Method and algorithm for wavelet detection of fetal ECG signal in the womb*

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Abstract

The article considers the problem of detecting the fetal ECG signal in conditions of dominance of the high-amplitude maternal ECG and the influence of numerous interferences, which is one of the key problems of modern perinatal diagnostics. The complexity is determined by the significant difference in amplitudes between the signals (the maternal signal dominates over the fetal signal), their quasi-periodic nature, as well as the presence of myogenic, motor and electromagnetic noise. To correctly reproduce the process, a mathematical model of the abdominal ECG recording was formed, which takes into account the multicomponent nature of the mixture, the periodicity of cardiac activity and the additive nature of noise influences.

Based on this model, a wavelet detection method of the fetal ECG signal is substantiated, in which the time-frequency processing algorithm based on the Morlet wavelet takes a central place. The algorithm involves sequential calculation of wavelet coefficients, formation of a three-dimensional spectral representation, construction of generalized two-dimensional projections and statistical identification of high-frequency QRS complexes of the fetus. This approach provides effective suppression of low-frequency components of the maternal ECG signal, amplification of characteristic rapidly changing structures of the fetal signal and resistance to noise artifacts.

Experimental studies in the MATLAB environment confirmed the effectiveness of the proposed algorithm: the method reliably distinguishes the fetal ECG signal in the frequency range of 2–3 Hz against the background of fluctuations of the maternal ECG signal with a frequency of 0.8–1.5 Hz. The results obtained indicate that the developed method and wavelet detection algorithm are an effective tool for increasing the reliability of non-invasive monitoring of fetal cardiac activity and reducing the risk of diagnostic errors.

Keywords

fetal ECG signal, maternal ECG signal, interference, mathematical model, detection method, detection algorithm, wavelet transform, Morlet basis, MATLAB

1. Introduction

According to the World Health Organization (WHO) [1], about 2 million cases of perinatal mortality are registered in the world every year, a significant part of which is associated with complications during pregnancy and childbirth. One of the leading reasons is the untimely diagnosis of hypoxia and fetal cardiac disorders. Therefore, the development of non-invasive methods of monitoring and timely detection of critical conditions is an important task of modern medicine.

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Among the methods of non-invasive monitoring, a special place is occupied by electrocardiography (ECG), which allows obtaining information about the heart rate, rhythm, and features of the electrical activity of the heart. However, the separation of the fetal ECG signal from a mixture of maternal signals and external interference remains a difficult task, since the signal amplitude is 3-100 times smaller than the amplitude of the maternal ECG signal.

It is important that before performing the analysis and diagnostic assessment of the fetal heart condition, it is necessary to detect the very fact of the presence of its ECG signal in a mixture with maternal signals and noise. Without reliable detection of a useful signal, further analysis (determination of heart rate, rhythm variability, pathological changes) loses its reliability. That is why the task of detecting and localizing fetal signals in noisy conditions is a fundamental stage of processing. Over the past decades, several processing methods have been proposed to solve this problem for detecting the fetal ECG signal against the background of the maternal ECG signal and noise: adaptive filters [2], the method of independent components [3,4], methods of blind signal extraction [5-7], combined approaches [8, 9] and statistical based on the Neyman-Pearson criterion [10]. They have shown high efficiency, but have a common drawback - the lack of consideration of fluctuating changes in signals on different time scales, which is critically important for early diagnosis of pathologies.

2. Formulation of work goals

An effective solution is the wavelet transform, which allows simultaneous analysis of signals in the time and frequency domains. The use of the Morlet basis, which structurally corresponds to the nature of ECG signals, provides increased sensitivity to local changes and resistance to interference. The combination of this approach with algorithmic and software in the MATLAB environment allows you to create an intelligent system - a tool that can not only automate the detection and processing of signals, but also generate analytical conclusions to support medical decision-making.

3. Mathematical model of the fetal ECG signal in the womb

During noninvasive abdominal recording of fetal ECG — that is, when electrodes located on the anterior abdominal wall of the mother record a mixed signal from the fetus, the mother, and various interferences — a total bioelectric potential is recorded, formed by the simultaneous activity of several sources. The main ordered components of this signal are maternal and fetal ECG, to which are added various noises and artifacts: myogenic noises from abdominal muscles, motion interference, electromagnetic interference of the network, and electronic noise of the equipment. In a typical abdominal ECG recording, the maternal signal has a much larger amplitude and often overlaps the weaker in spectral and temporal senses fetal signal, which complicates its reliable isolation and reproduction of morphology [12].

