

# Maternal and fetal heart rate extraction from abdominal recordings using multi-scale principal components analysis

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**Abstract**—A three-stage methodology for the extraction of maternal and fetal heart rate using abdominal ECG leads, is presented. In the first stage, the maternal R-peaks and fiducial points (maternal QRS onset and offset) are detected, using multiscale principal components analysis (MSPCA) and the Smoothed Nonlinear Energy Operator (SNEO). Maternal fiducial points are used to eliminate the maternal QRS complexes from the abdominal ECG recordings. In the second stage, again MSPCA and SNEO are employed in order to detect the fetal heart beats that do not overlap with the maternal QRSs (eliminated from the first stage). The extraction of the fetal heart rate is accomplished in the last stage, using a histogram based technique in order to identify the positions of the fetal heart beats that overlap with the maternal QRSs. Real signals, recorded from different pregnant women and different weeks of gestation, are used for the evaluation of the proposed methodology and the obtained results indicate high performance (accuracy 95%).

## I. INTRODUCTION

Fetal scalp electrodes could be used for fECG monitoring, however, due to the invasive nature of this technique, other methods should be preferred. The recording of the fECG from the maternal abdomen (abdECG) is non-invasive, and thus highly desirable, and its analysis could be a reliable diagnostic marker for fetal cardiac diseases, especially fetal arrhythmias and asphyxias. Like the classical ECG, the fECG consists of P, QRS and T waves (Fig. 1). However, due to background noise, only fetal R peaks and QRS complexes (fQRS) are usually recognizable. The fECG is commonly extracted from multiple leads information. ECG from the pregnant woman can be derived using leads placed on the abdomen and in some cases, on the thorax. The thoracic signals contain primarily the maternal ECG (mECG), with little (if any) contribution from the fECG. On the contrary, the abdominal leads record a composite signal (abdECG), consisting of the contributions from both the mECG and the fECG. There are several difficulties in recording the abdECG and, subsequently, extracting the fECG from it. Electrical activity recorded from the maternal abdomen suppresses the fECG while other sources of interference are also present, such as maternal muscle activity and electrical equipment contamination. In addition, the shape of the fECG signal depends on the electrode

position, the gestational age and the position of the fetus.

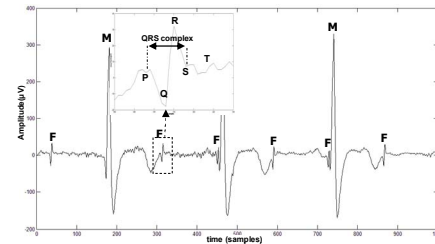


Fig. 1. Abdominal recording and fECG components (M : Maternal QRSs, F : Fetal QRSs).

The fECG extraction is a typical blind source separation (BSS) problem [1]. BSS based techniques recover unobserved signals (i.e. fECG and mECG) from observed mixtures of them [2-4]. A major disadvantage of the BSS based techniques is that they require a large number of recorded observed mixtures (ECG leads) in order to obtain satisfactory results. Besides BSS approaches, various research efforts have been proposed in the literature, including matched filtering [5], adaptive neuro-fuzzy inference systems [6], dynamic neural networks [7], temporal structure [8], fuzzy logic [9], frequency tracking [10], polynomial networks [11], wavelets [12], real-time signal processing [13] and time-frequency analysis [14]. Most of the approaches proposed in the literature, are evaluated using simulated signals or/and a very small dataset of real recordings. In addition, the presented results are only qualitative while most of the time, both abdominal and thoracic leads are used.

In this work, we propose a methodology for the automated detection of the mHR and fHR signals, based on the analysis of a small number of abdECG leads. Preprocessing is applied in all leads and then, a three stage methodology is employed (Fig. 2). In the first stage, the abdECG is analysed using MSPCA [15,16] and SNEO [17]. The positions of the maternal R-peaks (mR-peaks) and the maternal fiducial points (QRS onset and offset) are identified. The maternal fiducial points are used to eliminate the maternal QRS (mQRS) complexes from the abdECG. In the second stage, MSPCA and SNEO are used to detect the fetal R-peaks (fR-peaks) that do not overlap with the mQRSs. In the third stage, a histogram based technique is applied for the detection of the fR-peaks overlapped with mQRSs. The combination of the fR-peaks detected in stages two and three comprise the fHR. Evaluation was performed using abdominal recordings from the University of Nottingham [5] database.

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## II. MATERIALS AND METHODS

The proposed methodology consists of a preprocessing stage and three main stages: (a) mHR detection and elimination of mQRS complexes; (b) candidate fR-peaks detection and (c) overlapped fR-peaks detection and extraction of fHR. In these stages, known techniques are used, such as MSPCA and SNEO.

