Automatic channel selection using shuffled frog leaping algorithm for EEG based addiction detection

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ABSTRACT

Drug addiction is a complex neurobiological disorder that necessitates comprehensive treatment of both the body and mind. It is categorized as a brain disorder due to its impact on the brain. Various methods such as electroencephalography (EEG), functional magnetic resonance imaging (FMRI), and magnetoencephalography (MEG) can capture brain activities and structures. EEG signals provide valuable insights into neurological disorders, including drug addiction. Accurate classification of drug addiction from EEG signals relies on appropriate features and channel selection. Choosing the right EEG channels is essential to reduce computational costs and mitigate the risk of overfitting associated with using all available channels. To address the challenge of optimal channel selection in addiction detection from EEG signals, this work employs the shuffled frog leaping algorithm (SFLA). SFLA facilitates the selection of appropriate channels, leading to improved accuracy. Wavelet features extracted from the selected input channel signals are then analyzed using various machine learning classifiers to detect addiction. Experimental results indicate that after selecting features from the appropriate channels, classification accuracy significantly increased across all classifiers. Particularly, the multi-layer perceptron (MLP) classifier combined with SFLA demonstrated a remarkable accuracy improvement of 15.78% while reducing time complexity.

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1. INTRODUCTION

Drug addiction is a serious illness influenced by pathological or hard to manage drug seeking and use, given the negative impacts. The report released by the Ministry of Social Justice and Empowerment's on the "National survey on extent and pattern of substance use in India" (2019) states that, 14.6% of people use alcohol, 2.8% use cannabis, 2.06% use opioids, 1.08% use sedatives, 1.7% of children and adolescents use inhalants, and about 8.5 lakh people are injecting drugs. According to the data, almost 2,300 persons died of drug overdoses between 2017 and 2019, with the 30−45 year age group having the highest mortality. Each drug addict patient has different requirements for care so providing a specific treatment plan is essential. Some of the drug addict treatment includes practical suggestions, medication-assisted therapy, assessing and treating co-occurring diseases, and long-term relapse protection program. Electroencephalography (EEG) is a non-invasive diagnosis technique that recognizes the malfunctions in our brain waves or the brain's electrical activity. The overall activity of the brain can be detected using the EEG. With such a vast number of EEG channels, it is necessary to have effective channel selection algorithms, with variable degrees of importance depending on the application [1]-[4].

The main goal of the channel selection process is to decrease the computing complexity by picking the essential channels and therefore extracting the most important features, to limit the amount of overfitting that may occur as a result of the use of unnecessary channels, and to minimize the setup time. This work aims in implementing an optimization algorithm to select the appropriate combination of channels and to improve the classification accuracy in drug addiction detection. The further section involves the literature survey, proposed methodology, experimental results discussion, and conclusion.

2. LITERATURE SURVEY

The EEG signals collected are usually multi-channel in nature. To classify these signals either work on a selection of channels based on particular criteria or work on all channels. The challenges in selecting optimal channels from the EEG signal can be resolved by devising this as an optimization problem. The optimization algorithms have better performance in a hybrid approach, significant attention has been paid to the problems of optimization. Yang [5] suggested that after properly formulating an optimization problem, the main challenge is to find the best solutions using the right mathematical techniques employing some solution method. An optimization algorithm can be categorized in several aspects. One easy approach is to focus on the algorithm's nature, which groups the algorithms into two categories such as deterministic algorithms and stochastic algorithms.

2.1. Deterministic algorithms

Deterministic algorithms adopt a systematic method, replicating the direction and values of both the design variables and the functions. Several traditional or modern algorithms are deterministic. For instance, in linear programming the simplex method is deterministic. The gradient knowledge has been used by some determinist optimization algorithms and is called gradient-based algorithms.

