ISSN: 0975-8585

Research Journal of Pharmaceutical, Biological and Chemical Sciences

Fetal ECG Extraction Using ANFIS Trained With Genetic Algorithm.

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ABSTRACT

Nowadays, ICA based methods are widely used. However, ICA needs multiples channels for collecting electrocardiogram signals. One of the most significant advantages of utilizing ANFIS networks in FECG extraction is that the methods require only two record signals, one thoracic signal and one abdominal ECG signal. In the present work, ANFIS network is apply to extract the FECG signal from both ECG signals recorded at the thoracic and abdominal areas of the mother's skin. This can be performing using ANFIS to identify the nonlinear relationship between the maternal component in the abdominal ECG and the thoracic MECG which is assumed to include no fetal component in it. The Technique on both real and synthetic ECG signals will be validated with experiment result. In generating the synthetic abdominal ECG signals, multipath and nonlinear effects apply to the thoracic signal for simulate the transformation and it travels from the heart to the abdomen. Finally, noise can be suppressed by post processing methods such as wavelet de-noising that has proven useful with other FECG extraction methods.

Keywords: FECG; ECG; ANFIS

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INTRODUCTION

Fetal electrocardiography (FECG) gives a prominent method to see the fetal cardiac cycle. Generally two systems have been utilized: the first method is direct, in that the fetal ECG has been recorded with the help of an electrode combined to the scalp. The second method is indirect, in this case the fetal ECG is observed at the maternal abdominal [1], [2] wall. It is more invasive and risky in the previous technique owing to its worst performance. From the literature survey, it is revealed that in the United Kingdom approximately 5 fetuses per 1000 expired unknowingly before birth and 2 per 1000 from congenital abnormally. Therefore, it is a big issue which should be overcome with some prominent method; otherwise, child death rate may increase rapidly. Many techniques have been utilized for extraction of FECG such as independent component analysis, blind source separation [3], [4] and singular value decomposition.

Estimation of the FECG signal is one of the most classical problems in medical engineering. The signal from FECG reflects the electrical activity of the fetal heart and obtained information about health status of the fetus. Concurrently, its extraction can facilitate children's heart disease specialist to analysis the condition and health of the fetus after birth or during delivery. Numerous, active research projects revealed FECG signal processing. Cremer et al. [5] utilized galvanometric equipment to record FECG signal, but owing to the improvement in signal processing techniques, computer science, adaptive filtering techniques and automatic signal processing were used such as adaptive filtering [6], matched filtering [7], least square error fittings [8] IIR adaptive-filtering joined with genetic algorithm [9] have also been utilized for this purpose. In addition, the existing adaptive filtering techniques for maternal electrocardiogram artefact removal need various linearly independent channels approximately reconstruct any morphologic shape from the three references or need a reference maternal ECG channel that is morphologically like to the contaminating waveform [10]. Moreover, the linear decomposition techniques proposed wildly such as singular value decomposition [11], blind source separation [12], and wavelet transforms [13]. In spite of this, linear decomposition methods are very limited for degenerate or nonlinear mixtures of noise and signal. Besides, fetal signals and other noises and interferences are not always linearly separable. Accordingly, prominent aspects of non-linear fetal electrocardiogram signal processing exist such as dynamic neural network [14], fuzzy logic [15], adaptive neuro fuzzy logic technique [16] and polynomial network [17].

Nowadays, ICA based methods are widely used. However, ICA needs multiples channels for collecting electrocardiogram signals. One of the most significant advantages of utilizing ANFIS networks in FECG extraction is that the methods require only two record signals, one thoracic signal [18] and one abdominal ECG signal. Depends on this features of the ANFIS technique, mother can feel more comport. The inspiration behind the present work is to apply ANFIS for estimating the FECG component from one abdominal ECG recording and one reference thoracic MECG signal. We use ANFIS to nonlinearly align the thoracic MECG with the abdominal ECG signal. This nonlinear alignment between the two signals allows for cancelling the maternal component from the abdominal signal and hence offers an estimate of the FECG signal. We show results on both synthetic and real ECG data. We specifically show some analysis and comparative results of the proposed method and two other FECG extraction techniques: Normalized least means squares (NLMS), and polynomial networks.

