Surface Electromyographic Hand Gesture Signal Classification Using a Set of Time-domain Features

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Abstract. The surface electromyographic (sEMG) signal-based hand gesture recognition system has been widely adopted for the development of prosthetic control, robotics, and surgical systems. However, it is a challenging task to extract distinguishable features from the sEMG signal for accurate recognition of the gesture class. In this work, a set of time-domain features (SoTF) are extracted from each channel of the sEMG signal for effective recognition of the gesture class. The proposed SoTF is a combination of average, standard deviation, and waveform length features extracted from each channel. The classification accuracy using the SoTF is compared for three different classifiers such as k-nearest neighbors (KNN), support vector machine (SVM), and random forest (RF) on 52 gesture classes of NinaPro DB1 dataset. Variations in parameters of the classifiers are also analyzed to obtain the best classifier. Experimental results show that the SoTF with RF classifier achieves superior performance compared to the state-of-the-art techniques.

Keywords: surface electromyography (sEMG), time-domain features, hand gesture recognition, kNN, SVM, random forest

1 Introduction

Surface electromyography (sEMG) is the study of muscle activity based on the analysis of the electrical signals generated from the human skin surface using electrodes. A collection of signals are generated by all the muscle fibers of a single motor unit which is termed as motor unit action potential. The electromyographic signal is the aggregation of motor unit action potentials which are picked up by the sensor electrodes. Therefore, sEMG signals are the collection of information about the human hand gestures, movement of limb, and human intension [1]. EMG signals have a wide variety of applications [2–4] such as musculo-skeletal system, hand gesture recognition, interpretation of sign languages, prosthetics, biometric systems, human machine interactions etc.

Hand gesture recognition (HGR) is an important way to convey the information between deaf and dump people. It is also used as a human machine interface, robot control and in many more applications due to the advantage of high flexibility and user-friendliness [5]. But the performance of a HGR system depends on the sensor used for data acquisition, the feature extraction technique and the classifier. Several sensors are used by the researchers to acquire the raw input data. These sensors are data glove, vision-based sensor, sEMG sensor etc. The data glove is more accurate and robust but the user feels uncomfortable on wearing the glove. The vision-based sensors are very popular sensors due to its comfortability as there is no requirement to wear any device on the users hand. However, it's performance is affected by the complex environment and skin color noise [6]. In the past few years, the HGR using sEMG signals have gained popularity in the research society as they are physiological signals closely related to human motion. The advantages of the sEMG systems are its low cost, and portability.

In recent years many researchers have proposed novel feature extraction techniques and have developed several classifiers to recognize the gesture class using the sEMG signals. Some researchers have proposed several time domain features [7, 8] such as mean absolute value, waveform length, standard deviation and variance etc. and some frequency domain features [9] such as discrete wavelet transform, short-time Fourier transform etc are also proposed in the literature. From the several literature survey, we concluded that the performance of the recognition system mainly depends on the classification accuracy and the distinguishable features between the gesture classes in a dataset. Therefore in this work, a set of time-domain features (SoTF) is proposed for the recognition of gesture classes using the sEMG signal.

The contributions in this work are as follows:

- A set of time-domain features such as average, standard deviation, and waveform length (denoted as SoTF) are proposed to recognize the hand gesture using sEMG signals.
- Implementation of three classifiers such as kNN, SVM, and RF for the recognition process using the proposed SoTF feature.
- The performance of the recognition system is evaluated on publicly available 52 gesture classes of NinaPro DB1 dataset. In this study, exercise-wise the recognition performance of NinaPro DB1 dataset is also analyzed.

The rest of the paper is organized as follows. The recent works on SEMG based hand gesture are described in the Section 2. The methodology of the proposed work is discussed in Section 3. The Ninapro DB1 dataset, validation techniques, and detailed experimental results and discussions are presented in the Section 4. Section 5 concludes the paper and provides future scope of the work.

