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Short-term hand gestures recognition based on electromyography signals

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ABSTRACT

Electromyography pattern recognition to predict limb movements can significantly enhance the control of the prosthesis. However, this technique has not yet been widely used in clinical practice. Improvements in the myoelectric pattern recognition (MPR) system can improve the functionality of the prosthesis. This study proposes new sets of time domain features to enhance the MPR control system. Three groups of features are evaluated, time domain with auto regression (TD-AR), frequency domain (FD), and time-frequency domain (TFD). The electromyography signals (EMG) are obtained from the Ninapro database-5 (DB5), a publicly available dataset for hand prosthetics. The long-term signals of DB5 are divided into short-term signals to perform short-term signals recognition. The three feature sets are extracted from the short-term signals. The results showed that the performance of the proposed TD-AR features outperformed that of the FD and TFD feature sets. The TD-AR-based discrimination performance of 40 gestures achieved a precision of 88.8% and a sensitivity of 82.6%. The integration of short-term identification with reliable features can improve classification accuracy even for a large number of gestures. A comparison with the latest works shows the reliability of the proposed work.

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1. INTRODUCTION

Recent advances in sensors and mechatronics technologies have contributed to the presence of robotics in everyday life. Dexterous prosthetic design can increase amputee's ability to perform thier life activities. However, many patients refuse to use prosthesis for varous reasons; it lacks the robustness to control hand prostheses in a real-time application, incomplete functionality, and the changes in electromyography (EMG) signal properities over time [1]–[3].

Over the past two decades, EMG pattern recognition technology has undergone extensive research to recognize human motion intent. Pattern recognition-based-system has been proposed as an approach to extracting considerable information from EMG sensors. The EMG signals are electrical neuromuscular activity obtained during muscle contraction. EMG signals are an important source of neural information that can be used for controlling prosthetic hands [4], [5]. The myoelectric pattern recognition (MPR) systems typically include pre-processing data, identifying suitable features within these signals, and then categorize them into a set of commands to drive the prosthesis. Two factors can significantly influence the discrimination performance of myoelectric pattern recognition; feature extraction, and classification [6]–[8].

Many machine learning algorithms are used for hand gesture recognition such as support vector machine (SVM) [9], [10], K-nearest neighbour (KNN), random forest [11], linear discriminant analysis (LDA) [12], artificial neural network (ANN) [13], and recently deep learning methods [14]–[16]. Features may be obtained in time, frequency scale, and time-frequency scale [17], [18]. Hudgins *et al.* [19] proposed four-time domain features that are considered a benchmark used by many researchers. The time domain features are preferred due to their reliable performance and its simple computation. However, the non-stationary of EMG signal properties over time, caused by physiological and physical changes, is a major problem in neuromuscular control. Hahne *et al.* [20] and Zhang *et al.* [21] suggested retraining the classifier in real time to reduce the non-stationary in EMG signal properties. The classifiers' parameters are updated continuously. Nevertheless, these methods rely on changing the classifier model rather than using powerful features.

Too *et al.* [22] used the pre-processed EMG data to feed to the classifier directly without feature extraction, this process can reduce computational cost. However, extracting suitable features from EMG signals can enhance the inherent properties of EMG signals. The sEMG signal of the 52 hand motions was categorized by Kuzborskij *et al.* [23]. They showed that combining the characteristics of the mean absolute value (MAV) features with Nonlinear Support Vector Machines achieved a classification accuracy approximately of 80% for 52 classes of hand motions. Hargrove *et al.* [24] and Al-Timemy *et al.* [25] used Time Domain with Auto Regression (TD-AR) features based on LDA and SVM classifiers respectively, they achieved a classification accuracy of up to 97%. However, these studies [24], [25] considered a low number of classes for recognition (i.e. 10 and 15 classes). The results of the discrimination performance in the literature vary significantly. Many parameters can influence the classification accuracy such as several movements, class balance, and whether the person is healthy or amputated.

