Noninvasive Fetal Electrocardiogram Extraction: Blind Separation Versus Adaptive Noise Cancellation

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***Abstract*—The problem of the fetal electrocardiogram (FECG) extraction from maternal skin electrode measurements can be modeled from the perspective of blind source separation (BSS). Since no comparison between BSS techniques and other signal processing methods has been made, we compare a BSS procedure based on higher-order statistics and Widrow's multireference adaptive noise cancelling approach. As a best-case scenario for this latter method, optimal Wiener-Hopf solutions are considered. Both procedures are applied to real multichannel ECG recordings obtained from a pregnant woman. The experimental outcomes demonstrate the more robust performance of the blind technique and, in turn, verify the validity of the BSS model in this important biomedical application.**

***Index Terms*—Adaptive noise cancellation, blind source separation, fetal electrocardiogram extraction, higher-order statistics, independent component analysis, optimal Wiener-Hopf filtering.**

I. Introduction

During pregnancy, monitoring the fetus' heart condition in order to test their well-being and diagnose possible diseases is of paramount importance. An early diagnosis before delivery using noninvasive techniques increases the effectiveness of the appropriate treatment. The extraction of the *antepartum* fetal electrocardiogram (FECG) can be carried out through skin electrodes attached to the mother's body. Unfortunately, the desired fetal heartbeat signals appear at the electrode output buried in an additive mixture of undesired disturbances. The most important among these disturbances are the maternal ECG (MECG) contributions, of considerably higher amplitude than the fetal components. Mother's respiration and electromyographic (EMG) signals (e.g., owing to an uncomfortable position of the patient, uterus contraction, etc.) act as a second source of biological interference. Nonbiological interference sources, such as mains coupling and thermal noise due to the electronic equipment, corrupt the cutaneous recordings as well. Appropriate signal processing techniques are required in order to recover the wanted FECG components from the corrupted potential recordings.

Several different approaches have been proposed to address this problem. Techniques such as coherent averaging, matched filtering, auto- and cross-correlation based methods, adaptive filtering, sequenced adaptive filters, etc., were among these classical methods. However, the apparent lack of success of these early approaches (see, e.g., [2] and [14] for some of their major drawbacks) called for a complete reformulation of the problem, whereby attention would be paid to the fundamental aspects behind the biological problem in hand.

Effectively, in [9] it is shown that the problem can be reformulated in a more efficient manner by looking at the bioelectrical phenomena ruling the heart activity and the propagation of heartbeat signals across the body (see also [2], [11] and [17]). The result relies on an electrical model of the heart, the so-called *lead-vector* concept, which was introduced by Burger and Van Milaan as early as in the mid-forties [12], [13]. Considerations derived from this model lead to the statement that each of the p electrodes located on the patient's body, say $\mathbf{y}(k) = [y_1(k), y_2(k), \ldots, y_p(k)]^\dagger \in \mathbb{R}^p$, outputs an instantaneous linear combination of the bioelectric current sources (symbol k denotes a discrete-time index, and † the transpose operator). Assuming that the activity of all internal bioelectric current sources can be modeled by means of q unobservable independent *source signals*, $\mathbf{x}(k) = [x_1(k), x_2(k), \ldots, x_q(k)]^\dagger \in \mathbb{R}^q$, the electrode measurement vector accepts the matrix form

$$\mathbf{y}(k) = M\mathbf{x}(k). \tag{1}$$

Matrix $M \in \mathbb{R}^{p \times q}$ is called *mixing matrix*, and its structure is determined by the body geometry, the electrode and source positions and the conductivity of the body tissues [14]. Equation (1) corresponds to the familiar *blind source separation* (BSS) model of instantaneous linear mixtures [18]. As an immediate consequence, BSS techniques may be applied to tackle the FECG extraction problem. The reader is referred to, e.g., [9] for a more exhaustive discussion on the theoretical justifications for the validity of model (1) in this particular biomedical application.

The methods described in [2] and [14] rely on the second-order statistics (SOS) of the data, seeking the removal of second-order dependencies in the observations. This type of procedure is generally known as *principal component analysis* (PCA) [18]. Their major shortcoming is that the separation quality highly depends on a careful electrode placement selection. By contrast, exploiting the higher-order statistics (HOS) and looking for higher-order independence at the separator output surmount this obstacle. This yields a general class of methods known as *independent component analysis* (ICA). See [5] for the original mathematical definition of ICA.

