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EXTRACTION OF FETAL ECG USING ADAPTIVE VOLTERRA FILTERS

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ABSTRACT

In this paper we present a new method for extracting the fetal electrocardiogram (FECG) signal from one thoracic ECG signal and one or more abdominal signals. Our method is based on the use of an adaptive Volterra filter (AVF) that is capable of synthesizing the nonlinear relation between the mother thoracic ECG signal and the abdominal signals which contains a transformed mother ECG, the fetal ECG and other noise elements. An adaptive multi-sensory noise canceler structure is adopted for the extraction purpose. In the case where more than one abdominal signals are used, the proposed algorithm uses a linear combiner (LC) to form a primary signal from those abdominal signals. The LC and the AVF are updated by the RLS algorithm. The proposed method is applied to real ECG measurements to demonstrate its superior effectiveness.

1. INTRODUCTION

Fetal Electrocardiogram (FECG) provides important information about the health of the fetus and helps a lot in the assessment of the fetus heart condition during pregnancy. The FECG is derived by use of cutaneous ECG electrodes attached to the mother's abdomen and chest regions. However, the recorded signals from the abdomen electrodes are dominated by the mother ECG, where the power of the FECG doesn't exceed 20% the power of the maternal ECG in these signals. In addition, there are different sources of additive noise in the recorded ECG signals, such as power line interference, base line variation, and the mother respiration and electromyographic (EMG) signals.

Several approaches have been proposed to solve this problem, such as adaptive filtering, auto and cross-correlation based methods, blind source separation, singular value decomposition, wavelet transform and so on [1-5]. Blind source separation (BSS) methods proposed so far assume linear relation between the thoracic ECG and the maternal ECG (MECG) part in the abdomen signals. BSS methods are also based on the assumption that the noise and the ECG signals are stationary. However, it has been verified that the relation between the thoracic ECG and the maternal ECG part in the abdominal signals is of nonlinear nature [6]. Furthermore, usually neither the ECG signals nor the additive noise are stationary. Recently there have been a lot of efforts to solve the problem of FECG extraction using nonlinear approaches such as neural network [6], nonlinear state space projection [7] and so on.

In this paper we present a new method for the extraction of the FECG signal using one thoracic signal (a recording of the mother ECG) and one or more abdominal signals. The presented method proposes the use of an adaptive Volterra filters (AVF) to synthesize the nonlinear relation between the mother ECG in the thoracic signal and the mother ECG portion in the abdominal signal. An adaptive multi-sensory noise canceler (ANC) structure [8,9] is adopted. In the case where multiple abdominal signals are used, the proposed algorithm uses a linear combiner (LC) to form a primary noise signal from the abdominal signals for the multi-sensory ANC system. This LC assigns an adaptive weight for each signal. The parameter of the AVF and the LC are updated using the RLS algorithm such that the estimated FECG signal or the error signal of the ANC system indicates a better waveform than that produced by the conventional ANC using a single best abdominal signal.

This paper is organized as follows. The proposed algorithm is presented in Section 2. Simulation results with real data are presented in Section 3, and finally Conclusion is given in Section 4.

2. ADAPTIVE VOLTERRA FILTERING (AVF) ALGORITHM

2.1 Problem formulation

In this paper we propose the use of the ANC system with multi-sensory signals developed in [8] for the extraction problem being considered. This noise canceler structure is shown in Fig. 1. The problem of extracting the FECG can be formulated as follows. Assume that we have access to one thoracic signal $m_R(k)$ and one or more abdominal signals $d_i(k), i = 1,2,\ldots,l$, where l is the number of abdominal signals. The thoracic signal $m_R(k)$ is assumed to contain mainly the mother ECG, while the abdominal signals are assumed to follow a simplified model:

$$d_i(k) = g_i f(k) + m_i(k), \;\; i = 1,2,\ldots,l, \tag{1}$$

where $g_i, \;\; i = 1,2,\ldots,l$ are unknown scaling coefficients, $f(k)$ is the original fetus signal, $m_i(k)$ is the maternal ECG part which is uncorrelated with the original fetus signal $f(k)$. The signals are assumed to be related to the thoracic signal $m_R(k)$ through a set of filters as follows.

$$m_i(k) = H_i \, m_R(k), \;\; i = 1,2,\ldots,l, \tag{2}$$

where $H_i, \; i = 1,2,\ldots,l$ are either linear or nonlinear. The aim is to design an appropriate filter $\mathbf{w}$ that provides an optimal estimation of the desired FECG signal $f(k)$ at the output of the noise cancelation system shown in Fig. 1.

