve strength, balance, flexibility, or endurance in the elderly.

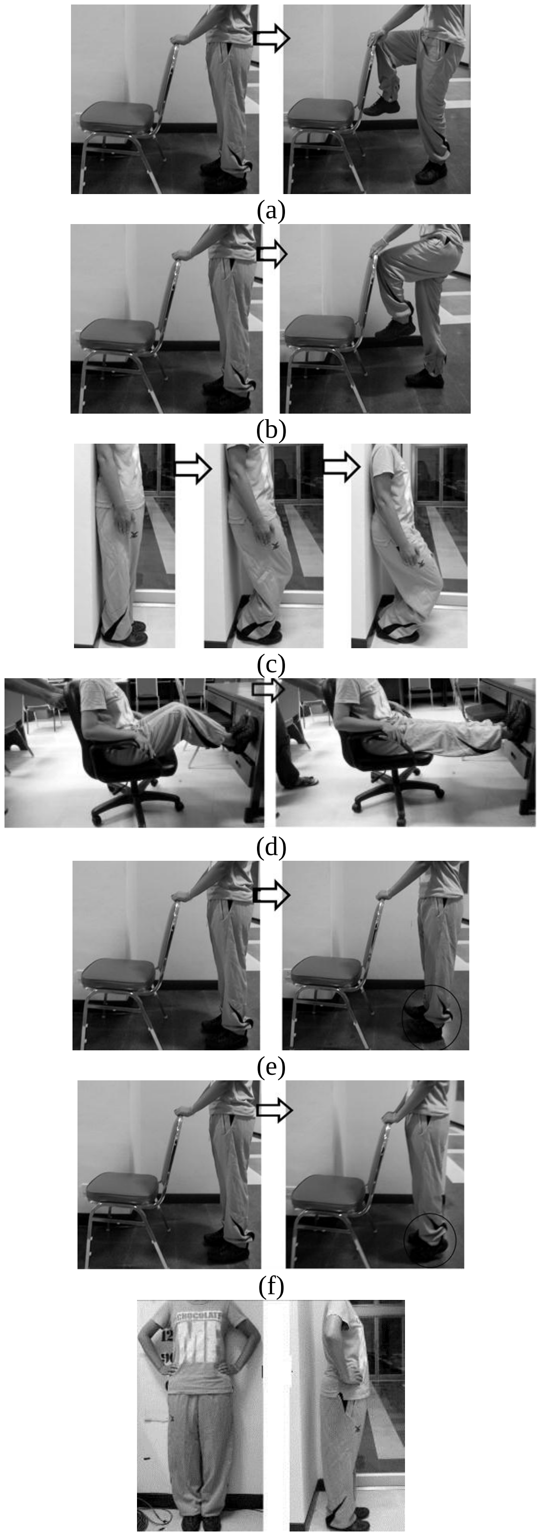


Figure 2. Preparation and execution stages of all exercises. (a) Standing hip flexion with the right leg (b) Standing hip flexion with the left leg (c) Half squats (d) Wall push-off with chair (e) Standing toe raises (f) Standing heel raises (g) Pulling stomach in.

3. Methodology

3.1 Feature Extraction

Eleven frequency-domain features proposed in the literature during the past decade were evaluated in this study. Usually, time-domain features were paid more an interest in the classification of EMG data, however, the frequency-domain features were also successful for the EMG classification, particularly in hand grasps recognition [11-12]. This may be useful for the classification of exercises in the elderly that the EMG data have a small difference in EMG signal amplitude in some exercises.

Frequency/spectral-domain features can be used to study not only muscle contraction but also muscle fatigue and motor unit (MU) recruitment analysis [13]. Power spectral density (PSD) becomes a major analysis in frequency-domain. Different types of the statistical properties were applied to the PSD which is defined as a Fourier transform of the autocorrelation function of the EMG data. It can be estimated using either Periodogram or parametric methods i.e. the AR model [14]. The definition of all frequency-domain features is described as follows:

1) Total power (TTP)

TTP is defined as an aggregate of the EMG power spectrum [15]. Another general name of TTP is zero spectral moment (SM0) [12]. The definition is as

$$TTP = \sum_{j=1}^{M} P_j = SM0\,, \tag{1}$$

where P_j is the EMG power spectrum at frequency bin j, and M is the length of frequency bin.

