Remi D *et al*, International Journal of Computer Science and Mobile Computing, Vol.3 Issue.4, April- 2014, pg. 1233-1239

Available Online at www.ijcsmc.com

International Journal of Computer Science and Mobile Computing

A Monthly Journal of Computer Science and Information Technology

ISSN 2320–088X

IJCSMC, Vol. 3, Issue. 4, April 2014, pg.1233 – 1239

RESEARCH ARTICLE

EXTENDED STATE KALMAN FILTERING BASED FETAL ECG, MATERNAL ECG EXTRACTION & ESTIMATE THE MATERNAL BLOOD PRESSURE USING SINGLE CHANNEL RECORDINGS

Remi D (1) , Jebila S (2)

(1)P.G student, Department of Biomedical Engineering, Udaya School of Engineering,

(2)Asst Professor, Department of Biomedical Engineering, Udaya School of Engineering,

Email: remibme@gmail.com (1)

Abstract-The fetal ECG (fECG) provides a mean to monitor non-invasively the fetal heart activity. In this paper, an extended nonlinear Bayesian filtering framework for extracting electrocardiograms (ECGs) from a single channel as encountered in the fetal and maternal ECG extraction from abdominal sensor is presented. The recorded signals are modeled as the summation of several ECGs. Each of them is described by a nonlinear dynamic model, previously presented for the generation of a highly realistic synthetic ECG. A modified version of this model is used in several Bayesian filters, including the extended kalman filter, Extended Kalman smoother, and Unscented Kalman filter. Consequently, each ECG has a corresponding term in this model and can thus be efficiently discriminated even if the waves overlap in time. This framework is also validated on the extractions of fetal ECG and maternal ECG from actual abdominal recordings, as well as of actual twin magneto cardiograms. In this paper, maternal blood pressure is estimated based on kalman filtering using single channel recordings.

Keywords: Extended Kalman filtering (EKF), fetal electrocardiogram (fECG) extraction, Maternal electrocardiogram (mECG) extraction, nonlinear Bayesian filtering

I INTRODUCTION

Heart diseases are the cause of many deaths during prenatal, childbirth and newborn periods. Fetal Heart Rate (FHR) analysis has become a widely accepted means of monitoring fetal status. Currently, Doppler ultrasound and FECG have proven to be reliable techniques for monitoring FHR. The use of Doppler ultrasound (non invasive manner**)** is not suitable for long periods of fetal heart rate monitoring. In [1] contrast, methods utilizing the abdominal electrocardiogram (AECG) has a greater prospect for long-term monitoring of FHR and fetal well being using signal processing techniques. The fetal ECG is an electrical signal that can be obtained non-invasively by applying a pair of electrodes to the abdomen of a pregnant woman. The characteristics of the FECG, such as presence of signal, rate, waveform and dynamic behavior are useful in determining the fetal life, fetal maturity and existence of fetal distress or congenital heart disease.

The abdominal ECG contains a weak fetal ECG signal, a relatively sound maternal ECG, maternal muscle noise (electromyographic activity in the muscles of the abdomen and uterus) and respiration, mains coupling, and thermal noise from the electronic equipment (electrodes, amplifiers, etc.). Maternal ECG is the most predominant interfering signal with FECG in the abdominal signal. The frequency spectrum of this noise source partially overlaps that of the ECG and therefore filtering alone is not sufficient to achieve adequate noise reduction. To investigate the relation of diastolic blood pressure in pregnancy with birth weight and perinatal mortality.The mean (SD) birth weight of babies born to mothers with no hypertension before 20 weeks' gestation or proteinuria was 3282 g (545 g) and there were 1335 perinatal deaths, compared with 94 perinatal deaths among women with proteinuria or a history of hypertension. The birth weight of babies being delivered after 34 weeks was highest for highest recorded maternal diastolic blood pressures of between 70 and 80 mm Hg and lower for blood pressures outside this range. Both low and high diastolic blood pressures were associated with statistically significantly higher perinatal mortality. Most of these excess deaths occurred with blood pressures below the optimal value. This Bayesian filter framework was used in to extract fECG ,mECG and estimate the blood pressure from single channel mixture of abdominal signal. The proposed system facilitates the prenatal procedures for monitoring of the cardiac condition of both the mother and the fetus, by developing a transabdominal device or long-term health monitoring. Therefore the study of the fetal and maternal cardiac signals might be very helpful in order to evaluate the fetal heart status for early detection of cardiac abnormalities.

