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RESEARCH ARTICLE

A Novel ECG Signal Quality Index Method Based on Skewness-MODWT Analysis

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ABSTRACT Wearable devices have gained significant popularity for continuous Electrocardiogram (ECG) monitoring due to their compactness and convenience. Day-by-day and 24/7 monitoring without gaps is demanded to promptly detect unusual symptoms that are short-term warning signs of dangerous diseases. Cost-saving criteria are the highest priority to extend the use time of devices and maintain the system operation. However, not all measured signals are useful because the signal quality will be affected by many things such as motion artifacts and muscle noise. Demands on classifying and sending only the usable signal is a requirement, it can save the battery on wearable devices and the expense on the server side (i.e., cloud-based processing), such as storage and processing resources. Therefore, Signal Quality Indices (SQIs) have been developed and researched to determine signal quality to meet the above requirements. This study introduces a novel SQI approach to classify signals. The proposed method has three contributions: 1) exponentially Weighted Mean-Variance (EWMV), a lightweight equation, to identify peaks, followed by applying an adaptive threshold to define peaks that have the same shape as R-peaks; 2) outlier elimination process is proposed to enhance the accuracy; and 3) maximal Overlap Discrete Wavelet Transform (MODWT) is employed to categorize ECG signals into a new class, potentially containing signals relevant to pathological analysis. Experimental results demonstrate that our algorithm achieves the highest sensitivity for both noisy and noiseless data sets. Specifically, it achieved a sensitivity of 99.31% for clean signals and 97.69% for noisy signals. In the case of the PhysioNet challenge data set, while our sensitivity of 96.37% may not be the highest, our accuracy stands out at 95.10%, surpassing other methods recently reviewed. Additionally, our approach demonstrates the lowest trade-off between sensitivity and accuracy among the surveyed SQI techniques.

INDEX TERMS Electrocardiogram (ECG), exponentially weighted mean-variance (EWMV), maximal overlap discrete wavelet transform (MODWT), signal quality indices (SQIs), wearable devices.

I. INTRODUCTION

According to World Health Organization (WHO), ischaemic heart disease is the leading cause of death globally, responsible for 16% of the world's total deaths and resulting in 8.9 million deaths in 2019 [1]. However, the good news is that 80% of heart attacks are preventable [2], and an Electrocardiogram (ECG) signal is a noninvasive method that can be used for early diagnosis of heart-related diseases. However, traditional hospital devices measuring ECG signals have certain disadvantages. Firstly, they require multiple sensors all over the body, which may cause discomfort. Moreover, hospital ECG measuring devices cannot function 24/7 because ECG measurement can only be done when the patient goes to the hospital. Therefore, wearable and compact healthcare devices for continuous ECG recording are essential for early diagnosis. Thanks to the development of wearable devices and Internet of Things (IoT) technologies,