2.2. Stochastic algorithms

Stochastic algorithms have certain randomness often. The sequences or solutions in the population may be different, because the algorithms use some pseudo-random numbers, and the final results might not be a major difference, but each individual's paths are not necessarily repeatable. Besides, there are two forms of stochastic algorithms: heuristic and metaheuristic, although their distinction is small. Heuristic algorithms can be expected to use the most but using them all the time is not appreciated. These algorithms are used in the cases where the good solutions are reached easily rather than the best solutions. The metaheuristic algorithms are the further advancement of heuristic algorithms. Generally, metaheuristic algorithms perform much better than heuristic algorithms. Additionally, all metaheuristic algorithms use local search and randomization. Metaheuristic algorithms can be further classified as population-based algorithms and trajectory-based algorithms. Simulated annealing (SA) is one of the examples for trajectory-based, genetic algorithm (GA), particle swarm optimization (PSO), artificial bee colony (ABC), gravitational search algorithm (GSA) are some of the examples of population-based metaheuristic algorithms.

2.2.1. Trajectory-based algorithms

Among the most common and earliest metaheuristic algorithms, Kirkpatrick [6] has first introduced simulated annealing and it has been implemented in almost every optimization field. This imitates the annealing process in the production of materials when the metal cools and freezes in a luminous state with less energy and larger particle sizes to minimize the defects in metallic structures. The key advantage of SA is its ability to avoid being stuck in a local minimum when compared to the gradient-based methods and other deterministic search methods.

2.2.2. Population-based based algorithms

For channel selection in the processing of EEG signals, many population-based optimization strategies have been examined. The GA is a model or approximation of biological evolution based on the theory of natural selection by Charles Darwin created in the 1960s and 1970s by Holland [7] and Jong [8]. Palaniappan *et al.* [9] has utilized GA to select the minimum number of channels that maximize classification performance for the features extracted from visual evoked potential signals. He *et al.* [10] has proposed a channel selection approach for EEG data sets for motor imagery in which an improved GA has been used to assess the optimum channel subset. Wang *et al.* [11] have recommended an algorithm incorporating Gaussian mixture model (GMM) and GA to assess the irregular EEG samples, and the results obtained were substantially improved compared to the traditional mixture model. A non-dominated sorting genetic algorithm (NSGA) [12] is used to detect the intruders and to identify the subject with the optimized three-channel combination.

PSO has been one of the most widely used swarm-based intelligence algorithms. Most swarm intelligence-related algorithms have taken inspiration from various sources, but are very similar to some of the components used in PSO. Atyabi *et al.* [13] explored the effectiveness of two methods for optimizing content exchange through a 90%+ reduction of EEG electrodes and features using the PSO. Afrakhteh and Mosavi [14] suggested a modified PSO that determines the optimal features for better EEG-signal classification efficiency.

The shuffled frog-leaping algorithm (SFLA) has emerged as a promising and effective multiobjective and combinatorial optimization method [15]. The SFLA refers to a group of perpetual frogs divided into different memeplexes, which connect. In every memeplex, SFLA executes a local independent search. Global search is performed by shuffling the perpetual frogs and restoring the frogs in different memeplexes. SFLA is used in a variety of optimization issues due to its resilience in discovering global solutions and solution speed. Panda *et al.* [16] has used the SFLA for channel equalization and also to train the multi-layer artificial neural network (ANN). Huang and Song [17] has performed a combined work of reorganizing the local search in SFLA with the multi-agent system (MAS). Dash *et al.* [18] has revealed a new metaheuristic method for gene selection, called the binary shuffled frog leaping algorithm (BSFLA).

Because every memeplex evolution and shuffling procedure can improve the quality of individuals, SFLA is resilient in determining the global solution. Hence, it is utilized in various applications deals with optimization problem [19]-[21]. These advantages have been inspired the development of optimal channel selection using SFLA for drug addiction detection. In this work, the SFLA algorithm is utilized to optimize the channels and to select the best combination of 8 channels from the overall 16 EEG channels. The wavelet features extracted from the selected features have been given to the five machine learning classifiers such as multi-layer perceptron (MLP), decision tree (DT), Naïve Bayes (NB), support vector machine (SVM), and random forest (RF) to evaluate the classification accuracy. Wavelet features provides the information in time-frequency analysis within signals. Due to its multiresolution properties, it is utilized in various signal processing applications [22]-[24]. With the combination of both SFLA and features extracted from the optimal 8 channels, the improvement of classification accuracy and reduction of time complexity is made possible.