2 Related Works

In this section, a literature survey on recent existing techniques for the recognition of hand gestures using S-EMG signals along with their limitations is described below. Several features such as mean absolute value (MAV), marginal discrete wavelet transform (mDWT), histogram (HIST), waveform length (WL), cepstral coefficients (CC), short-time fourier transform (STFT) and variance (VAR) were proposed by Atzori *et al.* [7] for the recognition of sEMG-based hand gesture signal. The combination of features were classified using four different classifiers, namely support vector machine (SVM), multi-layer perceptron (MLP), k-nearest neighbors (kNN) and linear discriminant analysis (LDA). Several of the feature-classifier combinations achieved a similar accuracy of around 76% for the NinaPro DB1 database. The authors found that advanced features like mDWT did not have any advantage over simpler features like MAV or WL. A feature combination of root mean square (RMS), HIST, mDWT and time domain statistics (TD) were put forward by Atzori *et al.* [9]. The features were analysed individually as well as in combinations using four classifiers, kNN, SVM, LDA and random forest(RF). The highest classification accuracy of 75.32% was obtained using all the feature combination and RF classifier on NinaPro DB1 dataset. Pizzolato *et al.* [10] applied the same set of features on two classifiers SVM and RF to compare six acquisition setups. The DB1 dataset in both the classifiers performed the best when trained with the combination of all the four features. The random forest classifier performed better than SVM giving an accuracy of 64.45%. Modified versions of the classifiers that are based on extreme learning machines (ELM) were introduced by Cene *et al.* [8]. A feature combination of RMS, Variance (VAR), MAV and Standard Deviation (SD) were used. The reliable version of the standard ELM and regularized ELM, which are S-ELM and R-RELM produced accuracies of 73.13% and 75.03% respectively on NinaPro DB1 dataset. A model combining long short term memory (LSTM) with multi layer perceptron (MLP) to incorporate temporal dependencies along with the static characteristics of the sEMG signal was designed by Y.He *et al.* [11]. The model on being evaluated on the NinaPro DB1 database produced an accuracy of 75.45%. Subsets of the NinaPro database consisting of 12 finger gestures and 8 isometric and isotonic hand gestures have been evaluated separately by Du *et al.* [12] and Saeed *et al.* [13]. [12] achieved an accuracy of 75% for the 12 finger gestures and 76% for the 8 hand gestures using random forest while [13] achieved an accuracy of 85.41% for the 12 finger gestures and 76% for the 8 hand gestures with a feature combination of MAV, ZC, SSC and WL using random forest classifier. Similar methods have also been evaluated on other sub-databases of NinaPro. Li *et al.* [14] has used a combination of MAV, RMS and difference absolute standard deviation value (DASDV) giving an accuracy of around 68% for SVM and kNN classifiers on DB5 dataset. Several combinations of RMS, MAV, WL, slope sign change (SSC), integral absolute value (IAV), zero crossing (ZC), mean value of square root (MSR), maximum amplitude (MAX) and absolute value of the summation of square root (ASS) have been experimented by Zhou *et al.* [15] producing an average accuracy of 84% using random forest on DB4 dataset. In this work, SoTF are proposed to recognized the hand gesture signals.

3 Methodology

The major steps to be followed for the recognition of gesture classes using sEMG signal is shown in Fig. 1. These steps are data acquisition, feature extraction, and classification. In data acquisition, the 10 channel sEMG signal is acquired using the MyoBock sensor. Then the time-domain features are extracted from each channel and finally, they are concatenated to represent a gesture class which is denoted as set of time-domain features (SoTF). The SoTF is classified using three different classifiers to find the best classification accuracy.

3.1 Data acquisition and pre processing

The sEMG signals have been taken from the NinaPro Database [7]. The gesture classes in the database are discussed in subsection 4.2. Ten active double differential OttoBock MyoBock 13E200 sEMG electrodes are used to acquire sEMG signals. The electrode output is an amplified, bandpass-filtered and root mean square rectified version of the raw sEMG signal. The amplification factor is set to 14000 and the two filter cut off frequencies are at 90 Hz and 450 Hz. The electrodes acquire data at a frequency of 100 Hz [7].

