EEG SIGNAL PROCESSING FOR FETAL AND MATERNAL ANALYSIS USING MATLAB

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Abstract :

Foetal electrocardiogram (FECG) extraction is the key to diagnosing the mother's and child's heartbeats throughout pregnancy. Doctors may be able to use the signal's correct information throughout labour and delivery. A user-friendly method has been developed using independent component analysis. Using the ICA, a more efficient method has been suggested. The method uses principal component analysis and independent component analysis to extract FECG signals. The FECG extraction method was put into operation using a MATLAB program. There is no background noise in the recovered FECG signal. After processing, the QRS complex was detected by counting the R-R peaks using an adaptive noise filtering approach. As seen in the final output, the detection technique is capable of counting the heart rate from the FECG signal. Using efficient algorithms and adaptive filters, this project builds a full FECG extraction model and generates the FECG data.

Keywords: *ECG(Electrocardiography), FECG (Fetal Electrocardiogram), ICA (Independent Component Analysis),PCA(Principal component analysis)*

I INTRODUCTION

A congenital cardiac problem affects 1 in 100 infants annually. Environmental factors, including substance misuse, or hereditary conditions, such as a genetic abnormality, may also play a role. No matter what, the baby's heart rate must be monitored often throughout pregnancy. Therefore, it is necessary to use Foetal ECG (FECG) signals to track the baby's heart rate throughout pregnancy. This allows doctors to correct any abnormalities that are found in a clinical setting. One typical way to identify and diagnose foetal anomalies is foetal electrocardiogram monitoring. The doctor may easily be ready for any foetal abnormalities by analysing the foetal ECG signal during the prenatal period. As far as cardiac diagnoses go, it's the quickest and safest option. The foetal electrocardiogram (FECG) is a valuable tool for assessing the heart's physiological status since it depicts the heart's diverse electrical activity. While the maternal electrocardiogram (MECG) signal may be easily obtained from the chest of a pregnant woman, the foetal electrocardiogram (FECG) signal can be readily obtained from her belly. Most people find it irritating when the MECG signal is added to the FECG transmission. Important diagnostic clues about the foetal condition may be gleaned from the electrocardiogram (FECG) signal produced by placing electrodes on the mother's abdomen. As with the electromyogram (EMG) and maternal electrocardiogram (MECG) signals, the foetal electrocardiogram (FECG) signal is also impacted by noise and skin impedance. The heart's electrical activity may be described using an electrocardiogram (ECG). Electrocardiogram signals consist of three primary waveforms. The AECG signal's heart rate is derived from the QRS complex peak value. Therefore, it is of the utmost importance for physicians to detect cardiac issues in pregnant women before they damage the unborn child or the mother. A composite signal is generated by combining the electrocardiogram (ECG) data from the leads located in the abdomen. Several methods exist for extracting foetal electrocardiogram (FECG) from amniotropic electrocardiogram (AECG), including adaptive filtering, wavelet transform, independent component analysis, principle component analysis, neural network, SWRLS adaptive filter, and least mean square algorithm. A congenital cardiac problem affects 1 in 100 infants annually. Environmental factors, including substance misuse, or hereditary conditions, such as a genetic abnormality, may also play a role. No matter what, the baby's heart rate must be monitored often throughout pregnancy. Therefore, it is necessary to use Foetal ECG (FECG) signals to track the baby's heart rate throughout pregnancy. This allows doctors to correct any abnormalities that are found in a clinical setting. One typical way to identify and diagnose foetal anomalies is foetal electrocardiogram monitoring. The doctor may easily be ready for any foetal abnormalities by analysing the foetal ECG signal during the prenatal period. It's the safest and most non-invasive method for diagnosing heart problems. The foetal electrocardiogram (FECG) is a valuable tool for assessing the heart's physiological status since it depicts the heart's diverse electrical activity. It is easy to get the foetal electrocardiogram (FECG) signal from a pregnant woman's belly, but the maternal electrocardiogram (MECG) signal may be obtained from her chest. It is common for patients to experience discomfort when the MECG signal is added to the FECG signal. Electrodes placed on the mother's abdomen provide an electrocardiogram (FECG) signal, which gives diagnostically crucial facts regarding the foetal health. While different types of noise and skin impedance contaminate the electromyogram (EMG) and maternal electrocardiogram (MECG) signals, they do the same to the far-field electrocardiogram (FECG) signal. The heart's electrical activity may be described using an electrocardiogram (ECG). Electrocardiogram signals consist of three primary waveforms. By analysing the QRS complex peak values, one may ascertain the heart rate from an abdominal electrocardiogram (AECG). Therefore, it is of the utmost importance for physicians to detect cardiac issues in pregnant women before they affect the mother or the foetus. A composite signal is generated by combining the electrocardiogram (ECG) data from the leads located in the abdomen.

