Automated ECG artefact reduction in EEG as a preprocessing step for neonatal seizure detection

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Abstract. Routinely recorded EEGs are often corrupted by artefacts. These artefacts make the visual interpretation and automated analysis of the EEG much more difficult. This paper addresses the problem of removing the ECG artefact from the EEG using Independent Component Analysis (ICA). The algorithm is tested on the neonatal EEG of newborn children with perinatal asphyxia. Results show that ICA is able to extract the ECG from the EEG as a separate source component and that it can be removed from the EEG. The correct ICA-component related to the ECG artefact is selected by correlation of the thresholded energy of the ICA-components with the thresholded energy of the simultaneously recorded ECG. We show that ECG removal is necessary for automated neonatal seizure detection, effectively lowering the false positive rate of the detection algorithm without change in sensitivity.

Keywords: Electroencephalography (EEG), artefact reduction, electrocardiogram (ECG)

1. Introduction

The neonatal EEG is frequently contaminated with the ECG artefact. This artefact obscures the real EEG activity and makes it more difficult for visual and automated analysis. We developed an automated neonatal seizure detector for the EEG of newborn children [Deburchgraeve et al., 2008]. During the validation of this method, we regularly encountered false positive detections due to the ECG artefact. To deal with this artefact and lower the false positive rate of the seizure detector we used an automated ECG artefact reduction algorithm as preprocessing step.

2. Material and methods

2.1 Material

All data were recorded at the Sophia Children's Hospital (part of the University Medical Center Rotterdam, the Netherlands). The dataset consisted of 2 long-term (24-48 hours) video-EEG recordings of full-term neonates with the 10-20 set of electrodes. An 8 hour long segment of EEG containing seizures was selected for each patient. Both datasets contained the ECG artefact which significantly disturbed the automated seizure detection algorithm leading to false positive detections.

2.2 Methods

The method is based on Independent Component Analysis (ICA) [Comon, 1994], a Blind Source Separation (BSS) technique. In the blind source separation problem, the observed time course $\mathbf{x}(t) = [x_1(t),x_2(t),...,x_K(t)]^T$,with $t = 1, ...,N$, with N the number of samples and K the number of sensors, is the result of an unknown linear mixture of a set of unknown source signals $\mathbf{s}(t)=[s_1(t),s_2(t),... s_K(t)]^T$:

$$\mathbf{x}(t) = \mathbf{A}.\mathbf{s}(t), \quad (1)$$

where **A** is the unknown mixing matrix. The goal is to estimate the mixing matrix and recover the original source signals $\mathbf{s}(t)$. This is carried out by introducing the de-mixing matrix **W** such that

$$\mathbf{z}(t) = \mathbf{W}.\mathbf{x}(t), \quad (2)$$

approximates the unknown source signals **s(t)**. Unless there are extra constraints imposed, it is in general impossible to solve this problem. ICA solves the problem by assuming the sources to be mutually statistically independent. Applied to the ECG-reduction problem, this assumption of statistical independence is valid as the ECG has no statistical relation to the real EEG activity. Fig. 1 shows the contaminated EEG (Fig. 1A) and the estimated ICA source signals (Fig. 1B). From Fig. 1B it can be seen that components 2 and 6 correspond to the ECG artefact. The EEG can be reconstructed without these components by setting the corresponding columns in the mixing matrix **A** to zero and then calculating equation (1) with this altered mixing matrix.

The most important step of the algorithm is the selection of the ICA-component corresponding to the ECG artefact. Calculating the direct correlation between the ICA-components and the simultaneously recorded ECG is not optimal as the morphology of the ECG artefact is different from the morphology of the measured ECG. To address this problem we calculate the correlation between the thresholded energy of the ECG with the thresholded energy of the ICA components. To calculate the energy of these signals, we make use of a non-linear energy operator (NLEO) as proposed by Kaiser [1990]. The key property of this operator is:

$$\psi[A.\cos(\omega_0 n + \phi)] = {}^1\!/_2 \,.A^2.\omega_0^2, \quad (3)$$

This indicates that the output ψ of this operator is proportional to the square of both the amplitude A and the frequency ω_0 of the signal. The result is that spike-like QRS complex of the ECG and the ECG artefact will be amplified relative to the background EEG (Fig. 2A).

