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Toward improved control of prosthetic fingers using surface electromyogram (EMG) signals

Rami N. Khushaba *, Sarath Kodagoda, Maen Takruri, Gamini Dissanayake

Centre for Intelligent Mechatronics Systems, Faculty of Engineering and Information Technology, University of Technology, Sydney (UTS), Broadway, NSW 2007, Australia

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A B S T R A C T

A fundamental component of many modern prostheses is the myoelectric control system, which uses the electromyogram (EMG) signals from an individual's muscles to control the prosthesis movements. Despite the extensive research focus on the myoelectric control of arm and gross hand movements, more dexterous individual and combined fingers control has not received the same attention. The main contribution of this paper is an investigation into accurately discriminating between individual and combined fingers movements using surface EMG signals, so that different finger postures of a prosthetic hand can be controlled in response. For this purpose, two EMG electrodes located on the human forearm are utilized to collect the EMG data from eight participants. Various feature sets are extracted and projected in a manner that ensures maximum separation between the finger movements and then fed to two different classifiers. The second contribution is the use of a Bayesian data fusion postprocessing approach to maximize the probability of correct classification of the EMG data belonging to different movements. Practical results and statistical significance tests prove the feasibility of the proposed approach with an average classification accuracy of ≈90% across different subjects proving the significance of the proposed fusion scheme in finger movement classification.

1. Introduction

The loss of the human forearm is a major disability that profoundly limits the everyday capabilities and interactions of individuals with upper-limb amputation (Kuiken et al., 2009). The interaction capability with the real-world can be restored using myoelectric control (Englehart & Hudgins, 2003; Hudgins, Parker, & Scott, 1993), where the electromyogram (EMG) signals generated by the human muscles are used to derive control commands for powered upper-limb prostheses. Typically a pattern recognition framework is utilized to classify the acquired EMG signals into one of a predefined sets of forearm movements (Englehart & Hudgins, 2003; Oskoei & Hu, 2008). Various feature sets and classification methods have been utilized in the literature demonstrating the feasibility of myoelectric control (Oskoei & Hu, 2007; Phinyomark, Phukpattaranont, & Limsakul, 2012; Rafiee, Rafiee, Yavari, & Schoen, 2011). Given the success of utilizing EMG signals in decoding the intended forearm movements, there have been recent attempts to achieve more dexterous individual finger control (Smith, Huberdeau, Tenore, & Thakor, 2009; Tenore et al., 2007). For example, Peleg, Braiman, Yom-Tov, and Inbar (2002) employed surface EMG signals to identify when a finger is activated and which finger is activated using only two electrodes placed on the forearm. Tsenov, Zeghbib, Palis, Shoylev, and Mladenov (2006) also utilized two EMG electrodes to detect four finger movements using time domain features and neural networks classifiers achieving nearly 93% accuracy. However, both of these attempts did not consider combined fingers movements. Tenore et al. (2007) extended the idea of EMG based finger control into movements that consisted of flexion and extension of all the fingers individually and of the middle, ring and little finger as a group achieving $\geqslant$98% accuracy with 32 electrodes (Tenore et al., 2007, 2009) and with 15 electrodes (Smith, Tenore, Huberdeau, Etienne-Cummings, & Thakor, 2008). However, a reduction in the number of electrodes, without compromising the classification accuracy, would significantly simplify the requirements for controlling state of the art prostheses. Andrews, Morin, and Mclean (2009) reported a unique attempt targeting the optimal electrode locations for EMG based finger control. It was suggested that similar outcomes can be obtained from a seven channel configuration and a three channel configuration, except for few subjects achieving <50% accuracy.

While much of the work presented in literature focus on experiments with able-bodied subjects, Cipriani et al. (2011) reports real-time experiments on both able-bodied and amputees participants. Eight pairs of electrodes were utilized to classify seven finger movements, including two classes of combined fingers movements. A k-nearest neighbor (kNN) classifier achieved an

* Corresponding author. Tel.: +61 295142968; fax: +61 295142655.
E-mail addresses: Rami.Khushaba@uts.edu.au (R.N. Khushaba), Sarath.Kodagoda@uts.edu.au (S. Kodagoda), Maen.Takruri@uts.edu.au (M. Takruri), Gamini.Dissanayake@uts.edu.au (G. Dissanayake).

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average classification accuracy of 79% (for amputees)-to-89% (for able-bodied participants). However, no experiments were conducted to validate the need for the total eight pairs of electrodes upon that of a smaller combination. Additionally, the *k*NN classifier requires large memory to store all the training patterns to compare each testing sample based on distances. Thus, an effective way to reduce the number of extracted patterns without compromising the classification accuracy is required.

Although there has been progress in single finger movement classification, a more focused design of a system that can classify multiple individual and combined movements for the same fingers has not yet been reported in the literature. Practical feasibility of such a system can be enhanced if a small number of channels to separate these classes of fingers movements can be developed, leading to minimal intrusion and lower computing cost. Such a system will enable the design of a more dexterous prosthesis that can follow the human intention of moving different fingers in a more natural way.

In this paper, we propose an EMG based individual and combined finger movement recognition system that employs only two EMG electrodes placed on the human forearm. The goal here is to employ effective knowledge discovery and pattern recognition methods to increase the classification accuracy where ten classes of individual and combined finger movements are to be recognized. The block diagram of the proposed system is shown in Fig. 1. Various feature sets are first extracted from the preprocessed raw EMG signals. A dimensionality reduction step is used to project extracted features into a new representation with enhanced discrimination ability. A suitable classifier is then utilized to recognize the signals from different classes of the fingers movements. This is followed by Bayesian fusion to enhance the classifier performance by eliminating spurious misclassification while minimizing the number of training patterns.

