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Removal of ECG Artifacts from EEG using a Modified Independent Component Analysis Approach

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***Abstract*— In this paper, we introduce a new automatic method for electrocardiogram (ECG) artifact elimination from the electroencephalogram (EEG) or the electrooculogram (EOG). It is based on a modification of the independent component analysis (ICA) algorithm which gives promising results while only using a single-channel EEG (or EOG) and the ECG. To check the effectiveness of our approach, we compared its correction rate with those obtained by ensemble average subtraction (EAS) and adaptive filtering (AF). For this purpose, we applied these algorithms to 10 excerpts of polysomnographic sleep recordings containing ECG artifacts and other typical artifacts (e.g. movement, sweat, respiration, etc.). Two hundred successive interference peaks were examined in each excerpt to compute correction rates. We found that our modified ICA was the most robust to various waveforms of cardiac interference and to the presence of others artifacts, with a correction rate of 91.0%, against 83.5% for EAS and 83.1% for AF.**

I. Introduction

ELECTROCARDIOGRAM (ECG) artifacts occur when the relatively high cardiac electrical field affects the surface potentials on the scalp and near the eyes. This leads to interference on the electroencephalograms (EEG) and electrooculograms (EOG) which can easily be recognized by its periodicity and its coincidence with the ECG peaks. Its waveform can vary from derivation to derivation and large inter-individual voltage variations can be observed [1].

ECG artifacts constitute a serious problem for the automatic interpretation and analysis of polysomnographic signals. Hence, some methods have been developed for removing them. Fortgens and De Bruin [2] proposed an algorithm whereby the correction was made by subtracting a linear combination of four ECG derivations. The weights of this combination were calculated so as to minimize the EEG variance after subtraction.

The Ensemble Average Subtraction (EAS) method was described and used by Nakamura and Shibasaki [3], Harke *et al*. [4] and Park *et al*. [5]. In this approach, an average ECG-artifact waveform was computed for each homogeneous EEG portion and an estimate of the artifact was generated by repeating this template synchronously with the interference peaks. This signal was then subtracted from the contaminated EEG to correct it.

Sahul *et al*. [6] introduced artifact cancellation by adaptive filtering (AF) using an ECG channel reference. Strobach *et al.* [7] showed that this method was not appropriate if the ECG and the real interference exhibit remarkably different waveforms. They introduced a two-pass adaptive filtering algorithm where an artificial reference was first generated by ensemble averaging, to be more related to the real interference than the ECG.

Finally, some authors investigated the use of independent component analysis (ICA) to eliminate the ECG artifact ([8]-[10]). Unfortunately, either their methods required many EEG channels and implied to visually select the origin of cardiac interference among estimated sources, or their methods were found to be somehow inefficient since the artifact was reduced but still visible.

In this paper, we introduce a new algorithm resulting from a modification of the ICA method. The algorithm gives promising results while using only a single-channel EEG (or EOG) and the ECG. To check its effectiveness, we have also implemented the EAS and AF methods and compared their correction rate and their robustness to the new algorithm.

Section II describes the algorithm based on the ICA method to remove ECG artifact. Section III presents the experimental results. Section IV discusses them and concludes this paper.

II. Method

Independent component analysis (ICA) was developed some years ago in the context of blind source separation. Its aim is to estimate N source signals $s_1(t)$, $s_2(t)$, …, $s_N(t)$ unknown but assumed to be statistically independent, from the observation of M signals $x_1(t)$, $x_2(t)$, …, $x_M(t)$ which result from a mixture of the underlying sources signals.

ICA requires at least as many mixtures as there are independent sources ($M \geq N$). In our case, we suppose M equal to N, and we try to estimate the original EEG and the original interference (the two source signals) from two observed signals: the ECG and the corrupted EEG.

In the simplest case, the mixture is supposed to be linear and instantaneous so that observations at time instant t result from a linear combination of the sources at that instant:

$$x_i(t) = \sum_{j=1}^{N} a_{ij} s_j(t) \quad i = 1 \ldots M \tag{1}$$

This is clearly not the case here, as the interference peaks are not exactly synchronised with the R-peaks of the ECG. As a matter of fact, we found experimentally that applying

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ICA with such hypotheses on our observed signals did not lead to efficient correction of the cardiac artifacts. We therefore applied the so-called convolutive linear model, where the observations result from a linear mixture of the sources filtered by FIR filters:

$$x_i(t) = \sum_{j=1}^{N} a_{ij}(t) * s_j(t) \quad i = 1 \ldots M \tag{2}$$

where $a_{ij}(t)$ is the transfer function between the j^{th} source and the i^{th} sensor.

