IJREB

ISSN 2321-743X

International Journal of Research in

Engineering and Bioscience

Volume 2 (Issue 2) Pages (77-91)

Journal home page: www.ijreb.org

TECHNIQUES FOR FETAL ECG EXTRACION- A MINI SURVEY

***Anisha.M[1], Dr.S.S.Kumar[2] and Benisha.M[3]**

[1*]Department of BioMedical Engineering, Noorul Islam University,kumaracoil, KK.Dist, Tamil Nadu,

[2]Department of Electronics & Instrumentation Engineering, Noorul Islam University, kumaracoil

[3]Department of Electronics &Communication Engineering, Jeppiaar Institute of Technology, Chennai.

ABSTRACT

Fetal Electrocardiogram (FECG) signal has the potential of being an efficient diagnostic tool for determining congenital cardiac defects. Clinical information in the FECG signal is often masked by Maternal Electrocardiogram (MECG) considered as the most predominant interference, power line interference, and maternal Electromyogram (EMG), Electrode content noise, motion artifact, inherent noise, ambient noise and baseline wander. FECG signal features may not be readily available due to the existence of huge amount of physiological and structural interferences. Therefore, Fetal ECG should be separated from composite AbdominalECG, and there are many powerful and well advanced methods for this purpose. In this paper a range of promising algorithms for Fetal ECG extraction based on adaptive filtering, artificial intelligence and wavelet transform are discussed.

KEYWORDS: Abdominal Electrocardiogram, Maternal Electrocardiogram, Fetal Electrocardiogram.

IJREB

ISSN 2321-743X

International Journal of Research in

Engineering and Bioscience

Volume 2 (Issue 2) Pages (77-91)

Journal home page: www.ijreb.org

INTRODUCTION

Heart defects are being the most common birth defects and the leading cause of sudden prenatal death (Minino *et al*., 2007).The cardiac defect may be very slight so that the baby appears healthy and normal for many years after birth, but suddenly becomes so severe due to that its life is in immediate danger. Congenital heart defects originate when the heart is forming and they can affect any of the parts or functions of the heart. Cardiac anomalies may occur due to a inherited disorder, genetic syndrome, or environmental factors such as infections or misuse of drug during pregnancy (Pajkrt *et al*.,2004). Every year one out of 125 babies is born with some kind of congenital heart defects.FECG carries vital information about the cardiac function of fetus.

The characteristics of the fetal electrocardiogram (FECG),such as heart rate, waveform, and dynamic behavior, are important in determining the fetal life, fetal development, fetal maturity, and existence of fetal distress or congenital heart disease.Fetal electrocardiography has proved an effective tool for imaging specific structural defects only at the time of labor not during pregnancy because FECG (Zuckerwar *et al*.,1993) is contaminated by fetal brain activity, myographic (muscle) signals (from both the mother and fetus), movement artifacts and multiple layers of different dielectric biological media through which the electrical signals must pass. Fetal monitoring is based entirely on the fetal heart rate and does not incorporate characteristics of the fetal ECG (fECG) waveform that are the cornerstone of cardiac evaluation. The main reason for this is there is no available technology to reliably measure fECG. Most of the heart defects have some manifestation in their morphology, which is believed to contain much more information as compared with other conventional methods (Peters *et al*.,2001).Most of the clinically useful information in the FECG signal is found in the amplitude and duration of its waveforms (Ananthanag & Sahambi,2003)

Early History of Fetal ECG

The fetal electrocardiogram was first observed by M. Cremer in 1906 (Cremer, 1906). The early works in this area were performed by using the galvanometric apparatus of that time, which were limited by the very low amplitude of the fetal signals. Fetal electrocardiography became more

IJREB

ISSN 2321-743X

International Journal of Research in

Engineering and Bioscience

Volume 2 (Issue 2) Pages (77-91)

Journal home page: www.ijreb.org

feasible and popular when measurement and amplification techniques are improved, (Goodyer *et al*., 1942 & Lindsley, 1942).

