Fetal Electrocardiogram Analysis Using Adaptive filters

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Abstract- It is critical to obtain information about the fetus early in pregnancy to avert stillbirth. Medical personnel use Cardiotocography (CTG) to monitor the fetus's health in the hospital, however, it is not possible to record continuous long-duration signals using this method. As a result, constant and long-term monitoring of fetal electrocardiogram[1] signals is required to determine the health condition utilizing portable instruments. The invasive approach is superior to an invasive method for measuring ECG signals. To retrieve FECG encoded in the mother ECG, compact electronics and advanced signal processing techniques were required. Because the Fetal Heartbeat from the abdomen is frequently contaminated or interfered with by the Maternal Heartbeat, which is essentially noise. As a result, an attempt is made to separate the Fetal Heartbeat from the interfering Maternal Heartbeat in this case. The Adaptive [2] Noise Canceller (ANC) is used to remove the signal's noise content. Different adaptive filtering schemes, such as Single Input Single Output (SISO) on ANC, where adaptive algorithms such as least mean squares (LMS), Normalized least mean squares (NLMS), and leaky least mean [7] squares (L-LMS) are implemented in MATLAB and simulation results show the extracted FECG noise-free signal.

Keywords: *Fetal ECG, Non invasive , LMS, NLMS, LLMS algorithms*

I. INTRODUCTION

An ECG captures the heart's electrical and mechanical activities. Currently, electrocardiography is among the most widely used techniques for determining heart health. Ballistocardiography is a prominent test used to identify and track cardiac problems in several scenarios, despite being a relatively new technique. Electrocardiograms, often known as ECGs or EKGs, are frequently carried out at a doctor's office, clinic, or [4] hospital room. Additionally, operating rooms and ambulances are starting to use it often.

Advantage of ECG: An electrocardiogram is a risk-free technique. Because the electrodes implanted on the body do not release electricity, there is no chance of receiving an electrical shock during the test. They merely record the heart's electrical activity.

Disadvantages of ECG: When the electrodes are removed from the bandage, there may be some slight pain. A response to the electrode glue might produce redness or swelling where the patches were applied on rare occasions. A stress test can cause abnormal cardiac rhythms and, in rare cases, a heart attack. These side effects are caused by the activity or medicine, not by the ECG. If you don't adjust the electrodes every day, a Holter monitor might cause skin irritation. Because it entails a minor surgical procedure, [1] an implanted loop recorder has a small risk of infection. In addition, some patients may have an inflammatory reaction to the device. In fetal monitoring, the extraction and identification of the FECG signal from composite abdominal data using strong and sophisticated techniques are becoming increasingly crucial. The goal of this review article is to show how various techniques and established algorithms for FECG signal identification and analysis may help fetal monitors comprehend the FECG signal and its nature more efficiently and effectively. A comparison study was conducted to demonstrate the performance and accuracy of several FECG signal analysis algorithms for fetal monitoring.

The electrical activity of the [6] heart is described by the ECG signal. The fetal ECG (FECG) signal represents the fetus's heart's electrical activity and gives important information about its physiological status. By placing skin electrodes on the maternal belly, non-invasive FECG has been utilized to collect vital clinical information regarding the fetal status throughout pregnancy. However, power line interference always taints abdominal ECG (AECG), but maternal ECG is never tainted (MECG).[7] The detection of R-peaks, or the peaks of the QRS complex in an (AECG) signal, offers information on heart rate and is thus an essential tool for physicians to diagnose abnormalities in cardiac activity.

II. LITERATURE REVIEW

The electrocardiogram (ECG) is one of the oldest methods for detecting and monitoring heart rate, however, it is mainly used invasively on adults or during childbirth. Recent research suggests that ECG can also be utilized for fetal monitoring. Even if worn daily during pregnancy, an ECG-based gadget will be comfortable enough for the mother and safe[8] for the baby. Adaptive filtering, correlation approaches, and a mixture of wavelet analyses have all been presented as ways to extract the FECG from the AECG. The R-R intervals from the extracted FECG can be used to compute the fetal heart rate (FHR).

