https://doi.org/10.31891/csit-2025-3-4
UDC: 519.24:004.4:616.12-073.96

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RESULTS OF APPLICATION OF INFORMATION TECHNOLOGY FOR PROCESSING AND ANALYSING ELECTROCARDIOGRAM SIGNALS TAKING INTO ACCOUNT THEIR MORPHOLOGICAL AND RHYTHMIC CHARACTERISTICS

This paper presents an information technology for comprehensive processing and analysis of electrocardiographic signals considering their morphological and rhythmic characteristics based on a cyclic random process mathematical model for improved cardiac pathology detection. The proposed information technology utilizes a cyclic random process (CRP) model that naturally accounts for the quasi-periodic structure of ECG signals with variable rhythm. The system implements sequential and parallel processing through interconnected functional blocks: preprocessing (baseline drift removal, noise filtering), automatic segmentation for cycle boundary detection, rhythm function formation using cubic spline interpolation, cyclic signal transformation ensuring equal sample counts per cycle, and separate statistical processing of morphological and rhythmic features. Experimental verification was performed on real ECG signals from patients diagnosed with atrial fibrillation and atrial flutter. The technology successfully segmented ECG signals and quantified both amplitude and temporal variability. For atrial fibrillation, the rhythm function demonstrated significant variability (400-800 ms range) with sharp transitions between adjacent values. For atrial flutter, the rhythm function showed greater stability (150-230 ms range) with smoother fluctuations. Statistical analysis revealed distinct patterns of morphological variability, with dispersion values reaching 0.004 mV² for atrial fibrillation and 0.025 mV² for atrial flutter. The key innovation lies in the simultaneous yet separate analysis of morphological and rhythmic characteristics through rhythm function incorporation, enabling comprehensive assessment of both amplitude variability and beat-to-beat dynamics within a unified CRP framework. The developed technology enables automated differentiation between various cardiac pathologies through independent classification of rhythmic and morphological abnormalities, supporting clinical decision-making in cardiac diagnostics and real-time monitoring applications.

Keywords: electrocardiographic signal modeling, model, analysis, diagnostics, information technology, cyclic discrete random process, amplitude-time characteristics, cardiac signal analysis, mathematical modeling, time rhythm function, cardiac diagnostics, amplitude variability, signal classification, artificial intelligence (AI), machine learning system (MLS), neural network.

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РЕЗУЛЬТАТИ ЗАСТОСУВАННЯ ІНФОРМАЦІЙНОЇ ТЕХНОЛОГІЇ ОПРАЦЮВАННЯ ТА АНАЛІЗУ ЕЛЕКТРОКАРДІОСИГНАЛІВ З ВРАХУВАННЯМ ЇХ МОРФОЛОГІЧНИХ ТА РИТМІЧНИХ ОЗНАК

У роботі представлено інформаційну технологію (ІТ) комплексного опрацювання та аналізу електрокардіографічних сигналів з урахуванням їх морфологічних та ритмічних характеристик на основі математичної моделі циклічного випадкового процесу для покращення виявлення серцевих патологій. Запропонована інформаційна технологія використовує модель циклічного випадкового процесу (ЦВП), яка природно враховує квазіперіодичну структуру ЕКГ-сигналів (ЕКС) зі змінним ритмом. Система реалізує послідовне та паралельне опрацювання через взаємопов'язані функціональні блоки: попередня обробка (усунення дрейфу базової лінії, фільтрація шумів), автоматична сегментація для визначення меж циклів, формування функції ритму з використанням кубічної сплайн-інтерполяції, перетворення циклічного сигналу із забезпеченням однакової кількості відліків на цикл та роздільна статистична обробка морфологічних і ритмічних ознак. Експериментальну верифікацію проведено на реальних ЕКС пацієнтів з діагностованою фібриляцією та тріпотінням передсердь. Технологія успішно сегментувала ЕКС та кількісно оцінила амплітудну й часову варіабельність. Для фібриляції передсердь функція ритму продемонструвала значну варіабельність (діапазон 400-800 мс) з різкими переходами між сусідніми значеннями. Для тріпотіння передсердь функція ритму показала більшу стабільність (діапазон 150-230 мс) з плавнішими коливаннями. Статистичний аналіз виявив чіткі патерни морфологічної варіабельності зі значеннями дисперсії до 0,004 мВ² для фібриляції передсердь та 0,025 мВ² для тріпотіння передсердь. Ключова інновація полягає в одночасному, але роздільному аналізі морфологічних та ритмічних характеристик через врахування функції ритму, що забезпечує комплексну оцінку амплітудної варіабельності та динаміки від циклу до циклу в рамках єдиної моделі ЦВП. Розроблена технологія дозволяє автоматично диференціювати різні серцеві патології через незалежну класифікацію ритмічних та морфологічних аномалій, підтримуючи клінічне прийняття рішень у кардіодіагностиці та застосуваннях моніторингу в реальному часі.

Ключові слова: моделювання електрокардіосигналів, модель, аналіз, діагностика, інформаційна технологія, циклічний дискретний випадковий процес, амплітудно-часові характеристики, аналіз кардіосигналів, математичне моделювання, часова функція ритму, кардіодіагностика, амплітудна варіабельність, класифікація сигналів, штучний інтелект (AI), система машинного навчання (MLS), нейронна мережа.

Received / Стаття надійшла до редакції 21.08.2025
Accepted / Прийнята до друку 20.09.2025

Introduction

Modern ECG processing methods often focus on individual aspects of the signal – either temporal characteristics (heart rate variability – HRV) or morphological features (waveform shape and amplitude). This separate approach does not account for the relationship between rhythmic and morphological changes, which is particularly important when diagnosing complex cardiac pathologies. Amplitude variability of key ECG components (P-wave, QRS complex, T-wave) reflects changes in myocardial electrophysiology, while temporal variability represents the dynamic interaction between sympathetic and parasympathetic branches of the autonomic nervous system [1, 2].

Existing models and methods have significant limitations. Integral Pulse Frequency Modulation (IPFM) models effectively describe heart rhythm generation but do not model P-QRS-T complex morphology. Deep learning approaches demonstrate high classification accuracy but operate as “black boxes”, not providing clinically interpretable parameters. Time-frequency methods analyze the signal as a whole without utilizing information about its quasi-periodic structure.

