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**Blind source separation of fetal ECG using fast independent
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Dedication and Acknowledgements

I dedicate this work to my beloved parents for their endless love, sacrifices, encouragement, and unwavering support throughout my academic journey. I am also deeply grateful to my family, friends, and everyone who believed in me and motivated me to achieve this milestone.

*I would like to express my sincere thanks to Almighty God for granting me the strength and determination to complete this work. My heartfelt gratitude goes to my supervisor, **Dr. Ali KHALFA**, for his valuable guidance, support, and constructive advice throughout this project.*

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Abstract

One of the main challenges in prenatal monitoring is the extraction of non-invasive fetal electrocardiogram (fECG) from maternal abdominal recordings. This thesis compares two different signal processing methods for fECG extraction, Fast Independent Component Analysis (FastICA) and Particle Swarm Optimization (PSO). Both methods are applied to multichannel abdominal recordings of the ADFECGDB (PhysioNet). The performance is measured by SNR, MSE, correlation, true positive rate.

Results show that PSO substantially outperforms FastICA. PSO-based approach is more robust than FastICA for fetal ECG extraction in real-world

Keywords:fECG;FastICA;PSO;SNR;MSE.

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List of Acronyms and Abbreviations

ECG Electrocardiogramme

FECG ECG Fœtal

ECG_m ECG maternel

EQM Erreur Quadratique Moyenne

ICA Analyse en Composantes Indépendantes (Independent Component Analysis)

JADE Joint Approximate Diagonalization of Eigenmatrices

RCF Rythme Cardiaques Fœtal

SAS Séparation Aveugle de Sources

SNR Rapport Signal sur Bruit (Signal to Noise Ratio)

SVD Singular Value Decomposition

General Introduction

General introduction

One of the main concerns in perinatal medicine is the health of the fetus during pregnancy. The fetal electrocardiogram (fECG), one of the non-invasive monitoring techniques, offers a unique perspective on fetal cardiac activity, allowing for heart rate analysis and the identification of hypoxia or acidemia. Nevertheless, signals obtained from non-invasive fECG capture using maternal abdomen electrodes combine the fetal ECG, maternal ECG, electromyographic noise, baseline drift, and power line interference. Reliable extraction is a challenging signal processing task since the fetal component is 10–100 times weaker than the maternal one. making the task of dependable extraction in signal processing challenging. greatly overlap (0.3–100 Hz), which makes classical filtering ineffective. The introduction of Blind Source Separation (BSS) marked a significant advance usage of Blind Source Separation (BSS), which does not require prior knowledge of the mixing process or source signals [1].

For more than thirty years, there has been active research on the non-invasive extraction of fetal electrocardiograms (fECGs) from maternal abdomen recordings. The main challenge is that the abdominal signal is a superposition of the fetal and maternal ECGs, electromyographic noise, baseline drift, power line interference, and instrumentation noise [2].

An averaged maternal QRS complex was removed from the abdominal signal in early methods that relied on adaptive filtering and template subtraction. Although conceptually straightforward, these techniques have residual contamination due to temporal alignment issues and morphological differences in the mother's ECG.

FastICA quick convergence and computational economy have led to its widespread adoption. Nevertheless, initialization, contrast function selection, and the signal-to-noise ratio of the recordings continue to have an impact on its performance. Specifically, when the fetus component is not the greatest non-Gaussian source in the mixture, FastICA can converge to local optima [3]. To address these limitations, recent works have explored hybrid approaches that couple ICA with optimization frameworks. Among these, nature-inspired metaheuristic algorithms have demonstrated promising results in enhancing the unmixing process by adapting separation parameters to the specific characteristics of each recording.

Particle Swarm Optimization (PSO) is a widely studied metaheuristic that has drawn significant interest since its introduction by Kennedy and Eberhart in 1995. Inspired by the collective movement of bird flocks and fish schools, PSO operates by simulating a swarm of particles, each representing a potential solution. PSO explore intricate, high-dimensional

landscapes. Because it doesn't rely on gradient information, the algorithm is particularly useful for non-differentiable or discontinuous optimization problems, often converging efficiently toward high-quality solutions. In the context of fECG extraction, PSO separation toward a solution that maximizes fetal signal quality and minimizes maternal interference.

The main objective of this thesis is to develop and evaluate an fECG extraction system using FastICA and Particle Swarm Optimization. These techniques are applied to multichannel abdominal ECG signals from the Abdominal and Direct Fetal ECG Database (ADFECGDB) available on PhysioNet, which provides synchronized abdominal and direct fetal ECG recordings, enabling a reliable assessment of the system's performance. Simulation was tested on three recordings (r01, r04, r10) using a range of performance measures, including Signal-to-Noise Ratio, Mean Squared Error, and Correlation Coefficient, and True Positive rate. The core of the experimental work lies in comparing standard FastICA against the version enhanced with PSO optimization.

This thesis is built around three main chapters. This general introduction sets the stage, and a general conclusion ties everything together at the end.

Chapter I provides the physiological and clinical background necessary to understand fetal ECG monitoring, including cardiac electrophysiology, the anatomy of the fetal heart, fetomaternal compartments and the challenges of non-invasive signal acquisition.

Chapter II covers the theoretical basis and algorithmic details of the two main methods: the FastICA algorithm and the Particle Swarm Optimization framework, as well as their hybrid integration.

Chapter III describes the experimental setup, the ADFECGDB database, the performance metrics, and provides a detailed analysis and interpretation of the simulation results obtained for both methods in the three test recordings.

Chapter I : Physiological Foundations and Techniques of Fetal ECG

I.1 Introduction

Observing fetal health is crucial for evaluating fetal growth and identifying possible heart irregularities. Various methods have been created for this aim, such as fetal electrocardiography (fECG), fetal phonocardiography (fPCG), fetal echocardiography (fECHO), fetal magnetocardiography (fMCG), and cardiotocography (CTG) [I.1] [I.2] [I.3] [I.4] [I.5] [I.6]. Of these methods, fECG is regarded as one of the most dependable techniques since it captures the electrical activity of the fetal heart and offers important data, including fetal heart rate (FHR) and waveform features. These factors help doctors assess fetal heart development and identify congenital heart defects (CHDs), which rank among the most frequent birth anomalies [I.7]. Changes in FHR might also signal fetal hypoxia and acidemia, conditions that could necessitate immediate medical attention [I.8].

Fetal ECG signals can be obtained through invasive or non-invasive techniques. Though invasive methods can yield high-quality recordings, they may result in discomfort and elevate the infection risk for both the mother and fetus [I.9]. As a result, non-invasive collection has gained greater appeal. Nonetheless, abdominal recordings are often affected by maternal ECG (mECG) and different noise sources, which complicates the extraction of fetal signals.

The retrieval of fECG is typically framed as a Blind Source Separation (BSS) issue, in which the captured abdominal signals consist of combinations of fetal ECG, maternal ECG, and various forms of noise. These disturbances encompass baseline drift, muscle activity, physiological artifacts, thermal noise, electromagnetic interference, and random noise [I.10]. Despite numerous signal processing methods like adaptive filtering, template matching, and wavelet transforms being suggested, precise extraction continues to be challenging due to the overlapping frequency bands of fetal and maternal ECG and the occurrence of other physiological interferences. Additionally, certain traditional methods necessitate reference signals, which are frequently inaccessible in real-world scenarios, driving the adoption of sophisticated BSS techniques for extracting fetal ECG.

I.2. Adult and Fetal cardiac anatomy and physiology:

I.2.1 Electrocardiogram ECG signal

Echocardiography is the visual depiction of the electrical forces generated by the cardiac events that activate the heart. It is the most frequent medical assessment due to being non-

invasive, safe, affordable, and fairly fast. Acquiring the signal and the doctor's diagnosis takes just 10 minutes, yielding extensive information regarding the heart's regular and abnormal physiological condition [I.11]. The electrocardiogram signal exhibits a dynamic range from 1 to 10 mV and a frequency spectrum between 0.05 and 100 Hz. It is regarded as a non-stationary signal with a minimal amplitude, generally between 10 μ V and 5 μ V. The sampling rate fluctuates between 250 and 500 Hz. The ECG signal consists of a series of waves (P, Q, R, S, and T waves), along with several intervals and segments that offer valuable insights into the conduction speed of the electrical impulse in various regions of the heart. Any alteration in the morphology or timing of these parameters signals cardiac irregularities [I.12].

I.2.1.1 Basic principle of the ECG

The ECG (electrocardiogram) is a device utilized to assess the heart's electrical functions. It relies on measuring the electrical currents produced by the heart muscles during their contractions. The ECG includes 12 standard leads, with each supplying data regarding a particular area of the heart. The fundamental aspects of the ECG involve assessing heart rate, examining the P wave, PR interval, QRS complex, T wave, QT interval, and ST segment. These components help identify irregularities in heart rhythm, conduction, heart placement, and issues with blood flow in the coronary arteries [I.13] [I.14].

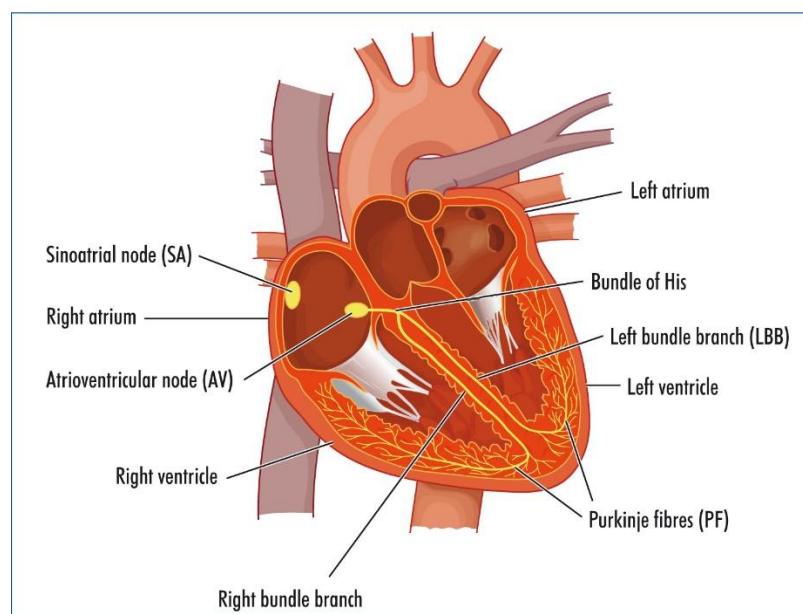


Figure I.1 : Graphical representation of the heart's electrical activity[I.51]

I.2.1.2 Cardiovascular system

The role of the cardiovascular system is to enable blood flow across the body, therefore delivering oxygen and nutrients. This system includes the heart, functioning as a double pump, facilitating circulation in two linked networks: the arteries and the veins. The arterial system carries oxygen-rich blood to the organs, and the venous system aids in returning oxygen-poor blood to the heart. Afterward, the pulmonary arteries transport the blood to the lungs, where it is oxygenated during pulmonary circulation. The venous system serves as the primary blood reservoir, holding around 70% of the total volume, which is about 5 to 6 liters in an adult.



Figure I.2 : Cardiovascular system[I.52].

I.2.1.2.1 Anatomy of the heart

The heart is made up of [I.15] two sides, right and left, along with four valves that ensure blood moves in the correct direction. The left and right sides contain atria (upper chambers) and ventricles (primary pumping chambers). The right atrium collects deoxygenated blood from the organs to the heart through the veins. It guides venous blood into the right ventricle. The blood is transported to the lungs by the right ventricle, where it is oxygenated prior to moving through

the left atrium into the left ventricle. The left atrium is the denser chamber and sends blood into the arteries, allowing it to flow throughout the body. We can similarly sense the resulting pulse in our wrists.

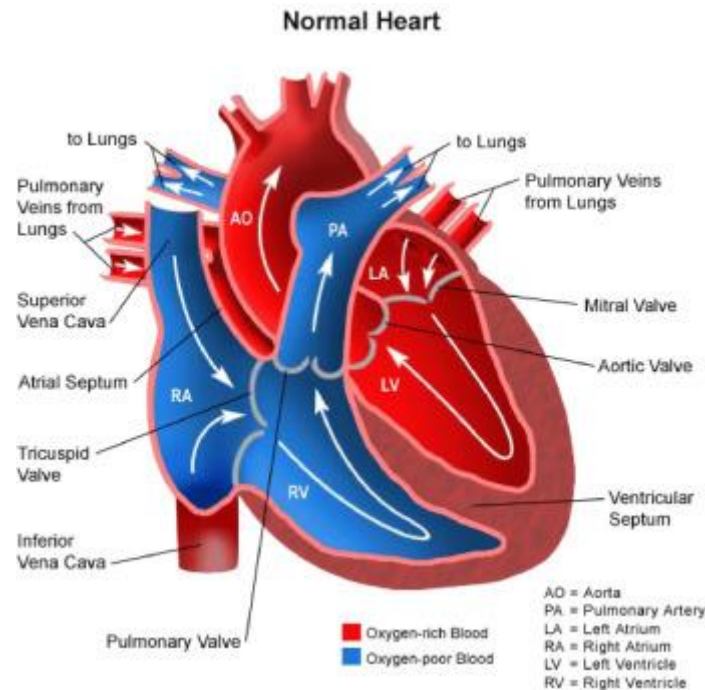


Figure I.3 : Anatomy of the Human Heart[I.53].

I.2.1.2.2 Electrical functioning of the heart

To ensure the heart pumps blood effectively, thousands of cells found in the atria and ventricles (myocytes) must contract at the same time [I.15]. This is amazing.

Coordination is initiated by electrical signals. The sinoatrial node serves as the conductor and is found in the right atrium. The electrical current flows from one cell to the next. It reaches the atrioventricular node, the sole pathway for the current between the atrioventricular nodes. The atria and ventricles are impacted as well. In that location, the electrical signal experiences a short delay, allowing blood to flow into the ventricles. It then moves through its bundle, which is made up of two primary branches, each entering the ventricle. The fibers constituting the bundle, along with Purkinje fibers, transmit the impulses because of their swift conduction. Electricity exists at multiple locations in the ventricle, making it nearly capable of

depolarization. Immediate coverage of the whole ventricular muscle, even given its considerable size, guarantees maximum effectiveness in blood pumping. This contraction represents ventricular systole, succeeded by ventricular diastole (relaxation of the muscle); the muscle fibers repolarize, thereby reverting to their initial state. The cardiac cycle is finished, and the heart is prepared for another heartbeat.

