ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 9, September 2015

Fetal ECG Extraction

Dr. R. Vasuki[1], K.Venkatraman (BM)*[2]

Professor & HOD, Dept. of Biomedical Engineering, Bharath University, Chennai, Tamil Nadu, India[1]

Assistant Professor, Dept. of Biomedical Engineering, Bharath University, Chennai, Tamil Nadu, India[2]

*Corresponding Author

ABSTRACT: Fetal ECG (FECG) signal contains potentially precise information that could assist clinicians in making more appropriate and timely decisions during pregnancy and labor. The extraction and detection of the FECG signal from the composite abdominal signals of the mother with powerful and advance methodology is becoming a very important requirement in fetal monitoring. This paper illustrates the algorithm developed based on neural network approach to provide efficient and effective way of separating FECG signal from the abdominal ECG signals. The FECG signal is isolated from the abdominal signal by back propagation neural network approach. The input signal is considered as maternal ECG (mECG) obtained from the thorax of the mother, and the target signal is abdominal signal (AECG) which has both MECG and FECG. The output of the network is subtracted from the target input (AECG). To reduce the difference between the input and target signal the weights have been updated every step, so that acceptable FECG signal can be obtained.

KEYWORDS: Neural Network, Fetal ECG, Abdominal ECG, Heart Rate Variability.

I. INTRODUCTION

Fetal Heart Rate (FHR) analysis has become a widely accepted means of monitoring fetal status. Such analysis uses fetal electrocardiogram (FECG) signal for long term monitoring of FHR and fetal well being using signal processing techniques[1]. FECG can be obtained non- invasively by applying electrodes to the abdomen of a pregnant woman. FECG is the source of information in early stage diagnosis of fetal health and status. The fetal ECG contains valuable information which will assist clinicians in making more appropriate and timely decisions during labor, but the difficulty of processing it accurately without significant distortion has been a great challenge[2]. The magnitude of the FECG signal at the maternal abdomen is of the order of several microvolts which is a fraction of the Maternal Electro Cardiogram (mECG) amplitude recorded at the maternal abdomen.

The abdominal ECG contains a weak fetal ECG signal, a relatively higher level of maternal ECG, maternal muscle noise (electromyographic activity in the muscles of the abdomen and uterus) and respiration, thermal noise from the electronic equipment (electrodes, amplifiers, etc.), power line interference and baseline wandering. The signal processing algorithm needs to enhance the fetal QRS complexes before foetal R peak can be detected perfectly. To get proper information of the fetal status and condition, it is necessary to improve the SNR of the abdominal signal. The frequency spectrum of the mECG signal overlaps partially that of the FECG. Therefore filtering alone is not sufficient to achieve adequate noise reduction. Techniques to get better FECG signal acquisition remain the subject of ongoing research.

A. Review of previous works

According to the review, existing FECG extraction approaches in the literature can be categorized by their methodologies[3], which include linear or nonlinear decomposition and adaptive filtering.

Linear decomposition method includes singular value decomposition[4], wavelet transform based techniques[5], Blind Source Separation(BSS)[6], BSS combined with wavelet techniques[7]. In linear decomposition technique it is usually assumed that signals and noises are mixed in stationary and linear manner. However, FECG and other noises are not always stationary mixed and linearly separable.

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 9, September 2015

Non linear decomposition method includes Principal Component Analysis(PCA) and Independent Component Analysis(ICA)[8],[9]. Non-linear decomposition methods have higher computational complexity in comparison to linear methods[10].

The adaptive filtering is based on training an adaptive filter for either removing the mECG using one or several maternal reference channels [11], or directly training the filter for extracting the fetal QRS waves[12].

Conventional signal processing algorithms have various limitations and considerable computational complexity. In this paper, to enhance the extraction of FECG signal from the abdominal ECG signal, the neural network (NN), based FECG extraction has been proposed. Since the neural network is adaptive to the nonlinear and time varying features of ECG signal, it has been used to extract the FECG signal. Here, the adaptive non linear neural network has been considered with single neuron[13]. The input signal is considered as maternal ECG and the target signal is abdominal signal. Using NN approach, the maternal ECG has been suppressed from the abdominal ECG (maternal and fetal ECG), so that the output can be considered as only fetal ECG. Then the 'R' peak of the fetal ECG is detected for calculating the fetal heart rate. The normal heart rate of the fetal is to be around 110 to 180 bpn. The plot of fetal heart rate with respect to time gives heart rate variability (HRV). From the HRV plot, any abnormality in the fetal if exists can be identified by the clinician so that correct decision can be made for the well being of fetus during the pregnancy[14],[15].