Thus, the development of IT that would provide comprehensive ECG analysis with simultaneous consideration of morphological and rhythmic characteristics, using the signal’s natural cyclic structure and providing clinically significant parameters for diagnostic decision support, is relevant.

Related works

ECGs provide critically important information about the heart’s electrical activity. Amplitude variability of key ECG components (P-wave, QRS complex, T-wave) reflects changes in myocardial electrophysiology, potentially signaling pathological conditions such as ischemia or conduction disorders. Temporal variability, particularly HRV, represents fluctuations in intervals between consecutive heartbeats and reflects the dynamic interaction between sympathetic and parasympathetic branches of the autonomic nervous system [3–5].

ECG variability modeling has evolved from traditional time and frequency analysis methods to complex nonlinear models and machine learning approaches. The main challenges remain: presence of noise and non-stationarity in ECG recordings, effective separation of amplitude and phase (temporal) variability, and the need to generate realistic synthetic data for algorithm validation [6–9].

Integral Pulse Frequency Modulation (IPFM) Models. The IPFM model conceptualizes heartbeat generation as an integrate-and-fire process, where the integrator output is modulated by neural inputs reflecting autonomic nervous system activity. Extensions of classical IPFM include chaotic and statistical threshold variations using logistic, Henon, Lorenz, and tent maps to enhance physiological realism [3]. Both linear features (mean, variance, standard deviation) and nonlinear features (Lyapunov exponent, Shannon entropy and its variants) are extracted from IPFM-generated signals, allowing validation of the model’s ability to reproduce real physiological variability [3].

Geometric Models and Functional Data Analysis. The modern approach considers ECGs as objects in infinite-dimensional functional spaces, allowing elegant separation of amplitude variability (shape or magnitude changes) from phase variability (temporal warping). Application of elastic metrics and functionally-adapted Principal Component Analysis (PCA) provides efficient representation of complex variability patterns [10]. These models find direct application in monitoring arrhythmias and ischemic events by determining "normal" variability boundaries, where signals outside these tolerance limits indicate potential cardiac dysfunction [10].

Machine Learning and Deep Learning Approaches. Traditional machine learning methods such as Support Vector Machines (SVM) and Random Forests use hand-crafted features for cardiac state classification. Deep neural networks, particularly Convolutional Neural Networks (CNN), automatically learn hierarchical representations from raw signals, detecting latent patterns that may be missed by traditional approaches [11, 12]. Hybrid models integrate classical signal processing with deep learning, while ensemble methods combine multiple algorithms to improve diagnostic accuracy. Dynamic updating and continuous learning maintain model accuracy over time, which is critical for real-time monitoring [13].

Chaos Theory and Entropy-Based Models. Application of chaotic systems theory in ECG modeling allows emulation of intrinsic nonlinearities and unpredictability of heart rhythms. Entropy metrics, including Shannon entropy and its variants, quantify uncertainty and complexity in ECGs. Recurrence Quantification Analysis (RQA) offers an approach to describing temporal structure through analysis of recurrent state trajectory visits [3, 4, 14].

Coupled Oscillator Models. The cardiovascular system (CVS) is modeled as a network of coupled nonlinear oscillators, where each oscillator represents a physiological subsystem. These models include linear and nonlinear couplings along with stochastic perturbations, reproducing characteristic features such as respiratory sinus arrhythmia [15, 16].

Shape-Based Models and Generative Adversarial Networks (GAN). Generative Adversarial Networks (GAN) represent a novel approach to ECG data synthesis. Anchored GANs allow independent control of temporal and amplitude components of synthetic signals, facilitating tailored data augmentation and improving classifier generalization [7, 8]. Absolute Amplitude Ordinal Partition Networks (AAOPN) extend ordinal partition methods by

integrating amplitude level information, providing multi-scale representation of waveform morphology for automated arrhythmia detection [17].

Time-Frequency Analysis. Wavelet and Synchrosqueezing Transform (SST) provide robust tools for ECG wave component detection, showing particular resistance to broadband noise. Adaptive harmonic models represent ECGs as sums of time-varying harmonic components with slowly fluctuating frequencies and amplitudes [18, 19].

Autonomic Modulation-Aware Models. Explicit modeling of autonomic nervous system influence on cardiac variability provides critical insights into physiological regulation. Parametric estimation methods allow quantification of sympathetic and parasympathetic contributions to heart rhythm modulation. In clinical contexts such as Brugada syndrome, model-based autonomic system estimates have demonstrated utility in sudden cardiac death risk assessment with high prognostic efficiency (AUC = 95%) [20].

The conducted review demonstrates the diversity of approaches to ECG modeling and analysis, each with its advantages and limitations.

Information Technology for ECG Processing and Analysis Considering Morphological and Rhythmic Features

For comprehensive ECG analysis considering both morphological and rhythmic features, we developed IT (Fig. 1) based on the mathematical model of Cyclic Random Process (CRP). This model naturally accounts for the quasi-periodic ECG structure with variable rhythm. CRP has proven effective in processing cyclic signals in medicine [21, 22], as it allows simultaneous processing of both morphological and rhythmic signal characteristics by accounting for the rhythm function. CRP allows describing the ECG as a separable random process $\xi(\omega, t)$ with cyclic structure and variable rhythm [23, 24]. The rhythm function $T(t, n)$ reflects the law of temporal interval changes between single-phase process values and ensures stochastic equivalence of cycles in a broad sense [23–25].

The developed IT consists of interconnected functional blocks that implement sequential and parallel ECG processing.

1. Preprocessing Block (PPB) – Performs primary signal preparation: removal of DC component, low-frequency trend (baseline drift) using least squares method and high-frequency noise filtering. The result is a cleaned ECG $\bar{\xi}_{\omega}(l)$, suitable for further segmentation.

2. Segmentation Block (SB) – Performs automatic determination of cycle boundaries and diagnostic zones within each cycle. R-peak detection methods, P-wave onset and T-wave offset determination are used. A segment-zone structure $\widehat{\boldsymbol{D}}_z = \{l_{i_j}, i = \overline{1,C}, j = \overline{1,Z}\}$ is formed [26].

