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Pattern Recognition of Single-Channel sEMG Signal Using PCA and ANN Method to Classify Nine Hand Movements

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Abstract: A number of researchers prefer using multi-channel surface electromyography (sEMG) pattern recognition in hand gesture recognition to increase classification accuracy. Using this method can lead to computational complexity. Hand gesture classification by employing single channel sEMG signal acquisition is quite challenging, especially for low-rate sampling frequency. In this paper, a study on the pattern recognition method for sEMG signals of nine finger movements is presented. Common surface single channel electromyography (sEMG) was used to measure five different subjects with no neurological or muscular disorder by having nine hand movements. This research had several sequential processes (i.e., feature extraction, feature reduction, and feature classification). Sixteen time-domain features were employed for feature extraction. The features were then reduced using principal component analysis (PCA) into two and three-dimensional feature space. The artificial neural network (ANN) classifier was tested on two different feature sets: (1) using all principal components obtained from PCA (PC1–PC3) and (2) using selected principal components (PC2 and PC3). The third best principal components were then used for classification using ANN. The average accuracy using all subject signals was 86.7% to discriminate the nine finger movements.

Keywords: artificial neural network (ANN); surface electromyography (sEMG); features extraction; single channel sEMG

1. Introduction

The number of people with disabilities due to hand amputation has increased significantly in developing countries, including Indonesia. Carmona et al. (2005) [1] reported that in Geneva, Switzerland over the past ten years, amputations of the main limb occurred in 209 elderly patients, of which 48% were caused by diabetes mellitus (DM), while the rest were caused by accidents and other diseases. The Ministry of Health in Indonesia reports that in 2000, there were 8.4 million DM patients in Indonesia, which increased significantly in 2003 to 13.8 million [2]. The World Health Organization (WHO) estimates that the DM population will reach 21.3 million by 2030 [2]. Indonesia, as the fourth most populous country in the world, has a percentage of diabetes mellitus sufferers of 8.6%, and 35% of DM sufferers end up with amputation [3]. Another data source is the Australia Indonesia Partnership for Economic Governance in 2017, which states that disability is a serious problem in Indonesia due to

its population reaching 10 million (4.3% of the population). It also stated that disability is a problem that affects many lives in Indonesia. People with disabilities account for around 10 million sufferers, which is 4.3% of the population. Meanwhile, according to the Social Service and Protection Program (PPLS) conducted in the same year, the number of people with disabilities had reached 3,838,985 people. This difference was due to the number of operational definitions or instruments used by each survey (Ministry of Health, 2018) [4].

The high population of people with hand disabilities and increasing trends is a serious problem in developing countries including Indonesia, and requires finding solutions to these problems. One solution that can be implemented is making artificial hands with functions like the original hand. One important element that needs to be prepared before making artificial hands is to choose an input signal to control it, and one of the best choices is the electromyography (EMG) signal. This study is a preliminary study in developing a below-elbow prosthetic hand. The multi-channel surface electromyography (sEMG) signal characteristics of nine hand movements were studied in this paper. The nine hand movements consist of typical activities for people to do daily activities. By understanding the characteristics of the nine hand movements, a proper signal processing and machine learning method can be developed. Thus, the final objective is to apply the selected methods to control a prosthetic hand in the future.

A study on myoelectric hands is necessary for recognizing the significant number of disabled people in Indonesia. This paper discussed a preliminary study of finger movement classification based on the EMG signal and artificial neural network (ANN). Over the decades, some studies in EMG signal for a myoelectric hand have been presented, which employed various feature extraction methods and feature classification algorithms. One previous study was conducted in Indonesia, where the study used 16 time-domain features and ANN to classify five finger movements [5]. A brief review of the selected studies is presented and summarized in Table 1.

The studies presented in Table 1 show that the support vector machine (SVM), k-nearest neighbors (KNN), and artificial neural network (ANN) have been commonly used for EMG pattern recognition as classifiers. Most of the previous research employed sEMG signals with more than one channel [6–14]. The range of the sample frequency of the sEMG data acquisition was from 1 kHz to 4 kHz. The number of classes that have been studied for the multiclass classification is from five to ten classes. The resulting average classification for this multiclass classification varied from 88% to 95%. Based on the result of this study from multiclass classification, the multi-channel sEMG is suitable for the higher number of classes in multi-class classification.

Table 1. Selected studies of electromyography (EMG) pattern recognition.