Fig. 1 shows a simplified diagram of the process of recording a fetal ECG in the womb.

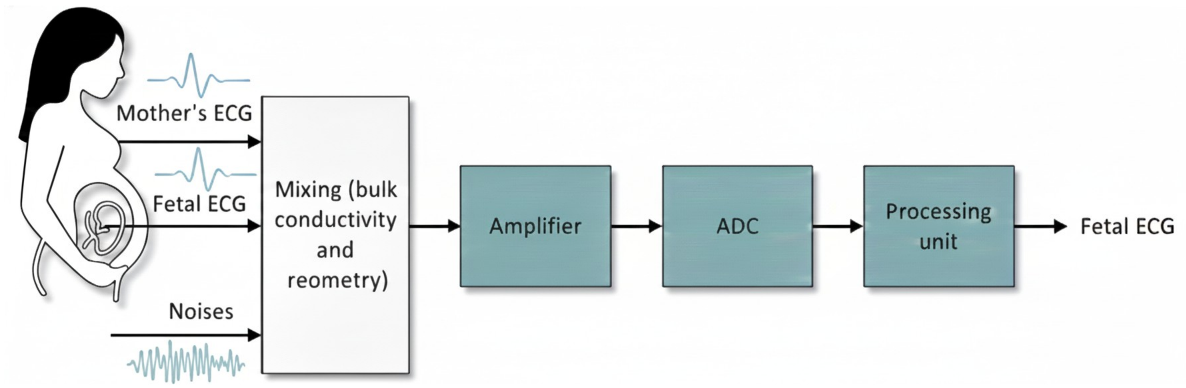

Figure 1: Simplified diagram of the fetal ECG signal registration and detection process.

The maternal ECG signal has a much larger amplitude. It dominates the signal mixture (fetal signal, maternal signal, noise (muscle contractions, body movements, or electrical interference from the environment). In contrast, the fetal signal is much weaker and is more often masked by the maternal ECG signal and various noises (myogenic, motor, electromagnetic) [11]. Electrodes located on the anterior abdominal wall record this mixture of mixed signals. The resulting signal is fed to a biopotential amplifier, then to an ADC and a processing system, where methods of filtering, separation, and detection of a hidden fetal ECG are applied.

Fig. 2 shows the implementation of a mixture of fetal ECG signal, maternal ECG signal, and interference.

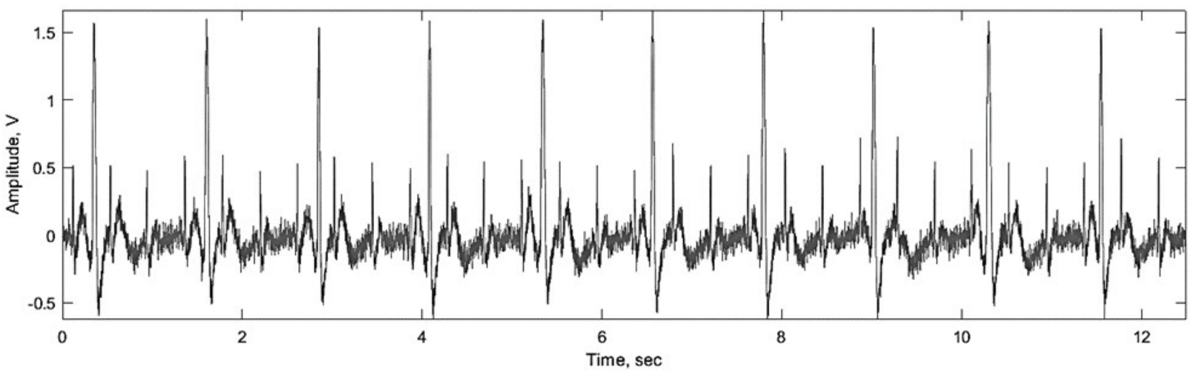

Figure 2: Implementation of fetal ECG in a mixture of maternal ECG and noise.

