Robust Hand Gesture Identification Using Envelope of HD-sEMG Signal

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ABSTRACT

Electromyography (EMG) pattern recognition has been used for different applications such as prosthesis, human-computer interaction, rehabilitation robots, and many industrial applications. In this paper, a robust approach has been proposed for High Density - surface EMG (HD-sEMG) features extraction by using envelopes of HD-sEMG signals. HD-sEMG signals have been recorded by a two-dimensional array of closely spaced electrodes. The recorded signals have been memorized in three datasets of CapgMyo database were employed to ensure the robustness of our experiment. The results display that the spatial features of Histogram Oriented Gradient (HOG) method combined with intensity features have achieved higher performance for Support Vector Machine (SVM) classifier compared with using classical Time-Domain (TD) features for the same classifier.

KEYWORDS

HD-sEMG, EMG pattern recognition, electrodes array, SVM classifier, spatial features component, HOG approach.

1 INTRODUCTION

Artificial limbs have been presented about 60 years ago, but amputee's acceptance for these limbs still low [1]. According to the survey performed about using the prosthesis by patients, 28% of patients are classified as prosthesis refuses, they may use prosthesis no more than a year [2]. The recent researches report that three reasons for rejecting the myoelectric prostheses: first, the non-intuitive control for the patient; second, the incomplete functionality, and feedback from the prostheses are insufficient [3,4].

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The EMG signals are stochastic in nature; also, many factors can Significantly influence the characteristic of the EMG signal and consequently the performance of EMG pattern recognition. These influences appear due to changing the signal over time, shifting the locations of electrodes, the muscle fatigue, inter subject variation, and variation in muscle contraction intensity [5,6].

Controlling the degree of freedom (DOF) of the prosthesis is still limited. This restriction essentially depends on the control strategies of a myoelectric prosthesis. One of this strategy is conventional control that uses the amplitude of EMG signal from muscle's pair for controlling one DOF. Hence for more DOF, amputees required to achieve more contraction to change prostheses mode, accordingly, non-intuitive control can be used to solve this problem. Pattern recognition technique reduced this limitation by direct mapping the human movements to prosthesis function by extracting features of multi-channel EMG signals and then classify these features into several gestures [2,3,7].

Two techniques are used to measure EMG signals. First, the electrode are placed precisely over the muscles (i.e. this is called sparse multi-channel). Second, electrodes are arranged in an array over specific muscle area such as EMG armband (i.e. electrodes organized in a single row) and HD-sEMG electrodes (high-density surface electromyography). HD-sEMG electrodes are arranged in the two-dimensional array with closely spaced electrodes. Its total number of electrodes are ranged from 32 [8] to over 350 [9]. While the EMG armband is limited by 16 electrodes as the maximum number [10].

Saponas [11] employ EMG armband at the forearm with eight channels. SVM classifier was presented to recognized 18 gestures that divided into 4 subsets (consisting of 4 to 8 classes each). Recognition accuracy reached from 78% to 95%. Saponas [12] investigate performance over cross session evaluation for different days use the wireless armband. Amma [13] introduced Naïve Bayes classifier for baseline recognition system using HD-sEMG array of 192 electrodes. Amma acquired sets of 27 gestures with accuracies reached 90 %. He showed that the best performance can be obtained when the number of electrodes increased over 100 electrodes. Stango[14] presented robust performance of classifier to electrode shift using spatial features of HD-sEMG array with accuracy 95% for 9 movements.

The HD-sEMG data recorded is allowed in both temporal and spatial domain. This leading to analyze EMG information using an image processing technique. Two methods can be used for analyzing HD-sEMG signals; instantaneous images and HD-sEMG map. The instantaneous image was established from the RawssEMG signals such that the number of pixel in the instantaneous image corresponds to the number of electrodes. Geng in [15,16] used the instantaneous image as an image classification problem and classified gestures by deep learning method, a simple majority voting is further used to enhance the recognition performance. Geng was achieved higher recognition accuracy reached 99.5%. Roja [9] proposed HD-sEMG map using three electrode array corresponds to 350 channels. Features extracted from five HD-sEMG maps by mean shift method and combined with five intensity features of these maps. Its classifier achieved higher performance with precision was 97.5% and sensitivity was 97.4%.

