FETAL ECG EXTRACTION FROM A SINGLE SENSOR BY A NON-PARAMETRIC MODELING

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ABSTRACT

This study deals with fetal ECG and MCG extraction from a single-channel recording. A recently proposed nonparametric model to describe second-order statistical properties of ECG signal, is simplified in this paper to make it computationally faster and easier to implement. In the proposed method an ECG signal is first decomposed to sub-bands, then each sub-band is modeled separately, so less complex model is required. There is no assumption about shape of ECG signal in the model, and experimental results show its high performance on extraction of fetal cardiac signals.

Index Terms— Non-parametric modeling, fetal ECG extraction, single sensor extraction

1. INTRODUCTION

Despite of the rich literature in the field of electrocardiogram (ECG) processing, the extraction of fetal ECG (fECG) from maternal abdominal ECG sensors remains a difficult problem for the biomedical engineering community. Although fetal echocardiography can be used for detecting R-peaks and monitoring the heart status, extracted fECG can provide more information for medical groups. The basic problem is to extract the fECG signal from the mixture of maternal ECG (mECG) and fECG signals and other interference sources. Nevertheless, although fECG is mixed with several sources of noise and interference, the main contamination is the mECG, because of its strong power [1].

The fECG extraction methods can be distinguished based on single or several sensors used in the method. Among several methods in the latter approach, one can quote blind source separation [2], semi-blind source separation [3] and adaptive filtering [4, 5]. In this approach, all the methods exploit the redundancy of the multichannel ECG recordings to reduce mECG and other interference sources. However, even if this reduction has been successful, the exogenous noise cannot be totally canceled in this way [6].

Single sensor methods mainly utilize the quasi repeatability of ECG to extract fECG. A simple solution of the problem is to construct the mECG beat template and subtract it from the original signal. In [7], singular value decomposition of the synchronized maternal beats has been performed to find the mECG template that should be subtracted. Another method [8] is to model the temporal dynamics of mECG signals by a set of state-space equations. Estimated mECG is then subtracted from the mixture to achieve a rough estimation of fECG. Finally, fECG is modeled using similar state-space equations and extracted from the residual signal. As shown in [8], this method is the most efficient among the single sensor based methods. However, as it is mentioned in [9], the method 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. In fact, Kalman filter relies on very strong assumption about state equation that models the dynamical evolution of the unobserved state. Therefore, it demands reliable prior information about the state to perform accurately.

In order to overcome the potential lack of prior information about the system, a preliminary study has recently been done: a nonparametric method to model the second order statistics of the signal instead of the signal itself [10] has been proposed. In other words, the statistical latent process is not directly parameterized as in parametric models (e.g., Kalman filter), but its statistics are parameterized thanks to hyper-parameters. In [10] a very complex class of positive-semidefinite functions is selected to describe the expected second order properties of ECG signal. Conversely in this paper, ECG signal is first decomposed into a few sub-bands, then for each sub-band a simpler class of positive-semidefinite functions is selected. This method considerably simplifies the modeling procedure, while expected second order properties of the ECG signal are still well described.

The rest of this paper is organized as follows. Section 2 presents the non-parametric approach to model ECG. Section 3 describes the proposed algorithm to extract fECG from a single sensor. Finally, the numerical results are given in Section 4 and Section 5 concludes this study.

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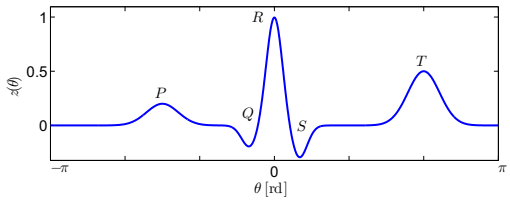


Fig. 1. Typical waveform of one ECG beat.

2. NON-PARAMETRIC MODELING OF ECG

In this section, the previous model [10] is briefly recalled before the description of the proposed modifications for simplifying it.