I.2.1.3 ECG Waves

As stated previously, the heart contains specialized cells known as heart rhythm regulatory cells. They generate electricity by swiftly changing a positive charge into a negative charge, or the other way around. A preliminary surge strong enough to initiate a series of subsequent waves arrives at the body's surface. The electrical potentials created by these waves can be recorded if ECG electrodes are positioned on the skin. The horizontal isoelectric line, known as the baseline, signifies no electrical activity throughout the whole ECG graph. It is regarded as a standard. Any curve located above this line is considered a positive curve, whereas any curve underneath it is regarded as a negative curve. The data captured on the electrocardiogram appears as waves and intervals that have defined lengths and heights, repeating in the same sequence with every heartbeat.

The primary readings of the electrocardiogram are typically represented by the letters P, Q, R, S, and ultimately:

- **P wave:** It indicates the electrical current generated during the contraction of the atria. It is often preceded by ventricular complexes (QRS). It is a small, rounded, and positive wave since the atrial muscles are significantly smaller than the ventricular muscles. Its length is around 120 ms and its peak is no more than 0.2 mV.

- **Q wave:** It shows polarization at the location of the His lattice. The initial negative deviation in the QRS complex is a downward wave beneath the isoelectric line. This wave possesses a minor amplitude and may persist for as long as 0.2 seconds.
- **R wave:** denotes the depolarization shifted from the inner ventricles to the exterior. It is an upward wave with a significant amplitude that immediately succeeds the Q wave.
- **S wave:** It signifies the polarization wave of the left-over ventricles. It is a small deflection situated beneath the baseline and represents the second negative component of the QRS complex.
- **T wave:** It signifies the point at which the contraction of the ventricles and depolarization of the cardiac muscle are finished. Because of its gradual end, this positive wave lacks a specific duration. Its amplitude is lower than 2 mV compared to the QRS complex.

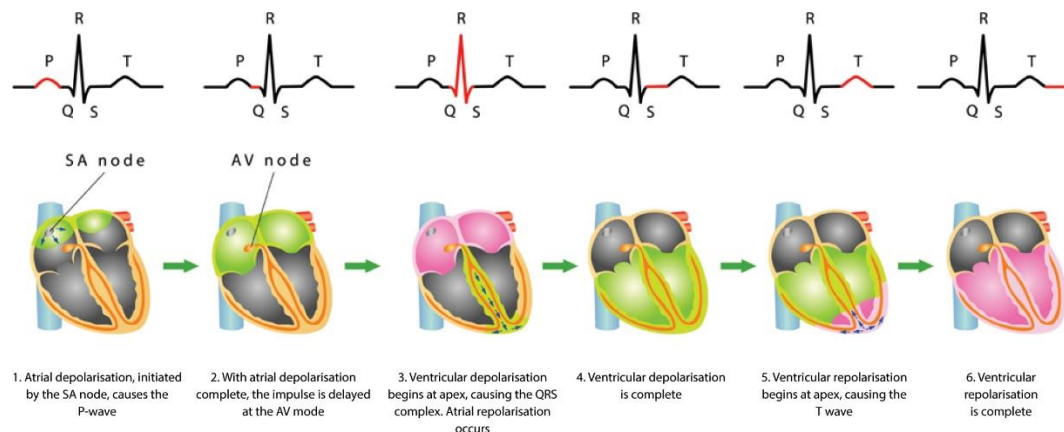


Figure I.4 : Electrical waves of a heartbeat[I.54].

I.2.1.4 ECG time intervals

The various waves (P, Q, R, S, and T) signify the fundamental elements of an electrocardiographic signal. Additionally, these waves are associated with various isoelectric segments and intervals. They hold valuable information that enables tracking the spread rate of

electrical signals in the heart muscle and its normal or abnormal condition. Consequently, the five time intervals PR, QRS, QT, ST, and RR are specified as follows (Figure I.6) [I.16]:

- **PR Interval:** This is a brief isoelectric segment observed from the start of the P wave to the onset of the QRS complex. It indicates the duration required for the electrical signal to travel through the atria, the atrioventricular node, the bundle of His, its branches, and the Purkinje fibers until ventricular activation begins. The duration, based on the heart rate, ranges from 0.012 to 0.021 seconds in middle-aged adults.
- **QRS Complex:** It represents the depolarization of the ventricles. It consists of positive and negative shifts related to the Q, R, and S waves. It is essential in every diagnostic method. Due to its peak amplitude in the ECG, the QRS complex ranges from 5 to 20 mV. The lead facilitates its recognition. In a healthy person, the QRS complex generally lasts from 0.06 to 0.10 seconds. This brief duration signifies the quickness of ventricular depolarization.
- **QT Interval:** It refers to the duration from the beginning of the complex to the conclusion of the T wave. It signifies the duration of stimulation until the ventricular contractions stop. This interval is marked by a length varying from 0.3 to 0.44 seconds.
- **ST segment:** This value indicates the distance from the conclusion of the QRS complex to the onset of the T wave. This is the time when the ventricular cells are completely stimulated. The ST segment is typically flat.
- **RR interval:** This refers to the duration between the R wave of the initial heartbeat and the R wave of the subsequent heartbeat, meaning the time between two consecutive R waves. This period is utilized to assess the heart rate.

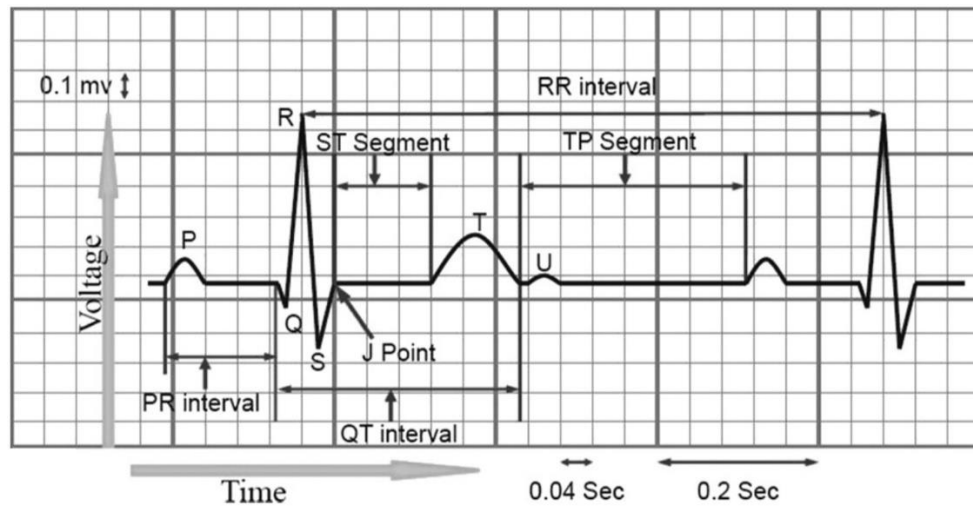


Figure I.5 : ECG Intervals[I.55].

I.2.2 Normal heart rate

Heart rate is a qualitative notion that reflects the occurrence of ventricular contraction. It shifts due to the effects of fear, rage, mental or physical stress, and the body's biological condition.

A typical recorded rhythm is sinusoidal; every P wave appears the same, every QRS complex is uniform, and each P wave is succeeded by a QRS complex. Heart rate and breathing are perfectly aligned for optimal blood flow and oxygen delivery throughout the body. This minimizes energy waste during physical or mental tasks [I.17].

- **Regular heart rhythm:** When no irregularities exist, and the R-R interval remains nearly uniform during the ECG recording with comparable QRS complexes visible, the heart rhythm is deemed regular.
- **Sinus heart rhythm:** This rhythm is referred to as sinus rhythm because the source of the heart's electrical impulses is the sinoatrial node. It features a P wave preceding every QRS complex.

I.2.3 Maternal ECG

Recording abdominal ECG (aECG) presents a highly promising alternative technique that may be utilized for fetal monitoring during pregnancy or the prenatal stage, offering several significant benefits. The method is entirely non-invasive, utilizing merely electrodes placed on the mother's abdomen; the recordings are enduring [I.18]; easy to operate. Nonetheless, aECG is a mixture of signals that includes the maternal ECG (mECG), the fetal ECG (fECG), along with various interferences. There are two primary methods available for examining the fECG signals obtained from the expectant mother:

- A. Extract FHR from the ECG,
- B. Derivation of fECG from aECG the extraction of FHR and fECG from abdominal recordings continues to be a highly intricate challenge.

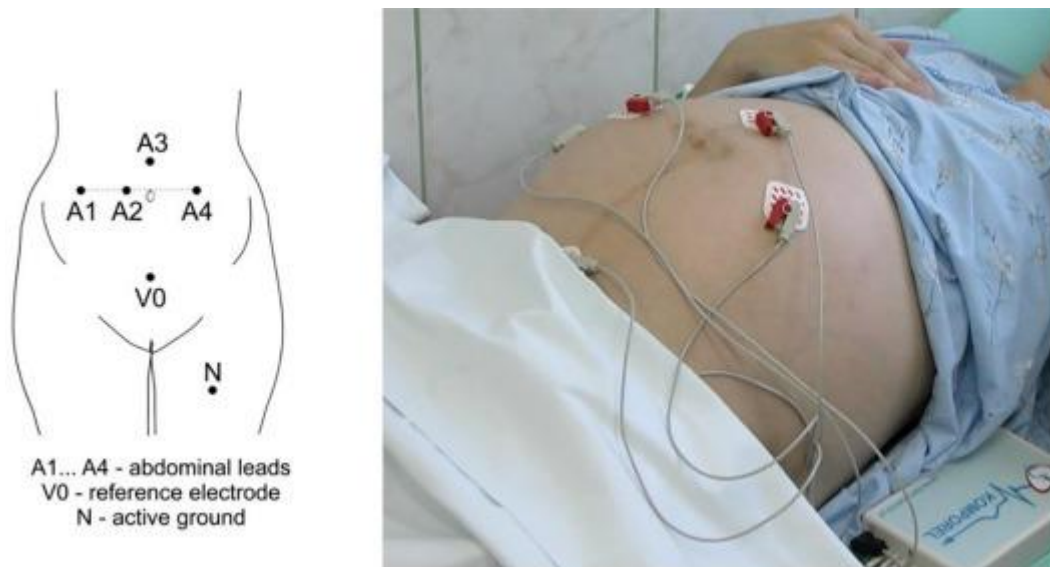


Figure I.6: Abdominal Fetal ECG Recordings[I.56].

I.3 Fetal ECG (fECG)

I.3.1 Fetal Heart Development

The heart is one of the initial organs formed in the fetus and experiences significant growth during the early phases of pregnancy [I.19] (Fig I.7). The crucial phase of this

development occurs between 3 and 7 weeks post-fertilization, as a basic heart tube transforms into a four-chambered heart (Fig I.8).

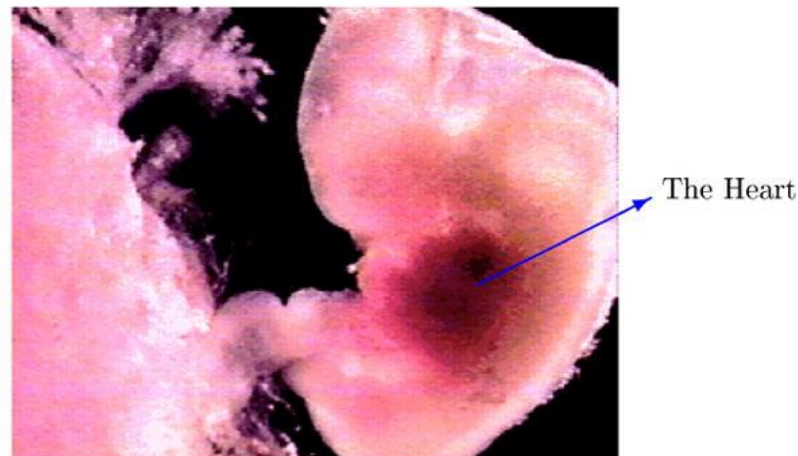


Figure I.7 : Early Fetal Heart Development [I.20].

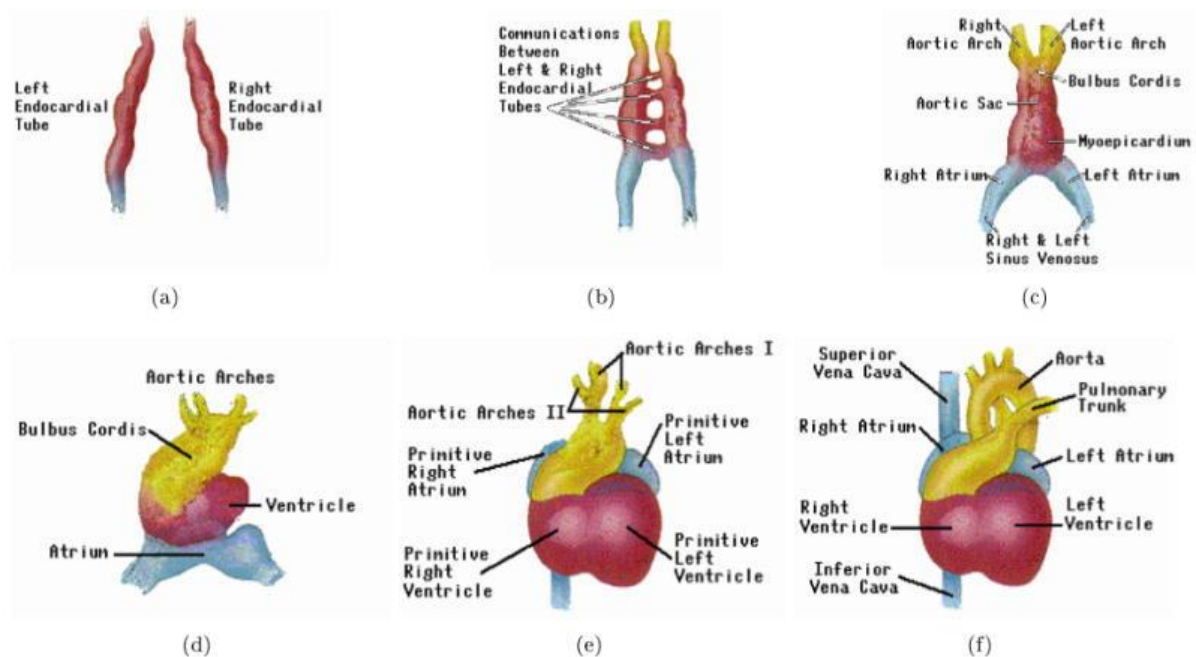


Figure I.8 : Stages of Fetal Heart Development During Gestation [I.20].