Selected Literature	No. of Finger Movements	Feature Extraction	Classification Algorithm	EMG Channel/Fs	Accuracy of Classification
Ariyanto et al. (2015) [5]	5 (thumb, little, ring, middle, index)	16 (IEMG, SSI, VAR, RMS, WL, MAV, MAV1, MAV2 DASDV, AR, Hjorth1, Hjorth2, Hjorth3)	ANN	1 channel/4 kHz	96.7%
Xing et al. (2014) [6]	7 (unknown finger movement)	Wavelet package transform (WPT)	SVM	4 channel/1024 Hz	98.39%
Riillo et al. (2014) [7]	5 (rest, fist, pinch, spread, pointing)	WPT	KNN		97.5%
		RMS-WA Willison Amplitudo (WA)	ANN	6 channel/1 kHz	88%
		M-RMS-(WA)	ANN		89%
		IEMG, MAV, MAV1, MAV2, SSI, VAR, Absolute Temporal Moment 3 (TM3), TM4, TM5, RMS, v-order (V), Log detector (LOG), WL, Average amplitude change (AAC), DASDV, Zero crossing (ZC), Amplitude of the first burst (AFB), Myopulse percentage rate (MYOP), Willison amplitude (WAMP), Slope sign change (SSC), Mean absolute value slope (MAVSLP), Multiple hamming windows (MHW), Multiple trapezoidal windows (MTW), Histogram (HIST), AR, Cepstral coefficients (CC), Total power (TTP), Spectral moment 1 (SM1), Spectral moment 2 (SM2), Spectral moment 3 (SM3), Mean frequency (MNF), Median frequency (MDF), Peak frequency (PKF), Mean power (MNP), Frequency ratio (FR), Power spectrum ratio (PSR), Variance of central frequency (VCF)			
Phinyomark et al. (2012) [8]	6 (hand open, hand close, wrist extension, wrist flex, forearm pronation, forearm supination)	Slope sign change (SSC), ZC, WL, AR, Hjorth parameters, Amady and Horwat, Sample Skewness (SS), AR	SVM KNN	2 channel/1 kHz	98.39% 97.5%
Kushaba et al. (2012) [9]	10 (thumb, index, middle, ring, little, thumb-index, thumb little, thumb-ring, thumb-middle, hand close)		LIBSVM KNN	2 channel/4 kHz	Approx. 92% Approx. 91%
Balbinot et al. (2013) [10]	7 (hand contraction, forearm rotation, hand abduction, hand adduction, wrist extension, wrist flexion, forearm flexion,)	RMS	Neuro-Fuzzy	8 channel/1 kHz	86%
Mane et al. (2015) [11]	3 (open hand, close hand, wrist extensor)	WPT	ANN	1 channel/1 kHz	93.25%
Lu et al. (2015) [12]	10 (open mobile phone, screw open bottle, take a coin and move to the palm, screw to open a big bottle using all five finger, roll a small cylinder, pick up a scissor and cut paper, pencil flips, remove the pencil from back of front for writing, pick up a pencil and simply rotate to write, pick up a pencil and complexly rotate to write.	AR, the autoregressive moving average (ARMA), integrated moving average (ARIMA), Wavelet, RMS, WAMP, motor unit action potential (MUAP)	Expectation Maximation (EM)	16 channel/NA	95%
Coelho et al. (2014) [13]	6 (unknown finger postures)	Fractal dimension	NA	8 channel/3 kHz	NA
Shin et al. (2014) [14]	6 (hand close, hand open, forearm pronation, forearm supination, wrist flexion, wrist extension, rest state)	TD, MAV, WL, ZC, SSC, AR4, RMS, AR6, AR4, AR6	SVM	2 channel/1 kHz	NA
Wu et al. (2018) [15]	5 (bend wrist down, bend wrist up, bend wrist down while in shake hand, bend wrist up while in shake hand, fist)	short time energy (EK), T (activity duration), EK, TH, T (activity duration), IEMG, MAV, VAR, SD, E, MAX, SSC, SK, KU	KNN SVM	1 channel/2 kHz	75.8% (KNN) 79.8% (SVM)

Multiclass classification with a single-channel sEMG sensor is quite challenging, especially with lower sampling frequency and a higher number class. The previous study conducted hand gesture multi-class classification of a single-channel sEMG sensor with a sampling frequency of 1000 Hz [5,11]. The number of classes that have been studied in the research is five and three, respectively. In this research, nine common daily finger movements were studied in this paper. An affordable single-channel sEMG sensor was used with a sampling frequency of 1 kHz. Sixteen features in the time domain were selected and employed for feature extraction. Principal component analysis (PCA) was utilized for feature reduction from sixteen into two and three-dimensional feature space. An artificial neural network (ANN) was selected as a classifier for this study.

In this study, we proposed a nine-class recognition method for hand gestures using a single-channel sEMG sensor. The highlighted summary of the proposed method can be summarized as follows:

- The acquisition of one-channel sEMG was carried out with a sampling rate of 1 kHz. The acquired signals were processed using 13-time domain and 3-frequency domain features that made them easier to process.
- All 16-features were reduced using PCA into two and three-dimensional space before processing to the classifier. The results from PCA could clearly show the separated pattern in 3-dimensional space for each subject.
- The proposed method was able to differentiate nine-classes of hand gestures with higher accuracy, especially for each subject classification.

2. Related Work

Pattern recognition methods for more than single-channel sEMG have been studied by many researchers worldwide. The studied pattern recognition of the hand gesture is summarized in Table 1. The utilized number of channels in sEMG varies from two to 16 channels [6–10,12–14]. The selected sampling rate for the hand gesture recognition varied from 1 kHz to 4 kHz. Lu et al. [12] studied ten hand gesture motions with 16 channels of the sEMG sensor. The acquired sEMG signals were processed using seven features. The expectation maximum (EM) algorithm was employed to differentiate between 10 hand gestures and the obtained average identification rate was 95%. Seven class classification was researched by Balbinot et al. [10] by utilizing only one feature (i.e., root mean square (RMS)), which was extracted for each channel from an eight-channel sEMG. The pattern recognition technique based on Neuro-Fuzzy was applied to recognize the seven distinct arm movements with an average accuracy of 86%. Eight sEMG channels enabled the hand movement recognition to implement only on features with high accuracy. Four and six-channel sEMG sensor classification with a sampling rate of 1 kHz has been studied to distinguish five to ten different hand gestures [6,7]. The overall accuracy results of these studies reached more than 85%. Multi-class classification of hand gesture recognition implementing two sEMG channels was studied by Phinyomark et al. [8] and Kushaba et al. [9] with the sampling rate of 1 kHz and 4 kHz, respectively. The classification results obtained was 97.5% for six hand gesture recognition and 91% for ten hand movement recognition.

Multi-class pattern recognition for single-channel sEMG is quite a challenging issue. It requires more features when compared to multi-channel sEMG hand recognition. Mane et al. carried out research to discriminate three hand movements using a neural network. The implemented sampling rate was 1 kHz with one channel sEMG. ANN was applied as a classifier and achieved an overall accuracy up to 93.25%. The previous study was carried out for five types of hand gesture recognition in a single-channel sEMG [15]. Fourteen-dimensional features were reduced into two-dimensional feature space using the PCA dimensionality reduction. Two men and two women were involved as study participants. The sEMG signals were acquired using a sampling rate of 2 kHz. The improved KNN and soft margin SVM algorithm were applied to classify five distinct hand gestures. The study showed that it could achieve an overall accuracy of 75.8% for the improved KNN and 79.4% for the soft margin SVM.