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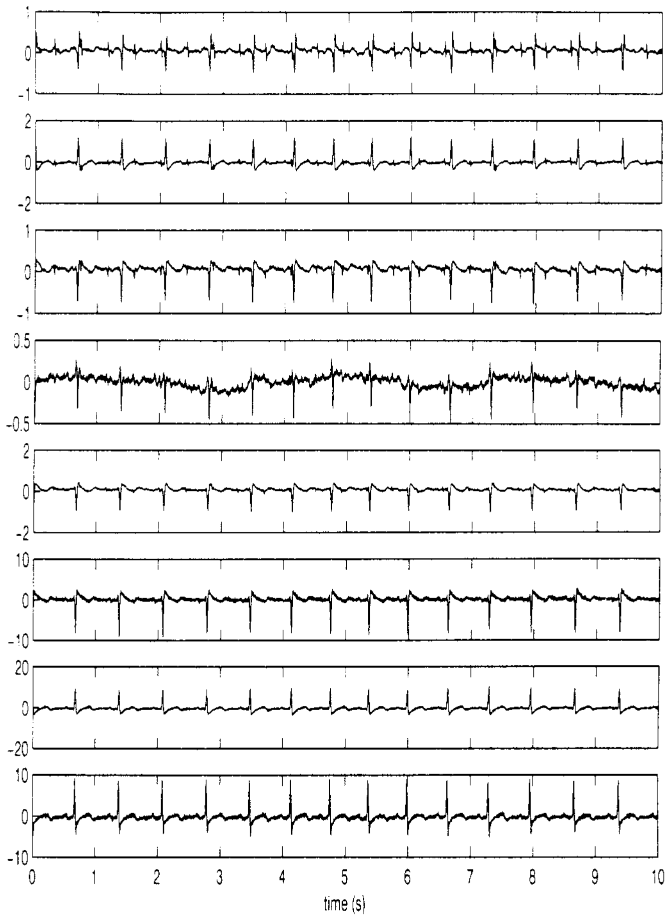

Fig. 1. A cutaneous electrode recording from a pregnant woman.

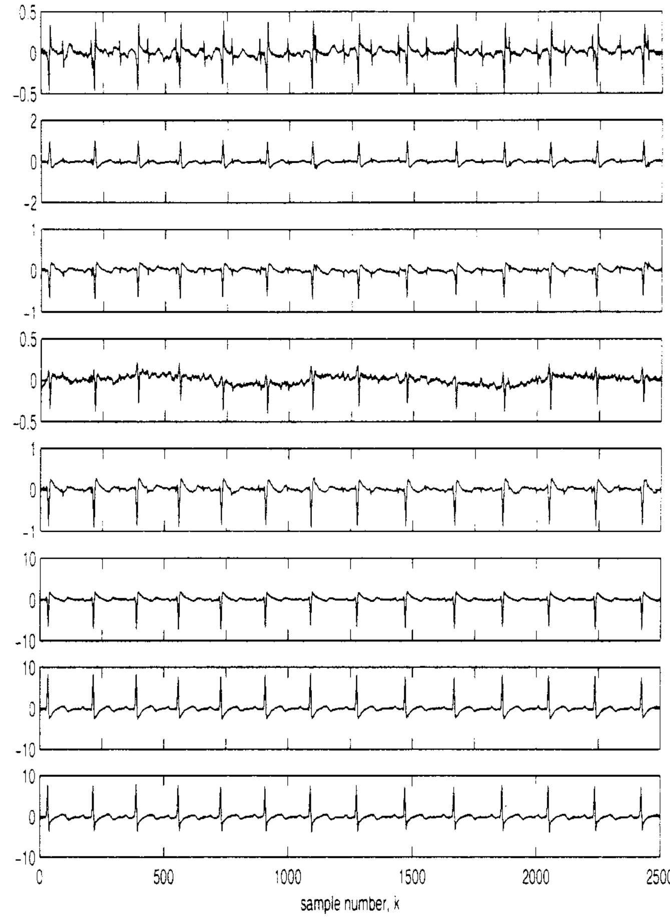

Fig. 2. Another skin electrode recording from a pregnant woman.

Various results obtained from the application of ICA-BSS methods to the biomedical problem in hand have already been reported in the literature [1], [9], [11], [17], [18]. Also, they have been compared to other PCA-BSS methods [1], [9], [17], [18]. Nevertheless, to date no comparison with any other conventional technique, like the procedures cited in the beginning, has been made. The question that still remains unanswered is then whether HOS-based BSS techniques are actually so advantageous relative to other methods. Inspired by this question, it is the primary objective of the present contribution to establish a comparison [22] between a specific BSS method and one of the most significant classical techniques proposed to solve this challenging problem: Widrow's multireference adaptive noise cancelling (MRANC) method [15].

To this end, the rest of the paper is given the following structure. In Section II the experimental data used in the comparison is presented. Section III is then devoted to recalling the rationale and *modus operandi* of the methods considered herein. Later, results from the experiments are reported in Section IV, and discussed in Section V. Section VI makes the concluding remarks.

