Fetal ECG Extraction using Adaptive Functional Link Artificial Neural Network

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***Abstract*—In this paper, a nonlinear adaptive noise canceller (ANC) based on the functional link artificial neural network (FLANN) is proposed for extracting fetal electrocardiogram (FECG). The FLANN is placed in parallel with an FIR filter. The two filters are designated to implement the linear and nonlinear mappings between the maternal ECG (MECG) and the composite abdominal ECG (AECG) acquired in the thoracic and abdominal areas, respectively. The AECG is used as the primary signal while the MECG serves as the reference signal in the ANC. The FLANN is essentially a linear combiner with nonlinear input, and thus enjoys many nice properties such as fast convergence, computational efficiency etc. The LMS algorithm is applied to the proposed ANC. Application to a real dataset reveals that the proposed system is quite effective and outperforms previous ANC with only FIR filters.**

I. Introduction

Fetal Electrocardiogram (FECG) presents the electrical activity of fetal heart. The FECG signal is of relatively low voltage and is severely contaminated by maternal Electrocardiogram (MECG) and other noises such as base line wandering, power line interference and electromyography (EMG) signals etc. If one can extract a clean FECG signal from the composite abdominal ECG (AECG) signal(s) recorded in the abdominal area, the fetal health and cardiac defects may be detected and monitored during pregnancy and necessary and appropriate treatments may be performed before delivery.

Extracting the FECG by using of both AECG and MECG recordings is a very difficult task. There are several reasons. Firstly, the FECG is very weak as compared with the MECG. Secondly, it is also seriously contaminated by other noise elements. Thirdly, the MECG portion contained in the AECG is not only linearly but also nonlinearly related to the MECG. Lastly, the FECG itself may also present some non-stationarity.

Despite all of the afore-mentioned difficulties, many approaches have been attempted to extract the FECG. Among those techniques are adaptive filtering algorithms [1], [2], Wavelet transform [3], blind source separation (BSS) [4], polynomial networks [5], artificial neural fuzzy inference system (ANFIS) [6] etc.

As the first successful approach to FECG extraction, a technique based on linear adaptive noise canceller (ANC) and the least mean square (LMS) was developed by Widrow et al. in 1975 [1]. In [4], Zarzoso and Nandi presented a noninvasive FECG extraction technique which uses the BSS technique based on higher-order statistics with multiple chest ECG recordings as well as one AECG recording. Their technique assumes that signal sources of those recordings are statistically independent to meet the requirements of the BSS. This complicated technique is very effective, but computational complexity is considerably high. Assaleh and Al-Nashash proposed polynomial networks to nonlinearly map the MECG signal recorded in the thoracic region to the AECG signal recorded from the abdominal lead [5]. They only adopted one primary channel and one reference channel, and this technique was non-iterative and can be applied to off-line FECG extraction in practice. Recently, a new extraction system, which uses a multi-sensory linear noise canceller with multiple reference channels and multiple primary signals, has been put forward [7]. A method based on the use of an adaptive Volterra filter (AVF) was proposed that is capable of synthesizing the nonlinear mappings between the mother's thoracic ECG signal and the abdominal signal [8]. Experimental results provided in [7] and [8] were very promising, but both approaches require large computational cost due to the use of RLS algorithm.

In this paper, we propose a novel extraction system by using of the unctional link artificial neural network (FLANN). The proposed ANC is equipped with multiple reference channels and a single primary channel. The FLANN has been successfully used in many applications, e.g., nonlinear active noise control [9], [10]. The FLANNs combined with FIR filters are capable of approximating the nonlinear relationship between the original MECG signal and the distorted MECG component. The coefficients of the FLANN and the FIR filters are updated by the LMS algorithm.

The organization of this paper is as follows. In Section 2, a new FECG extraction system is proposed. In Section 3, experiments with real ECG signals are conducted and the analysis of experimental results is provided. Finally, Section 4 presents conclusions as well as topics for future research.

II. A new extraction system based on FLANN

In this paper, a new FECG extraction system is proposed that consists of adaptive FLANN(s) combined with FIR filter(s). This type of nonlinear filter has its advantage over other adaptive nonlinear filters, e.g., kernel adaptive filters in terms of algorithm complexity and performance. The potentialities of this kind of FLANN filters can be explained by the fact that both sine basis functions and cosine basis functions, can be approximated by truncated Taylor series expansions including odd and even powers of the input samples, respectively. Hence adaptive FLANN filters are employed as part of the new FECG extraction system.

The basic formation process of a composite AECG signal is provided in Fig. 1. The original MECG signal travels through kinds of tissues and bodily humors from the chest to the abdominal area. It is usually very difficult, if not impossible, to identify the relationship between the original MECG and its distorted version [6]. This relationship is mainly of linear nature, but also contains some nonlinearity. It is this unknown nonlinearity that makes the extraction task difficult, complicated, and costly.

