



Estimation of Power spectral Density Analysis of Fetal ECG Signal

Aqib Javed & Dr Ajay Abrol

Research student of Govt.College of Engineering & Technology,Jammu (181122).

Associate Professor of Govt.College of Engineering & Technology,Jammu (181122).

Department of Electronics & Communication Engineering Govt.College of Engineering & Technology,Jammu,India.

Abstract: The Fetal Electrocardiogram (FECG) expresses valuable information about the health status of the mother and baby. An analysis of the complex signal helps experts in making decision during labor. The main interest of FECG analysis is in the field of biomedical applications and clinical diagnosis. Extracting FECG signals is considered a major challenge while the fetus is inside the mother's uterus. Number of methods are available that can be used to extract FECG from Mothers ECG and detect Fetal heart rate and power in the signals generated by the heart. An ECG signal is recorded by way of putting electrodes on the maternal stomach but the fetal ECG is always masked by maternal ECG and noise. In this research work one of band pass filter is used to get filtered FECG. The original signal is passed through filter which has a frequency of 150 to 160 Hz. Then the filtered signal is analyzed through spectrogram and the power in the signal is extracted that contains P1, P2, Pm amplitude values for Direct1, Abdoment1, Abdomen 2 and Abdomen3 of the ECG signal downloaded from PHYSIONET database. The power in the signal is more for Direct1 signal compared to Abdomen1, Abdomen 2 and Abdomen3 and Abdomen 4. In this analysis we use MATLAB R2013a.

Introduction: Cardiac abnormalities are frequent, affecting one out of every hundred babies born each year. These problems in the foetus occur as a result of an organic disorder, an acquired condition, or environmental factors such as overuse and abuse of pharmaceuticals. In any case, routine screening of an infant's heart before conception is critical. As a result, the Fetal ECG plays a critical role in determining the baby's heart condition. It aids in the detection of any anomalies and prompt treatment by the necessary specialists. Fetal ECG extraction is a technique used to identify fetal deviations from the norm. It's a non-invasive, multi-functional method for detecting various heart flaws. The Fetal ECG (FECG) monitors the electrical activity of the heart and hence provides important information about the foetus' physiological state. In pregnant women, the FECG signal can be recorded from the mid-region of the body. Maternal ECG is the ECG of a pregnant woman that is recorded from the mid-section of the body (MECG). In general, FECG appears as a riding wave on top of the MECG signal, making it difficult to extract fetal ECG from MECG. To record the FECG, the electrode terminals are put on the mother's abdomen, and so a record is created which gives minute details about the fetus development'

Literature Survey

P. P. Kanjilal, et al. [1] in this research work the fetal ECG component was extracted from a single composite maternal ECG signal received from an abdominal lead using SVD. The results show that the proposed approach works even when the SNR is low, and that drifts and low frequency interferences can be controlled. Automated extraction should be achievable because the extraction technique is straightforward and unambiguous. The suggested method has a high degree of numerical resilience thanks to the use of SVD, and the extraction may be done quickly according to efficient implementation. The notion of selective signal component extraction is generic in nature, and there is no analogous frequency domain method. The proposed approach should work for component separation in any composite signal, regardless of how complex the signals are.

A. Hyvärinen et al. [2] in this research, the fetal ECG component was recovered using SVD from a single composite maternal ECG signal acquired from an abdominal line. The results show that the proposed strategy can control drifts and low frequency interferences even when the SNR is low. Because the extraction technique is simple and unambiguous, automated extraction should be possible. Because of the usage of SVD, the proposed technique has a high level of numerical robustness, and the extraction can be done fast using efficient implementation. The concept of selective signal component extraction is broad, and there is no frequency domain equivalent. Regardless of how complicated the signals are, the proposed approach should work for component separation in any composite signal.

V. Zarzoso, et al. [3] the research work shows The HOS-based BSS was regarded as a more robust and successful method to the noninvasive FECG extraction problem than the MRANC, despite the fact that greater performance comes at the cost of increased computing complexity. However, the FECG-extraction quality attained suggests that ICA-BSS approaches could be useful in prenatal medical diagnostics. However, further research is needed before blind separation techniques may be used as a broad diagnosis tool. The relationship between physiological sources of heart activity and the statistically-independent sources estimated by signal separation methods needs to be defined as the most crucial point to be investigated.. The lack of knowledge on this relationship does not prevent BSS techniques from being useful in as important state-of-the-art applications as telemedicine, in which the physician merely considers the fetal cardiac rate. In addition to the heart rate, BSS presents the potential of offering more detailed information about the fetal heart, thus allowing a more accurate diagnosis.

