A Survey paper on FECG Extraction and Monitoring

Manisha Dodatale[1], Dr Shelke .R J.[2]

[1]*Dept. Of Electronics, Walchand Institute of Technology Solapur Maharashtra India*
[2]*Associate Professor, Dept. of Electronics, Walchand Institute of Technology Solapur Maharashtra India*

Abstract - *During pregnancy, it is critical to diagnose the mother's and child's heartbeats, and fetal electrocardiogram (FECG) extraction is the method utilised to do so. During pregnancy and labour, the signal carries accurate information that might assist doctors. Independent component analysis has been used to build an easy-to-use technique. An efficient approach has been proposed using the ICA. For FECG extraction, the technique employs PCA and ICA. An algorithm written in MATLAB was used to implement the FECG extraction approach. The FECG signal that was recovered is noise-free. Post processing was utilised to detect the QRS complex, which used an adaptive noise filtering method to count the R-R peaks. The detection method can count the heart rate of the FECG signal, as shown in the end result. This project creates a complete FECG extraction model utilising effective algorithms and adaptive filters, and then produces the FECG data.*

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

1. INTRODUCTION

Every year, one in every one hundred kids is born with a heart defect. This can be caused by a genetic syndrome, an inherited condition, or environmental causes such as drug abuse. In any event, regular monitoring of the baby's heart is required prior to birth. As a result, Fetal ECG (FECG) signals are required to monitor the baby's heart status, so that any anomalies discovered can be treated clinically by the concerned specialists.

Fetal ECG monitoring is a common method for detecting and diagnosing fetal abnormalities. By diagnosing the fetal ECG signal during the prenatal stage, the clinician can readily prepare himself or herself for any fetal anomalies. It's the simplest and least invasive way to diagnose a variety of cardiac conditions. The Fetal ECG (FECG) represents the heart's varied electrical activities and so provides useful information about its physiological state. The FECG signal can be easily collected from a pregnant woman's abdomen, whereas the maternal electrocardiogram (MECG) signal can be taken from her chest. The addition of the MECG signal to the FECG signal is usually a source of irritation. The FECG signal generated by putting electrodes on the maternal belly provides minute details about the fetal status that are particularly important during diagnosis. The maternal ECG (MECG) signal and electromyogram (EMG) signal are contaminated by various noise and skin impedance, whereas the FECG signal is contaminated by various noise and skin impedance. The electrocardiogram (ECG) is a method of describing the electrical activity of the heart. Three basic types of waves make up ECG signals. The heart rate of the abdominal ECG (AECG) signal is determined by the peaks value of the QRS complex. As a result, it is critical for doctors to diagnose heart problems before they cause harm to the fetus or the mother. When the ECG signals from the abdomen leads are combined, a composite signal is created.

2. LITERATURE REVIEW

Adaptive filtering, wavelet Transform, Independent component Analysis, Principle Component Analysis, Fatal ECG Extraction from Maternal Abdominal ECG Using Neural Network, Fetal ECG Extraction for Fetal Monitoring Using SWRLS Adaptive Filter and Extraction of Fetal ECG from Maternal ECG using Least Mean Square Algorithm are some of the methods for extracting FECG from AECG.

2.1 Adaptive Filtering Based FECG Extraction

An adaptive filter is one that self-adjusts its transfer function in response to an error signal that drives an optimization process. For the separation of fetal and maternal signals, various adaptive filters have been applied. These approaches extract the deadly QRS waves by training an adaptive or matching filter with one or more reference maternal signals[1][2], For MECG cancellation and FECG extraction, the kalman filter, a broad form of adaptive filter, requires simply an arbitrary MECG as a reference. The temporal dynamics of AECG signals were synthesized using a collection of state-space equations and a Bayesian filter, which was employed for ECG de noising. However, when the maternal and deadly components are completely overlapped in time, the filter is unable to distinguish between them. When the waves of mixed signals fully overlap in time, it is said to be wholly overlapped. This filter makes it difficult to filter out the required ECG. A superior strategy was proposed in Buses multistage adaptive filtering for FECG extraction, where MECG cancellation was conducted using thoracic ECG as a reference signal, and de noising methods were used to improve the quality of the resultant signal. Normally, an adaptive filter requires two input signals (AECG signal and Thoracic ECG), but in this case, the thoracic ECG has been scaled and squared. Adaptive filters were well calibrated to conduct the extraction once scaling factors were chosen. The advantage of this technique is that the input thoracic signal does not have to be original, as it was collected from a pregnant lady whose AECG was also provided as primary input; alternatively, a signal that is very similar can be used. This self-adjusting filter uses three alternative methods to boost the SNR ratio by altering filter coefficients: LMS, RLS, and NLMS. The FECG was extracted using a linear adaptive filter[3].The FECG was extracted using abdominal ECG as primary inputs and thoracic ECG collected from the mother's chest as reference inputs. Despite the fact that the offered method gives a solution, it fails to extract when maternal and lethal signals coincide. As a result, it is not appropriate for clinical use.

