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RESEARCH PAPER

Adaptive Myoelectric Pattern Recognition Based on Hybrid Spatial Features of HD-sEMG Signals

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Abstract
Myoelectric pattern recognition is a useful tool for identifying the user's intended motion. However, the inherent non-stationary properties of Electromyography (EMG) signals usually limited the use of real time commercial prostheses. These variations cause the degradation of myoelectric control performance and make it unstable over time, across subjects and sessions. In this study, this challenge is overcome by combining the use of robust spatial features and the supervised adaptive learning method to improve the myoelectric performance. Three types of spatial features are proposed based on histogram oriented gradient (HOG) algorithm and intensity features namely H, HI, and AIH features. H features correspond to extracting HOG features from the HD-sEMG map. HI feature is obtained by concatenating the H features with scalar intensity feature that calculated from HD-sEMG map. Finally, the hybrid AIH features are produced by combining the H features with the intensity features matrix (AI) that obtained from the segmented maps. Three sub-databases are used for evaluation. The proposal feature sets are compared with time-domain (TD) and a combination of intensity and center of gravity features (ICG) to show the powerful of these features. The offline results report the superiority of the classifier's performance in term of precision and sensitivity based on AIH features than other feature sets (i.e. H, HI, TD, ICG) with improvement 4.1%, 3.5%, 2.24%, 5.3% and 6%, 5%, 2.2%, 6.9% respectively. The adaptive classifier based on AIH features outperforms adaptive myoelectric control based on other feature sets and the original version. The adaptive classifier utilized testing data that update the original dataset which in turn has a significant effect on improving the myoelectric performance in the presence of the variation of EMG signal properties.

Keywords EMG signal classification · Myoelectric pattern recognition · HD-sEMG · Real time classification · Spatial features extraction · SVM classifier · Adaptive myoelectric control

1 Introduction

Myoelectric control techniques have been used for controlling the upper limb prosthesis. Regardless of the non-stationary of EMG signals and its statistical properties over time, it is considered as an important input for controlling the prosthesis. It contains rich information about the muscle. EMG signals are generated by muscle tissue using non-invasive electrodes that placed on the skin (Campbell et al. 2020; Hui et al. 2018). Myoelectric control system can be categorized as pattern recognition techniques and conventional control techniques. Conventional control systems allow patient to control single device in an on-off mode like an elbow or hand. The conventional control systems are limited to their degree of freedom (i.e. prosthetic's functions). While, Myoelectric Pattern Recognition techniques (MPR) are used for controlling more dexterous prosthesis. Moreover, various features are extracted from EMG channels rather than conventional control that depend on the EMG amplitude. MPR controls more prosthetic's functions intuitively (Parajuli and Sreenivasan 2019; Edwards and Hebert 2015).

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In the last decades, pattern recognition techniques are motivated many researchers to control the prosthetics hand. Myoelectric pattern recognition technique depends on recorded and pre-processed the EMG signals, identifying the suitable features then classifies them into sets of commands (Phinyomark et al. 2013). Although there are different classifiers can be used for gestures classification such as Artificial neural networks (ANN) (Ahsan et al. 2011), linear discriminate analysis (LDA) (He et al. 2012), support vector machines (SVM) (Gu et al. 2018) and deep learning techniques (Wei et al. 2019), many researchers concur that the classification's performance is not considerably depend on classifier algorithm (Hargrove et al. 2007; Zhang and Zhou 2007). Contrarily, the choice of convenient and robust features is a big challenge.

Multiple feature sets are employed to improve the classification performance such as time domain (TD) (Scheme and Englehart 2014), frequency domain (FD) (He et al. 2014), time frequency domain (TDF) features (Al-Timemy et al. 2016) and recently the spatial features that extracted from HD-sEMG signals (Zhang et al. 2019). Spatial features appeared with the growth of HD-sEMG techniques. HD-sEMG electrodes are several channels used for recording EMG signals that organized in two dimensional array with closely spaced electrodes. Stango et al. (2015) used HD-sEMG signals to classify 9 motions using an array of 192 electrodes. Spatial Variogram features are used to reduce the effect of shifting electrodes' locations.

HD-sEMG data can be analysed in two techniques; HD-sEMG map (topological map) (Nougarou et al. 2019; Jaber et al. 2020) and instantaneous image (Scheme and Englehart 2014). Geng et al. (2016) used instantaneous image with the powerful of deep learning technique to classify hand gestures. The instantaneous samples are used as a feature vector. Amador et al. (2019) used instantaneous image with LDA classifier. Image features extraction is used by dividing the instantaneous image into blocks. Jordanic et al. (2017, 2016) used spatial features extracted from HD-sEMG map to reduce the effect of long term identification and muscle fatigue that influences the robustness of the Myoelectric pattern recognition.

Although many researchers was achieved a good performance for the myoelectric pattern recognition, their experiments was employed in offline analysis (Amador et al. 2019; Jordanic et al. 2017, 2016). However, the implementation of the classification techniques in real time conditions is not reliable and robust because of the variation of EMG signals over time which in turn deteriorates the performance of myoelectric pattern recognition. The main reasons of the variability of EMG signals include physiological changes (i.e. muscle fatigue) or non-physiological changes (i.e. electrodes shift, impedance variations) (Kyranou et al. 2018). To overcome this problem, various solutions have been employed such as choosing robust feature set (Jordanic et al. 2016; Jaber and Rashid 2019), selecting special training protocols (Hargrove et al. 2008) or using adaptive learning methods (Spanias et al. 2016; Sensinger et al. 2009; Huang and Yang 2017; Liu et al. 2017). Adaptation can be presented in two categories; supervised manner (Spanias et al. 2016; Sensinger et al. 2009) and unsupervised manner (Huang and Yang 2017; Liu et al. 2017). The adaptive classifier guarantees the robustness of the classification accuracy by responding to the changes in the testing information through the retraining process (Sensinger et al. 2009).

