A Bayesian Filtering Framework for Accurate Extracting of the Non-Invasive FECG Morphology

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Abstract

Introduction: The electrocardiogram (ECG) allows for interpretation of the electrical activity of the heart. The information which can be derived from the foetal ECG (FECG) goes beyond heart rate and heart rate variability. However morphological analysis of the FECG waveform is usually not performed in clinical practice.

Methods: A Bayesian Filtering Framework based on an Extended Kalman Filter (EKF) for extracting the FECG from a single abdominal channel is described using a training database of 20, one minute maternal-foetal mixtures and evaluated on 200, one minute mixtures. (Data was generated using the simulator, fecgsyn, used to generate a subset of the signals of the Physionet Challenge 2013.) A single pass of the EKF (EKFS) was performed to cancel out the maternal ECG (MECG) in order to build an average FECG morphology. A dual EKF (EKFD, i.e. where both the MECG and FECG cycle morphology were modelled) was then applied to separate the three sources present in the signal mixture (noise, MECG and FECG). A normalised root mean square error and absolute QT error after EKFS and EKFD were calculated.

Results: An SNR improvement of 1.97 dB after EKFS and 14.14 dB after EKFD on the test set were achieved. Median absolute error on QT measurement was 17.0 ms for the EKFS and 4.0 ms for the EKFD.

Conclusion: This work is a proof of concept that the EKFD allows accurate beat to beat extraction of the FECG morphology from abdominal recordings.

1. Introduction

The electrocardiogram (ECG) allows for interpretation of the electrical activity of the heart. The information provided by the ECG goes beyond heart rate and heart rate variability. However morphological analysis of the foetal ECG (FECG) waveform is usually not performed in clinical practice because of technological limitations, as well as the the lack of agreement in how to interpret the FECG.

The scalp electrode (usually placed on the foetus' head) can only be placed at the very last stage of the pregnancy (antepartum) and has a small associated risk. It is therefore not routinely deployed. Conversely, the non-invasive foetal ECG (NI-FECG), uses electrodes on the abdomen, can theoretically be recorded at earlier stages of the pregnancy. However, the NI-FECG always manifests as a mixture of noise, foetal activity and the dominant maternal cardiac signal. Other methods for continuous foetal monitoring include foetal phonocardiography, Doppler ultrasound, cardiotocography, foetal magnetocardiography and foetal pulse oximetry. Thus there exists a range of monitoring methods and associated signals available for monitoring the foetus. However capturing useful physiological information from these signals still remains a challenge. This is partly due to the difficulty in extracting the signal of interest but also the lack of adequate algorithms to map features to clinically useful interventions.

Commercial NI-FECG monitors such as the MERIDIAN monitor from MindChild Medical (North Andover, MA) have proved to be accurate in detecting the foetal heart rate (FHR) and early works on extracting morphological information have been published [1, 2]. These recent advances in the field are very exciting but these studies are still limited in number and population size because the algorithms for extracting useful FECG are relatively new. Most commercial algorithms were not specifically designed to accurately extract the FECG morphology (they were designed for FHR extraction) and better algorithms focused on morphological extraction are now necessary. This was also highlighted during the Physionet/Computing in Cardiology challenge 2013 [3] where the QT event was unsuccessful due to both, (1) the difficulty for obtaining meaningful reference morphological annotations (QT) on the FECG data and (2) the scientific challenge in extracting the morphology of the FECG from abdominal recordings. Research in developing methods specifically focused at accurate morphological extraction of the NI-FECG is ongoing, but few studies have demonstrated any useful non-invasive FECG analysis techniques. Recently, we published studies to demonstrate accurate QT estimations can

be made on NI-FECG [2]. This current work partially aims at demonstrating that this can be automated. In particular, a Bayesian filtering framework for accurately extracting the FECG morphology from a single abdominal channel is described and evaluated.

2. Methods

The Kalman Filter (KF) framework using the dynamical Gaussian ECG model, introduced in Sameni *et al.* [4] has been extended here to model both the maternal and foetal signals jointly. The mathematical formulation is now briefly presented.

