Mathematical modeling and statistical validation of the amplitude variability function of electrocardiographic signals*

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Abstract

Cardiovascular diseases remain the leading cause of mortality worldwide, necessitating the development of advanced diagnostic methods for early detection and risk stratification. This study introduces a novel mathematical model for quantifying amplitude variability of electrocardiogram (ECG) characteristic waves based on cyclic random process theory. The proposed model $V_k(m) = A_k(m) - A_k(m-1)$ captures beat-to-beat amplitude variations of P, Q, R, S, and T waves, providing quantitative metrics for assessing cardiac electrical stability. Statistical analysis was performed on ECG recordings from three patient groups: conditionally healthy individuals, patients with extrasystole, and patients with incomplete left bundle branch block. The Kolmogorov-Smirnov test confirmed stationarity (p-values: 0.578-0.945), while the Anderson-Darling test validated normal distribution across all groups. Results revealed a 300-fold increase in variance for extrasystole patients (σ^2 = 0.8099) compared to controls (σ^2 = 0.0027), quantitatively reflecting electrical instability. Higher-order statistical moments (skewness and kurtosis) demonstrated distinct patterns for different pathologies, suggesting diagnostic specificity. The computational simplicity of the model enables real-time implementation in modern ECG monitoring systems. These findings establish amplitude variability as a complementary diagnostic biomarker to traditional heart rate variability, offering new insights into cardiac electrical heterogeneity. The confirmed statistical properties provide a robust foundation for developing automated diagnostic algorithms and machine learning applications in cardiology.

Keywords

electrocardiogram, ECG amplitude variability, cyclic random process, cardiac diagnostics, statistical analysis, heart rate variability, biomedical signal processing, cardiovascular diseases, stationarity, Anderson-Darling test, Kolmogorov-Smirnov test, machine learning in cardiology

1. Introduction

Electrocardiography remains a fundamental non-invasive diagnostic method for cardiovascular diseases (CVD), providing rapid and reliable assessment of cardiac electrical activity [1]. Graphical representation of electrocardiogram (ECG) signals serves as an indispensable tool for detecting a wide spectrum of cardiac pathologies, from simple rhythm disturbances to complex structural heart diseases [2]. ECG waveforms and temporal intervals contain important diagnostic information that enables medical professionals to identify deviations from normal cardiac function [3].

Despite significant progress in automated ECG analysis, existing methods predominantly focus on static characteristics of individual cardiac cycles or temporal intervals between characteristic points. Traditional heart rate variability analysis is limited to RR interval investigation, neglecting

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amplitude dynamics that may contain additional diagnostic information about myocardial electrical stability. Meanwhile, complex nonlinear analysis methods, such as entropy measures or fractal analysis, often lack direct clinical interpretation, complicating their practical application. This creates a need for developing new mathematical models that would combine high diagnostic sensitivity with interpretation simplicity and the possibility of integration into existing cardiac monitoring systems.

The aim of this work is to develop and validate a mathematical model of ECG wave amplitude variability based on cyclic random process theory for identifying additional diagnostic features of cardiovascular diseases. Section 2 presents a review of current ECG modeling and analysis methods. Section 3 describes the proposed mathematical model of amplitude variability and statistical analysis methodology. Section 4 presents experimental verification results of the model on real clinical data for various pathological conditions. The final section summarizes the obtained results and outlines prospects for further research.

2. Related Work and Mathematical Foundations

The development of mathematical ECG models creates a theoretical foundation for deeper understanding of cardiac electrophysiological processes and improving diagnostic accuracy [4]. Researchers have developed diverse modeling approaches—from elementary descriptions of individual signal components to complex simulations of the cardiac electrical conduction system [5].

Basic approaches include approximation of main ECG elements—P wave, QRS complex, and T wave—using mathematical functions, particularly Gaussian distributions or polynomial expressions, enabling automated recognition and quantitative assessment of signal parameters [6]. Evaristo and colleagues presented an autoregressive model based on a system of differential equations that successfully generates tachograms and ECG signals with high correspondence to experimental data [7]. Further development of this direction is presented in the work of Reis and colleagues, who improved the McSharry model by adding noise components for realistic reproduction of pathological conditions [8].