Time-variable filters with varying features are adaptive filters. This has an adaption mechanism that allows the user to change the filter coefficients. Filters of this kind are employed to handle signals whose statistics are unknown. For an adaptive filter, a primary input and at least one reference input are needed. The procedure involves removing maternal ECG using a few or just one maternal reference channel that has structurally identical maternal ECG. Because the morphology of maternal ECG[9] pollutants greatly depends on the electrode sites, this approach is rather practically awkward. As a result, adaptive filters with a single reference are quite useful.

Sara Lilia Lima-Herrera and Carlos Alvarado- "Fetal Serrano's ECG extraction based on Adaptive Filters and Wavelet Transform" An adaptive filter noise canceller is made using the least mean square technique (LMS), An automated method for the extraction of the FECG and FHR as well as the study of the HRV has been established using noninvasive data from the chest and abdomen mother.[10] The SWT and adaptive filters are the foundation of the proposed method for FECG extraction.

Such records employ both traditional methods for MECG decomposition and cancellation. Using a hybrid BSS approach, foetal electrocardiograms are extracted: Here, the author used Combi and Multicombi algorithms to estimate and compare the performance of five different techniques. The clustering technique needs to be optimized in order to separate the sources in the AECG because MULTICOMBI is ad hoc. For health monitoring during labor, fetal ECG is extracted from multichannel abdominal ECG recordings. The ICA Algorithm is a swift algorithm. The findings of this work demonstrated that fetal electrocardiogram morphological parameters could be determined consecutively after fetal ECG signals were extracted from a collection of AECG recordings using the Fast ICA approach and post processed [11] utilizing wavelet transform and an FFT/IFFT pair.

III. PROPOSED METHOD

ECG signs are typically observed on the chest and the abdomen, as shown in fig. 2. Unlike the chest leads, which exclusively pick up MECG, the abdomen leads detect a composite signal that contains contributions from both the maternal and fetal electrocardiograms (MECG and FECG).

The reported fetal ECG signal from the mother's belly is often overpowered by the maternal cardiac signal that travels from the chest cavity to the abdomen.

The maternal ECG signal is picked up from the mother's chest. In this challenge, the adaptive noise canceller's job is to adaptively separate the fetus's ECG signal from the mother's cardiac signal. The noise canceller needs a reference signal taken from the maternal ECG to carry out its function. Similar to the fetal electrocardiogram signal, the maternal ECG signal will have some additional broadband noise.

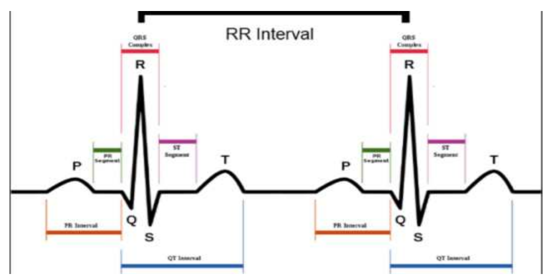

Fig.1. Typical ECG wave

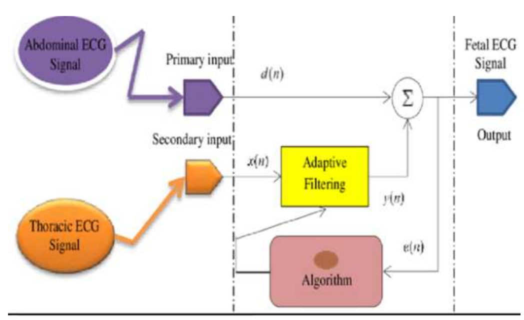

Fig.2. Adaptive filter block

$$(n)=s(n)+v(n) \quad (1)$$

$s(n)$ FECG & $v(n)$ MECG, When the desirable signal $s(n)$ and the unwanted signal $v(n)$ are present. The signals $v(n)$ and $s(n)$ are not linked in this case, and the adaptive filter is provided a reference input $x(n)$ that is identical to $v(n)$, i.e., Signals $v(n)$ and $x(n)$ are correlated.

To estimate s, the estimated signal from the adaptive filter is subtracted from $d(n)$, and $v(n)$ is calculated using the reference signal $x(n)$

$$s(n)=d(n)-\hat{v}(n) \qquad (2)$$

The desired signal is provided by the erroneous signal $e(n)$ in the ANC, which is then used by the adaptive filter to automatically update the filter weights. To reduce the inaccuracy of the intended signal, several adaptive algorithms like LMS, NLMS, and LLMS were applied in this case.

