

Continuous Portable Fetal Heart Rate Monitoring Device

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Abstract— The mortality rate for women who gave birth to new-born was 8.8 deaths per 100,000 live births. The abortion-related death rate was 0.6 deaths per 100,000 abortions. In one recent proportional study of pregnancy death rate in the United States, pregnancy-related problems were more communal in childbirth than in abortion. The miscarriage of pregnancy is due to the inappropriate diagnosis of fetal heart rate. To reduce the rate of abortions and monitoring the fetal heart continuously “Portable Fetal Heart Rate Monitoring Device” is critically needed in the gestational period. Better prospects are related with application of indirect fetal electrocardiography (fECG), especially for home telemonitoring of pregnancy. Monitoring fetal health early in pregnancy supports to avert possible fetal damage along with fetal death. Amongst several fetal monitoring techniques, the invasive fetal scalp electrode method be the most accurate process at labor. Though, this technique may cause risk of infection and deformation of the baby if used for antepartum monitoring. The non-invasive fetal ECG is the next best method to extract fetal heart rate (FHR). This device is used to monitor continuous fetal ECG, maternal ECG and UC (Uterine contractions) during labor. This ensure that there’s over all connectivity right from gestational period to intrapartum potentially reducing the mortality rate by the proposed device.

Keywords—maternal electrocardiogram, fetal electrocardiogram, Template Subtraction, Independent Component Analysis.

I. INTRODUCTION

One of the biggest difficulty in modern medical speciality is very limited possibility to obtain valid data about the health status of the fetus from different monitoring methods during childbirth. Morphological features of the fetal ECG can be successfully recognized using an invasive method using an electrode attached to the scalp of the fetus. Unfortunately, this direct measurement of the fECG has a utmost difficulty, as it is only used during labor after the membranes have ruptured. Recently, the dependability of fetal cardiac parameters extracted from a ECG copies along with their outstanding arrangement with values recorded from the scalp electrode signal have been confirmed.

The electrophysiological signals existed in a ECG capacities are maternal electrocardiogram (mECG), fECG along with electrohysterogram (EHG), which is the electrical activity of the uterus, very strong during labor. The fetal ECG is mixed with various sources of interference such as maternal muscle sound, breathing, baseline wander, electrode pop or contact noise, skin resistance interference, physiological noise, acoustic sound formed by fetal movements and power line disturbance so extraction of fetal ECG from abdominal mother records is a very stimulating task.

So far, various signal processing methods have been used to extract the fetal ECG from non-invasive recordings. One of the most common is Independent Component Analysis (ICA) based on several algorithms and other algorithms used for signal extraction are Principal Component Analysis, Augmented Kalman Filter, Joint Approximation Diagonalization of Eigen matrices, Template subtraction etc. Sometimes it is a combination of two or more algorithms provide better signal, e.g. TS-ICA, JADE-TS-JADE etc.

The use of ICA alone to extract and process fECG signals has applied drawbacks due to extremely elevated sounds that affects these signals. To control these limits, ICA was used in conjunction with discrete wavelet decomposition [6] and the JADE ICA algorithm supplemented with wavelet processing for baseline removal along with denoising was appealed to five sensors aECG recordings [7].

Consequently, this article pays attention to accurate fECG signal extraction using FastICA algorithm along with template subtraction algorithm highlights the post-processing stage liable for accurate FHR approximation in case the doctor can make the right decision for the health of the fetus during pregnancy.

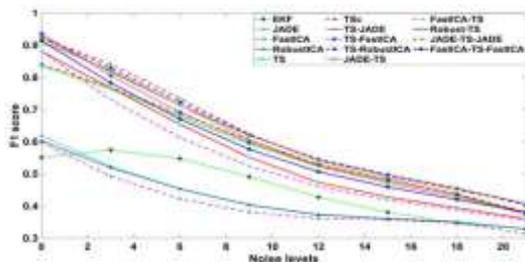
II. METHODOLOGY

This article uses three-channel ECG recordings obtained from multiple patients; during intrapartum process between 38 and 41 weeks of gestation. ICA and PCA are based on blind source separation (BSS), which separates an independent signal when no information about the sources is known. The principle of how this algorithm works is similar to how our brain works, when

a person is locked in a dark room and two different sources of speakers are playing with different songs, then we can focus on a particular song ignore the other.

