Fetal Electrocardiogram Detection And Analysis From Maternal Abdominal Ecg For Diagnosis Of Fetal Heart Rhythm Abnormalities

Claudia L. Angel
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FETAL ELECTROCARDIOGRAM DETECTION AND ANALYSIS FROM MATERNAL ABDOMINAL ECG FOR DIAGNOSIS OF FETAL HEART RHYTHM ABNORMALITIES

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Dean of the Graduate School
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by

Claudia Angel

2022
To my beloved children

ARIADNA and LEONEL
FETAL ELECTROCARDIOGRAM DETECTION AND ANALYSIS FROM MATERNAL
ABDOMINAL ECG FOR DIAGNOSIS OF FETAL
HEART RHYTHM ABNORMALITIES

by

CLAUDIA LETICIA ANGEL BARRON, M.ENG.

DISSERTATION

Presented to the Faculty of the Graduate School of
The University of Texas at El Paso
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of the Requirements
for the Degree of

DOCTOR OF PHILOSOPHY

Department of Metallurgical, Materials and Biomedical Engineering
THE UNIVERSITY OF TEXAS AT EL PASO
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Abstract

Fetal cardiac arrhythmias are present in about 1–3% of pregnancies and account for about 10–20% of the referrals to fetal cardiology around the world. Most fetal arrhythmias are benign; however, some can cause fetal hydrops, preterm delivery, and higher perinatal morbidity and mortality. The evolution and treatment of fetal arrhythmia depend on a timely and complete diagnosis. However, conventional methods used in clinical practice for fetal arrhythmia diagnosis are limited since they do not reflect the primary electrophysiological conduction processes in the myocardium. Fetal electrocardiography (fECG) has the potential to better support fetal arrhythmia diagnosis through the continuous analysis of the beat-to-beat variation of the fetal heart rate (FHR) and morphological analysis of the ECG waves.

To date, however, the acquisition and analysis of fECG during pregnancy are considered a challenging problem for obstetricians. This is mainly due to the lack of technology to separate the fECG signal from maternal abdominal recordings while preserving its morphology. Fetal ECG extraction is currently limited to FHR estimation in clinical applications. This limitation is due to the fact that fECG from abdominal signals is mixed with the maternal electrocardiogram (mECG), and artifacts. These make it difficult to extract the fECG and to preserve its morphology.

This study presents an efficient hybrid algorithm for fECG extraction from abdominal multichannel signal recordings based on independent component analysis (ICA), template subtraction, and wavelet denoising. Here, the ICA is based on the approximations of negentropy. The performance is measured with the estimation of sensitivity (SE), positive predictive value (PPV), and F1 score. QRS-peak detection accuracy is $SE = 97.4\%$, $PPV = 97.2\%$ and $F1 = 97.29\%$. In addition, an ECG morphology analysis for P-wave detection based on a multiresolution analysis of the maximal overlap discrete wavelet transform is presented. The P-wave detection accuracy in
signals under arrhythmic conditions is $SE = 99.4\%$, $PPV = 98.5\%$ and $F1 = 98.94\%$. The main contributions of this study are a fECG extraction algorithm from non-invasive ECG recordings that preserves the morphology of the P-wave, and an algorithm that enhances and localizes the extracted signals' P-waves.
# Table of Contents

Acknowledgments .................................................................................................................................................. v

Abstract .............................................................................................................................................................. vii

Table of Contents ................................................................................................................................................_ix

List of Tables ........................................................................................................................................................_xi

List of Figures ....................................................................................................................................................... xii

Chapter 1: Literature Review .................................................................................................................................. 1

1.1 Review of Non-invasive Fetal ECG Extraction Methods ............................................................................... 2

1.2 Review of Fetal Arrhythmia Diagnosis from ECG ....................................................................................... 7

1.3 Problem Definition .......................................................................................................................................... 9

1.4 Research Objectives ...................................................................................................................................... 10

1.5 Justification ................................................................................................................................................... 11

1.6 Scope and Delimitations ............................................................................................................................... 12

Chapter 2: Theoretical Framework ..................................................................................................................... 14

2.1 Fetal Heart ..................................................................................................................................................... 14

2.1.1 Functioning of Fetal Heart ..................................................................................................................... 14

2.1.2 Fetal Cardiac Conduction System ......................................................................................................... 16

2.1.3 Fetal Electrocardiogram ......................................................................................................................... 16

2.1.3.1 Invasive Fetal ECG ........................................................................................................................... 18

2.1.3.2 Non-invasive Fetal ECG ................................................................................................................... 18

2.1.4 Fetal Arrhythmia .................................................................................................................................... 19

2.1.4.1 Mechanism and Causes .................................................................................................................... 19

2.1.4.2 Diagnosis of Fetal Arrhythmia ......................................................................................................... 21

2.2 Signal Processing Techniques ....................................................................................................................... 22

2.2.1 Independent Component Analysis .......................................................................................................... 22

2.2.2 Pan-Tompkins' Algorithm ....................................................................................................................... 26

2.2.3 Principal Component Analysis ............................................................................................................... 29

2.2.4 Wavelet Transform ................................................................................................................................ 31

2.2.4.1 Continuous Wavelet Transform ....................................................................................................... 32

2.2.4.2 Discrete Wavelet Transform .......................................................................................................... 32
<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.2.5</td>
<td>Maximal Overlap Discrete Wavelet Transform</td>
<td>34</td>
</tr>
<tr>
<td>2.2.6</td>
<td>Multiresolution Analysis of the Discrete Wavelet Transform</td>
<td>35</td>
</tr>
<tr>
<td>2.3</td>
<td>Performance Evaluation Metrics</td>
<td>35</td>
</tr>
<tr>
<td>2.3.1</td>
<td>Sensitivity and Positive Predictive Value</td>
<td>35</td>
</tr>
<tr>
<td>3.1</td>
<td>Materials</td>
<td>37</td>
</tr>
<tr>
<td>3.1.1</td>
<td>Database</td>
<td>37</td>
</tr>
<tr>
<td>3.1.2</td>
<td>Instruments</td>
<td>38</td>
</tr>
<tr>
<td>3.2</td>
<td>Fetal ECG Extraction</td>
<td>39</td>
</tr>
<tr>
<td>3.2.1</td>
<td>Pre-processing</td>
<td>39</td>
</tr>
<tr>
<td>3.2.2</td>
<td>ICA to Separate Maternal ECG</td>
<td>41</td>
</tr>
<tr>
<td>3.2.3</td>
<td>Approximation of Maternal ECG</td>
<td>43</td>
</tr>
<tr>
<td>3.2.4</td>
<td>Cancellation of Maternal ECG</td>
<td>44</td>
</tr>
<tr>
<td>3.2.5</td>
<td>ICA to Separate Fetal ECG</td>
<td>45</td>
</tr>
<tr>
<td>3.2.6</td>
<td>Enhancement of Fetal ECG</td>
<td>46</td>
</tr>
<tr>
<td>3.3</td>
<td>Annotation of Fetal ECG Signals</td>
<td>48</td>
</tr>
<tr>
<td>3.4</td>
<td>Fetal P-Wave Detection</td>
<td>48</td>
</tr>
<tr>
<td>3.5</td>
<td>Arrhythmia Diagnosis</td>
<td>49</td>
</tr>
<tr>
<td>Chapter 4: Results</td>
<td>50</td>
<td></td>
</tr>
<tr>
<td>4.1</td>
<td>Fetal ECG Extraction Results</td>
<td>50</td>
</tr>
<tr>
<td>4.1.1</td>
<td>Performance Evaluation</td>
<td>54</td>
</tr>
<tr>
<td>4.2</td>
<td>Fetal P-Wave Identification Results</td>
<td>55</td>
</tr>
<tr>
<td>Chapter 5: Conclusions</td>
<td>57</td>
<td></td>
</tr>
<tr>
<td>5.1</td>
<td>Conclusions</td>
<td>57</td>
</tr>
<tr>
<td>5.1.2</td>
<td>Overview of the Specific Objectives</td>
<td>57</td>
</tr>
<tr>
<td>5.2</td>
<td>Significance of the Results</td>
<td>59</td>
</tr>
<tr>
<td>5.2</td>
<td>Future Work</td>
<td>60</td>
</tr>
<tr>
<td>References</td>
<td>61</td>
<td></td>
</tr>
<tr>
<td>Curriculum Vitae</td>
<td>70</td>
<td></td>
</tr>
</tbody>
</table>
List of Tables

Table 3.1: Details of non-invasive fetal ECG arrhythmia database.................................................. 49
Table 4.1: Average F1 score comparison between different methods............................................. 55
Table 4.2: P-wave identification performance evaluation. ............................................................... 56
List of Figures

Figure 2.1: Fetal circulation [45]. .................................................................................................................. 15
Figure 2.2: Fetal cardiac conduction system [46]. ......................................................................................... 16
Figure 2.3: Cardiac cycle [48]. ....................................................................................................................... 17
Figure 2.4: Forward DWT: a three-level two-channel iterative filter bank ...................................................... 33
Figure 2.5: Inverse DWT: a three-level two-channel iterative filter bank ....................................................... 34
Figure 3.1: Methodology. ................................................................................................................................. 37
Figure 3.2: Step-by-step illustration of the fetal ECG extraction algorithm ................................................... 39
Figure 3.3: Symlet 8 mother wavelet .............................................................................................................. 47
Figure 3.4: Symlet 6 mother wavelet .............................................................................................................. 49
Figure 4.1: Fetal ECG signal before (top) and after (bottom) pre-processing applied to record a23 from the Physionet Computing in Cardiology Challenge 2013 dataset [6]. .................................................. 51
Figure 4.2: Abdominal ECG, 6 sec intervals from record a23. ................................................................. 51
Figure 4.3: Independent components extracted from the dataset of figure 4.2 ........................................... 52
Figure 4.4: Independent components resulting from the ICA after maternal ECG cancellation... 53
Chapter 1: Literature Review

Real-time fetal electrocardiogram recording from the maternal abdominal surface and its applications in the diagnosis of fetal cardiac arrhythmias has not been done before.

Fetal cardiac arrhythmia an abnormality of cardiac rhythm may present as abnormal generation or propagation of cardiac impulses. It may manifest as fast and regular (tachycardia) or abnormally slow (bradycardia) rhythm. It is defined as any irregular fetal cardiac rhythm or regular rhythm at a rate outside the reference range of 110 to 160 beats per minute (bpm) [1]. Fetal arrhythmias are identified in about 1–3% of pregnancies and account for about 10–20% of the referrals to fetal cardiology consultants [1, 2]. Some of these arrhythmias may result in fetal hydrops, preterm delivery, and higher perinatal morbidity and mortality [2]. Therefore, the diagnosis of fetal arrhythmia during the routine obstetric checkup is crucial.

Currently, echocardiography is the most widely used tool for the diagnosis and follow-up of fetal arrhythmias in clinical practice [3]. It uses sound waves to check how the chambers and valves pump blood through the fetal heart. However, continuous echocardiographic recordings are usually short and require the specialist to manipulate the equipment. An alternative technique is magnetocardiography, which detects small magnetic fields related to the electrical signals in the fetal heart [4]. However, this technique is limited because it needs to be performed in a magnetically shielded room and is not available in low-income countries. Conventional methods used in clinical practice for fetal arrhythmia diagnosis are limited since they do not reflect the primary electrophysiological conduction processes that take place in the myocardium. Furthermore, fetal electrocardiography has the potential to better support fetal arrhythmia diagnosis through the continuous analysis of the beat to beat variation of the fetal heart rate and the morphological analysis of the electrocardiogram (ECG) waves.
The acquisition and analysis of fECG during pregnancy is a challenging problem for obstetricians. This is because of the low intensity of the fECG signal and multiple artifacts that hamper the visualization of its morphology. Advances in signal processing have revealed that fetal electrocardiogram (fECG) signals can be distinguished from maternal abdominal electrocardiogram (aECG) recordings [5].

