Fetal Electrocardiogram Extraction by Blind Source Subspace Separation[1]

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Abstract

In this paper we propose and motivate the emerging technique of Independent Component Analysis, also known as Blind Source Separation, as an interesting tool for the extraction of the antepartum fetal electrocardiogram from multilead cutaneous potential recordings. The technique is illustrated by means of a real-life example.

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Keywords— **Independent component analysis, blind source separation, fetal electrocardiogram, singular value decomposition.**

I. Introduction

THE mechanical action of the heart muscle is caused by the propagation of an electrical wavefront, known as the *depolarisation wave*, which is initiated by the nerve system, and followed by *repolarisation* (recovery). This quasi-periodical stimulus involves an electrical current, propagating through the body and resulting in potential differences. The potential differences can be measured between electrodes on the skin (*cutaneous* recordings). The registration of these potential signals, visualized as a function of time, is called the *electrocardiogram* (ECG). (We remark that in medical practice the term additionally implies that the electrodes are placed at standard locations on the person's chest and/or limbs.)

The ECG is a common and fairly effective cheap and painless diagnostic tool. It should be noted that, since the electrical activity is the driving mechanism behind the mechanical activity of the heart, the ECG reveals important medical information that cannot be extracted from audiorecordings (e.g. [23]). On the other hand, it is possible to obtain important information, not merely about the electrical system that controls the mechanical function of the heart, but also about the health of the heart muscle itself, from potential measurements: mechanical events can influence the electrical context to some extent.

Like for adults, it should be possible to visualize the electrical activity of a fetal heart: the *fetal electrocardiogram* (FECG) contains important indications about the health and condition of the fetus. In this respect, analysis of the *fetal heart rate* (FHR) has become a routine procedure for the evaluation of the well-being of the fetus [35] (variations of the FHR (*fetal heart rate variability* (FHRV)) are a result of a continuous interaction with the central nervous system - a loss of beat-to-beat variation may indicate that the fetus is under stress). The cardiac waveform reveals important diagnostic information as well, e.g. for the diagnosis of *arrhytmia* (abnormal heart rates). For some clinical applications of FECG-analyses, we refer to [5], [10], [17], [19], [24], [27], [30].

During delivery accurate recordings can be made by placing an electrode on the fetal scalp. However as long as the membranes protecting the child have not been broken (*antepartum*), one should look for non-invasive techniques. Currently the FHR is mostly measured using ultrasound techniques, based on a Doppler-shifted ultrasonic heart echo [15], [31]. The main advantage of this approach is that it is almost guaranteed that a FHR recording will be obtained. On the other hand, the method requires that the ultrasound beam is pointed at the fetal heart, which may be hard to achieve; an experiment may involve continuous replacement of the transducer, due to fetal and maternal movements. A second disadvantage is the poor accuracy, for a number of reasons: (a) the mechanical movement of the heart may introduce spurious FHRV, (b) most Doppler systems rely on a number of heart beats to compute an averaged instantaneous FHR, so they do not record the real beat-to-beat variability, and (c) monitoring units are often only able to process FHR's up to 220 bpm — in the case of higher rates, the number is divided by two, resulting in an apparently normal rate, which hides however the fact that the fetus is in *tachycardia* (FHR $>$ 200 bpm). These disadvantages are not shared by the alternative technique of examining the FECG from ECG-recordings measured on the mother's skin. As indicated before, ECG-data additionally allow to analyze the cardiac waveform. The main disadvantage is the poor SNR of most recordings, and the fact that the approach is less robust. We also mention that the amplitude of the FECG is observed to decrease around the 30th week of pregnancy — although this is considered to be an important period for fetal monitoring — due to the isolating effect of the *vernix caseosa*, which surrounds the fetus at that time [26]. Other means to obtain FHR-recordings are processing of the *fetal magnetocardiogram* (FMCG) and analysis of the audio sound emitted by the heart (*phonocardiography*). In [11] these different techniques are compared with respect to monitoring over larger periods of time (e.g. 24 hours) and long term ambulant use, and it was concluded that processing of the ECG can be qualified as the most appropriate approach.

The aim of this paper is to show that the emerging technique of *Independent Component Analysis (ICA)*, often called *Blind Source Separation (BSS)*, is a promising tool for the estimation of the FECG from recordings on the mother's skin. We introduced this idea in [12]; the current paper is the first elaborated version of it.

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In Sect. II we motivate that cutaneous recordings contain instantaneous linear mixtures of MECG and FECG, and we briefly situate the ICA-approach against other methods for the extraction of the FECG from cutaneous potential measurements. The ICA-method itself is further discussed at a conceptual level in Sect. III, and in its relation to the FECG extraction problem in Sect. IV. Sect. V contains application examples.

