Optimized Modelling of Maternal ECG Beats using the Stationary Wavelet Transform

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Abstract

Introduction: The ECG Bayesian filtering framework has been shown to be a promising method to extract the foetal electrocardiogram (FECG) from abdominal recordings. This framework requires an estimation of the ECG morphology, which is obtained by approximating an average beat with a number of Gaussian kernels. This approximation results in a high dimensional nonlinear optimization problem (finding ideal positions, width and height for these kernels).

Methods: Proposed methodologies in the literature initialize the optimization algorithm using fixed positions for the kernel functions. This contribution benchmarks alternative schemes for finding the Gaussian parameters, namely an approach based on the stationary wavelet transform and random search. The goal is minimizing the normalized mean squared error between the average beat and the approximated model, while increasing foetal QRS detection accuracy.

Results: The suggested methods are able to produce improved morphology approximations of the averaged beat up 4.05% (depending on the selected method). The proposed method using the stationary wavelet transform improves the goodness of the fit, while reducing the computational load. However, no immediate improvement on the accuracy of FQRS detections was noticed. Such findings render the proposed method a promising tool. However, further research should be directed at transferring the improved fit to an improvement of FQRS detections.

1. Introduction

Non-invasive foetal electrocardiogram (FECG) provides an alternative mean for ante and intrapartum assessment of an unborn child's cardiac activity. It can be measured using standard ECG electrodes attached to the abdomen of pregnant women. The abdominal recordings deliver a mixture of FECG, maternal ECG (MECG) and noise (e.g. muscular and movement artefacts). The FECG and MECG signals overlap in both the time and frequency domain and often mix in a non-stationary manner [1], making source separation a difficult task.

Motivated by current standard techniques' inability to reduce rates of neonatal mortality/morbidity [2], over the past decades a number of studies focused on the processing of abdominal FECG signals. Recently, a significant advance for such techniques was achieved by the Computing in Cardiology Challenge 2013 (here denoted as 'Challenge') [1,3], which focused on accurate detection of foetal peaks from abdominal recordings. In order to extract the foetal signal from the abdominal mixture, the challenge participants (including some top scorers) have successfully made use of the of the Bayesian filtering framework, which is based on the Extended Kalman Filter (EKF).

The EKF is a flexible framework for filtering nonlinear dynamical systems. In the scope of FECG extraction, it was firstly introduced by Sameni *et al.* [4] who used the EKF for estimating the MECG signal within a single channel abdominal ECG. The estimated MECG signal was subsequently subtracted from the mixture, thus obtaining an estimate of the FECG and the noise. EKF processes signals based on a dynamic ECG model suggested by McSharry *et al.* [5] (used for the prediction step) and the observations (i.e. abdominal signal itself) for the correction step. The dynamic model is obtained by wrapping and coherent averaging MECG beats to generate the so called MECG template, here denoted as T_m. For simplifying the notation, T_m was transformed to polar coordinates system, hence $T_m(\theta_k)$ being $\{\theta_k\} \in [-\pi, \pi]$ the phase as a function of k bins [4], in this work $k \in \{1, ..., 300\}$. In order to obtain a mathematical description of the modelled system, the template $T_m(\theta_k)$ is then approximated using a number N of Gaussian kernels. Each kernel is defined by three parameters, namely α_i (amplitude), b_i (width/standard deviation) and ϕ_i (position), so that $i \in \{1, ..., N\}$. Adapting N Gaussian kernels into the averaged template results in a nonlinear optimization problem. In order to solve

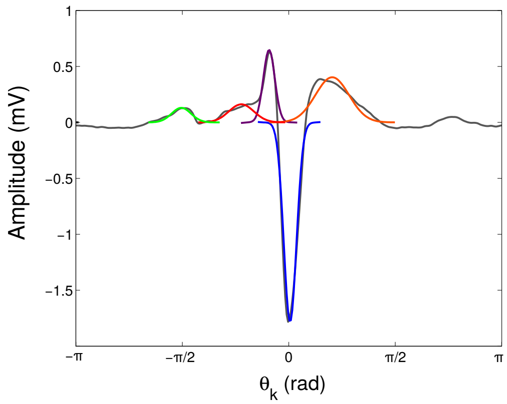

Figure 1: Example of Gaussians used in approximating an average beat $T_m(\phi_i)$. In the example $N = 5$ and $T_m(\phi_i)$ is shown in gray.

this problem, Clifford *et al.* [6, 7] used a nonlinear least-squares optimization approach.

