Fetal Electrocardiogram Enhancement by Time-Sequenced Adaptive Filtering

EARL R. FERRARA AND BERNARD WIDROW

***Abstract*—An adaptive method for performing optimal time-varying filtering of nonstationary signals having a recurring statistical character, e.g., recurring pulses in noise, has been proposed. This method, called time-sequenced adaptive filtering, is applied to the enhancement of abdominally derived fetal electrocardiograms against background muscle noise. It is shown that substantial improvement in terms of signal distortion is obtained when time-sequenced filtering, rather than conventional time-invariant filtering, is employed. The method requires two or more abdominal channels containing correlated signal components, but uncorrelated muscle noise components. The location of the fetal pulses in time must be estimated in order to synchronize the filter's time-varying impulse response to the fetal cardiac cycle.**

I. Introduction

Electrocardiograms recorded from the maternal abdomen can, in principle, be used to monitor the electrical activity of the fetal heart from early in pregnancy through delivery. In practice, the fetal electrocardiogram (fetal ECG) is of very low voltage and is frequently obscured by noise. The three main sources of interference are the maternal electrocardiogram (maternal ECG), maternal muscle noise (electromyographic activity in the muscles of the abdomen and uterus), and power-line pickup (60 Hz in the United States). The interfering maternal ECG and the 60 Hz pickup can be greatly reduced by an adaptive noise canceller [1]–[3]. Once the maternal ECG and 60 Hz interferences are removed, the result is the fetal ECG plus muscle noise. The noise can be reduced by the adaptive signal enhancer [4] of Fig. 1. An adaptive digital filter, composed of a tapped delay line and adjustable weights, is the primary component of the signal enhancer. At least two separate abdominal channels with their maternal ECG components cancelled are required. One of these channels is used as the "desired response" input to the adaptive filter; the other becomes the "filter input." Because the fetal ECG signal components are correlated between the two channels, but the interfering muscle noises are derived by surface electrodes spaced sufficiently apart so that they are essentially uncorrelated [5], [6], the adaptive filter attempts to pass the fetal ECG input signal component, while at the same time attenuating the uncorrelated noise. In this way, the mean-square error between the filter output and the desired response can be minimized. The adaptive filter output is a best least squares estimate of the fetal ECG component in the desired response. The fetal ECG components in the two channels need not be identical in waveshape. They only need to originate from a common source, viz. the fetal heart.

Fetal ECG signal enhancing has been attempted [7] using a conventional LMS adaptive filter [8] in the configuration of Fig. 1. Although the background muscle noise was substantially reduced, severe fetal ECG signal distortion was introduced by the least squares smoothing effects of the LMS adaptive filter. This is to be expected for the low SNR's obtained with abdominal recordings (see [4] for a discussion of signal distortion and noise power at the output of an adaptive signal enhancer).

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E. R. Ferrara is with ESL, Inc., Sunnyvale, CA 94086.

B. Widrow is with the Information Systems Laboratory, Stanford University, Stanford, CA 94305.

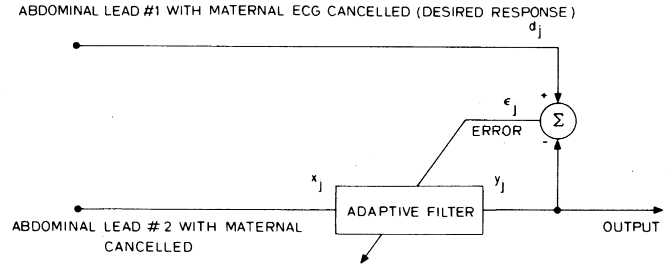

Fig. 1. Adaptive signal enhancer for the fetal electrocardiogram.

The fetal ECG, and more generally all signals composed of recurring pulses in noise, are examples of highly nonstationary signals due to their time-varying statistical character. The LMS adaptive filter, being unable to track such rapidly varying nonstationarities, would essentially converge to the best least squares time-invariant filter. For these signals, an adaptive filter which could exhibit a rapidly varying impulse response may perform in a vastly superior fashion to the LMS adaptive filter. The utility of time-variable filtering to electrocardiographic signals has been suggested in [9].

