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DEVELOPMENT OF A CRITERION FOR SELECTING THE LEVEL OF WAVELET DECOMPOSITION FOR QRS DETECTION IN ELECTROCARDIOGRAM SIGNALS USING ENERGY AND ENTROPY

Г. Щербакова, Д. Кошутіна. **Побудова критерію вибору рівня вейвлет-декомпозиції для QRS-комплексів в ЕКГ-сигналах з використанням енергії та ентропії.** Аналіз електрокардіографічних (ЕКГ) сигналів є одним із ключових напрямів сучасної біомедичної інженерії, що забезпечує можливість раннього виявлення порушень серцевої діяльності, таких як аритмії, ішемія та інші серцево-судинні патології. Найбільш інформативним фрагментом ЕКГ-сигналу вважається QRS-комплекс, який відображає електричну активність шлуночків серця і є важливим маркером для медичної діагностики. У цій роботі запропоновано підхід до вибору оптимального рівня вейвлет-декомпозиції, заснований на кількісному аналізі енергетичних та ентропійних характеристик сигналу на кожному рівні. Метою дослідження є побудова формалізованого критерію інформативності рівнів розкладу та оцінка ефективності різних типів материнських вейвлетів для задачі виділення QRS-комплексів у сигналах ЕКГ. У межах дослідження проаналізовано сигнали з відкритої бази даних MIT-BIH Arrhythmia Database, обчислено значення енергії, ентропії та їх відношення для кожного рівня дискретного вейвлет-перетворення. Отримані результати свідчать, що рівні з високим енергетичним вкладом та низькою ентропією найкраще відображають локалізацію QRS-комплексів. Показано, що вибір типу материнського вейвлета істотно впливає на розподіл цих характеристик. Найбільш ефективним для задачі автоматизованої QRS-детекції виявився вейвлет Daubechies, зокрема на рівнях d_3–d_5. Наукова новизна роботи полягає в інтеграції енергетично-ентропійного підходу до процесу автоматизованого вибору рівня декомпозиції без участі експерта. Практична значущість полягає у можливості впровадження цього методу в системи комп'ютерної діагностики з метою підвищення їхньої точності, надійності та адаптивності до різних типів біомедичних сигналів.
Ключові слова: електрокардіограма (ЕКГ), QRS-детекція, дискретне вейвлет-перетворення, ентропія сигналу, енергетичний аналіз, рівень декомпозиції

H. Shcherbakova, D. Koshutina. **Development of a criterion for selecting the level of wavelet decomposition for QRS detection in electrocardiogram signals using energy and entropy.** Analysis of electrocardiographic (ECG) signals is one of the key areas of modern biomedical engineering, providing the possibility of early detection of cardiac disorders such as arrhythmias, ischemia, and other cardiovascular pathologies. The most informative segment of the ECG signal is the QRS complex, which reflects the electrical activity of the heart ventricles and serves as an important marker for medical diagnostics. This work proposes a approach to selecting the optimal wavelet decomposition level based on quantitative analysis of energy and entropy characteristics of the signal at each level. The aim of the study is to construct a formalized criterion of informativeness for decomposition levels and evaluate the effectiveness of different types of mother wavelets for the task of extracting QRS complexes from ECG signals. Within the study, signals from the open MIT-BIH Arrhythmia Database were analyzed, and values of energy, entropy, and their ratio were calculated for each level of discrete wavelet transform. The results indicate that levels with high energy contribution and low entropy best reflect the localization of QRS complexes. It was shown that the choice of mother wavelet type significantly affects the distribution of these characteristics. The Daubechies wavelet was found to be the most effective for automated QRS detection, particularly at levels d_3–d_5. The scientific novelty of the work lies in the integration of the energy-entropy approach into the automated process of decomposition level selection without expert involvement. The practical significance is in the potential implementation of this method in computer diagnostic systems to improve their accuracy, reliability, and adaptability to various types of biomedical signals.
Keywords: electrocardiogram, QRS detection, discrete wavelet transform, signal entropy, energy analysis, decomposition level

1. Introduction

Accurate detection of cardiac abnormalities remains a major task in clinical diagnostics. Electrocardiography (ECG) provides detailed information about the heart's electrical activity and is commonly used to detect arrhythmias, ischemia, and other functional disorders. A crucial part of ECG signal analysis is the identification of QRS complexes-short, high-frequency fragments corresponding to ventricular depolarization. Reliable detection of these peaks is essential for heart rate analysis, spectral evaluation, and further diagnostic steps.

