International Workshop on Medical
Measurements and Applications – MeMeA 2007
Warsaw, Poland, May 4-5, 2007

Fetal Electrocardiogram Signal Modelling Using Genetic Algorithm

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Abstract- The fetal electrocardiogram signal (FECG) is a major tool in monitoring and diagnosis of the fetus high risk conditions and arrhythmias. This paper introduces an accurate mathematical model for fetal electrocardiogram based on a real template FECG signal. This is done after elimination of maternal electrocardiogram (MECG) signal interference measured during pregnancy. The parameters of the introduced model are optimized in terms of sum square error using a genetic algorithm (GA). Our precise fetal electrocardiogram model can be a benchmark for other prospective researches particularly in FECG extraction.

Key Words- Adaptive noise cancellation, fetal/maternal electrocardiogram, modeling, genetic algorithm.

I. Introduction

Modelling, detecting, and interpreting a desired biosignal buried in other signals and large background noise have been of extreme interest during recent years. A prime case is extracting the fetal electrocardiogram (FECG) from ECG recordings from mother's body during pregnancy, while eliminating maternal ECG (MECG) and other interfering signals. The FECG contains precious information about fetal maturity, position of the fetus, and multiple pregnancies, as well as being an influential diagnostic tool which can reflect any possible cardiac defects and arrhythmias. Also it is of vital importance to both mother and fetus when risk factors are present during pregnancy [1]-[3].

Despite noteworthy advances in medical technology in past years, existing fetal monitoring techniques such as cardiotocogram (CTG) have serious accuracy limitations and are only applicable in the clinical environments. Also, although the applications of advanced signal processing methods such as adaptive noise cancellation (ANC) and blind source separation (BSS) to FECG extraction are justified [4]-[6], the validity of their proposed configurations is still under discussion. Also the noisy and nonstationary nature of this signal challenges the conventional ANC and instantaneous BSS algorithms, which are often derived on the assumption that statistically time invariant sources are mixed in the absence of noise [7]. In practice, two main worries restrain the viability of the conventional aforementioned algorithms. Firstly, the FECG signals recorded at the mother's abdominal surface are dominated by the MECG, where FECG signals are between 5 and 1000 times smaller in intensity than in adults [6] and secondly, nonstationary nature of FECG due to fetus heart rate variability over time depending on the probable arrhythmias such as tachycardia and bradycardia, fetus comfort, additive noise Gaussian or otherwise due, for example to the recoding equipments.

Some recent publications attempt to overcome these practical problems [8]-[10]. In [8] the problem of FECG extraction with sequential blind source separation method in wavelet domain is addressed. Jafari *et al* [8] developed an approach when the mixing environment is noisy and time varying and improved the convergence rate of the classical natural gradient algorithm. The drawbacks of such BSS based algorithms, are the scaling and permutation of the output independent components.

To the authors' belief, developing and validation of a physiologically inspired parametric mathematical model of the fetal electrocardiogram signal that can be used as a basis of signal processing and robust parametric estimation technique is of great importance. This paves the way to new reliable model based extraction and interpretation methods for fetal electrocardiogram analysis.

In the following, we present a primal mathematical model for FECG signal in which the basic FECG template is obtained with adaptively elimination of MECG interference [5]. A mathematical model is proposed based on this template and optimized by a genetic algorithm where the sum square error (SSE) between FECG template and the artificially generated signal is minimized.

This paper is organized as follows. In Section II, we describe our experimental procedures for extracting FECG form ECG signal recorded from mother's abdominal area using a least mean square (LMS) based adaptive noise canceller. Then, we strive to set up a conditioned FECG template. In Section III, a mathematical model for FECG is proposed and its coefficients are optimized using a genetic algorithm. Section IV contains our results and a perspective for our future researches. Finally, our conclusions are included in Section V.

II. ADAPTIVE MECG SUPPRESSION

To investigate a FECG template, experiments are conducted on a real set of cutaneous electrode recordings. These signals were obtained from 5 seconds recording through eight skin electrodes placed on different points of a pregnant woman's body. Sampling frequency was set to be 500 Hz. As illustrated in Fig. 1, the upper five recordings correspond to electrodes located on the mother's abdominal region while the other three were obtained from mother's thoracic area. In the latter signals, due to long distance between thoracic electrodes and fetus' heart, no FECG components are apparent, whereas in the first five signals mixtures of fetal and maternal heartbeat components, noise and respiratory artefacts are observable.