This chapter reviews the state of the art in fECG extraction and arrhythmia diagnosis from ECG recordings before and during the current work. At the end of this chapter, the definition of the problem of interest, and the objectives of this work are presented.

1.1 Review of Non-invasive Fetal ECG Extraction Methods

Extraction of fetal QRS complexes from maternal abdominal recordings is essential to compute FHR and detect abnormalities of heart rhythm. In addition, accurate extraction and location of the QRS complexes are further used as an anchor point for extracting features from the fECG waveform. Hence, having a suitable source separation method capable of separating the fECG from the maternal ECG and all the unwanted noise is imperative.

During the last decade, many publications about fECG extraction from abdominal records have appeared; however, it is difficult to make conclusions from these works since they use different databases and performance metrics. It was not until 2013 when the PhysioNet/Computing in Cardiology Challenge addressed this problem. This challenge aimed to encourage the development of accurate algorithms for locating QRS complexes and estimating the QT-interval in non-invasive fECG signals, using carefully reviewed reference annotations from real maternal abdominal ECG recordings [6].
A variety of separation algorithms were proposed and evaluated in the 2013 PhysioNet Challenge [6]. However, in general, they have a five-step approach as follows:

1. First, the abdominal ECG signals are pre-processed to remove noise.
2. Then, the mECG component is estimated.
3. After that, the mECG component is removed.
4. Then, the heart rate and RR time-series of the fECG are estimated.
5. Finally, the resultant fECG is post-processed for enhancement.

The extraction methods used in the challenge with the best scores are described below. Behar et al. [7], use a fusion of multiple source separation methods, obtaining the top scores in the Physionet Challenge. This method is a combination of a subset of template subtraction (TS), principal component analysis (PCA), independent component analysis (ICA), and extended Kalman filter (EKF) [7]. The selected methods are run independently and the output with the smoothest detected fetal QRS (fQRS) time-series is selected. This improves the results in comparison to using any individual method. The reasoning for this approach is that the different source separation techniques have their strengths, and that combining some could lead to a higher performance.

Andreotti et al. [8], estimate the fECG employing two different techniques: the EKF smoother and template adaptation (TA). The fECG extraction is done by mECG estimation in each channel, followed by subtraction from the preprocessed channels. Both extraction methods can produce reliable fQRS detections. The authors conclude that the TA method delivers better results than the EKF, as TA avoids complete cancellation of the fetal peaks in cases of complete feto-maternal overlap leaving easily detectable fQRS complexes.
Varanini et al. [9], extracts the mECG through ICA; then, the maternal QRS (mQRS) complexes are detected using an empirical derivative filter. The mECG is estimated with a singular value decomposition (SVD) and canceled from each channel. Finally, a second ICA is applied to separate and enhance the fECG. Fetal QRS complexes are detected on each independent component (IC), and the best fetal RR series is selected. The approach by Behar et al. also use the mECG canceling technique based on SVD [10], identifying that this method is better than the methods based on average mECG subtraction used by Cerutti et al, and Martens et al [11, 12].

After the Challenge, many studies to extract fECG from non-invasive recordings have been done. Most of them are a combination or an enhancement of the methods used in the Physionet Challenge. However, some new methods have been proposed.

Ghazdali et al. [13], propose a new blind source separation (BSS) approach for non-invasive fECG extraction, based on the minimization of the Kullbak-Leibler divergence between copula densities to separate the observed data and a bilateral total variation (BTV) filter as a pretreatment step for denoising. The authors conclude that the proposed method outperform the ICA method.

Martinek et al. [14], suggest a multichannel adaptive neuro-fuzzy interference system to extract the fECG. The experimental results indicate that this method can potentially improve the diagnostic and monitoring qualities of fECG signals while preserving their morphology.

Liu and Luan develop the ICA-EEMD-WS method [15], which consists of ICA, ensemble EMD (EEMD), and wavelet shrinkage (WS). First, the FastICA algorithm is applied to obtain the noisy fECG. Then, the EEMD decomposes the noisy fECG by a three-step integrated algorithm. Finally, WS is used to reduce the high-frequency noise. This method is compared against Butterworth filter, pure WS, and EMD-WS. Synthetic fECG data and the MIT-BIH arrhythmia
database are used to obtain more significant signal-to-noise ratio (SNR), and a smaller mean square error (MSE) compared to other tested algorithms.

Wang et al. [16], propose a fECG extraction method through ICA based on negentropy. The ECG signals are picked up at the pregnant women’s thoracic and abdominal region. The Fast-ICA is used to obtain the fECG. Then, the separated signal is reconstructed by PCA. Finally, the reconstructed fECG signal is further denoised by wavelet transform (WT) to improve the algorithm’s performance. The results show that the algorithm can effectively separate the fECG from the aECG recordings.

Numerous methods for extracting fECG from non-invasive abdominal records have been published, such as adaptive filtering [17-19], WT [17, 19-21], soft computing tools like adaptive neural network, adaptive neuro-fuzzy inference system, support vector machine [22-24], blind source separation [16, 25-26], etc. Several surveys and systematic reviews of fECG extraction algorithms are found in the literature.

Andreotti et al. [27], compare the ability of eight extraction methods in terms of fQRS detection and morphological analysis (fetal QT and T/QRS ratio), using an extensive database of synthetic signals containing different events [27]. Three classes of extraction algorithms are evaluated: BSS, TS, and adaptive methods (AM). The authors identify that BSS based on ICA outperforms all the other methods in the estimation of fQRS. In addition, experiments show that simple TS class of methods performs better than BSS and AM on estimating morphological parameters, such as fetal QT- interval and fetal TQRS ratio. The authors conclude that the less adaptive the method, the fewer the distortions in the output fECG estimate. These results are consistent with the best fetal QT estimation scores from the Challenge by Podziemski and Gierałtowski, who also use TS [28].

5
Jaros et al. [29], present an extensive literature survey of different non-adaptive signal processing methods applied to fECG extraction and enhancement. Based on the comprehensive overview presented in their article, the hybrid methods, such as ICA-EEMD-WS [15], ICA & Adaptive Filter (AF) [30], ICA & projective filtering (PF) [31], have great potential to be used for fECG morphological analysis. ICA & PCA [32] and ICA & SVD [33] also enable morphological analysis; however, the efficacy is significantly affected by gestational age, fetal position, and SNR.

Sarafan et al, compare 15 fECG extraction algorithms using the non-invasive recordings from the PhysioNet 2013 Challenge [34]. The algorithms compared included TS, EKF, and different ICA variants (JADE, RobustICA, and FastICA based on kurtosis) and their combinations:

1. **TS-ICA**, in which the TS method is first applied to the aECG to remove the mECG component, then the ICA method is used to extract the fECG.
2. **ICA-TS**, in which the ICA method is first applied to the aECGs and the resultant independent components were then put through the TS method to eliminate the remaining mECG component.
3. **ICA-TS-ICA**, in which ICA is applied to the residual of ICA-TS.

Multiple experiments are presented by adding different types of noise to the original signals, and the combination of TS-FastICA shows the highest score.

Based on the up-to-date literature analyzed in this section, ICA is considered the most popular non-adaptive method for fECG extraction due to its simplicity, convergence speed, and satisfactory results in numerous applications. Also, it can be concluded that combining ICA and TS techniques in a hybrid method for fECG extraction might be the most promising direction in reaching an accurate fECG morphology estimation.
1.2 Review of Fetal Arrhythmia Diagnosis from ECG

According to the literature review, many studies have been published on arrhythmia diagnosis in adults using ECG. Anwar et al present a novel method for classifying various types of arrhythmia in adults using morphological and dynamic features [35]. Discrete wavelet transform (DWT) is applied to each heartbeat to obtain morphological features (QRS-complex, T-wave, and P-wave). An improved hybrid feature representation of heartbeat segments is used based on a mixture of derived morphological and dynamic features. These hybrid features are combined and fed to a neural network to classify the presence and type of arrhythmia. The proposed algorithm is tested over the MIT-BIH arrhythmia database using 13724 beats and the MIT-BIH supraventricular arrhythmia database using 22151 beats. The proposed methodology result in an average accuracy of 99.75%.

Zhu et al propose a novel method for recognizing and classifying cardiac arrhythmias in adults [36]. First, the QRS-complex, P-waves, and T-waves are segmented from the ECG waveform. Then, morphological features are extracted from ECG waves, and ECG segment features are extracted using PCA and dynamic time warping (DTW). Finally, a support vector machine (SVM) is applied to the features and automatic diagnosis results are presented. The ECG data set used in this study is derived from the MIT-BIH, in which ECG signals are divided into: normal beats, supraventricular ectopic beats, ventricular ectopic beats and fusion of ventricular and normal. The proposed method can distinguish between the four arrhythmia classes with an accuracy of 97.8% [36]. These studies confirm that arrhythmia can be successfully diagnosed from the analysis of the morphology of the ECG. However, little has been done regarding the detection of fetal arrhythmia from non-invasive ECG.
Lakhno et al, present two case reports in which atrioventricular (AV) block diagnosis is supported by the non-invasive fECG [37]. Atrial flutter (AFL) and second-degree AV block with conduction 2:1 are determined during fetal echocardiography. The non-invasive fECG tracing is obtained from the maternal abdominal wall with the usage of the fECG monitor Cardiolab Babycard (Scientific and research center “KhAI Medica”, Ukraine) [38]. This monitor provides FHR and morphology measurements (duration of PQ-interval, QRS, and QT, peak amplitudes R, S, and T). Characteristic drop of beats are identified in the non-invasive fECG enabling the identification of AV block events. This study demonstrates, for the first time, the feasibility of the non-invasive fECG as a supplementary method to be used in combination with ultrasound technologies for diagnosing fetal arrhythmia.

Rahman et al, propose a fECG signal feature extraction algorithm and extracts Q, R, S, and T waves, the average of SS, QQ, ST, and TT intervals [39]. Based on these features, a Kernel SVM classifier with Gaussian Kernel to detect fetal arrhythmia is presented. For his study, the fECG arrhythmia database from PhysioNet is used. The database consists of 12 arrhythmic and 14 normal ECG recordings. The results demonstrated an accuracy of 83.33% with 91.67% specificity and 75% sensitivity. Thus validating that fECG is useful in detecting fetal arrhythmia.

Corona-Figueroa presents a prototype for the detecting of fetal arrhythmias by analyzing the FHR and its variability [40]. This prototype consists of a portable electrocardiograph and a mobile application that extract the fECG from abdominal recordings for its analysis and diagnosis. The prototype is tested with synthetic aECG signals based on clinical fetal arrhythmia obtaining a detection rate of 88.88%. The author concludes that the proposed prototype can be used to render a diagnosis without entirely depending on expert assistance.
Behar et al. present a study where two perinatal cardiologists analyze non-invasive fECG and compare their diagnosis with a reference fetal echocardiography diagnosis [1]. Their dataset consists of 12 cases with fetal arrhythmias and a matching control number. The non-invasive fECG is recorded using the Cardiolab Babycard equipment [36]. From this study, it is concluded that it is possible to diagnose fetal arrhythmias using non-invasive fECG. However, this study also concludes that improvement in algorithms for reconstructing the P-wave is critical to understanding the mechanisms underlying the arrhythmias.

More recently, Keenan et al present a novel method of fetal arrhythmia detection in short-length, non-invasive fECG recordings [41]. Their method consists of extracting a FHR time series from each non-invasive fECG recording and computing entropy features such as SampEn (HS), FuzzyEn (HF) and TotalSampEn (HTS). This method classifies 318 non-invasive fECG recording as normal or arrhythmic using each entropy feature at a time, demonstrating excellent performance.