3.2 Proposed SoTF

Features are extracted from each of the 10 channels of the sEMG signal corresponding to a gesture. Time domain features are used here since they are quick and easy to implement [16], [13]. The three time-domain features extracted from the sEMG signals are average (AVG_{1-10}), waveform length (WL_{1-10}), and standard deviation (SD_{1-10}).

Average It is the sum of all the signal amplitudes a_i in an interval with N points.

$$AVG = \frac{\sum_{i=1}^{N} a_i}{N} \tag{1}$$

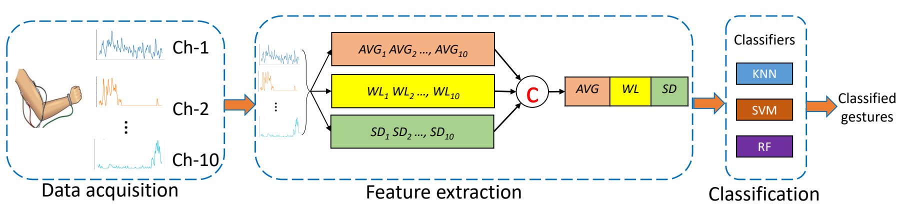


Fig. 1: Framework of the proposed sEMG-based hand gesture classification system.

Waveform Length It is the sum of the absolute differences between two adjacent samples in an interval with N points.

$$WL = \sum_{i=1}^{N-1} |a_{i+1} - a_i| \tag{2}$$

Standard Deviation It is the measure of variation of the signal values from the mean value $\overline{a}$ in an interval with N points.

$$SD = \sqrt{\frac{\sum_{i=1}^{N-1} |a_{i+1} - \overline{a}|}{N}} \tag{3}$$

The three features are concatenated to form a SoTF.

3.3 Classification

Three different classification models are used in this work. They are, kNN, SVM and Random Forest

K-Nearest Neighbor (kNN) kNN is a supervised machine learning algorithm that identifies the new data point as belonging to the majority class among its K nearest neighbors [17], [18]. In this work we have used the Euclidean distance to compute the nearest neighbors.

Support Vector Machine (SVM) SVM is a supervised machine learning algorithm that finds an optimal hyperplane that can separate the classes efficiently. Various kernels can be chosen based on the type of data to be classified. Since rbf kernel is suitable for classifying a non linear dataset in high dimensional space, it is chosen as the kernel [19]. An rbf kernel-based SVM is used when the similarity between points in the transformed domain is gaussian and is given by the equation [4].

$$rbf(a, b) = exp(-\frac{(a-b)^2}{\gamma^2}) \tag{4}$$

where γ determines the training time and is related to the number of support vectors. a and b are two vectors in the input space. The regularization parameter C decides the extend of miss classification that is allowed. More the value of C, lesser is the allowed miss classification.

Random Forest (RF) RF is a supervised machine learning algorithm that classifies the data based on the majority votes from N uncorrelated decision trees that together make up the larger random forest [18], [20]. It does not require the data to be normalized and is suitable for handling large data. It can perform well even with missing data and does not face over-fitting issues as it cancels out the bias on averaging all the predictions.

Fig. 2: 52 gesture classes of the NinaPro DB1 dataset [7]. (a) 12 basic finger movements and 8 isometric and isotonic hand configurations; (b) 9 basic wrist movements; (c) 23 functional and grasping movements.

4 Experimental Evaluation And Results

4.1 Experimental setup

The experiments were performed with an Intel(R) Core(TM) i5-9300H CPU @ 2.40GHz on a 64 bit operating system with 8GB RAM. The programming was carried out in spyder (Python 3.8) integrated development environment (IDE).

