MULTI-MODAL FETAL ECG EXTRACTION USING MULTI-KERNEL GAUSSIAN PROCESSES

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ABSTRACT

This study deals with fetal ECG extraction by multi-modal non-parametric modeling. In a recently proposed non-parametric approach, the fetal and maternal ECG are modeled from their respective references using Gaussian processes. The reference signals for maternal ECG and fetal ECG are the thoracic ECG and abdominal PCG, respectively. In this paper, multiple kernels are used instead of a single kernel for the covariance function of the Gaussian process. The proposed methodology improves the results of fetal ECG extraction as confirmed by experimental results.

Index Terms— Non-parametric model, fetal ECG, multi-modal, multi-channel, multi-kernel, Gaussian processes, PCG

1. INTRODUCTION

The fetal heart rate (fHR) and the morphological analysis of the fetal electrocardiogram (fECG) are two of the most important tools used nowadays in clinical investigations to examine the health state of the fetus during pregnancy [1, 2]. In physiological processes, the required signal is often not measurable directly and investigators may have to determine it from a composite signal. One such case is fECG. The main issue in extraction of fECG from an abdominal electrocardiogram (ECG) is that the maternal ECG (mECG) is stronger [3]. Different approaches have been proposed for extraction of the fetal ECG signal. These techniques are classified into single and multi-channel methods [4, 5, 2].

The methods proposed under single channel extraction includes Kalman filtering and non-parametric modeling. The non-parametric method is used to model the statistics of the signal instead of the signal itself [6]. Another method to model mECG is by state-space equations and to estimate fECG by subtracting from the mixture. Kalman filtering depends on strong assumptions about state equations that model the dynamic evolution of the unobserved state. So, it depends on prior information to perform accurately [7].

Multi-channel approaches includes methods like singular value decomposition (SVD), blind source separation and adaptive filters. They utilize quasi-periodicity of ECG to extract fECG by template subtraction. In [3, 6], SVD of the mECG is used to identify the mECG template to be subtracted from the residual signal. These methods include a number of channels, which makes the method costly considering time of processing the channels [7, 8].

In [4, 5], a multi-modal approach using non-parametric model using Gaussian processes (GP) to extract fetal ECG is proposed. Here, the separation of mECG and fECG is done by modeling using reference signals. The reference signals for mECG and fECG are the thoracic ECG and abdominal phonocardiogram (PCG), respectively. It uses different modalities: ECG (the electrical activity of heart) and PCG (the audio signal caused by closure of values of the heart). Figure 1 shows a synchronous ECG and PCG signal. The multi-modality provides complementary information about ECG in defining the Gaussian process. This method is a multi-channel method like adaptive filters, but is a non-linear method. This approach gives better results as it uses a different model for the fetus instead of the single modality using one model for mother [4, 5]. The heartbeat of fetal ECG signal is obtained from the PCG signal and the morphology of the ECG signal is obtained from the thoracic ECG signal.

In order to improve the data about morphology of an ECG signal, a multi kernel GP is proposed in this paper. Each kernel considers the shape and amplitude of the P wave, QRS complex and T wave [8, 9].

This paper is organized as follows Section 2 explains the non-parametric model of ECG signal using reference signal. Section 3 describes the algorithm for fetal extraction, while the numerical results are given in Section 4 and Section 5 concludes this study.

2. NON-PARAMETRIC MODELING OF ECG

An ECG signal can be modeled by a Gaussian process by its second order statistics: mean function $m(t)$ and covariance function $k(t, t')$ [4]. We can define mean and covariance functions as