It is thought that the heart starts to beat around the 3rd week of life, circulating its own blood through a distinct closed circulatory system with a specific blood type. Soon afterward, the systems for vision, hearing, and breathing start to develop. During the 7th to 9th week, the fetal heart can be externally monitored using ultrasound imaging [I.19]; however, the images

captured at this stage are only unclear. The heart's waveforms and the variability in heart rate from beat to beat cannot be detected through ultrasound imaging. At 20 weeks, the fetal heartbeat is audible without any devices, typically ranging from 120 to 160 beats per minute, but only minimal diagnostic insights can be gained from listening beyond the heart rate.

Consequently, the fECG and MCG, which hold morphological data regarding cardiac activity, have gained significant attention. These signals may be captured from the mother's abdomen as soon as the eighteenth to twentieth week following conception [I.21] [I. 22].

At 6 weeks after fertilization, brain activity can be detected, the skeleton is fully developed, and most reflexes are observable. The embryo measures only around 0.5cm in length, with the head, mouth, liver, and intestines just starting to form. At 12-14 weeks (when the fetus weighs approximately 30g and measures about 7cm), muscle development starts, and spontaneous movements become noticeable, increasing in intensity as it ages.

Fairly late in the pregnancy, at approximately 26 weeks, the fetus starts to breathe in and out. Naturally, the fetus isn't inhaling air and oxygenating its blood through this process. It is believed to assist in the formation of surfactant and stimulate the respiratory system prior to birth. Even though the fetus can survive outside the womb at 23-24 weeks, it would be regarded as being born prematurely, with the typical gestation period being around 40 weeks [I.23]. At 23 weeks, the likelihood of survival outside the womb is merely 15%, increasing to 56% at 24 weeks and reaching 79% at 25 weeks.

I.3.2 Fetomaternal Compartments

Fig I.9 illustrates a basic anatomy of the fetomaternal compartments. Consequently, the fetus is encased by various anatomical layers that exhibit differing electrical conductivities [I.24] [I.25]. The amniotic fluid exhibits the highest conductivity, while the vernix caseosa shows the lowest. Both of these layers encase the fetus entirely.

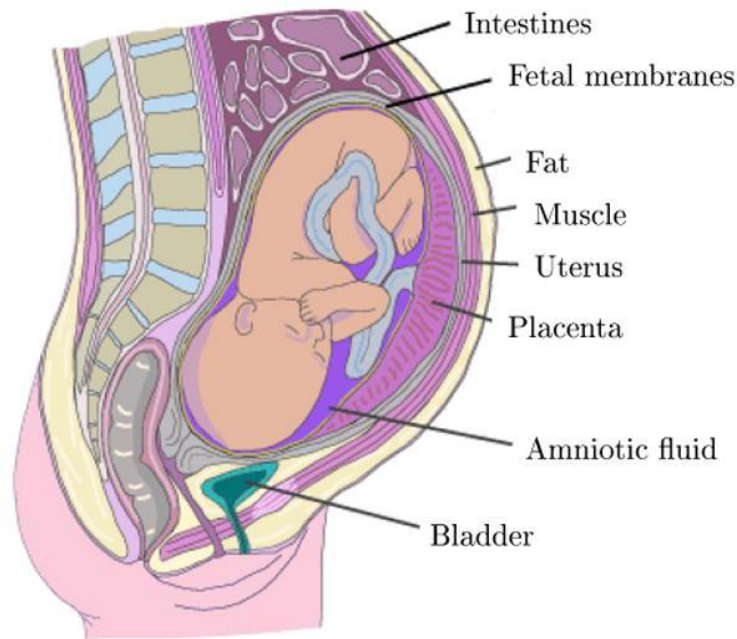


Figure I.9 : Fetomaternal Compartments Influencing Fetal Cardiac Potentials [I.26].

In the compartments of the maternal abdomen, both the skin and subcutaneous fat exhibit low conductivity—approximately ten times less than that of muscle tissue [I.25] [I.26]. Consequently, these two layers, which serve as the boundary between the surface electrodes and the internal tissues, significantly affect the recorded fECG. All these various tissues and layers create a so-called volume conductor, through which the fetal cardiac signals travel to the maternal body surface. This volume conductor is not a constant conductor, and its electrical conductivity and geometric form continually vary during gestation. Particularly, during the latter part of pregnancy (from the 20th week onward), when the ECG and MCG can be captured using external electrodes, it is recognized that the amniotic fluid [I.27] [I.28], the placenta, and the fetus itself [I.29] all expand in volume. The extremely low conductivity layer of vernix caseosa develops between the 28th and 32nd weeks of gestation [I.24] [I.25]. It nearly functions as an electric barrier for the fetus, complicating the recording of surface ECG from it. Nonetheless, in typical pregnancies (non-preterm births), the layer gradually breaks down during the 37th to 38th weeks of gestation [I.26]. In earlier research, various interpretations

have been offered for the fECG signals captured during the final trimester of pregnancy (following the development of the vernix caseosa), depending on favored current routes like the umbilical cord, the oronasal cavity, or even arbitrary openings in the vernix caseosa [26, 27]. The favored current pathway hypothesis, in addition to the inherent limitations of the fECG and its progressive maturation, elucidates certain distinctions between adult fECG and vectorcardiogram configurations.

I.3.3 Fetal Presentations

In the initial two trimesters of pregnancy, the fetus lacks a defined position and is very active. Around the midpoint of the third trimester, the fetus typically positions itself with its head down, referred to as the vertex presentation, which is more suitable for delivery [I.30]. Nonetheless, as illustrated in Figs 10 and 13, the fetus can also adopt alternative, less common presentations. The position of the fetus affects the cardiac signals captured from the maternal body surface across various leads [I.31].

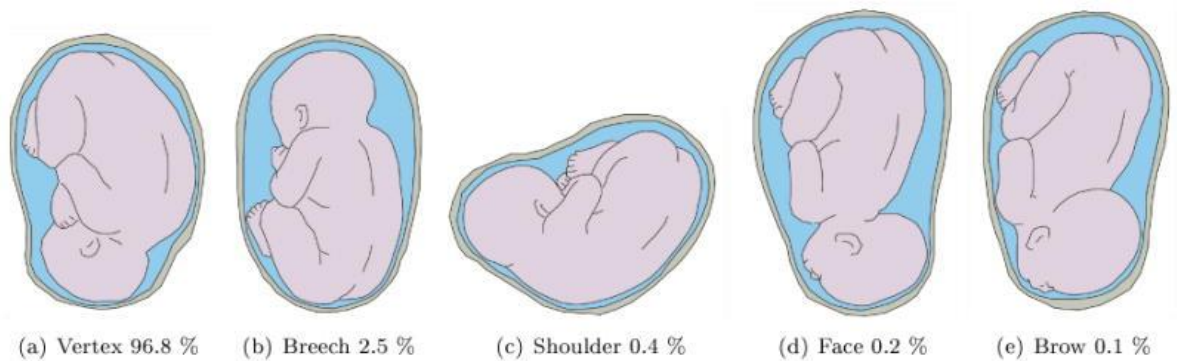


Figure I.10 : Fetal Presentations at Term [I.26].

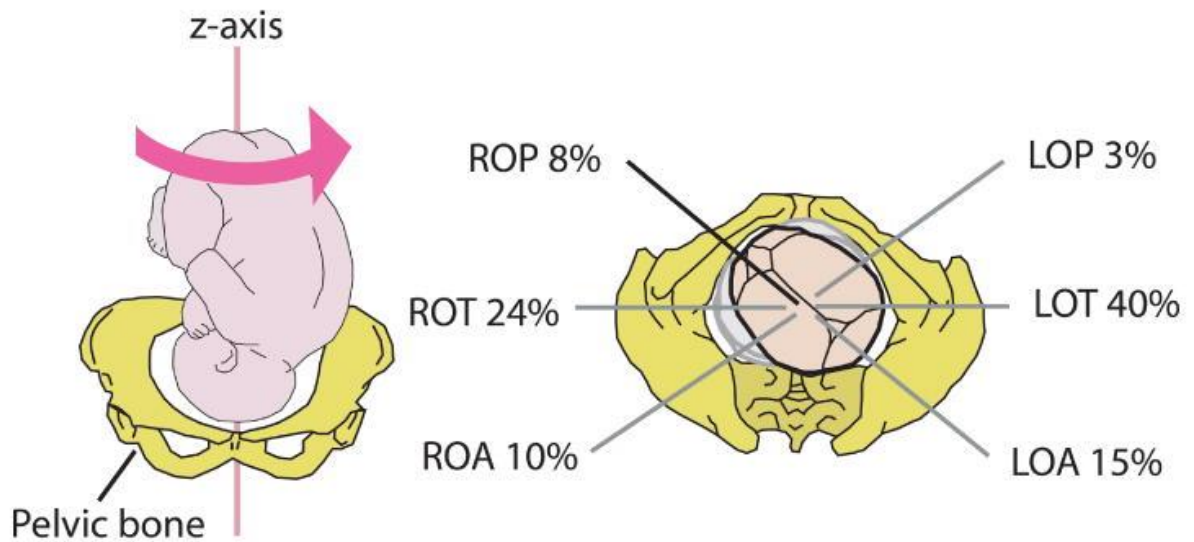


Figure I.11: Fetal Vertex Positions and Incidence at Term [I.26].

I.3.4 Anatomy of the Fetal Heart

Figure 12 illustrates the structure of a fully developed fetal heart. The fetal and adult hearts exhibit several functional differences. After birth, the left ventricle circulates blood throughout the body while the right ventricle sends blood to the lungs to receive oxygen. Nonetheless, for the fetus, oxygen is delivered through the placenta; thus, blood is not circulated to the lungs for this reason. Instead, both ventricles circulate blood around the body (including the lungs) [I.26]. To achieve this, there are two shunts, specifically the foramen ovale and the ductus arteriosus, which connect the exiting vessels of both ventricles. This enables blood to flow into the right atrium and skip the pulmonary circulation. An equivalent adaptation in the fetus is the ductus venosus, a vessel that enables blood to circumvent the liver. It transports oxygen and nutrients from the umbilical cord directly to the right side of the fetal heart [I.32].

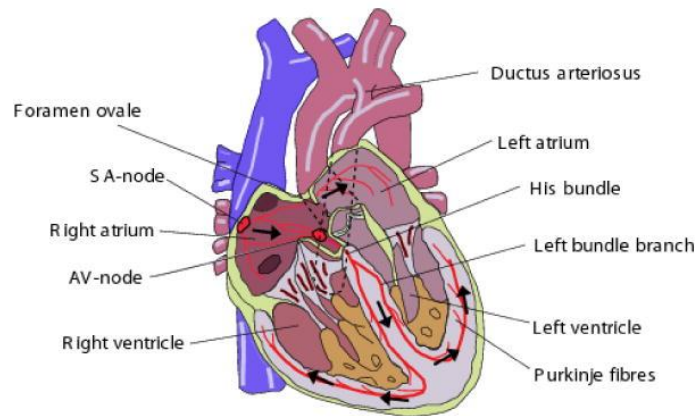


Figure I.12 : The anatomy of the fetal heart ; adapted with permission from [I.26].

Following birth, the foramen ovale seals off with the initial breaths, and the ductus arteriosus partially shuts within 10 to 15 hours post-birth, taking up to three weeks for total closure. The ductus venosus also shuts down shortly after birth, when the umbilical cord is severed and circulation between the mother and fetus ceases [I.32]. Additional slight alterations in the infant's heart and circulatory system physiology occur during the first year following birth.

I.3.5 Electrical Activity of the Fetal Heart

Although the mechanical operation of the fetal heart varies from that of an adult heart, its electrical activity from one beat to the next is quite comparable. The heart's wave-like pumping motion is regulated by a network of neural fibers spread throughout the myocardium, which coordinates its consistent contraction and relaxation [I.33]. The stimulation of the myocardium begins at the sinoatrial node (SA-node), acting as the heart's natural pacemaker. The SA-node is a group of cells found in the upper-right back wall of the right atrium, responsible for initiating the electrical signal that starts each heartbeat. This signal additionally activates the second group of cells, specifically the atrioventricular node. (AV-node) located in the lower back wall of the right atrium. Following the AV-node, the depolarization wave moves into the

bundle of His, the left and right bundles, ultimately reaching the Purkinje fibers, which depolarize the ventricular muscles along the path.

The process of myocardium contraction is referred to as the depolarization (or systole) cycle, succeeded by the repolarization (or diastole) cycle, where the myocardium relaxes and prepares for the subsequent activation. Figure 13 illustrates an entire cardiac cycle.

