EMG Feature Evaluation for Improving Myoelectric Pattern Recognition Robustness

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Abstract

In pattern recognition-based myoelectric control, high accuracy for multiple discriminated motions is presented in most of related literature. However, there is a gap between the classification accuracy and the usability of practical applications of myoelectric control, especially the effect of long-term usage. This paper proposes and investigates the behavior of fifty time-domain and frequency-domain features to classify ten upper limb motions using electromyographic data recorded during 21 days. The most stable single feature and multiple feature sets are presented with the optimum configuration of myoelectric control, i.e. data segmentation and classifier. The result shows that sample entropy (SampEn) outperforms other features when compared using linear discriminant analysis (LDA), a robust classifier. The averaged test classification accuracy is 93.37%, when trained in only initial first day. It brings only 2.45% decrease compared with retraining schemes. Increasing number of features to four, which consists of SampEn, the fourth order cepstrum coefficients, root mean square and waveform length, increase the classification accuracy to 98.87%. The proposed techniques achieve to maintain the high accuracy without the retraining scheme. Additionally, this continuous classification allows the real-time operation.

Keywords

Electromyography (EMG); feature extraction; linear discriminant analysis; myoelectric control; sample entropy.

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1. Introduction

Myoelectric control systems (MCSs) have been used to control assistive and rehabilitation devices for many years by conducting the classified patterns of surface electromyography (EMG) signal (Oskoei & Hu, 2007; Peerdeman et al., 2011; Zecca, Micera, Carrozza & Dario, 2002). Most of related literature on EMG pattern recognition focuses on the improvement of classification accuracy and the number of discriminated motions (Oskoei & Hu, 2007; Zecca et al., 2002). Although accuracy has achieved above 90% for multiple discriminated motions using various combinations of advanced techniques in feature extraction, dimensionality reduction and pattern classification (Peerdeman et al., 2011), the usability of MCSs is still challenged by some issues (Boschmann, Kaufmann, Platzner & Winkler, 2010; Chen, Geng & Li, 2011; Fougner, Scheme, Chan, Englehart & Stavdahl, 2011; Kaufmann, Englehart & Platzner, 2010; Tkach, Huang & Kuiken, 2010; Young, Hargrove & Kuiken, 2011, 2012; Zhang et al., 2007). These problems need to be solved for realizing practical applications of MCSs, such as effects of electrode location shift (Tkach et al., 2010; Young et al., 2010, 2011), variations in muscle contraction effort (Tkach et al., 2010), variations in limb position (Chen et al., 2011; Fougner et al., 2011), and changes in EMG patterns over time (Boschmann et al., 2010; Kaufmann et al., 2010).

Recently, the effect of long-term/prolonged usage has been emphasized in a few works (Boschmann et al., 2010; Kaufmann et al., 2010; Phinyomark, Phukpattaranont & Limsakul, 2012a; Zhang et al., 2007). The conditions controlled for collecting training and testing data in most of related literature are only from one or a few days. On the other hand, EMG data measured in one day are relatively different from that in another day even on the same subjects (Jain, Singhal, Smith, Kaliki & Thakor, 2012). In addition, the EMG data recorded in the laboratory are likely different from what would be expected in the real-world usage. Therefore, the classification accuracies that are measured and reported in the published literature and in the clinically observed results tend to be different.

To demonstrate the real-world use of MCSs, EMG data recorded under realistic conditions are required in order to provide the real classification accuracy. The long-term effect of fluctuating EMG signals in state-of-the art classification algorithms, with training and testing EMG data recorded from 21 days is presented clearly in Kaufmann et al. (2010). The results show that the classification accuracies decrease with increasing time difference between training and testing data and decrease gradually (>10%), if not being retrained, for four effective algorithms: multi-layer perceptron neural networks (MLP-NN) (Hudgins, Parker & Scott, 1993), support vector machine (SVM) (Oskoei & Hu, 2008), k-nearest neighbor (KNN) (Kim, Choi, Moon & Mun, 2011), and decision tree (DT) (Geethanjali & Ray, 2011) using Hudgins' time domain (TD) feature set (Kaufmann et al., 2010). On the other hand, the classification accuracy drops only 3.6% for linear discriminant analysis (LDA) classifier, thus LDA is recommended as the robust classifier and it has been employed in several recent literatures (Tkach et al., 2010; Young et al., 2010, 2011) for developing robust pattern recognition-based MCSs.

However, the classification accuracy achieved with LDA and Hudgins' TD feature set is approximately 80%. Moreover, due to a lack of evaluating the optimal robust EMG features (Boschmann et al., 2010; Kaufmann et al., 2010; Zhang et al., 2007), this paper proposes and investigates the behavior of fifty TD and frequency domain (FD) features to classify ten upper limb motions using EMG data recorded during 21 days, in order to fulfill the completion of the previous study (Kaufmann et al., 2010) on finding the most stable combination between EMG feature extraction and classification algorithm. All features were evaluated with LDA when trained on the initial data, most recent data, and all preceding data. In addition, the optimum configuration of MCSs for the robust features is explored.

2. Background

In the past decade's literature on MCSs (Englehart, Hudgins & Parker, 2001), myoelectric pattern recognition is often divided to three components: feature extraction, dimensionality reduction, and pattern recognition. The success of this system to achieve a high classification performance depends almost entirely on the selection of EMG features (Oskoei & Hu, 2007, 2008).

2.1 EMG Feature Extraction

Feature extraction is a technique to transform raw input data into a reduced representation set of features, which is called a feature vector. A suitable feature vector should contain the useful information and discard the irrelevant/noise information (Zardoshti-Kermani, Wheeler, Badie & Hashemi, 1995). Based on the literature, EMG features can be separated into several groups: TD, FD or spectral domain, and time-scale or time-frequency domain (TFD) (Oskoei & Hu, 2007). In other words, features of EMG can be computed based on both linear and nonlinear analysis.

TD features are extracted directly from raw EMG time series without any transformation, thus features in this group are easy to implement and require low computational load. On the other hand, FD features are usually statistical properties of power spectral density of EMG signal.

Fifty features are proposed in this study. They are based on TD and FD and also linear and nonlinear analysis, as shown in Table 1 with the specific parameters and references for mathematical definition. All of these features have been previously used in the analysis of surface EMG signal. TD features are presented in the first 33 rows in Table 1 and remaining 17 rows in the table are features in FD.

The optimal parameters for the EMG features that were implemented in this study are based on the suggestion of related works and the preliminary experiments, as presented in Table 1. For instance, the m and r parameters of approximation entropy and sample entropy are based on the suggestion in the literature (Zhao, Jiang, Cai, Liu & Hirzinger, 2006a; Zhao, Xie, Jiang, Cai, Liu & Hirzinger, 2006b), or the threshold value which is used in slope sign change and Willison amplitude is based on the preliminary experiments in this study.

However, features in the TFD group, e.g. discrete wavelet transform (DWT) and wavelet packet transform (WPT), are not included in this study based on two reasons:

(1) TD features achieve higher accuracy than TFD features for the LDA classifier, whereas TFD features achieve higher accuracy than TD features for the SVM classifier (Lorrain, Jiang & Farina, 2011; Phinyomark et al., 2012a). Due to a robustness of LDA over

SVM as described (Kaufmann et al., 2010), the development of EMG pattern recognition should be based on the LDA classifier.

(2) TD features show a better performance than TFD features in the classification of both transient and steady-state EMG signal using LDA (Lorrain et al., 2011). Due to a drawback of classifying only transient signal or only steady-state signal, the development of EMG pattern recognition should be based on the continuous classification of the both signal types (Yang, Zhao, Jiang & Liu, 2012).

