# Advanced Maternal ECG Removal and Noise Reduction for Application of Fetal QRS Detection

Jukka A Lipponen[1], Mika P Tarvainen[1,2]

[1] Department of Applied Physics, University of Eastern Finland, Kuopio, Finland
[2] Department of Clinical Physiology and Nuclear Medicine, Kuopio University Hospital, Kuopio, Finland

## Abstract

*The fetal heart rate (fHR) is commonly used as an indirect indicators of fetal condition. Noninvasive fHR monitoring uses electrodes placed on the mother's abdomen. However it is challenging to detect fetal QRS (fQRS) complexes from the signals measured in this way because of different types of noise and overlapping frequencies between maternal and fetal ECG. In this paper, we introduce an augmented multi-lead principal component regression (PCR) approach for maternal ECG removal and multichannel correlation based fHR detector. Using this method we participated to Computing in Cardiology, PhysioNet Challenge - and final results were for event 4: 28.893 bpm*[2] *and event 5: 4.844 ms. The proposed algorithm succeeded to remove maternal ECG from the abdomen signals with high accuracy.*

## 1. Introduction

Fetal heart rate (fHR) is an indirect marker of fetal condition, for example fHR decelerations are associated with fetal distress. Noninvasive fHR monitoring uses electrodes placed on the mother's abdomen. However it is challenging to detect fetal QRS (fQRS) complexes from the signals measured in this way. Challenges of this technique are related to the low amplitude of the fQRS complexes, the different types of noise and the overlapping frequencys between maternal ECG (mECG) and fetal ECG (fECG). After the fHR monitors were introduced as clinical practice, it was expected that this technology would reduce intrapartum fetal deaths. However due the technical difficulties fHR monitors were unreliable and rather than reducing fetal deaths, monitoring only increased the unnecessary cesarean deliveries.

Several techniques for mECG extraction from the abdominal signals have been proposed. Probably the most interesting ones are mECG template subtraction technique [1–3] and independent component analysis (ICA) based technique. Template subtraction technique is based on mECG division on the separate complexes and mECG extraction is made by subtracting linear combination of preceding mECG complexes from the current one. ICA estimates independent source signals from the measured abdomen signals and from the ICA components, mECG or fECG components can be separated for example using information of maternal heart rate (mHR) and physiological model for fHR [4]. Similar performance between these two techniques was observed in [3].

The main drawback of the template subtraction technique variation caused by respiration movements and inaccuracies of maternal R-peak detection causes distortion to templates and mECG is not fully removed, in addition information of only one lead is used for the mECG removing. In ICA based approaches, fECG information leaks always to components which are containing mostly mECG, this reduces fHR detection accuracy in low signal to noise ratio (SNR) situations.

In this paper we introduce an augmented multi-lead principal component regression (PCR) based approach for maternal ECG removing. In the multi-lead PCR approach, P- and T-waves, and QRS-complexes of all abdomen leads are segmented based on maternal R-peaks and collected into augmented observation matrices. Hence, the QRS-complex matrix, for example, contains complexes from all four leads. These matrices are then used to produce PCR model for mECG waveforms and mECG is then removed from all abdomen signals dynamically using produced model. Using augmented waveform matrices prior information of the mECG waveform can be maximized and morphological changes caused by respiration are captured to the model and all variation caused by mECG can be removed.

In addition envelope based method for noise power equalization of individual fECG leads is presented. Noise power for each time-point of each signal is estimated using envelope method, these estimates are then used as a weighting signals. By using envelope method leads containing less noise in certain time point are weighted more

during the fQRS detection. For fQRS detection multichannel template matching technique was used.

## 2. Materials

Proposed methods were developed and validated using PhysioNet challenge 2013 datasets [7]. Challenge dataset consist of 175 recordings which include four leads of one-minute long fetal ECG with 1000 Hz sampling frequency. The data were recorded using a variety of instrumentation with differing frequency response, resolution and lead configuration [7]. Reference annotations for fQRS time points were obtained from direct fECG signal, acquired from a fetal scalp electrode [7].

## 3. Methods

Abdominal fECG recordings contains noise from many different sources: EMG, power line noise and movement artifacts from respiration or other body movements cannot be avoided. Before applying the PCR method baseline drifts caused by chest movements were filtered from the ECG using sixth order butterworth high pass filter with the cutoff frequency 2Hz. Secondly power-line noise were removed, eliminating 50Hz peak in a Fourier domain. After these preprocessing steps, the maternal R-waves were detected using an adaptive QRS detector similar as Pan and Tompkins [8]. To obtain all possible information from the measured ECG leads, six virtual leads were calculated by subtracting measured leads from each others. All preprocessing steps were performed also for those virtual leads, however for the sake of simplicity, all equations and graphs are presented only for the four original leads.