$$m(t) = \mathbf{E}[ECG(t)] \tag{1}$$

$$k(t, t') = \mathbf{E}[(ECG(t) - m(t))(ECG(t') - m(t')] \tag{2}$$

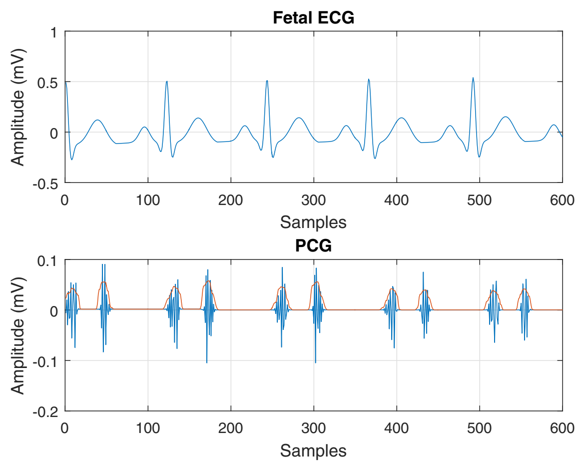

Fig. 1. Synchronous ECG and PCG.

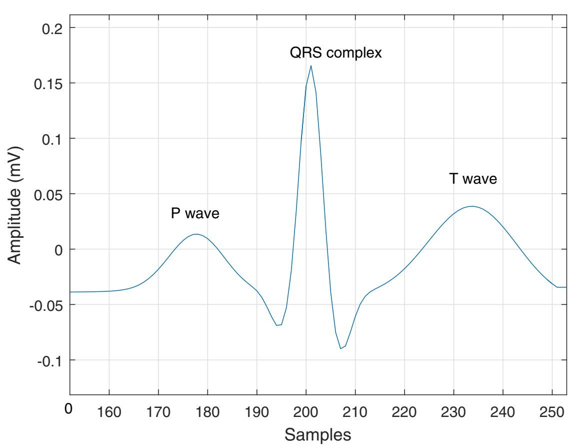

Fig. 2. One beat of ECG signal.

where $\mathbf{E}[\cdot]$ is the expectation operator and the GP is represented as

$$ECG(t) \sim \mathcal{GP}(m(t), k(t, t')). \tag{3}$$

The mean function is taken as zero for simplicity [4, 5]. So, the covariance function plays the crucial role in describing the GP as it reflects quasi-periodicity.

Consider $s(t)$ as noisy ECG signal and $r(t)$ as reference signal. We can define the covariance function of $s(t)$ using $r(t)$ if there is dependency between them. Assume that they are dependent. In [4], the covariance function with single squared exponential (SQE) kernel is defined as

$$k(r_N(t), r_N(t')) = \sigma^2 exp\left(-\frac{(r_N(t) - r_N(t'))(r_N(t) - r_N(t'))^T}{2\ell^2}\right) \tag{4}$$

where σ, N, ℓ are hyperparameters. σ^2 is scale factor which determines the average distance of the signal from its mean. N is window length of ECG signal. ℓ is length scale parameter which determines length of the wiggles in the signal.

We know that each ECG beat is composed of three parts: P wave, QRS complex and T wave (Fig. 2). Each one of them have different characteristics. So, it is important to have more than one kernel to define them. The standard way of combining kernels is to multiply them; it can be thought as an AND operation [8]. So the final kernel will have high value if all kernels have high value. The new covariance function (k_s) consists of multiple kernels to characterize each one of them. It is defined as

$$k_s(r_N(t), r_N(t')) = \prod_{i=1}^{I} k_i(r_N(t), r_N(t')) \tag{5}$$

where I is the number of the kernels and $k_1(\cdot,\cdot), k_2(\cdot,\cdot), ..$ ..., $k_n(\cdot,\cdot)$ is defined by (4).

Here kernels of the same type are used. In [9], the same approach is tested on geological data with different type of kernels. The results show that different types of kernels are better than kernels of the same type. Also, the reference signal can be ECG or PCG signal [5]. Here, which kernel models what part of the signal is not specified.

3. FETAL ECG EXTRACTION

The abdominal signal $y(t)$ is the superposition of maternal ECG $s_m(t)$, fetal ECG $s_f(t)$ and additive noise $n(t)$ as

$$y(t) = s_m(t) + s_f(t) + n(t). \tag{6}$$

Following [4], $x(t)$ is the reference signal for the maternal ECG and is the thoracic ECG recorded from the chest. The reference signal for the fetal ECG is the envelope of the PCG $p(t)$ recorded from the abdomen.