2.1. ECG model

The dynamical model which describes the states used in the KF was first proposed by McSharry *et al.* [5]. The equations of the model can be discretised by considering a small sampling period δ:

$$\begin{cases} \theta_{k+1} \equiv (\theta_k + \omega\delta) \bmod 2\pi \\ z_{k+1} = z_k - \sum_{i=1}^{N} \delta \frac{\alpha_i \omega}{b_i^2} \Delta\theta_{i,k} exp(-\frac{\Delta\theta_{i,k}^2}{2b_i^2}) + \eta_k, \end{cases} \tag{1}$$

where θ_k and z_k are the discrete phase and amplitude at time instant k, $\Delta\theta_{i,k} = \theta_k - \xi_i$ and η is a perturbation term that corresponds to random additive noise, modelling the error made by substituting the model for a real ECG. The parameters α_i, b_i and ξ_i correspond to the amplitude, width and position of the Gaussian kernels respectively. The extended Kalman filter (EKF), which is an adaptation of the KF for non-linear systems, was then used.

2.2. EKF equations

The ECG template cycles construction and Gaussian fitting were performed as detailed in [6]. We introduce the state equations for the dual EKF (EKFD) as follows:

$$\begin{cases} \theta_{k+1}^f \equiv (\theta_k^f + \omega^f \delta) \bmod 2\pi \\ \theta_{k+1}^m \equiv (\theta_k^m + \omega^m \delta) \bmod 2\pi \\ f_{k+1} = f_k - \sum_{i=1}^{N} \delta \frac{\alpha_i^f \omega^f}{(b_i^f)^2} \Delta\Theta_{i,k} exp(-\frac{\Delta\Theta_{i,k}^2}{2(b_i^f)^2}) + \eta_k^f \\ m_{k+1} = m_k - \sum_{i=1}^{N} \delta \frac{\alpha_i^m \omega^m}{(b_i^m)^2} \Delta\theta_{i,k} exp(-\frac{\Delta\theta_{i,k}^2}{2(b_i^m)^2}) + \eta_k^m \\ \alpha_{i,k+1}^f = \alpha_{i,k}^f + \varepsilon_{\alpha,i} \\ b_{i,k+1}^f = b_{i,k}^f + \varepsilon_{b,i} \\ \xi_{i,k+1}^f = \xi_{i,k}^f + \varepsilon_{\xi,i}. \end{cases} \tag{2}$$

The corresponding observation equations are:

$$\begin{cases} \varphi_k^f = \theta_k^f + v_{1,k} \\ \varphi_k^m = \theta_k^m + v_{2,k} \\ s_k = m_k + f_k + v_{3,k} \\ s_k - \sum_{i=1}^{N} \alpha_{i,k}^f \exp(-\frac{\Delta\Theta_{i,k}^2}{2(b_i^f)^2}) = m_k + v_{4,k}, \end{cases} \tag{3}$$

where the superscripts f and m stand for foetal and maternal respectively, $\Delta\theta_{i,k} = \theta_k - \xi_i^m$ and $\Delta\Theta_{i,k} = \theta_k - \xi_i^f$; φ_k correspond to the observed phases and s_k to the observed amplitude of the ECG; f_k and m_k corresponds to the foetal and maternal amplitudes which were considered as state variables; N is the number of Gaussian used to map the ECG cycle. Since we are particularly interested in morphology changes (parameters such as the QT interval) over time, the Gaussian parameters of the FECG were allowed to evolve i.e. $\alpha_{i,k}^f, b_{i,k}^f, \xi_{i,k}^f$ were considered state variables following a random walk with a perturbation term ε. However in order to limit computation time, the Gaussian parameters of the MECG were not considered as state variables. An additional observation equation (4^{th} in Equation 3) was added to act as a virtual observation of the MECG to help stabilise the filter similar to the work of Oster *et al.* [7]. The following assumptions were also made: (1) The FQRS and MQRS locations are known; (2) Seven Gaussians describe the template ECG cycle.

2.3. Database

Signals were generated using the *fecgsyn*, NI-FECG model from Behar *et al.* [8]. The open source simulator was used to generate maternal-foetal ECG mixtures with realistic amplitudes, morphology, beat-to-beat variability, heart rate changes, correlated noise and positional (rotation and translation-related) movements in the foetal and maternal heart due to respiration. A set of 20, 1-min signals were generated for the training set and 200, 1-min signals were generated for the test set. Parameters for the model were randomly sampled from a Gaussian distribution modelling various physiological parameters (see Table 1), electrode position was randomly selected from a set of 32 positions to simulate different views of the electrical cardiac activity. A set of 9 vectocardiograms with associated Gaussian parameters was available in *fecgsyn*. The first four (1-4) were used for generating the training set and the last five (5-9) were used for generating the test set data in order to ensure that the beat morphology was different in training and test.

