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Brain Emotional Learning based Brain Computer Interface with Independent Component Analysis

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ABSTRACT

Key performance characteristics of BCI systems are speed (i.e., how long it takes to make a selection) and precision (i.e., how often the executed selection is the one the user intended). Current systems allow for one selection within several seconds at a relatively high accuracy. Expressed in bit rate, which combines both speed and accuracy, the sustained performance of typical non-invasive and invasive BCI systems is still modest. The generation performance of a brain computer interface depends largely on the signal to noise ratio and translation algorithms. Current BCIs have low information transfer rates. Artifact and Redundancy with acquired data two another major reasons for this limited capacity of Current BCIs. Artifacts are undesired signals that can introduce significant changes in brain signals and ultimately affect the neurological phenomenon. In new BCI systems for increase accuracy, increased number of electrodes. In this case the increased number of electrodes causes a non-linear increase Redundancy. This article used Genetic Algorithm and independent component analysis (ICA) for select The Effective components of EEG signal and Redundancy Reduction. The experimental results show that the proposed approach has the superior performance to the traditional filtering method and is applicable in new BCI systems. Another major reason for the modest bit rate is translation algorithm. In this paper, we introduce adaptive classifiers for classify electroencephalogram (EEG) signals. The adaptive classifier is brain emotional learning based adaptive classifier (BELBAC), which is based on emotional learning process.

Keywords: *brain emotional learning (BEL); Genetic Algorithm; components Selection; Independent component analysis.*

1. INTRODUCTION

Most popular and many scientific speculations about BCIs start from the 'mind-reading' or 'wire-tapping' analogy, the assumption that the goal is simply to listen in on brain activity as reflected in electrophysiological signals and thereby determine a person's wishes. This analogy ignores the essential and central fact of BCI development and operation. A BCI changes electrophysiological signals from mere reflections of central nervous system (CNS) activity into the intended products of that activity: messages and commands that act on the world.

It changes a signal such as an EEG rhythm or a neuronal firing rate from reflection of brain function into the end product of that function: an output that, like output in conventional neuromuscular channels, accomplishes the person's intent. A BCI replaces nerves and muscles and the movements they produce with electrophysiological signals and the hardware and software that translate those signals into actions.

Present-day BCIs determine the intent of the user from a variety of different electrophysiological signals. These signals include slow cortical potentials, P300 potentials, and mu or beta rhythms recorded from the scalp, and cortical neuronal activity recorded by implanted electrodes. They are translated in real-time into commands that operate a computer display or other device [1].

Successful operation requires that the user encode commands in these signals and that the BCI derive the commands from the signals. Thus, the user and the BCI system need to adapt to each other both initially and continually so as to ensure stable performance.

Current BCIs have low information transfer rates. This limited capacity can be valuable for people whose severe disabilities prevent them from using conventional augmentative communication methods. At the same time, many possible applications of BCI technology, such as neuroprosthesis control, may require higher information transfer rates [2].

Future progress will depend on: recognition that BCI research and development is an interdisciplinary problem, involving neurobiology, psychology, engineering, mathematics, and computer science; identification of those signals, whether evoked potentials, spontaneous rhythms, or neuronal firing rates, that users are best able to control independent of activity in conventional motor output pathways; development of training methods for helping users to gain and maintain that control; delineation of the best algorithms for translating these signals into device commands; attention to the identification and elimination of artifacts such as electromyographic and electro-oculographic activity; adoption of precise and objective procedures for evaluating BCI performance; recognition of the need for long-term as well as short-term assessment of BCI performance; identification of appropriate BCI applications and

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appropriate matching of applications and users; and attention to factors that affect user acceptance of augmentative technology, including ease of use, cosmesis, and provision of those communication and control capacities that are most important to the user [3].