2) Mean power (MNP)

MNP is an average of the EMG power spectrum [15]. The calculation is defined as

$$MNP = \sum_{j=1}^{M} P_j \Big/ M\,. \tag{2}$$

3) Median frequency (MDF)

MDF is a frequency at which the EMG power spectrum is divided into two regions with equal amplitude. In other words, MDF is a half of TTP [7-8]. It can be expressed as

$$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^{M} P_j = \frac{1}{2}\sum_{j=1}^{M} P_j\,. \tag{3}$$

4) Frequency ratio (FR)

FR is aimed to distinguish between contraction and relaxation of the muscle using a ratio between the low frequency and the high frequency components of EMG signal [16]. The equation is defined as

$$FR = \sum_{j=LLC}^{ULC} P_j \Big/ \sum_{j=LHC}^{UHC} P_j\,, \tag{4}$$

where *ULC* and *LLC* are the upper- and lower-cutoff frequency of low frequency band and *UHC* and *LHC* are the upper- and lower-cutoff frequency of high frequency band, respectively. Such thresholds were defined based on the experiments as 10-60 Hz for low frequency component and 100-250 Hz for high frequency component. From mathematical definition, FR is an inverse case of high-to-low ratio (H/L ratio), which is widely used in the study of diaphragmatic fatigue [17].

5) Peak frequency (PKF)

PKF is a frequency at which the maximum EMG power occurs [15]. It is given by

$$PKF = \max(P_j), \quad j = 1,\dots,M\,. \tag{5}$$

6) Power spectrum ratio (PSR)

PSR is an extension of PKF and FR [18]. It is defined as a ratio between the energy P_0 which is nearby the maximum EMG power spectrum and the energy P which is the whole energy of the EMG power spectrum. Its calculation can be written by

$$PSR = \frac{P_0}{P} = \sum_{j=f_0-n}^{f_0+n} P_j \Big/ \sum_{j=-\infty}^{\infty} P_j\,, \tag{6}$$

where f_0 is a feature value of PKF and n is the integral limit. In this research, n is set at 20 and the energy of P ranges from 10 Hz to 500 Hz based on the previous recommendation [18].

7)-9) The first, the second, and the third spectral moments (SM1-SM3)

Spectral moment is an alternative statistical analysis way to extract feature from the EMG power spectrum. The first three spectral moments are useful in EMG feature classification [12]. The definitions of their equations can be expressed as

$$SM1 = \sum_{j=1}^{M} P_j f_j\,; \tag{7}$$

$$SM2 = \sum_{j=1}^{M} P_j f_j^2\,; \tag{8}$$

$$SM3 = \sum_{j=1}^{M} P_j f_j^3\,, \tag{9}$$

where f_j is a frequency value of the EMG power spectrum at frequency bin j.

10) Mean frequency (MNF)

MNF is an average frequency which is calculated as a sum of product of the EMG power spectrum and the frequency divided by the total sum of the spectrum intensity [7-8]. Other common names of MNF are central frequency (f_c) and spectral center of gravity [12]. It can be calculated as

$$MNF = \sum_{j=1}^{M} f_j P_j \Big/ \sum_{j=1}^{M} P_j\,. \tag{10}$$

11) Variance of central frequency (VCF)

VCF is one of the alternative statistical analysis ways to extract feature from the power spectrum [12]. It can be defined by using a number of spectral moments. It can be defined as

$$VCF = \frac{1}{SM0}\sum_{j=1}^{M} P_j \left(f_j - f_c\right)^2 = \frac{SM2}{SM0} - \left(\frac{SM1}{SM0}\right)^2. \tag{11}$$

3.2 Evaluation Function

Generally, the selection of EMG features can be implemented based on two criteria: (1) the measure of classification rate obtained from the classifier (i.e. neural networks or support vector machine), and (2) the measure of discrimination in feature space by

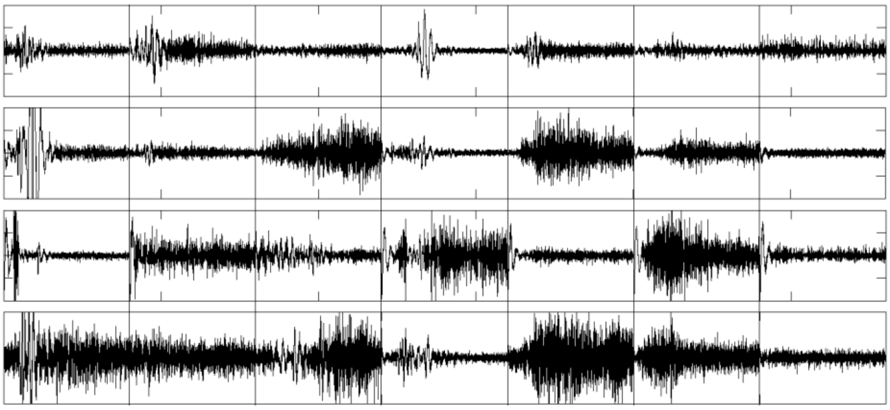


Figure 3. Four-channel surface EMG signals (top to bottom) from seven exercises (left to right: E1-E7) in the time domain. The x-axis ranges from 1 to 28000 samples and the y-axis ranges from -0.2 to 0.2 V. Sample data are from Subject 1.