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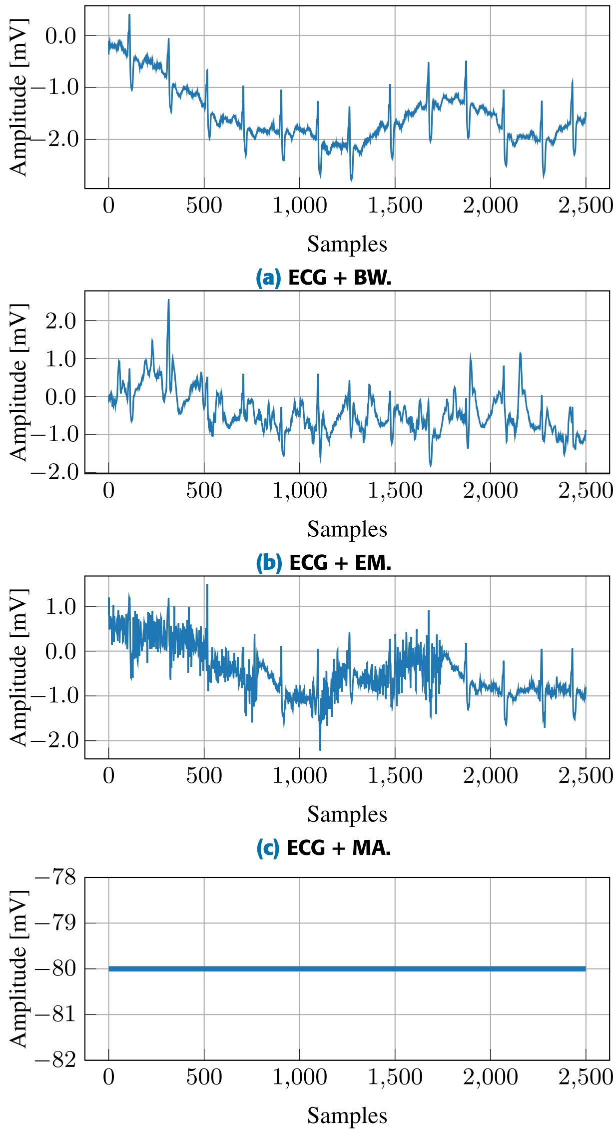
making the wearable ECG device was developed [3], [4], [5]. In [5], Tiago Rodrigues et al. presented a method that can detect R-peaks of ECG signals to calculate heart rate with high accuracy. Those ECG signals are measured by a device worn like a shirt, and users could have worn 24/7. Those wearable devices are lightweight and comfortable to wear, so the 24/7 measurement problems are resolved.

On the other hand, ECG signals measured from those devices are not always good for many reasons, such as poor electrode connection, user movement, Electromyogram (EMG) artifacts, Power Line Interference (PLI), Baseline Wander (BW), Muscle Artifact (MA) [6]. Figure 1 describes various types of noise. In Fig. 1a, the ECG signal is affected by BW, and the signal tends to vary along the low-frequency noise. However, this signal is considered a good signal because the PQRST complex shape is still visible. When the ECG signal is affected by electrode motion artifacts like Fig. 1b, due to electrode placement rapidly changing so the shape of the PQRST complex is destroyed, it can be seen that the small amplitude waves like P and T waves are covered by the large amplitude. Figure 1c shows the ECG signal affected by muscle artifact. Since muscle movement also interferes with the ECG signal, it can be seen that the ECG signal has many segments that are affected, leading to a complete loss of characteristics of the ECG signal. Sometimes, the disconnect between the electrode and the skin will cause a signal like a flat line like Fig. 1d. The filtering methods are usually used to remove the effect of noise and are usually embedded in the devices [4], [7]. However, the filtering approach has some weaknesses, including phase shifting and selection of optimized filter order. In reality, ECG signals are sensitive to filters because that could affect the quality of ECG signals, and it might cause misdiagnosis for clinical applications.

In addition to the challenges outlined, poor signals captured by ECG wearable devices can lead to a cascade of issues including misdiagnosis, false alerts, and wasted healthcare professionals' time. Moreover, in the context of cloud-based processing where all data is typically uploaded and analyzed remotely, inefficient utilization of server resources exacerbates these challenges. Sending the entirety of ECG signals from devices to servers or healthcare providers is unnecessary and inefficient. Instead, it's more practical and resource-efficient to transmit only high-quality signals, thereby reducing processing requirements on the server side. Furthermore, considering the limited battery capacity of compact wearable devices, it's essential to optimize energy usage by minimizing unnecessary data transmission. Transmitting only the requisite, high-quality signals helps prolong battery life, enhancing the usability and practicality of these devices for users. To address these issues, Signal Quality Indices (SQIs) serve as a crucial tool. By implementing SQIs, wearable devices can evaluate the quality of signals in real-time and selectively transmit only high-quality data to servers or healthcare professionals. This approach not only reduces the burden on server resources but also improves the efficiency of wearable devices by conserving battery power.



(a) ECG + BW.

(b) ECG + EM.

(c) ECG + MA.

(d) The flat line.

FIGURE 1. Types of noise and artifact.