II. Extraction of the FECG from abdominal recordings

Potential measurements on the mother's skin contain contributions from several bioelectric phenomena (maternal and fetal heart activity, potential distributions generated by respiration and stomach activity, ...) and are affected by various kinds of noise (thermal noise, noise from electrode-skin contact, ...). Two aspects have to be discussed here: first, the nature of the occurring signals, and secondly, the characteristics of the propagation from bioelectric source to electrode.

In [28] it is shown that, at a considerable distance from the mother heart, its activity as a bioelectric current source can be represented in first order approximation by a three-dimensional vector signal, that can be imagined as the effect of a rotating current dipole in the chest (the model has further been refined by means of *Body Surface Potential Mapping* (BSPM) [3]). The three-dimensional vector space, described by the discrete-time evolution of the maternal ECG (MECG) after sampling, will be called the *MECG-subspace*. On the other hand [26] states that the observed "dimension" of the fetal heart, i.e. the number of independent signals describing its electrical activity, is not necessarily equal to three, but subject to changes during the period of pregnancy. In this paper the term *FECG-subspace* will be used. In comparison with the low-voltage range of the FECG, other electrical signals can play an important role too: *electromyographic* activity (electrical potentials generated by the muscles, the uterus, etc.), 50 Hz net-interference, etc.

Moreover the ECG-recordings are corrupted by noise that is not necessarily generated by bioelectric mechanisms. A first cause of disturbance is thermal noise in the electronic recording equipment. A second example consists of noise generated by the electrode-skin contact: due to pressure, movements, etc., there exist electrode-specific contributions to the junction potential ([5], Sect. 2.3.3).

The transfer from bioelectric current source to body surface electrode can be assumed linear and resistive [28]. On the other hand the bioelectric source signals are relatively narrow-band, such that the frequency at which the cutaneous potential distribution is sampled (typically 250–500 Hz) can be considered as low, taking into account the high propagation velocity of the electrical signals. Hence, in first approximation, cutaneous potential measurements can be considered as instantaneous linear mixtures of potential signals generated by underlying bioelectric phenomena; noise can be taken into account as an additive perturbation.

The FECG and MECG in cutaneous potential recordings are overlapping in time as well as in frequency. As a consequence, separation of these signals cannot be realized by simple windowing or linear filtering. For a first overview of techniques that aim at the extraction of the FECG from the available measurements, we refer to [5], Sect. 2.2.3. Briefly, the earliest attempts involved a scaled subtraction of an approximate MECG-recording, obtained by measuring at a distance from the fetus (e.g. on the *thorax* (chest)), from a linear superposition of MECG and FECG, recorded on the mother's *abdomen* (belly). Among the more involved approaches we mention the use of matched filters, adaptive noise cancellers, and spatial filtering (in which the FECG is estimated as a linear combination of a number of electrode signals — the method to be discussed further, belongs to this class). Most of these techniques have one or more of the following drawbacks:

- together with the elimination of the MECG, important contributions of the FECG are eliminated as well, especially when the fetal and maternal heartbeat coincide,
- the FECG is only described by one signal,
- only the fetal *QRS-complex* (the central part of the cardiac waveform, having high potential values) is extracted.

Recently, a number of methods have been proposed to extract the FECG from a single-lead recording. The mathematics behind these approaches are diverse: the interpretation of the fetal cardiac waveform as the orbit of a non-linear stationary system [29], wavelet analysis [16], pattern matching (e.g. [1]), ... These techniques have the obvious advantage of a simple data acquisition set-up, but on the other hand, they all rely on some kind of pattern averaging to detect and isolate the FECG, making it unlikely that unforeseen (pathological) FECG-patterns can be successfully dealt with.

III. Independent Component Analysis

Assume the following basic linear statistical model:

$$Y = \mathbf{M}X + N \tag{1}$$

in which $Y \in \mathbb{R}^{\mathbb{I}}$ is referred to as the *observation vector*, $X \in \mathbb{R}^{\mathbb{J}}$ is called the *source vector* and $N \in \mathbb{R}^{\mathbb{I}}$ represents additive *noise*. $\mathbf{M} \in \mathbb{R}^{\mathbb{I}\times\mathbb{J}}$ is the *mixing matrix*.

The goal of ICA now consists of the estimation of the transfer matrix $\mathbf{M}$ and/or the corresponding realizations of the source vector X, given only realizations of the output vector Y, under the following assumptions:

- the columns of $\mathbf{M}$ are linearly independent,
- the components of X are mutually statistically independent, as well as statistically independent from the noise components.

Most of the current ICA-algorithms rely on the first assumption for identifiability. The second assumption is the actual key ingredient for ICA. It is a very strong hypothesis, but also quite natural in lots of applications.

It is impossible to determine the norm of columns of $\mathbf{M}$ in Eq. 1, since a rescaling of these vectors can be compensated by the inverse scaling of the source signal values. Similarly

the ordering of the source signals, having no physical meaning, cannot be identified. For non-Gaussian sources, these indeterminacies are the only way in which an ICA-solution is not unique [9], [33].