1. Single Input Single Output(SISO)
2. Multiple Inputs Single Output(MISO)

The electrical activity of the heart is described by an electrocardiogram (ECG). The contraction (depolarization) and relaxation (repolarization) of the atrial and ventricular muscles of the heart produce the ECG signal. The major cause of birth defect-related mortality is heart abnormalities, which are among the most prevalent birth defects. Every year, around one in every 150 newborns is born with a congenital cardiac problem. The issue might be minor enough that the infant seems healthy for several years after birth, or it could be serious enough to put the baby's life in jeopardy right away. Congenital heart problems develop during the first trimester of pregnancy when the heart is still growing, and they can damage any of the heart's components or activities.

P-wave: The depolarization of the atria before atrial contraction occurs as the activation (depolarization) wavefront travels through the atria, causing a slight low-voltage deviation away from the Baseline.
Q-wave: The interval between the start of ventricular and atrioventricular node depolarization.

QRS-Complex: The region of the FECG with the highest amplitude, induced by currents created as the ventricles depolarize before contracting. Even though ventricular depolarization happens first, atrial repolarization doesn't show on the FECG because the later waveform, the QRS-complex, has considerably bigger amplitude.

QT-interval: The interval between the beginning of ventricular depolarization and its conclusion. Clinical research has shown that when the RR-interval grows, the QT-interval also rises linearly (Malmivuo and Plonsey, 1995). Delay in ventricular repolarization, which can result in ventricular tachyarrhythmias and abrupt cardiac death, is a potential consequence of a prolonged QT interval.

ST-interval: The interval between the S-conclusion wave and the start of the T-wave heart disease is frequently accompanied by amplitudes that are noticeably raised or lowered from the baseline.

T-wave: Ventricular repolarization prepares the heart muscle for the upcoming ECG cycle. The FECG signal's structure is identical to that of the maternal ECG (MECG), but its values are entirely different. Table 1 displays how the ECG signal values differ between the mother and the fetus. The non-invasive FECG signal as a whole should be processed to have a shape similar to that shown in Figure 1 and to be around the values indicated in Table 1. Figure 1 displays the standard P, Q, R, S, T, and U complex signals. The author compared the mean fetal heart rate during the gestational period of roughly 120 beats per minute to the mother's normal heart rate of 72 beats per minute, which is considered the adult heart rate.

A. ECG Measuring Techniques:

The following techniques are suitable for measurement of ECG signal

- Removal of Baseline Wander
- Removal of Powerline Interference
- Removal of Electrode Motion Artifact
- Removal of Electromyographic (EMG) Noise

Different types of adaptive algorithms are used in an adaptive filter.

- LMS(least Mean Square).
- NLMS(Normalized least Mean Square).
- LLMS (Leaky Least Mean Squares).

Least Mean Square algorithm (LMS)

The simplest and most direct adaptive algorithms are the least mean squares (LMS) algorithms. The great efficiency and fidelity of recursive least squares (RLS) algorithms, on the other hand, come at a higher cost in terms of complexity and computation.

The least mean square (LMS) approach is a sophisticated use of stochastic gradient descent in a machine learning filter. Professionals refer to it as an adaptive filter that supports signal processing in a number of ways.

Normalized Least Mean Square algorithm (NLMS)

One of the fundamental flaws of the LMS algorithm is the set step size parameter for each iteration. Understanding the input signal's statistics is important before starting the adaptive filtering process. In actual life, it's very seldom achievable. The intensity and amplitude of the input signal will have an influence on how well the adaptive echo cancellation system functions, even if we assume that speech is the only input.

By determining the maximum step size value, the normalized least mean square algorithm (NLMS), a modification of the LMS method, avoids this problem. The following formula is used to get the step size value. 1/step size product (input vector, input vector)

The immediate inverse relationship between the step size of the coefficients in the input vector x and the total predicted energy (n). The dot product of the input vector or with itself, as well as the trace of the input vectors' auto-correlation matrix, are identical to the sum of the predicted energies of the input samples.

