Fetal ECG Extraction by Extended State Kalman Filtering Based on Single-Channel Recordings

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***Abstract*—In this paper, we present an extended nonlinear Bayesian filtering framework for extracting ECGs from a single-channel as encountered in the fetal ECG extraction from abdominal sensor. The recorded signals are modeled as the summation of several ECGs. Each of them is described by a nonlinear dynamic model, previously presented for the generation of a highly realistic synthetic ECG. Consequently, each ECG has a corresponding term in this model and can thus be efficiently discriminated even if the waves overlap in time. The parameter sensitivity analysis for different values of noise level, amplitude and heart rate ratios between fetal and maternal ECGs shows its effectiveness for a large set of values of these parameters. This framework is also validated on the extractions of fetal ECG from actual abdominal recordings, as well as of actual twin magnetocardiograms.**

***Index Terms*—fetal ECG extraction, twin MCGs extraction, extended Kalman filtering, nonlinear Bayesian filtering, model-based filtering.**

I. Introduction

Since the first demonstration of the fetal electrocardiogram (fECG) carried out in 1906 by Cremer [1], various methods for fECG monitoring have been proposed to obtain information about the heart status. The fECG can be measured by placing electrodes on the mother's abdomen. However, it has very low power and is mixed with several sources of noise and interference. Nevertheless, the main contamination is the maternal electrocardiogram (mECG) [2]. As a result, the basic problem is to extract the fECG signal from the mixture of mECG and fECG signals, where the interfering mECG is a much stronger signal. According to the review [3], existing fECG extraction approaches in literature can be categorized by their methodologies, which include linear or nonlinear decomposition and adaptive filtering.

Linear or nonlinear decomposition methods are common approaches in which, single or multi-channel recordings are decomposed into different components using suitable basis functions. Linear decomposition methods use either fixed basis functions (e.g., wavelets [4]), or data-driven basis functions (e.g., singular vectors [5]). This limits performance of decomposition in nonlinear or degenerate mixtures of signal and noise [3]. Blind or semi-blind source separation, which are categorized as linear decomposition approach, have also been used for fECG extraction [6], [7]. These methods are based on the assumption of independent components (or more generally independent subspaces [8] or partitions [9]) for the maternal and fetal signals, or of the existence of some temporal structure for the desired signals [10], [11], [12]. In [13], [14], wavelet decomposition was also combined with blind source separation for extracting and denoising fECG signals. In another recent work, a new technique was proposed to fasten traditional Independent Component Analysis (ICA) method [15]. In blind source separation methods it is usually assumed that signals and noises are mixed in a stationary and linear manner. However, fECG and other interferences and noises are not always stationary mixed and linearly separable [16].

Nonlinear transforms have been also used for mECG cancellation and fECG extraction. In these methods, constructed phase space of noisy signal and of its delayed versions is smoothed using conventional or Principal Component Analysis (PCA) smoothers [17]. The samples are then transferred back to the time-domain representation. Although these methods are interesting since they are applicable to as few as one single maternal abdominal channel, the selection of the required time-lags for constructing phase space representation is empirical and the important inter-beat variations of the cardiac signals can be wiped-out during the state-space smoothing. Moreover, they demand higher computational complexity in comparison to linear methods, and the correct embedding dimension can change as the noise statistics change [3].

Adaptive filtering is another common approach for mECG cancellation and fECG extraction [18]. The conventional adaptive filtering is based on training an adaptive filter for either removing the mECG using one or several maternal reference channels [18], [19], or directly training the filter for extracting the fetal QRS waves [20], [21]. However, existing adaptive filtering methods for mECG artifact removal, either require a reference mECG channel that is morphologically similar to the contaminating waveform or require several linearly independent channels to roughly reconstruct any morphologic shape from the references [18]. Both of these approaches are practically inconvenient and with limiting performance, because the morphology of the mECG contaminants highly depends on the electrode locations and it is not always possible to reconstruct the complete mECG morphology from a linear combination of the reference electrodes [3]. Practically, it has been shown that for fECG extraction, blind source separation methods outperform adaptive filters [22]. An important advantage of spatial filtering over conventional adaptive filters is their ability to separate mECG and fECG with temporal overlap but it often requires more than two sensors.

The Kalman filtering framework, which can be considered as a member of the general class of adaptive filters, is a promising approach for both mECG cancellation and fECG enhancement. In [16], [23] a set of state-space equations was used to model the temporal dynamics of ECG signals, for

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designing a Bayesian filter for ECG denoising. This Bayesian filter framework was used in [16, p. 50] to extract fECG from single channel mixture of mECG and fECG. However, as it is mentioned in [16], the filter fails to discriminate between the maternal and fetal components when the mECG and fECG waves fully overlap in time. The reason is that when mECG is being estimated, fECG and other components are supposed to be Gaussian noise. However, this assumption is not true, especially when mECG and fECG waves fully overlap in time it is difficult for the filter to follow desired ECG.

Clinical monitoring of fetal cardiac activity is usually based on a small number of electrodes located on mother's abdomen, and on a sound sensitive sensor. In such a context, in the present work, we wonder what performance can be obtained with only one electrode, by using a refined model of the signal recorded on the unique electrode: the model will explicitly take into account that the signal is the superposition of a few ECG signals. The rest of this paper is organized as follows. In section II equations and theory supporting our proposed method including the Bayesian filtering theory and dynamic ECG model are described. In section III results of the proposed method applied on different data and discussion about the results are presented. Finally, our conclusion is stated in section IV.