The ICA-assumptions do not allow to distinguish between the signal and the noise term in Eq. 1. Hence the source signals will be estimated as $\hat{X}$, by a simple matrix multiplication:

$$\hat{X} = \mathbf{W}^T Y \tag{2}$$

As an example, $\mathbf{W}^T$ can take the form of the pseudo-inverse $\hat{\mathbf{M}}^\dagger$, with $\hat{\mathbf{M}}$ an estimate of the mixing matrix. More generally, various beamforming strategies [36] can be applied.

Exploitation of the fact that the source signals are uncorrelated leads to a classical *Principal Component Analysis* (PCA), which only allows to estimate the sources as well as the mixing matrix up to an orthogonal transformation. To illustrate this, let us assume that the sources have unit variance. Then we have (we omit the noise term at this point, for clarity):

$$\mathbf{C}_Y = \mathbf{M}\mathbf{M}^T, \tag{3}$$

in which $\mathbf{C}_Y$ is the covariance matrix of Y. Substitution of the Singular Value Decomposition (SVD) of the mixing matrix $\mathbf{M} = \mathbf{U}\mathbf{S}\mathbf{V}^T$ shows that the Eigenvalue Decomposition (EVD) of the observed covariance allows to estimate the column space of $\mathbf{M}$ while the factor $\mathbf{V}$ remains unknown:

$$\mathbf{C}_Y = \mathbf{U}\mathbf{S}^2\mathbf{U}^T = (\mathbf{U}\mathbf{S})(\mathbf{U}\mathbf{S})^T. \tag{4}$$

As is well-known, $\mathbf{U}$ and $\mathbf{S}$ might be found directly, in a numerically more reliable way, from the SVD of the observed dataset [18].

The solution to the ICA-problem lies in the fact that the assumption of *statistical independence* is stronger than the notion of *uncorrelated* signals. Statistical independence is not only a claim on the second-order statistics of the signals, but also on their Higher-Order Statistics (HOS) [22], [25]. More precisely, it is not sufficient that the source covariance $\mathbf{C}_X$ is a diagonal matrix — in addition, the higher-order cumulants of the source vector should be diagonal higher-order tensors. (A higher-order tensor can intuitively be imagined as a multi-way matrix, of which the entries are characterized by more than two indices; its diagonal is defined as the entries for which all the indices are equal.)

If we focus at the fourth-order level (third-order cumulants vanish for even probability density functions), then we have the following. The fourth-order cumulant $\mathcal{C}_X^{(4)}$ of a real zero-mean stochastic vector X is defined by:

$$(\mathcal{C}_X^{(4)})_{i_1 i_2 i_3 i_4} \stackrel{\text{def}}{=} \mathtt{E}\{X_{i_1}X_{i_2}X_{i_3}X_{i_4}\} - \mathtt{E}\{X_{i_1}X_{i_2}\}\mathtt{E}\{X_{i_3}X_{i_4}\}$$
$$-\mathtt{E}\{X_{i_1}X_{i_3}\}\mathtt{E}\{X_{i_2}X_{i_4}\} - \mathtt{E}\{X_{i_1}X_{i_4}\}\mathtt{E}\{X_{i_2}X_{i_3}\}, \tag{5}$$

for all index values; $\mathtt{E}$ denotes the expectation. For every component X_i of X that has a non-zero mean, X_i has to be replaced by $X_i - \mathtt{E}\{X_i\}$. It can be proven that the link between the cumulant of the observations and the cumulant of the sources is a straight generalization of its second-order counterpart, Eq. 3:

$$(\mathcal{C}_Y^{(4)})_{i_1 i_2 i_3 i_4} =$$
$$\sum_{j_1 j_2 j_3 j_4} (\mathbf{M})_{i_1 j_1}(\mathbf{M})_{i_2 j_2}(\mathbf{M})_{i_3 j_3}(\mathbf{M})_{i_4 j_4}(\mathcal{C}_X^{(4)})_{j_1 j_2 j_3 j_4}, \tag{6}$$

for all index values, in which $\mathcal{C}_X^{(4)}$ is diagonal. A nice property is that higher-order cumulants are insensitive to additive Gaussian noise. Eq. 6 means that the unknown mixing matrix $\mathbf{M}$ is not only a diagonalizer of the covariance matrix $\mathbf{C}_Y$, but also of the cumulant tensor $\mathcal{C}_Y^{(4)}$, which leads to a sufficient amount of constraints to solve the problem. From an algebraic point of view, this means that the ICA-solution can be obtained by means of multilinear generalizations of the EVD (see e.g. [7], [9], [13]). Actually, since the first paper on the subject [20], ICA has become a hot topic in the signal processing world. Apart from multilinear algebra, solutions have been based on principles of neural networks, information theory, etc. Instead of discussing one particular algorithm, we refer the reader to [8], [21] and the references therein.

