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Channel selection using glow swarm optimization and its application in line of sight secure communication

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Abstract The brain computer interfaces (BCI), that are also known as brain machine interfaces or sometimes neural interface systems have a pathway of direct communication between a device and the brain. In BCI, certain devices acquire electrical signals from the brain like Electroencephalography (EEG) rhythm and further translate them in accordance to the user given commands. The acquired signals are translated by the BCI to meaningful commands. Common spatial pattern filters' discrimination and channels' number are incorporated for the search of the optimal channel group which is a non-deterministic polynomial (NP) problem. In this work, glow swarm optimization algorithm is used for solving the NP problem of selection of the electrodes that are optimal and that can improve the classification. Experiments were conducted for evaluating the proposed method. And the results of the experiments prove the proposed approach's performance. The channel optimized-Naïve Bayes (NB) achieves the best classification accurateness compared to k nearest neighbor (kNN), NB and channel optimized-kNN.

Keywords Brain-computer interface (BCI) · Glow swarm optimization (GSO) · Common spatial pattern (CSP) · k-Nearest neighbor (kNN) · Naïve Bayes

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1 Introduction

People suffering from severe disabilities of motor skills owing to reasons like muscular dystrophy, multiple sclerosis, cerebral palsy and sometimes severe cervical injuries. In such cases, the activity of the brain and its system of communication play a critical role in providing a new form of control and communication either for the purpose of increasing its integration inside the society or for providing the affected people a means of interaction with their environment with continuous assistance. There are several techniques and various paradigms in implementing BCI [1,2].

The purpose of directly using BCI to empower an individual with motor disabilities that are severe in having an effective means of control on devices like neural prostheses, assistive appliances, speech synthesizers and computers. This kind of an interface can lead to the individual's independence and thereby improve quality of life meanwhile bringing down social costs. A system in BCI can detect the availability of patterns that are specific to the ongoing brain activity of a person relating to the intention of a person to initiate the control. This system makes a simple translation of these kind of patterns into control commands that are meaningful. In order to identify these patterns some algorithms of signal processing have to be employed. Signal processing is an integral part of the BCI design as it is required for the extractions of information that are meaningful from the brain and its signal.

Most of the BCIs are EEG based which is a non-invasive method for recording the electrical fields that are a direct result of neuronal synaptic activity [3]. The electrocorticogram (ECoG) is an alternative to BCI and an EEG which is minimally invasive that provides a signal that is superior in terms of its characteristics that ensure quick user training and communication. According to studies certain regions of the brain like the auditory cortex is capable of controlling the BCI system with methods that are similar to those systems that train the motor regions of the brain. This is critical for those people who are affected by conditions like those which prevent use of sensorimotor cortex, head trauma or neurological diseases to use BCI control.

According to Fig. 1, the BCI system is so illustrated [4]. An impediment that is critical for the advancement of BCI applications for the refinement of those conditions that are operant for subjects for learning self-control and for needs of extensive training and calibration of individuals. It is also important to handle the variability for continuous behavioral performance for which the research on cognitive neuroscience is underway in finding correlates that are neuronal for explaining and controlling eventually all this variability. In spite of these challenges that are noted, some researchers in Germany are quite optimistic about gaming and media applications of BCI. They focus on the management of photos, music, web surfing, video etc., and even in their stages of infancy they developed an interface of a web browser for controlling Google Earth through BCI. This system has progressed to a great extent in improving communication systems for the disabled. There are also some devices for measurement that can assess and decode more states of the brain in real-time situations permitting measurement of the performance and the workload that is seamless. This can enhance the analysis of the state of the human brain and optimize the interfacing of the brain computer and the human machine analysis.

This BCI technology also creates opportunities for the neurosurgeons to involve in the improvement of the training and operations of the military mainly through modification of combat performance and optimization. By using neuroscientific approaches for these goals is currently part of an evolutionary research. In the recent decade, the Defense Advanced Research Projects Agency (DARPA) of the Pentagon has launched a program called Advanced Speech Encoding Program for developing the non-acoustic sensors for encoding the speech in environments that are hostile to acoustics like an urban environment or a military vehicle's inside. This division of the DARPA is now working on a program known as the Silent Talk which aims at developing communication which is user-to user that can be made on the battlefield by using EEG signals including intended speech and thus removing need for body gestures or vocalization. These will be of benefit to reconnaissance and settings of special operations as well as those applications that require interfaces of silent speech that have been reported.