Wavelet transform is often used in ECG signal processing due to its ability to represent signals simultaneously in time and frequency domains. This is particularly useful for non-stationary signals that contain short transients, such as QRS complexes. Yet, despite the widespread use of wavelets,

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there is still no clear consensus on how to choose the most suitable decomposition level or mother wavelet for precise QRS detection.

In many practical implementations, the decomposition level is selected arbitrarily or kept fixed, which limits flexibility when applying the method to signals of different origins or characteristics. A systematic approach is needed to assess the informativeness of individual levels.

This work addresses the problem of selecting an optimal wavelet decomposition level by combining energy and entropy-based criteria. Figure 1 shows an example of a typical ECG signal with the QRS complex marked.

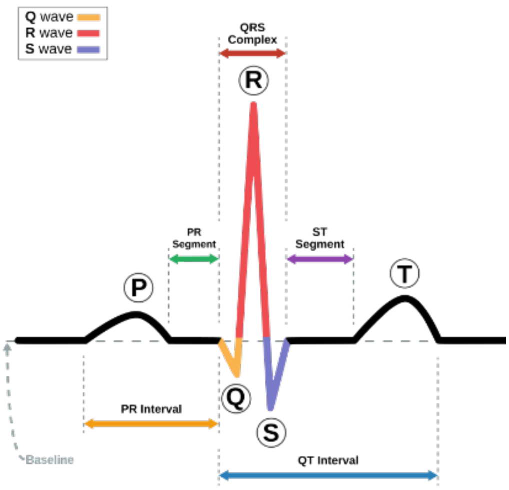

Fig. 1. QRS complex visualization

2. Literature Review and Problem Statement

Recent studies in ECG signal processing increasingly focus on improving the accuracy of detecting key components of the cardiac cycle, particularly QRS complexes. One of the most actively used tools for this purpose is wavelet transform (WT), which enables multilevel representation of the signal with simultaneous localization in both time and frequency domains. This makes it well suited for identifying short impulses and capturing morphological features of the signal.

The analysis of the literature showed that research in this area is conducted in three directions:

1. Improving signal preprocessing – noise removal, frequency filtering, and baseline correction;

2. Mathematical feature extraction – identifying characteristic patterns through formal analytical methods;

3. Hybrid approaches – combining statistical, clustering, and machine learning techniques.

Wavelet transform proves useful in all three areas. It can suppress noise and enhance relevant features, serve as a tool for extracting informative patterns, and act as a component within complex detection systems, such as classifiers based on neural networks or clustering algorithms.

Another important consideration when using WT is the choice of the mother wavelet, which should match the specific requirements of the task. Among the most widely used wavelets are:

– Daubechies 4 (db_4) – offers good time localization and is suitable for basic QRS detection;

– Daubechies 6 (db_6) – its shape closely resembles QRS morphology, which improves sensitivity to these components;

– Haar – often used for preprocessing tasks due to its computational simplicity;

– Symlet and Coiflet – provide improved symmetry and precise localization, which are crucial in tasks requiring exact peak positioning [1].

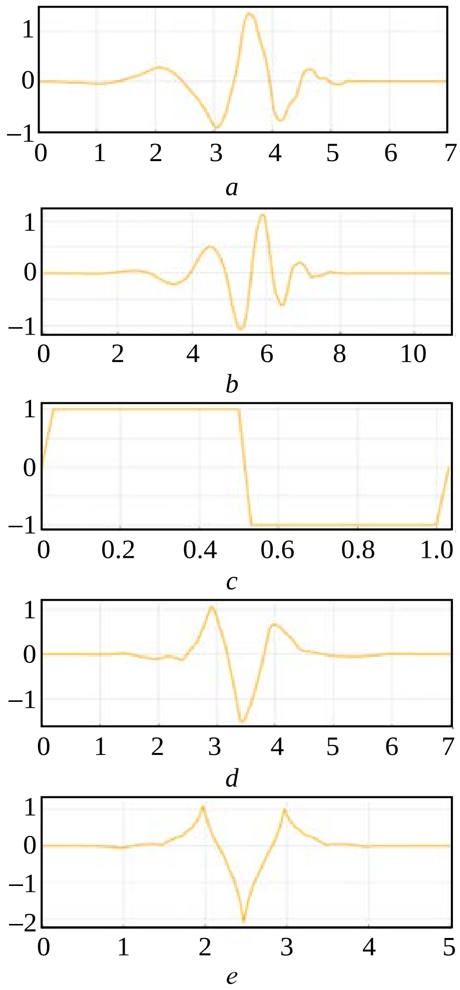

Fig. 2. Visualization of commonly used mother wavelets: Daubechies 4 (*a*); Daubechies 6 (*b*); Haar (*c*); Symlet (*d*); Coiflet (*e*)