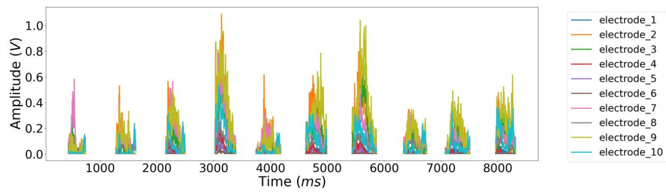
4.2 NinaPro DB1 Dataset

The NinaPro DB1 dataset is a collection of 52 hand gestures which are repeated 10 times by 27 subjects. Five seconds are spent performing each repetition, followed by three seconds of rest. The gestures are classified into three exercises. First exercise consists of 12 basic finger movements and 8 isometric and isotonic hand configurations. Second exercise comprises of 9 basic wrist movements while the third exercise includes 23 functional and grasping movements as shown in Fig. 2 [7].

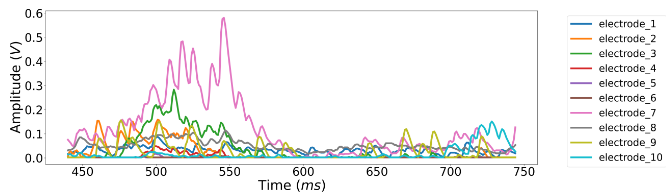
4.3 Experimental Method

As an initial step, the data needs to be properly represented for easy access. Each subject's sEMG signals are available as separate folders in the database. Each exercise file is stored in a separate mat file within each subject folder. For simplicity, the entire data is represented gesture wise in a single file. The data within the single file is arranged in such a way that the signals of all the repetitions of all subjects for the first gesture is followed by those for the second

(a)



(b)



(c)

Fig. 3: (a) Gesture pose of the dataset 'Gesture 1' [7], (b) Extracted signal for all the 10 repetitions of Subject 1, (c) Extracted signal for first repetition of Subject 1.

gesture. Now each of the repetitions are filtered out for feature extraction. Fig. 3 shows the signal extracted for the first gesture. The individual features extracted from the sEMG channels and SoTF are given to three different classifiers to compare the performances. The obtained features are of different scales which affects the modeling process and hence need to be standardized. On standardizing, the mean and the variance are converted to 0 and 1 respectively. 80% of this data is randomly chosen for training the classifiers while the rest 20% is used for testing [21].

4.4 Results and discussions

In this work, a set of time domain features (SoTF) have been proposed that can categorize different hand gestures based upon the sEMG signals from the forearm. To choose the best classifier for the SoFT, the classification accuracies are compared using kNN, rbf SVM and random forest classifiers. Fig. 4(a) offers the accuracies obtained for kNN classifier with varying number of neighbours (K). On classifying the sEMG signals based on waveform length, standard deviation and average features individually, they reach a maximum accuracy of 64%, 59% and 69% respectively at K=3. The SoTF gives a maximum accuracy of 82% at K=3. The accuracies obtained for SVM classifier with varying regularisation parameter (C) are shown in Fig. 4(b). Classification based on individual features,