P. Gao, et al. [4] the research presents a method for determining the heartbeat occurrence of fetal ECG from a single channel composite signal that integrates SVD and ICA. The genuine fetal ECG can be isolated from the composite signal using recognized methods based on heartbeat occurrences; the goal is to get the data into a higher dimension. The heartbeat occurrences are then obtained using ICA. With an evident use of domain knowledge, the ambiguities of ICA (lack of any ordering to the separated signals) can be managed. The majority of ICA algorithms are either iterative fixed point algorithms (such as Fast ICA) or gradient descent methods, both of which optimize a solution only locally and are sensitive to starting randomization conditions, which can result in very diverse solutions, even for the same problem. The technique of separating the spectral basis vectors first before sending the remixed time domain signals to ICA as a manner of establishing favorable beginning conditions that contribute to the stability of the time domain separation solutions. The suggested technique extracts a fetal ECG from a composite signal well, according to the results. Because it only uses single-channel recording, there are no concerns with having original signals that differ in more complex ways than just signal mixing levels.

M.A.Oudijk, et al. [5] the research proposed that Supraventricular tachycardia (SVT) was found in seven fetuses, atrial flutter in three, and ventricular tachycardia in one (VT). Nine fetuses changed to sinus rhythm on an average of 8.2 days after presentation, and six of these individuals had their hydrops resolved in an average of 8.8 days. At birth, the average gestational age (GA) was 35 + 4 weeks. Seven infants had normal cranial ultrasounds at birth, and all but one of them remained normal at follow-up. However, one infant who had no abnormalities at birth developed several cerebral lesions as a result of a malignant long QT syndrome (LQTS) and died at the age of two. On newborn cranial ultrasonography, three children developed periventricular echogenicity (PVE), which was linked to a pseudo cyst in one of them. The remaining baby had a prenatal

parenchymal hemorrhage that manifested as a porencephalic cyst at delivery. At follow-up, one of these infants was normal, one died two days after birth, and two showed neurological abnormalities, with one having mild hemiplegia with normal cognitive function and the other having a cognitive developmental delay.

M. G. Jafari, et al. [6] the problem of noisy instantaneous mixtures is addressed in this research work, Wavelet de-noising was used to separate the sources in the time-scale domain. The samplepdf of the wavelet coefficients of some 1-D source signals has been demonstrated to fit a generalized Gaussian distribution, and the global mixing-separating system is dependent on the sources' kurtoses, which are higher in the wavelet domain. As a result, while acting in the time-scale domain, the NGA has a faster convergence rate than when operating in the time domain. Finally, employing a single super-Gaussian nonlinearity, the time-scale technique has been proven to be capable of separating sub-Gaussian sources and mixes of both sub- and super-Gaussian signals. As a result, performing BSS in the wavelet domain can help to solve the problem of switching between activation functions.

J.M. Breuer, et al. [7] in this thesis work, seven fetuses had supraventricular tachycardia (SVT), three had atrial flutter, and one had ventricular tachycardia (VT). Following an average of 8.2 days after presentation, nine fetuses switched to sinus rhythm, and six of them had their hydrops cured in an average of 8.8 days. The average gestational age (GA) at birth was 35 + 4 weeks. All but one of the seven babies had normal cerebral ultrasounds at birth, and all but one of them stayed that way at follow-up. One infant, however, who had no abnormalities at birth, developed several cerebral lesions as a result of a malignant long QT syndrome (LQTS) and died at the age of two. Three children acquired periventricular echogenicity (PVE) on neonatal cranial ultrasonography, which was connected to a pseudo cyst in one of them, the remaining baby had a prenatal parenchymal hemorrhage that manifested as a porencephalic cyst at delivery. One of these babies was normal at follow-up, one died two days after birth, and two had neurological abnormalities, one with mild hemiplegia and normal cognitive function and the other with a cognitive developmental delay.

M. E. Davies et al. [8] in this research work, the notion of SCICA has been formalized and shown that it is an intriguing particular case of Cardoso's MICA. This shows that under certain conditions, single channel blind source separation may be addressed practically using the SCICA framework, but the independent source processes must have separate spectral support. When this isn't the case (as in the case of the ECG), more prior information is usually required, and separation becomes much more difficult. It has also discovered that the SCICA framework is actually complementary to the spatial ICA framework. As a result, these concepts can be combined into a space–time ICA codebook.

R. Sameni, et al. [9] This research has shown that the combined approach of Kalman sifting with Least mean square calculation as a simple technique to separate superior grade, high sign to clamor proportion fetal electrocardiogram from the combination of maternal ECG, fetal ECG, and different clamors gives clear image of fetal heart beat signal in the presence of strong commotions, according to the results of the proposed research. The least mean square calculation is presented and carried out successfully in this research endeavor in light of varied commotion wiping out arrangement with Kalman channel. With an overall Q-Peaks identification of 97 percent, the Kalman Filter showed to be a viable strategy in extracting ECG. A Kalman based Bayesian filter architecture was utilized to extract FECG from single channel recordings.

M. A. Hassan, et al. [11] this research is analysis of the FECG during labour could reveal vital new information regarding the fetus's health concerns and aid clinicians in avoiding unneeded medical intervention, according to the researchers. As a result, long-term FHR monitoring is essential during pregnancy and labour. As a result, the purpose of this study was to provide clear information about FECG and to describe the various signal analysis methodologies for successful FHR monitoring. The merits and limits of techniques for identifying and extracting FECG signals from a composite AECG signal were discussed. Because of a fault or lack in one way, newer, more effective methods are developed. This change clearly defines a variety of FECG signal analysis approaches, enabling for the use of precise procedures.

