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Fetal Phonocardiogram Extraction Using Double Channel Blind Source Separation

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Abstract: **Monitoring** fetal health, especially in high-risk pregnancies, remains a significant challenge due to the complexity of accurately detecting fetal heart sounds (FHS). This paper presents a novel, fully noninvasive approach to extract fetal heart sounds from acoustic signals recorded from the maternal abdominal surface. The proposed method utilizes a single-channel blind source separation (SCBSS) technique, combining empirical mode decomposition (EMD) and nonnegative matrix factorization (NMF) to effectively separate and extract fetal heart sounds from mixed audio signals. The performance of the algorithm was evaluated on a dataset of 110 pregnant women, collected at Hafez Hospital, Shiraz University of Medical Sciences. Testing on 50 randomly selected samples demonstrated the algorithm's ability to accurately separate the fetal heart sound, with the calculated fetal heart rate (FHR) achieving a 96% accuracy when compared to simultaneous ultrasound recordings. These results demonstrate the potential of the proposed noninvasive method for reliable, continuous fetal health monitoring, offering significant benefits in the management of high-risk pregnancies.

Keywords: Fetal, Phonocardiogram, Heart Rate;Two channel Blind Source Separation

I. INTRODUCTION

Pregnancy plays a critical role in the early diagnosis and prevention of various fetal abnormalities, making consistent monitoring essential, particularly during the third trimester. In developed countries, regular monitoring by a gynecologist is recommended to ensure the well-being of both the mother and fetus. Fetal heart rate (FHR) monitoring, which typically begins at the 24th week of gestation, is commonly performed through Doppler Ultrasonographic Cardiotocography (CTG). In high-risk pregnancies, continuous monitoring is essential to detect any potential complications. Although CTG is a noninvasive method for FHR monitoring, the use of ultrasound waves, especially over extended periods, raises concerns about possible adverse effects on the fetus. Consequently, there is growing interest in exploring alternative methods for long-term and continuous FHR monitoring that are both noninvasive and safer for the fetus.

One promising development in this area is the rise of telemedicine, which allows remote monitoring of pregnant women. This approach enables patients to record biological signals, such as fetal heart sounds, at home and send the data to healthcare professionals for analysis and diagnosis. Telemedicine can enhance patient satisfaction, improve access to care, and reduce healthcare costs. For this system to be effective, however, the devices used for data acquisition must be low-cost, easy to use, and noninvasive.

In the search for alternatives to CTG, several methods have been explored for FHR monitoring, such as fetal magnetocardiography (fMCG), fetal electrocardiography (fECG), and fetal phonocardiography (fPCG). While fMCG offers detailed information on FHR, its high cost and requirement for specialized equipment make it impractical for regular use, particularly in home settings. Advances in fECG have made it a more affordable option, yet its requirement for multiple electrodes makes it cumbersome and inconvenient for long-term monitoring. Among these alternatives, fPCG – which records the mechanical activity of the fetal heart – offers a promising solution due to its simplicity, low cost, and noninvasive nature. Unlike fECG or fMCG, fPCG does not require complex equipment and poses no risk to the fetus during recording.

Despite these advantages, fPCG faces challenges related to noise contamination from various sources such as maternal movements, uterine contractions, digestive sounds, and ambient noise. These noise factors make it difficult to accurately isolate the fetal heart sound, thus limiting its widespread adoption. Previous attempts to extract fPCG signals have relied on ad hoc filtering techniques, which, while helpful, often fail to fully address the complexities of the signal.

To overcome these challenges, this paper proposes a novel approach for FHR monitoring based on the processing of fetal heart sounds using single-channel blind source separation (SCBSS). By utilizing advanced signal processing techniques such as Empirical Mode Decomposition (EMD) and Nonnegative Matrix Factorization (NMF), the proposed method improves the extraction of the fetal heart sound from noisy recordings, offering a more robust solution for continuous and long-term FHR monitoring. This method is computationally efficient and can be applied in remote monitoring systems, contributing to the development of safer and more accessible prenatal care.The rest of the paper is organized as follows: Section II reviews the clinical and acoustic characteristics of fPCG, Section III describes the recorded database, Section IV presents the proposed method in detail, Section V discusses the experimental results, and Section VI concludes the paper with recommendations for future work.