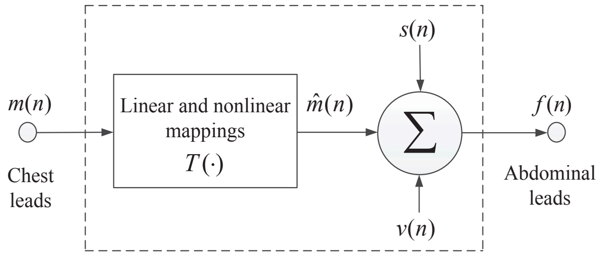

Fig. 1. Formation of an AECG signal.

In Fig. 1, the original MECG is represented by $m(n)$, the deformed version of the MECG is defined as $\hat{m}(n)$ which is derived from a nonlinear transformation of $m(n)$,

$$\hat{m}(n) = T(m(n)). \tag{1}$$

where $T(\cdot)$ indicates the linear and nonlinear mappings between the original MECG and its distorted version. The AECG signal $f(n)$ is a sum of the original FECG signal $s(n)$, the deformed MECG $\hat{m}(n)$ and an additive noise $v(n)$ that embodies various noise elements.

$$f(n) = s(n) + \hat{m}(n) + v(n). \tag{2}$$

In this paper, an ANC equipped with FLANNs and FIR filters is proposed to implement the linear and nonlinear mappings $T(\cdot)$ between the MECG and the composite AECG in Fig. 2. The proposed system has multiple reference channels, with each channel having one FLANN and one FIR filter. There is only one primary channel. This system structure can also be considered as a special case of an ANC developed for multi-sensory signals [11].

In the proposed FLANNs, the trigonometric functional expansion is adopted to process the reference measurements. In this section, the FLANN enjoys many nice properties such as fast convergence, computational efficiency etc. Moreover, the nonlinear expansions satisfy a time-varying property. A compact representation of the expansion function in the mean square sense is given below [9].

$$\{1, \cos(\pi u), \sin(\pi u), ..., \cos(p\pi u), \sin(p\pi u)\}. \tag{3}$$

where u denotes a reference input to the FLANN. The FLANN output depends linearly on the FLANN coefficients. The FLANN structure based on the trigonometric expansion in Fig. 2 is expected to approximate the nonlinear mappings between the MECG and its distorted version.

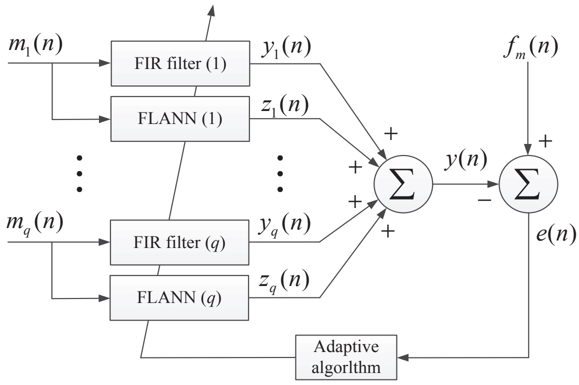

Fig. 2. The new FECG extraction system.

In the new extraction system, the primary signal acquired in the abdominal area is denoted by $f_m(n)$. There are q reference measurements, which are recorded by multiple thoracic leads and are denoted by $m_i(n)$, where i=$1, 2, ..., q$. The ANC output or error of the proposed system is given by

$$e(n) = f_m(n) - y(n). \tag{4}$$

where $y(n)$ is a summed output of all FIR and FLANN filters. The above error signal $e(n)$ may be regarded as an estimate of the original FECG $s(n)$.

In this paper, the LMS algorithm is adopted to update the parameters of the FLANNs and FIR filters. The coefficients of the ith FIR filter are $w_{i,j}$, $i = 1, 2, ..., q$, $j = 0, 1, \cdots, M_1-1$. M_1 presents the length of the FIR filter.