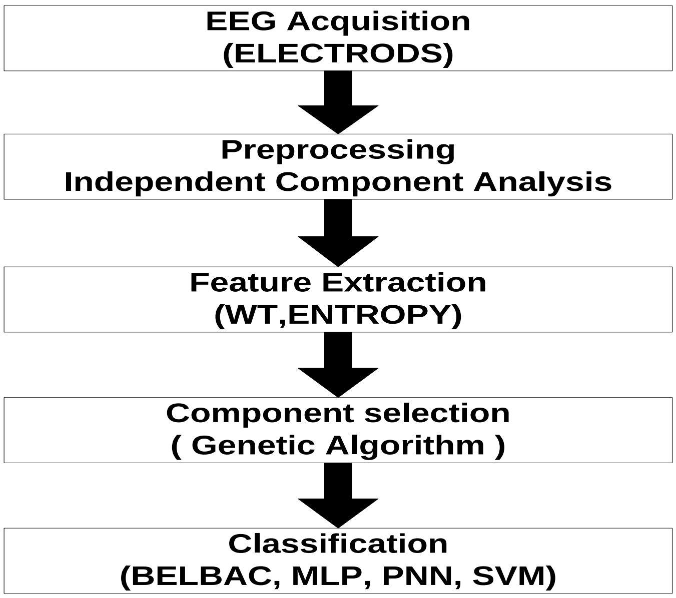

Fig. 1. Block diagram of the proposed method for EEG signal classification.

In this research we assume that user do best that one can do and focus on BCI system. In new BCI systems for increase accuracy, increased number of electrodes. In this case the increased number of electrodes causes a non-linear increase Redundancy [4]. This article used Genetic Algorithm and independent component analysis (ICA) for select The Effective components of EEG signal and Redundancy Reduction. The experimental results show that the proposed approach has the superior performance to the traditional filtering method and is applicable in new BCI systems.

The Achilles heel of BCI systems is translation algorithm. In this paper, we introduce adaptive classifiers for classify electroencephalogram (EEG) signals. The adaptive classifiers are brain emotional learning based adaptive classifiers (BELBAC), which is based on emotional learning process [5, 6]. The main purpose of this research is to use a structural model based on the limbic system of mammalian brain, for decision making and control engineering applications. We have adopted a network model developed by Moren and Balkenius, as a computational model that mimics amygdala, orbitofrontal cortex, thalamus, sensory input cortex and generally, those parts of the brain thought responsible for processing emotions.

The Emotional Learning Algorithm has been introduced to show the effect of emotions as well known stimuli in the quick and almost satisficing decision making in human. The remarkable properties of emotional learning, low computational complexity and fast training, and its simplicity in multi objective problems has made it a powerful methodology in real time control and decision systems, where the gradient based methods and evolutionary algorithms are hard to be used due to their high computational complexity. The developed method was compared with other methods used for EEG signals classification (support vector machine (SVM) and two different neural network types (MLP, PNN)). The result analysis demonstrated an efficiency of the proposed approach.

2. MATERIALS AND METHODS

In this research, EEG signal used as the basic data for classification. The EEG data is from an open EEG database of University of Tuebingen. Two types of the EEG database are employed as [7].

3. PROPOSED METHODS

The block diagram of the proposed method for EEG signal classification is depicted in Fig.1. The method is divided into five steps: (1) EEG acquisition and sampling, (2) EEG preprocessing by Independent Component Analysis, (3) calculation of feature vector, (4) component selection, (5) classification [8], [9], [10].

4. PRE PROCESSING

4.1 Blind source separation (BSS)

BSS techniques separate the EEG signals into components that ‘‘build’’ them. They identify the components that are attributed to artifacts and reconstruct the EEG signal without these components [11]. Among the BSS methods, Independent Component Analysis (ICA) is more widely used. ICA is a method that blindly separates mixtures of independent source signals, forcing the components to be independent. It has been widely applied to remove ocular artifacts from EEG signals [12]. Preliminary studies have shown that ICA increases the strength of motor-related signal components in the Mu rhythms, and is thus useful for removing artifacts in BCI systems [13].