Now there exists a problem with low fetal SNR, especially in presence of the strong maternal cardiac interference. In the 1960's electrodes were placed between the intact membranes of the fetus and the wall of the uterus to record FECG, had improved SNR for FECG analysis however, it is dangerous technique, may rupture the membrane of the premature by the insertion of the electrode. A new technique is (Hon, 1960) introduced, in which electrodes are placed directly on the fetal scalp by inserting through the cervix, to record FECG, so called invasive method but the procedure is inconvenient. Then by placing electrodes on the maternal abdomen, Abdominal ECG is recorded. This procedure is called non-invasive method can be done during pregnancy. Shortly afterwards, due to the rapid development in computer science and signal processing area, FECG extraction from Abdominal ECG has carried out by suitable signal processing and appropriate filtering techniques.

Morphology of FECG

Mechanical function of the fetal heart differs from an adult heart. The wave-like pumping action of the heart is controlled by a network of neural fibers that are distributed throughout the *myocardium* and also coordinates the hearts regular contraction and relaxation. The myocardial stimulation starts from the *sinoatrial node* (SA-node), which serves as the natural pacemaker for the heart. The S Anode is a cluster of cells located in the upper-right posterior wall of the right atrium, which ends the electrical impulse that triggers each heartbeat. This impulse further stimulates the second cluster of cells, namely the *atrioventricular node*. (AV-node) that is situated in the lower posterior wall of the right atrium.

After the AV-node, the depolarization front enters the bundle of His, the left and right bundles, and ends in the Purkinje fibers, depolarizing the ventricular muscles in its way.The procedure of myocardium contraction is known as the *depolarization* (or *systole*) cycle that is followed by the *repolarization* (or *diastole*) cycle, in which the myocardium relaxes and becomes ready for the next activation.

ISSN 2321-743X
International Journal of Research in
Engineering and Bioscience
Volume 2 (Issue 2) Pages (77-91)
IJREB
Journal home page: www.ijreb.org

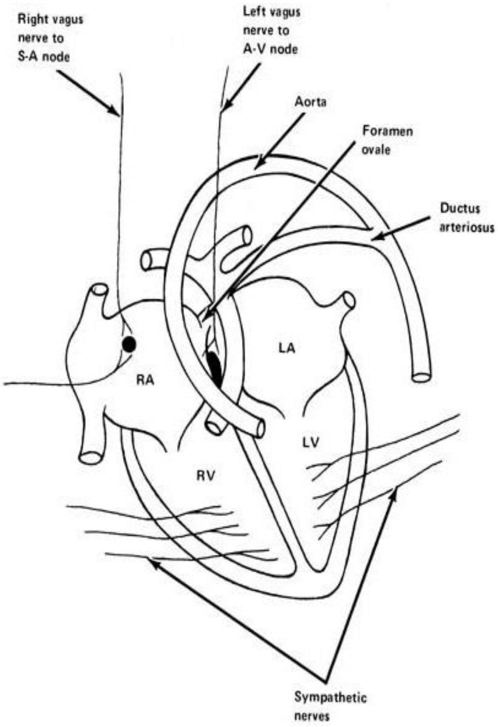

Fig.1 The fetal heart and its nervous connections. RA and LA, right atrium and left atrium; RV and LV, right ventricle and left ventricle. (Parer JT: Physiological regulation of fetal heart rate. J Obstet Gynecol Neonatal Nurs 5:265, 1976)

Electrical Activity of Fetal Heart

The Fetal Electrocardiogram (FECG) is a time-varying signal reflecting the ionic current flow which causes the cardiac fibers to contract and subsequently relax (Malmivuo & Plonsey,1995). The surface FECG is obtained by recording the potential difference between two electrodes placed on the surface of the skin (Lindsley,1942). The standard FECG signal consists of six peak signals each defined with a different letter, the P, Q, R, S, T and U peaks. This letter representation was first coined by Einthoven in 1895. Where the P peak results from the depolarization of the atrial, the P-R interval is the time between the depolarization of the atria and the depolarization of the ventricles. The QRS-complex results from the depolarization of the ventricles, The T wave displays the depolarization of the ventricles and the U wave is usually not present or not important resulting from a rest potential. The origin of the U wave is not clear but it probably represents “after depolarization’s” in the ventricles (Lenssen,2008). The FECG may be divided into the following sections.

P-wave: A small low-voltage deflection caused by the depolarization of the atria prior to atrial contraction as the activation (depolarization) wave front propagates from the SA node through the atria.