In this paper, envelop of HD-sEMG signals will be used which features are extracted by combination of Histogram Oriented Gradient algorithm (HOG) features and intensity features of Average HD-sEMG map. The resultant features denoted as AIH features. These features were employed for the classification of multiple hand movements of prostheses using the SVM classifier. The experiments and results proved the usefulness of spatial distribution of HD-EMG maps over the muscle. Our experiment was compared with the methods introduced by both Geng [16] and Roja [9].The paper is organized as follows: in section 2, gestures recognition has been described and study the required tools for this task. In section 3, the simulation of SVM classifier by MATLAB has been performed to test the accuracy of using proposal HD-sEMG features extraction algorithms. The final section contains the conclusions and discussions.

2 HD-sEMG PATTERN RECOGNITION

2.1 HD-sEMG Signal Acquisition

To ensure robustness and generalization of EMG pattern recognition, multiple dataset will be employed.

The Ninapro (noninvasive adaptive prosthesis) consists of (10-16) EMG channels with seven datasets at “http://ninapro.hevs.ch” which corresponds to spares electrodes. The HD-sEMG dataset contains Csl-hdemg dataset that records 6500 trails of 3s muscle For our system, CapgMyo will be used including its three sub-datasets. DB-a consists of 8 gestures obtained from 18 subjects. DB-b includes the same gestures of DB-a but produced from 10 subjects. Each subject participates in two sessions of the different day. DB-c contains 12 gestures acquired from 10 subjects.

The acquired HD-sEMG data were preprocessed using band-pass filtered at 20-380 Hz and sampled at 1000 Hz. Each gesture recorded ten trials for each subject. For each trial, the channel recorded 1000 samples of instants. HD-sEMG channels organized in a quadrature grid of closely spaced electrodes covering a muscle area as shown in Fig. 1.

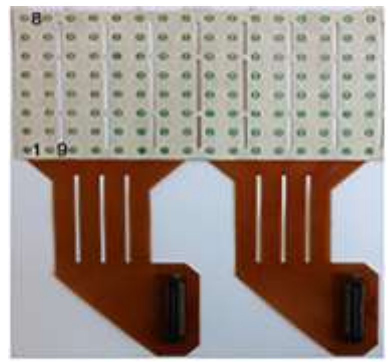

Figure 1: The form of HD-sEMG electrodes arranged as (16*8) electrode arrays [16].

2.2 Feature Extraction

Our study divided into two experiments, each experiment used SVM classifier to classify multiple gestures through three datasets based on two different feature sets (features extraction by AIH, and classical TD features respectively). Comparison between the performances of two experiments achieved. Moreover, our proposal compared with Rojas[9], Geng[16] that used the HD-sEMG map and instantaneous image for analyzing EMG signals respectively. Schematic representation of two experiments were shown in Fig. 2.

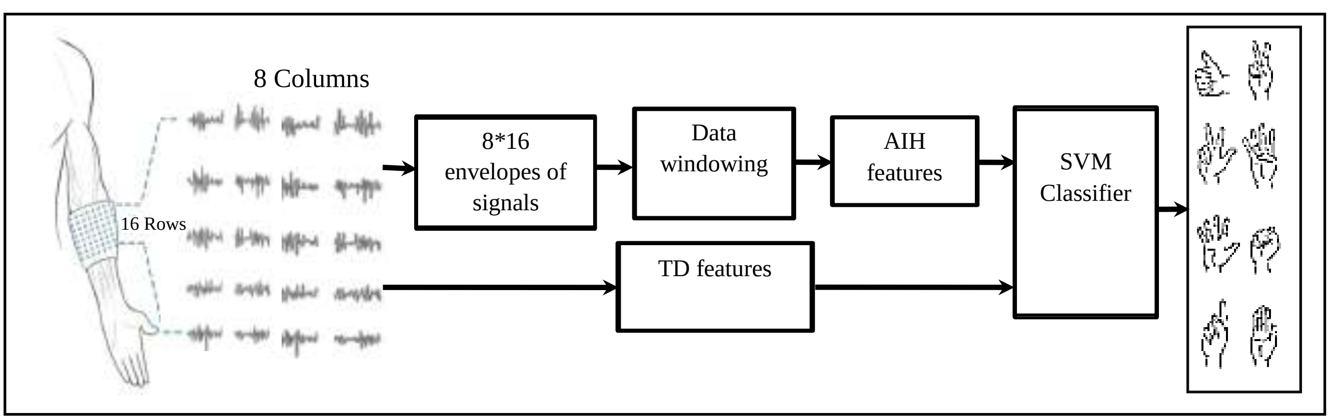

Figure 2: Schematic representation of SVM classifier based AIH, TD features.