Different wavelets vary in shape, symmetry, and the number of vanishing moments. These properties directly affect their ability to highlight characteristic ECG features in both time and frequency domains. As illustrated in Figure 2, a visual comparison of wavelet shapes helps in selecting the most appropriate one for reliable QRS complex detection.

One of the essential stages in this approach is the extraction of features used for further signal analysis. Informative features are quantitative or qualitative descriptors that capture the essential properties of the signal in a compact and processable form [2]. In the context of ECG, such features are crucial for identifying specific phases of the cardiac cycle, detecting pathological changes, and serving as input for classification algorithms. Features derived from wavelet transform play a central role in both classification tasks and the detection of cardiac abnormalities.

To better structure these features within the framework of wavelet analysis, Table 1 provides a generalized list along with examples of their application.

Table 1

Key Features Used in Wavelet-Based ECG Analysis and Their Applications

Feature	Application
Amplitude of waves (*R*, *P*, *T*)	Morphological analysis, pathology assessment (hypertrophy, ischemia) [17, 18]
Peak positions	Determination of RR intervals, heart rate calculation, arrhythmia detection
QRS complex duration	Diagnosis of ventricular disorders, conduction blocks [19]
Energy at decomposition level	Detection of dominant frequencies, distribution of signal activity
Shannon / Rényi entropy	Complexity assessment, rhythm change detection, atrial fibrillation identification [20]
Energy-to-entropy ratio	Automated wavelet decomposition level selection, signal optimization
Weighted average energy	Generalized description of signal's frequency content for classification
Root mean square (RMS) value	Denoising, extraction of active phases
Number of zero crossings	Selection of wavelet matching local wave symmetry

As shown in Table 1, each feature serves a specific purpose: some describe the morphology of the waves, while others characterize the frequency or statistical properties of the signal. Together, these features form a characteristic vector that can be used as input to classification systems, such as artificial neural networks (ANN), decision trees, or clustering methods (e.g., *K*-means or DBSCAN) [3]. Combining these features enables high accuracy in detecting arrhythmias, classifying types of heartbeats, and predicting pathological conditions.

To ensure effective performance of such models, it is necessary to select the most informative wavelet decomposition levels. Quantitative criteria are applied to objectively evaluate the significance of each level. Among the most common are energy-based metrics and entropy measures [4, 5, 6]. The signal energy at level j is defined as:

$$E_j = E_j = \sum_k \left| c_{\{j,k\}} \right|^2 . \quad (1)$$

Shannon entropy is defined as:

$$S_j = -\sum_k p_{j.k} \log(p_{j.k}) , \quad (2)$$

where:

$$p_{(j,k)} = \frac{\left| c_{j,k} \right|^2}{\sum_k \left| c_{j,k} \right|^2} . \quad (3)$$

In addition to Shannon entropy, Rényi entropy is also used in the literature as a more flexible criterion for assessing signal complexity in wavelet analysis [5]. One of its advantages is the ability to adjust sensitivity to probability distribution through the order parameter α\alphaα, which allows better differentiation between levels of signal complexity. This feature proves especially useful when working with unstable or noisy data. However, drawbacks include increased computational complexity and the need for a justified choice of the α\alphaα parameter, which can complicate automation of the analysis.