This paper presents a novel SQI method for assessing the quality of ECG signals based on skewness and Maximal Overlap Discrete Wavelet Transform (MODWT). In contrast to conventional approaches relying on fiducial features, template matching, or machine learning, the proposed method introduces a streamlined algorithm for isolating and identifying peaks resembling R-peaks. Subsequently, it calculates the skewness of peak-peak intervals to categorize signals as either "GOOD" or "BAD". Moreover, the method incorporates the MODWT,[1] a frequency domain approach commonly employed in processing various types of bio-electrical signals [8], [9], [10]. Typically utilized for feature extraction in disease classification or detection. In this study, MODWT

[1]MODWT is a highly redundant and non-orthogonal transformation, offers comprehensive signal information independent of sample size, unlike conventional orthogonal transformations.

is used to categorize signals into a distinct class labeled "CONSIDER", potentially containing signals pertinent for pathological analysis.

By implementing this method, we aim to improve the efficiency of wearable devices. Our primary goal is to extend the battery life of these devices, thereby enhancing their efficiency and user experience. By filtering out unusable signals, we can significantly reduce power consumption while still maintaining the reliability of the data. Additionally, our method is designed to optimize the use of health-related signals. Even signals that may seem unusual at first glance are not discarded, as they could indicate a health condition. This approach allows us to capture valuable health information that might otherwise be overlooked.

According to the above motivations, this paper has made the following contributions:

- Proposed using Exponentially Weighted Mean Variance (EWMV), a lightweight algorithm to isolate rapidly changed signals and eliminate the low-frequency effect. The detail will be presented in section III-A1.
- Added an outlier elimination process to enhance the method's accuracy. In the previous work [11], certain health-related data were categorized as "BAD". This paper introduces the outlier elimination method to reduce the effect of outliers, making the possibility of delimiting the threshold to eliminate bad signal cases accurately clear. Thus moving these anomalous instances to an additional level, termed "CONSIDER". This will be covered in the section from III-A2 to III-A5.
- Utilize MODWT to categorize the "CONSIDER" level using frequency domain features, which exhibit characteristics related to anomalies in the heart. This will be shown in section III-B.

This paper is organized into six sections. Section II introduces SQI types and their methods with pros and cons. Section III outlines the proposed method. Section IV presents performance results. Section V discusses the results and future works, and section VI is the conclusion.

II. SQI OVERVIEW

SQIs are indices used to assess the quality of signal and usually grade the ECG signal into two groups: good and bad. SQIs are usually computed based on the morphology of signals or based on feature extraction so that those indices can eradicate the limitation of ECG signal filtration. SQIs are divided into two categories: fiducial and non-fiducial. In the fiducial type, various morphological and interval features, including the duration of P-wave, QRS complex and T-wave [12], PR and ST segment, and intervals, QT and RR intervals [13] are extracted to predict whether the signal is good or bad. Moreover, the amplitude of R-peak or noise amplitude [14] is also used to assess the quality of the ECG signal. In [13], Orphanidou et al present an SQI method based on the PQRST shapes. This method recognizes R-peaks and uses them as coordinates to calculate the QRS template. The template is computed by getting the mean value of the set

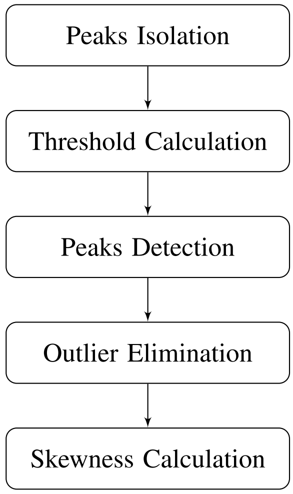


FIGURE 2. Flowchart of the proposed skewness method.

QRS complexes. Then, the correlation values between each QRS complex and the template are used to assess the quality of the ECG signal.

In non-fiducial type, can divide into three common approaches: SQI based on statistical [15], [16], [17], [18], [19], [20], SQI based on transformations, such as SQI in time domain [21], the frequency domain [22], or combining both time and frequency domain [23], and SQI based on machine learning [24], [25], [26]. In [22], Liping Li introduced an SQI method that transferred the ECG signal into the frequency domain to calculate the ratio between the power spectrum of 0.05-30 and 30-60 [Hz].