2.4. Protocol

Figure 1 presents the block diagram of the algorithm denoted EKFD; (1) one abdominal ECG channel is pre-filtered (pass band [0.7 100] Hz); (2) the single EKF

Table 1. Parameters for the abdominal ECG simulator.

Params	Definition	95% CI
MRES	maternal breathing rate	[0.2 0.3] Hz
FRES	foetal breathing rate	[0.7983 0.9533] Hz
FHR	foetal mean heart rate	[120 160] bpm
MHR	maternal mean heart rate	[70 110] bpm
SNRmn	signal to noise ratio (maternal to noise)	[6 18] dB
SNRfm	signal to noise ratio (foetal to maternal)	[-15 -5] dB

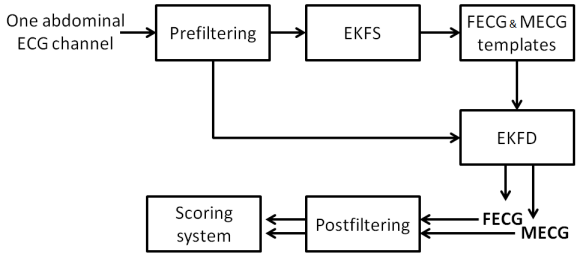

Figure 1. Block diagram of algorithm EKFD.

(EKFS [4]) was applied in order to remove the MECG contribution to the mixture; (3) Based on the residual of the EKFS step the template FECG was built; (4) the EKFD was applied to separate the three components of the mixture MECG, FECG and noise; (5) a postfiltering step (pass band [0.7 100] Hz) was applied, (6) finally the signal to noise ratio (SNR) was computed. The SNR, in decibels (dB), between a reference r and an extracted signal f with K samples was defined as: $SNR = 20 \cdot log(\sqrt{\sum_{i=1}^{K} r_i^2 / \sum_{i=1}^{K} (f_i - r_i)^2})$. The first and last five seconds of the records were not included in the SNR evaluation to account for border effects.

In addition, benchmarking was performed against the EKFS i.e. taking the residual of the first EKF pass as being the FECG. Benchmarking was also performed against EKFSS which corresponds to two single pass of EKF, one for removing the MECG and taking the residual as being the FECG and another single pass on the FECG residual in order to clean the signal. Finally benchmarking was additionally performed against the EKF model introduced in Niknazar *et al.* [9] (denoted EKFN in this article).

A random search [10] was performed on the training set in order to optimise the values of the entries of the observation and process noise covariance matrices. One hundred random search iterations were performed for the EKFD (10 free parameters), 90 random iteration for the EKFN (nine free parameters) and 50 for the EKFSS (five free parameters). Mean and median SNR across all training and test records were reported for the optimised parameters.

In addition to the SNR computation, QT measurement was performed using *ecgpuwave* [11] for the EKFS, EKFN and EKFD. *ecgpuwave* was run on the 1 min segment and QT intervals extracted from the interval 5-55 sec were kept

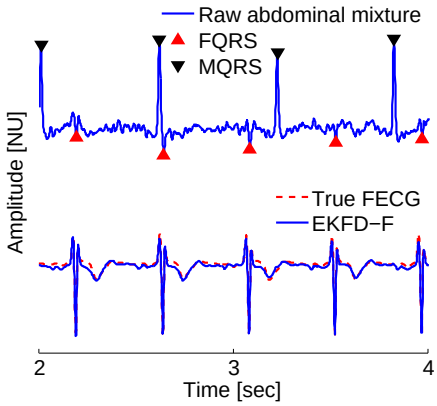

Figure 2. From top to bottom: abdominal mixture, EKFD pass on top of the true FECG.

Table 2. Results. EKFS: single EKF extracted ECG, EKFSS: ECG extracted after a second pass of EKFS, EKFD: dual EKF. M: maternal, F: foetal. SNR is in decibels.