In addition, it is clearly shown that raw wavelet coefficients are not possible to be used if additional feature extraction and/or feature projection is not applied. For instance, feature extraction that is applied for wavelet coefficients is usually TD techniques (Hariharan, Fook, Sindhu, Ilias & Yaacob, 2012; Phinyomark, Nuidod, Phukpattaranont & Limsakul, 2012b). Principle component analysis (PCA) and uncorrelated LDA (ULDA) are two popular used feature projection in EMG signal classification (Englehart et al., 2001; Phinyomark et al., 2012a). The classification performance of these features also depends on wavelet parameters such as mother families and decomposition level (Hariharan et al., 2012; Phinyomark et al., 2012b).

2.2 Dimensionality Reduction and Pattern Classification

Dimensionality reduction is a technique to reduce the dimension of an original feature vector, while preserving the most discriminative information and removing the remaining irrelevant information, for reducing the computational time in a classifier. This technique is mostly applied for TFD features (Englehart et al., 2001) which provide a high vector dimension. Additionally, it improves small accuracy of classification for the TD and FD features (Phinyomark et al., 2012a). Hence, the dimensionality reduction technique is not applied in this study.

LDA is used as a pattern classification algorithm in this study. In addition to the robust property of LDA, this classifier was chosen based on several reasons (Englehart et al., 2001; Jain et al., 2012; Kaufmann et al., 2010), i.e. it is a simple statistical approach and does not require any parameter adjustment. LDA is also a computationally efficient real-time operation. The classification performance of LDA is similar to more complex classification algorithms such as MLP-NN and SVM (Kaufmann et al., 2010; Oskoei & Hu, 2008).

3. Data Collection

The EMG dataset used to test the proposed EMG features was provided by the University of Paderborn in Germany. It is the same EMG dataset that is used in the evaluation of EMG classification algorithms (Kaufmann et al., 2010). The data were obtained using a portable EMG data recording device (NeXus-10, Mind Media BV). The EMG data were collected from a male non-amputee subject from four electrode-pair positions on the top, bottom, medial, and lateral sides of the forearm (ch0-ch3) with the reference (r) at the wrist, as shown in Fig. 1. These signals were sampled at 2048 Hz with a high resolution of 24 bits.

The EMG data were collected as the volunteer performed eleven upper limb motions including (m1) extension, (m2) flexion, (m3) ulnar deviation, (m4) radial deviation, (m5) pronation, (m6) supination, (m7) open, (m8) close, (m9) key grip, (m10) pincer grip, and (m11) extract index finger. Because, the energy of the pincer grip grows considerably over the trials, thus only ten motions (m1-m9, m11) were included for the data analysis (Kaufmann et al., 2010).

To investigate the long-term EMG effect, the EMG data were recorded for 21 days with five to six trials per day. In total, 121 trials are obtained from 21 days. Within each trial, all motions were performed in the same sequence by the subject and each motion is maintained for five seconds. At the start, the end, and between motions, the rest periods were introduced as can be observed from the example of one trial in Fig. 2. Each contraction period can be divided roughly into a one-second onset phase and a four-second subsequent steady-state phase. Therefore, only the data of the steady-state phase were used for the classification experiments (Kaufmann et al., 2010).

It should be emphasized that the exact electrode positions were marked specifically for the subject in order to be able to reestablish the experimental setup on different days. Furthermore, to approximate realistic conditions of MCSs, the recordings were performed under various subject conditions, such as after sleep and meals, and after periods of high and low physical activity.

4. Data Analysis

4.1 Investigation of Robust Single EMG Feature

All EMG features in Table 1 were used to investigate the effect of long-term usage of the pattern recognition-based myoelectric control. Three experiments that are proposed in the evaluating EMG classification algorithms (Kaufmann et al., 2010) were used.

The fluctuating EMG data, which are used as training and testing data, contained 121 trials in total from 21 days. All experiments used the EMG trials (i = 2-121) as the testing set, whereas the training set trials are different in each experiment: (1) training on the initial data (only the first day), (2) training on the most recent data (five recent preceding trials), and (3) all preceding data. For a test trial i, $2 \leq i \leq 121$, the indices of the training set can be defined respectively as follows:

1) $i, ..., \min(s, i-1)$,

2) $\max(i-s, 1), ..., i-1$,

3) $1, ..., i-1$.

where the number of trials s is set at 5, because five trials corresponded to the EMG data collected from one day and were enough to gain high classification accuracy for the classifiers (Kaufmann et al., 2010).

The classification accuracies were obtained from LDA with a segment length of 250 ms (512 samples). An overlapped segmentation with an increment of 125 ms (256 samples) was applied.

The selection of the most robust EMG features is based on the result of the first experiment. The stable feature should succeed in maintaining high classification accuracy (>80%) (Peerdeman et al., 2011), whether the time difference between training and testing data increased. Furthermore, the differences between accuracies obtained from three experiments can be observed in order to find the suitable training approach.

4.2 Investigation of Robust Multiple EMG Feature Sets

Using a single feature for the continuous classification may make it difficult to reach a high accuracy. Multiple feature sets have been employed and succeeded in the classification of multiple motions-based EMG signal (usually more than 4 motion classes) in many recent researches (Oskoei & Hu, 2007; Peerdeman et al., 2011).

The possible combinations of two to four features were applied to the LDA classifier. The number of multiple features in this study is based on the finding result in previous study (Phinyomark, Phukattaranont & Limsakul, 2012c) that many TD and FD features provide similar information and patterns in feature space. Thus, increasing the number of redundant features would improve a little classification performance and four features are enough to gain high classification accuracy. The features were computed from overlapped segments with a length of 250 ms and an increment of 125 ms. The possible combinations of two, three, and four multiple features from a total of 50 features are 1225, 19600, and 230300 feature sets.

4.3 Optimum Configuration of MCSs for Robust Features

The optimum configuration of robust features based MCSs was investigated consisting of the classification algorithm and the data segmentation.

For the classification algorithm, LDA shows more robust when not being trained iteratively compared to MLP-NN, SVM, KNN, and DT using the same EMG dataset (Kaufmann et al., 2010). In this study, two new state-of-the art classifiers, namely random forests (RFS) (Breiman, 2001) and quadratic discriminant analysis (QDA) (Kim et al., 2011), were compared with LDA.

The QDA classifier can be seen as a more general version of LDA, which separates the classes of objects by a quadratic surface instead of linear, as implemented in LDA classifier. The RFS classifier is closely related to DT. It is an ensemble classifier of DTs. RFS also shows better performances than LDA, QDA, KNN, MLP-NN and SVM in the classification of grasping of objects (Liarokapis, Artemiadis, Katsiaris, Kyriakopoulos & Manolakos, 2012).

For the data segmentation, a segment length which is used to compute features in the previous experiments is set at 250 ms. This segment length contains enough information to estimate a motion and can performs real-time operation (Oskoei & Hu, 2008). However, a segment smaller than 250 ms could reduce the computation time, while leads to increase the variation in estimated feature. On the other hand, a segment larger than 250 ms could decrease the variance of estimation, while it leads to increase the computational load.

To use a larger segment, the overlapped segmentation is applied instead of the disjoint segmentation. The accuracy of classification with a segment length of 125, 250, and 500 ms (256, 512, and 1024 samples) and an increment of 62.5, 125, and 250 ms (128, 256, and 512 samples) were examined for both types of segmentation. The increment can be defined as an interval of time between two consecutive segments and should be less than 300 ms to avoiding failure in real-time operation.

In total, eight options of segmentation (segment length, increment) were proposed: (125 ms, 62.5 ms), (125 ms, 125 ms), (250 ms, 62.5 ms), (250 ms, 125 ms), (250 ms, 250 ms), (500 ms, 62.5 ms), (500 ms, 125 ms), and (500 ms, 250 ms).

