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Features selection for estimating hand gestures based on electromyography signals

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ABSTRACT

Hand prosthesis controlled by surface electromyography (sEMG) is promising due to the control capabilities and the noninvasive technique that machine learning (ML) offers to help physically disabled people during daily life. Nevertheless, dexterous prostheses are still infrequently popular due to control problems and limited robustness. This paper proposes a new set of time domain (TD) features to improve the EMG pattern recognition performance. The effect of five feature sets is evaluated based on the three classifiers k-nearest neighbor (KNN), linear discriminate analysis (LDA), and support vector machine (SVM). The EMG signals are obtained from database-5 (DB5) of the ninapro project datasets. In this study, the long-term signals of DB5 are segmented into short-term signals to perform short-term recognition. The results showed that the LDA classifier based on the proposed features achieved high classification accuracy for classifing 17 gestures. The LDA classifier achieved about 96.47% compared to 94.12%, and 93.82% for KNN and SVM classifiers, respectively. The results confirm that the suitable features extracted from short term signals with the appropriate classifier, has an important impact on improving the performance of gesture classification.

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1. INTRODUCTION

Electromyography (EMG) signals are generated during muscular contraction. The control system that uses EMG signals to recognize human movements is called myoelectric pattern recognition (MPR). MPR has been employed in a wide variety of applications including upper limb prosthesis [1], [2], wheelchairs, and human-computer interaction [3]. These signals are produced by muscle tissue and detected by surface electrodes. Surface (sEMG) signals were utilized to control the movement of the robotic appendage with more actuators. The prosthesis makes amputees accomplish everyday tasks more easily and regain a significant portion of their lost hand capability. However, they are still insufficient for natural control [4], [5].

The use of a pattern recognition-based myoelectric control system has become practical thanks to current technology. The pattern recognition process can be summarized in four phases as shown in Figure 1. Data acquisition, signal pre-processing, feature extraction, and classification.

The feature extraction and classification approaches are two essential components for improving classification performance in MPR. The quality of the features to be extracted significantly affected the classification of EMG signals. Feature extraction is a technique to extract valuable information in surface

EMG signal characteristics and remove unnecessary EMG parts and interferences. EMG features are grouped into three categories time domain (TD), frequency domain (FD), and time-frequency domain (TFD). TD features are now one of the primary feature extraction techniques used to classify EMG signals, they are easy to implement and have low computational cost [6]-[10]. In the FD, the power spectral density (PSD) analysis plays an important role [11]. However, FD features only contain spectrum data, which limits the temporal information it can provide. On the other hand, time-frequency (TF) features that rely on the TF domain, including wavelet transform (WT) and short time fourier transform (STFT), are more complicated and costly to compute than TD features [8].

The creation of advanced myoelectric prosthesis control systems is seeing a spike in attention as a result of recent developments in machine learning (ML) and deep neural networks (DNNs), as well as advancements in rehabilitation technology [12]. Pizzolato *et al*. [13] classified 41 hand and wrist motions using sEMG signals. Wu *et al*. [14] presented long-convolutional neural network (LCNN) and long short-term memory (LSTM) CNN models. They achieved an accuracy of 12 and 17 gestures approximately 71.66% and 61.4%, respectively. Deep learning technology is frequently used in many recent types of research in different fields [15], [16], especially on the classification of sEMG signals, convolution neural network was constructed by Côté-Allard *et al*. [17] to further enhance the classification accuracy of sEMG signals. The researchers treated the original sEMG signals as an image. Shen *et al*. [18] developed a classification approach based on CNN and stacking ensemble learning to classify EMG signals. Deep learning gives the ability to learn features automatically from a raw signal. However, deep learning methods often need a lot of training data. Furthermore, CNN uses a large amount of memory and takes a long time to process, which might be a problem on embedded devices with few resources [19].