II. Methodology

A. EKF Framework for ECG Extraction

The goal of Kalman Filter (KF) is to estimate the state of a discrete-time controlled process. Consider a state vector $\mathbf{x}_{k+1}$ governed by a nonlinear stochastic difference equation with measurement vector $\mathbf{y}_{k+1}$ at time instant $k+1$:

$$\begin{cases} \mathbf{x}_{k+1} = f(\mathbf{x}_k, \mathbf{w}_k, k+1) \\ \mathbf{y}_{k+1} = h(\mathbf{x}_{k+1}, \mathbf{v}_{k+1}, k+1) \end{cases} \quad (1)$$

where the random variables $\mathbf{w}_k$ and $\mathbf{v}_k$ represent the process and measurement noises, with associated covariance matrices $Q_k = E\{\mathbf{w}_k \mathbf{w}_k^T\}$ and $R_k = E\{\mathbf{v}_k \mathbf{v}_k^T\}$. The Extended Kalman Filter (EKF) is an extension of the standard KF to nonlinear systems $f(\cdot)$ and $h(\cdot)$, which linearizes about the current mean and covariance [24]. In order to improve the estimations, EKF can be followed by a backward recursive smoothing stage leading to the Extended Kalman Smoother (EKS). However, since EKS is a non causal method, it can not be applied online but it is useful if a small lag in the processing is allowed.

In this work, a synthetic dynamic ECG model [25] is used to extract fECG from mixture of an mECG, one (or more) fECG(s) and other signals considered as noises. In polar coordinates [23], one ECG signal can be expressed as the sum of five Gaussian functions defined by their peak amplitude, width and center, denoted α_i, b_i and ψ_i, respectively: $z(\theta) = \sum_{i \in \mathcal{W}} \alpha_i \exp(-(\theta-\psi_i)^2/(2b_i^2))$. Each Gaussian function thus models one of the five waves $\mathcal{W} = \{P, Q, R, S, T\}$ of a heart beat. The state vector in equation (1) is defined by the phase θ and the amplitude z of the ECG: $\mathbf{x}_k = [\theta_k, z_k]^T$. Assuming a small sampling period δ, the state noise η_k, and defining $\mathbf{w}_k$ as $[0, \eta_k]^T$, the state process $f(\cdot)$ is

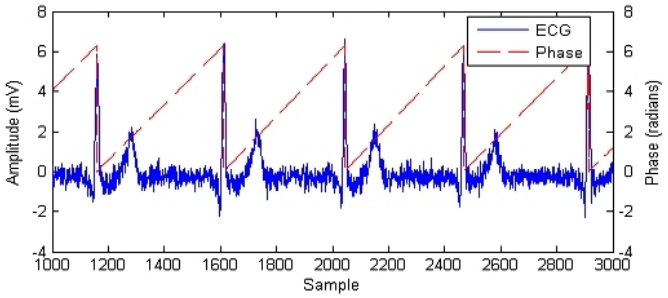

Figure 1. Illustration of the phase assignment approach on one ECG.

$$\theta_{k+1} = (\theta_k + \omega\delta) \bmod(2\pi), \quad (2)$$

$$z_{k+1} = -\sum_{i \in \mathcal{W}} \frac{\alpha_i \Delta\theta_{i,k} \omega \delta}{b_i^2} \exp\left(-\frac{\Delta\theta_{i,k}^2}{2b_i^2}\right) + z_k + \eta_k, \quad (3)$$

where ω is the phase increment, $\Delta\theta_{i,k} = (\theta_k - \psi_i) \bmod(2\pi)$. From the ECG, one can define the observed phase ϕ_k by a linear time wrapping of the R-R time intervals into $[0, 2\pi)$ (Figure 1). The measurement process $h(\cdot)$ is finally defined as $\mathbf{y}_{k+1} = \mathbf{x}_{k+1} + \mathbf{v}_{k+1}$, where $\mathbf{y}_{k+1} = [\phi_{k+1}, s_{k+1}]^T$.

The ECGs composing the observed mixture can be estimated by recursively applying the described EKF: at each step, one ECG is extracted according to a deflation procedure. In case of a mixture of mECG and one fECG, the first step extracts, from the raw recording, the dominant ECG (often the mECG) considering the concurrent ECG (resp. fECG) and other noises as a unique Gaussian noise. After subtracting the dominant ECG from the original signal, the second step is the extraction of fECG from the residual signal. This procedure is referred to as *sequential* EKF or EKS (seq-EKF or seq-EKS). In this recursive extraction, during the first step, the concurrent ECG (i.e. fECG) and additional noise are modeled by Gaussian noises $\mathbf{v}_k$ and $\mathbf{w}_k$, which is not a very relevant assumption. In fact, although this assumption may be acceptable when there are not strong artifacts interfering with the ECG, it is no longer accurate when other ECG artifacts are considerable (i.e. at the first step) since the noise is no longer normally distributed. In addition, concurrent ECGs can be confused with dominant ECG when their waves (especially QRS complexes) fully overlap in time. Meanwhile, resultant inaccuracies, which are generated by the previous steps of the ECG extraction, will propagate to the next steps while the residuals are computed.

