

# Application of Support Vector Machines in Upper Limb Motion Classification Using Myoelectric Signals

Mohammadreza Asghari Oskoei

Department of Computing and Electronic Systems  
University of Essex  
Wivenhoe Park, Colchester CO4 3SQ, U.K.  
Email: [masgha@essex.ac.uk](mailto:masgha@essex.ac.uk)

Huosheng Hu

Department of Computing and Electronic Systems  
University of Essex  
Wivenhoe Park, Colchester CO4 3SQ, U.K.  
Email: [hhu@essex.ac.uk](mailto:hhu@essex.ac.uk)

**Abstract** – This paper presents a novel Support Vector Machine (SVM) approach to upper limb motion classification using myoelectric signals. The main purpose of this paper is to compare SVM-based classifiers with LDA and MLP. SVM demonstrates exceptional classification accuracy and results in a robust way of limb motion classification with low computational cost. The validity of entropy, as an index to measure correctness of classification, is also examined. Experimental results show that entropy is a reliable measure for online training in myoelectric control systems.

**Index Terms** – Myoelectric Control, SVM, Entropy, Upper limb motion classification

## I. INTRODUCTION

Surface myoelectric signal (MES) contains rich information that can be used to recognize muscular activities in a non-invasive manner. A Myoelectric Control System (MCS), which uses MES as a reference signal to manipulate assistive robots or rehabilitation devices, has the potential to become a powerful and convenient user interface. Pattern recognition based MCS functions by recognizing different pre-trained signal patterns and applying corresponding pre-defined motion commands to the electric motors and/or actuators. It provides hands-free and proximal function control based on neuromuscular activities. The success of myoelectric control depends greatly on the classification accuracy. Feature extraction and classification methods are two crucial factors for achieving high classification performance in pattern recognition.

Pattern recognition-based myoelectric control [1] has been researched for more than three decades, but due to technical limits, the real time control was not feasible. Hudgins et al [2] were pioneers in the development of a real time pattern recognition based myoelectric control system. Time domain (TD) features of signal to a multilayer perceptron (MLP) neural network was applied to classify four upper limb motions with the accuracy of about 90%. Englehart et al [3] showed that linear discriminate analysis (LDA) outperforms MLP on time-scale features, which are dimensionally reduced by PCA. Vuskovic et al [7] introduced the modified version of fuzzy ARTMAP networks to classify prehensile myoelectric signals. Chan et al [9] applied hidden Markov models (HMM) to discriminate six classes of limb motions based on four-channel MES. It resulted in an average

accuracy of 94.63%. Furthermore, Huang et al [5] and Fukuda et al [6] employed Gaussian mixture model (GMM) as a classifier in their myoelectric control systems. The former showed the accuracy of 97%. As well, Fukuda et al [6] and Kato et al [18] introduced online training for myoelectric control. The former applied the entropy as a measure to evaluate classification, while the latter suggested the continuity of command for this purpose. In this paper, we are going to apply SVM as a classifier to recognize upper limb motions from myoelectric signal patterns, and suggest the entropy as an online index to evaluate the classification.

SVM is a relatively novel approach with the strong theoretical background that has become an increasingly popular tool for machine learning tasks involving classification and regression. It has recently been successfully applied into a number of applications ranging from face identification and text categorization to bioinformatics and database mining. SVM constructs an optimal separating hyper plane in a high dimensional feature space of training data that are mapped by a non-linear kernel function. Thus, although it uses linear learning machine method with respect to non-linear kernel function, it is in effect of non-linear classifier. SVM is binary classification, so for multi-class classifications the pair-wise classifications such as one-against-all or one-against-one should be used. It shows better results than (or comparable outcomes to) ANN and other statistical models, on the most popular benchmarks.

The rest of paper is organized as follows. In Section II, we introduce basic issues of SVM, soft margin, nonlinear SVM, kernels, and multiclass classification. Section III presents the methods applied on data acquisition, experiments, and evaluation. Section IV provides some experimental results: comparison of classifiers and validity of entropy in evaluation. Finally, a brief conclusion and future work are summarized in Section V.