In this paper, three types of spatial features are proposed based on histogram oriented gradient (HOG) algorithm and intensity features namely H, HI, and AIH features. H features correspond to extracting HOG features from the HD-sEMG map. HI feature is obtained by concatenating the H features with scalar intensity feature that calculated from the HD-sEMG map. Finally, the hybrid AIH features are produced by combining the H features with the intensity features matrix (AI) obtained from the segmented maps. Three sub-databases are used for evaluation. The proposal feature sets are compared with time-domain (TD) and a combination of intensity and center of gravity features (ICG) to show the powerful of these features. The offline results report the superiority of the classifier's performance in terms of precision and sensitivity based on AIH features than other feature sets (i.e. H, HI, TD, ICG). The adaptive classifier based on AIH features outperforms adaptive myoelectric control based on other feature sets and the original version. The adaptive classifier utilized testing data that update the original dataset which in turn has a significant effect on improving the myoelectric performance in the presence of the variation of EMG signal prosperities.

The main contribution of this study is

1. Combined the robust spatial features with the adaptive learning to overcome the variability of EMG signals over time and across sessions. Three spatial features are proposed using histogram oriented gradient method and intensity features. These features are evaluated in offline and online phases. A comparison with conventional and spatial features are made to show the powerful and robustness of our proposed features.
2. Proposed supervised adaptive classifier that utilized the test data to update the original dataset continuously. Accordingly, the classifier is retrained after each online testing stream by the updated dataset. A certain amount of samples (i.e. correctly predicted samples) are added to the original dataset after each online stream. The proposed adaptive classifier is considerably depending

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on the robustness of the spatial features to predict the gestures and subsequently retrain the classifier.

The rest of the paper organized as follows: Sect. 2 gives a description of gestures recognition such as experimental data, features extraction and classification. Section 3 tackles the simulation of SVM classifier based different feature sets. Both intra and inter session evaluation are implemented. Finally a conclusion is introduced.

2 Gestures Recognition

2.1 HD-sEMG Database

Three sub databases in CapgMyo are used in this work (Du et al. 2017a, b). The electrodes were arranged in two dimensional array in the form of 8×16 matrix. The EMG signals were sampled at 1 kHz and pre-processed by Band pass filter at 20–380 Hz. DB-a consists of 8 gestures acquired from 18 subjects in single session. DB-b has the same gestures of DB-a, but each subject participate in two session held at separate days. DB-c consists of 12 gestures performed by 10 subjects in one session. Each gesture was repeated 10 times. The gestures of DB-a and DB-b is shown in Fig. 1.

2.2 Features Extraction

The HD-sEMG technique is increased the spatial information of the muscle activity. It is capable of analysing EMG signals in both temporal and spatial domains. The spatial domain allows the potential of using the image processing techniques (Angkoon and Erik 2018).

HD-sEMG map is used for analysing HD-sEMG signals. HD-sEMG map is calculated using root mean square (RMS) or other feature extraction that depend on amplitude such as mean absolute value (MAV) and waveform length (WL) for individual channels that organized in two dimensional array. In this work, HD-sEMG map is calculated as root mean square (RMS). The signal of each channel is divided into several non-overlapping windows. The length of window is chosen to be 200ms (as suggested by many pattern recognition studies) (Smith et al. 2011). HD-sEMG map is computed for each window as segmented map (Jaber et al. 2019; Rojas et al. 2012)

$$\underset{k}{\mathrm{SM}_{i,j}} = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1}\left(\mathrm{EMG}_{i,j}\right)^2} \tag{1}$$

where $\underset{k}{\mathrm{SM}_{i,j}}$ is segmented map of window k at channel (i, j), N denotes the number of samples in the EMG window, $\mathrm{EMG}_{i,j}$ is window of EMG signal at channel i, j.

Accordingly, for each window of EMG signals, there is an equivalent segmented map. The number of segmented maps in a channel is correspond to the number of non-overlapping windows. The average map (AM) is obtained by averaging the segmented maps per channel as

$$\mathrm{AM}_{i,j} = \mathrm{mean}\left(\mathrm{SM}_{i,j}\right) \tag{2}$$

Each element of AM is obtained by averaging the segmented map at that channel. The computing of the Average Map is illustrated in Fig. 2. The average map AM is considered as an image in which each pixel corresponds to channel. Thus, the image size is corresponds to the electrodes number of HD-sEMG signals in that array. The spatial features can be used either individually or combined with other features to improve the classifier's performance. Three types of feature sets are extracted from the Average Map (AM). Histogram Oriented Gradient method is employed to extract HOG features from AM. The cell size to be used is 4×4 (Dalal and Triggs 2005). This features denoted as H features. HI features is a combination of H features and intensity features that calculated as a logarithm of the summation of all pixels in AM (Jordanic et al. 2016)

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

The scalar intensity feature is concatenated with HOG features to form HI features. The third feature sets is AIH features. The intensity features in this type is calculated in different way than Eq. (3). It is denoted as AI (i.e. average intensity). It is calculated from the segmented maps per channel as

