Fast Technique for Noninvasive Fetal ECG Extraction

Ruben Martín-Clemente*, *Member, IEEE*, Jose Luis Camargo-Olivares, Susana Hornillo-Mellado, Mar Elena, and Isabel Román

***Abstract*—This letter describes a fast and very simple algorithm for estimating the fetal electrocardiogram (FECG). It is based on independent component analysis, but we substitute its computationally demanding calculations for a much simpler procedure. The resulting method consists of two steps: 1) a dimensionality reduction step and 2) a computationally light postprocessing stage used to enhance the FECG signal.**

***Index Terms*—Blind source separation, fetal electrocardiogram extraction, independent component analysis.**

I. Introduction

CURRENTLY, there is an intense research into noninvasive methods for detecting the fetus at risk of damage or death in the uterus. The fetal electrocardiogram (FECG) provides useful information about the fetus's condition: for example, there is strong evidence that certain fetal heart rate patterns are closely related to fetal acidemia; in addition, the duration of the ST-segment is important in the diagnosis of fetal hypoxia, and it has been also shown that both the QT interval and T-wave changes are associated with fetal acidosis [1].

Given electrical signals from electrodes placed on a pregnant woman's abdomen, the technique of independent component analysis (ICA) [2] can be used to separate out the FECG, which is extremely low voltage, from the maternal ECG (MECG), and from other unwanted background interferences, such as the electrical activity produced by the uterus muscles. It has been suggested that ICA outperforms most of the other signal processing techniques [3]. However, ICA is computationally demanding due to its use of higher-order statistics, and hence, it is not well suited for implementation in real-time applications nor in lightweight and portable monitors, as would be desirable to provide mothers freedom of movement. To cope with this problem, traditional approaches have been based on adaptive algorithms or, more recently, on the use of *a priori* information on the ECG signal [4]. The solution proposed in this letter is one in which the computationally intensive step of ICA is substituted for a much simpler procedure—specifically, it does not require the estimation of statistics—without appreciable loss of performance. We present experiments with real data showing that the resulting algorithm is fast and effective.

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*R. Martín-Clemente is with the Department of Signal Theory and Communications, University of Seville, Seville 41092, Spain (e-mail: ruben@us.es).

J. L. Camargo-Olivares and S. Hornillo-Mellado are with the Department of Signal Theory and Communications, University of Seville, Seville 41092, Spain (e-mail: jlcamargo@yahoo.es; susanah@us.es).

M. Elena is with the Department of Electronic Engineering, University of Seville, Seville 41092, Spain (e-mail: mar@gte.us.es).

I. Román is with the Department of Automatica and System Engineering, University of Seville, Seville 41092, Spain (e-mail: isabel@trajano.us.es).

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II. Preprocessing

Let $v_1(t), \ldots, v_p(t)$ be zero-mean signals recorded from electrodes placed on the mother's body, where $t \in \mathbb{Z}$ is the discrete time, and let $\mathbf{v}(t)$ be the vector whose ith component is $v_i(t)$. The proposed preprocessing consists in reducing the number of signals under consideration and it is intended to speed up the estimation process. Our preprocessing is based on principal component analysis (PCA), which has the added advantage of reducing appreciably the MECG interference [5]. Consider that we are given N samples $\mathbf{v}(1), \ldots, \mathbf{v}(N)$ of the vector signal $\mathbf{v}(t)$. Preprocessing starts from the data covariance matrix $\mathbf{R}_v = (1/N) \sum_{t=1}^{N} \mathbf{v}(t)\, \mathbf{v}^T(t)$. This matrix can be always factorized into $\mathbf{R}_v = \mathbf{Q}\,\mathbf{D}\,\mathbf{Q}^T$, where

$$\mathbf{D} = \text{diag}\,(\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p)$$

