A hybrid nonlinear adaptive noise canceller for fetal ECG extraction

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***Abstract*—In this paper, a hybrid nonlinear adaptive noise canceller (ANC) with single- or multi-reference channels is proposed to perform the task of extracting fetal electrocardiogram (FECG). A Volterra filter and a functional link artificial neural network (FLANN) are equipped in parallel in each reference channel to approximate the linearity and nonlinearity between the maternal ECG (MECG) and its distorted version within the abdominal ECG (AECG). Two (2) real ECG datasets are utilized to demonstrate the improved effectiveness of the proposed ANC as compared with other three (3) existing ANCs using FIR filter, Volterra filter, and FLANN alone.**

I. Introduction

Fetal electrocardiogram (FECG), if available, will provide us with important information that indicates the health status of the fetus and contributes to early detection of fetal congenital heart defects. Extraction of the FECG may be accomplished by using both abdominal ECG (AECG) recordings and maternal ECG (MECG) measurements. The AECG and MECG signals can be acquired by a non-invasive measurement technique.

The FECG signal buried in the AECG signal is severely polluted by a distorted version of the MECG signal as well as some small interferences or noises such as baseline wander, powerline interference, electromyography (EMG), and so on [1], [2]. Moreover, FECG itself presents extremely low magnitude as compared with that of the MECG signal and also indicates non-stationarity due to breath, body movement, etc. of both the mother and the fetus. The extraction task is to eliminate the above-mentioned interferences to obtain a relatively clean FECG estimate by use of multiple thoracic and abdominal recordings.

A vast number of DSP-based techniques have been attempted to conduct the extraction task, such as adaptive filtering, blind source separation (BSS), state space projection, wavelet transform, artificial neural network, etc. The pioneer work by Widrow et al. was based on the use of a linear adaptive noise canceller (ANC) that has multi-reference channels and a single primary one [1]. This ANC-based technique is quite effective and efficient in tracking the normal and abnormal changes with the MECG signal and a distorted version of it that resides in the AECG. However, the accuracy of extraction is inadequate and needs improvement, because in this method the nonlinearity between the MECG and a transformed version of it within the AECG signal was not considered. This nonlinearity was considered by K. Assaleh in [3], etc. Several variants of blind source separation (BSS) algorithm have been successfully applied to the FECG extraction, see, e.g., [4], [5], where multiple AECG and MECG recordings were adopted under the assumption that the relationship between the MECG signal and its transformed version is linear and all signals and noises involved are stationary. These BSS-based techniques are quite effective as compared with the linear ANC proposed in [1], but their computational complexity is considerably high. In [3], a promising technique based on adaptive neuro-fuzzy inference systems (ANFIS) was successfully designed to deal with the nonlinearity. However, many user parameters were introduced and their selection is quite delicate and signal dependent. Initial training is also needed in this technique.

A Volterra filter based ANC was proposed in [6], where both linear and nonlinear mappings between the MECG and the AECG can be approximated. In this ANC, a multi-sensory noise canceller structure is introduced that has a single reference channel and multiple primary signals or channels. The ability of this nonlinear filter to approximate nonlinearity tends to be limited if kernels up to second or third order are used. However, the use of higher order kernels poses heavy computational load, and the improvement of extraction results was not significant according to our experience [6]. Last year, we proposed a functional link artificial neural network (FLANN) based nonlinear ANC to execute the FECG extraction [7]. Though some improvement was obtained, the performance improvement is not enough. The lack of cross terms in FLANN is considered to be a major cause that limits the performance of the FLANN.

In summary, extraction techniques that cope with the nonlinearity are more effective and sophisticated owning to above-mentioned efforts. However, development of more capable and efficient nonlinear adaptive filters is still needed.

In this paper, we propose a hybrid nonlinear ANC where a Volterra filter without 2nd- and higher-order exponential terms and an FLANN possessing only exponential terms are equipped in parallel in each reference channel to implement linear and nonlinear mappings. The Volterra filter and the FLANN have been successfully used in FECG recovery [6], [7], acoustic echo cancellation [8], [9], etc.