In this study, we implemented 13-time domain features and 3-frequency domain features for nine-class classification of hand gesture recognition based on an affordable one-channel sEMG sensor with a sampling rate of 1 kHz. Two women and three men with healthy and normal hands were involved in this study. Based on the previous study, the sampling rate of 1000 Hz is sufficient for hand gesture recognition to achieve a higher accuracy result [16]. The 16 features were reduced using the PCA algorithm into two-dimensional and three-dimensional space features. ANN was employed as classifiers to discriminate the nine hand gestures for five subjects. The pros and cons of the proposed hand gesture recognition method are summarized in Table 2.

Table 2. Pros and cons of the proposed method compared to other methods.

Advantages	Disadvantages
Because it utilizes only one-channel of the sEMG sensor, the acquisition can be reduced in terms of cost and complexity.	The placement of the sEMG sensor pad needs to be attached carefully and correctly.
The algorithm for feature computation is easy to compute and has a faster processing speed because most of the features use time domain features.	It needs sixteen features before they can be reduced into two or three features using PCA dimension reduction.
The acquisition uses a sampling rate of 1000 Hz for discriminating nine hand gestures.	The wireless data acquisition needs Bluetooth 3.0 technology and above.

3. Methods

This research begins with the process of acquiring data using EMG sensors from Bitalino Inc. The data was then extracted using 16 time-based features. The next process is the feature reduction using PCA. The reduced signal was then classified using an artificial neural network (ANN). The results of the classification process were used to draw conclusions in this study. The research sequence is shown in Figure 1.

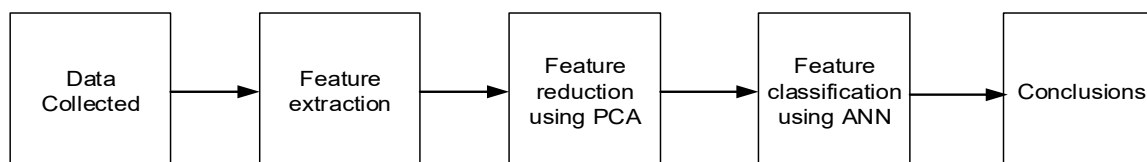


Figure 1. Flowchart of research methods.

The EMG sensor system from Bitalino Inc. has an internal Butterworth low-pass filter with a cut-off frequency of 400 Hz. The available sampling rates on this sensor system were 1 Hz, 100 Hz, and 1 kHz. The sampling rate of 1 kHz was used in this process. The analog port of this device has four 10-bit inputs. The Bluetooth v2.0 wireless communication in this sensor system has a range of up to 10 m with a bandwidth of 10–400 Hz. The device uses a battery as the energy source. It is not connected to an AC power line, so that electromagnetic field interference caused by electric power lines at 50 Hz is negligible.

3.1. Feature Extraction

It is commonly known that the feature extraction of electromyography signals is classified as two types: (1) features based on time-domain, and (2) features based on frequency-domain [17]. This paper uses sixteen time-domain features and three frequency-domain features. The calculation process for all extraction features was implemented in MATLAB software (MATLAB R2013b, MathWorks, MA, USA). The feature definition and feature equation are presented as follows:

- Integrated EMG (IEMG): IEMG is used as a feature evaluation for electromyographic pattern recognition and movement control in EMG studies [18,19]:

$$\text{IEMG} = \sum_{i=1}^N |x_i| \quad (1)$$

- Mean absolute value (MAV): MAV is used as an onset detection index in the surface EMG signal for prosthetic limb control [20,21]:

$$\text{MAV} = \frac{1}{N} \sum_{i=1}^N |x_i| \quad (2)$$

- MAV1 (modified mean absolute value type 1): MAV1 is an extension of the MAV feature [21,22]:

$$\begin{aligned} \text{MAV1} &= \frac{1}{N} \sum_{i=1}^N w_i |x_i| \\ w_i &= \begin{cases} 1, & \text{if } 0.25N \leq i \leq 0.75N \\ 0.5, & \text{otherwise} \end{cases} \end{aligned} \quad (3)$$

- MAV2 (modified mean absolute value type 2): MAV2 is an expansion of the MAV1 feature, which was used in [21,22]:

$$\begin{aligned} \text{MAV2} &= \frac{1}{N} \sum_{i=1}^N w_i |x_i| \\ w_i &= \begin{cases} 1, & \text{if } 0.25N \leq i \leq 0.75N \\ 4i/N, & \text{else if } i < 0.25N \\ 4(i-N)/N, & \text{otherwise} \end{cases} \end{aligned} \quad (4)$$

- SSI (simple square integral) or integral square is a feature that calculates the energy of the EMG signal [23]:

$$\text{SSI} = \sum_{i=1}^N x_i^2 \quad (5)$$

- VAR (variance of EMG): Variance of EMG is defined as an average of the square values of the deviation of the EMG signal [19,24]:

$$\text{VAR} = \frac{1}{N-1} \sum_{i=1}^N x_i^2 \quad (6)$$

- RMS (root mean square): Root mean square has been used in previous studies to analyze the EMG signal [25,26]:

$$\text{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2} \quad (7)$$

- WL (waveform length): WL is the cumulative length of the EMG signal being observed [20,21]:

$$\text{WL} = \sum_{i=1}^{N-1} |x_{i+1} - x_i| \quad (8)$$

- DASDV (difference absolute standard deviation value): DASDV is a standard deviation value of the wavelength [26]:

$$\text{DASDV} = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (x_{i+1} + x_i)^2} \quad (9)$$

where a digitized sEMG signal in Equations (1)–(9) contains samples x_1, x_2, \dots, x_N and N refers to the number of samples of each digitized sEMG signal.

- Autoregressive coefficients (AR): AR is a method to model univariate time series [19,24,25]:

$$y_t = a_1 y_{t-1} + a_2 y_{t-2} + \dots + a_n y_{t-n} + \varepsilon_t = \sum_{i=1}^n a_i y_{t-i} + \varepsilon_t \quad (10)$$

Autoregressive coefficients can be denoted by a_1 to a_n ; y_t is the time series under investigation; and n is the order of the AR model. ε is the residual, which is always assumed to be Gaussian white noise. In this paper, $n = 4$ was used for AR feature extraction. Therefore, there are four AR features: AR1, AR2, AR3, and AR4.

