Telehealth, Telemedicine and mHealth implementations for Maternal and Child Health in Low and Middle Income Countries

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1 State of the Art for Fetal ECG and Mother ECG Extraction

This section provides an overview of the latest techniques and technologies developed for the extraction of fetal and maternal electrocardiogram (ECG) signals. Given the complexity of separating fetal ECG from overlapping maternal signals and environmental noise, advanced signal processing methods have emerged as essential tools. We also explore the integration of these methods into wearable devices and embedded systems, highlighting their potential to improve prenatal monitoring accessibility and accuracy in some populations.

1.1 Challenges in Fetal ECG extraction in Low-Income Countries

As outlined in previous sections, access to specialized prenatal monitoring tools, such as fetal ultrasound or clinical ECG equipment, is often extremely limited in low-income regions due to shortages in infrastructure, trained professionals, and high-cost devices [1]. In such contexts, a remote maternal ECG monitoring system must rely on low-cost wearable sensors, capable of recording only abdominal signals. These recordings are typically complex mixtures of maternal ECG (MECG), fetal ECG (FECG), and various forms of physiological and environmental noise [2].

Extracting a clean fetal ECG signal from this mixture could be challenging. The FECG waveform has significantly lower amplitude compared to the dominant maternal signal and is easily obscured by artifacts from motion, respiration, uterine activity, or electromagnetic interference [3]. Moreover, visually inspecting these signals or using traditional threshold-based detection methods is insufficient, prompting the need for more advanced signal processing techniques.

FECG extraction has therefore become a crucial field within biomedical signal processing, especially for enabling non-invasive and affordable prenatal care. The primary technical hurdle lies in isolating the faint fetal component from overlapping and often more powerful interfering signals. In response, recent research has focused on Blind Source Separation (BSS) algorithms, machine learning, and embedded real-time systems that improve the accuracy, robustness, and feasibility of fetal signal monitoring, particularly in resource-constrained environments.

1.2 Key Algorithms and Methods for FECG and MECG Separation

The problem of separating FECG from the abdominal signal is typically framed as a Blind Source Separation (BSS) task, where neither the original source signals nor the mixing process is known a priori. The difficulty is exacerbated by overlapping frequency spectra, low signal-to-noise ratios (SNR), and the morphological similarity between maternal and fetal QRS complexes.

Below, we explore several core methods proposed in the literature to address these issues.

Independent Component Analysis (ICA)

Independent Component Analysis (ICA) is one of the most prominent techniques in FECG extraction [4, 5]. ICA assumes that the abdominal signal is a linear combination of statistically independent sources and attempts to recover those sources without prior information about their nature.

When at least two electrodes are placed on the maternal abdomen, ICA can be used to decompose the signal into independent components. Among the popular ICA variants:

- JADE (Joint Approximate Diagonalization of Eigenmatrices) uses fourth-order cumulants (kurtosis) to isolate non-Gaussian, independent components. It has shown high accuracy and robustness in separating maternal and fetal signals, although it lacks tunable parameters and can be computationally heavy in real-time settings.
- FastICA is a more computationally efficient algorithm that employs a fixed-point iteration scheme to maximize non-Gaussianity (using measures such as kurtosis or negentropy). It is particularly well-suited for embedded and mobile applications due to its speed and flexibility.

A comparative evaluation done by Ramli et al., 2020 [4] show that while JADE may yield cleaner FECG waveforms with less residual interference, FastICA offers more adaptability and efficiency, especially when system resources are constrained.

Principal Component Analysis (PCA)

PCA is another widely-used decomposition method, although less effective than ICA in the context of BSS. PCA transforms the input signals into orthogonal components ordered by variance. While it can help isolate the fetal signal by removing components with dominant maternal activity, it does not enforce statistical independence, which limits its separation capabilities when signal variances overlap [4].

However, a hybrid PCA/ICA approach was explored in [6], where PCA was used to attenuate maternal QRS complexes before ICA separation. This combination yielded a high fetal heart rate (FHR) detection accuracy and demonstrated robust performance on public datasets.