The rest of this paper is organized as follows. Section II presents a hybrid nonlinear ANC. In Section III, extensive simulations are conducted by using two (2) real datasets [10],

[11], and some representative results are provided to confirm the effectiveness and capabilities of the proposed nonlinear ANC. Finally, conclusions and future research topics are given in Section IV.

II. Proposed hybrid nonlinear ANC

The AECG signal contains not only the FECG but also some other noises [2], [3]. One of the noises is due to the MECG. The MECG propagates to the abdominal area and dominates the AECG signal. What is more, the transformation from the MECG to its deformed version is of nonlinear nature, and we have no clue to how to model it. It is this unknown nonlinearity that makes the extraction task difficult, complicated, and costly.

Here, we propose a new ANC, as depicted in Fig. 1, where a Volterra filter and an FLANN are equipped in parallel in each reference channel. The Volterra filter usually contains both exponential terms and cross terms. However, in this work the Volterra filter is intentionally set to contain 1st-order exponential and cross terms only, while the FLANN has exponential terms only in its original form. Here, it should be noted that the 1st-order exponential terms in the Volterra filter can not be removed, even though the same terms are also included in the sine functions of the FLANN. This is because the exponential terms in the FLANN are expressed in the form of sine and cosine functions rather than explicit terms. Therefore, in some sense the Volterra filter and the FLANN are complementary to each other. Here, the proposed system is called hybrid nonlinear ANC.

The Volterra filter with 1st- and 2nd-order kernels is widely used in various applications, and the number of kernels used is usually limited to 2 or 3 in order to facilitate its implementation. In contrast, the FLANN is essentially a linear combiner with nonlinear inputs. It is characterized by some orthogonal basis functions [9] like cosine and sine waves, and can express high-order exponential terms. However, no cross term is included in it. Obviously, the proposed hybrid nonlinear ANC possesses simultaneously exponential terms and cross terms, which implies that it might be more powerful than ANCs using FIR or Volterra filter or FLANN alone.

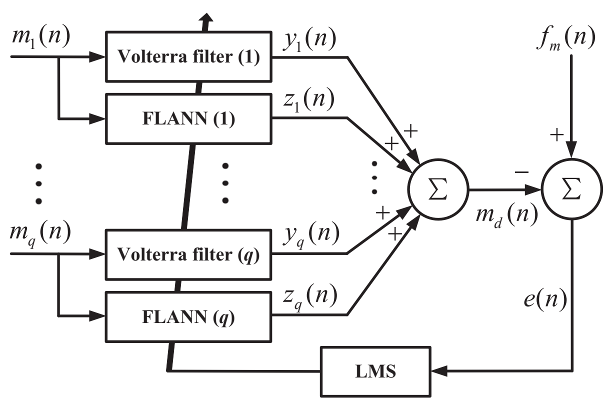

Fig. 1. The proposed hybrid nonlinear ANC structure.

In Fig. 1, the composite AECG signal $f_m(n)$ is regarded as primary input, while there are q MECG signals $\{m_i(n)\}_{i=1}^{q}$ that serve as reference inputs in the ANC. The output of the whole ANC is represented as $m_d(n)$. It should be noted that $e(n)$ is considered as an estimate of the true FECG signal

$$e(n) \quad = \quad f_m(n) - m_d(n). \tag{1}$$

In this work, a Volterra filter with only 1st- and 2nd-order kernels is employed, as we have found from our experience that the use of the 3rd-order kernel does not bring significant performance improvement [6]. The output of the 2nd-order Volterra filter in the ith channel is calculated as

$$\begin{aligned} y_i(n) \quad = \quad & \sum_{j=0}^{L_1-1} w_{1,i,j}(n) m_i(n-j) + \\ & \sum_{j=0}^{L_2-1} \sum_{k=j+1}^{L_2-1} w_{2,i,j,k}(n) m_i(n-j) m_i(n-k) \end{aligned} \tag{2}$$

where $w_{1,i,j}(n)$ and $w_{2,i,j,k}(n)$ are filter weights of the 1st- and 2nd-order kernels, respectively. L_1 and L_2 correspond to the length of the two kernels. It should be noted that the 2nd-order kernel includes only cross terms. The quadratic exponential terms are intentionally removed.