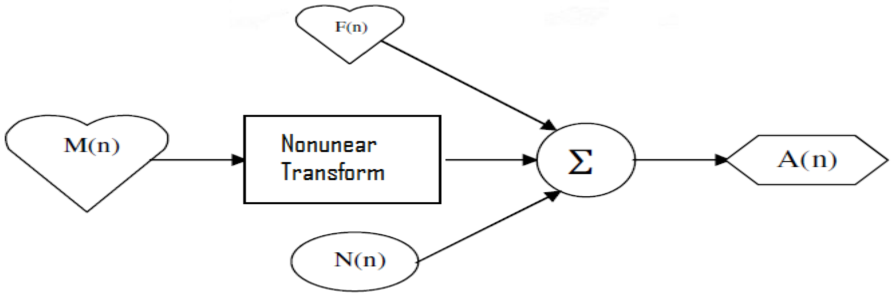

Fig 1. Block diagram of Fetal ECG Extraction

Fig 1shows the basic blocks diagram. The project is organized as follows: we present the formulation of the FECG extraction and demonstrate the need for nonlinear mapping and will briefly review the theory of ANFIS. We describe our proposed solution for FECG extraction using ANFIS which describes the ECG data used for testing the proposed algorithm. It also describes the methodology for modelling nonlinearity in synthesizing the abdominal ECG data. And we demonstrate the performance of the algorithm on both real and synthetic ECG signals.

PROPOSED METHODS

ADAPTIVE NEURO FUZZY INFERENCE SYSTEM (ANFIS)

The ANFIS approach learns the rules and membership functions from data. ANFIS is an adaptive network of nodes and directional inks. Associated with the network is a learning rule - for example back propagation. It is also known as adaptive because some, or all, of the nodes have parameters which affect the output of the node. These networks are learning a relationship between inputs and outputs as shown in Figure 2.

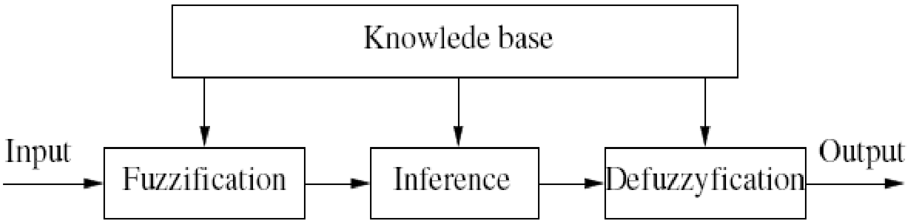

Fig 2. Basic Block Of ANFIS

STRUCTURE OF ANFIS

Adaptive networks cover a number of different approaches. The concentration of the present work is ANFIS. ANFIS architecture is shown in Figure 3. The circular nodes represent nodes that are fixed whereas the square nodes are nodes that have parameters to be learnt as shown in Figure 3.

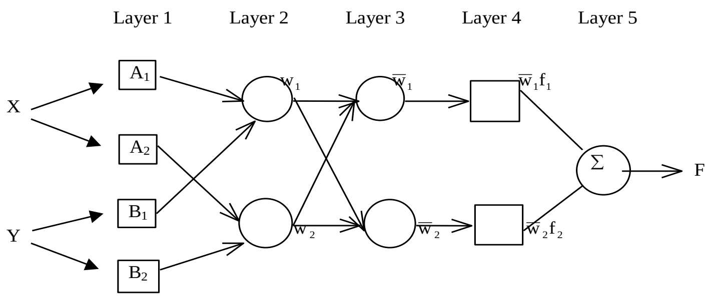

Fig 3. An ANFIS Architecture For A Two Rule Sugeno System

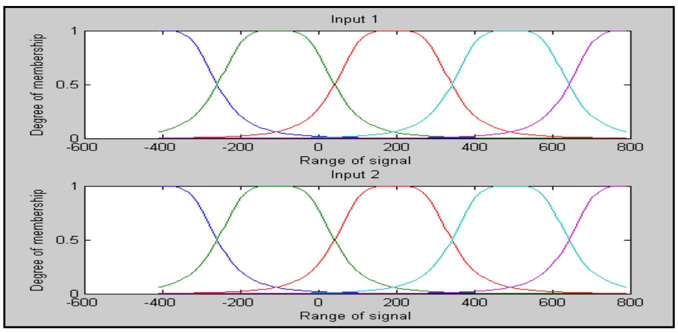

Fig 4. Membership Function

A Two Rule Sugeno ANFIS has rules of the form:

If x is A_1 and y is B_2 then $f_1 = p_1x+q_1y+r_1$
If x is A_1 and y is B_2 then $f_2 = p_2x+q_2y+r_2$

For the training of the network, there is a forward pass and a backward pass. We now look at each layer in turn for the forward pass. The forward pass propagates the input vector through the network layer by layer. In the backward pass, the error is sent back through the network in a similar manner to back propagation.