Maternal ECG $s_m(t)$ is modeled using M samples of reference signal $x(t)$ as [4]

$$s_m(t) \sim \mathcal{GP}(0, k_m(x_M(t), x_M(t'))) \tag{7}$$

where $k_m(\cdot,\cdot)$ is the covariance function of maternal ECG signal as (5). It gives information about morphology and characteristics of the ECG signal. So, the multi-kernel covariance function is used for maternal ECG in order to get more knowledge to model the signal.

The fetal ECG is dependent on the fetal PCG envelope. So, the fetal ECG $s_f(t)$ is modeled using P samples of the reference signal $e(t)$ as [4]

$$s_f(t) \sim \mathcal{GP}(0, k_f(e_P(t), e_P(t'))) \tag{8}$$

where $k_f(\cdot,\cdot)$ is the covariance function of fetal ECG signal as defined by (4). It gives information about heart beat information (R peaks) of the fetal ECG signal. So, the multi-kernel covariance function is not necessary in this case.

A GP model of noise $n(t)$ can be defined as [4]

$$n(t) \sim \mathcal{GP}(0, k_n(t, t')) \tag{9}$$

Table 1. Estimated hyperparameters of the signal.

no. of kernels	σ_1, ℓ_1	σ_2, ℓ_2	σ_3, ℓ_3	σ_4, ℓ_4	σ_5, ℓ_5	σ_6, ℓ_6	σ_7, ℓ_7	σ_8, ℓ_8	σ_9, ℓ_9
1	0.22,17								
2	0.15,30	0.20,55							
3	0.21,35	0.90,37	0.26,57						
4	0.16,35	0.89,35	0.20,55	0.15,15					
5	0.15,33	0.76,35	0.26,55	0.12,15	0.20, 9				
6	0.12,35	0.89,37	0.24,57	0.10,15	0.18, 9	0.60,12			
7	0.14,26	0.80,37	0.26,55	0.12,13	0.18, 9	0.56,12	0.15,25		
8	0.13,26	0.80,37	0.26, 5	0.12,13	**0.18, 9**	0.15,25	**0.18, 9**	0.56,12	
9	0.10,26	0.80,37	0.26,55	0.12,13	**0.18, 9**	0.56,12	**0.15,25**	**0.18, 9**	**0.12,25**

where $k_n(t,t') = \sigma_n \delta(t-t')$, σ_n models noise amplitude and $\delta(\cdot)$ is the Dirac delta function.

The hyperparameters of the covariance function of the maternal ECG signal are σ_i and ℓ_i of each kernel, the fetal ECG signal are σ_f and ℓ_f, and noise is σ_n. These parameters have to be estimated for the calculation of the covariance function. One method of estimation is maximization of log marginal likelihood given by [10]

$$\log(p(\mathbf{y}/\theta)) = -\frac{1}{2}\log(2\pi) - \frac{1}{2}\log(|\mathbf{K}|) - \frac{1}{2}\mathbf{y}^{\mathbf{T}}\mathbf{K}^{-\mathbf{1}}\mathbf{y} \quad (10)$$

where θ is the total number of parameters.The matrix inversion of $\mathbf{K}$ is computed using Cholesky decomposition instead of direct inversion as it is quick and numerically stable [10].

The $(j,k)^{th}$ value of the $\mathbf{K}$ matrix is [5]

$$K_{j,k} = k_m(x_M(t_i), x_M(t_j) + k_f(e_P(t_i), e_P(t_j)) + k_n(t_i, t_j). \quad (11)$$

The fetal ECG signal can be estimated by [4, 9]

$$s_f(t*) = \mathbf{k_f}(t*)\mathbf{K}^{-1}\mathbf{y} \quad (12)$$

where $\mathbf{k_f}(t*) = [k_f(e_P(*), e_P(t_1)), ..., k_f(e_P(*), e_P(t_n))]$, $\mathbf{y} = [y(t_1), y(t_2), ...y(t_n)]^T$ and n is the length of the signal.