## II. SUPPORT VECTOR MACHINE

SVM was initially introduced by Vapnik and Chervonenkis in 1965 and then developed for classification and regression in 1992. In SVM, the training is reformulated and represented in such that a (convex) quadratic programming (QP) problem is formulated. The solution to this QP problem is global and unique. In this approach, it is possible to choose several types of kernel functions including

linear, polynomial, RBF, and sigmoid. More details are available in [14], [15], [16].

SVM is a binary classifier  $f: R^N \mapsto \{\pm 1\}$  that is estimated by the given empirical data

$$(x_1, y_1), \dots, (x_m, y_m) \in R^N \times \{\pm 1\} \quad (1)$$

Nonlinear classification problems are solved by mapping the original data into a “feature space”, in which the mapped data are linearly separable. Function  $\phi(\cdot)$ , which maps training vector  $x_i$  into a higher (maybe infinite) dimensional space, requires belonging to dot product space. The dot product of mapping function is named as kernel.

$$k(x_i, x_j) = \phi(x_i) \cdot \phi(x_j) \quad (2)$$

For a group of data that are mapped into the linearly separable space, the hyperplanes that divides the data into two labeled classes are shown as:

$$w\phi(x) + b = 0 \quad w \in R^N, b \in R \quad (3)$$

There are many hyperplanes separating data, but there exists a unique one yielding the maximum margin of separation between the classes. To construct this optimal hyperplane, we need to solve the following QP problem:

$$\begin{aligned} \min_{w,b} \quad & \frac{1}{2} \|w\|^2 + C \sum_{i=1}^m \xi_i \\ & y_i(w\phi(x_i) + b) \geq 1 - \xi_i, \quad i = 1, \dots, m \end{aligned} \quad (4)$$

Due to noise and/or contradictory data in myoelectric signals, a separating hyperplane with hard margin may not exist. A possible realization to cope with violating samples is tolerating some errors in training data. To allow for possibility of error samples, one introduces slack variables ( $\xi_i \geq 0$ ) that the sum of them ( $\sum \xi_i$ ) provides an upper bound on the number of training errors in optimization problem. They represent samples in training set that are placed in wrong side of hyperplane. The constant  $C \in [0, \infty)$  makes a trade-off between capacity of the classifier and error in training data. A way to solve (4) is through its Lagrangian dual as:

$$\begin{aligned} \max_{\alpha} \quad & \sum_{i=1}^m \alpha_i - \frac{1}{2} \sum_{i,j=1}^m \alpha_i \alpha_j y_i y_j k(x_i, x_j) \\ & 0 \leq \alpha_i \leq C, \quad i = 1, \dots, m, \quad \sum_{i=1}^m \alpha_i y_i = 0 \end{aligned} \quad (5)$$

Problems (4) and (5) are called primal and dual problems, respectively. Under certain conditions, the primal and dual problems have the same optimal objective values. Therefore, we can instead solve the dual which may be easier than the primal. Sometime when working in kernel mapped feature spaces, solving the dual may be the only way to do. The dual problem (4) or (5) for any given  $\alpha_i$  leads to the optimal decision function as

$$f(x) = \text{sgn}\left(\sum_{i=1}^m y_i \alpha_i k(x_i, x) + b\right) \quad (6)$$

The decision function (6) shows the classifier has an expansion in terms of a subset of the training data, namely those patterns whose  $\alpha_i$  is non-zero, called support vectors. Though many different kernels can be proposed depending on data structure, the most popular ones are

- Radial basis function (RBF):  $k(x_i, x_j) = e^{-\gamma \|x_i - x_j\|^2}$
- Polynomial:  $k(x_i, x_j) = (\gamma x_i \cdot x_j + r)^d$
- Sigmoid:  $k(x_i, x_j) = \tanh(\gamma x_i \cdot x_j + r), \gamma > 0$
- Linear:  $k(x_i, x_j) = x_i \cdot x_j$

Here,  $\gamma, r, d > 0$  are kernel parameters and need to be selected properly before classification.

