Classification in EEG-Based Brain Computer Interfaces Using Inverse Model

Senthilmurugan.M, Latha.M and Dr.Malmurugan.N

***Abstract*—We propose a novel approach using Inference System for classification in EEG based Brain Computer Interfaces. Our FIS algorithm is based on inverse model. Our result shows that FIS classifier reached the same level of accuracy as SVM classifier. FIS is outperformed with MultiLayer Perceptron and Linear classifier. As a result FIS based classification is suitable for Brain Computer Interface design. In addition to FIS algorithm is easily readable.**

***Index Terms*—Brain Computer Interface, Electroencephalogram, Band Power, Artificial Neural Networks and Multi Layer Perceptorn.**

I. Introduction

Hans Berger first measured human brainwaves in 1924. Today, the EEG has become one of the most useful tools in the diagnosis of epilepsy and other neurological disorders. A Brain Computer Interface (BCI) is a direct communication pathway between brain and computer. BCI system measures the specific features of brain activity and translates them into device control signals. Electroencephalography (EEG) is an electrical signal recorded from a person's scalp, and is used to monitor the neurological state of the patient. EEG signal analysis and classification is one of the prominent researches in the field of Brain Computer Interface [1]. The process of EEG signal analysis and classification consists of the signal preprocessing, feature extraction and the classification process. A digital EEG system converts the waveform into a series of numerical values. The values can be stored in the computer memory, manipulated and then redisplayed as waveforms on a computer screen. Traditionally, the BCI systems are divided into several categories. Dependent BCI to independent BCI, invasive BCI to non-invasive BCI as well as synchronous BCI to asynchronous (self-paced) BCI. Really, in order to use a BCI, two phases are generally required: an offline training phase which calibrates the system and an online phase which uses the BCI to recognize mental states and translates them into commands for a computer [4]. More precisely, it focuses on the EEG signal processing and classification techniques in order to designing and use Self-based BCI. A BCI is a complex and difficult task which requires multidisciplinary skills such as computer science, signal processing, neurosciences or psychology. An online BCI requires the following closed-loop process; and it is composed of the following six steps: brain activity measurement, preprocessing, feature extraction, classification, translation into a command and feedback [4]. These steps are depicted in FIG.1.

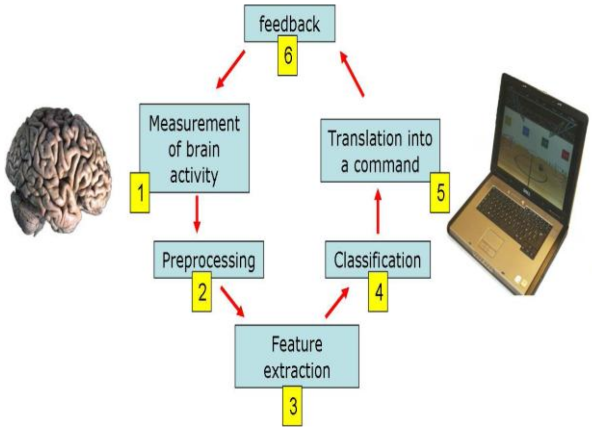

Fig.1 General Architecture of an Online Brain-Computer Interface

II. Review of Literature

The most important work in the early history of classification is that Anderson C W [7]. In his work, he divided the classification algorithms are used to design BCI systems into different categories: linear classifiers, neural networks, nonlinear Bayesian classifiers, nearest neighbor classifiers and combinations of classifiers. Two main kinds of linear classifiers have been used for BCI design, namely, Linear Discriminant Analysis (LDA) and Support Vector Machines (SVM) [2]. The LDA (also known as Fisher's LDA) is to use hyperplanes to separate the data representing the different classes [2, 3]. LDA has a very low computational requirement which makes it suitable for the online BCI system. Moreover this classifier is simple to use and generally provides good results. Consequently, LDA has been used with success in a great number of BCI systems such as motor imagery based BCI or asynchronous BCI [4, 5]. SVM reached the best results in several synchronous experiments, should it be in its linear or nonlinear form, in binary or multiclass BCI. When compare to the LDA (Linear Discriminant Analysis), the SVM (Support vector Machines) performance is more [5, 6]. Neural Networks (NN) are, together with linear classifiers, it is mostly used in BCI research [6, 7]. Consequently, MLP (Multi Layer Perceptorn), which are the most popular NN,