A combined criterion in the form of entropy to energy ratio (4) is employed to identify the most informative decomposition level-i.e., the level at which the ratio between the signal energy and entropy reaches its maximum. This ratio helps determine the level where the signal energy is high (indicating the presence of components significant for analysis), while the entropy remains moderate (indicating lower randomness). Such a level typically corresponds to segments of the signal containing QRS complexes and is therefore the most suitable for feature extraction and classification:

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$$C_j = \frac{E_j}{S_j}. \tag{4}$$

Such criteria have gained wide acceptance in wavelet analysis of biomedical signals due to their ability to objectively identify decomposition levels containing the most relevant information – that is, information of diagnostic value for detecting characteristic components of the ECG signal, particularly QRS complexes. They also enable precise identification of changes in heart rhythm and wave morphology. Specifically, Li et al. [4] proposed using sub-signal entropy combined with a random forest classifier for ECG classification. Cornforth et al. [5] analyzed the application of Rényi entropy for early detection of neuropathies – dysfunctions of the autonomic nervous system affecting heart rate regulation. Rekik et al. [6] first introduced a combined criterion merging energy and entropy to determine the most informative decomposition level.

In Rekik et al. [6], entropy features were employed to generate attributes for detecting *P* waves based on a combined criterion accounting for the information content across decomposition levels. Li et al. [4] performed detection of *R*, *P*, and *T* waves using thresholding of wavelet coefficients, which improved the accuracy of identifying key ECG points. Lenis et al. [7] proposed a method for *P* wave detection using stationary wavelet transform (SWT), validated against intracardiac electrograms, achieving enhanced localization accuracy even in the presence of noise.

As a summary, Table 2 presents a comparative overview of methods, features, and data sources applied in the literature for QRS detection.

Table 2

Comparison of Methods for Detection and Classification of QRS Complexes

Task	Method	Signal Features	Dataset	Reference
QRS complex detection	WT + *K*-means	Amplitude, coefficient positions	MIT-BIH	[8]
Rhythm classification	DWT + ANN	Energy, peak coordinates, QRS duration	–	[3]
P wave detection	SWT + Coiflet	Amplitude, low-amplitude waves	Intracardiac EG + ECG	[7]
R, *P*, *T* waves detection	DWT + thresholding	Peak positions	MIT-BIH	[5]
ECG classification	WT packet + Random Forest	Sub-signal entropy	–	[4]
P wave detection	Local entropy + WT	Entropy profile	MIT – BIH, QT	[7]
WT optimization	Vanishing moments	Spectral energy	–	[9]

In study [10], a classification method based on Haar wavelets combined with Shannon entropy criterion was proposed to identify informative segments of the signal. The authors implemented an adaptive approach for optimizing classifier coefficient ranges, taking into account the effects of noise and limited computational resources. Although the research primarily focused on image processing, the methodology can be extended to biomedical signals, particularly ECG, where fast processing, temporal feature localization, and reduction of false alarms are also critical. Applying such an approach to QRS complex analysis opens prospects for developing highly accurate adaptive real-time systems.

The analysis shows that wavelet transform improves detection sensitivity, especially in cases of arrhythmias and low-amplitude waves. The use of adaptive level selection based on the ratio (4) or combined metrics is a promising direction for creating universal ECG analysis algorithms.

To objectively evaluate the performance of these algorithms, most studies employ standard metrics: sensitivity (Se), specificity (Sp), accuracy (Acc), average delay (Delay), and others. Sensitivity measures the algorithm's ability to correctly detect true QRS complexes, which is essential for medical safety.

Specificity reflects the algorithm's capacity to correctly identify the absence of events, thereby avoiding false-positive detections. This metric is critical for medical monitoring systems, as it reduces the likelihood of false alarms and prevents excessive interventions by medical personnel. For example, in automated diagnostic systems, false alarms may lead to overload with clinically insignificant signals [11, 4]. High specificity indicates the algorithm's ability to distinguish true cardiac rhythm signals from artifacts, a crucial factor for real-time monitoring systems [11, 4]. This is particularly important in clinical settings where false positives (e.g., confusing noise with QRS complexes) may cause unnecessary alerts, burden medical staff, or prompt excessive intervention.

Accuracy is an overall metric that reflects the proportion of correctly classified instances among all cases. It provides a quick assessment of an algorithm's performance, especially when positive and negative classes are balanced. High accuracy indicates a well-balanced algorithm, which is critical for medical applications, particularly in mobile or wearable heart rate monitoring devices [8, 3]. It summarizes the algorithm's ability to correctly identify both true positives (e.g., actual QRS complexes) and true negatives (e.g., absence of peaks), a factor important in practical deployment.

