ABSTRACT

Electroencephalography (EEG) has become an important and necessary tool for both clinical and non-clinical neurological research and applications because of its non-invasive signal acquisition mechanism and high temporal resolution. However, EEG signals often get contaminated by various non-neuronal signals or artifacts which significantly distort the neural activities and hamper EEG-based research and processing. Appropriate separation of artifacts is the mandatory pre-processing tasks for all EEG-based applications and analysis. The sources of artifacts can be both non-physiological and physiological. The occurrence of non-physiological artifacts can be reduced by taking some precautions during EEG signal recording. But the physiological artifacts mainly occur from ocular activities (electrooculogram (EOG)) muscle activities (electromyogram (EMG)) and cardiac pulse (electrocardiogram (ECG)), which are impossible to suppress. Hence, the main focuses of this thesis is the correction of physiological artifacts or mainly EOG and EMG artifacts from EEG signal. The EOG and EMG artifacts exhibit critical contamination pattern due to spectrum overlapping with clean EEG and wide range of amplitude variation. These type of contamination not only restricts the utilization of conventional frequency selective filters but also imposes serious challenge on artifact reduction methods. Although, a large number of artifact correction methods have been developed in the past but the majority of them still suffer from some serious drawbacks like basis dependency, manual correction, neural leakage etc. Hence, a major research gap exists in this domain. The research gaps have been addressed in this thesis by incorporating signal processing and deep learning.

For the case of EOG artifact correction, the suppression of neural leakage is an essential task and the entire EOG artifact estimation process should be automatic as well. To execute these two tasks simultaneously, the sparse dictionary learning (K-SVD) and deep learning (LSTM) are jointly utilized in the first contribution of this thesis. First a LSTM based network is designed and trained to detect EOG contaminated region, then K-SVD based de-noising is used to estimate the EOG signal from detected contaminated region only. Therefore the uncontaminated region remain fully unaltered, which significantly suppress the neural leakage and the overall method remains fully automatic. The second contribution of this thesis involves the development of a new EOG structure estimation technique which overcomes the severe implementation complexity of K-SVD. The relaxed sparse representation by Orthogonal Matching Pursuit (OMP) and thresholding are unitedly implemented for this purpose. Only necessary OMP coefficients are allowed by thresholding for EOG structure estimation. Thresholding is done on OMP coefficients as per its exhibited pattern of relaxed representation. The utilization of sine and cosine waves as dictionary atoms makes this method basis independent. This proposed method also extended for multichannel EOG artifact correction as well. The third contribution of this thesis integrates deep learning and our developed OMP based EOG estimation process. Two individual LSTM networks are designed and trained, where one network first detects contaminated region from OMP coefficient vector and second one selects only necessary OMP coefficient from detected contaminated region for EOG structure estimation. This OMP and LSTM integration makes the entire process automatic, threshold independent estimation and also ensures the unaltered uncontaminated region.

The critical contamination pattern of EMG artifacts impose serious challenge on conventional signal processing based source separation techniques. So, the correction based on learning is much more acceptable here. The EEGdenoiseNET dataset provides ground truth signals for learning those necessary parameters. However, it has been observed that the ground truth EMG segments of this dataset are significantly different from true EMG signal due to the coexistence of unwanted trend signals. The fourth contribution of this thesis involves data pre-processing and a comparative analysis between pre-processed and raw data in terms of deep learning (LSTM and Bi-LSTM) based EMG artifact correction quality.