### 3.1. PCR model for maternal ECG

The maternal QRS-complex, P- and T-wave epochs from fECG recordings were modeled using the PCR approach. The aim was to model maternal ECG waveforms using PCR basis vector and then using this model remove maternal ECG from the abdominal signals.

In the PCR method, maternal P- and T-waves, and QRS-complexes are modeled separately for every heart beat within the measurement. Here we first describe shortly how a single wave epoch, i.e. P, T or QRS epoch (referenced as wave epoch) is modeled using the PCR. For a more detailed presentation of the PCR modeling see [5,6].

First, the maternal P- and T-wave and QRS complex epochs are extracted from the ECG according to the detected R-wave peak. The $j$:th extracted wave epoch from the $k$:th channel with $N$ data points is denoted as

$$z_{kj} = \left[ z_{kj,1} \dots z_{kj,N} \right]^T . \tag{1}$$

As an observation model, we use an additive noise model

$$z_{kj} = s_{kj} + e_{kj} \tag{2}$$

where $s_{kj}$ is the maternal wave epoch (P- or T-wave, or QRS-complex) and $e_{kj}$ is measurement noise, note that fECG is first treated as a component of noise. Each epoch $z_{kj}$ can be approximated as a linear combination of basis vectors $\varphi_k$

$$z_{kj} = H_S \theta_{kj} + e_{kj} \tag{3}$$

where $H_S = (\varphi_1 \dots \varphi_K)$ is $N \times K$ matrix of basis vectors and $\theta_j$ is a $K \times 1$ column vector of weights related to $j$:th epoch.

In the PCR the model basis vectors $\varphi_k$ are selected to be the eigenvectors of the data correlation matrix *R*. First observation matrix for wave epoch is created by collecting all (number of $M$) wave epochs from all leads $(z_1, z_2, z_3, z_4)$ to the single observation matrix:

$$Z = \begin{pmatrix} \mathrm{z}1_{1,1} & \mathrm{z}2_{1,1} & \cdots & \mathrm{z}3_{\mathrm{M},1} & \mathrm{z}4_{\mathrm{M},1} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathrm{z}1_{1,\mathrm{N}} & \mathrm{z}2_{1,\mathrm{N}} & \cdots & \mathrm{z}3_{\mathrm{M},\mathrm{N}} & \mathrm{z}4_{\mathrm{M},\mathrm{N}} \end{pmatrix} \tag{4}$$

By collecting wave epochs from all leads into a measurement matrix, epoch number can be maximised and stronger prior information of the wave shape can be attained.

By using measurement matrix $Z$, correlation matrix for waves can be estimated as

$$R = \frac{1}{M} Z Z^T \tag{5}$$

and the eigenvectors (i.e. basis vectors $\varphi_k$) can be solved from the eigendecomposition.

The eigenvectors of the correlation matrix are orthonormal and therefore the least-squares solution for the parameters $\theta$ is

$$\hat{\theta}_{kj}^{PC} = H^T z_{kj} \tag{6}$$

and the estimate for wave epoch can be computed as

$$\hat{z}_{kj}^{PC} = H \hat{\theta}_{kj}^{PC} . \tag{7}$$

In other words, the P- or T-wave, or QRS complexes for the $M$ consecutive beats, from all leads are placed into the columns of $Z$. The correlation matrix is then calculated using equation (5) and the eigenvectors are solved using eigendecomposition. The most significant eigenvectors are fitted back to individual wave epochs using equations (6) and (7). This procedure is done for every beat within the measurement, individually for P and T-waves, and QRS-complexes.

The most significant eigenvectors contain the information of the maternal waveform and its normal variation, secondly fECG and noise is distributed into less significant