Delay is a critical metric for real-time systems. It measures the time elapsed between the occurrence of an event (e.g., a QRS complex) and its detection by the system. Excessive delay in clinical applications may lead to late alerts or loss of vital information. Low delay is essential in devices such as cardiac monitors, automated defibrillators, or remote patient monitoring systems [5, 12]. Timely detection of QRS complexes – at or before their appearance on the monitor – is crucial, especially for automated alerting systems where every second can be decisive, for example, in detecting life-threatening arrhythmias or during remote patient supervision. Excessive delay may cause loss of valuable information or delayed medical response.

For instance, Xia et al. [8] demonstrated a sensitivity of 99.54% and accuracy of 99.52% using Daubechies 4 wavelets for peak clustering. Agrawal et al. [3] employed wavelet-based features as inputs to an artificial neural network for cardiac rhythm classification.

3. Aim and Objectives of the Study

The aim of this study is to extend and experimentally validate a criterion for selecting the wavelet decomposition level based on a combination of energy and entropy characteristics of the ECG signal, enabling accurate and automated detection of QRS complexes. Unlike previous research [13], which focused on a single wavelet (Daubechies 6), this paper emphasizes a comparison use of various mother wavelets to test the generalizability of the method and its robustness to variations in signal morphology.

The objectives of the study are as follows:

– to systematize approaches for feature extraction within the context of wavelet-based ECG analysis;

– to establish the relationship between decomposition level and signal informativeness;

– to verify a quantitative criterion based on the energy-to-entropy ratio (coefficient C_i);

– to validate the approach using signals from the MIT-BIH database and several types of mother wavelets (Daubechies 4, Daubechies 6, Haar, Symlet, Coiflet);

– to assess the consistency of the selected decomposition level with the morphological characteristics of QRS complexes;

– to test the stability of the C_i criterion across different ECG recordings and generalize the range of optimal levels (d_3–d_5) [14, 15].

Thus, this paper aims to lay the groundwork for developing adaptive algorithms for detecting cardiological markers, where decomposition parameters are not fixed but selected automatically based on intrinsic signal characteristics. This approach allows algorithms to adapt to individual patient features and improve diagnostic accuracy [16].

4. Algorithms and Research Methods

Within the scope of this study, a method was proposed based on calculating the energy and entropy at each level of the wavelet decomposition of the ECG signal. The signal energy at a given decomposition level reflects the total power of the wavelet coefficients at that level. This measure allows identifying where the greatest amount of information about the dynamic changes in the signal is concentrated – for example, those associated with QRS complexes. High energy indicates active regions of the signal that are potentially relevant for detecting cardiac impulses [17].

Entropy, particularly Shannon entropy, serves as a measure of the disorder or complexity in the distribution of wavelet coefficients. It indicates how chaotic or structured the signal's composition is. For QRS complex detection [18], levels with structured information (i.e., low entropy) are of interest, as these are more likely to localize stable morphological features characteristic of QRS complexes.

Combining these indicators allows assessing how simultaneously energy-significant and structured a particular level is, which is critical for automated QRS detection. The combination of these two

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metrics, expressed as a ratio shown in Equation 4, forms an informative criterion for selecting the level where the signal contains the highest amount of ordered energy. Thus, the level at which the coefficient Ci reaches its maximum is considered optimal for QRS complex detection.

From a practical standpoint, this approach enables objective identification of the decomposition level containing the most structured and clinically significant information about QRS complexes [19]. This is especially useful in situations where the shape and amplitude of the signal may vary significantly depending on the patient or the type of ECG recording. Automatic determination of the informative level significantly enhances detection accuracy and reliability, reducing the risk of false positives or false negatives. Such an approach allows automated parameter selection without the need for manual tuning or fixed levels, increasing the method's flexibility and adaptability in real-world clinical recordings.

The experimental part was based on signals from the open MIT-BIH Arrhythmia Database [13], which is regarded as a standard in ECG research. This database includes 48 records of 30 minutes each, digitized at a sampling rate of 360 Hz [14]. The study focused on record number 109, which contains characteristic QRS complexes with clear morphology. This particular record was chosen due to its distinct structure and the presence of diverse impulse types, allowing the proposed method to be tested under conditions close to clinical reality. This choice ensures the representativeness of the results and supports generalized conclusions about the method's effectiveness [20].