S. Kiranyaz et al. [14] in this thesis work growing neural network is used to process each patient's input patterns. Graphing calculators include the TI-DWT and the PCA. The following signal processing technologies are used in the suggested feature extraction method. The following are the properties of wavelet-based morphology: the ECG data is taken and reduced to a single digit. Create a lower-dimensional feature vector using the PCA

method. The feature vector that was constructed to represent concise morphological information with two important temporal features. Each ECG heartbeat is used as an input by MLP classifiers, which are produced automatically (network structure and content), and the suggested approach is used to optimize the connection weights.

Kok Beng Gan, et al. [15] in this research work, using a commercially accessible silicon photo-detector and low-cost, very low-power (68 mW) IR light, a low-power OFHR detection device was conceived and built. The digital synchronous detection and adaptive filtering algorithms were successfully developed using LabVIEW 7.1. Using digital synchronous detection and adaptive filtering techniques, the FHR was measured with satisfactory precision (maximum error of 4%) when compared to Doppler ultrasound. Probe position impacts the quality of the recorded signal and, as a result, the FHR results, as clinical results show. Signal quality and FHR measurement accuracy can be improved by locating the closest fetal tissues to the probe (rather than just the head or buttocks).

V. Vigneron et al. [18], the research work found seven fetuses abnormally large. BSS was used to retrieve FECG data in this study. Wavelets appear to be a well-connected and promising strategy for recovering fetal PQRST complexes, and it has been shown that employing ECG non-stationarity to improve source separation can improve source separation. Further research will focus on (i) a quantitative comparison of the performance of BSS algorithms, with a particular focus on wavelet denoising for improving PQRST complex extraction, and (ii) a qualitative evaluation (by physicians) of the fetal PQRST extracted by this method, particularly in pathological cases.

K. V. K. Ananthanag, et al. [19] the research shows BSS uses higher-order statistics-based algorithms that are unaffected by electrode location. When the input SNR was high, all of the algorithms were able to extract ECG quite well. The researcher computed and compared the performance of five BSS-based algorithms in a semi-synthetic database in the challenge of extracting the FECG in this study. The WASOBI method performs the worst, but when both WASOBI and EFICA are combined in COMBI and MULTICOMBI algorithms, the strengths of both techniques are used, resulting in improved performance. The algorithm MULTICOMBI outcomes, on the other hand, are more spread. This is due to the fact that MULTICOMBI is an ad hoc technique, so the clustering scheme must be optimized for the goal of distinguishing the sources in the dataset.

G.Dapoian, et al. [20] The Research uses the Gaussian functions sparse decomposition approach offers separating maternal and fetal components. The various BSS and JBSS algorithms were evaluated, and the JBSS CUM4 method was shown to be the most effective in terms of separating MECG and FECG. The proposed compression and detection framework was tested on two publicly available datasets, yielding promising results (sensitivity $S = 92.5$ percent, $P = 92$ percent, $F1 = 92.2$ percent for the Silesia dataset and $S = 78$ percent, $P = 77$ percent, $F1 = 77.5$ percent for the Challenge dataset A, with average reconstruction quality $PRD = 8.5$ percent and $PRD = 7.5$ percent, respectively).

M.A.Yaping, et al. [22] the research demonstrates how FECG was extracted using a hybrid nonlinear adaptive noise canceller with single or multi-reference channels. A key classical strategy for FECG extraction, such as Widrow's multi-reference adaptive noise cancellation and also optimum Wiener-Hopf filtering solutions, is contrasted with a blind source separation method based on higher-order statistics. Real multi-channel ECG recordings from a pregnant lady are used in both procedures. To extract the FECG from a composite AECG signal, this study uses a hybrid nonlinear ANC based on the Volterra filter and the FLANN. To deal with the linearity and nonlinearity between the MECG and its distorted form residing in the AECG, a Volterra filter and a FLANN are placed in parallel in each channel in the suggested ANC. Extensive simulations were run with two separate genuine ECG datasets. Among the four ANCs investigated in the simulations, the proposed ANC gives the best extraction quality, according to some typical findings. As a result, the new hybrid ANC, which incorporates both exponential and cross components, is better able to approximate the nonlinearity between the MECG at the chest and a transformed counterpart at the belly.

Mohammad Reza Mohebbian, et al. [23] in this research work in order to map maternal and fetal ECG, a novel architecture based on the attention layer, sine activation function, and cycle generative adversarial neural network is investigated. The quality of FECG derived from MECG is assessed first. Second, the detection of

fetal QRS using MECG is evaluated. Based on subject-leave-out validation, a 98 percent R-Square [CI 95 percent: 97 percent, 99 percent] as the goodness of fit and a 99.7% F1-score [CI 95 percent: 97.8 percent, 99.9 percent] for QRS estimate were achieved on the abdominal and direct FECG (A&D FECG) dataset. The effect of maternal and fetal heart rates on performance was investigated using a synthetic dataset, which revealed that the suggested method may be applied in a variety of fetal and maternal heart rate changes. These results are comparable to and better than current state-of-the-art results.