5. Results and Discussion

5.1 Robust Single EMG Feature

The averaged classification accuracies obtained from LDA of all test trials for 50 features for 3 experiments are presented in Table 2. SampEn has the highest classification accuracy, followed by ApEn and MFL. Without retraining scheme, the accuracy of SampEn is 93.37%. It drops only by 3.24% and 2.45% compared with training in recent preceding data and all preceding data, respectively. The SampEn provides 8.69% accuracy higher than ApEn, the second rank of the 50 features. The accuracy of ApEn is 84.68%. Furthermore, the results clearly show that the best single feature, SampEn achieves better classification performance than Hudgins' TD feature set i.e. MAV, WL, ZC, and SSC. The classification accuracy increases from 78.73% to 93.37% (Kaufmann et al., 2010).

The SampEn also has better classification performance than the other EMG features using five recent preceding trials for training, followed closely by the MFL and DASDV. On the other hand, the MFL has a bit improved classification accuracy than the SampEn using all receding trials for training. However, the accuracy of MFL and DASDV degrades with rising time difference between training and testing data (when test trial $i > 30$ or > 6 days), as can be seen in Fig. 3. Note that the horizontal axis in Fig. 3 shows the test trial i and the vertical axis shows the corresponding test accuracy.

Based on the discriminating ten upper limb motions using four forearm EMG channels, the SampEn performs the best in both classification accuracy and stability.

There are several interested issues from the experimental results that could be discussed as follows:

(1) The difference of classification accuracies when trained in recent preceding five trials and all preceding trials, as shown in Table 3, is not statistically significant in 40 features and the accuracy of using five recent trials (T1) for training is higher than the another scheme (T2) for 35 features. It means that it is not necessary to use all preceding data as a training set and we can reduce the size of training set by using only the recent EMG data. This may be due to the variation in muscle contraction effort and the difference in subject conditions between days, thus the excluded trials would have provided less relevant information for the classification system.

(2) SampEn shows a success as the robust muscle activity onset detection against the spurious spikes in surface EMG signal by using global tolerance r (Zhang & Zhou, 2012). The global tolerance scheme is also recommended to use in the estimation of grasping force (Kamavuako, Farina, Yoshida & Jensen, 2012) compared to the local tolerance scheme or standard SampEn. In this study, the global tolerance scheme is applied. This scheme sets a uniform tolerance for the signal of all the analysis segments instead of each analysis segment,

as implemented in the local tolerance scheme. This parameter is critical in reducing the effect of large variations in motions-based EMG signal.

The tolerance r is set as $0.20 \times \sigma$, in this study, where σ is the standard deviation of the EMG time series. This value is based on the suggestion of Richman and Moorman (2000). The global tolerance r, which was set as $0.20 \times \sigma$, also provides good performances in the classification of finger motions-based surface EMG signal (Zhao et al., 2006a) and the estimation of grasping force-based intramuscular EMG signal (Kamavuako et al., 2012). More details about the theory of SampEn are presented in the Appendix.

(3) As mentioned above that SampEn with global tolerance scheme showed a success as both the onset detection method (compared to the amplitude thresholding and Teager-Kaiser Energy operation-based methods (Zhang & Zhou, 2012) and force estimation method (compared to the global discharge rate and RMS methods (Richman & Moorman, 2000), the SampEn feature would be useful not only in continuous classification, as presented in this study, but also in discrete classification. In other words, it would be useful to classify and estimate both type and force level of movements simultaneously, while improve the robustness to noise.

(4) The stable single features i.e. SampEn, ApEn, and MFL are nonlinear signal processing methods (Arjunan & Kumar, 2010; Phinyomark, Phukpattaranont & Limsakul, 2012d; Zhang & Zhou, 2012; Zhao et al., 2006a, 2006b). As mentioned in several studies, one of the major properties of surface EMG signal is nonlinearlity. Nonlinear analysis techniques can extract the real hidden information from surface EMG data and these techniques are robust to the low-level muscle contraction (Phinyomark et al., 2012d) and noise (Zhang & Zhou, 2012). These features contain the complexity information and can be used to highlight bursts of surface EMG signal.

(5) TD features imposed relatively high performance of classification and low load of computation compared to FD features. All FD features provided weak performance during classification (< 67%), except three FD features (i.e. MNP, TTP, and SM), that have the same discrimination in feature space as TD features. It means that the patterns of FD features are not sufficiently discriminative to identify the upper limb motions. However, the patterns of the TD and FD features are different, and multiple TD and FD features may increase the class separability, as can be observed in Table 4, such as SampEn + MNF and SampEn + FR.

5.2 Robust Multiple EMG Feature Sets

Based on the results in the previous study (Phinyomark et al., 2012c), most of TD and FD features are redundant. In other words, they share similar properties and information. Hence, it does not guarantee that combinations of several good robust single features would provide good robust multiple-feature sets. For instance, both SampEn and ApEn are entropy estimation techniques (Richman & Moorman, 2000), or TD features like IAV, MAV, and RMS are based on the energy information (Phinyomark et al., 2012c).

In this study, the classification performance obtained with all the possible combinations of 50 features to make two, three and four multiple-features are evaluated and the best ten combinations in each multiple-feature type are presented in Table 4.

Classification accuracies obtained from the multiple feature sets increase compared to the single features. They reach 97-98%, while the variation in the accuracy during test trials decreases (<3%) for the robust multiple feature sets. The best feature sets for two, three, and four features are respectively SampEn + CC, SampEn + CC + MAV2, and SampEn + CC + RMS + WL/AAC.

Based on the discriminating ten upper limb motions using four forearm EMG channels, the best feature set (i.e. SampEn, CC, RMS and WL) provides 97.75% accuracy with the real-time operation and stability of classification performance. It should be noted that WL is chosen instead of AAC because WL and AAC provide the same feature space when WL requires less computational cost than AAC. The dimension of feature vector is 7 (one value from each of SampEn, RMS and WL, and four values from CC). Moreover, the patterns in space of four features in the best robust set are different. These four features provide the useful information based on the similarity, the energy, the complexity, and the predicting model (Phinyomark et al., 2012c).

5.3 Optimum Configuration for Robust Features

The accuracies of LDA with the robust single feature and multiple-feature sets are compared with RFS and QDA. The results are shown in Fig. 4. The features were computed with a segment length of 250 ms and an increment of 125 ms and all classifiers were trained in the first five trials or only the first day. It can be clearly seen that the LDA classifier yields better performance than the RFS and QDA classifiers. Among the proposed classifiers, LDA performs the best in classification accuracy, stability, and computational load.

Table 5 shows the performance of classification in different segment lengths. The results show that accuracy increases by increasing the segment length from 125 ms to 500 ms. This is because a larger segment provides additional information and yields small bias and variance in the estimation of feature. The optimal segment length is 500 ms. The results also show that it does differ significantly by changing the segment length from 125 ms to 250 ms (about 2-3%), but it does not largely differ by changing the segment length from 250 ms to 500 ms (<1%). In addition, the performance of the overlapped segmentation has no improvement of classification accuracy, but it is significant to employ the large segment (greater than 200 ms) in order to avoiding a delay time.

6. Conclusion

For realizing practical applications of MCSs, the effect of long-term usage or reusability is carefully considered in this study. Fifty EMG features in TD and FD are evaluated by using EMG recorded from 21 days. From the results, four main points are summarized as in the following:

(1) SampEn is the best robust single feature and SampEn + CC + RMS + WL set is the best robust multiple-feature set.

(2) Features based on TD show a better performance than FD features for robust EMG pattern classification.

(3) LDA shows a better performance in the classification of fluctuating EMG signals compared to several classifiers i.e. RFS, QDA, MLP-NN, SVM, KNN, and DT.

