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MATHEMATICAL MODELING OF THE FETAL ELECTOCARDIOSIGNAL FOR THE DEVELOPMENT OF SOFTWARE FOR RELIABLE EXTRACTION IN COMPUTER CARDIODIAGNOSTIC SYSTEMS

Fetal electrocardiogram (FECG) signal extraction is a critical component of modern perinatal care, enabling continuous, non-invasive monitoring of fetal health. This approach is

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essential for the early detection of complications such as fetal hypoxia, arrhythmias, and other potentially life-threatening conditions. Traditional methods of fetal monitoring, including Doppler and intermittent auscultation, often do not provide the resolution and continuity required for timely intervention, especially in resource-limited settings where access to advanced technology is limited. To address these challenges, this study presents an innovative algorithm to extract FECS signals with improved accuracy and reliability. The algorithm uses a structured sequence of processing steps, including noise filtering, R-peak detection, and advanced filtering techniques to isolate fetal ECS from maternal signals and environmental noise. High-pass and low-pass filters and normalization ensure signal clarity and consistency in various conditions. Adaptive filtering dynamically adjusts to fluctuations in noise levels, increasing stability while preserving critical waveform characteristics such as the P-wave, QRS complex, and T-wave. These improvements are key to accurately assessing fetal heart rate and variability, enabling healthcare providers to detect early signs of fetal distress. Quantitative analysis demonstrates significant improvements in signal-to-noise ratio (SNR), supporting reliable and accurate diagnosis. The continuous, real-time monitoring capabilities align with the World Health Organisation's goal of reducing perinatal mortality to less than 12 per 1,000 births by 2030. In addition, its scalability and cost-effectiveness make it a promising solution for addressing disparities in antenatal care, especially in low- and middle-income countries. This study highlights the transformative potential of fetal echocardiography to improve maternal and fetal health globally, increase diagnostic accuracy, and promote health equity through innovative, affordable technology.

Keywords*: fetal cardio diagnostic systems, fetal ECG signal, maternal ECG signals, method and algorithm for detecting, normalizing, band-pass filter, adaptive filter, low-pass filter, high-pass filter, MATLAB.*

Франчевська Г., Яворська Є. Математичне моделювання електрокардіосигналу плода для розробки програмного забезпечення для його достовірного виділення в комп'ютерних кардіодіагностичних системах. *Виділення сигналів електрокардіограми плода (фЕКС) є критично важливим компонентом сучасної перинатальної допомоги, що дозволяє здійснювати безперервний, неінвазивний моніторинг здоров'я плода. Такий підхід має важливе значення для раннього виявлення ускладнень, таких як гіпоксія плода, аритмії та інші потенційно небезпечні для життя стани. Традиційні методи моніторингу стану плода, включаючи допплерометрію та переривчасту аускультацію, часто не забезпечують достатньої роздільної здатності та безперервності, необхідних для своєчасного втручання, особливо в умовах обмежених ресурсів, де доступ до передових технологій є обмеженим. Для вирішення цих проблем у цьому дослідженні представлено інноваційний алгоритм для вилучення сигналів фЕКС з підвищеною точністю та надійністю. Алгоритм використовує структуровану послідовність кроків обробки, включаючи фільтрацію шуму, виявлення R-піків та вдосконалені методи фільтрації для ізоляції ЕКС плода від сигналів матері та шуму навколишнього середовища. Високочастотні та низькочастотні фільтри в поєднанні з нормалізацією забезпечують чіткість та узгодженість сигналу в різних умовах. Адаптивна фільтрація динамічно підлаштовується до коливань рівня шуму, підвищуючи стабільність, зберігаючи при цьому критичні характеристики форми хвилі, такі як зубець P, комплекс QRS і зубець T. Ці покращення є ключовими для точної оцінки частоти та варіабельності серцебиття плода, що дозволяє медичним працівникам виявляти ранні ознаки дистресу плода. Кількісний аналіз демонструє значне покращення співвідношення сигнал/шум (SNR), що підтримує надійну і точну діагностику. Можливості безперервного моніторингу в режимі реального часу відповідають меті Всесвітньої організації охорони здоров'я щодо зниження перинатальної смертності до менш ніж 12 на 1000 пологів до 2030 року. Крім того, його масштабованість та економічна ефективність роблять його перспективним рішенням для усунення диспропорцій у сфері пренатальної допомоги, особливо в*