Advanced Matrix Transformations

A more recent contribution from [7] introduced a method using a Null Space Idempotent Transformation Matrix (NSITM), which exploits the null space of the mixing matrix to isolate both FECG and MECG components. This approach demonstrated increased sensitivity and accuracy across a wide range of signal-to-noise ratios, suggesting it is a promising alternative to traditional ICA-based techniques, especially when dealing with noisy, real-world recordings.

Deep Learning and Generative Models

Machine learning, particularly deep learning, has recently gained traction in biomedical signal analysis. Neural networks can learn complex nonlinear mappings, making them well-suited for noisy and variable data. Several models have been tested and developed but we highlight the following:

- CycleGANs [8] have been applied to transform maternal ECG into fetal ECG using adversarial training and attention mechanisms. These architectures excel at reconstructing waveform morphology and minimizing signal distortion.
- Attention R2W-Net [2] combines recurrent residual U-Nets with attention gates, resulting in state-of-the-art performance on both synthetic and real-world datasets. These models are capable of operating in end-to-end pipelines and can generalize well to variable input conditions.

Despite their high performance, deep learning methods often require large labeled datasets and high computational resources, limiting their direct use in embedded or offline scenarios without cloud integration.

Adaptive Filtering Techniques

Adaptive filtering can further enhance signal separation, especially when combined with BSS. One approach [3] evaluated 11 ICA variants integrated with Fast Transversal Filters (FTF). This hybrid framework significantly improved fetal heart rate detection accuracy (up to 91.14% F1-score) while maintaining fast execution times, making it suitable for real-time monitoring without requiring thoracic reference channels.

1.3 Real-Time Embedded Systems for FECG Processing

For practical deployment in low-resource settings, real-time signal processing must be implemented on embedded platforms. Noteworthy efforts include:

- An ICA-based FECG extraction system built on Arduino DUE [5], featuring real-time acquisition, processing, display, and Bluetooth-based data transmission to a smartphone. This compact and cost-effective design is ideal for remote or rural healthcare environments.
- Mekhfioui et al., 2020 [9] presented a comparative evaluation of several BSS algorithms, including JADE, SOBI, and AMUSE, running on embedded microcontrollers. Algorithm selection was guided by signal-to-interference ratio (SIR), ensuring optimal performance despite hardware limitations.

These implementations highlight the feasibility of deploying advanced signal processing algorithms on low-power systems, paving the way for scalable prenatal care solutions.

1.4 Available Wearable Maternal and Fetal ECG Monitoring Devices

Continuous and non-invasive monitoring of maternal and fetal vital signs is a critical need, particularly in resource-limited settings. Several innovative wearable technologies have emerged to address the limitations of conventional monitoring systems. In this section, we present an overview of some of the most relevant wearable devices and systems for fetal and maternal ECG monitoring, highlighting their main features, technologies, and clinical applicability.

Building on these innovations, recent wearable systems have been specifically engineered to deliver high-fidelity, continuous maternal and fetal monitoring across various clinical environments. A notable platform described by Ryu et al. (2021) [10] consists of three flexible, soft sensors placed on the chest and abdomen that communicate wirelessly with a mobile tablet. This system achieves synchronized maternal and fetal monitoring, where the abdominal sensor specifically isolates fetal ECG by eliminating maternal ECG components through sensor-to-sensor communication. It processes signals in real-time using mobile algorithms such as a modified Pan-Tompkins method for R-peak detection and heart rate extraction. Its integration with the cloud opens possibilities for machine learning applications, predictive analytics, and remote clinical interventions. Tested in a cohort of over 500 pregnant individuals, including those from low-resource settings in Zambia, this system demonstrated the feasibility of continuous, comprehensive monitoring during labor, providing a promising alternative to conventional, intermittent methods, which have limited evidence of benefit in these environments.

The GE Novii™/Novii+ Wireless Patch [11] offers a compact and beltless intrapartum monitoring solution through a peel-and-stick patch with integrated electrodes. It captures maternal and fetal ECG signals, as well as uterine electromyography (EMG), transmitting the processed data via

Bluetooth to a CTG monitor. One of its major strengths is the ability to maintain a high-quality signal acquisition despite maternal movement by automatically selecting the best electrode configuration. It separates the larger maternal ECG from the fetal ECG signals to avoid confusion in heart rate readings. Approved for use from 34 weeks of gestation, the Novii system is praised for its comfort, mobility, and simplicity, making it a user-friendly alternative to traditional belt-based CTG systems, although the cost remains relatively high, particularly when factoring in the need for specific monitors and consumable patches.