The maternal ECG signal is the dominant signal in the abdominal leads: the amplitude is 5-10 times higher than the fetal signal. The fetal ECG signal has a much lower amplitude on the abdominal surface. The morphology is similar to the adult signal, but the repetition rate is higher (shorter RR intervals). Noise and artifacts include: Baseline wander (0.15-0.5 Hz) - caused by breathing and movements; muscle activity (EMG signal) [13]- broadband noise; contact noise and hardware interference; impulse artifacts (electrode movements).

The maternal and fetal hearts operate autonomously. This means that the maternal and fetal signals are not harmonically related signals, but two separate processes with their own periods and QRS complex shapes. The electrical fields of the heart propagate through the conductive medium (the mother's body, amniotic fluid).

Therefore, naturally, the fetal ECG signal model should reflect multicomponentity, different amplitude scales, temporal structure, and additivity of noise according to the expression:

$$\xi(t)=s_m(t)+s_f(t)+n(t), \quad (1)$$

where $s_m(t)$ – Maternal ECG signal (useful for maternal cardiac monitoring, but an obstacle to fetal ECG signal extraction);

$s_f(t)$ – Fetal ECG signal (detection target);

n(t) — total noise (artifacts, EMG, drift).

Considering the multi-channel case (M leads):

$$\xi(t)=a_m s_m(t-\tau_m)+a_f s_f(t-\tau_f)+s+n(t), \tag{2}$$

where $\xi(t)\in R^M$ – measurement vector;

a_m, a_f – vectors of spatial coefficients (depending on electrode positions and tissue conductivity);

τ_m, τ_f – signal time delays.

Each signal is quasi-periodic:

$$s_m(t)=\sum_k h_m(t-kT_m-\delta_{m,k}),\ s_f(t)=\sum_k h_f(t-kT_f-\delta_{f,k}), \tag{3}$$

where $h_m(t), h_f(t)$ – QRS-T complex shapes for mother and fetus;

T_m, T_f – average RR intervals (maternal and fetal);

$\delta_{m,k}, \delta_{f,k}$ – variations (cardiac variability).

The noise is decomposed as:

$$n(t)=b(t)+e(t)+w(t), \tag{4}$$

where b(t) – low-frequency drift;

e(t) – muscle noise (EMG signal), which can be modeled as white noise,

w(t) – white Gaussian noise (hardware).

Taking into account all components, the signal model has the form:

$$s_m(t)=a_m\sum_k h_m(t-kT_m-\delta_{m,k})+a_f\sum_k h_f(t-kT_m-\delta_{f,k})+b(t)+e(t)+w(t). \tag{5}$$

The justification for such a structure of the mathematical model of the fetal ECG signal (5) is due to the following factors:

– Additivity follows from the linearity of the propagation of electrical potentials through tissues.

– Multicomponentity (maternal signal + fetal signal + noise) explains the different sources of signals and noise.

– Vector shape allows the use of multichannel methods (PCA, ICA, beamforming).

– A periodicity model is required to use structural information (e.g., cyclic methods, detection by RR intervals).

– The presence of scale factors and offsets reflects the variability of amplitudes and delays between channels.

– The noise model separately accounts for low-frequency drift and broadband artifacts, which is important for constructing adequate filters and statistics for GLRT.

The task of detecting the presence of a fetal ECG signal is formulated through two hypotheses:

$$\begin{gathered} H_0: \xi(t)=a_m s_m(t)+n(t) \\ H_1: \xi(t)=a_m s_m(t)+a_f s_f(t)+n(t) \end{gathered} \tag{6}$$

Presence detection $s_f(t)$ is a hypothesis testing problem, an optimal test in Gaussian noise.

4. Wavelet detection method for fetal ECG signals against background noise

An intelligent system for analyzing/processing biomedical signals must have a tool capable of detecting weak and non-stationary components of the fetal ECG signal in complex mixtures.

The wavelet processing method is well-suited for the task of detecting the fetal ECG signal $s_f(t)$ against the background of the maternal signal and noise due to its features of working with non-stationary signals, to which the ECG signal belongs.

Unlike the classical Fourier transform, which only provides a global spectrum, the wavelet transform allows for simultaneous analysis of the signal in the time and frequency domains. This is critical for ECG signals, as cardiac complexes (QRS, P, T) have distinct time limits and different energy concentrations.

Wavelets allow for the decomposition of the signal mixture into subbands where the maternal ECG signal and the fetal ECG signal appear with different intensities.