In our analysis, two signals namely, Abd1 and Thr3, are used as inputs of our LMS based adaptive noise canceller. By eliminating the effects of undesired MECG, Thr3, from the mixed signal Abd1, we achieved a relatively well filtered FECG. The structure of this ANC is depicted in Fig. 2. Although by using the method proposed in [5], [11], based on the Multichannel Noise Reference Adaptive Filtering, better results would be achieved, the result of single channel noise reference adaptive filter is sufficient for introducing a mathematical model for FECG signal.

B. Adaptive Noise Cancellation

One of the first successful approaches to FECG extraction problem was developed by Widrow *et al.* based on an adaptive filter framework [11] and continued in [5]. An abdominal lead, Abd1, mainly containing a combination of FECG and MECG signals, acts as a primary input to the adaptive noise canceller. The MECG interference that corrupts the abdominal leads is considered as the 'noise' to be annihilated. In this configuration, the reference input to the MECG canceller is Thr3 signal, mostly composed of maternal ECG signal. The output at instant k is then given by

$$\varepsilon_k = \mathbf{d}_k - \mathbf{X}_k^{\mathrm{T}} \mathbf{W}_k \tag{1}$$

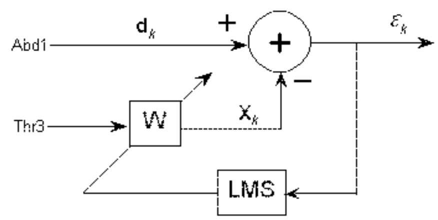
where $\mathbf{W}_k$ is the weight vector at k, $\mathbf{d}_k$ and $\mathbf{X}_k$ are the primary and reference input vectors, respectively.

The learning algorithm is based on classic LMS where the impulse response of the adaptive filter is optimized using

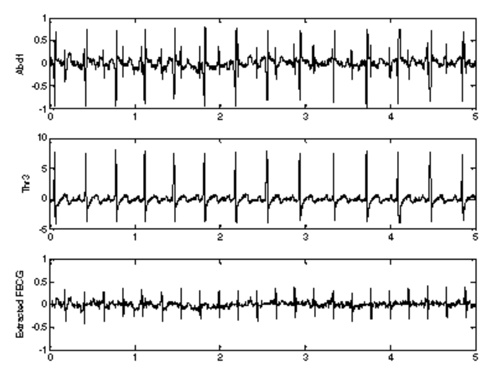
$$\mathbf{W}_{k+1} = \mathbf{W}_k + 2\mu(t)\varepsilon_k \mathbf{X}_k \tag{2}$$

where $\mu(t)$ is the learning rate. The adaptive filter minimizes the MSE, $E(\varepsilon_k^2)$, where $E(\cdot)$ stands for expectation operator. Abd1, Thr3 and the extracted FECG signals are shown in Fig. 3. In the following, we use these extracted FECG heartbeat for setting up our mathematical FECG model.

"Fig. 1." An 8-channel cutaneous potential recording from a pregnant woman. The signals denoted Abd1–5 were recorded from the abdominal area, while the lower-most recordings Thr1–3 were obtained from the thoracic area.



"Fig. 2." ANC configuration to extract FECG from the Abd1.

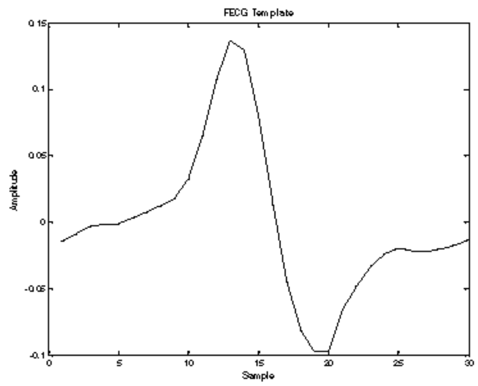


"Fig. 3." Extracting FECG (Lowermost) from Abd1 primary input (Uppermost) and Thr3, the MECG noise reference (Middle).