Eq 3 demonstrates how the NLMS updates filter weights and coefficients.

$$w(n+1)=w(n)+\beta.e(n).^{x(n)}\|(x(n)^2\| \qquad (3)$$

A modified version of the conventional LMS algorithm.
Variable step size over time.
This step size accelerates the adaptive filter's rate of convergence.
The convergence range of β is between0 and 2.

The input signal's intensity won't be constant in a real-time situation. It impacts the pace of convergence of the filter and causes issues with gradient noise amplification. To solve this issue, the step size in NLMS is normalized.

$\mu(n)$ = step size

β = normalized step-size ($0 < \beta < 2$)

c = safety factor

MATLAB has been used to implement the NLMS method. The NLMS method exhibits far improved stability with unknown signals since the step size parameter is selected depending on the current input values.

Leaky Least Mean Square algorithm(L-LMS)

Due to the Leaky Least Mean Square (LLMS) approach's fixed leak factor, the weight vector wanders past its maximum value. The suggested control scheme includes an adaptive Variable Leaky Least Mean Square (VLLMS) algorithm for producing switching signals, a Reinforcement Learning (RL) algorithm for producing maximum power point tracking (MPPT), and a Sliding Mode approach for producing RIC (Reference Inverter Current) to address this issue. For the optimum power extraction from PV panels with fluctuating solar isolation, the MPPT is built using an RL algorithm. When operating under dynamic load circumstances, a Voltage Source Inverter receives a switching signal from a Sliding Mode Controller (SMC) (VSI). MATLAB is needed to implement the suggested VLLMS-RL-SMC control technique.

Eq.4 shows how filter weights/coefficients are updated in L-LMS.

$$(n+1)=(n)(1-\mu\gamma)+\mu.e(n).x(n) \qquad (4)$$

Ifγ=0, the leaky LMS algorithm becomes the same as the LMS algorithm.
Large leaky factor results in a large steady error.
More stable compared to LMS due to the introduction of leaky factor.
It has ranged between $0 < \gamma < 0.001$.
There may be an issue if the input process' autocorrelation matrix has one or more zero Eigen values. In this case, the adaptive filter won't reach a singular result. Additionally, some uncoupled coefficients (weights) could keep growing unrestrictedly until hardware overflow or underflow has a place. This issue may be resolved by using coefficient leakage. Where both the leakage coefficient r and the adaptation constant have tiny positive

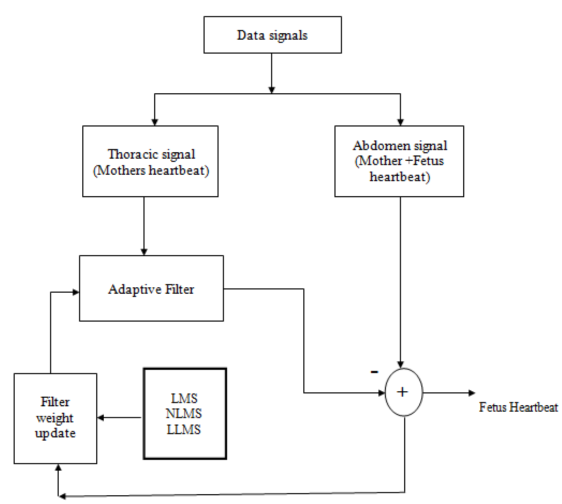

Fig.3. Flow diagram

IV. RESULTS AND DISCUSSION

After executing the MATLAB code for separating the fetus heartbeat from the mother's heartbeat in both SISO and MISO systems, the obtained results are explained in this report. The data obtained here consists of three thoracic signals and five abdominal signals. The thoracic signals solely contain the heartbeat of the mother, but the abdominal signals contain the heartbeats of both the mother and the fetus The input data signal was first separated from the thoracic and abdominal signals. The figure below shows the abdominal signals.

