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Pornchai Phukpattaranont, Sirinee Thongpanja, **Khairul Anam**, Adel Al-Jumaily, Chusak Limsakul

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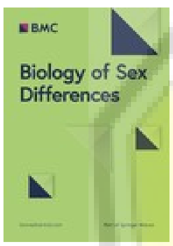

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ORIGINAL ARTICLE

Evaluation of feature extraction techniques and classifiers for finger movement recognition using surface electromyography signal

Pornchai Phukpattaranont[1] · Sirinee Thongpanja[1] · Khairul Anam[2] · Adel Al-Jumaily[2] · Chusak Limsakul[1]

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Abstract
Electromyography (EMG) in a bio-driven system is used as a control signal, for driving a hand prosthesis or other wearable assistive devices. Processing to get informative drive signals involves three main modules: preprocessing, dimensionality reduction, and classification. This paper proposes a system for classifying a six-channel EMG signal from 14 finger movements. A feature vector of 66 elements was determined from the six-channel EMG signal for each finger movement. Subsequently, various feature extraction techniques and classifiers were tested and evaluated. We compared the performance of six feature extraction techniques, namely principal component analysis (PCA), linear discriminant analysis (LDA), uncorrelated linear discriminant analysis (ULDA), orthogonal fuzzy neighborhood discriminant analysis (OFNDA), spectral regression linear discriminant analysis (SRLDA), and spectral regression extreme learning machine (SRELM). In addition, we also evaluated the performance of seven classifiers consisting of support vector machine (SVM), linear classifier (LC), naive Bayes (NB), *k*-nearest neighbors (KNN), radial basis function extreme learning machine (RBF-ELM), adaptive wavelet extreme learning machine (AW-ELM), and neural network (NN). The results showed that the combination of SRELM as the feature extraction technique and NN as the classifier yielded the best classification accuracy of 99%, which was significantly higher than those from the other combinations tested.

Keywords Electromyography (EMG) · Feature extraction · Dimensionality reduction · Finger movement classification · EMG pattern recognition

1 Introduction

The loss of finger functions is a major disability that limits everyday capabilities and interactions [1]. Hence, myoelectric control-based devices using residual muscles, such as the muscles of the shoulder and/or arm, are used for improving the quality of life for people with physical disabilities [2, 3]. Surface electromyography (EMG) observes electrical activities of the muscles by detection with surface electrodes [4]. The EMG signal contains useful information related to muscular activity, neuromuscular disease, and movements intended [5]. It can be used for controlling a prosthetic arm or hand, as well as with other devices such as a wheelchair, a mouse, and a keyboard. This requires that the pattern of an EMG signal is classified into a predefined class that is matched with the command for controlling the device [6, 7].

A finger movement classification system consists of three main modules, namely preprocessing, dimensionality reduction, and classification. In the preprocessing module, a *D*-dimensional vector of numerical features is generated from

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each segment of EMG data. Then, to increase the classification accuracy and decrease the computational complexity, the dimensionality reduction techniques are applied in the second module. As a result, a d-dimensional vector is obtained. Note that the dimension of the reduced feature vector is smaller than the dimension of the original feature vector ($d < D$). Finally, the reduced feature vector is used as an input of a classifier for finger movement classification in the last module.

When the number of movements to be classified was small, the dimensionality reduction was not applied because the dimension of the original feature vector was also not high. Classification of eight finger movements was proposed in [8] using mean absolute value (MAV), and the spectra from Gabor transform as feature values. The number of EMG channels was 2, resulting in the dimension of the feature vector 16. The classification accuracy was 85.10%. Uchida et al. [9] reported that the classification accuracy of five finger movements with the feature values based on fast Fourier transform (FFT) was 86% when the feature vector with dimension 20 (10 FFT coefficients × two-channel EMG) was used.

When the number of movements to be classified increases, the number of elements in the feature vector increases to improve the classification accuracy. The high-dimensional feature vector has been proposed by combining time domain, frequency domain, and/or statistical feature values. However, the increase in the dimension of feature vector can introduce redundancy and add to the computational complexity of classification. Therefore, various dimensionality reduction techniques were proposed to reduce the redundancy and computational complexity [10]. There are two main strategies of dimensionality reduction, i.e., feature extraction and feature selection. While feature extraction tries to determine the best combinations of the original feature vectors to form a new feature vector with smaller dimension, feature selection chooses the best subset of elements from the original feature vector. Previous studies applied various feature extraction methods in EMG classification including principal component analysis (PCA) [11, 12], linear discriminant analysis (LDA) [13, 14], uncorrelated linear discriminant analysis (ULDA) [15], orthogonal fuzzy neighborhood discriminant analysis (OFNDA) [16], and spectral regression linear discriminant analysis (SRLDA) [17].

Our previous study [18] proposed a new feature extraction, namely spectral regression extreme learning machine (SRELM), and evaluated its performance along with other feature extraction techniques, including SRLDA, ULDA, OFNDA, and PCA. Moreover, in [18], five classifiers including adaptive wavelet ELM (AW-ELM), radial basis function ELM (RBF-ELM), support vector machine (SVM), k-nearest neighbors (KNN), and linear classifier (LC) were evaluated for their performances in classifying two channels of EMG signals from 10 hand and finger movements. We reported that SRELM gave the best performance. Moreover, we found that the classification accuracy depended on the classifier. In other words, while SREML provided the best performance when the KNN classifier was used, ULDA gave the best performance with the SVM classifier. These results indicated that the pairing of a feature extraction technique with a type of classifier affects the classification accuracy. Therefore, another effective classifier, neural network (NN), which was not used in [18], was investigated in this current study.