II. METHODOLOGY

Back propagation neural network is used in this paper for FECG extraction from the abdominal signal. The process flow of this project is shown in the following block diagram (fig.1).

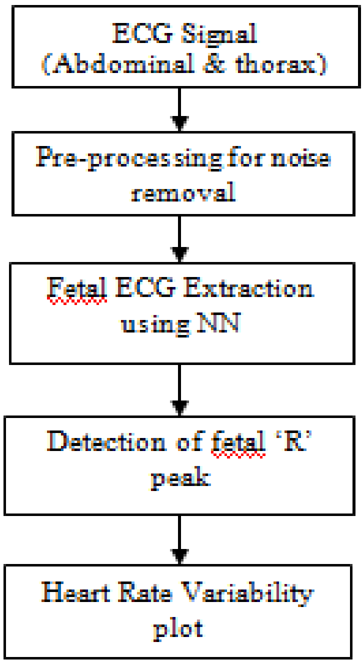

Fig 1 Flow diagram of the project

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 9, September 2015

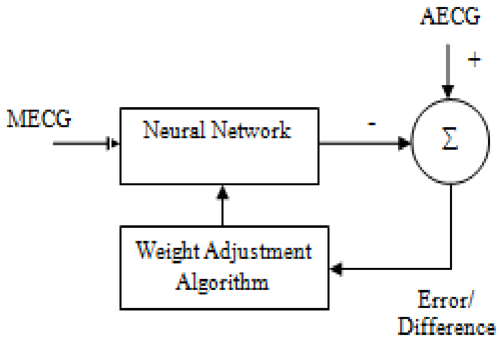

Fig.2 Neural Network architecture

Feed forward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors [16]. The designed Back propagation neural network has two layers of tan-sigmoid/linear network. Each layer has a weight matrix *W*, a bias vector *b*, and an output vector *a*. There is no definite way of determining the right number of neurons in the hidden layer [17].

The number of hidden layer neurons is chosen based on Kolmogorov's theorem. It states that if the number of input neuron is 'm', then the number of neurons in the hidden layer is 2m+1, that can exactly map the input to the output. However this theorem did not specify whether this network is an optimum solution for this mapping [18].

The number of neurons in the output layer is 1 with 'purelin' transfer function. Finally the training function has been considered 'trainlm' (ie.,) Levenberg-Marquardt second order training speed-training functions. The network is initialized with maximum epoch as 2500 and the goal as $1e^{-5}$. It means maximum epoch for training is 2500 and the goal is to reach error at $1e^{-5}$. For each training session, the training stops when reaches either maximum epochs or goal error [19].

The input signal is considered as mECG and the target signal is abdominal signal(AECG). The output of the network is subtracted from the target input (AECG). To reduce the difference between the input and target signal the weight has been updated every step [20]. Therefore, the difference is considered the FECG by suppressing the AECG. The best the network can predict is the mECG in AECG of the pregnant women due to the correlation of the two signals. Thus the error signal is not actually an error; instead it's the FECG that is extracted.

III. RESULTS

Experimental data is obtained from Database for the Identification of Systems (DaISy). In the database, signals were recorded from pregnant women by surface electrode, which included 8 channels signals: five maternal abdominal signals and three maternal chest signals. The sampling frequency is 250Hz, collecting time is 10 seconds, and each channel collects 2500 samples.

The input signal and the target to the network is selected from any of the three maternal chest signals and five maternal abdominal signals respectively. The output of the network gives the enhanced FECG along with mECG. Hence mECG is suppressed in the maternal abdominal signal by identifying the R peak in the maternal chest signals and zeroing that particular QRS wave samples in the maternal abdominal signal. Then fetal ECG signal alone exists which is the desired signal.

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 9, September 2015

The results obtained by applying the above described procedure are as follows. In fig.3, the first signal is the mECG from the thorax of the mother, second signal is the abdominal signal containing both mECG and FECG. Third signal shows the output from the neural network depicting the enhanced FECG. Fourth signal shows the result after suppression of mECG and the last one shows the identified 'R' peaks of extracted FECG being marked as '*'.