3. Rhythm Function Formation Block (RFFB) – Based on the detected segment structure, estimates the discrete rhythm function $\hat{T}(l_{ij}, n)$ and its uninterrupted analog $\hat{T}(l, n)$ through cubic spline interpolation methods [27–29]. This allows mathematical description of heart rhythm irregularity.

4. Cyclic Signal Formation Block (CSFB) – Transforms the input ECG with varying number of samples on cycles into a signal with equal number of samples Q on each cycle through resampling procedure considering the rhythm function. This ensures correctness of subsequent statistical processing.

5. Statistical Processing Block (SPB) – Calculates statistical estimates considering the rhythm function: mathematical expectation and variance. These estimates characterize the averaged cycle morphology and its variability.

6. Parallel branch for rhythmic characteristics analysis:

Duration of Segment Structure Formation Block (**DSSFB**) – calculates durations of all diagnostic zones $\hat{T}_{i_j} = l_{i_{j+1}} - l_{i_j}$.

Duration Spread Formation Block (**DSFB**) – determines duration deviations from reference (first) cycle: $\overset{\circ}{T}_{i_j} = \hat{T}_{i_j} - \hat{T}_{1_j}$.

Statistical Processing of Durations Block (**SPDB**) – calculates statistical characteristics of rhythmic variability.

7. Parallel branch for amplitude characteristics analysis:

Amplitude Value Spread Formation Block (**AVSFB**) – calculates amplitude deviations from mathematical expectation: $\overset{\circ}{f}_{i_j}(l) = \hat{f}_{i_j}(l) - \hat{m}_{\xi_{T(l,1)_j}}(l)$ or inter-cycle differences: $\dot{f}_{i_j}(l) = \hat{f}_{i_j}(l) - \hat{f}_{i+1_j}(l)$.

Statistical Processing of Amplitude Spreads Block (**SPASB**) – forms statistical estimates of amplitude variability.

8. Modeling blocks (MDB, MASB) – generate synthetic realizations of durations and amplitude values based on obtained statistical characteristics for classifier training.

9. Classification blocks (CRB, CMB) – use machine learning methods (neural networks, SVM) for normal/pathology state classification separately by rhythmic and morphological features.

The key advantage of the developed IT is separate analysis of morphological and rhythmic characteristics, allowing identification of different pathology types; statistical processing considering the signal's cyclic structure and comprehensive analysis of both amplitude and temporal variability.

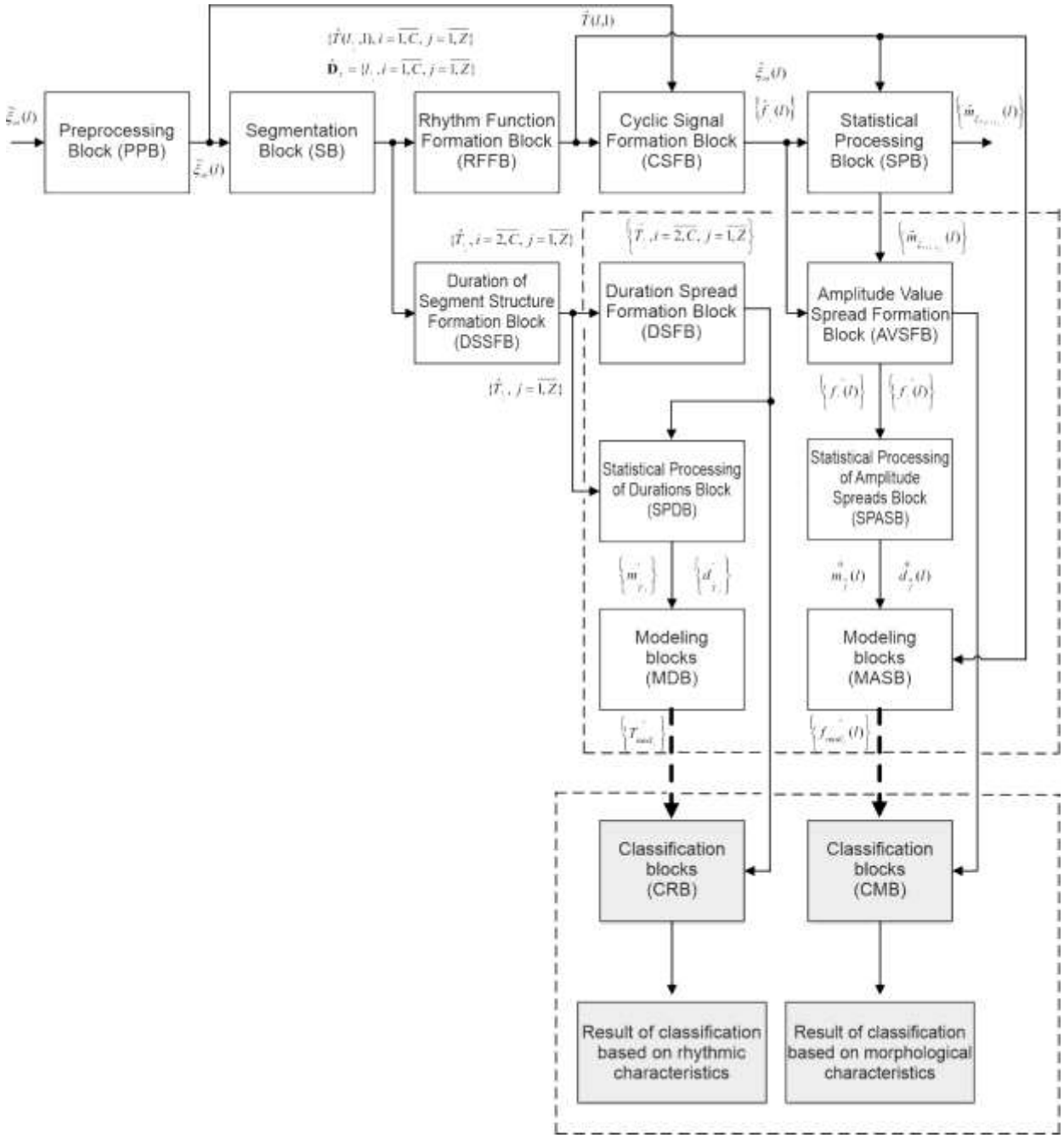
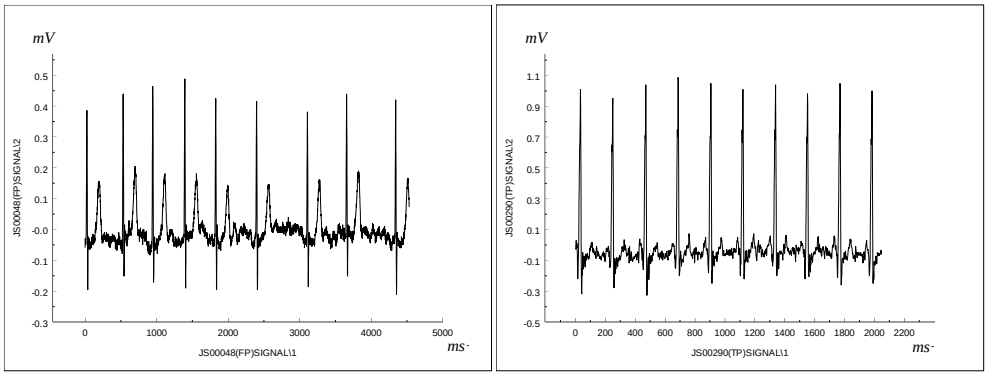