Although generally PCA does not allow to identify the mixing matrix nor the source signals, there are some cases in which it does lead to a reasonably good source separation. A straightforward example consists of the situation in which the mixing matrix has mutually orthogonal columns (having mutually distinct norms, if we assume that the sources have unit variance), as is clear from Eq. 4. A second example is the situation in which the source variances are very different (assuming that the norms of the corresponding columns of $\mathbf{M}$ have a comparable magnitude). Next, consider a set-up with e.g. two sources, of which the variances are given by σ_1^2 and σ_2^2, with $\sigma_1^2 \gg \sigma_2^2$. [34] proved that in this case PCA yields, for both source estimates, an Interference-to-Signal Ratio of the order of σ_2^2/σ_1^2. This corresponds to the fact that the dominant eigenvector of $\mathbf{C}_Y$ turns out to be an accurate estimate of the first column of $\mathbf{M}$ in this scenario; the second eigenvector however, is not necessarily a good estimate of the second column of $\mathbf{M}$ but it is approximately orthogonal to the first one. In the context of research on ICA, similar results have independently been obtained in [14] and [32].

IV. Extraction of the FECG by means of BSSS

As explained in Sect. II, the propagation of q bioelectric sources to an array of p body surface electrodes ($p \geqslant q$), can be formulated as:

$$Y(t) = \mathbf{M}X(t) + N(t) \tag{7}$$

where $Y(t) = (y_1(t) \dots y_p(t))^T$ contains the potential recordings, $X(t) = (x_1(t) \dots x_q(t))^T$ contains the signal values of the bioelectric sources, and the noise on each channel is represented by $N(t) = (n_1(t) \dots n_p(t))^T$. The matrix $\mathbf{M}$ describes the propagation from source to electrode, i.e. its entry with row number i and column number j gives the gain of the jth bioelectric source signal w.r.t.

the ith channel data ($1 \leqslant i \leqslant p; 1 \leqslant j \leqslant q$). It is natural to assume that the different bioelectric sources — since they originate at different locations, correspond to different mechanisms, etc. — can be approximately modelled as statistically independent. The noise components $n_i(t)$ ($1 \leqslant i \leqslant p$) are assumed to be Gaussian, with variance σ_N^2, mutually independent as well as independent from the source signals.

As a conclusion, the derivation of the antepartum FECG from multilead cutaneous recordings can be considered as an example of BSS, as discussed in Sect. III, in which however the sources are of a multidimensional nature; we will use the term *Blind Source Subspace Separation* (BSSS). The fact that only the different source subspaces have to be separated, instead of all the source components allows to reduce the computational cost, in comparison to conventional ICA, without loss of medical information. E.g. in the Jacobi-type algebraic algorithms of [7], [9], [13] the multidimensional character of the sources limits the number of Jacobi-rotation angles that have to be identified, since rotations of the basis vectors within one and the same source subspace are irrelevant.

Since there is a large gap between the amplitudes of the MECG and the FECG, a good separation can already be expected from merely PCA, as explained in Sect. III. This is the philosophy behind the important class of SVD-techniques for the extraction of the FECG [4], [5], [6]. To enhance the performance, one often tries to choose the electrode positions in a way that is more or less likely to correspond to an orthogonal transfer (see also Sect. III), but this is still a matter of heuristic rules and trial-and-error.

Conceptually the higher-order processing step in ICA may add the following advantages to the second-order approach:

• It is possible to enhance the quality of separation: whereas the PCA-error only decreases proportionally to the ratio of the power of the weak source vs the power of the strong source, ICA directly aims at a correct reconstruction of the mixing matrix. Sect. V contains an illustration. In case the higher-order ICA-step would fail, one can still resort to the results of the PCA, which forms the first step in many ICA-algorithms.

• The propagation of the electrical signals can be characterized in an essentially unique way. We mention three important implications:

- The transfer vectors indicate how strongly the different electrodes capture each source signal; from this information, better measurement positions might be deduced. We mention that the positioning of the electrodes is still the most crucial factor for the success of the PCA-method [6].

- An important aspect in the evaluation of the fetal well-being is the quantification of fetal movements [5]. At this moment the required information can only be obtained by echography or, simply, by asking the mother. The number of significant changes in the FECG-subspace, which could be obtained from an on-line adaptive ICA-implementation, could be very useful information here.

- The properties of the human body as a conducting medium are, in their own, subject of medical research [28]. The study of the propagation of the fetal heart signal to the mother's skin is an important subaspect [26]. The transfer matrix can provide more understanding with respect to the propagation of electrical signals through the body.

• The physician can resort to a more intuitive interpretation of the results: the separation of the measured signals into statistically independent source signals with a physical meaning, is easier to interpret than a decomposition in time-orthogonal principal components.