II. LITERATURE REVIEW:

Recent advancements in fetal and biomedical signal processing have led to promising approaches for non-invasive diagnostic methods. In 2024, Mohamed Moustafa proposed a novel technique for fetal gender identification using modified Mel-Frequency Cepstral Coefficients (MFCCs) based on Fast Discrete Curvelet Transform (FDCT). This method integrates advanced signal processing with machine learning to offer a safer alternative to traditional diagnostic tools. Complementing this line of work, Jinshu Yu, Guoxu Zhou, and Shengli Xie (2018) introduced a deep learning framework based on non-smooth Nonnegative Matrix Factorization (NMF) to learn hierarchical parts of objects, capturing their structural and compositional features effectively. Similarly, in 2019, Wei Yan, Bob Zhang, and Zuyuan Yang developed a similarity learning-induced symmetric NMF model aimed at image clustering. Their approach emphasized maintaining nonnegativity in matrix factorization to enhance interpretability and clustering accuracy.

In the realm of bioinformatics, Y. Li and A. Ngom (2012) presented a kernel NMF technique designed to handle the complexity and noise prevalent in biological datasets, especially in microarray data analysis. This approach improved both classification accuracy and interpretability. Going further back, D. Mantini, G. Alleva, and S. Comani (2005) validated an automatic tool for beat-to-beat detection on fetal magnetocardiography (fMCG), contributing significantly to the accurate measurement of fetal cardiac time intervals—a critical aspect of fetal health assessment. Lastly, J.P. Newnham, S.F. Evans, and C.A. Michael (1993) examined the effects of frequent ultrasound exposure during pregnancy. Their study aimed to determine any significant health impacts, ultimately providing evidence-based recommendations for safer and more effective prenatal care.

III. RESEARCH METHODOLOGY

- A fetal heart signal denoising framework is a structured approach or system designed to extract clean and interpretable fetal heart signals from noisy recordings. This is essential because precise analysis of fetal heart activity—such as detecting heart rate variability, arrhythmias, or cardiac time intervals—relies on the accuracy of the recorded signals.
- The existing algorithm is based on single channel blind source separation (SCBSS),which utilizes empirical mode decomposition (EMD) and nonnegative matrix factorisation (NMF) to extracts different sources from audio signal mixtures.

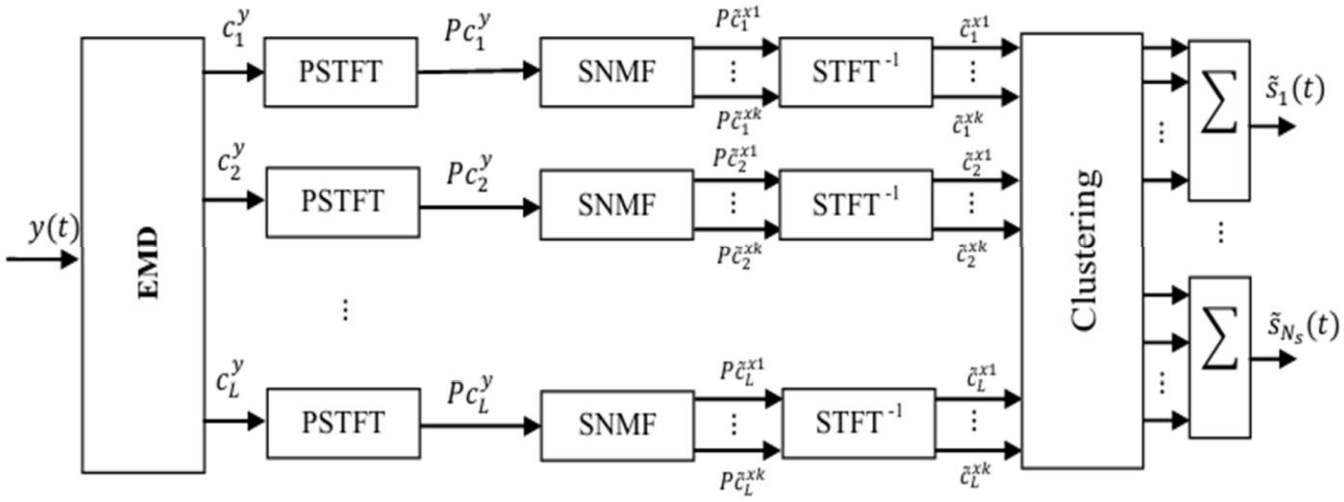

FIG 1. Fetal Heart Signal Denoising Framwork

- Our proposing algorithm is based on two channel phonocardiogram device,which will be able to provide external noise cancelation and using adaptive and model-based denoising techniques as shown in above figure.