An adaptive filter has been proposed [10] which is especially suited for the estimation of a class of nonstationary signals having a recurring (but not necessarily periodic) statistical character, e.g., recurring pulses in noise. This new filter, called the time-sequenced adaptive filter, is an extension of the LMS adaptive filter and uses multiple sets of adjustable weights in order to achieve a rapidly varying impulse response.

Fetal ECG pulse shapes vary from beat-to-beat, but have similar properties. If the fetal ECG is modeled as a nonstationary stochastic process, the pulses could conceptually be aligned in time, and statistics could be computed over the ensemble of pulses. Using this model, the statistical properties of the fetal ECG, although not periodic, will repeat from beat-to-beat. We can define a point between pulses for which the statistical properties of the signal renew. These points will be called regeneration times. Each set of weights in the time-sequenced adaptive filter becomes an expert in filtering a particular portion of the interval between statistical regeneration times. For this procedure, an external input to the filter, called the sequence number and denoted s_j, is required to determine the appropriate set of weights to use at time j. Thus, when $s_j = i$, the ith set of weights is used to form the filter output and then is adjusted via an adaptive algorithm. The convergence time of the adaptive filter, in pulses, should be greater than the number of weights per set. The sequence number is reset to zero at the regeneration times. In order to set the sequence number, some *a priori* knowledge of the filter input is required. For pulse-type signals, this *a priori* knowledge could be the location of the pulses in time. A more detailed description of the time-sequenced adaptive filter and its properties can be found in [10] and [7].

II. Fetal ECG Enhancement

After removing the interfering maternal ECG from an abdominal recording with an adaptive noise canceller, there is still a considerable amount of muscle noise remaining. This noise can be significantly reduced without severely distorting the fetal ECG by using the time-sequenced adaptive filter in the signal enhancer of Fig. 1. A time-sequenced adaptive filter is required to ensure optimum performance since the underlying fetal ECG pulses make the input signals highly nonstationary.

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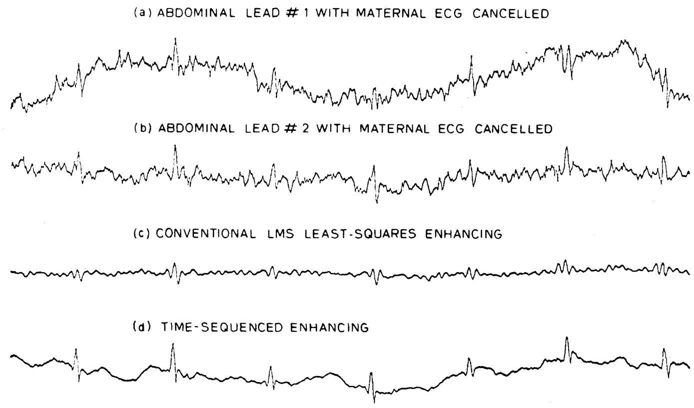

Fig. 2. Comparison of time-sequenced and conventional LMS enhancing of the fetal electrocardiogram.

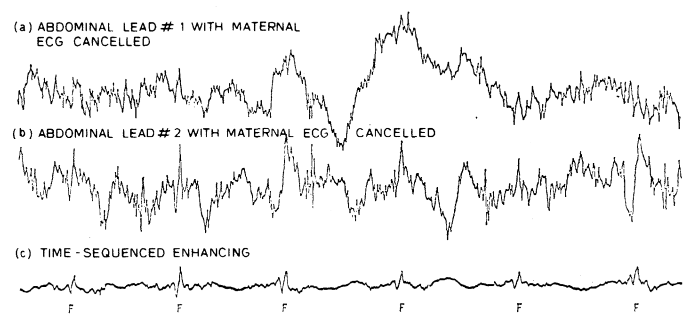

Fig. 3. Time-sequenced enhancing of a fetal electrocardiogram having very poor SNR.