Another promising device is the wearable fetal ECG monitoring system proposed by Zhang et al.,2022 [12], which focuses on developing a low-noise, high-precision portable setup for home-based fetal heart monitoring. The system captures abdominal ECG (AECG) signals containing both maternal and fetal components and employs a combination of adaptive dual threshold (ADT) techniques and independent component analysis (ICA) algorithms to extract the fetal ECG. The researchers emphasize the potential of such home-monitoring solutions for early detection of fetal distress and congenital heart abnormalities. However, challenges remain, particularly in ensuring signal quality across various maternal postures and in minimizing interference from respiration and motion artifacts, which often complicate reliable fetal ECG extraction.

Philips Avalon series introduces an additional commercial option, characterized by Smart Pulse technology that differentiates maternal and fetal heart rates without additional sensors [13]. Its wireless setup facilitates beltless monitoring of both heart rates and uterine activity, with seamless integration into hospital information systems. Avalon prioritizes ease of use and automatic data transfer, although it largely remains within the clinical environment rather than extending its application for home monitoring, limiting its use outside structured healthcare facilities.

Further innovations include smartphone-integrated systems that leverage lightweight wearable ECG collectors transmitting data via Bluetooth [14]. One such system implements a FastICA-based algorithm for fetal ECG extraction combined with sample entropy analysis to identify the correct fetal signal channel. The real-time heart rate calculation and waveform display on the smartphone app demonstrate the growing potential for personalized prenatal care. However, current implementations require improvements in automation, as fetal signal channel identification still partly relies on visual inspection, limiting their full autonomy for non-expert users.

The TeleFetal Care project [15] introduced a textile-based wearable system integrating electrodes into a stretchable bodysuit made from cotton and lycra. Designed for continuous at-home monitoring, the bodysuit transmits the recorded signals for storage and potential hospital evaluation.

Finally, research by Mekhfioui et al.2024 [5] focuses on a minimalistic acquisition system using only two electrodes placed on the thorax and abdomen, processed through blind source separation (BSS) techniques implemented on a low-cost Arduino DUE platform. This setup aims to democratize access to fetal monitoring by offering an inexpensive, low-energy solution capable of extracting separate maternal and fetal ECG signals, computing vital parameters, and enabling real-time remote supervision via smartphone applications.

Across all these devices, common strengths include their non-invasive nature, wireless or mobile connectivity, and the use of advanced signal processing methods to isolate fetal ECG from maternal interference. Many integrate user-friendly designs suitable for both clinical and at-home monitoring, often coupled with mobile or cloud-based platforms for real-time data visualization and remote access. Nevertheless, challenges remain in achieving consistently high signal quality, ensuring robustness across diverse maternal activities and postures, minimizing dependence on manual signal inspection, and expanding usability to lower-resource settings without compromising accuracy.

2 Implemented Solution: Signal Simulation and Preprocessing

This section details the methodology employed to simulate realistic registrations of abdominal ECG signals and the preprocessing steps used to separate fetal and maternal ECG components from noise.

2.1 Dataset Selection

To evaluate our fetal ECG (FECG) extraction algorithm under controlled yet realistic conditions, we utilized the Fetal ECG Synthetic Database (FECGSYNDB)[16]. This comprehensive database comprises 1,750 five-minute simulations of 34-channel recordings (32 abdominal and 2 thoracic channels), sampled at 250 Hz with 16-bit resolution. The simulations encompass ten different pregnancies, each subjected to seven distinct physiological scenarios, including baseline conditions, fetal movements, heart rate accelerations/decelerations, uterine contractions, ectopic beats, and twin pregnancies.

The FECGSYN simulator models maternal and fetal hearts as point dipoles with varying magnitudes and spatial positions. Each signal component, maternal ECG (MECG), FECG, and noise, is treated as an individual source propagated to observational electrodes. This approach allows for the generation of separate waveform files for each source, facilitating the creation of customizable signal mixtures.