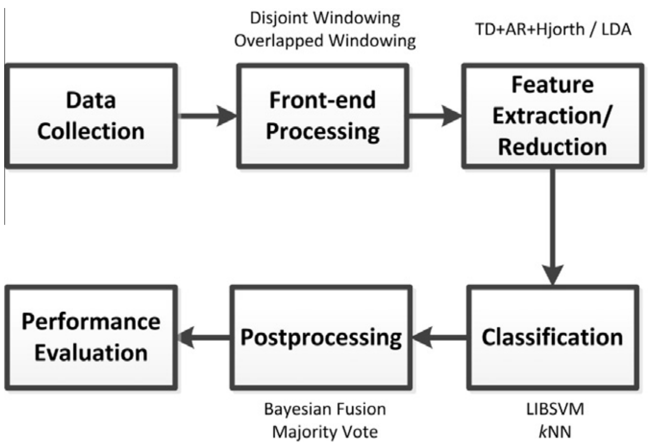


Fig. 1. Block diagram of the experimental evaluation of the EMG-pattern recognition system.

The structure of this paper is as follows: Section 2 describes the data collection procedure, the feature extraction and reduction step, classification and postprocessing. Section 3 describes the proposed Bayesian fusion approach that is applied on the outcome of the classifier and the real-time implementation. Section 4 presents the experimental results and finally, conclusions are provided in Section 5.

2. Methods

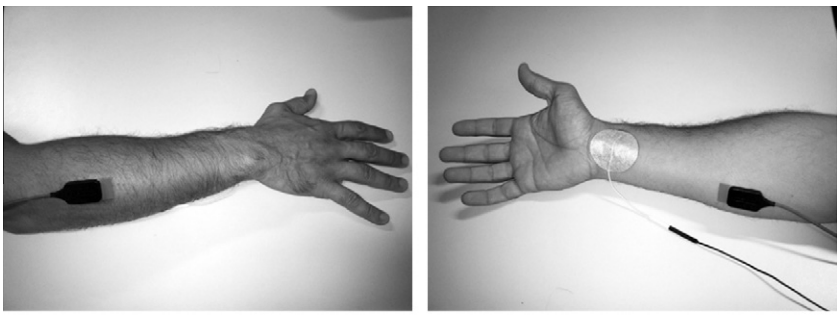
2.1. Data collection

Eight subjects, six males and two females, aged between 20 and 35 years were recruited to perform the required fingers movements. The subjects were all normally limbed with no neurological or muscular disorders. All participants provided informed consent prior to participating in the study. Subjects were seated on an armchair, with their arm supported and fixed at one position to avoid the effect of different limb positions on the generated EMG signals (Scheme, Founger, Stavdahl, Chan, & Englehart, 2010).

The EMG data was collected using two EMG channels (Delsys DE 2.x series EMG sensors) and processed by the Bagnoli Desktop EMG Systems from Delsys Inc. A 2-slot adhesive skin interface was applied on each of the sensors to firmly stick the sensors to the skin. A conductive adhesive reference electrode (Dermatrode Reference Electrode) was utilized on the wrist of each subject. The positions of these electrodes are shown in Fig. 2. The EMG signals collected from the electrodes were amplified using a Delsys Bagnoli-8 amplifier to a total gain of 1000. A 12-bit analog-to-digital converter (National Instruments, BNC-2090) was used to sample the signal at 4000 Hz; the signal data were then acquired using Delsys EMGWorks Acquisition software. The EMG signals were then bandpass filtered between 20 and 450 Hz with a notch filter implemented to remove the 50 Hz line interference.

Ten classes of individual and combined fingers movements were implemented including: the flexion of each of the individual fingers, i.e., Thumb (*T*), Index (*I*), Middle (*M*), Ring (*R*), Little (*L*) and the pinching of combined Thumb–Index (*T–I*), Thumb–Middle (*T–M*), Thumb–Ring (*T–R*), Thumb–Little (*T–L*), and finally the hand close (HC) as shown in Fig. 3.

Two experiments were performed: EMG data for offline classification was collected in the first while the second included continuous EMG data collection for online classification. In the offline experiment, the subjects were instructed by an auditory cue to elicit a contraction from rest and hold that finger posture for a period of 5 s, with the transitions from a relaxation state to a movement class also included in the collected data. Each movement was



(a) position of first electrode (b) position of second electrode

Fig. 2. Electrodes placement on the right forearm.

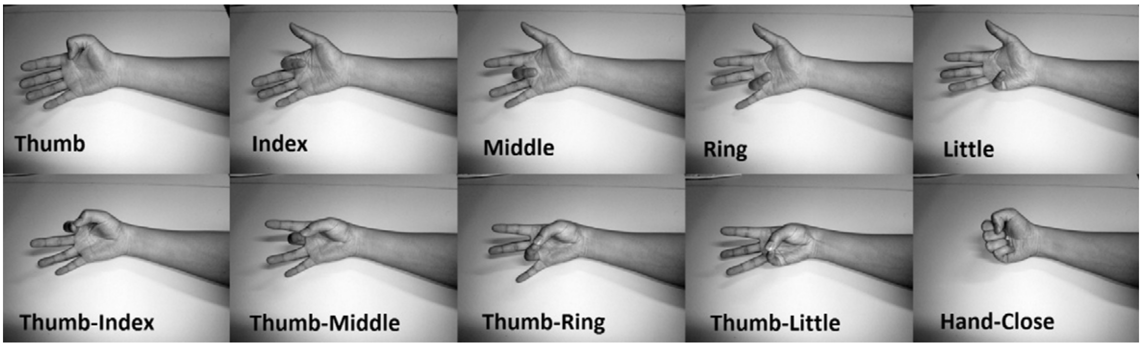


Fig. 3. Different movement classes considered in this paper.