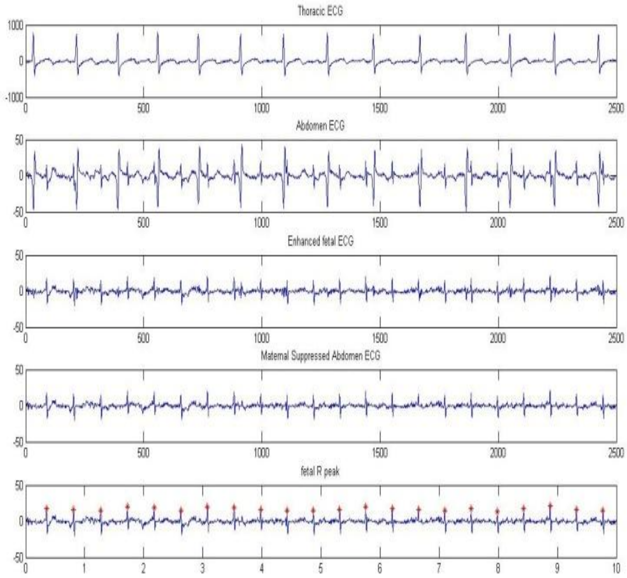

Fig 3: Result of Extracted fetal ECG using the channel no.2 for AECG and 9 for MECG.

IV. HEART RATE VARIABILITY

Heart rate variability (HRV) is the physiological phenomenon of variation in the time interval between heartbeats. It is measured by the variation in the beat-to beat interval. Thus the heart rate variability can be measured based on the beat intervals, which are more easily observed as RR intervals. The heart rate is calculated using the formula

$$HR = 60/RR \text{ interval (beats per minute)} \qquad (1)$$

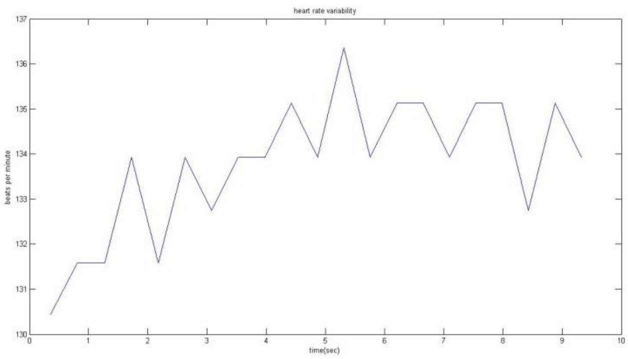

Fig 5: Fetal Heart Rate Variability plot

The acceptable range of fetal heart rate is between 110 to 180 bpm. If the fetal heart rate is beyond this normal range for prolonged interval of time then the condition may be either tachycardia in case of increased heart rate above 180bpm and bradycardia in case of decreased heart rate below 110bpm.

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 9, September 2015

V. CONCLUSION

FECG signal contains the valuable information that could assist clinicians in making more appropriate and timely decisions. The neural network technique is used in this paper to extract the FECG signal from the AECG. The fetal 'R' peak identification and fetal heart rate variability is very helpful for the evaluation of the fetus well being.

VI. ACKNOWLEDGMENT

We acknowledge Anna University's National Hub for Health Care instrumentation Development at Anna University funded by Technology Development and Transfer, Department of Science and Technology for supporting this work.