B. Extension to multiple ECGs: extended state EKF

In this paper the dynamic equations (2) and (3) are extended for simultaneously modeling N ECGs mixed in a single observation. The related extended state vector $\mathbf{x}_k =$

$[\theta_k^{(1)}, z_k^{(1)}, \ldots, \theta_k^{(N)}, z_k^{(N)}]^T$ is thus defined by

$$\begin{cases} \theta_{k+1}^{(1)} &= (\theta_k^{(1)} + \omega^{(1)}\delta) \bmod(2\pi) \\ z_{k+1}^{(1)} &= -\sum_{i\in\mathcal{W}_1} \frac{\alpha_i^{(1)}\omega^{(1)}\delta}{b_i^{(1)^2}} \Delta\theta_{i,k}^{(1)} \exp\left(-\frac{\Delta\theta_{i,k}^{(1)^2}}{2b_i^{(1)^2}}\right) \\ & \quad + z_k^{(1)} + \eta_k^{(1)} \\ & \vdots \\ \theta_{k+1}^{(N)} &= (\theta_k^{(N)} + \omega^{(N)}\delta) \bmod(2\pi) \\ z_{k+1}^{(N)} &= -\sum_{i\in\mathcal{W}_N} \frac{\alpha_i^{(N)}\omega^{(N)}\delta}{b_i^{(N)^2}} \Delta\theta_{i,k}^{(N)} \exp\left(-\frac{\Delta\theta_{i,k}^{(N)^2}}{2b_i^{(N)^2}}\right) \\ & \quad + z_k^{(N)} + \eta_k^{(N)} \end{cases}$$

where each $[\theta_k^{(i)}, z_k^{(i)}]^T$ is related to one of the ECGs. Finally, the measurement process leads to express the measurement vector $\mathbf{y}_{k+1} = [\phi_{k+1}^{(1)}, \cdots, \phi_{k+1}^{(N)}, s_{k+1}]^T$ as

$$\begin{cases} \phi_{k+1}^{(n)} = \theta_{k+1}^{(n)} + v_{k+1}^{(n)}, & \forall\, n \in \{1, \cdots, N\} \\ s_{k+1} = \sum_{n=1}^{N} z_{k+1}^{(n)} + v_{k+1}^{(N+1)}. \end{cases} \quad (4)$$

This extended state Kalman filtering procedure is referred to as *parallel* EKF or EKS (par-EKF, or par-EKS, respectively). As shown in the results section (Section III), this par-EKF or par-EKS is more accurate to extract fECG from abdominal sensors than the seq-EKF or seq-EKF. Indeed, in the proposed method all ECGs are jointly modeled by dynamic states so that only the state and measurement noise vectors are assumed to be normally distributed. Moreover, the extended state par-EKF fully models overlapping waves of several ECGs. Finally, the state and observation noises, η_k^n and v_k^n, respectively, allow to fit some variabilities of the ECG shapes. Even if the model do not fit too large variations (for example due to arrythmia), but an inspection of the residue will reveal these abnormal beats.

C. Model parameters estimation

The proposed par-EKF and par-EKS lie on several state parameters $\{\alpha_i^{(n)}, b_i^{(n)}, \psi_i^{(n)}\}_{i\in\mathcal{W}_n}, \forall n \in \{1, \ldots, N\}$. The procedure described below is an extension of the single ECG parameter estimation [23].

The parameters estimation procedure first needs the R-peaks detection for all ECGs to perform the time-wrapping of the R-R intervals into $[0, 2\pi)$ to define $\phi_k^{(n)}$. The R-peaks are found from a peak search in windows of length T, where T corresponds to the R-peak period calculated from approximate ECG beat-rate. R-peaks with periods smaller than $\frac{T}{2}$ or larger than T are not detected. Although maternal R-peaks are easily detectable from the mixture, fetal R-peaks detection is more complex due to its lower amplitude than mECG. Therefore, a rough estimation of fECG is obtained by using the seq-EKF algorithm, which now allows to detect easily the fetal R-peaks[1]. Now, for each ECG, each beat (defined by the signals between two consecutive R-peaks) is time wrapped into $[0, 2\pi)$. The average of the ECG waveform is obtained by the mean of all time-wrapped beats, for all phases between 0 and 2π. Finally, by using a nonlinear least-squares approach [26], the best estimate of the parameters in the minimum mean square error (MMSE) sense is found.

[1]In practice, one could also use a sound sensor to have a reliable R-peak detector. In this case, even if there exists a delay, it does not impact the method, since it can be synchronized.

III. Results and Discussions

Both synthetic and actual data have been used to study performance of the proposed method. In the first subsection, quantitative results coming from simulations and influence of the main parameters of mixed ECGs on performance of the method has been studied. They will present the conditions in which, the proposed method is efficient. In the second subsection the effectiveness of the method on actual data has been examined.

A. Experimental Performance Analysis on Synthetic Data

Since there is neither ground truth nor golden standard on single channel recording, it is important to provide quantitative performance with simulations to validate the behavior of the proposed method. In order to do so, realistic synthetic mixtures of mECG and fECG with white Gaussian noise have been generated for different situations and the proposed method has been applied on them to extract mECG and fECG.