This procedure was initialized using for each Gaussian a height defined by the local template amplitude (i.e. $\alpha_i = T_m(\phi_i)$) and the fixed width $b_i = 0.04$ rad. Although Clifford [7] allowed these positions to vary, Sameni *et al.* [4] fixed the initial positions for these kernels (ϕ_i) for simplicity and stability. This fitting is here denoted as the "Fixed Fitting" (FF).

This work aims at improving the abdominal FECG extraction based on the hypothesis that:

1. The approximation of the mean beat $T_m(\phi_i)$, compared to fitting models depicted in literature, can be improved by i) introducing an intelligent initialization procedure; and ii) relying on a repetitive procedure and exploiting the effects of random initialization.

2. A better approximation of the MECG template might result in an improvement of fetal QRS detection accuracy.

2. Materials and Methods

2.1. Gaussian Fitting

This section presents different models used to approximate $T_m(\theta_k)$ using Gaussian kernels (see Figure 1). Beyond FF described in the literature, this work compares alternative methods for initializing the optimization function. The proposed methods allow the model to adapt itself to a waveform not requiring any prior information on the expected locations of PQRST waves.

2.1.1. Fixed and Uniform Fitting

For the FF initialization, the kernel positions were obtained from publications that followed McSharry's [5] work, i.e. for $N = 5$ [5], $N = 6$ [6], $N = 7$ [6, 8] and for $N = 9 - 11$ [9]. A model for $N = 15$ was extrapolated from the model using 11 kernels by inserting 4 new kernels between the existing ones. A similar approach for the FF can be achieved by simply distributing these N kernels uniformly within the interval $[-\pi, \pi]$, which is here denoted "Uniform Fitting" (UF).

The optimization procedure was performed considering as lower/upper bounds ± 2 its initial values for each parameter α_i, b_i and ϕ_i, indenpendently of their units (i.e. mV or rads). For these experiments, the number of steps permitted for the optimization procedure was $100 \times N$.

2.1.2. Stationary Wavelet Transform Fitting

Clifford [7] proposed an intelligent algorithm for positioning the Gaussian kernel functions using cross-correlation between the MECG template and pre-defined Gaussian functions with varying standard deviations. As suggested by Clifford, the use of wavelet scaling functions is an immediate alternative to the procedure. Therefore, in this contribution, the Stationary Wavelet Transform (SWT) using the quadratic spline wavelet [10] is applied. The SWT provides a computational efficient framework, meanwhile using the scaling function belonging to the quadratic spline wavelet is qualitatively comparable to having Gaussian-like approximations at different resolutions. The SWT is a variant of the discrete wavelet transform, that permits translation-invariant decompositions at cost of being a redundant scheme, i.e. signals are not decimated at each level. The SWT was calculated by applying the *algorithme à trous* [11], i.e. on every level zeros are inserted between the low-pass filter coefficients.

The kernels used to approximate $T_m(\theta_k)$ were positioned at the absolute maxima of the low-pass coefficients, which can be interpreted as cross-correlation between the template and the scaling function at different widths. In other words, the approach does not rely on the wavelet coefficients itself, but exploits a side effect of the iterative scheme to calculate the transform, namely the low-pass coefficients. The first six dyadic scales were used i.e. $2, j \in \{1, ..., 6\}$. Since the scaling function represent low-pass filters with different widths, the power of the scaling functions vary. In order to normalize the scaling functions, the SWT was calculated and divided by the standard deviation of the scaling coefficients and template. The SWT model was applied iteratively to obtain each kernel's initial position. For each kernel, the nonlinear least squares optimization procedure was employed with a maximal number of 100 steps, for fitting α_i and b_i parameters, allowing a small shift in ϕ_i of $\pm\pi/10$. This iterative variant is denoted as "SWT Fitting" (SWTF).

Alternatively, the selected positions were used as input for the optimization procedure described in section 2.1, i.e. performing the optimization of all N kernels at once, method here named "SWTF2".