Methodology: The overall thesis flowchart is shown in Figure 3.1. The first step is to suppress the MECG signal in the AECG signal using bandpass filter. The next stage is to eliminate noise from the FECG signal and track the peaks using a Spectrogram. Physionet's abdominal and direct FECG (ADFECG) database is used to test the functionality of the designed procedures.

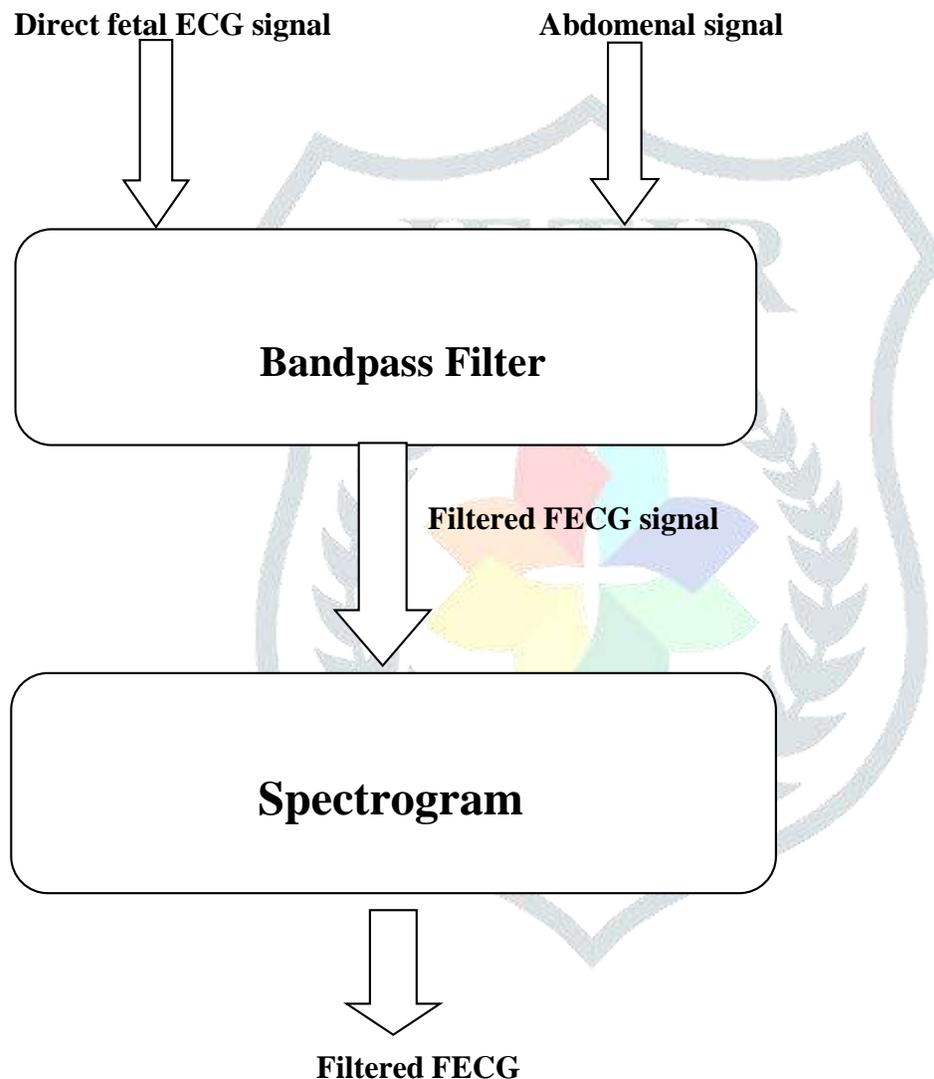


Fig 3.1: Flow chart of proposed system methodology

Direct fetal ECG and abdominal signals

PhysioNet's Abdominal and Direct Fetal Electrocardiogram Database was used to design and evaluate the suggested approach. Five separate women's multichannel fetal ECG recordings are included in the database. When the recordings were made, each lady was in labour and between 38 and 41 weeks pregnant. Each recording is made up of four signals taken from the maternal abdomen and a direct fetal ECG taken from the fetal head. A reference electrode was inserted above the pubic symphysis and four abdominal electrodes were implanted around the navel. To ground the signal, a reference electrode was put on the left leg.

Bandpass filtering

Bandpass filtering is based on the principle of adjusting a variable filter until the difference between the variable filter output and the target signal is as minimal as possible. A signal from the abdomen, $x(n)$, is put through a variable filter, which changes $x(n)$ according to $w(n)$, a weighted vector that regulates the filter. The revised signal's output, denoted by $y(n)$, is then compared to the desired output, denoted by $d(n)$.

Locating Peaks using Spectrogram

Spectrogram is used to locate the peaks once the fetal ECG signal has been separated from the abdominal signal. The signal is initially preprocessed. The noise is then filtered out using a band pass filter with a frequency of 150-160Hz. Then the filtered signal is passes through Spectrogram and Welch Power to get the filtered FECG.