We stress the fact that the FECG-extraction is formulated as a *blind identification* problem, since it is less meaningful in practice to resort to a more parametric approach:

• The transfer coefficients are subject to a large uncertainty: the development of propagation models is still in its infancy. Moreover it is clear that length, weight, contour, etc. are significantly different from patient to patient.

• The geometrical and resistivity parameters of the body of a single patient are not constant in time. Fetal growth, a different position of the fetus in the uterus, the variation in the characteristics of the amniotic fluid and the placenta during pregnancy, the changing geometry, ... imply important changes of the transfer matrix.

• For the application in medical diagnosis and treatment it is crucial that *un*expected ECG-patterns can be detected and examined. E.g. the parametric formulation of the quasi-periodicity of a regular heart rate pattern would hamper the detection of *extrasystoles* (extra heart beats between the regular beat-to-beat pattern).

• Potentially interesting is also the application of BSSS to *cardiac electrical imaging*, a recent generalization of the ECG, in which more information is acquired by using a larger array of (e.g. 200) electrodes to record a sequence of "electrical images" of the body [3]. This technique can be seen as an emerging modality for medical imaging, complementary to e.g. Computed Tomography and Magnetic Resonance Imaging; it is worth mentioning that in Japan the technique is already common practice (BSPM).

We may conclude that conceptually BSSS is a very promising technique to tackle the problem of FECG-extraction. Sect. V contains a real-life example. At this moment however, our database is too limited to assess to which extent the assumptions, underlying the ICA-model, are valid in medical practice. With this respect, hard conclusions on the merits and drawbacks of the method can only be drawn after intensive medical testing.

V. Examples

Fig. 1 shows the first 5 seconds of a set of potential signals measured in a one-minute 8-channel experiment. The horizontal axis displays the time in seconds; with respect to the vertical axes only the relative values are important. The sampling frequency was 500 Hz. For details about the data acquisition we refer to [6]. Channels 1 to 5 show abdominal signals; for channels 6 to 8 the electrodes have been placed further away from the fetus, e.g. on the thorax. Channels 1 and 3 clearly contain weak fetal contributions. Due to the large amplitudes of the MECG in the thoracic

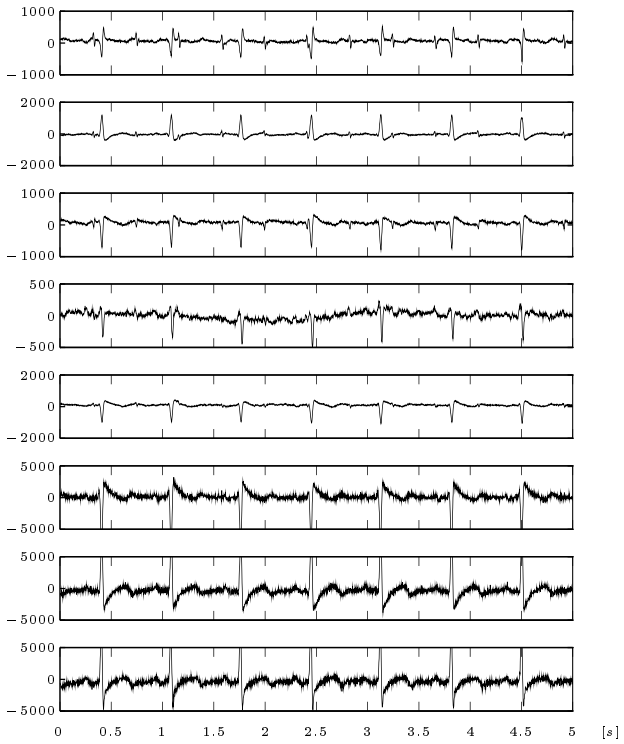

Fig. 1. 8-channel set of cutaneous data recordings.

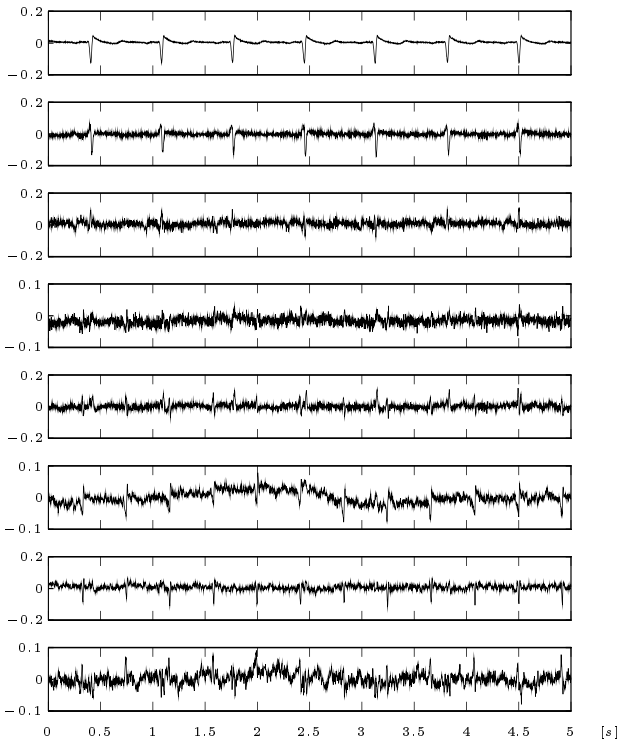

Fig. 2. Source estimates obtained by means of PCA.

signals, the FECG is less visible.