is the $p \times p$ diagonal matrix whose elements are the eigenvalues of $\mathbf{R}_v$ and $\mathbf{Q}$ is the matrix containing the corresponding eigenvectors. If the MECG is strong enough, Callaerts *et al.* [5] showed that the M largest eigenvalues in $\mathbf{D}$ are associated with the MECG. Matrices $\mathbf{D}$ and $\mathbf{Q}$ can be then partitioned into two groups:

$$\mathbf{D} = \begin{pmatrix} \mathbf{D}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{D}_2 \end{pmatrix}, \qquad \mathbf{Q} = (\mathbf{Q}_1 \quad \mathbf{Q}_2)$$

where $\mathbf{D}_1$ contains those M largest eigenvalues and the columns of $\mathbf{Q}_1$ are the corresponding eigenvectors. The MECG can be reduced significantly by projecting the data onto the subspace spanned by $\mathbf{Q}_2$ [5]. Specifically, this can be written as

$$\mathbf{z}(t) = \mathbf{D}_2^{-1/2}\, \mathbf{Q}_2^T\, \mathbf{v}(t) \tag{1}$$

where $\mathbf{z}(t)$ is a $(p - M) \times 1$ vector that contains little MECG contribution. Matrix $\mathbf{D}_2^{-1/2}$ is a mere scale factor, which ensures that the signals in $\mathbf{z}(t)$ are of unit variance. Of course, the determination of M is an important problem. Some previous works consider $M = 3$ [5]; however, it has been recently argued that from $M = 4$ to $M = 6$ may be required in some cases [6]. In practice, experiments suggest finding M empirically from the gap between the eigenvalues of the data covariance matrix. Finally, observe that we have projected the data from a vector space of p dimensions to a vector space of $p - M$ dimensions. The complete procedure can be accomplished in real time with low computational cost by using, for example, the method in [7].

III. Method

This section presents our original contribution. After the preprocessing, the SNR is still poor and further processing is required. The method is based, like many ICA algorithms, on maximizing the kurtosis (fourth-order cumulant) of the FECG estimates. The optimization procedure is the main innovation, and its interpretation is discussed in the context of the FECG-estimation problem. The FECG-extraction method itself is described in Section III-A. Mathematical justification is then presented in Section III-B.

A. Algorithm

Given $\mathbf{z}(1), \ldots, \mathbf{z}(N)$:

1) Define $\mathbf{z}(K)$ as the vector $\mathbf{z}(t)$ with the largest length.

2) *Output* $y(t) = \dfrac{\mathbf{z}^T(K)}{\|\mathbf{z}(K)\|}\,\mathbf{z}(t)$.

Observe that, to speed up the process, $\mathbf{z}(K)$ can and *should* be calculated at the same time that $\mathbf{z}(t)$ is calculated in the preprocessing step.

B. Justification

Given an arbitrary vector $\mathbf{w}$, it follows from the central limit theorem that

$$y(t) = \mathbf{w}^T\,\mathbf{z}(t) \tag{2}$$

is more Gaussian when it is a sum of the FECG and the interferences than when it is equal to only one of them. In consequence, to find $\mathbf{w}$ in such a way that the distribution of $y(t)$ is as far as possible from Gaussian seems to be a promising idea. This general approach to the problem of "unmixing" mixed signals is very common in ICA and is usually called *maximization of nonGaussianity* [2].

The simplest measure of nonGaussianity is the kurtosis or fourth-order autocumulant, defined by:

$$\kappa_y = \frac{1}{N}\sum_{t=1}^{N} y^4(t) - \frac{3}{N}\sum_{t=1}^{N} y^2(t). \tag{3}$$

We maximize the kurtosis of $y(t)$ under the unit-power constraint

$$\frac{1}{N}\sum_{t=1}^{N} y^2(t) = 1 \tag{4}$$

which avoids the solution $y(t) \to \infty$. It is easily shown that this is equivalent to constraining the norm of $\mathbf{w}$ to be the unity. Next, let us deal with the maximization of κ_y. Traditional ICA algorithms use standard procedures such as gradient cancellation. However, as explained in Section I, we have devised a simpler method without sacrificing much on accuracy. First, consider the following theorem, which is stated without proof due to the lack of space:

Theorem 1: Let $\{v(t),\, t = 1, \ldots, N\}$ be the samples of a generic discrete-time signal. The kurtosis of $v(t)$, defined by

$$\kappa_v = \frac{1}{N}\sum_{t=1}^{N} v^4(t) - \frac{3}{N}\sum_{t=1}^{N} v^2(t)$$

is maximized under the unit-power constraint $\frac{1}{N}\sum_{t=1}^{N} v^2(t) = 1$ by signals of the form

$$v_*(t) = \pm\sqrt{N}\, e_k(t)$$

where $e_k(t)$ is a discrete-time signal that equals 1 at $t = k$ and is 0 elsewhere.

To explore the vicinity of the maximum $\sqrt{N}\, e_k(t)$, where $k \in \{1, \ldots, N\}$, we perform a first-order Taylor expansion of the kurtosis around this point:

$$\kappa_v \approx N - 3 + \left(4\sqrt{N} - \frac{6}{\sqrt{N}}\right)\left[v(k) - \sqrt{N}\right] \tag{5}$$

where $N - 3$ is the value of the kurtosis at the maximum. The unit-power constraint implies that $\sum_{t\neq k}^{N} v^2(t) = N - v^2(k)$. Adding $[y(k) - \sqrt{N}]^2$, we obtain

$$\left[v(k) - \sqrt{N}\right]^2 + \sum_{t\neq k}^{N} v^2(t) = -2\sqrt{N}\left[v(k) - \sqrt{N}\right].$$

Substituting this formula into (5), we obtain after a little bit of algebra that, for any practical value of N

$$\kappa_v \approx N - 3 - 2\sum_{t=1}^{N}\left(v(t) - \sqrt{N}\, e_k(t)\right)^2. \tag{6}$$

This formula approximates the kurtosis of the unit-power sequences that are in the neighborhood of $\sqrt{N}\, e_k(t)$. Since $y(t)$ is by definition of unit power, we also use this formula to approximate κ_y

$$\kappa_y \approx N - 3 - 2\sum_{t=1}^{N}\left(y(t) - \sqrt{N}\, e_k(t)\right)^2. \tag{7}$$

According to (7), the kurtosis κ_y is maximized when

$$\sum_{t=1}^{N}\left(y(t) - \sqrt{N}\, e_k(t)\right)^2 \tag{8}$$

is minimum—in other words, the optimum $y(t)$ is the signal that is as close as possible to $\sqrt{N}\, e_k(t)$. To determine the best value for the index k, it is assumed that the accuracy of the approximation (7) increases as (8) decreases. Consequently, we minimize (8) among all possible values of k. Taking into account that $y(t) = \mathbf{w}^T\,\mathbf{z}(t)$, a bit of algebra shows that the minimum is obtained simply by setting

$$\mathbf{w}_* = \frac{\mathbf{z}(K)}{\|\mathbf{z}(K)\|},\ \text{where } K = \operatorname*{argmax}_k \|\mathbf{z}(k)\|. \tag{9}$$

By construction, $y(t)$ is the signal that is as close as possible to the impulse signal $\sqrt{N}\, e_K(t)$. Furthermore, if $\mathbf{z}(t)$ is periodic, one can prove easily that $y(t)$ is also the best approximation to an impulse train having the same period and centered upon $t = K$. Consider then the following additional interpretation: the ECG resembles an impulse train, but the interferences degrade the measurements and disturb this property. The algorithm restores this property and, as a result, restores the signal itself. The method may be then considered as a particular application of