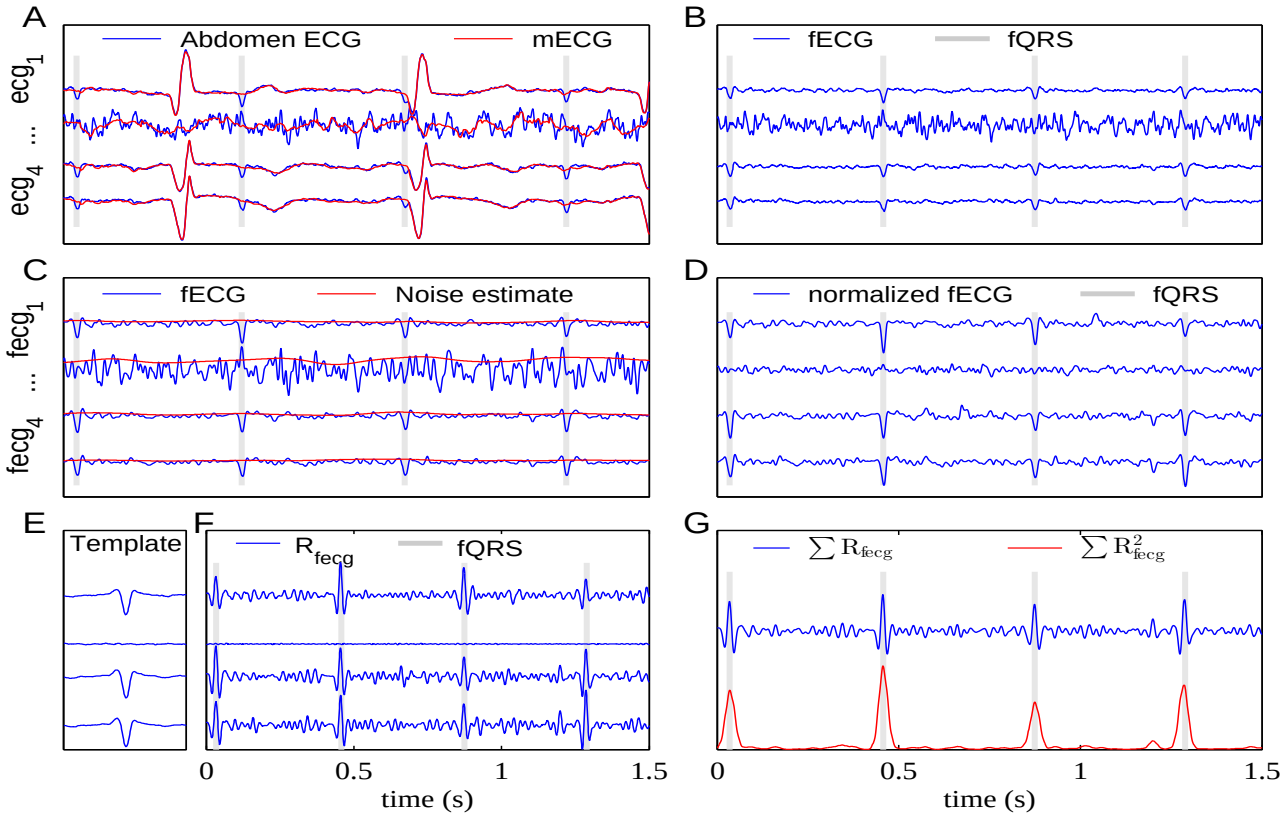


Figure 1. Prepresentative example of fQRS detection algorithm. In a subfigure A there is four leads of preproccessed abdominal ECG signal in blue solid line and estimated mECG as a red line. Subfigure B presents fECG i.e. abdominal ECG signal were estimated mECG has been substracted. Noise estimates (red line) of individual leads (blue line) are shown in subfigure C and fECG leads after noise level is normalized is shown in subfigure D. Estimated fQRS templates are shown on subfigure E and correlation products of fECG (subfigure D) and fQRS teplates (subfigure E) are shown on subfigure F. Sum of lead correlations (blue line) and finally squared signals (red line) are presented in subfigure G.

eigenvectors. Thus maternal waveforms can be removed without affecting fECG component by using the few most significant eigenvectors in the wave model and extracting model result from the abdomen signal. The appropriate number of eigenvectors used in the approximation depends on the level of variation in the mECG waveforms as a function of time. Here we used six eigenvectors for the QRS complex and four eigenvectors for P and T-wave modeling. Result of mECG estimation can be seen in Figure 1 sub-figure A and fECG after mECG removing can be seen in sub-figure B.

### 3.2. Envelope method for noise power estimation

In a multi-signal analysis there is often problematic to detect which signals contain useful information and which ones contains only noise. In this paper special signal envelope were used to normalize noise power between measured channels and between different time-points in each channel. Signal envelope as a noise level estimate were based an assumption that fetal QRS-complexes has only two peaks, because envelope value was attained as the third largest peak from the closest peaks at the time. Noise level estimate was then attained by smoothing envelope estimate using 100ms moving average filter. All signals were divided by their noise estimates and then noise levels were assumed equal between all signal leads and between all time-points in a lead. Noise level estimates are shown on Figure 1 sub-figure C and normalized signals in sub-figure D.