*Multiclass SVM:* SVM inherently is a binary classifier and classifies the samples as being positive or negative. In contrast, many problems we are interested in solving, such as limb motions classification, are of multiclass problems. SVM performs very well for binary problems, and it is desirable to extend its capabilities into multiclass problems. Hence, we need a classifier  $f: R^N \mapsto \{1, \dots, k\}$  that estimates the most suitable class upon the given empirical data

$$(x_1, y_{x_1}), \dots, (x_m, y_{x_m}) \in R^N \times \{1, \dots, k\} \quad (7)$$

Probably the simplest scheme for  $k$ -class classification problem is to train  $k$  independent binary classifiers that each one is trained to distinguish the training samples in one class against the all remaining classes. To classify a new sample,  $k$  classifiers work separately, and one that outputs the largest decision function value is chosen as an estimated class. This scheme is referred to as the “one-against-all” or OAA scheme. It is very simple in implementation, relatively fast in running, obvious and producing results that are often as or more accurate than other methods. Training OAA simply requires training  $k$  binary SVMs. Another method is the “one-against-one” or OAO. In this method,  $k(k-1)$  binary classifiers are trained to separate a pair of two classes. To classify a new sample, a class that gains more votes of the binary classifiers is chosen as the final output. Same as OAA, this method has a simple conceptual justification and it can be implemented to train and test as quickly as OAA.

The advantage of OAO is that conducts binary classifications on all pairs of classes and computes the probability for each class [17]. This supports analytic concept for generalization and certainty. Given  $r_{ij}$  is an estimate for probability of output of a pair wise binary classifier between class  $i$  and  $j$  (i.e.  $r_{ij} \approx P(y=i | y=\{i, j\}, x)$ ,  $r_{ij} + r_{ji} = 1$ ) and  $p_i$  is the probability of  $i^{\text{th}}$  class, the class probability  $p = (p_1, \dots, p_k)$  can be derived by quadratic optimization problem (8).

$$\min_p \sum_{i=1}^k \sum_{j:j \neq i}^k (r_{ij} p_j - r_{ji} p_i)^2 \quad (8)$$

$$\sum_{i=1}^k p_i = 1, \quad p_i \geq 0, \quad i = 1, \dots, k,$$

This paper employs LIBSVM [15] as the core of SVM classifier, and conducts multiclass classifications using C-SVM and OAO method.

### III. METHODOLOGY

This section introduces the methods applied for data collection, experiments, and evaluation.

#### A. Data acquisition

Four-channel myoelectric signal (MES) is collected from four sites placed on the forearm above the wrist flexors and extensors, as shown in Fig. 1, using bipolar active electrodes (Biometrics Ltd SX230). The active electrodes have a pre-amplifier, band-pass filter with range 10-450Hz, and pickup filter that removes unwanted line-frequencies (50/60Hz). An electrode is also placed on the wrist providing a common ground reference. Signals are sampled at 1000Hz using a 12-bit A/D converter and mapped linearly from  $\pm 300\text{mV}$  into  $\pm 1$  with resolution 0.0001.

Data are collected from 11 healthy subjects. Each subject performs five limb motions plus rest that makes up six states of motion. The motions are isotonic and comprised of hand flexion/extension, abduction/adduction and keeping straight. Two sequences of six motions, in which each motion is held fixed for the five seconds, is called a block. Four blocks of data are gathered from subjects in each session.

Utmost two sessions are conducted for each subject, and totally 17 sessions are conducted for experiments. For each session, the accuracy of classification is computed by 4-fold cross-validation method

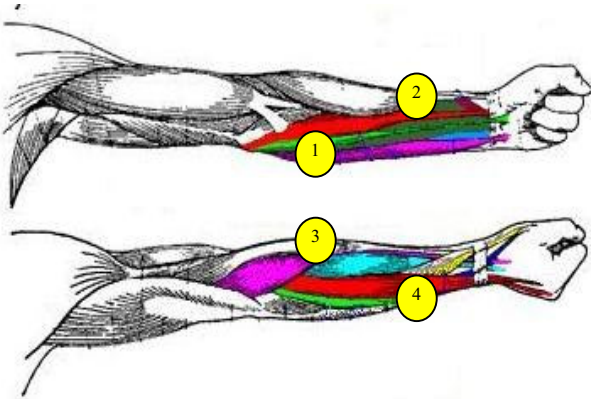


Fig. 1 Electrode placement for four-channel MES

#### B. Features

Because of significance of features in classification, feature selection is an essential stage in myoelectric control design [12]. The features should be capable to present the