The contribution of this paper is,

- This work presents short-term signals of Ninapro DB5. EMG signals of DB5 are long-term signals. The long-term signal contains several gestures with their repetitions. Thus, each long-term signal is divided into several short-term signals corresponding to the number of gestures. This work gives the ability to represent each gesture as short-term muscular activity. Further, this allows for the possibility to combine DB5 exercises to recognize more gesture classes.
- The short-term signals are used then for extracting useful information, a new set of time domain and frequency domain features have been proposed such as average amplitude change (AAC), root mean square (RMS), mean absolute deviation (MAD), mean absolute value (MAV), skewness (SKEW), standard deviation (SD), and interquartile range (IQR), These features are organized into three groups (TD-AR), frequency domain (FD), and time-frequency domain (TFD). The classification performance is evaluated for the three feature sets. The best feature set is evaluated for a different number of gestures.

2. MYOELECTRIC PATTERN RECOGNITION

2.1. Dataset

Myo signals are obtained from the Ninapro dataset (DB5), a publicly accessible dataset for hand prosthetics. Myo-sensor is an 8-channel with built-in noise reduction filters, dry-electrodes, and a low-sampling rate (200Hz). The recorded data is transmitted via Bluetooth. The armband allows measurements of acceleration, angular velocity, and orientation of the input axis via the built-in inertia measurement unit. In this study, only the EMG portion is used. The Myo armband is generally less expensive than other sEMG sensors. It is placed near the elbow. It is comfortable to wear and easy to use [26]. The Myo sensor may be a viable alternative to an expensive, previously used instrument. Figure 1(a) represents 8 channels of the Myo sensor, and Figure1(b) shows samples of DB5 movements used in this work.

(a) 8- channels Myo armband sensor (b) Samples movements in ninapro BD5

Figure 1. Myo armband sensor with its recorded gestures; (a) 8- channels of Myo armband sensor, and (b) Samples of Ninapro DB5 movements

2.2. Data analysis

In this study, the Ninapro DB5 dataset was used for evaluations, DB5 consists of ten subjects. The EMG signals are recorded using two Myo wearable sensors. The first Myo sensor is placed near the elbow while, the second sensor is inserted slightly below the first one, closer to the hand. The dataset has three exercises: Exercise A contains 12 basic finger movements; Exercise B contains 8 isometric and isotonic hand configurations, as well as 9 basic wrist movements, and Exercise C contains 23 grasping functional actions. Each gesture is performed for 5 sec. There are six repetitions for each gesture [16], [26], [27].

In this paper, only the EMG signals of a single Myo armband are used without the inertia measurement unit (IMU) signals. The sEMG signals of a single Myo armband is used. Each subject performed an ordered sequence of movements in a long-term sEMG signal. The long-term signals are divided into multiple sub-signals that correspond to the number of movements performed by the subject. To illustrate the process of data analysing into short-term signals, let the sEMG signal of the subject1 in DB5 of exercise B is considered. This signal is a long-term signal containing a lot of gestures with their trials (i.e. in this case, it consists of a sequence of 17 gestures, each one repeated 6 times). Therefore, the long term signal is segmented into several short-term signals corresponding to their gestures and trials (i.e. the long term is divided into 17×6 sub signals). The long-term EMG signal has an ordered sequence of movements to simulate the repetition of unconscious movements in human. Figure 2 shows the analysis and segmentation of long-term signals of Ninapro DB5.