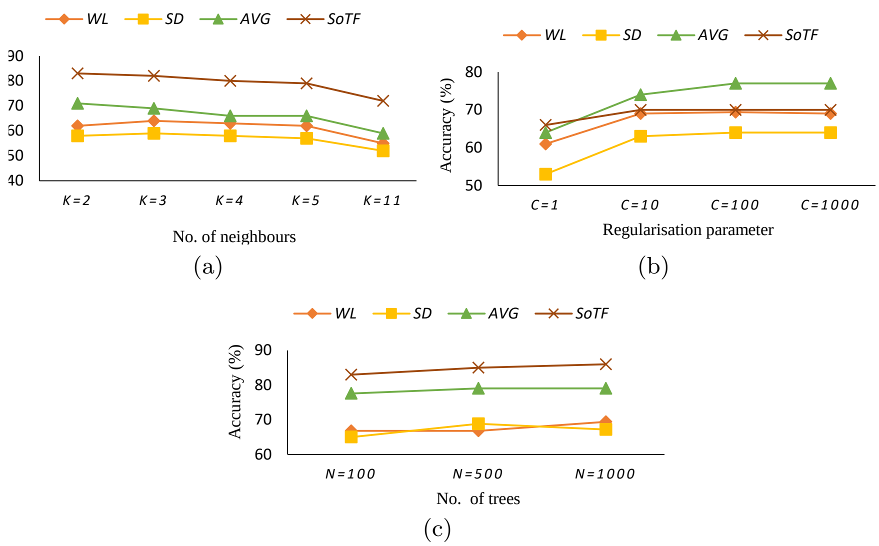
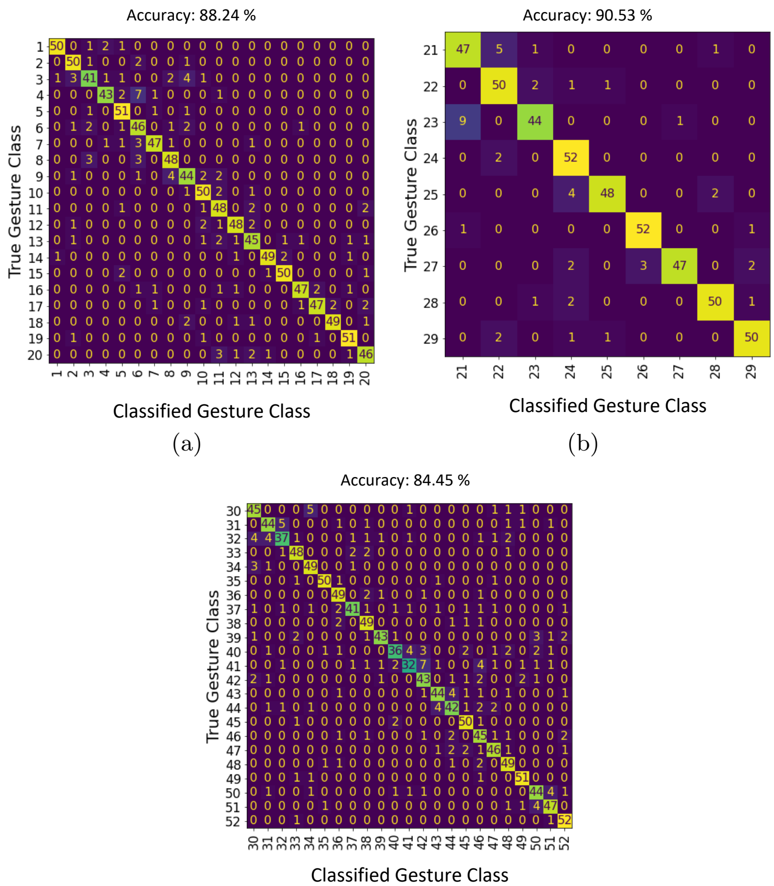


Fig. 4: Parameter study of different classifiers. (a) Classification accuracy obtained on varying the number of neighbors K in kNN classifier, (b) Classification accuracy obtained on varying regularization parameter C in SVM classifier, (c) Classification accuracy obtained on varying the number of trees N in RF classifier

waveform length, standard deviation and average features achieve maximum accuracies of 69%, 64% and 77% respectively at C=100. A maximum accuracy of 70% is achieved for the SoFT at C=10. Fig. 4(c) shows the accuracies obtained for random forest classifier with varying number of trees (N). A maximum accuracy of 69.08%, 67.3%, 79.05% and 86.07% are obtained on classifying the sEMG signals based on waveform length, standard deviation, average features and SoTF respectively at N=1000. The best accuracies obtained with the SoTF are presented in Table 1 along with the exercise wise accuracies obtained for the three classifiers at their best parameter values. The random forest achieves an accuracy of 86% which is the best among the three classifiers.