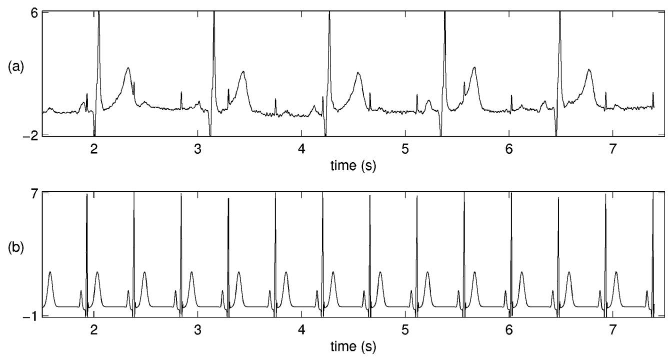

Fig. 1. Simulated data: (a) measured signal, (b) FECG dipole component.

the class of waveform-preserving methods for recovering ECG signals.

Observe that this is actually an approximate optimization procedure. Furthermore, to the best of our knowledge, this procedure is presented here for the first time. Further discussion is illustrated with examples in the Section IV.

C. Sequential Estimation

To extract sequentially more signals, we can use the procedure described in [2, ch. 4]. Basically, we remove $y(t)$ from the mixture by $\mathbf{z}'(t) = \mathbf{z}(t) - \mathbf{w}\, y(t)$. Then, PCA is applied again to reduce the dimensionality in one unit. The algorithm is repeated until all the desired signals are recovered.

IV. Experiments and Results

A. Experiment and Results With Simulated Data

We have used the *Open Source ECG Toolbox* for generating synthetic maternal and fetal ECG mixtures with realistic ECG noises [8]. Eight simulated recordings of 5000 samples each were generated (SNR $= 10$). Fig. 1 shows part of one of the signals recorded on the mother's abdomen and one of the original fetal cardiac dipole components [6], where both of them have been normalized to unit-variance. In the preprocessing step, M was set to 4. Fig. 2 represents the four elements of $\mathbf{z}(t)$—observe that $z_4(t)$ is a residue of the MECG. We have plotted a vertical dotted line at $t = K$, which is the instant at which $\mathbf{z}(t)$ yields its largest norm. There is a fetal R wave at $t = K$, as expected: the ECG is maximum at the time instants in which there is an R wave. We have $\mathbf{z}(K)/\|\mathbf{z}(K)\| = [-0.39, 0.44, 0.79, -0.15]^T$ and

$$y(t) = -0.39\, z_1(t) + 0.44\, z_2(t) + 0.79\, z_3(t) - 0.15\, z_4(t).$$

The larger the peak value of the R wave, the larger the contribution of $z_i(t)$ to $y(t)$, i.e., the signals $z_i(t)$ with a more significant presence of the FECG are more weighted. Signal $y(t)$ is shown in Fig. 3. Even though the preprocessing step has done "half of the job," in the sense that the location of the R waves is perfectly visible, the SNR of $y(t)$ is, at least, 2.54 dB better than that of any of the signals $z_i(t)$, at a minimum computational cost. The correlation coefficient between $y(t)$ and the true FECG signal is 0.9046. To compare, FastICA, which is other ICA method [9], produced a correlation coefficient equal to 0.9080. In both cases, before calculating the correlation, we applied a simple filtering for the removal of the FECG baseline.