repeated six times with a resting period of 3 to 5 s between trials. Data collected from four of the trials were used for training and the remaining 2 were allocated for testing. On the other hand, during the online experiment, the previously collected six trails were used for training while the testing data involved the subjects performing a continuous random sequence of the ten selected movements with random resting periods between movements.

The classification decision in both experiments was based on subsets of data over periods of few milliseconds as will be explained in the next section.

2.2. Feature extraction

Due to the stochastic nature of the EMG, any instantaneous sample of the EMG contains relatively little information about the overall muscle activity and hence some form of smoothing or windowing must be performed on the data (Farrell, 2007).

Features are usually computed from the preprocessed EMG using a sliding window approach (Oskoei & Hu, 2007; Phinyomark et al., 2012; Rafiee et al., 2011). Either a disjoint windowing scheme or an overlapped windowing scheme can be utilized (Englehart & Hudgins, 2003; Huang, Englehart, Hudgins, & Chan, 2005). It has been demonstrated that the overlapped windowing scheme produces better classification performance than that of the disjoint windowing scheme (Englehart & Hudgins, 2003). However this strategy leads to higher computational costs in the training phase and even in the testing phase for certain classifiers (Cipriani et al., 2011). This in turn is a factor that depends on the selected window size and the associated window increments, where the number of training samples is usually estimated by the following formula:

$$\text{No. of training samples} = \frac{\text{data length} - \text{window size}}{\text{window increment}} + 1. \qquad (1)$$

For certain classifiers, including the *k*NN classifier utilized by Cipriani et al. (2011), testing a new sample requires the distance computation between the sample and the whole training set. In such a case, reducing the number of training samples would also reduce the testing phase computational time. Thus, in this paper we focus on enhancing the performance of the disjoint windowing scheme due to its simplicity and reduced computational cost.

Various feature sets based on reported literature were extracted from the EMG signals. These consisted of Slope Sign Changes (SSC), Number of Zero Crossings (ZC), Waveform Length (WL) based on Hudgins et al. (1993), Hjorth Time Domain Parameters (HTD) based on Hjorth (1970), Amady and Horwat (1996), Sample Skewness (SS), and AutoRegressive (AR) Model Parameters based on Goge and Chan (2004). All of the extracted features from the two EMG channels were concatenated to form one large feature set. These features were then reduced in dimensionality with the Linear Discriminant Analysis (LDA) feature projection producing at most $c-1$ features (with c being the number of problem classes, leading to 9 features for this problem) (Alkan & Gnay, 2012; Goge & Chan, 2004; Khushaba, Al-Ani, & Al-Jumaily, 2010; Khushaba, Kodagoda, Liu, & Dissanayake, 2011). The application of LDA is justified by the high variance nature of the EMG signal which causes the information to be liberally dispersed amongst the original feature set extracted from the EMG. Englehart (1998) proved that feature projection methods can consolidate such information more effectively than feature selection based methods in EMG classification problems. Chu, Moon, and Mun (2006), further compared the performance of LDA against that of nonlinear projection methods in EMG classification problems proving the low computational cost of LDA compared to nonlinear projection methods and its effectiveness upon the baseline (using all features without projection).

2.3. Classification and postprocessing

The final step in the EMG system employs a suitable classifier to recognize the signals from different classes of the fingers movements. After the class decision of a particular window is made, postprocessing techniques are usually utilized to prevent overwhelming the prosthetic controller with varying classification decisions, and to enhance the classifier performance by eliminating spurious misclassification (Englehart & Hudgins, 2003).

The EMG classification accuracies are usually smoothed using a majority vote (MV) technique (Chan & Englehart, 2005). The number of decisions used in the majority vote is determined by the processing time $T_{process}$ (time consumed during feature extraction, projection and classification) and the acceptable delay T_{delay} (the response time of the control system). For a given decision point d_i, the majority vote decision d_{mv} includes the previous m decisions and may also include the future m decisions (with m satisfying the inequality of $m \times T_{process} \leqslant T_{delay}$, as given in Englehart & Hudgins (2003), Huang et al. (2005)). The value of d_{mv} is simply the class label with the greatest number of occurrences in the $2m+1$ decisions.

In a disjoint windowing scheme, given that the window increment is equal to the window size, then the number of future decisions utilized is limited by the real time processing delay requirements. For example, using a disjoint windowing scheme with the current window of 100 ms and the future 3 votes that each was generated from a 100 ms window will increase the processing delay limits way beyond the optimal controller delay of 100-to-125 ms recommended in the literature (Farrell & Weir, 2007, 2008). In such a case, the current decision and the previous m decisions only can be utilized in the voting process without having to wait for future decisions, i.e., the system can still work within the real-time processing delay requirements.

Despite the effectiveness of MV in smoothing the classification output, the MV approach treats the output decisions in a naive manner without considering the actual probabilities of misclassification. Thus, in this paper we investigate an alternative approach based on Bayesian fusion that aims to further enhance the classification accuracy.