(4) The suitable data segmentation is the overlapped segment with a length of 500 ms and an increment of 125 ms. This segment condition can be operated in real-time and provides high accuracy.

(5) The performance of the fifty EMG features proposed in this paper has been reported before in the literature, but it is difficult to compare their performances due to the difference in the experiments. The performance of the fifty features is compared under the same EMG dataset in this paper. This could be useful in the selection of EMG features for MCSs in future research.

The findings in this study can be applied in many EMG applications. In human computer interaction (HCI) (Saponas et al., 2009), for instance, a novel fusion of an interactive surface and EMG signal (Benko, Saponas, Morris & Tan, 2009) would provide useful interaction capabilities if the EMG system can be used in many days without retraining schemes as same as the interactive surfaces that do not require the retraining procedure.

Appendix

SampEn is feature extracted similarity information in time series. This entropy feature is developed from the ApEn in order to avoid the bias caused by self-matching. SampEn can be expressed as

$$\mathrm{SampEn}(m, r, N) = -\ln\left[A^m(r)/B^m(r)\right], \tag{A1}$$

where $B^m(r)$ and $A^m(r)$ are the probability that two series will match for m and m+1 points, respectively. Hence, the SampEn is the negative natural logarithm of an estimate of the conditional probability that the patterns of the time series that are similar to each other within a predefined tolerance r will remain similar for the next comparison point (Richman & Moorman, 2000).

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Figure captions

Fig. 1. The electrode placement used in the four-channel EMG acquisition (*Anatomy of the human body*, 1918).

Fig. 2. The example of EMG data from one trial from ch0.

Fig. 3. Test classification accuracy (%) in the trial i, where $2 \leq i \leq 121$, of (a) SampEn, (b) ApEn, (c) MFL, (d) DASDV, when trained in the first five, recent preceding five, and all preceding trials.

Fig. 4. Averaged test classification accuracy (%) of the best single feature and multiple-feature sets, when trained in the first five trials using the LDA, RFS and QDA classifiers with a segment length of 250 ms and an increment of 125 ms. The error bars show the standard deviation across trials.

***Highlights (for review)**

Highlights

- The medium-term robustness of EMG signals for prosthetic control is investigated.
- The effect of 50 EMG features has been extensively examined.
- A single optimal robust EMG feature is sample entropy.
- Linear discriminant analysis is better than other state-of-the-art classifiers in robustness.
- Average accuracy is 98.87% without retraining classifier for EMG recorded for 21 days.

Table 1

Table 1 Fifty TD and FD features with specific parameters and mathematical definition references.

Feature extraction: Full name	Abbr.	Parameters	References
Average amplitude change	AAC	-	(Kim et al., 2011; Phinyomark et al., 2012c)
Approximate entropy	ApEn	$m=2, r=0.2\times\sigma$	(Zhao et al., 2006a)
Auto-regressive coefficients	AR	$order=4$	(Tkach et al., 2010; Zardoshti-Kermani et al., 1995)
Box-counting dimension	BC	$k_{\max}=\lfloor \log_2(N) \rfloor - 1$	(Gitter & Czerniecki, 1995)
Cepstral coefficients	CC	$order=4$	(Tkach et al., 2010; Phinyomark et al., 2012c)
Difference absolute standard deviation value	DASDV	-	(Kim et al., 2011; Phinyomark et al., 2012c)
Detrended fluctuation analysis	DFA	$b=2^i, i=2-6, O_{fp}=2$	(Phinyomark et al., 2012d)
Higuchi's fractal dimension	HG	$k_{\max}=128$	(Arjunan & Kumar, 2010; Phinyomark et al., 2012d)
Histogram	HIST	$segment=3$	(Tkach et al., 2010; Zardoshti-Kermani et al., 1995)
Integral absolute value	IAV	-	(Kim et al., 2011; Zardoshti-Kermani et al., 1995)
Katz's fractal dimension	Katz	-	(Gupta, Suryanarayanan & Reddy, 1997)
Kurtosis	Kurt	-	(Nazarpour, Al-Timemy, Bugmann & Jackson, 2013; van den Broek, Schut, Westerink, Herk & Tuinenbreijer, 2006)
Log detector	LOG	-	(Tkach et al., 2010; Zardoshti-Kermani et al., 1995)
Modified mean absolute value 1	MAV1	-	(Oskoei & Hu, 2008; Phinyomark et al., 2012c)
Modified mean absolute value 2	MAV2	-	(Oskoei & Hu, 2008; Phinyomark et al., 2012c)
Mean absolute value	MAV	-	(Hudgins et al., 1993; Tkach et al., 2010)

Mean absolute value slope	MAVS	$segment = 2$	(Hudgins et al., 1993; Phinyomark et al., 2012c)
Maximum fractal length	MFL	-	(Arjunan & Kumar, 2010; Phinyomark et al., 2012d)
Multiple hamming windows	MHW	-	(Phinyomark et al., 2012c)
Multiple trapezoidal windows	MTW	-	(Phinyomark et al., 2012c)
Myopulse percentage rate	MYOP	$threshold = 16$	(Phinyomark et al., 2012c)
Root mean square	RMS	-	(Kim et al., 2011; Oskoei & Hu, 2008)
Sample entropy	SampEn	$m = 2, r = 0.2 \times \sigma$	(Zhang & Zhou, 2012; Zhao et al., 2006b)
Skewness	Skew	-	(Khushaba, Al-Ani & Al-Jumaily, 2010; van den Broek et al., 2006)
Slope sign change	SSC	$threshold = 16$	(Hudgins et al., 1993; Tkach et al., 2010)
Simple square integral	SSI	-	(Phinyomark et al., 2012c)
Absolute temporal moment	TM	$order = 4$	(Phinyomark et al., 2012c)
Variance	VAR	-	(Tkach et al., 2010; Zardoshti-Kermani et al., 1995)
Variance fractal dimension	VFD	$k_{\max} = \lfloor \log_2(N) \rfloor$	(Ehtiati, Kinsner & Moussavi, 1998)
v-order	V	$v = 3$	(Tkach et al., 2010; Zardoshti-Kermani et al., 1995)
Willison amplitude	WAMP	$threshold = 10$	(Tkach et al., 2010; Zardoshti-Kermani et al., 1995)
Waveform length	WL	-	(Hudgins et al., 1993; Tkach et al., 2010)
Zero crossing	ZC	$threshold = 10$	(Hudgins et al., 1993; Tkach et al., 2010)
Amplitude of the first burst	AFB	$w_f = 32\text{ms}$	(Phinyomark et al., 2012c)
Critical exponent analysis	CEA	$\alpha_\Delta = 0.01$	(Phinyomark, Phothisonothai, Phukpattaranont & Limsakul, 2011)
Maximum-to-minimum drop in power density ratio	DPR	-	(Kendell, Lemaire, Losier, Chan & Hudgins, 2012)

Frequency ratio	FR	$f_{lb} = [15\ 45],\ f_{hb} = [95\ 500]$	(Phinyomark et al., 2012c)
Maximum amplitude	MAX	$O_{lp} = 6,\ f_{\infty} = 5\text{Hz}$	(Kendell et al., 2012)
Median frequency	MDF	-	(Oskoei & Hu, 2008; Phinyomark et al., 2012c)
Mean frequency	MNF	-	(Kendell et al., 2012; Oskoei & Hu, 2008)
Mean power	MNP	-	(Oskoei & Hu, 2008; Phinyomark et al., 2012c)
Power spectrum deformation	OHM	-	(Kendell et al., 2012)
Peak frequency	PKF	-	(Phinyomark et al., 2012c)
Power spectral density fractal dimension	PSDFD	-	(Talebinejad, Chan, Miri & Dansereau, 2009)
Power spectrum ratio	PSR	$n = 20$	(Phinyomark et al., 2012c)
Spectral moment	SM	$order = 2$	(Phinyomark et al., 2012c)
Signal-to-motion artifact ratio	SMR	-	(Kendell et al., 2012)
Signal-to-noise ratio	SNR	-	(Kendell et al., 2012)
Total power	TTP	-	(Phinyomark et al., 2012c)
Variance of central frequency	VCF	-	(Phinyomark et al., 2012c)

w_f = window size of Hamming function, m = maximum epoch length, r = tolerance, σ = standard deviation, $order$ = model/moment order, $k_{\max}$ = maximum time interval, N = window size, α_{Δ} = step size of moment exponent, b = box size conditions, O_{fp} = order of fitting procedure, f_{lp} = cutoff frequency of low frequency band, f_{hp} = cutoff frequency of high frequency band, $segment$ = number of segments, O_{lp} = order of low-pass Butterworth filter, f_{co} = a cutoff frequency, b = box size conditions, $threshold$ = pre-defined threshold value, n = integral limit, v = order of v.