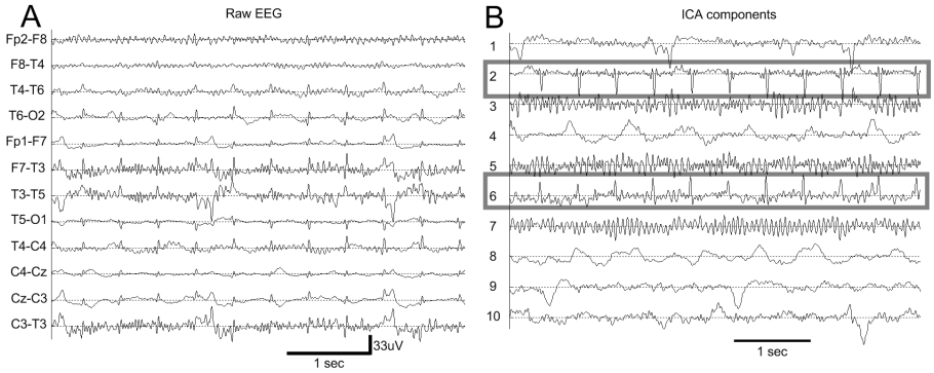


Figure 1*. A: EEG contaminated with the ECG artefact, B: ICA components of the EEG, 2 and 6 correspond to the ECG artefact.*

Next this energy is thresholded using an adaptive threshold:

$$Threshhold = 0{,}8.std(signal) + q3(signal), \quad (4)$$

with 'std' and 'q3' the standard deviation and 75th percentile of the epoch, respectively. Everything above the threshold is set to '1', everything below to '0' (Fig. 2A). Subsequently, the correlation between every thresholded ICA-component and the thresholded ECG is calculated. If this correlation coefficient is higher than 0.6, this component is removed from the mixing matrix and the EEG is reconstructed (Fig. 2B).

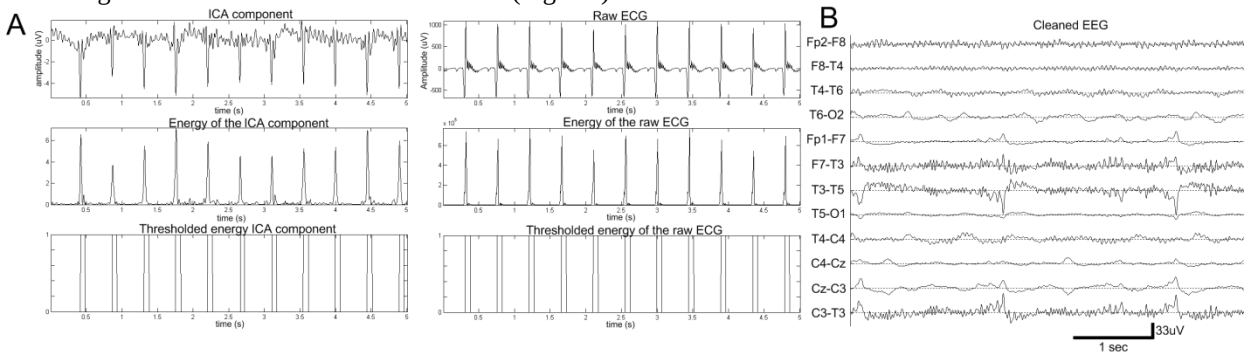


Figure 2. *A: Energy transform and thresholded ECG and ICA components, B: cleaned EEG.*

3. Results

The method was tested as a preprocessing step during automated seizure detection and run on consecutive 5 s windows (non-overlapping). Without the ECG reduction the complete EEG of both datasets was falsely detected by the seizure detector due to the ECG artefact. With ECG reduction there were no false positive detections due to the ECG for the first dataset and only 5 short false positive detections due to the ECG on the second dataset. No seizures were missed because of the ECG reduction.

4. Discussion

We developed an algorithm to remove the ECG artifact in neonatal EEG. Used as a preprocessing step in a seizure detection algorithm, the false positive rate of the seizure detector improved in those cases where the ECG artefact was present in the EEG, without lowering the sensitivity. A similar strategy could be followed for the other artefacts in the EEG (movement, electrode artefacts, …).

5. References

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