Fig.5 shows the confusion matrix obtained for the SoTF for each exercise. We can see that there are several gestures that show miss classification. Gestures in exercise 3 have more number of miss classifications than those in 1 and 2. Gesture 4 (middle finger extension) from exercise 1 is misclassified as gesture 6 (ring finger extension). Nine of the test samples of gestures 23 (Wrist supination with rotation axis through little finger) are classified as gesture 21 (Wrist supination with rotation axis through middle finger). Ball grasping gestures 40, 41 and 42 belonging to exercise 3 which are three finger, precision sphere and tripod respectively show the highest misclassification in exercise 3 due to their high similarity. Also, gesture 32 (large diameter) gets misclassified as gesture 30 (small



(a) (b) (c)

Fig. 5: Exercise-wise confusion matrices of the proposed SoTF with RF classifier on NainaPro DB1 dataset (a) Exercise 1, (b) Exercise 2, (c) Exercise 3

diameter) and 31 (fixed hook). The misclassification in the gestures is due to the activation of the same muscles due to similarity in gestures. Table 2 compares the classification accuracy of the proposed method with existing methods in literature. Furthermore, Table 3 compares the classification accuracy of 12 finger gestures and 8 isometric and isotonic hand gestures separately.

5 Conclusions

This paper has introduced a set of time domain features (SoTF) to classify 52 hand gesture classes of sEMG signals. The proposed SoTF is able to generate a distinguishable feature for each gesture class. Three different classifiers, namely

Table 1: Best accuracies (in %) obtained for the SoTF using three classifiers for each exercise

Exercise	**Classifiers**		
	kNN ***(K=3)***	**SVM** ***(C=1000)***	**RF** ***(N=1000)***
1 (20 gestures)	86	73	88.24
2 (9 gestures)	91	74	90.53
3 (23 gestures)	81	69	84.45
All (52 gestures)	82	70	86

Table 2: Comparison of classification accuracies obtained for the proposed SoTF with existing methods on 52 gestures of the NinaPro DB1 database

Author	**Feature**	**Classifier**	**Accuracy (%)**
Atzori *et al.* [7]	*WL*	kNN	73
Atzori *et al.* [7]	*WL*	SVM	75
Atzori *et al.* [9]	*RMS, mDWT*	kNN	65
Atzori *et al.* [9]	*MS + TD + HIST + mDWT*	RF	75
Pizzolato *et al.* [10]	*RMS + TD + HIST + mDWT*	SVM	60
Pizzolato *et al.* [10]	*RMS + TD + HIST + mDWT*	RF	65
Cene *et al.* [8]	*RMS + VAR + MAV + SD*	R-RELM	75.03
Y.He *et al.* [11]	-	LSTM + MLP	75.45
Proposed work	*SoTF*	kNN	82
Proposed work	*SoTF*	SVM	70
Proposed work	*SoTF*	RF	86

Table 3: Comparison of classification accuracies obtained for the proposed SoTF with existing methods on a subset of NinaPro DB1 Database

Author	**No. of gestures**	**Feature**	**Classifier**	**Accuracy (%)**
Du *et al.* [12]	12	-	RF	75
Saeed *et al.* [13]	12	*MAV + ZC +SSC + WL*	LDA	85.41
Proposed work	12	*SoTF*	RF	87.65
Du *et al.* [12]	8	-	RF	76
Proposed work	8	*SoTF*	RF	88.42

kNN, SVM and RF are implemented using the SoTF feature. Various parameter studies is presented to develop the best classifier using the proposed feature. The experimental results show that a recognition accuracy of 86% is achieved using the SoTF and RF classifier on 52 gesture classes of NinaPro DB1 dataset which is superior than the earlier reported techniques. The exercise-wise recognition performance of the benchmarked dataset is also analyzed using the proposed feature. The confusion matrix results show that the confusion among the gesture classes of exercise 1 and exercise 2 are less compared to that of exercise 3. Therefore, the performance of exercise 3 gesture classes are limited. In future work, deep learning technique with the current system may be introduced to overcome the above limitation.

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