2 Theory

2.1 Preprocessing methods

In the preprocessing methods, we transform segments of EMG data into an original feature vector. Feature values, which are elements of the original feature vector, are usually determined from the EMG data in the time domain and/or the frequency domain [6]. Recent studies have proposed further feature values based on statistical methods. In this paper, we used Hudgins's feature set [2, 3, 19]: MAV, waveform length (WL), zero crossing (ZC), and slope sign change (SSC), which are popular time domain features used in previous studies. In addition, we also used the fourth-order autoregressive (AR) coefficient for representing information on the prediction model [12, 20], mean frequency (MNF) for representing information on the power spectral density [21], kurtosis (KURT) for representing information on peakedness of distribution [22], and skewness (SKW) for representing information on the symmetry of distribution in the EMG signal [13]. As a result, the original feature vector of 11 elements from each segment of EMG data per EMG channel consists of (1) MAV, (2) WL, (3) ZC, (4) SSC, (5)–(8) four AR coefficients, (9) MNF, (10) KURT, and (11) SKW. The detailed mathematical definition of each feature is as follows:

(1) MAV represents the signal energy, which is frequently used for detecting the onset of an EMG signal. MAV feature is the average of the absolute value of the EMG signal. It can be defined as [2]

$$\mathrm{MAV} = \frac{1}{N}\sum_{i=1}^{N}|x_i| \quad (1)$$

where x_i is the amplitude of the EMG signal at sample i and N is the length of the EMG signal.

(2) WL is the cumulative length of the EMG waveform over the segment and is indicative of the complexity of the EMG signal. It can be expressed as [2]

$$\mathrm{WL} = \sum_{i=1}^{N-1} |x_{i+1} - x_i|. \quad (2)$$

(3) ZC is the number of times that the EMG signal amplitude crosses zero. In other words, it is the number of times that the signal amplitude changes its sign. A threshold must be set to reduce the noise (i.e., threshold was set to 10 μV). It can be defined as [2]

$$\mathrm{ZC} = \sum_{i=1}^{N-1} [f(x_i \times x_{i+1}) \cap |x_i - x_{i+1}| \geq 10] \quad (3)$$

$$f(x) = \begin{cases} 1, & \text{if } x < 0 \\ 0, & \text{otherwise} \end{cases}. \quad (4)$$

(4) SSC is the number of times that the slope of the EMG signal changes sign. It is defined as [2]

$$\mathrm{SSC} = \sum_{i=2}^{N} [s\{(x_i - x_{i-1})(x_i - x_{i+1})\} \cap \{|x_i - x_{i-1}| \geq 10 \cup |x_i - x_{i+1}| \geq 10\}] \quad (5)$$

$$s(x) = \begin{cases} 1, & \text{if } x > 0 \\ 0, & \text{otherwise} \end{cases}. \quad (6)$$

(5) AR model describes each sample of the EMG signal as a linear combination of the previous sample plus a white noise error term, which can be defined as [20]

$$x_i = \sum_{p=1}^{P} a_p x_{i-p} + w_i \quad (7)$$

where a_p is the coefficient in the AR model, P is the order of the AR model, and w_i is the white noise or error sequence. In this paper, P is set to 4. As a result, the number of feature values from the AR model is 4.

(6) MNF is the average frequency. It is defined as the sum of the product of power spectrum and frequency divided by the total spectrum intensity, which can be expressed as [21]

$$\mathrm{MNF} = \sum_{j=1}^{M} f_j P_j \Big/ \sum_{j=1}^{M} P_j \quad (8)$$

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

(7) KURT is a classical higher-order statistical characteristic, indicating non-Gaussianity, and is used to quantify the peakedness of a distribution. It is the fourth-order cumulant of the data, which can be defined as [22]

$$\mathrm{KURT} = \left[\frac{1}{N} \sum_{i=1}^{N} y_i^4 \Big/ \left(\frac{1}{N} \sum_{i=1}^{N} y_i^2 \right)^2 \right] - 3 \quad (9)$$

where y_i represents the ith normalized EMG amplitude, which has zero mean and unit variance. N denotes the total number of the normalized EMG samples. Kurtosis can be either positive or negative.

(8) SKW is a measure used for characterizing the degree of asymmetry of the distribution of a random variable y. It is the third-order cumulant of the data, which can be defined as [13]

$$\mathrm{SKW} = \frac{1}{N} \sum_{i=1}^{N} (y_i - \bar{y})^3 \Big/ \left(\sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \bar{y})^2} \right)^3. \quad (10)$$

2.2 Feature extraction

Six feature extraction techniques are evaluated in this paper including PCA, LDA, ULDA, OFNDA, SRLDA, and SRELM. It should be noted that the dimension of the reduced feature vector from each feature extraction technique except PCA was 13, matching the total number of movements minus 1. On the other hand, the dimension of the reduced feature vector from PCA was 14. The brief details on each technique are as follows:

- PCA tries to find a set of orthogonal basis vectors that captures maximum information from the original dimensions. PCA decomposes the covariance structure of the original dimensions by calculating the eigenvalues and eigenvectors of the data. The components, i.e., eigenvalues and eigenvectors, are ranked according to their variance to the principal axes ranging from the highest contribution to the lowest.

- LDA tries to find an optimal transformation vector by maximizing the ratio of the between-class distance to the within-class distance, so that the maximum class discrimination is achieved.
- ULDA is an extension of classical LDA, such that the features in the transformed space are uncorrelated, so the redundancy in the transformed space could be reduced. The objective of ULDA is to find the optimal discriminant vectors.
- OFNDA minimizes the distances within the classes and maximizes the distances between the centers of different classes, while taking into account the contribution of the samples to the different classes and to efficiently overcome the singularity problems of classical LDA by employing the QR decomposition.
- SRLDA combines the spectral analysis of the graph matrix and regression techniques and is essentially developed from LC [23]. A set of linear regression problems is solved to obtain the transformation vectors.
- SRELM was proposed in our previous study [18]. It is integrated from ELM and spectral regression (SR), which utilizes the obtained eigenvector to project the hidden layer output to the output layer. The hidden layer weights are determined randomly. The output weight is computed using SR. There are two parameters in optimizing SRELM performance: the number of hidden nodes and alpha. In order to evaluate the optimal parameters in this paper, the number of hidden nodes was varied from 100 to 1500 nodes with an increment of 100 nodes and alpha was varied from 1 to 20 with an increment of 1.