After defining the research objectives and selecting the data source, the next logical step was to develop a structured methodology to implement the proposed approach in practice. The research consisted of the following stages:

Stage 1. Construction of the wavelet decomposition using the Discrete Wavelet Transform (DWT);

Stage 2. Calculation of energy and entropy values at each decomposition level;

Stage 3. Determination of the informativeness coefficient C_i;

Stage 4. Identification of the level at which C_i is maximal;

Stage 5. Comparative analysis of various mother wavelets (Daubechies 4, Daubechies 6, Haar, Symlet, Coiflet).

For all wavelet types, decomposition was performed up to the eighth level inclusive. This choice was motivated by theoretical considerations regarding frequency coverage, as well as results from previous studies [14], which indicated the highest informativeness in levels d_3–d_5. To verify this hypothesis, an experiment was conducted for Daubechies 6, with results presented in Table 3.

Table 3

Results of Calculating the C_i Coefficient for the Daubechies 6 Wavelet

Decomposition Level	d_1	d_2	d_3	d_4	d_5	d_6	d_7	d_8
C_i	5.3532	21.3872	27.1572	27.7161	2.3309	0.2752	0.0903	0.0078

As shown in the table, the maximum value of the C_i coefficient occurs at decomposition level d_4, which aligns with theoretical expectations and confirms the effectiveness of the criterion for automated selection of the decomposition level.

Furthermore, deeper decompositions (beyond eight levels) lead to excessive loss of high-frequency information [15], which is crucial for localizing QRS complexes, while shallower decompositions may fail to capture all relevant signal features. Thus, eight levels provide a compromise between frequency resolution and preservation of key cardiac rhythm characteristics.

The calculations were implemented in the Python environment using the PyWavelets library, which offers a convenient interface for constructing multilevel discrete wavelet decompositions and allows easy modification of the mother wavelet type. This facilitates conducting a series of experiments with different wavelets without significantly complicating the code.

During the signal analysis, two key metrics-energy and entropy-were calculated for each decomposition level j. To avoid redundancy, the study used previously defined formulas for computing energy, entropy, and the informativeness coefficient C_i, which enable identification of the level with the highest concentration of ordered information.

This level is considered optimal for QRS detection, as it combines both high energy significance and low entropy complexity. The level was deemed optimal when C_i reached its maximum.

Additionally, a stability analysis of the C_i criterion results was conducted to assess the unambiguity of the wavelet decomposition level choice across different patients. This step is particularly important for future adaptation of the method to real-time applications or variable signal characteristics.

The approach reduces the dependency of QRS detection accuracy on manual intervention or preset parameters, which is especially valuable in developing automatic monitoring systems. It also allows evaluating the method's sensitivity to morphological variations and automatically selecting the most informative decomposition level.

5. Research Results

Within the conducted study, a series of experiments were performed using five of the most common wavelets: Daubechies 4, Daubechies 6, Haar, Symlet, and Coiflet. For each wavelet type, discrete wavelet transform was applied to signal No. 109 from the MIT-BIH database, and the informativeness coefficient C_i was calculated at each of the eight decomposition levels.

The results were visualized in Figure 3. As observed, regardless of the mother wavelet type, the maximum values of the C_i criterion are predominantly localized within the range of levels d_3–d_5. This range corresponds to the frequency spectrum of 5…20 Hz, within which the energy of the QRS complexes is typically concentrated. This finding confirms the stability of the C_i criterion and its effectiveness in the task of automated QRS detection.