3. The proposed real-time postprocessing

3.1. Bayesian fusion postprocessing

The data for each movement, being trials of 5 s length each, is divided into N disjoint equal data sets of 50, 100, or 150 ms that we refer to simply as windows, from which features were extracted. Feeding the features extracted from each window to the classifier results in M conditional probabilities $p(C_i|w_n)$, with $i = 1,2,\ldots,M$, corresponding to the probability that the data within the window w_n belongs to a certain class C_i. The summation of these conditional probabilities for one window should always add to one, i.e., $\sum_{i=1}^{M} p(C_i|w_n) = 1$.

Initially, when the data from the first window arrives at the classifier, the probability that the data belongs to a certain class C_i is expressed by $p(C_i|w_1)$. When the data from the second window arrives, the probability that the data belongs to a certain class C_m is expressed by $p(C_i|w_2)$ and so on. The probability of the class C_i given that data from both windows have arrived (the class posterior) is given by $p(C_i|w_1,w_2)$. By Bayes rule:

$$p(C_i|w_1,w_2) = \frac{p(w_1|C_i,w_2)p(C_i|w_2)}{p(w_1|w_2)} \tag{2}$$

Theoretically, the Bayesian fusion scheme assumes statistical independence of the entities being combined (Kuncheva, 2004). In order to comply with the independence condition in the current EMG classification system, a set of statistically independent windows that occupy disjoint positions on the time axis (and thus being independent) are utilized to segment the EMG data into small equal sets. The result of the segmentation process is a set of temporal signals in adjacent, but non-overlapped, windows. Given the stochastic (random) nature of the EMG signal (Parker, Englehart, & Hudgins, 2004) and the disjoint positions of the resultant signals on the time axis then the resultant signals are very weakly correlated justifying the statistical independence assumed here. According to Domingos and Pazzani (1997a), there are also some proofs that even when the independence assumption is violated, sometimes severely, Bayesian fusion approach can succeed. Domingos and Pazzani (1997a, 1997b) further proved with empirical evidence that attempts to amend the naive Bayes by including estimates of some dependencies do not always pay off. These results motivated the use of the Bayesian fusion approach in our current EMG classification system. Thus, using the following simplifications of $p(w_1|C_i,w_2) = p(w_1|C_i)$ and $p(w_1|w_2) = p(w_1)$, Eq. (2) reduces to:

$$p(C_i|w_1,w_2) = \frac{p(w_1|C_i)p(C_i|w_2)}{p(w_1)}. \tag{3}$$

Expanding the term $p(w_1|C_i)$:

$$p(w_1|C_i) = \frac{p(C_i|w_1)p(w_1)}{p(C_i)} \tag{4}$$

This simplifies (3) to:

$$p(C_i|w_1,w_2) = \frac{p(C_i|w_1)p(C_i|w_2)}{p(C_i)} \tag{5}$$

From this result we can see that the class posterior $p(C_i|w_1,w_2)$ is actually equal to the product of the conditional probabilities of the class C_i across the windows scaled by a constant value. This can be generalized for N windows as follows:

$$p(C_i|w_1,w_2,\ldots,w_N) = \Delta \cdot \prod_{n=1}^{N} p(C_i|w_n) \tag{6}$$

where Δ is the normalization constant to make $p(C_i|w_1,w_2,\ldots,w_n)$ a valid probability density function. The class with higher probability across the M windows is taken as the best classification of the input data $\max_{i=1}^{M}\{p(C_i|w_1,w_2,\ldots,w_N)\}$.

However, a zero as an estimate of any of the probabilities $p(C_i|w_n)$ automatically nullifies $p(C_i|w_1,w_2,\ldots,w_N)$ regardless of the rest of the estimates. On the other hand, when transitioning from one class to another, the previous m decisions stored in the queue might cause delays to the outputs (delay in terms of accurate transition from one class to another). This can be avoided by a weighting scheme that assigns higher weights for the current decision and gradually decreasing weights for the previous decisions. Thus, we modify the above equation by including a weighting factor for each window's probabilities vector K_j as:

$$p(C_i|w_1,w_2,\ldots,w_N) = \Delta \cdot \prod_{n=1}^{N} \left(p(C_i|w_n) + k_j\right) \tag{7}$$

where j is the location of the current window in the queue. The above equation is utilized to adjust the range of the probabilities associated with each of the windows w_N across all i classes by adding a weighting factor k_j to each of the probabilities associated with the current window w_n. In such a case, the weighting factor k_j is simply acquired by the proposed function below:

$$k_j = 10 \times \frac{\exp\left(-0.5 \times j/(m+1)\right)}{\sum_{l=1}^{m+1} \exp\left(-0.5 \times l/(m+1)\right)} \tag{8}$$

where $j = 1,2,\ldots,m+1$, with the last window inserted in the queue taking the first position of 1. Thus, higher priorities are assigned for the current decisions and lower priorities for previous decisions stored in the queue so they might not bias the estimation toward previous decisions.

3.2. Real-time EMG classification

To quantify the amount of real-time processing delay, all processing algorithms were implemented in Matlab, with the computationally intensive portions compiled to increase speed. The processing was performed on a 1.6-GHz Intel Core i7 CPU based workstation with 8 GB of Random Access Memory (RAM). The processing time for different windows' length was computed with a maximum achieved for a 250 ms analysis window corresponding to a processing delay of roughly 1.25 ms as shown in Fig. 4.