In the first experiment, AIH features have been employed for HD-sEMG signals recognition. For each subject, envelopes of HD-sEMG signals are calculated for all channels by the preprocessing procedure, and then the features are extracted from these envelopes. Accordingly, envelopes of 128 signals are evaluated and formed as an array of 8*16 corresponding to electrodes positions. Envelopes of signals are segmented into a non-overlapping window has a length of 200 ms where there are many studies of myoelectric pattern recognition were suggested window length to be 150 ms – 200 ms [17].

HD-sEMG map is the spatial distribution of intensities of the active motor unit over the muscle. sEMG - map or sEMG – topography was proposed for medical application. Each pixel in map corresponds to RMS value of a channel at location (i,j) of 2D array electrodes.

The segmented HD-sEMG map was calculated for each segmented window as [18]

$$SM_{i,j} = \sqrt{\frac{1}{N}\sum_{n=0}^{N} EMG_{i,j}^{2}(n)} \tag{1}$$

$EMG_{i,j}$is segmented envelope of signal of i,j channel, SM is segmented map of envelope window at location i,j, N corresponds to samples number in each envelope window of sEMG signal. Accordingly, an average segmented map was obtained as

$$ASM_{i,j} = \frac{1}{M}\sum_{m=1}^{M} SM_{i,j} \tag{2}$$

Where M relates to number of non-overlapping window, $ASM_{i,j}$ is average segmented map located at (i,j) channel.

The intensity feature was calculated as common logarithmic of average segmented map [18,19].

$$I = \log_{10}\frac{1}{N}\sum_{i,j} SM_{i,j} \tag{3}$$

where I is the intensity features.

The average segmented map can be considered as an images of size 8*16 whereas each pixel corresponds to channel. Hence, the problem of hand gesture can be reframed as the problem of image classification. HOG algorithm is an efficient feature extraction technique. Consequently, intensity features concatenated with HOG features of average segmented map to form AIH features. AIH feature extraction algorithm is shown in Fig. 3.As depicted by the flowchart there are three main parts; signals manipulation that considered in the first three blocks of Fig. 3. This part consists of calculating envelop signal of 128 channels each of 1000 samples. Then segmented each envelop signal into 5 frames of 200ms windows length. The second part is computing HD-sEMG map for each window by equation (1). Then the average segmented map was calculated for five frames according to equation (2). In feature extraction part, reframe the average segmented map to 8*16 that corresponds to electrode locations and extract spatial features by Hog method and combined with Intensity features computed by equation (3) to obtain AIH features.

