Fetal ECG Extraction using an FIR Neural Network

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Abstract

Non-invasive electrocardiography reveals itself as a very interesting method to obtain reliable information about the fetus state thus assuring his well being during pregnancy.

In this communication a Finite Impulse Response (FIR) neural network is included in the familiar Adaptive Noise Cancellation scheme in order to provide with highly non-linear dynamic capabilities to the recovery model. A novel methodology for selecting the optimal topology is also presented.

Results from its application to both simulated and real registers are shown and benchmarked with the classical LMS and Normalized LMS (NLMS) algorithms. Outcomes indicate that the FIR network is a reliable method for the fetal electrocardiogram recovery.

1. Introduction

SINCE the early work of Cremer in 1906 [1], various methods for fetal monitoring have been proposed to obtain information about the heart status. Non-invasive electrocardiography reveals itself as a very interesting method to obtain reliable information about the fetus state and thus assure his well being during pregnancy. This technique has the additional advantage that no energy is supplied to the fetus and thus long-term studies could be accomplished. The obtained signals are nevertheless characterized by a great amount of overlapped noise (base-line wander, power line interference, maternal electrocardiogram (MECG), electromyogram (EMG)) and its variability is increased by factors related to gestational age, position of the electrodes, skin impedance, etc. However, the main noise contribution is the maternal electrical activity since its amplitude is much higher than that of the fetus. In addition, the spectra of both maternal and fetal signals overlap; it is consequently not possible to separate them through conventional frequency selective filtering.

Numerous methods have been used for the maternal signal cancellation: substraction of an averaged pattern [2, 3, 4], orthogonal basis functions [5], spatial filtering [6], adaptive filters [7], etc. An early approach to the use of neural networks to FECG extraction was presented in [8] but just a single register was used. In this communication a Finite Impulse Response (FIR) neural network is included in the familiar Adaptive Noise Cancelling (ANC) structure in order to provide with highly non-linear dynamic capabilities to the recovery model. In the next section, we will describe our proposal to FECG recovery from an adaptive filtering perspective. We will also introduce a novel methodology to aid in the identification of the model. The results are then presented in Section 3. Finally, Section 4 contains concluding remarks and a proposal for further work.

2. Material and method

One of the most commonly used approaches to FECG recovery is based on adaptive filters and uses an ANC structure (Fig. 1). The reference input is a thoracic maternal

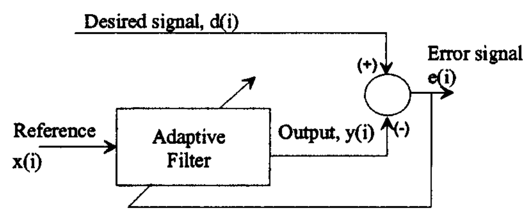

Figure 1. Typical Structure of an Adaptive Noise Canceller

signal which is assumed to be free from fetal contributions, while the desired signal is the abdominal signal. Although the original Widrow's scheme considered several reference signals [7], only one thoracic reference is considered in this work. In this way, all the correlated components (maternal signal) vanish and the FECG register is obtained as the error signal. The essence of such a scheme is the principle of orthogonality [9].

An extension to these adaptive filters is provided by the use of neural networks. The traditional model of a multilayer neural network is composed of a layered arrangement of artificial neurons in which each neuron of a given layer feeds all the neurons of the next layer. A multilayer perceptron extends the use of the static neuron and forms a complex mapping from the input of the first layer to the output of the last layer [10]. It is, nevertheless, a *static* mapping; there are no internal dynamics. In order to introduce dynamic capabilities in a static neural network we have substituted the static synaptic weights by dynamic connections. A temporal extension to the classical multilayer perceptron is accomplished by the FIR network.

2.1. The FIR neural network

The ability of this network to deal with temporal patterns led us to consider its inclusion in the familiar ANC scheme. In this approach, the FIR neural network models the maternal abdominal component from a thoracic reference. The error reference constitutes the recovered fetal signal.

The FIR network models each weight as a basic FIR linear filter [11]. This filter can be modeled with a tapped delay line as illustrated in Fig. 2a. For this filter, the output $y(k)$ corresponds to a weighted sum of past delayed values of the input:

$$y(k) = \sum_{n=0}^{T} w(n)x(k-n). \tag{1}$$

Continuing with notation, the coefficients for the synaptic

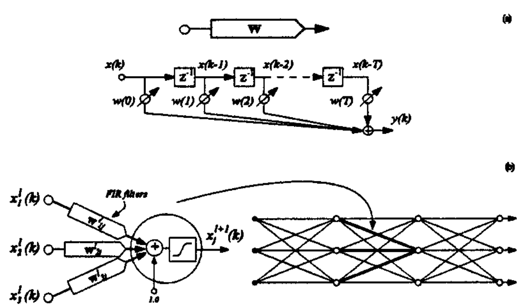

Figure 2. (a) FIR filter model: A tapped delay line shows the functional model of the Finite Impulse Response "synapse" (z^{-1} represents a unit delay operator, i.e., $x(k-1) = z^{-1}x(k)$). (b) FIR neuron and network: input signals are passed through synaptic filters and all connections are modeled as FIR filters.