The source estimates after PCA are displayed in Fig. 2. Two MECG-free FECG-components were obtained as resp. the 6th and the 7th right singular vector of the data-matrix. The signals 1 and 2 partially describe the MECG-subspace; the MECG also appears in signals 3 and 5. Channels 4 and 8 mainly show noise contributions.

The result after BSSS is shown in Fig. 3 (we used the algorithm proposed in [9], which is an approximate maximum-likelihood solver; e.g. the methods reported in [7], [13] yield comparable results). The result is an excellent source separation. We remark that, just like in the PCA-approach [4], [5], [6], the statistics of the non-stationary signals have been estimated "roughly" by simple time-averaging. Whereas the PCA-method obtained only two clear MECG-components (the 3rd signal is heavily perturbated by noise and the fifth principal component contains important FECG-contributions), BSSS accurately reconstructed the full three-dimensional MECG-subspace (signals 1 to 3 in Fig. 3). As far as the FECG is concerned, the quality of the 7th principal component and the 8th BSSS-signal are comparable, but in the 6th BSSS-signal the Signal-to-Noise Ratio is somewhat better than in the 6th PCA-estimate. The off-set in the 6th PCA-signal is found back as an extra source signal (the 7th signal in Fig. 3; this sequence continues as a low-periodic signal and deserves further medical interpretation — it might e.g. be due to respiration). The 5th BSSS-signal mainly shows noise contributions.

Figs. 4 and 5 visualize some information extracted from the 6th ICA-component. Fig. 4 plots the evolution of the instantaneous beat-to-beat FHR. Fig. 5 shows the average FECG waveform. In short, we first determined the position of the fetal heartbeats by developing a high-precision robust fetal QRS-complex detector; both an expert-system and a pattern classification approach were followed. In a second step, the instantaneous FHR and the average waveform were calculated as accurately as possible by maximizing the correlation between consecutive pulses. For details about the procedure we refer to [2].

Figs. 6 and 7 illustrate what happens in the case of an atypical FHR and show the importance of a blind approach, as already motivated in Sect. IV. The data of Fig. 6 were constructed as follows. A small piece of data around $t = 0.75s$ in Fig. 1 was copied to $t = 3.5s$, to simulate an extrasystolic fetal heartbeat. In addition, the fetal heartbeat around $t = 2s$ was skipped by setting the five abdominal signals to zero. Nevertheless, Fig. 7 still shows an excellent BSSS.

Figs. 8 and 9 show an artificially constructed situation of fetal twins. The data of Fig. 8 were obtained as follows. First, the two fetal ICA-components of Fig. 3 were shifted over approximately $t = -0.25s$ to artificially generate an independent heartbeat, to be attributed to a second fetus. These signals were added to the original dataset after multiplication by mixing vectors, obtained by independent random permutations of the abdominal and the thoracic entries of the original mixing vectors; the permutations are meant to ensure that the dimensionality of the intersection of both FECG-subspaces is zero. Fig. 9 shows that

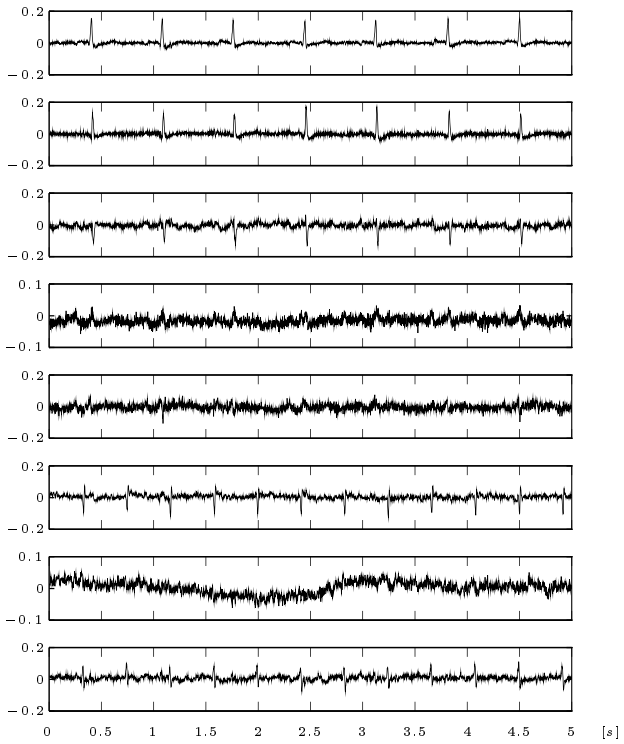

Fig. 3. Source estimates obtained by means of BSSS.