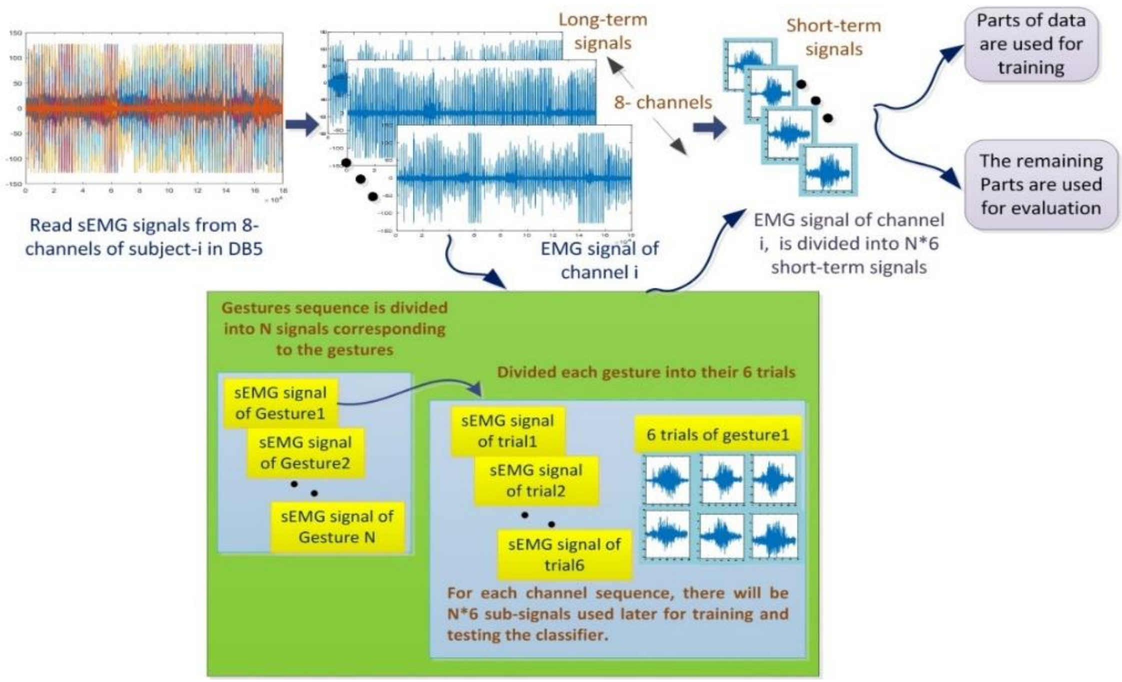

Figure 2. The schematic block diagram of obtaining the short-term EMG signals

2.3. Feature selection

Myoelectric pattern recognition control relies on extracting high-quality information from EMG wearable sensors to recognize human movement intent. Pattern recognition techniques restore a greater degree of freedom than conventional control. Since the properties of EMG signals are unstable, feeding an EMG signal directly to a classifier is impractical. therefore, extracting appropriate properties from EMG signals can effectively direct the signals to expand their information density and reduce the dimensional space [9].

A classifier discriminates the signal patterns and classifies them into their categories. Several studies [6], [10], [28] have shown that pattern recognition (PR) based control depends entirely on the selection and extraction of high-quality features. Feature selection is considered a key to improving recognition accuracy. In this study, three groups of features were presented to show their effect on improving classification performance. These feature sets are TD-AR, FD, and TFD. New combinations of features have been proposed for TD-AR, FD, and TFD. The myoelectric pattern recognition stages used in this work are shown in Figure 3.

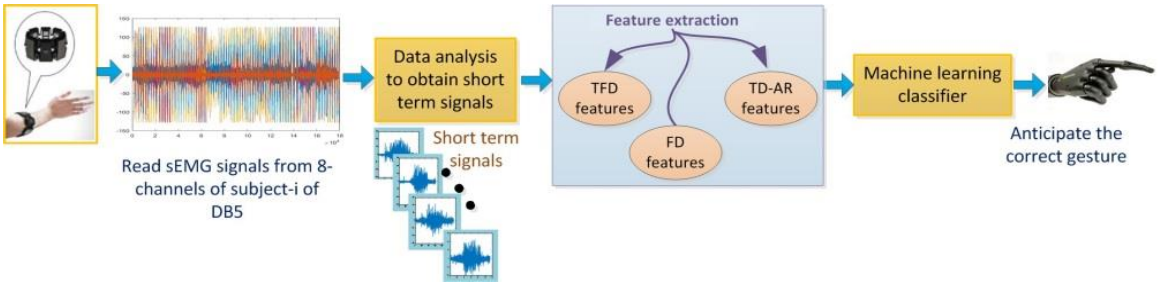

Figure 3. The stages of the overall proposed myoelectric pattern recognition system

2.3.1. Time domain with auto regression (TD-AR) features

In contrast to the strategies proposed by Hudgins [19], this work proposes a new combination of TD features that include average amplitude change (AAC), mean absolute deviation (MAD), root mean square (RMS), standard deviation (SD), mean absolute value (MAV), skewness (SKEW), and interquartile range (IQR). On the other hand, the parameters of the auto regressive (AR) model are combined with TD features to form an eight-time domain auto-regression features (TD-AR) [10], [18], [29]. The TD-AR features are extracted from the short-term EMG signals without using window techniques in order to reduce computational complexity. The mathematical expression of TD-AR features is computed,