Existing fiducial SQI methods highly demand robust for accurate R-peak detection algorithms. If the algorithm gives wrong results, the assessment will also be wrong. In addition, this method is only suitable for regular heartbeats. It does not have the presence of various heart rhythms, such as normal (N-type) and premature ventricular contraction beats (V-type) in the signal segment. In the non-fiducial type, both statistical and transformation approaches have shown promising results in noise-free ECG signals. However, the accuracy of those methods is significantly decreased when the ECG signals are affected by noises or artifacts. Because when noise or artifacts interfere with the power spectrum from 0.05 [Hz] to 30 [Hz], the ratio used to assess the signal quality gives the same results as when the signal is good. Machine learning SQI approaches demand large ECG recordings and the balance among the number of ECG signals, types of ECG, and noise signals to build an accurate prediction model. In practice, this is very difficult because the amount of unique ECG signal and noise occupied is meager compared to the standard signal.

III. PROPOSED METHODOLOGY

This section elucidates the process of categorizing signal quality into three distinct levels. The initial phase designates signals as "BAD" utilizing the skewness technique. Subsequently, the remaining signals undergo processing through

Algorithm 1 Algorithm of Peak Detection

Require: Set of boundary **Bo**, set of exponentially weighted variance $\mathbf{Var}_{\mathrm{EW}}$

```
for i = 1 → N do                                         ▷ N is the number of elements in Var_EW
    if Var_EW[i] > Bo[i] then
        if Var_EW[i] − Bo[i] > 2 × Bo[i] and Var_EW[i] ≥ Var_EW[i − 1] then
            C ← i                                        ▷ Set C contains the coordinate of peaks
        end if
    end if
end for
```

the MODWT to classify them into the categories of "GOOD" and "CONSIDER".

A. SKEWNESS METHOD

Figure 2 describes the proposed skewness method. The input ECG signal first goes through a peak isolation step to isolate peaks similar to the R-peak. Then, an adaptive boundary is calculated to eliminate the non-QRS area from the processed signal by isolation step, and peaks similar to the R-peak are detected. After that, the distance between adjacent peaks will be used to calculate skewness, which is the crucial SQI to decide if the signal is diagnosed as "BAD".

1) PEAKS ISOLATION

This step isolates peaks that have a shape that is similar to R-peak, and the EWMV is chosen to satisfy two purposes: first is making the peaks that are similar to R-peak stand out more and minimize the effect of low-frequency noise and artifacts, and second, is to make sure that the algorithm will be low complexity. The EWMV is explained in (1)

$$\mathrm{Var}_{\mathrm{EW}}[n] = (1-\alpha)[\mathrm{Var}_{\mathrm{EW}}[n-1] + \alpha(x[n] - \mu_{\mathrm{EW}}[n-1])^2], \quad (1)$$

where $\mu_{\mathrm{EW}}[n]$ and α computed in (1a) and (1b)

$$\mu_{\mathrm{EW}}[n] = (1-\alpha)x[n] + \alpha\mu_{\mathrm{EW}}[n-1], \quad (1a)$$

$$\alpha = 1 - \frac{2}{N-1}. \quad (1b)$$

Where $x[n]$ is the input ECG signal and (1) shows the signal's variance. This value will be big when there is a significant change from the signal and vice versa. Moreover, (1a) calculates the signal's mean contains α, which is the influence factor of the previous sample on the current sample, with the N as the number of samples that corresponds with half of the QRS interval and half of the QRS interval chosen to isolate the R peak. In [27], the QRS interval in adults is between 80 to 110 milliseconds, so 50 milliseconds are chosen as half of the QRS interval in this paper. This is a crucial first step as it provides a peak isolation process. Without this step, the remaining components would have to deal with a noisy and potentially misleading signal.