3. SHUFFLED FROG LEAPING ALGORITHM

Eusuff *et al.* [25] have developed SFLA as a meta-heuristic to implement an intelligent heuristic analysis using a heuristic method to look for a solution to a problem of combinatorial optimization. This algorithm includes the collaboration among individuals, which in turn results in memes development and global knowledge transmission between them. Evolutionary algorithms usually depend on the idea of the population. A set of individuals is termed as population and every individual will have fitness value which determines the effectiveness of that particular individual. Figure 1(a) shows a complete process flow of the proposed work.

SFLA is a combined approach of randomness and determinism. The consistency and the robustness of the search in the SFLA depend on the randomness strategy. The heuristic search is guided efficiently by the deterministic approach to use the surface information obtained. In the space, the search begins with all the randomly generated populations of frogs. The whole population is again partitioned into memeplexes and the search continues for each memeplex. This causes memetic evolution which as a result improves the quality of the meme of the individual enhancing the performance of the frog. The shuffling process takes place considering all the memeplexes and the search continues until the final solution is reached. The local search of SFLA has been shown in Figure 1(b).

Since, SFLA has not been exploited in channel selection optimization, in this work, SFLA is utilized to select the optimal channel for EEG based addiction detection. Initially, total number of 16 EEG channels has been used to obtain the data. The objective of the work is to find the optimal 8 channels out of these 16 channels using SFLA to extract the relevant features from the selected channels that can be further analysed with the various machine learning classifiers.

3.1. Mathematical formulation

Frogs denote solutions in a search space and memeplexes denote the partitions made to perform the local search. Let Ch be the set of channels, where $Ch = \{ch_1, ch_2 \ldots\ldots ch_k\}$ and 'k' is the number of channels. Let N be the population size, where $F = \{f_1, f_2 \ldots\ldots f_n\}$ and 'n' is the number of frogs. Let M be the number of the memeplex, where $M = \{m_1, m_2 \ldots\ldots m_m\}$ and 'm' is the number of the memeplex. Let the change in frog position be Δp, where:

$$\Delta p = rand() * (M_{best} - M_{worst}) \quad (1)$$

$$\Delta p = rand() * (F_{best} - M_{worst}) \quad (2)$$

Let the new position be np, were:

$$np = M_{worst} + \Delta p \quad (3)$$

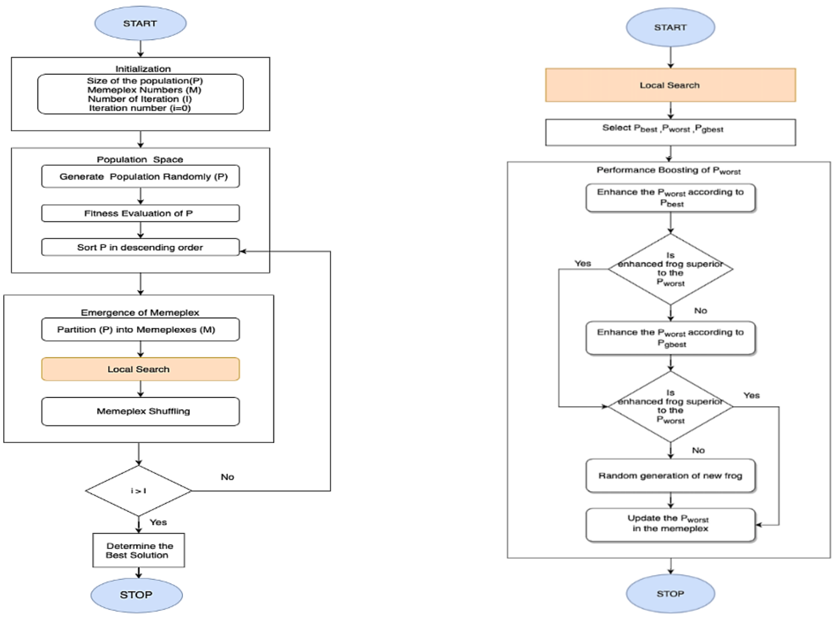
The best frogs denote the selected channels which maximize:

$$f(x) = \max(accuracy) \tag{4}$$

The pseudo-code of the algorithm is:

```
Algorithm 1. Pseudocode of SFLA
Input: Number of Channels (Ch), Population size (N), Number of memeplex (M), Number of
Iteration (I).
Fitness Function: f(t) = Max(accuracy).
Output: List of selected channels.
Outcome: Improved classification Accuracy.

1: Initialize N, M, I, Ch
2: Generation of random F frogs as population, where F ranges from f_1 …..……. f_n
3: for <each frogs f_i in population F > do
4:      calculate fitness f(t)
5: End for
6: Sort F based on f(t)
7: Partition F into memeplex M
8: For <each M_i in F > do
9:      Calculate M_best, M_worst, F_gbest
10:     Enhance the M_worst according to M_best,
11:             np = M_worst + Δp
12:             Δp = rand() × (M_best − M_worst)
13:     If (f(np)>f(M_worst))
14:             Update M_worst to np in M_i
15:     Else
16:             Enhance the M_worst according to F_gbest,
17:                     np = M_worst + Δp
18:                     Δp = rand() × (F_gbest − M_worst)
19:                     If (f(np)>f(M_worst))
20:                             Update M_worst to np in M_i
21:                     Else
22:                             Randomly generate new frogs
23:                     End if
24:     End if
25: End for
26: Shuffle f_i across M in population space F
27: If (i>I)
28:     Return F_gbest
29: Else
30:     Go to step 6
```



(a) (b)

Figure 1. Proposed work flow: (a) SFLA process flow and (b) local search process in SFLA

4. METHODOLOGY

This section relies on the work that has been proposed and implemented using SFLA for the optimal channel selection. It has detailed insights into the initialization, frog encoding, memeplexes, decoding of frogs into solution, fitness evaluation, training, and testing phase respectively. Using this SFLA optimization, 8 channels are selected out of 16 channels and the experimental results show that the performance is increased.

4.1. Initialization and frog encoding

In this work, the initialization of the algorithm includes population size (N), number of memeplex (M), number of iteration (I), a new position (np), and velocity concerning M_{best} and F_{gbest}. Table 1 gives the parameter initialization of the SFLA. In SFLA algorithm, frogs denote the solutions. Initially, each frog in the population represents 8 randomly generated combinations of channels out of 16 channels. The fitness function will be calculated and evaluated for every combination of channels in the population. Finally, the frog with better accuracy is taken into consideration and is determined as the best combination of channels respectively.

Table 1. Initialization of SFLA parameters

Parameters	Values
Population size	100
Number of memeplex	10
Total number of channels	16
Optimal channels	8

4.2. Memeplexes representation representation and decoding of frogs into solution

Memeplexes denote the partitions made for the frogs to perform a local search within each partition. The representation of the partitioned memeplexes is shown in Figure 2. The final solution obtained is the optimal selection of the best combination of 8 channels from the 16 channels out of various combinations. The decoding of the obtained frogs into the 8 optimal selected channels is decoded as shown in Table 2.