The wavelet transform is particularly sensitive to rapid changes in the ECG signal. The fetal QRS complex, although small in amplitude, has steep fronts that are clearly visible at certain levels of the wavelet decomposition. This allows:

- suppress the low-frequency component of the maternal ECG signal (maternal P and T waves and her baseline);
- to amplify high-frequency QRS complexes of the fetal ECG signal,
- apply thresholding to highlight fetal ECG signal peaks.

The wavelet transform gives a set of coefficients [12]:

$$W_\xi(a,b)=\frac{1}{\sqrt{a}}\int_{-\infty}^{\infty}\xi(t)\psi*\left(\frac{t-b}{a}\right)dt, \tag{7}$$

where $\psi(t)$ – basis function, a – scale, b – shift.

On scales corresponding to the frequency range of the signal, the coefficients Wy(a,b) exhibit regular peak patterns at the moments of fetal heart contractions. Their presence in the recording indicates the presence of a fetal ECG signal.

The fetal ECG signals are rhythmic and consist of short rapid complexes (QRS) with a clearly defined frequency spectrum. Morlet fits well with such oscillatory structures, because it is itself a short wave with harmonic filling. This allows it to “fit” to QRS complexes and makes them easily visible in the wavelet transform coefficients.

A Morlet wavelet is defined as a harmonic wave localized by a Gaussian envelope:

$$\psi(t)=\pi^{\frac{-1}{4}}e^{j\omega_0 t}e^{\frac{-t^2}{2}}. \tag{8}$$

Wavelet processing in the Morlet basis $\psi(t)$ is well suited for fetal ECG detection, since:

– reproduces the oscillatory nature of QRS complexes;
– provides simultaneous localization in time and frequency;
– allows you to distinguish between maternal, fetal and noise components;
– increases sensitivity to weak but rhythmic fetal signals.

Wavelet processing in the Morlet basis for a discrete ECG signal $\xi[n]$ with a step Δt has the form, taking into account formulas (7) and (8):

$$W_{\xi}(a,b) \approx \frac{\pi^{\frac{-1}{4}}}{\sqrt{a}} \sum_{n=0}^{N-1} \xi[n] e^{-j\omega_0 \frac{n\Delta t - b}{a}} e^{\frac{-\left(\frac{n\Delta t - b}{a}\right)^2}{2a^2}} \Delta t’ \tag{9}$$

where n – discrete signal reference number;

n=0,N-1; Δt – discretization step.

Thus, using the Morlet wavelet as a basis creates conditions for effective detection of even a weak fetal ECG signal against the background of a strong maternal signal and noise.

Therefore, the wavelet detection method in the Morlet basis is not just a mathematical tool, but a basic functional link of an intelligent system for effective detection of even a low-level fetal ECG signal against a strong maternal signal and interference.

In the structure of an intelligent system, the wavelet method performs the following functions::

– Preliminary analysis: decomposition of the signal into time-frequency components.

– Feature detection: identification of regular maxima of Morlet coefficients corresponding to fetal QRS complexes.

– Forwarding: analysis results are used to train classifiers, build templates, or confirm the presence of fetal signs in the ECG signal recording.

Thus, wavelet processing in the Morlet basis is the core of the recognition mechanism in the intelligent system, which ensures the selection of the hidden useful signal of the fetus against the background of the powerful signal of the mother and noise.

5. An algorithmic intelligent fetal ECG signal detection system

The algorithm of the intelligent system for detecting the fetal ECG signal against the background of the maternal ECG signal and noise, according to the figure, shown in Fig. 3.