Factors Affecting the Abdominal ECG Signal

Electrode Contact Noise: Electrode contact noise is transient interference caused by loss of contact between the electrode and skin, which effectively disconnects the measurement system from the subject. Electrode contact noise can be modeled as a randomly occurring rapid baseline transition, which decay exponentially to the baseline value and has a superimposed 60Hz component. The transition may occur only once or may rapidly occur several times in succession.

Motion Artifact: When motion artifact is introduced to the system, the information is skewed. Motion artifact causes irregularities in the data. There are two main sources for motion artifact, Electrode interface and Electrode cable. Motion artifact can be reduced by proper design of the electronic circuitry and set-up.

Inherent Noise in Electronics Equipment: All electronic equipments generate noise. This noise cannot be eliminated; using high quality electronic components can only reduce it.

Ambient Noise: Electromagnetic radiation is the source of this kind of noise. The surfaces of the human bodies are constantly inundated with electric-magnetic radiation and it is virtually impossible to avoid exposure to ambient noise on the surface of earth.

II METHODOLOGY

In this work the maternal and fetal ECG signals are extracted from the abdominal ECG recording. In addition to this, maternal blood pressure is estimated by using single channel recordings. The block diagram of the overall methodology used in this study is shown in Figure 1.

2.1 Abdominal signal

Electrical signals recorded from the abdomen of a pregnant woman consist of mixtures of various signals including the mECG, fECG, fetal electroencephalogram (fEEG), baseline wanders and muscle contractions considered as noise.

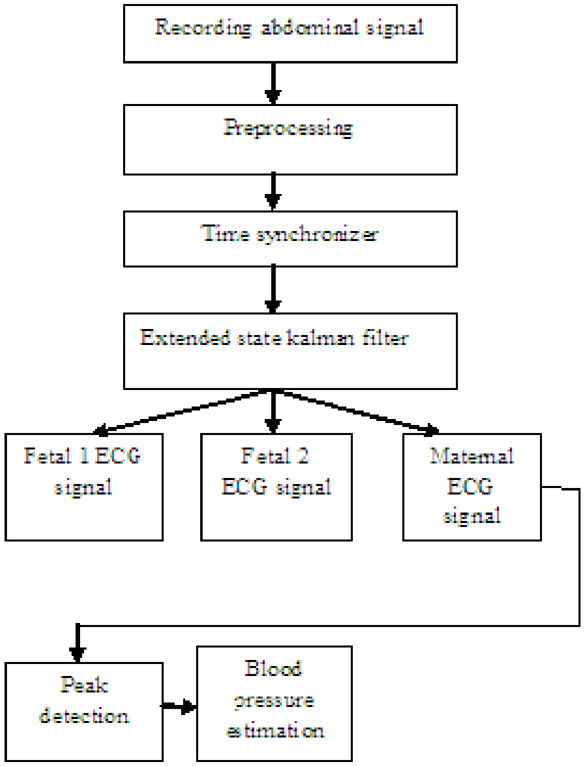


Fig 1 Over all block diagram

2.2 Pre-processing

Pre-processing included the application of a band pass filter. It allows only the required frequencies and rejects all those frequency outside that range. The frequency ranges from 0.01Hz to 100Hz was chosen. Savitzky-Golay filter is mainly used to remove the noise from the data. Savitzky-Golay smoothing filters also called digital smoothing polynomial filters are typically used to “smooth out” a noisy signal whose frequency span (without noise) is large. In this type of application savitzky-Golay smoothing filters perform much better than standard averaging FIR filters which tend to filter out a significant portion of the signals high frequency content along with the noise. Although savitzky-Golay filters are more effective at preserving the pertinent high frequency components of the signal they are less successful than standard averaging FIR filters at rejecting noise**.**

2.3 Time synchronizer

In this paper the signals will be extracted in accordance to the time synchronizer. The signals are extracted depend upon the time and amplitude.