characteristics or properties of the signal for different limb motions. The load of computation, as well, should be considered in feature selection procedure. In this work, the relative performance of mean absolute value (MAV) [12], TD\* feature set comprising of MAV, WL, ZC, SSC† [2], and feature set RMS+AR6‡ [5] is determined in the context of a SVM-based classifier. The features of each channel are extracted from segments of data with length of 200ms, and then concatenated together and fed into the classifier. The dimension of feature vector of single MAV, TD feature set, and RMS+AR6 are 4, 16 and 28, respectively.

#### C. Classification

In pattern-recognition-based myoelectric control, the MES patterns corresponding to each motion are recognized and classified into the distinctive classes. Hence, the classifier is an important module and it should perform perfect classification. The following experiment compares SVM with two well-known classifiers including the linear discriminate analysis (LDA) and multilayer perceptron (MLP) neural networks. Moreover, four popular SVM kernels including RBF, linear, polynomial, and sigmoid are examined in this investigation.

SVM and MLP, both require to be optimized based on data sets before application. The parameters of SVM and layout of MLP should be chosen properly regarding data set. Hence, model selection is applied for each subject/session and feature/segment individually. The grid-search is used to select the optimized SVM (i.e. SVM with optimized parameters). In this method, the performance of SVM is examined based on the wide range of parameters and then the ones with the best performance is picked. The 5-fold random cross-validation scheme is used to evaluate the parameters.

Table 1 – Parameters and layouts to adjust before classification

Classifier	Adjusted Parameters
SVM (coarse grid)	C: {1 10 20 50 80 100 200 600 1000} $\gamma, r$ : {0.5 2 5 8 10 50}
SVM (fine grid)	$\pm 5, 10, 15, 20\%$ of selected parameters in coarse grid
MLP	Hidden layer nodes: {4 5 6 8 10 12 15 20}

Since doing a complete grid-search is time-consuming, it is applied in two stages: coarse grids, and then fine grids. The 5-fold random cross-validation scheme yields the mean of accuracy of five individual classifications when the whole data (training and test set) is randomly divided into five subsets, of which is chosen as a test set and the rest is used as a training set. Cross-validation prevents the overfitting in classification. The layout of MLP is as well selected optimally based on data before using. Since back propagation algorithm

\* Time domain

† Mean absolute value, waveform length, zero crossing, slope sign changes

‡ Root mean square, autoregressive coefficients of order 6

begins with randomly initializing, the performance for each session is averaged over four iterations.

Table 1 illustrates the range of parameters that are examined and selected optimally before experiments. The range of parameters is obtained in preliminary experiments. The experiments in this work are based on optimized classifier for each subject/session and feature/segment.

### C. Evaluation

Accuracy is the main index to illustrate the performance of classification. It is defined as the rate of correct classifications to all data in the test set.

$$Accuracy = \frac{Corrects\_Test\_Set}{All\_Test\_Set} \times 100 \quad (9)$$

As it mentioned before, each session includes four blocks of data. The accuracy of each session is computed by 4-fold cross validation. In each fold, a block is chosen as the test set and the rest as the training set. The accuracy of each session is the average accuracy of four classifications.

$$Accuracy_s = \frac{1}{4} \sum_{i=1}^4 Accuracy_i \quad (10)$$

Recently, the entropy has been noticed as an internal measure to evaluate the correctness of classification for online training [6]. In myoelectric control systems, it is an unsupervised evaluation that can be used during the control operation. The next experiment attempts to examine the correlation of entropy and accuracy in SVM-based classification. It investigates trust on entropy as an internal measure to evaluate the correctness of classification. This comparison is done for MAV features with segment length of 200ms.

SVM outputs the probability of each class as well as the selected one in each classification. It is obvious that the estimated class has the most probability comparing with other classes. Given  $p_i(n)$  is the probability of assigning the  $n^{th}$  estimation into the class  $i$  of  $k$ -class classification problem, the entropy of  $n^{th}$  segment of data is defined as:

$$E(n) = - \sum_{i=1}^k p_i(n) \log[p_i(n)] \quad (11)$$

## IV. EXPERIMENTAL RESULTS

This section presents the result of experiments that are conducted to achieve an optimum configuration for SVM-based myoelectric control. Moreover, statistical analyses are applied to interpret the experimental results.

