LINEAR DISCRIMINANT ANALYSIS VERSUS ARTIFICIAL NEURAL NETWORK AS CLASSIFIERS FOR ELBOW ANGULAR POSITION RECOGNITION PURPOSES

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Abstract: The increasing popularity of an Artificial Neural Network for pattern recognition and the absence of comparative studies showing its real superiority over Discriminant Analysis Methods motivated the present study, aiming at comparing the accuracy levels achieved for a Feed-Forward Multilayer Perceptron (MLP) and a Linear Discriminant Analysis (RLDA) applied to myoelectric signals to classify elbow angular positions. The results showed that there were no significant differences (t-student test $p<0.05$) between the average classification accuracies achieved for both methods even with the search of configuration parameters more appropriate to each situation. Both methods achieved average classification accuracies above 80% for a number of classes up to 4. However, 5 subjects achieved good results in a 5-class setup, which means a 20o shift between consecutive classes. Considering that for MLP there is an effort to define the architecture parameters and also learning parameters, its use is only justified if there is a need of generalization that cannot be achieved by the RLDA that does not require the predefinition of parameters, it is practical and fast, and performs very well.

1 INTRODUCTION

An Artificial Neural Network (ANN) is a system composed of many processing elements operating in parallel, the neurons, that are organized in interconnected layers. This structure allows the knowledge acquisition through a learning process that is built based on the mathematical function that defines each neuron and the strengths of interneuron connections. So, the ability to learn and to generalize to data that it has never seen before have made ANN an attractive tool for pattern recognition (Zhang, 2000); (Basu et al., 2010).

On the other hand, according to statisticians, a Feed-Forward Multilayer Perceptron (MLP) can be seen as a multiple linear or nonlinear regression or discrimination models. In those procedures, a functional form is imposed on the data, some assumptions about the input-output relationship are done, and also probabilistic models are considered in order to define classification decision boundaries. The effectiveness of these methods depends on the assumptions that are made, and so, on the user knowledge of both model and data properties. However, if this causes some difficulties, on the other hand, it allows you to test the relationships among process variables (Cheng and Titterington, 1994)0; (Sarle, 1994); (Warner and Misra, 1996).

A MLP with sigmoid activation function can be used as a universal curve-fit, but it will never reveal the functional relations among the variables. Furthermore, the number of hidden layers and the number of neurons, activation function and learning parameters, usually are defined empirically (Warner and Misra, 1996); (Zhang, 2000).

The increasing popularity of ANN for pattern recognition is a fact and it is not clear its superiority when compared with Discriminant Analysis Methods (Parker et al., 2006); (Ahsan et al., 2010); (Scheme and Englehart, 2011); (Peederman et al., 2011). So, the present study aims at comparing the accuracy levels reached for a MLP and a Linear Discriminant Analysis (LDA) applied to myoelectric signals to classify elbow angular positions.

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2 MATERIALS AND METHODS

2.1 Data

Seven volunteers (4 men and 3 women) keeping a low level of contraction of biceps and triceps, developed elbow flexion and extension movements from 0o to 90o with 3s of steady position each 10o shift. Myoelectric signals were sampled at 1000Hz, filtered within the range 20-500 Hz, rectified, and smoothed with a low pass filter to obtain the amplitude envelope (PowerLab – AdInstruments). This protocol was approved by COEP – USJT – No.076/2010.

For each volunteer there were at most g=18 steady positions or classes (9 for flexion and 9 for extension) and Ni=15 samples of d=200ms dimensional data per class.

2.2 Linear Discriminant Analysis

The LDA achieves class separation by means of using linear combinations of features to maximize the between-class scatter matrix Sb and to minimize the within-class scatter matrix Sw. According to Fisher criterion, this can be seen as a typical problem of eigenvectors for $S_w^{-1}S_b$ (Thomaz et al., 2006).

However, in practical applications, S_w^{-1} may not exist, and in order to overcome this limitation, a Regularized LDA (RLDA) adds a constant α to the diagonal elements of the Sw, where 0< α<1 is known as the regularization parameter (Guo et al., 2007).

The method Leave One Out was chosen as the classification algorithm, due to the small sample size. This was applied for each class, in order to ensure the same number of samples in each class. So, there is a training matrix with N-g samples and a test matrix with g samples, one of each class. Finally, class assignment was done based on Euclidean distances.