II. Experimental Data

The two real cutaneous electrode recordings used in the experiments are displayed in Figs. 1 and 2. The signals in Fig. 1[1] were recorded from eight skin electrodes located on different points of a pregnant woman's body. The sampling frequency was 500 Hz and the sampling time 10 s, so each signal is composed of $T_1 = 5000$ samples. Regarding the vertical axes, only the relative amplitudes are important. The first five recordings correspond to electrodes located on the mother's abdominal region. In them a mixture of FECG, MECG and noise is visible. The last three signals were digitized from the mother's thoracic region, and no FECG heartbeat component can be perceived at all, due to the longer distance between these electrodes and the fetal heart. A similar set-up holds for the signals of Fig. 2, which were obtained from [10]. This is a shorter dataset, composed of $T_2 = 2500$ samples.[2]

The choice of abdominal and thoracic (chest) electrode positions is justified by the fact that the strongest interference comes from the maternal heartbeat. Then it seems reasonable to look for clear MECG components so that they can be subtracted, after suitable processing, from the abdominal leads, leaving only the desired fetal heart components. Also the sought MECG signals must be as free as possible from FECG contribution, in order to prevent the latter from being cancelled out in the abdominal lead when performing the subtraction; hence the chest leads.

[1]The authors are grateful to L. De Lathauwer, D. Callaerts and J. Vandewalle, from K. U. Leuven, Belgium, for providing the recordings.

[2]The sampling frequency given in [10] results in too high heart rates for both mother and fetus. Therefore, we will refer in the sequel to the sample number k and not the actual time instant to describe the time evolution of this dataset.

III. Methods

A. Blind Source Separation

Relying on the assumption that the surface potentials are generated according to model (1), the reconstruction of the FECG contributions to the recordings is reduced to the identification of the independent sources of fetal cardiac activity and the corresponding elements of the mixing matrix. This goal requires, firstly, the estimation of the source signals $\mathbf{x}$ and the mixing matrix M via a BSS method. In these experiments, we consider the BSS method developed in [19].[3] Essentially, it is a two-step procedure. An initial PCA stage (also known as *prewhitening*) comprises second-order decorrelation and power normalization, resulting in a set of prewhitened signals $\mathbf{z} = [z_1, \ldots, z_q]^\dagger$. PCA is followed by a higher-order processing part—the actual ICA—aiming at higher-order independence. The latter stage is composed of pairwise Givens rotations, i.e., matrix transformations of the form $\hat{Q} = [\begin{smallmatrix} \cos\hat{\theta} & -\sin\hat{\theta} \\ \sin\hat{\theta} & \cos\hat{\theta} \end{smallmatrix}]$, which are applied in turn to each prewhitened signal pair $[z_i, z_j]^\dagger$. Angle $\hat{\theta}$ is computed at each iteration in closed form as

$$\hat{\theta} = \frac{1}{4}\arg(\xi \cdot \mathrm{sign}(\gamma)), \quad \text{with} \begin{cases} \xi = E[\rho^4 e^{\jmath 4\phi}] \\ \gamma = E[\rho^4] - 8 \end{cases} \qquad (2)$$

where $\rho e^{\jmath\phi} = z_i + \jmath z_j$ and $\jmath^2 = -1$. Symbol $E[\cdot]$ denotes the mathematical expectation, or ensemble average, which in practice is replaced by averages over the signal samples. Expression (2) is shown to generalize an approximate maximum-likelihood estimator earlier suggested in the literature. This pairwise process is repeated in sweeps over the $p(p-1)/2$ signal pairs until convergence, usually taking about $(1+\sqrt{p})$ sweeps (which coincides with the value originally found for the method of [5]). Since the expectations in (2) can be expressed as a function of the data fourth-order cumulants, the method is indeed based on HOS. Also, remark that this procedure operates in *batch processing* mode, in which a whole block of data samples is processed to generate a separation result for that signal block. Batch processing generally achieves better separation results than adaptive processing, and it will suffice to the comparative purposes of this paper. See [19] for more details about this BSS method.

B. Multireference Adaptive Noise Cancellation

One of the first successful approaches to the FECG extraction problem was developed by Widrow and colleagues in the 1970s from an adaptive filtering standpoint [15]. An abdominal lead $a(k)$, mainly containing a mixture of FECG and MECG signals, acts as a primary input to an adaptive noise canceller (Fig. 3). The MECG interference that corrupts the abdominal leads is considered as the 'noise' to be eliminated. The n reference inputs to the canceller $\{r_i(k), i = 1, \ldots, n\}$ are thoracic leads, mostly composed of maternal heartbeat components. The reference inputs are adaptively processed by means of finite impulse response (FIR) filters $\{w_i(k), i = 1, \ldots, n\}$ of tap-length N, and subtracted from the primary input. The output at instant k is then given by $\varepsilon(k) = a(k) - s(k)$, with $s(k) = \sum_{i=1}^{n} w_i(k) * r_i(k)$, symbol '$*$' standing for the convolution operator. The adaptation criterion whereby the filter coefficients are updated consists of minimizing the output-signal power, or mean square error (MSE), $E[\varepsilon^2]$.

[3] A priori, there is no reason why this particular method should be preferred over other BSS procedures to deal with the FECG extraction. Our choice is merely made for illustrative purposes, and motivated by the fact that other different ICA-BSS methods have already been applied to this problem, so that comparisons may be established from the new results presented in this paper.