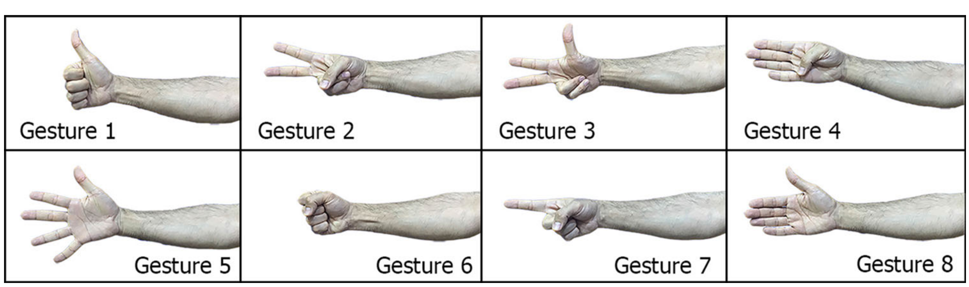

Fig. 1 The hand gestures

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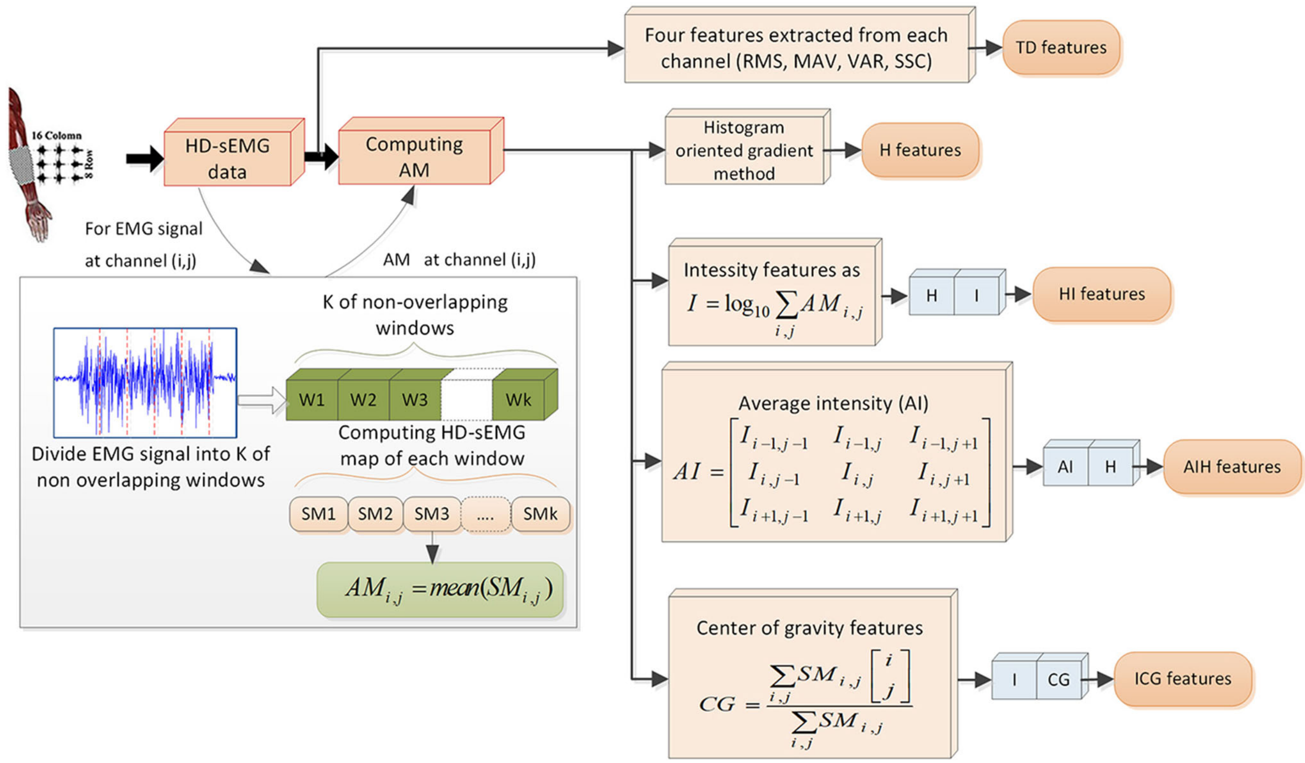

Fig. 2 The extraction of feature sets

$$I_{i,j} = \log_{10}\left[\text{mean}\left(\text{SM}_{i,j}\right)\right] \quad (4)$$

$$\text{AI} = \begin{bmatrix} I_{i-1,j-1} & I_{i-1,j} & I_{i-1,j+1} \\ I_{i,j-1} & I_{i,j} & I_{i,j+1} \\ I_{i+1,j-1} & I_{i+1,j} & I_{i+1,j+1} \end{bmatrix} \quad (5)$$

The intensity features is calculated for each channel from segmented maps at that channel. AI features represent the spatial distribution of intensity features for the channels. As a result, intensity feature matrix denoted by AI is concatenated with H features to form AIH features. AIH features considered as a hybrid of spatial features.

In order to report the powerful of the proposed feature sets, two sets of features are presented; time domain (TD) and intensity centre of gravity (ICG) feature sets. TD features are corresponds to four features extracted from each channel RMS, MAV, SSC, variance (VAR) (Chowdhury et al. 2013).

The ICG features is a combination of intensity feature that calculated by Eq. (3) combined with the centre of gravity features calculated from the segmented maps per channel as

$$CG = \frac{\sum_{i,j}\left(\text{ASM}_{i,j}\right)\begin{bmatrix} i \\ j \end{bmatrix}}{\sum_{i,j}\left(\text{ASM}_{i,j}\right)} \quad (6)$$

i, j denote channel's position of the segmented map. $\text{ASM}_{i,j}$ denote the average segmented maps at channel i, j.

The block diagram that illustrated the extraction of feature sets is illustrated in Fig. 2

2.3 Adaptive SVM Classifier

In real time application, the amputee can control the myoelectric prosthesis at certain time but cannot accommodate the changes of statistical properties of EMG signals as time moves on which in turn degraded the myoelectric system's performance. However the adaptive learning method can overcome this challenge. Adaptive classifier changes its parameter continuously by responding to the changes occur in EMG signals. In this study, the test data is utilized to update the classifier and improved its performance. Supervised adaptive method is used in which the patient's intended class is known. Initially, the baseline dataset is used to calculate the non-adaptive classifier (NASVM). The supervised adaptive classifiers (sASVM) are calculated from the updated dataset after each online testing stream. The updated data set is combined the baseline dataset and samples that correctly predicted from the testing stream. To illustrate the process, let the first online testing stream is S1 (it is consists of few samples), the initial classifier is trained by the baseline dataset. So, S1

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stream is evaluated by NASVM. The correctly predicted of S1 samples are added to the baseline data set. At the end of S1 stream, sASVM classifier is calculated by the updated dataset. For the next online stream S2, both NASVM and sASVM is used for evaluated S2 stream and again the truly classified samples are added to the updated dataset. This cycle is repeated for all the testing streams. The flowchart of supervised adaptive classifier is displayed in Fig. 3.