2.3 Feed-forward MLP

A MLP with sigmoid, as activation function, was used. The number of hidden layers and the number of neurons were empirically investigated, and the results will be discussed. Back propagation was the learning algorithm chosen, with a learning rate of 0.3, momentum rate of 0.9 and a maximum number of epochs of 10000. The generalized delta rule with gradient descent was utilized in each network's learning process.

Prior to the application of the MLP, dimensionality reduction was done using Principal Components Analysis. The number of components defined the number of neurons in the input layer while the number of neurons in the output layer was coincident with the number of classes to be recognized. The method Leave One Out was also applied for MLP as the classification algorithm.

3 RESULTS

The 2-class setup matches the extreme positions 0o and 90o and the 3-class setup matches 10o, 50o and 90o positions. In the 4-class setup, positions differ by 30o shift while in the 5 and in the 10 classes setup they differ by 20o and by 10o respectively.

Table 1: Average classification accuracies.

		RLDA	MLP
g	Phase	Rate(%)	Rate(%)
2	Flex.	96.19	95.24
	Ext.	97.14	98.10
3	Flex.	79.36	80.63
	Ext.	86.35	88.89
4	Flex.	77.14	77.14
	Ext.	77.62	79.05
5	Flex.	61.71	59.05
	Ext.	66.86	70.29
10	Flex.	43.90	39.14
	Ext.	46.10	42.19

Table 2: Best classification accuracies for volunteers A and B.

		RLDA		MLP	
g	Phase	Rate(%)		Rate(%)	
		V_A	V_B	V_A	V_B
2	Flex.	100	83.33	100	76.67
	Ext.	100	90.00	100	90.00
3	Flex.	100	64.44	100	68.89
	Ext.	100	57.78	100	66.67
4	Flex.	88.33	53.33	90.00	51.67
	Ext.	85.00	58.33	83.33	56.67
5	Flex.	89.33	41.33	85.33	49.33
	Ext.	80.00	36.00	82.67	48.00
10	Flex.	66.67	22.00	61.33	21.33
	Ext.	55.33	26.00	52.00	24.67

(g - number of classes, Flex. - flexion, Ext. - extension, Rate (%) - classification rate, V_A - V_B – Volunteers A and B).

Average classification accuracies are presented in Table 1, showing rates above 80% for 2 and 3 classes. The rates achieved for both methods were almost the same and for all configurations they were higher during the extension phase. However, as the number of classes increases, the effect was the decrease of classification accuracies. This occurred even for different regularization parameters for RLDA and different network parameters such as the number of hidden layers and the number of neurons.

Table 2 shows individual results, corresponding to the best and to the worst results, for each method. Volunteer A reached high classification accuracies until 5 classes, and the results for flexion phase were better than those for extension phase. Other five volunteers had classification accuracies similar to this volunteer and only one had results similar to the volunteer B.

4 DISCUSSION

Despite the increasing popularity of ANN in pattern recognition applications due to the belief of better performance and better generalization ability, the results showed a different situation. Table 1 showed in 50% of the cases classification accuracies of MLP greater than those obtained with RLDA and in 40% of the cases classification accuracies of RLDA greater than those obtained with MLP. The other 10% the result was the same for both methods. However, the differences are not significant for the classes setup (t-student test $p<0.05$). The fact that the classification accuracies were the same for both methods can be explained due to the linearity between class boundaries as shown in a previous work (Castro, 2011) that used RLDA in order to separate up to 18 classes. What was surprising is that it was possible to linearly separate those classes, while the results here showed that the classifiers, based on the same feature, did not achieve a good performance for the same number of classes.

In Englehart et al. (1999), LDA showed in some cases using time-frequency features better performance than MLP, however using time domain features MLP exhibited better performance. According to them, the difference was due to the fact that as the feature set dimensionality grows, the degree of nonlinearity between class boundaries diminishes, and so decreases the advantage that a MLP may have over an LDA. Oskoei and Hu (2006) found similar results investigating the discriminant information provided for many features in time and frequency domain, using LDA and MLP as classifiers. Hargrove, Englehart and Hudgins (2007) in other work comparing surface and intramuscular myoelectric signal, the performance of the LDA was again better than the MLP. In a more recent work showing the state of the art, Scheme and Englehart (2011) mentioned a comparative study aiming at investigating the performance of various classifiers in 11-class motion setup, with nondisabled subjects and transradial-amputation subjects, which also showed the superiority of LDA over ANN in both cases. These results disagree with the current assumption that an ANN is always better than a statistical approach.