Synthetic mECG and fECG used in this study are based on a three-dimensional canonical model of the single dipole vector of the heart, proposed in [27] and inspired by the single-channel ECG dynamic model presented in [25]. Sampling frequency is set to 500 Hz and signals include 20,000 samples. The main parameters that can affect the mixtures are input noise power, ratio between amplitudes of fECG and mECG, and ratio between fetal and maternal heart rates. In order to investigate the performance of the proposed method hundred trials were carried out under each value of these parameters. In the output, estimated mECG and fECG signals, $\hat{s}_m$ and $\hat{s}_f$, are assumed to be the sum of mECG, fECG and noise, such that:

$$\begin{aligned} \hat{s}_m &= \alpha_1 s_m + \alpha_2 s_f + \alpha_3 n, \\ \hat{s}_f &= \beta_1 s_m + \beta_2 s_f + \beta_3 n, \end{aligned} \quad (5)$$

where coefficients α_1, α_2, α_3, β_1, β_2, and β_3, have to be estimated and s_m, s_f, and n denote mECG, fECG and noise, respectively. In order to estimate the coefficients, s_m, s_f, and n are assumed to be orthogonal, i.e., decorrelated. The orthogonality principle states that an estimator $\hat{s}$ achieves MMSE if and only if $E\left\{(\hat{s} - s)^T \hat{s}\right\} = 0$. Satisfaction of this criteria leads to:

$$\begin{aligned} \hat{\alpha}_1 &= \frac{E(\hat{s}_m^T s_m)}{E(s_m^T s_m)}, \quad \hat{\alpha}_2 = \frac{E(\hat{s}_m^T s_f)}{E(s_m^T s_f)}, \quad \hat{\alpha}_3 = \frac{E(\hat{s}_m^T n)}{E(s_m^T n)}, \\ \hat{\beta}_1 &= \frac{E(\hat{s}_f^T s_m)}{E(s_f^T s_m)}, \quad \hat{\beta}_2 = \frac{E(\hat{s}_f^T s_f)}{E(s_f^T s_f)}, \quad \hat{\beta}_3 = \frac{E(\hat{s}_f^T n)}{E(s_f^T n)}. \end{aligned} \quad (6)$$

In a successful estimation, contribution of desired ECG in output should be much more than contribution of undesired ECG and noise. In other words, in extraction of fECG the power of $\beta_2 s_f$ should be much larger than power of $\beta_1 s_m + \beta_3 n$, which means the contribution of mECG and noise is very

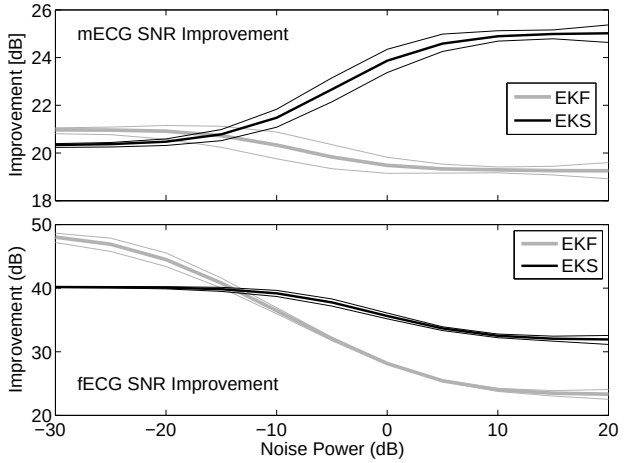

Figure 2. Mean SNR improvement results of the EKF and EKS against input noise power (bold lines) . Upper and lower borders (thin lines) present maximum and minimum, respectively.

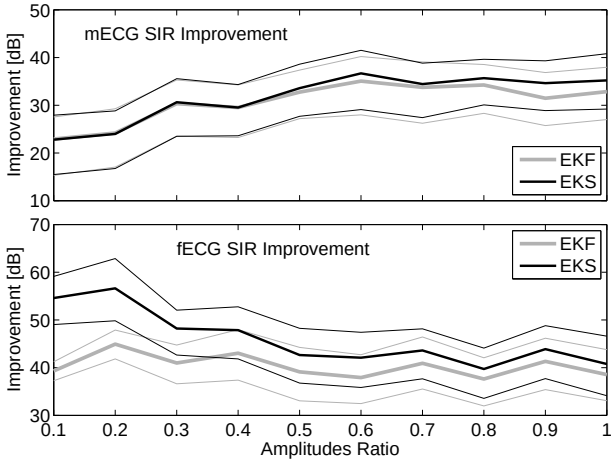

Figure 3. Mean SIR improvement results of the EKF and EKS against amplitude ratio (bold lines). Upper and lower borders (thin lines) present maximum and minimum, respectively.

low in the fECG estimate. In the same manner, the power of $\alpha_1 s_m$ should be much larger than power of $\alpha_2 s_f + \alpha_3 n$ in mECG extraction. In order to quantize contribution of the desired ECG in the output, output Signal to Noise Ratio (SNR) for maternal and fetal ECG are defined as:

$$\begin{aligned} SNR_{m_{out}} &= \frac{\hat{\alpha}_1^2 P_{s_m}}{\hat{\alpha}_2^2 P_{s_f} + \hat{\alpha}_3^2 P_n}, \\ SNR_{f_{out}} &= \frac{\hat{\beta}_2^2 P_{s_f}}{\hat{\beta}_1^2 P_{s_m} + \hat{\beta}_3^2 P_n}. \end{aligned} \tag{7}$$

where P_{s_m}, P_{s_f}, and P_n denote power of mECG, fECG, and noise, respectively. Output SNR is now compared to input SNR to investigate performance of desired ECG extraction. Input SNRs are defined as:

$$SNR_{m_{in}} = \frac{P_{s_m}}{P_{s_f} + P_n} \quad \text{and} \quad SNR_{f_{in}} = \frac{P_{s_f}}{P_{s_m} + P_n} \tag{8}$$