The flowchart of the real-time postprocessing step is shown in Fig. 5. During the real-time process, the square of the average value of the two EMG signal channels was employed to detect the active segments of the signals representing a movement. If the average crossed a certain threshold, a movement was assumed, otherwise a resting state was assumed providing a corresponding zero at the output while emptying the queue. The active portions of the data was segmented into windows and feature extraction, projection, and classification steps were performed. The acquired class decision for the specific window of EMG data was then placed in a buffer (or stack) that is populated with the new decisions. Each current decision is then smoothed by an MV process, or using the proposed Bayesian fusion to produce a smoothed output. However, it should be mentioned here that when there are no enough decisions to form the voting process, i.e., queue does not have m decisions yet, then the system can just implement the voting between the current and the available number of votes in the queue

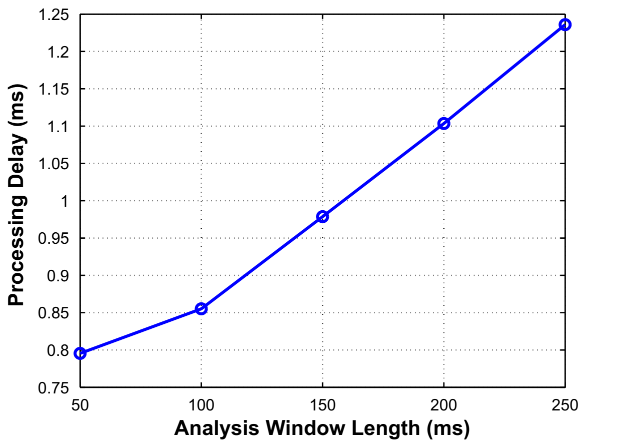


Fig. 4. Dependency between the analysis window length and the processing delay $T_{process}$. These results are for a 1.6-GHz Intel Core i7 CPU based workstation using Matlab code.

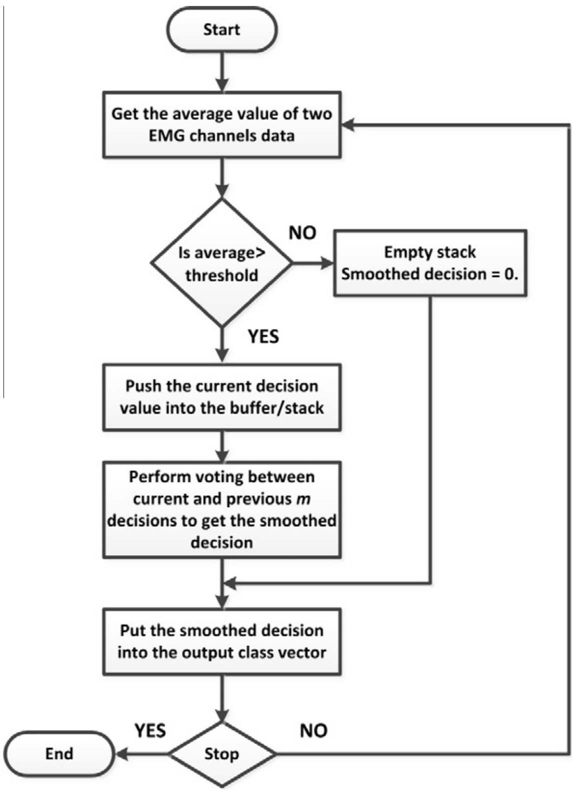


Fig. 5. Flowchart of the postprocessing step.

without having to wait for more decisions to be generated. In such a case, the system might show some errors, especially at the transitions, unless the subject is well trained to exhibit the same patterns for the specific fingers movement. However, it should be also mentioned that such specifications will allow the system to operate within the real-time delay requirements of 100–125 ms, especially when disjoint windows are utilized.

4. Experiments and results

In the first part of the experiments, we evaluate the effect of the analysis window length on the achieved classification accuracies on EMG datasets collected from eight subjects. The window lengths were varied between 50, 100, and 150 ms. Two different classifiers were utilized to demonstrate the effectiveness of the proposed Bayesian fusion approach; Support Vector Machine (SVM) with the LIBSVM implementation (Chang & Lin, 2001), and the *k*NN classifier that was recently employed by Cipriani et al. (2011) in their real-time EMG pattern recognition experiments. The LIBSVM classifier's parameters were optimized as: (SVM type: C-SVC), cost parameter: $c = 8$ and kernel type: radial basis function with $\gamma = 12$/number of features. For each subject, the classifier was trained on the data extracted from the first four trials for all movements and then tested with the data extracted from the remaining two trails for all movements. All of the features were projected with LDA before applying the features to the chosen classifier. The average classification error rates achieved across all subjects with two different classifiers with both MV and Bayesian fusion approaches are shown in Fig. 6. Both MV and Bayesian fusion approaches employed the current classification result, along with the previous M classification results (add to a total of $M + 1$ decisions, that varied between 3 and 15), which were stored in a queue achieving the overall delay of 100-to-125 ms recommended in the literature (Farrell & Weir, 2007, 2008).

The results show few important points. Firstly, the proposed feature set with LDA projection and LIBSVM/*k*NN with both MV and Bayesian fusion postprocessing provided accurate, individual and combined, fingers movements recognition when using only two EMG channels. Further, the Bayesian fusion approach managed to maintain lower error rates than the MV approach by utilizing the probability output of the classifier, for all number of votes and across different classifiers. Secondly, using large number of voting decisions does not always improve the classification results as both the analysis window length and the number of voting decisions influence the outcome. For example, using more than 9 voting decisions improves the classification results when employing analysis windows of 50 ms length, however, it leads to higher error rates with analysis windows of 100 ms or 150 ms length as shown in Fig. 6. Thirdly, large window size results in lower classification error rates when an appropriate number of voting decisions are utilized. However, the optimal window size should be a compromise between the accuracy and acceptable controller delay (Farrell & Weir, 2008).