2.1.3. Random Search Fitting

A random search for positioning the used kernels provides an alternative to the deterministic approaches (e.g. SWTF approach). This method, denoted as RSF, initially centers the Gaussian kernels in random positions and repeats the optimization procedure several times. The best results, defined as the minimal normalized mean square error (NMSE) in fitting the Gaussian to the ECG template, are kept and further used. This approach was previously used to determine the Gaussian parameters by Behar et al. [12, 13]. To initialize each iteration, the Gaussian kernels were randomly positioned using hundred iterations. In order to reduce the total number of iterations, a tolerance can be included i.e. when the model reaches an acceptable fitting error, the optimization procedure is terminated.

2.2. Database and Validation

In order to evaluate hypothesis 1, i.e. which of the proposed methodologies can most accurately approximate T_m, 23 abdominal ECG recordings were used [14]. Each abdominal recording consisted of 5 minutes and 7 abdominal channels. Template generation was performed on 30 seconds epochs for each abdominal channel, therefore totalizing 1,610 templates. The goodness of the fit (GOF) was measured with respect to the NMSE as follows:

$$GOF = 1 - \underbrace{\left\| \frac{T_{M(\theta_k)} - \widehat{T}_M(\theta_k)}{T_m(\theta_k) - mean(T_m(\theta_k))} \right\|^2}_{\text{NMSE}},$$

$$\widehat{T}_m(\theta_k) = \sum_{i=1}^{N} \alpha_i \cdot exp\left(-\frac{(\theta_k - \phi_i)^2}{2 \cdot b_i^2} \right),$$

where $NMSE = 1$ represents a perfect fit.

After extracting the FECG signals using the proposed methodologies, the accuracy of the foetal QRS (FQRS) detection was evaluated to test the second hypothesis, using $N = 5, 10$ and 15. The F_1-measure was used, as in Behar *et al.* [12], for assessing FQRS detection accuracy. The measure equally weights sensitivity (SE) and positive predictive value (PPV) and is described as:

$$F_1 = 2 \cdot \frac{SE \times PPV}{SE + PPV}.$$

3. Results

Figure 2 demonstrates the goodness of the fit using the different methodologies and number of kernels N. UF performed considerably poorly ($GOF = 0.73 \pm 0.08$) and no trend could be observed, therefore it is not shown in

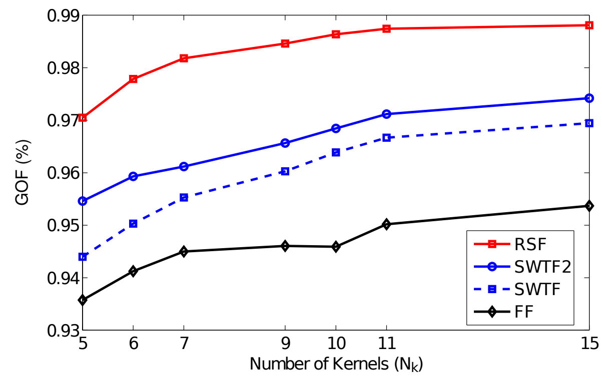

Figure 2: Goodness of the fit in terms of the NMSE.

Figure 2. The computational times using the various techniques are shown in Table 1. Increasing the number of kernels N did not shown relevant changes in terms of FQRS detection accuracy. Using FF the average F_1 for the best channel across different N was $81.71 \pm 0.55\%$, whilst using SWTF was 81.35 ± 0.60.

Table 1: Average computational time (in seconds) of algorithms using different N. Tests were performed using one recordings in a Dell Optiplex 760 desktop computer with Intel® Core™2 Duo E8400 3.00 GHz processor with 8 GB RAM. RSFTOL is a RSF variant considering as tolerance the GOF value of SWTF2 for each N.

	Number of kernels (N)		
Model	5	10	15
FF	0.104	0.304	0.354
UF	0.149	0.487	0.524
SWTF	0.120	0.168	0.199
SWTF2	$7.21 \cdot 10^{-3}$	0.112	0.218
RSF	46.3	157	269
RSFTOL	0.531	17.7	34.1

4. Discussion and Conclusions

Figure 2 shows that both SWTF and RSF methodologies were able to provide better fits for the average MECG beat than the fixed model in the NMSE sense. Moreover, the poor performance obtained by UF highlights how sensible the nonlinear least-squares optimization procedure is to its initialization, which enforces the use of non-parametric techniques as SWTF and RSF. SWTF2 results demonstrate that if the many initial parameters are well adjusted, the optimization routine is able to produce even better results than iteratively positioning each kernels (as in SWTF). Hence, hypothesis 1 was confirmed. The SWTF and SWTF2 approaches allow much faster modelling than RSF (see Table 1). The RSF method can provide a faster convergence if a tolerance criteria is included (i.e. RS-FTOL is used), at cost of lowering the GOF.