2.4 Kalman filter

The Kalman filter, also known as linear quadratic estimation (LQE) an algorithm that uses a series of measurements observed over time, containing noise (random variations) and other inaccuracies, and produces estimates of unknown variables that tend to be more precise than those based on a single measurement alone. The Kalman filter has numerous applications in technology. Furthermore, the Kalman filter is a widely applied concept in time series analysis used in fields such as signal processing and econometrics. he algorithm works in a two-step process. In the prediction step, the Kalman filter produces estimates of the current state variables, along with their uncertainties. Once the outcome of the next measurement (necessarily corrupted with some amount of error, including random noise) is observed, these estimates are updated using a weighted average, with more weight being given to estimates with higher certainty. Because of the algorithm's recursive nature, it can run in real time using only the present input measurements and the previously calculated state and its uncertainty matrix; no additional past information is required.

2.5 Extended Kalman Filter Framework for ECG Extraction

The goal of KF is to estimate the state of a discrete-time controlled process. Consider a state vector x_{k+1} governed by a nonlinear stochastic difference equation with measurement vector y_{k+1} at time instant k + 1:

$$\begin{Bmatrix} x_{k+1} = f(x_k, w_{k,} k+1) \\ y_{k+1=h(x_{k+1}}, v_{k+1}, k+1 \end{Bmatrix}$$

where the random variables w_k and v_k represent the process and measurement noises, with associated covariance matrices. The extended Kalman filter (EKF) is an extension of the standard KF to nonlinear systems ,which linearizes about the current mean and covariance. In order to improve the estimations, EKF can be followed by a backward recursive smoothing stage leading to the extended Kalman smoother (EKS). However, since EKS is a noncausal method, it cannot be applied online but it is useful if a small lag in the processing is allowed. The ECGs composing the observed mixture can be estimated by recursively applying the described EKF: at each step, one ECG is extracted according to a deflation procedure. In case of a mixture of mECG and one fECG, the first step extracts, from the raw recording, the dominant ECG (often the mECG) considering the concurrent ECG (respectively, fECG) and other noises as a unique Gaussian noise. After subtracting the dominant ECG from the original signal, the second step is the extraction of fECG from the residual signal. This procedure is referred to as sequential EKF or EKS (seq-EKF or seq-EKS). In this recursive extraction, during the first step, the concurrent ECG (i.e., fECG) and additional noise are modeled by Gaussian noises v_k and w_k , which is not a very relevant assumption. In fact, although this assumption may be acceptable when there are not strong artifacts interfering with the ECG, it is no longer accurate when other ECG artifacts are considerable (i.e., at the first step) since the noise is no longer normally distributed. In addition, concurrent ECGs can be confused with dominant ECG when their waves (especially QRS complexes) fully overlap in time. Meanwhile, resultant inaccuracies, which are generated by the previous steps of the ECG extraction, will propagate to the next steps while the residuals are computed.

2.6 Fetal & maternal ECG Signal

The fetal ECG records the electrical activity of a fetus. Fetal ECG signal contains potentially precise information that could assist clinicians in making more appropriate and timely decisions during labor. The extraction and detection of the FECG signal from composite abdominal signals with powerful and advance methodologies are becoming very important requirements in fetal monitoring. Maternal ECG signal provides the valuable information about the early detection of the cardiac abnormalities.

2.7 Peak detection

The idea is to clean up the signal, and then set some dynamic threshold, so that any signal crossing the threshold is considered a peak. The peak can be counted per time window.