In order to demonstrate the statistical significance of the achieved results with the proposed Bayesian fusion approach against MV, a Bonferroni corrected analysis of variance test (ANOVA) was utilized (ANOVA with significance level set to 0.05), as reported in Table 1 (Demsar, 2006). The achieved p-values from an ANOVA test were less than the 0.05 indicating a significant decrease in the classification error rates when using the Bayesian fusion approach in comparison to that when using the MV approach.

In the second part of the experiments, we verify the significance of using each of the EMG channels alone to determine the optimal regions for acquiring the EMG-signals for the different fingers movement classification. It was decided to use an analysis window length of 100 ms along with 9 voting decisions for both MV and Bayesian fusion. The classification error rates achieved with individual channels and combined channels with the aforementioned settings are shown in Fig. 7.

These results indicate that using individual channels with the LIBSVM classifier can provide lower classification error rates when compared to that of the *k*NN classifier. It also shows that the second channel (denoted as Ch2) is more informative than the first channel (denoted as Ch1). This is due to the location where they were mounted. The second channel, located as shown in Fig. 2(b), can capture the signals mainly from the Flexor digitorum superficials (that extends into portions feeding the index, thumb, ring and little fingers) and palmaris longus muscles depending on the anatomical structure. On the other hand, the first channel,

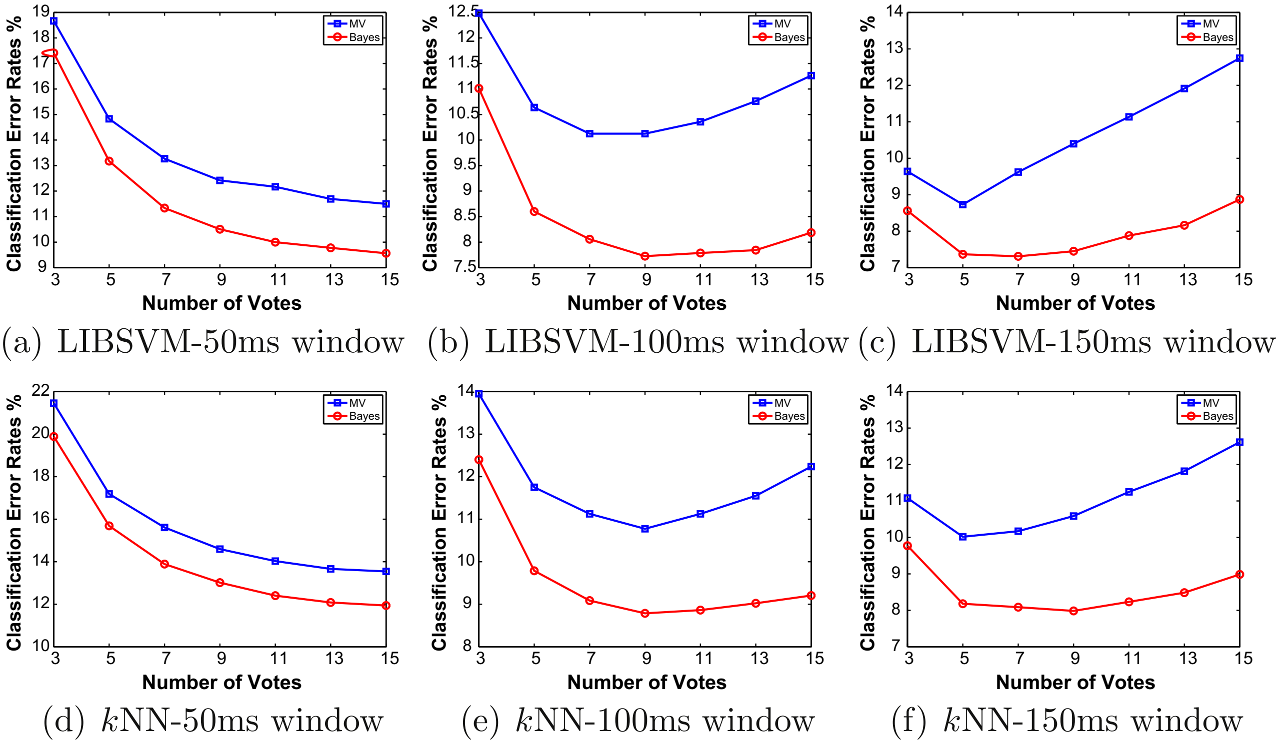


Fig. 6. Average classification error rates achieved across eight subjects using different postprocessing methods with the LIBSVM and the *k*NN classifiers, with features projected using LDA (note the different scales in the different figures for clarity).

Table 1
Statistical significance test results from a pair-wise comparison of classification errors determined at different window length values and voting decisions for the proposed Bayesian fusion vs. MV.