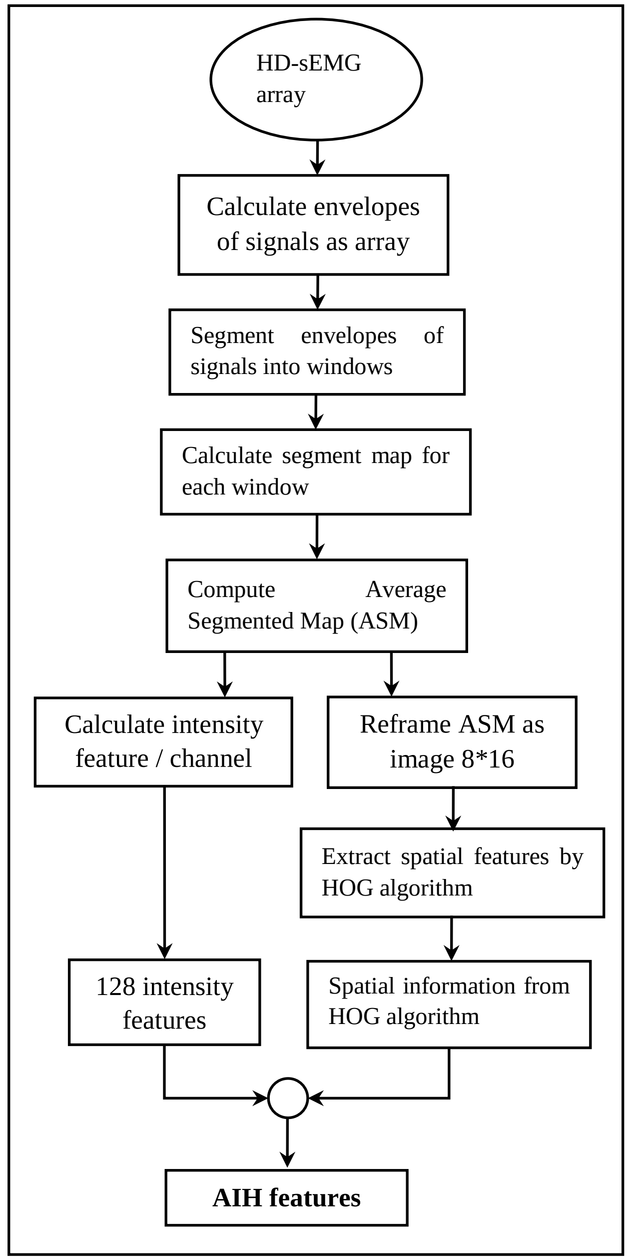

Figure 3: AIH feature extraction algorithm.

In the second experiment, TD features were used for HD-sEMG signals classification which five features were extracted from HD-sEMG signals of each channel. These features are zero crossing (ZC), Root Mean Square (RMS), Mean Absolute Value (MAV), waveform length (WL) and Variance (Var). These features are calculated as [20,21].

$$RMS = \sqrt{\frac{1}{M} \sum_{m=1}^{M} z_m^2} \tag{4}$$

$$MAV = \frac{1}{M} \sum_{m=1}^{M} |z_m| \tag{5}$$

$$WL = \sum_{m=1}^{M} |z_{m+1} - z_m| \tag{6}$$

$$ZC = \sum_{m=1}^{M-1} \left[\operatorname{sgn}(z_m * z_{m+1}) \cap |z_m - z_{m+1}| \geq thrashold \right] \tag{7}$$

$$\operatorname{sgn} = \begin{cases} 1 & z \quad \geq threshold \\ 0 & otherwise \end{cases}$$

$$VAR = \frac{1}{M-1} \sum_{m}^{M} z_m^2 \tag{8}$$

2.3 Criterion of the Classification Performance

Fast training and ease of implementation have prompted the use of SVM classifier. In order to achieve an honest assessment of the true accuracy of our classifier, ten-fold cross-validation was used. Whereas, the data set is divided into ten portions or "folds". One fold is designated as the validation set, while the remaining nine folds are all combined and used for training.

The performance of classifier was evaluated in term of sensitivity (S), Precision (P) and Accuracy (ACC) as [22,23]

$$\left. \begin{aligned} S &= \frac{T_P}{T_P + F_N} \\ P &= \frac{T_P}{T_P + F_P} \\ Acc &= \frac{T_N + T_P}{T_N + F_P + T_P + F_N} \end{aligned} \right\} \tag{9}$$

where

T_P (true positive) is the number of samples that were classified properly to a specific class.

T_N (true negative) is the number of samples that does not pertain to a definite class and were not categorized to that class.

F_N (false negative) is the number of samples pertaining to a specific class but erroneously classified into another class.

F_P (false positive) is the number of samples not pertaining to a definite class but incorrectly classified into that class.

3 SIMULATION AND RESULTS

HD-sEMG signals recorded by 2D array of electrodes arranged in 8*16 matrix with 1000 samples. For each trial envelopes of signals were evaluated for all channels. SVM classifier based on AIH features was trained for 70% of trials and tested on remaining 30%. Our first experiment applied for three datasets of CapgMyo to ensure the robustness of our proposal for different datasets. DB-a, DB-b consists of 8 gestures, DB-c has 12 gestures. DB-b consists of two session. However, the second session was used for the evaluation.

Table I displays the performance of SVM classifier based on AIH features, it was averaged between five subjects in term of means and standard deviation.

Table (I): The accuracy, precision and sensitivity of SVM classifierfor three datasets.

Datasets	The performance of SVM classifier		
	Accuracy %	**Precision %**	**Sensitivity %**
DB-a	100 ± 0%	100 ± 0%	100 ± 0%
DB-b	99.15 ± 1.27%	97.5 ± 4.5%	96.6 ± 6%
DB-c	99.5 ± 0.83%	98.75 ± 2.8%	97.5 ± 6.2%

As noted in Table I, SVM classifier has higher performance for DB-a compare with other Datasets. Moreover, the performance of SVM for DB-c outperform from that for DB-b although DB-c has 12 gesture compared with 8 gesture for DB-b. Whereas the augment the number of movement can affect the recognition accuracies of classifier.