As illustrated on Fig. 1, the purpose of ICA in this case is to find a source separation system, whose outputs should be equal to the original sources:

$$s_i(t) \approx y_i(t) = \sum_{j=1}^{N} w_{ij}(t) * x_j(t) \tag{3}$$

By using the FIR linear algebra notation[1], equations (2) and (3) can be written as:

$$\mathbf{x_t} = \mathbf{A}\,\mathbf{s_t} \tag{4}$$

$$\mathbf{s_t} \approx \mathbf{y_t} = \mathbf{W}\mathbf{x_t} \tag{5}$$

where the element $A_{ij}(z)$ of the mixing matrix $\mathbf{A}$ corresponds to the transfer function between the j^{th} source and the i^{th} sensor, and the element $W_{ij}(z)$ of the separating matrix $\mathbf{W}$ corresponds to the transfer function between the j^{th} sensor and the i^{th} estimated source.

To find the unknown separating matrix $\mathbf{W}$, Bell and Sejnowski [11] proposed to maximize the joint entropy $H(\mathbf{g})$ of the vector $\mathbf{g_t}=[g_1(t), g_2(t), \ldots, g_N(t)]^T$, whose components $g_i(t) = g(y_i(t)) \approx F_s(y_i(t))$ are the sources $y_i(t)$ transformed by a sigmoid function g which approximates to the cumulative density function F_s of the sources (seen as random signals). In the convolutive case, this suggests to work with a feedforward architecture, as illustrated on Fig. 2.

A common choice for the sigmoid function g is the logistic function $g(y_i) = (1 + \exp(-y_i))^{-1}$.

The separating matrix which maximizes the joint entropy $H(\mathbf{g})$ can be found by a gradient-ascent algorithm which consists in iterating on:

$$w_{ij}(k) \leftarrow w_{ij}(k) + \mu \frac{\partial H(\mathbf{g})}{\partial w_{ij}(k)} \quad \forall i, j \in [1, \ldots, N] \quad \forall k \in [1, \ldots, K] \tag{6}$$

where μ is the learning rate and $w_{ij}(k)$ is the k^{th} coefficient of the FIR filter between the j^{th} sensor and the i^{th} estimated source.

Torkkola [12] has shown that this results in iterating on:

$$w_{ij}(k) \leftarrow w_{ij}(k) + \mu \cdot \begin{cases} E\left[\dfrac{1}{\det(\mathbf{W}_{k=0})} \cdot (-1)^{i+j} . \Delta_{ij}(0) + \dfrac{\partial p_s(y_i)}{\partial F_s(y_i)} \cdot x_j\right] & for \quad k = 0 \\ E\left[\dfrac{\partial p_s(y_i)}{\partial F_s(y_i)} \cdot x_{j_{(-k)}}\right] & for \quad k \neq 0 \qquad \forall i, j \in [1, \ldots, N] \end{cases} \tag{7}$$

with

$$\mathbf{W}_{k=0} = \begin{bmatrix} w_{11}(0) & \cdots & w_{1N}(0) \\ \vdots & \ddots & \vdots \\ w_{N1}(0) & \cdots & w_{NN}(0) \end{bmatrix} \tag{8}$$

[1] In the FIR linear algebra notation, matrices are composed of FIR filters instead of scalars and the multiplication between two such FIR matrix elements is defined as their convolution.

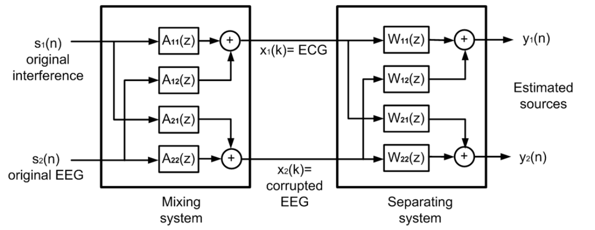

Fig. 1. Convolutive linear mixture of two sources, and the corresponding source separation system.