PQ-interval: The time between the beginning of atria depolarization and the beginning of ventricular depolarization.

QRS-complex: The largest-amplitude portion of the FECG caused by currents generated when the ventricular contraction.

IJREB

ISSN 2321-743X

International Journal of Research in

Engineering and Bioscience

Volume 2 (Issue 2) Pages (77-91)

Journal home page: www.ijreb.org

QT-interval: The time between the onset of ventricular depolarization and the end of ventricular repolarization. Clinical studies have demonstrated that the QT-interval increases linearly as the RR-interval increases. Prolonged QT-interval may be associated with delayed ventricular repolarization which may cause ventricular tachyarrhythmia's leading to sudden cardiac death.

ST-interval: The time between the end of S-wave and the beginning of T-wave. Significantly elevated or depressed amplitudes away from the baseline are often associated with cardiac illness.

T-wave: Ventricular repolarization, whereby the cardiac muscle is prepared for the next cycle of the ECG.

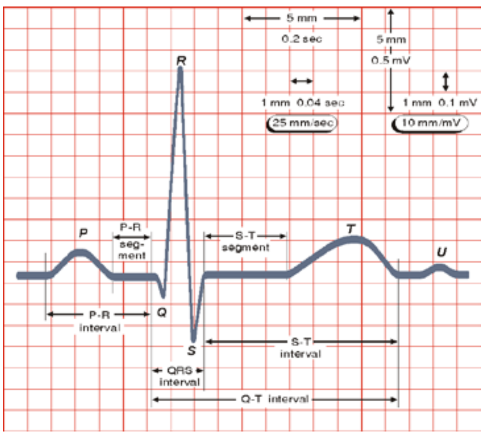

Fig. 1: Standard P, Q, R, S, T and U wave form of human heart; adopted from (Adam & Shavit, 1990).

DIRECT ANALYSIS OF FETAL ECG

Larks (Larks, 1962) reported that when fetus is in vertex presentation, fetal R-peaks are positive peaks where as maternal peaks are negative peaks. During the first two trimesters of pregnancy the fetus does not have a specific presentation and moves about a lot. By the middle of the third trimester the fetus commonly settles in ahead-down position known as the *vertex* presentation, which is more appropriate for birth (Osei *et al.*,1999). In such cases fetal R peaks are detected easily even without removing MECG by simple peak detection method by calculating R-R intervals, is not always possible, because this method depends on the fetal presentation and gestational age.

ADAPTIVE FILTERING

Different types of adaptive filters have been used for fetal and maternal signal separation. These methods use one or more reference maternal signals(Widrow et al., 1962 & Outram et al.,1995 & Mihaela et al.,2011& Prasanth et al.,2013)for training an adaptive or matched filter, or directly training the filter without reference signal (Farvet, 1968 & Park et al.,1992) for extracting the fetal QRS waves. Ad hoc filters such as least square error fittings and partition-based weighted sum filters (Shao et al., 2004) have also been used for FECG extraction. The kalman filter, a general class of adaptive filter (Sameni, 2008 & Niknazar et al 2013) uses only an arbitrary MECG as reference for MECG cancellation and FECG extraction.

Set of state-space equations (Sameni, 2007) was used to model the temporal dynamics of ECG signals, for designing a Bayesian filter for ECG denoising. This Bayesian filter framework was used to extract fECG from single channel mixture of mECG and fECG. However, the filter fails to discriminate between the maternal and fetal components when the mECG and fECG waves fully overlap in time. The reason is that when mECG is being estimated, fECG and other components are supposed to be Gaussian noises.However, this assumption is not true, especially when mECG and fECG waves fully overlap in time it is difficult for the filter to follow desired ECG.

An improved method (Swarnalatha & Prasad, 2010) uses multistage adaptive filtering for FECG extraction in which MECG cancellation has been done by considering thoracic ECG as reference signal also denoising methods were used to improve the quality of extracted signal. A linear adaptive filter (Widrow & Stearns, 1985) was used to extract the FECG by considering abdominal ECG as primary inputs where as thoracic ECG taken from maternal chest as reference inputs. Though this method provides a solution it fails to extract when maternal and fetal signals are overlapped each other. So it is not best for clinical practice.