країнах з низьким та середнім рівнем доходу. Це дослідження висвітлює трансформаційний потенціал вилучення фетального ехографа для покращення здоров'я матері та плоду в усьому світі, підвищення точності діагностики та сприяння рівності у сфері охорони здоров'я за допомогою інноваційних, доступних технологій.
***Ключові слова**: системи кардіодіагностики плода, сигнал ЕКГ плода, сигнали ЕКГ матері, метод та алгоритм виявлення, нормалізація, смуговий фільтр, адаптивний фільтр, фільтр низьких частот, фільтр високих частот, MATLAB.*

Description of the problem. Fetal electrocardiogram (FECG) signal extraction is an important component of perinatal care, widely recognized for its ability to support early detection and continuous monitoring of fetal health. According to the World Health Organization (WHO), approximately 2.6 million stillbirths occur worldwide each year [1]. Many of these tragic outcomes can be prevented through timely and accurate fetal monitoring, which allows for early detection of conditions such as fetal hypoxia, arrhythmias, and other life-threatening complications. Effective monitoring is crucial during high-risk pregnancies and plays a key role in reducing the global stillbirth rate [2, 3]. The non-invasive, modern nature of FET extraction meets these goals by offering a technologically advanced solution for continuous fetal health assessment.

In today's world, efficient processing of large amounts of information is essential in various fields, including healthcare.

Traditional approaches to fetal monitoring, such as Doppler ultrasound, are limited in providing continuous, high-resolution data. With advances in technology, fetal electrocardiogram extraction has become a noninvasive, scalable solution that not only improves the quality of monitoring but also supports the WHO's goals of ensuring equity in maternal and child health. By offering continuous, real-time fetal well-being data, fetal electrocardiogram extraction provides critical information to detect subtle signs of fetal distress.

This research is significant because it can improve prenatal care by reducing the number of stillbirths, improving diagnostic accuracy, and making advanced monitoring technologies more widely available.

Its practical applications include significant improvements in maternal and fetal health outcomes, cost savings, and the potential to eliminate perinatal mortality in health care.

Despite advances in prenatal medicine, traditional fetal monitoring methods have significant limitations, including the inability to provide continuous, high-resolution data and the difficulty of detecting subtle cardiac anomalies. These limitations are particularly pronounced in resource-limited settings where state-of-the-art monitoring systems are not readily available. The challenge is to develop scalable, cost-effective FECG technologies that can overcome these barriers while ensuring equal access to advanced prenatal care.

Analysis of the latest research and publications. Recent studies have highlighted the profound implications of limited access to quality fetal monitoring in low- and middle-income countries, where health systems may lack the resources and advanced technology required for continuous fetal monitoring [4]. Traditional approaches, such as intermittent auscultation and fetal heart rate (FHR) monitoring using Doppler, provide only periodic assessments and lack the continuity needed to detect subtle, critical signs of fetal distress. This limitation can delay medical intervention in the event of adverse events that could have been prevented with continuous real-time monitoring. In contrast, extracting ECGs from abdominal records provides a continuous understanding of fetal cardiac function, allowing for rapid response to any abnormalities, supporting the WHO's mission to reduce the stillbirth rate to less than 12 per 1,000 births by 2030 [5].

The advantages of extracting the ECS for fetal monitoring are significant and can be viewed from three main perspectives:

- Non-invasive, continuous monitoring: Unlike traditional monitoring methods, ECS extraction uses non-invasive abdominal sensors, shown in Figure 1, that continuously capture fetal ECS signals, minimizing risks to both mother and fetus. This real-time data is particularly important during labor, as it allows healthcare providers to immediately recognize signs of fetal distress, such as abnormal heart rhythms or reduced heart rate variability (HRV), which are early indicators of hypoxia or cord problems.

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Studies have shown that continuous monitoring is associated with improved perinatal outcomes, as it allows for early intervention [1].