### 3.3. Fetal QRS detection

After the maternal ECG was removed from abdomen signals and envelope method were used to normalize signal noise levels, fetal QRS detection procedure were applied. For fQRS detection multichannel template matching

technique was used. In first phase of this method 20 certain positions of fQRS complexes were located by squaring and summing fECG leads together and locating maximum peak values. By using these peak positions templates for fQRS complex were constructed individually for all leads, templates are shown on Figure 1 sub-figure E. Correlation of templates and fECG signals were then estimated (see sub-figure F) and the sum of these correlation estimates were then used for fQRS detection.

## 4. Results

Figure 1 shows representative example of fQRS detection algorithm steps. First mECG was estimated using PCR estimation method, presented in section 3.1. mECG removing is presented on sub-figures A and B, it is observed that model basis vectors can model maternal ECG waves with high accuracy, whereas fQRS complexes appearing asynchronously with maternal heart beats cannot be modeled and thus after mECG subtraction fQRS complexes are most visible peaks in fECG. Noise level is estimated and equalized as explained in section 3.2, result of this procedure is presented in sub-figures C and D. Purpose of the noise equalization is best visible in fECG lead 2 which seems to contain only strong noise component, after the procedure noise power of all leads are equal and strongest peaks can be used for fQRS template estimation. fQRS templates are shown on sub-figure E. Correlations of templates and fECG leads are presented in sub-figures F and G. In a lead 2 were no fQRS complex is shown, correlation product is near zero and in other three leads fQRS complex amplitude is even increased as compared to noise amplitude between the peaks. Finally individual correlations are summed, squared and filtered with 30ms long moving average filter to obtain easily detectable fQRS peak locations (see sub-figure G, red line). After that fQRS locations are detected with adaptive fQRS detector similar as Pan and Tompkins [8].

## 5. Discussion

PCR based maternal ECG removing algorithm has been introduced. As seen in Results section mECG extraction succeeds without decrease of fQRS amplitude, when number of model basis vectors is appropriate fQRS amplitude is preserved even when fQRS appears at the same time as mQRS complex. In a presented version of algorithm all maternal P- and T-waves, and QRS complexes are used for construction of corresponding PCR model, however in longer measurement PCR model can be created using initialization period and model basis vectors can be then updated dynamically during the measurement.

Biggest effort in this study has been used for mECG removing algorithm and for final fQRS detection well known template matching technique was used. Template matching technique works quite well on such short measurements (1 minute) as used in this study, however in longer measurements and especially during labor fetal movements cause significant changes to fQRS morphology and templates can be very hard to update to correspond current situation.

All in all presented algorithm works well on measurements used on Computing in Cardiology, PhysioNet challenge 2013 and the final scores achieved were for event 4: 28.893 $bpm^2$ and event 5: 4.844 ms.

## Acknowledgments

## References


[1] Cerutti S, Baselli G, Civardi S, Ferrazzi E, Marconi AM, Pagani M and Pardi G. Variability analysis of fetal heart rate signals as obtained from abdominal electrocardiographic recordings. Journal of Perinatal Medicine 1986; 14:445–452.

[2] Ungureanu M, Bergmans JWM, Oei SG and Strungaru R. Fetal ECG extraction during labor using an adaptive maternal beat subtraction technique. Biomedizinische Technik 2007; 52:56–60.

[3] Vullings R, Peters CHL, Sluijter RJ, Mischi M, Oei SG and Bergmans JWM. Dynamic segmentation and linear prediction for maternal ECG removal in antenatal abdominal recordings. Physiological measurement 2009; 30:291–307

[4] Comani S, Mantini D, Lagatta A, Esposito F, Di Luzio S and Romani GL. Time course reconstruction of fetal cardiac signals from fMCG: independent component analysis versus adaptive maternal beat subtraction. Physiological measurement 2004; 25:1305

[5] Lipponen JA, Gladwell VF, Kinnunen H, Karjalainen PA and Tarvainen MP. The correlation of vectorcardiographic changes to blood lactate concentration during an exercise test. Biomedical Signal Processing and Control 2013; 8: 491–499.

[6] Lipponen JA, Tarvainen MP, Laitinen T, Lyyra-Laitinen T and Karjalainen PA. A principal component regression approach for estimation of ventricular repolarization characteristics. Biomedical Engineering, IEEE Transactions on 2010; 57: 1062–1069.

[7] PhysioNet. PhysioNet/Computing in Cardiology Challenge 2013. http://www.physionet.org/challenge/2013/

[8] Pan J and Tompkins WJ. A real-time QRS detection algorithm. Biomedical Engineering, IEEE Transactions on 1985; 3: 230-236.



Address for correspondence:

Jukka A. Lipponen
Department of Applied Physics, University of Eastern Finland
P.O.Box 1627, FI-70211 Kuopio, FINLAND
jukka.lipponen@uef.fi