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http://dx.doi.org/10.5339/qfarc.2016.HBPP3376

Design of a Time-Frequency Algorithm for Automatic Eeg Artifact Removal

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1) The method

The injuries suffered by newborns during birth are a major health issue. To improve the health outcomes of sick newborns using EEG measurements, a number of recent studies focused on the use of high-resolution Time-Frequency Distributions to extract critical information from the collected signals [1]. Several algorithms have been proposed. A major problem in the implementation of such algorithms for fully automated EEG signal classification systems is caused by artifacts. In particular, previous studies have shown that a respiratory artifact looks like a seizure signal and can be misinterpreted by the automatic abnormality detection system thus resulting in false alarms. Hence, the successful removal of the artifacts is important, as shown in several previous studies [2]; and, there are two basic approaches for this: (1) use machine learning technique to detect and reject EEG segments corrupted by artifact; but this would result in the loss of EEG data [2]. (2) Correct EEG segments corrupted by artifacts; some artifacts can be corrected by a simple filter in a frequency domain, e.g. notch filter can be used to remove 50 Hz noise. This approach does not require any reference signals. For more complicated cases, when the spectrum of artifacts overlaps with the spectrum of EEG signals, blind source separation (BSS) algorithms can be used. Typically a multi-component EEG signal is transformed into a linear combination of independent components (that can be interpreted as channels (ICs)) by blind source separation techniques such as the independent component analysis (ICA) or canonical correlation analysis. The independent channels that are corrupted by artifacts are identified either manually or automatically using correlation information from a reference signal. The artifact free signal is then constructed by combining only artifact-free ICs.

Cite this article as: Boashash B, Ouelha S, Maqsood SA. (2016). Design of a Time-Frequency Algorithm for Automatic Eeg Artifact Removal. Qatar Foundation Annual Research Conference Proceedings 2016: HBPP3376 http://dx.doi.org/10.5339/qfarc.2016.HBPP3376.

The abovementioned artifact correction approach has two problems:

1) Sometimes, multicomponent or multi-channel BSS methods fail to split artifacts from sources, i.e. some independent components may have some useful EEG information.
2) In some cases only single component or channel recordings are produced.

The empirical mode decomposition (EMD), a time-frequency (TF) filtering algorithm has been used to remove artifacts from single channel multicomponent recordings as well as remove artifacts from ICs obtained as results of ICA algorithm [3]. The EMD splits a single channel multicomponentchannel multicomponent EEG recording or the given IC into a number of intrinsic mode functions (IMFs), thus converting a single channel multicomponent recording into several monocomponent signals that can be interpreted as a multi-channel EEG signal. One way to remove artifacts is to simply discard IMF sources in the signal reconstruction [4]. Another approach is to treat IMFs as separate components (or channels) and then apply multi-component (or multi-channel) BSS algorithms to remove artifacts [5].

From a signal processing perspective, the EMD cannot resolve close signal components in the time-frequency (t,f) domain. So, if some artifacts are closely placed to EEG signals in the (t,f) domain, the EMD will fail to separate them.

In this study, the aim is to design a new EEG artifact removal algorithm that uses TF filtering and high resolution time –frequency distributions (TFDs) to extract close signal components.

The key steps of the proposed method are given below:

1. Analyze EEG signal using a high resolution TFD;
2. Localize the signal components in the (t,f) domain by estimating their IF using component linking method [6].
3. Once the signal components are located in the (t,f) domain, they can be extracted by TF filtering. In this study, the fractional Fourier transform is used as a TF filter to separate signal components [6].
4. Identify signal components corrupted by artifacts using prior information or correlation from reference signals.
5. Once the artifactual components are identified, they can be removed during the inverse blind source separation (BSS) transformation by simply subtracting them from the EEG signal.

2) Results and discussions

The proposed TF filtering algorithm can be used to remove respiratory artifacts that cause a major is a major problem in the automated implementation of EEG signal classification algorithms as its morphology is similar to that of seizure.

Let us consider a simulated EEG seizure signal corrupted by the respiratory artifact. The EEG signal is then given by

$$s(t)=Seiz(t)+artif(t) \tag{1}$$

Previous studies have shown that aan EEG seizure signal can be modeled by a non-linear FM signal which generalizes simpler piece wise linear FM models used in earlier studies i.e.:

$$Seiz(t)=\cos(2\pi[1e^{(-6)}\, t^3+0.075t]) \tag{2}$$

The respiratory artifact which appears as a quasi-regular rhythmic activity is modeled as a pure sinusoid.

$$artif(t)=\cos(2\pi 0.052t) \tag{3}$$

This signal is sampled at 32 Hz. The simulated signal, s(t), is analyzed using the adaptive directional TFD (ADTFD) as shown in Figure 1 [6]. The proposed TF filtering algorithm is then applied to extract signal components. The extracted components are shown in Figure 2. The EMD is also applied to separate signal components. The EMD algorithm decomposed the given signal into 6 IMFs. The IMFs closest to the desired seizure and artifact signals are plotted.

Experimental results show the EMD fails to correctly extract sources from time duration 0 to 4s as two sources are close to each other in the (t,f) domain during this time interval. When signal components become well separated in the (t,f) domain, i.e. from 4-s to 8-s, the EMD algorithm accurately extracts the signal components. The proposed TF filtering method yields an improved superior performance as it correctly extracts the sources even when they are close to each other in the (t,f) domain. The superior performance achieved by the proposed method is due to the selection of a high-resolution TFD that results in an accurate IF estimation for close signal components.

3) Conclusion and Future Works

A time-frequency filter is designed for the removal of EEG artifacts. The approach is applied to the removal of simulated respiratory artifacts from simulated signals. The algorithm assumes that the artifacts and EEG background have TF signature that are non-overlapping in the (t,f) domain. The algorithm can be extended for more realistic situations by using methods that can estimate the IF of intersecting signal components using directional information for example. Moreover, the proposed TF filtering algorithm (just like the EMD) decomposes a signal into a number of components thus making a single channel multicompoonent signal into several monocomponents that can be interpreted as a multi-channel signal.

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