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Artifacts removal from EEG signal: FLM optimization-based learning algorithm for neural network-enhanced adaptive filtering

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ABSTRACT

Electroencephalogram (EEG) denotes a neurophysiologic measurement, which observes the electrical activity of the brain through making a record of the EEG signal from the electrodes positioned on the scalp. The EEG signal gets mixed with other biological signals, called artifacts. Few artifacts include electromyogram (EMG), electrocardiogram (ECG) and electrooculogram (EOG). Removal of artifacts from the EEG signal poses a great challenge in the medical field. Hence, the FLM (Firefly + Levenberg Marquardt) optimization-based learning algorithm for neural network-enhanced adaptive filtering model is introduced to eliminate the artifacts from the EEG. Initially, the EEG signal was provided to the adaptive filter for yielding the optimal weights using the renowned optimization algorithms, called firefly algorithm and LM. These two algorithms are effectively hybridized and applied to the neural network to find the optimal weights for adaptive filtering. Then, the designed filtering process renders an improved system for artifacts removal from the EEG signal. Finally, the performance of the proposed model and the existing models regarding SNR, computation time, MSE and RMSE are analyzed. The results conclude that the proposed method achieves a high SNR of 42.042 dB.

1. Introduction

Recently, a number of EEG-based applications, such as wheelchair controllers and word speller programs [1–3] are used by the researchers. Using the non-invasive measurement of EEG, the activities of the brain can be observed by placing the electrodes on the scalp of the human brain in multiple areas [4]. The signal that results from recording the brain activities are not only the pure form of the brain signal because some defected signals, called artifacts (such as, power line noise, muscle contraction, heart activity and eye movement), also gets mixed with it [5,6]. Due to the existence of the artifact signal, the examination of EEG signal from the EEG recordings becomes more complex because it is perplexed with the neurological patterns. To generate a correct analysis and diagnosis [7], the unwanted signals must be eliminated from the recorded EEG signal.

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Once the artifacts from the EEG signal were removed, the original brain signal can be extracted from the EEG recordings [4]. Though the removal of artifacts from the EEG signal is a more complex process, it is utmost necessary for the progress of practical systems with low amplitude signal distortion [8]. Nowadays, more common methods are used to remove the artifacts from the EEG signals. Some of them includes linear filtering and regression model [9,10], ICA (independent component analysis) [11], WT (wavelet transform) [12–14] and (ANFIS) adaptive neuro-fuzzy inference system [7,15,16], adaptive filters and neural networks [3] and cascaded adaptive filters [17]. ICA is one of the important analyses for sorting out the EEG signals, which obtained from the electrodes that positioned on the scalp, into a self-governing mechanism. However, the ICA algorithm fails to yield better results during source separation. The artifacts signal was eliminated by the PCA technique, which is used to handle the high dimensional, boisterous and concurrent data. However, the orthogonal rotation gets reduced by the PCA analysis. Another technique is the eye-blink artifacts removal by the adaptive filter technique. Here, the adaptive filter subtracts the EEG source signal from the estimated inference signal to remove the artifacts [18]. Also, the adaptive filters remove the artifacts in real-time mode with less computation complexity. However, no complete assurance can be given that the reference signal is a perfect signal. Investigation on the fault classification performance by the fuzzy logic techniques has also been carried out [7].

The primary intention of this research is to design and develop a technique for removing the artifacts from the EEG signal. Here, we have planned to develop an FLM optimization-based learning algorithm for the neural network-enhanced adaptive filtering. This neural network-based adaptive filtering performs the removal of artifacts from the EEG signals. At first, the EEG signal is given to the proposed adaptive filtering to obtain the optimal weights using the well-known optimization algorithm, called firefly algorithm and LM (Levenberg Marquardt). These two algorithms were effectively hybridized and it is applied to the neural network to find the optimal weights for adaptive filtering. Then, the designed filtering was utilized for the removal of artifacts from the EEG signal. Finally, the comparison made against ICA, wavelet ICA, Fast ICA, wavelet-based method that is given in [19] and the LM based optimization, regarding SNR, percentage root mean square difference (PRD), and mean square error (MSE).

2. Problem formulation

While recording the EEG signal through the biomedical equipment, a variety of large signal contaminations or noise may affect the original signal data. The artifacts would dramatically alter the signal that was recorded at all scalp sites, especially at those sites that are closest to the source of the noise. Hence, the artifact or noise cancelation serves as a necessary stage of EEG processing [1,4,7,8,19–23].

One of the biggest challenges of using EEG is the very small signal-to-noise ratio of the brain signals that we are trying to observe, due to the coupling of the wide variety of noise sources [24]. Additionally, the EEG signals are of very small amplitudes, and because of that, they can be easily contaminated by noise.

The main difficulty of the EEG artifact removal problem is the selection of the threshold level. The reason is that it should not remove the original EEG signal coefficients and at the same time, it should never keep the artifact signals as the original ones.

In the case of the time varying signals that arise from the human body, adaptive filtering is found to serve as an appropriate method for the EEG artifact removal. Although the adaptive linear filters are the most widely used filters from among the various available adaptive filters, their performance is not satisfactory for dealing with the nonlinear problems.

In [20], an adaptive FLN–RBFN-based filter was proposed to remove ocular, muscular and cardiac artifacts from the EEG signals. But, this adaptive neural network had not considered the weights optimally, when the learning process was performed. Hence, the finding of the optimal weights for adaptive filtering is a heuristic search problem, and it should be performed optimally by handling all the constraints to obtain a good artifacts removal performance.

3. Adaptive noise cancelation for artifacts removal

Basically, adaptive noise cancelation is used to eliminate the artifacts from the EEG signal. Fig. 1 shows the basic block diagram representation for achieving adaptive noise cancelation [20]. As shown in the figure, the adaptive noise cancelation process requires two inputs. The first input is generated from the EEG signal source and it is represented as $S(t)$. Then, the second input is collected from the source of the artifact signal and it is denoted as $A(t)$. The noise source considered here represents the origin, where the various artifacts such as, EOG, EMG and ECG generate. The noisy source signal of the artifacts signal gets passed through unidentified non-linear dynamics, resulting in the generation of the interference signal $I(t)$. Then, the combination of both the interference signal and the clean signal generates the primary input signal and it is represented as follows:

$$P(t) = S(t) + I(t) \tag{1}$$

where $S(t)$ is defined as the input source signal and $I(t)$ indicates the interference signal that is generated from the noise source. Meanwhile, the signal generated from the noise source is applied to an adaptive filtering process to get the filtered output. The filtered output is as close to the interference signal that is generated from the result of nonlinear dynamics. The aim of this adaptive noise cancelation is to retrieve the clean EEG signal. In order to retrieve the clean EEG signal, the filtered output is subtracted from the primary input and it is shown below:

$$S_o(t) = S(t) + I(t) - F(t) \tag{2}$$

where $F(t)$ denotes the filtered output and the output signal of the entire adaptive noise cancelation is represented as $S_o(t)$.

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