2.3 Feature evaluation

In this paper, we applied the statistical criteria, namely the ratio of a Euclidean distance to a standard deviation (RES) index, to evaluate class separation performance of the reduced feature vector obtained from each feature extraction technique. The advantage of the RES index is that its result is independent of any classifier. The RES index can be defined as [24]

$$\text{RES index} = \frac{\overline{ED}}{\overline{\sigma}}. \tag{11}$$

$\overline{ED}$ is the distance between coordinates of a pair of clusters p and q in n-dimensional Euclidean space, which can be defined as

$$\overline{ED} = \frac{2}{K(K-1)} \sum_{p=1}^{K-1} \sum_{q=p+1}^{K} \sqrt{\left(\overline{m}_1^p - \overline{m}_1^q\right)^2 + \left(\overline{m}_2^p - \overline{m}_2^q\right)^2} \tag{12}$$

where m is the average value of feature, p and q are indexes representing the movements, and K is the total number of movements ($1 \le k \le K$, $K = 14$). $\overline{\sigma}$ is dispersion of clusters p and q, which can be expressed as

$$\overline{\sigma}_i = \frac{1}{IK} \sum_{i=1}^{I} \sum_{k=1}^{K} s_{ik} \tag{13}$$

where s is the standard deviation of a feature and I is the length of feature vector ($1 \le i \le I$, $I = 13$ or 14). The RES index increases when the class separation performance of EMG features increases.

2.4 Classification

Seven classifiers are tested and compared in this paper, i.e., SVM, LC, naive Bayes (NB), KNN, RBF-ELM, AW-ELM, and NN. Brief details of each classifier and its corresponding parameters used are as follows:

- SVM uses a discriminant hyperplane to separate the classes [25]. SVM aims to find the optimal hyperplane that maximizes the margins between the points of different classes. The margins are the distances between the hyperplane and the nearest training points. In this study, SVM type was C-support vector classification. Kernel type was radial basis function. Gamma in kernel function was set to 1/number of features, and cost was set to 1.
- LC was implemented using a simple max gate function as a classification rule [26]. It is assumed that the feature vectors have multivariate normal distribution with mean vector and common covariance matrix.
- NB classifier aims to reach the best hypothesis through a given training data set [27]. Bayes theorem provides a way to calculate the probability of a hypothesis based on its prior probability of both the data found and the total data. NB often performs well although independence assumptions between data are violated.
- KNN is a process to assign a new feature vector to a class in all available cases using a similarity measure such as distance functions [26]. After the distances between the feature vector and all the training samples are determined, the new case is assigned to the class with the largest probability. In other words, it is

classified by a majority vote of its k neighbors. In this paper, k was set to 14.

- RBF-ELM is a variant of ELM classifier, which is single-layer feed-forward network with radial basis function [28]. It employs a randomized method to initialize the centers and widths of RBF kernels, and the output weights of RBF network are calculated analytically. In order to select the optimal parameters, a grid search method was used. From the step sizes at 0.1, 0.5, 1, 5, 10, 15, and 20, we can obtain 49 combinations of cost and kernel parameters under test. The optimal parameters were selected from the combination that gave the maximum accuracy.
- AW-ELM proposed by Anam and Al-Jumaily [29] is the combination of ELM with wavelet neural network. It utilizes a wavelet function as the activation function in the hidden node. The function is adjusted according to changes in the input. In order to select the optimal parameter, the number of hidden nodes was varied from 25 to 500 nodes with an increment of 25 nodes
- NN is a multilayer perceptron, which is composed of several layers: one input layer, one layer or several hidden layers, and one output layer [30]. Each neuron in each layer is connected with the output of the previous one. In this paper, we designed three layered feed-forward back-propagation neural networks consisting of input layer, tan-sigmoid hidden layer, and linear output layer. The number of neurons in the input layer was either 13 for PCA or 14 for other feature extraction techniques. The number of neurons in the hidden layer was 10, 20, or 30, with the best alternative selected for obtaining maximal accuracy. The number of neurons in the output layer was 14, i.e., one neuron per movement type. In addition, NN was trained using scaled gradient descent algorithm.

3 Materials and methods

3.1 EMG data acquisition and experimental setup

A commercial EMG measurement system (Mobi6-6b, TMS International B.V.) with built-in band-pass filter (20–500 Hz) and amplifier with a gain factor of 19.5 was used for recoding EMG signals at a sampling rate of 1024 Hz. The EMG signals from six forearm muscles were recorded using 12 pairs of bipolar disposable Ag/AgCl electrodes (H124SG, Kendel ARBO) with an inter-electrode distance of 20 mm. In addition, an Ag/AgCl electrode was placed on the wrist to provide a common ground reference. Figure 1 (left) shows the electrode placements on the six forearm muscles used for EMG data acquisition. While the first group of muscles, namely extensor carpi ulnaris (CH6), extensor carpi radialis longus (CH5), and extensor digitorum (CH4), is located on the posterior compartment of the forearm to perform extension at the fingers, the second group of muscles, namely flexor carpi ulnaris (CH3), palmaris longus (CH2), and flexor carpi radialis (CH1), is located on the anterior compartment of the forearm to produce flexion at the fingers.