One advantage of using BSS methods such as ICA is that they do not rely on the availability of reference artifacts for separating the artifacts from the EOG signals. One disadvantage of ICA, along with other BSS techniques, is that they usually need prior visual inspection to identify artifact components [12]. However, some automatic methods have been proposed [14].

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4.2. Artifacts removal using ICA and GA

The step of proposed method as fallow: at first using ICA algorithm extract Independent components (ICs) of each trial then GA select the best and related ICs among the hole ICs these steps illustrated in “Fig. 2”.

The proposed approach to the use of GAs for Artifact removal involves encoding a set of d, ICs as a binary string of d elements, in which a 0 in the string indicates that the corresponding IC is to be omitted, and a 1 that it is to be included. This coding scheme represents the presence or absence of a particular IC from the IC space (see Fig. 3). The length of chromosome equal to IC space dimensions. Finally the selected ICs used as input data for classifiers. This paper used the fitness function shown below to combine the two terms:

$$\text{Fitness} = \text{classification error} + \alpha * (\text{Number of Active } Gens\ ) \qquad (1)$$

5. FEATURE EXTRACTION

For features extraction from the raw EEG data many methods such as time domain, frequency domain, and time–frequency domain are used. In this article we used Entropy and Wavelet Transform for feature extraction.

5.1. Entropy

Entropy is the basic concept of information theory. The Entropy of a random variable can be interpreted as the degree of information that the observation of the variable gives. The more “random”, i.e. unpredictable and unstructured the variable is, the larger it’s Entropy. More rigorously, Entropy is closely related to the coding length of the random variable, in fact, under some simplifying assumptions, Entropy is the coding length of the random variable. For introductions on information theory, see [15]. Entropy H is defined for a discrete random variable Y as:

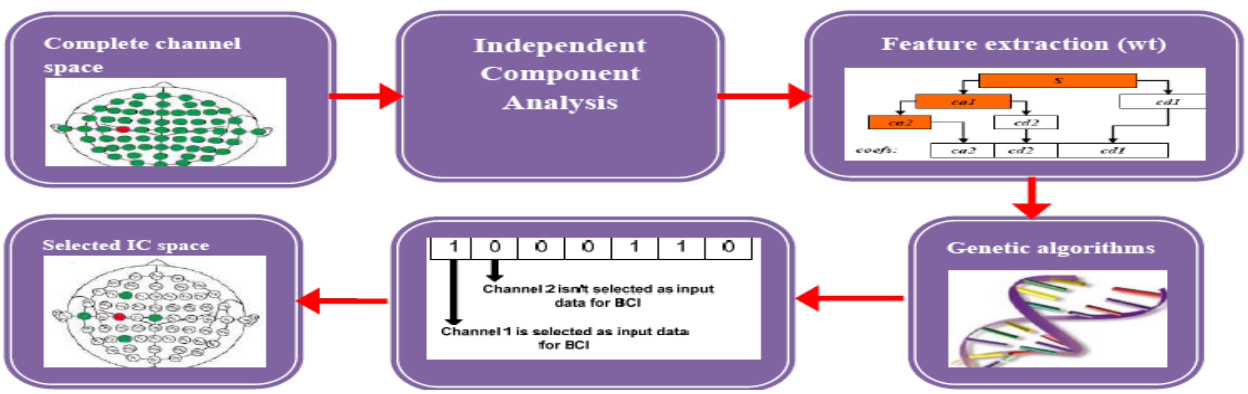

Fig. 2. steps of proposed Artifacts removal method using ICA and GA

Where error corresponds to the classification error that used elected ICs and active Gens corresponds to the number of ICs selected (i.e., ones in the chromosome). In this function α is considered between (0, 1) and the higher α results in less selected features. In this paper α = 0.01 is chosen.