In this paper we propose the use of a second order AVF of length N for the adaptive filter $\mathbf{w}$. The output of a second order AVF filter of length N at time instant k is defined by

$$\begin{aligned}\hat{m}(k) &= \sum_{i=0}^{N-1} w_1[i] m_R(k-i) \\ &\quad + \sum_{j=0}^{N-1}\sum_{i=0}^{N-1} w_2[i,j] m_R(k-i) m_R(k-j) \\ &= \mathbf{w}^T(k)\bar{m}_R(k),\end{aligned} \tag{3}$$

where

$$\begin{aligned}\mathbf{w}(k) &= [w_1(0,k), w_1(1,k), \ldots, w_1(N-1,k), w_2(0,0;k), \\ &\quad w_2(0,1;k), w_2(0,N-1;k), w_2(1,1;k), \\ &\quad \cdots, w_2(N-1,N-1;k)]^T\end{aligned}$$

and

$$\begin{aligned}\bar{m}_R(k) &= [m_R(k), m_R(k-1), \ldots, m_R(k-N+1), m_R^2(k) \\ &\quad m_R(k)m_R(k-1), \ldots, m_R(k)m_R(k-N+1), \ldots, \\ &\quad m_R^2(k-N+1)]^T,\end{aligned}$$

are the AVF input and coefficient vectors, respectively.

To estimate the original source signal $f(k)$ as indicated in Fig. 1, one needs to use the LC with a parameter vector $\mathbf{v} = [v_1, v_2, \ldots, v_l]$ and an input vector that includes the abdominal signals $d_i(k), i = 1, 2, \ldots, l$, as elements to form a primary noise signal $d(k)$ as follows:

$$d(k) = \sum_{i=1}^{l} v_i d_i(k), \tag{4}$$

with a natural constraint

$$\sum_{i=1}^{l} v_i = 1. \tag{5}$$

The ANC output is then given by

$$\hat{f}(k) = \sum_{i=1}^{l} v_i d_i(k) - \hat{m}(k) = d(k) - \hat{m}(k), \tag{6}$$

The task now is to estimate the coefficients of the adaptive filter $\mathbf{w}$ and the weight parameter vector of the LC $\mathbf{v} = [v_1, v_2, \ldots, v_l]$ providing that only the signals $d_i(k), i = 1, 2, \ldots, l$ and $m_R(k)$ are known.

2.2 Simultaneous adaptation of the LC and the AVF

The ANC system with multi-sensory signals shown in Fig. 1 operates toward a goal of minimizing the output or error signal power subject to the constraint given in Eq. (5). This leads to the Lagrangian [8]

$$L = \frac{1}{2}\sum_{j=1}^{N} (\mathbf{v}^T \mathbf{d}(j) - \hat{m}(j))^2 + \lambda(\mathbf{v}^T \mathbf{e} - 1)) \tag{7}$$

where

$$\begin{aligned}\mathbf{d}(k) &= [d_1(k), d_2(k), \ldots, d_l(k)]^T, \\ \mathbf{e} &= [1, 1, \ldots, 1]^T,\end{aligned} \tag{8}$$

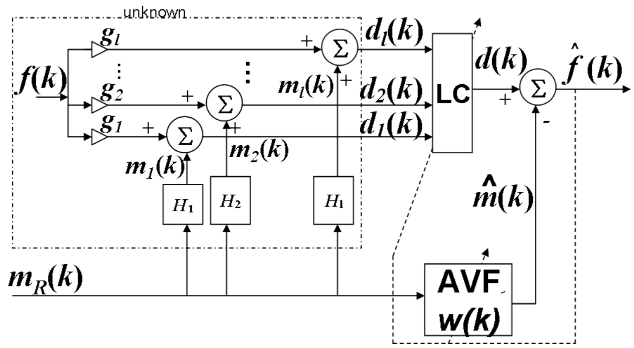

Figure 1: A multi-sensory adaptive noise canceler for FECG extraction.

and λ is a non-negative Lagrange multiplier.