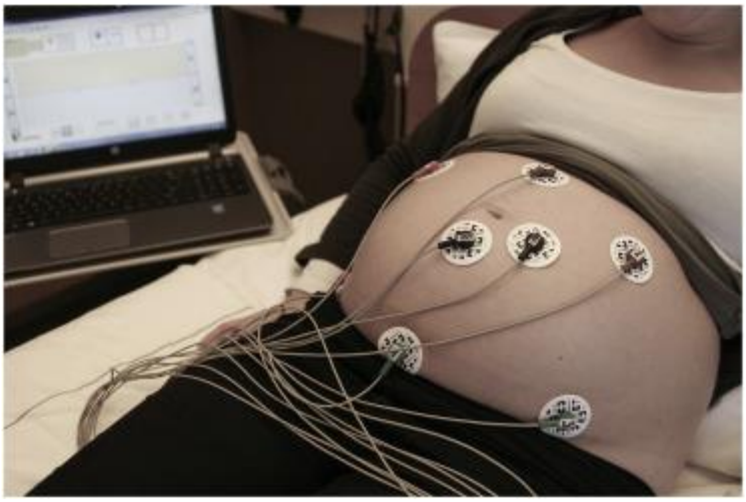

Fig. 1 – Example of electrode positioning

- Improved detection of subtle cardiac anomalies: ECS extraction offers more accurate measurements of fetal cardiac health than standard methods. By continuously assessing key cardiac characteristics such as QRS complexes, fetal heart rate (FHR), and HRV, patterns can be detected that indicate major complications. Among them, HRV is particularly important, as it gives an idea of how the autonomic nervous system regulates the fetal heart, serving as a sensitive indicator of fetal health. Continuous high-resolution monitoring is especially useful in high-risk pregnancies when a quick response to fetal distress is essential [6, 7].
- Promoting the WHO Goals for Equity in Maternal and Child Health: WHO advocates for universal access to high-quality prenatal care. However, inequalities in monitoring capacity remain, especially in low- and middle-income countries. The development of cost-effective, non-invasive FETS systems integrated into standard antenatal care practices can bridge these gaps by offering equal access to advanced monitoring technologies. By supporting continuous and accurate assessment of fetal health, FETS extraction directly contributes to reducing the number of preventable stillbirths and neonatal complications, thus contributing to the WHO's goals of achieving health equity worldwide [5].

Modern methods used to identify fetal ECS include both traditional approaches and the latest innovations.

Classical methods: often based on the use of fetal monitoring and electrocardiographic technologies. Although they are well established, their sensitivity can be significantly reduced due to the presence of artifacts.

Adaptive algorithms: Recent work has introduced new adaptive algorithms that use mathematics to improve signal extraction with additional noise. They allow to automatically adjust signal processing parameters to each specific situation, which is extremely important in clinical practice, where differences can be significant.

The use of artificial intelligence (AI) in fetal ECS extraction has become a significant step forward. AI technologies can analyze large amounts of data, applying machine learning to improve diagnostic accuracy.

Studies using deep neural networks have demonstrated a significant increase in sensitivity in detecting severe cases of EBV. For example, systems trained to recognize patterns in fetal electrocardiograms can achieve a sensitivity of up to 90% combined with high specificity [8].

Algorithms can automate the process of detecting abnormalities, allowing doctors to focus on treatment rather than the analysis process. This is important in cases where time is of the essence, such as when serious birth defects are suspected.

Recent studies further emphasize both the obstacles and progress in reducing the stillbirth rate. A 2023 study analyzing facility-based stillbirths found that the introduction of early detection systems can significantly reduce adverse outcomes [7]. In addition, a study by the Collaborative Group for Stillbirths confirms that continuous and accurate fetal monitoring is vital to preventing stillbirths associated with conditions such as preterm birth complications or fetal growth retardation [2]. As the WHO continues to advocate for more advanced prenatal monitoring technologies, non-invasive fetal electrocardiogram extraction is emerging as a highly effective solution. Research shows how the integration of hybrid algorithms combining adaptive filtering with state-of-the-art machine learning improves the quality of fetal heart rate estimation, even in environments prone to strong interference from maternal movements. Moreover, studies of multimodal datasets show that the inclusion of various physiological recordings, including Doppler ultrasound data, provides a complete picture of fetal health, thereby improving clinical applications and training.

By providing an accurate assessment of fetal health in real-time, fetal echocardiography is closely aligned with the WHO's goals of reducing perinatal mortality and promoting health equity. If adapted to resource-limited settings where high-quality monitoring is less readily available, this technology can be transformative in addressing current maternal and fetal health challenges around the world.

Future advances are expected to focus on real-time processing capabilities and the introduction of new signal processing techniques, such as wavelet transforms, to improve extraction methodologies further and increase diagnostic accuracy [8, 9]. An additional promising area is the validation of noninvasive methods using publicly available datasets, such as the Noninvasive Fetal ECS Arrhythmia Database (NIFEA DB), which plays a key role in the comparative analysis of algorithms for comparative evaluation [6].