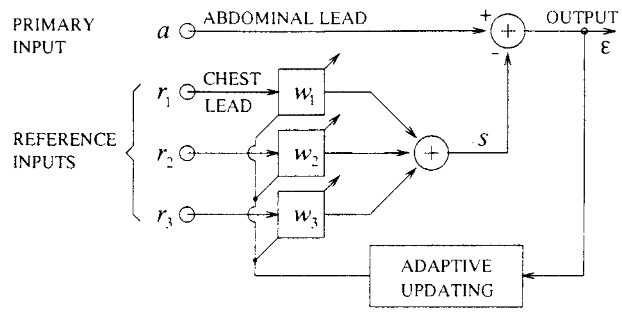

Fig. 3. MRANC solution to the FECG extraction problem.

Practical adaptive implementations of this general procedure, such as the popular least mean square (LMS) method and its variants, are achieved via specific recursive stochastic approximations of the above optimization criterion and its gradient (as well as its Hessian matrix in the Newton-like algorithms) [6]. Such stochastic approximations mean that, in practice, the MSE obtained after convergence is actually higher than the minimum MSE (MMSE) achievable for the given system parameters, a phenomenon known as misadjustment [16]. The MMSE is calculated from the standard theory of optimal *Wiener-Hopf* (WH) filtering [6], [7], [15] by assuming stationary signals and fixed filter weights. Hence, WH solutions describe the asymptotic (or 'best possible') performance of the associated adaptive scheme. In addition, the extraction of these optimal filters is carried out in a batch-processing fashion, as the BSS method outlined in the previous section operates. This increases the fairness of the subsequent comparison.

The mathematical description of optimal WH filtering is very well known [6], [7], [15], and will, therefore, be omitted in this paper. We simply recall that only second-order correlations of the reference signals and the primary sequence at different time lags are involved. Effectively, for a given number of reference inputs n and filter taps N (which, for simplicity and owing to the identical nature of the reference signals in our problem, as will be seen in the next section, is chosen to be equal for all filters), the optimal impulse responses are the solutions in $\mathbf{w}_j \triangleq [w_j(0), w_j(1), \ldots, w_j(N-1)]^\dagger$ of the n equation systems

$$\sum_{j=1}^{n} R_{ij}\mathbf{w}_j = \mathbf{p}_i, \quad i = 1, \ldots, n. \qquad (3)$$

Matrices $R_{ij} \in \mathbb{R}^{N\times N}$ are built up as $R_{ij}(u,v) \triangleq E[r_i(k-u+1)r_j(k-v+1)]$, and vectors $\mathbf{p}_i \in \mathbb{R}^N$ as $\mathbf{p}_i(u) \triangleq E[r_i(k-u+1)a(k)]$, with $i,j = 1,\ldots,n$ and $u,v = 1,\ldots,N$. Equation (3) can easily be recast into a single matrix expression. The problem is then characterized by an $(nN)\times(nN)$ symmetric matrix composed of Toeplitz blocks with dimension $N \times N$.

[4] For the sake of clarity in the presentation, continuous lines are abusively employed to represent the tap weights associated to the second and the third reference-signal filters. Remark that the filters are discrete in nature and, hence, their impulse responses are only defined at integer values of time index k.

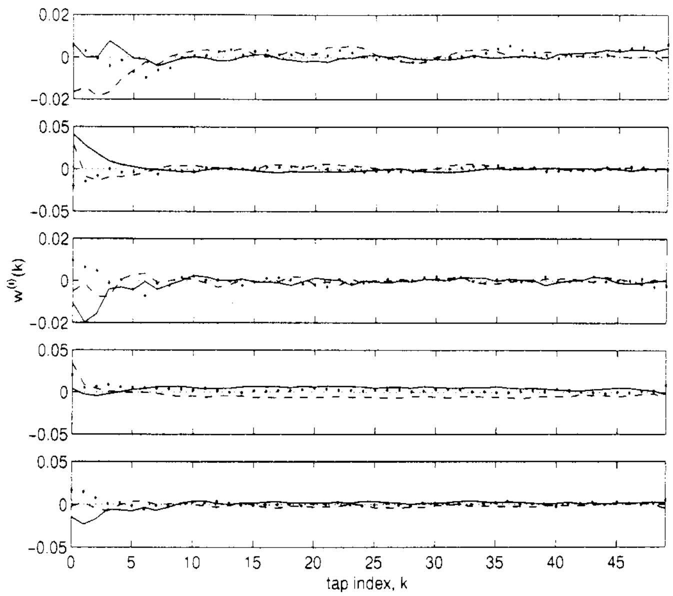

Fig. 4. Optimal filter weights of the MRANC solution for the dataset of Fig. 1, with tap-length $N = 50$. Each plot represents the WH filter coefficients associated to a primary input. Filter of ith reference signal: dotted line: $i = 1$; solid line: $i = 2$; dashed line: $i = 3$.[4]