Figure 2. Representation of memeplex

4.3. Evaluation of fitness

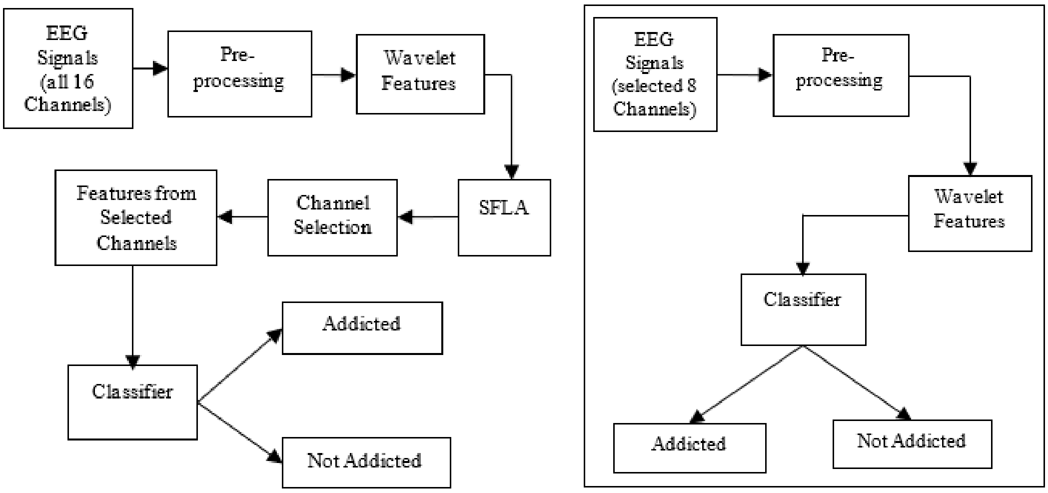
After the random generation of frogs, the fitness is calculated and evaluated. The evaluation of fitness performed in this work considers the 8 combinations of channels to determine the best combination in terms of accuracy, sensitivity, specificity, and precision. During the training phase, the wavelet features are extracted from all 16 channels. The SFLA algorithm is used to select the optimal channel to improve the accuracy of the drug addiction detection classification. During the testing phase, the features are extracted only from the optimally selected channels from the EEG input signals. The training phase and the testing phase have been depicted in Figure 3(a) and Figure 3(b) respectively.

4.4. Data acquisition

In this work, the data are acquired using the "g.Tech" recorder which consists of 16 electrodes/channels (P3, F7, FP2, O2, FP1, F8, T4, F3, F4, C4, P4, T6, C3, T3, T5, O1, and ref). The electrodes are positioned using the 10–20 placement system, which is an international standard. The sampling frequency is set to 512 Hz. The sensitivity is set to 2.5 volts per millimeter. To reduce high-frequency noise, a 1.0 Hz low pass filter is used. The data are acquired from totally seven subjects with different number of trails (age group between 20 and 25) after getting their consent. The subjects are made to sit on a chair in a comfortable position. Six easy mental arithmetic calculations are given to the subjects as cognitive stimuli and asked them to solve it while recording the brain signals. Each mental task is displayed for 19 s to 20 s, and each task is followed by a resting interval of 20 s. Two trials are taken from each subject.

Table 2. Decoding of frogs

Obtained channels	1	5	15	10	2	6	9	7
Decoding of frogs	FP2	T6	T5	F3	F4	T4	FP1	T6



(a) (b)

Figure 3. Drug addiction detection system: (a) training phase and (b) testing phase

4.5. Training phase

The EEG signals from the subjects obtained considering all the 16 channels are processed. The wavelet features are being extracted from the signals of 16 channels. The features are fed into the SFLA to optimize the best combination of 8 channels. Then, the features from the selected combination of channels are fed into the classifier to classify the addicted and not addicted subjects.

4.6. Testing phase

The testing phase includes only the EEG signals from the selected combination of 8 channels in the training phase. The EEG signals are processed and the extracted wavelet features of the optimized channels are fed into the classifier to classify the addicted and not addicted subjects. Thus, reducing and optimizing the number of channels increases the classification accuracy and also reduces the computation complexity.

5. RESULTS AND DISCUSSION

Due to the advantages of SFLA, it performs well than other optimization algorithms and hence in this work, SFLA has been chosen to optimize the combination of channels from 16 to 8. The wavelet features from all 16 channels are given to the SFLA to determine the best combination of 8 channels to improve the classification accuracy. The classifiers combined with SFLA have been evaluated with the performance metrics such as the classification accuracy, specificity, sensitivity, and precision.

From Figure 4, the sensitivity, specificity, precision, and accuracy of the various classifiers have been analyzed with and without SFLA. In all classifiers, features extracted from the optimal channel selection using SFLA achieve improved precision over the classifiers without optimal channel selection. It is observed that even though the channels have been reduced, the features extracted from the channels selected through SFLA provides better feature and these features are good enough to discriminate the drug addiction detection.

The wavelet features extracted from the optimally selected channels have been input to the various machine learning classifiers to evaluate the performance of the drug addiction detection system. The performance analysis based on the accuracy is shown in Table 3 and it is noted that the classifiers used with SFLA (W-SFLA) for channel selection show better accuracy than the classifiers used without SFLA (WO-SFLA). The optimal channel selection with SFLA provides an improvement of 2.85% for SVM, 15.78% for MLP, 12.47% for RF, 0.4% for DT and 7.69% for NB.