2.2 Wavelet Transform Based FECG Extraction

The subjective signal and the wavelet function are convolutioned in the Wavelet Transform. The Wavelet Transform divides a signal into two parts, the detail signal and the approximation signal. The detail signal is found in the upper half of the frequency component, while the approximation signal is found in the lower half. In the discrete wavelet domain, multi-resolution analysis is thus possible[4]. A significant number of well-known wavelet families and functions are available for a wide range of applications. Bi-orthogonal, Coiflet, Harr, Symmlet, and db (Daubechies) wavelet are some of the wavelet families. The wavelet function is utilized depending on the application. These wavelet families have been used in a variety of research projects. It is not possible to select a certain wavelet. To obtain the wavelet analysis, we use the MATLAB application. The wavelet toolkit in MATLAB is quite extensive. We employ the db (Daubechies) wavelet in the algorithm because it resembles the waveform of a human heart beat outcome of the daubechies is excellent. In this research, we employ the daubechies wavelet transform to construct an algorithm in MATLAB that decomposes the signal into approximation and detailed coefficients. The Wavelet Transform is based on the convolution of the subjective signal and the wavelet function.

2.3 Independent component Analysis Based FECG Extraction

Independent component analysis is a technique for isolating additive subcomponents from a multivariate signal. SVD-based approaches for fetal ECG extraction were proposed in[5.] Singular Valued decomposition modes of the suitably setup data matrices were used to identify MECG components. By selecting separating SV deconstructed components, those identified maternal components were deleted to obtain FECG. Because this method does not require a reference signal (Thoracic MECG), it is computationally efficient and reliable. For obtaining FECG components from multi-channel AECG recordings, independent component analysis [6] is a useful approach.

Methods for data-driven decomposition [7][8], A MICA-based strategy to ECG extraction has been presented, which was found to be more effective than ICA in fetal ECG extraction. Pre-processing, MECG estimation, and post-processing blocks are all part of the proposed method's design. Using a FIR band pass filter and a notch filter, the pre-processing removed noise caused by the patient's breathing at the time of observation (baseline wander), physiological interference (Maternal Electromyogram), and structural noise (50 or 60 Hz power line interference). The filter used in [9][10] produced a synthetic MECG that addressed the issue of MECG estimation. The maternal signals were estimated and removed from the AECG, but this method failed when the fetal ECG was weaker than the residual noise. The approach published in[11] was based on independent component analysis which substituted computationally intensive calculations for an easier FECG extraction procedure. This approach is simple and fast, and it has a low computing complexity. It can also be implemented in real time. Although some of the other proposed solutions could be performed in real time, due to the complexity of the calculations, they took longer to execute.

For FECG signal separation from AECG [12] used an approach that included two techniques: singular value decomposition (SVD) and independent component analysis. For extracting FECG, BSS methods based on ICA were applied, in which ICA utilized higher order statistics, resulting in computational complexity. FECG extraction and MECG cancellation using an ICA based technique. When the Signal to Noise Ratio was -200 dB without quantification noise, the efficacy of the system dropped with quantification.

2.4 Neural Network Extraction of Fetal ECG from Maternal Abdominal ECG

In [13] a new approach for determining FHR baselines using ANNS was proposed. On AECG data, two approaches were used: baseline estimation and baseline classification using multi-layer perceptual artificial neural networks. On the basis of their practical application, the outcomes of different approaches were compared. By using the thoracic maternal signal as a reference signal, the FIR neural network was able to give strong nonlinear dynamic capabilities during FECG extraction. In[14], an adaptive linear neural network-based FECG extraction method was described, which trained the input composite AECG signal to cancel out the maternal signal, isolating the fetal ECG signal. Because the electrical activity produced by the fatal heart is substantially weaker than that of the maternal heart due to its dominance nature, MECG may be easily calculated and then subtracted from the AECG to obtain FECG. This produces superior results when compared to traditional filtering procedures. A novel technique for detecting the Fatal Heart Rate pattern, as well as the acceleration and deceleration of the fatal heart signal, has been proposed in [15]. However, while ANN-based FECG extraction methods have benefits they also have drawbacks. For example in [16] non-convex quadric minimization resulted in multiple minima and the risk of over fitting has increased significantly. In[17] an adaptive technique for extracting FECG was presented utilizing an adaptive linear neural

International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 08 Issue: 12 | Dec 2021 www.irjet.net p-ISSN: 2395-0072

network (ADALINE) for easy fatal monitoring in which the network error was balanced using the proper learning rate, momentum, and initial weights until it matched fatal E.