Table 2

Table 2 Averaged test classification accuracy (%) and its standard deviation of fifty features, when trained in the first five, recent preceding five, and all preceding trials. Sorting is done based on the first five trials column from maximum mean to minimum mean values. Bold numbers represent the highest three classification accuracies achieved in each experiment.

Feature	First 5 trials		Preceding 5 trials		All preceding trials	
	Mean	SD	Mean	SD	Mean	SD
SampEn	**93.37**	5.03	**96.61**	3.15	**95.82**	3.82
ApEn	**84.68**	7.35	92.29	4.84	91.78	5.20
MFL	**82.07**	9.54	**96.49**	3.96	**96.05**	4.28
IAV	81.24	7.45	92.89	5.26	92.37	5.15
MAV	81.24	7.45	92.89	5.26	92.37	5.15
MAV2	81.18	7.34	92.69	5.15	92.27	4.91
RMS	81.10	7.45	93.07	5.02	92.93	5.03
MAV1	81.05	7.50	92.69	5.20	92.27	5.03
DASDV	81.00	11.97	**94.65**	4.70	**93.44**	5.34
V	79.98	7.46	92.58	5.01	92.63	4.94
AAC	79.88	12.40	94.56	4.73	93.03	5.60
WL	79.88	12.40	94.56	4.73	93.03	5.60
AR	78.96	9.18	88.80	5.28	87.42	5.95
WAMP	75.33	10.67	89.74	5.35	87.63	6.34
LOG	74.28	8.26	86.94	5.92	86.58	5.06
MYOP	73.31	11.39	85.61	6.36	83.23	6.64
CC	73.20	10.64	82.03	6.08	80.51	6.98

SSC	71.29	9.04	80.24	5.97	76.95	12.86
DFA	71.28	10.10	78.87	6.98	77.51	6.92
SSI	71.14	12.06	80.35	7.98	82.59	6.53
VAR	71.14	8.25	80.35	7.98	82.59	6.53
MNP	71.14	8.25	80.36	7.98	82.57	6.52
TTP	71.14	8.25	80.36	7.98	82.57	6.52
MTW	71.12	8.25	79.76	7.67	82.09	6.36
SM	71.09	8.27	82.33	8.97	82.84	7.93
MHW	69.01	7.23	76.31	6.97	79.02	5.74
ZC	66.68	8.21	74.01	5.35	71.58	6.87
MNF	66.33	10.05	76.79	7.76	75.46	7.89
BC	62.96	11.22	74.05	6.58	70.44	8.06
MAX	62.86	6.37	59.89	7.20	65.27	7.04
TM	60.25	7.68	60.13	9.36	63.45	7.94
MDF	57.18	9.08	65.93	7.27	65.08	7.61
AFB	57.03	4.08	57.66	4.88	60.53	4.58
HG	52.34	5.50	58.40	5.94	57.64	5.78
FR	47.79	6.88	52.46	6.13	52.36	6.56
Katz	47.09	5.89	54.98	6.09	54.85	6.34
OHM	46.88	6.45	50.82	6.53	49.28	5.93
HIST	41.49	9.17	51.41	7.86	49.75	8.15
PSR	37.63	5.94	41.47	6.23	41.20	5.77

PKF	32.53	4.06	34.94	3.90	33.96	3.71
PSDFD	25.08	3.22	27.25	3.77	26.91	3.73
Kurt	21.41	4.68	26.80	5.30	26.66	4.71
VFD	18.85	3.24	19.11	3.17	19.83	3.41
MAVS	17.47	1.73	17.27	2.00	17.33	1.45
Skew	16.57	16.90	49.76	12.02	26.32	17.18
DPR	13.18	2.08	13.21	2.10	12.69	1.85
SNR	10.75	1.71	10.41	1.46	10.81	1.58
SMR	10.67	0.82	10.65	1.17	10.01	0.65
CEA	10.41	2.00	10.86	2.28	11.07	1.72
VCF	10.39	1.84	10.72	2.20	10.16	1.96

Table 3 The difference of classification accuracies when trained in recent preceding five (T1) and all preceding (T2) trials.

No significant difference ($p > 0.01$)		Significant difference ($p < 0.01$)	
T1 < T2	T1 > T2	T1 < T2	T1 > T2
V, SSI, VAR, MNP, TTP, MTW, SM, VFD, MAVS, SNR, CEA	SampEn, ApEn, MFL, IAV, MAV, MAV2, RMS, MAV1, DASDV, AAC, WL, AR, LOG, CC, SSC, DFA, MNF, MDF, HG, FR, Katz, OHM, HIST, PSR, PKF, PSDFD, Kurt, DPR, VCF	MHW, MAX, TM, AFB	WAMP, MYOP, ZC, BC, Skew, SMR
11 features	29 features	4 features	6 features

Table 4 Highest averaged test classification accuracy (%) and its standard deviation of ten single features and ten of each multiple-feature groups, when trained in the first five trials.

Feature		First 5 trials		Feature				First 5 trials	
#1	#2	Mean	SD	#1	#2	#3	#4	Mean	SD
SampEn		93.37	5.03	SampEn	CC	MAV2		97.53	2.95
ApEn		84.68	7.30	SampEn	CC	MAV1		97.50	3.03
MFL		82.07	9.45	SampEn	CC	IAV		97.50	3.06
IAV		81.24	7.36	SampEn	CC	MAV		97.50	3.06
MAV		81.24	7.36	SampEn	CC	HG		97.42	2.67
MAV2		81.18	7.27	SampEn	CC	Katz		97.39	2.74
RMS		81.10	7.33	SampEn	CC	RMS		97.36	3.14
MAV1		81.05	7.42	SampEn	CC	V		97.34	3.05
DASDV		81.00	11.91	SampEn	CC	PSDFD		97.28	2.67
V		79.98	7.33	SampEn	CC	LOG		97.28	2.95
SampEn	CC	97.25	2.76	SampEn	CC	RMS	WL	97.75	2.73
SampEn	DFA	97.13	2.96	SampEn	CC	RMS	AAC	97.75	2.73
SampEn	AR	96.44	3.37	SampEn	CC	IAV	WL	97.73	2.86
SampEn	MNF	95.96	3.83	SampEn	CC	MAV	WL	97.73	2.86
SampEn	HG	95.31	3.93	SampEn	CC	IAV	AAC	97.73	2.86
SampEn	FR	94.88	4.69	SampEn	CC	MAV	AAC	97.73	2.86
SampEn	ZC	94.84	4.18	SampEn	CC	MAV2	ApEn	97.71	2.83
SampEn	PSR	94.40	3.85	SampEn	CC	MAV1	ApEn	97.65	2.94
SampEn	MDF	94.22	4.21	SampEn	CC	V	MYOP	97.62	3.35
SampEn	Kurt	94.10	4.29	SampEn	CC	MAV2	MHW	97.57	2.98

Table 5 Averaged test classification accuracy (%) of SampEn and SampEn + CC + RMS + WL, when trained in the first five trials using LDA by changing the segment length and increment.