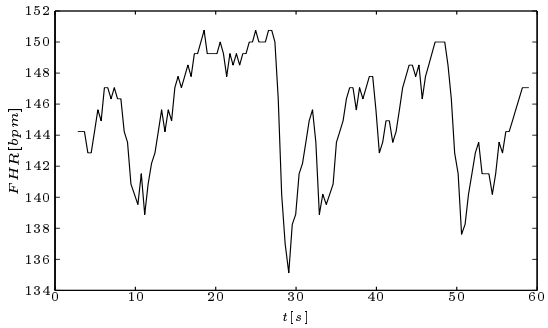

Fig. 4. Evolution of the instantaneous FHR.

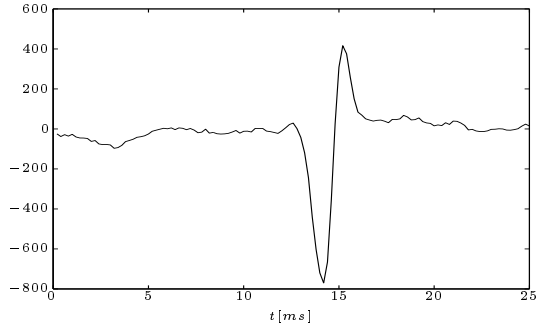

Fig. 5. Average waveform of the fetal heartbeat in the 6th ICA component (Fig. 3).

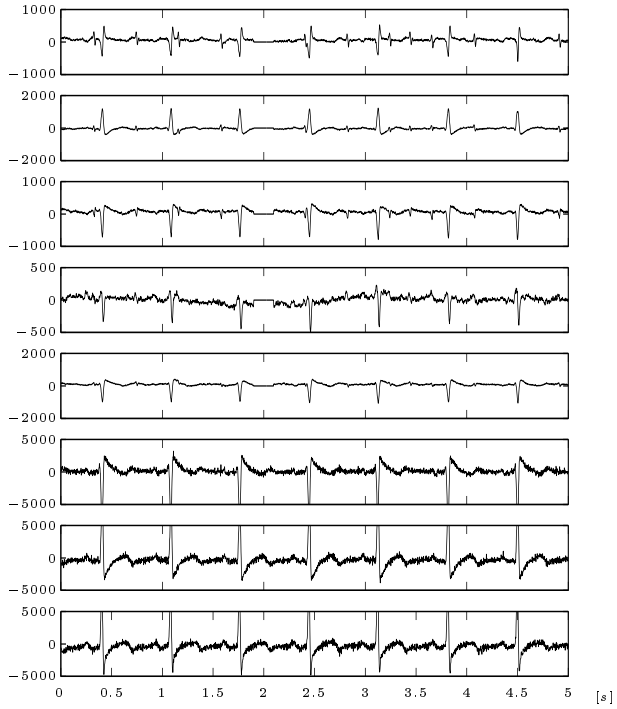

Fig. 6. 8-channel set of cutaneous data recordings, missing a fetal heartbeat around $t = 2s$, and containing an extrasystole around $t = 3.5s$.

8-channel data were sufficient for the extraction of a two-dimensional FECG-subspace (channels 6 and 8; first fetus) and an additional FECG signal (channel 7; second fetus).

VI. Conclusion

In this paper we have proposed BSSS as an innovating way to solve a classical problem in biomedical engineering, namely the extraction of the FECG from multilead potential recordings on the mother's skin. In comparison to the important class of SVD-based methods, proposed earlier, the higher-order ICA-step additionally requires the estimation and the (partial) diagonalization of the fourth-order cumulant tensor of the data. From a conceptual point of view, ICA is a very ambitious approach: it aims at the direct reconstruction of the different statistically independent bioelectric source signals, as well as the characteristics of their propagation to the electrodes, each revealing important medical information. It is non-parametric and is not based on pattern averaging, which could hamper the detection and analysis of atypical fetal heartbeats.

