CHAPTER 8

8 Conclusion and Summary

The primary goal of this research work is to improve signal processing algorithms for MI-BCI and SSVEP-BCI using pattern recognition methods. EEG is the most widely used modality in BCI systems. During the acquisition of EEG, The interference of eyeblink and eyeball movements is the most prominently observed in reordered EEG. Eye muscles-related artifacts are referred as Ocular Artifacts (OAs). The magnitude of OAs is in the range of mV, which is larger than compared to that of EEG signals (uV). In BCI systems, EEG signals are acquired and translated into commands by extracting useful information from the signal and applying pattern recognition methods. Therefore, the cleaning of EEG signals is a vital step before extracting useful information for BCI applications. Also, the BCI system targets to use a fewer number of EEG channels. Hence it is essential to remove OAs from single-channel EEG. This thesis proposed an effective adaptive threshold algorithm based on the quantum theory of information to remove OAs from the single-channel EEG signal. In the experiment, contaminated EEG is decomposed using DTCWT. The performance of DTCWT is superior to DWT because it is nearly shift-invariant and gives perfect reconstruction of the signal. A comparative study is conducted between the performances of the proposed quantum-inspired adaptive threshold algorithm and standard thresholding methods such as soft threshold and hard threshold. The obtained results in terms of RRMSE suggest that the proposed method outperformed other standard methods. Moreover, the proposed approach suppresses the OAs from single-channel EEG without degrading the main information of the EEG.

In the medical field, MI BCI research has investigated the use of brain signals of patients suffering from stroke to regain their motor functionality. MI- BCI has been finding wide scope to assist paralyzed patients or people with neuromuscular disorders. However, the MI BCI signal processing research is still progressing.

For MI-BCI models, where features are extracted based on various statistical, time, frequency, and phase analysis of EEG, MI task classification can be improved by incorporating feature selection methods. In this work, we present a method based on RNCA to improve the MI classification accuracies. The superiority of the proposed feature selection method compared with standard filter and wrapper feature selection approaches is shown by conducting a comparative study. The proposed method removes the irrelevant features from the feature space of two-class MI-EEG data and enhances the SVM classifier's speed and accuracy. The limitation of the proposed method is that it takes more execution time than the filter-based feature selection method during the training phase. However, in the testing phase, the proposed method is faster.

In spatial filtering-based MI signal processing models, CSP is the most commonly used method. However, its performance is dependent on the choice of frequency band and filtering technique. To optimize spectral-spatial MI features, this work proposed a novel algorithm, namely, DTCWT-CSP (NCA). In this approach, we filtered the EEG signals into sub-bands using DTCWT based filter bank. The proposed filter bank provided more band power compared to traditional filtering methods. Then, spatial features using conventional CSP are extracted from the filtered EEG data. Subsequently, sub-bands are optimized using a novel approach based on neighbourhood component analysis. An experimental study conducted on standard BCI datasets validates the superiority of the proposed methods compared to the standard state-of-the-art methods.

Neural response to MI task has different time latency in different subjects. Identification of relevant time intervals and eliminating the irrelevant sample points from the EEG time series is important. Thus, time window optimization further enhances the MI task classification. Consideration of time window optimization in spectral-spatial model increases the dimensionality of the MI-EEG feature space and makes it a higher-order tensor data. For tensor data analysis, the primary goal of optimization algorithm is to preserve the internal structure of the feature space. This work proposed a novel feature optimization algorithm for the selection of the spatial features that occur at multiple frequency bands and time windows. In this approach, we segmented the MI-EEG into multiple overlapped time windows using sliding time window method. Each time window is filtered using a DTCWT based filter bank at multiple frequency bands. Afterward, spatial features are extracted using CSP method. Therefore, the final feature space has three dimensions. The proposed method optimized the spatial features at multiple time windows and frequency bands simultaneously, without affecting the internal structure of the MI data. The performance of the proposed method is found significantly better than the standard methods' performance.

Apart from MI-BCI, another popular BCI is based on SSVEP's. It is more popular for real-time control applications such as home appliances and wheelchair control. In SSVEP-BCIs, many existing signal processing algorithms are effective in recognizing the correct frequency while the subject is performing the task. However, conventional methods also detect one of the target frequencies when the subject is in idle stage, i.e., not performing the task. These false-positive outcomes highly affect the performance of SSVEP-BCI and make it challenging to use in real-life applications, where achieving a high specificity and precision is a must. To tackle this issue, we proposed the combined use of CCA and LDA. Obtained results show that the proposed method is capable of differentiating between the idle state and the intended target. Hence this method can be efficaciously executed in SSVEP BCI, and the same BCI system can be extended to many more real-life applications.

8.1 Scope for Further Work

EEG dataset used in BCI systems consists of multiple matrices of trails, where each matrix has EEG channels in the rows and time points in the columns. Thus, EEG dataset naturally has three dimensions. To extract useful information from the data and create a feature space for classification, researchers perform spectral, spatial, and temporal analysis. Hence these analyses further increase the dimensions of the feature space and make it a higher-order tensor data. Optimization of higher-order feature space is a challenging exercise to perform. In a few approaches, researchers optimize the tensor data by converting it into a larger single matrix using unfolding and concatenating approach. However, this approach results in loss of internal structure of the tensor data.

To study more complex structural relationships of higher-order tensor data, more sophisticated algorithms based on subspace regularization have been proposed in many fields, including imaging processing, brain disease diagnosis, and so on [275–279,293–298]. Also, common and linked feature analysis on multiple datasets, structural tensor data decomposition, and multiway learning have shown promising potentials for complex biomedical data analysis [187,252,253,284–286]. Accordingly, we consider designing a more sophisticated algorithm based on these advanced methods to further benefit the EEG classification in BCI systems.