### A. Multiscale Principal Components Analysis

PCA can be used for dimensionality reduction in a dataset while retaining the dataset's characteristics that contribute most to its variance, by keeping high-order principal components and ignoring lower-order ones. Such high-order components often contain the "most important" aspects of the data. On the other hand, according to multi-resolution analysis, any signal can be approximated by successively projecting it down onto scaling and wavelet functions.

Our methodology uses an approach that combines the properties of PCA and wavelet analysis. MSPCA combines the ability of PCA to decorrelate the variables by extracting a linear relationship, with that of wavelet analysis to extract deterministic features and approximately decorrelate autocorrelated measurements [15]. MSPCA computes the PCA of the wavelet coefficients at each scale and then combines the results at relevant scales. Due to its multiscale nature, MSPCA is appropriate for modeling of data containing contributions from events whose behavior changes over time and frequency. Process monitoring by MSPCA involves combining only those scales where significant events are detected. Approximate decorrelation of wavelet coefficients also makes MSPCA effective for monitoring autocorrelated measurements without matrix augmentation or time-series modeling. In addition, MSPCA simultaneously extracts those features that represent abnormal operation, in order to improve the ability to detect deterministic changes [15].

The steps of MSPCA are shown in Fig. 2 and are explained next:

Step 1: Perform the wavelet transform (WT) at level  $L$  of each column of the initial multivariate signal  $X$  ( $\{d_1^i, d_2^i, \dots, d_L^i, a_L^i\} = WT(x_i)$ ,  $i = 1, \dots, N$ , where  $x_i$  is the  $i^{\text{th}}$  column of  $X$  and  $N$  is the number of columns of  $X$ ). This results to several detail coefficients ( $d_j^i$ ,  $i = 1, \dots, N$ ,  $j = 1, \dots, L$ ) and approximation coefficients ( $a_L^i$ ,  $i = 1, \dots, N$ ).

Step 2: For  $j = 1, \dots, L$ , perform PCA of the matrix  $D_j$  ( $D_j = \{d_j^i, i = 1, \dots, N\}$ ) and select an appropriate number  $p_j$  of useful principal components (suppress the detail  $D_j$ ), resulting to  $\hat{D}_j$  ( $\hat{D}_j = \{\hat{d}_j^i, i = 1, \dots, N\}$ ).

Step 3: Similarly, perform PCA of the matrix  $A_L$  ( $A_L = \{a_L^i, i = 1, \dots, N\}$ ) and select  $p_{L+1}$  principal components, resulting to  $\hat{A}_L$  ( $\hat{A}_L = \{\hat{a}_L^i, i = 1, \dots, N\}$ ).

Step 4: Construct  $\hat{x}_i$ , performing inverse wavelet transform (IWT) on  $\hat{d}_j^i$ ,  $j = 1, \dots, L$  and  $\hat{a}_L^i$  ( $\hat{x}_i = IWT\{\hat{d}_1^i, \hat{d}_2^i, \dots, \hat{d}_L^i, \hat{a}_L^i\}$ ,  $i = 1, \dots, N$ ). Then construct  $\hat{X}$  as:  $\hat{X} = \{\hat{x}_i\}$ ,  $i = 1, \dots, N$ .

Step 5: Finally, perform the PCA of the matrix  $\hat{X}$  extracting the retained principal components.

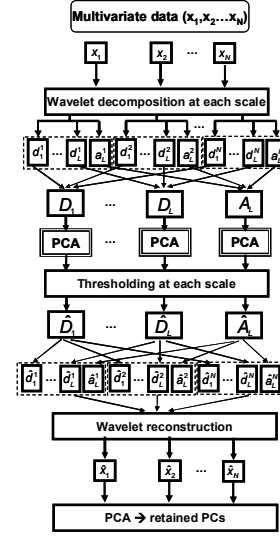


Fig. 2. MSPCA.

The final PCA step is necessary in order to reduce dimensionality since, in general,  $rank(\hat{X}) = rank(X)$ .

### B. Smoothed Nonlinear Energy Operator

The nonlinear energy operator (NEO) is reported to be sensitive to any discontinuity of the signal. A new interpretation of the discrete time implementation of NEO is for accentuation of the high-frequency content and detection of spikes in biomedical signals. In order to reduce the cross terms, a smoothed version of NEO (SNEO), is used. The extremely low computational complexity is a major attraction of SNEO model.