The FIR filter output in the ith channel is calculated by

$$y_i(n) = \sum_{j=0}^{M_1-1} w_{i,j} m_i(n-j). \tag{5}$$

The output of the ith FLANN contains both sine and cosine components that are expressed by

$$z_{s,p,i}(n) = \sum_{j=0}^{M_2-1} h_{s,p,i,j} \sin[p\pi m_i(n-j)]. \tag{6}$$

$$z_{c,p,i}(n) = \sum_{j=0}^{M_2-1} h_{c,p,i,j} \cos[p\pi m_i(n-j)]. \tag{7}$$

where p is the order of expansion ($p = 1, 2, \cdots, P$), P is the upper bound of p, and M_2 is the length of expansion in time domain. The total output of the reference channels can be obtained as

$$y(n) = \sum_{i=1}^{q} y_i(n) + \sum_{i=1}^{q} \sum_{p=0}^{P} [z_{s,p,i}(n) + z_{c,p,i}(n)]. \tag{8}$$

The FIR filter coefficients are updated by the LMS algorithm.

$$w_{i,j}(n+1) = w_{i,j}(n) + \mu_{1,i} e(n) m_i(n-j). \quad (9)$$

where $\mu_{1,i}$ denotes the step size of the ith FIR filter. Similarly, the weights of the ith FLANN are updated by

$$\begin{aligned} h_{s,p,i,j}(n+1) &= h_{s,p,i,j}(n) \\ &\quad + \mu_{2,i} e(n) \sin[p\pi m_i(n-j)]. \quad (10) \\ h_{c,p,i,j}(n+1) &= h_{c,p,i,j}(n) \\ &\quad + \mu_{2,i} e(n) \cos[p\pi m_i(n-j)]. \quad (11) \end{aligned}$$

where $\mu_{2,i}$ denotes the step size of the ith FLANN.

III. Experimental results

In our experiments, the performance of the proposed systems is evaluated by applying it to a real ECG dataset which was developed by De Moor [12]. The recorded signals in this dataset are 10 seconds long, the sampling frequency is 250 Hz, and there are eight (8) cutaneous potential recordings which contain five (5) abdominal ECG and three (3) thoracic ECG signals. An AECG signal as shown in Fig. 3 and three (3) thoracic ECG signals as shown in Fig. 4 are used as primary and reference signals in the proposed ANC system, respectively.

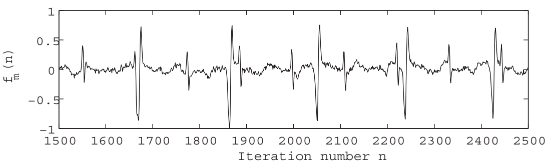

Fig. 3. Later part of an AECG sequence $f_m(n)$.

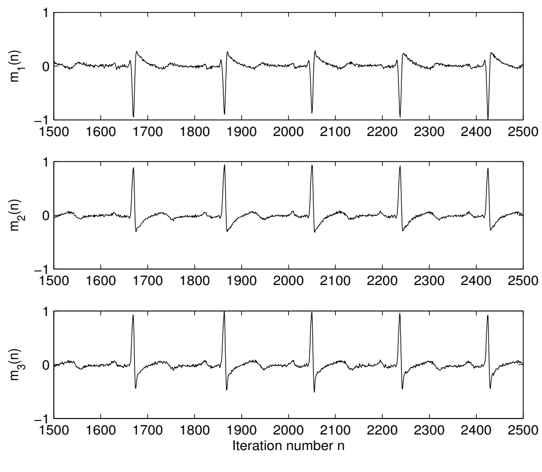

Fig. 4. Later part of three thoracic ECG sequences, ($m_1(n)$, $m_2(n)$, $m_3(n)$).

To verify the effectiveness of the new FECG extraction system, extensive simulations using the above-mentioned real data have been conducted. The representative results to be shown below are divided into four (4) different cases. The FLANN(s) and FIR filter(s) are all updated by the LMS algorithm with different step sizes in the four cases.

In Case 1, there is only one reference channel and only a single FIR filter is used in the ANC. The reference signal is $m_1(n)$. An FLANN is equipped in parallel with an FIR filter in Case 2, where the same reference signal $m_1(n)$ is used.

In Cases 3 and 4, we attempted to incorporate more reference signals to improve the performance of the proposed system. Multiple reference signals ($m_1(n)$, $m_2(n)$, $m_3(n)$, $q = 3$) are used in both cases. In Case 3, only FIR filters are adopted, while multiple FLANNs are also incorporated in Case 4 as shown in Fig. 2.

In all cases, the length of the linear FIR filters (M_1) as well as the expansion length in time (M_2) of the FLANNs were all set to be 75, and the upper bound of expansion order of the FLANNs was chosen as $P = 20$. The selection of values of parameters such as P or step sizes was determined through lots of practical experiments in consideration of computational efficiency and fast convergence. In Case 1 and Case 2, the step sizes of the linear FIR filer(s) and the FLANN(s) were 0.05 and 0.0001, respectively. Fig. 5 shows two estimated FECG signals of Case 1 and Case 2. The step sizes in Case 3 and Case 4 were 0.05/3 and 0.00005 for the FIR filers and the FLANNs, respectively. Estimates of FECG signals in Case 3 and Case 4 are shown in Fig. 6.