There are three aspects to BCI which are acquisition of data, reduction of noise and classification. In the acquisition of data, the features are duly extracted from the brain of the human that is generated when there is a thought about some object. Such signals are duly analyzed and given to techniques of noise reduction as they are not noise free. There are some disturbances in the signals of EEC and they have to be reduced. Algorithms for proper reduction of noise is run on them to bring down the level of noise [5]. Finally, the algorithms are used for the differentiation of the signals and the mapping of them with the particular object that was in the thoughts of the user. The task of classification is the most challenging task in the signals of the brain as every user does not produce similar signals. It is different from person to person that is classified on the basis of suitable algorithms for classification.

Generally the features of the signal used in today's BCI, reflects the events of the brain like specific firing of the cortical neuron of rhythmic or synchronized activation in the cortex of the sensorimotor that can produce a mu rhythm. The knowledge of such evens can help in the guiding of BCI development. The cortical area's location function and size that generates a pulse or evokes a latent can show by what means it can be recorded and how the users can acquire to regulate its amplitude as well as to remove its consequences on artifacts that are non-central nervous system (CNS). The BCI can also use features of signals like the parameters that are autoregressive and correlate that the intent of the user by does not necessarily show specific events of the brain.

The selection of a set of channels that are discriminative is an increase that is meaningful to the accuracy of classification and the promotion of the BCI's stability. There are many methods to choose channels like the heuristic procedure [6] and the greedy algorithm. The greedy algorithm is easily trapped within a local minima and is also time. In the motor imagery of BCI, the neurophysiology indicates that the Mu as well as the Beta rhythms are idle-rhythms that are macroscopic and are mainly located on the postcentral somatosensory and precentral motor cortex. The Sensorimotor channels can have some malfunctioning. To detect the subset of channels that is most discriminant in a heuristic way is by calculation of maximal r^2-values belonging to spectra for every channel. A more sophisticated as well as convenient approach to do this is the construction of a channel bank that can be completely immune to the artifact.

A selection of feature and reduction of dimensionality component is enhanced to this system once the stage of extraction of feature is complete. The primary objective of this is to bring down the actual features as well as channels that are practiced to enable exclusion of noisy data and data that is of high dimension. Normally these features are useful as well as meaningful in the stage of classification that is identified and selected whereas the other artifacts and outliers are duly omitted.

The methods for extraction of features that have been used in the systems of BCI are related closely to the neuromechanisms that are used by the BCI. Owing to the close relation of the algorithms for feature classification with the

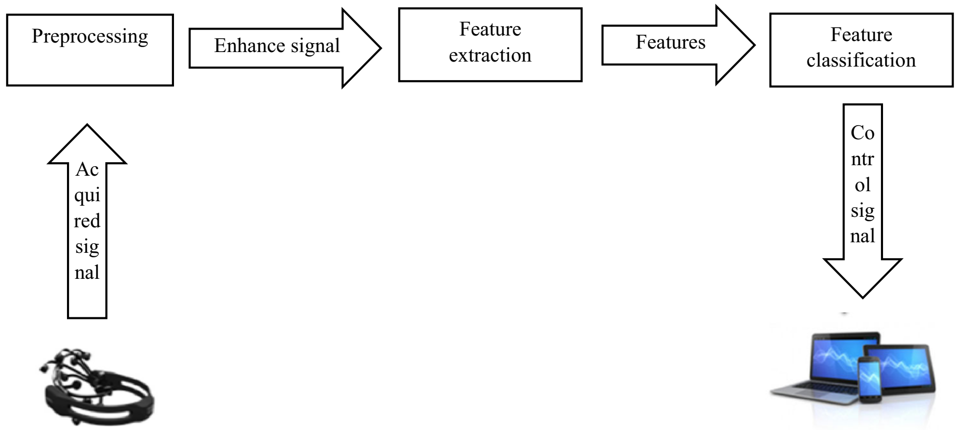

Fig. 1 BCI system

type of features they classify the algorithms for classification of feature is also grouped on the basis of the methods of extraction of features. By categorizing them, the usage of a specific classification feature on a specific method is not limited. This is the same in case of the feature extraction method classification that is based on the neuro-mechanisms of the BCI systems.