Ten able-bodied subjects (seven males and three females) with ages ranging from 20 to 23 years participated in the experiments. Each subject performed 14 different finger movements in a random sequence for a trial consisting of thumb flexion (M1), index flexion (M2), middle flexion (M3), ring flexion (M4), little flexion (M5), hand close (M6), index-middle-ring-little flexion (M7), middle-ring-little flexion (M8), ring-little flexion (M9), middle-ring flexion (M10), index-middle-ring flexion (M11), thumb-little flexion (M12), thumb-ring-little flexion (M13), and thumb-middle-ring-little flexion (M14), as shown in Fig. 1 (right). Within the trial, the beginning of each movement activity is triggered by an auditory

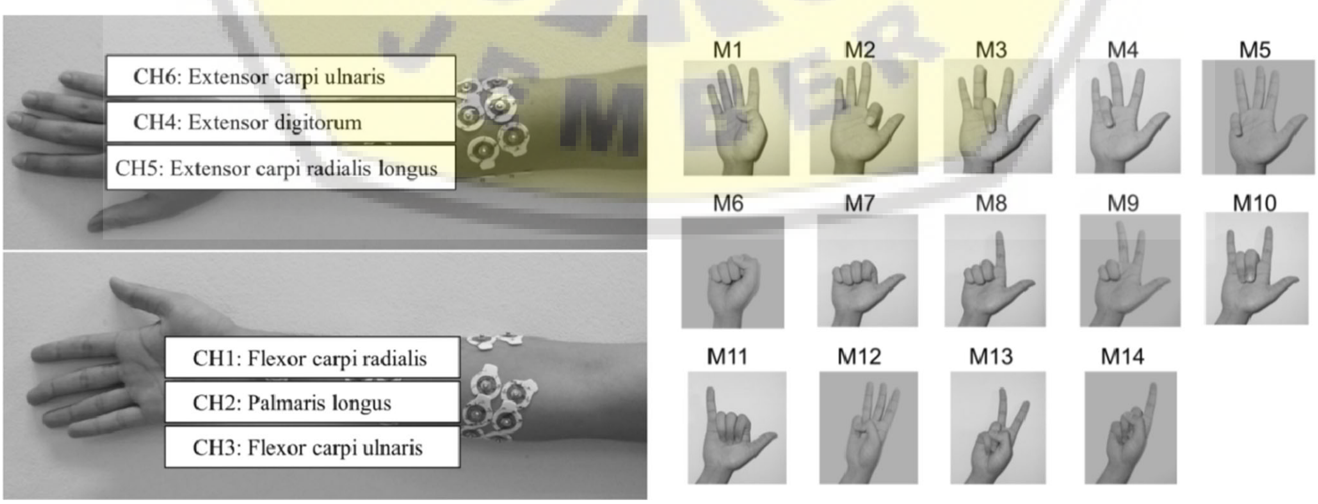

Fig. 1 Left: the electrode locations on forearm muscles. Right: the 14 finger movements

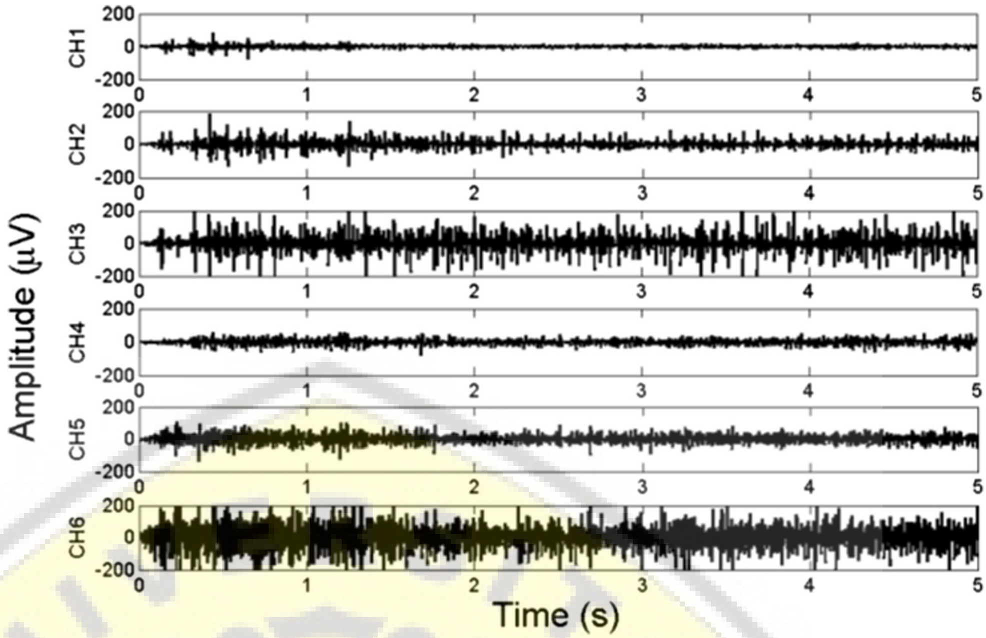

Fig. 2 Example of the six-channel EMG signal from thumb flexion (M1)

clue. Following the clue, the subject performed the movement and held the contraction for 5 s in duration until a rest cue was given. A 1-min period rest state was taken between each movement in the trial. The trial was repeated five times with a 10-min period rest state. As a result, each movement was performed five times.

Figure 2 shows an example of EMG signals obtained from six muscles during thumb flexion (M1). The EMG signals with 5 s in duration (5120 samples) from CH1 to CH6 were shown in the top to bottom rows, respectively. The differences in amplitudes of EMG signals from different muscles are clearly seen. While the amplitudes of EMG signals from CH6 are largest, the amplitudes of EMG signals from CH1 are smallest.