Table 3. Performance analysis on various classifiers without and with channel selection

Classifiers	Performance metric based on accuracy	
	Without SFLA	With SFLA
SVM	80	82.35
MLP	80	95
RF	71.42	81.6
DT	80	80.35
NB	60	65

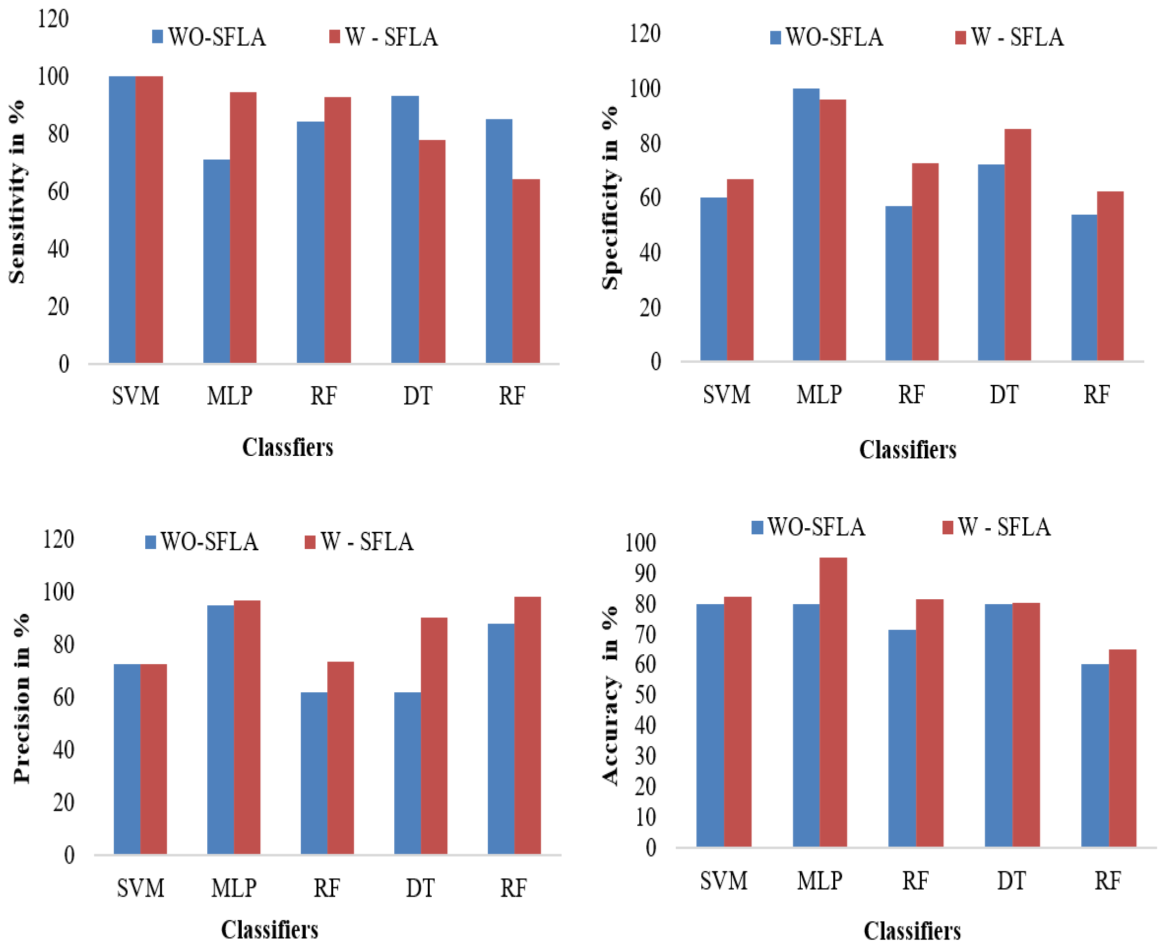


Figure 4. Performance of various classifiers in terms of sensitivity, specificity, precision, and accuracy for without and with SFLA