As it mentioned, the experiments are founded on data collected at 17 sessions from 11 subjects. Enough long time is taken between sessions that have common subjects to provide independent data for the experiments. The accuracy in each session is obtained by averaging the accuracy of four independent classifications. Therefore, each experiment has 17 independent observations with identical distribution. The purpose of statistic analysis is to find statistically meaningful differences over observations with the certain significance.

Analysis of variance (ANOVA) is a statistic approach, in which the variance of observations is partitioned into components due to different explanatory variables. It is powerful tools but only applicable for data with normal distribution. To analysis the results of experiments in this paper, due to a low rate of observations and their unknown distribution, non-parametric approaches are strongly suggested. Wilcoxon rank-sum and Kruskal-Wallis are two non-parametric statistic methods that are adopted in this paper to compare samples from two and more than two groups, respectively.

Wilcoxon rank-sum is a two-sided test for two groups of data with independent samples and identical distribution to recognise whether their medians are equal. The Kruskal-Wallis tests the equality of samples' median among groups. Intuitively, it is identical to the one-way ANOVA and extension of the Wilcoxon rank-sum for more than two groups. In both data are replace by their ranks in analyses. Both methods provide p-value. The p-value is a probability that the groups are drawn from the same population or from different populations with same median. If the p-value is near zero, this suggests that at least one group's median is significantly different from the other median. The critical p-value, which determines whether the result is judged "statistically significant", is chosen 0.05, in this paper.

At the rest of this section, the results of two experiments are presented. The former compares SVM applied by different kernels with other classifiers, and the later investigates validity of entropy in evaluation. The summary of options examined by this paper is shown in Fig. 2, i.e. a schematic block diagram of a myoelectric control system.

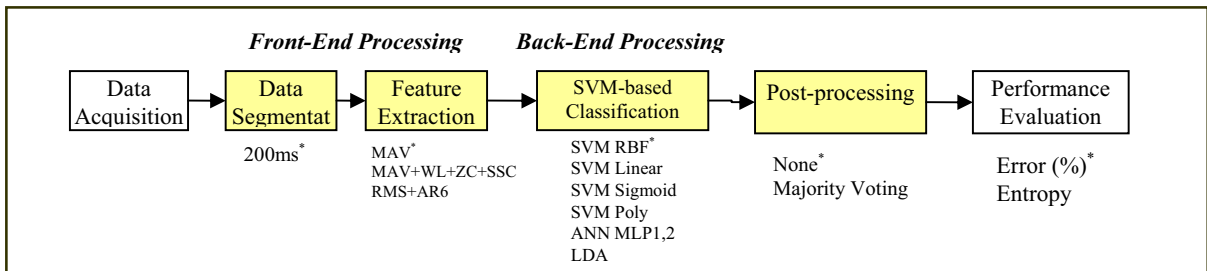


Fig. 2 Design of experiments for myoelectric control modules

### A. Classifiers

To achieve an optimal classifier, the following experiment compares the accuracy of SVM-based classifiers with LDA and MLP. The classifiers are examined one-by-one over single-feature MAV, TD feature set (MAV+WL+SSC+ZC) and feature set RMS+AR6, individually.

The experimental results are demonstrated as a graph in Fig. 3. The first four items of the graph are SVM-based classifiers with kernels RBF, linear, sigmoid, and polynomial, respectively. As the graph shows, the four applied kernels perform similarly over considered features. The average accuracy of SVM for all kernels is about 95%. The performance of LDA, especially for feature sets, is very similar to SVM. The accuracy of LDA applied on feature sets (i.e. TD feature set or RMS+AR6) is about 96%, while for single-feature MAV is about 92%. The last two items of the graph (i.e. MLP1 and MLP2) are belonging to result of MLP with one and two hidden layers, respectively. As can be seen, the accuracy of MLP with one hidden layer drops about 6% while MLP with two hidden layers performs same as SVM and LDA.