Finding an optimal solution to the Lagrangian (7) can be achieved if one uses the RLS algorithm to update the weights of the LC and the parameters of the AVF. The AVF update procedure is carried out as follows:

$$\begin{aligned}\mathbf{w}(k) &= \mathbf{w}(k-1) + \frac{\mathbf{Q}^{-1}(k-1)\bar{m}_R(k)}{\alpha + \bar{m}_R^T(k)\mathbf{Q}^{-1}(k-1)\bar{m}_R(k)}\hat{f}(k) \\ \mathbf{Q}^{-1}(k) &= \frac{1}{\alpha}\cdot\mathbf{Q}^{-1}(k-1) - \\ &\quad \frac{1}{\alpha}\cdot\frac{\mathbf{Q}^{-1}(k-1)\bar{m}_R(k)\bar{m}_R^T(k)\mathbf{Q}^{-1}(k-1)}{\alpha + \bar{m}_R^T(k)\mathbf{Q}^{-1}(k-1)\bar{m}_R(k)},\end{aligned} \tag{9}$$

where $\mathbf{Q}(k) = \sum_{k=1}^{M} \bar{m}_R(k)\bar{m}_R^T(k)$, M denotes the number of observations, and α is a forgetting factor.

Similarly, for the update of the weights of the LC, the least square estimation is derived as

$$\tilde{\mathbf{v}} = \left(\sum_{j=1}^{M} \mathbf{d}(j)\mathbf{d}^T(j)\right)^{-1} \times \left(\sum_{j=1}^{M} \mathbf{d}(j)\hat{m}(k)\right), \tag{10}$$

and a covariance matrix is given by $\mathbf{P} = \sum_{j=1}^{M} \mathbf{d}(j)\mathbf{d}^T(j)$.

At time instant k, the covariance matrix $\mathbf{P}$ can be represented by

$$\begin{aligned}\mathbf{P}(k) &= \sum_{j=1}^{k-1} \mathbf{d}(j)\mathbf{d}^T(j) + \mathbf{d}(k)\mathbf{d}^T(k) \\ &= \mathbf{P}(k-1) + \mathbf{d}(k)\mathbf{d}^T(k).\end{aligned} \tag{11}$$

The LC weight vector $\mathbf{v}(k)$ is tuned by the RLS algorithm as follows.

$$\begin{aligned}\mathbf{P}^{-1}(k) &= \mathbf{P}^{-1}(k-1) - \frac{\mathbf{P}^{-1}(k-1)\mathbf{d}(k)\mathbf{d}^T(k)\mathbf{P}^{-1}(k-1)}{1 + \mathbf{d}^T(k)\mathbf{P}^{-1}(k-1)\mathbf{d}(k)} \\ \tilde{\mathbf{v}}(k) &= \tilde{\mathbf{v}}(k-1) + \frac{\mathbf{P}^{-1}(k-1)\mathbf{d}(k)}{1 + \mathbf{d}^T(k)\mathbf{P}^{-1}(k-1)\mathbf{d}(k)}\hat{f}(k) \\ \mathbf{v}(k) &= \tilde{\mathbf{v}}(k) - \mathbf{P}^{-1}(k)\frac{\mathbf{e}^T\tilde{\mathbf{v}}(k) - 1}{\mathbf{e}^T\mathbf{P}^{-1}(k)\mathbf{e}}\mathbf{e}.\end{aligned} \tag{12}$$

Note that this procedure is fully adaptive and able to track changes in the input signals. It has been shown in [8] that the minimal value of the cost function defined by the error or output signal of the ANC system shown in Fig. 1, which can be achieved by Eqs. (9) and Eqs. (12), will be always not larger than the one achieved for a single abdominal signal setting.

It should be noted that other adaptive algorithms such as LMS or normalized LMS can also be used instead of the RLS; however we have used here the RLS to insure faster convergence and good steady-state performance.

3. EXPERIMENTAL RESULTS

In our experiments we use real ECG data to evaluate the performance of the proposed algorithm. The ECG data used in our work were downloaded from the database developed by De Moor [10]. The measured signals are 10 seconds long in time and their sampling frequency is 250 Hz.

To evaluate the performance of the proposed method and to highlight the usefulness of using polynomial Volterra filter as well as LC for multi-reference signals, we compare the performance of three methods. The first is the method proposed in Section 2 with five (5) abdominal signals and one thoracic signal. We call this method multi-reference Volterra RLS algorithm (MRVRLS). The second method is the same as the first one but with one abdominal signal only and is referred to as VRLS. The third method that uses the ANC with linear FIR filter and RLS algorithm is referred to as LRLS.

A linear FIR filter with length $N = 4$ for LRLS method and a Volterra filter with length 3 for VRLS and MRVRLS methods were simulated. Fig. 2 shows five (5) abdominal signals. Fig. 3 shows the obtained results. As can be visually noticed, the ANC with AVF and one abdominal signal (VRLS) gives better performance than the ANC with linear filter (LRLS). The AVF could better synthesize the mother ECG portion embedded in the abdominal signal. The proposed algorithm MRVRLS with the LC and five (5) abdominal signals provides significantly better performance compared to the LRLS and VRLS. Figs. 4 and 5 show two close parts of the obtained results. As can be seen from these two figures, the MRVRLS could detect the FECG and cancel completely the mother ECG portion even when there is an overlap between the mother ECG and the original FECG.