Special attention deserves the work of Ukrainian scientists in the field of cyclic random processes. Lupenko developed the theory of rhythm-adaptive methods for statistical estimation of probabilistic characteristics of cyclic processes, proving their advantage over classical approaches for ECG analysis [9, 10]. The cyclic discrete random process model with temporal rhythm function, proposed in works [9, 10], effectively accounts for both the cyclic nature of cardiac signals and their stochastic variability. The conditional linear cyclostationary and multivariate random processes have been analyzed in [11, 12] with application to biomedical signal modelling. Researchers [13–15] extended these approaches for vector analysis of synchronously registered cardiac signals of different physical nature.

The effectiveness of automated cardiac diagnostic systems critically depends on the quality of extracting relevant diagnostic features from electrocardiogram signals [16]. Modern approaches use three main categories of characteristics: temporal, frequency, and morphological parameters.

Temporal parameters include measurements of duration and intervals between main ECG components. The RR interval serves as a basic metric for assessing heart rate variability and detecting arrhythmias [17]. Precise determination of individual cardiac cycle boundaries constitutes a critically important initial stage of automated analysis [18]. Analysis of amplitude characteristics and durations of main waves allows detection of chamber hypertrophy, conduction blocks, and myocardial ischemic changes [19].

Heart rate variability (HRV), assessed by time and frequency domain methods, provides important information about the state of autonomic cardiac regulation [20]. Poincaré plots represent an effective tool for visualization and quantitative assessment of heart rhythm asymmetry [21].

Spectral ECG analysis through Fourier and wavelet transforms reveals signal energy distribution across frequency bands [22]. These methods allow identification of dominant frequency components and detection of pathological spectral patterns characteristic of specific cardiac conditions.

ECG waveform shape and amplitude contain diagnostically significant information about myocardial electrical activity [23]. Accurate R-peak detection is crucial for correct heart rate calculation, while using HRV information helps eliminate false detections [24]. Morphological parameters are sensitive to changes in impulse conduction velocity, repolarization processes, and ventricular activation sequences.

Integration of advanced signal processing technologies with mathematical modeling has significantly improved ECG interpretation capabilities [25]. Wavelet analysis methods demonstrate high efficiency in studying time-frequency characteristics of cardiac signals [22, 26]. Application of Q-wavelet transform with tunable parameters allows adaptation of analysis to specific features of different arrhythmia types [4].

Spatial modeling of electrical impulse propagation through cardiac muscle provides understanding of arrhythmia mechanisms [27]. Such models integrate detailed anatomical data and electrophysiological properties of cardiomyocytes [28], helping to determine optimal zones for catheter ablation [26].

The combination of physical elements (sensors), digital systems, and the Internet of Things (IoT devices) for continuous or periodic measurement of physiological parameters of the body, such as ECG, together with computational elements (algorithms, software), provide automated collection, analysis, and interpretation of biomedical data in real time [36, 37].

Revolutionary changes in ECG analysis are associated with the implementation of deep learning methods, which demonstrate classification accuracy up to 99% [11]. Convolutional neural networks (CNN) and their modifications successfully recognize complex patterns without the need for manual feature engineering [29]. Hybrid architectures, such as CNN-Transformer and neuro-fuzzy systems, combine advantages of different approaches [11].

AI integration into clinical practice opens opportunities for early disease detection through remote monitoring and development of personalized therapeutic strategies [30]. The use of large data arrays, including medical images, electronic health records, and genomic information, allows AI systems to identify complex patterns for risk prediction [31].

Further development of rhythm-adaptive methods for cyclic signal analysis opens new horizons for more accurate modeling and processing of ECG with irregular rhythm [32–34]. Adaptive methods for estimating discrete rhythmic structures using various interpolation techniques increase the accuracy of cyclic biomedical signal processing [35].