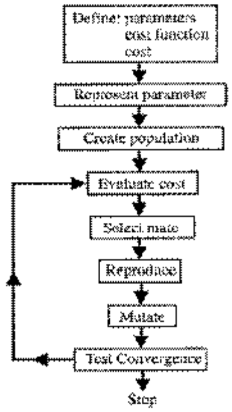
III. FECG MODEL

The extracted FECG signals, after conditioning i.e., filtering high frequency components and removing the mean, are divided into 22 segments; each corresponds to 30 samples of a single fetal ECG. The FECG template which is illustrated in Fig. 4, is then computed with averaging these 22 segments. To fit an *optimum* model to the derived FECG template, the following summation with only 3 individual *sinc* functions and a *dc* bias is proposed

$$FECG\_Model = a + \sum_{i=1}^{3} b_i \,\mathrm{sinc}(c_i t + d_i) \tag{3}$$



"Fig. 4." Average FECG signal.



"Fig. 5." A typical GA Process.

Using a Genetic Algorithm, the 10 unknown factors in the model are driven. The simplicity of the equation along with its high accuracy is of the main advantages of the proposed model.

A. Model Optimization Using Genetic Algorithm

GA is currently one of the most popular stochastic optimization techniques. It is inspired by natural genetics and the biological evolutionary process, and can be characterized by the following features [12]:

- A scheme for encoding solutions to a problem in the form of a chromosome (chromosomal representation).
- An evaluation function which indicates the *fitness* of each chromosome relative to the others in the current set of chromosomes (referred to as population).
- An initialisation procedure for the population of chromosomes.
- Genetic operators which are used to manipulate the composition of the population.
- A set of parameters that provide the initial settings for the algorithm: the population size and probabilities employed by the genetic operators.

The GA uses three basic operators to manipulate the genetic composition of a population: reproduction, crossover and mutation [12]. Reproduction consists in copying chromosomes according to their objective function (strings with higher merit will have more chances to survive).

The crossover operator mixes the genes of the two chromosomes selected in the phase of reproduction, in order to combine the features, especially their positive ones. Mutation is occasional, producing with low probability an alteration of some of the gene values in a chromosome.

To perform the GA, it is first very important to define the fitness function. This fitness function is constructed bearing in mind that the output signal must be fit to our FECG template. For this purpose, we must utilize a measure of the secondary structural element (SSE).

B. Fitness Function

To minimize the error between our proposed model and the template, the following fitness function is considered in the GA process:

$$Fitness = \sum_{i=1}^{30} (FECG\_Model(i) - FECG\_Template(i))^2. \quad (4)$$

By minimizing this function, one could expect to reach to an exact mathematical model of the FECG template. The available parameters for GA to minimize the above fitness are 10 unknown factors in (3).

IV. Results

The parameters of the GA are: population size = 50, number of generation = 500, crossover probability = 0.8 and probability distribution of mutation is set to be Gaussian. After executing the GA, SSE value of less than 0.004 is derived. The convergence process is shown in Fig. 6. The resulted optimized model is in the following form

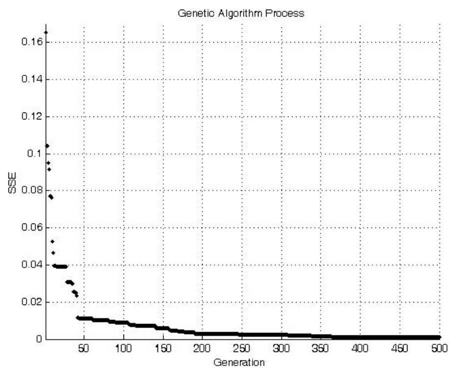
$$FECG\_Model = -0.018278 + \sum_{i=1}^{3} b_i \sin c(c_i t + d_i). \quad (5)$$

The nine other parameters are provided in Table 1

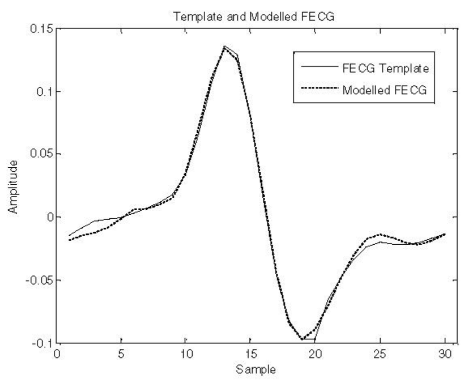
Using the above optimized function, the derived model is plotted in Fig. 7. It is seen that the constructed model has acceptable similarity to the FECG template. This model can be effectively used in development of an efficient constrained BSS system for separation of the desired FECG signal.