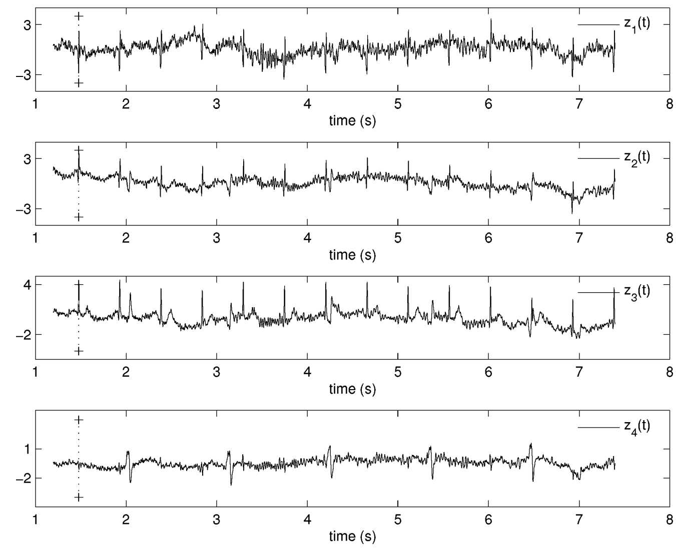

Fig. 2. Simulated data: Signals $z_i(t)$ obtained in the preprocessing step.

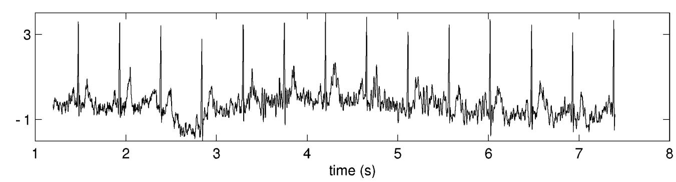

Fig. 3. Simulated data: Estimated fetal heartbeat signal.

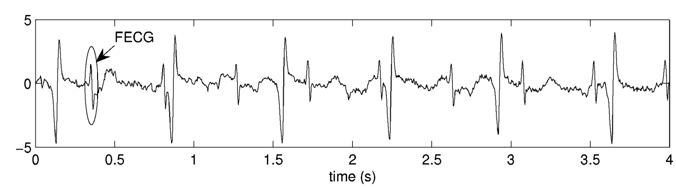

Fig. 4. Real data: Abdominal recording from a pregnant woman.

B. Experiment and Results With Real Data

Eight real cutaneous potential recordings of a pregnant woman have been obtained from [10]. Data were recorded at University Hospitals Leuven with the informed consent of the patient [11]. The first five signals correspond to electrodes placed on the woman's abdominal region. The last three signals correspond to the electrodes located on the mother's thoracic region. The sampling rate is 250 Hz with 12-bit resolution. Fig. 4 shows a portion of one of the abdominal's recordings. Even though the FECG is much weaker than the MECG, it is slightly visible. Parameter M was set to 4. Following the procedure of Section III-C, we extracted sequentially the four signals shown in Fig. 5. The first and the second one from the top correspond to the FECG, since the heart rate is about twice the maternal one. The first signal is also displayed in Fig. 6(a). According to the most usual interpretation of ICA [3], these signals are estimates of the cardiac dipole vector components [6]. To validate the method, we repeated the experiment using FastICA. Fig. 6(b)

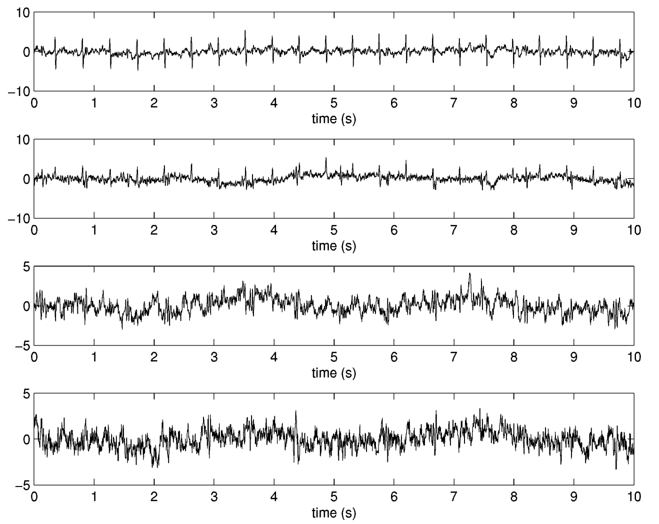

Fig. 5. Real data: Output signals generated sequentially by the algorithm.