The article focuses on creating a mathematical model and an innovative algorithm for the reliable extraction of fetal electrocardiogram (FECG) signals. This will improve diagnostic accuracy and allow continuous, non-invasive fetal monitoring, especially in resource-limited settings. **The goal is** to enhance the early detection of fetal distress and other complications, thereby contributing to global efforts to reduce perinatal mortality and promote equitable access to advanced prenatal care.

Summary of the main material. The additive-multiplicative model is the most appropriate approach when there is a significant interaction between signals - for example, when fetal heart signals modulate maternal signals, or vice versa [10]. This model reflects the complex physiological processes occurring in the mother-fetus system, taking into account both the independent components of the signals and their interaction, which allows for a more accurate separation of the signals [11].

Let $s_{obs}(t)$ be the observed maternal ECS, $s_f(t)$ the fetal ECS, $n(t)$, and the noise component. Thus, the observed signal $s_{obs}(t)$, recorded by the fetal electrodes is modeled as [12]:

$$s_{obs}(t) = A_m s_m(t) + A_f s_f(t) + B_m S_m(t) s_f(t) + n(t), \quad (1)$$

where:

• A_m – scaling factors representing the relative strength of the maternal and fetal signals. Because the mother's heart is usually closer to the electrodes, A_m is usually larger than A_f, reflecting the greater amplitude of the maternal ECS;

• B_m models the multiplicative interaction between the maternal and fetal signals, representing the nonlinear coupling between the two cardiovascular systems due to their physiological proximity or recording artifacts;

• $n(t)$ represents the noise component, which may include electrical interference, muscle artifacts, or random disturbances.

The additive terms $A_m s_m(t)$ and $A_f s_f(t)$ account for the independent contributions of the maternal and fetal signals to the observed signal, while the multiplicative term $B_m S_m(t) s_f(t)$ introduces the nonlinear interaction between these signals, making it difficult to separate them.

The electrocardiograms of both the mother and the fetus are quasi-periodic, i.e., they consist of repeating cycles with little variability. This quasi-periodicity allows each signal to be represented as a sum of sinusoidal components through a Fourier series expansion. For example, the mother $s_m(t)$ can be expressed as [28]:

$$s_m(t) = \sum_{k=1}^{K} A_k\, cos(\omega_k t + \phi_k), \quad (2)$$

where:

- A_k is the amplitude of the kth harmonic;
- $\omega_k = 2\pi f_k$ s the angular frequency of the kth harmonic, where f_k is the corresponding frequency;
- ϕ_k is the phase shift of the *k*-th harmonic.

Similarly, the fetal ECS $s_f(t)$ can be represented as:

$$s_f(t) = \sum_{l=1}^{L} B_l \cos(\omega_l t + \psi_l), \tag{3}$$

where B_l, $\omega_l = 2\pi f_l$, and ψ_l are the amplitude, angular frequency, and phase shift of the lth harmonic, respectively.

The noise component $n(t)$ is usually modeled as a Gaussian process with zero mean and variance σ_n^2:

$$n(t) \sim N(0, \sigma_n^2), \tag{4}$$

Thus, the total observed signal in the time domain consists of additive and multiplicative terms, as well as noise.

The additive-multiplicative time-domain representation of the model emphasizes how the mother and fetal signals interact to produce the observed signal. The multiplicative term $B_m S_m(t) s_f(t)$ is particularly important because it introduces a cross-frequency interaction between the mother and fetal harmonics.

To understand this effect, we can expand the product $s_m(t)s_f(t)$, by plugging in the Fourier series for both signals and applying trigonometric identities for products of cosines. This expansion gives:

$$s_m(t)s_f(t) = \sum_{k=1}^{K} \sum_{l=1}^{L} \frac{A_k B_l}{2} \cos\big((\omega_k + \omega_C)t + (\phi_k + \psi_l)\big) + + \cos\big((\omega_k - \omega_C)t + (\phi_k - \psi_l)\big), \tag{5}$$

This extension shows that the multiplicative interaction introduces new frequency components at $\omega_k + \omega_C$ and $\omega_k - \omega_C$. These additional frequencies create inter-frequency interactions that complicate the spectral structure of the observed signal, making it difficult to separate the maternal and fetal electrocardiograms using simple filtering techniques because their frequency components now overlap.