3. Proposed Mathematical Model of Amplitude Variability of ECS waves

The investigation of ECG wave amplitude variability indicators in each cardiac cycle enables the detection of hidden pathological states in cardiovascular system functioning. Application of mathematical modeling methods allows development of effective methods for studying ECG amplitude variability based on its mathematical model to identify additional diagnostic features of CVD.

To model the amplitude variability of ECG waves (which is modeled as a random process [11]), a set $I = \{P, Q, R, S, T\}$ is introduced, representing the types of characteristic signal waves. For each type of wave $m \in Z$, the amplitude value $A_k(\omega, m)$, $\omega \in \Omega$ (where Ω is the space of elementary events) is determined, which represents the amplitude (which is a random variable) of the corresponding wave within the corresponding cardiac cycle. The mathematical model of amplitude variability is presented in the form of a random function $V_k(\omega, m)$, which takes into account the amplitude values of the characteristic teeth of the ECG:

$$V_k(\omega, m) = A_k(\omega, m) - A_k(\omega, m-1), \qquad k \in \{P, Q, R, S, T\}, \qquad m \in Z, \tag{1}$$

where $A_k(\omega, m)$ – amplitude of the k-th type peak in the m-th cardiac cycle (mV);

$A_k(\omega, m-1)$ – amplitude of the *k*-th type peak in the previous valid cardiac cycle (mV);
$V_k(\omega, m)$ – the value of the amplitude variability function of ECG waves, reflecting the change in the amplitude of the *k*-th type wave between the current *m* and the previous cardiac cycle *(m-1).*
Further, to simplify the text, we will omit the variable ω in the notation of random functions.

For quantitative characterization of $V_k(m)$ and its diagnostic evaluation [11], a statistical processing method was used, which enables the calculation of the following statistical indicators:

1. The average value of $V_k(m)$ for the *k*-th type of peaks:

$$\mu_V(k) = \frac{1}{M}\sum_{m=1}^{M} V_k(m). \tag{2}$$

2. Standard deviation $V_k(m)$:

$$\sigma_V(k) = \sqrt{\frac{1}{M}\sum_{m=1}^{M}\left(V_k(m) - \mu_V(k)\right)^2}. \tag{3}$$

3. Coefficient of variation $V_k(m)$:

$$CV_V(k) = \frac{\sigma_V(k)}{\left|\mu_V(k)\right|} \times 100\,\%. \tag{4}$$

4. Range of values (variation range) $V_k(m)$:

$$\text{Range}\left(V_k(m)\right) = \max_m V_k(m) - \min_m V_k(m). \tag{5}$$

3.1. Statistical analysis of amplitude variability properties

To validate the proposed mathematical model and assess its suitability for further diagnostic analysis, a comprehensive statistical study of the properties of the amplitude variability function $V_k(m)$ was conducted. The statistical analysis included two critically important aspects: verification of process stationarity and analysis of conformity to normal distribution.

3.2. Stationarity test

The stationarity of a random process is a fundamental property that determines the constancy of its statistical characteristics over time. To test the hypothesis of stationarity of amplitude variability, the two-sample Kolmogorov-Smirnov test was used. This nonparametric criterion allows comparing the empirical distribution functions of two samples without any prior assumptions about the type of distribution.

The testing procedure consisted of dividing the time series $V_k(m)$ into two equal parts and comparing their distributions. The null hypothesis H_0 states that both samples come from the same distribution, which indicates the stationarity of the process. At a significance level of $\alpha = 0.05$, if p-value > α, the null hypothesis is not rejected, confirming stationarity.

3.2.1.Analysis of normality of distribution

Determining the type of amplitude variability distribution is critical for selecting adequate methods of statistical analysis and interpretation of diagnostic signs. To test the hypothesis of normality of distribution, the Anderson-Darling goodness-of-fit test was used, which is characterized by high sensitivity to deviations in the tails of the distribution, which is especially important for detecting rare pathological conditions.