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

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

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x_i| \tag{3}$$

x_i represents the short-term EMG signal, N denotes the sample's number of short term EMG signals. The mean absolute deviation (MAD) measures the average distance between each sample of the EMG signal and its mean value and is defined as,

$$MAD = \frac{1}{N}\sum_{i=1}^{N}|x_i - x'| \tag{4}$$

where x' represents the mean value of the EMG signal. Autoregressive model (AR) describes each sample of EMG signal as a linear combination of previous samples. The fourth order of the AR model is used and computed,

$$x_i = \sum_{p=1}^{p} a_p x_{i-p} + e_i \tag{5}$$

P denotes the AR model's order, a_p are coefficients, $x_{i-p}$is previous samples and the white noise error term is e_i. Skewness (Skew) describes asymmetry in a statistical distribution around the mean value. It is defined as,

$$Skew = \frac{M3}{M2}\sqrt{M2} \tag{6}$$

$$M_k = \frac{1}{N}\sum_{i=1}^{N}(x_i - x')^k \tag{7}$$

$$SD = \left[\frac{1}{N-1}\sum_{i=1}^{N}(x_i - x')^2\right]^{1/2} \tag{8}$$

interquartile range (IQR) parameter is computed as a difference between the first quartile Q1 (i.e. the 25th percentile) and the third quartile Q3 (i.e. the 75th percentile) of samples in EMG signal; where Q1 is the median of the first half and Q3 is the median of the second half of the samples distribution. For more details see [30]. IQR is defined as,

$$IQR= Q3-Q1 \quad (9)$$

2.3.2. Frequency domain features (FD)

The power spectral density (PSD) is used to extract the statistical properties that represent FD features. Fast Fourier transform of EMG signal is used to extract FD features. In this study, four frequency domain features are used including OHM ratio (Ω), signal to noise ratio (SNR), mean frequency (MNF), and median frequency (MDF) [29]–[31]. OHM ratio computes the spectral deformation as,

$$\Omega = \sqrt{\frac{M_2}{M_0}} \div \frac{M_1}{M_0} \quad (10)$$

where M_n is the nth spectral moment that computed as,

$$M_n = \sum P_I \, f_i^{\,n} \quad (11)$$

P_I is the power spectral density at frequency f_i. Signal to noise ratio (SNR) feature displays the ratio of the EMG signal versus the unwanted noise signal.

2.3.3. Time- frequency domain features

A discrete wavelet transforms (DWT) was applied using Haar wavelet. Five features are extracted from the wavelet at the third level. These features like waveform length (WL), mean absolute value (MAV), standard deviation (SD), zeros crossing (ZC), and variance (Var). The TFD features are computed as [18], [29],

$$WL = \sum_{i=1}^{N}(|x_i - x_{i-1}|) \quad (12)$$

$$ZC = \sum_{I=1}^{N-1}[sgn(x_i x_{i+1}) \cap |x_{i-}x_{i+1}| \geq threhold] \quad (13)$$

$$sgn(x) = \begin{cases} 1 \; if \; x \geq threshold \\ \quad 0 \; otherwise \end{cases}$$

$$VAR = \frac{1}{N-1}\sum_{i=1}^{N} xi^2 \quad (14)$$

2.4. Classification metrics

There are many machine learning algorithms used for classification. In this study, the SVM classifier is used because of its solid mathematical structure and fast training. The performance rating has been assessed using sensitivity (S), precision (P), and accuracy (ACC) metrics [2], [3], [32]. Where,

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (15)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (16)$$

$$Accuracy = \frac{TN+TP}{TN+FP+TP+FN} \quad (17)$$

where TP is true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). Some experiments are evaluated using the classification accuracy (CA) is calculated as,

$$CA\% = \frac{number\ of\ correctly\ predicted\ samples}{total\ number\ of\ testing\ samples} \quad (18)$$

3. RESULTS AND DISCUSSION

Several experiments have been performed to show the effect of classifying the short-term EMG signals based on the three feature sets. SVM classifier is trained by four trials (i.e. trials 1,3,4,6) and tested by two trials (i.e. trials 2,5). The first experiment shows the classification performance based on three feature sets. The second experiment illustrates the evaluation of the best feature set in experiment 1 on a different number of gestures. Experiment 3 presents the effect of an increasing number of training trials on classification performance. Finally, experiment 4 shows a comparison with the existing previous works.