In conclusion, there is still an excellent opportunity to improve the detection of fetal arrhythmia from non-invasive recordings since the studies performed to date have the following limitations:

1) They are very few.
2) They do not identify the P-wave, which is imperative to understand the mechanisms underlying the arrhythmia and provide the correct treatment.
3) They diagnose arrhythmia based on the FHR and HRV and do not take into account the morphology of the ECG signal.

1.3 Problem Definition

After conducting a detailed review of the literature, it was found that considerable research and clinical work still must be performed to diagnose the different types of fetal arrhythmia from
non-invasive fECG recordings. There is a need for an extraction method that preserves the morphology of the fECG and technology that analyzes the P-wave to diagnose the different types of arrhythmia and understand its mechanism.

1.4 Research Objectives

Recognizing the needs described in previous sections, the objective is to address the challenges of extracting and analyzing fECG signals from maternal abdominal recordings while preserving their morphology to support fetal arrhythmia diagnosis.

The present work is meant to be beneficial in detecting possible arrhythmias by analyzing the morphology of the fECG signal from non-invasive recordings. More specifically, the main objective of this research is to extract the fECG from maternal abdominal recordings and preserve the morphology of the QRS peak and P-wave. The detailed objectives of this research are as follows:

Objective 1. To combine the most promising signal processing methods with high performance, as reported in the literature, and to develop a hybrid algorithm to reliably extract fECG signals from abdominal ECG recordings preserving their morphology.

Objective 2. To develop a feature extraction algorithm to identify P-waves from normal and arrhythmic fECG signals extracted from aECG recordings.

Objective 3. To quantitatively evaluate the performance of the fECG signal extraction method to prove its effectiveness in preserving the QRS- peak.

Objective 4. To diagnose the signals with arrhythmia based on the heart rate and the location of the P-wave.

Objective 5. To quantitatively evaluate the performance of the feature extraction method to identify the P-wave.
The reliable extraction of fECG signals from real abdominal recordings and the robust detection of the P-wave will serve as essential criteria to achieve the objectives.

1.5 Justification

ECG interpretation requires a structured assessment of the waves and intervals on the ECG. The basic ECG waves are QRS-complex, P-wave and T-wave. The QRS-complex represents the ventricle depolarization, P-wave reflects atrial depolarization, and the T-wave represents ventricle repolarization [42]. Among these basic features, the P-wave is the most complicated component to detect due to the following reasons:

1) P-waves have a low voltage, resulting in a low SNR.
2) They have no exclusive time and frequency characteristics.
3) They have high variability between patients.
4) In the case of AV dissociations, P-waves do not respect normal time ordering of an ECG sequence and, thus, can be missing or redundant.
5) During tachycardia, P-waves can be hidden within the T-waves.
6) During atrial fibrillation (AFIB) and AFL, P-waves are missing or replaced by atrial fibrillatory waves.
7) And in the case of ventricular ectopy, P-waves are usually not present at all.

P-wave location is essential to diagnose arrhythmia. Mainly, the location of the P-waves can be used to diagnose AV block. It is also a key point for differentiation between supraventricular and ventricular tachycardias and for identification of junctional and ventricular ectopic beats or rhythm, atrial fibrillation, and flutter [42].
The evolution and treatment of arrhythmia depend on an accurate and complete diagnosis, which is usually done by echocardiography. However, fetal echocardiography does not capture cardiac time interval waveforms, such as P-wave duration, QRS duration, or QT interval. Therefore, an incomplete or incorrect diagnosis can lead to poor management and incorrect treatment, which can risk the fetus’s and the mother’s well-being.

The literature review has supported that P-wave detection in fECG is still a challenging task, especially in non-invasive fECG and signals that manifest cardiac pathologies. Therefore, there is a need for an accurate automated detection of the P-wave in non-invasive fECG to provide fast correct arrhythmia diagnosis and select suitable strategies for patients’ treatment.

Here a novel method for accurate and reliable P-wave detection in non-invasive fECG is presented, which works well in both normal and arrhythmic signals. This method uses a combination of ICA and TS techniques to extract the fECG. The selection of these techniques is based on the literature review, as a combination of ICA and TS has shown satisfactory results in numerous applications. This method also uses wavelet transform to detect the P-waves as it provides better time and frequency resolution of the electrocardiogram signals.

1.6 Scope and Delimitations

This study addresses the challenges in non-invasive fECG signal extraction and analysis. This study is to focus on extracting the fECG component from maternal abdominal recordings and preserving QRS-peak and P-wave morphology. Signals used for fetal ECG extraction are selected from publicly available databases; no data is recorded for the purpose of this study. This study is performed by using the following datasets:
1) A collection of 75 one-minute aECG recordings under normal conditions. Each recording includes four channels of maternal abdominal ECG sampled at 1 KHz [6].

2) A set of 5 one-minute fECG signals recorded directly from the fetal head at 1 KHz [43].

3) A collection of 12 non-invasive fECG with arrhythmia diagnosis. Each recording contains a set of four or five abdominal channels and one chest maternal channel sampled at 500 Hz or 1 kHz for 10-13 minutes [1].
Chapter 2: Theoretical Framework

This chapter introduces the function of the fetal heart and the morphology of the fetal electrocardiogram. A description of fetal arrhythmia, its causes and types, and a review of diagnostic methods currently used in clinical practice are provided. In addition, a description of the signal processing techniques used for the fECG extraction method is included in this chapter.

2.1 Fetal Heart

2.1.1 Functioning of Fetal Heart

The heart is one of the first organs to form and function in a fetus; it is vital for oxygen and nutrients distribution [44]. The placenta is also a vital organ for the development of the fetus. The placenta pulls nutrients and oxygen from the maternal circulation to the fetus and removes the built-up waste from the fetal circulation to the maternal circulation [45].

The placenta attaches to the fetus via the umbilical cord. The umbilical cord is made up of one umbilical vein that carries oxygenated and nutrient-rich blood from the placenta to the fetus, and two umbilical arteries that carry deoxygenated blood from the fetus to the placenta.

During fetal development, the lungs are not functional and are full of fluid. Therefore, the fetal cardiovascular system is adapted to ensure that oxygenated blood is delivered preferentially from the placenta to the brain and the heart while being diverted away from the lungs through three shunts. The ductus arteriosus and foramen ovale shunts push blood away from the lungs, and the ductus venosus pushes blood from the liver to the inferior vena cava.

The placenta pulls oxygenated blood from the maternal circulation to the umbilical vein (please refer to Figure 2.1). Some of this blood enters the portal vein to supply the fetus liver with oxygen and nutrients, but most of it is shunted by the ductus venosus to the inferior vena cava.
The oxygenated blood from the inferior vena cava enters the right atrium. Some of this blood goes into the right ventricle, but the majority of this blood is shunted to the left atrium through the foramen ovale. Also, deoxygenated blood from the superior vena cava enters the right atrium. This deoxygenated blood, along with some of the oxygenated blood from the umbilical vein, flows down into the right ventricle. This partially oxygenated blood flows into the pulmonary artery and is shunted to the aorta via the ductus arteriosus. Some of this blood will go to the lower extremities through the descending aorta, and some will return to the placenta via the umbilical arteries that arise from the internal iliac arteries. Maternal circulation will clear the build-up of waste and re-supply it will remain fresh oxygen and nutrients [45].

Figure 2.1: Fetal circulation [45].
2.1.2 Fetal Cardiac Conduction System

The fetal cardiac conduction system (Figure 2.2) is functionally developed at 16 weeks of gestation [46]. The normal cardiac impulse starts at the sinoatrial node (SA-node), located in the upper part of the right atrial wall. The impulse is conducted across the atria causing atrial contraction, then progresses to the atrioventricular node (AV-node) on the right side of the atrioventricular junction. The impulse then progresses through the His bundles to the right and left ventricles, causing ventricular contraction. The atrioventricular junction acts as electrical insulation, preventing direct conduction between the atria and ventricles and vice versa.

![Fetal cardiac conduction system](image)

Figure 2.2: Fetal cardiac conduction system [46].

2.1.3 Fetal Electrocardiogram

The fECG reflects the electrophysiological activity of the fetal heart. The fECG is similar to the adult electrocardiogram (ECG) in that it contains a similar pattern (P, QRS, and T-Waves). However, the FHR is usually higher than the adult one, with the normal range varying with the gestational age (GA) [47].
Electrical impulses flow through the heart muscle generating the PQRST complex. The impulse starts in the SA-node, which serves as the natural pacemaker for the heart. The SA-node represents the P-wave or atrial contraction (depolarization) on the ECG tracing. This impulse further stimulates the atrioventricular node (AV-node), the bundle of His, the left and right bundles, and ends in the Purkinje fibers, depolarizing the ventricles in its way resulting in the QRS-complex. At the same time, the atria are relaxed (repolarized); however, this repolarization is masked by the depolarization of the ventricles. Finally, the T-wave corresponds to the repolarization of the ventricles [48]. Figure 2.3 shows a complete cardiac cycle.

![Cardiac cycle diagram](image)

Figure 2.3: Cardiac cycle [48].

Recent studies confirm that fECG signals provide information that clinicians can use to monitor and diagnose cardiac defects, fetal distress, intrauterine hypoxia and arrhythmia [49].
Currently, there are two methods to acquire fECG signals, which are the invasive and non-invasive methods.

2.1.3.1 Invasive Fetal ECG

The invasive method consists of recording the fECG signals by placing an electrode on the fetal scalp. The recorded signals with this method are of high quality; however, these signals can only be recorded during labor and delivery [50]. Therefore, this technology is unsuitable for continuous long-term fetal heart electrical activity monitoring. Thus, there is currently a diminished likelihood of early detecting a fetal cardiac abnormality and a hypoxic condition that threatens the fetus’s well-being. This, in turn, limits the opportunity for the clinicians to provide timely intervention and take effective measures before permanent damage to the fetus can occur.

2.1.3.2 Non-invasive Fetal ECG

As an alternative to the invasive method, fECG signals can be recorded at any stage of pregnancy with the non-invasive method. This technique consists of recording fECG signals by placing multiple electrodes on the maternal abdomen. This method is suitable for long-term monitoring purposes due to its non-invasive nature. However, this method is currently limited to measuring the FHR alone [49]. The main reason for this limitation is that the non-invasive fECG is contaminated with multiple undesirable signals such as the maternal ECG (mECG), fetal brain activity, maternal and fetal myographic signals, and maternal and fetal movement artifacts, among others. These interfering influences complicate the accurate detection and interpretation of the fECG. Such limitations and problems pose particular challenges in detecting cardiac defects, fetal distress, arrhythmia, and intrauterine hypoxia.
There are different types of noise present in noninvasive aECG signals, commonly encountered noises are impulsive noise, baseline wander, power line interference, and high-frequency noise [51]. Impulsive noise is caused by the displacement or shedding of the electrodes and seriously affects the accuracy of QRS detection [52]. Baseline wandering is a type of low-frequency noise caused by the movement and breathing of the subjects, leading to a change of distance between the source of the signal and the electrodes resulting in a varying baseline [51]. Power line interference is generated by the power grid’s alternative 50/60 Hz sinusoidal current. Power line interference is a significant source of noise that degrades the signal quality and overwhelms small features that may be critical to monitoring fetal well-being [53].

2.1.4 Fetal Arrhythmia

Arrhythmia is defined as an irregular heartbeat. The normal FHR ranges between 110 and 160 bpm. Fetal cardiac arrhythmia is defined as a HR that is beyond the normal ranges, or that has an irregular rhythm [4].