It should be noted that even though the FECG signals obtained by the proposed technique look much improved compared with those produced by the LRLS and the VRLS algorithms, there is some noise of random nature that still pollutes the estimated waveforms. The technique proposed in [1] may be used to further shake off the noise. The order of the Volterra filter is limited to 2 in our simulations. However, it can be increased at the expense of more computational requirements. The LMS algorithm, rather than the RLS, may be used to update the filter coefficients corresponding to the higher order nonlinear terms of the Volterra filter. More simulations are needed to be conclusive.

4. CONCLUSION

We have proposed a new technique for the extraction of FECG from one thoracic ECG signal and one or more abdominal signals. It has been shown that the use of the nonlinear Volterra filter provides better estimated FECG waveforms because the AVF used is more capable of representing the complicated relation between the mother ECG and the mother ECG portion contained in the abdominal signals. The proposed method also uses an LC that assigns an adaptive weight to each abdominal signal in a way that a better primary noise signal could be formed. Application to real ECG data has revealed the significantly improved effectiveness of our proposed method. Applying the proposed method to a larger data base is a future topic. Modification of the multi-sensory ANC structure adopted in this work is also a future topic for further explorations.

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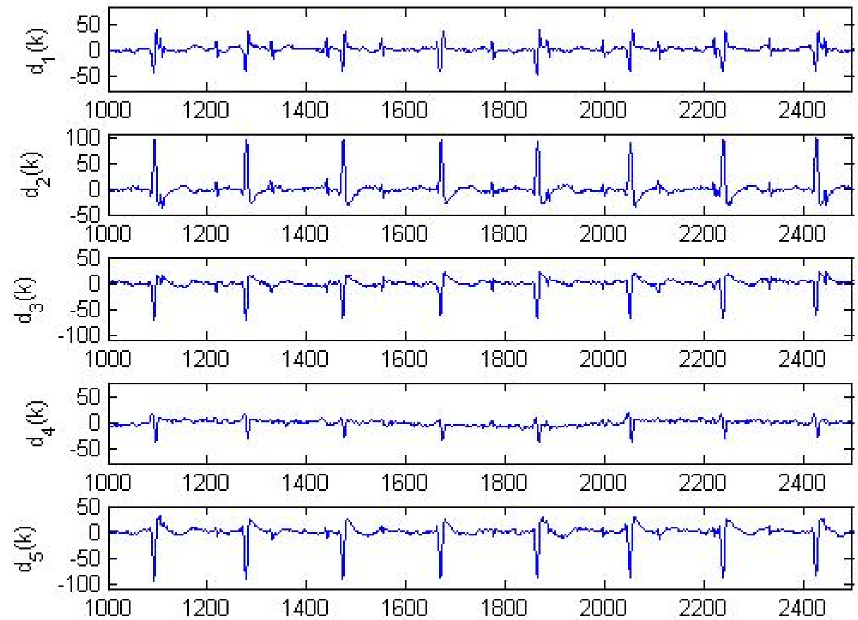

Figure 2: The five (5) abdominal signals used in our simulations.

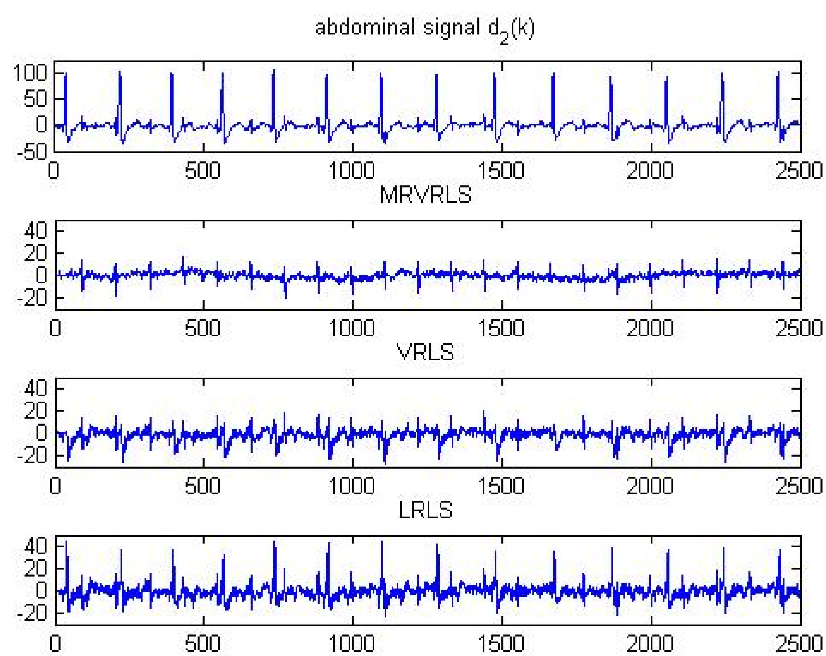

Figure 3: An abdominal signal and estimated FECG signals using the three methods MRVRLS, VRLS, and LRLS.