Classically ICA, this technique is applied to reduce noise in images, remove artifacts from time series information, or identify of driving components in financial information. ICA is based on a generative model i.e., it adopts an underlying procedure that makes the observed data. The ICA model is simple, it assumes that some independent source signals are linearly united by a mixing matrix. We will be using a multi-channel (multiple linear mixture of signal) signal as input for ICA to calculate a mixing matrix that will return the same number of output channels as inputs.

Fig.1. Signal Filtering



In above Fig.1. Filtering the required signals using different signal processing techniques which include ICA, JADE, TS, TS-FastICA, TS-JADE etc.

How does ICA work?

As ICA assumes the independent sources of signal are statistically independent and non-gaussian.

Based on that independent sources of signals (S) are linearly combined with mixing matrix A. So, the detected signal X can be written as:

$$X=AS \dots(1)$$

Now, the independent sources of signals can be retrieved as:

$$S=A^{-1}X \dots(2)$$

Assuming two channels observed data, independent source data can be written in terms of matrix will be, n is the length of data.

$$\begin{bmatrix} s_1^1 & s_1^2 & \dots & s_1^n \\ s_2^1 & s_2^2 & \dots & s_2^n \end{bmatrix} = \begin{bmatrix} a_1 & a_2 \\ a_3 & a_4 \end{bmatrix} * \begin{bmatrix} x_1^1 & x_1^2 & \dots & x_1^n \\ x_2^1 & x_2^2 & \dots & x_2^n \end{bmatrix} \dots(3)$$

c1 and c2 are two channels of data points.

Here, two independent resources are returned in the first and second row.

Similarly, if we use an abdominal ECG signal (aECG) collected from the patient’s abdomen. So maternal ECG (mECG) and fetal ECG (fECG) will be independent sources. In the Same way, we can use multiple channel data to get clearer separate independent signals. In addition to the mECG and fECG signals, there are other noises in the various channels, sometimes even a mixture



of mECG and fECG. Because in our case we used a 3-channel signal. So, the independent sources returned were mECG, mECG+fECG and noise.

One fast and efficient way to calculate ICA is to use fastICA algorithm.

Alternative to ICA:

- Principal Component Analysis (PCA)
- Factor Analysis (FA)
- Projection
- Wavelets
- Blind deconvolution
- Artificial Neural Networks (ANNs)

In terms of processing speed and accuracy, fastICA with template subtraction (TS) seems best.

Let’s see the flow to separate out the required independent signal.

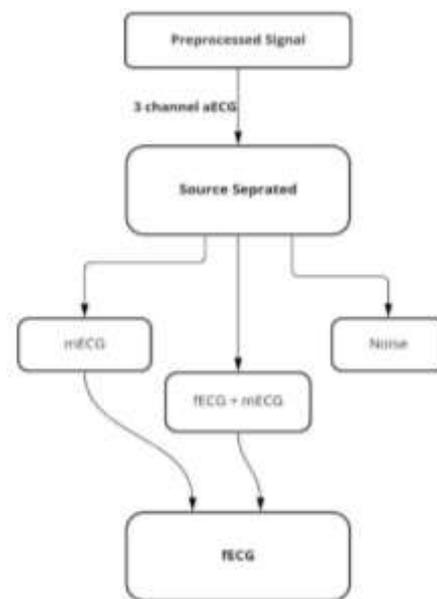


Fig.2. Flowchart

Above Fig.2. Flowchart showing how the signal is separated from the noise and how fECG and mECG is separated.

Once the fECG is obtained the fetal peaks can be detected and different features like heart rate, heart rate variability, etc to detect disease related to heart can be obtained.

Heart Rate calculation

Heart rate is the rate of heart heat produced by heart contraction. It is measured in bpm and for an eight- to nine-month-old fetus the heart rate range is around 110-160.

Over the course of the period, two methods are mainly used for detecting FHR, one is ECG and the other one is doppler ultrasound.

How to calculate heart rate using ECG signal?

In ECG waveform, the cardio activity of the heart reflects the heart beat as a QRS form. Heart rate is simply calculated by counting peaks per minute. Another way of saying the same thing is 60 times the number of peaks in one second.