2.1.4.1 Mechanism and Causes

The types of fetal arrhythmia can be broadly divided into irregular heart rhythms with an average overall rate, tachycardias, and bradycardias. Irregular fetal heart rhythm is commonly described as extra or missing beats and is most often due to extrasystoles (premature atrial beats). Pathological fetal tachycardia is defined as a FHR above 160–200 bpm, but most affected fetuses have ventricular rates ranging from 220 to 300 bpm [4].
Arrhythmias can also be divided by where they happen, which is essential to understand their mechanism and provide the proper treatment. If the arrhythmia starts in the ventricles, they are called ventricular. However, when they begin in the atria, they are called supraventricular.

Ventricular arrhythmias include [51]:

- **Premature ventricular contractions** are extra heartbeats that begin in one of the heart's two lower pumping chambers, causing a sensation of the skipped heartbeat.
- **Ventricular tachycardia.** This is a rapid heart rhythm starting from the ventricles.
- **Ventricular fibrillation.** Disorganized heart signals cause the ventricles to quiver (twitch) and cannot contract. As a result, the heart does not pump blood to the rest of the body.
- **Long QT syndrome.** The ventricles take too long to contract and release. This may cause dangerous rhythm problems and death.

Supraventricular arrhythmias include [51]:

- **Premature atrial contractions.** These are early extra heartbeats.
- **Atrial fibrillation.** The atrium contract in an unusual way and causes an irregular and often abnormally fast heart rate.
- **Atrial flutter.** It is characterized by a much faster rate of atrial contraction compared with ventricular contraction.
- **Paroxysmal supraventricular tachycardia.** Episodes of rapid heart rate, usually with a regular rhythm.
- **Accessory pathway tachycardias.** Rapid heart rate because of microscopic muscular bundles connecting the atrium and ventricle, and bypassing the normal conduction system.
• **Sinus arrhythmia** refers to a changing sinus node rate with the respiratory cycle, on inspiration and expiration.

Bradyarrhythmia is another type of fetal arrhythmia. It is characterized by a slow HR and irregular heart rhythm or slow HR that is pathologic. Types of bradyarrhythmia include [51]:

• **Sinus node dysfunction.** Slow heart rate and an irregular heart rhythm are caused by a problem with the heart's sinus node.

• **Atrioventricular block.** The electrical signal that controls the heart rate is partially or completely blocked, slowing the heart rate and causing the heart to beat at an irregular rhythm.

### 2.1.4.2 Diagnosis of Fetal Arrhythmia

Currently methods for detecting fetal arrhythmias include cardiotocography (CTG), echocardiography, and magnetocardiography (MCG). Cardiotocography is a continuous recording of the FHR obtained via an ultrasound transducer placed on the maternal abdomen. This technology registers the fetal heart rate variability (HRV) as well as the uterine contractions [2]. However, the use of CTG is usually limited to up to 30 weeks of gestation and functions poorly during fetal tachycardia or AV block.

Echocardiography is a technology that uses electrodes to check the heart rhythm and ultrasound technology to see how blood moves through the heart [2]. Fetal echocardiography is the most widely used tool for diagnosis of fetal arrhythmia. However, it cannot assess the electrical waveform morphology or repolarization characteristics.

Magnetocardiography is a noninvasive contactless method to measure the magnetic fields produced by electrical currents in the heart using the extremely high sensitivity superconducting
quantum interference device (SQUID) sensors [2]. This technology can precisely characterize fetal heart rhythm and conduction; however, it requires expensive and highly specialized equipment.

Conventional methods used in clinical practice for fetal arrhythmia diagnosis are limited since they do not reflect the primary electrophysiological conduction processes that take place in the myocardium. Furthermore, the fetal electrocardiogram has the potential to better support fetal arrhythmia diagnosis through the continuous analysis of the beat-to-beat variation of the FHR and morphological analysis of the PQRST complex.

2.2 Signal Processing Techniques

2.2.1 Independent Component Analysis

The ICA is a statistical method for finding a linear representation of non-Gaussian data so that the components are statistically independent or as independent as possible [54, 55]. That is that the occurrence of one component does not affect the probability of occurrence of the other component. In other words, ICA is a statistical method for transforming an observed multidimensional random vector into components that are statistically as independent from each other as possible. This method reduces the higher-order dependencies in the data, thus generating statistically independent components. This is achieved by rotating the axes to correspond to the directions of maximum statistical independence.

The separation of mixed signals through ICA assumes that the source signals are independent of each other and that the values in each source signal have non-Gaussian distributions. However, ICA considers that the signal mixtures are not independent, as they share the same source signals. Also, according to the central limit theorem, the distribution of a sum of independent random variables with finite variance tends towards a Gaussian distribution. Finally,
the complexity of any signal mixture is greater than that of its most straightforward source signal. These principles contribute to the fundamental establishment of ICA. If the signals extracted from a set of mixtures are independent, and have non-Gaussian distribution, then they are considered source signals (also called independent components).

Usually, in order to simplify and reduce the complexity of the source signal separation, the mixing signals are preprocessed using centering (subtract the mean to create a zero mean signal), whitening to ensure that all dimensions are treated equally a priori before the ICA algorithm is run. Well-known algorithms for ICA include infomax, FastICA, JADE, and kernel-independent component analysis, among others.

To define ICA in a general way, two recorded time signals containing a mix of two source signals can be separated with ICA. These recorded signals can be denoted by \(x_1(t)\) and \(x_2(t)\), with amplitudes \(x_1\) and \(x_2\), and time index \(t\). Each recorded signal is a weighted sum of the source signals, denoted by \(s_1(t)\) and \(s_2(t)\). This can be expressed as the following linear equations:

\[
\begin{align*}
  x_1(t) & = a_{11} s_1 + a_{12} s_2 \\
  x_2(t) & = a_{21} s_1 + a_{22} s_2
\end{align*}
\]

where \(a_{11}, a_{12}, a_{21},\) and \(a_{22}\) are some parameters that depend on the recording of the signals. Now to estimate the two original signals \(s_1(t)\) and \(s_2(t)\), using only the two recorded signals \(x_1(t)\) and \(x_2(t)\), \(a_{il}\) is estimated with ICA based on the information of their independence.

Now assuming that \(n\) linear mixtures \(x_1, \ldots, x_n\) of \(n\) independent components are observed

\[
  x_j = a_{j1}s_1 + a_{j2}s_2 + \cdots + a_{jn}s_n
\]

each mixture \(x_j\) as well as each independent component \(s_k\) is a random variable. Therefore, the observed values \(x_j(t)\) are then a sample of this random. Using the vector-matrix notation, the ICA model is written as:
\[ x = As \] (2.4)

where the random vector whose elements are the mixtures \( x_1, \ldots, x_n \) is denoted by \( x \). Similarly, the random vector with elements \( s_1, \ldots, s_n \) is denoted by \( s \), and the matrix with elements \( a_{ij} \) is denoted by \( A \). Then, the matrix \( A \) is estimated using the random vector \( x \), and the independent components are obtained from its inverse \( W \).

\[ s = Wx \] (2.5)

ICA finds the independent components by maximizing the statistical independence of the estimated components. This can be achieved in two ways, minimization of mutual information (MMI) and maximization of non-Gaussianity. The MMI family of ICA algorithms uses measures like Kullback-Leibler divergence and maximum entropy. While the non-Gaussianity family of ICA algorithms uses kurtosis and negentropy. For this study, only the ICA based on the maximization of non-Gaussianity using negentropy is described.

The key to estimating the ICA model is non-Gaussianity. Negentropy is based on the information-theoretic quantity of entropy. Entropy is the basic concept of information theory. The entropy of a random variable can be interpreted as the degree of information that the observation of the variable gives. Entropy \( H \) is defined for a discrete random variable \( Y \) as:

\[ H(Y) = -\sum_i P(Y = a_i)\log P(Y = a_i) \] (2.6)

where the \( a_i \) are the possible values of \( Y \). This very well-known definition can be generalized for continuous-valued random variables and vectors, in which case it is often called differential entropy. The differential entropy \( H \) of a random vector \( y \) with density \( f(y) \) is defined as:

\[ H(y) = -\int f(y)\log f(y)\,dy \] (2.7)
To obtain a measure of non-Gaussianity that is zero for a Gaussian variable and always non-negative, a slightly modified version of the definition of differential entropy, called negentropy, is used. Negentropy $J$ is defined as follows:

$$J(y) = H(y_{gauss}) - H(y)$$ (2.8)

where $y_{gauss}$ is a Gaussian random variable of the same covariance matrix as $y$. Due to the properties as mentioned earlier, negentropy is always non-negative, and it is zero if and only if $y$ has a Gaussian distribution. When the negentropy reaches the maximum value, that is, the maximum non-Gaussian components, the independent components are entirely separated.

Estimating negentropy is computationally difficult; hence these functions remain mostly theoretical, and some approximations of negentropy are used in practice. The classical method of approximating negentropy uses higher-order moments, as follows:

$$J(y) \approx \frac{1}{12} E\{y^3\}^2 + \frac{1}{48} kurt(y)^2$$ (2.9)

where the random variable $y$ is assumed to be of zero mean and unit variance. However, the validity of such approximations may be relatively limited as they suffer from the non-robustness encountered with kurtosis.

Another approximation based on the maximum-entropy principle is:

$$J(y) \approx \sum_{i=1}^{p} k_i[E\{G_i(y)\} - E\{G_i(v)\}]^2$$ (2.10)

where $k_i$ are some positive constants, and $v$ is a Gaussian variable of zero mean and unit variance. Also, the variable $y$ is assumed to be of zero mean and unit variance, and the functions $G$ are some non-quadratic functions. In the case where only one non-quadratic function $G$ is used, the approximation becomes:

$$J(y) \propto [E\{G(y)\} - E\{G(v)\}]^2$$ (2.11)
for practically any non-quadratic function $G$. Moreover, the following choices of $G$ have proved very useful:

$$G_1(u) = \frac{1}{a_1} \log \cosh a_1 u$$  \hspace{1cm} (2.12)

$$G_2(u) = -\exp(-u^2/2)$$  \hspace{1cm} (2.13)

### 2.2.2 Pan-Tompkins' Algorithm

Pan and Tompkins (PTA) algorithm is one of the most common algorithm for QRS detection [56]. Figure 2.4 shows the data flow diagram of the PTA algorithm, which consists of band pass filter, differentiation, squaring, moving window integration, and adaptive threshold detection [57].