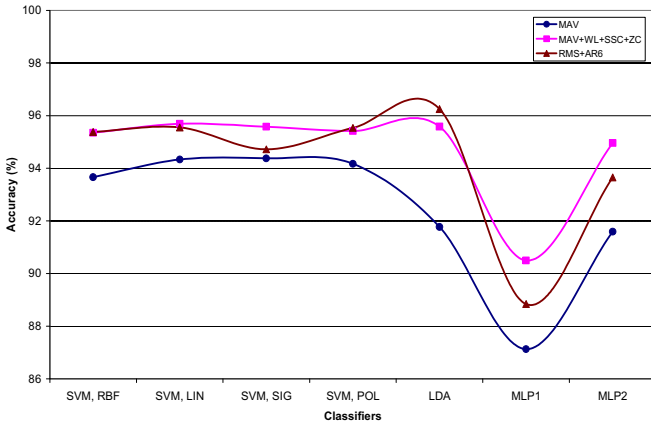


Fig. 3 Performance of seven classifiers

Statistic analysis depicts there is no meaningful difference among the performance of considered classifiers over MAV (Fig. 5) and TD (Fig. 4) feature set, while MLP performs significantly weak over feature set of RMS+AR6 (Fig. 6). The training process of MLP (i.e. back propagation) is much longer than SVM and LDA. The experimental results show the time needed to train an MLP with one hidden layer is about 8 times more than the time needed for SVM. Having comparable conditions, the optimized classifiers that their layout or parameters are selected optimally based on unique data set are compared in this experiment. The training process of MLP is not repeatable, since it initiates from random initial weights and seeks local minimum error rather than global ones. The training process of SVM and LDA are both repeatable and fast.

### B. Entropy

The next experiment examines validity of entropy as an evaluation index for correctness of classification. The result,

which is founded on more than 14000 independent observations, shows a significant difference between correct and non-correct classifications (Fig. 7). The entropy of correct classifications is about 0.13 with a confidence interval between 0.07 and 0.28. For non-correct classifications, it is about 0.74 with a confidence interval between 0.49 and 0.94 (p-value=0.05). Fig. 8 and Fig. 9 illustrate histograms of entropy in two cases of correct and non-correct classifications. As can be seen, they are distinct with different medians.