- Hjorth 1 (Activity): Hjorth 1 measures the surface of power spectrum in the frequency domain [27].

$$H1 = \text{var}(x) \quad (11)$$

- Hjorth 2 (Mobility): Hjorth 2 calculates the mean frequency, or the standard deviation of the power spectrum [27]:

$$H2 = \sqrt{\frac{\text{var}\left(x \frac{dx}{dt}\right)}{\text{var}(x)}} \quad (12)$$

- Hjorth 3 (Complexity): Hjorth 3 measures the change in frequency by comparing the signal's similarity to a pure sine wave [26]:

$$H3 = \frac{\text{mobility}\left(x \frac{dx}{dt}\right)}{\text{mobility}(x)} \quad (13)$$

3.2. Feature Reduction: Principal Component Analysis (PCA)

Two commonly used methods for data classification and dimensionality reductions are principal component analysis (PCA) and linear discriminant analysis (LDA) [28]. PCA is a method that is typically used as a dimensional reduction method in the pattern recognition method. PCA employs mathematical principles (eigenvalue and eigenvector) to transform the number of calculated features into a significantly smaller number of extracted features called principal components [29]. This study used the PCA method implemented in MATLAB software to reduce the features.

Let a set of centered data input vectors \mathbf{x}_t ($t = 1, \dots, l$ and $\Sigma \mathbf{x}_t = 0$), each of which is of m dimension $\mathbf{x}_t = [x_t(1), x_t(2), \dots, x_t(m)]^T$, ordinarily $m < l$, \mathbf{s}_t linearly transforms each vector \mathbf{x}_t as in Equation (14):

$$\mathbf{s}_t = \mathbf{U}^T \cdot \mathbf{x}_t \quad (14)$$

where \mathbf{U} is the $m \times m$ orthogonal matrix whose i th column, \mathbf{u}_i is the eigenvector of the sample covariance matrix \mathbf{C} . The \mathbf{C} matrix can be calculated using Equation (15):

$$\mathbf{C} = \frac{1}{l} \sum_{t=1}^l \mathbf{x}_t \cdot \mathbf{x}_t^T \quad (15)$$

Completion of eigenvalues in PCA can be solved using Equation (16):

$$\lambda_i \mathbf{u}_i = \mathbf{C} \cdot \mathbf{u}_i, \quad i = 1, \dots, m \quad (16)$$

In the equation, λ_i is one of the eigenvalues of \mathbf{C} . The components of \mathbf{s}_i are then calculated as the orthogonal transformations of \mathbf{x}_t based on the estimated \mathbf{u}_i

$$\mathbf{s}_t(i) = \mathbf{u}_i^T \mathbf{x}_t, \quad i = 1, \dots, m \quad (17)$$

The number of principal components in \mathbf{s}_t is the result of the new extracted feature, which is reduced using the first several eigenvectors sorted in descending order of the eigenvalues.

3.3. Feature Classification: Artificial Neural Network (ANN)

The feature classification process in this study used ANN with a two-layer feed-forward structure implemented in MATLAB software, as presented in Figure 2. The ANN structure consisted of two transfer functions (i.e., hyperbolic tangent sigmoid transfer function in the hidden layer and softmax transfer function in the output layer).

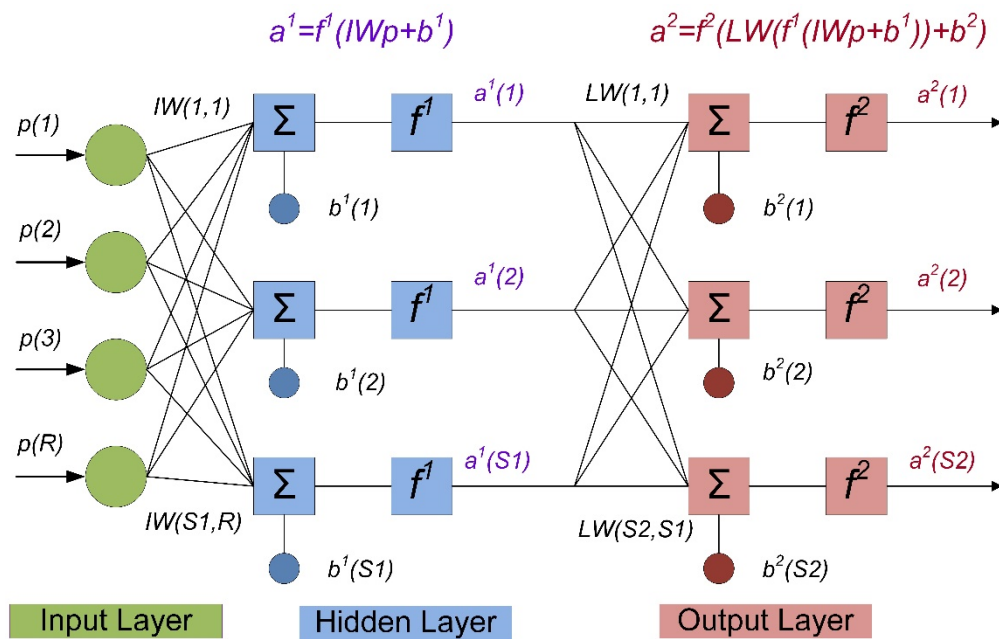


Figure 2. Artificial neural network (ANN) structure.

The first output neuron of the hidden layer can be displayed in Equation (18):

$$a^1 = f^1(IWp + b^1) \quad (18)$$

where a^1 is the output vector from the input layer; p is the n -length input vector; IW is the input weight matrix; f^1 is the transfer function of the hidden layer; and b^1 is the bias vector of the hidden layer.

The first output neuron of the output layer as written in Equation (19):

$$a^2 = f^2(LW(f^1(IWp + b^1)) + b^2) \quad (19)$$

where a^2 is output vector from the output layer; LW is the output layer weight matrix; f^2 is the transfer function of the output layer; and b^2 is the bias vector of the output layer.

