Author manuscript, published in "3rd International Brain-Computer Interfaces Workshop and Training Course, Graz : Austria (2006)"

inria-00134951, version 1 - 6 Mar 2007

THE USE OF FUZZY INFERENCE SYSTEMS FOR CLASSIFICATION IN EEG-BASED BRAIN-COMPUTER INTERFACES

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ABSTRACT: *This paper introduces the use of a Fuzzy Inference System (FIS) for classification in EEG-based Brain-Computer Interfaces (BCI) systems. We present our FIS algorithm and compare it, on motor imagery signals, with three other popular classifiers, widely used in the BCI community. Our results show that FIS outperformed a Linear Classifier and reached the same level of accuracy as Support Vector Machine and neural networks. Thus, FIS-based classification is suitable for BCI design. Furthermore, FIS algorithms have two additionnal advantages: they are readable and easily extensible.*

INTRODUCTION

Most BCI systems use classification algorithms to identify specific mental activities. Several classification algorithms have been used to design BCI, such as linear classifiers, Support Vector Machine (SVM) or neural networks [9]. Surprisingly, fuzzy classifiers have been scarcely used by the BCI community. However, fuzzy classifiers were proved efficient for several classification problems [1], including non-stationary biomedical signals classification [2] and brain research [3].
A specific kind of fuzzy classifiers, namely, Fuzzy Inference System (FIS), has three main advantages: it is readable, extensible [4], and a universal approximator [5]. Therefore, in this paper, we propose to use a FIS for BCI design.
In the following paper we will first describe the FIS algorithm that we have set-up to classify EEG data corresponding to motor imagery. Then, we will report on an evaluation of the FIS classifier as compared with three other classifiers: Linear Classifier, Neural Network, and SVM.

FIS ALGORITHM USED

The FIS that we used is based on the Chiu's algorithm [4]. This algorithm is robust to noise and according to its author, it is generally more efficient than Neural Networks.

Training of the FIS: As any FIS, our algorithm uses fuzzy "if-then" rules. Three steps are required to learn the fuzzy rules from N dimensionnal data:

1. *Clustering of training data.* First, a clustering algorithm, known as "substractive clustering" [4], is applied to the training data of each class. This algorithm is used because it is noise resistant and can automatically determine the number of clusters. It requires the user to specify the clusters radius R_a.

2. *Generation of the initial fuzzy rules.* A fuzzy "if-then" rule is generated for each cluster found previously. For a given cluster j, belonging to class Cl_i, the generated fuzzy rule is:

$$\text{if } X_1 \text{ is } A_{j1} \text{ and } X_2 \text{ is } A_{j2} \text{ and } \ldots \\ \text{then class is } Cl_i$$

X_k is the k^{th} element of a feature vector X and A_{jk} is a gaussian membership function:

$$A_{jk}(X_k) = exp\{-\frac{1}{2}(\frac{X_k - x_{jk}}{\sigma_{jk}})^2\} \qquad (1)$$

where x_{jk} is the k^{th} element of the vector representing the center of the cluster, and σ_{jk} is a positive constant, which is initialy the same for all A_{jk}.

3. *Optimization of the fuzzy rules.* Last, each membership function A_{jk} is tuned according to gradient descent formulas [4]:

$$x_{jk} \Leftarrow x_{jk} - \lambda\frac{\partial E}{\partial x_{jk}} \ \textit{and} \ \sigma_{jk} \Leftarrow \sigma_{jk} - \lambda\frac{\partial E}{\partial \sigma_{jk}} \qquad (2)$$

where λ is a positive learning rate and E a classification error measure. To increase accuracy, membership functions can be "two-sided" Gaussian functions [4], with a plateau and different standard deviations on the left and right sides, as displayed on Fig. 1.

FIS Classification: Once trained, the FIS can classify a new feature vector X using its set of fuzzy rules. The output class of X corresponds to the class associated with the rule j for which $\prod_{k=1}^{N} A_{jk}(X_k)$ is the highest. Thus, the standard multiplication is used as the *and* operator.