The complex spectral structure of the observed signal requires advanced filtering techniques to effectively separate fetal ECS. Traditional linear filters, such as simple bandpass filters, are inadequate due to the overlap of maternal and fetal frequencies. Therefore, more sophisticated methods such as Wiener filtering and wavelet filtering are used.

The Wiener filter is an optimal linear filter designed to minimize the mean square error (MSE) between the estimated and actual signal, which in this case is the fetal ECS. The transfer function of the Wiener filter in the frequency domain is as follows:

$$H_f(\omega) = \frac{P_{s_f}(\omega)}{P_{s_f}(\omega) + A_m^2 P_{s_m}(\omega) + B_m^2\left(P_{s_m}(\omega) \cdot P_{s_f}(\omega)\right) + P_N(\omega)}, \tag{6}$$

where:

- $P_{s_f}(\omega)$ and $P_{s_m}(\omega)$ are the spectral power density of the fetal and maternal ECS, respectively;
- $B_m^2\left(P_{s_m}(\omega) \cdot P_{s_f}(\omega)\right)$ is the PSD of the multiplicative interaction;
- $P_N(\omega)$ is the PSD of the noise.

By balancing these components, the Wiener filter suppresses the maternal ECS and noise, while enhancing the fetal ECS.

Due to the non-stationary nature of the signals, a time-frequency representation such as the continuous wavelet transform (CWT) may be even more suitable. CWT decomposes the signal into time-frequency components, which allows for separation based on different time-frequency characteristics of maternal and fetal ECS.

In addition to filtering, statistical methods such as independent component analysis (ICA) are valuable for separating maternal and fetal ECS. ICA assumes that the observed signals are linear mixtures of independent sources and attempts to separate them based on statistical independence.

Let $s_{obs}(t)$ represent the vector of observed signals from multiple electrodes, and $s(t) = \left[s_m(t), s_f(t)\right]^T$ be the vector of output signals. The observed signals can be expressed as:

$$s_{obs}(t) = As(t) + n(t), \tag{7}$$

where A is the mixing matrix and $n(t)$ is the noise vector. ICA calculates the mixing matrix W to separate the maternal signal from the fetal signal:

$$\hat{s}(t) = Ws_{obs}(t), \tag{8}$$

where $\hat{s}(t)$ is the estimated source vector that approximates the true signals $s(t)$. The ICA iteratively updates W to maximize statistical independence between the separated signals, effectively isolating the fetal ECS.

The negentropy $J(\omega)$ is a key metric in independent component analysis (ICA), quantifying the deviation of a random variable from Gaussianity. This measure is particularly useful for separating inherently non-Gaussian signals, such as fetal and maternal electrocardiograms. Since independent sources are typically less Gaussian than their mixtures, maximizing non-Gaussianity allows ICA algorithms to effectively separate these sources in complex signal environments, such as abdominal ECG recordings.

In the context of ICA, negentropy is used as a cost function to optimize the mixing matrix ω. This matrix, when applied to the observed signals, helps to isolate individual source signals by maximizing their statistical independence. The negentropy-based cost function can be expressed as:

$$J(\omega) = |E[G(\omega^T s_{obs})] - E[c(z)]|, \tag{9}$$

where:

• $G(.)$ – is a contrast function that quantifies non-Gaussianity; the most common choice is $G(u) = u^4$, which emphasizes the peakiness of non-Gaussian signals;

• z is a Gaussian random variable with the same variance as the observed signal;

• E denotes the expected value operator that captures the average impact of $G(.)$ on the distribution of the observed signal.

Using this value function, ICA iteratively updates the mixing matrix ω to maximize the negentropy, thereby increasing the statistical independence of the extracted components. In practice, this process helps the algorithm distinguish between maternal and fetal signals that have different non-Gaussian characteristics. By separating these signals based on their unique statistical properties, rather than relying solely on frequency or amplitude, ICA can more accurately isolate fetal ECS, even when the signals overlap in the time or frequency domain.

Maximizing negentropy is particularly beneficial in fetal ECS isolation, where the maternal signal is typically stronger and has a different statistical distribution than the fetal signal. By utilizing negentropy, ICA provides a more efficient approach to signal separation than traditional filtering methods, which often try to differentiate between signals with overlapping spectral content. Thus, this approach significantly increases the reliability of fetal ECS extraction, improving the diagnostic accuracy in maternal-fetal monitoring systems.

The proposed algorithm for fetal ECG extraction illustrated in Fig. 2.