Fig. 1. Structural Scheme of IT for ECG Analysis

Experiments

To verify the effectiveness of the developed IT, experimental research was conducted on real ECGs of patients with diagnosed heart rhythm disorders. Two pathologies with pronounced electrical heart activity disturbances were selected: 1) atrial fibrillation (AF) and 2) atrial flutter (AFL).

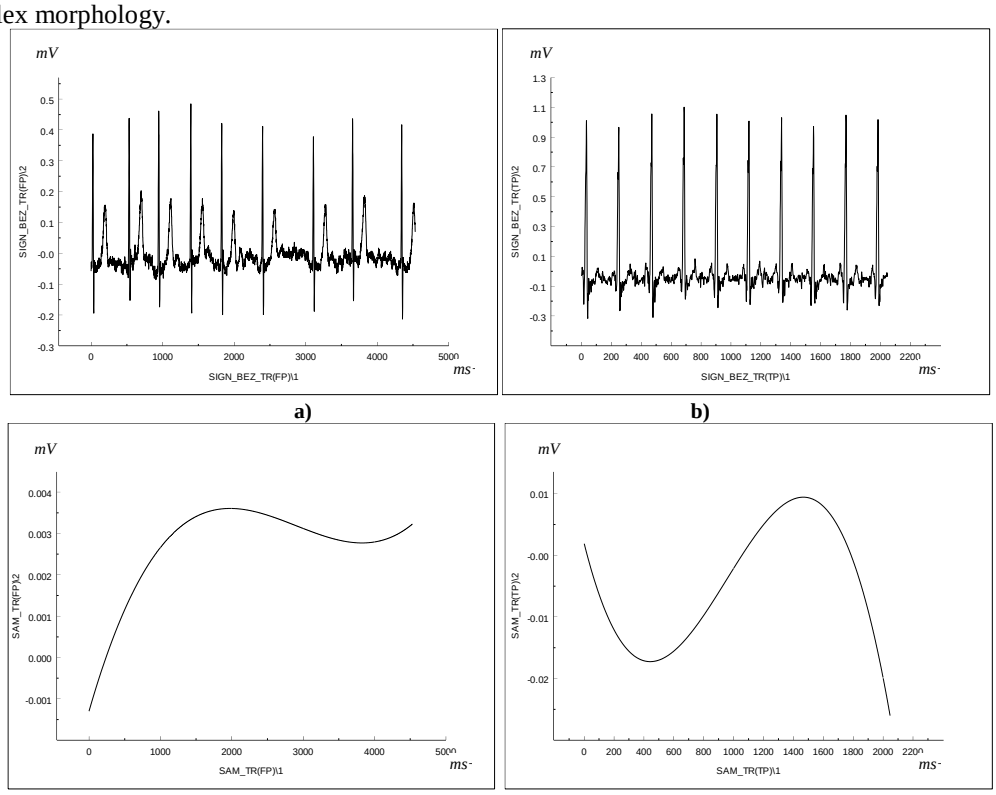
Let's consider in detail the results of each processing stage in the IT structural scheme for both pathology types.



a) **b)**

Fig. 2. Input ECGs: a) AF pathology; b) AFL pathology

The trend removal results (Fig. 3) confirm the effectiveness of the applied least squares method. For AF, a low-frequency trend with amplitude up to 0.004 mV was detected (Fig. 3c), whose removal stabilized the signal baseline. For AFL, the trend has amplitude ranging from -0.02 to 0.01 mV (Fig. 3d). Comparison of signals before and after detrending (Fig. 3a, 3b) demonstrates successful removal of slow baseline oscillations while preserving QRS complex morphology.