The Anderson-Darling goodness-of-fit test is based on comparing the empirical distribution function with the theoretical normal distribution function. The test statistic A^2 is calculated taking into account the quadratic deviations weighted by the variance. At a significance level of 0.05, if the test statistic is less than the critical value, the hypothesis of normality is not rejected.

3.2.2.Results of statistical analysis

Analysis of amplitude variability indicators was performed for three groups of patients with different cardiac conditions: healthy, with extrasystole, and with incomplete left bundle branch block. The test results are presented in Figures 1–3.

For healthy patients (Ch_2_P_FAV_nr):

- Kolmogorov-Smirnov test: p-value = 0.578, which significantly exceeds the significance level of 0.05, confirming the stationarity of the process.
- Anderson-Darling goodness-of-fit test: test statistic = 0.721 is less then critical value = 0.752, indicating compliance with normal distribution.
- Statistical characteristics: mean = 0.0000, variance = 0.0027, skew = 0.3196, kurtosis = 2.2285

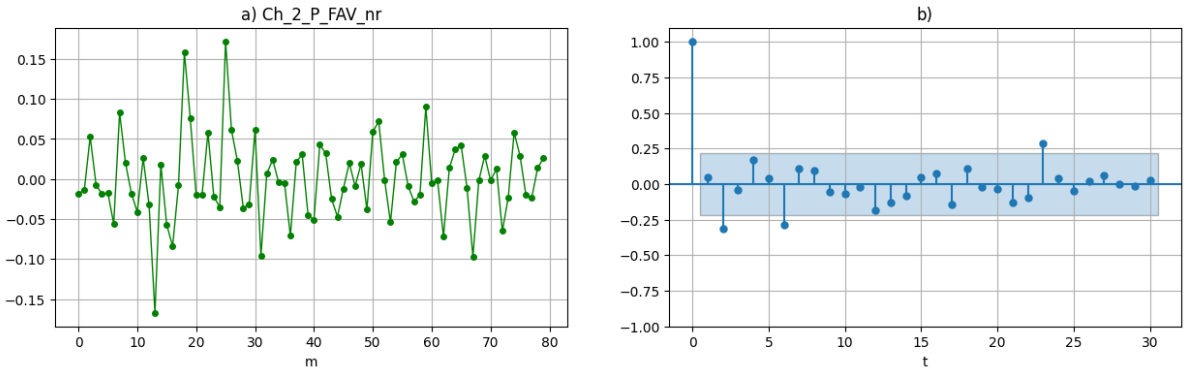

Figure 1: a) P-wave amplitude variability function $V_P(m)$ for healthy person, b) estimation of the autocorrelation function of $V_P(m)$, the filled area represents the bounds $\pm 1.96 / \sqrt{M}$ for testing the hypothesis that P-wave amplitude variability function is stationary white noise.

For patients with extrasystole (Ch_2_P_FAV_es):

- Kolmogorov-Smirnov test: p-value = 0.808, confirms stationarity.
- Anderson-Darling test: test statistic = 0.309 is less then critical value = 0.743, corresponds to normal distribution.
- Statistical characteristics: mean = 0.0147, variance = 0.8099, skew = 0.3048, kurtosis = -0.5394