6. CONCLUSION

EEG signals are considered to be more efficient and effective while considering the changes in the brain signals. Drug addiction is one of the merging problems all around the world, especially among the youths. Many existing kinds of research have been performed with machine learning, deep learning, and optimization algorithms on EEG signals for drug addiction. Since optimization and selection of the best combination of 8 channels is a vital role, in this work SFLA is implemented to determine the best combination of 8 channels. The results have been compared with the features of 16 channels and the classifiers such as SVM, MLP, RF, NB, DT. The experimental results show that SFLA with the classifiers gives better performance in terms of increased accuracy. Among all the classifiers MLP with SFLA provides improved performance of 15.78% accuracy than the MLP without SFLA and it also reduces time complexity. Further, this work can be improved by choosing the channels dynamically and not by any fixed number of channels selection which in turn can improve the performance. Deep learning techniques can also be applied to improve performance.

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REFERENCES

[1] T. Alotaiby, F. E. A. E. -Samie, S. A. Alshebeili, and I. Ahmad, "A review of channel selection algorithms for EEG signal processing," *EURASIP Journal on Advances in Signal Processing*, no. 66, 2015, doi: 10.1186/s13634-015-0251-9.
[2] A. Affes, A. Mdhaffar, C. Triki, M. Jmaiel, and B. Freisleben, "Personalized attention-based EEG channel selection for epileptic seizure prediction," *Expert Systems with Applications*, vol. 206, 2022, doi: 10.1016/j.eswa.2022.117733.
[3] H. Varsehi and S. M. P. Firoozabadi, "An EEG channel selection method for motor imagery based brain-computer interface and neurofeedback using Granger causality," *Neural Networks*, vol. 133, pp. 193-206, 2021, doi: 10.1016/j.neunet.2020.11.002.
[4] G. Ghorbanzadeh, Z. Nabizadeh, N. Karimi, P. Khadivi, A. Emami, and S. Samavi, "DGAFF: Deep genetic algorithm fitness Formation for EEG Bio-Signal channel selection," *Biomedical Signal Processing and Control*, vol. 79, 2023, doi: 10.1016/j.bspc.2022.104119.
[5] X. -S. Yang, "Nature-inspired optimization algorithms: Challenges and open problems," *Journal of Computational Science*, vol. 46, 2020, doi: 10.48550/arXiv.2003.03776.
[6] S. Kirkpatrick, "Optimization by simulated annealing: Quantitative studies," *Journal of statistical physics*, vol. 34, pp. 975-986, 1984, doi: 10.1007/BF01009452.
[7] J. H. Holland, *Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence*. Cambridge, MA, USA: MIT Press, 1992. [Online]. Available: https://mitpress.mit.edu/9780262581110/adaptation-in-natural-and-artificial-systems/
[8] K. A. D. Jong, *Analysis of the behavior of a class of genetic adaptive systems*. Technical Report No. 185, Department of Computer and Communication Sciences, University of Michigan, 1975. [Online]. Available: https://deepblue.lib.umich.edu/handle/2027.42/4507
[9] R. Palaniappan, P. Raveendran, and S. Omatu, "VEP optimal channel selection using genetic algorithm for neural network classification of alcoholics," *IEEE Transactions on Neural Networks*, vol. 13, no. 2, pp. 486-491, 2002, doi: 10.1109/72.991435.
[10] L. He, Y. Hu, Y. Li, and D. Li, "Channel selection by Rayleigh coefficient maximization based genetic algorithm for classifying single-trial motor imagery EEG," *Neurocomputing*, vol. 121, pp. 423-433, 2013, doi: 10.1016/j.neucom.2013.05.005.
[11] B. Wang, C. M. Wong, F. Wan, P. U. Mak, P. -I. Mak, and M. I. Vai, "Trial pruning based on genetic algorithm for single-trial EEG classification," *Computers & Electrical Engineering*, vol. 38, no. 1, pp. 35-44, 2012, doi: 10.1016/j.compeleceng.2011.07.008.