2.4 Classification Performance

The simple implementation and fast training of SVM classifier motivated the use of this classifier. Five different SVM classifiers are implemented in this paper according to different feature sets extracted from HD-sEMG data

- Classifier based H features.
- Classifier based HI features.
- Classifier based AIH features.
- Classifier based on TD features.

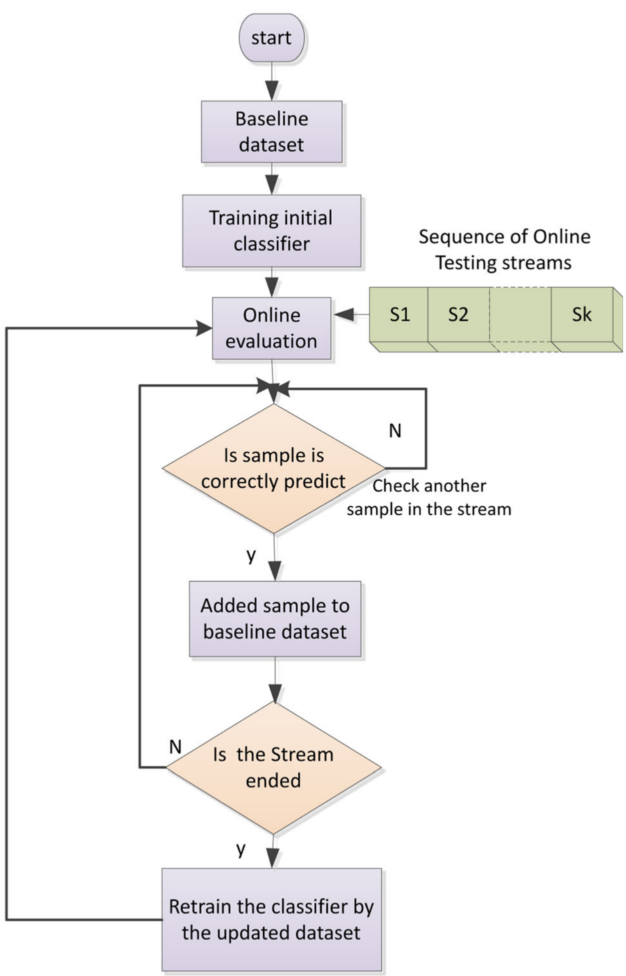

Fig. 3 The flowchart of supervised adaptive classifier

- Classifier based on ICG features.

The performance of SVM classifier is evaluated in term of Sensitivity, Precision for each gesture based on confusion matrix. The confusion matrix specifies the number of exemplars in testing data that classified as true positive (TP), true negative (TN), false negative (FN) and false positive (FP). The precision and sensitivity is defined as

$$S = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{7}$$

$$P = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{8}$$

The classification accuracy is widely used in several myoelectric control studies. In this study, it is used to assess the online stream. It is defined as the percentage of correctly predicted samples of testing data over all testing data. It is calculated as

$$CA = \frac{\text{number of correct predicted samples}}{\text{total number of testing samples}} * 100 \tag{9}$$

3 Results of Experiments

In order to validate the performance based on the three proposal feature sets, offline evaluation is introduced for intra-session and inter-session recognition. In intra-session, a part of data during a session is used for the training. While, other remaining parts that belong to the same session are used for evaluation. This case is used to investigate the long-time recognition. The inter-session recognition is required to train the classifier on a session and evaluate on another session. However, In Inter-session, the recorded EMG signals are significantly changes because of the donning and doffing of the prosthetic device that cause the deterioration of the classifier's performance.

3.1 Offline Assessment

3.1.1 Intra-session Recognition

Eight able-bodied subjects of database DB-a are used in this part. For each subject, the classifier is trained by five trails of each gesture and tested on the remaining five trails for single session. The performance of SVM classifier is evaluated based on the proposed feature sets (H, HI, and AIH). A comparison with conventional and spatial features sets (TD and ICG) are performed to show the potential of the proposed features. Tables 1 and 2 display the performance of SVM classifier based on five feature sets in term of precision and sensitivity.

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Table 1 The Precision of eight-gesture recognition by SVM classifier using five features sets (i.e. H, HI, AIH, TD and ICG)

Gestures	H features	HI features	Precision (%) AIH features	TD features	ICG features
G1	95.8 ∓ 7.7	95.4 ∓ 8.5	97.9 ∓ 5.9	95.8 ∓ 7.73	90.47 ∓ 17.8
G2	94.3 ∓ 10.9	94.3 ∓ 10.9	100.0 ∓ 0.0	100.0 ∓ 0.0	93.3 ∓ 12.44
G3	95.8 ∓ 7.7	95.8 ∓ 7.7	97.9 ∓ 5.9	97.9 ∓ 5.9	95.8 ∓ 7.73
G4	93.2 ∓ 13.7	94.4 ∓ 15.7	94.3 ∓ 10.9	91.87 ∓ 15.5	81.9 ∓ 13.4
G5	93.3 ∓ 9.26	93.3 ∓ 9.26	97.9 ∓ 5.9	92.28 ∓10.87	95.3 ∓ 13.25
G6	93.7 ∓ 8.64	95.8 ∓ 7.7	97.9 ∓ 5.9	97.9 ∓ 5.9	91.24 ∓ 12.96
G7	95.8 ∓ 11.8	95.8 ∓ 11.8	100.0 ∓ 0.0	95.8 ∓ 7.73	97.9 ∓ 5.9
G8	88.5 ∓ 20.3	91.0 ∓ 19.3	97.9 ∓ 5.9	93.73 ∓ 8.64	95.4 ∓ 8.54
Average	93.8 ∓ 11.2	94.4 ∓ 11.35	97.9 ∓ 5	95.66 ∓ 7.78	92.6 ∓ 11.5

Each gesture averaged between eight subjects and presented in term of mean and standard deviation

Table 2 The Sensitivity of eight-gesture recognition by SVM classifier using five features sets (i.e. H, HI, AIH, TD and ICG)