The function of the tangent sigmoid generates outputs between 0 and 1, while the softmax function generates the output as 1, as the neuron's net input goes from negative to positive. The description of the activation function can be seen in Figure 3.

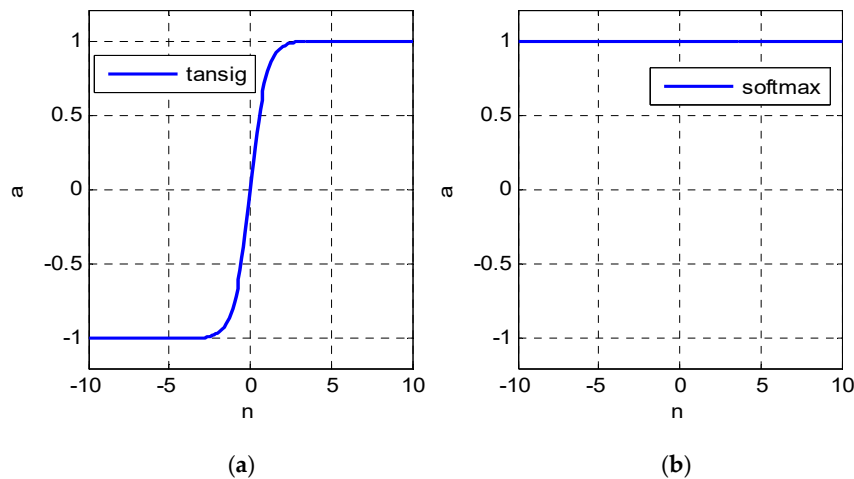


Figure 3. Neuron activation function: (a) tansig activation function; (b) softmax activation function.

In the ANN training process, the Levenberg–Marquardt algorithm is selected due to its characteristic to accelerate the time computation of second-order training. The performance function of this training algorithm can be calculated using the Hessian matrix, as presented in Equation (20):

$$H = J^T J \quad (20)$$

and the gradient can be calculated as follows:

$$g = J^T e \quad (21)$$

where J in Equation (21) is a Jacobian matrix that is the first derivative of network errors related to weights and biases, and e represents the vector of network errors.

Equation (22) is used in the Levenberg–Marquardt training algorithm to approximate the Hessian matrix:

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \quad (22)$$

Equation (22) has two conditions: (1) when the scalar μ is zero, then using the Hessian estimation matrix, and (2) when μ is large, then it becomes a gradient descent with a small step size.

The classification stage of ANN in this study used the mean square error (MSE). The MSE is presented in Equation (23) and measures the magnitude of the estimated error. Smaller values of MSE indicate a better model:

$$mse_{error} = \frac{\sum (y_1 - y_2)^2}{m} \quad (23)$$

Equation (23) consists of three variables: (1) y_1 is the real output in classification; (2) y_2 is the output from ANN classification; and (3) m is the total number of samples in classification. The ANN structure in this study had three inputs to classify nine classes. Details of the inputs and the classes are presented in Figure 4.

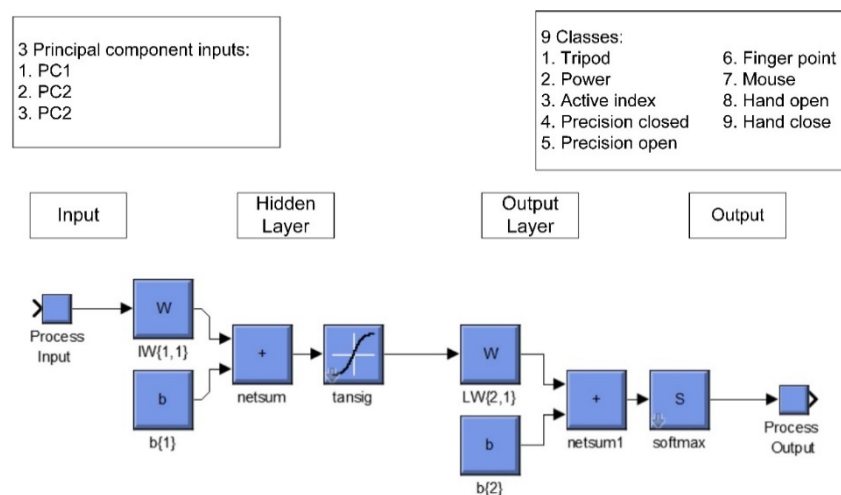


Figure 4. ANN input and output for the proposed pattern recognition.

3.4. Experimental Setup

The EMG data used in this paper were collected from five subjects consisting of three males and two females. The five selected subjects did not have neurological or muscular disorders. The characteristics of each subject participant is shown in more detail in Table 3. Prior to the experiment, each subject was advised to fill out a consent form. During the experiment, each subject was seated in a relaxed condition. The EMG data were acquired using a one channel EMG sensor and acquisition software (OpenSignal software (v.2014, BITalino, Lisbon, Portugal)) supplied by Bitalino Inc. with a sampling rate of 1000 Hz at a 10-bit resolution. The sEMG electrodes were attached on the flexor digitorum superficialis, as shown in Figure 5.

Table 3. Characteristics of the study participants involved in this study.

Subject	Sex	Age (years)	Height (cm)	Weight (kg)	Hand
Subject 1	Female	30	164	60	Right
Subject 2	Female	21	165	61	Right
Subject 3	Male	22	169	70	Right
Subject 4	Male	21	168	69	Left
Subject 5	Male	35	168	70	Right

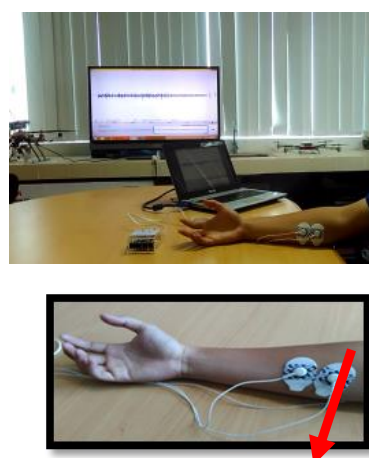


Figure 5. Subject in the EMG experiment and the EMG sensor location on the *flexor digitorum superficialis*.