For our analysis, we focused on Case 0 (baseline with noise) across all ten simulated pregnancies. Specifically, we selected the 0.0 dB signal-to-noise ratio (SNR) level and considered the five repetitions done per pregnancy, resulting in a total of 50 recordings. Each recording includes separate files for FECG, MECG, and two noise sources (noise 1 and noise 2). These files are provided in the standard WFDB format, comprising .dat files which contain the binary signal data, .hea files, header files with metadata describing the signal and .qrs files, annotation files indicating the locations of QRS complexes. Figure 1 illustrates the individual downloaded signals from recording sub01_l1_c0., while Figure 2 presents the synthesized composite signal resulting from the combination of the four components for that recording.

As the database does not provide pre-mixed abdominal signals, we simulated the abdominal signal mixtures by combining the individual components: FECG, MECG, noise1, and noise2. This approach allowed us to create realistic composite signals for testing our extraction algorithms.

For each subdirectory corresponding to a simulated pregnancy, we saved five combined signals, corresponding to the original five repetitions per pregnancy, culminating in a total of 50 synthesized abdominal ECG recordings. These combined signals were stored in the .dat format, ensuring compatibility with standard ECG analysis tools and facilitating subsequent processing and evaluation.

Drawing a parallel to the objective of our project, these synthesized combined signals serve as proxies to recreate scenarios wherein, using a device equipped with only two electrodes, a pregnant woman in a low-resource setting could detect and capture a composite signal comprising fetal ECG (FECG), maternal ECG (MECG), and various noise artifacts. This simulation enables the development and evaluation of signal processing algorithms under conditions that closely mimic real-world challenges encountered in such environments.

2.2 Signal preprocessing

The first critical step in processing the received abdominal ECG mixture is the separation of the maternal and fetal ECGs components from background noise and interference. Given the nature of the problem, this scenario falls under the domain of Blind Source Separation (BSS), where the challenge lies in recovering original source signals from observed mixtures without prior information about the mixing process.

To address this, we employed the Fast Independent Component Analysis (FastICA) algorithm, a well-established BSS technique known for its efficiency and simplicity in implementation. FastICA is particularly effective in scenarios where source signals are statistically independent and non-Gaussian, assumptions that hold reasonably well for physiological signals like ECG.

We applied FastICA to extract the independent components. The algorithm was executed over the 50 combined signal files, each corresponding to a simulated abdominal ECG recording composed of maternal ECG, fetal ECG, and two noise sources. The separated components were saved for subsequent analysis and feature extraction.

This step simulates the signal preprocessing pipeline that would run on a low-cost, remote monitoring device deployed in resource-limited settings, where only a few electrodes are available, and robust separation from noisy abdominal recordings is essential.

2.3 Signal Evaluation and Component Analysis

To assess the effectiveness of the Independent Component Analysis (ICA) in separating fetal and maternal ECG signals from abdominal recordings, we conducted a comprehensive evaluation across all generated dataset. This analysis aimed to identify the ICA components that best correspond to the original fetal and maternal ECG signals and to extract cleaned versions of these signals for further processing.

Firstly, for each of the 50 combined signals we loaded the four Independent Components, previously saved in .npy files. Then, the original fetal and maternal ECG signals were loaded from the dataset to serve as ground truth references. These signals were truncated to match the length of the ICA components to ensure accurate comparisons. QRS annotations for both fetal and maternal ECGs were used to identify R-peaks, from which the true heart rates were calculated. Each ICA component was analyzed to estimate heart rates by detecting peaks and computing the average RR intervals. Additionally, the Pearson correlation coefficient was calculated between each component and the ground truth fetal and maternal ECGs to quantify the similarity. The components with the highest absolute correlation coefficients to the fetal and maternal ECGs, supported by a p-value lower than 0.05, were identified as the best representations of the respective signals. The analysis results, including estimated heart rates and correlation coefficients, were documented in text files for each combined signal. Furthermore, the selected fetal and maternal components were saved as cleaned signals in .npy format for subsequent processing.