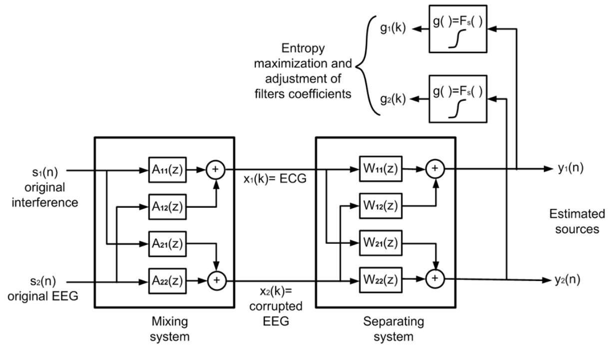

Fig. 2. Network architecture for ICA based on the maximization of the joint entropy.

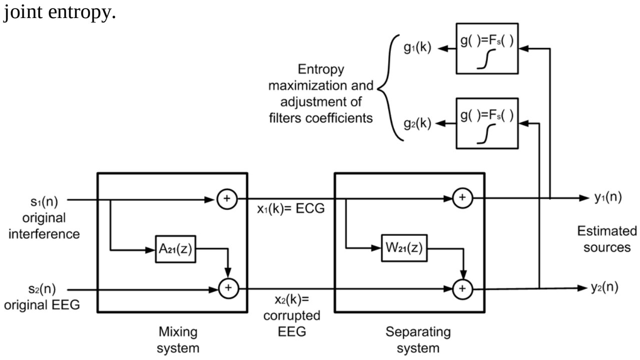

Fig. 3. Network architecture for our modified ICA algorithm.

and where $\det(\mathbf{W}_{k=0})$ is the determinant of the matrix $\mathbf{W}_{k=0}$, $\Delta_{ij}(0)$ is the determinant of the matrix obtained by removing the i^{th} row and the j^{th} column from $\mathbf{W}_{k=0}$, $F_s(y_i) = g(y_i)$, $p_s(y_i) = \dfrac{\partial g(y_i)}{\partial y_i}$ and $E\,[.]$ is the mathematical expectation.

We implemented this ICA algorithm and noted experimentally (as Harke *et al.*[4]) that it has some difficulties to converge towards the correct solution, especially when the sampling rate is high. We therefore considered an additional hypothesis to improve the convergence: we supposed that the interference on the EEG is a filtered version of the first observed signal (the ECG). The resulting architecture is illustrated on Fig. 3, with a mixing matrix and a separating matrix of the form:

$$\mathbf{A} = \begin{pmatrix} h_{impulse} & 0 \\ h & h_{impulse} \end{pmatrix} \quad \text{and} \quad \mathbf{W} = \begin{pmatrix} h_{impulse} & 0 \\ -h & h_{impulse} \end{pmatrix} \tag{9}$$

where $h_{impulse} = \{1\,0\,0\,0\,0\,0 \ldots\}$ is the identify FIR filter, and h corresponds to the unknown interference shaping.

The iterative algorithm simplifies to:

$$w_{21}(k) \leftarrow w_{21}(k) + \mu \cdot \begin{cases} E\left[\dfrac{1}{\det(\mathbf{W}_{k=0})} \cdot (-1)\ .\Delta_{21}(0) + \dfrac{\partial p_s(y_2)}{\partial F_s(y_2)} \cdot x_1\right] & for \quad k = 0 \\ E\left[\dfrac{\partial p_s(y_2)}{\partial F_s(y_2)} \cdot x_{1_{[-k]}}\right] & for \quad k \neq 0 \end{cases} \tag{10}$$

with $\mathbf{W}_{initial} = \begin{pmatrix} h_{impulse} & 0 \\ h_{initial} & h_{impulse} \end{pmatrix}$ (11)

It should be noted that, while this additional assumption (i.e. the interference can be well approximated by applying a simple FIR to the reference signal) is identical to the one made in the adaptive filtering approach, the separation criterion is completely different. So are the results, as we will see in section III.

It remains that this assumption can be discussed if the ECG is directly used as the reference signal. Indeed, the interference and ECG signals can sometimes exhibit remarkably different waveforms although they are synchronized temporally.