In this article, GSO algorithm is introduced. GSO algorithm is a new swarm intelligence algorithm. The common GSO algorithm inspiration originates from the occurrence that one glowworm can be enticed by other one with greater luciferin value and it advances toward it [7]. In the nature, glowworms connect with each other by discharging luciferin. Glowworms discharge luciferin once they are in the air, hence they can reveal luciferin light. Glowworms attract each other's around them by spreading fluorescent light. The greater the luciferin concentration, the higher the fluorescence intensity, and then glowworm can be capable to attract more other glowworms. By pretending this occurrence, the artificial GSO algorithm features can be drawn: the search scheme of this algorithm is multi-point parallel global randomly search based on population and without the difficult operations evolution. It consistent with the individual glowworm's decision range regulates the search path, and then attains the best effect. To this point, GSO algorithm has been employed successfully in the noise test, simulation of the sensor machine crowd, clustering analysis, numerical optimization calculation, knapsack issue, etc.

This paper, deals with the patterns that are of common spatial that is used for the extraction of feature and the method of GSO that is used for the selection of the features. The NB classifier and the kNN classifier is used for the purpose of classification of feature. Section 2 reviews the related work the Sect. 3 enumerates the methods that are used for this work. In Sect. 4 the results of the experiment are discussed and the conclusion is duly made in Sect. 5.

2 Literature survey

Kevric and Subasi [8] examined three popular signal processing methods (empirical mode decomposition, discrete wavelet transform (DWT), and wavelet packet decomposition) for the decomposition of EEG) signals in BCI system for a classification task. Publicly available BCI competition III dataset IVa, a multichannel two-class motor-imagery dataset, was practiced for this persistence. multi-scale principal component analysis (PCA) method was exploited for noise removal purpose.

The BCI makes a processing of the signals of the brain for extracting features that can be classified through the classification algorithms. The sets of features from signals are quite huge so to ensure a classifier is optimized the techniques for feature selection chooses a feature subset that is discriminative. Noh and Min [9] displayed how the relevant features of a space of high dimension can be chosen by using a nearest neighbor method for the purpose of estimation of measure of theoretic information with a Jensen-Shannon divergence.

Ohize and Dlodlo [10] brought an algorithm for new channel hopping for choosing a channel of control in a time varying, spatial and heterogeneous environment spectrum which does not have any infrastructure like a base station or an access point. Al Moubayed et al. [11] further introduced a Smart discrete multi objective particle swarm optimization (SDMOPSO) that was multi-objective and using decomposition. This method made use of the approach of decomposition in the MOEA/D or the multi-objective evolutionary algorithm (MOEA/D) in which a multi-objective problem (MOP) is shown as problems that have many scalar aggregations.

Arvaneh et al. [12] introduced a new sparse common spatial pattern (SCSP) algorithm for EEG channel selection. The presented SCSP algorithm is expressed as an optimization issue to choose the least channels under a classification accuracy constraint. By itself, the presented concept can be modified to produce the optimal classification accuracy by eliminating the noisy and unrelated channels, or maintain the least channels without compromising the classification accuracy attained through each the channels. Dai and Wei [13] presented a new backtracking search optimization algorithm to choose mechanically optimal CSP channel set. Every individual in the population is an N-dimensional vector, with every component signifying one channel. A binary codes population create arbitrarily in the opening, and also channels are chosen based on such code evolution. The number and positions of 1's in the code signify the number and positions of the selected channels. The objective function of backtracking search optimization algorithm is described as the classification error rate and relative channels combination. Experimental consequences suggested that greater classification accuracy had been attained with lesser channels contrasted over customary common spatial pattern with entire channels.

3 Methodology

To evaluate the proposed channel selection mechanism, the IVa dataset available in the public domain was used [14]. In this section, the glow swarm optimization algorithm and common spatial pattern and classifiers are explained.