Segment length (ms), increment (ms)	SampEn		SampEn+CC+RMS+WL	
	Mean	SD	Mean	SD
125, 62.5	89.93	5.22	95.71	3.71
125, 125	90.28	5.20	95.49	3.73
250, 62.5	93.39	5.07	97.79	2.77
250, 125	93.37	5.03	97.73	2.73
250, 250	93.46	5.15	97.91	2.72
500, 62.5	93.31	5.18	98.79	2.25
500, 125	94.33	5.19	98.87	2.12
500, 250	94.49	5.13	98.75	2.14

Figure 1
Click here to download high resolution image

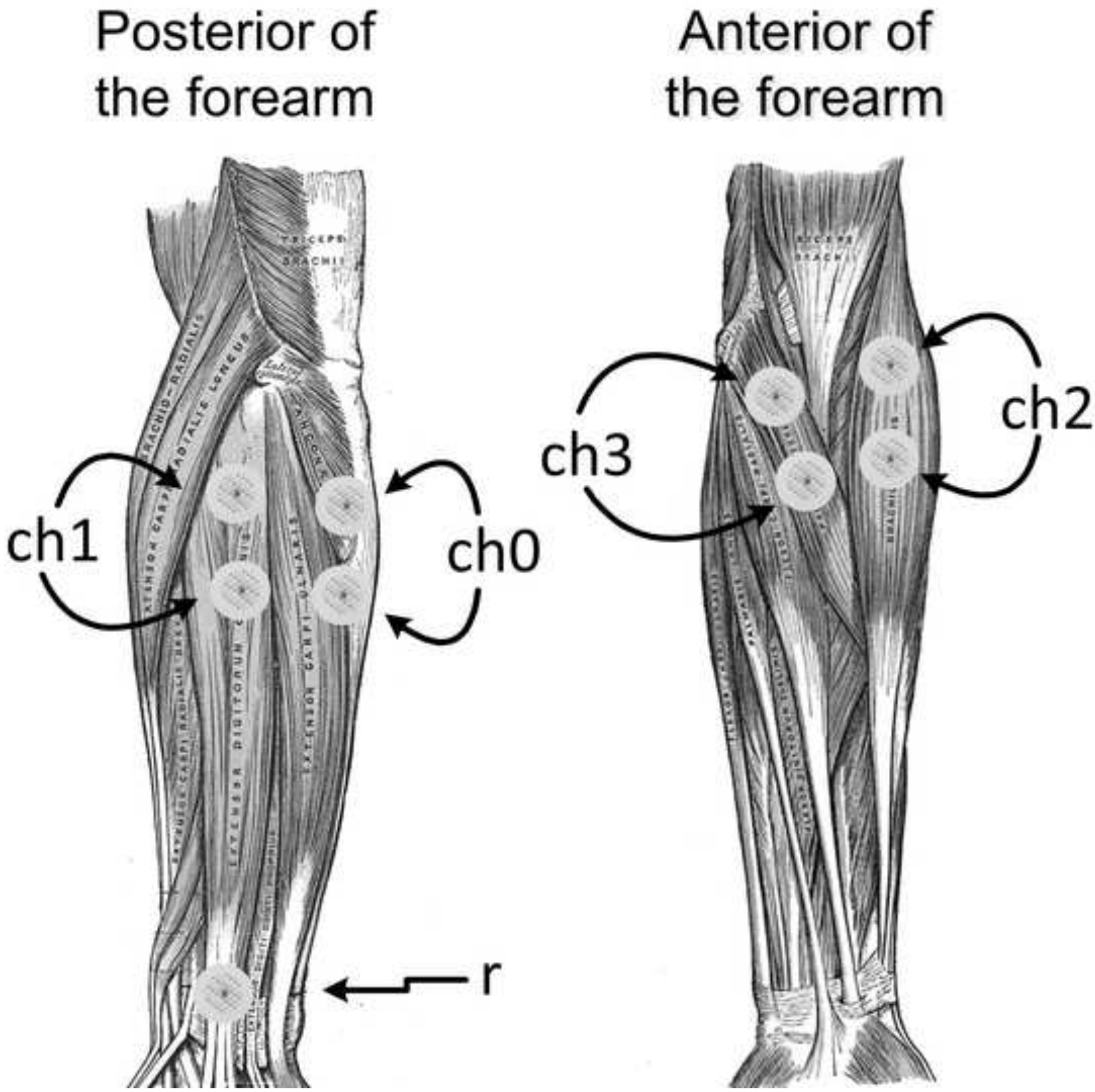
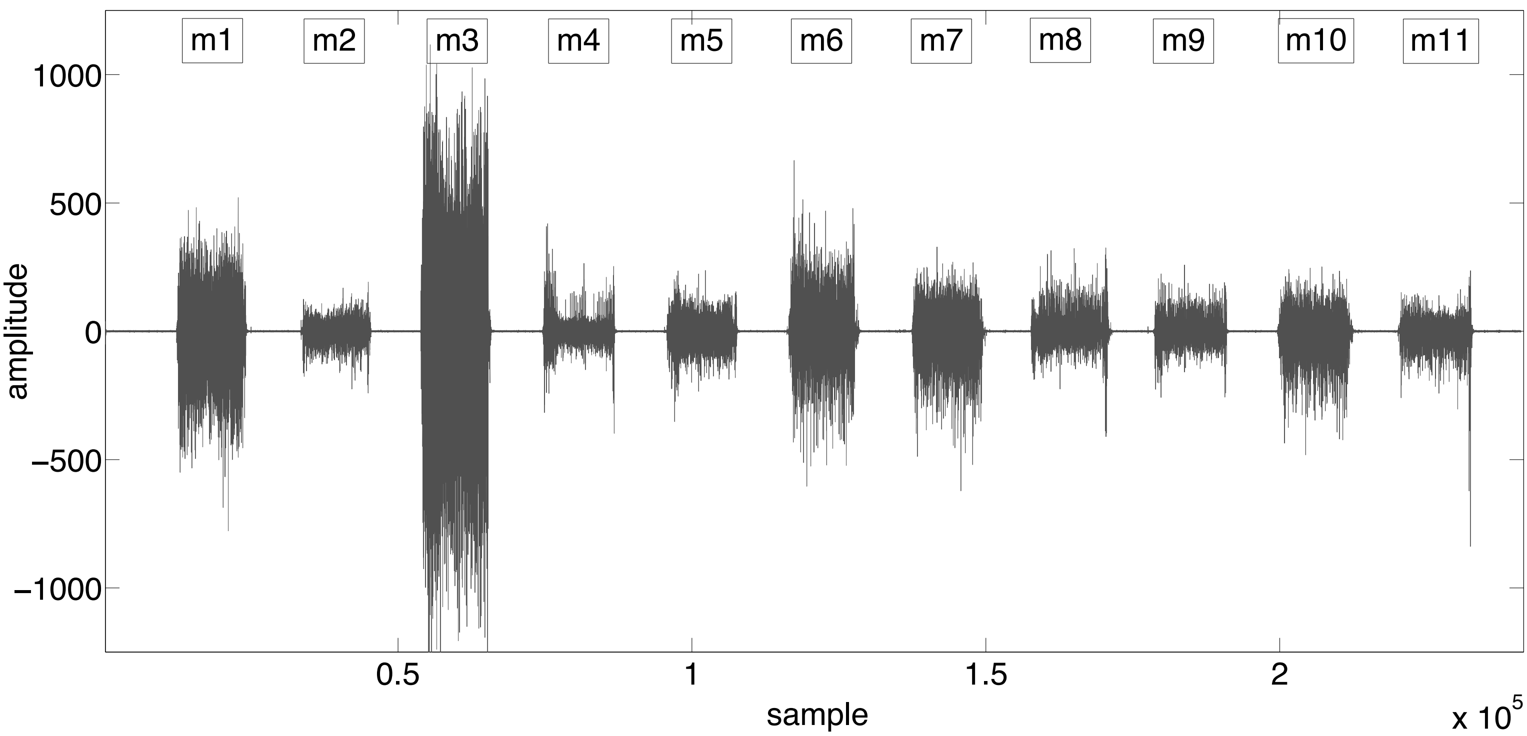