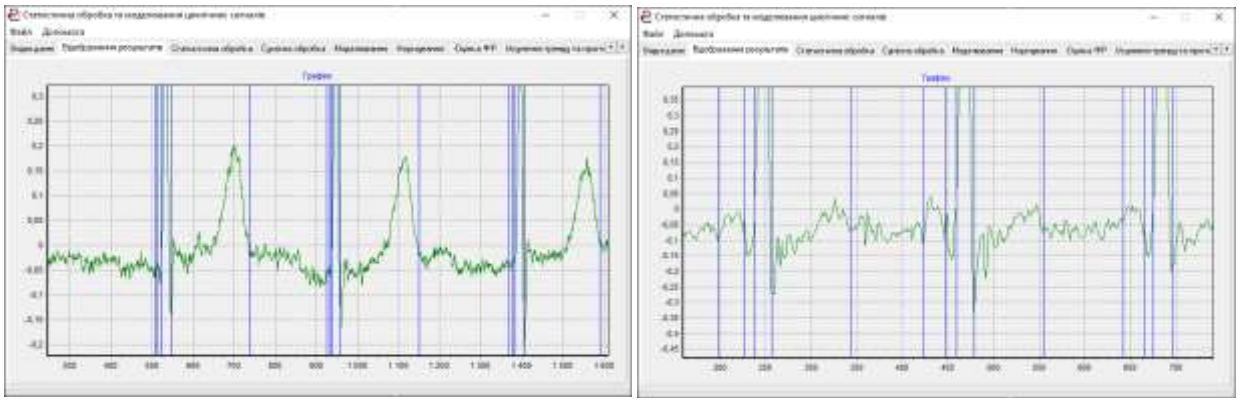


a) **b)**

c) **d)**

Fig. 3. ECG trend removal: a) ECG without trend – AF; b) ECG without trend – AFL; c) ECG trend – AF; d) ECG trend – AFL

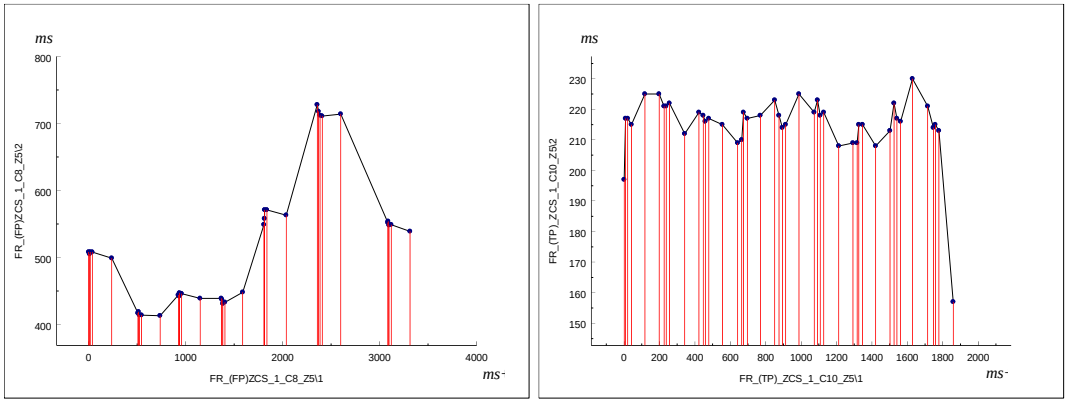
Automatic segmentation results (Fig. 4) demonstrate successful detection of cardiac cycle boundaries. In Figure 4a for AF, a fragment with highlighted segments is visualized, where significant cycle duration variability is noticeable. Vertical lines mark boundaries of detected diagnostic zones. For AFL (Fig. 4b), segmentation shows a more regular structure with uniform intervals between cycles. Blue vertical markers indicate detection points of characteristic ECG elements.



a) **b)**

Fig. 4. ECG segmentation fragments: a) AF pathology; b) AFL pathology

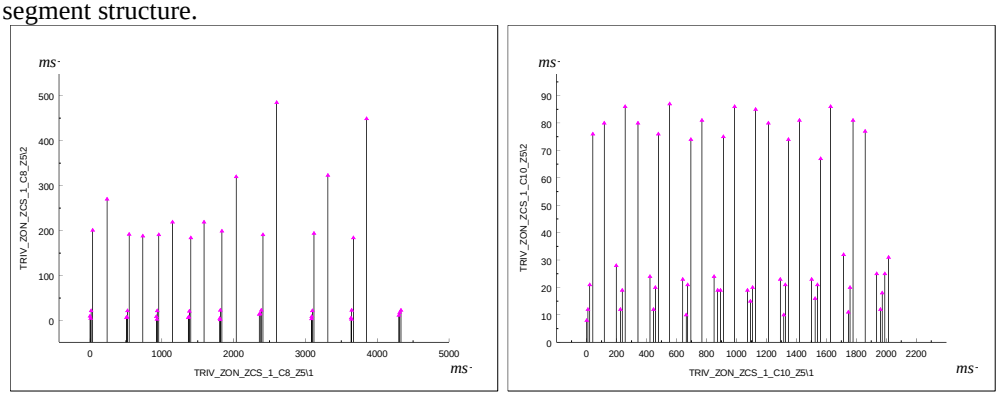
The estimated rhythm function quantitatively characterizes heartbeat variability. For AF (Fig. 5a), the rhythm function demonstrates significant variability, fluctuating in the range of approximately 400-800 ms according to the ordinate axis. Sharp transitions between adjacent values are observed, characteristic of chaotic atrial electrical activity. For AFL (Fig. 5b), the rhythm function is significantly more stable, being in a narrower range of 150-230 ms, with smoother oscillations reflecting the quasi-periodic nature of this pathology.



a) **b)**

Fig. 5. Discrete rhythm function for ECG: a) AF pathology; b) AFL pathology

Analysis of segment structure durations revealed significant differences between pathologies. In AF (Fig. 6a), significant variability of different zone durations is observed, ranging from about 0 to 500 ms. Both short segments (less than 100 ms) and significantly prolonged ones (300-500 ms) are present, indicating signal structure irregularity. In AFL (Fig. 6b), zone durations are in a smaller range (0-90 ms), demonstrating greater uniformity and stability of segment structure.