We therefore also tested the use of an artificial reference signal as suggested by Strobach *et al*. for the adaptative filtering [7]. This artificial reference signal is generated by repeating the average artifact waveform synchronously with the position of the *R* peaks of the ECG (Fig. 4):

$$x(n) = a(n) * T(n) \tag{12}$$

where $x(n)$ is the artificial reference signal (see an example on Fig. 4c), $T(n)$ is a trigger indicating the positions of the *R* peaks of the ECG, and $a(n)$ is the average artifact waveform recomputed for each 20s-fragment, by averaging segments of corrupted signal located around each interference peak.

In this work, we tested these two approaches.

III. RESULTS

A. Recordings

The data used in this study were recorded at the Sleep Laboratory of the André Vésale hospital (Montigny-le-Tilleul, Belgium). They are composed of 10 excerpts of 15 minutes-long polysomnographic sleep recordings, randomly selected during the night. The recordings were taken from patients (7 males and 3 females aged between 40 and 73) with different pathologies (dysomnia, restless legs syndrome, insomnia, apnoea/hypopnoea syndrome). They all contain cardiac interference as well as other typical artifacts (e.g. movement, sweat, respiration, etc.). The sampling rates were 50, 100 and 200Hz. Only the ECG channel and the corrupted signal (EEG or EOG) were used to perform the ECG artifact correction. For each method, two hundred successive interference peaks of each excerpt were visually examined to compute the number of corrected peaks.

A total of 2000 interference peaks were thus examined to compute the final correction rate.

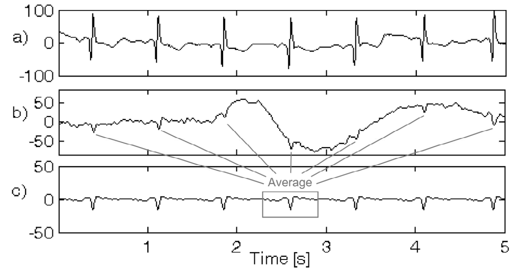

Fig. 4. a) ECG, b) EEG corrupted by ECG artifact, c) artificial reference.

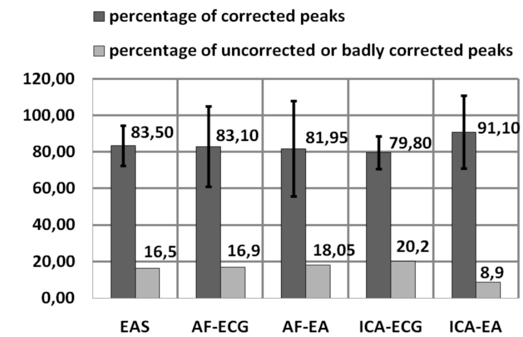

Fig. 5. Global correction rates of the five processes computes on the 10 excerpts (2000 interference peaks)

B. Experimental results

To check the effectiveness of our new algorithm, we have implemented other existing methods to compare their correction rate and their robustness. Five algorithms were then tested:

- The ensemble average subtraction (EAS);
- The adaptive filtering (AF-ECG), using an ECG reference;
- The adaptive filtering (AF-EA), using an artificial reference generated by ensemble averaging;
- The independent component analysis (ICA-ECG), using the corrupted EEG and the ECG as observed signals;
- The independent component analysis (ICA-EA), using the corrupted EEG and an artificial signal generated by ensemble averaging as observed signals.

As it can be seen on the correction rates of the five processes (Fig. 5), the first four algorithms exhibit quite similar correction rate, while our new method reaches a higher correction rate of 91.1%, against 83.5% for ensemble average subtraction and 83.1% for adaptive filtering.

If we look at the number of corrected peaks obtained for each patient (Fig.6), we see that the ICA approach using an artificial reference is not systematically the algorithm which provides the best results. Its correction rate is sometimes higher than in the other methods, and sometimes lower. However, while other methods sometimes completely fail on some excerpts (e.g pat1 for AF-EA, pat4 for AF-ECG and pat7 for ICA-ECG), the ICA-EA method always provides very satisfactory results. The reasons of this superiority will be discussed in the following section but we can already notice that our new method seems to be more robust to various types of polysomnographic signals than the other processes.