Surprisingly, no direct link between the goodness of the template fit and FQRS detection accuracy was found (hypothesis 2). The finding may be attributed to the ability of the EKF to produce good estimates of the maternal signal, even if its dynamic model is imprecise. This result emphasizes the need for a more profound characterization of the filtering steps after modelling the maternal beat, as well as, the morphology of the estimated signals.

Aside from the lower computational load, using the SWTF has some advantages over RSF. For example, the wavelet coefficients could be used for segmenting the average template [15]. This segmentation can be used for providing morphological analysis of the maternal or foetal signal (i.e. using a Dual Kalman Filter using the wavelet coefficients [13] scheme) assisted by the phase information contained in EKF. Moreover, since the approach is non-parametric, other biomedical signals (e.g. photoplethysmographic signals) can also be filtered efficiently.

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References

[1] Clifford GD, Silva I, Behar J, Moody GB. Non-invasive fetal ECG analysis. Physiol Meas 2014;35(8):1521–1536.

[2] Alfirevic Z, Devane D, Gyte G. Continuous cardiotocography (CTG) as a form of electronic fetal monitoring (EFM) for fetal assessment during labour. CDSR 2013; 5:CD006066.

[3] Silva I, Behar J, Sameni R, Zhu T, Oster J, Clifford GD, Moody GB. Noninvasive Fetal ECG: the PhysioNet/Computing in Cardiology Challenge 2013. In Comp. in Card., volume 40. 2013; 149–52.

[4] Sameni R, Shamsollahi MB, Jutten C, Clifford GD. A nonlinear Bayesian filtering framework for ECG denoising. Biomedical Engineering IEEE Transactions on 2007; 54(12):2172–2185.

[5] McSharry PE, Clifford GD, Tarassenko L, Smith LA. A Dynamical Model for Generating Synthetic Electrocardiogram Signals. IEEE Trans Biomed Eng 2003;50(3):289–294.

[6] Clifford GD, Shoeb A, McSharry PE, Janz BA. Model-based filtering, compression and classification of the ECG. IJBEM 2005;7(1):158–161.

[7] Clifford GD. A novel framework for signal representation and source separation: Applications to filtering and segmentation of biosignals. Journal of Biological Systems 2006;14(02):169–183.

[8] Clifford GD, Villarroel MC. Model-based determination of QT intervals. In Computers in Cardiology, 2006, volume 33. Sept 2006; 357–360.

[9] Sameni R, Clifford GD, Jutten C, Shamsollahi MB. Multi-Channel ECG and Noise Modeling: Application to Maternal and Fetal ECG Signals. EURASIP J Advances Sig Processing 2007;ID: 43407.

[10] Mallat S, Zhong S. Characterization of signals from multiscale edges. IEEE Trans Biomed Eng Trans Pattern Anal Mach Intell Jul 1992;14(7):710–732.

[11] Holschneider M, Kronland-Martinet R, Morlet J, Tchamitchian P. A real-time algorithm for signal analysis with the help of the wavelet transform. In Time-Frequency Methods and Phase Space. Springer Berlin / Heidelberg, 1989; 289–297.

[12] Behar J, Oster J, Clifford GD. Combining and Comparing Benchmarking Methods of Foetal ECG Extraction Without Maternal or Scalp Electrode Data. Physiol Meas 2014; 35(8):1569–1589.

[13] Behar J, Andreotti F, Oster J, Clifford GD. A Bayesian Filtering Framework for Accurate Extracting of the Non Invasive FECG Morphology. In Comp. in Card. 2014, Boston, USA, 7th-10th September, 2014, volume 41. 2014; .

[14] Andreotti F, Riedl M, Himmelsbach T, Wedekind D, Wessel N, Stepan H, Schmieder C, Jank A, Malberg H, Zaunseder S. Robust fetal ecg extraction and heart rate detection from abdominal leads. Physiol Meas 2014;35(8):1551–1567.

[15] Martínez JP, Almeida R, Olmos S, Rocha AP, Laguna P. A wavelet-based ECG delineator: evaluation on standard databases. IEEE Trans Biomed Eng April 2004;51(4):570–81.

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