Input Signal to Interference Ratio (SIR) and output SIR are also defined as:

$$\begin{aligned} SIR_{m_{in}} &= \frac{P_{s_m}}{P_{s_f}}, \qquad SIR_{f_{in}} = \frac{P_{s_f}}{P_{s_m}}, \\ SIR_{m_{out}} &= \frac{\hat{\alpha}_1^2 P_{s_m}}{\hat{\alpha}_2^2 P_{s_f}}, \quad SIR_{f_{out}} = \frac{\hat{\beta}_2^2 P_{s_f}}{\hat{\beta}_1^2 P_{s_m}}. \end{aligned} \tag{9}$$

1) SNR Analysis: Figure 2 shows SNR improvement results of EKF and EKS over a wide range of input noise power. The SNR improvement in dB is defined as the output SNR of the filter minus the input SNR. In all trials, power of mECG signals is normalized to 1 (0 dB) and the ratio of amplitudes of fECG and mECG is 0.3. Maternal and fetal heart rates are set to 1.1 Hz and 2 Hz, respectively. Moreover, in order to have more realistic signals, mECG and fECG are allowed to have slight random fluctuations (5%) in amplitude and duration at each beat. Moreover, initial phases of ECGs are random. As it can be seen in Figure 2, both EKF and EKS successfully improved the SNR for all ranges of the input SNRs. When the mixture is rather noise free (noise power -30 dB) the minimum SNR improvement of fECG is 40 dB, which means efficient cancellation of mECG. Nevertheless, even for very noisy mixtures (noise power 20 dB), the SNR improvement of fECG remains over 20 dB. According to this figure, EKF is more effective when a rather clean signal is available. However, as power of noise increases, EKS significantly outperforms EKF. As it has been explained in the previous section, the EKS algorithm consists of a forward EKF stage followed by a backward recursive smoothing stage. Therefore, if a rather clean signal is available, the recursive smoothing stage will deteriorate EKF output, because the output is smooth enough and recursive smoothing leads to over-filtering. Conversely, if the signal is very noisy, EKF output is not denoised enough yet. Therefore, recursive smoothing stage can be successfully used to cancel more noise from the signal.

2) Amplitude Ratio Analysis: The basic problem of fECG monitoring is to extract the fECG signal from the mixture of mECG and fECG signals, where the interfering mECG is a stronger signal. Therefore, it is necessary to evaluate the performance of the method for different ratios of fECG and mECG amplitudes. For this purpose, SIR improvement of output signals have been calculated in the range of 0.1 to 1 of amplitude ratio of fECG and mECG. Figure 3 shows SIR improvement results of the EKF and EKS for different values of amplitude ratios. Power of mECG signals are normalized to 1 (0 dB) with 5% random fluctuation, input SNR with respect to (w.r.t.) mECG is 10 dB, and average maternal and fetal heart rates are 1.1 Hz and 2 Hz, respectively. As it is seen in Figure 3, although the fetal SIR improvements of both EKF and EKS remain over 30 dB for all ranges of the amplitude ratios, results of EKS are slightly better.

3) Heart Rate Ratio Analysis: Since fetal heart rate may vary in a wide range [28], the performance of the method was studied on a wide range of 0.3 Hz to 3.6 Hz of fetal heart rate. Figure 4 shows SIR improvement results of EKF and EKS. Power of mECG signals are normalized to 1 (0 dB) with 5% random fluctuation and the ratio of amplitudes of fECG and mECG is 0.3. Input SNR w.r.t. mECG is 10 dB, and maternal heart rate is set to 1.1 Hz. In this section, heart

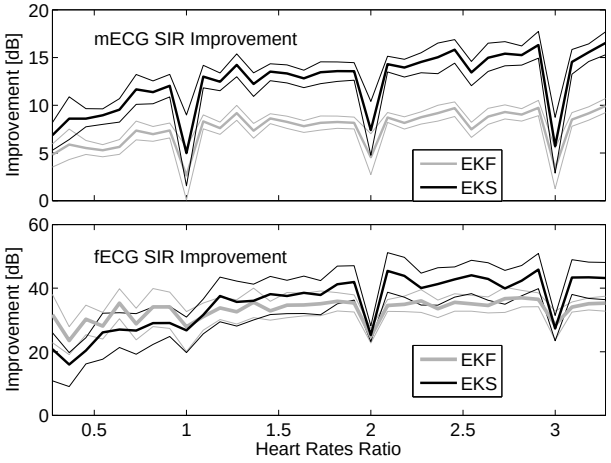

Figure 4. Mean SIR improvement results of the EKF and EKS against heart rate ratio (bold lines). Upper and lower borders (thin lines) present maximum and minimum, respectively.