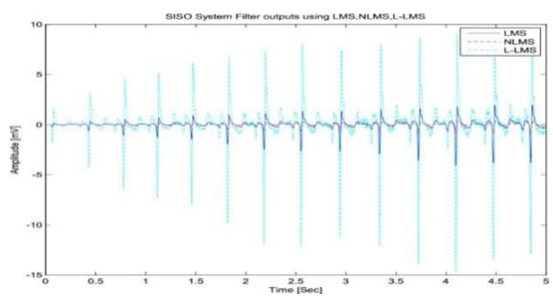

Fig.4. Filter output in SISO system using all algorithms

SISO system output: Here Fig4 represent the average of all abdominal signals is taken as primary input and of all thoracic signals is taken as a reference input to the SISO system. The selected step size in this instance of the LMS algorithm is 0.00000001. According to condition (02), the normalized step size is thus equal to 0.00009.

The author has selected the leaky coefficient for the L-LMS algorithm to be = 0.0005 by condition 0 1.

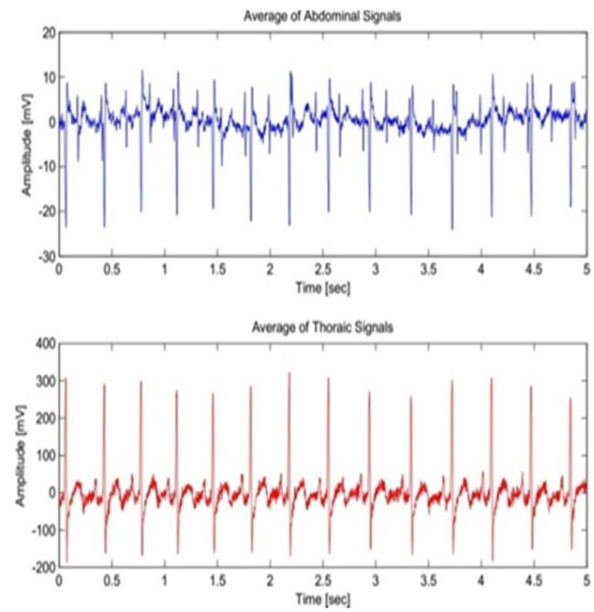

Fig.5. Data Signals

Table 1: Normal FECG Output Signal

	Normalized amplitude	**Normalized Time in sec**	**LMS**		**NLMS**		**LLMS**	
			Obtained amplitude	Obtained time	Obtained amplitude	Obtained time	Obtained amplitude	Obtained time
P wave	Max2.5mm	0.11 sec	1.92mm	0.03sec	1.93mm	0.03sec	2.01mm	0.06sec
QRS wave	3mm At least above the base line Rwave <20mm	0.6-0.10sec	7.2mm	0.05-0.07sec	7.0mm	0.053-0.08sec	6.9mm	0.06-0.09sec
T wave	Above2mm	0.10-0.13sec	4.2mm	0.102sec	4.1mm	0.102 sec	3.9mm	0.104 sec

R-RPeak:0.07-0.17

V. CONCLUSION

The statistics show that LLMS has a faster convergence rate than LMS and NLMS because to its variable step size and leaky factor. Furthermore, we can deduce from the fetus ECG plot that the L-LMS peak is less than the LMS and NLMS peaks, indicating a less noisy fetal heartbeat. Based on the obtained fetal heartbeat charts, we may draw the conclusion that LLMS has superior extracted fetal heartbeat with less noise. In addition, it was found that SISO was more stable than other ANC systems and produced less errors and optimizations (such as SISO)