Each subject was instructed through auditory cues to move one of the finger postures from the rest position, holding the movement for a period of 7–10 s for each movement and carried out five times. Between each movement of the finger posture, the subject had a rest time of about 5–7 s. Nine finger postures such as a tripod, power, active index, precision close, open precision, finger point, mouse, open hand, and close hand were collected from each subject and all postures were performed consecutively on each subject. These movements were chosen because these finger movements are common in daily activities. Segmentation of the five trials on each finger posture was performed visually by signal separation based on the same time period of 10 s. Details of the finger posture and examples of EMG signals from subject 5 are presented in Table 4.

Table 4. Nine finger movements and EMG signal.


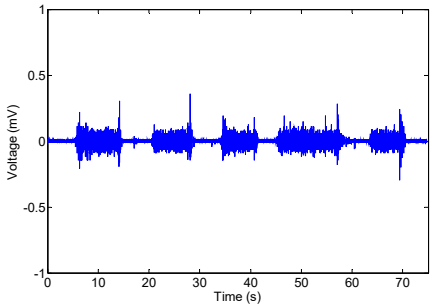

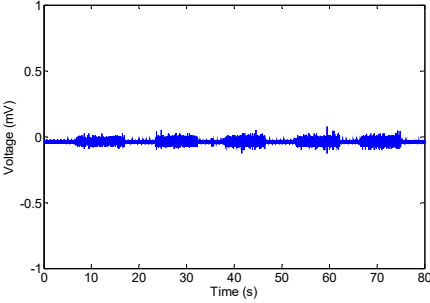

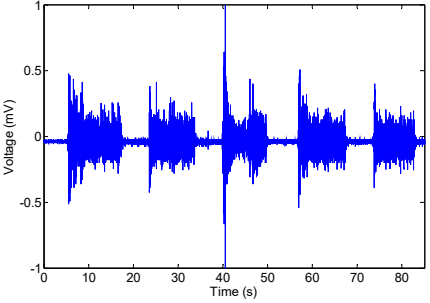

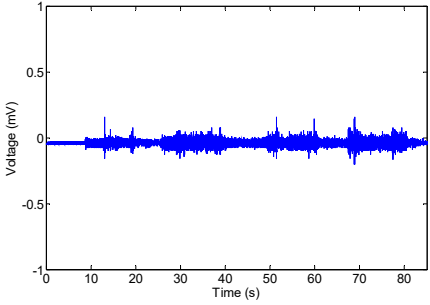

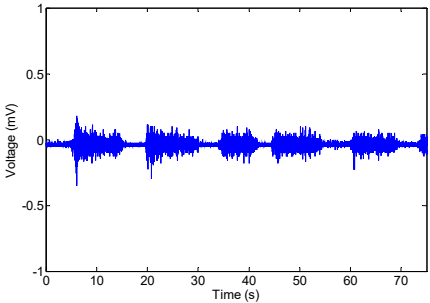
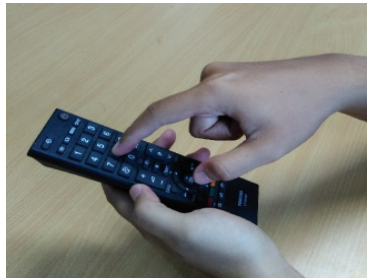
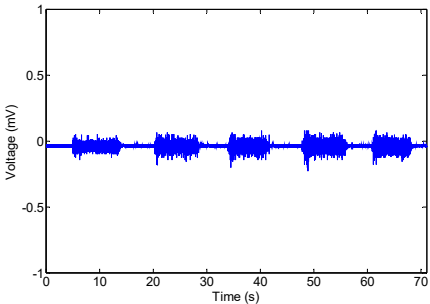

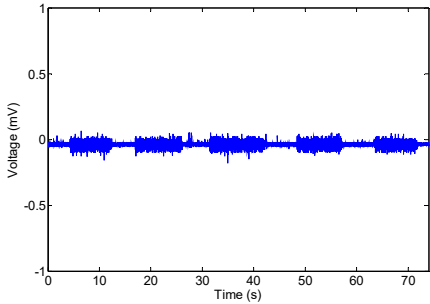

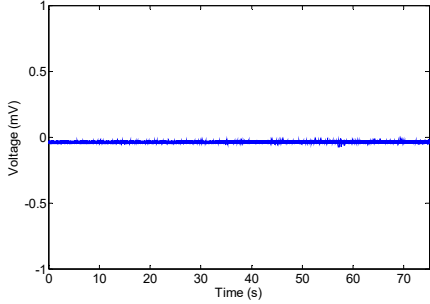

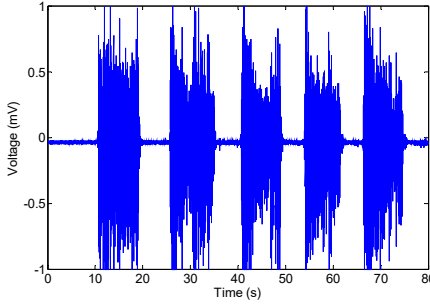
Finger Movement	Image	Example of EMG Signal
1. Tripod		
2. Power		
3. Active index		
4. Precision closed		

Table 4. Cont.

Finger Movement	Image	Example of EMG Signal
5. Precision open		
6. Finger point		
7. Mouse		
8. Hand open		
9. Hand closed		

4. Results and Discussion

4.1. Principle Component Analysis (PCA)

Sixteen features were extracted from one finger posture of each subject. For five subjects with five measurements, the total features matrix was 225×16 . This matrix was then reduced from 16 features to three significant features using PCA. The result of PCA was 225×3 , where the column of the matrix indicates principal component 1, principal component 2, and principal component 3. The result of PCA is presented in Figure 6. It can be seen from the images in Table 4 that the nine finger postures can be classified. Visually, Subjects 1 and 5 had a clearer separation region between each finger posture. Two types of data input were prepared for the ANN classifier: (1) all principal components (PCs), and (2) selected PCs. The objective was to analyze which of the best pair features were suitable for the ANN classifier.