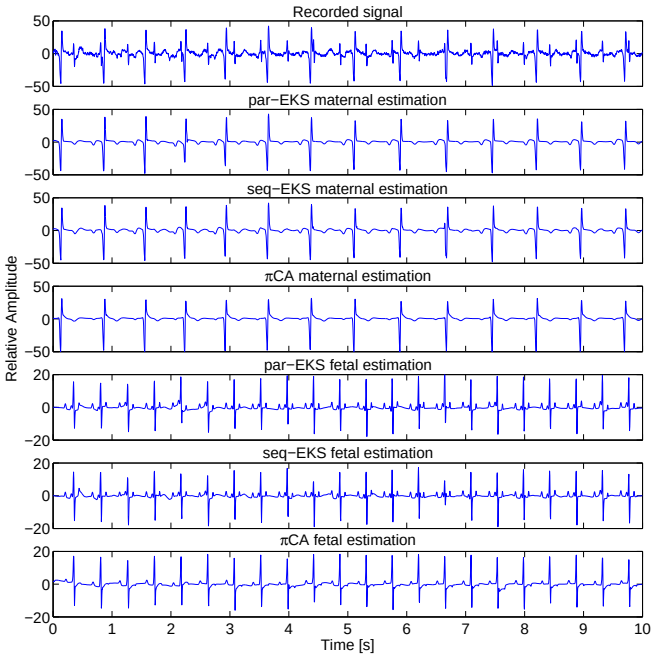

Figure 5. Comparison of fECG extraction by par-EKS, seq-EKS and πCA on the first channel of DaISy data.

rate fluctuations are slighter (1%) to study harmonic issues more accurately. As expected, SIR improvement diagram has three deep local minima at ratios 1, 2 and 3. The reason is that when main frequencies of mECG and fECG are proportional, the signals overlap more closely in the frequency domain. Therefore, discrimination of mECG and fECG is more difficult for these ratios. Nevertheless, these situations are unlikely happening because the heart rates ratio is usually more than 1 and less than 2. Even in these cases, fetal SIR improvement remains over 20 dB. Here again, EKS slightly outperforms EKF.

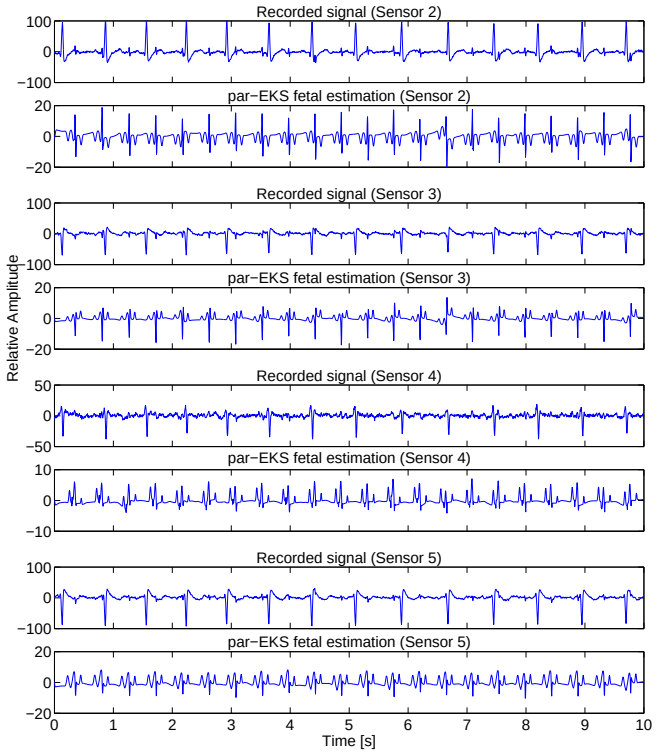

Figure 6. Results of fECG extraction using par-EKS applied on channels 2 to 5 of the DaISy dataset (up to down). Note differences of scales, according to the channels and the fetal estimates.

B. Fetal ECG Extraction on Actual Data

In the previous subsection, efficiency of the proposed method in fECG extraction for a wide range of possible configurations has been examined using synthetic data. In this subsection, the results of application of the proposed method on actual data are presented.

1) DaISy Database: The DaISy fetal ECG database [29] consists of a single dataset of cutaneous potential recording of a pregnant woman. A total of 8 channels (5 abdominal and 3 thoracic) are available, sampled at 250 Hz and lasting 10 seconds.

Figure 5 presents the results of par-EKS and seq-EKS using the first channel of the dataset. Moreover, the periodic component analysis (πCA) [8] using the height channels, which is a multi-channel method, is also included as the golden standard. Results of πCA method are then post-processed via EKS on the best ECG estimate [23]. As already mentioned, unlike seq-EKS, par-EKS does not fail when mECG and fECG fully overlap in time. This is particularly noticed between t = 6s and t = 7s in Figure 5 in which, some parts of fECG signal have been deteriorated during mECG extraction by the seq-EKS method. On the contrary, the proposed par-EKS jointly models the fECG and mECG, resulting in a better estimate of fECG than seq-EKS. Since par-EKS estimates a single component while πCA can estimate several components (typically one or two), the cosine between subspaces is used, and is equal to 0.92 in this experiment. With a value closed to 1, these estimates are quite similar. Finally, Figure 6 shows the results of fECG extraction using par-EKS applied on the other