REFERENCES

1. IEEE Intelligent Adaptive Noise Cancellation System for the Extraction of Fetal Electrocardiogram, Ravi Kumar Jatoth, saladi s v k k Anoop, ISBN: 978-960-474-054-3.
2. IEEEFetalECGExtractionusingAdaptiveFilters,ArunA,Balakrishnan. "Realtime monitoring system for FECG signal utilizing virtual instrumentation," IEEE Transactions on Biology and Biomedicine, vol. 3, pp. 638–643, 2006. Kumar, A., Dewan, L., Singh, M., and Kurukshetra
3. Ferrara, Fetal ECG improvement by time-sequenced adaptive filtering, IEEE Trans. Biomed. Eng. 29, 458–460, 1982. Ferrara, E. R. and Widrow, B.
4. Design and Implementation of Least Mean Square Adaptive Filter on Fetal Electrocardiography by Muhammad Wasimuddin and Navarun Gupta, ISBN 978-1-4799-5233-5.
5. Maternal ECG removal from non-invasive fetal ECG recordings. Vullings, R.; Peters, C.; Mischi, M.; Oei, G.; Bergmans, J. 28th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, New York, NY, USA, 30 August-3 September 2006; Proceedings of the EMBS'06; pp. 1394-1397.
6. Ten Broeke, E.D., P.Andriessen, B. Vermeulen , R.C. Berendsen, P. F. Wijn, and S. G. Oei. Doppler ultrasound cardiotocography is compared to direct ECG cardiotocography in the time and frequency domain for beat-to-beat fetal heart rate monitoring. 24, 585 in Physiol. Meas. 2004. [CrossRef] [PubMed]
7. B.F. Chez and S.M. Baird Where are we with electronic fetal heart rate monitoring?Neonatal Nursing 2011, 25, 80–192. J. Perinat. [CrossRef]
8. Hussain, M.S.; Ibrahim, M.I.; Reaz, M.B.I.; Hasan, M.A.; Uddin, J. approaches for FECG signal detection and processing for fetal monitoring. Online Biol. Proceed. 2009, 11, 263-295
9. "Fetal heart rate monitoring," LWW, 2012. Freeman, R. K., Garite, T. J., Nageotte, M. P., and Miller.Kumar, A., Dewan, L., Singh,M., and Kurukshetra, H., "Realtime monitoringsystemforECG signalusing virtual instrumentation",IEEE Transactionson Biologyand Biomedicine,vol. 3,pp. 638–643,2006.
10. "Fetal ECG enhancement by time-sequenced adaptive filtering", IEEE Trans. Biomed. Eng. 29, pp. 458-460, 1982. Ferrara, E. R. and Widrow, B.
11. "Monitoring the fetal heart non-Ananthanag, K., and Sahambi, L., "Investigation of blind source separation methods for extraction of ffetalECG," In Canadian Conference on Electrical and Computer Engineering. May 2003.
12. "Fetal ECG extraction by sequential source separation in the wavelet domain," IEEE Transactions on Biomedical Engineering, vol. 52, no. 3, pp. 390–400, 2005.
13. Haykin, S., "Adaptive Filter Theory," Prentice-Hall, 2002, Third Edition.
14. Shik Ryu, B., and Lee, J. K., "The Performance of an Adaptive Noise Canceller with DSP Processor," 40th Southeastern Symposium on System Theory, New Orleans, USA, March 16–18, pp. 42–45, 200
15. Fetal heart rate monitoring, LWW, 2012. Freeman, R. K., Garite, T. J., Nageotte, M. P., and Miller, L. A.
16. Kumar, A., Dewan, L., Singh, M., and Kurukshetra, H. (2006). "Realtime monitoring system for ECG signal utilizing virtual instrumentation," IEEE Transactions on Biology and Biomedicine, vol. 3, p. 638–643.
17. IEEE Trans. Biomed. Eng. 29, pp. 458–460, 1982, "Fetal ECG improvement by time-sequenced adaptive filtering." E. R. Ferrara and B. Widrow
18. "Monitoring the fetal heart noninvasively: a review of techniques," Journal of Perinatal Medicine, vol. 29, no. 5, 2001, pp. 408–416. Shakespeare, S., Hayes-Gill, B., Quarter, H., Peters, M., Crowe, J., Pieri, J. F., James, D., and Stinstra.published in the May 2003
19. Canadian Conference on Electrical and Computer Engineering. "Investigation of blind source separation strategies for extraction of fetal ECG," by K. Anantnag and L. Sahambi. IEEE Transactions on Biomedical Engineering, vol. 52, no. 3, pp. 390-400, 2005. "Fetal ECG extraction by sequential source separation in the wavelet domain."
20. Manjula B M ,Prashanta H S , Goutham M A , " Low Power Fault Tolerant System for Biomedical implants and Ballistocardiogram signal" Published in ICTACT UGC care journal.
21. Manjula B.M, Dr.Prashanth,Dr.Goutham M.A "Delayed LMS Algorithm for BallistocardiogramBomedical signal" Submitted to IJEAT a scopus indexed journal and will be published in August 2020