In experiment 2, the performance of SVM classifier based on AIH features compared with TD features as shown in Fig. 4. The comparison was performed in term of precision and sensitivity for three datasets. As noted AIH, considerably outperform TD features. This is explicit in average precision and sensitivity of DB-a (100%, 100%, 98.7%, 98.3% for AIH, TD features respectively); for DB-b (97.5%, 96.6%, 94%, 94% for AIH, TD features respectively) and for DB-c (98.75%, 97.2%, 96.8%, 96.6% AIH, TD features respectively). It can be noticed that using spatial features for gesture recognition improves the performance of classifier.

Moreover, SVM classification based on AIH features can train with lower time reached to 0.754 sec compared with SVM classification based on TD features that have good average accuracy but required more time which reaches to 164.3 s for training. The average processing time has measured by the personal computer has an Intel Core i7 CPU, 2.6 GHz, and 6 GB memory.

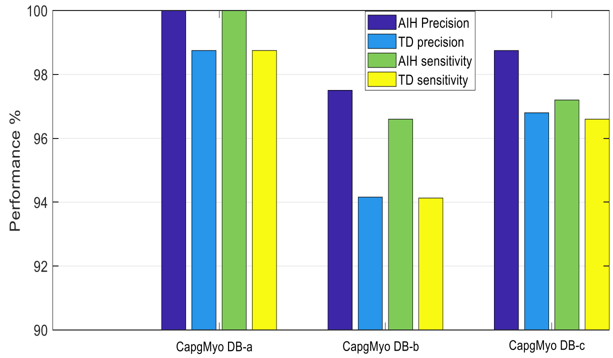

Figure 4: The performance of SVM classifier in term of precision and sensitivity based on AIH, and TD features respectively for three sub Databases.

Reducing the number of trials for training the classifier leads the performance has slightly degenerated. Therefore, the SVM classifier based on AIH features has been trained for the different number of trials as shown in Fig. 5. It can be observed that accuracy of classifier training for three subjects over three trials were 98.4%, 96.8%, 93.7% respectively with average accuracy 92.9%, which was an acceptable accuracy for three-trial training. Whereas the training for single trials attained minimum performance of 91.4 %.

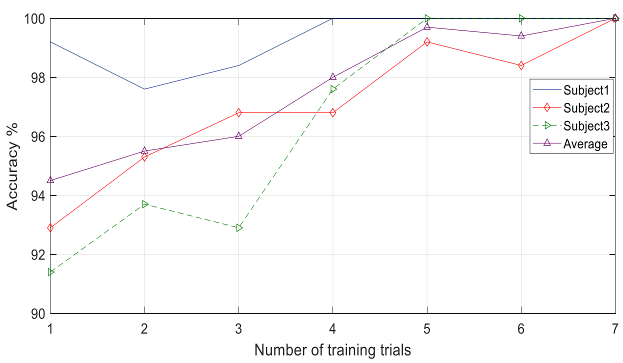

Figure 5: Recognition accuracy based different number of training trials.

Our results of the first experiment were compared with the results of both Geng [15,16] and Roja [9]. Geng has used the same database of our study, which employed the deep learning to classify the instantaneous images by simple majority voting over 40 to 150 frames to enhance the recognition accuracies. Geng has used 50% trails for training (corresponding to odd trials) and 50% for testing (corresponding to even trials) accordingly our experiment changed to be familiar with the latest work [16]. Hence, for each subject, SVM classifier was trained by using 50% of trials and tested by the remaining half of the trials. Table (II) illustrates the comparison between the results of our experiments and Geng results [16].

Table (II):Comparison of SVM classifier results based on AIH with the previous study [16].

Datasets	Performance	Our study	Geng[16]
DB-a	Acc	99.5 ± 0.8 %	99.5%
	P	98.45 ± 3.46%	
	S	98 ± 3.3%	
DB-b	Acc	99.18 ± 1.67%	98.6%
	P	97.9 ± 4.6%	
	S	98 ± 4.45%	
DB-c	Acc	98. 8 ± 1.4%	99.2%
	P	95.8 ± 8.7%	
	S	93 ± 11.2%	

As noted From TABLE II, our results was altered from Table I this is due to change the training sets to 50% of trials rather than 70% of TABLE I. Consequently, the number of trials that used for training and testing can affect the performance of the classifier. Furthermore, TABLE II displayed the comparison of our first experiment with Geng [16]. As can be seen, the same accuracies using DB-a for recognition eight gestures. While slight differences for DB-b, DB-c whereas our proposal achieved an accuracy of 99.18 % for DB-b with improvement 0.58% than the previous study [16]. In other word, the latest work [16] outperform our proposal for DB-c with improvement 0.4%.