Fig. 2 compares the results obtained using the time-sequenced and LMS adaptive filters in the enhancing configuration of Fig. 1 for a 40-week-old fetus. Two abdominal leads with the maternal ECG previously cancelled by an adaptive noise canceller were used as the inputs to the signal enhancer. The recording bandwidth of the electrocardiograms was 0.5–200 Hz. The sampling interval was 1 ms. The time-sequenced approach requires knowledge of the location of the fetal ECG complexes (the sensitivity to errors in the pulse locations is discussed in [7]). This was accomplished using an approximately matched filter followed by a peak detector (other methods for detecting the peak of the R wave may be found in [11]–[14]). The regeneration times were assumed to occur 150 ms before detected peaks. The sequence number was initialized to zero at the estimated regeneration time and then incremented after each data point until 300 sets of weights had been cycled through. This 300 ms window spanned a distance of approximately ten times the width of the fetal QRS complex, but was less than the time between complexes. A 301st set of weights was used until the next regeneration was detected. Each set contained 75 weights and an adjustable "bias weight" whose input is constant. Fig. 2(d) shows the result of time-sequenced enhancing. Fig. 2(c) shows enhancing by an LMS adaptive filter also having 75 weights and a bias weight. The superiority of the time-sequenced approach is apparent. The time-sequenced enhancing of the fetal ECG does not employ simple beat-to-beat averaging, so that individual variations in pulse shape and beat-to-beat interval are retained. This fact was verified in [10] using synthetic data. Furthermore, time-sequenced enhancing does not involve simple low-pass filtering, so that the individual pulses are sharp in detail.

The time-sequenced enhancing technique has been tested with data in which the interference due to muscle noise is more severe than that in Fig. 2. Fig. 3 shows a result obtained with data having a very poor SNR on both channels 1 and 2. Considering the quality of the data, the output result of Fig. 3(c) is quite remarkable.

III. Conclusion

Application of time-sequenced adaptive filtering to the enhancement of abdominally derived fetal electrocardiograms against background muscle noise has been shown. The method requires two channels containing correlated (but not necessarily identical in waveshape) fetal ECG components and uncorrelated noise components. The adaptive signal enhancer discriminates between the signal and noise on the basis of their channel-to-channel correlation. Even better results might be obtained if the method were extended to handle more than two input channels.

The fetal ECG, and more generally all signals composed of recurring pulses in noise, are examples of highly nonstationary processes. For these signals, an adaptive filter which exhibits a rapidly varying impulse response will perform in a superior fashion than any time-invariant filter. Time-sequenced adaptive filtering has been shown to provide a close approximation to optimal time-varying filtering for these signals [7]. Consequently, time-sequenced enhancing provides a sharper, more accurate estimate of the underlying fetal ECG than does conventional LMS signal enhancing. The time-sequenced approach has the advantage over simple beat-to-beat averaging in that individual variations in pulse shape and beat-to-beat interval are retained.

The principle advantage of adaptive signal enhancing techniques is that the power spectra of the signal and noise need not be known *a priori*. However, the time-sequenced method requires that good estimates be available for the pulse locations in time in order to synchronize the filter regeneration cycle with the fetal cardiac cycle. Better methods of locating the fetal pulse positions may be necessary in order to use the time-sequenced approach with recordings having SNR's lower than that presented here.

The time-sequenced filtering technique might also be applied to the enhancement of other types of electrocardiograms.

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Parameter Estimates in a Five-Element Respiratory Mechanical Model

J. G. EYLES, R. L. PIMMEL, J. M. FULLTON, AND P. A. BROMBERG

***Abstract*—Using four sets of forced random noise impedance data from each of five normal subjects and five patients with obstructuve lung disease, we computed parameter estimates for a three-element series model and a five-element parallel compartment model. For normal subjects, the five-element model provided no better fit to the impedance data than did the simple series model. Estimates obtained from normal subjects using this three-element model were reasonable and reproducible within 25 percent. For all subjects with lung disease, the five-element model provided a significantly ($p \leqslant 0.05$) better fit than the three-element model. Estimates for parameters representing central inertance and resistance, airway compliance, and peripheral resistance were reasonable and reproducible within 18 percent. However, estimates for the compliance of the lung and chest wall were more variable since measured impedance appeared to be insensitive to this parameter in the frequency range used.**