WAVELET TRANSFORM

Wavelet technique was applied (Datian & Xuemei, 1996) to detect the presence of distorted MECG signal and then MECG component has eliminated from the composite signal. Sometimes even after the elimination of MECG, FECG observation was still complicated and challenging because the wavelet analysis could enhance FECG signal alone. It also detects the singularity of signal either in time or frequency domain.

The method developed in (Echeverria et al.,1996) uses wavelet analysis and pattern matching, in which at pre-processing stage low and high frequency noises in the AECG signal was suppressed based on optimal wavelet multi resolution decomposition and then maternal QRS complexes were cancelled by means of

IJREB

ISSN 2321-743X

International Journal of Research in

Engineering and Bioscience

Volume 2 (Issue 2) Pages (77-91)

Journal home page: www.ijreb.org

pattern matching and template subtraction. Then by applying a QRS detection algorithm, fetal QRS complexes were identified.

FECG was separated and monitored in (Mallat & Hwang, 1992) by calculating lipschitz exponent. This method fails to locate the FECG, if it was obscured by the MECG, which continues more than 2 times in a 10-s period that may be a main drawback of this method. Also there is a need to set the thresholds on the wavelet co-efficients dynamically due to the existence of more noise content because of uterine contraction.

Wavelet transforms based approach proposed in (Papadimitriou et al., 1996) that efficiently eliminates transient spikes and reduces both Gaussian and colored noise without affecting or destroying the information content of the signal. Noise components were detected by analyzing the evolution of the WT modulus maxima across scales. Multi-scale maxima that correspond to noise components were eliminated then de-noised fetal signal was reconstructed by taking inverse WT.

Wavelet based multi resolution analysis(MRA) has developed in (Mochimaru & Fujimoto,2002)to remove the base line wander and the other existing noises, Daubechies 20 wavelet function with 12 levels of decomposition was performed on the raw ECG data. Noise conponents were eliminated by thresholding the wavelet co-efficient at each level. Complex continuous wavelet transform (CCWT) based technique has implemented in (Karvounis et al.,2004) along with modulus maxima theory to detect fetal QRS complexes from multi channel MECG recordings. CCWT was used to identify stationary sections and to locate as well as characterize singularities.

In (Karvounis et al.,2006), FHR extraction from composite AECG signal has been done based on time frequency analysis, procedure composed of three stages. In the first stage maternal QRS complexes were eliminated by detecting maternal R-peaks and fiducial points using time-frequency analysis.At the second stage fetal R peaks were located using complex wavelets and pattern matching techniques,finally based on histogram technique overlapped fetal R peaks were detected at the third stage.

Combination of Wavelet and ICA,called WICA technique proposed in (Azzerboni et al.,2005) used each row data into an n-dimensional orthogonal basis.The extended-

IJREB

International Journal of Research in

ISSN 2321-743X

Engineering and Bioscience

Volume 2 (Issue 2) Pages (77-91)

Journal home page: www.ijreb.org

INFOMAX is a learning rule which was used to compute the demixing matrix. By this algorithm the independent components (ICs) were extracted and the IC accounting for FECG was selected. Using WICA method FHR was detected and the Q, R, and S waves were visible without any signal amplification.

An algorithm proposed in (Almagro et al., 2006) to design a new mother wavelet (MW) called abdominal ECG mother wavelet(AECG MW) for extraction of fetal ECG. Unlike other MWs which were used in extraction of fetal ECG, this newly proposed MW was designed to have a shape similar to AECG. To design such an MW, at least eight Gaussians should be used to model the 4 peaks in QRST of MECG and 4 peaks in QRST of FECG.

A way for detecting QRS complex based on dyadic wavelet transform (*D WT y*) has represented in (Kadambe, et al.,1999). They have designed a Spline wavelet for detecting QRS complex which was the transient part in the ECG signal.Here detection process was based on "the property that the absolute value of *D WT y* has localized maxima across several consecutive scales at the instant of the occurrence of transient." In this case, for each scale they found the local maxima of the absolute value of dyadic wavelet transform by using threshold method,the position of each local maxima was considered to be the location of a QRS complex. They have computed the heart rate by calculating the inverse of the time interval between two consecutive R waves.