2.8 Maternal Blood Pressure:

Blood pressure can be determine depends upon the threshold value .Normal blood pressure is below 140/90 mmHg (Systolic Blood Pressure (SBP)/Diastolic Blood Pressure (DBP)). Routine blood pressure and urine protein checkup during ante natal care is for the early detection of a condition known as pre-eclampsia, also known as pre-eclamptic toxaemia, or just toxaemia. Pre-eclampsia is a serious pregnancy disorder of pregnancy characterised by high maternal blood pressure, protein in the urine, and severe fluid retention. The placenta in uterus is a special organ that allows oxygen and nutrients to pass from the mother's bloodstream to the baby, and waste products (such as carbon dioxide) to pass from the baby's bloodstream to the mother. In pre-eclampsia, blood flow to the placenta is obstructed. In severe cases, the baby can be gradually starved of oxygen and nutrients, which may affect its growth.

III RESULTS

3.1 Fetal ECG Signal Extraction

The fHR varies for different reasons. In most cases, there is no connection to oxygen deficiency. Instead, the variations are signs of normal adaptation to changes in the environment. Some reasons include changes in placental blood flow, hypoxia, external stimuli, increases in temperature and drugs. When classifying a fECG, the baseline fHR, variability, reactivity and the appearance of decelerations have to be assessed. On the basis of these parameters, a fECG can be classified as normal, intermediate, abnormal or preterminal . Baseline fHR is the mean fHR rounded to increments of 5 beats per minute during a 10-minute segment, excluding periodic changes and periods of marked fHR variability (segments of the baseline that differ by more than 25 beats per minute). Fetal tachycardia is defined as a baseline heart rate greater than 160 bpm and is considered a non reassuring pattern. Tachycardia is considered mild if the heart rate is from 160-180 bpm and severe if it is greater than 180 bpm. Tachycardia greater than 200 bpm is usually due to fetal tachyarrhythmia or congenital anomalies rather than hypoxia alone. If the baseline fHR is less than 110 beats per minute, it is termed bradycardia. Fetal bradycardia is defined as a baseline heart rate less than 120 bpm. Bradycardia from 100- 120 bpm with normal variability is not associated with fetal acidosis. Bradycardia less than 100 bpm occurs in fetuses with congenital heart abnormalities or myocardial conduction defects, such as those occurring in conjunction with maternal collagen vascular disease. Moderate bradycardia from 80-100 bpm is a non-reassuring pattern. Severe bradycardia, less than 80 bpm lasting for three minutes or longer, indicates severe hypoxia and is often a terminal event. If the cause cannot be identified and corrected, immediate delivery is recommended. Fetal electrocardiogram (FECG) signal contains potentially precise information that could assist clinicians in making more appropriate and timely decisions during labor. The ultimate reason for the interest in FECG signal analysis is in clinical diagnosis and biomedical applications. FECG signals might be very helpful in order to evaluate the fetal heart status for early detection of cardiac abnormalities.

3.2 Noninvasive fECG Database

This database consists of a series of 55 multichannel abdominal fECG recordings, taken from a single subject between 21 and 40 weeks of pregnancy. The signals were recorded at 1 kHz, 16-bit resolution with a bandpass filter (0.01–100 Hz) and a main notch filter (50 Hz). The results of seq-EKS and par-EKS using channel 3, and πCA using all channels of the first 20s of namely the ecgca771 dataset. To show the effectiveness of the proposed method in extraction of the fECG at different periods of pregnancy, and from different channel locations, the first 20s of the mixtures and fetal par-EKS outputs of the datasets ecgca274 channel 5, ecgca748 channel 4, and ecgca997 channel 3 are plotted .

3.3 Twin Magneto cardiograms Extraction

The proposed method has been principally designed for ECG signals. Nevertheless, due to the morphological similarity of the ECG and the magneto cardiogram (MCG), it is also directly applicable to MCG recordings. In this section, twin fetal cardiac magnetic signals recorded by a SQUID Biomagneto meter system are 29 extracted. Finally, it is worth noting that the crucial part of the proposed par-EKS is the R-peak detection. Although this detection is quite direct when a single fetus is present, some words should be added on twin data. Indeed, on such data, the detection of the mothers R-peaks is still direct since it is the dominant signal. On the contrary, the discrimination between the two fetal R-peaks is much more difficult.