IV. RESULTS AND DISCUSSIONS

To evaluate the performance of the proposed algorithm, 50 randomly selected signal samples were processed, each containing fetal heart sound data collected from a set of 110 pregnant women. The original recordings were resampled to 3 kHz to reduce the computational load, given that the major components of the **fetal phonocardiogram (fPCG)** lie below 1.5 kHz.

In the noise simulation phase, various noise levels were added to the original signals to test the algorithm's robustness under different **signal-to-noise ratio (SNR)** conditions. Realistic respiratory sounds, recorded from the upper back thorax of ten adults during deep breathing, were mixed with **white Gaussian noise** and incorporated into the signals at three distinct SNR levels: **10 dB**, **5 dB**, and **0 dB**. A 10-second segment of the noisy signal with an SNR of 0 dB The results showed that the algorithm was able to process and extract fetal heart sounds from the noisy signals effectively, even at low SNR levels.

To isolate the fetal heart sound from the noise, **Empirical Mode Decomposition (EMD)** was applied to the noisy signals, extracting several **intrinsic mode functions (IMFs)**. Using **Short-Time Fourier Transform (STFT)**, the spectrograms of the IMFs were computed, providing a frequency-domain view of the signals. The spectrograms confirmed that the fetal heart sound could be clearly isolated from noise, even in challenging conditions.both time-domain waveforms and spectrograms of the extracted IMFs.

For the source separation, the extracted channels were grouped based on their **covariance matrix** similarities. The **clustering algorithm** identified three distinct groups corresponding to the fetal heart sound, Gaussian noise, and respiratory noise. These clusters were visually confirmed in which displays the covariance matrix, and the final extracted signals were shown in .

To validate the algorithm's performance, it was compared against the **gold standard reference** of **ultrasound-based CTG**. During the data collection, the FHR from CTG was recorded every 10 seconds. The comparison showed that the algorithm's **beat detection accuracy** ranged from **83% to 100%** across various samples, depending on the environmental noise and maternal condition. The algorithm demonstrated robust performance, particularly under controlled conditions, with a **96% overall accuracy** in detecting **1196 out of 1245 fetal heartbeats** from the signal data shown in the below figure 2.

These results highlight the efficacy of the proposed method in accurately extracting fetal heart rate data from noisy signals, demonstrating its potential for reliable, long-term fetal health monitoring in real-world, noisy environments.