Layer 1

The output of each node is:

$$O_{1,i} = \mu A_i(x) \text{ for } i=1,2$$
$$\mu_{Bi-2}(y) \text{ for } i=3,4$$

So, the $O_{1,i}(x)$ is essentially the membership grade for x and y. The membership functions could be anything but for illustration purposes we will use the bell shaped function given by

$$\mu_A(x) = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b_i}}$$

where a_i, b_i, c_i are parameters to be learnt. These are the premise parameters.

Layer 2

Every node in this layer is fixed. This is where the t-norm is used to 'AND' the membership grades - for example the product:

$$O_{2,i} = w_i = \mu A_i(x)\, \mu B_i(y),\ i=1,2$$

Layer 3

Layer 3 contains fixed nodes which calculate the ratio of the firing strengths of the rules:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}$$

Layer 4

The nodes in this layer are adaptive and perform the consequent of the rules:

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i)$$

The parameters in this layer (p_i, q_i, r_i) are to be determined and are referred to as the consequent parameters.

Layer 5

There is a single node here that computes the overall output:

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

The single node here is the fixed node. It gives the overall output.

This then is how, typically, the input vector is fed through the network layer by layer. We now consider how the ANFIS learns the premise and consequent parameters for the membership functions and the rules.

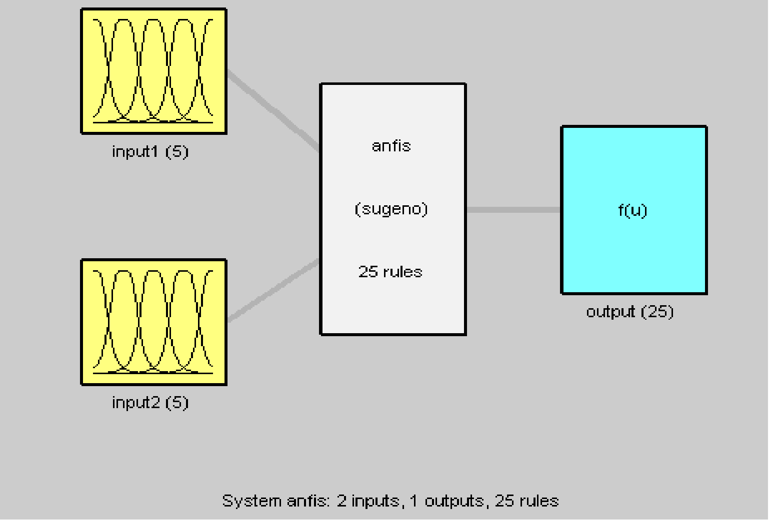

Fig 5. Output of ANFIS

There are a number of possible approaches but we will discuss the hybrid learning algorithm which uses a combination of Steepest Descent and Least Squares Estimation (LSE). This can get very complicated so here we have provided a very high level description of how the algorithm operates. It can be shown that for the network described if the premise parameters are fixed the output is linear in the consequent parameters. So, the hybrid learning algorithm uses a combination of steepest descent and least squares to adapt the parameters in the adaptive network.

SOLUTION FOR FECG EXTRACTION

To account for the possibility of the nonlinear transformation might be time-variant, we structure our algorithm to be frame-based. Consequently, 0 signals and are partitioned into -samples long overlapping frames with overlap of samples. The frames of and are given by where

$$x_i(m) = x(i(N-P)+m)$$
$$w_i(m) = w(i(N-P)+m)$$
$$0 \le m \le N-1,\ i \ge 0$$

The ANFIS is used here to align with the maternal component. Therefore, the inputs of the ANFIS in this case are data points (vectors) whose elements are derived from the desired output of the ANFIS. The ANFIS is then trained to learn the mapping between vector and matrix notation, and for the frame, the ANFIS network is presented with the vector sequence (matrix) and the vector as the training data. This training data is constructed from the thoracic and abdominal data frames such that

$$X_i = [\ X_i(0), X_i(1), \ldots\ldots. X_i(N-1)]^T$$

$$X_i(m) = [x_i(m), x_i(m-1), \ldots\ldots x_i(m-j)]$$
$$W_i = w_i(m) = [\, w_i(0), w_i(1), \ldots\ldots w_i(N-1)^T]$$