For a discrete signal  $x(n)$ , NEO and SNEO are defined as:

$$NEO[x(n)] = x^2(n) - x(n+1)x(n-1) \quad \text{and}$$

$SNEO[x(n)] = NEO[x(n)] \otimes w(n)$ , where  $\otimes$  represents the convolution operator and  $w(n)$  represents the smoothing window. In our case, a Barlett window function has been used. The threshold value for SNEO is chosen as

$T = C \frac{1}{N} \sum_{n=1}^N SNEO[x(n)]$ , where  $N$  is the number of samples and  $C$  is the scaling factor.

### C. Preprocessing Stage

Two digital filters are used for the removal of the electromagnetic noise and the correction of the baseline wandering. Substantially, a bandpass filter with cut-off frequencies 4 and 100 Hz is applied, since in this range of frequencies the maternal and fetal ECG is concentrated.

### D. Stage 1: Maternal HR detection and elimination of maternal QRS complexes

In this stage MSPCA is performed using a three stage wavelet decomposition of the initial multivariate signal  $X$ . Coiflets of order 3 (Coif3) wavelet is used for the wavelet analysis, while only the three simplified approximation matrices were used; the nine detail matrices (three for each scale) are composed essentially of noise with small contributions from the desired signal. Removing the noise leads to de-noising. As final step, only one retained principal component for the final PCA, is selected.

The mR-peaks are identified performing a SNEO procedure in the retained principal component (Fig. 3). A scaling factor equal to 4 and a Barlett window of width 5 are used. The maternal Q wave start (mQRS onset) and S wave end (mQRS offset) are detected, using the signal produced from SNEO and the positions of the mR-peaks. Local minima of SNEO are found in both sub windows on both sites of the mR-peaks. After the maternal fiducial point detection, the mQRSs are eliminated from the multivariate signal (initial abdominal recordings).

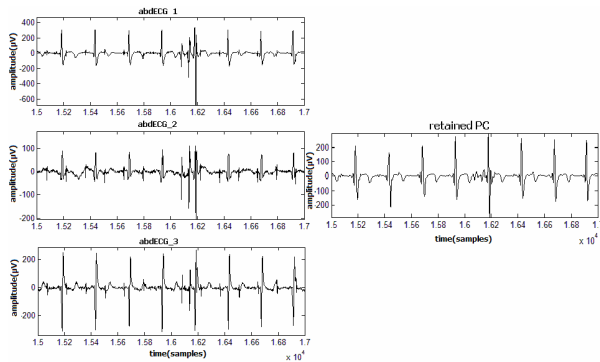


Fig. 3. The three abdECGs on the left and the selected retained principal component on the left.

### E. Stage 2: Candidate fetal R-peaks detection

In this stage MSPCA is performed in the  $\hat{X}$  signal. A three stage wavelet decomposition using the Coif3 wavelet, is performed. Details are composed mainly of fetal contributions from the signal, therefore, two simplified details matrices from each scale are used for wavelet reconstruction. Only one principal component is retained after the final PCA (Fig. 4).

The positions of the fR-peaks are identified performing a SNEO procedure in the retained principal component (Fig. 5). The same parameters values of scaling factor and Barlett window as in the previous stage are used.

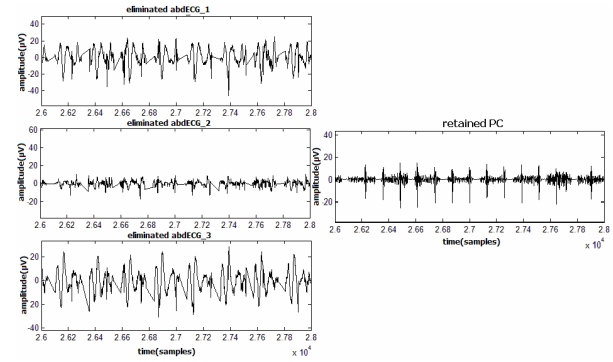


Fig. 4. The three eliminated abdECGs on the left and the selected retained principal component on the left.

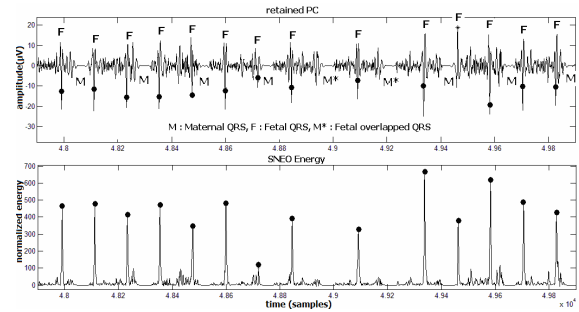


Fig. 5. Transformation SNEO of the retained principal component.