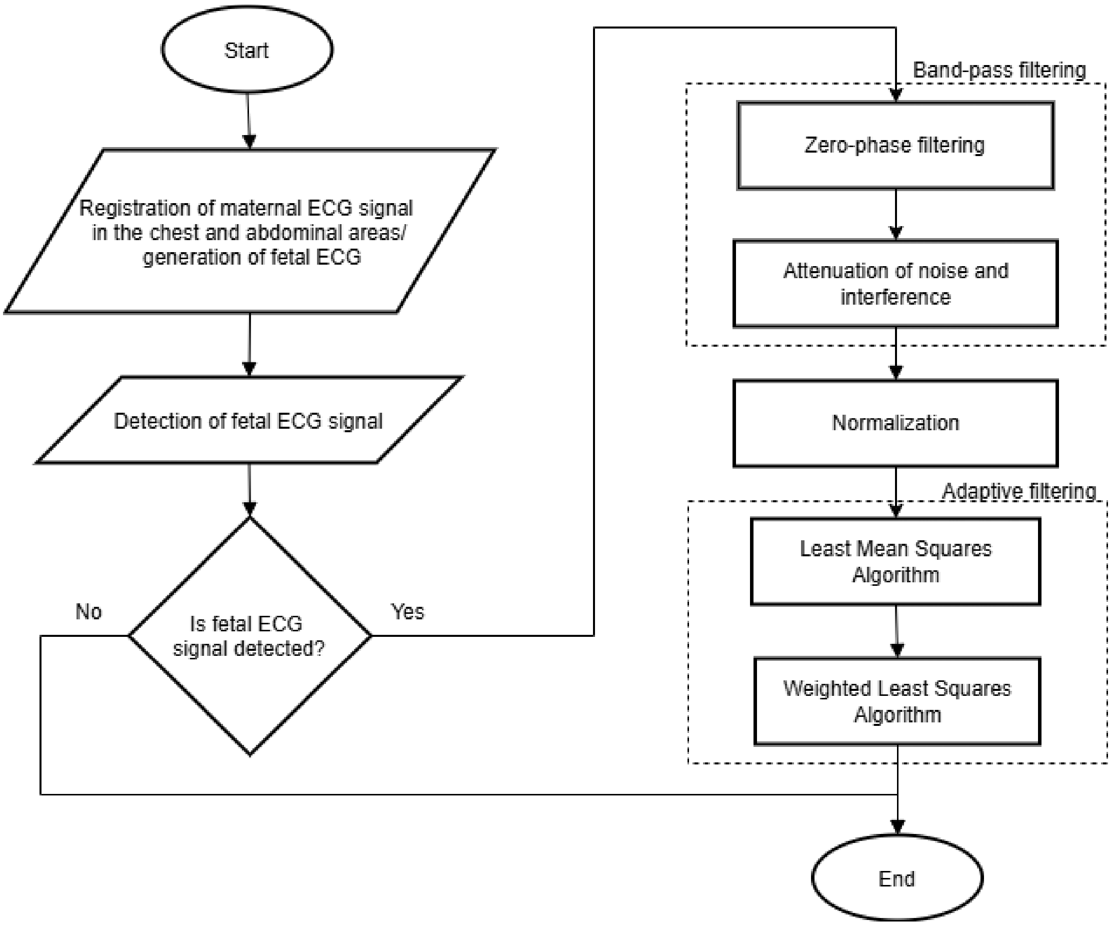

Fig. 2 – Algorithm for extracting fetal ECG signal

The first step in the proposed fetal ECS extraction algorithm, shown in Figure 1, involves recording the mother's electrocardiograms from both the chest and abdominal regions. Non-invasive electrodes are carefully placed on the mother's chest and abdomen to record these signals. After recording, the signals are filtered to remove high-frequency noise caused by electrical sources, muscle movements, and other environmental factors. After noise reduction, the signals are amplified to improve the signal-to-noise ratio, resulting in a clearer electrocardiogram. This amplified signal is then processed to detect the R-peaks in the ECS waveform that correspond to each heartbeat. A peak detection algorithm is used to accurately identify these R-peaks, providing clear markers to distinguish the maternal ECS signal, which will help separate fetal components in subsequent stages [13].

The second step of the algorithm focuses on fetal ECS detection. This is achieved by analyzing the morphological differences between the maternal and fetal signals. As a rule, fetal ECS signals are weaker and contain lower-frequency components than maternal signals. To isolate these low-frequency fetal components, the algorithm applies a low-pass filter that removes high-frequency content associated with the maternal ECS, while a high-pass filter is used to suppress low-frequency noise. This two-layer filtering effectively isolates the fetal signal, allowing the algorithm to focus on it without interference from maternal and ambient noise.