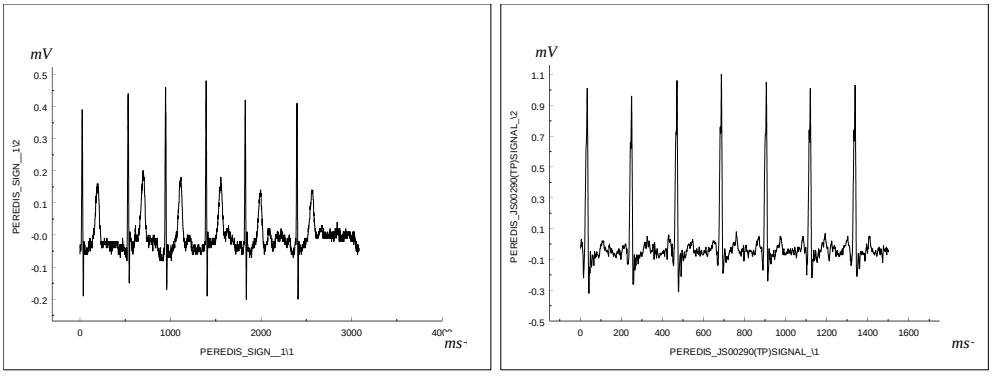


a) **b)**

Fig. 6. Segment structure durations of ECG: a) AF pathology; b) AFL pathology

The resampling procedure result demonstrates successful signal normalization. In Fig. 7a for AF, the cyclic signal after equalizing the number of samples on all cycles is presented. The morphology of QRS complexes and other characteristic ECG elements is preserved, the signal has uniform temporal structure within 0 to 4000 ms range. For AFL (Fig. 7b), an analogous procedure was performed in the 0-1600 ms range. Visual comparison with original

signals confirms preservation of main diagnostic features while ensuring equal number of discrete samples for each cycle, which is a necessary condition for correct statistical processing within the cyclic random process model framework.



a) **b)**

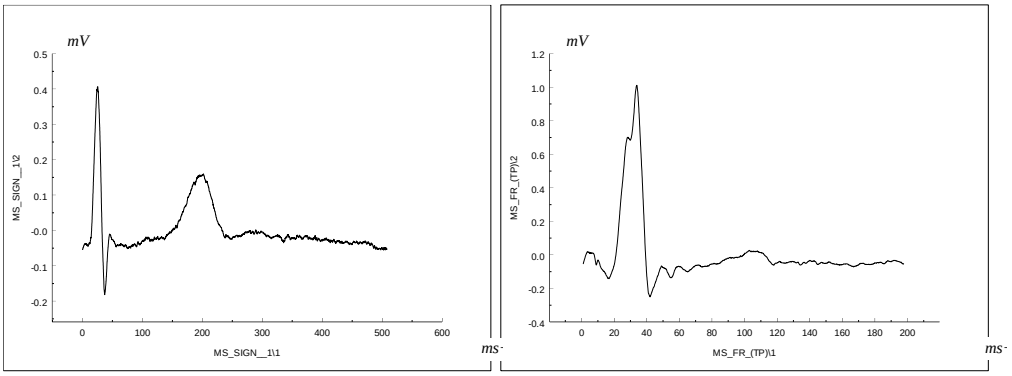
Fig. 7. Cyclic ECG (equal number of samples on each cycle): a) AF pathology; b) AFL pathology

Mathematical expectation estimates represent the averaged cycle morphology for each pathology. In AF (Fig. 8a), the averaged signal demonstrates a characteristic pattern with dominant positive peak around 0.4 mV and subsequent negative deviation to -0.2 mV according to the scale. In AFL (Fig. 8b), the averaged morphology shows a pronounced initial peak with amplitude around 1.0 mV with subsequent oscillations. Additional oscillations noticeable between main complexes may reflect high-frequency atrial activity characteristic of this pathology.

Analysis of deviations from averaged morphology (Fig. 9) shows the amplitude of fluctuations relative to the reference cycle. In AF, spreads are within ±0.10 mV, in AFL – in a wider range ±0.3 mV.

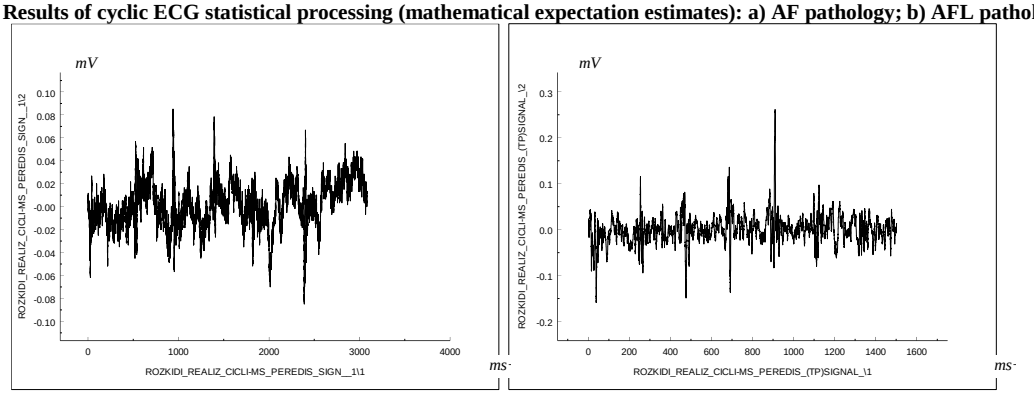
Inter-cycle variability (Fig. 10) demonstrates morphology change dynamics. In AF, differences between consecutive cycles reach ±0.14 mV, in AFL – up to ±0.3 mV.

Mathematical expectation values are close to zero, confirming calculation correctness.



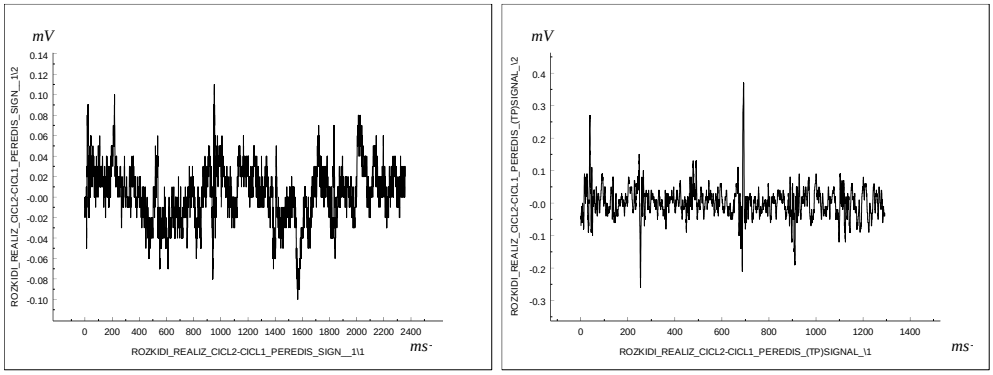
a) **b)**

Fig. 8. Results of cyclic ECG statistical processing (mathematical expectation estimates): a) AF pathology; b) AFL pathology



a) **b)**

Fig. 9. Amplitude value spreads (cycles – mathematical expectation estimate): a) AF pathology; b) AFL pathology