3.2 Methods

Figure 3 shows the method for evaluating feature extraction techniques and classifiers used in recognizing the EMG signals from finger movements in this paper. After six channels of EMG signals from 14 hand and finger movements were acquired, they were processed using the analytical method consisting of five steps, i.e., (1) segmentation, (2) feature generation, (3) feature extraction, (4) performance evaluation with RES index, and (5) performance evaluation with classifiers. The details on each step are as follows:

Step 1: *segmentation*: In this step, the collected EMG data with a length of 5120 samples was segmented by the disjoint windowing technique with a window length of 256 samples (250 ms), resulting in 20 segmented EMG data for each EMG channel of each movement.

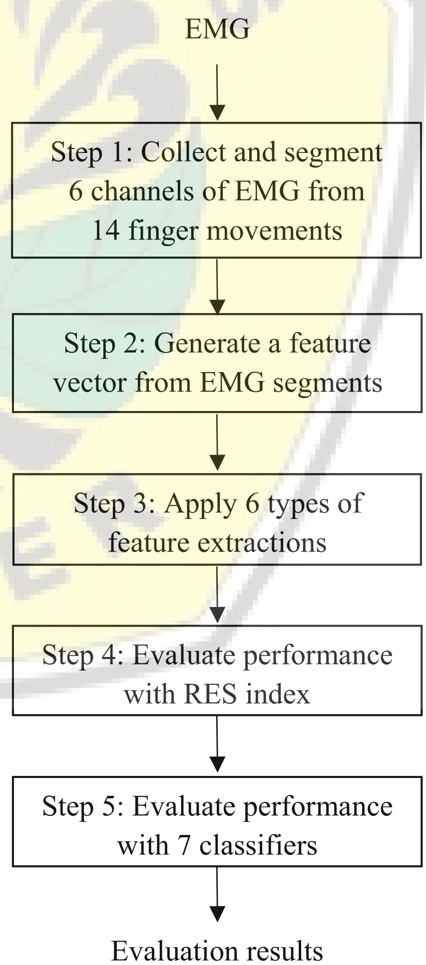

Fig. 3 EMG acquisition and analytical method

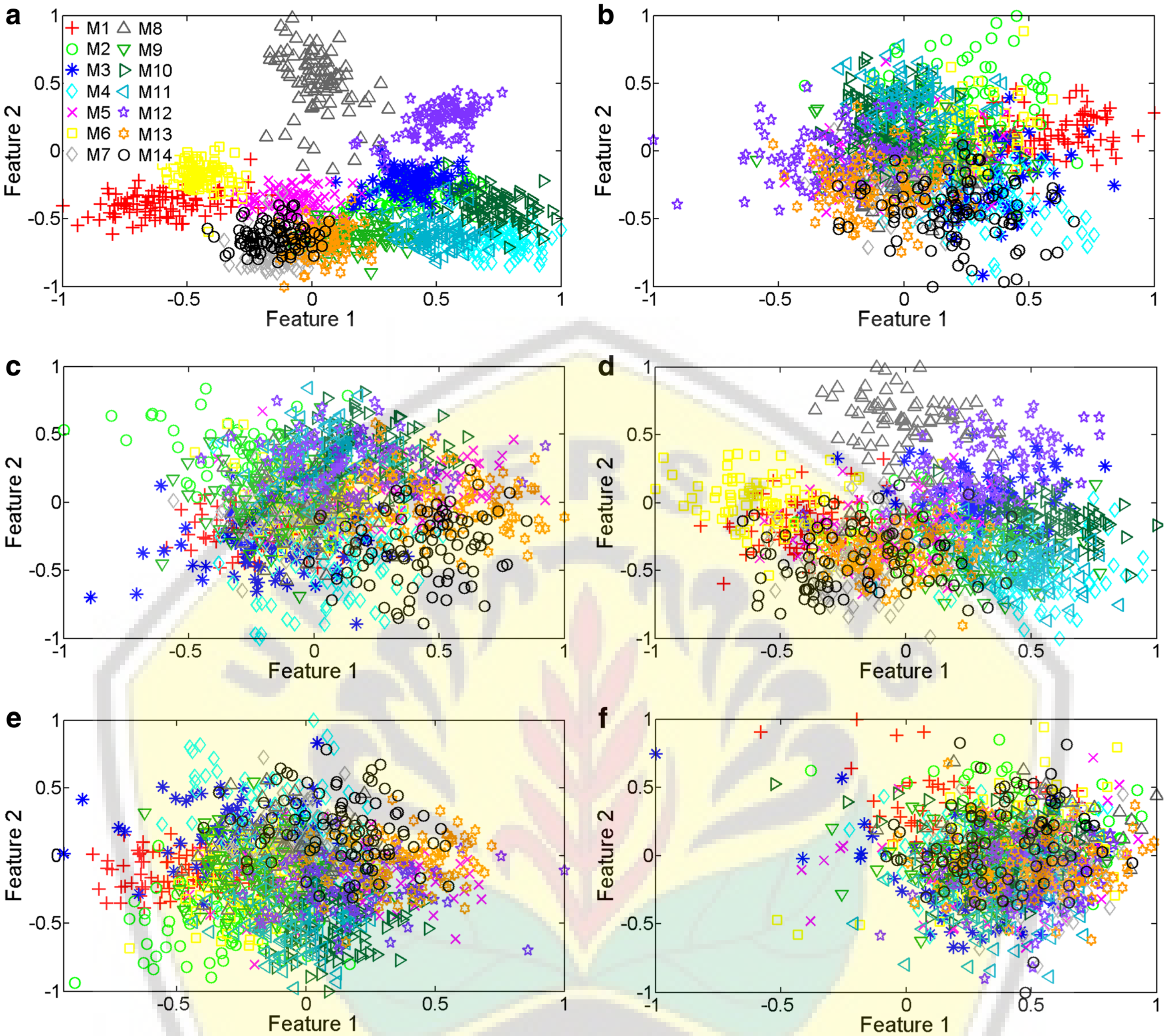

Fig. 4 Scatter plots of the first two elements of the reduced feature vectors when using **a** SRELM, **b** LDA, **c** ULDA, **d** SRLDA, **e** OFNDA, and **f** PCA