CLASSIFYING MOTOR IMAGERY WITH FIS

EEG data: The data used corresponds to the EEG data set IIIb of the BCI competition III. Three subjects had to imagine left or right hand movements. Hence, the two classes to be identified are "Left" and "Right". EEG were recorded using electrodes C3 and C4, and were filtered between 0.5 and 30 Hz (see [6] and [7] for further details).

Feature extraction: Band Power (BP) features were extracted, in a statistically optimal time window, for both electrodes C3 and C4. The optimal time window

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was found to start 0.4 s after the beginning of the feedback presentation for subject 1 and 1.4 s for subjects 2 and 3. It was 2.5 s long for subject 1 and 1.5 s long for subjects 2 and 3. The most reactive frequency bands were selected using a statistical paired t-test which compared the two classes means for all overlapping 2 Hz frequency bands between 1 Hz and 30 Hz. As expected, the optimal frequencies for discrimination were found in the α and β bands. This led to a four dimensionnal feature vector: $[C3_\alpha, C3_\beta, C4_\alpha, C4_\beta]$ in which Cp_y is the BP value for eletrode Cp in the y band. Naturally, the exact frequency bands depended on the subject.

FIS Classifier: The FIS algorithm was trained using the data set and the features described above. For each subject, two fuzzy rules were extracted. The rules obtained for the first subject are displayed on Fig. 1.

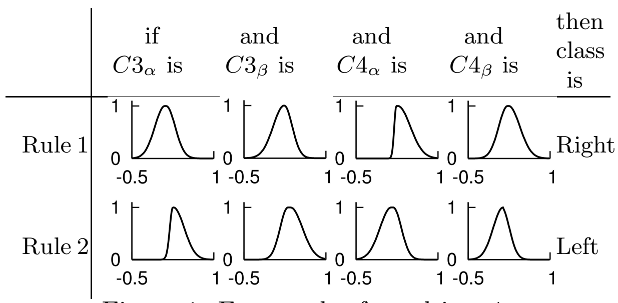

Figure 1: Fuzzy rules for subject 1

The interpretation of the rules shows that the power for electrode C3, in the α and β bands, is lower during imagined right hand movements than during imagined left hand movements. A symmetric behaviour can be observed for electrode C4. In EEG research, this phenomenon is known as contralateral Event Related Desynchronisation (ERD) [10]. This proved that FIS classifiers are readable systems which can be useful to extract knowledge about the brain dynamics. Another advantage of FIS is that fuzzy rules, such as rules made by brain experts, could be easily added as "a priori information".

PERFORMANCES EVALUATION

Our FIS was compared to three other popular classifiers widely used in the BCI community [9]: a SVM with gaussian kernel, a MultiLayer Perceptron (MLP) which is a neural network and a perceptron as a Linear Classifier (LC). Implementation of LC, SVM and MLP was achieved using the Torch C++ library [8]. The optimal values for the hyperparameters of all classifiers (radius R_a for the FIS, regularization parameter C for the SVM, etc.) were chosen using 10-fold cross validation. The four classifiers were compared using the same test set and the same features as described above. Tab. 1 sums up the accuracy obtained by each classifier.

Table 1: Accuracy of the different classifiers

Subject	FIS	SVM	MLP	LC
Subject 1	86.7%	86.8%	86.6%	84.1%
Subject 2	74.7%	75.9%	75.5%	71.8%
Subject 3	75.7%	75.4%	74.6%	72.7%
Mean	79%	79.4%	78.9%	76.2%

Our results show that our FIS outperformed LC and reached the same level of accuracy as SVM and MLP. Finally, the average computation time to classify a feature vector using an FIS is 0.008 ms. Thus, the algorithm is suitable for a real-time and online use within a BCI system.

CONCLUSION

In this paper we have described the use of a Fuzzy Inference System (FIS) for classification in Brain-Computer Interfaces. An FIS classifier outperformed a linear classifier and was found as accurate as Support Vector Machine or neural networks for the classification of motor imagery. Furthermore, FIS classifier is fast, readable and easily extensible which make it suitable and useful for real-time BCI design.

Acknowledgement: This work was supported by the French National Research Agency and the National Network for Software Technologies within the OpenViBE project.

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