ANFIS FOR FECG EXTRACTION

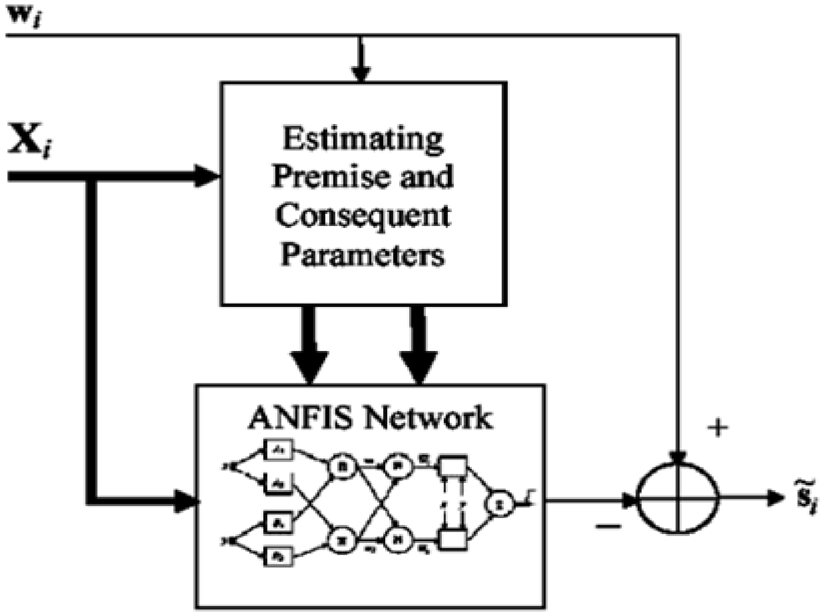

Fig 6. Use of ANFIS for FECG Extraction

Therefore, from pattern recognition point of view, the row of is a dimensional data point whose desired output is wi(k). The rows of the matrix are composed from the sequence and its sample delays as shown in Figure 6. The inclusion of the delays helps in incorporating the dynamics of the signal and makes the mapping easier and more accurate since the transformation of into can include echoes of as it travels from the mother's heart to her abdominal area .Using the training vector sequence and the desired output sequence , an ANFIS network is constructed. Once the network is constructed, the training vector sequence is evaluated through it to yield a nonlinearly transformed version of denoted by that is aligned with the maternal component.

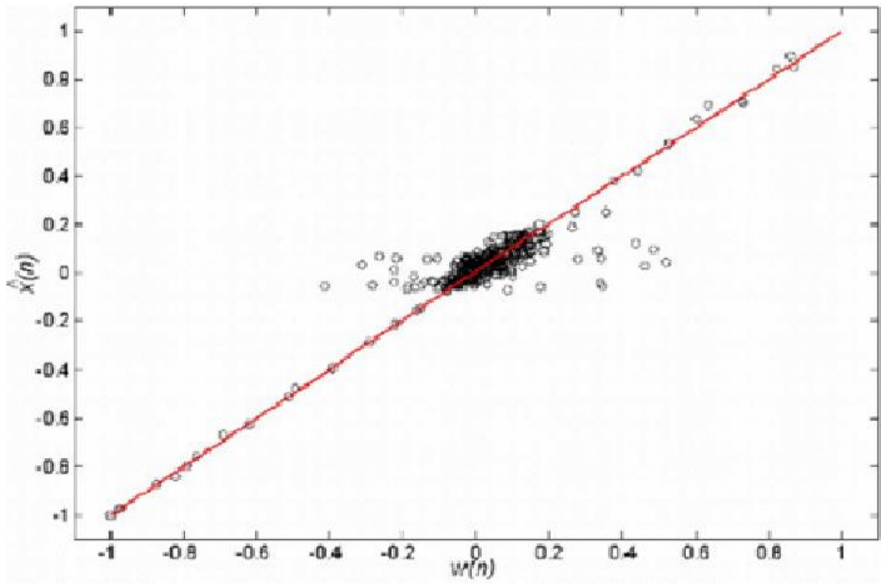

Fig 7. Alignment between w(n) and x^(n)