using the statistical criterion method [6-7]. In this research, the second criterion was used because the first criterion has a major disadvantage that the evaluation of features depends on the classifier type but the second one is not problematic in this way [19].

During the past decade, there have been many statistical indices deployed for the evaluation of EMG features i.e. scattering index [7], Fishers linear discriminate index [16], Bhattacharyya distance [20], fuzzy-entropy-based feature evaluation index [21], and Davies-Bouldin index [22]. In one of our previous studies, a simple and effective statistical criterion method namely, RES index [23] was proven its better performance as EMG feature evaluation index.

A good quality in class separation means that the result of classification accuracy will be as high as possible. In other words, the maximum separation between classes is yielded and the small variation in subject experiment is reached. The definition of the RES index [23], the ratio between the Euclidean distance and standard deviation that used in this research, is as follows.

$$RES_i = \frac{\overline{ED_i}}{\bar{\sigma}_i}, \tag{12}$$

where

$$\overline{ED_i} = \frac{2}{\mathrm{K(K\text{-}1)}} \sum_{p=1}^{\mathrm{K\text{-}1}} \sum_{q=p+1}^{\mathrm{K}} \sqrt{(\bar{m}_{ip} - \bar{m}_{iq})^2}, \tag{13}$$

$$\bar{\sigma}_i = \frac{1}{\mathrm{K}} \sum_{k=1}^{\mathrm{K}} s_{ik}, \tag{14}$$

where m is the mean EMG feature, s is the standard deviation of feature, i is the channel number ($1 \le i \le \mathrm{I}$, I = 4), and p, q and k are the exercise number ($1 \le k \le \mathrm{K}$, K = 7). The optimal class separation performance is yielded when the RES index has a high value. It should be noted that the values of EMG features from each EMG channel of all exercises were normalized to be in the range of 0 and 1, which can be expressed as

$$m_{norm} = \frac{m - \min(m)}{\max(m) - \min(m)}. \tag{15}$$

It should be noted that the definition in this research is slightly different to the definition in our previous work [23]. In that study RES index was computed as an average of all EMG channels, whereas in this study RES index was computed for each EMG channel in order to find the usefulness of EMG channel. However, the RES index was proven that it exhibited the same trend with the efficient classifiers.

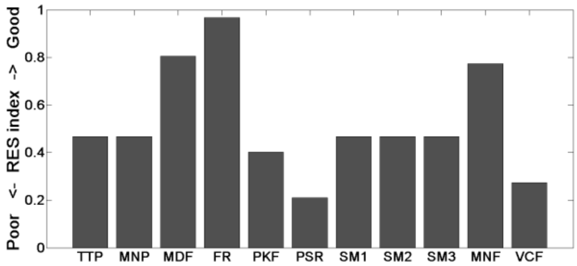
4. Results and Discussion

The EMG data in this research acquired from the long movement duration. It should be noted that when the muscle contraction is maintained for a long period the amplitude of EMG signal is dropped. This may be difficult to classify the correct movement [24].

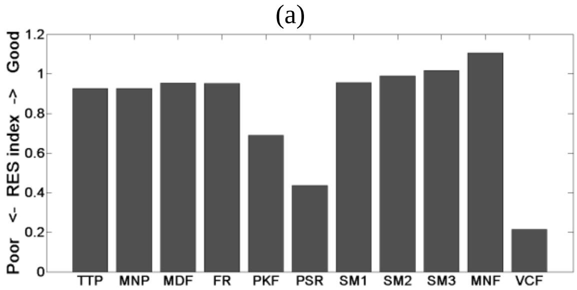
4.1 Characteristics of EMG Signal

Figure 3 shows a sample of the EMG data from four muscles during seven exercises in time domain. As can be clearly observed from all columns in Fig. 3 except the last one, the pattern of EMG data have a significant difference between each of the four muscles. Thus such exercises are possible to classify using the EMG signals. On the other hand, in the last column, the EMG signal amplitudes are small. The patterns of EMG data from each muscle are slightly different because the EMG data were measured from only the muscles on the right leg, but the exercise, pulling stomach in, did not directly respond on the leg muscles. However, to minimize the EMG channels, the EMG data were measured from only four EMG channels on the right leg in this study.