2.1. Previous non-parametric modeling

By considering the ECG amplitude of a beat $z(\theta)$ as a second order random process, it can be fully described by its mean function $m(\theta) = \mathbb{E}[z(\theta)]$ and covariance function $k(\theta_1, \theta_2) = \mathbb{E}[(z(\theta_1) - m(\theta_1))(z(\theta_2) - m(\theta_2))]$ [11]. As a consequence, the ECG beat $z(\theta)$ is a Gaussian process (GP) $\mathcal{GP}(m(\theta), k(\theta_1, \theta_2))$. Since a ECG beat can be decomposed (mainly) into three parts (Fig. 1), the P wave, the QRS complex and the T wave, which have different characteristics (e.g., temporal correlation and power), the following covariance function has been proposed

$$k(\theta_1, \theta_2) = \sigma(\theta_1)\sigma(\theta_2)\sqrt{\frac{2l_d(\theta_1)l_d(\theta_2)}{l_d(\theta_1)^2 + l_d(\theta_2)^2}} \times \exp\left(-\frac{\left(\theta_1 - \theta_2\right)^2}{l_d(\theta_1)^2 + l_d(\theta_2)^2}\right), \quad (1)$$

with

$$\sigma(\theta) = a_m + (a_M - a_m)\exp\left(-\frac{(\theta - \theta_0)^2}{2\sigma_T^2}\right),$$

$$l_d(\theta) = l_M - (l_M - l_m)\exp\left(-\frac{(\theta - \theta_0)^2}{2\sigma_l^2}\right),$$

where $\sigma(\theta)$ and $l_d(\theta)$ allow to have a time-varying power (between a_m and a_M) and a time-varying length scale correlation (between l_m and l_M), respectively. The full ECG is modeled as a repetition of beats and is thus also a Gaussian process, whose covariance function is given by

$$k_s\big(t, t'\big) = \sum_{n=1}^{N}\sum_{n'=1}^{N} k\big(t - \tau_n, t' - \tau_{n'}\big), \quad (2)$$

where $\{\tau_n\}_{1\leq n\leq N}$ is the set of R peak instants that can be estimated easily from the raw signals.

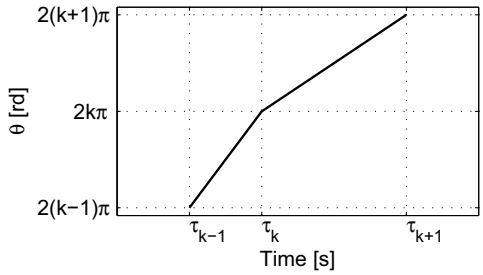


Fig. 2. Illustration of the time wrapping: each heart beat is linearly wrapped into a 2π interval.

Even if this model has been shown to be efficient [10], it suffers from several drawbacks. Indeed, to fit well the specifications of an ECG beat, it requires many parameters leading thus to a quite complicated model, particularly a time varying length scale correlation $l_d(\theta)$. As a consequence, it is tricky to optimize all the parameters. Moreover, from a computational point of view, the double summation into (2) is quite CPU intensive.

2.2. Proposed modeling of ECG

To overcome the drawbacks of the previously proposed model (2), some modifications are proposed both to simplify the model and to lead to a less computationally intensive algorithm.

The model is thus modified in two ways. Firstly, to avoid a time varying length scale, the recordings are decomposed into several parts thanks to a filter-bank: in each subband, the length scale correlation is considered as a constant. Secondly, to avoid too large computational cost, the R peak detection is then used to wrap the time into a linear phase from 0 to 2π for each heart beat: $\theta(t)$ is defined such that each interval $[\tau_k, \tau_{k+1})$ is mapped into interval $[2(k-1)\pi, 2k\pi)$ (Fig. 2). The ECG signal $s(t)$ is then decomposed by a filter bank into several signals $s_i(t)$. Each of them can then be wrapped to 2π quasi-periodic signals $z_i(\theta)$ thanks to $\theta(t)$. In each subband, i, this wrapping allows to use the periodic covariance function defined by the following expression