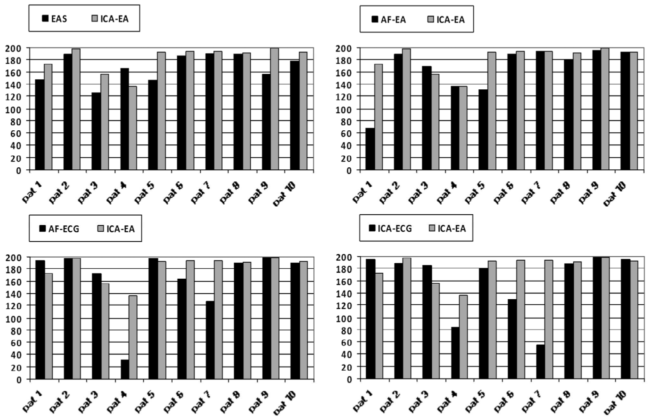

Fig. 6. Comparison between the ICA-EA method and the four other algorithms: number of corrected peaks for each patient.

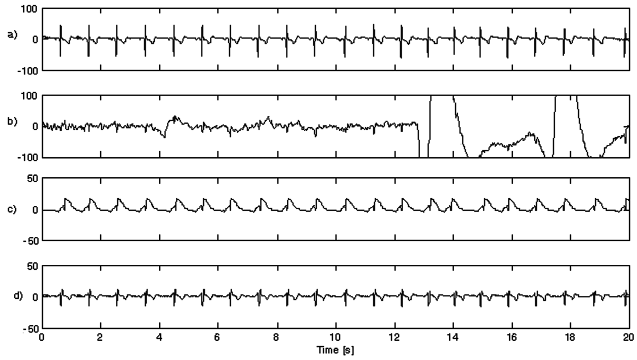

Fig. 7. Results obtained on a 20s excerpt from patient 10: a) ECG, b) corrupted signal, c) estimate of the cardiac interference by the EAS methods , d) estimate of the cardiac interference by ICA-EA

IV. Discussion and Conclusion

To carry out an automatic analysis of polysomnographic signals (such as a sleep stage classification) in a hospital, it is important for the system to be robust to the noise and independent of derivations used during the recording.

The EAS algorithm is rather sensitive to noise. On one hand, the others artifacts (such as those due to eye blinks, movements, sweat, etc.) prevent an accurate detection of the interference peaks; on the other hand these artifacts can have a big influence on the computed average interference waveform as it can be seen on Fig.7.

The AF-ECG and ICA-ECG methods are more robust to artifacts, but their performance completely fail for patients 4 and 7 (Fig. 6). This is due to the fact that the cardiac interference waveform is rather different from the ECG signal in the recordings of these patients. The use of artificial reference is then very beneficial: it facilitates convergence towards the correct solution, increasing the number of corrected peaks by the AF-EA and ICA-EA methods.

When the cardiac interference waveform is similar to that of the ECG, the artificial reference signal is also quite similar to the ECG (since it is obtained by averaging segments of corrupted signal located around each interference peak). However, the slight differences between the artificial signal and the ECG can sometimes decrease the performance of the AF-EA and ICA-EA processes (patients 1 and 3 on Fig. 6). Fortunately, this loss of performance is small compared with the increase in the number of corrected peaks when the cardiac interference waveform is different from that of the ECG. In addition, it seems that adaptive filtering is more sensitive to this problem than the ICA method. This shows again the robustness of our new process, this time to a slight modification of the reference.

In conclusion, we presented a new method for correcting ECG artifacts, based on independent component analysis (ICA). The algorithm uses only two observed signals: the corrupted EEG (or EOG) and an artificial signal generated by repeating the average artifact waveform each time the ECG trigger is different from zero. An additional hypothesis is considered, which improve the convergence of the algorithm: the interference which is added to the EEG is assumed to be a filtered version of the artificial signal. This new process is much more robust to various waveforms of cardiac interference and to the presence of others artifacts than other tested processes (i.e. the ensemble average subtraction and the adaptive filtering). This probably explains why, on average, we found that our new algorithm was the most promising correction method, with a correction rate of 91.1%, against 83.5% for ensemble average subtraction and 83.1% for adaptive filtering.

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