II BACKGROUND

Foetal electrocardiogram (FECG) extraction is the procedure used to diagnose the heartbeats of both the mother and the kid, according to Manisha Dodatale et al. 2021. Doctors may be able to use the signal's correct information throughout labour and delivery. A user-friendly method has been developed using independent component analysis. Using the ICA, a more efficient method has been suggested. The method uses principal component analysis and independent component analysis to extract FECG signals. The FECG extraction method was put into operation using a MATLAB program. There is no background noise in the recovered FECG signal. After processing, the QRS complex was detected by counting the R-R peaks using an adaptive noise filtering approach. As seen in the final output, the detection technique is capable of counting the heart rate from the FECG signal. Using efficient algorithms and adaptive filters, this project builds a full FECG extraction model and generates the FECG data.

In 2016, Esha Ahuja and colleagues To learn about the fetus's health and to help physicians decide on the delivery method and time, foetal electrocardiogram (FECG) extraction is essential. Foetal electrocardiogram (FECG) activity includes foetal cardiac depolarisation and repolarisation. This research presents a straightforward method for extracting FECG from a mother's Abdominal Electrocardiogram (AECG) using Independent Component Analysis (ICA). The database used is physionet.org's non-invasive foetal electrocardiogram and direct foetal electrocardiogram. The Blind Source Separation (BSS) approach includes ICA in its categorisation. When a signal comes in from an unknown source, ICA acts as a filter to bring it in. In this case, the signal is foetal electrocardiogram (ECG), and its origin is unclear. Originating from the mother's pure electrocardiogram (ECG), which consists of a thorax signal and an abdomen ECG,

Md. Islam Kafiul et al. in 2020 In the final stages of signal categorisation, EEG recordings are often impacted by a variety of artefact types that originate from non-neural sources. Consequently, there is a lot of activity in the field of automated signal processing algorithms that can consistently identify and remove artefacts from EEG. Here, we provide a wavelet-based artefact removal technique for EEG data that, by choosing the most effective threshold values, achieves the highest possible artefact removal performance. Based on a reference dataset, the suggested method decides to sweep the wavelet filter and threshold settings until the accuracy and/or distortion are as low as possible. An optimised selection criterion is a statistic that measures the degree of distortion in the signal and the amount of artefact removal in the time domain and frequency domain, respectively. In order to quantify the algorithm's effectiveness using various temporal and frequency domain metrics, it is evaluated using synthesised EEG data that incorporates several artefact templates. In comparison to using a fixed threshold parameter and/or a predefined mother wavelet, the optimal combination of adaptively chosen parameter values yields superior performance in terms of both signal distortion and artefact removal. The EEG signal analysis community would have a solid foundation to build upon from this study, allowing them to more effectively choose wavelet parameters in the future.

III Adaptive Filtering Based FECG Extraction

When an error signal is used to drive an optimisation process, an adaptive filter will self-adjust its transfer function. There are a number of adaptive filters that have been used to separate signals from the mother and the foetus. These methods train an adaptive or matching filter using one or more reference maternal signals in order to extract the lethal QRS waves[1][2], The kalman filter, an adaptive filter with diverse applications, needs only an arbitrary MECG for FECG extraction and MECG cancellation. In order to denoise ECG data, a Bayesian filter and a set of state-space equations were used to synthesise the temporal dynamics of the signals. But the filter can't tell the difference between the maternal and lethal components when their timing is totally overlapping. It is considered to be thoroughly overlapped when the waves of mixed signals completely overlap in time. It is challenging to exclude the necessary ECG data with this filter. Buses multistage adaptive filtering for FECG extraction offered a better approach, which included cancelling out the MECG with a reference signal from a thoracic ECG and then utilising de noising techniques to make the resulting signal better. Here, the thoracic ECG has been squared and scaled, rather than the usual AECG signal and thoracic ECG, which are the two input signals needed by an adaptive filter. The extraction was successfully carried out using the adaptive filters once the scaling factors were selected. The technique's main benefit is that the input thoracic signal doesn't need to be unique. Alternatively, a signal that is substantially similar may be utilised; this particular signal was obtained from a pregnant woman whose AECG was also supplied as primary input. This adaptive filter takes use of three different approaches to improve the signal-to-noise ratio (SNR): LMS, RLS, and NLMS. Using a linear adaptive filter, the FECG was recovered [3].The electrocardiogram (ECG) from the mother's abdomen served as the main input for the FECG extraction, while the electrocardiogram (ECG) from her chest served as the reference input. Even though the proposed approach finds a workaround, it can't determine when maternal and fatal signals are converging. So, it's not fit for usage in the medical field.