The output of the ith FLANN is expressed by

$$\begin{aligned} z_i(n) \quad = \quad & \sum_{p=1}^{P} \sum_{j=0}^{M-1} \{h_{s,i,p,j}(n) \sin[p\pi m_i(n-j)] + \\ & h_{c,i,p,j}(n) \cos[p\pi m_i(n-j)]\} \end{aligned} \tag{3}$$

where P is the upper bound of expansion order p, and M is the length of each FLANN. Both $h_{s,i,p,j}(n)$ and $h_{c,i,p,j}(n)$ stand for the weights of the ith FLANN. Detailed description of the FLANN structure can be found in [7], [8]. The total output of the reference channels is obtained as

$$m_d(n) \quad = \quad \sum_{i=1}^{q} [y_i(n) + z_i(n)]. \tag{4}$$

In this paper, the LMS-like algorithm is adopted to update all weights of the Volterra filters and FLANNs. First, the weights of the 1st- and 2nd-order Volterra kernels in the ith channel are updated by

$$w_{1,i,j}(n+1) \quad = \quad w_{1,i,j}(n) + \mu_{1,i} e(n) m_i(n-j) \tag{5}$$

$$\begin{aligned} w_{2,i,j,k}(n+1) \quad = \quad & w_{2,i,j,k}(n) + \\ & \mu_{2,i} e(n) m_i(n-j) m_i(n-k) \end{aligned} \tag{6}$$

where $\mu_{1,i}$ and $\mu_{2,i}$ denotes the step sizes of 1st-order and 2nd-order kernels in the ith channel, respectively. Similarly, weight update of the ith FLANN is as follows:

$$\begin{aligned} h_{s,i,p,j}(n+1) \quad = \quad & h_{s,i,p,j}(n) + \\ & \mu_{f,i} e(n) \sin[p\pi m_i(n-j)] \end{aligned} \tag{7}$$

$$\begin{aligned} h_{c,i,p,j}(n+1) \quad = \quad & h_{c,i,p,j}(n) + \\ & \mu_{f,i} e(n) \cos[p\pi m_i(n-j)] \end{aligned} \tag{8}$$

where $\mu_{f,i}$ denotes the step size of the ith FLANN. For simplicity, uniform step sizes (μ_1, μ_2, μ_f,) are used in this work, namely, $\mu_1 = \mu_{1,i}$, $\mu_2 = \mu_{2,i}$, and $\mu_f = \mu_{f,i}$ for $i = 1, 2, \cdots, q$.

III. Simulation results

Two (2) real ECG datasets are utilized to verify the improved effectiveness of the proposed ANC as compared with other three (3) existing ones. Four (4) ANCs are compared in this work. The first ANC is based on the FIR filter [1]. A Volterra filter is adopted in the second ANC [6]. The third ANC uses the FLANN filter [7]. The proposed hybrid nonlinear ANC is the fourth one.

A. The DaISy database

The first real ECG dataset is known as DaISy, which was downloaded from [10]. Its length is 10 seconds and the sampling frequency is 250 Hz. Here the first channel of this dataset was chosen as the single primary input $f_m(n)$. Recordings in channel 6-8 contain three (3) MECG time sequences which were used as reference signals $\{m_i(n)\}_{i=1}^{q}$ in the ANCs.

Extensive simulations were conducted to verify the superior performance of the proposed ANC. The user parameters were adjusted carefully to provide the best performance for each ANC. Some recovery results are shown in Fig. 2. The regressive relation between the normalized primary signal and the normalized MECG $m_1(n)$, and the normalized $m_d(n)$, is illustrated in Figs. 3 and 4, where large values at the extreme right and left of the figure correspond to the peaks of $m_1(n)$ and $m_d(n)$. The last 500 data of each signal were used in those plots.