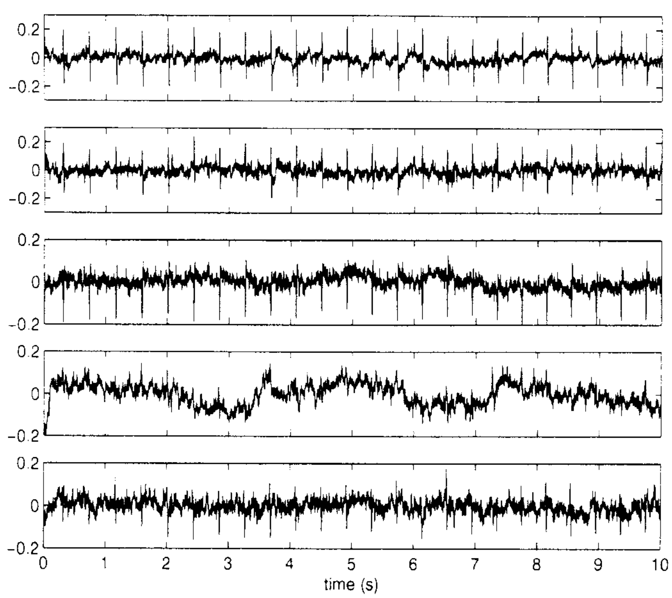

Fig. 5. Fetal contributions to the abdominal electrodes (first five signals) of Fig. 1 obtained by the MRANC method.

IV. Experimental Methodology and Results

For Widrow's MRANC solution, the three thoracic leads of Fig. 1 are employed as reference inputs to the canceller (i.e., $n = 3$, as depicted in Fig. 3), whereas the abdominal leads play (one after the other) the role of primary inputs. The optimal WH filters for $N = 50$ taps are shown in Fig. 4, and the corresponding output waveforms appear in Fig. 5. The impulse responses decay with the tap number, so we might as well have taken fewer coefficients by truncating the displayed tap sequences. As a matter of fact, results with as little as $N = 10$ weights are virtually identical to those in Fig. 5. Nevertheless, as the number of weights is reduced the MECG cancellation is seen to worsen. Obtained along similar lines, the MRANC results for the second dataset are shown in Fig. 6.

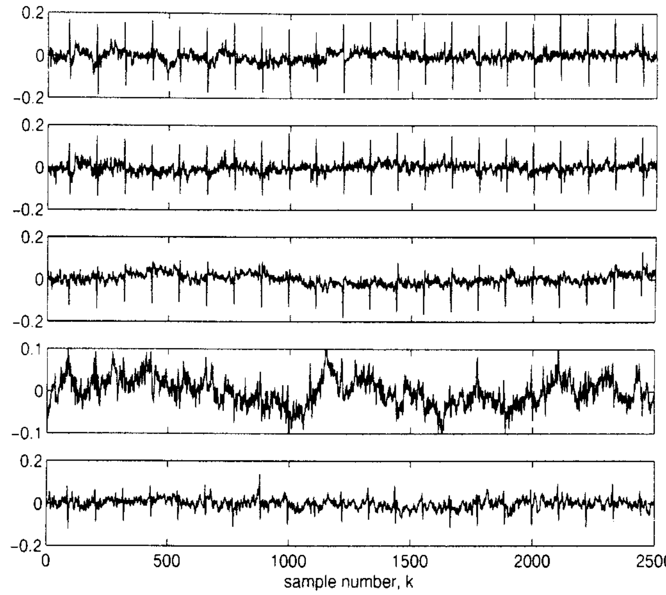

Fig. 6. Fetal contributions to the abdominal recordings (first five signals) of Fig. 2 obtained by the MRANC method.