$$k_s^{(i)}(t, t') = \gamma^2(i)\exp\left(-\frac{\sin^2\Big(\big(\theta(t) - \theta(t')\big)/2\Big)}{l_d^2(i)}\right), \quad (3)$$

where i refers to the i-th subband, $\gamma^2(i)$ and $l_d(i)$ are the power, and the length scale of the sub-signal $s_i(t)$, respectively. It is worth noting that this covariance function allows to fit well *quasi-periodic* signals as ECG thanks to the linear wrapping $\theta(t)$. Moreover, using such a nonparametric model, no assumption is made about the shape of the ECG signals but its (quasi-) periodicity and its smoothness which are defined by $\theta(t)$ and $l_d(i)$, respectively.

3. FETAL EXTRACTION FROM A SINGLE SENSOR

Suppose that the observed signal $x(t)$ is the superposition of the mECG $s_m(t)$, the fECG $s_f(t)$ and an additive noise $n(t)$:

$$x(t) = s_m(t) + s_f(t) + n(t). \quad (4)$$

Moreover, assume that these three signals are all pairwise uncorrelated. Finally, thanks to the proposed modeling of ECG signals (Section 2.2), maternal and fetal ECGs are modeled as GPs $\mathcal{GP}(0, k_m^{(i)}(t,t'))$ and $\mathcal{GP}(0, k_f^{(i)}(t,t'))$ in each subband, respectively, where covariance functions are defined by (3). The additive noise is modeled as a zero-mean GP whose covariance function $k_n^{(i)}(t,t')$ is given by

$$k_n^{(i)}(t,t') = \sigma_n^2(i) \exp\left(-\frac{(t-t')^2}{2l_n^2(i)}\right) + \sigma_w^2(i)\delta(t-t'), \quad (5)$$

where $\delta(\cdot)$ is the delta Dirac function, $\sigma_n^2(i)$ and $l_n(i)$ are used to model a smooth baseline and $\sigma_w^2(i)$ is the power of a white Gaussian noise.

In each subband, the set of hyper-parameters $\boldsymbol{\phi}(i) = \{\sigma_n^2(i), l_n(i), \sigma_w^2(i), \gamma_m^2(i), l_{d,m}(i), \gamma_f^2(i), l_{d,f}(i)\}$ are estimated by maximizing the evidence (log marginal likelihood) given by

$$\log p\big(\mathbf{x}^{(i)} | \{T_k\}_k, \boldsymbol{\phi}(i)\big) = -\frac{1}{2}\mathbf{x}_i^T \big(K_m^{(i)} + K_f^{(i)} + K_n^{(i)}\big)^{-1}\mathbf{x}_i - \frac{1}{2}\log\Big|K_m^{(i)} + K_f^{(i)} + K_n^{(i)}\Big| - \frac{M}{2}\log(2\pi), \quad (6)$$

where $\{T_k\}_k$ is the set of recording times, $K_\cdot^{(i)}$ is the covariance matrix whose (p,q)-th entry is $k_\cdot^{(i)}(T_p, T_q)$, $\mathbf{x}_i = [x_i(T_1), \cdots, x_i(T_M)]^T$ and M is the number of recorded samples. With GP modeling, the $s_{m,i}(t)$ and $\mathbf{x}_i$ are jointly Gaussian distributed [12]. Consequently, the estimation of mECG in the i-th subband, which maximizes the posterior distribution of the i-th subband of the given recording, $\mathbf{x}_i$, is then given by

$$\hat{s}_{m,i}(t) = \mathbf{k}_m^{(i)^T}\Big(K_m^{(i)} + K_f^{(i)} + K_n^{(i)}\Big)^{-1}\mathbf{x}_i, \quad (7)$$

where $\mathbf{k}_m^{(i)} = [k_m^{(i)}(t,T_1), \cdots, k_m^{(i)}(t,T_M)]^T$. In the same way, fECG in the i-th subband is estimated by

$$\hat{s}_{f,i}(t) = \mathbf{k}_f^{(i)^T}\Big(K_m^{(i)} + K_f^{(i)} + K_n^{(i)}\Big)^{-1}\mathbf{x}_i, \quad (8)$$

where $\mathbf{k}_f^{(i)} = [k_f^{(i)}(t,T_1), \cdots, k_f^{(i)}(t,T_M)]^T$.