Figure 2


m1
m2
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m10
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1000
500
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amplitude
0.5
1
1.5
2
sample
x 10^5

Figure 3a

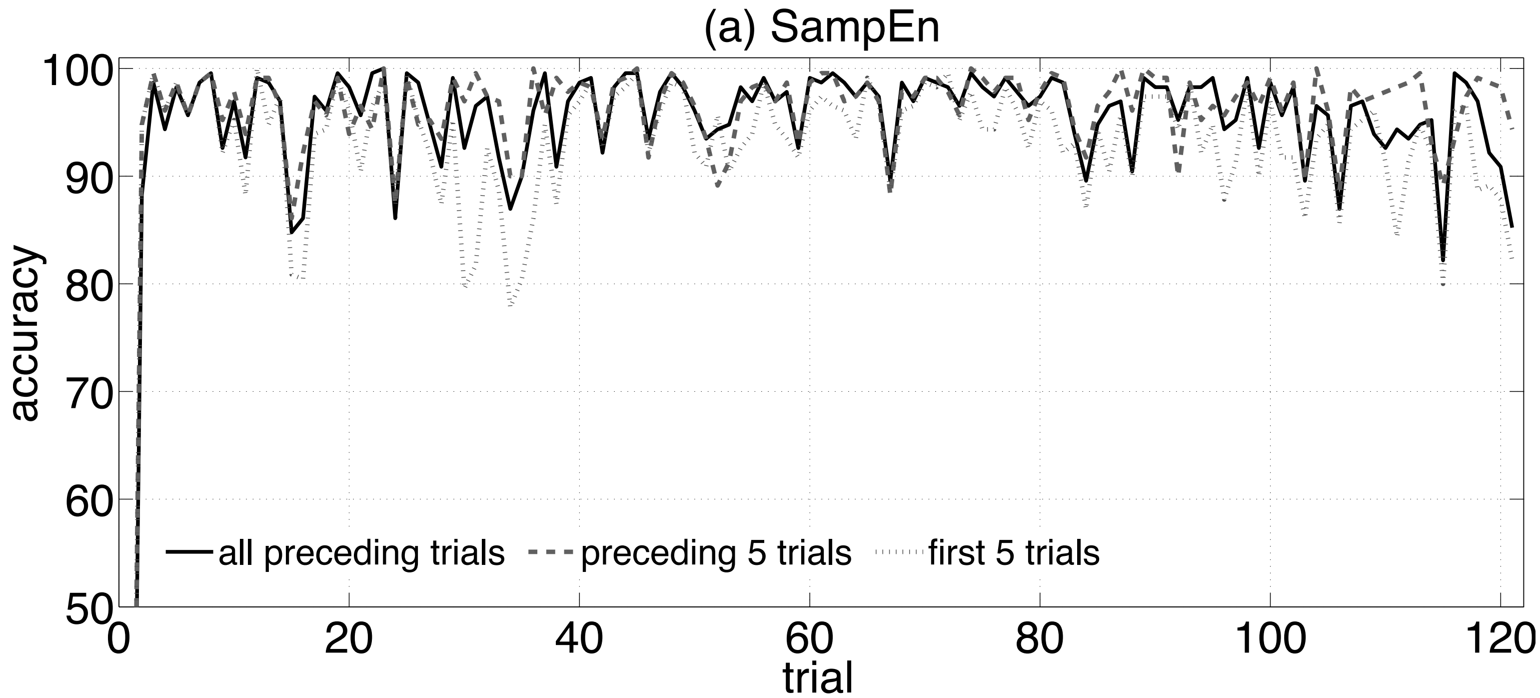

(a) SampEn
accuracy
trial
100
90
80
70
60
50
0
20
40
60
80
100
120
all preceding trials
preceding 5 trials
first 5 trials