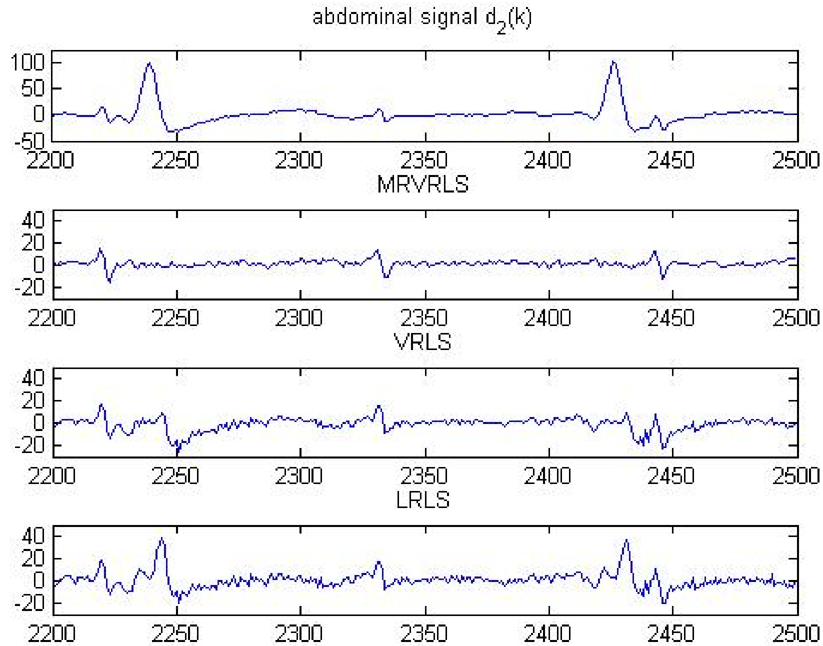

Figure 4: Parts of an abdominal signal and the estimated FECG signals using the three methods MRVRLS, VRLS, and LRLS.

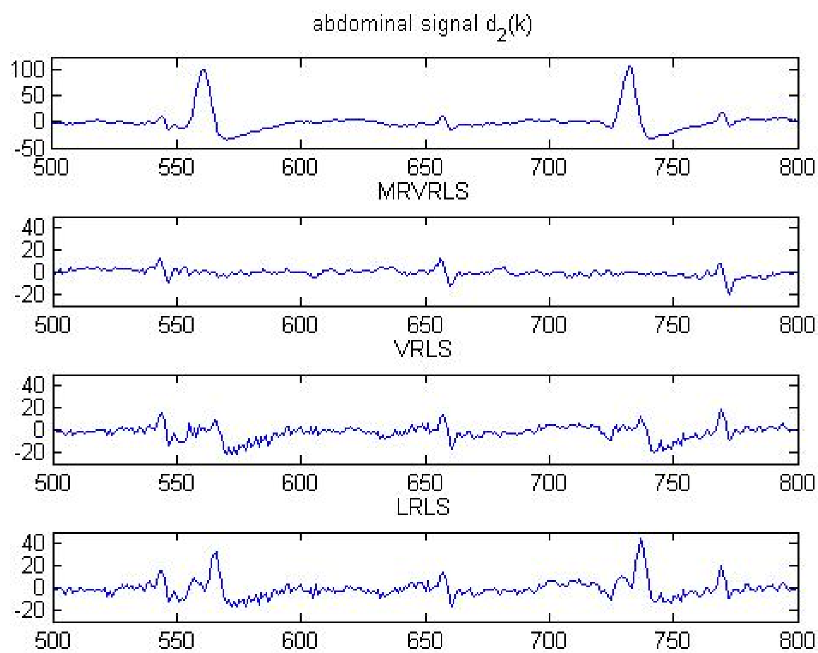

Figure 5: Parts of an abdominal signal and the estimated FECG signals using the three methods MRVRLS, VRLS, and LRLS.