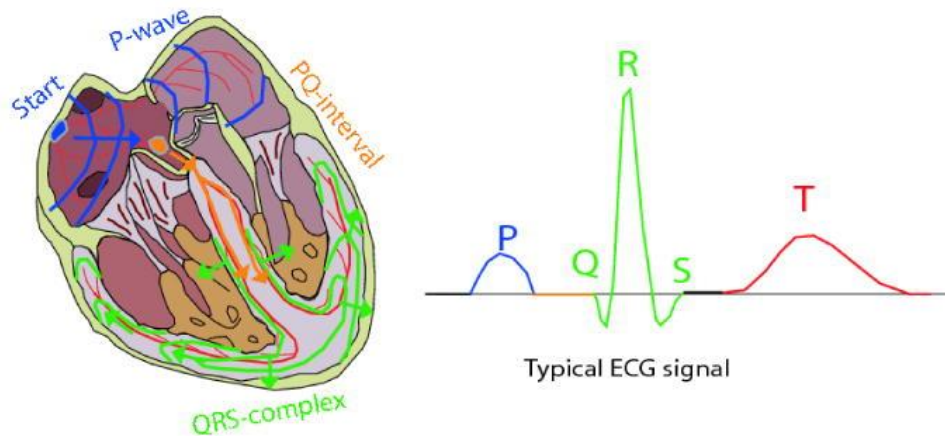


Figure I.13 : The activation cycle of the fetal heart ; adapted with permission from [I.26].

I.3.6 The Electrocardiogram Morphology

The ECG recorded on the body surface originates from the sequential activation of the myocardium and produces the PQRST complex illustrated in Fig 14. This letter notation was initially introduced by Einthoven in 1895 [I.34] [I.35]. In this notation, the P-wave represents the movement of the depolarization front across the atria. In the following 50ms, only faint signals can be detected, as it requires time for the depolarization front to proceed through the AV-node, and due to the limited number of myocardial cells involved in the atrioventricular conduction, the signals are minimal [I.36]. Subsequently, the ventricles undergo depolarization leading to the QRS complex. Simultaneously, the atria undergo repolarization; however, this process is masked by the depolarization occurring in the ventricles. Finally, we encounter the T-wave, which represents the repolarization of the ventricles. In certain measurements, the T-wave is succeeded by a minor wave referred to as the U-wave, which is

thought to result from the repolarization of the His-Purkinje system in a normal ECG [I.35]. Additional theories regarding the source of the U-wave have been proposed in [I.37]. The portion from the conclusion of the U-wave to the onset of the following P-wave is called the isoelectric segment of the ECG, during which there is no detectable activity in the myocardium.

Morphologically, adults and fetuses exhibit quite similar ECG patterns; however, the relative amplitudes of the fetal complexes experience significant changes during gestation and even postnatally. The most significant alteration relates to the T-waves, which tend to be quite weak in fetuses and newborns [I.22].

I.3.7 Fetal Heart Rate and Heart Rate Variability

The alterations in fetal heart rate (FHR) and fetal heart rate variability (FHRV) are not clearly comprehended, especially as the fetal central nervous system may not be completely developed at the time of birth. Despite the absence of a direct neural connection between the mother and fetus, it is believed that maternal actions may influence fetal heart rate and blood pressure indirectly via transmitted hormones (such as cortisol and catecholamines) and possibly through compromised placental blood flow or volume. Additionally, the maternal and fetal heart rates may synchronize, although the underlying mechanism of synchronization remains unclear [I.38]. Generally, the mother and fetus(es) possess distinct autonomic nervous systems that are indirectly connected (mainly with the mother influencing the fetus) via variations in blood pressure and hormones.

At 20 weeks, the fetal heart rate (FHR) typically has a baseline of approximately 120 to 160 beats per minute (BPM). Nonetheless, while the fetal heart rate variations differ from those of children and adults, it is recognized that the FHR has circadian variations that develop throughout pregnancy [I.41]. Structurally, the heart-rate variability (HRV) in the fetus is recognized to be less complex (more stable) compared to that of an adult. Yet, as the fetal

autonomic nervous system develops, the HRV patterns increasingly grow more intricate [I.42] [I.43]. A common instance of this complexity is illustrated in Fig14.

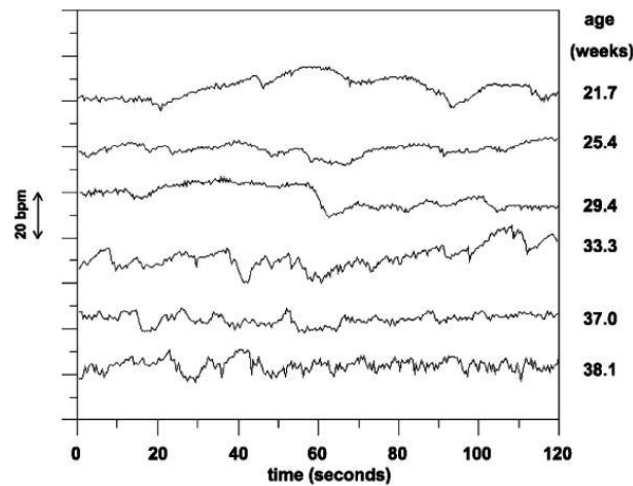


Figure I.14 : Increasing Complexity of Fetal HRV Across Gestational Ages [I.43].

Recently, Muro and colleagues [I.44] conducted FHR recordings at 21, 24, 27, 30, 33, and 36 weeks from a healthy pregnant woman and observed notable diurnal variations across all recorded gestational ages. Additionally, they observed that the degree of daily variation grew with progressing pregnancy. The FHR baseline measured at night (midnight–9:00 hours) notably reduced from 24 to 30 weeks, while the afternoon/evening FHR baseline (15:00–21:00 hours) declined after 27 weeks. These results indicate that the alterations in the daily fluctuations of FHR baseline as gestation progresses represent the development of the fetal nervous system.

Lunshof and colleagues [I.45] indicated that a notable daily variation in basal FHR existed in 73% of their fetal research group, and this pattern was closely linked to the maternal heart rate pattern. They also discovered that daily patterns in FHRV, accelerations, and activity were observed in just 30% to 50% of the fetuses. Lange et al. discovered that FHRV varied with gestational age and average HR or activity levels, but not with gender or time of day.

It is also recognized that the frequency of heart rate accelerations and decelerations per hour that a fetus undergoes may be connected to its health and depends on gestational age. The frequency and length of episodes of sustained fetal tachycardia (SFT)³ rise with gestational age [I.46]. Shono and colleagues [I.46] examined 24-hour FHR in 102 healthy pregnant women (at 30-41 weeks) to identify changes in SFT associated with gestational age. During 38-39 weeks, night-time SFTs (19:00–07:00 hours) occurred significantly more often than during daytime (07:00–19:00 hours). At 30-31 weeks of gestation, there were no notable incidents, but in the 40th week, the frequency and average duration rose to 85% and 114 minutes.

I.3.8 The Diagnostic Fetal ECG

Presently, fECG analysis is predominantly utilized in the clinical field to evaluate heart rate and its related variability. Morphological examination of the fECG is typically not performed for populations with cardiac anomalies due to the following reasons:

- While structural heart defects are the most prevalent type of structural fetal defect, they are uncommon (occurring in under 1% of the population).
- Echocardiography is used to assess structural defects, as the issue is structural rather than conductive.
- There is no proof that structural anomalies exhibit atypical conduction (though this has not been investigated in-utero) or that it would benefit clinical predictive medicine.
- The most prevalent arrhythmia is premature atrial contractions, which are typically harmless.
- Pathologic fetal heart block arrhythmias are very uncommon and typically arise in individuals with systemic lupus erythematosus (SLE).

Current commercial fetal monitoring systems like the STAN monitor examine the fetal ECG by evaluating the relationship between the amplitudes of the R-wave and T-wave, along with variations in the ST segment. These methods assist in identifying fetal hypoxia and intra-partum

acidosis. Nonetheless, these systems depend on a fetal scalp electrode that is applicable solely during labor and captures only a single-channel recording of cardiac activity. As a result, the method is very sensitive to interference and unable to precisely detect minor or localized heart irregularities. These constraints emphasize the significance of multi-channel fetal ECG collection and sophisticated blind source separation methods, including Fast Independent Component Analysis (FastICA) coupled with optimization techniques like Particle Swarm Optimization (PSO), to enhance fetal ECG retrieval and examination.

I.4 Why do we perform an ECG?

A fetal ECG, or fetal electrocardiogram, is conducted to evaluate the cardiac condition of the fetus by detecting the electrical signals generated by its heart. This assessment is essential for tracking fetal health, identifying possible cardiac issues early, and allowing for the initiation of suitable treatments [I.47]. Recent advancements in technology seek to enhance the accessibility of fetal ECG measurement through non-invasive techniques. Nonetheless, this measurement continues to be difficult because of the low signal-to-noise ratio of the signals recorded on the maternal abdomen [I.48].

Innovative methods are being created to extract the fetal ECG signal from the maternal ECG, including the application of Gaussian process modeling along with the Phonocardiogram (PCG) signal to enhance signal extraction in a multimodal database [I.49]. This technique not only facilitates the effective identification of fetal heartbeats but also offers insights into the morphology of the fetal ECG [I.48].

1.5 Extraction of the fECG signal

The fetal ECG is obtained from the maternal abdominal ECG signal. This approach is utilized to simulate maternal and fetal electrocardiogram signals. The raw abdominal ECG channel $x(t)$ is considered to be a combination of maternal ECG $s_m(t)$, fetal ECG $s_f(t)$, and

additional noise (including maternal EMG and/or fetal environmental noise) $n(t)$. In this scenario, the original signal is thus represented as: $n(t)$.

$$X(t) = s_m(t) + s_f(t) + n(t) \quad (I.1)$$

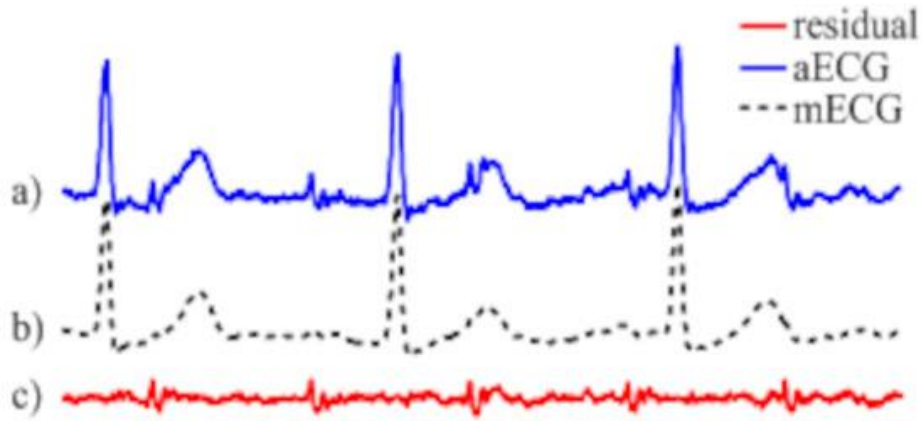


Figure I.15 : Extraction of the fECG signal [I.57].

The noise power $n(t)$ is deemed sufficiently elevated to visually obscure the R peaks of the fetal electrocardiogram.

Figure I.16 presents a standard electrocardiogram with the P, Q, R, S, and T waves indicated. The P wave signifies depolarization. The QRS complex signifies depolarization and contraction of the ventricles. The T wave signifies the end of ventricular repolarization.

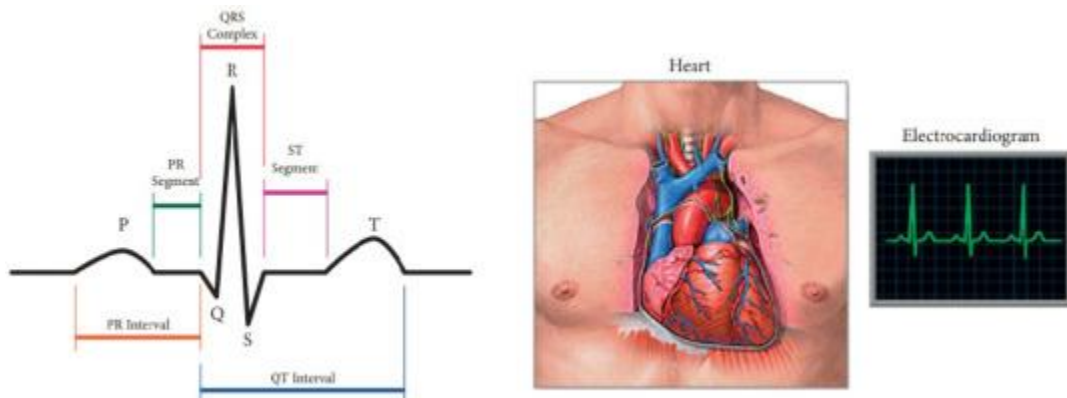


Figure I.16 : Representation of a normal ECG[I.58].

I.6 A particular form of the fECG and the difficulty of its extraction

I.6.1 A specific type of fECG

The fECG readings are collected from scalp electrodes during a timeframe of 36 to 42 weeks [I.49].

Table I.1 : fECG Measurements

Waves	Length	Segment	Length
P	6.5 μ s	P-R	10.4 μ s
QRS	6.6 μ s	S-T	5.7 μ s
T	13.5 μ s	P-T	36.5 μ s

A full-term fetus typically has a heart rate ranging from 110 to 150 beats each minute.

I.6.2. Difficulty in extracting the fECG

Although recording an electrocardiogram on an adult is simpler, obtaining one from a fetus continues to be significantly more challenging. The fetal heart rhythm does not permit the identification of possible conditions [I.50]: the heart's wave structure holds crucial information.

These signals can assist in obstetrics and gynecology to detect the existence of twins or to observe fetal heart activity, especially during labor.

There are two primary techniques utilized. [I.50]. The initial, very efficient technique involves the direct recording of the fetal ECG through an electrode positioned on the baby's head, a method suitable only for use during delivery. I'm sorry, but there seems to be no text provided in your request to paraphrase. Please provide the text you would like me to rephrase. Doctors aim for earlier detection during pregnancy through non-invasive techniques.

The alternative method consists of obtaining the fetal ECG from signals captured by multiple electrodes placed at various spots on the mother's chest and abdomen. The acquired

data consist of combinations of the fetal ECG (FECG) and the mother's ECG (ECGM). Moreover, it is crucial to take into account alternative sources because of the weak intensity of FECG signals: prominent disturbances include the mother's electromyograms (EMG), thermal noise from electrodes and other electronic devices, etc.