![Pan and Tompkins algorithm](image)

First, in order to attenuate the noise, the ECG signal is filtered by a 15 Hz low pass filter follow by a 5 Hz high pass filter, as shown in equations 2.14 and 2.15, respectively. These two filters form a band-pass filter to remove unnecessary low, and high- frequency noise signals such as muscle noise and baseline wanders.
\[ y(nT) = 2y(nT - T) - y(nT - 2T) + x(nT) - 2x(nT - 6T) + x(nT - 12T) \]  
(2.14)

\[ y(nT) = 32x(nT - 16T) - [y(nT - T) + x(nT) - x(nT - 32T)] \]  
(2.15)

Next, to obtain information about the slope of QRS, the signal is differentiated, as shown in equation 2.16 to highlight the slope information of QRS complex, which usually contains the steepest slope compared to the other peaks.

\[ y(nT') = (1/8T) [-x(nT - 2T) - 2x(nT - T) + 2x(nT + T) + x(nT + 2T)] \]  
(2.16)

The differentiated output is then squared to intensify the slope of the frequency response curve of the derivative and restrict false positives caused by T-waves with higher than usual spectral energies, as shown in equation 2.17. It also aims to convert all the signal amplitude values become positive values.

\[ y(nT) = [x(nT)]^2 \]  
(2.17)

After that, the squared output signal passes through a moving windows integrator (MWI) to smooth the signal by removing the fluctuations in signal peaks. The MWI produces a signal that includes information about the slope and the width of the QRS complex. This is done by summing several data points and calculating the average value of each window (equation 2.18).

\[ y(nT) = (1/N)[x(nT - (N - 1)T) + x(nT - (N - 2)T) + \cdots + x(nT)] \]  
(2.18)

Lastly, the QRS complex is determined by applying a threshold to the output of the moving window integrator. An adaptive voltage threshold is applied. Compared to the fixed threshold, the adaptive threshold does not need to be manually set prior to the ECG processing but is automatically set after processing the first few seconds of early ECG recording, which function as the parameter training. Initially, every peak is considered as either a noise peak or a signal peak. An initial signal and noise threshold is then generated for QRS detection. These threshold values are not fixed and will keep changing and adapting from time to time along the ECG data.
processing. In other words, whenever the ECG data is changed along the ECG record, the threshold values will be updated automatically accordingly. The first 2 seconds of ECG data are used for parameter training to compute the initial parameter value, as shown in equations 2.19 to 2.22.

\[
\text{Signal Peak} = \text{MAX (training set)} \quad (2.19)
\]

\[
\text{Signal Threshold} = \text{Signal Peak}/3 \quad (2.20)
\]

\[
\text{Noise Peak} = \text{MEAN (training set)} \quad (2.21)
\]

\[
\text{Noise Threshold} = \text{Noise Peak}/2 \quad (2.22)
\]

After the first 2 seconds of parameter training, the parameter will keep changing along the ECG data processing to set the adaptive threshold according to equations 2.23 to 2.25. If a QRS-complex is detected, in which the value is larger than the signal threshold, then the algorithm will skip 0.2 seconds; this is to prevent double QRS detection at the nearest location, which would be physically impossible.

\[
\text{Signal Peak} = 0.125 (\text{Current Peak}) + 0.875 \text{Signal Peak} \quad (2.23)
\]

\[
\text{Signal Threshold} = \text{Noise Peak} + 0.25(\text{Signal Peak} - \text{Noise Peak}) \quad (2.24)
\]

\[
\text{Noise Threshold} = \text{Signal Threshold}/2 \quad (2.25)
\]

On the other hand, if the detected beat falls within the signal threshold and noise threshold range, the system needs to be aware of this peak. Hence, the noise peak, noise threshold, and signal threshold parameters are adapted and changed according to equations 2.26 to 2.28.

\[
\text{Noise Peak} = 0.125 (\text{Current Peak}) + 0.875 (\text{Noise Peak}) \quad (2.26)
\]

\[
\text{Signal Threshold} = \text{Noise Peak} + 0.25(\text{Signal Peak} - \text{Noise Peak}) \quad (2.27)
\]

\[
\text{Noise Threshold} = \text{Signal Threshold}/2 \quad (2.28)
\]
2.2.3 Principal Component Analysis

PCA attempts to find an independent set of vectors onto which the data can be transformed. The data that are projected onto each vector are the independent sources. The primary goal in PCA is to decorrelate the signal by projecting the data onto orthogonal axes. With PCA, the data undergoes a decorrelation using variance as the metric. Projections onto these axes are independent in a second-order sense and are orthogonal [58].

The basic idea in applying PCA to a dataset is to find the component vectors $y_1, y_2, \ldots, y_N$ that explain the maximum amount of variance possible by $N$ linearly transformed components. PCA can be defined in an intuitive way using a recursive formulation. The direction of the first principal component $v_1$ is found by passing over the data and attempting to maximize the value of $v_1$,

$$v_1 = \arg \max_{\|v\| = 1} E\{(v_1^T X)^2\}$$

(2.29)

where $v_1$ is the same length $M$ as the data $X$. Thus, the first principal component is the projection on the direction in which the variance of the projection is maximized. Each of the remaining $N - 1$ principal components are found by repeating this process in the remaining orthogonal subspace (which reduces dimensionality by one for each new component discovered). The principal components are then given by the projection of $X$ onto each $v_i$:

$$y_i = v_i^T X (i = 1, \ldots, N)$$

(2.30)

Although the basic goal in PCA is to decorrelate the data by performing an orthogonal projection, the dimension of the data from $N$ to $p$ ($p < N$) is reduced to remove unwanted components in the signal. Therefore, the PCA representation is an optimal linear dimension reduction technique in the mean-square sense.
In practice, the computation of the $v_i$ can be simply accomplished using the sample covariance matrix:

$$ C = X^TX $$

(2.31)

The $v_i$ are the eigenvectors of $C$ (an $M \times M$ matrix) that correspond to the $N$ eigenvalues of $C$. The eigenvalues can be determined in this manner by SVD which is described next.

### 2.2.3.1 Singular Value Decomposition

The principal components of a multi-dimensional signal can be determined through Singular Value Decomposition [58]. A real $M \times N$ matrix $X$ of observations is considered and decomposed as follows;

$$ X = USV^T $$

(2.32)

where $S$ is an $M \times N$ non-square matrix with zero entries everywhere, except on the leading diagonal with elements $s_i (= S_{MN}, M = N)$ arranged in descending order of magnitude. Each $s_i$ is equal to $\sqrt{\lambda_i}$, the square root of the eigenvalues of $C = X^TX$. A stem plot of these values against their index $i$ is known as the singular spectrum or eigenspectrum. The smaller the eigenvalue, the smaller the total energy is projected along the corresponding eigenvector. Therefore, the smallest eigenvalues are often associated with eigenvectors that describe the noise in the signal. The columns of $V$ form an $N \times N$ matrix of column vectors, which are the eigenvectors of $C$. The $M \times M$ matrix $U$ is the matrix of projections of $X$ onto the eigenvectors of $C$. A truncated SVD of $X$ is performed such that only the most significant ($p$ largest) eigenvectors are retained. In practice choosing the value of $p$ depends on the nature of the data, but is often taken to be the knee in the eigenspectrum or the value where $\Sigma_{i=1}^{p} s_i > \alpha \Sigma_{i=1}^{N} s_i$
and $\alpha$ is some fraction $\approx 0.95$. The truncated SVD is then given by equation 2.33, and the columns of the $M \times N$ matrix $Y$ are the noise-reduced signal.

$$Y = US_pV^T$$

(2.33)

SVD is performed as follows:

1. The $N$ non-zero eigenvalues are estimated, $\lambda_i$ of the matrix $C = X^T X$. Then, a non-square diagonal matrix $S$ by placing the square roots $s_i = \sqrt{\lambda_i}$ of the $N$ eigenvalues in descending order of magnitude on the leading diagonal and setting all other elements of $S$ to zero is formed.

2. The orthogonal eigenvectors of the matrix $X^T X$ corresponding to the obtained eigenvalues are estimated and arranged in the same order. This ordered collection of column vectors forms the matrix $V$.

3. The first $N$ column-vectors of the matrix are estimated: $u_i = s_i^{-1}Xv_i (i = 1: N)$. Note that $s_i^{-1}$ are the elements of $S^{-1}$.

4. The rest of $M - N$ vectors are added to the matrix $U$ using the Gram-Schmidt orthogonalization process.

### 2.2.4 Wavelet Transform

Wavelet transform is a new mathematical analysis tool based on a set of analyzing and scaling wavelets, which decompose the ECG signal into a sequence of coefficients. These coefficients reflect the ECG components in a specified time duration and frequency band [59].
2.2.4.1 Continuous Wavelet Transform

The continuous wavelet transform (CWT) transforms a continuous signal into a highly redundant signal of two continuous variables: translation and scale [59]. The resulting transformed signal is easy to interpret and valuable for time-frequency analysis. The continuous wavelet transform of continuous function, \( x(t) \) relative to real-valued wavelet, \( \psi(t) \) is described by:

\[
W_\psi(s, \tau) = \int_{-\infty}^{+\infty} x(t) \psi^*_s(t) dt
\]

(2.34)

\[
\psi_s(\tau) = \frac{1}{\sqrt{s}} \psi\left(\frac{t-\tau}{s}\right)
\]

(2.35)

Where \( s \) and \( \tau \) are called scale and translation parameters, respectively. \( W_\psi(s, \tau) \), denotes the wavelet transform coefficients, and \( \psi \) is the fundamental mother wavelet.

2.2.4.2 Discrete Wavelet Transform

The discrete wavelet transform has become a powerful technique in biomedical signal processing. It can be written in the same form as equation 2.34, which emphasizes the close relationship between CWT and DWT. The most obvious difference is that the DWT uses scale and position values based on the powers of two. Therefore, the values of \( s \) and \( \tau \) are: \( s = 2^j \), \( \tau = k * 2^j \) and \((j, k) \in Z^2\) as shown in equation 2.36.

\[
\psi_{s,\tau}(t) = \frac{1}{\sqrt{2^j}} \psi\left(\frac{t-k*2^j}{2^j}\right)
\]

(2.36)

The key issues in DWT and inverse DWT are signal decomposition and reconstruction, respectively. The basic idea behind decomposition and reconstruction is low-pass and high-pass filtering using down sampling and up sampling, respectively. The result of wavelet decomposition is hierarchically organized decompositions. The level of decomposition \( j \) is chosen based on a desired cutoff frequency. Figure 2.4 shows an implementation of a three-level forward DWT based on a two-channel recursive filter bank, where \( h_0(n) \) and \( h_1(n) \) are low-pass and high-pass analysis
filters, respectively, and the block ↓ 2 represents the downsampling operator by a factor of 2. The input signal \( x(n) \) is recursively decomposed into a total of four subband signals: a coarse signal \( C_3(n) \), and three detail signals, \( d_3(n), d_2(n), \) and \( d_1(n) \), of three resolutions.

\[ \begin{align*}
\tilde{h}_0(n) &= \tilde{h}_0(L + 1 - n) & (2.37) \\
\tilde{h}_1(n) &= (-1)^{n-1} \tilde{h}_0(L + 1 - n) & (2.39)
\end{align*} \]

Figure 2.4: Forward DWT: a three-level two-channel iterative filter bank.

Figure 2.5 shows an implementation of a three-level inverse DWT based on a two-channel recursive filter bank, where \( \tilde{h}_0(n) \) and \( \tilde{h}_1(n) \) are low-pass and high-pass synthesis filters, respectively, and the block ↑ 2 represents the up sampling operator by a factor of 2. The four subband signals \( C_3(n), d_3(n), d_2(n), \) and \( d_1(n) \), are recursively combined to reconstruct the output signal \( \tilde{x}(n) \). The four finite impulse response filters satisfy the following relationships:

\[ h_1(n) = (-1)^n h_0(L + 1 - n) \]
\[ \tilde{h}_0(n) = h_0(L + 1 - n) \]
\[ \tilde{h}_1(n) = (-1)^{n-1} h_0(L + 1 - n) \]

where \( L \) is the length of filters, and \( n = 1, 2, \ldots, L \). So that the output of the inverse DWT is identical to the input of the forward DWT.
Figure 2.5: Inverse DWT: a three-level two-channel iterative filter bank.

There is no absolute way to choose a specific wavelet. However, the choice of wavelet depends upon the type of signal to be analyzed and the application. Wavelet families include Haar, Daubechies (db), Biorthogonal, Coiflets, Symlets, Morlet, Mexican Hat, and Meyer.

2.2.5 Maximal Overlap Discrete Wavelet Transform

The MODWT is a modified version of the DWT. It partitions a signal's energy across detail coefficients and scaling coefficients. If the input data are samples of a function $f(x)$ evaluated at $N$-many time points. The function can be expressed as a linear combination of the scaling function $\phi(x)$ and wavelet $\psi(x)$ at varying scales and translations as:

$$f(x) = \sum_{k=0}^{N-1} c_k 2^{-J_0/2} \phi(2^{J_0} x - k) + \sum_{j=1}^{J_0} f_j (x)$$

(2.40)

where $f_j(x) = \sum_{k=0}^{N-1} 2^{-j} \phi(2^{-j} x - k)$ and $J_0$ is the number of levels of the wavelet decomposition. The first sum is the coarse scale approximation of the signal, and the $f_j(x)$ are the details at successive scales. MODWT returns the $N$-many coefficients $\{c_k\}$ and the $(J_0 \times N)$ — many detail coefficients $\{d_{j,k}\}$ of the expansion.