An example of this process is illustrated in Figure 3, where the four independent components separated by ICA are shown. Yellow crosses mark the estimated QRS peaks, green dots indicate Maternal QRS annotations, and red dots represent Fetal QRS annotations. When a colored dot coincides with a yellow cross, it means the component closely matches the FECG or MECG signal. Each component also displays an estimated heart rate that can be compared to the original signal's heart rate. This visual explanation complements the described procedure, showing that component 1 is a strong candidate for MECG, component 4 for FECG, while components 2 and 3 correspond to noise.

This systematic approach enabled us to effectively isolate and extract clean fetal and maternal ECG signals from the mixed abdominal recordings, facilitating accurate analysis and potential clinical applications.

Given that, in the majority of cases, the correlation coefficients between the separated components and the original fetal and maternal ECG signals were close to 1.0 (or -1.0), we determined that the FastICA algorithm was sufficiently effective for our purposes. Consequently, we did not explore alternative signal separation algorithms, as FastICA provided accurate and reliable separation of the ECG components from

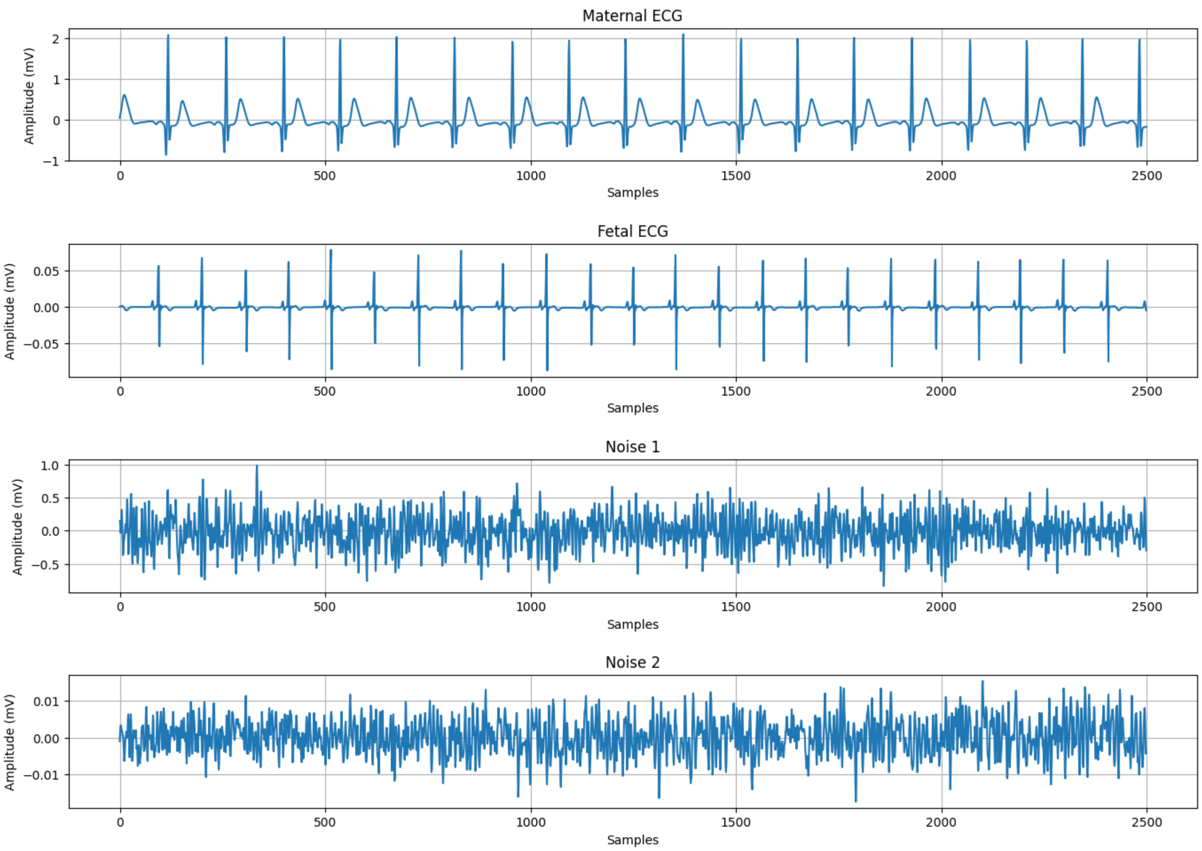

Figure 1: Individual signal components from the FECGSYNDB dataset: fetal ECG (FECG), maternal ECG (MECG), and two noise sources (noise1 and noise2) from sub01_l1_c0.