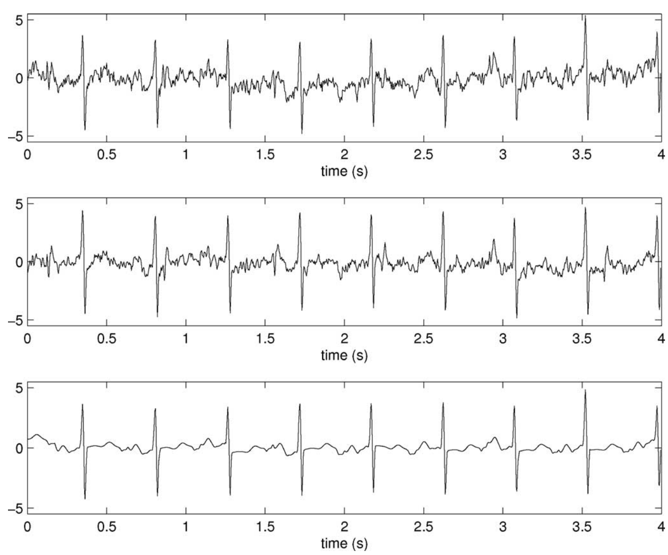

Fig. 6. Real data: (a) FECG estimated by the proposed method, (b) FECG estimated by FastICA, (c) signal (a) after postprocessing.

shows the FECG estimated by FastICA: there is a strong similarity with the results obtained by our algorithm. To show that the algorithm retains enough information on the FECG, in Fig. 6(c), we show a simple postprocessing of the signal generated by our method using the filter described in [12]. Observe that the location of the P and T waves has been improved significantly.

We also estimated the FECG using other ICA methods: π-ICA [4], which is a powerful ICA algorithm specifically devised for the FECG estimation problem, JADE [2], and Pearson ICA [13]. Similarity between the estimates was measured by the correlation coefficient $\rho_i = \sum_{t=1}^{N} (y(t)\, y_i(t)) / \sqrt{\sum_{t=1}^{N} y^2(t) \sum_{t=1}^{N} y_i^2(t)}$, where $y(t)$ is the best FECG estimate obtained by our algorithm, and $y_i(t)$ represents the best FECG estimate obtained by: FastICA ($i = 1$), π-CA ($i = 2$), JADE ($i = 3$), and Pearson ICA ($i = 4$). A measure of the execution time for generating all the estimates was defined by $\lambda_i = T_i/T$, where T is the time required by our proposed method (0.01 s) and T_i represent the mean time required by the others, averaged over ten experiments (the actual time may depend on the initialization point). Here, index i has the same meaning as mentioned earlier. Results are shown in Table I. In addition, to reduce further the baseline wander and the high-frequency noise, we filtered all the estimated fetal heartbeat signals with a simple bandpass filter with cutoff frequencies at 1 and 100 Hz. After this postprocessing, the correlation coefficients mentioned earlier increased to 0.9492, 0.9277, 0.9491, and 0.9647, respectively.

TABLE I
COMPARISON BETWEEN FIGURES OF MERIT FOR EACH ICA METHOD

ρ_1 :	0.88	ρ_2 :	0.84	ρ_3 :	0.87	ρ_4 :	0.91
λ_1 :	4.01	λ_2 :	11.2	λ_3 :	7.10	λ_4 :	22.5

V. CONCLUSION

The algorithm is simple and fast. Execution time should be considered here as a measure of computational complexity. Even though other methods are also able to operate in real time, they carry out very complex calculations that result in increased execution time. From this viewpoint, the proposed algorithm is advantageous for the design of battery-powered devices, since it is usually admitted that computational complexity is related to energy consumption.

Results are comparable to those obtained by other more complex ICA-based approaches. However, note that only R–R intervals can be reliably determined in general at the current state of the art.

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