In this study, the long-term Myo-signals of DB-5 are converted into short-term signals. The long-term signal contains a lot of gestures with their trials. The long-term signals are segmented into several short-term signals corresponding to their gestures. The short-term signal represents the muscular activity of a gesture. The short-term EMG signals are considered as an input to the EMG pattern recognition system. The short-term signals are used for extracting useful information. New time-domain features have been concatenated to form several sets of features. The effect of these feature sets is examined to show their effect in improving the accuracy rate. The feature sets are evaluated for different numbers of gestures based on three classifiers (support vector machine (SVM), linear discriminate analysis (LDA), and k-nearest neighbor (KNN)).

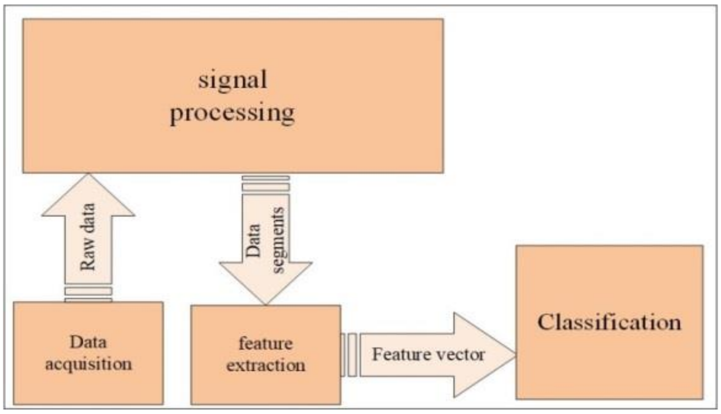

Figure 1. EMG pattern recognition

2. EMG PATTERN RECOGNITION

2.1. Data acquisition

A wearable technological gadget is the Myo wristband. It is an open-source, low-cost, high-performance gadget. Myo armband was created by Thalmic labs. The Myo armband has an inertial measurement unit (IMU) with nine axes, eight EMG sensors, and a Bluetooth module. The IMU has a 3-axis magnetometer, 3-axis accelerometer, and 3-axis gyroscope sensors. Human muscle signals are detected using EMG electrodes. These signals are transmitted using the Bluetooth module found within the Myo wristband. With the Bluetooth module, wireless usage is possible [20]. Figure 2 shows the Myo armband.

In this study, sEMG signals of two Myo armbands are used without the need for IMU signals. sEMG signals of Myo armband are obtained from DB5, a publicly available database for a low cost with 16 channels and 200 Hz sampling. DB5 contains ten participants. Each subject participated in three exercises. Exercise A consists of 12 fundamental movements. Exercise B consists of 8 isometric and isotonic hand configurations and 9 fundamental wrist motions. On the other hand, exercise C consists of 23 functional grasping movements. Each subject in DB5 performs a single long-term EMG signal. The long-term signal has several gestures depending on the type of experiment applied. Each movement is repeated six times [21]-[23].

Figure 2. Myo armband

2.2. Short-term sEMG signals

In this study, the long-term signals of DB-5 are segmented into several short-term signals. In this regard, the long-term signals are divided into N short-term signals, where N represents the number of gestures included in the long-term signals. The short-term signal represents the sEMG signal of a single gesture.

To demonstrate the segmentation procedure, let the sEMG signal of subject i of exercise B be obtained. There are 16 channels in this signal (i.e. data from two Myo armbands). The EMGj for channel j consists of 17 motions. Each motion was repeated six times in the same signal. According to the proposed work, EMGj is segmented into 17×6 short-term signals. The proposed approach for analyzing Myo signals of DB5 has been shown in Figure 3.