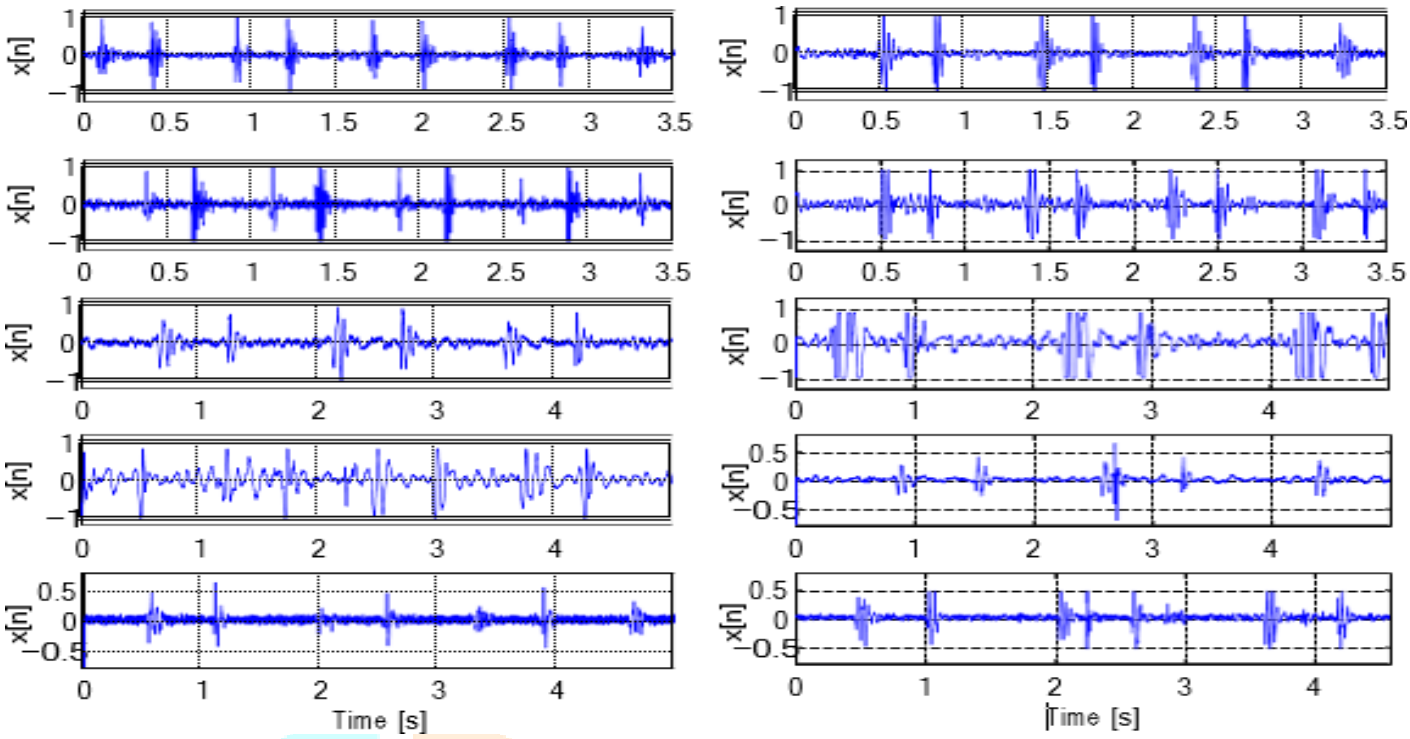

Fig 2: Acquired PCG Signals of Different Subjects

To analyze the variability and patterns in heart sounds, phonocardiogram (PCG) signals were collected from multiple subjects using a digital stethoscope under controlled and standardized clinical conditions**.** Each subject was instructed to remain in a resting position during the recording to minimize motion artifacts and ensure consistent acoustic environments. The recordings primarily capture the mechanical activity of the heart, including the first (S1) and second (S2) heart sounds, which correspond to the closure of the atrioventricular and semilunar valves, respectively. In addition, the presence of any abnormal heart sounds such as murmurs, clicks, or gallops was also noted.

The PCG signals were sampled at a frequency of 1,000 Hz to preserve the fine temporal features of the heart sounds. Prior to further analysis, the raw signals underwent a preprocessing pipeline that included band-pass filtering (typically in the range of 20–500 Hz) to remove low-frequency baseline drift and high-frequency noise. Additional steps such as normalization and envelope extraction were applied to enhance signal clarity and facilitate feature extraction.

The following figure (Fig. 2) displays representative PCG signals obtained from a subset of the study participants. These waveforms illustrate both the general consistency of key cardiac sound events across individuals, as well as inter-subject variability in amplitude, duration, and timing of the acoustic features—potentially reflecting underlying physiological differences or pathological conditions.

Table 1. Description of Test Databases for Performance Evaluation

Test Database	Total Records	PCG Signal Description	Test Records
PASCAL HSC	832	S1, S2, Murmurs	50
PhysioNet/CinC	1277	Normal, Murmurs	50
EGM	64	S1, S2, S3, S4, Splits, Murmurs, Clicks	60
MHSM	23	S1, S2, Murmurs (regurgitation, stenosis)	20
BHS	25	S1, S2, Murmurs (regurgitation, stenosis)	20
WHSM	16	S1, S2, Murmurs (regurgitation, stenosis)	15
CAHS	25	S1, S2, S3, S4, Splits, Snaps, Murmurs	20
HS	11	S1, S2, S3, S4, Gallops, Murmurs, Rubs	10
LHS	10	S1, S2, S3, S4, Splits, Murmurs, clicks	8
AUHS	25	S1, S2	25