	Train		Test	
Params	SNR (mean)	SNR (med)	SNR (mean)	SNR (med)
EKFS-M	14.64	14.86	16.53	16.70
EKFN-M	18.89	18.74	16.28	15.98
EKFD-M	16.91	16.56	14.96	14.51
EKFS-F	1.50	2.95	1.32	1.97
EKFSS-F	8.86	9.42	7.74	8.28
EKFN-F	14.96	15.47	13.00	13.01
EKFD-F	15.06	16.43	13.71	14.14

(to account for possible edge effects). Since *ecgpuwave* was not designed for foetal data and is imperfect, records with at least three successful measures on the reference FECG and on EKFD and EKFS were kept. For each filtering method, the QT interval estimate was taken to be the median of the individual QT measurements on all beats in the 50 sec interval taken into account in the recording.

3. Results

Table 2 presents the quantitative results of the analysis and Figure 2 gives a qualitative example of the algorithm performances. The EKFD SNR on the test set was 14.14 dB against 1.97 dB for the EKFS, 8.28 dB for the EKFSS and 13.01 dB for the EKFN.

A QT measure could be extracted from a total of 196 files of the test set on the reference FECG, EKFS, EKFN and EKFD. QT estimates from the EKFD and EKFS were compared to the true QT (Figure 3). Mean and median absolute errors were (19.77 ms, 17.0 ms) for the EKFS, (8.46 ms, 4.0 ms) for EKFN and (7.58 ms, 4.0 ms) for EKFD. The EKFD had a smaller bias that the EKFS and EKFN with a slope closer to unity, an offset closer to zero and a higher goodness of fit ($R^2 = 0.64$).

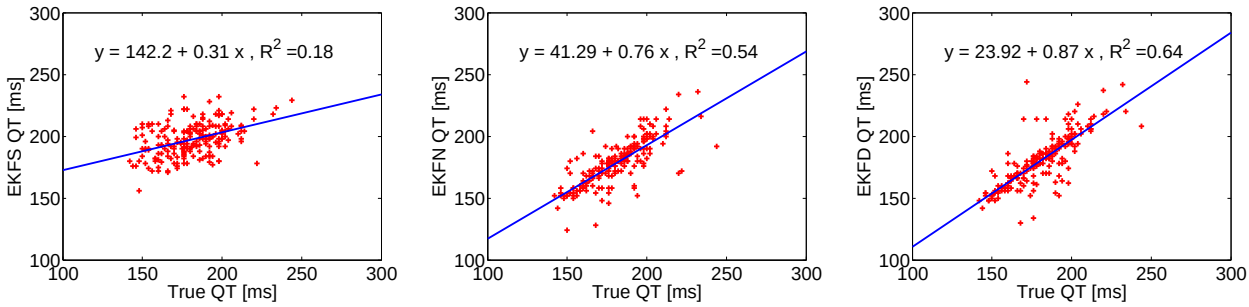

Figure 3. From left to right: QT estimated from EKFS, EKFN and EKFD processed FECG compared to the model's QT (red crosses). Also shown is the linear regression (blue line) and R^2 (coefficient of determination or goodness of fit).

4. Discussion and conclusion

The EKFD method relies on accurate and precise FQRS and MQRS detection using usch methods as the ones evaluated in Behar *et al.* [6, 12]. The residual signal from any of these methods can then be used instead of the single-pass EKF in order to build the template FECG.

Ultimately the ability of an algorithm to extract an accurate FECG morphology should be assessed in terms of clinically significant parameters such as QT segment length and ST level. This is because the RMS based similarity measure is weighted towards large amplitude features (like the QRS complex) but can provides little insight into subtle but clinically significant changes.

The EKFD performed better than the EKFS, EKFSS and EKFN and allowed more accurate QT measurement than the EKFS and EKFN. Although the improvements over EKFN were modest, the lower bias may indicate an even higher improvement on pathological data. We also note that the EKFN resulted in an NI-FECG with a baseline drift, which is an unexpected behaviour which might result in instabilities and errors in ST analysis. By adding the additional observation equation and considering the Gaussian parameters as state variables, this phenomena was not observed in EKFD, and the result was a more stable set of equations. Future work includes evaluating the EKFD algorithm on real data with clinical labels.

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