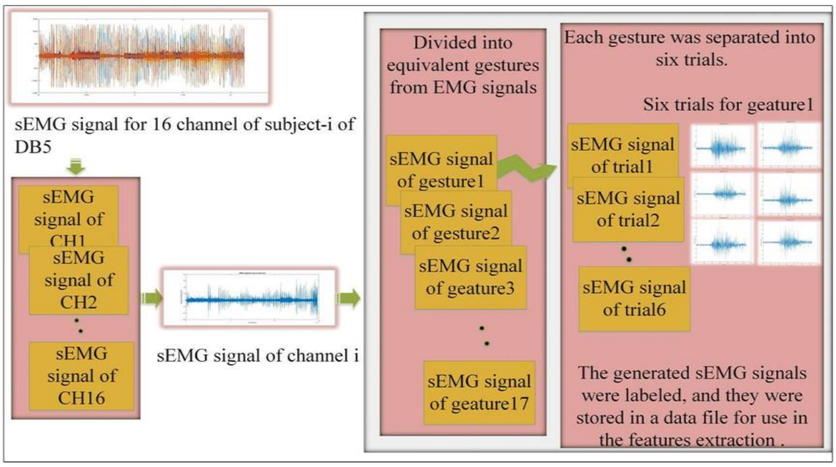

Figure 3. Data analysis and segmentation

2.3. Features extraction

Feature extraction is an important stage in the MPR system to extract the beneficial information which is hideaway in surface EMG signals and remove undesirable components. The reason for feature extraction is to distinguish various gestures as far as possible and represent them through specific sEMG feature data. In this work, eight EMG features are utilized. These features are selected to have a promising performance for gesture recognition [6], [24].

TD features are mean absolute deviation (MAD), average amplitude change (AAC), mean absolute value (MAV), root mean square (RMS), auto regressive (AR), interquartile range (IQR), standard deviation

(STD), and skewness (SKEW) [24]-[27]. In this study, TD features are precisely extracted from the short-term signals without using overlapping or non-overlapping windows. The proposed TD features are formulated as follows: IQR is referred to the EMG signal's variability measure, and it works by dividing the entire EMG signal into quartiles. It is defined as (1):

$$IQR = Q3 - Q1 \tag{1}$$

Where Q1 and Q3 are the 25th and 75th percentile of the EMG signal respectively.

The MAD is the average distance between each sample of the EMG signal and its mean value. It is measured as (2):

$$\mathrm{MAD} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} |\mathrm{x_i} - \mathrm{x}'| \tag{2}$$

Where x_i is the EMG signal and N is the number of samples of the EMG signal, and x' represents the mean value of the EMG signal.

$$\mathrm{AAC} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} \sum|\mathrm{x_{i+1}} - \mathrm{x_i}| \tag{3}$$

$$\mathrm{MAV} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} |\,\mathrm{x_i}| \tag{4}$$

$$\mathrm{RMS} = \sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{x_i}^2} \tag{5}$$

Each sample of an EMG signal is described by an autoregressive model (AR) as a linear mixture of earlier sample plus the error term. Fourth order AR model is applied and defined as (6):

$$\mathrm{x_i} = \sum_{\mathrm{k}=1}^{\mathrm{k}} \mathrm{a_k}\, \mathrm{x_{i-k}} + \mathrm{e_i} \tag{6}$$

Where k is the order of the AR model, a_k are coefficients, x_{i-k} is previous samples and the white noise error term is e_i.

$$\mathrm{STD} = \left[\frac{1}{\mathrm{N}-1}\sum_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{x_i} - \mathrm{x}')^2\right]^{1/2} \tag{7}$$

Asymmetry in a statistical distribution that revolves around the mean value is described by the SKEW, it explains as (8) and (9):

$$\mathrm{SKEW} = \frac{\mathrm{M_3}}{\mathrm{M_2}}\sqrt{\mathrm{M_3}} \tag{8}$$

$$\mathrm{M_k} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{x_i} - \mathrm{x}')^{\mathrm{k}} \tag{9}$$

2.4. Performance metrics

To evaluate the classification performance of gesture recognition, three well-known ML algorithms SVM, LDA, and KNN are used. These ML algorithms were chosen because of their fast training and good performance. Two performance metrics are used in this study, sensitivity, and precision. There are four possible test results for every study: true positive (TP), true negative (TN), false positive (FP), or false negative (FN) [28]-[30]. The ratio of TP to the sum of TP and FN is called sensitivity, sometimes referred to as the true positive rate.

$$Sensitivity = \frac{TP}{TP+FN} \tag{10}$$

The ratio of TP to the sum of TP and FP is called precision.

$$Precision = \frac{TP}{TP+FP} \tag{11}$$

3. RESULTS AND DISCUSSION

In this study, the experiments include two parts. The first part examined the effect of selecting five feature sets on classification performance for three types of classifiers (SVM, LDA, and KNN). The second part shows the impact of the best feature set on the classification performance of a different number of gestures. The classifiers trained on trials 1, 3, 4, and 6, while the remaining trials were used for testing.