Real time fetal electrocardiogram (FECG) feature extraction system was developed in (Desai et al., 2012) based on multi-scale discrete wavelet transform (DWT). Wavelet based peak detection detects QRS complex more accurately for identifying peaks and valleys of noisy FECG signal. Two channel perfect reconstruction (PR) filter banks were used to implement the efficient way discrete wavelet transform.

ARTIFICIAL INTELLIGENCE

In (Liszka- Hackzell, 1994) back propagation network and the SOM network were used to categorize the FHR patterns.A new method for FHR baseline determination using ANNS was proposed in (Marques et al., 1994). Two methods namely baseline estimation and baseline classification with multi layer perception artificial neural networks were applied on AECG data. Results obtained by these approaches were compared based on

IJREB
ISSN 2321-743X
International Journal of Research in
Engineering and Bioscience
Volume 2 (Issue 2) Pages (77-91)
Journal home page: www.ijreb.org

their practical application. In (Magenes.et al., 1999) a method was implemented with neural and fuzzy classifiers to differentiate the normal and pathological fetal states also to improve the diagnostic information contained in CTG signals.

In (Selvan & Srinivasan,2000) neural network real time recurrent learning algorithm was applied for training which converges faster to a lower mean squared error and also it is well suitable for real-time processing.In (Camps et al.,2001) FIR neural network was used for FECG extraction, in order to provide highly nonlinear dynamic capabilities. In this method thoracic maternal signal was considered as a reference signal, doesn't have fetal contributions and the desired signal was composite abdominal ECG signal.Though in (Widrow et al.,1975) many reference signals had taken into consideration, the proposed method has considered only one thoracic signal.

In (Reaz, & Wei,2004)adaptive linear neural network based FECG extraction method was proposed which trained the input composite AECG signal to vanish out the maternal signal therefore fetal ECG signal was isolated. Fetal heart is so small when compared with the maternal heart so the electrical activity produced by fetal heart is much weaker than the maternal due to its domination nature, MECG can be estimated easily then subtracted from the AECG, to get FECG. When compared to the conventional filtering techniques this produce better result because instead of elimination subtraction was used. In (Warrick et al., 2005) signal processing tools and neural networks were used to develop an automated technique to detect the FHR pattern of baseline, acceleration and deceleration. However, ANN based FECG extraction methods have advantages also drawbacks, such as non-convex quadric minimization, which may result in multiple minima and the risk of over fitting.

A new method described in (Amin et al.,2011) using ADALINE for FECG extraction which emulates maternal signal as closely as possible to abdominal signal, thus only predict the maternal ECG in the abdominal ECG. The network error equals abdominal ECG minus maternal ECG, which is the fetal ECG. The characteristic that enables fetal extraction is due to the correlation between maternal ECG signals and the abdominal ECG signal of pregnant woman.A method described in (Maryam, 2012) combines ANFIS and genetic

IJREB

ISSN 2321-743X

International Journal of Research in

Engineering and Bioscience

Volume 2 (Issue 2) Pages (77-91)

Journal home page: www.ijreb.org

Algorithm to extract FECG, Here ANFIS has been used to determine the non linear transformation (MECG).FECG is extracted by Subtracting the aligned version of the determined MECG signal from the abdominal ECG (AECG) signal.

In(Assaleh,2007) adaptive neuro-fuzzy inference system (ANFIS) for Fetal Electrocardiogram extraction was presented.ANFIS is used to nonlinearly align the maternal ECG signal with the components of maternal ECG in the abdominal ECG signal. Hence identified maternal components were cancelled from the abdominal ECG signal and finally Fetal ECG signal was extracted.

In (Kezi et al., 2005) an adaptive neuro-fuzzy logic method has proposed for FECG extraction and MECG cancellation. Rather than using conventional filtering techniques, adaptive filter was used for noise cancellation in the proposed technique, because it is a self adjusting filter, can change according to the environment and also when the signal was passed through a filter it suppress the nose and the signal remains unchanged while leaving the filter. Also this filter does not require a prior knowledge of signal or noise characteristics.