Step 2: *feature generation*: In this step, the 11 feature values described in Section 2.1 including MAV, WL, ZC, SSC, MNF, KURT, SKW, and four coefficients from the AR model were calculated for each EMG segment. The feature values from six EMG channels were formed as an original feature vector. As a result, the dimension of

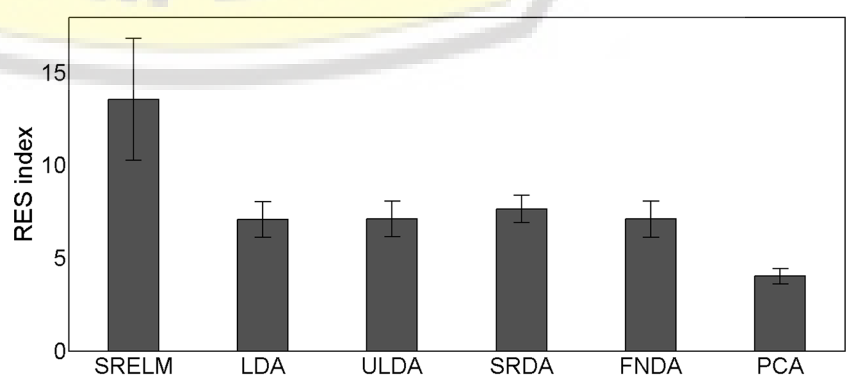

Fig. 5 RES index determined using all reduced feature vectors from six feature extraction techniques

Table 1 Mean and standard deviation of classification accuracies for 14 movements obtained with various pairs of feature extraction (FE) and classifier

FE	SVM	LC	NB	KNN	RBF-ELM	AW-ELM	NN
SRELM	92.92 ± 4.35	*93.64 ± 4.00*	90.04 ± 4.57	*93.04 ± 4.09*	93.24 ± 3.88	*92.12 ± 4.34*	*99.09 ± 0.83*
LDA	93.30 ± 3.91	92.42 ± 3.69	*90.39 ± 4.41*	92.29 ± 4.37	93.33 ± 4.11	91.08 ± 4.55	95.51 ± 2.74
ULDA	93.01 ± 3.97	92.34 ± 3.77	90.01 ± 4.30	92.15 ± 4.46	93.12 ± 4.06	90.76 ± 4.98	95.58 ± 2.82
SRLDA	*93.70 ± 3.55*	92.13 ± 3.89	89.81 ± 4.39	93.01 ± 3.65	*93.89 ± 3.54*	92.07 ± 4.17	95.12 ± 3.08
OFNDA	93.09 ± 3.98	92.31 ± 3.84	90.30 ± 4.21	92.06 ± 4.30	93.31 ± 3.90	90.84 ± 4.68	95.59 ± 2.76
PCA	83.96 ± 6.93	83.23 ± 6.46	72.61 ± 7.26	79.51 ± 7.76	81.91 ± 8.27	75.46 ± 7.67	85.59 ± 6.58

The italics indicate the highest classification accuracy for each classifier

the original feature vector was 66 for each movement (11 feature values per EMG channel × 6 EMG channels).

Step 3: *feature extraction*: In this step, the six feature extraction techniques described in Section 2.2 including PCA, LDA, ULDA, OFNDA, SRLDA, and SRELM were applied to the original feature vector in step 2. As a result, the dimension of the original feature vector, which was 66 from step 2, was reduced to 14 for PCA and 13 for the others in this step.

Step 4: *performance evaluation with RES index*: In this step, the performance on class separation ability of all reduced feature vectors from each feature extraction technique resulting from step 3 was evaluated with the RES index described in Section 2.3. As a result, six RES indexes from six feature extraction techniques were obtained and compared.

Step 5: *performance evaluation with classifiers*: In this step, all reduced feature vectors from each feature extraction technique in step 3 were used as the inputs of seven classifiers, which were briefly described in Section 2.4. Therefore, there are 42 combinations of the reduced feature vector with the classifier under test. The performance based on classification accuracy from each combination was evaluated and compared.

Table 2 Mean and standard deviation of classification accuracies for 14 movements obtained from the NN classifier with three alternative sizes of the hidden layer

FE	10 neurons	20 neurons	30 neurons
SRELM	*99.09 ± 0.83*	*99.57 ± 0.42*	*99.54 ± 0.46*
LDA	95.51 ± 2.74	96.61 ± 2.45	96.84 ± 2.25
ULDA	95.58 ± 2.82	96.68 ± 2.34	96.83 ± 2.21
SRLDA	95.12 ± 3.08	96.37 ± 2.33	96.49 ± 2.40
OFNDA	95.59 ± 2.76	96.47 ± 2.56	96.86 ± 2.25
PCA	85.59 ± 6.58	87.87 ± 6.21	88.47 ± 6.01

The italics indicate the highest classification accuracy for each size of the hidden layer

Note that the reduced feature vectors were classified with a 10-fold cross-validation. In other words, the reduced feature vectors were randomly partitioned into 10 subsets. The classifier training was performed using nine subsets, and the remaining subset was used for classifier testing. This process was repeated 10 times such that each of the 10 subsets was used as the testing data. Finally, the performance of each pairing of the reduced feature vector with the classifier was evaluated and compared using the mean and standard deviation of classification accuracies. The classification accuracy can be expressed as

$$\text{classification accuracy} = \frac{\text{Number of correct classifications}}{\text{Total number of finger movements under test}} \times 100\% \tag{14}$$

4 Results

4.1 Characteristics of the reduced feature vectors

Figure 4 shows, as an example, the scatter plot between the first two elements of the reduced feature vectors from each feature extraction technique. The result shows that the first two elements of the reduced feature vectors by SRELM provided better separation than those from other feature extraction techniques, while the first two elements of the reduced feature vectors from LDA, ULDA, OFNDA, and SRLDA are quite overlapped. In addition, PCA provided results that had the worst performance in separating finger movements.