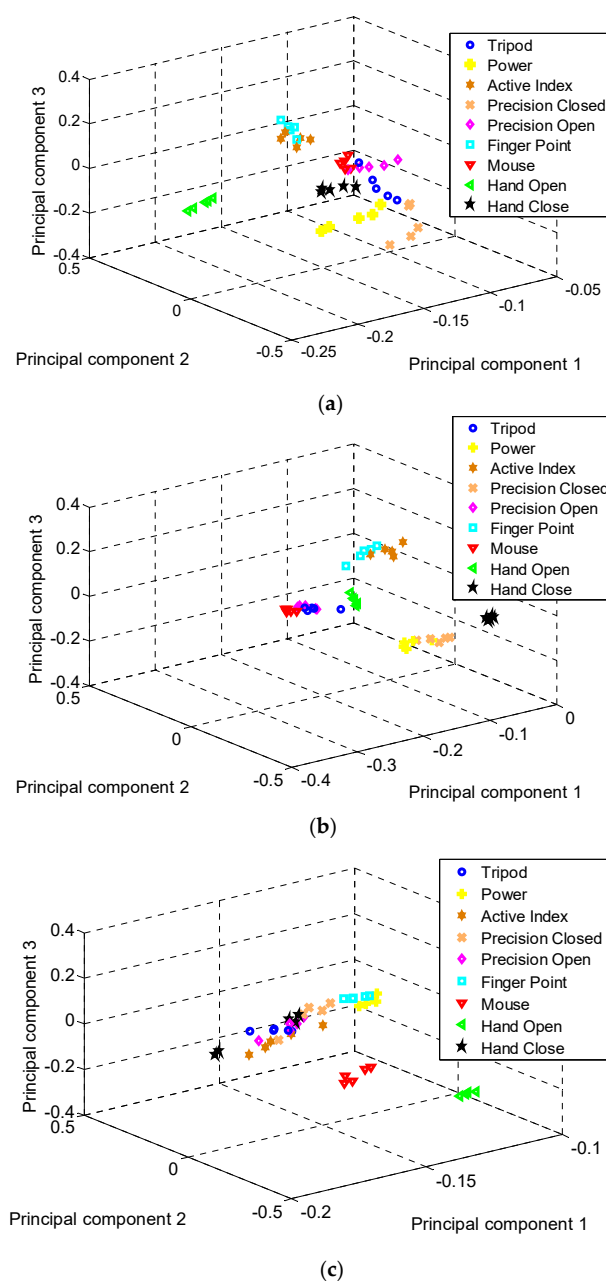


Figure 6. Cont.

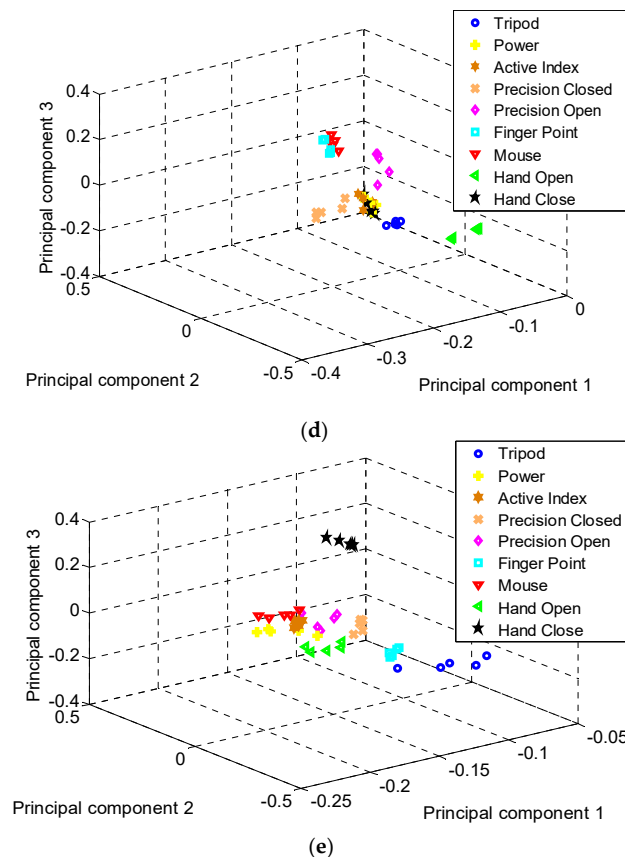


Figure 6. Principle component analysis (PCA) results. (a) Subject 1; (b) Subject 2; (c) Subject 3; (d) Subject 4; (e) Subject 5.

4.2. Artificial Neural Network (ANN)

The pattern recognition of nine finger movements for all subject was designed by arranging the three principal components as rows and 225 data samples as columns in a 3×225 matrix. This matrix was used as the input vector in the ANN. The target vector had nine classes where each of the elements consisted of the value 0 or 1. The 225 sample dataset of finger movement were divided into three sub-sets: training, testing, and validation using specified samples. Out of the 157 samples used in training, 34 samples for the test, and 34 were for validation. The ANN used 70 neurons in the hidden layer and nine neurons in the output layer.

The training of ANN pattern recognition used the Levenberg–Marquardt training algorithm and the performance utilized MSE. In Figure 7, at 24 epochs, the MSE of the training, test, and validation were 0.0089, 0.0455, and 0.0570, respectively. At about 22 epochs, the MSE of the training, test, and validation converged to a constant value, and the MSE was low for all subject pattern recognition. These results mean that the network produces a high enough accuracy of pattern recognition in finger movement classification.