Gestures	H features	HI features	Sensitivity (%) AIH features	TD features	ICG features
G1	92.5 ∓ 21.2	95.0 ∓ 9.2	97.5 ∓ 7	95.0 ∓ 9.258	92.5 ∓ 10.35
G2	87.5 ∓ 18.3	87.5 ∓ 18.3	90.0 ∓ 15	95.0 ∓ 9.25	90 ∓ 15.1
G3	95.0 ∓ 9.25	95.0 ∓ 9.2	100.0 ∓ 0	100. 0 ∓ 0	87.5 ∓21.23
G4	90.0 ∓ 21.38	90.0 ∓ 21.38	95.0 ∓ 9.2	85.0 ∓ 17.72	100. 0 ∓ 0
G5	90.0 ∓ 15	90.0 ∓ 15	100.0 ∓ 0.0	92.5 ∓ 14.88	90 ∓ 21.38
G6	97.5 ∓ 7	97.5 ∓ 7	97.5 ∓ 7	97.5 ∓ 7.07	95 ∓ 9.25
G7	82.5 ∓ 19.8	87.5 ∓ 21	100.0 ∓ 0.0	100.0 ∓ 0	90 ∓ 21.38
G8	97.5 ∓ 7	97.5 ∓ 7	100.0 ∓ 0.0	97.5 ∓ 7.07	80 ∓ 18.5
Average	91.5 ∓ 14.87	92.5 ∓ 13.56	97.5 ∓ 4.78	95.3 ∓ 8.15	90.6 ∓ 14.6

Each gesture averaged between eight subjects and presented in term of mean and standard deviation

The tables exhibit the superiority of AIH features than other feature sets. It can be noticed that the performance based on AIH is improved by 2.24% for precision and 2.2% for sensitivity than that of TD features. However, a significant difference of the performance is observed based on H, HI and ICG with improvements reach to 4.1%, 3.5%, 5.3% respectively for precision and 6%, 5%, 6.9% respectively for sensitivity. Moreover, the performance of SVM classifier in term of precision based on AIH features is achieved lowest standard deviation compared with that of H, HI, TD and ICG feature sets (approximately 5% vs. 11.2, 11.3, 7.7, 11.5 respectively). Likewise, the AIH features have lowest standard deviation for sensitivity (approximately 4.78 vs. 14.8, 13.5, 8.15, and 14.6 respectively). Our results confirm that the choice of features is more important and considerably affect the classifier's performance. Moreover, the spatial features can be employed to improve the performance of simple classifier such as SVM classifier.

To show the verification of our proposed features, three sub databases of CapgMyo database is used, where DB-a consists of eight gestures, DB-b consists of eight gestures with two sessions. Accordingly, session 2 is used in this experiment while DB-c has twelve gestures. As can be seen from Figs. 4 and 5 that the performance based on AIH features achieved higher precision and sensitivity than other features for all databases. For DB-a, the performance of classifier based on AIH features is achieved an improvements reached to (5.1%, 7.5%), (4.4%, 6.5%) than H and HI features respectively. While, for DB-b the improvement of AIH is approximately the same for both H, HI features (1.3%, 5.7%, 5.5%), (1.3%, 5.5%, 5.5%) respectively. In addition, the performance of DB-c is decreases for all features compared with other databases. This is due to increase the gestures' number to 12 gestures rather than 8 gestures. Accordingly, the performance with AIH features remain have accurate performance with improvement (0.7%, 3.7%, 3.8%), (0.8%, 3.8%, 4.7%) compared with H, HI features respectively. Recognition based on AIH features achieved relative lower standard deviation compared with other features.

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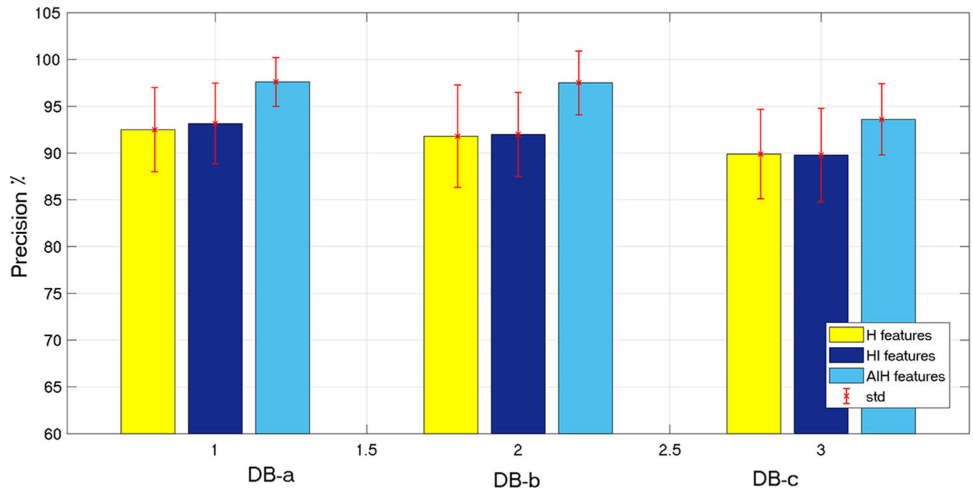

Fig. 4 The Precision of SVM classifier averaged between five subjects and presented in term of mean and standard deviation

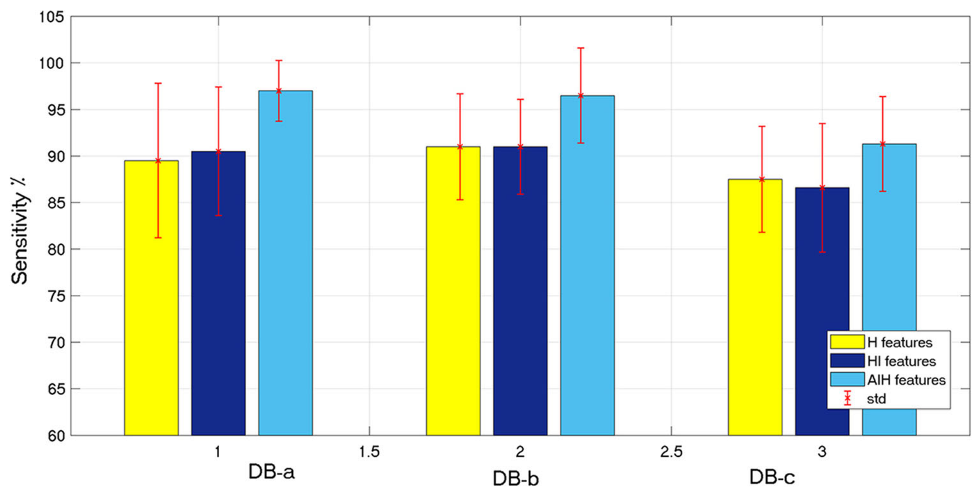

Fig. 5 The sensitivity of SVM classifier averaged between five subjects and presented in term of mean and standard deviation