When elements like learning rate(LR), momentum(M), and beginning weights(IW) had specific values, this method offered very high accuracy (high LR, Low M, Small IW). For detecting and identifying nonlinear high frequency components of maternal electrocardiograms, the Adaptive Nero-Fuzzy Inference System (ANFIS) was developed (MECG).

2.5 Extraction of Fatal ECG from Maternal ECG using Least Mean Square Algorithm

In[18] is an example. Adaptive filters are time changeable filters that can change their characteristics over time. Add an adaptive mechanism for adjusting filter coefficients Filters of many types are used to process signals with unknown statistics. Adaptive filters require a primary and at least one reference input. The method comprises of removing maternal ECG using numerous or one maternal reference channel that includes maternal ECG that is anatomically similar? Because the morphology of maternal ECG pollutants is greatly dependent on electrode sites, this approach is rather inconvenient. As a result, an adaptive filter with only one reference is quite useful LMS is a form of adaptive filter that mimics a desired filter by determining the filter co-efficient that correlates with LMS of error signal (differentiated between desired and actual signal). The challenges of obtaining FECG are numerous. Low amplitude FECG is caused by low conductivity layers surrounding the fetus and weak cardiac potentials from the fetus. The electrocardiogram's (ECG) heart rate, waveform and dynamic behavior are important in detecting the fatal life, development, maturity and presence of fatal distress or congenital heart disease. Motion artifacts, uterine contractions, movements caused by maternal breathing, and maternal ECG interference

2.6 Other methods

The goal of [19] was to offer a lightweight technique for extracting and upgrading the signal of interest (FECG), with the goal of decreasing computational complexity to execute in real-time by anticipating the signal's skewness. The fetal heart rate (120 to 160 beats per minute) is substantially faster than the maternal heart rate, and the electrical activity produced by the fetal heart is of low amplitude, resulting in a low and negative skewness (rate of asymmetry) score. The cost function is determined by the skewness of the weight vector after it has been changed to give FECG. SNRsvd and SNRcor are increased. This method's efficiency has improved. The proposed method was also compared to existing extraction methods in [20], [21], and [22]. Although there is some uncorrelated noise after processing, this method has a reduced computational complexity.

3. PROPOSED SYSTEM

An automated approach is used to extract the Fetal Electrocardiogram (FECG) from the Abdominal Electrocardiogram. In [23], a (AECG) recording was described. The information was gathered in a non-invasive manner. Data is collected using external electrodes inserted on the abdomen. An AgAgCl transducer is used to boost SNR, and electrode positions are altered. To capture signals, electrodes were placed on the mother's abdominal wall. The.edf format of the abdominal electrocardiogram (AECG) data employed in this technique was converted to a Matlab-readable format.

There are three main procedures that are considered.

Pre-processing, FECG extraction and post-processing are all steps in the process. First read the recorded mothers Abdominal ECG signal in MATLAB and then use PCA to eliminate undesirable noise from the AECG signal. After pre-processing, the FECG signal was extracted using the ICA approach. Then R-Peak is discovered, and Fetal Heart Rate Calculation is performed.