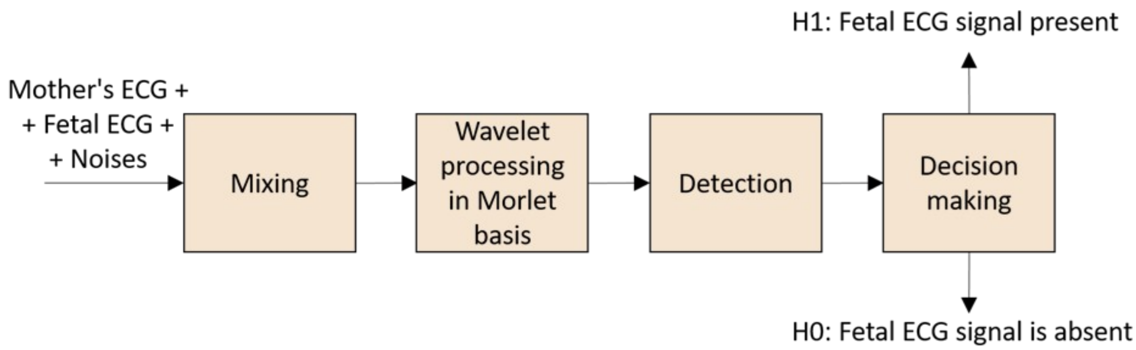

Figure 3: Algorithm of the intelligent fetal ECG signal detection system.

The algorithm of the intelligent fetal ECG signal detection system is that first a mixture of signals is removed from the surface of the pregnant woman's abdomen, which contains a weak fetal ECG signal, a dominant maternal ECG signal, and various noises. After that, this mixture is processed using wavelet transform based on Morlet to isolate characteristic high-frequency fetal components and suppress maternal signal and noise. Then, fetal QRS complexes are detected based on amplitude-time characteristics and threshold criteria, and at the final stage, a decision is made by assessing the fetal heart rate, rhythm regularity, and possible deviations, which allows forming a medically significant conclusion about the state of cardiac activity.

Fig. 4 shows the extended algorithmic support of the intelligent system for wavelet detection of the fetal ECG signal.

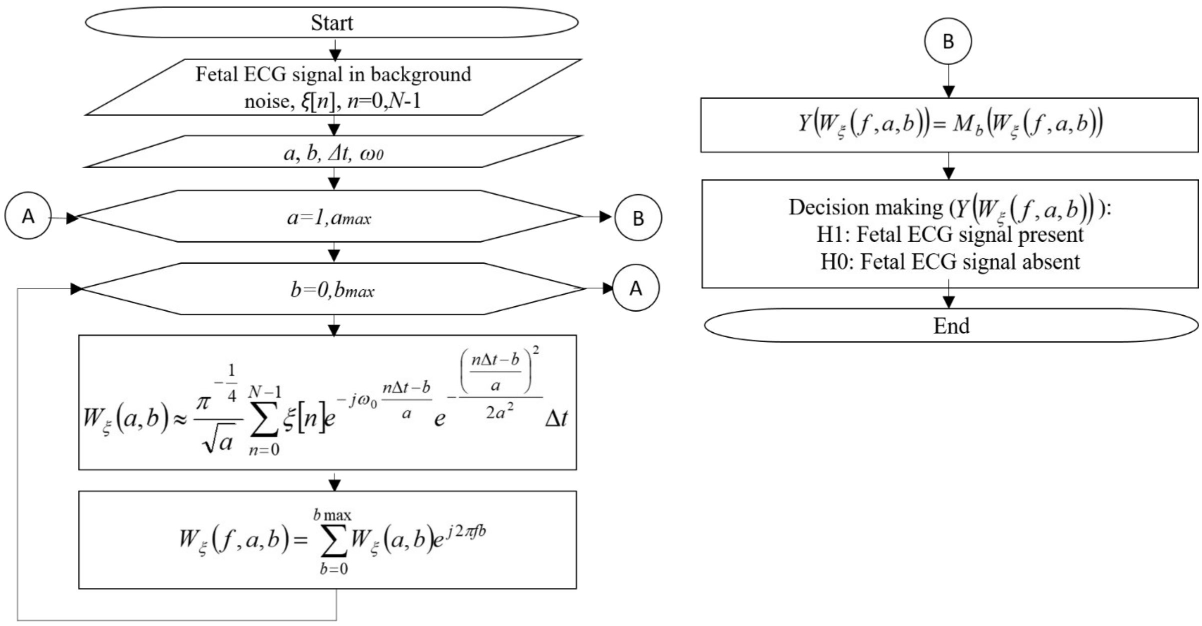

Figure 4: Algorithmic support of the intelligent system of wavelet detection of the fetal ECG signal using the Morlet basis.

Algorithmic support for wavelet processing/detection of the fetal ECG signal in the Morlet basis implements a sequence of stages aimed at detecting characteristic components of the fetal signal. At the initial stage, an input signal is introduced, which is a mixture of the fetal ECG signal, the maternal ECG signal, and noise interference.