V. Summary And Conclusions

In this paper FECG beat has been accurately modelled by developing a template matching criterion using GA. The template is extracted from the mixtures of MECG/FECG, by means of an adaptive noise canceller. This template can consequently be used for separation of the FECG. The proposed method overcomes the inherent limitations of some



"Fig. 6." Normalized fitness function.



"Fig. 7." Template and Modeled FECG

TABLE I
THE NINE COEFFICIENTS (SCALING AND SHIFTING) OF THE PROPOSED MODEL

Model Elements	$i=1$	$i=2$	$i=3$
b	0.15817	-0.07287	-0.73326
c	0.26913	0.29047	4.3456
d	-12.7520	-20.3793	-7.2490

previously developed methods based on adaptive filtering or BSS. Future work includes developing a robust constrained blind source separation algorithm to extract FECG from the mixtures of MECG/FECG, for which the FECG proposed model will be used as a constraint.

ACKNOWLEDGMENT

The authors are thankful to L. De Lathauwer of Catholic University of Leuven, Belgium, for providing the researchers with the FECG data at: http://www.tsi.enst.fr/icacentral/.

Also the authors would like to thank Mr. S. A. Sattarzadeh at IUST, Tehran, Iran, for his valuable comments.

REFERENCES

[1] L. Y. Shyu, C. F. Huang, Y. S. Wu, W. C. Hu, and K. C. Chao, "The use of thoracic-abdominal transfer function in extracting fetal electrocardiogram," in *Proc. Annu. Int. Conf. IEEE/EMBS*, vol. 4, pp. 1644–1645, 1996.

[2] L. D. Lathauwer, B. D. Moor, and J. Vandewalle, "Fetal electrocardiogram extraction by blind source subspace separation," *IEEE Trans. Biomed. Eng.*, vol. 47, no. 5, pp. 567–572, May 2000.

[3] K. Assaleh and H. Al-Nashash, "A novel technique for the extraction of fetal ECG using polynomial networks," *IEEE Trans. Biomed. Eng.*, vol. 52, no. 6, pp. 1148-1152, June 2005.

[4] V. Zarzoso and A. N. Nandi, "Noninvasive fetal electrocardiogram extraction: Blind separation versus adaptive noise cancellation," *IEEE Trans. Biomed. Eng.*, vol. 48, no. 1, pp. 12–18, Jan. 2001.

[5] E. R. Ferrara and B. Widrow, "Fetal electrocardiogram enhancement by time-sequenced adaptive filtering," *IEEE Trans. Biomed. Eng.*, vol. 29, pp. 458–460, 1982.

[6] A. Kam and A. Cohen, "Maternal ECG elimination and fetal ECG detection—Comparison of several algorithms," in *Proc. Annu. Int. Conf. IEEE?EMBS*, vol. 1, pp. 174–177, 1998.

[7] A. Cichocki and S. Amari, *Adaptive Blind Signal and Image Processing: Learning Algorithms and Applications*. New York: Wiley, 2002.

[8] M. G. Jafari and J. A. Chambers, "Fetal Electrocardiogram Extraction by Sequential Source Separation in the Wavelet Domain," *IEEE Trans. Biomed. Eng.*, vol. 52, no. 3, pp. 390-400, May 2005.

[9] D. L. Jones, "A new method for blind source separation of nonstationary signals," in *Proc. IEEE ICASSP*, vol. 5, pp. 2893–2896, 1999.

[10] D. Pham and J. F. Cardoso, "Blind separation of instantaneous mixtures of nonstationary sources," *IEEE Trans. Signal Process.*, vol. 49, no. 9, pp. 1837–1848, Sep. 2001.

[11] B. Widrow *et al.*, "Adaptive noise cancelling: Principles and applications," *Proc. IEEE*, vol. 63, pp. 1692–1716, Dec. 1975.

[12] D. E. Goldberg, *Genetic Algorithms in Search, Optimization and Machine Learning*, Addison Wesley, Reading, MA, 1989.