When taking the MODWT of a signal of length $N$, there are $\text{floor}(\log_2(N))$—many levels of decomposition (by default). Detail coefficients are produced at each level. Scaling coefficients
are returned only for the final level. The MODWT partitions the energy across the various scales and scaling coefficients: $\| X \|^2 = \sum_{j=1}^{J_0} \| W_j \|^2 + \| V_{j_0} \|^2$ where $X$ is the input data, $W_j$ are the detail coefficients at scale $j$, and $V_{j_0}$ are the final-level scaling coefficients.

2.2.6 Multiresolution Analysis of the Discrete Wavelet Transform

The MODWTMRA projects a signal onto wavelet subspaces and a scaling subspace. This multiresolution analysis enables the detection of patterns that are not visible in the raw data. MODWTMRA returns the function $f(x)$ projections onto the various wavelet subspaces and final scaling space. That is, MODWTMRA returns

$$\sum_{k=0}^{N-1} c_k 2^{-j_0/2} \phi(2^{-j_0}x - k)$$

(2.41)

and the $J_0$-many $\{f_j(x)\}$ evaluated at $N$-many time points. Each row in multiresolution analysis is a $f(x)$ projection onto a different subspace. This means the original signal can be recovered by adding all the projections because they are orthogonal or nearly orthogonal.

2.3 Performance Evaluation Metrics

2.3.1 Sensitivity and Positive Predictive Value

When evaluating the results of a diagnostic test, it is important to understand how reliable the results obtained from it are. This can be achieved by using sensitivity (SE), positive predictive value (PPV), and their harmonic mean (F1).

SE is a parameter that measures the proportion of genuinely positive that give a positive samples that give a positive result using the test in question. SE is the proportion of true positives ($TP$) divided by the sum of $TP$ and false negatives ($FN$). The following equation is used to calculate the sensitivity of a test:
\[ SE = \frac{TP}{TP+FN} \]  \hspace{1cm} (2.42)

PPV is a parameter that measures the probability that a sample that returns a positive result is really positive. PPV is the proportion of \( TP \) divided by the sum of \( TP \) and false positives \( (FP) \), which is:

\[ PPV = \frac{TP}{TP+FP} \]  \hspace{1cm} (2.43)

F1 is the harmonic mean between PPV (precision) and SE (recall). It is used as a statistical measure to rate performance. The higher the PPV and SE, the higher the F1 score. The F1 score ranges between 0 and 1; the closer it is to 1, the better the model. It is defined as:

\[ F1 = \frac{2 \cdot PPV \cdot SE}{PPV + SE} \]  \hspace{1cm} (2.44)
Chapter 3: Methodology

A method for fECG extraction and automatic detection of P-wave that can be used in the diagnosis of fetal arrhythmia using non-invasive ECG recordings is presented in this chapter. The overall sequential multistep methodology used in this study is illustrated in Figure 3.1.

Figure 3.1: Methodology.

3.1 Materials

3.1.1 Database

An essential component to achieving the objectives of this research is the use of high-quality representative data. Real aECG signals under normal and arrhythmic conditions are used. The characteristics of each of the databases are described below.

The first database (DB1) consists of the real abdominal ECG recordings used in the PhysioNet CinC Challenge 2013 [6]. This dataset consists of a collection of 75 records of one-minute long aECG recordings. Each record includes four channels of maternal abdominal ECG sampled at 1 KHz.
The second database (DB2) consists of the Non-invasive Fetal ECG Arrhythmia Database from Physionet [1]. This database provides a series of recordings of fetal arrhythmia (n=12) and a number of control normal rhythm recordings (n=14) performed using the non-invasive fetal electrocardiography technique. Each recording contains a set of four or five abdominal channels and one chest maternal channel sampled at 500 Hz or 1 kHz of 10-13 minutes duration.

For the third database (DB3), the Abdominal and Direct Fetal Electrocardiogram Database from Physionet is used [43]. For this database, fECG recordings were obtained from five women in labor, between 38 and 41 weeks of gestation. Each recording comprises four differential signals acquired from the maternal abdomen and one direct ECG recorded from the fetal head.

### 3.1.1 Instruments

The specifications of the device and the software used to develop the algorithms for this study are as follows:

**Device Specifications**

<table>
<thead>
<tr>
<th>Device</th>
<th>Dell LATITUDE E6410</th>
</tr>
</thead>
<tbody>
<tr>
<td>Processor</td>
<td>Intel(R) Core(TM) i5 CPU M 580 @ 2.67GHz 2.67 GHz</td>
</tr>
<tr>
<td>Installed RAM</td>
<td>8.00 GB (7.86 GB usable)</td>
</tr>
<tr>
<td>Product ID</td>
<td>00329-00000-00003-AA055</td>
</tr>
<tr>
<td>System type</td>
<td>64-bit operating system, x64-based processor</td>
</tr>
</tbody>
</table>

**Operative System Specifications**

<table>
<thead>
<tr>
<th>Operative System</th>
<th>Windows 10 Enterprise</th>
</tr>
</thead>
<tbody>
<tr>
<td>Version</td>
<td>20H2</td>
</tr>
<tr>
<td>OS build</td>
<td>19042.1706</td>
</tr>
</tbody>
</table>
Software
MATLAB R2021a

3.2 Fetal ECG Extraction

The overall sequential multistep fECG extraction method developed here (NFastICA-TS-NFastICA) is illustrated in Figure 3.2. Four aECG channels are first pre-processed to remove impulsive artifacts, baseline wandering, and power line interference. Then, the mECG is extracted from each channel through a negentropy-based ICA. The component with the best maternal QRS is selected. Then, the mECG is estimated through weighted SVD and canceled from each channel. A second negentropy-based ICA is applied to the residual signals to enhance fECG. Finally, the component with the best fetal QRS annotations is denoised by wavelet transform to improve the performance of the algorithm.

![Diagram of the fetal ECG extraction algorithm](image)

Figure 3.2: Step-by-step illustration of the fetal ECG extraction algorithm.

3.2.1 Pre-processing

As mentioned in chapter 2, section 2.1.3, non-invasive fECG signals contain significant interferences and noise sources. For an accurate extraction of the fECG, a clean aECG signal is of
great importance. As the electrodes are sensitive to minimal electrical changes, internal or external sources can easily produce noise, which may lead to false interpretations. Therefore, before the extraction of the fECG, the aECG channels are preprocessed to remove most of the undesired noise.

A moving median filter (60ms window) is applied to the signal to remove noise with impulsive character. Then, the absolute difference between the original and the median filtered signal is estimated. A threshold value is computed based on the maximum absolute differences. Finally, the ECG signal in each interval, where the absolute difference exceeded this threshold, is replaced with the average of the signal before and after the interval.

To eliminate the baseline wander, the signals are filtered with a high-pass filter. First, a low pass first-order Butterworth filter (cutoff frequency at 5 Hz) is applied in the forward and backward directions to estimate a baseline signal. The detrended signal is the difference between the original and the estimated baseline signal.

Power line interference is removed by applying a notch filter (forward-backward, zero phase, 1 Hz bandwidth) at the detected peak frequency and its following three harmonics. The power spectral density was estimated by the Welch method (averaged windowed periodogram, eight sections with 50% overlap, Hamming window). Then, the existence of a power-line component is assessed by comparing the peak of the power density in a narrow interval around 50 Hz and around 60 Hz with the average power density in the neighbors of such frequencies.

After the removal of all of these sources of noise, the aECG record is prepared for the mECG separation and cancelling. First, each aECG channel is centered by subtracting its mean value. The zero-mean signal is obtained using equation 3.1, where $x$ is denoted as the matrix of the observed mixed sources and $E\{x\}$ the mean from $x$. 

40
\[ x_c = x - E\{x\} \quad (3.1) \]

Then the signals are decorrelated through a whitening procedure. The whitening is performed using the eigenvalue decomposition of the covariance matrix (equation 3.2), where \( V \) is the orthogonal matrix of eigenvectors and \( D \) is the diagonal matrix of its eigenvalues as follows:

\[ E\{x_c x_c^T\} = VDV^T \quad (3.2) \]

Whitening decorrelates and orthogonalizes the original mixtures reducing the number of parameters to estimate. Lastly, a whitened vector is created as follows:

\[ x_w = VD^{-1/2}V^Tx_c \quad (3.3) \]

### 3.2.2 ICA to Separate Maternal ECG

Once the aECG is ready, the mECG is separated from the aECG using ICA. The aECG signals of the datasets consist of four channels, as four electrodes are placed in the maternal abdomen in different locations. Therefore, from equation 2.3, each channel is a weighted sum of the fetal ECG, maternal ECG and noise signals denoted by \( s_1(t) \), \( s_2(t) \), \( s_3(t) \), and \( s_4(t) \):

\[
\begin{align*}
    x_1(t) &= a_{11}s_1 + a_{12}s_2 + a_{13}s_3 + a_{14}s_4 \quad (3.4) \\
    x_2(t) &= a_{21}s_1 + a_{22}s_2 + a_{23}s_3 + a_{24}s_4 \quad (3.5) \\
    x_3(t) &= a_{31}s_1 + a_{32}s_2 + a_{33}s_3 + a_{34}s_4 \quad (3.6) \\
    x_4(t) &= a_{41}s_1 + a_{42}s_2 + a_{43}s_3 + a_{44}s_4 \quad (3.7)
\end{align*}
\]

where \( a_{11}, a_{12}, a_{13}, \ldots, a_{44} \) are some parameters that depend on the location of the electrodes. ICA is used to estimate the \( a_{ij} \) based on the information of their independence, which allows to separate the source signals \( s_1(t) \), \( s_2(t) \), \( s_3(t) \), and \( s_4(t) \) from their mixtures \( x_1(t), x_2(t), x(t), \) and \( x_4(t) \). It assumes that \( s_1(t), s_2(t), s_3(t), \) and \( s_4(t) \), at each time instant \( t \), are statistically independent.
The ICA model (equation 2.4), drops the time index $t$ and assumes that each mixture $x_j$ as well as each independent component $s_k$ is a random variable instead of a proper time signal.

$$x_1 = a_{11}s_1 + a_{12}s_2 + a_{13}s_3 + a_{14}s_4$$  \hspace{1cm} (3.8)

$$x_2 = a_{21}s_1 + a_{22}s_2 + a_{23}s_3 + a_{24}s_4$$  \hspace{1cm} (3.9)

$$x_3 = a_{31}s_1 + a_{32}s_2 + a_{33}s_3 + a_{34}s_4$$  \hspace{1cm} (3.10)

$$x_4 = a_{41}s_1 + a_{42}s_2 + a_{43}s_3 + a_{44}s_4$$  \hspace{1cm} (3.11)

The starting point for ICA is the assumption that the components $s_i$ are statistically independent (generated by unrelated processes). It is also assumed that the independent components must have a non-Gaussian distribution. The independent components are obtained by estimating $W$, the inverse of matrix $A$ (equation 2.5). The approximation of negentropy is calculated using equation 2.11, with the non-quadratic function $G$ described in equation 2.13.