Consequently, and according to, an estimate of denoted by can be obtained by subtracting the estimate of from the method is depicted in Figure 7. It should be noted that the ANFIS is not used in the typical pattern recognition scenario. Instead, for each frame we train an ANFIS with as input feature vectors, and as a sequence of outputs. Then, we evaluate the trained ANFIS on the same input data, and use the resulting sequence, in estimating the FECG for that frame as before we demonstrate the FECG extraction results of our algorithm we examine its effectiveness in aligning the thoracic MECG with the maternal component in the composite abdominal signal.

RESULT AND DISCUSSION

Having illustrated that our algorithm is capable of aligning the thoracic signal with the abdominal signal, we need to show how well it can extract the FECG component. To do so we test the algorithm using synthesized and real ECG data.

SYNTHETIC ECG DATA GENERATION

For generating the synthetic ECG signals we use the dynamical model recently developed by McSharry. Both feta land maternal ECG signals (and) are synthesized using this model using different parameters to account for different shapes and beat rates of the two signals.

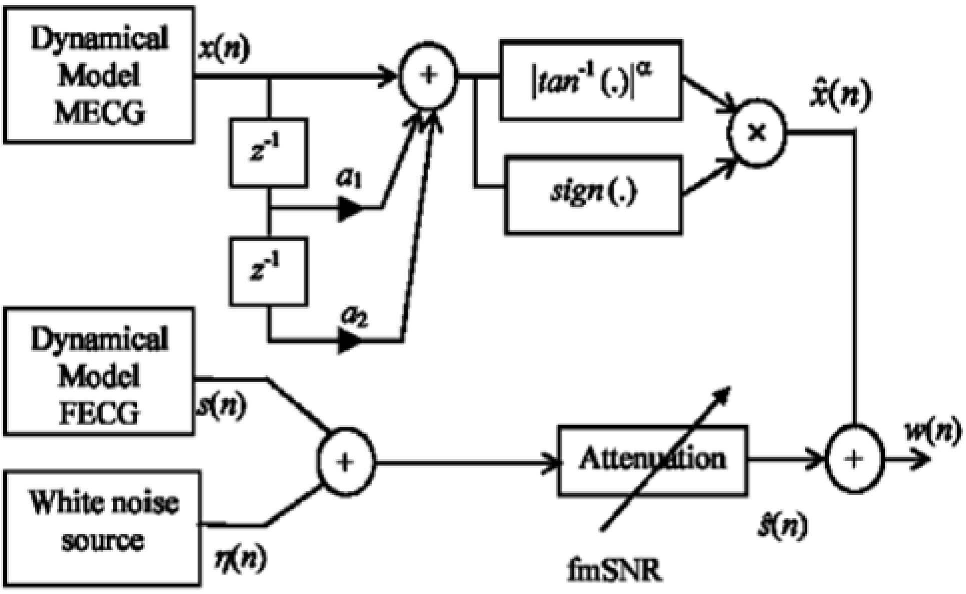

Fig 8. Block diagram for simulating the abdominal ECG signal, w(n)

The real ECG data used in this paper was a subset of a dataset contributed by Lieven De Lathauwer. The ECG signals in this dataset were recorded from eight different skin electrodes located on different points of a pregnant woman's body with 500-Hz sampling frequency. Five of these simultaneous signals were obtained from the mother's abdominal region while the other three were obtained from the mother's thoracic region. We have only used one thoracic recording and one abdominal recording. We have selected the first abdominal recording which appeared to have the highest fmSNR, and we arbitrarily chose the last thoracic recording since all three thoracic recordings appear to be hugely maternal.

As we mentioned earlier, in a controlled setting, one would want to place the two electrodes properly to obtain good SNRs.

The two (thoracic and abdominal) ECG signals that we selected from the dataset are shown in Figure 8.