CONCLUSION

The fetal electrocardiogram (FECG) was first demonstrated 114 years ago, but initial progress of research into the subject was slow and limited. As improved amplifiers became available, the detection of the waveform became easier, but observation of waveform morphology was still difficult because of background noise.The signal-to-noise ratio of the original FECG waveform was improved considerably with the use of directly applied fetal electrodes and the development of signal processing and computer techniques which allowed signal enhancement. In this survey paper techniques based on adaptive filtering, artificial intelligence and wavelet transform for FECG signal extraction from the composite AECG signal were discussed along with their advantages and drawbacks.

REFERENCES

1. Minino, AM.; Heron, MP.; Murphy, SL.; Kochanek, KD. Deaths: Final data for 2004. National Vital Statistics Reports.(2007)

2. Pajkrt, E.; Weisz, B.; Firth, HV.; Chitty, LS. Fetal cardiac anomalies and genetic syndromes; Prenat Diagnp. 1104-1115, (2004)[Online]. Available: http://dx.doi.org/10.1002/pd.1067.

3. Zuckerwar A, Pretlow R, Stoughton J, Baker D. Development of a piezopolymer pressure sensor for a portable fetal heart rate monitor. IEEE Trans Biomed Eng.,40(no. 9):963–969, (1993)

4. Peters M, Crowe J, Piéri JF, Quartero H, Hayes-Gill B, James D, Stinstra J, Shakespeare S.Monitoring the fetal heart non-invasively: a review of methods. J Perinat Med.; 29:408–416, (2001)

5. K. V. K. Ananthanag and J. S. Sahambi, "Investigation of Blind Source Separation

Methods for Extraction of Fetal ECG," CCECE 2003-CCGEI 2003, pp.2021-2024,(2003)

6.Cremer M. Über die Direkte Ableitung der Aktionstrome des Menschlichen Herzens vom Oesophagus und Über das Elektrokardiogramm des Fetus. Münchener Medizinische Wochenschrift, 53:811–813,(1906)

7. Goodyer AVN, Geiger AJ, Monroe WM. Clinical fetal elecrocardiography. Yale J Biol Med.(no. 15):1–19,(1942)

8. Lindsley DB. Heart and Brain Potentials of Human Fetuses in Utero. The American Journal of Psychology. 55(no. 3):412–416,(1942)

8. Hon EH. The instrumentation of fetal heart rate and fetal electrocardiography - a fetal heart rate monitor. Conn Med.24:289–293,(1960)

9. Stinstra, J. PhD dissertation. University of Twente; Enschede, The Netherland:. Reliability of the fetal magnetocardiogram.(2001) [Online]. Available: http://doc.utwente.nl/35964/

10. Sexton, MJ.; Latson, LA. Fetal blood flow. Healthwise, Inc.(2005)[Online]. Available: http://www.memorialhermann.org/

11. Malmivuo, J. and R. Plonsey, Bioelectromagnetism-Principles and Applications of Bioelectric and Biomagnetic Fields, Oxford University Press, New York,(1995) [online] available: http://www.bem.fi/book/index.htm.

12. Einthoven W. Über die Form des menschlichen electrocardiogramms. Arch Gesamte Physiol. 60:101–123,(1895)

13. Hurst JW. Naming of the waves in the ECG, with a brief account of their genesis. Circulation. (no. 18):1937–1942,(1998)

14.Lenssen, A.M.J., From cardiac electrical activity to the ECG: A finite element model, Master thesis, Eindhoven University of Technology,(2008)

15. Adam, D. and D. Shavit,. Complete foetal ECG morphology recording by synchronized adaptive filtration. Med.

IJREB

ISSN 2321-743X

International Journal of Research in

Engineering and Bioscience

Volume 2 (Issue 2) Pages (77-91)

Journal home page: www.ijreb.org

Biological Eng. Comp, 28: 287-292,(1990)

16. Larks SD. Present status of fetal electrocardiography. Bio-Medical Electronics, IRE Transactions,(no. 3):176–180,(1962)

17. Osei EK, Faulkner K. Fetal position and size data for dose estimation. Br J Radiol.,72(no. 856):363–370,(1999)

18. Widrow B, Glover J, McCool J, Kaunitz J, Williams C, Hearn H, Zeidler J, Dong E, Goodlin R.Adaptive noise cancelling: principles and applications. Proc IEEE.63(no. 12):1692–1716.(1975)