Once the fetal ECS is detected, the algorithm proceeds to the third step, which applies a bandpass filter to further process the fetal signal. The band-pass filter is tuned to a specific frequency range specific to the fetal ECS, enhancing the clarity of the signal and removing any remaining noise or non-essential frequency components. This step is important to preserve the integrity of the fetal signal by minimizing interference from maternal artifacts or environmental noise that may remain after the initial filtering.

The fourth step is normalization, during which the algorithm adjusts the fetal signal amplitude to a standardized scale. Normalization ensures that signal levels are consistent across recordings, which is crucial for accurate analysis and comparison. By scaling the fetal ECS, normalization reduces the variability that can result from different recording conditions or electrode placement, making the fetal ECS more suitable for interpretation for diagnostic purposes.

Finally, the fifth step involves adaptive filtering to further improve fetal ECS by dynamically adjusting the filter parameters based on changing noise conditions. Adaptive filtering is particularly useful in real-world settings where noise levels can change due to maternal movements, breathing, or slight changes in electrode position. By continuously adjusting to these changes, the adaptive filter fine-tunes the extraction process, ensuring a clear and stable fetal electrocardiogram. This final stage is crucial in creating a reliable and valid fetal ECS suitable for continuous monitoring and clinical diagnosis [14].

The results of the proposed algorithm demonstrate a clear and successfully extracted fetal ECG signal, with a marked improvement in signal clarity, reliability, and diagnostic accuracy. The sequential approach, starting with maternal ECS identification, followed by targeted filtering, normalization, and adaptive enhancement, effectively isolates the fetal signal from mixed maternal, fetal, and noise components.

The isolated electrocardiogram shown in Fig. 3 displays prominent and distinguishable waveforms, including P waves, QRS complex, and T waves, which are important for assessing fetal heart health. These features appear consistently throughout the signal, indicating that the algorithm steps, especially the combination of high-pass and low-pass filters followed by adaptive filtering, have effectively reduced interference from maternal ECS artifacts and ambient noise. Preserving these key waveforms supports accurate monitoring of fetal heart rate, rhythm, and variability-critical parameters for detecting potential fetal distress, arrhythmias, or other heart-related problems.

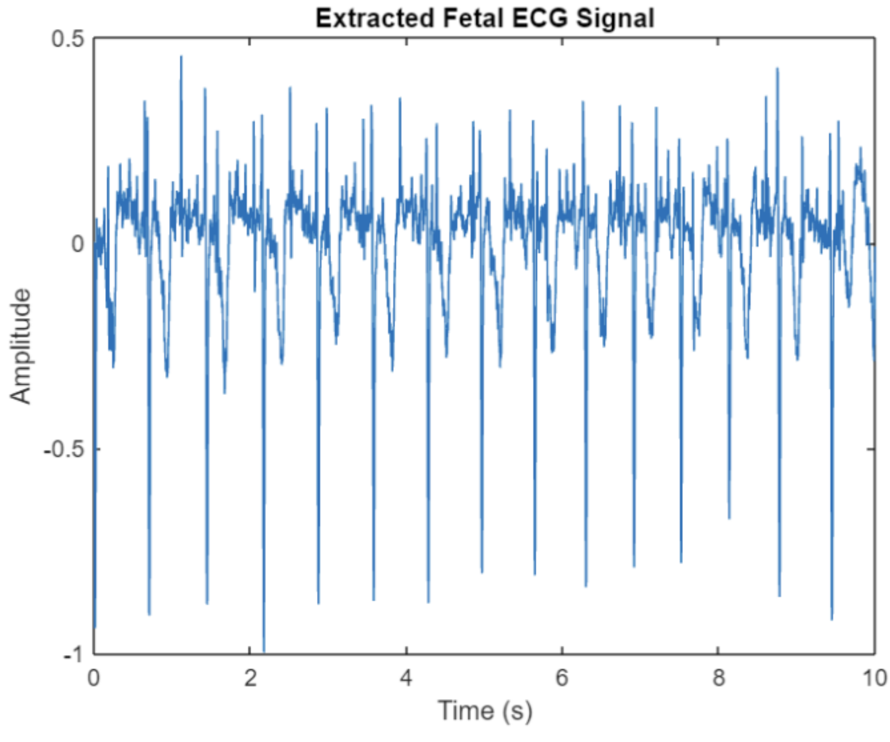

Fig. 3 – Extracted fetal ECG signal

Quantitative analysis further confirms the effectiveness of the algorithm, showing a high signal-to-noise ratio (SNR) and reduced crosstalk from maternal signals. Compared to traditional methods, this approach significantly improves the accuracy of fetal ECS by ensuring that the extracted signal maintains a stable amplitude and clear waveform morphology under different noise conditions. In addition, the normalization step results in a constant amplitude, making fetal ECS more interpretable and ready for comparison between different time points or sessions.