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Senthilmurugan.M, Assistant Professor, Department of Computer Applications, A.V.C College of Engineering, Mayiladuthurai, Mannampandal – 609305, Nagapattinam District, Tamil Nadu, S.India,Ph-+91-9842091911, (email: smsenthil@hotmail.com)
Latha.M, Senior Lecturer, Department of Electrical and Electronics Engineering, A.V.C Polytechnic College, Mayiladuthurai, Mannampandal – 609305, Nagapattinam District, Tamil Nadu, S.India
Dr.Malmurugan.N, Director, CARE College of Engineering and Technology, Tamilnadu, India

used in classification. It have been applied to almost all BCI problems such as binary or multiclass, synchronous BCI [8]. In most BCI, the classification is achieved using a single classifier. A recent trend is to use several classifiers, aggregated in different ways.

For further classification, it is first necessary to extract features from these EEG signals. The most important work in the early history of feature is that F. Lotte [13]. Since Band power (BP) features are known to be efficient for motor imagery classification. The main drawback of such features is that subject-specific frequency bands, in which the BP is to be computed, must be identified before use. Indeed, the strong real-time constraints that are imposed when using a BCI online prevent the use of non-linear inverse solutions as they are computationally demanding. Several linear and distributed inverse solutions have been used for BCI, such as ELECTRA [12], or the depth-weighted minimum norm technique [9]. In most of the BCIs are the synchronous based, and the low information transfer rate at the feature extraction level and at the classification level. So we proposed the new algorithm for improving the existing one.

III. Need for the Study

A BCI "produces" different mental states, we can say that a user is performing a mental task or generating a given neurophysiological signal is being measured and processed by the system. Current BCI systems have a relatively low information transfer rate that is the rate is equal to or lower than 20 bits/min [6]. This means that the user needs a relatively long period of time in order to send only a small number of commands. In order to tackle this problem, we can deal with the following point: designing interpretable BCI systems [6]. In order to increase the information transfer rates of current BCI systems and to design interpretable BCI, improvements can be brought at all processing levels: at the preprocessing level, at the feature extraction level and at the classification level. To improve the information transfer rate at the feature extraction level, we could design more robust and efficient features [12]. To this end, we should design algorithms that can capture the relevant information related to each targeted mental state while filtering away noise or any unrelated information. Moreover, it is known that each subject is different from the other, regarding the spectral or spatial components of his brain activity for instance. Consequently, an ideal feature extraction algorithm for BCI should be trainable in the sense that it should be able to learn and use subject-specific features. Moreover, it is particularly important to design feature extraction methods that can be trained on multiclass data [11].

IV. Proposed Method - Designing Interpretable BCI Using FIS Classifier

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. Surprisingly, fuzzy classifiers have not been used by the BCI. The classification steps are depicted in the following Fig. 2.

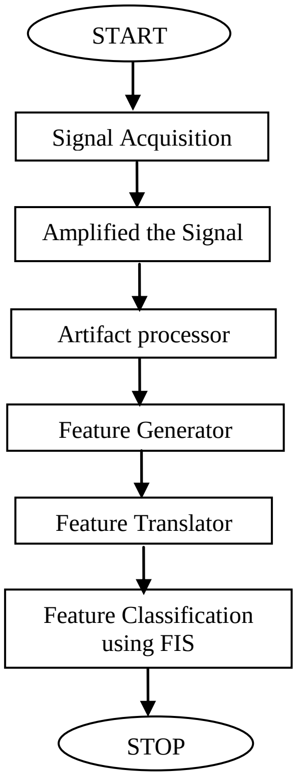

Fig. 2 Flow diagram for Classification

We proved that the fuzzy classifiers efficient for several classification problems, including non-stationary biomedical signals classification and brain research. A specific kind of fuzzy classifiers, namely, Fuzzy Inference System (FIS), has three main advantages: it is readable, extensible, and a universal approximator. Therefore, we proposed to use a FIS for BCI design[10]. Our FIS, algorithm uses fuzzy "if-then" rules. Three steps are required to learn the fuzzy rules from N dimensional data: 1. Clustering of training data, 2. Generation of the initial fuzzy rules and 3. Optimization of the fuzzy rules. We 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".