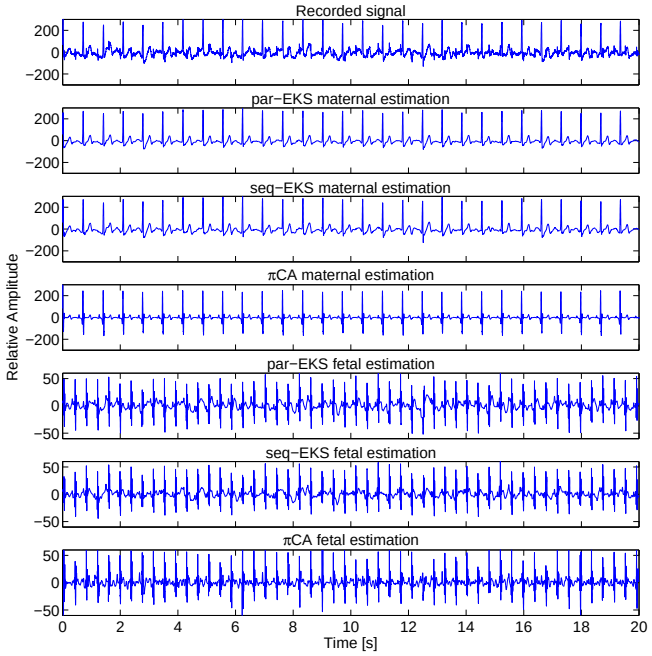

Figure 7. Comparison of fECG extraction by par-EKS, seq-EKS and πCA on ecgca771 of the PhysioNet database.

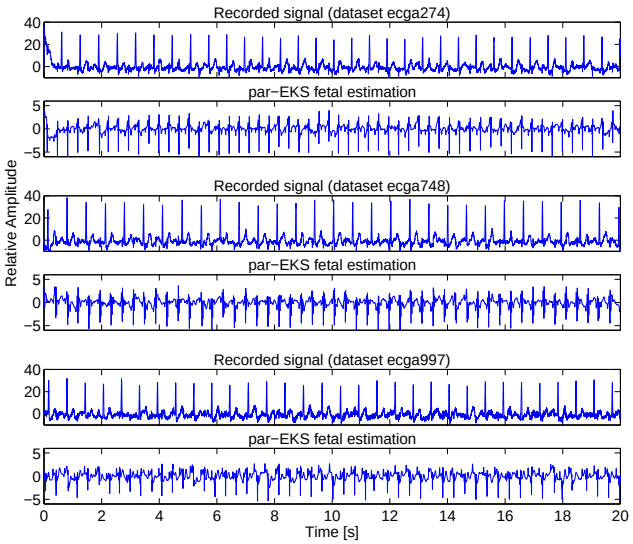

Figure 8. ECG mixtures of the datasets ecgca274 channel 5, ecgca748 channel 4, and ecgca997 channel 3 and their fetal par-EKS outputs.

abdominal channels of the DaISy dataset. It experimentally proves that par-EKS is able to extract fECG even in ill-conditionned mixtures, such as channels 4 or 5.

2) Non-Invasive Fetal Electrocardiogram Database: This database consists of a series of 55 multichannel abdominal fECG recordings, taken from a single subject between 21 to 40 weeks of pregnancy. The recordings include 2 thoracic signals and 3 or 4 abdominal signals. The signals were recorded at 1kHz, 16-bit resolution with a bandpass filter (0.01Hz-100Hz) and a main notch filter (50Hz) [30]. Figure 7 shows results of seq-EKS and par-EKS using channel 3, and πCA using all channels of the first 20s of namely the ecgca771 dataset. To show the effectiveness of the proposed method in extraction of the fECG at different periods of pregnancy, and from different channel locations, the first 20s of the mixtures and fetal par-EKS outputs of the datasets ecgca274 channel 5, ecgca748 channel 4, and ecgca997 channel 3 are plotted in Figure 8.

3) Twin MCGs Extraction: The proposed method has been principally designed for ECG signals. Nevertheless, due to the morphological similarity of the ECG and the magneto-cardiogram (MCG), it is also directly applicable to MCG recordings. In this section, twin fetal cardiac magnetic signals recorded by a SQUID Biomagnetometer system are extracted. The dataset has been recorded in the Biomagnetic Center of the Department of Neurology (Friedrich Schiller University, Jena, Germany) and it consists of 208 channels sampled at 1025Hz over 30 minutes.

Figure 9 presents the results of the proposed par-EKS to extract the two fetal MCG signals from a single sensor. A typical channel (indexed 92) of namely the q00002252 dataset has been selected. Even though the multichannel πCA method provides better results in this case than single channel methods (par-EKS or seq-EKS), the proposed par-EKS succeeds to