Figure 5 shows the RES index calculated from all reduced feature vectors by each feature extraction technique. The RES index of reduced feature vectors by SRELM is higher than that of other feature extraction techniques. In other words, SRELM provides the reduced feature vectors that have the best performance in separating finger movements.

Table 3 Mean and standard deviation (SD) of classification accuracies for 14 movements obtained from the SRELM feature extraction and the NN classifier as the number of available EMG channels is reduced step by step

Channel combination	Mean ± SD	Note
CH1-CH2-CH3-CH4-CH5-CH6	*99.57 ± 0.52*	6 channels
CH2-CH3-CH4-CH5-CH6	*99.24 ± 0.51*	Remove CH1
CH1-CH2-CH3-CH4-CH5	98.71 ± 1.12	
CH1-CH2-CH3-CH4-CH6	98.90 ± 0.90	
CH1-CH2-CH3-CH5-CH6	99.05 ± 1.00	
CH1-CH2-CH4-CH5-CH6	98.90 ± 1.60	
CH1-CH3-CH4-CH5-CH6	98.86 ± 1.31	
CH2-CH3-CH5-CH6	*97.95 ± 1.52*	Remove CH1 and CH4
CH2-CH3-CH4-CH5	97.33 ± 1.70	
CH2-CH3-CH4-CH6	97.90 ± 1.06	
CH2-CH4-CH5-CH6	96.95 ± 2.24	
CH3-CH4-CH5-CH6	97.90 ± 1.29	
CH3-CH5-CH6	*93.71 ± 3.94*	Remove CH1, CH4, and CH2
CH2-CH3-CH5	93.38 ± 2.68	
CH2-CH3-CH6	92.81 ± 3.79	
CH2-CH5-CH6	92.90 ± 3.32	
CH3-CH6	*85.38 ± 4.55*	Remove CH1, CH4, CH2, and CH5
CH3-CH5	84.76 ± 4.92	
CH5-CH6	80.19 ± 5.67	
CH3	*58.95 ± 8.49*	Remove CH1, CH4, CH2, CH5, and CH6
CH6	56.24 ± 9.45	

The italics indicate the highest classification accuracy for each subset of channels

The RES indexes of reduced feature vectors from SRLDA, OFNDA, LDA, and ULDA are quite similar, while the reduced feature vectors from PCA give the lowest RES index. We can clearly see that the RES index of reduced feature vectors in Fig. 5 is consistent with the scatter plot of reduced feature vectors in Fig. 4.

4.2 Classification accuracy

Table 1 presents the classification accuracy using various feature extraction techniques paired with different classifiers. While the best classification accuracies from LC, KNN, AW-ELM, and NN are obtained with the reduced feature vectors from SRELM, the best classification accuracies from SVM and RBF-ELM are obtained with the reduced feature vectors from SRLDA. However, for each feature extraction technique, we can observe that NN with 10 nodes in the hidden layer provides the highest classification accuracy. Moreover, the combination of SRELM and NN gives the maximum classification accuracy at 99.09%.

Table 2 presents the classification accuracies for 14 movements obtained from the NN classifier with different numbers of nodes in the hidden layer, i.e., 10, 20, or 30 neurons. When we increase the number of neurons in the hidden layer from 10 to 20 and to 30, the classification accuracy changes slightly for each feature extraction technique. Results show that 20 neurons in the hidden layer give the best accuracy at 99.57% among all combinations of feature extraction techniques and classifiers, when the reduced feature vectors from SRELM are used.

Table 3 presents classification accuracies with channel reduction. The subset of channels was optimized by considering the classification accuracies obtained from all combinations of each channel set. Firstly, all possible combinations of five channels out of the six total were trialed for classification. Only the set of five channels providing the highest classification accuracy was selected. Secondly, all possible combinations of four channels out of the five total from the first step were trialed for classification. For instance, the accuracies from all combinations of five channels are shown in the second row to the seventh row in Table 3. We can see that the combination of CH2, CH3, CH4, CH5, and CH6 provides the highest classification accuracy, so this channel set was selected as the best combination of five channels. Then, all possible combinations of four channels out of the five selected channels from the first step were trialed. As a result, the combination of CH2, CH3, CH5, and CH6 provides the best classification accuracy and it was chosen as the optimal set of four channels. The procedure was repeated for three channels, two

Table 4 Mean and standard deviation of classification accuracies for movement reduction obtained from the SRELM feature extraction and the NN classifier using the EMG signals from CH3 and CH6

No. of movements	Mean ± SD	Movement removal
14	85.38 ± 4.55	–
13	99.08 ± 0.68	M7
12	99.28 ± 0.59	M7 and M13
11	99.94 ± 0.19	M7, M13, and M6
10	100.00 ± 0.00	M7, M13, M6, and M14

channels, and one channel, respectively. The results show that the classification accuracy decreases from 99.57 to 58.95% when the number of channels decreases from 6 to 1. Moreover, to obtain a high classification accuracy, EMG signals from the muscles located on the anterior and posterior compartments of the forearm are needed. For example, the maximum classification accuracy from two EMG channels at 85.38% can be obtained from the combination of flexor carpi radialis (CH3) and extensor carpi ulnaris (CH6), which are located on the anterior and posterior compartments of the forearm, respectively.