EXPERIMENTAL RESULTS

To illustrate the effectiveness of our proposed algorithm in extracting FECG signals we test it on both synthetic and real signals. The goodness of the algorithm is measured both objectively and visually in the case of the synthetic data since we have the original FECG signal. However, in the case of the real ECG data we provide the results and comment on their visual quality.

As for the ANFIS that we used throughout our experiments, we have used 400 pairs of input data frame (0.8 s). The algorithm is not sensitive to the frame size. As a matter of fact we can use a larger frame size as the signals we dealt with are found to be stationary over several frames. We have also used 4 membership rules which correspond to 16 fuzzy rules, 53 nodes, 48 consequent (linear) parameters, 24 (nonlinear) parameters.

The choice of 4 membership rules was simply done by trial and error as we tried 2, 4, and 6 membership rules and found the choice of 4 rules to be optimal in terms of the FECG signal quality and the computational complexity of the ANFIS. With 400 two-dimensional feature vectors and four membership rules, the computational complexity of training an ANFIS is a secondary issue if this algorithm is to be implemented on a standard digital signal processing. The delay caused due to computations will certainly be a fraction of the frame time (i.e.,0.s), something that is totally acceptable for such an application.

RESULTS ON SYNTHETIC ECG DATA

Both the maternal thoracic ECG and the fetal ECG signals are generated as described. These two signals are processed through the model depicted in Fig.8.1 to generate the abdominal signal .The output of our proposed algorithm for where the extracted FECG signal is superimposed on the original FECG signal. Visually, the match between the two signals is clearly impressive. To quantify this match we calculate a quality signal to noise ratio qSNR defined as (21) for this particular example we found that the qSNR is equal to 22.7 dB.

$$\mathrm{qSNR} = 10\log_{10}\frac{\sum_n (\tilde{s}(n))^2}{\sum_n (s(n)-\tilde{s}(n))^2}.$$

To study the effect of the strength of the FECG component in the abdominal signal on the quality of the extracted signal, we varied the fmSNR between and in steps of 5 dB, and we computed the qSNR of the extracted FECG signal. To further assess and validate our proposed technique, we compare our ANFIS-based qSNR results on synthetic datawith two other FECG extraction techniques: The first technique is based on classic adaptive filtering, and the second is our own recent polynomial-networks-based method.

The adaptive filtering method that we select is the normalized least means squares (NLMS) following Camps-Valls.in their recent work in which they compared dynamic neural networks with classical adaptive methods based on LMS. The qSNR results illustrate the robustness of the proposed ANFIS-based technique as compared to the two other techniques. The figure also shows that the NLMS-based method yields the poorest FECG extraction quality, and degrades quite rapidly as the fmSNR decreases. Moreover, Fig. 8.1shows that the qSNR values of the extracted FECG signal for both the proposed ANFIS-based method and the polynomial-networks-based method are comparable for relatively high fmSNR values. However, for fmSNR values below, the ANFIS-based method is clearly superior to the polynomial-networks-based method. Another commonly used assessment measure for quantifying the quality of the extracted FECG signal is the correlation coefficient. To complement our results using qSNR, we report additional comparison results with NLMS and polynomial network using the correlation coefficient as a quality measure of the extracted FECG signal.

We continue to follow the work of Camps-Valls*.* In which they studied and reported results on numerous cases including the case which focuses on maternal ECG as the main source of interference. For this case, they evaluated the FECG recovery using LMS, NLMS and dynamic neural networks for varying fmSNRs between their results on synthetic data for this particular case showed that both NLMS and dynamic neural networks.

CONCLUSION

In this paper, we have applied ANFIS to extract the FECG signal from two ECG signals recorded at the thoracic and abdominal areas of the mother's skin. This is done by employing ANFIS to identify the nonlinear relationship between the maternal component in the abdominal ECG and the thoracic MECG which is assumed to include no fetal component in it. Once the MECG is nonlinearly transformed to be aligned with the maternal component in the abdominal ECG, the FECG can be extracted by subtracting the aligned version of the MECG signal from the abdominal ECG signal. We have validated our technique on both real and synthetic ECG signals. In generating the synthetic abdominal ECG signals we have applied multipath and nonlinear effects to the thoracic signal to simulate the transformation it undergoes as it travels from the heart to the abdomen. We believe that such noise can be suppressed by post processing methods such as wavelet de-noising that has proven useful with other FECG extraction methods.

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