filter connecting neuron i to neuron j in layer l are specified by the vector $\mathbf{w}_{ij}^l = [w_{i,j}^l(0), w_{i,j}^l(1), ..., w_{i,j}^l(T^l)]$. Similarly $\mathbf{x}_i^l(k) = [x_i^l(k), x_i^l(k-1), ..., x_i^l(k-T^l)]$ denotes the vector of delayed states along the synaptic filter. This allows us to express the operation of a filter by a vector dot product $\mathbf{w}_{i,j}^l \cdot \mathbf{x}_i^l(k)$, where time relations are now implicit in the notation. The output $x_j^{l+1}(k)$ of a neuron in layer l at time k is now taken as the sigmoid function of the sum of all the filter outputs which feed the neuron (Fig. 2b):

$$x_j^{l+1}(k) = f\left(\sum_i \mathbf{w}_{ij}^l \cdot \mathbf{x}_i^l(k)\right) \tag{2}$$

There are striking similarities in appearance between this equation and that of a static model. Notationally, scalars are replaced by vectors and multiplications by vector products. These simple analogies carry through when comparing standard backpropagation for static networks with *temporal backpropagation* for FIR networks [10, 12].

2.2. Identification methodology

It is a common practice to select a FECG recovery model through visual inspection of the algorithm performance. Since the maternal contribution to the abdominal signal is obviously unknown in real registers, a method to generate simulated signals can be adopted. This constitutes a novel methodology for the identification of the model and allows interesting advantages:

1. To define accuracy measures in order to benchmark different models and decide, over a wide range of situations, which one can offer a more robust solution.
2. A great many trainings are thus done and substantial information about the range of optimal free parameters can be obtained.

Synthetic signals, nevertheless, must represent all the real-life conditions and extrapolation to real registers must be verified. This will allow assessment, in principle, of whether the simulated signals are useful or not in the identification of a model.

2.2.1 Synthetic and Real Registers

A MATLAB function has been developed to generate two different abdominal composite signals and a reference thoracic signal from two real registers with two leads each. Its programmable parameters are the fetal/maternal (SNRfm), the fetal/Gaussian noise (SNRfn) and the fetal/electromyogram (SNRfe) signal-to-noise ratios together with the addition of base-line wander (BW) and power line interference (PLI).

SNRfm was varied from -5 to -30 dB with a -5 dB step and the following discrete values of SNRfn were used: {100, 15, 10, 5} dB. Since ECG are usually re-acquired when a high level of SNRfe is obtained, this parameter remained constant (SNRfe = 100 dB); no contribution is then considered. A preprocessing stage is supposed to be applied to registers in order to eliminate the BW and the PLI and thus these parameters are not considered in our simulations. In addition to these simulated signals, we have also used some real registers provided by other authors to validate the methodology.

2.2.2 Network structure selection

The popular cross-validation method has been used to select the optimal network structure and the correlation coefficient (r) has been adopted as a measure of fit. The *temporal backpropagation* algorithm was used to train the networks. Very short trainings (<10 epochs) and low learning rates were used to avoid overfitting since this is a major problem because it may cause the model not to capture the underlying dynamic; it would be unable to recognize masked fetal contributions. A topology of one hidden layer with one input node, M hidden neurons and one output node was selected (1xMx1).

A great many sweeps over the free parameters have been performed in order to get reliable models as independent as possible of the signal features. Weights initialization range, number of hidden neurons, taps per neuron in a layer (i:j), learning rate together with the SNRfm and SNRfn have been varied in the cross-validation process. This process has proven to be more tedious than usual and very expensive computationally with the FIR network because of its complexity; the number of free parameters increases geometrically with the number of inputs, as shown in [11]. In Table 1 the ranges of the training parameters are shown.

Table 1. Parameters used in the training of the models†.

Registers	Models		
	LMS‡	NLMS	FIR Net
Synthetic	L=2:1:100	L=2:1:10	M=2:1:5
			i=j=1:1:5
	μ=0.001:0.002:0.2	μ=0.01:0.01:0.2	μ=0.01:0.02:0.2
Real	L=2:1:10	L=2:1:10	M=2:1:5
			i=j=1:1:5
	μ=0.01:0.01:0.2	μ=0.01:0.01:0.15	μ=0.01:0.02:0.2

† Matlab notation is used as follows `InitialValue:Step:FinalValue`

‡ L indicates the number of taps in the filter and μ represents the adaptive constant.