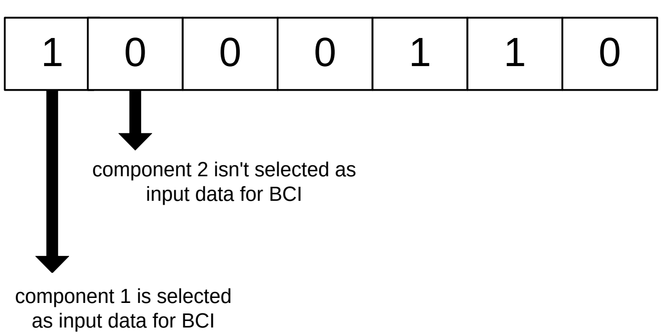

Fig. 3. Schema of the proposed GA-based component selection approach

$$H(y) = -\sum P(Y = a_i)\log P(Y = a_i) \qquad (1)$$

Where the a_i are the possible values of Y and P the probability of a_i.

5.2. Wavelet Transform

For features extraction from the raw EEG data many methods such as time domain, frequency domain, and time–frequency domain are used. Since the EEG is non-stationary in general, it is most appropriate to use time–frequency domain methods like wavelet transform as a mean for feature extraction [16]. The WT provides a more flexible way of time–frequency representation

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of a signal by allowing the use of variable sized windows. In WT long time windows are used to get a finer low-frequency resolution and short time windows are used to get high-frequency information. Thus, WT gives precise frequency information at low frequencies and precise time information at high frequencies. This makes the WT suitable for the analysis of irregular data patterns, such as impulses occurring at various time instances. The EEG recordings were decomposed into various frequency bands through fourth-level wavelet packet decomposition (WPD). The decomposition filters are usually constructed from the Daubechies or other sharp mother wavelets, when the data has discontinuities. In this research, based on the analysis of the data, Daubechies mother wavelet was used in the decomposition. The power spectrum, variance and mean of the signal (each channel) are extracted as features. So the feature set for each subject in each trial consisted of 3*number of channels. As a result, the feature matrix was 266*18 and 200*21 for subject A and B respectively. Finally the feature matrix is normalized.

6. BRAIN EMOTIONAL LEARNING MODEL

In this section, the structure of BELBAC is introduced. BELBAC is a simple composition of Amygdala and Orbitofrontal cortex in the brain.

In Thalamus, some poor pre-processing on sensory input signals such as noise reduction or filtering can be done in this part. As a matter of fact, Thalamus is a simple model of brain real thalamus. The Thalamus part prepares Sensory Cortex needed inputs which to be subdivided and distinguished [17].

Based on the context given by the hippocampus, the Orbitofrontal Cortex part is supposed to inhibit the inappropriate responses from the Amygdala, [17].

The emotional evaluation of stimuli signal is carrying out through the Amygdala, which is a small part in the medial temporal lobe in the brain. As result, this emotional mechanism is utilized as a basis of emotional states and reactions. [17].

At first, Sensory Input signals are going into Thalamus for pre-processing on them. Then Amygdala and Sensory Cortex will receive their processed form and their outputs will be computed by Amygdala and Orbitofrontal based on the Emotional Signal received from environment. Final output is subtraction of Amygdala and Orbitofrontal Cortex [17].

One of Amygdalas' inputs is called Thalamic connection and calculated as the maximum overall Sensory Input S as equation (2). This specific input is not projected into the Orbitofrontal part and cannot by itself be inhibited and therefore it differs from other Amygdalas' inputs.

$$A_{th} = \max_i(S_i) \qquad (2)$$

Every input is multiplied by a soft weight V in each A node in Amygdala to give the output of the node. The O nodes behaviours produce their outputs signal by applying a weight W to the input signals as well as A nodes. To adjust the V_i, difference between the reinforcement signal and the activation of the A nodes is been made use. For tuning the learning rate the parameter α is used and it sets to a constant value. As shown in equation (3) Amygdala learning rule is an example of simple associative learning system, although this weight adjusting rule is almost monotonic. For instance, V_i can just be increased.

$$\Delta V_i = \alpha(S_i \max(0, rew - \sum A_j)) \qquad (3)$$

The reason of this adjusting limitation is that after training of emotional reaction, the result of this training should be permanent, and it is handled through of the Orbitofrontal part when it is inappropriate [17].