3.1 Data set IVa

The IVa dataset consists of experiments carried out with five subjects using 118. All through the sessions of recording these subjects were given visual cues for indication of the motor imageries, whether the left or the right hand or the right foot have to be performed for further 3.5 s. Random length intermissions of about 1.75–2.25 s were given after every session to relax the subjects. Even though only three of the imageries are recorded the EEG recordings for the right hand and foot was made accessible. For every subject about 280 trials were partitioned in accordance to the set of training and the set of testing. In this work the subject 'al' was used to complete the experiments.

3.2 Common spatial patterns (CSP)

CSP was a method that was suggested first for classifying multi-channel EEG in imagery hand movements. This was suggested Ramoser et al. Its primary aim was using a linear transform for the projection of the EEG data of a multi-channel into a subspace that is low dimensional with a matrix for projection in which every row has weights for channels. This change can increase the variance of the matrices of the two-class signals. The CSP method depends on instantaneous matrix diagonalization of covariance of both of the classes.

A spatial filter of CSP w can maximize the variance of EEG signals that are band-pass filtered based on the condition that its minimization is based equivalently on minimizing a common variance. As the variance of the filtered signal of a band-pass is equal to that of the band power, there in an enhancement of the power of the band among two conditions by the CSP. This problem of CSP is solved by maximizing the condition 1 of the Rayleigh quotient.

$$R(w) = \frac{w^T \Sigma_1 w}{w^T \{\Sigma_1 \Sigma_2\} w}$$

In which Σ_1 and Σ_2 denote the matrices of average covariance from class 1 as well as class 2. It has to be noted that this Rayleigh quotient maximization can be formulated again as a problem of constrained optimization [15],

$$\max_{w} w^T \Sigma_1 w$$
$$\text{subject to } w^T \{\Sigma_1 + \Sigma_2\} w - C = 0$$

where C is equal to an arbitrary constant the norm of w is chosen to enable the holding of Eq. (3) and is solved by making use of Lagrange multipliers.

3.3 Feature selection

The selection of feature is a global problem of optimization that can bring down features, remove irrelevant data, noisy data as well as redundant data and lead to accuracy of recognition at an acceptable level. It can be a tool for pre-processing for solving issues related to classification and can lead to new patterns in applications of data mining, medical data processing, machine learning, biometrics, remote sensing, analysis of data and retrieval of multimedia information.

3.3.1 Glowworm swarm optimization (GSO) algorithm

In this algorithm the agents or the physical entities are taken to be distributed randomly in the workspace. The agents belonging to this algorithm transmit a luminescence amount known as luciferin with them. The agents are the glowworms that can release a light that has an intensity that is proportional to the luciferin associated with it and has a rid which is a variable range of decision that is bounded by a range of circular sensor $r_s (0 < r_d^i \leq r_s^i)$.

Every glowworm gets attracted to the glow that is brighter. It detects other glowworm as its neighbor when it is under the local decision domain. The agents in the algorithm of glowworm are dependent on the information that is available in the range of local decision for making their due decisions. The algorithm that results is a decentralized one and caters to the needs of all other collective robotic systems.

This GSO algorithm begins by positioning randomly the glowworms within the work area to ensure they are well scattered. Firstly, all these glowworms have equal luciferin. Every iteration has an update of luciferin phase that is followed by a phase on the basis of the rule of transition.

Those equations that model the update of luciferin are distributed by selecting a neighbor and the update for the local decision range is given as [16]

$$l_i(t) = \max\{(0, (1-\rho) * l_i(t-1) + \gamma * J(x_i(t)))\}$$
$$P_j(t) = \frac{l_j(t)}{\sum_{k \in N_i(t)} l_k(t)}$$
$$x_i(t+1) = x_i(t) + s\left(\frac{x_j(t) - x_i(t)}{\|x_j(t) - x_i(t)\|}\right)$$
$$r_d^i(t+1) = \frac{r_s}{1+\beta * D_i(t)}$$

where,

$$N_i(t) = \{j : \|x_j(t) - x_i(t)\| < r_d^i(t); l_i(t) < l_j(t)$$

Here the neighbors of the glowworms that consist of those glowworms that have higher value of luciferin and are located inside a domain of decision that is dynamic. If this value of the glowworm i is greater than that of j and the due distance that exists between glowworm $i$and glowworm j is lower than the domain of dynamic decision domain, the glowworm j is divided into the glowworm of the neighbor i.