Figure 3b

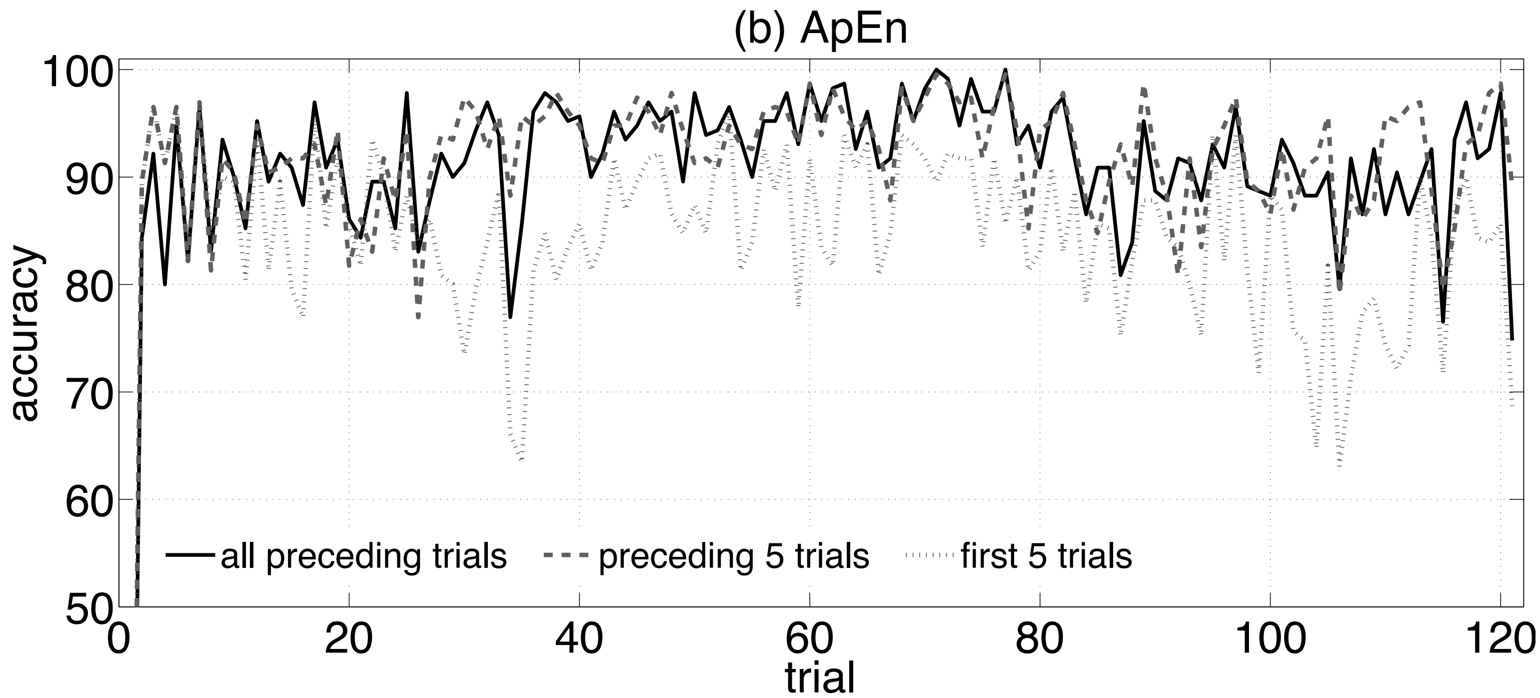
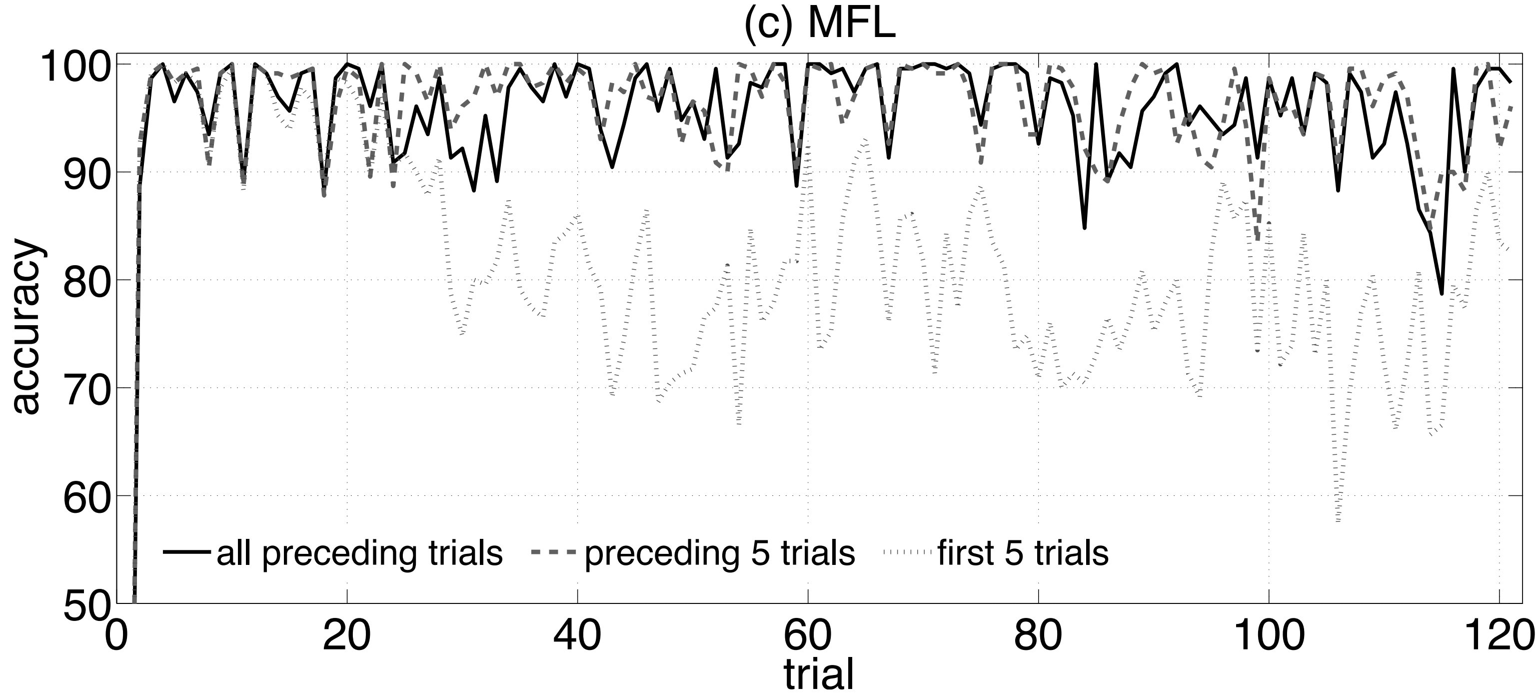
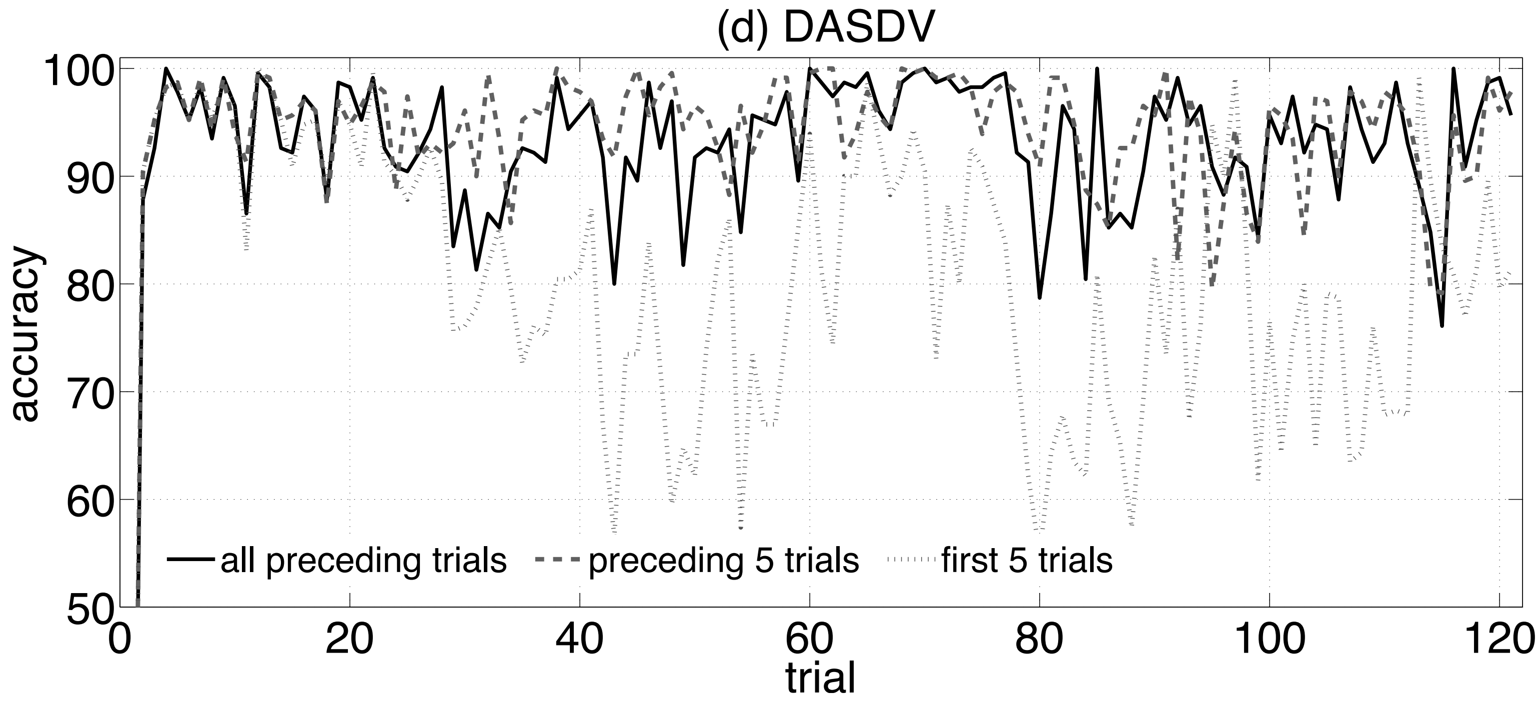

(b) ApEn
accuracy
trial
100
90
80
70
60
50
0
20
40
60
80
100
120
all preceding trials
preceding 5 trials
first 5 trials

Figure 3c



(c) MFL
100
90
80
70
60
50
accuracy
0
20
40
60
80
100
120
trial
all preceding trials
preceding 5 trials
first 5 trials

Figure 3d


(d) DASDV
accuracy
trial
all preceding trials
preceding 5 trials
first 5 trials
100
90
80
70
60
50
0
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60
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100
120