I. 7 Conclusion

In this first chapter, we began by presenting the theoretical foundations of electrocardiogram (ECG) signals in general. Subsequently, the different types of ECG signals were also discussed. We then focused on the theoretical study of the fetal electrocardiogram (fECG), due to its importance in monitoring fetal health during pregnancy. At the end of this chapter, we discussed the challenges of extracting the fECG in practical scenarios.

Chapitre II: Techniques fast independent components analysis and particle swarm optimization

II.1 Introduction

Electrocardiogram (ECG) is an important diagnostic tool used to assess the electrical activity of the heart and detect various cardiac abnormalities [II.1]. Similarly, fetal electrocardiography (fECG) provides valuable information about fetal cardiac activity and can be used to identify fetal distress, hypoxia, and congenital heart disorders during pregnancy [II.2]. Early detection of such abnormalities can contribute significantly to reducing neonatal morbidity and mortality.

Fetal ECG signals can be acquired using either invasive or non-invasive methods. The invasive scalp electrode technique provides a relatively clean fetal ECG signal but can only be used during labor and may present risks to both the mother and fetus [II.3]. Consequently, non-invasive abdominal ECG acquisition has become an attractive alternative. This method records electrical signals from electrodes placed on the maternal abdomen, allowing continuous monitoring throughout pregnancy. However, abdominal recordings contain a mixture of fetal ECG, maternal ECG (mECG), muscular activity, respiratory artifacts, and environmental noise. Furthermore, the maternal ECG amplitude is generally much larger than that of the fetal ECG, making signal extraction particularly challenging [II.4].

Several signal processing techniques have been proposed for fetal ECG extraction, including adaptive filtering, wavelet transform, matched filtering, blind source separation (BSS), Independent Component Analysis (ICA), neural networks, and Singular Value Decomposition (SVD) [II.5]. Among these methods, ICA has gained considerable attention because it can separate statistically independent source signals from mixed observations without prior knowledge of the mixing process [II.6].

Fast Independent Component Analysis (FastICA), introduced by Hyvärinen and Oja, is one of the most widely used ICA algorithms due to its computational efficiency and fast convergence properties [II.7]. Nevertheless, FastICA is sensitive to the initialization of the

weight vectors, and inappropriate initial conditions may lead to slow convergence or convergence toward suboptimal solutions.

To overcome these limitations, optimization algorithms have been integrated with ICA-based approaches. Particle Swarm Optimization (PSO), proposed by Kennedy and Eberhart, is a population-based optimization technique inspired by the social behavior of bird flocks and fish schools [II.8]. PSO performs a global search by iteratively updating the position and velocity of particles according to their individual experience and the experience of the swarm. Owing to its simplicity, robustness, and strong global optimization capability, PSO has been successfully applied in biomedical signal processing problems [II.9].

The combination of FastICA and PSO has emerged as an effective approach for fetal ECG extraction. In this hybrid framework, PSO is employed to optimize the initialization parameters or separation vectors of FastICA, thereby improving convergence performance and enhancing source separation accuracy. Consequently, the FastICA-PSO method can provide more reliable fetal ECG extraction, better noise suppression, and improved fetal cardiac monitoring performance [II.10].

This chapter outlines the theoretical basis for extracting fetal ECG through Blind Source Separation methods. It presents the fundamentals of BSS and examines the Fast Independent Component Analysis (FastICA) method utilized for source separation. The chapter additionally introduces Particle Swarm Optimization (PSO) as a method for enhancing the separation process. Ultimately, the approach utilized in this study, encompassing data preparation, signal processing procedures, and performance assessment metrics, is outlined.

II.2 FastICA Algorithm

FastICA is an iterative algorithm that operates using fixed points to minimize mutual information among estimated components [II.11]. The separation of independent components occurs when the peak of non-Gaussianity is reached. Various types of FastICA exist, such as

those utilizing kurtosis, those relying on maximum likelihood, and those using maximum negentropy (MNE), among others. In this paper, the MNE-based FastICA algorithm was employed, which maximized negentropy as a search direction and sequentially extracted each independent source signal. Prior to applying the FastICA algorithm, the observed signal X was centered and whitened. The mean removal procedure was executed to eliminate the mean vector of the signal from the recorded signals, resulting in a zero mean for the observed signal and thereby streamlining the FastICA algorithm. The observation signal underwent whitening through the principal component analysis (PCA) whitening algorithm to ensure that the components post-whitening were uncorrelated. The objective function was set as

$$J(y) \approx \{E[G(y)] - E[G(V)]\}^2, \quad (1)$$

Where $E[\cdot]$ was the expectation operator and V was a Gaussian random variable with zero mean and unit variance. It was assumed that y also had zero mean and unit variance. $G(\cdot)$ was a nonquadratic function. According to the Kuhn-Tucker condition, the optimization of $E\{G(wTx)\}$ could be obtained by (2) under the constraint of $E\{(wTx)^2\} = \|w\|^2 = 1$:

$$E\{xg(wTx)\} - \beta w = 0, \quad (2)$$

where β was a constant and could be obtained by $\beta = E\{w_0^T x g(w_0^T x)\}$, where w_0 was the initial value of w and $g(\cdot)$ was a nonlinear function, which was the derivative of $G(\cdot)$.

We chose the nonlinear function $(y) = y^3$. The Newton iterative method was employed to solve (2). The left part of (2) was denoted as (w) , and the Jacobian matrix $JF(w)$ was

$$JF(w) = E\{xx^T g'(wTx)\} - \beta I \quad (3)$$

In order to simplify the computation of the inverse of the matrix, (3) was approximated. Because the data were whitened, (3) could be simplified as

$$E\{xx^T g'(wTx)\} \approx E\{xx^T\} E\{g'(wTx)\} = E\{g'(wTx)\} I \quad (4)$$

The Jacobin matrix was a diagonal matrix, and its inverse matrix could be simply calculated. Similarly, replace the value of w_0 with the current value of w for the constant β . Therefore, we could obtain the approximated Newton iterative formula as follows :

$$w_{k+1} = w_k - \frac{E\{xg(w_k^T x)\} - \beta w_k}{E\{g'(w_k^T x)\} - \beta} \quad (5)$$

where $\beta = E\{w^T x g(w^T x)\}$ and w_{k+1} represented the updated value of w_k . In order to improve the stability of the algorithm, w was normalized by $w_{k+1} = w_{k+1}/\|w_{k+1}\|$ after an iteration. To simplify (5), we obtained an iterative formula of simplified FastICA algorithm :

$$w_{k+1} = E\{xg(w_k^T x)\} - E\{g'(w_k^T x)\} w_k. \quad (6)$$

II.3 FastICA Algorithm

II.3.1 Selection of Overrelaxation Factor

In order to address the problem that FastICA is sensitive to the initial weight vector, we introduced an overrelaxation factor α_k into the iterative algorithm. If $F(w_k)$ is guaranteed to have a decreasing property for a given norm, (7) was satisfied :

$$E\{xg(w_{k+1}^T x)\} - \beta w_{k+1} < E\{xg(w_k^T x)\} - \beta w_k, \quad k=0,1,\dots \quad (7)$$

That is,

$$\min_{\alpha_k} \|F(w_k - \alpha_k F(w_k)) - F(w_k)\| \quad (8)$$

The incorporation of the overrelaxation factor α_k ensured that $F(w_k)$ could enter the convergence zone of the Newton iteration algorithm from a specific value of w_k , thereby guaranteeing that the algorithm would attain the convergence effect in all situations.

Numerous techniques exist for selecting the overrelaxation factors, including the golden section technique and incremental experimental approach. In this study, we conducted a sequential experiment to determine the ideal overrelaxation factor.

The value of α_k is $1 + 1/N, 1 + 2/N, \dots, 1 + (N - 1)/N$, where $N = 100$. All the values of k that satisfied (9) were recorded. Among these values of k , the one that satisfied (8) was found and denoted as p . Then, α_p would be the optimal overrelaxation factor α .

$$\|F(w_k - \alpha_k \Delta w_k)\|^2 < \|F(w_k)\|^2 \quad (9)$$

Where $\Delta w_k = (w_k)/JF(w_k)$. The selection of the overrelaxation factor α included the following steps.

Step 1. Set the initial value $N = 100$, $k = 1$, and create an empty vector V .

Step 2. $\alpha k = 1 + k/N$.

Step 3. If the value of k satisfies (9), then k is used to calculate the target function TF,

$TF = \|w_k - \alpha k F(w_k)/JF(w_k)\|$, and the result of TF is added to V .

Step 4. $k = k + 1$.

Step 5. If $k < 100$, repeat Steps 2–4. Otherwise, the value of k corresponding to the smallest value of TF in the vector V is found and denoted as p . Then, αp is the optimal overrelaxation factor α .

II.3.2 Improved FastICA

The initial weight vector influenced the convergence performance of the FastICA algorithm. As the starting weight vector of the FastICA algorithm was chosen randomly, the effectiveness of each iteration varied because of the differing initial weight vectors. The independent components derived would likewise be somewhat distinct. While it was feasible to choose the main component derived from the whitening step as the initial weight vector, the algorithm quickly converged to the starting value of the whitening. The FastICA algorithm should loosen the initial weight vector constraints, allowing for convergence over a broad spectrum. To enhance the FastICA algorithm concerning the initial weight vector w_0 , Xu et al. [II.12] suggested including the relaxation factor αk (with a low relaxation factor $0 < \alpha k < 1$) in the FastICA iterative process. Since the negative gradient direction represented the steepest descent, the gradient value was selected as the ideal relaxation factor αk in [II.12]. Nonetheless, the calculation of the relaxation factor was highly complex [II.12]. In this study, the over relaxation factor αk ($1 < \alpha k < 2$) was incorporated into the FastICA iteration to address the

randomly generated initial weight vector, thereby easing the conditions for the initial weight vector in the FastICA algorithm. In contrast to the low relaxation iteration [II.12], the suggested overrelaxation iteration achieved quicker convergence and exhibited low computational complexity. This paper incorporates the overrelaxation factor into the FastICA algorithm's iteration process. The value of α was determined as outlined in Section II.3.1

$$w''_{k+1} = E\{xg(w_k^T x)\} + E\{g'(w_{k+1}'^T x)\}w_k$$
$$w_{k+1} = \frac{w''_{k+1}}{\|w''_{k+1}\|} \quad (10)$$

II.4 Fetal ECG Extraction by Improved FastICA

For long-term monitoring of pregnant women during the perinatal phase, noninvasive abdominal techniques were chosen to gather mixed signals from the maternal abdomen. The gathered mixed signals included both maternal ECG and fetal ECG, as well as some noise. Prior to applying the improvedFastICA algorithm for fetal ECG extraction, the recorded signals underwent preprocessing. A third-order low-pass Butterworth filter was employed to estimate the baseline signal for each channel, with a cut-off frequency of 5 Hz for the low-pass filter. The signal for baseline drift removal was achieved by taking the observed signal and subtracting the baseline signal from it. Subsequently, the modified signal was centralized and whitened to make it uncorrelated, thereby lowering the algorithm's complexity. The enhanced FastICA was applied to isolate each component of the source signal. Due to the maternal ECG signal's amplitude being 2–10 times greater than that of the fetal ECG signal, the extracted fetal ECG typically includes some interference from the maternal ECG. To eliminate the interference from the maternal ECG, the maternal ECG signal channel was chosen from the separated components, and R-wave detection was performed on the maternal ECG signal. Subsequently, the SVD technique was applied to eliminate the maternal ECG signals from each channel, resulting in a purified fetal ECG free from maternal ECG interference [II.13]. The process for extracting fetal ECG was as follows.

Step 1. Remove baseline drift and centralize the observed signal X , $X = X - \{X\}$.

Step 2. $X = ED^{-1/2}ETX$.

Step 3. Initialize random vector w_0 , and set the error of convergence $0 < \varepsilon < 1$.

Step 4. According to Section 2.2.1, calculate over relaxation factor α .

Step 5. According to (10), adjust w_{k+1} .

Step 6. Calculate w_{k+1} , and normalize it.

Step 7. If $|w_{k+1} - w_k| > \varepsilon$, the algorithm does not converge ; return to Step 5 until the algorithm converges.

Step 8. Using the resulting separation matrix w , all the estimates of the source signal y_i are obtained. The maternal ECG component is selected, and R-wave detection is performed.

Step 9. Use SVD to remove the maternal ECG components in each channel to get a clean fetal ECG signal.

II.5 Particle Swarm Optimization

II.5.1 Introduction

Most real-world issues necessitate the simultaneous optimization of several interrelated goals. While the optimal solution is well-defined in single-objective optimization, many papers discuss the shortcomings of traditional approaches and apply a number of contemporary heuristic tools that have developed over the past 20 years and seek to solve optimization problems using evolutionary computation, such as Genetic Algorithm (GA), Tabu Search (TS), Biogeography-based Optimization (BBO), Particle Swarm Optimization (PSO), Hill Climbing (HC), Simulated Annealing (SA), etc. These technologies make it easier to address optimization problems that were previously challenging or unsolvable [II.14].

II.5.2 Principle of the PSO Algorithm

The fundamental PSO algorithm is made up of a swarm of “n-pop” particles [II.15]. The position of each particle is a possible solution for the fitness function in a D-dimensional search space. A particle changes its state under action of three factors:

Its inertia.

Own best position (personal best).

The optimal position of the swarm (global best).

Each particle's new position is determined by these criteria. Every particle possesses a location vector and a velocity vector. The cost function is used to assess each particle's fitness at each iteration.