Classifier	Analysis window length		
	50 ms	100 ms	150 ms
LIBSVM	$p = 0.3087e{-}005$	$p = 0$	$p = 0.0007$
*k*NN	$p = 0.1199e{-}008$	$p = 0.0182e{-}003$	$p = 0.0002$

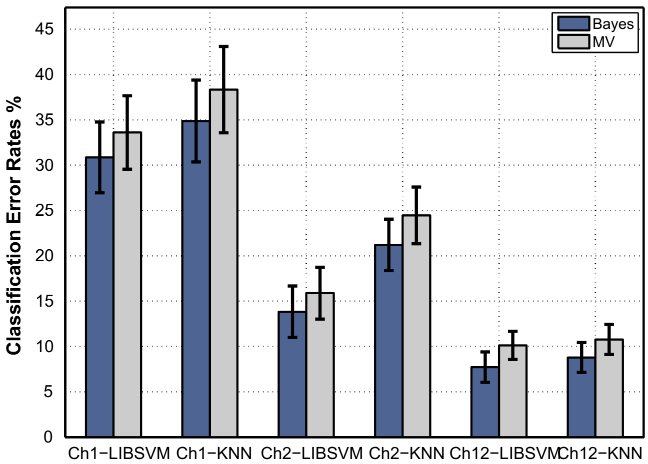


Fig. 7. Classification error rates from different combinations of channels with 100 ms windows and 9 voting decisions.

located as shown in Fig. 2(a), mainly captures the EMG signals propagated to the surface of the skin from the Extensor carpi ulnaris and Extensor digiti minimi muscles. Although the second channel has relatively higher information, utilizing both channels together lead to better classification accuracies.

In the third part of the experiments, the diagonals of the confusion matrices (class-wise classification accuracies) across the eight subjects were averaged in order to investigate the different classes recognition capability of the proposed system across all subjects. The average diagonal of the confusion matrices is shown in Fig. 8 with error bars representing standard deviations. In this case, a disjoint windowing scheme with an analysis window length of 100 ms was utilized for extracting features. These features were classified by both the LIBSVM and *k*NN classifiers and the outputs of the classifiers were smoothed by considering each 9 decisions using Bayesian fusion.

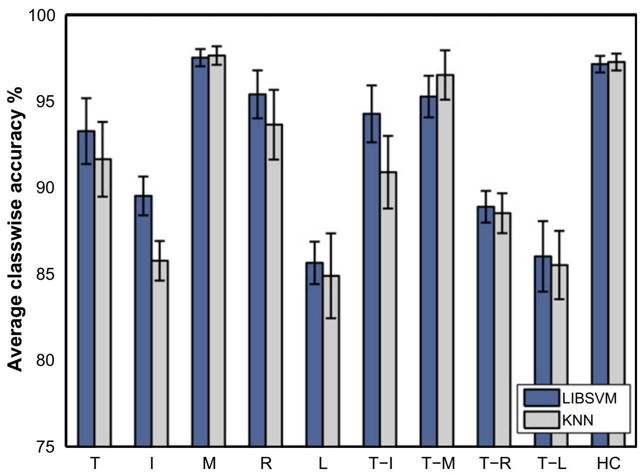
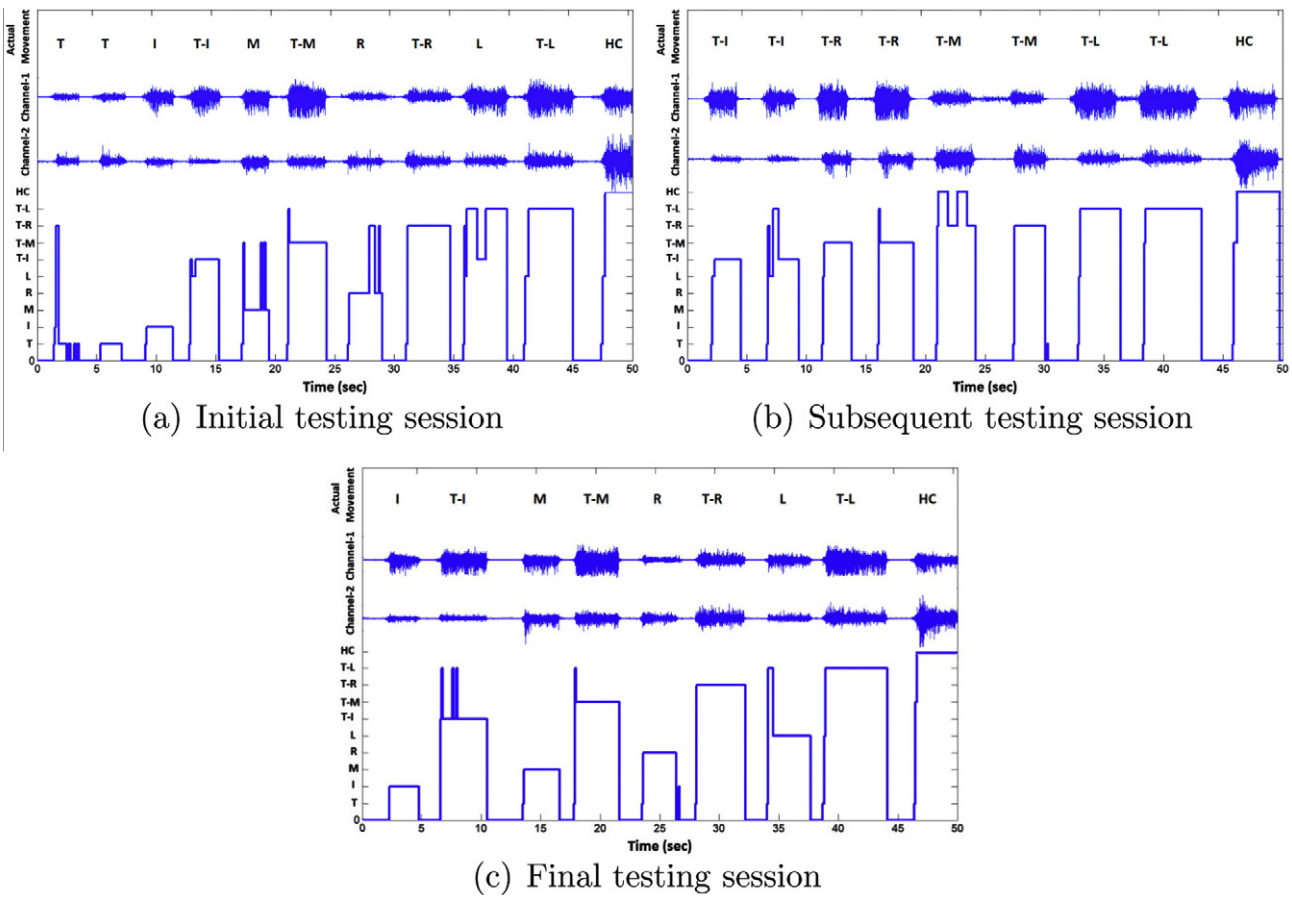