Results:

Direct 1

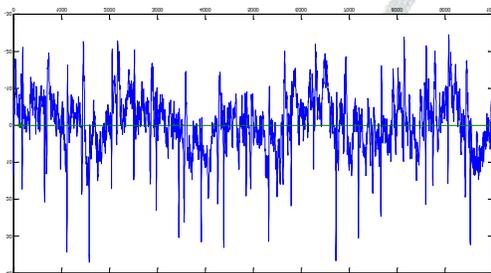


Figure 4.1(a) Fetal Signal

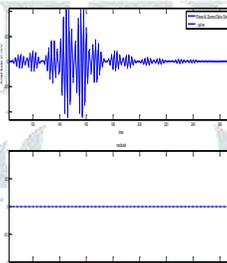


Figure 4.1(b) Spline fit with residual with scatter plot

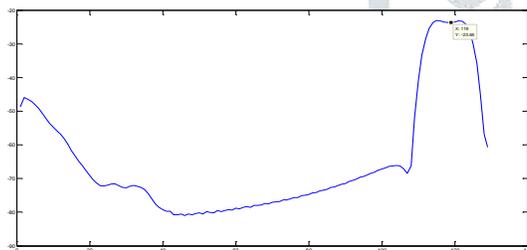


Figure 4.1 (c) Welch Power

ABDOMEN 1

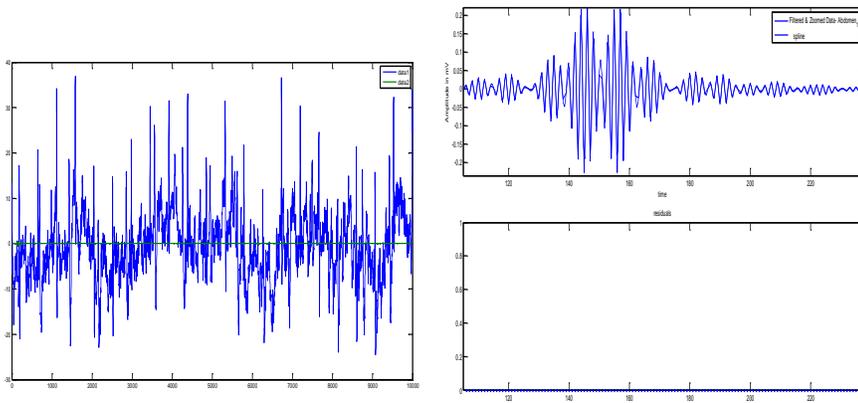


Figure 4.2(a) Fetal Signal

Figure 4.2(b) Spline fit with residual with scatter plot

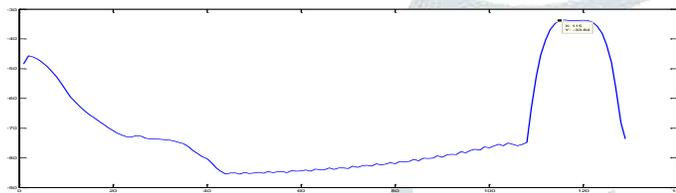


Figure 4.2 (c) Welch Power

ABDOMEN 2

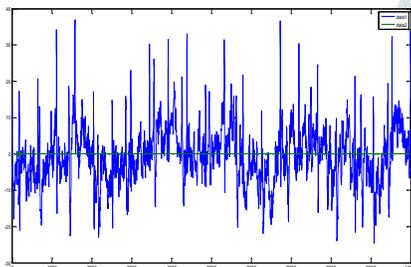