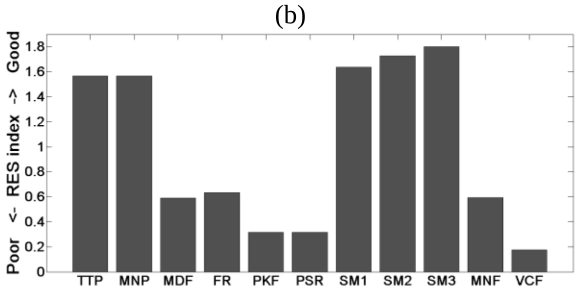
Another interest is on the first and the fourth columns in Fig. 3, the EMG signals were greatly contaminated by the movement artifacts although a high-pass filter with a corner frequency of 10 Hz was implemented. This may be due to much dynamic movement in both exercises, standing hip flexion with the right leg and wall push-off with chair, on the muscles located surface electrodes. The appropriate filter specifications to remove these artifacts should be determined in further study [25].



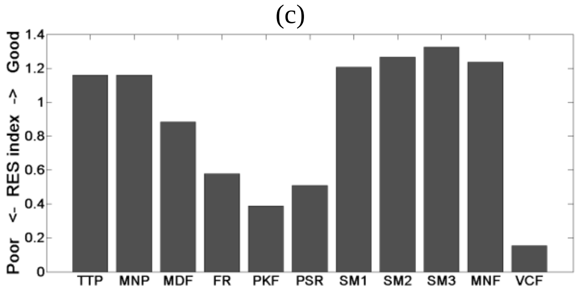
(a)



(b)



(c)



(d)

Figure 4. Averaging RES indices of eleven frequency-domain EMG features for the classification of seven exercises with four lower-limb muscles: (a) biceps femoris, (b) vastus medialis, (c) gastrocnemius, and (d) tibialis anterior, from ten elderly subjects.

4.2 Evaluation of EMG Features

Overall eleven frequency-domain features were computed from four EMG muscle channels and were calculated their RES indices for each of four channels as shown respectively in Fig. 4(a) through Fig. 4(d). From the results in Fig. 4(a), FR has the maximum RES index. From the distribution of FR in the first channel, seven exercises can be grouped as E6, E4-E7, E1-E2-E5, and E3 (from maximum to minimum). MNF and MDF are other two features that provided a high RES index. This muscle, the biceps femoris, is a large muscle located on the back of the thigh. From the results in Fig. 4(b), MNF has a slightly better performance than other features including FR, MDF and SM1-SM3. MNF can effectively separate four exercises: E2, E4, E5, and E6. This muscle, the vastus medialis, is a major muscle located on the front of the thigh. The first two muscles were respectively used as the representative muscles of the hamstrings muscle group and the quadriceps muscle group.

The gastrocnemius and the tibialis anterior, the third and the fourth muscles, are the muscles located in the lower part of the leg. In Fig. 4(c) and Fig. 4(d), SM3 was the best feature, followed closely by SM2, SM1, TTP and MNP. The SM3 computed from both muscles can effectively discriminate three exercises consisting E1, E6 and E7. Furthermore, all features provide only one value per channel, which is small enough to combine with the other features to make a more powerful feature vector, while it does not increase the computational burden for the classifier.

Among four muscles, the information obtained from the gastrocnemius muscle provided the highest RES indices. However, four EMG channels (the biceps femoris, the vastus medialis, the gastrocnemius and the tibialis anterior) are still important in the balance and strength exercise recognition system for preventing falls in the elderly because such muscles cover all important lower-limb muscle groups located in both the front and the posterior of the upper and the lower legs. It will be useful for providing information for the physiotherapists and the doctors. Therefore, such four muscles are recommended to be used in the classification of lower-limb exercises.

5. Conclusion and Future Research

Based on the experimental results, feature sets included FR, MNF, and SM3 are suggested to further improve the performance of the exercise recognition system in the elderly. This feature sets may combine with other useful time-domain EMG features to form an optimal feature vector for the pattern recognition and should be tested with the effective classifiers i.e. the linear discriminant classifier or the support vector machine in future research. Moreover, there are many exercises that can be employed to improve strength, balance, flexibility or endurance in elderly persons such as plantar flexion, hip extension, knee flexion, knee extension and side leg raise. All of these exercises can be applied for the recognition system based on EMG signal analysis in future research.

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