[12] L. A. Moctezuma and M. Molinas, "Multi-objective optimization for EEG channel selection and accurate intruder detection in an EEG-based subject identification system," *Scientific reports*, vol. 10, no. 5850, 2020, doi: 10.1038/s41598-020-62712-6.
[13] A. Atyabi, M. H. Luerssen, and D. M. W. Powers, "PSO-based dimension reduction of EEG recordings: implications for subject transfer in BCI," *Neurocomputing*, vol. 119, pp. 319-331, 2013, doi: 10.1016/j.neucom.2013.03.027.
[14] S. Afrakhteh and M. R. Mosavi, "Applying an efficient evolutionary algorithm for EEG signal feature selection and classification in decision-based systems," in *Energy efficiency of medical devices and healthcare applications*, 2020, pp. 25-52, doi: 10.1016/B978-0-12-819045-6.00002-9.
[15] Y. Huang, X. -N. Shen, and X. You, "A discrete shuffled frog-leaping algorithm based on heuristic information for traveling salesman problem," *Applied Soft Computing*, vol. 102, 2021, doi: 10.1016/j.asoc.2021.107085.
[16] S. Panda, A. Sarangi, and S. P. Panigrahi, "A new training strategy for neural network using shuffled frog-leaping algorithm and application to channel equalization," *AEU - International Journal of Electronics and Communications*, vol. 68, no. 11, pp. 1031-1036, 2014, doi: 10.1016/j.aeue.2014.05.005.
[17] Q. Huang and W. Song, "A land-use spatial optimum allocation model coupling a multi-agent system with the shuffled frog leaping algorithm," *Computers, Environment and Urban Systems*, vol. 77, 2019, doi: 10.1016/j.compenvurbsys.2019.101360.
[18] R. Dash, R. Dash, and R. Rautray, "An evolutionary framework based microarray gene selection and classification approach using binary shuffled frog leaping algorithm," *Journal of King Saud University-Computer and Information Sciences*, vol. 34, no. 3, pp. 880-891, 2022, doi: 10.1016/j.jksuci.2019.04.002.
[19] Y. Fan, P. Wang, A. A. Heidari, X. Zhao, H. Turabieh, and H. Chen, "Delayed dynamic step shuffling frog-leaping algorithm for optimal design of photovoltaic models," *Energy Reports*, vol. 7, pp. 228-246, 2021, doi: 10.1016/j.egyr.2020.12.013.
[20] Y. Liu *et al.*, "Simulated annealing-based dynamic step shuffled frog leaping algorithm: Optimal performance design and feature selection," *Neurocomputing*, vol. 503, pp. 325-362, 2022, doi: 10.1016/j.neucom.2022.06.075.
[21] X. Shen, Q. Chen, H. Pan, L. Song, and Y. Guo, "Variable speed multi-task allocation for mobile crowdsensing based on a multi-objective shuffled frog leaping algorithm," *Applied Soft Computing*, vol. 127, 2022, doi: 10.1016/j.asoc.2022.109330.
[22] A. B. Buriro *et al.*, "Classification of alcoholic EEG signals using wavelet scattering transform-based features," *Computers in Biology and Medicine*, vol. 139, 2021, doi: 10.1016/j.compbiomed.2021.104969.
[23] P. D. Barua *et al.*, "Automated EEG sentence classification using novel dynamic-sized binary pattern and multilevel discrete wavelet transform techniques with TSEEG database," *Biomedical Signal Processing and Control*, vol. 79, 2023, doi: 10.1016/j.bspc.2022.104055.
[24] W. A. -Salman, Y. Li, P. Wen, F. S. Miften, A. Y. Oudah, and H. R. A. Ghayab, "Extracting epileptic features in EEGs using a dual-tree complex wavelet transform coupled with a classification algorithm," *Brain Research*, vol. 1779, 2022, doi: 10.1016/j.brainres.2022.147777.
[25] M. Eusuff, K. Lansey, and F. Pasha, "Shuffled frog-leaping algorithm: a memetic meta-heuristic for discrete optimization," *Engineering optimization*, vol. 38, no. 2, pp. 129-154, 2006, doi: 10.1080/03052150500384759.

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