Subtraction of reinforcing signal rew from previous output E makes the signal of reinforcement for O nodes. To put it another way, comparison of desired and actual reinforcement signals in nodes O inhibits the model output.

The learning equation of the Orbitofrontal Cortex is drawn in Eq. (4).

$$\Delta W_i = \beta(S_i \sum(O_j - rew)) \qquad (4)$$

Amygdala and Orbitofrontal learning rules are much alike, but the Orbitofrontal weight W can be changed in both ways of increase and decrease as needed to track the proper inhibition. And rule of β in this formula is similar to the α ones.

$$\begin{aligned} A_i &= S_i V_i \\ O_i &= S_i W_i \\ E &= \sum A_i - \sum O_i \end{aligned} \qquad (5)$$

As presented in equation (5) the difference between A nodes and O nodes computes output E. The A nodes outputs are produced according to their rule in prediction of rew signal (reward or stress), though the responsibility of O nodes are inhibition of output E in while it is necessary.

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7. CLASSIFICATION APPROACHES

An artificial neural network (ANN) is an interconnected group of artificial neurons simulating the thinking process of human brain. One can consider an ANN as a “magical” black box trained to achieve expected intelligent process, against the input and output information stream. ANN are useful in application areas such as pattern recognition, classification etc [18].

The Emotional Learning Algorithm has been introduced to show the effect of emotions as well known stimuli in the quick and almost satisficing decision making in human. The remarkable properties of emotional learning, low computational complexity and fast training, and its simplicity in multi objective problems has made it a powerful methodology in real time control and decision systems, where the gradient based methods and evolutionary algorithms are hard to be used due to their high computational complexity. The developed method was compared with other methods used for EEG signals classification (support vector machine (SVM) and two different neural network types (MLP, PNN)). The result analysis demonstrated an efficiency of the proposed approach.

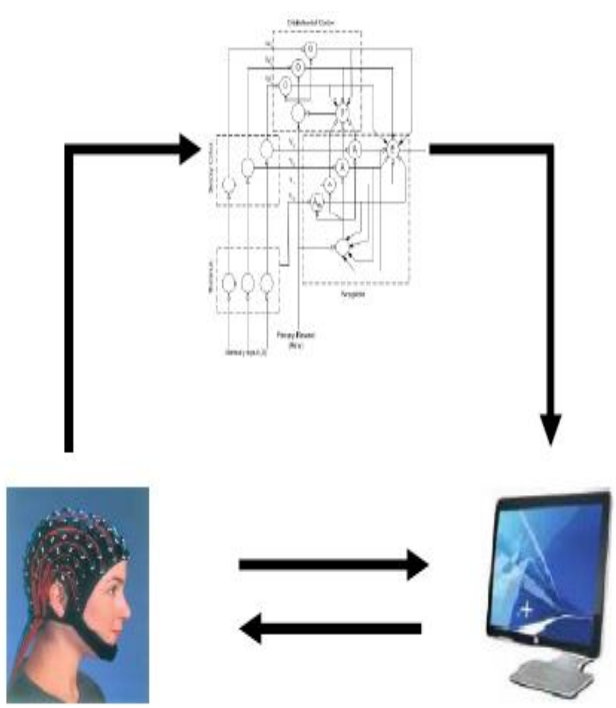

Fig. 4. Brain emotional learning based adaptive classifiers (BELBAC)

8. SIMULATION RESULTS

To classify cursor movements two types of the EEG database are used, 70% of each dataset used for training and the rest for test classifiers. In this paper we used three artifact removal methods. The results from different methods are given in tables I and II. In case of applying ICA, we use a predetermined number of IC's as main independent components and we use the same number for every trial. On the other hand, in case of applying ICA+GA we select the IC's using the genetic algorithm, in which the number of them may vary in different trial. Since the mu and beta rhythms of the EEG are those components with frequencies distributed between 8 and 32 Hz for artifact rejection EEG data are first filtered to the frequency range between 8 and 32 Hz with a Butterworth band-pass filter. Finally, we transform the result signals back to the time domain in order to extract their features.