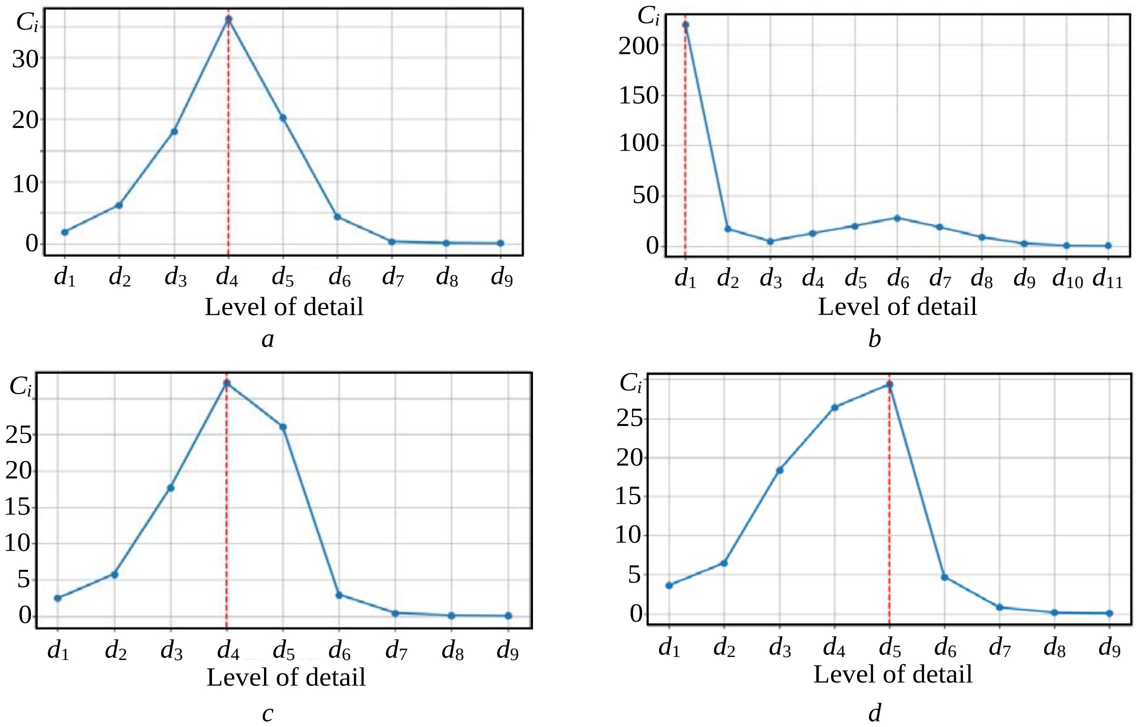

Fig. 3. Dependence of the C_i Criterion Value on the Decomposition Level for Different Types of Wavelets: Daubechies 4 (*a*); Haar (*b*); Symlet (*c*); Coiflet (*d*)

Summarizing the results obtained for different types of mother wavelets, it can be noted that the best values of the informativeness criterion C_i were recorded in the following combinations: for Daubechies 4, at level d_4 ($C_i = 36.21$); for Daubechies 6, also at d_4 ($C_i = 27.71$); for Symlet, at d_4 ($C_i = 32.15$); and for Coiflet, at d_5 ($C_i = 29.34$). Although the Haar wavelet demonstrated the highest criterion C_i value (219.85) at the first level, such localization is overly sensitive to noise and less stable for clinical use. Thus, the most stable results were achieved at levels d_3–d_5 for wavelets db_6, sym_4, and $coif_1$, confirming their suitability for QRS detection.

A detailed comparison of the results for different wavelet types revealed certain trends. Specifically, the Daubechies 6 wavelet showed the highest C_i values at level d_4, while Haar peaked at level d_3, and Symlet and Coiflet had their maxima slightly shifted toward d_5. Meanwhile, Daubechies 4 exhibited a more "blurred" maximum, indicating somewhat lower selectivity.

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Therefore, the C_i criterion allows not only the selection of the decomposition level for a specific signal but also provides a quantitative assessment of the wavelet's relevance to the task of QRS complex detection. This approach can be used as a component of more general adaptive ECG processing systems that automatically adjust to the signal's morphology and help avoid fixed parameters.

6. Conclusions

The conducted analysis confirmed the effectiveness of the criterion C_i for selecting the optimal level of wavelet decomposition when detecting QRS complexes in ECG signals. Regardless of the type of wavelet, the maximum values of C_i consistently occur within levels d_3–d_5, which corresponds to the frequency spectrum of QRS complexes.

Among the wavelets studied, Daubechies 6, Coiflet 1, and Symlet 4 proved to be the most suitable for QRS detection due to their stable C_i maxima at levels d_4–d_5. Although the Haar wavelet showed extremely high C_i values at the first level, it is less suitable because of its excessive sensitivity to noise and lack of localization. The Daubechies 4 wavelet demonstrated a broader distribution of informativeness, which may be useful for more complex signals but is less optimal for precise detection.

Thus, the experimental results demonstrate the advisability of an adaptive approach in selecting the wavelet and decomposition level depending on the signal morphology. The proposed method can be integrated into automated ECG diagnostic and monitoring systems to improve detection accuracy and reduce false positives.

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