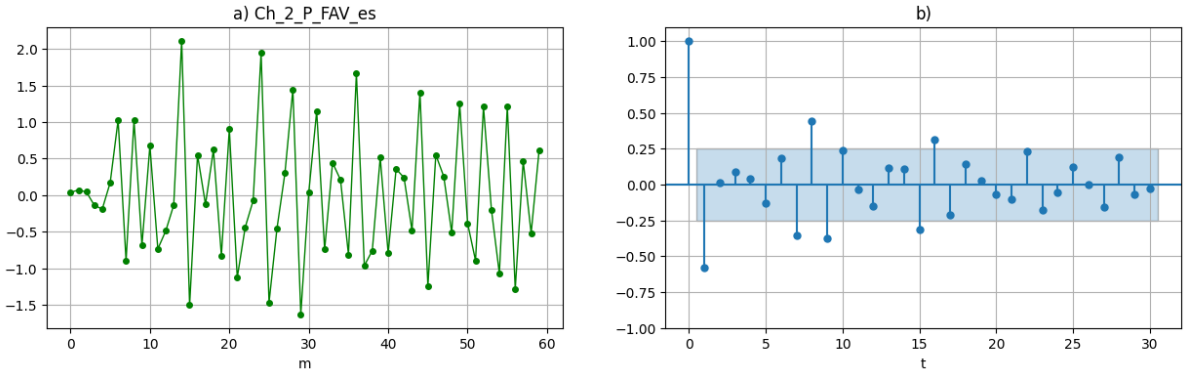

Figure 2: a) P-wave amplitude variability function $V_P(m)$ for the case of extrasystoles, b) estimation of the autocorrelation function of $V_P(m)$, the filled area represents the bounds $\pm 1.96/\sqrt{M}$.

For patients with incomplete blockage of the left bundle branch of the His bundle (Ch_2_P_FAV_mb1):

- Kolmogorov-Smirnov test: p-value = 0.945, highest stationarity among the studied groups.
- Anderson-Darling test: test statistic = 0.290 is less then critical value = 0.75, corresponds to normal distribution
- Statistical characteristics: mean = 0.0101, variance = 0.0020, skew = 0.6509, kurtosis = 1.2413

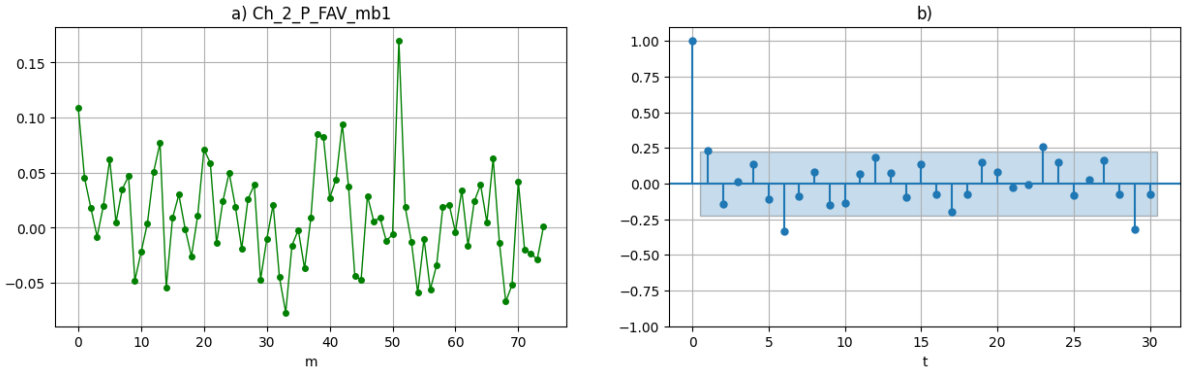

Figure 3: a) P-wave amplitude variability function $V_P(m)$ for the patient with incomplete blockage of the left bundle branch of the His bundle, b) estimation of the autocorrelation function of $V_P(m)$, the filled area represents the bounds $\pm 1.96/\sqrt{M}$.

3.3. Interpretation of results

The confirmed stationarity of amplitude variability for all studied patient groups demonstrates the stability of statistical process properties over time, which is a necessary condition for applying classical spectral analysis and forecasting methods. This allows the use of averaged statistical characteristics as reliable diagnostic features, independent of the ECG registration moment.

The correspondence to normal distribution of amplitude variability has important clinical significance. First, it justifies the application of parametric statistical methods, which are characterized by higher power compared to non-parametric analogues. Second, distribution normality allows the use of the three-sigma rule for detecting anomalous values that may indicate pathological conditions.

The identified differences in statistical characteristics between patient groups demonstrate the diagnostic potential of the proposed model. In particular, the significant increase in variance for the extrasystole group (0.8099 versus 0.0027 for normal) reflects increased instability of cardiac electrical activity. Changes in skewness and kurtosis coefficients may also serve as additional markers of specific pathologies.