Our results are compared with Geng et al. (2016), Du et al. (2017b). The researchers used the same databases. The same evaluation procedures are used (i.e. the same training and testing sets 50% for all sub databases and session2 of DB-b). The researchers used instantaneous value of HD-sEMG signals as an image to classify hand gestures. The features used for conventional classifier was the instantaneous value of EMG signals as a feature vector. The researchers compared their results with the conventional classifier such as KNN, SVM, random forest and LDA for three sub databases. Their results showed that the performance of conventional classifier such as SVM achieved relative lower classification accuracy. While, our results reported that the performance of SVM based on AIH features achieved good results with classification accuracy (CA) CA% = 97.5 for DB-a, CA% = 96.5 for DB-b and CA% = 91.3 for DB-c. HD-sEMG map is used in our study rather than instantaneous image. The comparison is shown in Fig. 6. Our results confirm that the choice of features is more important than the choice of classifier. Accordingly, simple classifier as SVM is preferable.

On the other hand, our study also compared with the previous work (Amador et al. 2019). They used instantaneous image with LDA classifier and the same databases (i.e. sub database DB-a with 18 subjects). Hence, our experiment is extended to include 18 subjects. It is observed that the performance of SVM classifier based on AIH features superior than the previous work (Amador et al. 2019). Our work has great improvement in the performance than (Amador et al. 2019) as illustrated in Table 3. Our work improved TPR to 5%, precision improved by 5.8%. Moreover, the F-Meas. improvement by 4.4%.

3.1.2 Inter-session Recognition

In this experiment, DB-b is employed. It is consists of two sessions held in two separate days. The HD-sEMG signals acquired from ten subjects. The SVM classifier is trained

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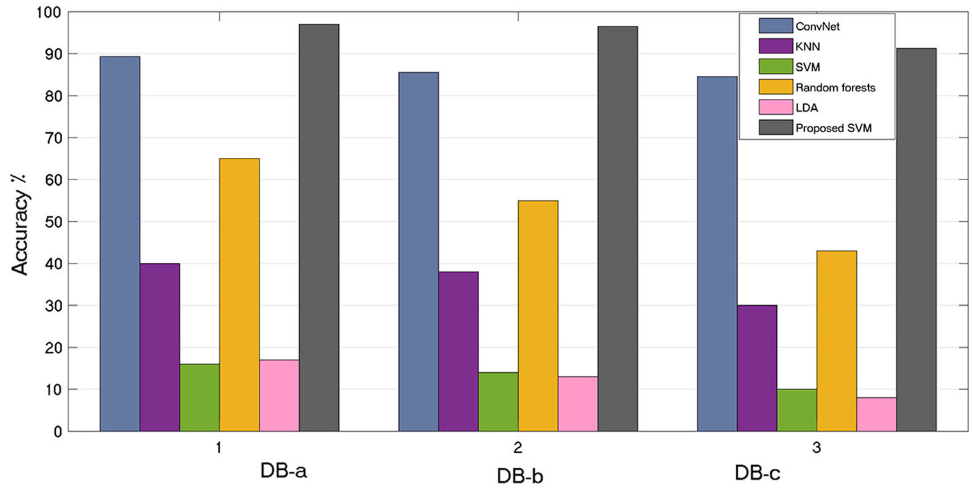

Fig. 6 The classification accuracy of hand gestures for three databases include the comparison of the previous work (Geng et al. 2016; Du et al. 2017a) and our work

Table 3 Comparison of our method with previous work (Amador et al. 2019)

	TPR	FPR	Pr.	F-Meas.
Previous work Amador et al. (2019)	0.911	0.0126	0.912	0.914
Our work	0.961	0.0055	0.97	0.958

The classifier's performance averaged between eight gestures and eighteen subjects of DB-a

by session1 and two trials of each gestures in session2 while the remaining part of session2 are used for evaluation (i.e. session1 and 20% of samples of session2 is used for the training, 80% of session2's samples is used for testing). The recorded EMG signals across sessions augment the variability of signals' properties over time. The classification accuracy of SVM classifier based on five feature sets (i.e. H, HI, AIH, TD and ICG features) is shown in Table 4

The results show the deteriorated performance based on H and HI features. While AIH, TD, ICG features remain achieved an accurate performance. AIH features outperform the other features sets for all gestures. The results report the robustness of AIH features that achieved higher classification accuracy than TD and ICG (i.e. 91.2% vs. 84.2%, 81.2 respectively) with lower standard deviation (i.e. 14.26% vs. 19.3%, 22.3% respectively). It is observed that spatial distribution of intensity features combined with HOG features has a considerable effect for discrimination of gestures compared with only HOG features or computing scalar intensity feature for the average map. Moreover, the results report the potential of intensity features of individual channel that represent the muscle activity rather than four TD features or the spatial ICG features. The intersession results report the robustness of AIH features to overcome the variability of EMG signals across sessions.