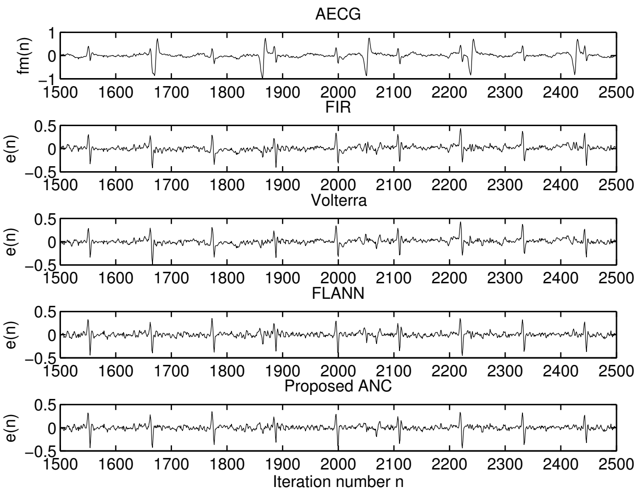

Fig. 2. FECG waves extracted by the four ANCs (DaISy database, FIR-based ANC: $\mu_1 = 0.02$, $L_1 = 75$; Volterra filter: $\mu_1 = 0.02$, $\mu_2 = 0.01$, $L_1 = 75$, $L_2 = 50$; FLANN: $\mu_f = 0.0001$, $M = 35$, $P = 30$, $q = 3$).

As seen from Fig. 2, on the whole, the extracted FECG wave obtained by the proposed technique is visually clearer than those generated by other 3 ANCs. If one takes a close look at the results between iteration number 2400 and 2500, for example, it is easy to find that the influence of maternal beat decreases gradually from the 2nd subfigure to the bottom one. From Figs. 3 and 4, we can see that the proposed ANC results in the strongest linearity of regression. This implies that the proposed hybrid ANC is more capable of approximating nonlinearity than other 3 ANCs.

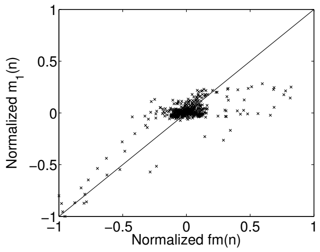

Fig. 3. Regressive relation between $f_m(n)$ and $m_1(n)$ (DaISy database).

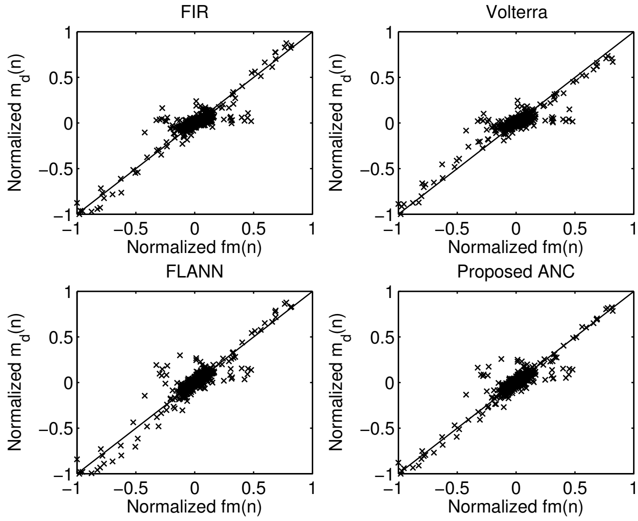

Fig. 4. Regressive relation between $f_m(n)$ and synthesized $m_d(n)$ ($q = 3$, DaISy database).

B. The $nifecgdb$ database

The second real database is the Non-Invasive Fetal ECG Database ($nifecgdb$) [11], which consists of a series of 55 multichannel abdominal FECG recordings taken from a single subject over a period of 20 weeks. One typical dataset named as 'ecgca771' was chosen from this database and utilized to further verify the effectiveness of the proposed nonlinear ANC. The data length (N) is 9500. Two reference channels ($q = 2$) were included in all multichannel ANCs. The recordings in the third channel was used as the primary signal. Again, all user parameters were adjusted carefully such that each ANC could provide its best performance.

The recovery results are shown in Fig. 5. Figures 6 and 7 present the regressive relation between the normalized primary signal and the normalized MECG $m_1(n)$, and the normalized $m_d(n)$, where the last 1200 data from each signal were included in the plots. As one may notice from Figs. 5-7, following insights can be obtained: 1) the FECG signal produced by the proposed ANC is relatively cleaner than other extracted FECG waves, though the FECG itself is still seriously contaminated by the MECG and other additive noises. For example, around iteration number 9000, the FECG wave by the proposed ANC looks the best, even though the fetal and maternal beats overlap in a complete way, 2) the regression plots also reflect the improved effectiveness of the proposed system as compared with other ANCs using FIR filter or Volterra filter or FLANN alone.