As it is shown in tables I and II, the results from ICA and ICA+GA are better than the ones from linear filtration, while ICA and ICA+GA have produced almost same results. The efficiency of ICA+GA compare to ICA is that ICA+GA selects the main components or IC's automatically which exclude the need for expert to do that. In addition, when we use ICA solely, only fixed number of IC's is used in all trials which possibly in some cases they are more or less that what are required. In contrast, in the mixed method using the genetic algorithm an appropriate number of IC's is used which is not necessarily the same in different trials.

One of the main privileges of the mixed method used in this paper is that, the redundant data are removed by the selection power of the genetic algorithm. This fact reduces the data dimensions and reduced the time response of system significantly. Moreover, the accuracy of classifiers has not only reduced but also in most cases it has increased sensibly.

9. CONCLUSION

In this paper, we proposed a scheme to combine independent component analysis, Genetic Algorithm, and a novel classifier, BELBAC, for EEG signal classification. ICA is used to extract important factors from EEG signals. The GA select essential EEG components and the best ICA-based features then selected features serve as input feature vector for the following classifiers. three artifact handling methods and Two neural networks, including probabilistic neural network (PNN), Multilayered Perceptron (MLP) and support vector machine (SVM) were employed in the study and their effects were compared.

Novel classifier, BELBAC and Both neural network classifiers and SVM demonstrated high classification accuracies with relatively small number of features. The Emotional Learning Algorithm has been introduced to show the effect of emotions as well known stimuli in the quick and almost satisficing decision making in human. The remarkable properties of emotional learning, low computational complexity and fast training, and its simplicity in multi objective problems has made it a powerful methodology in real time control and decision systems, where the gradient based methods and evolutionary algorithms are hard to be used due to their high computational complexity.

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Results Obtained by the Different Artifact Removal Methods for Dataset I

artifact handling method / Classifier		ICA	Liner filtering	ICA + GA
MLP	Train	96.9	99.56	99.7
	Test	85.87	84.75	85.45
PNN	Train	100	99.98	100
	Test	87.65	85.63	88.05
SVM	Train	98.86	99.95	99.95
	Test	90.89	89.25	90.51
BELBAC	Train	99.75	99.90	100
	Test	91.13	93.32	95.01

Results Obtained by the Different Artifact Removal Methods for Dataset II

Artifact Handling Method / Classifier		ICA	Liner filtering	ICA + GA
MLP	Train	97.85	99.56	98.15
	Test	84.33	85.25	86.26
PNN	Train	100	99.97	100
	Test	85.37	85.75	86.45
SVM	Train	99.75	99.95	99.95
	Test	87.21	88.25	88.63
BELBAC	Train	99.27	99.96	99.98
	Test	93.11	94.10	95.71

Between the three classifiers (i.e. MLP, PNN and SVM), SVM shows slightly better performance than MLP and PNN in terms of classification accuracy and robustness to different number of features and BELBAC has a superior performance. The results prove that the proposed scheme a promising model for the discrimination of clinical EEG signals. The performance of a classifier is not just measured as the accuracy achieved by the network, but aspects such as computational complexity and convergence characteristics are just as important.

The performance of a classifier is not just measured as the accuracy achieved by the network, but aspects such as computational complexity and convergence characteristics are just as important. To reduce complexity, ICA is used to extract important factors from EEG signals and the GA used to select essential EEG components. This approach to BCI helps to reduce the computational complexity of the Classification process, and helps to improve transfer rate in real-time BCI systems.

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