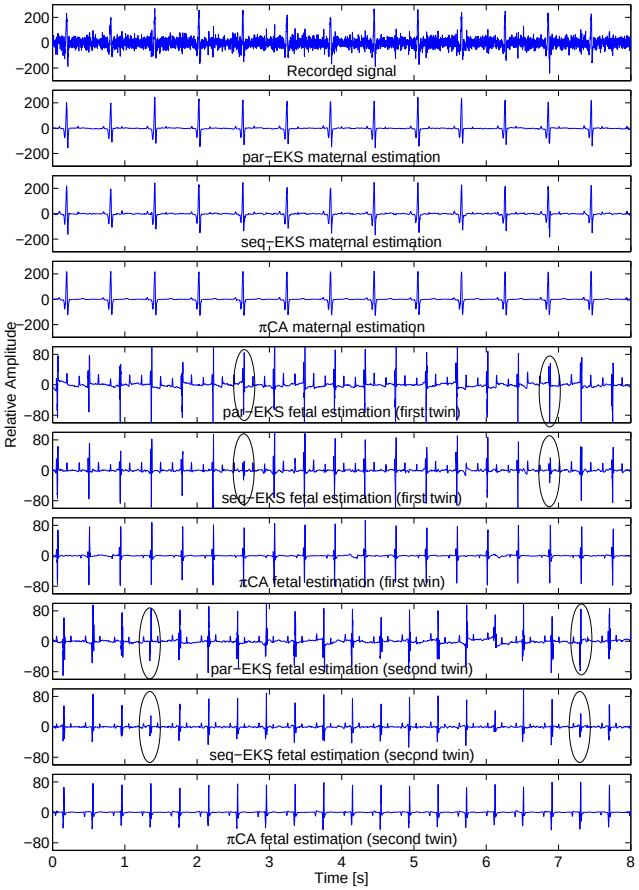

Figure 9. Results of the seq-EKS, par-EKS, and πCA on twin MCG data.

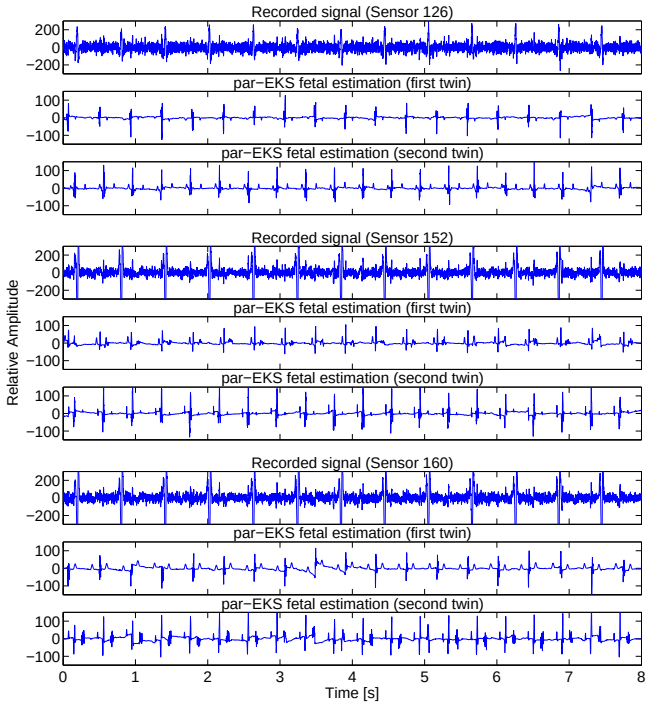

Figure 10. MCG mixtures of the channels 126, 152, and 160 and their fetal par-EKS outputs.

extract the two fetal MCG (fMCG) while seq-EKS fails to discriminate correctly the two fMCGs when they overlap (see highlighted signal parts, Fig. 9). In order to show the good behavior of par-EKS in several configurations, par-EKS is applied on other sensors (Fig. 10). One can note that the proposed par-EKS succeeds to extract the two fetal MCGs.

Finally, it is worth noting that the crucial part of the proposed par-EKS is the R-peaks detection. Although this detection is quite direct when a single fetus is present (Section II-C), some words should be added on twin data. Indeed, on such data the detection of the mother's R-peaks is still direct since it is the dominant signal. On the contrary the discrimination between the two fetal R-peaks is much more difficult. Even though in this study, the oracle is obtained using several sensors and applying an ICA algorithm (here, we used Fast-ICA), it can be replaced in practice by a sound sensor located on the mother's abdomen.

IV. Conclusion

In this paper, a synthetic dynamic ECG model within a KF framework has been extended to jointly model several ECGs to extract desired ECGs from a unique mixture (i.e. one channel recording) of maternal and fetal ECGs and noise. Although the proposed method only uses a single channel to separate different ECGs, since each ECG has a corresponding term in the model, the proposed model can efficiently discriminate ECGs even if desired and undesired ECG waves overlap in time. As proved on synthetic data and illustrated on actual data (single and multiple fetal pregnancy), the main merit of the proposed algorithm relies on its performance in a large class of situations. Performance of the proposed method on extraction of fECG from one mixture of mECG and fECG was examined according to noise level, amplitude ratio and heart rate ratio parameters: results show that the proposed method can be successfully employed in many scenarios. According to the obtained results, as long as R-peaks are correctly detected, the proposed model achieves good results. Although a reliable R-peaks detection is a straight forward procedure in a single fetal pregnancy (which most likely happens) even with a single sensor, it is much more difficult in multiple fetal pregnancy (twin or more). Nonetheless, in these situations, the R-peaks detection can be provided by other modalities such as echocardiography.

Finally, the proposed method compares favorably with efficient multi-sensor methods such as πCA (which also requires reliable R-peaks detection), while it requires only one sensor. The latter criterion is of high interest, since using a single channel does not only mean less electronic components (such as analog to digital converters or amplifiers) and thus a cheaper device, but also a more convenient and portable device for a long term monitoring system or at home since only a single electrode has to be placed on the mother's abdomen.

Perspectives include extension of the proposed method to apply on multichannel (but with a small number of channels, e.g., up to 3 or 4) mixtures of mECG and fECG. Moreover, synchronous echocardiography data can also be used in future works, especially for a reliable R-peaks detection.

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