Fig. 8. Average class-wise classification accuracies achieved across eight subjects using the LIBSVM and *k*NN classifiers with decisions smoothed by Bayesian fusion.

As can been seen from the average diagonals of the confusion matrices, both classifiers were, on average, successful in recognizing the different fingers movements. However, it can be noted here that there were some difficulties in separating the index, little, thumb-ring and thumb-little fingers movements from the rest of the classes as these were the most confounded movements across all subjects on average. Such misclassification result may be justified by two factors: the first is the difficulty in separating the patterns associated with movements that incur large degrees of nonlinear overlapping among each other. Thus, nonlinear feature extraction methods should be investigated in a future work in this area. The second factor might be associated with the number of EMG channels utilized, i.e., more channels could be added to produce perfect classification results for each individual movement individually. In the current system with just 2 EMG channels, both classifiers performed nearly in a similar manner achieving an average class wise accuracy of ≈90% which seems acceptable in comparison to other work from the literature.

In the final part of the experiments, we test the effectiveness of the proposed 2-channel based EMG-pattern recognition system in a real-time environment. Continuous data collection sessions were carried out with the subjects randomly performing different fingers movements with random resting periods between movements. The classifications were only performed on the active segments, which were determined by a thresholded average values of the two EMG channels. Firstly, none of the subjects was trained on the system, a factor which has contributed to significant errors as can be seen in the initial testing session in Fig. 9(a). As an example, the little finger movement (*L*) (in Fig. 9 (a)) was misclassified mostly as a thumb–little movement (*T–L*) with a small portion misclassified as thumb–index movement (*T–I*). This is justified by the fact that the subject was not trained to elicit the same level of contractions introducing misclassification errors. This was successfully avoided by proper training in the subsequent sessions as shown in Fig. 9(b) and (c). These sessions were collected in the same day with random resting periods between sessions. As a result, significant enhancements in classification accuracies were achieved. In the current experiments, three real-time testing sessions were implemented with accuracies of 85.5%, 90.2%, and 95.2% for the first, subsequent, and final testing sessions respectively with an average real-time accuracy of 90.3% across the different sessions.

In terms of computational cost, the above results of Bayesian fusion postprocessing also prove that one can utilize an analysis window length of 100 ms with 7-to-9 voting decisions (that achieved the best accuracy with 100 ms windows) while still complying with the optimal desired controller delay of less than 125 ms. Unlike a system with an overlapping window scheme during the feature extraction process that might utilize the future voting decisions into the computational delay analysis, the current system does not employ the future voting decisions but only those related to the previous decisions that are stored in a queue. Thus, the time taken to make a decision upon each analysis window is reported as the system's overall delay performance. As an example, the time taken by the proposed system to produce a decision for each of the analysis windows of $T_a = 100$ ms is made up by adding 100 ms to the time taken to extract, project, and classify the features of that specific window. For a computer with 1.6-GHz Intel Core i7 CPU with 8 GB RAM, the feature extraction step took ≈0.85 ms (per window feature extraction time), LDA feature



(a) Initial testing session

(b) Subsequent testing session

(c) Final testing session

Fig. 9. Real-time testing session with a subject performing a random sequence of the different fingers movements with random resting periods.

projection step took ≈0.025 ms (as it only involves the multiplication by a precomputed projection matrix), and the time taken by the classifier to make a decision upon each feature vector was ≈0.47 ms. Thus, a total delay of 101.345 ms = 100 ms + 0.85 ms + 0.025 ms + 0.47 ms is taken by the system to produce the decision for each current window.

5. Conclusion

A two channel EMG pattern recognition system was proposed in this paper to classify individual and combined finger movements. Various features were extracted from the two channels and reduced in dimensionality using LDA. In order to enhance the output classification decisions made by the current EMG pattern recognition system, a Bayesian fusion postprocessing was proposed to remove spurious misclassification results and was compared with other postprocessing techniques utilized in EMG pattern recognition in the literature. Experiments conducted on EMG datasets belonging to ten different finger movements collected from eight subjects for the purpose of this research proved the feasibility of the proposed system using different classifiers achieving ≈92% offline and ≈90% online classification accuracy results with the LIBSVM classifier and Bayesian fusion. The current results suggest the success of the two EMG channels system in classifying ten different individual and combined finger movements.

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