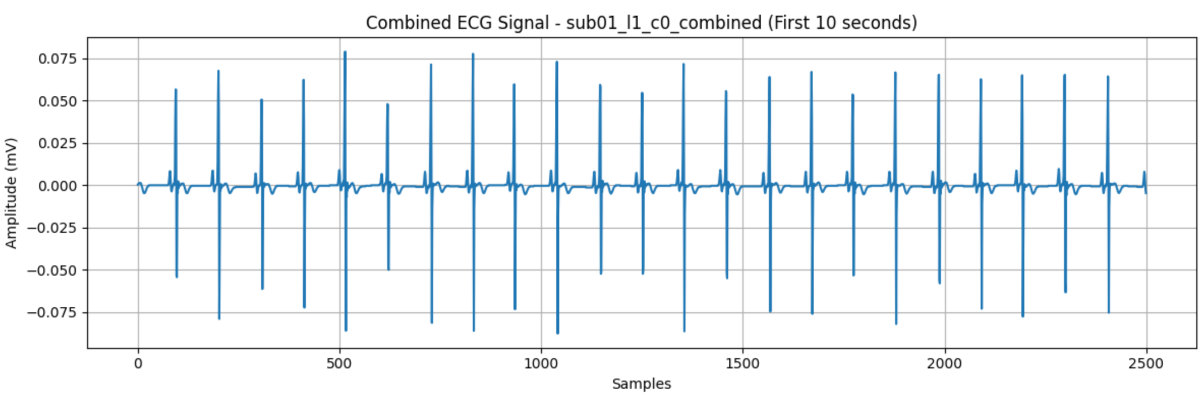

Figure 2: Composite abdominal ECG signal generated by combining fetal ECG, maternal ECG, and noise components, simulating real-world recordings.

the mixed abdominal signals.

3 Signals Analysis

Following the signal separation phase, we obtained a total of 100 cleaned electrocardiogram signals, comprising 50 maternal and 50 fetal recordings. These signals underwent a comprehensive post-processing pipeline designed to extract clinically relevant features and assess signal quality, ensuring the reliability of subsequent analysis.

To begin, each ECG signal was subjected to a quality assessment procedure. This step is crucial, as the signals were acquired by individuals without medical training, increasing the likelihood of recording artifacts or improper electrode placement. The quality check involved bandpass filtering the