Table 2. Performance of fundamental heart sound Recognition

Signal Type	S1 Recognition			S2 Recognition			OA (%)
	TN	FP	Se(%)	TP	FN	Sp(%)	
Org.	2474	26	98.96	2478	22	99.12	99.04
30 dB	2474	26	98.96	2478	22	99.12	99.04
25 dB	2472	28	98.88	2480	20	99.20	99.04
20 dB	2468	32	98.72	2480	20	99.20	98.96
15 dB	2476	24	99.04	2476	24	99.04	99.04
10 dB	2475	25	99.00	2477	23	99.08	99.04

The performance of fundamental heart sound recognition, specifically identifying the first (S1) and second (S2) heart sounds, plays a crucial role in accurate cardiac assessment. Reliable recognition enables effective segmentation of the cardiac cycle, essential for detecting abnormalities such as murmurs, arrhythmias, and valve disorders. Advanced preprocessing techniques like wavelet transforms and adaptive filtering, combined with robust segmentation methods such as Hidden Semi-Markov Models (HSMM), significantly enhance recognition accuracy. Feature extraction methods using time, frequency, and time-frequency domains, along with classification through machine learning and deep learning models (e.g., SVM, CNN, LSTM), further improve system performance. Modern systems report accuracy levels above 90% under controlled conditions. However, challenges such as noise, variability in heart signals, and low signal quality—especially in fetal monitoring—can impact performance, making robust noise handling and adaptive models essential for clinical-grade applications.

V.CONCLUSION

The PCG signals provide most valuable quantitative and qualitative information of heart sounds and murmurs associated with many cardiac abnormalities, including the valvular heart disease, the rate and rhythm, congestive heart failure, and anatomical defects of the heart.

Most studies highlight that the cardiac murmurs are analyzed by the intensity, frequency, configuration, quality, duration, direction of radiation, and timing of the murmurs in the cardiac cycle.

Furthermore, a variety of heart sound parameters such as amplitude, duration, frequency and split duration are extracted from the PCG signal in many pathological and non-pathological applications such as valvular split analysis, cardiac stress test, pulmonary artery pressure analysis, systolic pressure estimation, noninvasive blood pressure estimation, and PCG based biometric systems.

FUTURE SCOPE

The parameter extraction accuracy of PCG (phonocardiogram) signal delineation methods is a key performance indicator in the development of intelligent cardiac monitoring systems. This research aims to systematically evaluate the precision with which essential cardiac parameters—such as the onset, duration, and timing of fundamental heart sounds (S1 and S2), systolic and diastolic intervals, and murmur characteristics—are extracted from a broad spectrum of pathological and non-pathological PCG signals. The inclusion of diverse signal types ensures the generalizability of the framework across various clinical scenarios, from healthy individuals to patients with heart murmurs, valve abnormalities, or arrhythmic conditions.

A major focus will be placed on testing the robustness of a unified PCG signal delineation framework under a range of realistic interference conditions. This includes physiological interferences such as overlapping respiratory sounds (lung sounds), gastrointestinal noises (bowel sounds), and maternal body sounds in fetal monitoring. Additionally, the system will be challenged with external noise sources, including motion artifacts due to patient movement, ambient speech, and instrumental interference from nearby electronic devices. These tests are vital to ensure the framework's reliability in both clinical and field environments where noise is inevitable.

To bridge the gap between theoretical development and real-world application, the feasibility of real-time implementation will be studied using embedded processors, such as ARM Cortex or DSP-based systems. These embedded platforms are representative of the computational environments found in portable diagnostic devices, such as electronic stethoscopes. The envisioned stethoscope will not only record high-fidelity heart sounds but will also feature real-time automatic extraction of clinical indices, enabling frontline healthcare professionals to make informed decisions on-site. The system will also incorporate time-frequency analysis and visualization tools, offering an intuitive graphical representation of the heart sounds and murmurs—crucial for identifying complex pathological patterns.

Moreover, a key component of the framework involves the assessment of PCG signal quality. In real-world recordings, signal quality can vary significantly due to improper sensor placement, background noise, or patient movement. By integrating a signal quality evaluation module, the system can flag low-quality segments, apply noise mitigation strategies, or discard unreliable data altogether. This proactive approach is intended to minimize false alarms, which are a common problem in automated auscultation systems, thereby improving the overall diagnostic reliability and reducing clinician workload.

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