Abdominal Recording

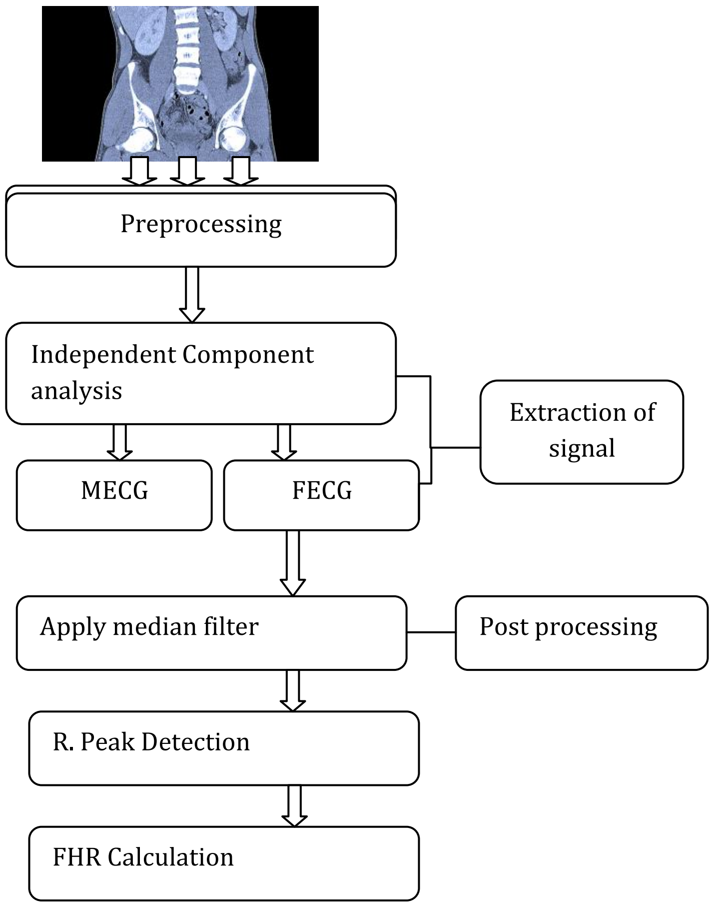

Fig -1: Flow Chart of FECG Extraction

3.1 Data Acquisition

Data was collected using a non-invasive manner. External electrodes are placed on the abdomen and data are obtained. To increase SNR, an AgAgCl transducer is employed, and electrode locations are changed. To collect signals, electrodes were placed on the mother's abdomen wall. The AECG signals used in this technique were in.edf format, which was transformed to MATLAB readable format. The data set was gathered from the PhysioNet non-invasive fetal ECG database, which is available on the website, and was taken from a single participant between the ages of 21 and 40 weeks of pregnancy, with each signal lasting 10 seconds.

3.2 Pre-processing

The proposed pre-processing reduces the number of signals to be considered, with the goal of speeding up the estimating process. The covariance of the signal, the standard deviation, and the Eigen vector or Eigen value are all determined throughout this procedure.

3.3 Extraction of Signal

The ICA fixed point algorithm is derived from entropy optimization approaches, and its speed is comparable to a second order function. NonGaussian could be used as a criterion for measuring the interdependence of random signals, according to the central limit theorem. It stated that we had accomplished the separation of mix-signals when non-Gaussian reached maximum. Negentropy could be used as an independence condition, according to information theory. As a result, we chose Negentropy as the independence criterion, and we separated the independence component from the observation Signal.

3.4 Post Processing.

To boost the SNR, the FECG signal is filtered again with the median filter in post-processing. When the goal is to minimize noise while preserving edges median filtering is a nonlinear technique that is more successful than convolution.

4. CONCLUSIONS

The fatal electrocardiogram (FECG) has a humble beginning dating back to 1901, when the first expansion of research in the associated arena was severely limited. The identification of the waveform was greatly eased with the introduction of improved amplifiers and filters, yet waveform morphology surveillance was a difficult issue due to the presence of background noise after the contaminated signal was filtered. The signal-to-noise ratio of the original FECG was dramatically improved thanks to sophisticated signal processing and computer technologies, notwithstanding the signals' non-invasive acquisition. The document beautifully displays the evaluation of a variety of methodologies that have been widely used for the extraction of FECG up to this point.