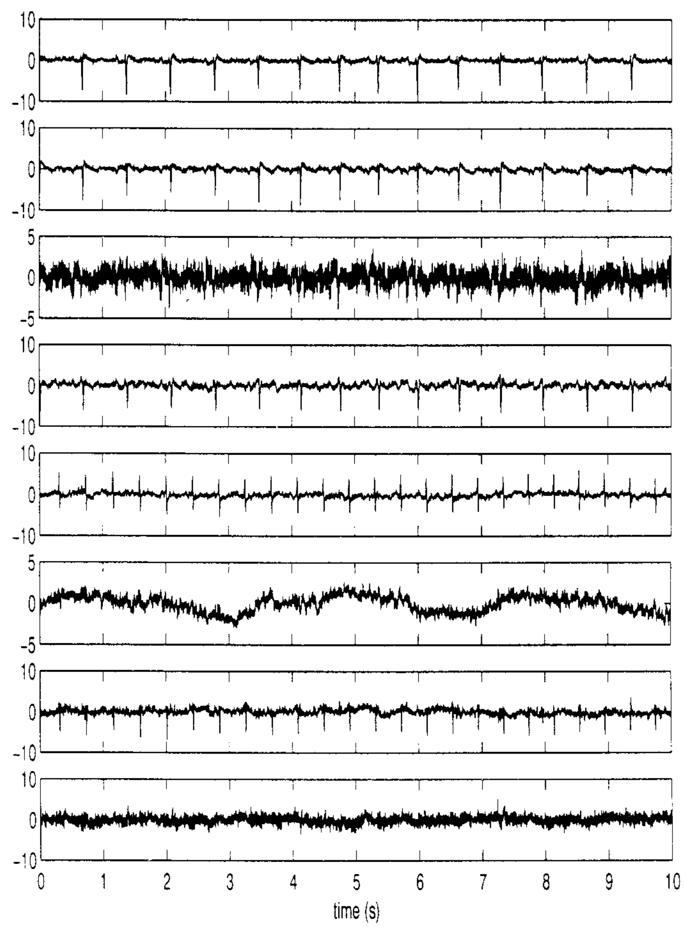

Fig. 7. Source signals estimated by the BSS method from the recordings of Fig. 1.

On the other hand, Fig. 7 shows the independent source signals obtained by the BSS method from the recordings of Fig. 1.

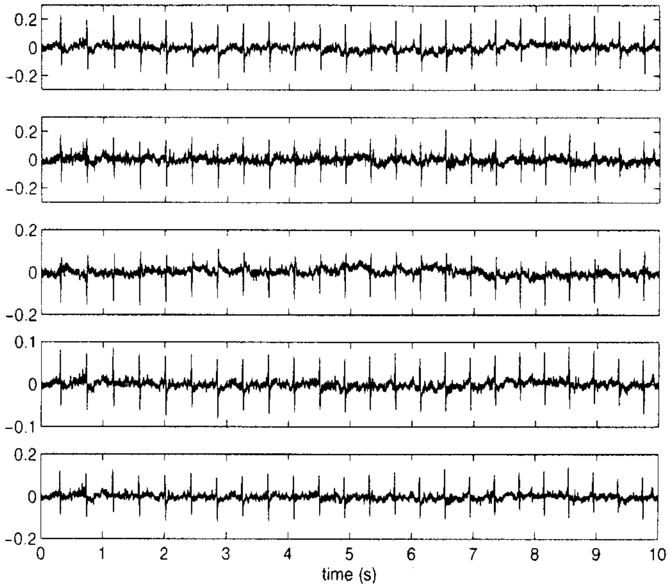

Fig. 8. FECG contributions to the abdominal electrodes (first five signals) of Fig. 1 obtained by the BSS method.

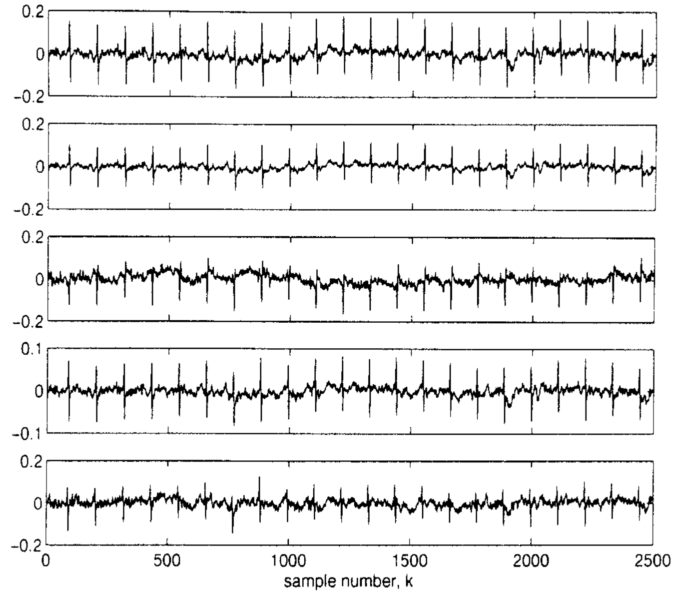

Fig. 10. FECG contributions to the abdominal leads (first five signals) of Fig. 2 obtained by the BSS method.

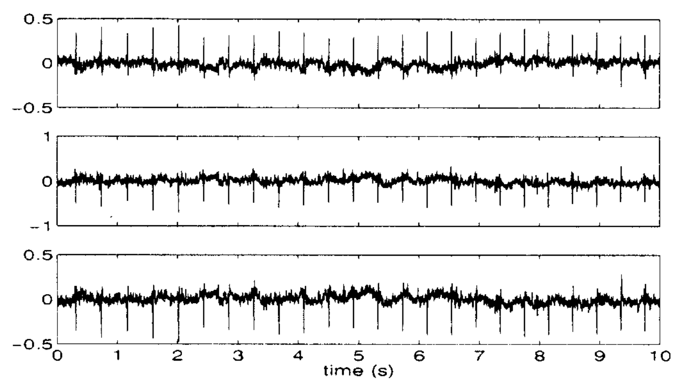

Fig. 9. FECG contributions to the thoracic electrodes (last three signals) of Fig. 1 obtained by the BSS method.