IV METHODOLOGY

The Wavelet Transform convolutionally combines the subjective signal with the wavelet function. The Wavelet Transform separates an input signal into its detail and approximation components. The top half of the frequency component contains the detail signal, while the bottom half contains the approximation signal. So, multi-resolution analysis is feasible in the discrete wavelet domain. For many different uses, you may choose from a large library of popular wavelet families and functions. A few families of wavelets include bi-orthogonal, coiflet, harr, symmlet, and db (Daubechies) wavelet. The application determines the use of the wavelet function. Many studies have made use of these wavelet families. Choosing a certain wavelet is not an option. The wavelet analysis is obtained using the MATLAB program. In MATLAB, you may get a comprehensive wavelet toolset. The technique makes use of the db (Daubechies) wavelet, which is a good fit as it mimics the waveform of a human heartbeat. Our MATLAB approach for signal decomposition into approximation and detailed coefficients is based on the daubechies wavelet transform, which we used in this study. Combining the subjective signal with the wavelet function forms the basis of the Wavelet Transform. It is possible to get the foetal electrocardiogram (FECG) from an abdominal electrocardiogram using an automated method. A recording of an electrocardiogram (AECG) was documented in reference [23]. The data collection process was painless. An external set of electrodes is placed on the abdomen in order to gather data. The signal-to-noise ratio (SNR) is increased by moving the electrodes and using an AgAgCl transducer. Electrodes were affixed to the mother's belly wall in order to record signals. The abdominal electrocardiogram (AECG) data used in this method was transformed from its original.edf file into a Matlab-readable format. Three primary methods are taken into account. There are three stages to the process: pre-processing, FECG extraction, and post-processing. After reading the recorded mother's abdominal ECG signal in MATLAB, the unwanted noise may be removed from the AECG signal using principal component analysis (PCA). Following the necessary preprocessing, the ICA method was used to extract the FECG signal. The next step is to find R-Peak and calculate the foetal heart rate.

V.BLOCK DIAGRAM

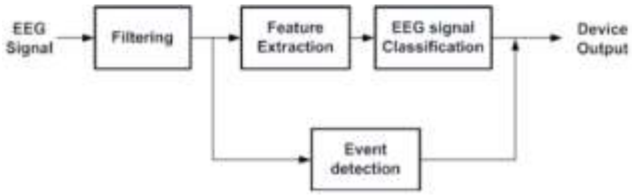

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Fig 1: Block Diagram of the overall system

VI INTERPRETATION

The use of electroencephalogram (EEG) signals to assess the activity of various brain regions is convenient, inexpensive, and risk-free.

Accurate measures of time

Modern electroencephalogram (EEG) technology has the ability to precisely identify brain activity with a granularity of one millisecond.Put simply, EEG electrodes are applied to the scalp. As a result, it is a non-invasive process. EEG equipment is easy to use and costs less than other devices. It is possible to get the foetal electrocardiogram (FECG) from an abdominal electrocardiogram using an automated method. A recording of an electrocardiogram (AECG) was documented in reference [23]. The data collection process was painless. An external set of electrodes is placed on the abdomen in order to gather data. The signal-to-noise ratio (SNR) is increased by moving the electrodes and using an AgAgCl transducer. Electrodes were affixed to the mother's belly wall in order to record signals. The abdominal electrocardiogram (AECG) data used in this method was transformed from its original.edf file into a Matlab-readable format. Three primary methods are taken into account. There are three stages to the process: pre-processing, FECG extraction, and post-processing. After reading the recorded mother's abdominal ECG signal in MATLAB, the unwanted noise may be removed from the AECG signal using principal component analysis (PCA). Following the necessary preprocessing, the ICA method was used to extract the FECG signal. The next step is to find R-Peak and calculate the foetal heart rate.

V CONCLUSION

An modest origin story begins with the fatal electrocardiogram (FECG) in 1901, when initial study in the field was severely constrained. While better amplifiers and filters made waveform identification much easier, waveform morphology surveillance remained a challenge because of residual noise even after filtering out the polluted data. Even though the signals were acquired non-invasively, the original FECG's signal-to-noise ratio was greatly enhanced by means of advanced processing and computer technology. Various approaches that have been commonly employed for FECG extraction up till now have their evaluations elegantly shown in the text.

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