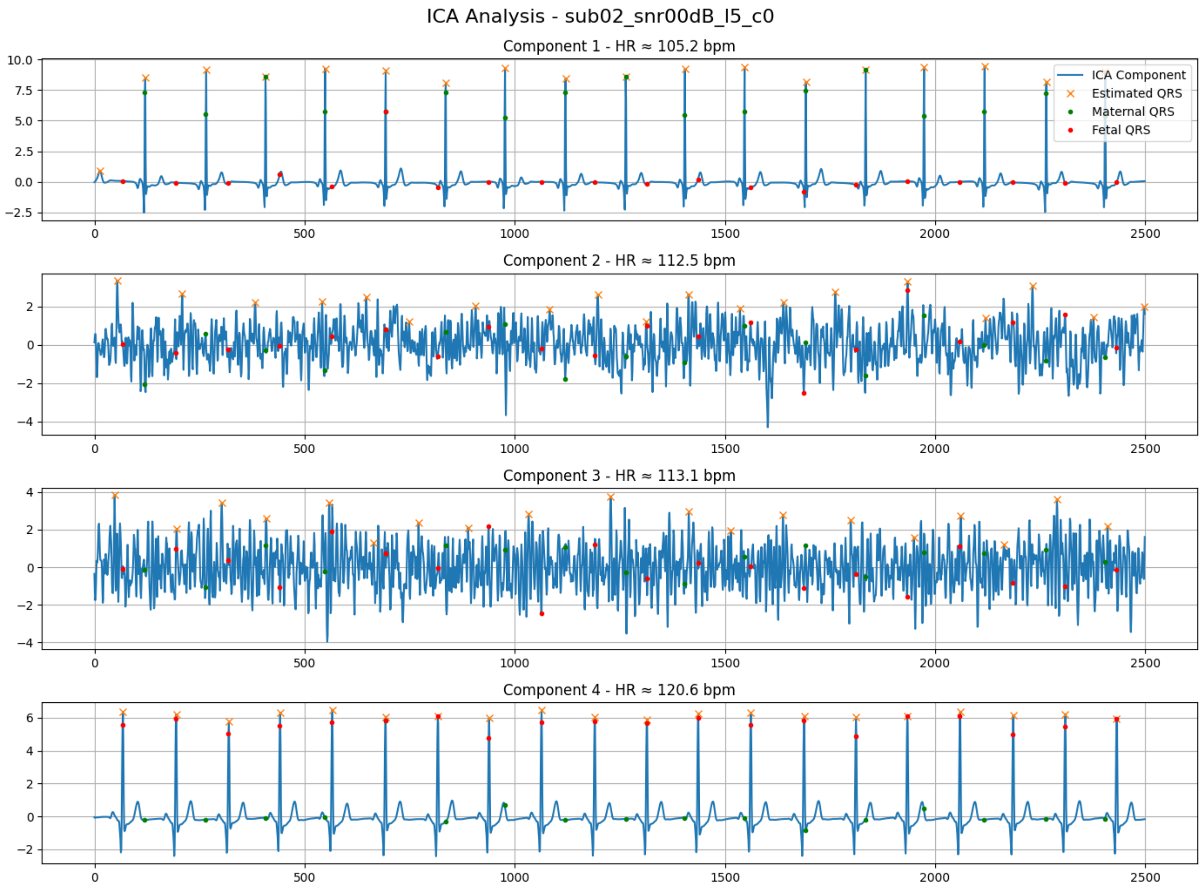

Figure 3: Four independent components extracted by ICA from a combined abdominal ECG signal. The estimated QRS peaks, maternal QRS, and fetal QRS annotations are overlaid according to the color scheme shown on the image. Estimated heart rates for each component are displayed and can be compared with the ground truth signals.

signal between 0.5 and 40 Hz to eliminate baseline wander and high-frequency noise. Subsequently, the signal was analyzed using the NeuroKit2 library, which facilitated the detection of R-peaks and the computation of signal quality metrics. Signals exhibiting fewer than three R-peaks or a standard deviation below 0.05 were deemed unreliable and excluded from further analysis.

For signals that passed the quality assessment, a series of features were extracted to evaluate cardiac function and identify potential anomalies.

We began by measuring the Mean Heart Rate (HR), calculated from the intervals between successive R-peaks, providing an average beats per minute (bpm) value. We considered a normal resting HR range between 60 and 115 bpm in pregnant women, based on [17]. This choice is supported by [18], where it is stated that a threshold of 100 bpm would be too low for many women, potentially leading to unnecessary investigations, while a threshold of 120 bpm would likely be too high, resulting in false reassurance and the risk of missing important diagnoses. Fetal HR typically ranges from 110 to 160 bpm [17]. This metric can assist physicians in identifying signs of tachycardia or bradycardia in both the fetus and the mother.

The PR Interval was also measured, defined as the time from the onset of the P wave to the onset of the QRS complex, reflecting atrioventricular conduction time. In pregnant women, normal PR intervals range from 120 to 200 milliseconds [19], while for fetuses, values between 110 and 130 milliseconds have been reported [20]. Deviations from these values may indicate conduction abnormalities, such as first-degree atrioventricular block (prolonged PR interval) or pre-excitation syndromes like Wolff-Parkinson-White (shortened PR interval).

QRS Duration represents the time required for ventricular depolarization, measured from the start to the end of the QRS complex. A normal QRS duration is typically between 10 and 120 milliseconds in pregnant women [21], and between 40 and 60 milliseconds in fetuses [22]. Prolonged QRS durations may suggest the presence of bundle branch blocks or ventricular hypertrophy.