Geng in [16] compared his results with conventional classifiers such as SVM but he was showed that SVM classifier achieved not well performance with recognition accuracy 18%. Whilst our SVM classifier was achieved results with high performance with respect to approaches of the previous study [16] (D-Ba, 99.5%; DB-b, 99.18%; DB-c, 98.8%).This indicate that the choice of features to be extracted is more important than the choice of classifier.

Roja [9] has created a dataset by achieved several experiments which are different from our database. He has computed the activation map for five muscle through three electrodes array of 192 channels. Features were extracted by mean shift method and concatenated with five intensity features corresponds to five activations map. As a result, LDA classifier used to recognize 12 gestures corresponds to four motion type with three effort levels. Our intensity features are calculated for each channel to obtain 128 intensity features. While Rojas was computed intensity features for activation map to get five intensity features. Roja's experiment has been done for eight subjects, therefore, our experiment extended to ten subjects with the same training and testing set as Rojas [9] (i.e The classifier was trained using the first seven trials and used the remaining three trails for testing). The performance evaluated in term of precision and sensitivity averaged between ten subjects of our approach, which the comparison is shown in TABLE (III).

TABLE 3 has introduced the precision and sensitivity results of all gestures recognition, which are averaged between ten subjects in term of mean and standard deviation. Our experiments were used DB-c to be familiar with 12 gestures as Roja [9]. As noticed from TABLE 3, the average precision of our results achieved 98.2% with an improvement of 0.7%, than Roja [9], on the other hand, the average sensitivity of latest work [9] outperform our results by 0.4%.

TABLE (III): Comparision between the precision and sensitivityof roja [9] and our aih approach for 12 gesture recognition averaged between ten subjects and presented in term of mean and standard deviation.

Gestures	Rojas [9]		Our results	
	Precision%	Sensitivity %	Precision %	Sensitivity %
G1	99.9±0.3%	98.2±2.8%	97.5±7.9 %	93.3± 21%
G2	97±3.1%	98.7±1.1%	100±0%	100±0%
G3	98.6±1.1%	97.7±2.9%	100±0%	100±0%
G4	99.6±1.1%	99.7±0.6%	100±0%	96.6±10%
G5	97.5±2.1%	97.4±3.4%	95±10%	100±0%
G6	98.2±2.9%	97.7±2.3%	100±0%	96.6±10.5 %
G7	99±0.2%	99.7±0.5%	97.5±7.9 %	96.6±10.5 %
G8	96±5.1%	95.2±7.1%	100±0%	96.6±10.5 %
G9	95.4±6.3%	96.6±4.9%	100±0%	96.6±10.5 %
G10	99.4±1.1%	99.8±0.2%	94.28±18 %	100±0%
G11	93±11.3%	93.8±12.3 %	97.5±7.9 %	93.3±14%
G12	94.2±11.9 %	93.7±11.9 %	96±12.6%	93.3±21%
Average	97.5±3.9%	97.4±4.2%	98.2±5.4 %	97±9%

4 DISCUSSION AND CONCLUSION

In this paper, robust recognition for HD-sEMG signals has been achieved. HD-sEMG signals have extracted by the two-dimensional array of closely spaced electrodes which it did not required exact position of muscle as sparse electrodes. Further HD-sEMG electrodes have significantly augmented the size of data. Our proposal was AIH features related to combined of H features and intensity features, whereas, these features extracted from the envelopes of the HD-sEMG signals. In addition, TD features have been used for gesture recognition in which five features computed for each channel RMS, MAV, ZC, WL, VAR. The gesture recognized using SVM classifier based features sets. Moreover, three dataset were used to demonstrate the efficiency of AIH. Our proposal reported that spatial features have a significant impact on classifier type selection with respect to achieve good performance. SVM classifier based AIH features have good results compared with classifier based TD features(i.e. the performance of SVM classifier in term of precision and sensitivity based AIH features outperform TD features with improvement for DB-a 1.3% , 1.7% respectively, for DB-b 3.5%, 2.6% respectively, and for DB-c 1.95%, 0.6% respectively). Accordingly, this offered that the choice of features has an important effect on the performance of the classifier.

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