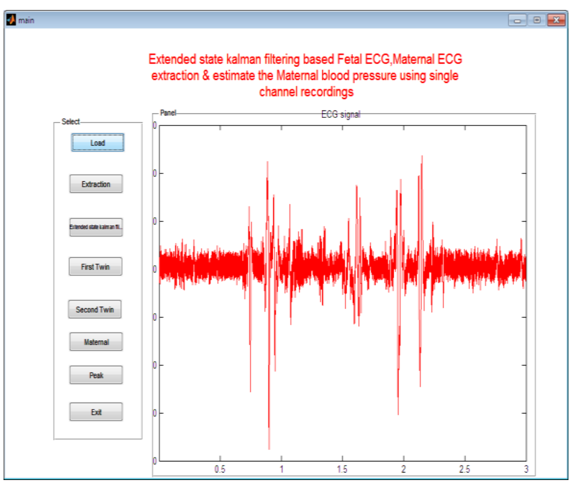


Fig.2 Abdominal signal

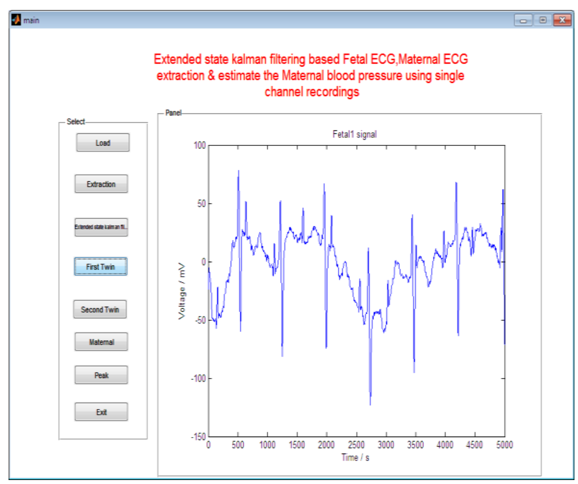


Fig.3 Fetal 1 ECG signal

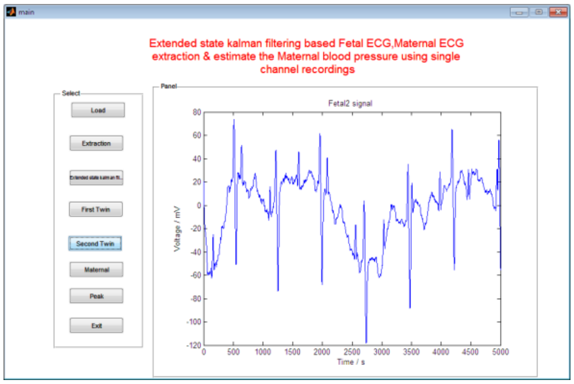


Fig.4 Fetal 2 ECG signal

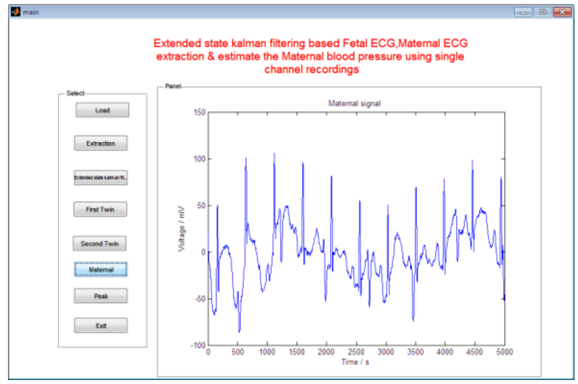
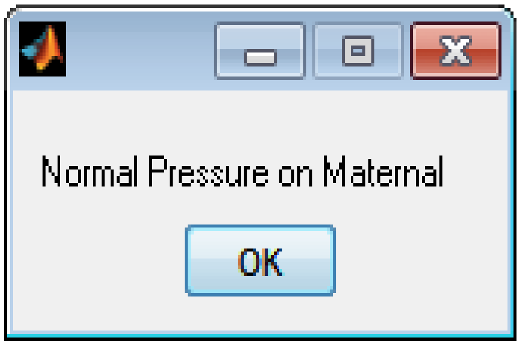