19. Outram NJ, Ifeachor EC, Eetvelt PWJV, Curnow JSH. Techniques for optimal enhancement and feature extraction of fetal electrocardiogram. IEE Proc-Sci Meas Technol. 142(no. 6):482–489,(1995)

20. G. Mihaela Ungureanu, Ana Maria Ilincai, Werner Wolf, Ilinca Gussi, Dragos D. Taralunga, Rodica Strungaru Improved Fetal ECG Extraction by Applying Adaptive Filtering,International symposium on ADVANCED TOPICS IN ELECTRICAL ENGINEERING,(2011)

21.Prasanth K., Baby Paul, Arun A. Balakrishnan, Fetal ECG Extraction Using Adaptive Filters, International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering Vol. 2, Issue 4, (2013)

22. Farvet AG. Computer Matched Filter Location of Fetal R-Waves. Medical & Biological Engineering. September,6(no. 5):467–475,(1968)

23. Park Y, Lee K, Youn D, Kim N, Kim W, Park S. On detecting the presence of fetal R-wave using the moving averaged magnitude difference algorithm. IEEE Trans Biomed Eng. 39(no. 8):868–871,(1992)

24. Martens, SMM.; Rabotti, C.; Mischi, M.; Sluijter, RJ. A robust fetal ECG detection method for abdominal recordings; Physiol Meas, p. 373-388,(2007)[Online].Available:http://dx. doi.org/10.1088/0967-3334/28/4/004

25. Shao M, Barner K, Goodman M.

An interference cancellation algorithm for noninvasive extraction of transabdominal fetal electroencephalogram(TaFEEG). IEEE Trans Biomed Eng.51(no.3):471–483,(2004)

26. Sameni, R. PhD dissertation. Sharif University of Technology – Institute National Polytechnique de Grenoble, Extraction of Fetal Cardiac Signals from an Array of Maternal Abdominal Recordings.(2008)[Online].Available: http://www.sameni.info/Publications/Thesis/PhDThesis.pdf

27. Sameni R, Shamsollahi MB, Jutten C, Clifford GD. A Nonlinear Bayesian Filtering Framework for ECG Denoising. IEEE Trans Biomed Eng,54(no. 12):2172–2185,(2007)

28. Sameni R, Shamsollahi MB, Jutten C. Model-based Bayesian filtering of cardiac contaminants from biomedical recordings. Physiological Measurement,29(no. 5):595–613, (2008)

29. Mohammad Niknazar, Bertrand Rivet, and Christian Jutten Fetal ECG Extraction by Extended State Kalman Filtering Based on Single-Channel Recordings IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 60, NO. 5, 1345, (2013)

30..R.Swarnalatha ,D.V.Prasad,A Novel Technique for Extraction of FECG using Multistage Adaptive Filtering,Journal of Applied Sciences 10(4):319-324, ISSN 1812-5654,(2010)

31. Widrow B., Stearns S. Adaptive signal processing. Prentice-Hall, Upper Saddle River, (1985)

32. Datian, Y., Xuemei, O.Application of wavelet analysis in detection of fetal ECG. Engineering in Medicine and Biology Society. Bridging Disciplines for Biomedicine.Proceedings of the 18th Annual International Conference of the IEEE, vol. 3. p. 1043–1044, (1996)

33. Echeverria, J. C., Ramirez, N., Pimentel, A.B., et al,Fetal QRS extraction based on wavelet analysis and pattern matching.Engineering in medicine and biology society.Bridging disciplines for biomedicine.Proceedings of the 18th Annual International Conference of the IEEE.vol. 4. p. 1656–1657, (1996)

34. Mallat S., Hwang W. L.Singularity detection and processing with wavelets.IEEE Trans Inf Theory 38:617–643,(1992)

35. Papadimitriou, S., Gatzounas ,D. ,Papadopoulos, V., et al.Fetal heart rate signal denoising by processing the wavelet transform modulus maxima.Engineering in Medicine and Biology Society, Bridging Disciplines for Biomedicine.Proceedings of the 18th Annual International Conference of theIEEE. vol. 3. p.1029–1030,(1996)