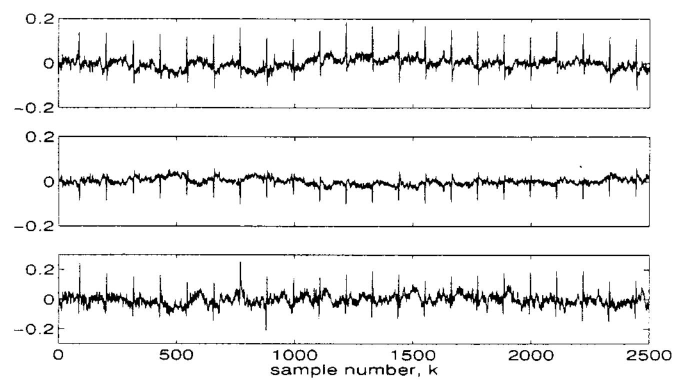

Fig. 11. FECG contributions to the thoracic electrodes (last three signals) of Fig. 2 obtained by the BSS method.

A straightforward visual inspection (more involved mechanisms for source-type automatic identification are currently under development) confirms that waveforms 1, 2, and 4 correspond to the MECG sources, whereas waveforms 5 and 7 belong the the FECG. The rest are interference sources. The two fetal sources are isolated in vector $\hat{\mathbf{x}}_f = [\hat{x}_{f_1}, \hat{x}_{f_2}]^\dagger$. Accordingly, the corresponding columns of the estimated mixing matrix are stored in matrix $\hat{\mathbf{m}}_f = [\hat{\mathbf{m}}_{f_1}, \hat{\mathbf{m}}_{f_2}]$. The fetal heartbeat contributions to the recordings are then obtained by

$$\hat{\mathbf{y}}_f = \hat{\mathbf{m}}_f \hat{\mathbf{x}}_f. \tag{4}$$

Observe that this procedure allows the estimation of FECG contributions to *all* leads. Only the abdominal signals are shown in Fig. 8 for the sake of a more meaningful comparison with the MRANC. For the interested reader, the fetal contributions to the thoracic leads are displayed in Fig. 9. Analogous results are obtained in the second dataset, from which another two sources of fetal cardiac activity are also identified. Figs. 10 and 11 show the FECG components present in the abdominal and thoracic leads, respectively, of the second recording.

V. Discussion

Although noise and some residual MECG components remain noticeable, waveforms 1, 2, 3, and 5 of Fig. 5 show fairly clear fetal heartbeat signals by the MRANC. Waveform 4 is still corrupted by an important baseline wandering, presumably due to the mother's respiration, which hinders the observation of the fetal heart complexes in such electrode. Since there is hardly any of this wandering component present in the chest leads, it cannot be filtered and subtracted from the fourth abdominal electrode, where it appears. The effect on the estimated optimal filters is that the weights of the fourth primary input (fourth plot in Fig. 4) do not converge to zero: the system is 'searching' in the reference inputs, without success, for a component correlated with the baseline wandering that corrupts the fourth electrode. The results of Fig. 6 can be interpreted in a totally analogous manner. Therefore, the performance of the MRANC method seems very dependent on the electrode placement, similarly as occurs with SOS-based BSS. The reference electrodes must be such that they contain signal components correlated with the interference in the primary electrodes.

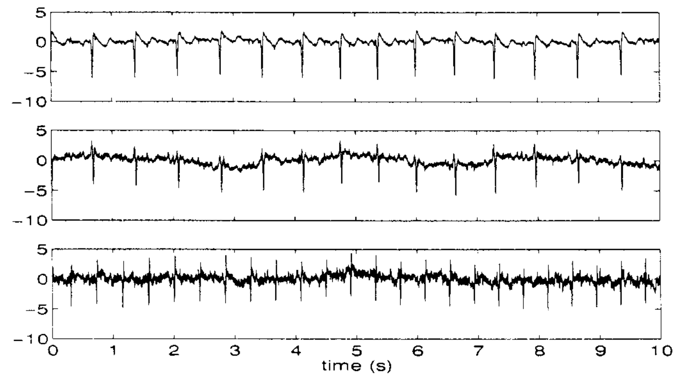

Fig. 12. Source signals recovered by the BSS method from only three abdominal electrodes (waveforms 3, 4, and 5) of the ECG recordings of Fig. 1.

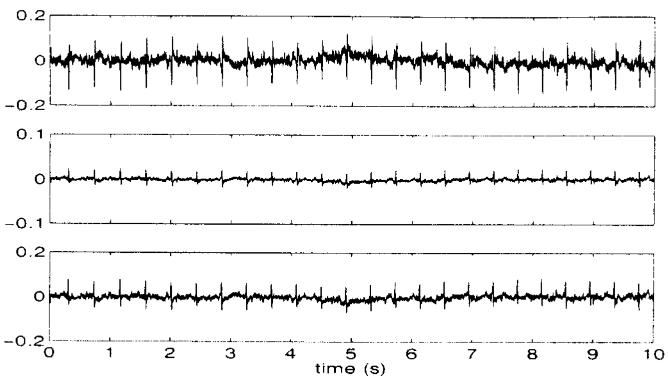

Fig. 13. FECG contributions to electrodes 3, 4, and 5 obtained from the source signals of Fig. 12.