The QT Interval, spanning from the beginning of the QRS complex to the end of the T wave, encompasses both ventricular depolarization and repolarization. Since the QT interval is heart rate-dependent, it is corrected using Bazett's formula, resulting in the corrected QT (QTc). Normal QTc values range between 350 and 450 milliseconds in pregnant women [23], and between 250 and 400 milliseconds in fetuses [23]. A prolonged QTc interval can predispose individuals to the development of arrhythmias.

Sinus Rhythm Verification was performed by evaluating the regularity of RR intervals and the presence of P waves preceding each QRS complex. A regular rhythm, with a P wave before every QRS complex, indicates a normal sinus rhythm, while irregular patterns may suggest the presence of arrhythmias.

It is important to note that all these reference values must be adapted according to the trimester of pregnancy, as well as other factors such as maternal age and any pre-existing cardiac conditions.

The extracted features were compiled in separate files, each containing the computed metrics alongside metadata such as the subject type (maternal or fetal) and the corresponding filename. To ensure compatibility with data analysis tools and facilitate storage, all numerical values were converted to standard Python data types. The resulting dictionaries were serialized into JSON format and saved in a designated directory for subsequent analysis.

For now, and to facilitate the visualization and evaluation of ECG signal quality and extracted features, an interactive dashboard was developed using Streamlit. This dashboard enables users to select specific subjects, recording levels, and signal types (maternal or fetal), subsequently displaying the corresponding ECG waveform for the initial three seconds of the recording. Alongside the waveform, key metrics such as Heart Rate Mean, PR Interval, QRS Duration, QT Interval, Sinus Rhythm status, and Signal Quality are presented. Each metric is accompanied by its respective healthy range, tailored to the subject type, allowing for immediate identification of values that deviate from expected norms. This visual tool serves as a valuable asset for both data validation and preliminary clinical assessment, offering an intuitive interface for exploring and interpreting ECG data.

4 Envisioned Remote ECG Monitoring Device and Comparison with Our Implemented System

In previous stages of this project, we developed a signal acquisition station using a BITalino device, which allowed us to capture physiological signals in real time via a Bluetooth connection. The system involved scanning nearby devices, connecting to the BITalino board, reading and plotting biosignals (like ECG) continuously on a computer. This setup gave us hands-on experience with wireless data acquisition, real-time signal monitoring, and device communication protocols, skills that directly inform our vision for a more advanced and application-specific system.

Our ultimate goal was to imagine a device capable of remotely monitoring the vital signs of a pregnant woman in a low-income country, focusing particularly on electrocardiogram (ECG) acquisition. As discussed previously, in many low-resource regions, access to healthcare facilities where such monitoring would normally take place can be severely limited or even impossible. The envisioned device builds upon the same fundamental ideas we practiced but would be specifically designed for maternal and fetal monitoring. Inspired by the system described by Mekhfioui et al., 2024 [5], our proposed solution would also rely on a minimalist and robust approach with only two electrodes. One electrode placed on the thorax to capture the maternal ECG with high signal quality and another placed on the abdomen to pick up the fetal ECG (FECG).

These signals, naturally mixed, would then be separated by an embedded processing system using blind source separation algorithms, providing two clean, distinct signals, one from the mother and one from the fetus, for consistent clinical analysis.

The device would communicate wirelessly, similarly to our BITalino project, but in a more robust and automated way. The mother would be notified through a mobile application about the quality of the acquired signal. If poor quality was detected, she would be prompted to retry the acquisition. The app would also display key health metrics and generate alerts if any vital signs fall outside the normal range, prompting her to contact a healthcare professional.

Meanwhile, all recorded data would be securely transmitted to a hospital or clinic server. Medical professionals could then review the raw ECG signals and associated metrics remotely. This professional review would allow for more accurate interpretation and guidance, especially if abnormalities were detected.

In the next sections, we will explore how to technically implement the transfer of data from the patient's local station to the hospital server. We aim to use HL7 FHIR for structured text messages and DICOM standards for transmitting ECG images.

5 Code

The source code is available at https://github.com/lauracar6/icsts-project.git

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