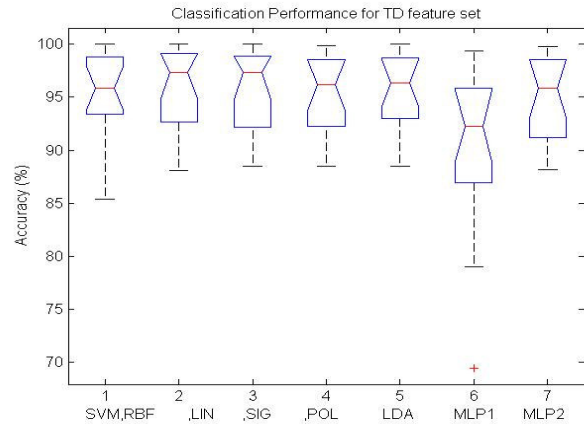


Fig. 4 Performance of 7 classifiers applied on TD feature set

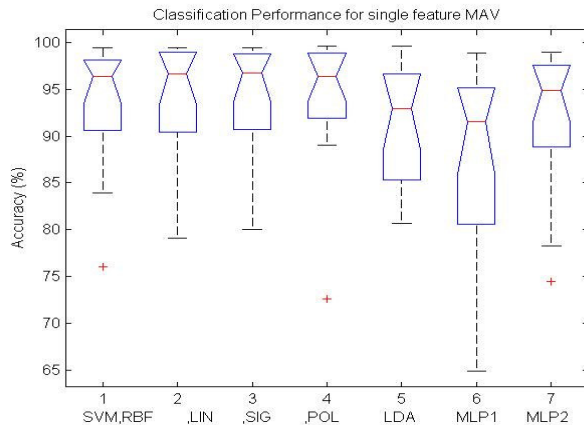


Fig. 5 Performance of 7 classifiers applied on single feature MAV

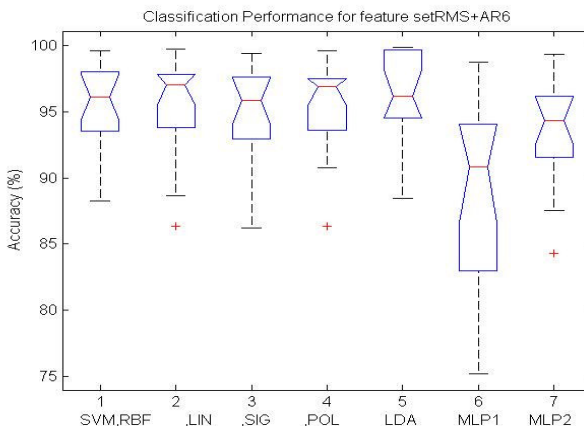


Fig. 6 Performance of 7 classifiers applied on feature set RMS+AR6

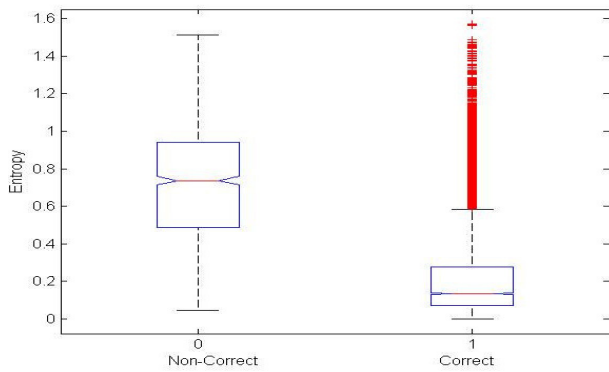


Fig. 7 The entropy of correct and non-correct classifications

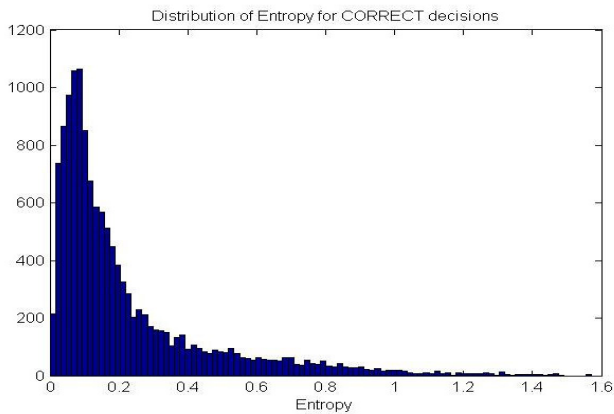


Fig. 8 Histogram of entropy for correct classifications

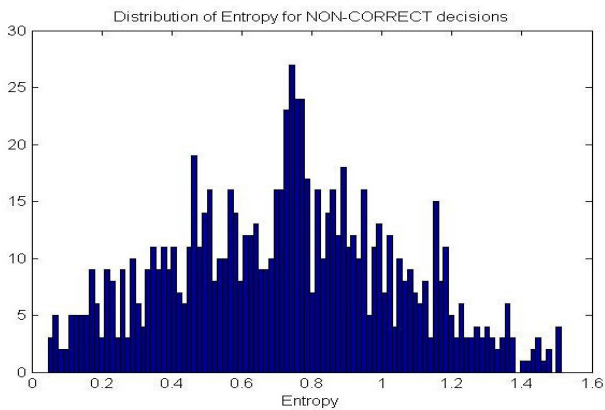


Fig. 9 Histogram of entropy for non-correct classifications

## V. CONCLUSION AND FUTURE WORK

This paper compares the performance of SVM-based classifiers with LDA and MLP-based ones. SVM demonstrates exceptional classification accuracy and results in a robust way of limb motion classification with a low computational cost. It is observed that the optimized SVM (i.e. SVM with parameters chosen optimally) with different kernels (i.e. linear, RBF, polynomial, Gaussian) yields good accuracy over all features.

It is clear that the entropy of output of a SVM classifier could be used as a reliable index to evaluate classification

correctness. Hence, the application of entropy as a measure for online training in myoelectric control is feasible. Our future research will be focused on the development of online training algorithms for SVM-based myoelectric control.

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