Fig.5 Maternal ECG signal



IV CONCLUSION

In this paper a method was proposed for extracting the fECG and mECG signal from maternal abdomen recordings. The idea is based on separating the contribution of the fetal & maternal ECG signals in each of the channels from the other contaminating signals and noises, through a multistage interference and noise cancellation scheme. This paper the kalman filtering approach has been used to extract the fetal & maternal ECG signal from the abdominal ECG that is the agreeable output.

As a part of future work, it is possible to estimate fetal blood pressure and disease diagnosis based on estimated blood pressure.

REFERENCES

1.H. M. Jenkins, *Technical progress in fetal electrocardiography—A review* J. Perinat. Med., vol. 14, no. 6, pp. 365–370, 1986.
2.G. Camps, M. Martinez, and E. Soria, "*Fetal ECG extraction using an fir neural network*," in Proc. Comput. Cardiol., 2001, pp. 249–252.
3.R. Sameni and G. D. Clifford, *A review of fetal ECG signal processing; Issues and promising directions* Open Pacing, Electrophysiol. Ther. J., vol. 3, pp. 4–20, 2010.
4.A. Khamene and S. Negahdaripour, *A new method for the extraction of fetal ECG from the composite abdominal signal*, IEEE Trans. Biomed. Eng., vol. 47, no. 4, pp. 507–516, Apr. 2000.
5.P.P. Kanjilal, S. Palit, and G. Saha, Fetal *ECG extraction from single channel maternal ECG using singular value decomposition* IEEE Trans. Biomed. Eng., vol. 44, no. 1, pp. 51–59, Jan. 1997.
6.J.-F. Cardoso, *Multidimensional independent component analysis*, in Proc. IEEE Int. Conf. Acoust., Speech, Signal Process., May 1998, vol. 4, pp. 1941–1944.

7.L. de Lathauwer, B. de Moor, and J. Vandewalle, *Fetal electrocardiogram extraction by blind source subspace separation* IEEE Trans. Biomed. Eng., vol. 47, no. 5, pp. 567–572, May 2000.
8.R. Sameni, C. Jutten, and M. B. Shamsollahi, *Multichannel electrocardiogram decomposition using periodic component analysis* IEEE Trans. Biomed. Eng., vol. 55, no. 8, pp. 1935–1940, Aug. 2008.
9.J. L. Camargo-Olivares, R. Marti-Clemente, S. Hornillo-Mellado, M. M. Elena, and I. Roman, *The maternal abdominal ECG as input to MICA in the fetal ECG extraction problem* IEEE Signal Process. Lett., vol. 18, no. 3, pp. 161–164, Mar. 2011.
10.A. K. Barros and A. Cichocki, *Extraction of specific signals with temporal structure* Neural Comput., vol. 13, no. 9, pp. 1995–2003, Sep. 2001.
11.Z. Yi and Z. Zhang, *Extraction of temporally correlated sources with its application to non-invasive fetal electrocardiogram extraction* Neurocomputing, vol. 69, no. 7–9, pp. 894–899, 2006.
12.Y. Li and Z. Yi, *An algorithm for extracting fetal electrocardiogram* Neurocomputing, vol. 71, no. 7–9, pp. 1538–1542, 2008.
13.V. Vigneron, A. Paraschiv-Ionescu, A. Azancot, O. Sibony, and C. Jutten, *Fetal electrocardiogram extraction based on non-stationary ICA and wavelet denoising* in Proc. 7th Int. Signal Process. Appl. Symp., 2003, vol. 2, pp. 69–79.
14.M. G. Jafari and J. A. Chambers, *Fetal electrocardiogram extraction by sequential source separation in the wavelet domain* IEEE Trans. Biomed. Eng., vol. 52, no. 3, pp. 390–400, Mar. 2005.