Figure 4.3(a) Fetal Signal

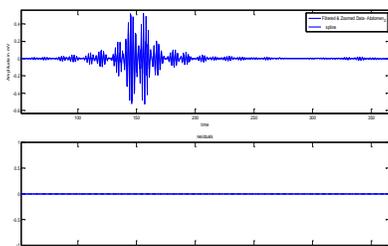


Figure 4.3(b) Spline fit with residual with scatter plot

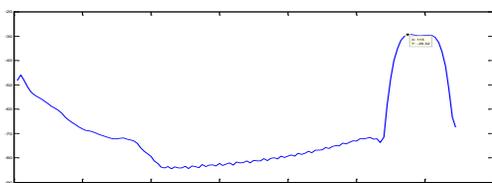
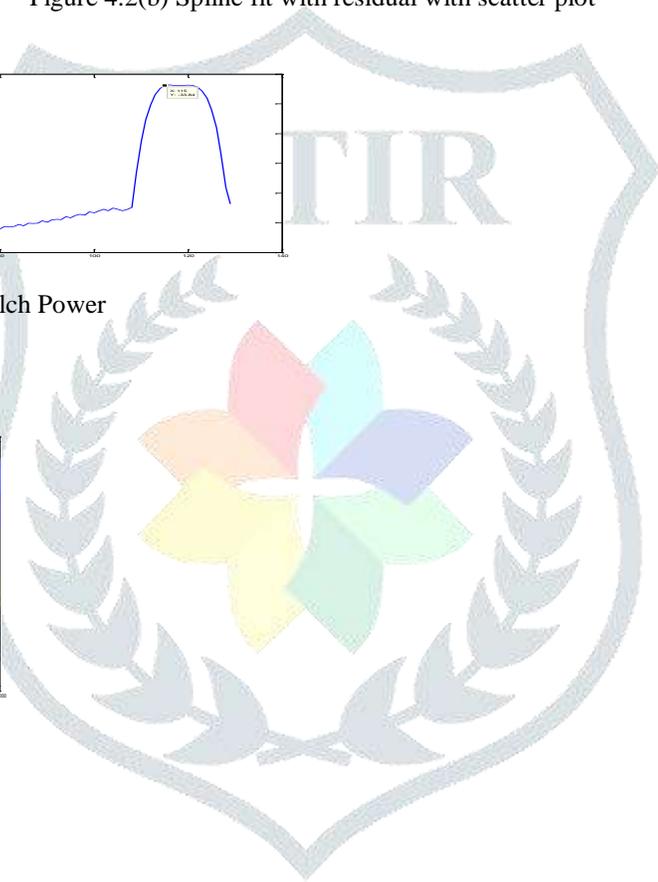


Figure 4.3 (c) Welch Power



ABDOMEN 3

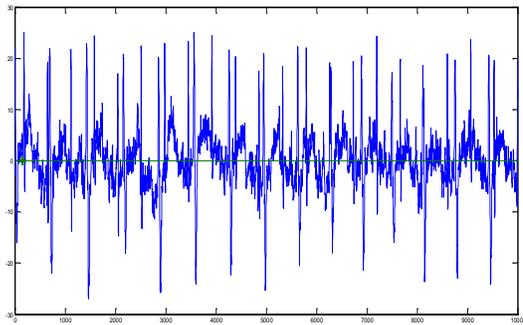


Figure 4.4(a) Fetal Signal

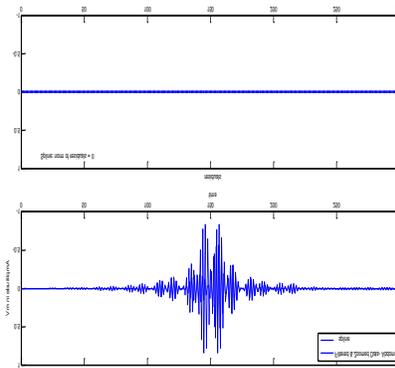


Figure 4.4(b) Spline fit with residual with scatter plot

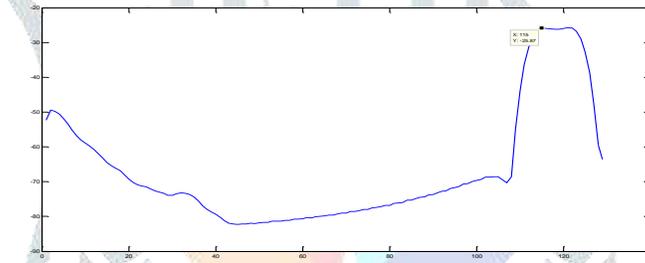
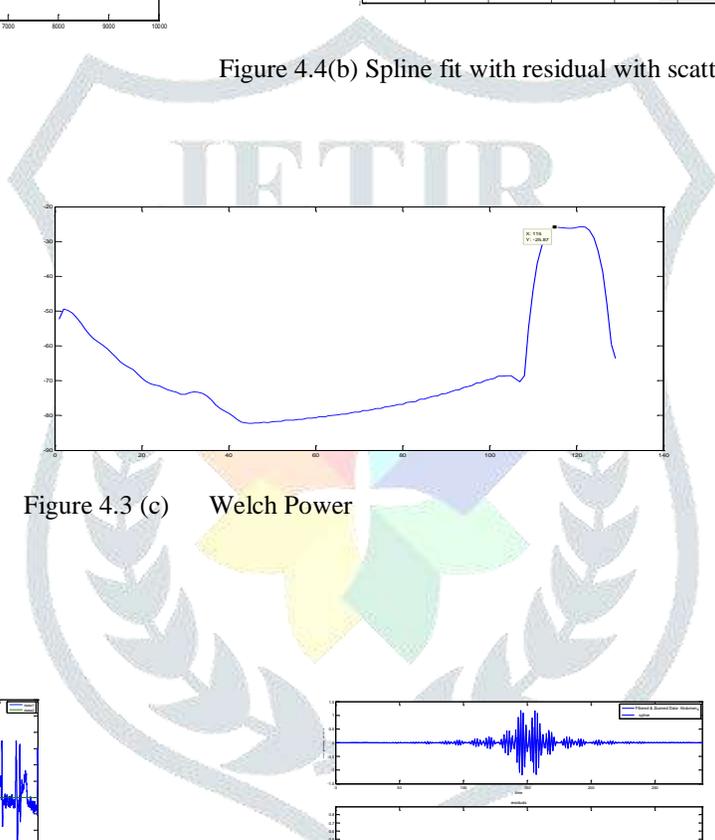