### F. Stage 3: Fetal HR detection

The detection of the overlapped fetal QRS is accomplished using a histogram based technique [14]. The results from the second stage (fR-peaks not overlapping with the mQRSs) and the third stage (fR-peaks overlapping with the mQRSs) are combined to form the fetal R-R interval signal and the fHR is extracted from it.

## III. RESULTS

The database from the University of Nottingham [5] is used for the evaluation of the proposed methodology. Table I presents the results obtained for the fHR extraction. The signals are acquired using four electrodes (three leads and a common) placed on the mother's abdomen. The sampling frequency is 300 Hz. The database consists of 6 recordings of 10 min, acquired between gestation week 24 and 34 and the achieved accuracy was high (~95%).

TABLE I  
EVALUATION RESULTS FOR FHR EXTRACTION

Record	Gestation week	Se <sup>1</sup> (%)	PPA <sup>2</sup> (%)	Acc <sup>3</sup> (%)
1	20 <sup>th</sup>	97.13	97.13	94.42
2	20 <sup>th</sup>	98.74	98.74	97.51
3	24 <sup>th</sup>	97.57	97.42	95.12
4	24 <sup>th</sup>	95.88	96.36	92.53
5	28 <sup>th</sup>	99.65	99.30	98.95
6	32 <sup>th</sup>	97.61	96.19	93.97
<b>Total</b>		<b>97.76</b>	<b>97.52</b>	<b>95.42</b>

<sup>1</sup>Sensitivity (Se)

<sup>2</sup>Positive Predictive Accuracy (PPA)

<sup>3</sup>Accuracy (Acc):  $Acc = TP / (TP + FP + FN)$ .

#### IV. DISCUSSION

The proposed methodology extracts the fHR from the abdECG signal while addresses several issues related to the fHR extraction: (a) the method can be used with a minimum number of leads. This is a major advantage compared to BSS-based methods, since they require a large number of recorded leads to reach a reliable fECG extraction; (b) thoracic leads are not required, in contrast to several approaches proposed in the literature, such as adaptive filtering; (c) our method automatically extracts the fHR from the abdECG leads, in contrast to the BSS-based methods, where fECG channel is defined by visual inspection; (d) it is evaluated using real abdECG recordings, covering a large period of the gestation.

Table II presents several methods proposed in the literature for the extraction of the fHR. Due to the fact that there is no benchmark database, each approach is evaluated using a different dataset. Therefore, a direct comparison between the results is not feasible. All the methods were validated using real records (no simulated signals were involved). The proposed method provides comparable results with the other methods. Pieri et al. [5] uses the larger dataset among all the methods presented on Table II (400 records of 5-10 min each), but the results are rather poor (65%). The method proposed by Martinez et al. [3] uses additional thoracic records while the signal's duration is not clarified. The fuzzy-based approach by Azad [9] performed very well (89% average accuracy), but there is no reference about the exact number and duration of abdECG records that were used for the evaluation. Karvounis et al., in [12] presented excellent results using a relatively small dataset, while in [14] also presented very good results, however there is no noise handling in the proposed method; thus this is a more compact approach and is expected to more adequately handle noisy and multivariate recordings.

#### V. CONCLUSIONS

A methodology for the automated extraction of the fHR from the abdECG signal has been developed. The method is based on the MSPCA analysis and SNEO. MSPCA is a very promising technique in the field of multivariate analysis but it has never been used for fHR extraction. Real abdECG

records are incorporated for the evaluation of the method and the presented results indicate very high efficiency, since an overall accuracy of almost 95% is achieved. The main drawback of the method is the difficulty to extract the fetal R-peaks in cases where the fECG is not distinguishable. The proposed fHR detection method can be further improved, in terms of noise handling and QRS enhancement. Finally, further validation, is needed.

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TABLE II  
EVALUATION RESULTS

Author	Description	Dataset (records/length)	Acc (%)
Martinez et al., [3]	adaptive algorithm	10	81 <sup>1</sup>
Pieri et al., [5]	matched filter	400/5-10 min	65
Azad [9]	fuzzy approach	5	89 <sup>2</sup>
Karvounis et al., [12]	complex wavelets	15/1 min	98
Ibahimy et al., [13]	statistical analysis	5/20 min	89 <sup>3</sup>
Karvounis et al., [14]	t-f analysis	10/15 min	97
<b>Current Work</b>	MSPCA - SNEO	6/10 min	95

<sup>1</sup>Calculated using Se and PPA.

<sup>2</sup>Defined as:  $performance = 100 \frac{(TP - (FP + FN))}{TP} \%$

<sup>3</sup>Correlation coefficient (method vs. FHR from Doppler ultrasound).