Finally, the full estimation of signals are given by the summation over subbands

$$\hat{s}_m(t) = \sum_{i=1}^{I} \hat{s}_{m,i}(t), \quad (9)$$

$$\hat{s}_f(t) = \sum_{i=1}^{I} \hat{s}_{f,i}(t). \quad (10)$$

The full algorithm is described in Fig. 3.

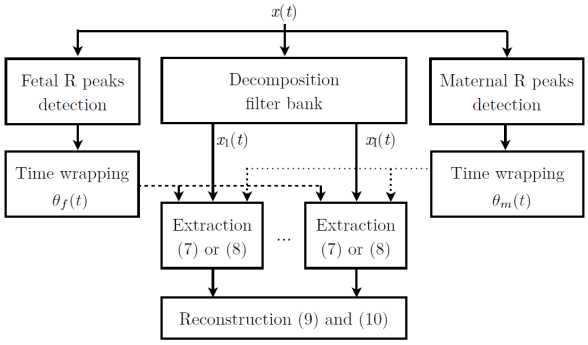


Fig. 3. Algorithm to extract fetal ECG from a single sensor.

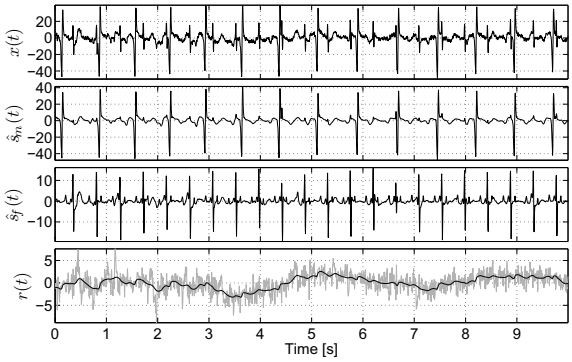
4. RESULTS

4.1. Fetal ECG extraction

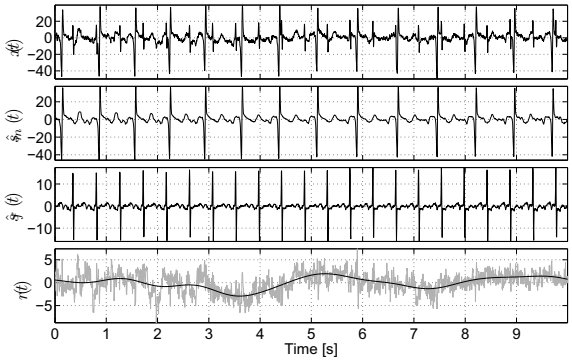
The DaISy fetal ECG database [13] has been used to examine the performance of the method on actual data. The database consists of five abdominal and three thoracic channels recorded from the abdomen and chest of a pregnant woman with a sampling rate of 250 Hz. In this work, only the first channel of this dataset is used and decomposed in 0-30 Hz, 30-60 Hz and 60-125 Hz sub-bands to apply proposed method. Fig. 4 shows results of the sequential Kalman filtering method [9, Ch. 5, p. 50] and the proposed method for mECG and fECG extraction on this dataset. In the sequential Kalman filtering method, a synthetic dynamic ECG model within an Extended Kalman Filtering (EKF) framework has been used. This framework has been applied in two steps on the mixture of mECG and fECG to extract fECG. The first step is extraction of mECG, considering fECG and other noises as a unique Gaussian noise and the second step is subtraction of mECG from original signal and extraction of fECG from the residual signal. As it is seen in Fig. 4, unlike sequential Kalman filtering method, proposed methid does not fail when mECG and fECG waves fully overlap in time. It can be seen in Fig. 4(a) that between t = 6s and t = 7s, sequential Kalman filtering method fails to discriminate between maternal and fetal components. Therefore, some parts of fECG signal have been deteriorated during mECG extraction. Whereas, temporal overlapping did not lead to deteriorating desired signals in the proposed method, because unlike Kalman filtering method which directly parameterizes ECG signals, in the proposed method statistics of ECG signals are parameterized.

