ABSTRACT

Brain-Computer Interface (BCI) is a communication framework that facilitates communication between the human brain and different intelligent devices such as wheelchairs, smart home appliances, and neuroprosthetics. It takes brain signals as input, processes them, and converts them into computer-based control commands that are relayed to an output device to carry out the desired action. BCI systems use Electroencephalogram (EEG) signals due to their high time resolution and the relative ease and cost-effectiveness of brain signal acquisition when compared to other methods such as functional magnetic resonance imaging (fMRI) and magnetoencephalography (MEG). In EEG-based BCI communication, Motor Imagery (MI) is an important paradigm that deals with imagination-based muscular activities. A subject is required to imagine in his brain about a limb movement without performing any physical task. However, the implementation of MI-based BCI systems is notoriously difficult because high dimensional data results in a slow training procedure.

In general, EEG signals are noisy, nonstationary, nonlinear, and multichannel in nature. Therefore, a set of optimization methods is required in the preprocessing phase to improve the signal quality. In EEG signal processing, MI-specific signals are collected from definite scalp sites referred to as channels or electrodes. A dense arrangement of electrodes on the human scalp explores a lot of information about the underlying mechanism of neuronal activity as a result it induces an abundant amount of redundant and irrelevant information in the form of noise and high-dimensional data. Additionally, it increases the hardware complexity of the BCI system, which requires more effort during the BCI preparation setup. Therefore, it is essential to reduce these efforts using a minimal but informative set of channels. Since the year 2000, researchers have become increasingly interested in proposing different types of optimization techniques for dealing with high-dimensional brain data. The primary objective of these methods is to improve the global performance of inbuilt classification models in terms of classification accuracy and minimize redundancy and irrelevancy of the channels. However, the field still has a limited understanding of several issues, including experiment design, stimulus type, training, calibration, and the examined features. The main aim of the research in this thesis is to develop advanced optimization algorithms for addressing the above-mentioned issues that have not been solved in previous studies.

To resolve the above-mentioned issues in neural signal modeling, we performed numerous experiments using different optimization methods and obtained some interesting results. In

these demonstrations, we mainly focused on the elimination of less significant channels without compromising the classification accuracy. We compared our results with different state-of-the-art methods published in the last ten years (2011-2021) to show the effectiveness of applied optimization methods. The overall comparative studies show that proposed improvement strategies boost the global performance of multi-channel BCI systems in terms of classification accuracy and preserving only significant channels. We summarized the details of all the performed experiments in this thesis so that these methods can be used in advanced neuroprosthetic devices to serve disabled persons.

This thesis is organized into eight chapters. In the first chapter, theoretical aspects and types of BCI systems are discussed while fundamentals and existing works are covered in chapter two. In the third chapter, we discuss our first published work based on four MI activities classification using spatial-temporal features and the eXtreme Gradient Boosting (XGB) algorithm. This chapter concludes that prior handling of the noise level in EEG classification provides a better approximation. Chapter four introduces a filter-based channel selection method based on information-theoretic concepts and different machine learning methods. In this chapter, we describe a novel three-way interaction maximization strategy to maintain a good balance between relevancy and redundancy levels associated with the selected channel subset. The proposed optimization scheme merges two mutual information paradigms: (1) Gini Index (GI) and (2) Mutual Information Coefficient (MIC) to measure the importance and redundancy of a selected channel. The obtained results show that the proposed method performs better in terms of superior classification accuracy, higher channel reduction rate, and lesser response time.

Two different wrapper-based channel selection methods are introduced in chapters five and six. In both approaches, stochastic properties of two metaheuristics: (1) Firefly Algorithm (FA), and (2) Butterfly Optimization Algorithm (BOA) are used to determine the correlation between known candidate solutions and newly selected channels. In both chapters, we seek the most feasible solution from a large search space using a metaheuristic-inspired iterative search strategy. In both experiments, we tried to maintain a good trade-off between exploration (large channel space) and exploitation (optimal channel subset) using the local and global search schemes of the mentioned metaheuristic algorithms. In the FA-based optimization method, we designed a bi-objective function with two goals: (1) Spectral entropy, and (2) Lyapunov exponent to compute the similarity between the individual channel and candidate solution. Using this optimization scheme, we obtained significant results on small datasets (in terms of channels) as compared to some recently published results that show the novelty of the proposed work. However, this method showed limited improvements on large datasets. This limitation was resolved in Chapter 5 where an improved X-shaped binary variant of the BOA was used to determine a better channel subset. This method utilized two sigmoid components to generate two different solutions and their quality is evaluated using a bi-objective function with two goals: (1) minimum classification accuracy error, and (2) minimum number of selected channels. The computed solution effectively resolved the limitation of the FA-based channel selection approach and obtained good classification accuracy on a large-size dataset (> 100 channels). This method not only obtained high classification accuracy but also gained a superior convergence rate as compared to various baseline methods.

In chapter seven, we describe our last published work where we provide a hybrid search-space optimization method by combining a Dynamic variant of BOA (DBOA) and mutual information to eliminate irrelevant and redundant attributes. In this approach, we enjoyed the improvement mechanism of the mutation-based local search scheme and movement strategy of butterflies to compute the optimal feature subset. The significance of each obtained solution is evaluated using the Mutual Information Maximization (MIM) principle. Here, the relevance of each solution is computed in terms of the classification accuracy and number of selected features in the respective feature subset. The performance of the proposed approach was validated on twenty high-dimensional datasets from different research domains. The results are compared with ten baseline algorithms in terms of classification accuracy, feature reduction rate, specificity, sensitivity, fitness function score, and computational complexity. The overall results show the superiority of the proposed method over most of the state-of-the-art methods and datasets.

Finally, we highlight the main contribution of our work in chapter eight. Here, we discuss the summary of each proposed optimization approach in terms of its novel findings and limitations. We have also included five new research directions based on deep learning paradigms and graph mining to enhance the performance of the experiments discussed in this thesis.