The steps in the algorithm of glowworm swarm optimization,

Step 1: Population P has to be initialized and dimension m, which is the number of glowworms lm, step size st is continued so on.

Step 2: P the population is divided into many sub-populations. The actual number of sub-populations are l. The due size of the sub-populations is m. Every sub-population known as a tribe.

Step 3: The glowworms are randomly placed within the search space of the function's object.

Step 4: The tribes independently operate. $J(xi(t))$ is put into the $li(t)$, $li(t)$ which represents that luciferin level which is associated with glowworm i at a time t. $J(xi(t))$ here represents the objective function's value at glowworm i's present location at time t.

Step 5: Every glowworm in the tribe chooses a neighbor which has a value of luciferin that is higher that itself to make the $Ni(t)$.

Step 6: The glowworm present i in tribe selects a neighbor and moves towards it, and later the location of glowworm i is updated.

Step 7: Glowworm $i$updates the value of the range of its variable neighborhood.

Step 8: The glowworm with the light that is the brightest in each tribe at time t, is selected and a second level is formed by using them.

Step 9: The glowworm belonging to the second level obeys the formula of GSO in order to choose the glowworm that has the brightest light.

Step 10: Once the maximum number of iterations is reached, step (11) is executed else step (4).

Step 11: Output of the results is made and the process is duly ended.

In the proposed technique, given the total number of electrodes E = {e1,e2,…,e118}, a subset of E represents a solution and is mapped by

	e1	e2	e3	………	en
g1	1	1	1		0
g2	1	0	1		1
…					
…					
gn	0	1	0		1

where '1' represents the electrode as selected and '0' represents the electrode as not selected. Since both the motor imageries are of equal importance, misclassification rate was used as the fitness function.

3.4 Classification

The data that is filtered data is duly classified into one of those categories or classes that are established in the phase of classification. The work that is proposed uses kNN algorithm [17] as well as NB [18] for the classification of data. The last task here is the classification of the records into a single label by using training that is defined. This model is built as the training is performed in cases of early learner approach or whenever the classification has to be performed in cases of later learner approach.

3.4.1 k-Nearest neighbour algorithm (kNN)

The kNN technique aims at assigning to a point that is unseen a dominant class in its k nearest neighbors inside the training set. For the BCI these nearest neighbors are got with the metric distance. Keeping a reasonably high value of k and sufficient samples of training, kNN can make an approximation of any function that can make it to produce boundaries of nonlinear decisions. The kNN algorithms are not considered popular within the BCI community as they are sensitive to the dimensionality curse and so they fail in the BCI experiments. But when they are employed in the systems of BCI

Table 1 Summary of results

	kNN	NB	Channel optimized—kNN	Channel optimized—NB
Classification accuracy	85.19	87.65	90.74	92.59
Recall for normal	0.7949	0.8462	0.8846	0.9103
Recall for AD	0.9048	0.9048	0.9286	0.9405
Precision for normal	0.9048	0.9048	0.9286	0.9405
Precision for AD	0.7949	0.8462	0.8846	0.9103

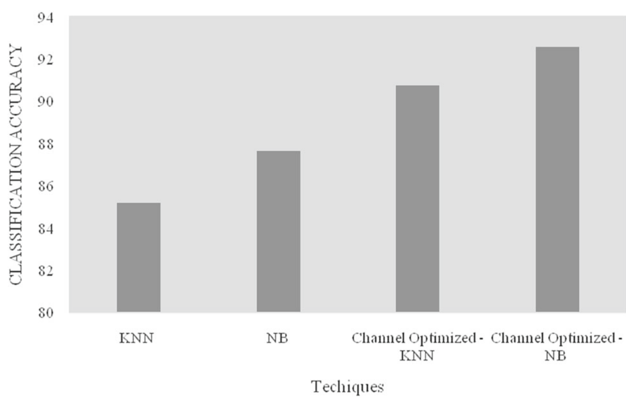

Fig. 2 Classification accuracy

with vectors of low dimension kNN proves to be efficient in its performance.