Next, the analysis is parameterized, which involves determining the range of scales $a \in [1, a_{max}]$ and time shifts $b \in [0, b_{max}]$.

The next step is to calculate the wavelet transform coefficients $W_\xi(a,b)$ for each pair of parameters a and b, which provides a time-frequency decomposition of the signal.

After this, a spectral representation $W_\xi(f,a,b)$ is formed, which reflects the distribution of signal energy in the scale-frequency space.

Further processing involves calculating the aggregated characteristic $Y(W_\xi(f,a,b))$, which concentrates the informative features necessary for decision-making. The final stage consists in applying a statistical criterion to choose between two hypotheses: H1 – presence of a fetal ECG signal; H0 – absence of a fetal ECG signal.

6. Fetal ECG signal detection results

Fig. 5-6 presents the result of wavelet processing/detection of a mixture of fetal, maternal, and noise ECG signals in the form of a 3D image.

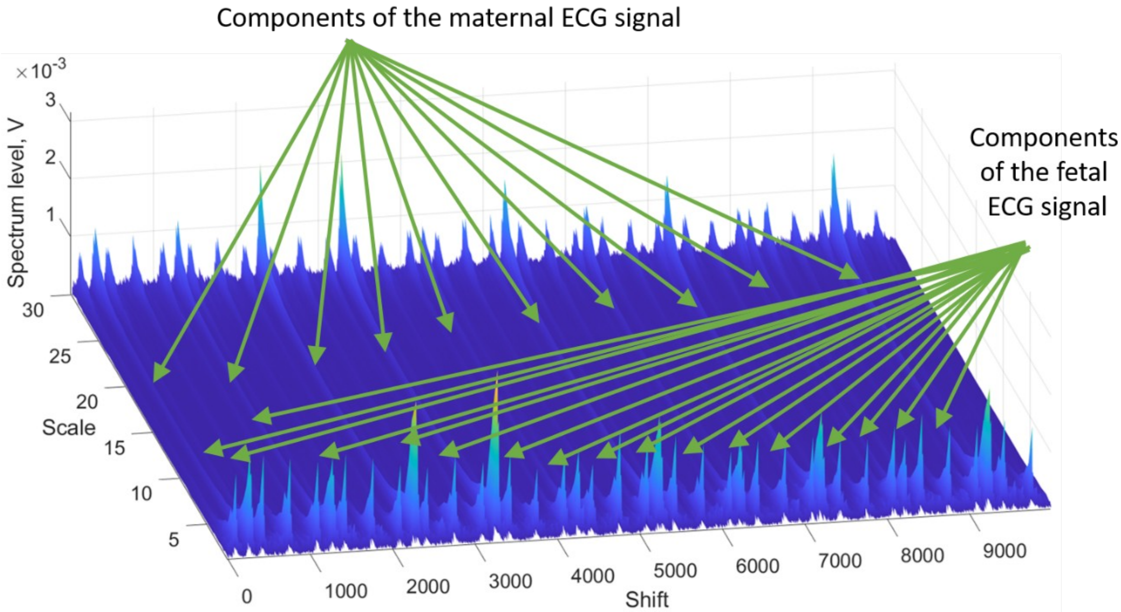

Figure 5: 3D wavelet components of the fetal ECG signal and the maternal ECG signal.