Thus, the results of statistical analysis confirm the adequacy of the proposed mathematical model of ECG amplitude variability and justify the possibility of its use for developing new diagnostic criteria for cardiovascular diseases.

4. Results/Discussions

The statistical analysis of amplitude variability function $V_k(m)$ revealed significant quantitative differences between patient groups, validating the diagnostic potential of the proposed mathematical model. The most prominent finding was a 300-fold increase in variance for patients with extrasystole ($\sigma^2 = 0.8099$) compared to the control group ($\sigma^2 = 0.0027$), quantitatively reflecting the electrical instability characteristic of arrhythmic conditions. In contrast, patients with incomplete left bundle branch block maintained variance levels ($\sigma^2 = 0.0020$) comparable to controls, suggesting that conduction abnormalities primarily affect temporal rather than amplitude characteristics. Analysis of higher-order moments provided additional discriminatory features: the extrasystole group exhibited negative excess kurtosis ($\gamma_2 = -0.5394$), indicating a platykurtic distribution with fewer extreme values, while the incomplete LBBB group showed the highest skewness ($\gamma_1 = 0.6509$) with positive excess kurtosis ($\gamma_2 = 1.2413$), corresponding to intermittent but intense amplitude variations characteristic of sporadic conduction delays.

The confirmed stationarity (p-values: 0.578-0.945) and normality of amplitude variability across all groups enable robust parametric diagnostic criteria development and application of the three-sigma rule for pathological outlier detection. These findings establish amplitude variability as a complementary diagnostic metric to traditional heart rate variability analysis, capturing orthogonal information about cardiac electrical stability. The computational simplicity of the model (Equation 1) facilitates real-time implementation in modern ECG monitoring systems, while the clear physical interpretation of variance as electrical instability enhances clinical adoption. The distinct statistical patterns observed for different pathologies suggest that amplitude variability metrics could serve as input features for machine learning classifiers, potentially achieving high diagnostic accuracy for early arrhythmia detection and risk stratification.

Future research should focus on validating these findings in larger, diverse cohorts to establish population-specific reference ranges and diagnostic thresholds. Extension to multi-lead synchronized analysis could reveal spatial patterns of electrical heterogeneity, while integration with existing ECG analysis protocols would enhance diagnostic capabilities in ambiguous cases where traditional morphological assessment yields inconclusive results.

Conclusion

This study presents a novel mathematical model for quantifying amplitude variability of ECS characteristic waves based on cyclic random process theory. The proposed model $V_k(m) = A_k(m) - A_k(m-1)$ successfully captures beat-to-beat amplitude variations, providing a quantitative framework for assessing cardiac electrical stability. Statistical validation confirmed both stationarity (p-values: 0.578-0.945) and normality of the amplitude variability function across different cardiac conditions, establishing a robust foundation for parametric diagnostic analysis.

The key finding of a 300-fold increase in variance for extrasystole patients compared to controls demonstrates the model's sensitivity to pathological electrical instability. The distinct statistical signatures observed-including variance, skewness, and kurtosis patterns-for different cardiac conditions (normal, extrasystole, incomplete LBBB) indicate that amplitude variability metrics can serve as effective diagnostic biomarkers complementary to traditional ECS parameters. The computational simplicity and clear physical interpretation of these metrics facilitate their integration into existing ECS analysis systems and enable real-time monitoring applications.

Future work should focus on validating these findings in larger, diverse patient populations to establish standardized diagnostic thresholds and reference ranges. The confirmed statistical properties of amplitude variability open pathways for machine learning integration and automated

diagnosis systems. This research contributes to the advancement of quantitative ECS analysis by introducing a mathematically rigorous, clinically interpretable method for characterizing dynamic cardiac electrical behavior, ultimately supporting more accurate and timely diagnosis of cardiovascular disorders.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to grammar and spell check, and improve the text readability. After using the tool, the authors reviewed and edited the content as needed to take full responsibility for the publication's content.

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