As to the higher-order BSS method, the quality of all the reconstructed FECG contributions is notably superior. For instance, the baseline wandering which corrupted the fourth signal obtained by the MRANC solution (Fig. 5) is now completely eliminated in Fig. 8, since it is found to be generated by an independent source of interference (sixth waveform in Fig. 7) and, hence, it is extracted from the fourth recording as a separate noise signal. Also, all reconstructed fetal components are much less noisy than their MRANC counterparts, thanks to the two additional independent noise sources extracted (waveforms 3 and 8 in Fig. 7). Very similar outcomes are obtained for the second recording (Fig. 10).

Besides the abdominal electrodes, the BSS method is able to reconstruct the FECG contributions to the thoracic leads as well, as commented at the end of Section IV and featured in Figs. 9 and 11. The apparently too high amplitude of the obtained signals could be a product of the processing. Nevertheless, the resulting waveforms appear outstandingly clean from maternal and other sources of disturbance.

The BSS robustness with respect to the electrode placement and number was evidenced through further experiments whereby FECG sources were clearly revealed by exploiting a few abdominal leads exclusively. Favorable results were obtained by processing the output of up to only three electrodes, as illustrated by Figs. 12 and 13. In Fig. 12, the fetal and maternal subspaces are successfully separated, and an FECG source (third signal) practically free from MECG interference is recovered. From the fetal source, the FECG contributions to the electrodes involved are obtained as explained in Section IV, and are displayed in Fig. 13 (cf. last three plots of Figs. 5 and 8). The dimension of the estimated fetal subspace is now lower than in the full-recording processing, which accounts for the dissimilar results in both cases. However, the FECG extraction achieved from such smaller number of electrodes can still be considered as satisfactory. This robustness arises as an important major advantage of BSS techniques.

The computational cost is another relevant issue. Straightforward calculations lead to a number of flops[5] of $O(n^2NT)$ for the WH-MRANC to extract the FECG components from a single primary lead, for N and T large (or just $O(nNT)$ if operating on-line via LMS). On the part of the BSS method, the sources are extracted in roughly $O(p^{5/2}T)$ flops, for T large. Therefore, the relative cost, under the same conditions and n of the order of p, depends on the number of taps in the MRANC filters. For the parameter values of these particular experiments, however, the BSS method is more expensive.

Although the optimal WH solutions are obtained in batch-processing mode, it must be remarked that the MRANC is adaptive by nature (see in [21] results in adaptive mode), whereas the BSS method employed in these experiments processes the data in sample blocks (off-line or batch processing). For the application in a clinical environment, on-line (or adaptive) processing is certainly more convenient. Adaptive BSS methods do exist as well (e.g., [3], [20]), but additional experiments on these ECG data confirm that more samples are needed for these adaptive algorithms to reach a satisfactory stable solution. This is connected with the fact that larger sample sizes are required to compute HOS with a reasonable estimation accuracy. In the MRANC, by contrast, only SOS are (implicitly) used.

Results obtained in this biomedical context by other BSS methods are reported in [1], [4], [9], [14] and [17]. In [1] and [17] the recordings of Fig. 1 are processed through the PCA and the techniques of [5] (ICA-HOEVD) and [8] (HOSVD). Basically, results from the BSS method evaluated here are much more precise than from the PCA and the HOSVD, and very similar to the ICA-HOEVD.

VI. Conclusion and Outlook

The experiments presented and discussed in this paper show HOS-based BSS as a more robust and successful approach to the noninvasive FECG extraction problem than the MRANC, although the superior performance is attained at the expense of an increased computational complexity. Yet the achieved FECG-extraction quality offers promising prospects for the use of ICA-BSS techniques in prenatal medical diagnosis.

For the introduction of blind separation techniques as a generalized diagnosis tool, however, further research is still necessary. As the most important point to be explored, the relationship between physiological sources of cardiac activity and the statistically-independent sources that the signal separation methods estimate needs to be clarified. The lack of knowledge on this relationship does not prevent BSS techniques from being useful in as important state-of-the-art applications as telemedicine, in

[5]Additions are neglected, so that we define a *flop* as a real multiplication.

which the physician merely considers the fetal cardiac rate. In addition to the heart rate, BSS presents the potential of offering more detailed information about the fetal heart, thus allowing a more accurate diagnosis.

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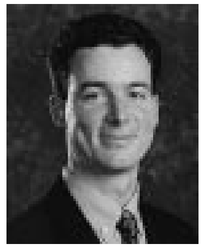

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