As seen from Fig. 3, it is obvious that the FECG and the MECG waveforms overlap in time domain between iteration number 1600 and 1700. Fig. 5 shows that the extraction results obtained in Case 2 are visually clearer to identify than those in Case 1. The FLANN placed in parallel with the FIR filter can improve the performance of FECG extraction even though the FECG and MECG waveforms overlap at some points.

In Cases 3 and 4, multiple reference channels are designated to increase the extraction accuracy. It can be observed that the estimated FECG signal in Fig. 6 is much cleaner than that shown in Fig. 5, for an iteration range between 1600 and 1700. Moreover, the extraction outcome in Case 4 does look better than that of Case 3. For example, on an iteration range between 2400 and 2500, where the FECG and the MECG partially overlap, the extracted FECG in Case 4 may be given a better visual judgment than that of Case 3. This implies that the proposed system outperforms the previous one with only FIR filter(s). That is to say, the use of the FLANN(s) makes the proposed system more capable of coping with the nonlinearity than the FIR filter(s) based extraction system.

To summarize, the experimental results from these four cases demonstrate that, 1) the new extraction system consisting of both FLANN(s) and FIR filter(s) can provide better extraction performance than the conventional technique with FIR filter(s) alone, and 2) the more reference signals are included, the improved FECG extraction one may achieve.

It should be noted that some noise elements still remain in the extracted waveforms, though the quality of FECG signals obtained by the proposed system looks improved as compared with those produced by the conventional FIR filter(s). Furthermore, the expansion length of the FLANNs may significantly increase the computational cost, which inspires us to pursue a fast algorithm for the FLANN in the future.

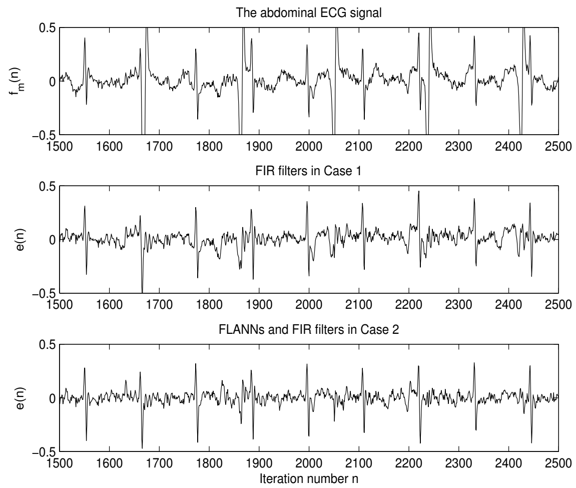

Fig. 5. The estimated FECG signal in Case 1 and Case 2 (LMS, $f_m(n)$, $m_1(n)$).

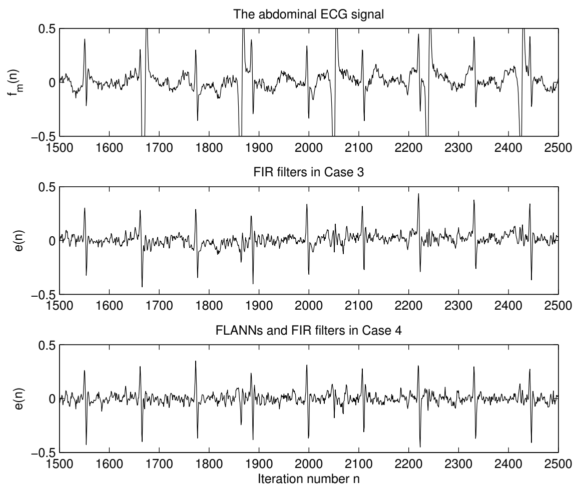

Fig. 6. The estimated FECG signal in Case 3 and Case 4 (LMS, $f_m(n)$, $m_1(n)$, $m_2(n)$, $m_3(n)$).

IV. Conclusions

We have proposed an adaptive nonlinear filter based on the FLANN to extract FECG from the composite AECG signal. The new ANC system consists of both FIR filter(s) and FLANN(s) which are all updated by the LMS algorithm. Application to the Daisy database reveals that the use of the nonlinear FLANN structure provides improved extraction performance as compared with the use of FIR filter alone. That is, the adaptive FLANN filter is more capable of approximating the complex relationship between the original MECG and its transformed version. Extending the proposed system to a case with multiple primary signals is a future topic. Developing a fast algorithm for the FLANN is also an open topic for further research.

Acknowledgments

This work was supported in part by a JSPS Grant-in-Aid for Scientific Research (C) 19560425, Japan. This work was also supported in part by the Program for Interdisciplinary Basic Research of Science-Engineering-Medicine in Harbin Institute of Technology as well as the China Scholarship Council.

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