Fig.3. ECG signal

In above Fig.3. QRS complex and T-wave of ECG signal is shown along with difference between two R-waves will give the heart rate value.

Using a notch filter completely eliminates the t-wave from the ECG signal, making other tasks easier.

Rolling mean:

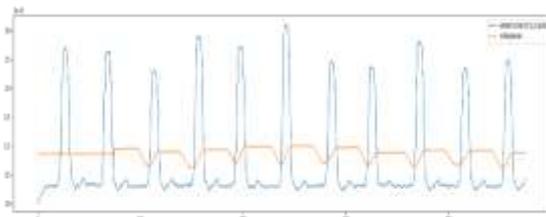
After the signal is processed with filters and normalized, it is passed to calculate the moving average. A moving average is an average of a certain number of previous periods in a time series or otherwise it can be called a moving average.

A particular window overlaps the signal data and continuously returns the mean value over that particular window. The window is selected so that there is exactly one vertex inside the window. Mathematically, it is most precisely given by heart rate variability (hrv) times the sampling rate (f_s) of the signal.

$$\text{Window size} = \text{hrv } f_s \dots (4)$$

Since the size of the window is really an important and decisive factor in the heart rate calculation. So heart rate variability and sample rate should be chosen wisely.

Fig.4. Rolling mean



In above Fig.4. After the ECG signal is processed with filters the moving average of the signal is taken to calculate heart rate.

Peak detection:

There are different ways to detect peaks in any signal. One basic way is to find the maxima so that the values first increase and then decrease. Then by placing all the peaks over the threshold you get the maxima. But such an approach has high chances of spurious peak detection inaccuracy, which means it can detect peaks that are not of our interest. While our interest lies in the R-peaks of the ECG wave.

Another approach is to use the rolling means to detect the R-peaks that were calculated above. After the rolling means are stored. Values above the mean are exceeded and the maximum value in the window is considered as R peak.

Fig.5. Peak detection

In above Fig.5. Detecting R peaks by using the moving average technique in the raw signal and the average is 69.5 BPM.

R-R distance:

To find out the heart rate, the easiest way is to calculate the time between two R-wave peaks. Since the R-peaks represent a heart beat, also knowing the exact sample rate

of the signal will give the distance between the two R-peaks the time between the heart beats.

Duration of two R-peaks can be represented as,

$$\text{DurR-R(in ms)} = (\text{R-interval})f_s1000 \dots(5)$$

BPM

Heart rate in bpm can easily be returned by calculating the total number of beats in one minute. Mathematically the same can be represented as,

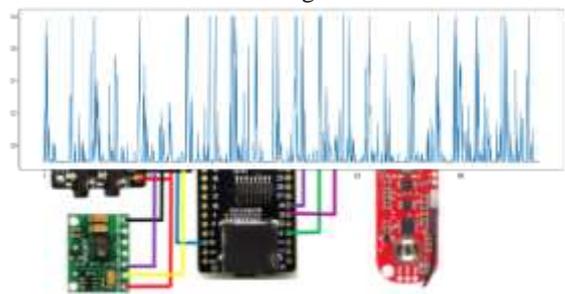
$$\text{Heart Rate (in bpm)} = 60000\text{DuR-R(ms)} \dots(6)$$

There is a term heart rate variability which means that a person's heart rate varies. This occurs when the distance between the two consecutive heartbeat varies, resulting in highly variable heart rate readings. Thus, to solve this problem, the root mean square (rms) of all peak distances should be passed to return a less variable heart rate.

$$\text{Rrms} = \sqrt{R1^2+R2^2+R3^2+\dots+Rn^2} \dots(7)$$

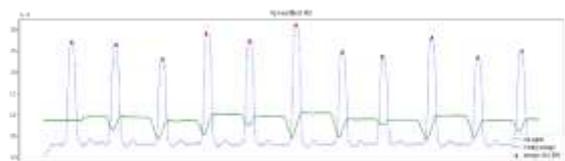
III. Result and discussion

Circuit diagram



It is a non-invasive process, three electrodes are used to obtain uterine contractions. The reference electrode is placed on the bone area and the remaining two electrodes are placed near the naval point. A 3-channel ECG is used to get mECG and fECG by placing five electrodes on the mother's womb. A doppler is placed on the mother's abdomen to record FHR. Max30102 is a pulse oximeter that is used to obtain MHR, the mother's index finger is inserted into the pulse oximeter which calculates beats per minute. ADS1293, MAX30102, MyoWare muscle sensor and doppler are used to collect mECG, fECG, MHR, FHR and UC data. All these sensors are connected to ESP32 TTGO T1. mECG and fECG are acquired from the protocal and this data is sent to the microcontroller. MAX30102 is used to collect the bpm data, uterine contractions are obtained by muscle sensor, fhr is obtained by the doppler.