3.1. Evaluation of the three feature sets based on the SVM classifier

In the first experiment, exercise B of the Ninapro DB5 which contains 17 gestures was used. Therefore, 102 short-term EMG signals is obtained for each channel of Myo armband. These signals corresponding to 17 gesture of exercise B. each gesture repeated 6 times. Ten subjects are used in this experiment.

Three feature sets are extracted from the resulting short-term signals; TD-AR, FD, and TFD features. The classification performance of the SVM classifier based on three feature sets is shown in Table 1. It is noticeable that TD-AR features outperform other feature sets. The improvement rate for TD-AR features compared to TFD and FD features are 0.56%, 4.95%, and 4.66% for accuracy, precision, and sensitivity respectively.

Table1. The classification performance based on TD-AR, TFD, and FD features sets

Classification performance	Feature sets		
	TD-AR	TFD	FD
Accuracy%	**98.58**	98.02	93.7
Precision%	**92.4**	87.45	53.58
Sensitivity%	**87.9**	83.24	46.9

The classification performance of 17 gestures is evaluated based on TD-AR features and averaged over ten subjects as shown in Figure 4. Obviously, precision and sensitivity vary greatly between gestures. Some of the movements are almost the same, so distinguishing them is not accurate.

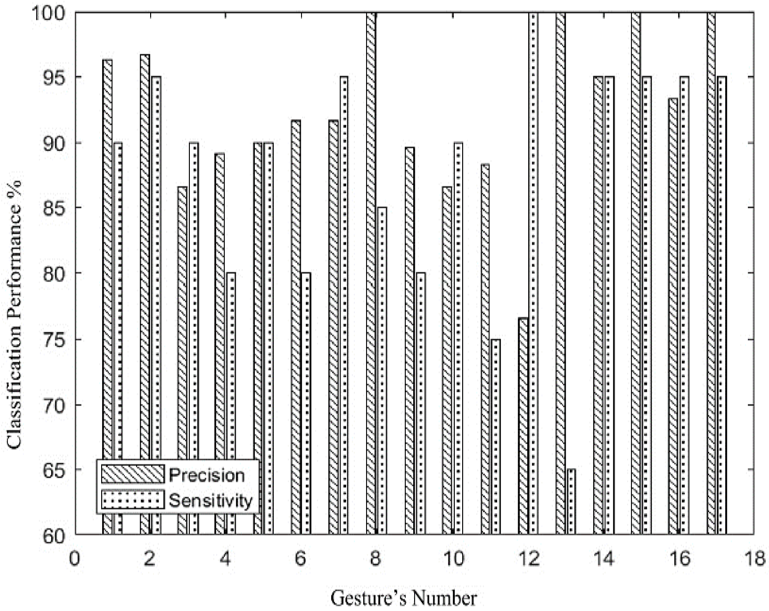

Figure 4. The performance rating of TD-AR features based on SVM classifier

3.2. Evaluating TD-AR features in three exercises with a different number of gestures

To show the reliability of the TD-AR feature set, three exercises of DB5 are used to evaluate TD-AR features with a different number of gestures. The performance rating is assessed in term of average precision and sensitivity over ten subjects. In fact, classification accuracy can be greatly affected as the number of gestures increases under the same features and classifier. Precision and sensitivity decrease when the number of gestures increases as shown in Table 2. Although exercise A contains 12 gestures which are lower than the gestures of exercise B and C, the classification performance of exercise A achieved lower precision and sensitivity compared to exercise B and C. The lower accuracy of exercise A is due the nature of EMG signals recorded, and possibly the similarity between the movements that further complicates the recognition process.