Another observation is that the classification accuracy decreased with the increase of the number of classes in the same way for both methods, even with the use of different configuration parameters aimed to better adapt to the data. The generalization ability of the classifier depends not only to its own characteristics but also to the data characteristics, number of input components and the number of classes. Data characteristics are represented by features extracted from the original raw data. This study used amplitude envelope that, for a small number of classes was adequate, however with the increase of the number of classes this feature has not provided sufficient discriminant information for both classifiers. Some authors have studied the duo feature-classifier, feature of providing discriminant information and the classifier in recognizing this information, showing that for each classifier there is a feature or subset of features that is more adequate to it and so, resulting in better classification accuracies (Englehart et al., 1999; Oskoei and Hu, 2006; Hargrove, Englehart and Hudgins, 2007).

Table 2 showed the classification accuracies for two volunteers, that reached the best and the worst scores. Other five volunteers had similar distribution of classification rates from the Volunteer A and another one had results close to the volunteer B. And for all of them the performance of both methods was the same. The poor results obtained for two volunteers were due to electrode positioning problems and a poor skin electrode interface. If those data were eliminated, the average classification accuracy would improve above 80% for at most 4-class setup. However, there were volunteers that reached good classification accuracies for 5-class setup, which positions differ by 20o between consecutive ones.

It is important to note that besides to the great similarity between classes, which occurs mainly from the configuration of 4 classes, the contraction level was kept at low levels during the movements, making them close to the normal way to perform them, and so, making SME hardly discernible from background activity. Itakura et al. (1996) in a similar experiment using 4 classes of wrist angular positions classified by a MLP achieved averages of discrimination rates from 70.3% to 76.0% that were smaller than those obtained here.

This configuration differs from the other works which use very different positions in each class and to reach each one some muscle strength is applied. Another difference is the use of amplitude envelope instead of some other feature combination in time or frequency domain. This may be the reasons to the smaller classification accuracies for a number of classes greater than 5 compared to the results obtained from other authors, which continue with classification rates above 90 for these class configurations (Hargrove, Englehart and Hudgins, 2007; Ahsan, Ibrahimy and Khalifa, 2010; Basu, Bhattacharyya and Kim, 2010; Scheme and Englehart, 2011). However, considering the type of movement and distinctive classes, the low level of contraction and the use of the amplitude envelope, which require a minimum processing effort, for a small number of classes, the systems had performed well.

On the other hand, the process based on RLDA was very fast, while the process based on MLP was time consuming as much to define adequate parameters as for as network training. There was no pattern for the number of hidden layers and the number of neurons. These parameters varied for each volunteer and for each class configuration, aimed at obtaining the best classification accuracies. Usually, 2 or 3 hidden layers were enough, but the number of neurons varied from 9 to 100 depending on the case. Englehart et al. (1999) and other researchers such as Basu, Battacharyya and Kin (2010) and Zhang (2000) defend that MLP, as long as properly trained and with an appropriate configuration will always match, if not exceed, the performance of an RLDA. But usually, due to the need to automate MLP training over a large number of interactions, the number of hidden layers and also the number of neurons are fixed. For a given subject and a specific number of classes however, the configuration may be inappropriate, and will be inhibit the generalization performance of the MLP. The RLDA, on the other hand does not require these specifications, and performs very well.

5 CONCLUSIONS

This study showed the same performance for RLDA and MLP in a problem of elbow angular position classification, based on the SME amplitude envelope. Both methods achieved average classification accuracies above 80% for a number of classes until 4 but individually, 5 subjects achieved similar results in a 5-class setup, which means a 20o shift between consecutive classes. May be a better classification accuracy can be reached with another feature instead of amplitude envelope that was used. However, this probably will also change the comparative performance between the methods. Considering that for MLP there is a great effort to define the architecture and also learning parameters, its use is only justified if there is a need of generalization that cannot be achieved by the RLDA that does not require the predefinition of parameters, it is practical and fast.

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