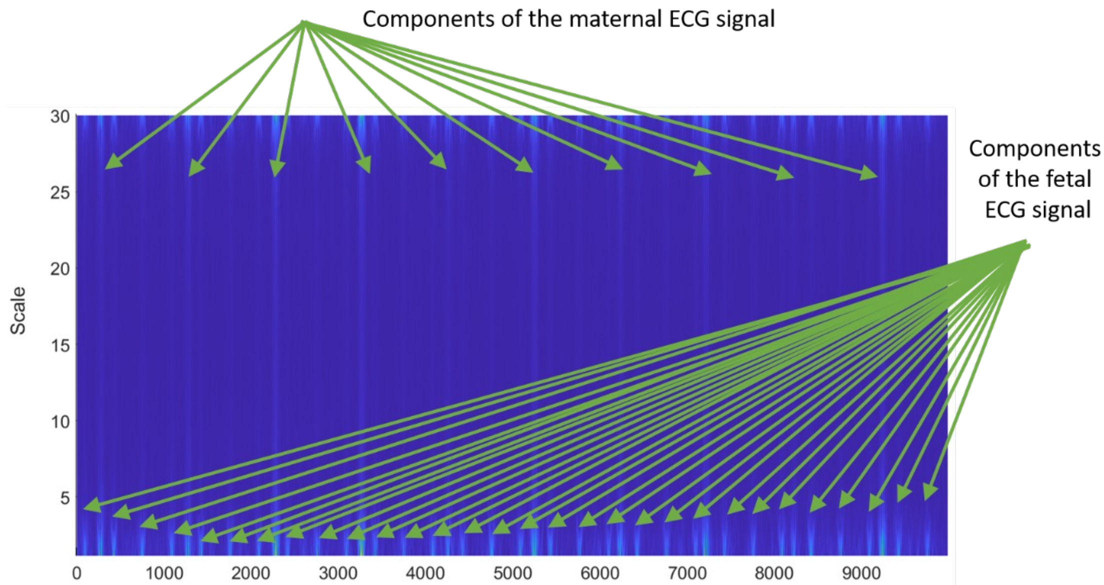

Figure 6: Wavelet components of the fetal ECG signal and the maternal ECG signal (spectrogram).

As a result of wavelet processing of ECG signals, a 3D spectrum was obtained, reflecting the spatiotemporal distribution of energy components in the coordinates "shift – scale – spectral level". The analysis demonstrated that the components of the maternal ECG signal are formed in the scale range of 0-5 with shifts of 0–10000, where the amplitude peaks reach values of 2.5×10-3 V. This corresponds to the characteristic frequencies of maternal cardiac activity within 0.8–1.5 Hz (heart rate of about 50–90 beats/min). Instead, the fetal ECG signal is detected in the range of scales 5-25 at shifts 0-10000, where regular wave structures with a spectral amplitude of the order of 0.5×10−3 V are recorded, which corresponds to a frequency range of 2-3 Hz (fetal cardiac activity 120-180 beats/min). The amplitude ratio is more than 3:1 in favor of the maternal signal, which explains the need to use complex separation methods.

The applied intelligent system is based on multilevel wavelet decomposition with automated identification of spectral features, which allows not only to separate maternal and fetal ECG signals, but also to adaptively isolate weak fetal components in the presence of powerful interference and noise. Thanks to the combination of time-frequency analysis algorithms and machine decision-making, increased accuracy of non-invasive monitoring of fetal cardiac activity is ensured, which is of significant importance for clinical diagnostics and prediction of obstetric complications.

In the task of detecting a fetal electrocardiogram against the background of the maternal signal and noise, not only the qualitative visualization of the three-dimensional wavelet spectrum is of key importance, but also the quantitative and qualitative assessment of its components. The three-dimensional representation of «shift – scale – energy» allows identifying the localization of energy maxima, however, for objective analysis and automated processing it is necessary to switch to two-dimensional averaged components, which are constructed by convolution (averaging) over time shift:

$$\hat{Y}(a)=M_b\{W(a,b)\}, \tag{10}$$

Thus, calculating a 2D projection of the averaged components allows us to estimate the contribution of signals at different scales without being tied to a specific point in time.

The intelligent system uses this very approach: 3D wavelet space is used to detect ECG signals in a time-frequency distribution, while 2D averaged estimates provide quantitative extraction of stable spectral features of the fetus, which allows to increase the reliability of diagnostics and minimize the impact of noise artifacts.

Fig. 7 shows the result of averaging 3D wavelet coefficients.