Introduction

The mechanical function of the respiratory system has been characterized by the frequency dependence of its impedance measured during forced sinusoidal and random excitation [1]-[9]. Although the mechanical behavior of the respiratory system is certainly nonlinear and nonstationary, impedance data obtained in this way often are interpreted using linear lumped-parameter models with elements representing resistive, inertial, and compliant effects [5]-[15]. The simplest model is the series resistance, inertance, and compliance combination shown in Fig. 1(a). Although this model fits impedance data from normal adult subjects, it fails to explain impedance data from subjects with lung diseases, and several more complicated parallel compartment models have been proposed to explain such data [16]-[19]. Estimation of the parameters in these more complex models is not straightforward, and iterative minimization algorithms or empirical curve fitting techniques must be employed [7], [12]-[15].

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J. G. Eyles, J. M. Fullton, and P. A. Bromberg are with the Department of Medicine, University of North Carolina, Chapel Hill, NC 27514.

R. L. Pimmel is with the Department of Electrical Engineering, University of Missouri, Columbia, MO 65211.

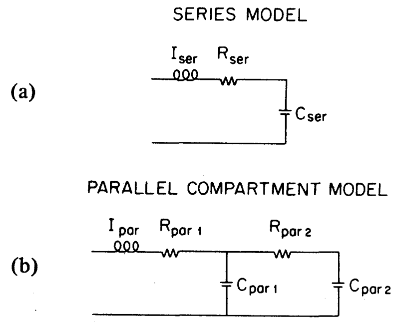

Fig. 1. Respiratory mechanical models.

TABLE I
INDIVIDUAL DEMOGRAPHIC AND SPIROMETRIC DATA

Subject	Age	Sex	Ht. (in)	FEV1/FVC	FVC[a]	FEV1[a]	FEF75-25 Percent[a]
*N*1	24	M	72	0.85	98	100	85
*N*2	25	M	70	0.86	100	105	100
*N*3	31	M	73	0.85	111	116	109
*N*4	23	F	66	0.69	100	97	97
*N*5	22	F	67	0.84	82	88	86
*P*1	66	M	71	0.50	68	47	21
*P*2	37	F	68	0.54	95	59	28
*P*3	41	F	66	0.42	71	33	11
*P*4	59	F	65	0.37	61	28	11
*P*5	39	F	66	0.46	74	40	12

[a]Expressed as a percent of predicted.

In a previous study, we evaluated three parallel compartment models and four iterative parameter estimation algorithms, and we found that the combination of a two-stage simplex algorithm with the five-element model shown in Fig. 1(b) provided the most stable parameter estimates and the best agreement with experimental impedance data in the range 4-35 Hz [15]. The elements in this model may be interpreted as central airway inertance (I_{par}), central airway resistance (R_{par1}), airway compliance (C_{par}), peripheral resistance (R_{par2}), and lung and chest wall compliance (C_{par2}). The present study was undertaken to evaluate the consistency of estimated parameter values with this interpretation and to define the reproducibility of these parameter estimates.

Methods

Five normal nonsmoking adult subjects (*N*1-*N*5) and five patients with obstructive lung disease (*P*1-*P*5) were studied. Pertinent subject data are given in Table I. From each subject we obtained four independent impedance spectra over a period of approximately 5 min using the forced random noise technique previously described [5], [6], [9], [10], and [15]. Briefly, a loudspeaker was coupled to the respiratory system using a mouthpiece and was excited by a random signal with a bandwidth of 4-35 Hz. With the subjects wearing a noseclip and their cheeks supported, 30 s records of the induced pressure and flow signals were recorded and later digitized at 512 samples/s.

Spectral analysis of the digitized signals using 1 s ensembles produced values for the complex impedance as a function of frequency from 4 to 35 Hz at 1 Hz intervals. These data were corrected for the impedance of the bias tubing and the mouthpiece by subtracting the effects of these two impedances, which were measured independently [5], [9].

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