Table 2. The performance rating of TD-AR for several movment's number

Number of Gestures	Classification performance	
	Precision %	Sensitivity%
Exercise A (12 gestures)	*88.2*	*85*
Exercise B (17 gestures)	*92.4*	*87.9*
Exercise C (23 gestures)	*89.6*	*84.5*
Exercise (B+C) (40 gestures)	*88.8*	*82.6*

3.3. The effect of increasing the trials for training

This experiment demonstrates the effect of using different numbers of trials to train SVM classifier. Increasing the number of trials for training can increase the classification accuracy. However, this is achieved at the cost of increased training time and increasing the burden on the amputee. The classification accuracy of the SVM classifier for the different training trials is shown in Figure 5. It is noticed that training the classifier by two trials can achieve an acceptable classification performance equivalent to 81% and 84% for sensitivity and precision respectively. Moreover, there is a significant difference between training the classifier in one trial and two trials. The improvement rate for training the classifier by two trials is 11% and 17% for precision and sensitivity, respectively, compared to training with a single trial.

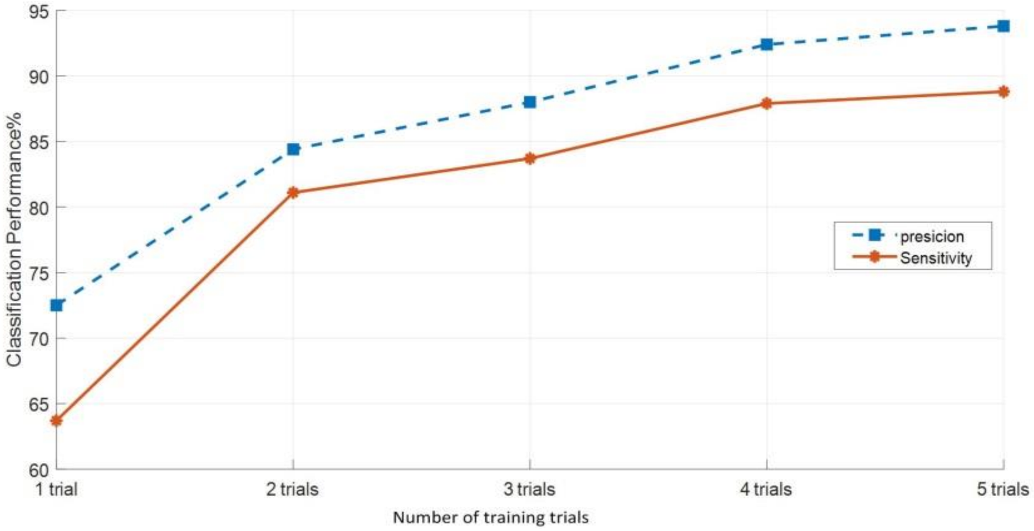

Figure 5. The classification accuracy of SVM classifier for different training trials

3.4. Comparison with the literature works

The reliability of the proposed work is achieved through comparison with recent works. The same experimental procedure is performed under the same conditions as previous works. The comparison with the previous literature works is shown in Table 3.

Table 3. Comparison of the proposed work with the existing previous works based on different number of movements

The previous work	Classification Algorithm	The Classification Accuracy		
		Exercise A 12 gestures	Exercise B 17 gestures	Exercise (B+C) 40 gestures
The proposed work	**SVM**	**85%**	**87.94%**	**82.6%**
Wu *et al.* [26]	LCNN	65%	60%	×
Pizzolato *et al.* [11]	SVM	×	×	55.31%
Shen *et al.* [15]	Stacking Ensemble Learning	×	×	58.74%

Three exercises are evaluated based on TD-AR features and compared with the latest work. This work resulted in a significant improvement in the classification rate compared to previous works. The proposed work confirms that short-term identification can achieve high classification accuracy compared to long-term identification. Moreover, the reliability of the proposed features considerably improved the performance of myoelectric pattern recognition. It is noteworthy that the best selection of features has an important role in classification performance.

4. CONCLUSION

To identify patterns in EMG signals, a variety of "classification" and "feature extraction" approaches are applied. This paper presents three feature sets to improve the performance of the myoelectric pattern recognition system. The effect of the new selection of feature sets on the classification performance is presented. Furthermore, the long-term EMG signals of DB5 are analysed into short-term signals in order to perform short-term gesture recognition based on the proposed selection of the feature set. The error rate of classifier performance is 12%, 53%, and 16.7% for TD-AR, FD, and TFD feature sets respectively. The result confirms that TD-AR features outperformed the features extracted from Fourier Transform and Wavelet Transform (WT) to predict hand movements based on EMG signals.

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