REFERENCES

1. Wenjuan JIA, Chunlan YANG, Guocheng ZHONG, Mengying ZHOU, Shuicai WU (2010) "Fetal ECG Extraction Based on Adaptive Linear Neural Network" 3rd International Conference on Biomedical Engineering and Informatics.
2. Lydia Caroline M., Vasudevan S.,"Growth and characterization of l-phenylalanine nitric acid, a new organic nonlinear optical material", Materials Letters, ISSN : 0167-577X, 63(1) (2009) pp. 41-44.
3. A. Khaled, "Adaptive neuro-fuzzy inference systems for extracting fetal electrocardiogram," 2006 IEEE International Symposium on Signal Processing and Information Technology, pp. 122-126.
4. Jayalakshmi T., Krishnamoorthy P., Ramesh Kumar G., Sivamani P., "Optimization of culture conditions for keratinase production in Streptomyces sp. JRS19 for chick feather wastes degradation", Journal of Chemical and Pharmaceutical Research, ISSN : 0975 – 7384, 3(4) (2011) PP.498-503.
5. R. Sameni and G. D. Clifford, "A review of fetal ECG signal processing; Issues and promising directions," Open Pacing, Electrophysiol. Ther. J., vol. 3, pp. 4–20, 2010.
6. P.P. Kanjilal, S. Palit, and G. Saha, "Fetal ECG extraction from singlechannel maternal ECG using singular value decomposition," IEEE Trans.Biomed. Eng., vol. 44, no. 1, pp. 51–59, Jan. 1997.
7. Langeswaran K., Gowthamkumar S., Vijayaprakash S., Revathy R., Balasubramanian M.P., "Influence of limonin on Wnt signalling molecule in HepG2 cell lines", Journal of Natural Science, Biology and Medicine, ISSN : 0976-9668, 4(1) (2013) PP. 126-133.
8. Khamene and S. Negahdaripour, "A new method for the extraction of fetal ECG from the composite abdominal signal," IEEE Trans. Biomed. Eng., vol. 47, no. 4, pp. 507–516, Apr. 2000.
9. Jebaraj S., Iniyan S., "Renewable energy programmes in India", International Journal of Global Energy Issues, ISSN : 0954-7118, 26(4Mar) (2006) PP.232-257.
10. L. de Lathauwer, B. de Moor, and J. Vandewalle, "Fetal electrocardiogram extraction by blind source subspace separation," IEEE Trans. Biomed. Eng., vol. 47, no. 5, pp. 567–572, May 2000.
11. M. G. Jafari and J. A. Chambers, "Fetal electrocardiogram extraction by sequential source separation in the wavelet domain," IEEE Trans. Biomed. Eng., vol. 52, no. 3, pp. 390–400, Mar. 2005.
12. V. Vigneron, A. Paraschiv-Ionescu, A. Azancot, O. Sibony, and C. Jutten, "Fetal electrocardiogram extraction based on non-stationary ICA and wavelet denoising," in Proc. 7th Int. Signal Process. Appl. Symp., vol. 2, pp. 69–72,2003.
13. A. Hyvaerinen, and E. Oja, 'Independent Component Analysis: Algorithm and Application', Neural Networks, Vol.13, No.4-5, pp.411- 430, June 2000.
14. Gopalakrishnan K., Prem Jeya Kumar M., Sundeep Aanand J., Udayakumar R., "Thermal properties of doped azopolyester and its application", Indian Journal of Science and Technology, ISSN : 0974-6846, 6(S6) (2013) PP. 4722-4725.
15. 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, pp.1345-1352, May 2013.
16. M. B. I. Reaz and L. S. Wie, "Adaptive linear neural network filter for fetal ECG extraction," Proceedings of International Conference on Intelligent Sensing and Information Processing, Chennai, India, pp. 321–324, January 2004.
17. Y.-Y. Shi, Z.-P. Gou, Y.-F. Zhang, Y. Zhang, and Q.-Y. Chen, "Extraction the signal of fetal electrocardiogram based on the optimal empirical mode decomposition adaptive filter," Biomedical Engineering and Clinical Medicine, vol. 14, no. 1, pp. 5-9, 2010.
18. M. A. Hasan, M. I. Ibrahimy and M. B. I. Reaz, "Fetal ECG Extraction from Maternal Abdominal ECG Using Nerual Network" J.Software Engineering & Applications, pp.330-334. July 2009.
19. Shou-yi Wei, Yao-Sheng Lu, Xiao-lei Liu (2012), "Fetal Heart Rate Analysis using a Non-linear Baseline and Variability Estimation Method" 5th International Conference on BioMedical Engineering and Informatics.
20. M. Ungureanu, J. W. M. Bergmans, M. Mischi, S. G. Oei, and R. Strungaru, "Improved method for Fetal Heart Rate Monitoring," Proceedings of the 2005 IEEE Engineering in Medicine and Biology 27th Annual International Conference, Shanghai, China, pp. 5916–5919, January 2006.
21. AR.Arunachalam, Spectrum Reuse in MultiplePrimaryUser Environment, International Journal of Innovative Research in Computer and Communication Engineering, ISSN(Online): 2320-9801,pp 1475-1480, Volume 1, Issue 7, September 2013
22. B.Sundar Raj, A Third Generation Automated Teller Machine Using Universal Subscriber Module with Iris Recognition, International Journal of Innovative Research in Computer and Communication Engineering, ISSN (Online): 2320 – 9801,pp 565-571, Vol. 1, Issue 3, May 2013
23. B.Sundar Raj, The Efficiency of the Scalable Architecture forRevealing and Observing the Environment using Wireless Sensor, International Journal of Innovative Research in Computer and Communication Engineering, ISSN (Online): 2320 – 9801,pp 63-67, Vol. 1, Issue 1, March 2013
24. C.Anuradha, An Efficient Detection of Black Hole Attacks in Tactical MANETs, International Journal of Innovative Research in Computer and Communication Engineering, ISSN(Online): 2320-01,pp 1636-1645, Volume 1, Issue 8, October 2013