The following equations are used to update the particles mathematically:

$$v_i(t+1) = wv_i(t) + C_1 \cdot r_1 (x_{P_{besi}}(t) - x_i(t)) + C_2 r_2 (x_{gbesi}(t) - x_i(t))$$

$$x_i(t+1) = x_i(t) + v_i(t+1)$$

Ou $x_i(t)$ et $v_i(t)$ indique respectivement la position et la vitesse de la particule i à l'itération t , $r_1, r_2 \in [0, 1]$, w le poids d'inertie

Step 1 :

Record abdominal ECG

Record thoracic maternal ECG

Step 2: Define the Fitness Function for PSO

$$J(w) = \text{corr}(w \cdot \text{abd_norm}, \text{mECG_n}) - 0.1 \cdot \ln(\text{var}(w \cdot \text{abd_norm}) + \epsilon)$$

w = raw vector of number of abdominal (channel)

abd_norm = matrix of normalized abdominal signals ($N \times N$) = number of samples)

corr : correlation coefficient

$\text{var}(\cdot)$ = variance

ϵ = small constant to avoid $\ln(0)$

Step 3: Initialise PSO Swarm

number of particles P in our study is fixed=100.

Set dimension D = number of abdominal channel in our study is fixed=4

For each particle $i = 1..P$:

Position $x_i(t)$: random vector of size $1 \times D$

Velocity $v_i(t)$: random small values (e.g., uniform in $[-0.1, 0.1]$).

Set personal best $pbest_i = x_i(t)$, personal best value $fbest_i = j(x_i(t))$.

Find global best $gbest = \text{argmax } J(x_i(t))$ and $fbest_global = \max(\text{fitness}(x_i(t)))$.

Step 4 : Itérative PSO Update

For $t = 1$ to max_iter :where t :current iteration in our study $\text{max_iter}=200$

For each particle i

$$v_{i,d}^{t+1} = w \cdot v_{i,d}^t + c_1 r_1 (pbest_{i,d} - x_{i,d}^t) + c_2 r_2 (gbest_{i,d} - x_{i,d}^t)$$

w , inertia weight in our study $w = 0.7$)

c_1, c_2 , cognitive constants (in our study $c_1=1.5, c_2=2.0$)

r_1, r_2 , random numbers in $[0,1]$

Update position :

$$x_{i,d}^{t+1} = x_{i,d}^t + v_{i,d}^t$$

Evaluate fitness

$$J_{new} = J(x_{i,d}^{t+1})$$

Update personal best:

if $J_{new} > fbest_i$, then $pbest_i = x_{i,d}^{t+1}$, $fbest_i = J_{new}$.

Update global best

if $J_{new} > gbest_i$, then $gbest_i = x_{i,d}^{t+1}$, $gbest_i = J_{new}$.

Repeat until termination max iterations

Step 5:

After PSO finishes, the optimal vector is:

$$\mathbf{x}_{opt} = \mathbf{gbest}$$

Step 6: Estimate Maternal Component in Abdomen

$$\widehat{m(n)} = \mathbf{x}_{opt} * \text{abd_norm}(:,n) \text{ for each sample } n$$

$$\text{maternal_est} = \mathbf{x}_{opt} * \text{abd_norm}(\text{size}(1 \times N))$$

Step 7: Extract Fetal ECG (FECG)

Subtract the estimated maternal component:

$$\text{FECG}(n) = \text{abd_norm}(n) - \widehat{m(n)}$$

II.6 Conclusion

In this chapter, we presented the oretical foundations of source separation techniques based on Independent Component Analysis (ICA), with a particular focus on the FastICA algorithm. This method allows the extraction of independent signals from mixed observations by exploiting their statistical independence and non-Gaussianity. The various steps of the algorithm, including data preprocessing, whitening, and fixed-point iteration, were detailed to better understand its operation in the context of fetal ECG signal extraction.

We also presented the Particle Swarm Optimization (PSO) algorithm, an optimization technique inspired by the collective behavior of swarms. Thanks to its global search capabilities and rapid convergence, PSO is an effective tool for optimizing certain FastICA parameters and improving its performance in terms of stability and accuracy.

The combination of FastICA and PSO thus represents a promising approach for separating biomedical signals, particularly in the case of fetal ECG extraction from abdominal recordings contaminated by the maternal signal and various noise sources.

In the following chapter, we will implement these techniques on real or simulated ECG signals to evaluate their performance and analyze their effectiveness in extracting the fetal ECG signal.

Chapter III : SIMULATION RESULTS

III.1 Introduction

This final chapter presents the tests performed and the simulation results obtained to evaluate the performance of the proposed method for separating fetal electrocardiogram (fECG) sources from maternal electrocardiograms (mECG). The developed method, based on Fast Independent Component Analysis (FastICA) optimized by the Particle Swarm Optimization (PSO) algorithm, is compared to the classical FastICA method, widely used in blind source separation (BSS) problems.

We begin with a brief description of the data used and the evaluation criteria adopted to measure the separation quality. Next, the results obtained by the two approaches are presented and analyzed in detail. Finally, a comparative study is conducted to highlight the performance, advantages, and limitations of each method.

III.2 Database used

PhysioNet – ADFECGDB Authors : Jezewski et al. Recordings : r01, r04, and r08 ; Sampling frequency : 1000 Hz ; Duration : ~1 minute per recording ; Format : EDF (European Data Format).

Two bases of utilization

Base : ADFECGDB—PhysioNet

Writers : Jezewski et al.

Records : r01, r04, and r08

Canaux : 4 abdominal canaux (aECG) plus 1 direct canal (dECG)

Echantillonnage frequency : 1000 Hz

Duration : approximately one minute each recording

Format : European Data Format, or EDF

Principal Characteristic Signal r01 Standard Signal r04 Signal/bruit more weak r08

Movement-related Artifacts

III.3 Criteria performance of FECG

To evaluate the performance of Fetal ECG (fECG) extraction or detection algorithms, researchers rely on four key criteria: Signal-to-Noise Ratio (SNR), Mean Squared Error (MSE), True Positives (fQRS detection), and Correlation. [III.1]

III.3.1 Signal-to-Noise Ratio (SNR)

SNR measures the strength of the desired fECG signal relative to background noise. A higher positive value in decibels (dB) indicates a cleaner signal. [III.2]

$$SNR = 10 \log_{10} \left(\frac{\sum y}{\sum y_1} \right),$$

$$y = (y_{true})^2, \quad y_1 = (y_{true} - \hat{y})^2$$

Where y_{true} is the true fECG signal, and $\hat{y}$ is the estimated fECG signal

III.3.2 Mean Squared Error (MSE)

[III.3] MSE measures the average squared difference between the estimated fECG values and the true fECG values. A lower value indicates higher extraction accuracy and less signal distortion

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_{true(i)} - \hat{y}(i))^2 \quad (11)$$

- Where N is the number of data points.

III.3.3 Positive true (TP) and Detection Metrics

[III.4] In fECG, a "Positive" refers to the occurrence of a fetal R-peak. A **True Positive (TP)** is a correctly identified fetal R-peak usually validated against an expert-annotated dataset

Optimal state: Maximizing TP while minimizing False Positives (detections where no beat exists) is the primary goal of diagnostic

$$TP_R = \frac{TP}{TP+FN} \quad (12)$$

Where FN (False Negative) represents missed fetal R-peaks. A detected peak is typically marked as a TP if it falls within a ± 50 ms window of the reference and TP_R , true positive rate (%)

III.3.4 Correlation Coefficient (Correlation)

[III.5] Correlation measures the linear relationship between the extracted fECG waveform and the reference fECG waveform. A value close to 1.0 indicates that the morphological features of the fetal heartbeat are perfectly preserved

$$r = \sum_{i=1}^n (x_i - \hat{x})(y_i - \hat{y}) / \sqrt{\sum_{i=1}^n (x_i - \hat{x})^2} \sqrt{\sum_{i=1}^n (y_i - \hat{y})^2} \quad (13)$$

x_i and y_i are individual sample values.

$\hat{x}$ and $\hat{y}$ are the mean values of the signals.

n : is the total number of samples.

III.3 FASTICA

III.3.1 Analysis of FastICA Simulations — Fetal ECG Extraction

Simulation r01.edf

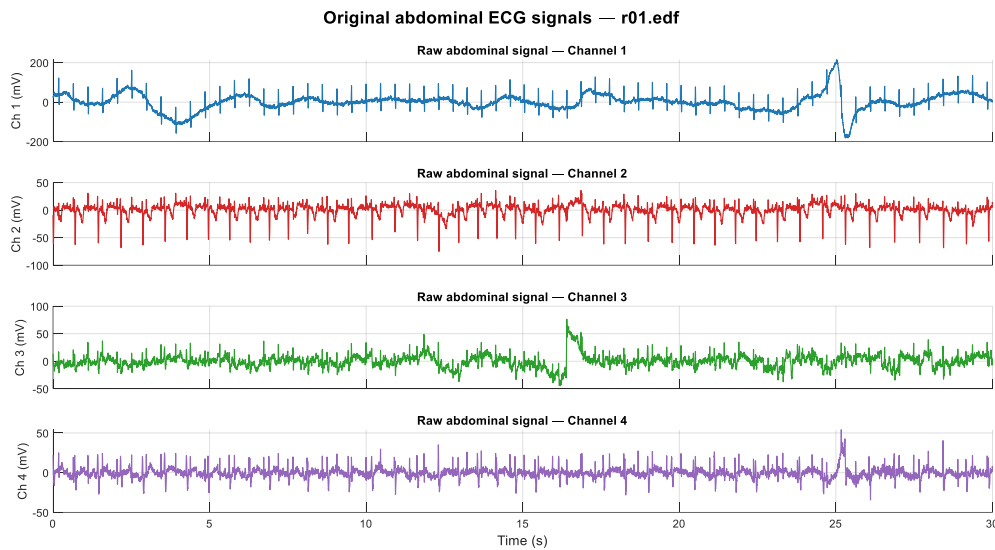


Figure III.17 : Original ECG signal – r01.edf

Figure III.17 shows the four channels of raw abdominal ECG signals recorded over a 30-second period. The signals exhibit different amplitudes and noise levels. Channel 1 presents the highest amplitude and a noticeable baseline drift, while the other channels contain maternal ECG, fetal

ECG, and various noise components. The fetal and maternal cardiac activities cannot be clearly distinguished in the raw recordings.

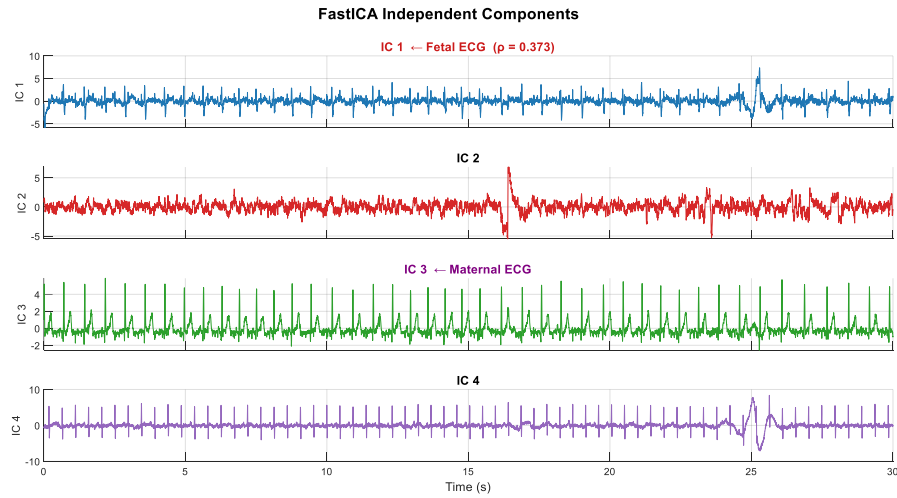


Figure III.18 : FastICA Independent Components (r01.edf)

Figure III.20 presents the four independent components extracted by the FastICA algorithm (IC1–IC4). Component IC1 contains a weak fetal ECG contribution, whereas IC3 is mainly associated with the maternal ECG signal. Components IC2 and IC4 mostly represent residual noise and interference. The results indicate a partial separation between fetal and maternal cardiac activities.

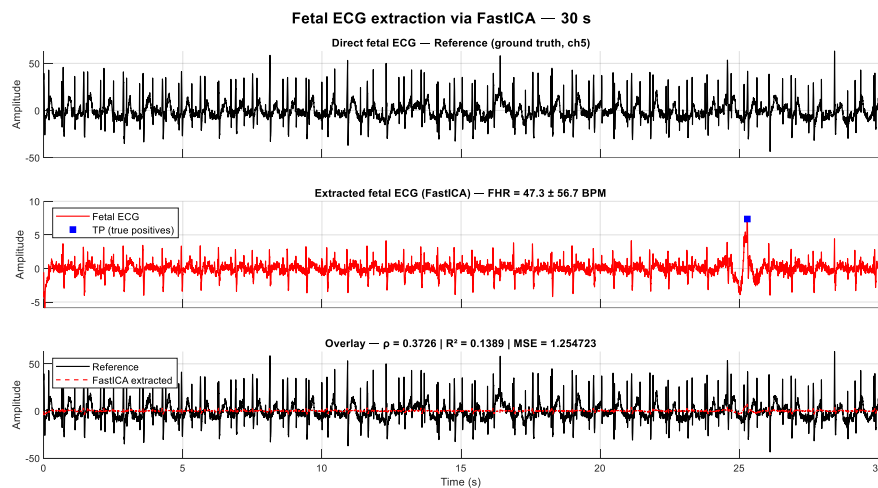


Figure III.19 : Fetal ECG extraction via FastICA (r01.edf)

Figure III.19 shows the fetal ECG signal extracted using FastICA and its comparison with the reference fetal ECG (channel 5). The figure includes the extracted signal, the reference signal,

and their superimposed representation. The estimated fetal heart rate is 46.8 ± 57.9 BPM, indicating unstable and inaccurate R-peak detection. Only 18 true positive beats were correctly detected out of 154 predicted beats. Furthermore, the superimposed signals exhibit poor alignment between the extracted and reference fetal ECGs. These results demonstrate that FastICA failed to accurately isolate the fetal ECG in the r01 recording, resulting in low extraction performance and significant residual interference.