The ESP32 processes the data and converts analog signal into discrete signal for data visualization.

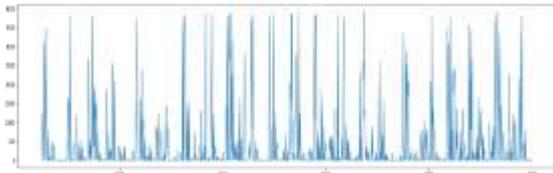


This device is implemented to work wirelessly. The device can be placed away from the display unit. This design is made according to the hospital requirements. Bedside space may not be available in many hospitals.

The device is very small and compact, easy to use. It is a user-friendly device.

Raw data received from doppler ultrasound behaves differently compared to ECG data. Doppler ultrasound data is essentially analog audio with a voltage range of 0-3V. The signal output is shown below.

Fig.6. Doppler signal



In above Fig.6. Fetal heart rate raw data received from doppler ultrasound in analog format with voltage of 0-3V.

Thus, can't be directly passed through above steps.

Let's call the steps for calculation of heart rate in ECG be process hr. Now, before passing the signal to process hr it needs to pass through a few more steps such that it gets almost similar to the ECG signal.

Let's discuss those steps:

Thresed

The values of the doppler analog signal reach a maximum of 3V, but the average of the peak values is less than 3V. So, to overcome the values higher than the threshold (the reason for overcoming the value higher than threshold was discussed later) a simple logic was implemented that says if the analog value is greater than the threshold it will return the actual value.

Here is the graphical representation of the output after applying a threshold of 80% of maximum values of signal.

Fig.7. Doppler signal with 80% threshold

Fig.7. Fetal heart rate obtained from doppler signal after adding 80% of threshold to the output signal to get the original signal.

Moving Window Integration (MVI):

In an ECG signal, it is very convenient to detect different wave properties. Detection features can help to detect different types of cardiac diseases. For example, Sleep Apnea is a syndrome categorized by abnormal pauses in breathing through sleep. Sleep Apnea is a condition where respiration is interrupted by a physical blockage of airflow despite breathing effort. It is based on the fact that the dynamics of the hr of a healthy person differs from the dynamics of a person suffering from this disease. Certain changes in the QRS complex can help reveal the disease.

The MVI process is performed to get the details about both slope along with width of the QRS complex. A window size of 0.15*(sample frequency) is used for more accurate results.

The moving window integration has the recursive equation:

$$Y(nT) = [y(nT-(N-1) T) + x(nT-(N-2) T) + \dots + x(nT)]/N \dots(8)$$

Where, N = number of samples in the width of the integration window.



Fig.8. fECG after applying MVI

In above Fig.8. Electrocardiogram signal after applying MVI will look similar to this image.

Why was threshold applied?

If the threshold were not applied, then the MVI would predict a different width and slope for that particular complex.

After this step, the signal looks something similar to ECG wave demonstrating the QRST complex. Now it can be passed for processing to calculate the heart rate that was demonstrated in the ECG section.

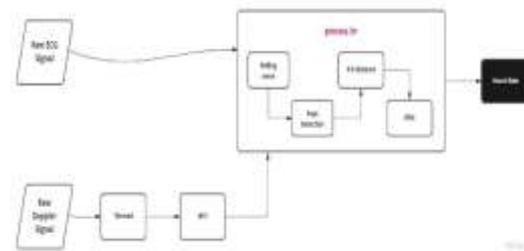


Fig.9. block diagram of moving window integration.