Table 4 presents classification accuracies from movement reduction using two channels of EMG signals, namely CH3 and CH6. The selection of these two EMG channels was guided by Table 3. The subset of finger movements was optimized by considering classification accuracy of each movement. All EMG signals from 14 finger movements were firstly classified, and then the classification accuracy was individually investigated for each movement from the confusion matrix [31]. The movement providing the lowest classification accuracy was removed from the movement set. The procedure was repeated until the number of movements decreased to two movements. The results show that the classification accuracy increases from 85.38 to 100% when the number of movements decreases from 14 to 10 movements. In other words, the reduction in the number of movements decreases the complexity of classification, resulting in better classification accuracy.

5 Discussion

Results of the scatter plot shown in Fig. 4 and the RES index shown in Fig. 5 show that the reduced feature vectors from SRELM provide the best performance in separating finger movements. Anam and Al-Jumaily [18] reported that SRELM is an ELM for supervised feature extraction with consideration of the class label. The aim of the training is to produce output that is very close to the output target. In other words, the training tries to minimize the error between the actual output and target. As a result, the reduced feature vectors from SRELM show better performance in separating 14 finger movements than those from other feature extractions. In addition, LDA considers also class label in the extraction step (i.e., supervised feature extraction) and ULDA is developed to solve the limitation of LDA by producing a set of uncorrelated discriminant features employing the singular value decomposition [14]. In contrast, as Chu et al. [32] reported the PCA does not consider the class labels in the extraction process (i.e., it performs unsupervised feature extraction). Therefore, the output is another representation of the reduced feature vectors and its performance is lower than with other feature extraction techniques.

Table 5 Performance comparisons with other techniques from previous publications

Ref.	#M	#Ch	Features in each EMG channel	#DF	FE	Classifiers	Acc. (%)
[8]	8	2	MAV, SGT	16	–	NN	85.10
[9]	5	2	FFT	20	–	NN	86.00
[13]	10	2	7th-order AR coefficient, SSC, ZC, WL, SKW, HTD	28	LDA	SVM	≈ 92.00
[18]	10	2 + 1	6th-order AR coefficient, SSC, ZC, WL, SKW, MAV, HTD	42	SRELM	AW-ELM	86.73
[A]	10	2	4th-order AR coefficient, SSC, ZC, WL, SKW, MAV, MNF, KURT	22	SRELM	NN	100.00
[11]	12	32	WL	32	PCA	NN	94.30
[12]	15	6	6th-order AR coefficient, RMS, WL, ZC, IEMG, SSC	66	OFNDA	LDA	98.25
[19]	11	7	IEMG, WL, VAR, ZC, SSC, WAMP	42	–	NN	93.90
[20]	15	4	4th-order AR coefficient, WL, RMS	24	–	SVM	97.60
[B]	14	6	4th-order AR coefficient, MAV, WL, ZC, SSC, MNF, KURT, SKW	66	SRELM	NN	99.57

#M the number of movements, *#Ch* the number of EMG channels used, *#DF* the dimension of the feature vector before applying feature extraction, *FE* feature extraction, *Acc* accuracy, *SGT* the spectra from Gabor transform, *FFT* fast Fourier transform, *HTD* Hjorth time domain, *IEMG* integrated EMG, *VAR* variance of EMG, *RMS* root mean square, *[A]* the proposed method when using two-EMG channels for classifying 10 finger movements, *[B]* the proposed method when using six-EMG channels for classifying 14 finger movements

Table 5 presents the performance comparisons of the proposed method with those from previous publications. The classification performance can be divided into two groups. In the first group, the number of EMG channels used is 2 [8, 9, 13, 18, A]. The dimensions of feature vectors from [8, 9] are 16 and 20, respectively. The classifier used is NN. The classification accuracy is 85–86%. It is important to note that there is no application of feature extraction for classifying movements from both individual and combined fingers in [8, 9]. This may be the cause of poor classification accuracy. However, feature extraction is applied for reducing a dimension of the feature vector in [13, 18, A]. The classification accuracy of the proposed technique for classifying 10 movements from two-channel EMG signals achieves 100% [A] compared to 86.72 and 92.00% in [13, 18], respectively. Note that, in [18], the feature vectors were generated from two EMG channels plus one channel formed from summation of the two channels. Moreover, Bayesian fusion was applied as a post processing in [13]. The comparison between [A] and [18] indicates that the pairing of a feature extraction technique with a type of classifier affects the classification accuracy. Another way to increase classification accuracy when the number of movement increases is to increase the number of EMG channels as shown in [11, 12, 19, 20, B]. Results show that the proposed technique achieves good accuracy in classifying 14 movements from six-channel EMG signals at 99.57% [B]. The results of this study clearly illustrate that using high-dimensional feature vectors with feature extraction could improve the classification performance.

6 Conclusions

This paper proposed a system for classifying 14 finger movements, involving individual and combined finger flexion observed by six channels of EMG signals. Six feature extraction techniques were evaluated including principal component analysis (PCA), linear discriminant analysis (LDA), uncorrelated linear discriminant analysis (ULDA), orthogonal fuzzy neighborhood discriminant analysis (OFNDA), spectral regression linear discriminant analysis (SRLDA), and spectral regression extreme learning machine (SRELM). The results show that the reduced feature vectors from SRELM give the best performance in terms of feature separation among these feature extraction techniques. In addition, the best feature separation ability obtained with SRELM was confirmed by a quantitative measure, namely the RES index. Subsequently, seven classifiers were validated, namely support vector machine (SVM), linear classifier (LC), naive Bayes (NB), *k*-nearest neighbors (KNN), radial basis function extreme learning machine (RBF-ELM), adaptive wavelet extreme learning machine (AW-ELM), and neural network (NN). The results show that NN provides the best performance in separating six-channel EMG signals to identify 14 finger movements. Classification accuracy of up to 99% was reached when using SRELM and NN in combination.

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