3. Results

3.1. Synthetic registers

In Table 2 the best results are shown for all synthetic registers. A slight improvement can be appreciated using the FIR neural network compared to the NLMS algorithm, specially significant with low values of SNRfm. However, this improvement locates precisely on the maternal elimination and thus, the recovered signal appears rather cleared from spurious peaks.

In Fig. 3, the models' performance is represented for two synthetic registers. An excellent performance is shown with low SNRfm although when its value is increased, the maternal contribution is not completely removed and a more complex structure is identified for all the models.

Table 2. Correlation coefficient between the extracted and the desired FECG of the identified models with simulated registers†.

SNRfm	SNRfn	LMS	NLMS	FIR Net
-5	100	0.812	0.822	0.900
-5	15	0.817	0.824	0.895
-5	10	0.793	0.815	0.907
-5	5	0.825	0.799	0.900
-10	100	0.701	0.732	0.750
-10	15	0.701	0.733	0.776
-10	10	0.702	0.737	0.772
-10	5	0.705	0.738	0.769
-15	100	0.519	0.809	0.850
-15	15	0.518	0.803	0.844
-15	10	0.522	0.794	0.825
-15	5	0.530	0.846	0.853
-20	100	0.361	0.733	0.770
-20	15	0.364	0.736	0.755
-20	10	0.366	0.737	0.744
-20	5	0.367	0.740	0.746

† Since r degrades as SNRfm increases, only SNRfm < 25 dB are indicated.

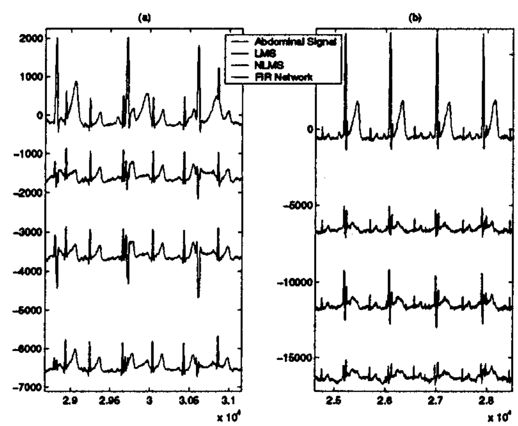

Figure 3. Models' performance for synthetic registers. (a) SNRfm=-5, SNRfn=100 (b) SNRfm=-20, SNRfn=10. Recovered signals are biased to allow proper visualization.

This points out that the more determinant factor in the identification of the models is, reasonably, the SNRfm value. Regarding the NLMS, variability is greater and quite different optimal topologies can be found for the same value of SNRfm. The FIR network works properly in a wide range of parameters, showing its versatility but, unfortunately, it appears difficult to select the best network.

3.2. Real registers

In Fig. 4, the best models' performance is represented for two real registers. The FIR network offers the best solution in the Horner's register since the maternal contribution is successfully removed. Arrow markers indicate some

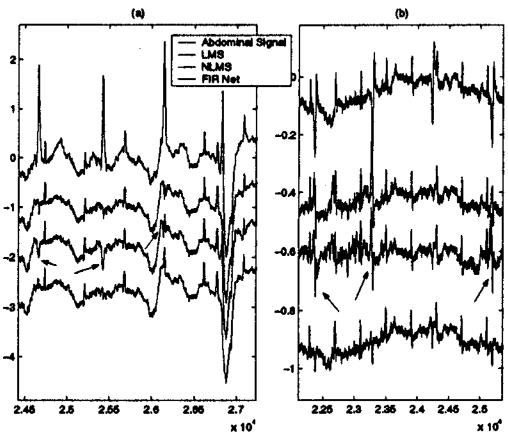

Figure 4. Models' performance for the real registers labeled as (a) `Horner` and (b) `Mex1`.

maternal contributions which are not completely removed by the NLMS algorithm. Regarding the `Mex1` record, all the models showed good recovery levels and, once again, the FIR network highly attenuated the maternal contribution thus smoothing the extracted signal. LMS and NLMS network performed similarly.

Even though training problems can appear and make the model unstable when using a highly complex non-linear model, the FIR neural network has proven to be a well-suited technique for this task, tracing a confident maternal signal. We conclude that the FIR network showed reliable outcomes with simulated and real registers. However, the best topology identified using synthetic registers has not proven to be exactly the optimal one to use with real registers and therefore, simulations of some other real conditions become necessary.

4. Conclusions and further work

In this communication an FIR neural network was included in the familiar ANC structure in order to provide with highly non-linear dynamic capabilities to the FECG extraction model. This network has solved complex situations more reliably than classical adaptive methods. A methodology for topology selection has also been presented.

The future work is tied to the use of more complex dynamic models such as IIR and Gamma networks. In order to completely validate this novel FECG recovery technique and methodology, more real registers must be evaluated. It is also necessary to perform robustness tests using registers with several abdominal leads. These attempts are expected to give a robust method for the FECG extraction.

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