Table 4 The Classification Accuracy of SVM classifier using five features sets (i.e. H, HI, AIH, TD and ICG)

Gestures	H features	HI features	Classification Accuracy (%) AIH features	TD features	ICG features
G1	53.7 ∓ 45.28	53.75 ∓ 41.6	97.5 ∓ 7.9	90 ∓ 8.8	91.25 ∓ 15.6
G2	38.7 ∓ 35.5	42.5 ∓ 38.7	80 ∓ 19.72	80 ∓ 22.97	72.5 ∓ 21
G3	48 ∓ 51.5	52.5 ∓ 48.1	91.25 ∓ 13.24	91.2 ∓ 13.2	77.5 ∓ 28.1
G4	37.5 ∓ 34.8	51.2 ∓ 44.68	88.75 ∓ 10.9	81.2 ∓ 31.3	68.75 ∓ 28.4
G5	46.2 ∓ 35.8	62.5 ∓ 33.3	95 ∓ 8.7	88.7 ∓ 13.7	82.5 ∓ 30.7
G6	75 ∓ 34.8	73.7 ∓ 36	92.5 ∓ 23.7	81.25 ∓ 27.1	92.5 ∓ 13.4
G7	43.75 ∓ 40.5	42.5∓ 39.6	96.25∓ 6.03	95∓ 8.7	93.7∓ 8.8
G8	42.5 ∓ 36.8	47.5 ∓ 35.2	88.7 ∓ 23.89	66.2 ∓ 27.6	71.2 ∓ 32.3
Average	48.2 ∓ 39.4	53.28 ∓ 39.6	91.25 ∓ 14.26	84.2 ∓ 19.3	y81.25 ∓ 22.3

Each gesture averaged between ten subjects of DB-b and presented in term of mean and standard deviation

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3.2 Online Assessment with Adaptation

In this part, supervised adaptive classifier (sASVM) and non-adaptive classifier (NASVM) are applied for both intra-session and inter-session cases. The testing data are divided into streams. Each stream consists of one trail of eight gestures. These streams are assessed individually. NASVM as well as sASVM classifiers are trained offline, and evaluated online by sequence of the streams. After each stream, the dataset is updated. The correctly predicted samples are added to the original dataset. Accordingly, the classifier is retrained by the updating dataset.

3.2.1 Intra-session Evaluation

In this experiment, long time identification is applied. DB-a with single session is used. For each subject, the dataset is divided into ten streams such that the first three streams are used for training the classifier in offline, while the remaining seven streams are used for online evaluation. The testing streams are evaluated online for both NASVM and sASVM based on the proposal feature sets as shown in Fig. 7. It can be observed that the adaptive learning is improved the classification accuracy for all feature sets. However, the classification accuracy of sASVM based on H, HI is achieved a slight difference than NASVM. While sASVM with AIH features has significant difference than NASVM. The classification accuracy of NASVM classifier with AIH features is achieved always above 87.5% compared with 71.8 for NASVM based on H, HI features. This indicates that the improvement rate is about 16% which is a significant rate. Although the adaptive classifier based on H, HI is improved the classification accuracy, it is achieved classification accuracy above 73% which is relative lower accuracy. While, sASVM classifier is satisfied high classification accuracy and stable performance as streams move on. This confirms that updating the data set from the test sample is improved the performance of the classifier for long term identification. The proposed supervised adaptive classifier utilized a specific amount of test samples that added to the original dataset (i.e. only the correctly predicted samples). Moreover, the proposed adaptive classifier considerably depends on the powerful of feature set to correctly predict the test samples before added them to the original dataset.

3.2.2 Inter Session Evaluation

Inter-session evaluation is more practical for the application of the prosthesis since there is a time gab between recording the training and testing data. This causes a considerable variations of EMG signals' characteristics over sessions. These variations hinder the use commercial prostheses and deteriorate the performance of myoelectric pattern recognition approach. In this experiment, the SVM classifier is trained offline by session1 and 20% of session2's samples. The remaining 80% of samples of session2 is used for online evaluation as eight batches. The comparison of three feature sets AIH, TD, and ICG for both sASVM and NASVM are implemented. H and HI features are not considered in this experiment because previously in offline evaluation the performance is degraded across sessions. These features are inapplicable for inter sessions recognition. Even with adaptive learning, H and HI are not robust enough to predict the gestures. Thus the adaptive learning has a relative augmentation of classification accuracy for these feature sets. The NASVM and sASVM based three feature sets AIH, TD and ICG is shown in Fig. 8 respectively.

It is obvious that the classification accuracy of sASVM classifier is outperformed NASVM classifier for all feature sets. sASVM classifier is improved the classification

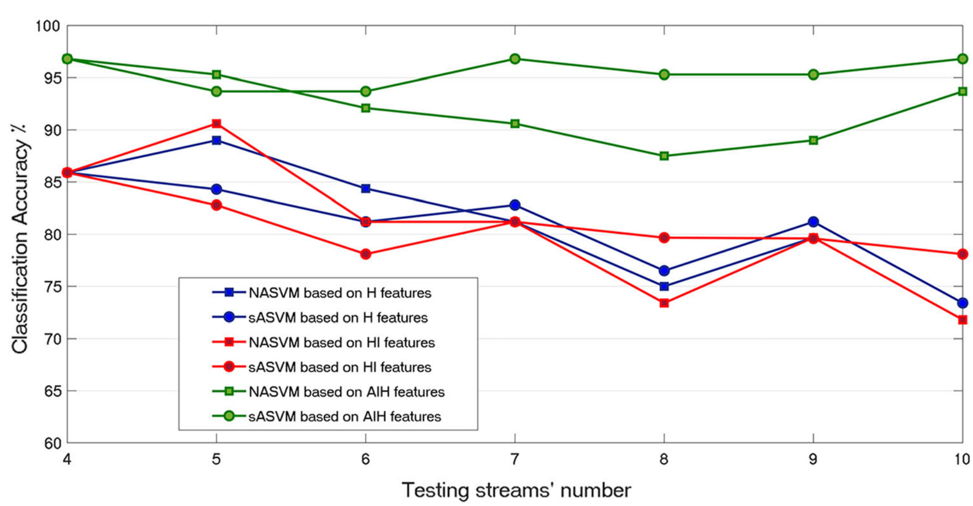

Fig. 7 Online evaluation of SVM classifier for adaptive and non-adaptive classifier based on H, HI and AIH. The classification accuracy of each testing stream averaged between eight subjects