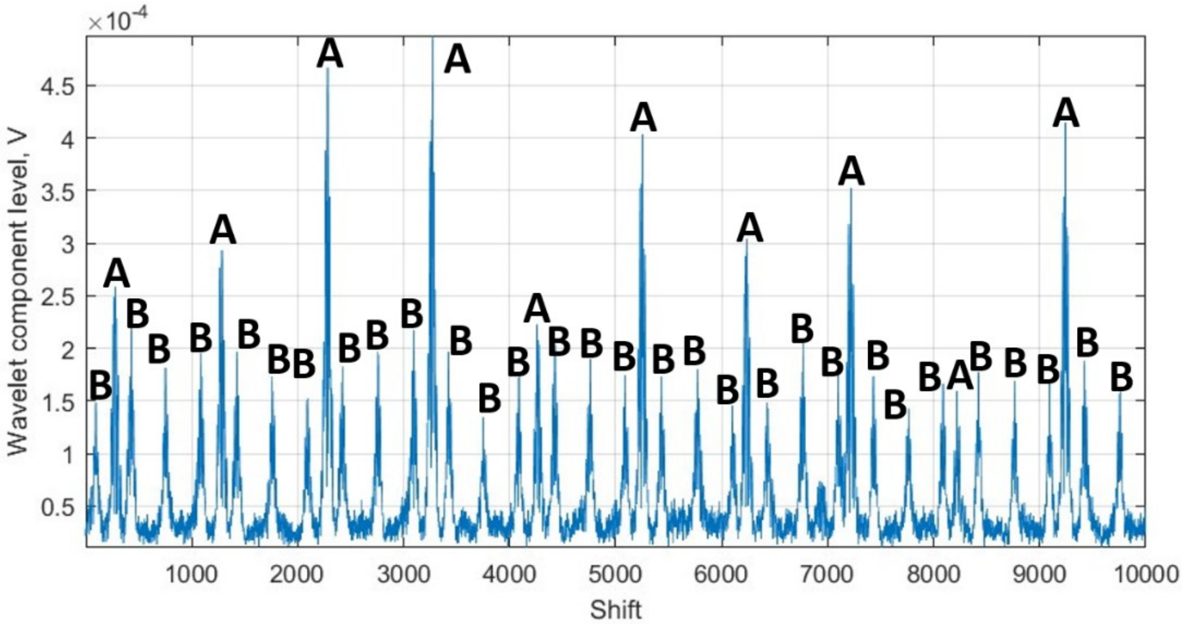

Figure 7: Averaged 3D wavelet coefficients (A – component of the maternal ECG signal; B – component of the fetal ECG signal).

Fig. 7 shows the result of the averaged estimation of wavelet components by time shifts, which reflects the integral spectral distribution of the signal after 3D wavelet processing. This allows us to move from a multidimensional time-frequency structure to a clear 2D representation, where the components of the maternal and fetal ECG signals are well separated.

The maternal ECG signal components (labeled «A») have a larger amplitude (up to 4.5×10^{-4} V) and form periodic pronounced peaks in the offset range of approximately 0-500, 2000-2500, 3000-3500, 4500-5000, 6000-6500, 7000-7500, and 9000-9500. This corresponds to the lower maternal heart rate (≈0.8-1.5 Hz or 50-90 beats/min), which is manifested in the spectrum as stable high peaks.

The fetal ECG signal components (labeled «B») have a smaller amplitude (≈1.0×10^{-4} V) but are more frequently located between maternal complexes, with a greater number of peaks within a single time interval. This corresponds to a higher fetal heart rate (≈2-3 Hz or 120-180 beats/min).

Thus, averaging the wavelet components allowed us to clearly distinguish two groups of signals: high and rare maternal peaks and lower, but more regular fetal ones. This confirms the effectiveness of the technique: in the 3D wavelet space, maternal and fetal components were separated, and the transition to 2D-averaged estimates based on the proposed characteristics made it possible to quantitatively compare and automatically detect the fetal ECG signal against the background of the stronger maternal signal and noise.

The proposed detection method has great practical significance and can be applied to problems in other industries [14-17].

7. Conclusions

The obtained wavelet processing results indicate that the intelligent fetal ECG signal detection system operates on the basis of two-dimensional transformation using the Morlet basis, after which the wavelet coefficients are averaged over time shifts. At the output, such a system forms averaged 2D wavelets, which are an informative reflection of the dynamics of amplitude changes in the specified scale ranges corresponding to the frequency characteristics of fetal cardiac activity. The use of this approach allows for effective suppression of powerful components of the maternal ECG signal and background noise, leaving pronounced periodic structures that correlate with the fetal heart rate (approximately 2-3 Hz). It is the 2D averaged wavelets that serve as the key detection criterion for automatic selection of fetal peaks that reflect fetal electrocardiographic activity. Thus, the system provides reliable detection of a weak fetal ECG signal against the background of the dominant maternal and fetal ECG signal, which creates the basis for increasing the reliability of non-invasive real-time fetal monitoring.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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