3.4.2 Naïve Bayes (NB)

The NB classifiers are simple and probabilistic classifiers that use the Bayes' theorem with assumptions of their own. They make a prediction of class and membership probabilities that one sample belongs to one particular class. They assign to an unlabeled vector a class label. All these classifiers make an assumption that the value of one feature is independent of another's value when a class variable is given. For instance, if a fruit is round, 4" in diameter and red it is taken to be an apple. This particular classifier takes each feature to be contributing independently to the possibility of this fruit being in reality an apple. This is an assumption that is called class conditional independence and it simplifies the computation and so considered "Naive" [19].

According to Bayes' theorem, the probability may be estimated from the given data,

$$P(H|X) = \frac{P(X|H)P(H)}{P(X)}$$

For the k nearest neighbor algorithm since the K value selection is critical, the bootstrapping technique following the square root of the number of instances was used. The generalization error obtained from Naïve Bayes was extremely low and hence not modified.

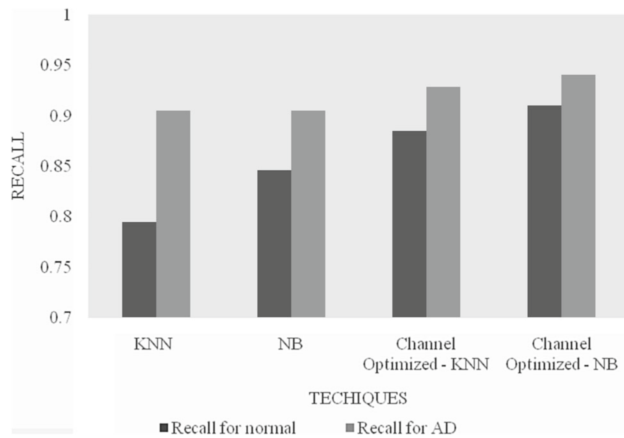

Fig. 3 Recall

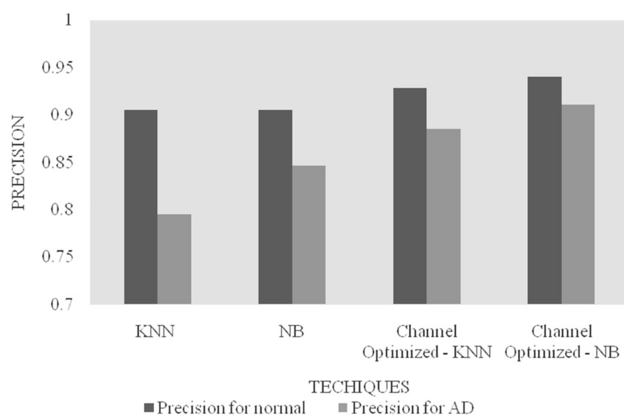

Fig. 4 Precision

4 Results and discussion

For the experiments, dataset Iva is used from BCI competition. The results compared with one another. Table 1 shows the results for the accuracy, recall and precision.

Figure 2 shows that the proposed feature selection with kNN improved accuracy by 6.31% when compared with kNN and proposed feature selection with NB increased accuracy by 5.48% than NB.

From the Fig. 3, it can be observed that the proposed optimization with NB increased recall by 7.29% for normal and by 3.86% for AD when compared with NB classifier.

From the Fig. 4, it can be observed that the proposed optimization with NB increased recall by 3.86% for normal and by 7.29% for AD when compared with NB classifier.

5 Conclusion

When the EEG signals are used as a communication vector between the man and the machines it indicates one of the challenges currently faced in the research of signal theory. BCI is the principal aspect of such a system of communication. This BCI interprets the EEG signals that are related to the parameters of the activity of the electrical system of the brain. In this article, CSP and GSO algorithm is presented. The presented GSO algorithm is a simple method to acquire several multi-modal function peaks because of its dynamic sub-groups. GSO algorithm also has a capability to divide into disjoint groups. Eventually creates the GSO algorithm's search accurateness and optimization efficacy has been improved better. Consequences reveal that this presented feature selection with kNN increased accuracy by about 6.31% once compared with kNN and presented feature selection with NB improved accuracy by about 5.48% than NB.

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