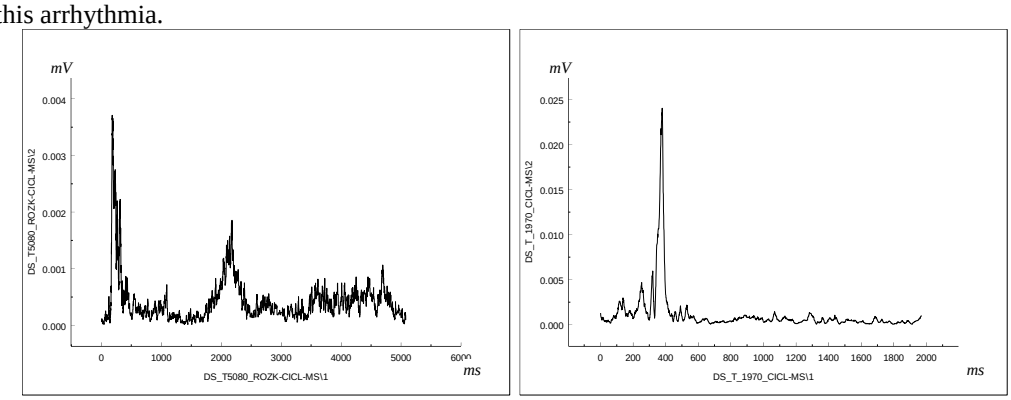


a) **b)**

Fig. 10. Amplitude value spreads (current cycle – previous cycle): a) AF pathology; b) AFL pathology

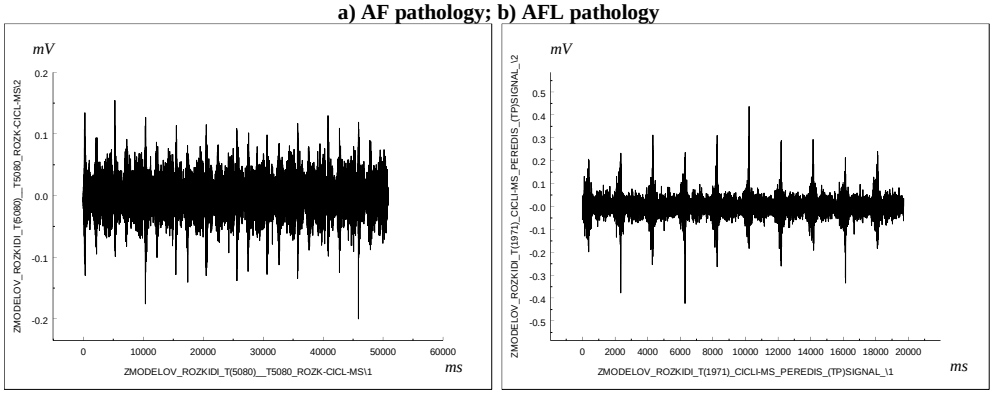
Variance estimates characterize the degree of amplitude value variability relative to averaged cycle morphology. In AF (Fig. 11a), spread variance is within 0-0.004 mV² with maximum values at cycle onset. In AFL (Fig. 11b), higher variance values are observed – up to 0.025 mV², with pronounced peak at recording onset. Higher variance in AFL indicates greater amplitude variability, despite the more regular rhythm of this pathology.

Modeled realizations demonstrate the character of amplitude value spreads for long recordings. In AF (Fig. 12a), the generated realization with duration up to 60000 ms shows fluctuations within ±0.2 mV with uniform deviation distribution throughout the entire recording. The stochastic character of spreads corresponds to the chaotic nature of fibrillation. For AFL (Fig. 12b), the modeled realization (duration up to 20000 ms) demonstrates a wider fluctuation range – from -0.5 to 0.5 mV, with noticeable pattern structure, which may reflect the quasi-periodic nature of this arrhythmia.



a) **b)**

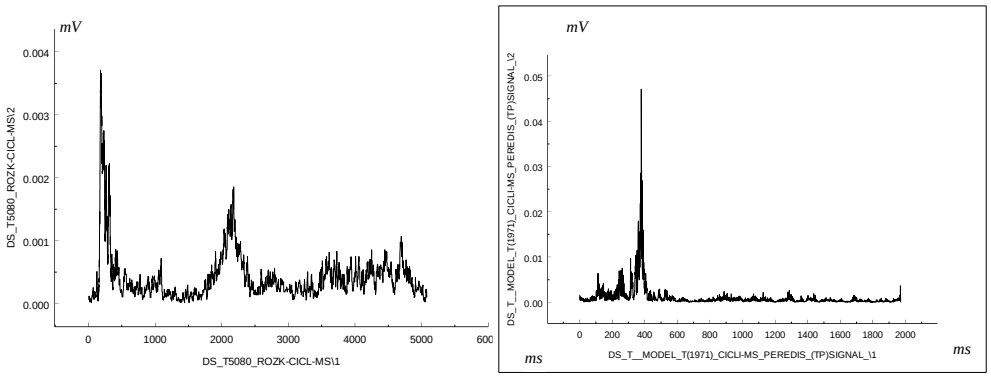
Fig. 11. Results of statistical processing of ECG amplitude value spreads (variance) (cycles – mathematical expectation estimate): a) AF pathology; b) AFL pathology



a) **b)**

Fig. 12. Results of computer modeling of ECG amplitude value spreads (cycles – mathematical expectation estimate): a) AF pathology; b) AFL pathology

The variance of modeled data confirms the adequacy of synthetic realization generation. For AF (Fig. 13a), model variance is within 0-0.004 mV² with characteristic initial peak and subsequent stabilization, which agrees with real data variance (Fig. 11a). In AFL (Fig. 13b), variance reaches 0.06 mV² with pronounced maximum at onset, which also corresponds to the real data pattern, albeit with somewhat higher absolute values. Comparison of real and modeled data variances indicates the proposed model's ability to reproduce main statistical properties of amplitude variability in the studied pathologies.