REFERENCES

[1] B. Widrow, J. Glover, J. McCool, J. Kaunitz, C. Williams, H. Hearn, J. Zeidler, E.Dong, and R .Goodlin, Adaptive noise cancelling: principles and applications Proc IEEE,Vol. 63.no. 12,pp. 1692–1716, 1975
[2] K. Prasanth, Baby Paul, and A. Arun Balakrishnan, ―Fatal ECG Extraction Using Adaptive Filters, International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, Vol. 2, Issue 4, 2013.
[3] B.Widrow, and S.Stearns, Adaptive signal processing, Prentice-Hall, Upper Saddle River, 1985
[4] Shashi Kala Nagarkoti, Balraj Singh, Manoj Kumar, "An algorithm for Fatal Heart rate detection using wavelet transform.", IEEE Trans, 1st Intl Conf. on Recent Advances in Information Technology (RAIT),2012
[5] C. Kezi Selva Vijila, P. Kanagasabapathy, S. Johnson,Adaptive neuro fuzzy inference system for extraction of FECG,Proceedings of IEEE India Annual Conference, pp. 224–227, 2005.
[6] P. P.Kanjilal, S. Palit, G. Saha, Fatal ECG extraction from singlechannel maternal ECG using singular value decomposition, IEEE Trans Biomed Eng, vol. 44,pp. 51–59,1997.
[7] Lieven De Lathauwer, Bart De Moor, and Joos Vandewall,Fatal Electrocardiogram Extraction by Blind Source Subspace Separation. IEEE Transactions On Biomedical Engineering, vol. 47, no. 5, 2000.
[8] J. L. Camargo-Olivares, R. Martín-Clemente, S. Hornillo-Mellado, M. M. Elena, and I. Román,The Maternal Abdominal ECG as Input to MICA in the Fatal ECG Extraction Problem, IEEE Sisnal Processing Letters, vol. 18, no. 3, 2011.
[9 J. F. Cardoso, ―Multidimensional independent component analysis, in Proc. ICASSP'98, pp. 1941– 1944, 1998.
[10] R. Sameni, M. Shamsollahi, C. Jutten, and G. Clifford, ―A nonlinear bayesian filtering framework for ECG denoising, IEEE Trans.Biomed. Eng, vol. 54, no. 12, pp. 2172–2185, 2007.
[11] Ruben Mart´ın-Clemente, Jose Luis Camargo-Olivares, Susana HornilloMellado, Mar Elena,and Isabel Roman, Fast Technique for Noninvasive Fatal ECG Extraction, IEEE Transactions On Biomedical Engineering, vol. 58, no. 2, 2011.
[12] G.Ping , C. Ee-Chien, and L.Wyse, ―Blind separation of fatal ECG from single mixture using SVD and ICA,"ICICS-PCM,vol. 3, pp. 1418–1422, 2003.
[13] P.Marques de Sa, L. P. Reis, J. N.Lau, et al, ―Estimation and classification of fatal heart rate baselines using artificial neural Networks, Computers in Cardiology, pp. 541–544,1994. .
[14] M. B. I. Reaz, and L. S. Wei ,Adaptive linear neural network filter for fatal ECGextraction,Proceedings of

international conference on intelligent sensing and information processing, pp. 321–324.
[15] P. Warrick, E. Hamilton, and M.Macieszczak, ―Neural network based detection of fatal heart rate patterns, Proceedings of International Joint Conference on Neural Networks, vol. 4, pp. 2400–2405, 2005.
[16] L. Xia, J. Meng, R. Xu, B. Yan, and Y. Guo, ―Modeling of 3-D vertical interconnect using support vector machine regression,IEEE Microw. Wireless Compon. Lett., vol. 16, no. 1,pp. 639-641.
[17] M. S. Amin, Md. Mamun, F. H. Hashim and H. Husain, ―Separation of fatal electrocardiography (ECG) from composite ECG using adaptive linear neural network for fatal monitoring.
[18]A. Widrow et al., "Adaptive noise cancelling: Principles and applications". Proc. IEEE, vol.63, pp. 1692-1716, Dec. 1975
[19] Kavuri Swathi Sri, Jagath C. Rajapakse, "Extracting EEG rhythms using ICA-R", Neural Networks 2008. IJCNN 2008. (IEEE World Congress on Computational Intelligence). IEEE International Joint Conference on, pp. 2133-2138, 2008, ISSN 1098-7576.
[20] Fahimeh Jafari, Mohammad A Tinati, and Behzad Mozaffari, A New Fatal ECG Extraction Method Using its Skewness Value Which lies in Specific Range, Proceedings of ICEE, vol. 978, 2010.
[21] Shiqiu Li,Ziqiang Hou and Qihi Li, ―A New Algorithm For ExtractionFatal ECG Signal Using Singular Value Decomposition Method, IEEE Trans on Biomed Eng,vol. 3,pp. 585-588,Mar 1992.
[22] A. K. Barros and A. Cichocki, ―Extraction of specific signals with temporal structure,Neural Comput, vol. 13, no. 9, pp. 1995–2003,2001.
[23] 2014 IEEE International Conference on Advanced Communication Control and Computing Technologies (lCACCCT) -An Automated Methodology for FECG Extraction And Fetal Heart Rate Monitoring Using Independent Component Analysis Neha Dhage1,Swati Madhe