The FastICA is performed based on a fixed-point iteration scheme for finding a maximum of the non-Gaussianity of $w^Tx$. To estimate the independent components, the following steps are followed to estimate each of the independent components (four in this case):

1. A weight vector $w$ is selected randomly
2. The fixed-point iteration is performed using equation 3.12, where $g$ and $g'$ are the first and second derivative of the contrast function $G$ (equations 3.13 and 3.14).

$$w^+ = E\{xg(w^Tx)\} - E\{g'(w^Tx)\}w$$  \hspace{1cm} (3.12)

$$g(u) = u\exp(-u^2/2)$$  \hspace{1cm} (3.13)

$$g'(u) = (1 - u^2)\exp(-u^2/2)$$  \hspace{1cm} (3.14)
3. Standardization,

\[ w_{K+1} = w_k / \|w_k\| \]  

(3.15)

4. If there is no convergence, steps are repeated from step 2 to here.

Note that convergence means that the old and new values of \( w \) point in the same direction. To prevent different vectors from converging to the same maxima, the outputs are decorrelated after every iteration through whitening (equation 3.3). The independent components are given by equation 2.5.

3.2.3 Approximation of Maternal ECG

After separating the mECG from the other components through ICA, the independent component with the best mECG is selected. The selection of this mECG is based on a priori knowledge of the QRS complex pseudo periodicity. To get a precise time location of the mQRS, all four independent components obtained from the ICA are upsampled from 1 to 4 KHz with the Fast Fourier Transform (FFT) interpolation. This is accomplished by computing the FFT of the signal to produce its frequency domain samples. Next, zero-valued samples are stuffed to the beginning and the end of the original signal transform to yield a 4-fold zero-padded FFT. Then the inverse FFT is performed to obtain the interpolated signal corresponding to a 4 KHz sampling rate.

A derivative filter is applied to each IC to enhance the mQRS with respect to the fQRS. Considering that the maternal heart rate is between 70 to 140 bits per minute (bpm), at least one mQRS complex should occur in a 1 sec wide window. However, in some instances, the fECG is of comparable amplitude to the mECG; therefore, a window of 0.2 sec wide should not have more than one mQRS. Random artifacts can occur in some 8 sec wide windows but only a few in 1 sec wide windows. These observations are used to estimate a signal quality indicator (SQI) from the derivative signals to identify the component with the best mECG (higher SQI):
\[
SNI = \frac{md1}{md02 + md8}
\] (3.16)

where \(md02, md1, md8\) are the average of maximum derivatives \((md)\) on windows of 0.2, 1, and 8 sec respectively.

The maternal QRS detection is performed on the selected best ICA component. The maternal QRS complexes are detected with the implementation of PTA. First, the signal passes through a 5-15 Hz digital band-pass filter composed of cascaded high-pass and low-pass filters to increase the SNR. Then, a derivative filter is applied to the signal to acquire information about the slope of the QRS. In addition, a squaring process is applied to intensify the slope of the frequency response curve of the derivative and help restrict the false positives caused by T-waves with higher than usual spectral energies. Lastly, a 150 ms moving window integrator is applied to produce a signal that includes information about the slope and width of the QRS complex. To detect a QRS complex, the local peaks of the integrated signal are found. Mathworks provides a complete MATLAB PTA implementation [60].

### 3.2.4 Cancellation of Maternal ECG

The mECG is cancelled from each independent component through Varanini’s method. Each mECG beat is approximated by PCA implemented by SVD. First, a trapezoidal window is used to select and weigh the signal around each detected maternal QRS. These weighted PQRST segments represent the columns of a matrix \(X\) of dimension \(nd \times nq\) where \(nd\) is the length of the PQRST segments and \(nq\) is the number of maternal QRSs. Then matrix \(X\) is decomposed by SVD as follows:

\[
X = USV^T
\] (3.17)
where $S$ is the diagonal matrix of the singular values, $U$ and $V$ are the unitary matrices of the left and right singular vectors, respectively. The first columns of the matrix $U$, corresponds to the first eigenvectors, giving the largest contribution to covariance, representation of the maternal PQRST waves. The matrix $X_r$ (containing the PQRST waves) is then rebuilt using the first three singular vectors (SVD truncation) as follows:

$$X_r = U_r S_r V_r^T$$

where $S_r$ is the diagonal matrix of the first three singular values, and $U_r$ and $V_r$ are the matrices of the first three left and right singular vectors, respectively. Experiments were performed using more singular vectors; however, the estimated PQRST segments contain more high-frequency noise. The estimated maternal PQRST segments are then unweighted by the trapezoidal window and connected with a straight line obtaining an approximation of the mECG. Lastly, the estimated mECG is subtracted from each of the independent components.

### 3.2.5 ICA to Separate Fetal ECG

After the mECG is cancelled from each independent component, a second ICA is applied to the residual signals to separate the fECG from the other components. The FastICA algorithm applied for fECG extraction is the same as described for mECG extraction (section 3.2.2).

The selection of a fECG component is based on *a priori* knowledge of typical FHR values (between 110 and 160 bpm). The fetal QRS is detected in the resultant independent components with the implementation of a PTA adaptation for fECG. This adaptation is conceptually equal to the original PTA but with different parameters. A bandpass filtering between 9 and 27 Hz and a moving-window integration performed over an 80 ms window are found to be adequate for fetal QRS detection [61]. These parameters are calculated by assuming that the mean FHR is about 1.8 times the mean adult heart rate. Finally, the best fECG is selected based on the number of detected
fetal QRSs and the number of detected fQRSs matching maternal QRSs. Then the selected signal is denoised by wavelet transform to enhance the fECG.

### 3.2.6 Enhancement of Fetal ECG

The separated fECG signal contains a certain amount of noise, including frequency interference, baseline drift, and random noise. Therefore, the selected independent component is denoised by wavelet transform to enhance the fECG. Because wavelets localize features in the data to different scales, important signal features can be preserved while removing noise. The basic idea behind wavelet denoising, or wavelet thresholding, is that the wavelet transform leads to a sparse signal representation. This means is that the wavelet transform concentrates signal features in a few large-magnitude wavelet coefficients. Wavelet coefficients that are small in value are typically noise and they can be shrunk or removed without affecting the signal quality. After thresholding the coefficients, the data is reconstructed using the inverse wavelet transform.

The most general model for the sampled noisy signal has the following form:

\[
s(n) = f(n) + \sigma e(n)
\]  

(3.19)

where time \( n \) is an integer. In the simplest model, \( e(n) \) is Gaussian white noise \( N(0, I) \), and the noise level is \( \sigma \). The denoising objective is to suppress the signal’s noise part of the signal \( s \) and to recover \( f \).

The denoising procedure has three steps:

1. **Decomposition** — Where mother wavelet and level \( N \) are selected. The wavelet decomposition of the signal \( s \) at level \( N \) is computed.
2. Detail coefficients thresholding — For each level from 1 to \( N \), a threshold is selected, and soft thresholding to the detail coefficients is applied. The soft thresholding is:

\[
n(x) = \begin{cases} 
    x - T & x > T \\
    0 & |x| \leq T \\
    x + T & x < -T 
\end{cases}
\]

(3.20)

3. Reconstruction — Wavelet reconstruction based on the original approximation coefficients of level \( N \) and the modified detail coefficients of levels from 1 to \( N \) is computed.

In this case, the fECG signal is denoised by wavelet function Symlet 8, level 8, with a soft threshold and a rigorous denoising method (Stein’s unbiased risk estimator). The symlets are nearly symmetrical wavelets proposed by Daubechies as modifications to the db family. Also, this wavelet shows similarity with the QRS-complex and its energy spectrum is concentrated around low frequencies. The Stein’s unbiased risk estimator method (SURE), uses a threshold selection rule based on Stein’s Unbiased Estimate of Risk (quadratic loss function). One gets an estimate of the risk for a particular threshold value (\( t \)). Minimizing the risks in (\( t \)) gives a selection of the threshold value.

![Figure 3.3: Symlet 8 mother wavelet.](image)
3.3 Annotation of Fetal ECG Signals

After the extraction of the $f$ECG from the abdominal recordings, the fetal P-waves of 10 randomly selected records from DB1 and the 12 records with arrhythmia from DB2 were annotated by an expert. Everything was conducted manually without the use of automated software. To facilitate the work of the ECG expert, the plotted signal in Matlab was used for manual marking of P-waves. The expert annotated only the P-waves that are clearly visible by eye and not hidden in the T-waves or in the QRS complexes. The saved position corresponds to the peaks of P-waves (positive or negative).

Additionally, for DB3, the five direct $f$ECG records were similarly annotated. Everything was conducted manually without the use of automated software. The saved positions correspond to the peaks of P-waves (either positive or negative P waves). The annotations are meant to be used as a reference for testing the algorithm designed to automatically detect visible P-waves.

The Physionet database provides the reference of the exact locations of the fQRS complexes, which enables the assessment of both fQRS detection accuracy and the extraction method’s ability to preserve fECG’s morphological features.

3.4 Fetal P-Wave Detection

For the identification of the P-waves on the ECG signal, the feature extraction via Maximal Overlap DWT and its Multiresolution Analysis are implemented. First, a MODWT is applied to the $f$ECG using the Daubechies least-asymmetric wavelet with six vanishing moments (symlet 6) at level 6. Then, a multiresolution analysis based on the resultant MODWT using symlet 6 at level 6 is estimated to enhance the P-waves.
A peak finding algorithm (findpeaks) is applied to the level 5 details to identify the location of all the peaks. As the R-peaks were previously located, they are taken as a reference to locate the first P-wave visually. Once the location of the first P-wave is introduced, the algorithm locates the rest of the P-waves on the ECG.

![Waveform](image)

Figure 3.4: Symlet 6 mother wavelet.

### 3.5 Arrhythmia Diagnosis

An expert analyzed the extracted non-invasive abdominal ECG records from DB2. The following rhythm disorders are recognized in the dataset: premature atrial contractions, supraventricular tachycardia, irregular atrial rhythm, and sinus arrhythmia. The detailed diagnosis information of the extracted fECG is given in Table 3.1.

<table>
<thead>
<tr>
<th>Record</th>
<th>Arrhythmia diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARR 1</td>
<td>Premature atrial contractions</td>
</tr>
<tr>
<td>ARR 2</td>
<td>Atrial bradycardia</td>
</tr>
<tr>
<td>ARR 3</td>
<td>Premature atrial contractions</td>
</tr>
<tr>
<td>ARR 4</td>
<td>Sinus arrhythmia</td>
</tr>
<tr>
<td>ARR 5</td>
<td>Sinus arrhythmia</td>
</tr>
<tr>
<td>ARR 6</td>
<td>SV tachycardia</td>
</tr>
<tr>
<td>ARR 7</td>
<td>Sinus arrhythmia</td>
</tr>
</tbody>
</table>

Table 3.1: Details of non-invasive fetal ECG arrhythmia database.
Chapter 4: Results

The previous chapter describes a fECG extraction for non-invasive fECG and a P-wave identification method. This chapter presents the results obtained by evaluating and comparing different extraction methods and arrhythmia diagnosis techniques using evaluation criteria such as SE, PPV, and F1 score.

4.1 Fetal ECG Extraction Results

The proposed fECG extraction methodology described in chapter 3, section 3.2, was tested on DB1, the Physionet Computing in Cardiology Challenge 2013 dataset. Figures 4.1 to 4.5 present the results of the proposed multistep fECG extraction method (Figure 3.2) applied to record a23.

For an accurate extraction of the fECG, a clean aECG signal is of great importance. As the electrodes are sensitive to minimal electrical changes, internal or external sources can easily produce noise, which may lead to false interpretations. Therefore, before the extraction of the fECG, the aECG channels are pre-processed to remove most of the undesired noise. Figure 4.1 shows a 6 second (sec) length interval selected from record a23 before and after the pre-processing.
Figure 4.1: Fetal ECG signal before (top) and after (bottom) pre-processing applied to record a23 from the Physionet Computing in Cardiology Challenge 2013 dataset [6].