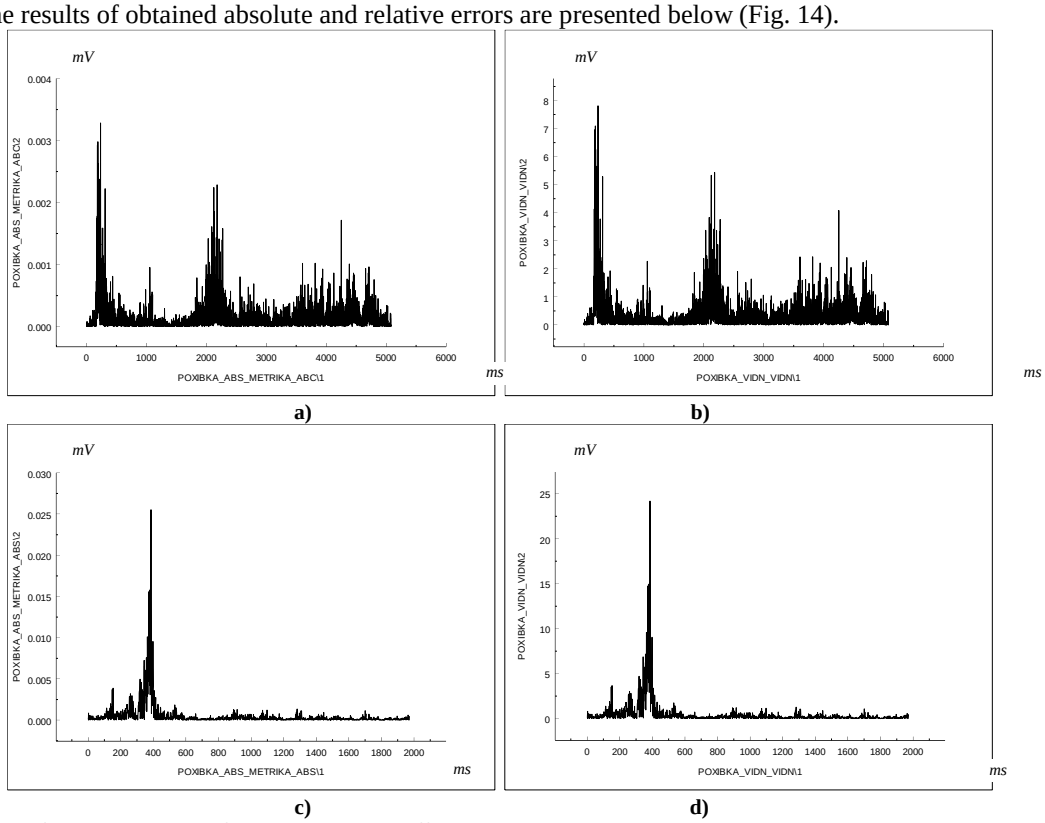
a) **b)**

Fig. 13. Results of variance estimation of statistical characteristics of computer modeling of ECG amplitude value spreads (cycles – mathematical expectation estimate): a) AF pathology; b) AFL pathology

Estimation of ECG amplitude value spread modeling errors is performed according to the formula:

$$\Delta(l) = |d(l) - d_{mod}(l)| \;\; \delta(l) = \frac{\Delta(l)}{|d_{mod}(l)|} \tag{1}$$

where $\Delta(l)$ – absolute error value; $\delta(l)$ – relative error value.
The results of obtained absolute and relative errors are presented below (Fig. 14).



a) **b)**

c) **d)**

Fig. 14. Results of error calculation of variance estimate differences a) absolute, b) relative (AF pathology); c) absolute, d) relative (AFL pathology)

Modeling error analysis allows evaluation of the accuracy of amplitude variability statistical characteristics reproduction. For AF, absolute error (Fig. 14a) is predominantly within 0-0.004 mV² with isolated peaks up to 0.006 mV² at recording onset. Relative error (Fig. 14b) demonstrates greater variability – from 0 to 8 units, with maximum values in the initial part, which may be related to modeling transient processes or small variance values in the denominator when calculating relative error. For AFL, absolute error (Fig. 14c) reaches higher values – up to 0.035 mV², with pronounced peak at onset and subsequent decrease to baseline level around 0.005 mV². Relative error (Fig. 14d) also shows maximum at onset (up to 25 units) with subsequent stabilization at level around 5 units.

Conclusions

The developed IT for ECG processing and analysis based on the CRP model provides a comprehensive approach to detection and classification of cardiac pathologies. The key advantage of the proposed approach is

simultaneous but separate processing of ECG morphological and rhythmic characteristics, allowing identification of different types of cardiac activity disorders with high accuracy. Experimental verification on real ECGs of patients with atrial fibrillation and flutter confirmed the effectiveness of the developed technology. For AF, significant rhythm function variability (400-800 ms) with chaotic transitions was revealed, while AFL was characterized by more stable rhythm (150-230 ms) with more regular oscillations. Statistical analysis of amplitude variability showed clear differences between pathologies: spread variance for AF did not exceed 0.004 mV², while for AFL it reached 0.025 mV².

Using the rhythm function within the CRP model framework allowed correct consideration of cardiac cycle irregularity during statistical processing, ensuring adequacy of mathematical expectation and variance estimates. Separate analysis of deviations from averaged morphology and inter-cycle differences provided the ability to separate static and dynamic components of amplitude variability, which is important for understanding arrhythmia pathophysiological mechanisms.

Further development of the proposed technology will be carried out in several directions:

Integration of machine learning and artificial intelligence methods for automatic classification of a wider spectrum of cardiac pathologies, including ischemic heart disease, cardiomyopathies and conduction disorders.

Modification of algorithms for processing Holter monitoring data and telemedicine systems considering circadian rhythms and physical exercise influence.

Combination of ECG analysis with data from other diagnostic methods (blood pressure variability, photoplethysmography) for comprehensive CVS state assessment.

Conducting larger-scale clinical studies to validate the developed technology on different patient populations and in real clinical practice conditions.

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