4. RESULTS

Since a public database is not available with both fECG and PCG, the proposed algorithm is tested using synthetic data. The synthetic abdominal ECG data is the summation of maternal ECG, fetal ECG and additive white Gaussian noise. The synthetic PCG is generated according to fetal ECG. The envelope of the PCG is obtained using Hilbert transform with moving average filter [4]. The hyperparameters of the covariance function are computed using GPy and GPML toolbox [10, 11]. The initial values for hyperparameters are set to 1. One to ten kernels are taken for the calculation of covariance function of the maternal signal. The fetal ECG signal is estimated in each case. The mean square error (MSE) in estimation of fetal signal is shown in Fig. 4. The covariance function of seven kernels gives a better result compared to one kernel by 4.2% change in MSE. The performance of the system increases with addition of kernels from one upto seven. An increase in number of kernels after seven deteriorates the performance of the estimation. We expect the system reach to saturation or have the optimization algorithm fail. Figure 4 shows the optimization starts to fail at eight kernels. The covariance function or the kernel is the measure of variations in the signal. Number of kernels means more information about the signal. So, the error in the estimation is decreased (Fig. 4). Table 1 shows the estimated hyperparameters in different cases. The bolded numbers in the table indicates near repeated kernels. The values in each box represents similar kind of kernels in each case. The average of the values of kernel parameters in each box is computed. The resultant kernels versus seven kernels are considered for estimation of fECG extraction. Still, the seven number of kernels approach is better than previous case by 3.3% change in MSE. One of the reasons for the failure in the algorithm after seven kernels is repetition of the same kernel (Table 1). Based upon the obtained hyperparmeters seven kernels capture the approximate variations of the ECG signal shown in Fig. 5. The start of P, end of T wave and P, Q, R, QRS complex duration has been recognized by covariance function (Fig. 5). The estimated fetal ECG with seven kernels is shown in Fig. 3. In Fig. 3, (b) is the reference for maternal ECG signal and (d) is the reference for fetal ECG signal. The fetal ECG signal Fig. 3(e) is extracted from composite signal Fig. 3(a) with MSE of 0.2867.

5. CONCLUSION

In this study, multi-channel non-parametric modeling to define ECG is discussed. The maternal ECG and fetal ECG are defined using different modal signals. In this way more information is obtained to model the ECG signal. ECG signal consists of P wave, QRS complex and T wave. By considering different kernel to define them increases the knowledge about variations in ECG signal. Thereby, the fetal ECG extraction is