36. Mochimaru F., Fujimoto Y. Detecting the fetal electrocardiogram by wavelet theory-based methods. Prog Biomed Res 7:185–193, (2002)

37. Karvounis, E. C., Papaloukas, C., Fotiadis,D. I., et al. Fetal heart rate extraction from composite maternal ECG using complex continuous wavelet transforms. Comput Cardiol 737–740, (2004)

38. Karvounis. E. C., Tsipouras, M. G., Fotiadis, D. I., et al. A method for fetal heart rate extraction based on time-

frequency analysis,19th IEEE Symposium on Computer-Based Medical Systems (CBMS'06). p.347–347,(2006)

39. B. Azzerboni, F. Foresta, N. Mammone and F. C. Morabito, "A New Approach BasedOn Wavelet-ICA Algorithm for Fetal Electrocardiogram Extraction," presented at the European Symp. Artificial Neural Networks, (2005).

40.S Almagro, MM. Elena, MJ. Bastiaans and JM. Quero, "A New Mother Wavelet for Fetal electrocardiography, to Achieve Optimal De-noising and Compressing results," in computers in cardiology, pp. 157-160,(2006)

41. S. Kadambe, R. Murray and F. Boudreaux-Bartels, "Wavelet Transform-Based QRS Complex Detector," IEEE Trans. Biomed. Eng., vol. 46, no. 7, pp. 838-847,(1999)

42. K.D. Desai,Manoj S. Sankhe A Real-Time Fetal ECG Feature Extraction Using Multiscale Discrete Wavelet Transfor 5th International Conference on BioMedical Engineering and Informatics (2012)

43. Liszka-Hackzell, J.Categorization of fetal heart rate patterns using neural networks.Comput Cardiol 97–100, (1994)

44. Marques de Sa, J. P., Reis, L. P., Lau, J. N.et al. Estimation and classification of fetal heart rate baselines using artificial neural networks. Comput Cardiol 541–544,(1994)

45. Magenes. G., Signorini, M. G., Arduini, D.Detection of normal and pathological fetal states by means of neural and fuzzy classifiers applied to CTG parameters. Engineering in Medicine and Biology. 21st Annual Conference and the 1999 Annual Fall Meeting of the Biomedical Engineering Soc. BMES/EMBS Conference,vol. 2. p.936–936, (1999)

46. Selvan, S., Srinivasan, R. "A novel adaptive filtering technique for the processing of abdominal fetal electrocardiogram using neural network" Adaptive systems for signal processing, communications andcontrol symposium p. 289–292. (2000).

47. Camps, G., Martinez, M., Soria, E. Fetal ECG extraction using an FIR neural network. Comput Cardiol 249-252. (2001)

48. Widrow B., Glover J. R. Jr, McCool J. M.et al. Adaptive noise canceling: principlesand applications. Proc IEEE 63:1692–1716, (1975)

49. Reaz, M. B. I., Wei, L. S. Adaptive linear neural network filter for fetal ECGextraction. Proceedings of international conference on intelligent

sensing and information processing. p. 321–324, (2004)

50. Warrick, P., Hamilton, E., Macieszczak, M.Neural network based detection of fetal heart rate patterns. Proceedings of International Joint Conference on Neural Networks. vol. 4. p. 2400–2405, (2005)

51.L. Xia, J. Meng, R. Xu, B. Yan, Y. Guo, Modeling of 3-D vertical interconnect using support vector machine regression, IEEE Microw. Wireless Compon. Lett., vol. 16, no. 1, 639-641,(2006)

52.M. S. Amin, Md. Mamun, F. H. Hashim and H. Husain Separation of fetal electrocardiography (ECG) from composite ECG using adaptive linear neural network for fetal monitoring International Journal of the Physical Sciences Vol. 6(24), pp. 5871-5876, (2011) Available online at http://www.academicjournals.org/IJPS

53. Maryam, Extracting Fetal Electrocardiogram Signal Using ANFIS Trained by Genetic Algorithm International Conference on Biomedical Engineering (ICoBE), (2012)

54.K. Assaleh, "Extraction of Fetal Electrocardiogram Using Adaptive Neuro-Fuzzy Inference System," IEEE Trans. Biomed. Eng., vol. 54, no. 1, pp. 59-68,(2007).