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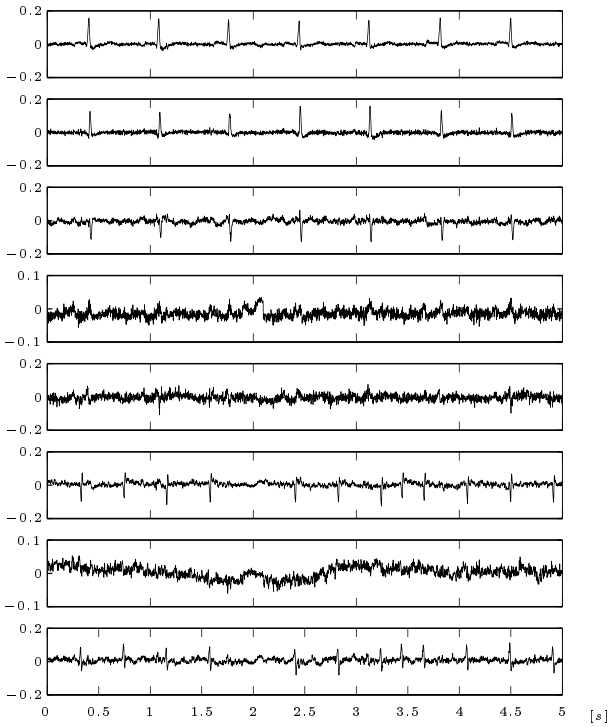

Fig. 7. Source estimates obtained from the data in Fig. 6 by means of BSSS.

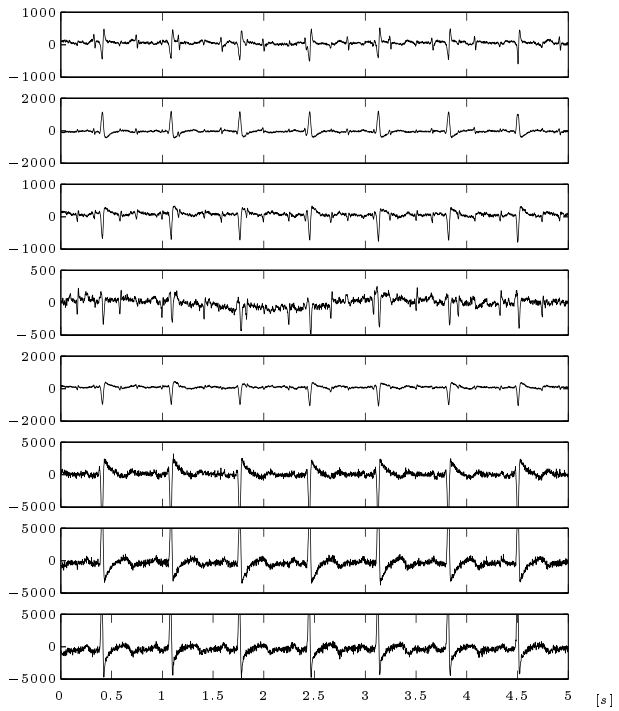

Fig. 8. 8-channel set of observations containing heartbeats of fetal twins.

space System Identification, Extension to Special Cases), (3) the F.W.O. Research Communities ICCoS (Identification and Control of Complex Systems) and ANMMM (Advanced Numerical Methods for Mathematical Modelling), and by the Belgian State, Prime Minister's Office - Federal Office for Scientific, Technical and Cultural Affairs: the Interuniversity Poles of Attraction Programmes IUAP P4-02 (Modeling, Identification, Simulation and Control of Complex Systems) and IUAP P4-24 (Intelligent Mechatronic Systems (IMechS)). L. De Lathauwer is a post-doctoral researcher with the F.W.O. B. De Moor is a senior Research Associate with the F.W.O. and an Associate Professor with the K.U.Leuven. J. Vandewalle is a Full Professor with the K.U.Leuven. The scientific responsibility is assumed by the authors.

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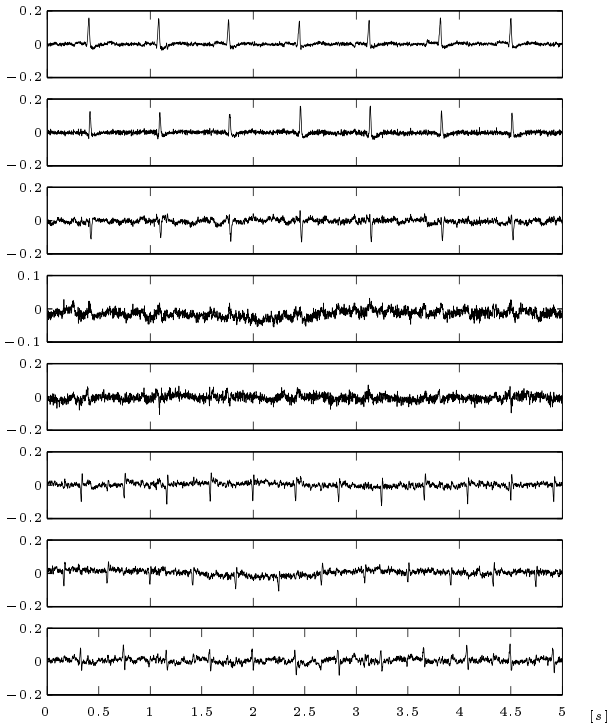

Fig. 9. Source estimates obtained from the data in Fig. 8 by means of BSSS.

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