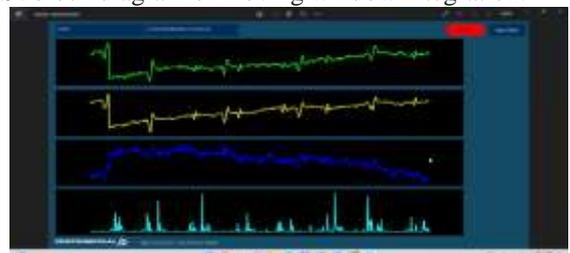


Fig.10. 3-channel mECG and fECG signal along with doppler output in serial port plotter.



Fig.11. Uterine contractions

Fig.11. uterine contractions and uterine contraction count displayed in the serial port plotter.

Programming code is uploaded in the Arduino IDE instead of viewing data in Arduino plotter serial port plotter is used to display data in subplots.

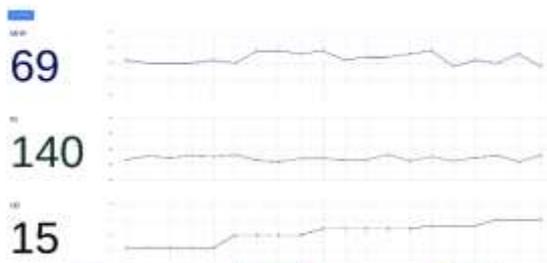


Fig.12. Numerical and graphical representation of signal

Above Fig.12. web plotter which is used to display mhr, fhr and uc in numerical and graphical format.

This works with the wifi connection ssid and password of the device should be mentioned in the code. When the device is connected to the wifi then it starts collecting data wirelessly.

IV. Conclusion

It can be stated that this system is to develop a cheap, affordable, reliable and effective smart health monitoring system, this system is based on continuous monitoring of the patient's condition during the prenatal and intrapartum process by measuring FHR, MHR, and UC. Using a wifi connection, data from the device is transmitted wirelessly to the display. The device can thus be placed away from the display according to the user's requirements.

REFERENCES

- [1] G.D. Clifford, R. Sameni, J. Ward, J. Robinson and A. Wolfberg, "Clinically accurate fetal ECG parameters acquired from maternal abdominal sensors", *Am. J. Obstet. Gynecol.*, 47, pp.1-5, March 2011.
- [2] A. Hyvarinen and E. Oja, "Independent Component Analysis: Algorithms and Applications", *Neural Networks*, 13(4-5), pp.411-430, May-June 2000.
- [3] H. Wan, Q. Liu and J.Chai, "A method for extracting fECG based on ICA algorithm", 9th IEEE International Conference on Signal Processing, Beijing, China, pp.2761-2764, 26-29 October 2008.
- [4] R.Sameni, C. Jutten and M.B. Shamsollahi, "What ICA provides for ECG processing: Application to noninvasive fetal ECG extraction", 2006 IEEE International Symposium on Signal Processing and Information Technology, Vancouver, BC, pp.656-661, 27-30 August 2006.
- [5] D.E. Marossero, D. Erdogmus, N.R. Euliano, J.C. Principe K.E Hild, "Independent Components Analysis For Fetal Electrocardiogram Extraction: A Case For The Data Efficient Mermaid Algorithm", 13th IEEE Workshop on Neural Networks for Signal Processing, Toulouse, France, pp.399-408, 17-19 September 2003.

[6] B. Azzerboni, F. La Foresta, N. Mammone and F.C. Morabito, "A new approach based on wavelet - ICA algorithms for fetal electrocardiogram extraction", *Proc. ESANN'2005*, Bruges, Belgium, pp.193-198, 27-29 April 2005.

[7] V. Vigneron, A. Paraschiv-Ionescu, A. Azancot, O. Sibony and C. Jutten, "Fetal Electrocardiogram Extraction Based On Non-Stationary ICA And Wavelet Denoising", 7th IEEE International Symposium on Signal Processing and Its Applications Proceedings, Paris, France, pp.69-72, 1-4 July 2003.

[8] I.Viorel, H. Mihaela "Fetal Heart Rate Detection and Monitoring From Noninvasive Abdominal ECG Recordings", 5th IEEE International Conference on E-Health and Bioengineering - EHB 2015, Romania, November 19-21, 2015.

[9] M. Varini, G. Tartarisco, L. Billeci, A. Macerata, G. Pioggia and R. Ballochi, "A multi-step approach for non-invasive fetal ECG analysis", *Computing in Cardiology Conference*, Zaragoza, Spain, pp.281-284, 22-25 September 2013.