After the data have been pre-processed, the ICA is applied to separate the maternal and fetal ECGs from the abdominal recordings. Figures 4.2 shows 6 sec length intervals from record a23 where fetal and maternal QRS-peaks are visible.

Figure 4.2: Abdominal ECG, 6 sec intervals from record a23.
Figure 4.3 shows the 6 sec length intervals from Figure 4.2 after the ICA is applied to separate mE CG from the rest of the components. The first and third independent components (IC1 and IC3) have the most resemblance with the mE CG, while the second component (IC2) contains mixed maternal and fetal ECGs, and the fourth component (IC4) contains mostly noise.

After the mE CG is canceled from each independent component, a second ICA is applied to the residual signals. Figure 4.4 shows the resulting signals from the ICA application. Based on the number of detected fetal QRSs and the number of detected fQRSs matching maternal QRSs, the second independent component (IC2) contains the best fECG.
Figure 4.4: Independent components resulting from the ICA after maternal ECG cancellation.

The second independent component is denoised using wavelets. Figure 4.5 shows the noisy fECG and the fECG after wavelet denoising. The use of wavelet denoising attenuates the high-frequency noise. From Figure 4.5, it can be seen that the mECG is suppressed from the abdominal recordings, and that fetal QRS and P waves can be identified from the resulting fECG.

Figure 4.5: Fetal ECG signal before (top, blue) and after (bottom) wavelet denoising.
4.1.1 Performance Evaluation

A subset of 68 records from the Physionet Computing in Cardiology Challenge of 2013 dataset (DB1) is selected, excluding poorly annotated records (a18, a38, a42, a54, a71, a74, and a75). The performance of the fECG extraction method for DB1 is evaluated with SE, PPV, and F1 score.

The performance of the algorithm is measured based on QRS-complex detection. Sensitivity, positive predictive value, and F1 score using equations 2.42, 2.43, and 2.44, respectively are estimated. In this particular case, TP refers to correctly identified fQRS complexes, FN refers to the missed fQRS detections, and FP refers to the falsely detected fQRS complexes. A detected fQRS is considered a true positive within 50 ms from the reference annotation, as suggested in [7, 9].

For this study, SE refers to the proportion of fQRS complexes that are correctly identified. PPV refers to the estimated probability that the identified fQRS complexes correspond with the true fQRS complexes in the reference signal. F1 assesses the accuracy of the detected fQRS compared with the positions of the annotated fQRS.

The performance of the extraction algorithm on the selected 68 records from DB1 was $SE = 97.4\%, PPV = 97.2\%$, and F1=97.29\%. A sensitivity of 97.4\% tells that the algorithm is successful at finding the true fetal QRS. A positive predictive value of 97.2\% tells that the algorithm successful identifies true fetal QRS out of all the detections it makes.

Comparing the results obtained from the proposed method in this study (NFastICA-TS-NFastICA) with the fECG extraction methods found in the literature, NFastICA-TS-NFastICA showed the highest F1 score. Table 4.1 compares the average F1 score of 12 fECG extraction algorithms. Table 4.1 compares the average F1 score of 12 fECG extraction algorithms. Sarafan
et al, recently compared all these extraction algorithms using the data from the PhysioNet 2013 Challenge [34]. The description of each of the algorithms can be found in chapter 1, section 1.1.

Table 4.1: Average F1 score comparison between different methods.

<table>
<thead>
<tr>
<th>Method</th>
<th>%F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>NFastICA-TS-NFastICA</td>
<td>97.29</td>
</tr>
<tr>
<td>TS-FastICA</td>
<td>92.61</td>
</tr>
<tr>
<td>JADE-TS-JADE</td>
<td>91.56</td>
</tr>
<tr>
<td>TS-JADE</td>
<td>91.16</td>
</tr>
<tr>
<td>TS-RobustICA</td>
<td>90.71</td>
</tr>
<tr>
<td>JADE-TS</td>
<td>90.57</td>
</tr>
<tr>
<td>RobustICA-TS-RobustICA</td>
<td>89.29</td>
</tr>
<tr>
<td>RobustICA-TS</td>
<td>87.43</td>
</tr>
<tr>
<td>FastICA-TS-FastICA</td>
<td>87.07</td>
</tr>
<tr>
<td>TSsc</td>
<td>83.12</td>
</tr>
<tr>
<td>FastICA-TS</td>
<td>82.96</td>
</tr>
<tr>
<td>TS</td>
<td>82.65</td>
</tr>
<tr>
<td>JADE</td>
<td>61.27</td>
</tr>
<tr>
<td>FastICA</td>
<td>60.08</td>
</tr>
<tr>
<td>RobustICA</td>
<td>59.60</td>
</tr>
<tr>
<td>EKF</td>
<td>54.34</td>
</tr>
</tbody>
</table>

4.2 Fetal P-Wave Identification Results

The effectiveness of the P-wave identification is validated with all three datasets, real non-invasive fECG, fetal arrhythmia ECG, and direct fECG. The performance of P-wave identification is measured in terms of SE, PPV, and F1 using equations 2.42, 2.43 and 2.44, respectively.
Sensitivity measures the ability to detect P-waves, whereas PPV tells how good the algorithm is at identifying true P-waves out of all the detections it makes. F1 assesses the accuracy of the detected P-waves compared with the positions of the annotated P-waves. The average SE, PPV, and F1 score for each dataset are presented in Table 4.2.

Table 4.2: P-wave identification performance evaluation.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>%SE</th>
<th>%PPV</th>
<th>%F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>DB1</td>
<td>99.5</td>
<td>98.6</td>
<td>99.04</td>
</tr>
<tr>
<td>DB2</td>
<td>99.4</td>
<td>98.5</td>
<td>98.94</td>
</tr>
<tr>
<td>DB3</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

No related studies were found in the literature; therefore, these results could not be compared with other methods. However, these results indicate that the algorithm succeeds in finding the fetal P-waves.
Chapter 5: Conclusions

The purpose of this chapter is to conclude with the overall results of the study and give an overview of the specific objectives (chapter 1, section 1.4) and how they were achieved. The future work section explains what questions arose from this work, where researchers need to look next, and a recommended direction for future experiments is given.

5.1 Conclusions

This work introduces a novel method for accurate and reliable fECG extraction and P-wave detection, which has been shown to perform successfully in both normal and pathological cases. Unique versions and combinations of signal processing techniques significantly improved the extraction of fECG from non-invasive recordings, which is still a challenging task. The algorithm showed very high performance; therefore, it could be used in clinical practice to monitor fetal well-being.

By accurate automatic detection of P-waves in fECG, this method can potentially improve the diagnostic yield of routine fECG examination and simplify the daily work of perinatal cardiologists. The method may also improve the accuracy of arrhythmia detection by wearable devices. The proposed P-wave detector represents a significant step towards fully automated systems for ECG analysis and diagnosing fetal cardiac arrhythmias.

5.1.2 Overview of the Specific Objectives

Objective 1. To combine the most promising signal processing methods with high performance, as reported in the literature, and to develop a hybrid algorithm to reliably extract fECG signals from abdominal ECG recordings preserving their morphology.
Based on the literature review, a combination of ICA and TS techniques in a hybrid method for fECG extraction might be the most promising direction to accurately estimate fECG morphology. Furthermore, 15 fECG extraction algorithms were compared, and a combination of TS and ICA based on kurtosis showed the highest score [34]. However, the ICA based on negentropy has shown greater precision and robustness than the ICA based on kurtosis [26].

It can be concluded that objective one has been successfully achieved since this study presents a hybrid algorithm to extract fECG from non-invasive abdominal recordings that combines TS and ICA based on negentropy. With this extraction method, the morphology of the ECG is preserved, since the expert could annotate the QRS and P waves from the extracted fECG.

**Objective 2.** To develop a feature extraction algorithm to identify P-waves from normal and arrhythmic fECG signals extracted from aECG recordings.

Among the basic features of the ECG, the P-wave is the most difficult to detect due to its low SNR, interpatient variability, and because during certain types of arrhythmias, the P-wave is not visible or does not respect the normal temporal order of the PQRST complex [42]. However, objective two has been successfully achieved since, in this study, an algorithm based on the multiresolution analysis of maximum overlap DWT for fECG P-wave identification is presented. In addition, the P-wave identification algorithm has been tested in signals under normal and arrhythmic conditions.

**Objective 3.** To quantitatively evaluate the performance of the fECG signal extraction method to prove its effectiveness in preserving the QRS- peak.
The performance of the fECG extraction method has been measured based on the detection of the QRS-peak. Performance metrics such as SE, PPV, and F1 score have been estimated as $SE = 97.4\%$, $PPV = 97.2\%$, and $F1 = 97.29\%$. Therefore, objective three has been successfully achieved.

**Objective 4.** To diagnose the signals with arrhythmia based on the heart rate and the location of the P-wave.

The expert identified premature atrial contractions, supraventricular tachycardia, irregular atrial rhythm, and sinus arrhythmia disorders in the database based on heart rate and P-wave location of fECGs extracted from abdominal recordings. Therefore, it can be concluded that objective four has been achieved.

**Objective 5.** To quantitatively evaluate the performance of the feature extraction method to identify the P-wave.

The performance of the P-wave identification algorithm has been measured based on three different datasets. SE, PPV, and F1 performance metrics have been estimated with average F1 scores of 98.94\%, 99.04\%, and 100\%. Therefore, objective 5 has been successfully achieved.

**5.2 Significance of the Results**

1. This study significantly outperformed current fECG extraction algorithms from non-invasive abdominal ECG recordings.
2. This study provides a method to quantitatively measure whether the fECG extraction algorithm preserves the R-peak and P-wave morphology.
3. This study provides a method to enhance ECG features for application in ECG interpretation.
4. Physionet CinC Challenge 2013 abdominal ECG recordings (DB1) and Physionet non-invasive fetal ECG arrhythmia databases (DB2) were annotated by experts.

5. This study will assist clinicians in diagnosing fetal arrhythmia from aECG recordings.

6. This study allows a complete diagnosis of fetal arrhythmia for timely and correct treatment.

5.2 Future Work

The P-wave identification from non-invasive fECG performed in this study is an important step in diagnosing fetal arrhythmia from ECG. This study demonstrates that a complete diagnosis of arrhythmia is feasible from maternal abdominal ECG recordings.

As a future phase of this study, there is a need to develop a fetal arrhythmia automatic detection and classification method. The following are recommendations to continue to expand on the current research introduced in this work:

1. Create a large non-invasive fECG database with the different types of arrhythmic cases.
2. Test the P-wave detection algorithm to identify the P-wave in all types of arrhythmia.
3. Analyze the morphology of the P-waves in signals with arrhythmia.
4. Define decision rules based on the heart manifestation during arrhythmias in order to improve P-wave detection in pathological signals.
5. Elaborate a computational classification algorithms to distinguish the different arrhythmia types from non-invasive fECG recordings.
References


Curriculum Vitae

Claudia Angel was born and raised in Ciudad Juarez, Chihuahua, Mexico. She holds a B.Sc. degree in Mechatronics Engineering and M.Eng. degree in Manufacturing Engineering, from the University of Ciudad Juarez, Mexico. She has over five years of experience in the Medical Device Manufacturing Industry. She has worked for three top medical device companies: Johnson and Johnson, Cardinal Health and ICU Medical. She has held several positions, each with increasing responsibility, including supervising positions at a senior level. She has also worked in academia as a teaching assistant in the Department of Industrial and Manufacturing Engineering at the University of Ciudad Juarez, Mexico.

In the fall of 2014, she entered the Doctoral Program in Biomedical Engineering at The University of Texas at El Paso. She was awarded a fellowship by the Council of Science and Technology of Mexico (CONACYT) to complete and achieve her doctoral studies. Since 2014, her research interests have been medical devices and biomedical signal processing.

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