1) *Clustering of training data.* A clustering algorithm is applied to the training data of each class. This algorithm can automatically determine the number of clusters and it is noise resistant. And specified the cluster radius R_a.
2) *Generation of the initial fuzzy rules.* A fuzzy if-then rule is generated for each cluster. For a given cluster k, belonging to class Cj_i, the generated fuzzy rule is as fallows
   If Y_1 is A_{k1} and Y_2 *is* A_{k2} and then class is Cj_i,
   Y_n is the nth element of a feature vector Y and A_{kn} is a Gaussian membership function.
   $$A_{kn}(Y_n) = \exp\{-\frac{1}{2}(\frac{Y_n - y_{kn}}{\sigma_{kn}})^2\} \qquad (1)$$
   Where y_{kn} is the nth element of the vector representing the centre position of the cluster, and σ_{kn} is a positive constant.
3) *Optimization of the fuzzy rules.* According to gradient descent each membership function A_{kn} is tuned using the following formulas [6].
   $$y_{kn} \Leftarrow y_{kn} - \lambda \frac{\partial y}{\partial x_{kn}} \, and \, \sigma_{kn} - \lambda \frac{\partial y}{\partial \sigma_{kn}}$$

Where y is a classification error and λ is a positive learning rate. To increase the accuracy, the membership functions can be two-sided Gaussian functions [6] with a standard deviation on the left and right sides.

FIS Classification: After trained the data, the FIS can classify a feature vector Y using its set of fuzzy rules. The output of Y corresponds to the class association with the rule k for which $\prod_{n=1}^{M} A_{kn}(Y_n)$ is the highest.

V. RESULTS AND DISCUSSION

We used the EEG data set IV of the BCI competition 2003, provided by the Berlin group. These data contain EEG signals recorded while a subject was performing self-paced left and right finger tapping tasks. We also used the EEG data set IIIa of the BCI competition 2005, provided by the Graz group.

A. Designing Interpretable BCI using FIS Classifier:

FIS was compared to three other popular classifiers widely used in the BCI community: a SVM with Gaussian kernel, a MultiLayer Perceptron (MLP) which is a neural network and a perceptron as a Linear Classifier (LC). The optimal values for the hyper parameters of all classifiers (radius Ra 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 below. Tab. 1 sums up the accuracy obtained by each classifier.

TAB. 1 – SUMS UP THE ACCURACY OBTAINED BY EACH CLASSIFIER

SUBJECT	FIS	SVM	MLP	LC
Subject 1	86.7%	86.8%	86.6%	84.1%
Subject 2	74.8%	75.2%	75.5%	71.8%
Subject 3	75.8%	75.3%	74.6%	72.7%
Mean	79.1%	79.1%	78.9%	76.2%

VI. CONCLUSION

Through this paper we have proposed a Inference System for Classification in Brain Computer Interfaces (BCIs). The designed interpretable BCI using FIS Classifier outperformed Linear Classifier and MultiLayer Perceptron classifiers and was found as the same level of accuracy as Support Vector Machine.

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Mr. Senthilmurugan Muthukrishan born in the year of 1972 at Chidambaram, Tamilnadu, India. He had completed MCA in the year 1997 at Bharathidasan University, Tamilnadu, India. He is presently working as Professor and Head, Department of Software Engineering and Information Technology at A.V.C College of Engineering, Mayiladuthurai, Tamilnadu, India. He has published more than 20 technical papers in national and international conference and journals. He is pursuing research in the filed of image processing and Bio medical under the guidance of Dr. Malmuruagn Nagarajan at Vinayaga Missions University, Salem. He is a fellow member of ISTE, CSI, IACSIT and IAENG.

Mr. Latha M born in the year of 1976 at Perlam, Tamilnadu, India. She had completed B.E in the year 1998 at Annamalai University, Tamilnadu, India. She is presently working as Senior Lecturer, Department of Electrical and Electronics Engineering at A.V.C. Polytechnic College, Mayiladuthurai, Tamilnadu, India. She has published more than 10 technical papers in national and international conference and journals. She is pursuing M.Tech in the filed of VLSI design at Kings College of Engineering, Pudukottai.

Dr. Malmurugan Nagarajan born in the year of 1965 at Kodaikanal, Tamilnadu, and India. He had graduated M.Tech in ECE from Pondicherry University in the year 1991. He had completed Ph.D from Bharathiyar University in the year 2005.He has received Post Doctoral Fellowship at School of Computing, National University of Singapore in the year 2009. He is presently chaired as editor-in-chief various international journals. Currently he is working as a Director at CARE College Engineering and Technology, Tamilnadu, and India. His research interest include image processing, networks etc. He has published more than 90 Technical papers in international and national level journals and conferences. He is the fellow member of IEEE, ISTE, and CSI.