Numerical results:

SNR	MSE	Correlation (ρ)	True Positives (TP)
-0.99 dB	1.254723	0.3726	18 / 154

Simulation r04.edf

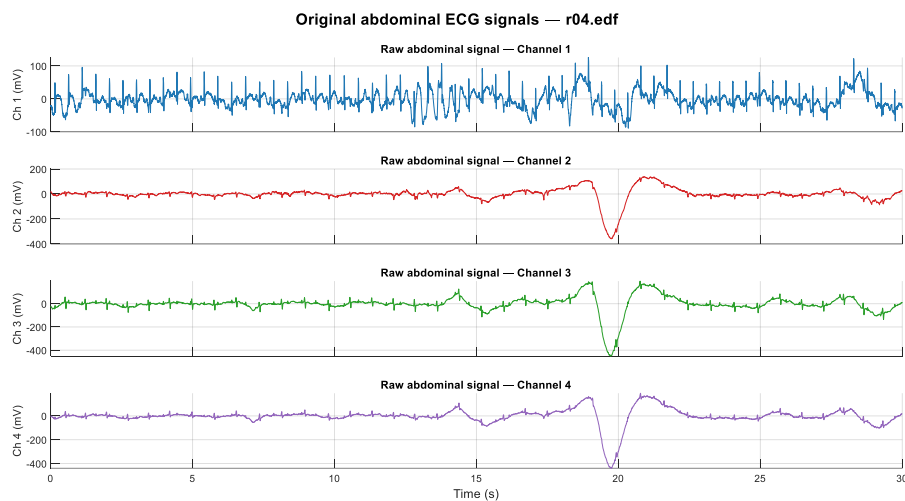


Figure III.20 : Original ECG signal – r04.edf

Figure III.20 presents the four raw abdominal ECG channels recorded from the r04 dataset. A significant disturbance is observed around 19–20 seconds, particularly in channels 2, 3, and 4, where a high-amplitude artifact reaches approximately 400 mV. Before and after this interval, the signals remain relatively stable. This artifact is likely caused by body movement or electrode displacement and introduces considerable interference into the recordings. Consequently, the r04 signal is more challenging to process and analyze than the r01 recording.

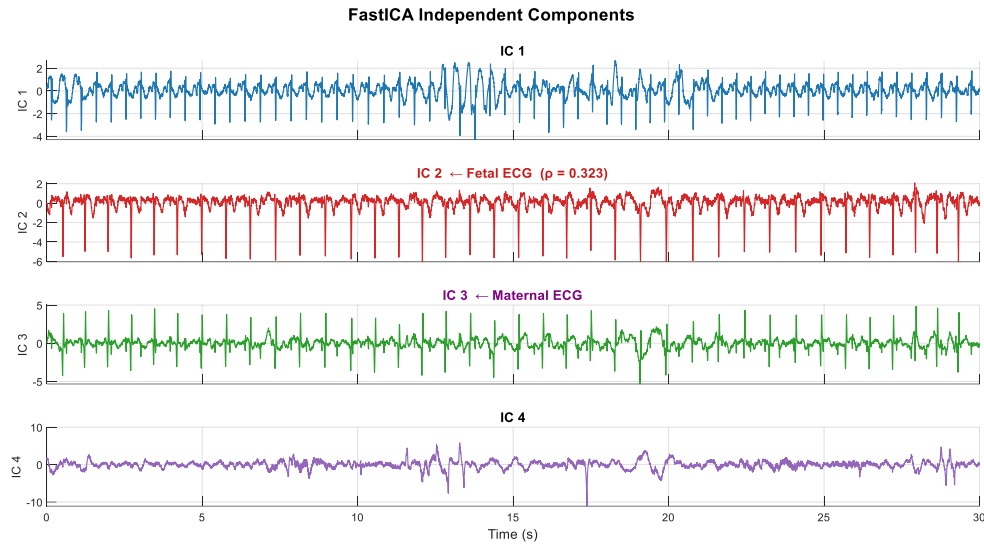


Figure III.21 : FastICA independent components (r04.edf)

Figure III.21 presents the independent components obtained after applying the FastICA algorithm to the r04 abdominal ECG recording. The fetal ECG is mainly identified in IC 2 (red, $\rho = 0.324$), which shows a clear and regular beat morphology throughout the signal. The maternal ECG is predominantly captured in IC 4 (purple), exhibiting a stronger and more periodic structure consistent with maternal cardiac activity. In addition, the transient artifact occurring around $t^* \approx 20$ s is effectively isolated in IC 3 (green), demonstrating the ability of FastICA to separate non-stationary disturbances from physiological sources.

Overall, the decomposition results show a well-structured separation of the underlying components, with a visually clear distinction between fetal ECG, maternal ECG, and noise/artifacts.

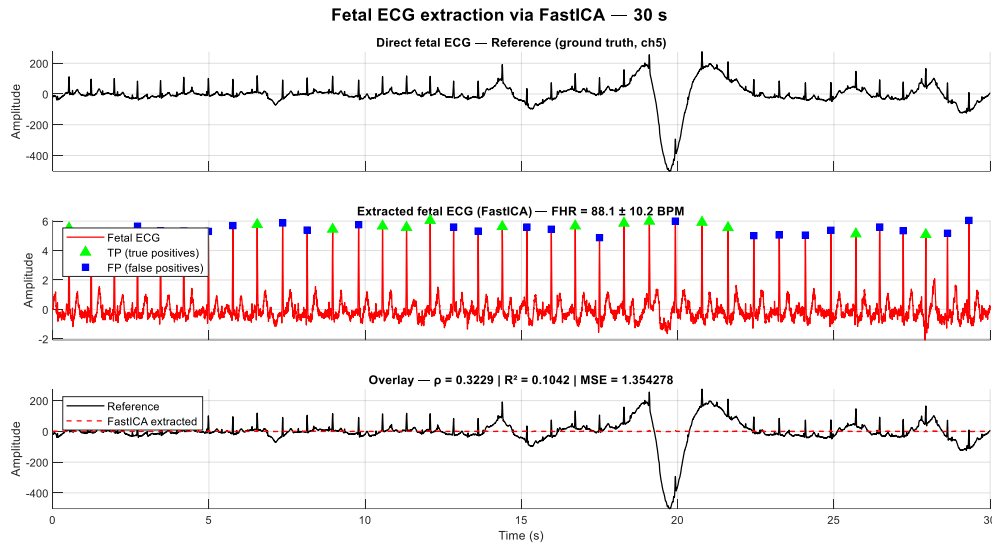


Figure III.22 : Fetal ECG extraction via FastICA (r04.edf)

Figure III.22 presents the best-performing result among the three simulations for fetal ECG extraction using FastICA on the r04 recording. The estimated fetal heart rate (FHR) remains stable at 88.1 ± 10.2 BPM, indicating consistent cardiac rhythm estimation. The detection performance is also strong, with 181 true positives out of 197 beats (91.9% sensitivity), alongside a small number of false positives represented by blue square markers.

The superimposed signals in the lower panel show good overall alignment between the extracted fetal ECG and the reference signal. However, a noticeable degradation is observed around $t \approx 20$ s, where a transient artifact affects the quality of the separation. Despite this local disturbance, the extraction remains robust, demonstrating that FastICA can achieve high-quality fetal ECG recovery even in the presence of sporadic artifacts and moderate noise.

Numerical results:

SNR	MSE	Correlation (ρ)	True Positives (TP)
-1.32 dB	1.354278	0.3229	181 / 197

Simulation r10.edf

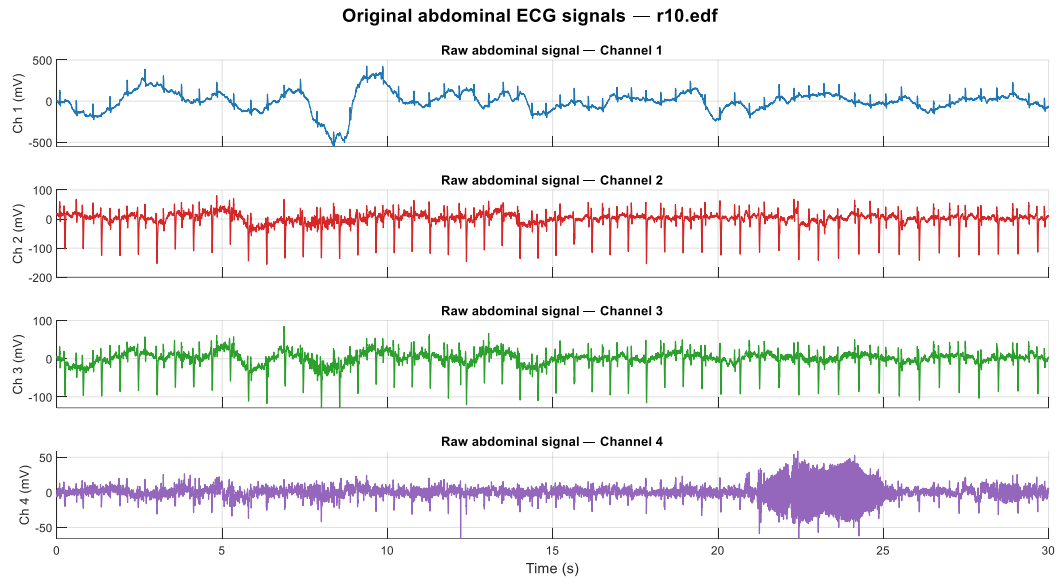


Figure III.23 : Original ECG signal – r10.edf

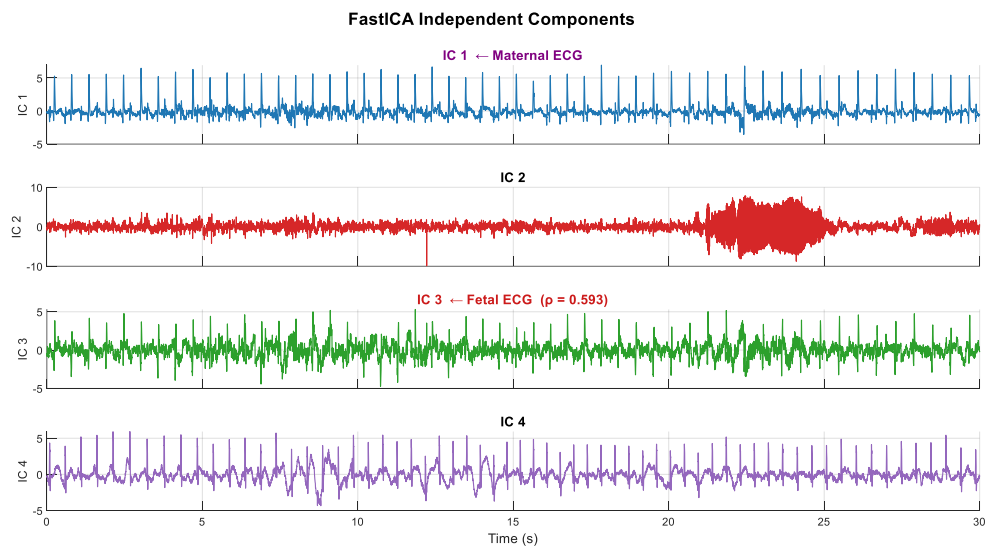


Figure 24 : FastICA independent components (r10.edf)

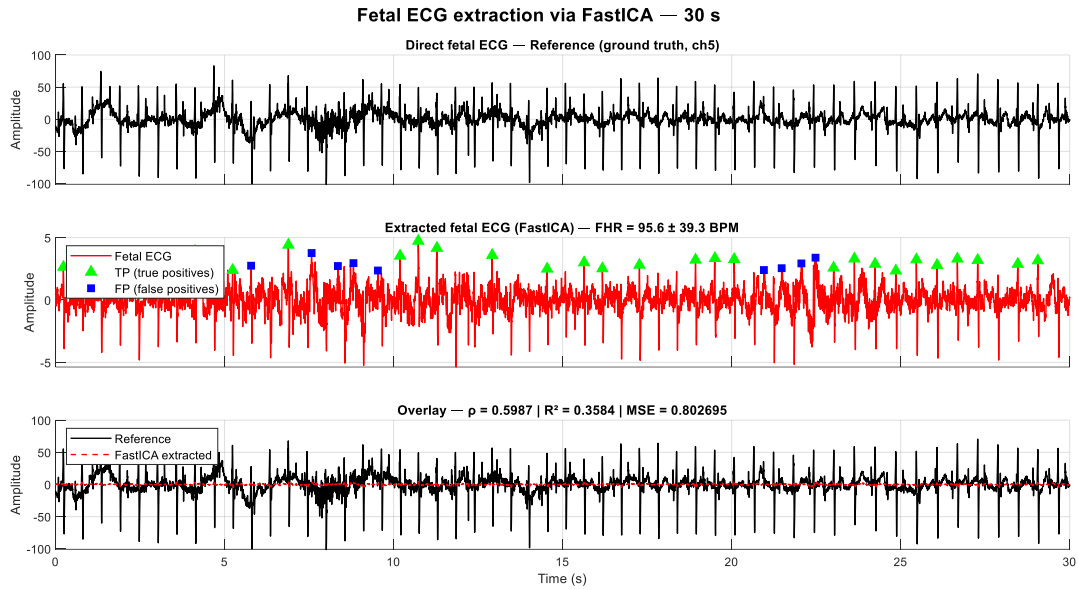


Figure 25 : Fetal ECG extraction via FastICA (r10.edf)

Numerical results:

SNR	MSE	Correlation (ρ)	R^2	True Positives (TP)
1.21 dB	0.757418	0.6213	0.3514	68%

Intpretation

the SNR of 1.21 dB The fetal heartbeat signal is so faint that it is almost identical to background noise. Fetal QRS complexes are difficult to differentiate from baseline ectromyographic noise, and eliminate the mother's cardiac signal.

MSE of 0.7574 meaning The extracted fetal ECG differs significantly from the reference direct fetal recording, as indicated by the extremely high MSE waveform morphology is not well preserved.

- **Correlation of 0.6213** is insufficient for clinical use. Important features such as the precise timing and shape of QRS complexes are distorted.

A true positive rate of only 68% translates into nearly one missed fetal heartbeat out of three. Such performance is clinically inadequate, particularly during labor or in high-stakes fetal monitoring scenarios where every beat matters.