3.1. Experiment 1: effect of selecting the feature sets

The classifier can recognize movements based on the information extracted from sEMG signals. Feature selection is critical for extracting data from sEMG signals. In this experiment, The classification performance of LDA classifier based on eight features (MAD, AAC, MAV, RMS, AR, IQR, STD, and SKEW) was evaluated for five subjects of exercise B. The effect of removing some features such as IQR, AR, and SKEW features is also evaluated. The IQR, AR, and SKEW features are not standard features like RMS, MAV, and STD. However, they greatly impact the accuracy rate as shown in Figure 4.

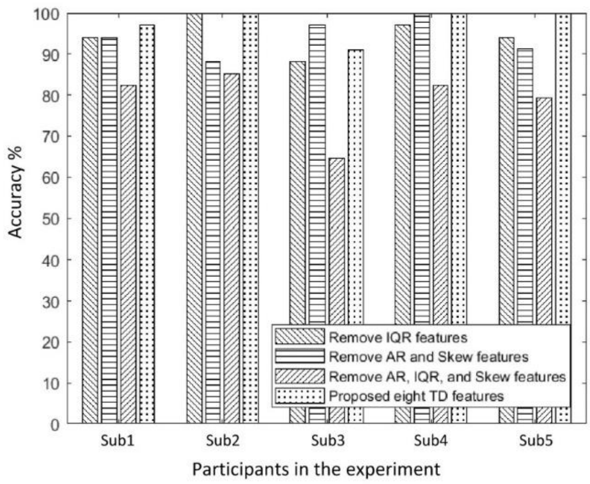

Figure 4. The classification accuracy of LDA classifier for five subjects when removing three features from eight TD feature set

It is noticed that the classification accuracy based on eight TD features achieved high accuracy whereas removing the three features (IQR, SKEW, and AR) could significantly affect the accuracy. The results indicate that IQR, SKEW, and AR features can offer promising performance. Moreover, the accuracy rate is altered between subjects due to the different physiological characteristics of the subjects. Combining multiple features can obviously improve classification accuracy because many features are extracted from EMG signals. The effect of five feature sets on the classification accuracy for three classifers was examined. Classification accuracy was assessed for 17 gestures and averaged over five subjects as shown in Table 1.

Table 1. Average accuracy of three classifiers based on five feature sets

Feature sets	Average accuracy (%)		
	LDA	SVM	KNN
(MAD, AAC, MAV, RMS, AR, IQR, STD, SKEW)	97.65	95.88	94.12
(MAD, AAC, MAV, AR, IQR, STD, SKEW)	97.65	95.29	93.53
(MAD, AAC, MAV, RMS, AR, STD, SKEW)	94.71	92.94	91.76
(MAD, AAC, MAV, RMS, AR, IQR, SKEW)	97.65	95.29	93.53
(MAD, AAC, MAV, RMS, STD)	78.82	92.94	91.76

The results showed that the LDA classifier based on eight TD features outperformed other classifiers and other feature sets. Moreover, removing RMS features reduces the accuracy rate of both SVM and KNN classifiers compared to the LDA classifier. However, removing IQR, AR, and SKEW features have a significant affect on the LDA classifier of about 78.8% compared to 92.9%, 91.7% for the SVM and KNN classifiers respectively. This confirms that classifier selection has an impact on classification accuracy of the same feature set.