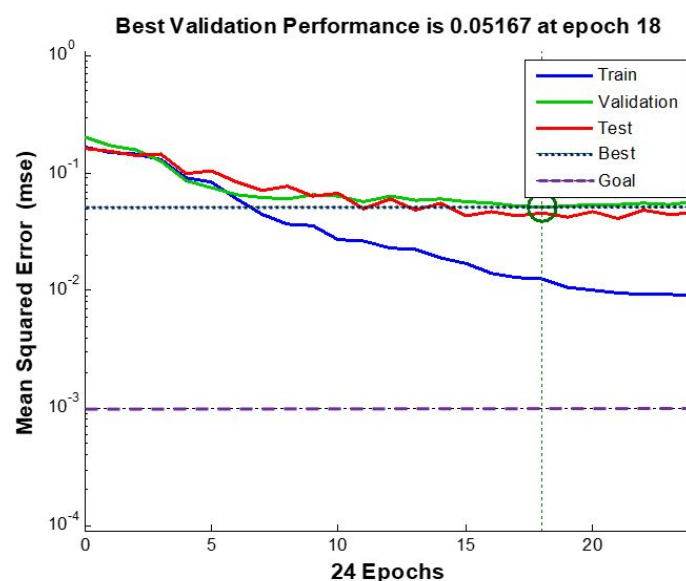


Figure 7. Performance of the ANN during training, validation, and testing.

The output of all pattern recognition schemes in the nine fingers daily posture movement classification is presented in Tables 5 and 6. Table 5 presents the ANN accuracy result during training, validation, and test for all subjects. The accuracies of nine finger movement for all subjects using all principal component and selected principal components are 86.7 % and 68.9 % respectively. The better performance for all subject classification can be reached using all principal component. Table 6 shows the ANN accuracy results during training, validation, and testing for each subject. The average classification accuracies for each subject using all principal components and the selected principal component were 73.34 % and 92.9 %, respectively.

Table 5. ANN results in the classification of all subjects.

Utilized PCs	ANN Accuracy Results (%)			
	Training	Validation	Testing	Overall
All PC (PC1–PC3)	92.4	70.6	76.9	86.7
Selected PCs	75.2	50	58.8	68.9

Table 6. ANN results in each subject classification.

Selected PCs	Subject	ANN Accuracy Results (%)			
		Training	Validation	Testing	Overall
All PCs (PC1–PC3)	1	64.5	42.9	57.1	60
All PCs (PC1–PC3)	2	38.7	57.1	14.3	37.8
All PCs (PC1–PC3)	3	96.8	85.7	71.4	91.1
All PCs (PC1–PC3)	4	90.3	57.1	57.1	80
All PCs (PC1–PC3)	5	100	100	85.7	97.8
PC2–PC3	1	96.8	100	85.7	95.6
PC2–PC3	2	100	57.1	71.4	88.9
PC2–PC3	3	93.5	85.7	57.1	86.7
PC2–PC3	4	100	85.7	71.4	93.3
PC2–PC3	5	100	100	100	100

Based on the ANN accuracy results, it is apparent that the selected ANN parameters can classify the finger movement with high accuracy and minimal error of classification results. A summary of the present study can be seen in Table 7.

Table 7. Summary of the present study.

Finger Movement	Features Extraction	Classification Algorithm	EMG Channel/Fs	Accuracy of Classification
9 (tripod, power, active index, precision closed, precision open, finger point, mouse, hand open, hand closed)	16 (IEMG, MAV, MAV1, MAV2, SSI, VAR, RMS, WL, DASDV, AR, Hjorth1, Hjorth2, Hjorth3)	ANN	1 channel/1 kHz	86.7% for all subject average 92.9% using selected PC for an individual subject

4.3. Discussion

Based on the experimental results on the hand classification results for all subjects, the three-dimensional feature space of PCA pattern recognition had higher overall accuracy than the overall accuracy result of the two-dimensional space of PCA. In each subject classification result, the three-dimensional feature space of PCA had a lower overall accuracy than the accuracy results in the two-dimensional space of PCA. The classification results also showed that the level of accuracy for the classification of all samples as a whole on the selected PC was worse. The accuracy for the classification of each subject was much better. This was due to the use of mixed data from all subjects for the training and testing at the validation procedure stage. Subject 5 had the highest accuracy results among the other subjects as study participants. This is because Subject 5 already knew and had previously used the sEMG sensor. The results of the analysis using the principal component analysis method are shown in Figure 6, where it can be seen that the nine models of hand movement recognition could be grouped well. This means that signals from the nine movement modes could be classified properly. The artificial neural network (ANN) test results yielded an overall classification accuracy of up to 92.9%. These results indicate that the accuracy of the results obtained was quite high compared to the results of previous similar studies. These results have positive implications for increasing the level of accuracy of technology that utilizes EMG signals as a controller input such as myoelectric prosthetic hands.

5. Conclusions

The study on the pattern recognition method using a single-channel Bitalino sEMG sensor was performed and presented. The EMG signals of nine hand movements were processed using thirteen features in the time-domain and three features in the frequency-domain. These features were reduced using PCA to increase the classification accuracy and to shorten the ANN computation time. Sixteen features were reduced into two and three-dimensional space. This study demonstrated that the selected PCs (PC2 vs. PC3) from the PCA feature reduction process outperformed the three PCs (PC1 to PC3) evaluated using the ANN classifier. The classification results showed that the selected PC (PC2 vs. PC3) was able to classify nine hand movements better than other PC combinations (e.g., PC1 vs. PC2 and PC1 vs. PC3). The overall classification accuracy for the selected PCAs (PC2 and PC3) was greater than 85%, while Subject 5 achieved 100% accuracy. On the other hand, the classification results of the five subjects for all PCs varied from 37.8% to 97.8%.

In future work, the number of test subjects should be increased to more than five test subjects so that the data obtained will be more representative to a wider group of people. The frequency sampling of the sEMG data acquisition will be raised to more than 1 kHz. By increasing the sampling rate of the sEMG acquisition, the classification of accuracy might improve. The on-line sEMG pattern recognition will be performed by employing a stream processing method in the MATLAB/Simulink environment. Then, the on-line classification result from the stream processing classification will be fed into the developed six degree of freedom (DoF) myoelectric hand.

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