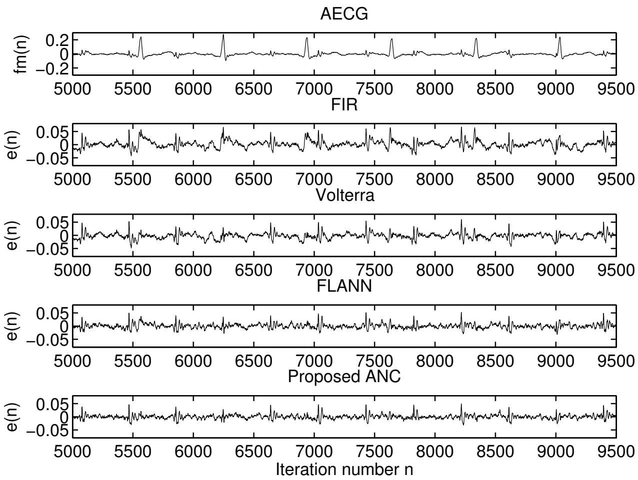

Fig. 5. FECG waves extracted by the four ANCs ($nifecgdb$ database, FIR-based ANC: $\mu_1 = 0.005$, $L_1 = 80$; Volterra filter: $\mu_1 = 0.005$, $\mu_2 = 0.0005$, $L_1 = 80$, $L_2 = 50$; FLANN: $\mu_f = 0.00003$, $M = 80$, $P = 20$, $q = 2$).

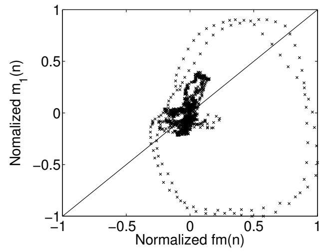

Fig. 6. Regressive relation between $f_m(n)$ and $m_1(n)$ ($q = 2$, $nifecgdb$ database).

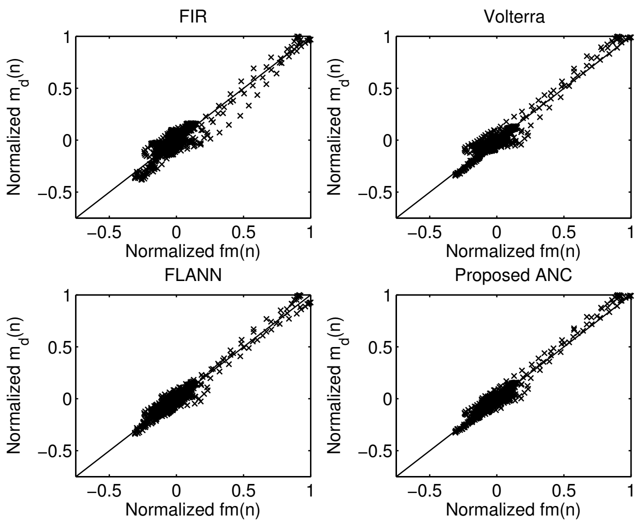

Fig. 7. Regressive relation between $f_m(n)$ and synthesized $m_d(n)$ ($q = 2$, $nifecgdb$ database).

In summary, the FECG signals obtained by the proposed system provide best visual quality as compared with those by the previous ANCs. However, some noise elements still remain in the extracted FECG waves, which make the FECG estimate unclear. Pursuing more powerful nonlinear filters to improve the extraction accuracy is a topic for further research. Introducing some post-denoising technique is also an attractive future research topic.

IV. Conclusions

We have proposed a hybrid nonlinear ANC based on the Volterra filter and the FLANN to extract the FECG from composite AECG signal. A Volterra filter and an FLANN are placed in parallel in each channel in the proposed ANC to cope with the linearity and nonlinearity between the MECG and its distorted version residing in AECG.

Extensive simulations with two different real ECG datasets were conducted. Some representative results demonstrate that the proposed ANC provides the best extraction quality among the four ANCs considered in the simulations. As a result, the new hybrid ANC including both exponential terms and cross terms is more capable of approximating the nonlinearity between the MECG at the chest and a transformed version of it at the abdomen.

Developing more capable and efficient nonlinear filters is an open topic for further research.

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