3.2. Experiment 2: effect of the proposed feature set for different exercises with different number of gestures

In this experiment, the best feature set obtained from experiment 1 is examined to test the three classifiers SVM, KNN, and LDA on three exercises. Exercise A contains 12 gestures, exercise B has 17 motions, and combine exercises B and C to increase the number of gestures to 40. The experiment was conducted on ten subjects of DB5. Figure 5 shows the classification performance in terms of precision and sensitivity for three classifiers with a different number of gestures.

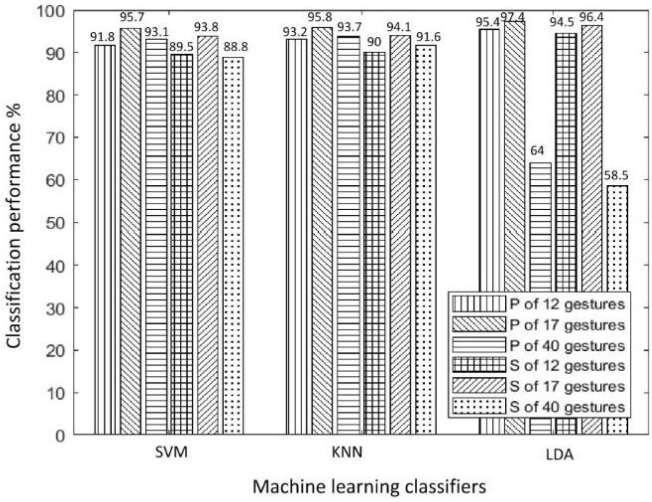

Figure 5. Classification performance for three classifiers based on three exercises A, B and (B+C)

It is noticed that the LDA classifier outperforms other classifiers for classifying 12 and 17 gestures. However, the LDA classifier weakens the classification accuracy when the number of gestures is increased. The KNN classifier achieves high classification performance for classifying 40 gestures compared to other classifiers. Obviously, increasing the number of gestures reduces the accuracy of classification. However, the performance of SVM and KNN is slightly affected compared to the LDA classifier. This confirms that the SVM and KNN classifiers are more powerful than the LDA classifier at classifying a lot of gestures.

3.3. Experiment 3: comparison with the existing literature works

The comparison with previous work should take into account several factors such as the number of movements to be classified, the subjects who participated in the experiments are intact or amputees, and the same dataset. The accuracy rate decreases with the increase in the number of movements. Moreover, the classification accuracy based on healthy people is usually better than that of amputees. The muscle signals of amputees are almost weak compared to healthy people which affected the classification accuracy.

In this experiment, all the previous works used DB5 with intact subjects. The same number of gestures are compared. Table 2 presents a comparison of the proposed work with existing literature works. The classification accuracy of the proposed work is significantly superior to earlier works. The considerable improvement of the proposed work is due to the integration of appropriate features and the use of EMG signals in the short term. whereas, previous works used long-term signals.

Table 2. Comparision of the proposed work with previous works

Model	Comparison with previous work using DB5		
	Author	No. of gestures	Accuracy (%)
TL CNN	Côté-Allard *et al.* [17]	18	68.98
LCNN	Wu *et al.* [14]	12	71.66
		17	61.4
Stacking ensemble learning	Shen *et al.* [18]	40	72.09
SVM	Pizzolato *et al.* [13]	41	69.04
LDA	This study	12	94.58
LDA	This study	17	96.47
KNN	This study	40	91.63

4. CONCLUSION

In this study, short-term hand gestures were recognized. Each EMG signal in the DB5 consists of several gestures, each of which is repeated six times. The long-term signals of DB5 are divided into several short-term signals. The short-term signal represents the muscle activity of a single gesture. Eight TD features (RMS, STD, MAV, MAD, ACC, IQR, SKEW, and AR) are extracted from the short-term signals. The effect of five feature sets on the classification accuracy of three classifiers was examined. It can be concluded that the SVM and KNN classifiers are more robust than the LDA classifier in recognizing a large number of gestures. The system's accuracy is significantly influenced by the number of motions. Moreover, The results show that removing three features (IQR, AR, and SKEW) has a significant impact on classification accuracy. The accuracy rate decreases by approximately 15% at removing these features. This confirms the effectiveness of these features.

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