Figure 4.3 (c) Welch Power

ABDOMEN4

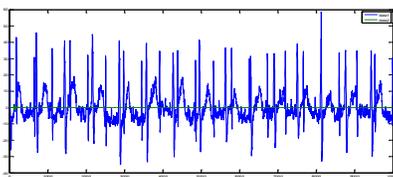


Figure 4.4(a) Fetal Signal

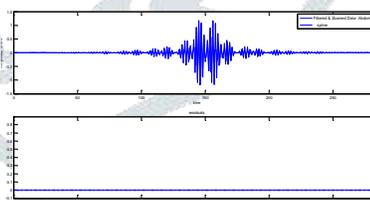


Figure 4.4(b) Spline fit with residual with scatter plot

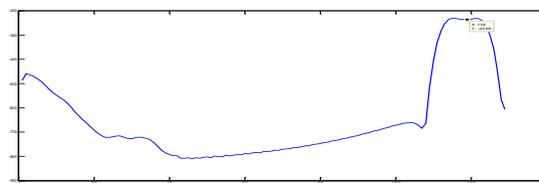


Figure 4.4 (c) Welch Power

Table 1			
Direct1 (signal extracted for freq 150 to 160 Hz)			
X1=115	Xm1=118	X2=122	
Y1=-23.48	Ym1=-23.95	Y2=-23.66	-0.18

Table 2			
Amplitudes of power spectral density of Abdomen 1, Y1, Ym1 and Y2			
X1=115	Xm1=118	X2=121	
Y1=-33.84	Ym1=-33.9	Y2=-33.86	-0.02

Table 3			
Amplitudes of power spectral density of Abdomen 2, Y1, Ym1 and Y2			
X1=115	Xm1=119	X2=122	
Y1=-29.32	Ym1=-29.83	Y2=-29.66	-0.34

Table 4			
Amplitudes of power spectral density of Abdomen 3, Y1, Ym1 and Y2			
X1=115	Xm1=119	X2=122	
Y1=-25.87	Ym1=-26.18	Y2=-25.87	0

Table 5			
Amplitudes of power spectral density of Abdomen 4, Y1, Ym1 and Y2			
X1=115	Xm1=119	X2=122	
Y1=-23.11	Ym1=-23.65	Y2=-23.27	-0.16

Table 6				
Amplitude variation in the filtered signal with a difference of 11 samples				
Direct 1	Abdomen 1	Abdomen 2	Abdomen 3	Abdomen 4
-0.133	-0.0027	-0.002	-0.001	-0.005

Conclusion: FECG signals downloaded from Physionet are filtered using band pass filter and analysed for power spectral densities. It has been observed that power in Direct 1 signal is of larger magnitude with values of $Y1=-23.48$, $Ym1=-23.95$, $Y2=-23.66$. $Y1$ is the power at first peak, middle peak and last peak as presented in 4.1 a, 4.1 b, 4.1 c and 4.1 d. Similarly respective values of $Y1$, YM and $Y2$ are presented in Tables 2-6. It is concluded that the power spectral density in FECG for Direct1 is more compared with Power spectral densities of Abdomen1, Abdomen2, Abdomen3, Abdomen4 and are comparable with studies by [Karin, J., M. Hirsch, and S. Akselrod. "An estimate of fetal autonomic state by spectral analysis of fetal heart rate fluctuations." *Pediatric research* 34, no. 2 (1993): 134-138.

References

- [1] P. P. Kanjilal, S. Palit, and G. Saha,(1997), "Fetal ECG extraction from single- channel maternal ECG using singular value decomposition," *Biomedical Engineering, IEEE Transactions on*, vol. 44, no. 1, pp. 51 - 59.
- [2] A. Hyvärinen and E. Oja, (1997) "A fast fixed-point algorithm for independent component analysis," *Neural computation*, vol. 9, no. 7, pp. 1483 - 1492.