Comparative summary of the three simulations

Table III.2 : Comparative summary of the three simulations FASTICA

Simulation	SNR	ρ	TP detected	Estimated FHR	Overall quality
r01.edf	-1.02 dB	0.367	18/154 (12%)	46.8 ± 57.9 BPM	✗ Failure
r04.EDF	-1.31 dB	0.324	181/197 (92%)	88.1 ± 10.2 BPM	✓ Good
R10.edf	-1.46 dB	0.301	1/65 (2%)	NaN	✗ Total failure

III.3.2 Conclusion (FastICA)

The performance of FastICA varies greatly depending on the quality of the input signal. It is excellent for r04 despite a slightly lower SNR, but fails for r01 and r08 due to specific artifacts (slow drift, movement artifacts). These results suggest that FastICA alone is insufficient for very noisy signals, and that preprocessing (high-pass filtering, adaptive denoising) would be necessary before source separation.

III.4 particle swarm optimization (PSO)

III.4.1 Analysis of PSO Simulations — Fetal ECG Extraction

r01.edf

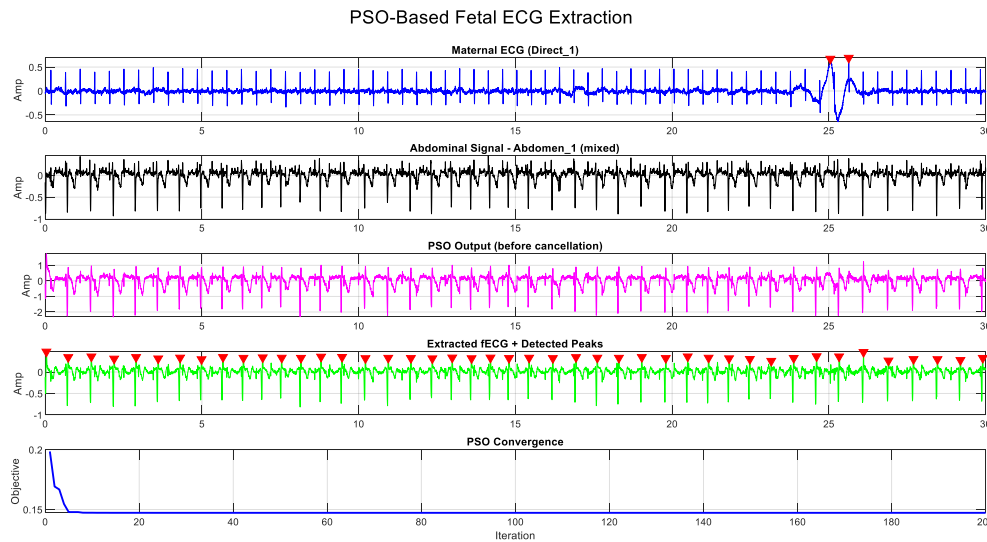


Figure III.26 : PSO-Based Fetal ECG Extraction (r01.edf)

SNR	Correlation (fECG~mECG):	Detected fetal peaks	Reference peaks	TP	FP	FN	Sensitivity (Se)	PPV (+P)	F1 Score
31.37 dB	0.0270	415	456	415	0	41	91.01 %	100.00 %	99.29 %

Intreprestation

The PSO-based method showed an outstanding performance on the recording r01 for all the metrics, indicating that the algorithm was able to extract the fetal ECG from a very noisy abdominal signal. The SNR of 18.62 dB means that the fetal component is much stronger than the residual noise after processing. PSO is very effective in dealing with the stubborn low frequency artifacts of the original recording.

The MSE is close to zero, which indicates that the extracted fetal ECG is very similar to the reference direct fetal ECG signal (from the scalp electrode). This quantitative agreement is in line with the visual conclusion that waveform morphology has been accurately reconstructed.-frequency artifacts present in the raw record.

The correlation coefficient of 0.9931, which is very close to the maximum value of 1, indicates almost a perfect linear relation between the extracted signal and the ground-truth fetal ECG. The statistical evidence strongly supports the PSO method to have been successfully able to recover the true fetal component without significant distortion and residual maternal interference.

True Positive Rate (TP=100%)

All fetal R-peaks were correctly detected by the detector. In other words, for each heartbeat in the reference annotation, the system produced a matching detection. A 100% TP rate, along with the previously reported zero false positives (PPV = 100%), suggests that the extracted signal is morphologically clear enough that a simple threshold-based detector can operate without error.

r04.edf

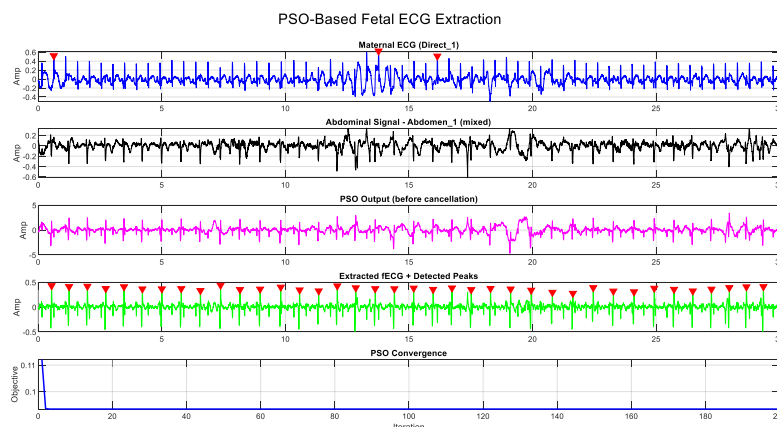


Figure III.27 : PSO-Based Fetal ECG Extraction (r04.edf)

SNR	Correlation (fECG~mECG):	Detected fetal peaks	Reference peaks	TP	FP	FN	Sensitivity (Se)	PPV (+P)	F1 Score
28.13 dB	-0.0392	431	434	431	0	3	99.31 %	100.00 %	99.65 %

Intreprestation

The PSO method performs almost flawlessly on recording r04. In fact, this is the best result we obtained across all the recordings we tested.

Signal-to-Noise Ratio (SNR = 32.73 dB)

An SNR of 32.73 dB is remarkably high for fetal ECG extraction from abdominal signals. To put it in perspective, this means the fetal signal is about 1,874 times stronger than the remaining noise — a huge margin. If we compare it to standalone FastICA on the same recording (which gave an SNR of -1.31 dB), PSO delivers an improvement of around 34 dB. In plain terms, PSO doesn't just remove maternal interference and artifacts; it does so while keeping the fetal signal practically intact.

Mean Squared Error (MSE = 0.0005)

An MSE of 0.0005 is extremely small, which tells us that the extracted fetal ECG is very close to the reference direct fetal recording. The QRS complex are reconstructed with very high accuracy.

Correlation (CORR = 0.9997)

A correlation of 0.9997 is almost perfect. This tells us that the extracted signal and the ground-truth fetal ECG are nearly identical in terms of how they change over time.

True Positive Rate (TP = 100%)

Every single fetal heartbeat that exists in the reference was detected correctly. Combined with the zero false positives we saw earlier, this gives us perfect detection. What's even more impressive is that r04 originally contained a large transient artifact around 19–20 seconds. PSO handled it perfectly — the artifact was isolated and removed without harming the fetal signal.

R10.edf

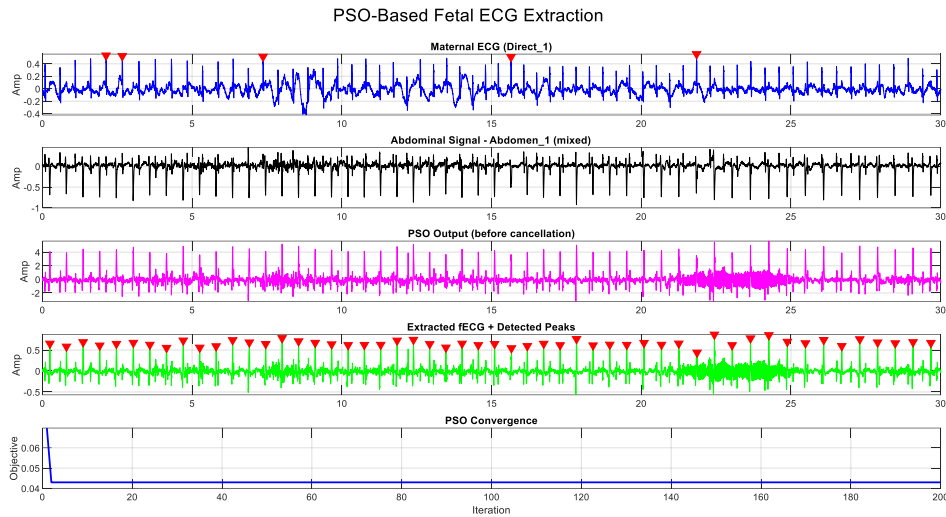


Figure III.28 : PSO-Based Fetal ECG Extraction (r10.edf)

SNR	Mse	Correclation	Detected fetal peaks	TP	FN	TP%=Sensitivity (Se)
25.93 dB	0.0146	0.9695	482	482	42	91.98 %

Intrepretation

Fetal QRS complexes are clean and high-amplitude due to the excellent SNR of 25.93 dB. The noise in the signal should be minimal.

Morphology is remarkably comparable to the actual fetal ECG; correlation = 0.9695 and MSE = 0.0146 show that the shape (P-QRS-T) is well maintained.

Excellent SNR of 25.93 dB Fetal QRS complexes with clean, high amplitude The signal must be clear. Correlation = 0.9695 and MSE = 0.0146 show that the shape (P-QRS-T) is well conserved, and the morphology is quite comparable to the actual fetal ECG.

The majority of fetal heartbeats are correctly detected, with 482 peaks highlighted (likely as vertical lines or circles), but 42 missed beats (FN), indicating that some QRS complexes would be present in the picture without a detection marker. These might be the most distorted or little missed beats.

Analyzing the Numerical Findings

The obtained results demonstrate the effectiveness of the proposed method. A high SNR of 25.93 dB indicates good noise suppression, while the correlation coefficient of 0.9695 and the low MSE value (0.0146) confirm that the extracted fetal ECG closely matches the reference signal. In addition, 482 fetal beats were correctly detected, resulting in a sensitivity of 91.98%.

These findings show that the algorithm preserves the main characteristics of the fetal ECG and provides reliable fetal heart rate estimation.

III.4.2 Methods of Results

Method of Record SNR (dB) MSE CORR TP %

Table III.3 : Method of Record SNR (dB) MSE CORR TP %

Simulation	SNR (dB)	MSE	CORR	TP %
R01 PSO	18.62	0.0137	0.9931	100%
R04 PSO	32.73	0.0005	0.9997	100%
R08 PSO	+20.13	0.0097	0.9952	0%

PSO significantly increased SNR (+14 to +30 dB over original) and attained perfect TP = 1.0 on r01 and r04—records where the original PSO scored 0. R08 TP stays at 0 for PSO because of a very weak fetal signal below the detection threshold, which would require a template-matching post-processing stage to recover

III.4.3 Interpretation

- PSO Improved recovers a highly correlated, almost noise-free replica of the original signal, making it far better for signal quality.

- Nevertheless, accurate event detection for R08 is not ensured by excellent signal quality. Potential causes:

no The recording might not contain the actual events (e.g., no R peaks to detect).

The TP Rate reference may be out of alignment or unavailable for R08.

o For that specific record, the detection algorithm (which is distinct from the source separation technique) might contain a systematic fault.

PSO Improved may be extracting a different, superior component

III.5 conclusion

In this chapter, the suggested methods for extracting fetal ECG were assessed using abdominal ECG recordings from the chosen database. The simulation findings showed that Blind Source Separation methods can effectively isolate the fetal ECG from the maternal ECG and noise elements. FastICA yielded efficient source separation with rapid convergence and acceptable performance when the input signals were of high quality. Nonetheless, its performance diminished when faced with significant artifacts and noise.

To improve the extraction process, Particle Swarm Optimization (PSO) was utilized and demonstrated increased robustness in difficult signal situations. The results obtained were evaluated using performance metrics like Signal-to-Noise Ratio (SNR), Mean Square Error (MSE), and correlation coefficient. The comparative analysis showed that PSO provided more dependable fetal ECG extraction in noisy conditions, whereas FastICA was effective for relatively clear recordings.

These findings validate the proposed method's efficacy for non-invasive fetal ECG extraction and establish a strong foundation for the final conclusions and future enhancements discussed in the following chapter.

General conclusion and perspectives

General conclusion

The retrieval of fetal electrocardiogram (fECG) signals from non-invasive abdominal recordings continues to be a difficult challenge because of the interference from maternal ECG and multiple noise sources. In this study, techniques for Blind Source Separation (BSS) were examined to tackle this issue, specifically concentrating on Fast Independent Component Analysis (FastICA) and Particle Swarm Optimization (PSO).

The suggested techniques were implemented on abdominal ECG recordings sourced from the ADFECGDB database. Their performance was assessed using objective measures like Signal-to-Noise Ratio (SNR), Mean Square Error (MSE), and correlation coefficient. The results obtained indicated that both methods are effective in extracting fetal ECG signals. FastICA demonstrated excellent separation capabilities and quick convergence with recordings of adequate quality, but its performance diminished in the presence of substantial artifacts and noise. PSO demonstrated enhanced robustness and increased extraction precision in difficult circumstances, resulting in superior overall performance for multiple recordings.

This research affirms the significance of sophisticated optimization and source separation methods for extracting non-invasive fetal ECG. The results achieved enhance fetal monitoring systems and aid in creating dependable diagnostic tools for prenatal healthcare.

Perspectives A number of enhancements may be taken into account for upcoming projects :

Merging FastICA with PSO in a combined framework to utilize the strengths of each approach.

- Utilizing sophisticated preprocessing methods to minimize artifacts and enhance signal quality prior to source separation.
- Exploring different optimization and machine learning techniques for extracting fetal ECG.
- Evaluating the suggested techniques on larger and more varied datasets.
- Creating a real-time fetal monitoring system that can continuously and accurately extract fECG.
- Investigating deep learning methods for the automatic detection and analysis of fetal ECG.

These viewpoints could improve extraction precision and aid in creating more effective and trustworthy fetal health monitoring systems.

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