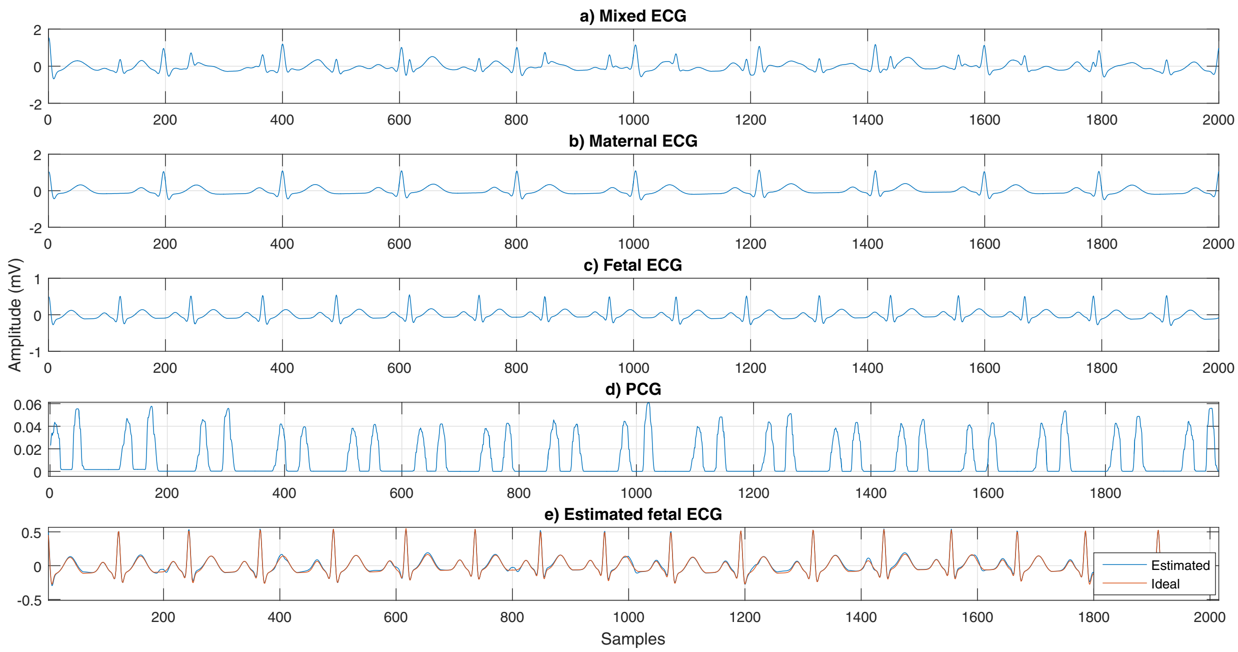

Fig. 3. Experimental results: (a) Mixed ECG (b) Maternal ECG (c) Fetal ECG (d) PCG (e) Estimated fECG.

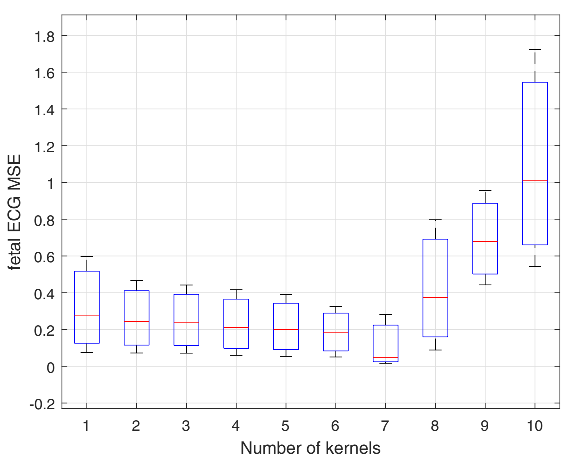

Fig. 4. Error estimation of fECG.

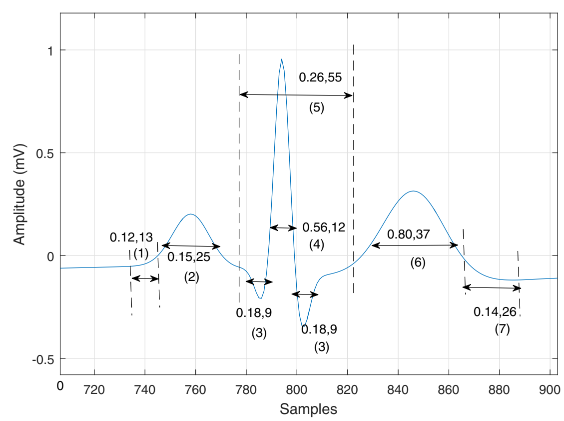

Fig. 5. Approximate kernels for maternal ECG for 7 kernels case in Table 1

improved. The results show that the error in the estimation of fetal ECG signal is minimum when the number of kernels are taken as seven. Even though multi-kernel approach has advantages compared to other methods, the accurate covariance function is essential for better results. As the number of the kernels increases, the hyperparameters are increased. So, the estimation of hyperparameters becomes difficult task and time consuming. So, the highly efficient optimization algorithm is required. Also, prior information about the ECG signal helps in the optimization. The performance of the proposed algorithm is limited by computational time. The difference in the run time for single kernel and seven kernels is 30 secs. If the specified time duration is acceptable, it is advisable to go for multiple kernels. To decide if seven is the approximate value for number of kernels, it has to be tested with data set and real data. The accuracy of modeling of the signal by multi-kernel and single kernel approach is not specified. Future work includes the kernels of different types in covariance function.

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