4.2. Twin fetal MCG extraction

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

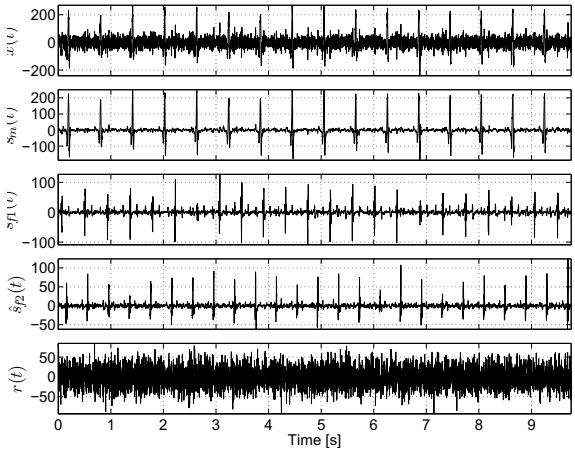


(a) Sequential Kalman filtering

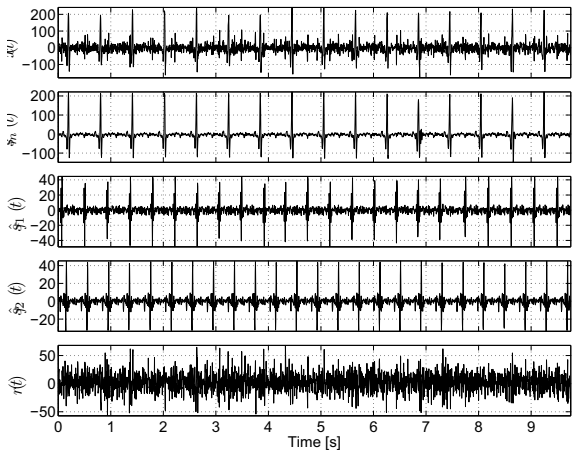


(b) Proposed method

Fig. 4. Fetal ECG extraction from a single sensor.



(a) Sequential Kalman filtering



(b) Proposed method

Fig. 5. Twin fetal MCG extraction from a single sensor.

Department of Neurology, in Friedrich Schiller University, Jena, Germany [1]. It consists of several sets of magnetocardiogram (MCG) and other signals, in arrays of 208 channels recorded over 30 minutes, with a sampling rate of 1025 Hz. The current results have been achieved on the ninety second channel of one of the available datasets, namely the *q00002252* dataset. The signal is first resampled using *resample* MATLAB function, then decomposed to 0-30 Hz, 30-60 Hz and 60-125 Hz sub-bands. Fig. 5 shows results of the sequential Kalman filtering method and proposed method on the first 10000 samples of the data. Comparison between Fig. 5(a) and Fig. 5(b) shows that here again sequential Kalman filtering method fails when maternal and twin MCG waves overlap in time (e.g. between t = 1s and t = 2s, and between t = 6s and t = 7s), while the proposed method does not fail.

5. CONCLUSIONS AND PERSPECTIVES

In this study a simpler nonparametric model has been proposed to describe second-order statistical properties of ECG signal. This model, which is in fact simplified version of a recently proposed nonparametric model, leads to a less complex optimization problem with less number of parameters. Therefroe, it is computationally faster and easier to implement. This nonparametric method models the second order statistics of the signal instead of the signal itself. In other words, since the statistical latent process is not directly parameterized, there is no assumption about shape of desired signals. Therefore, it can effectively be used even if signals overlap in time. Future work is further modification of the model and performance comparison with multichannel methods.

6. REFERENCES

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