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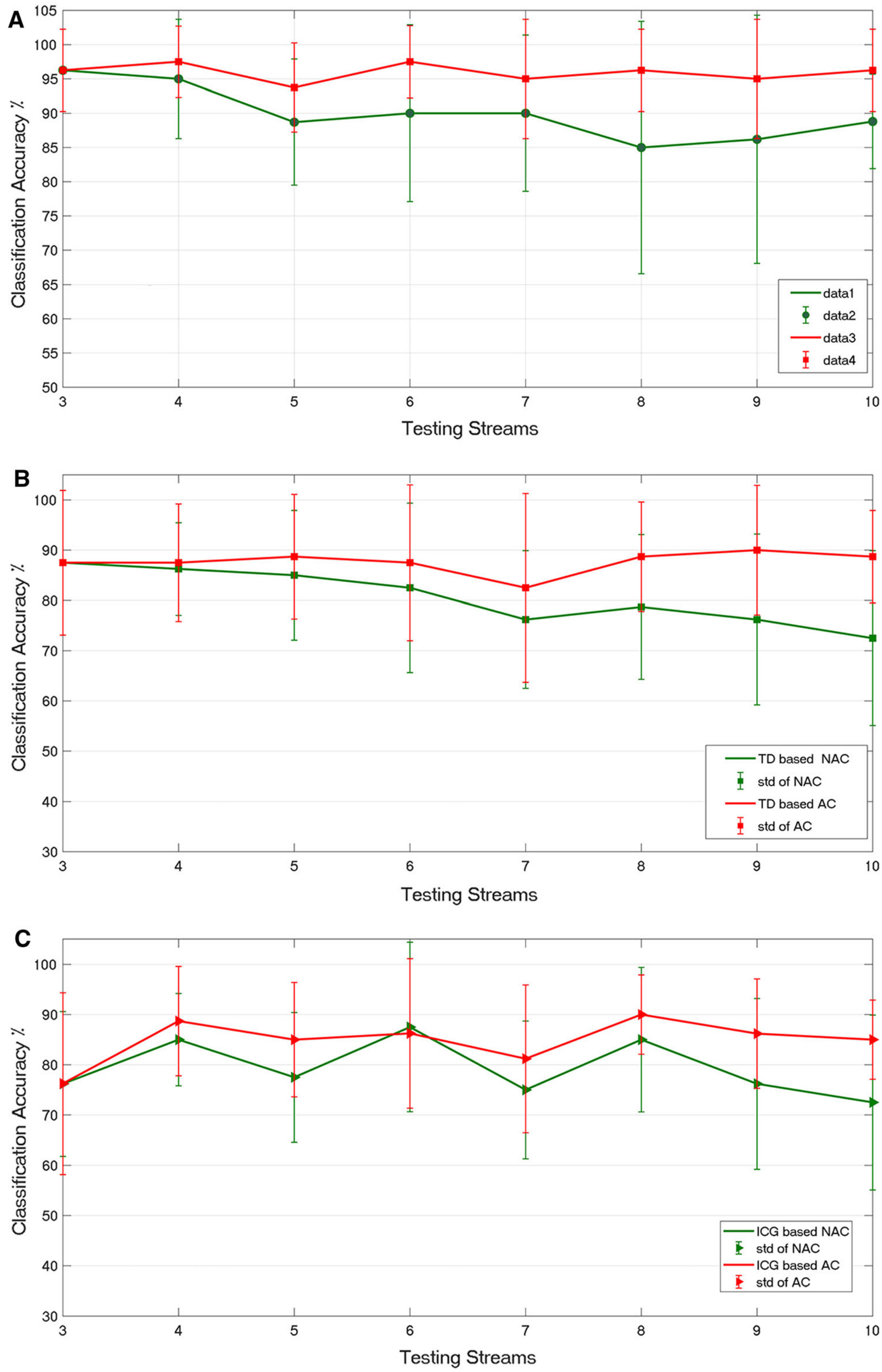

Fig. 8 Adaptive and non-adaptive SVM classifier based on **a** AIH features, **b** TD features, **c** ICG features. The classification accuracy of each stream averaged between ten subjects in term of mean and standard deviation

accuracy averaged between all streams by 7%, 5.5%, 7% than NASVM classifier based on AIH, ICG, TD respectively. Moreover, the NASVM classifier based on AIH features is fulfilled an improvement than NASVM based on TD and ICG features reach to 9.3%, 10.6% respectively. While the sASVM classifier based on AIH features is improved the classification accuracy than sASVM based on TD, ICG by 9.1%, 8.3%. Furthermore, the standard deviation is relatively reduced by adaptive classifier. The results of NASVM classifier for three feature sets report the

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robustness of AIH features between sessions than conventional and other spatial features. The spatial distribution of intensity features for individual channel has significant effect for improving the accuracy. Furthermore, the combination of adaptive classifier and robust features guarantee the improving of classifier's performance. The limitation of this work is the application of inter session is limited to only two sessions. Moreover, unsupervised adaptive learning is more applicable since amputee has no knowledge about the gestures.

4 Conclusion

The variation of EMG signals' characteristics over time and across sessions is limiting the commercialization of upper limb devices. In this paper, a combination of adaptive classifier and robust features is proposed to improve the classification performance. Three proposed feature sets are proposed (H, HI, and AIH) and evaluated in offline and online experiments with intra-session and inter-session recognitions. The proposed feature sets are compared with other conventional and spatial features (TD and ICG) to show the powerful of the proposed features. The offline experiments show the superiority of AIH features than other feature sets. The supervised adaptive classifier is exploited the test data for responding to the changes of test data across sessions and over time. The dataset is updated after each online testing stream. Accordingly, the classifier is updated its parameter by retraining from the updated dataset. The results report that the classification accuracy is improved by sASVM classifier based on AIH features than the NASVM classifier with improvement reach to 7%. Moreover, the sASVM classifier based on AIH features is improved the classification accuracy than sASVM based on TD, ICG by 9.1%, 8.3%. This work confirms that the choice of features is more important and affects the classification accuracy. Furthermore, the combination of robust features and adaptive classifier guarantee the improvement of the classification performance.

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