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Conclusions

The proposed methodology for fetal ECG signal extraction demonstrates significant advantages over existing methods and has several innovative aspects that expand the possibilities of its application in clinical and research settings. Unlike traditional methods, this approach uses an additive-multiplicative model that takes into account both the independent contributions of maternal and fetal ECG signals and their interaction. This model provides a more accurate representation of the physiological processes occurring in the mother-fetus system, eliminating the limitations of simpler linear models that cannot account for nonlinear dynamics.

The key advantage of the methodology is its advanced noise reduction capabilities. Adaptive filtering techniques dynamically adjust to changes in noise caused by maternal movements or environmental interference, ensuring reliable signal clarity even in challenging conditions. By utilizing spectral techniques such as Wiener filtering and wavelet transforms, the methodology effectively isolates fetal ECS even in the presence of strong maternal signals or noise. Innovative aspects of the methodology include the integration of independent component analysis (ICA) with non-Gaussian optimization, which exploits the statistical independence and non-Gaussian properties of the maternal and fetal signals for better separation. The combination of bandpass filtering and adaptive wavelet transforms improves fetal signal extraction, while normalization ensures signal consistency across different recording conditions. These innovations increase diagnostic reliability and signal accuracy, which distinguishes this methodology from traditional approaches.

The methodology also has the potential to be integrated with artificial intelligence-based systems, such as machine learning algorithms, to further optimize signal processing and improve diagnostic accuracy. Its adaptability makes it suitable for a variety of clinical and non-clinical settings, providing a scalable solution for continuous and reliable fetal monitoring. Overall, this approach represents a transformational advance in prenatal medicine that has the potential to significantly improve maternal and fetal health outcomes through more accurate and reliable signal extraction methods.

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ДОСТУПНЕ ЛІКУВАННЯ ДІАБЕТУ: СТРАТЕГІЇ РОЗРОБКИ ЕКОНОМІЧНО ЕФЕКТИВНИХ НЕІНВАЗИВНИХ СИСТЕМ МОНІТОРИНГУ РІВНЯ ГЛЮКОЗИ

У статті розглядається розробка оптичних неінвазивних методів для визначення рівня глюкози в крові у пацієнтів з діабетом. Основна мета дослідження полягає у вивченні різних методик вимірювання концентрації глюкози, включаючи традиційні техніки, такі як хімічний аналіз крові, яка забирається шляхом проколювання пальця або з вени на передпліччі, а також альтернативні неінвазивні підходи. Дослідження спрямоване на виявлення переваг неінвазивного моніторингу, які включають уникнення болю та ризиків, пов'язаних із використанням гострих предметів, можливість збільшення частоти тестів, що забезпечує більш жорсткий контроль за рівнем глюкози. Робота також зосереджена на описі потенційних комерційних переваг неінвазивних пристроїв для моніторингу глюкози. Методи дослідження включають оптичні технології та аналіз наукової літератури. Отримані результати включають розгляд можливостей створення неінвазивних оптоелектронних пристроїв та методик підвищення точності вимірювання кров'яних компонентів. Запропонована техніка та оптичний датчик можуть значно підвищити точність неінвазивного вимірювання кров'яних компонентів, враховуючи внутрішню структуру капілярів та стан шкіри. Рекомендується комбінувати цей метод з іншими визнаними методами неінвазивного визначення кров'яних компонентів in vivo, такими як глюкоза, білірубін та кисень, адже він сам по собі не може повністю вирішити проблему неінвазивного аналізу крові у діабетичних пацієнтів. Висновки дослідження підкреслюють значимість основних оптичних технологій для неінвазивного моніторингу глюкози та їх економічну ефективність у порівнянні з перевагами та недоліками.

Ключові слова: *діабет, аутоімунне захворювання, глюкоза, неінвазивні методи, оптичні методи.*

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