- [3] V. Zarzoso and A. K. Nandi, (2001) “Noninvasive fetal electrocardiogram extraction: blind separation versus adaptive noise cancellation,” *Biomedical Engineering, IEEE Transactions on*, vol. 48, no. 1, pp. 12 – 18.
- [4] P. Gao, E. C. Chang and L. Wyse, (2003) “Blind separation of fetal ECG from single mixture using SVD and ICA” , Proceedings of the Joint Conference of the Fourth International Conference on Information, Communications and Signal Processing and Fourth Pacific Rim Conference on Multimedia, vol. 3, pp. 1418 – 1422.
- [5] M.A.Oudijk, R.H. Gooses, P.Stoutenbeek, L.S. De Vries, and G.H.Visser, (2004) “Neurological Outcome of children who were treated for fetal tachycardia complicated by hydrops,” *Ultrasound obstetric Gynecology* 24. 154-158.
- [6] M. G. Jafari and J. A. Chambers (2007), “Fetal electrocardiogram extraction by sequential source separation in the wavelet domain,” *IEEE Trans. Biomed.Eng.*, vol. 52, no. 3, pp. 390 – 400.
- [7] J.M. Breuer, R.H. Gooskens, L.Kapusta, P.Stoutenbeek, and G.H. Visser, (2007) “Neurological outcome in isolated congenital heart block and hydrops fetalis” , *Fetal Diagnostic Therapy* 22. 457-461.
- [8] M. E. Davies and C. J. James (2007) “Source separation using single channel,” *Signal Processing*, vol. 87, no. 8, pp. 1819 – 1832.
- [9] R. Sameni, (2008) “Extraction of fetal cardiac signals from an array of maternal abdominal recordings,” Ph.D. thesis, Sharif University of Technology— Institute National Polytechnique de Grenoble.
- [10] R.Sameni, C.Jutten, and M.B.Shamsollahi, (2008) “Multichannel electrocardiogram decomposition using periodic component analysis,” *Biomedical Engineering, IEEE Transactions on*, vol. 55, no. 8, pp. 1935 – 1940.
- [11] M. A. Hassan, M. B. I. Reaz, M. I. Ibrahimy, M. S. Hussain, (2008) “Retracted: Artifacts and noise removal in electrocardiograms using independent component analysis,” *International journal of cardiology*, vol. 129, no. 2, pp. 278 – 281.
- [12] Y. Ye, Z.-L. Zhang, J. Zeng, and L. Peng (2008) “A fast and adaptive algorithm with its application to fetal electrocardiogram extraction,” *Applied Mathematics and Computation*, vol. 205, no. 2, pp. 799 – 806.
- [13] M. Rachid, M. Feham, et al, (2009) “Algorithm of remote monitoring ECG using mobile phone: Conception and implementation,” *African Journal of Information & Communication Technology*, vol. 5, no. 2, p. 11.
- [14] S. Kiranyaz, T. Ince, and M. Gabbouj, (2009) “A generic and robust system for automated patient-specific classification of ECG signals,” *Biomedical Engineering, IEEE Transactions on*, vol. 56, no. 5, pp. 1415 – 1426.
- [15] Kok Beng Gan, Edmond Zahedi and Mohd. Alauddin Mohd. Ali, (2011) “Application of Adaptive Noise Cancellation in Transabdominal Fetal Heart Rate Detection Using Photo plethysmography,” *Computers in biology and Medicine*, vol. 36, no. 3, pp. 241 – 252.

- [16] K. Prasanth, B. Paul, and A. A. Balakrishnan, (2013) “Fetal ECG extraction using adaptive filters,” *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, vol. 2, no. 4.
- [17] V. Zarzoso, J. M. Roig and A. K. Nandi, (2013) “Fetal ECG extraction from maternal skin electrodes using blind source separation and adaptive noise cancellation techniques” , *Computers in Cardiology*, vol. 27, pp. 431-434, Sept.
- [18] V. Vigneron, A. Paraschiv-Ionescu, A. Azancot, O. Sibony, and C. Jutten, (2015), “ Fetal electrocardiogram extraction based on non-stationary ICA and wavelet denoising, ’ ’ in Proc. 7th Int. Signal Process. Appl. Symp. vol. 2, pp. 69 - 72.
- [19] K. V. K. Ananthanag and J. S. Sahambi, (2015) “Multidimensional independent component analysis,” in *Acoustics, Speech and Signal Processing, 1998. Proceedings of the 1998 IEEE International Conference on*, vol. 4, pp. 1941 - 1944, IEEE.
- [20] G. Dapoian, Riccardo Bernardini, Roberto Rinaldo, (2016) “Separation and analysis of fetal- ECG signals from compressed sensed abdominal ECG Recordings” , *IEEE transactions on Biomedical Eng.*, Vol. 63, issue 6.
- [21] S. Sargolzaei, K. Faez and A. Sargolzaei, (2017), “Signal processing based techniques for fetal electrocardiogram extraction” , *Proceedings of International Conference on BioMedical Engineering and Informatics (BMEI)*, vol. 2, pp. 492-496.
- [22] M.A. Yaping, Yegui Xia, Guo Wei, Jinwei Sun, and Hongyun Wei, (2018) “A hybrid nonlinear adaptive noise canceller for fetal ECG extraction” , *Asia-Pacific Signal and Information Processing Association Annual Summit and conference (APSIPA)*. vol.7. pp. 423-431.
- [23] Mohammad Reza Mohebbian, Seyed Shahim Vedaei, Khan A Wahid, Anh Dinh, Hamid Reza Marateb, Kouhyar Tavakolian, (2021), “Fetal ECG Extraction From Maternal ECG Using Attention-Based CycleGAN,” *IEEE Journal of Biomedical and Health Informatics*, vol. 89, no. 1, pp. 71 - 89.
- [24] Karin, J., M. Hirsch, and S. Akselrod. "An estimate of fetal autonomic state by spectral analysis of fetal heart rate fluctuations." *Pediatric research* 34, no. 2 (1993): 134-138.

Websites

- [24] www.academia.edu/es/69563328/Fetal_Heart_Diseases