2) THRESHOLD CALCULATION

This step generates a boundary that covers a high percentage of data. This boundary is used as the adaptive threshold to eliminate most of the non-QRS area and is calculated using the following

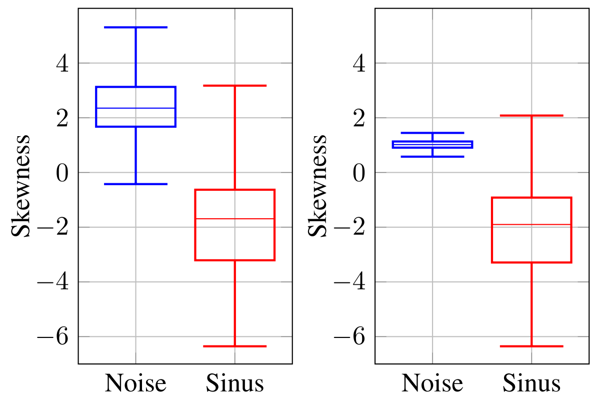
$$\mathrm{Bo}[n] = (1-\alpha)\mathrm{Thr}[n] + \alpha\mathrm{Bo}[n-1], \quad (2)$$

where $\mathrm{Thr}[n]$ is computed by three times $b[n]$ from $a[n]$ with

$$b[n] = \sqrt{(1-\alpha)[b[n-1] + \alpha(\mathrm{Var}_{\mathrm{EW}}[n] - a[n-1])^2]}, \quad (2a)$$

$$\mathrm{a}[n] = (1-\alpha)\mathrm{Var}_{\mathrm{EW}}[n] + \alpha a[n-1], \quad (2b)$$

and α is the influence factor like (1b).



(a) Before elimination. **(b) After elimination.**

FIGURE 3. Effect of upper outlier elimination on noisy and noiseless data.

3) PEAKS DETECTION

After acquiring the boundary, we will use it like the threshold to detect the peaks by checking the difference between values in set $\mathbf{Var}_{\mathrm{EW}}$ and **Bo**. If the variance is greater than two times the boundary's value, the coordinate of $\mathbf{Var}_{\mathrm{EW}}$ will be defined as a peak. Set **C** contains the coordinate of detected peaks, and the detail of this step is explained in Algorithm 1.

4) OUTLIER ELIMINATION

The set of R peaks obtained above is similar to that of the previous research [11], but this set can be inaccurate as it is affected by outliers, which may cause it to be classified as "BAD" and then be discarded. To solve this problem, this paper implements an outlier elimination process to reduce the impact of outliers on the data.

First, the set of peak-peak intervals is calculated in (3) and contained in set **P**

$$\mathrm{P}[k] = \mathrm{C}[k+1] - \mathrm{C}[k], \tag{3}$$

where C[k] is the coordinate of k^{th} peaks which is defined in Algorithm 1. However, an upper outlier elimination process is deployed to control the skewness value. The upper outlier elimination plays an important role, and it changes the sign of the skewness value if the good signal is positive skewness and converges the skew values if the value is bad. The upper outlier points are defined as elements in set **P** that have values more than three scaled Median Absolute Deviation (MAD) from the median. The scaled MAD is defined as

$$\mathrm{MAD}_{\mathrm{scaled}} = \mathrm{C}.\mathrm{median}\left(|\mathbf{A} - \mathrm{median}\left(\mathbf{A}\right)|\right), \tag{4}$$

where C is constant and is calculated by

$$\mathrm{C} = \frac{-1}{\sqrt{2}\,\mathrm{erfcinv}\,(1.5)}, \tag{5}$$

which erfcinv is the inverse complementary error function. This function is defined as the functional inverse of erfc, and the $erfc(x)$ function has form

$$\mathrm{erfc}(x) = 1 - \left(\frac{2}{\sqrt{\pi}}\int_0^x e^{-t^2}dt\right). \tag{6}$$

Figure 3 shows the impact of upper outlier elimination on Skewness value when applied to noisy and noiseless data. Figure 3a and Fig. 3b show the Skewness value with and without the upper outlier, respectively. It's clear that the variance of the noise set has significantly decreased. Meanwhile, the sinus set remains almost unchanged, making it easier to determine the threshold.

Algorithm 2 Algorithm of Signal Quality Assessment

Require: ECG signal, Fs

1: No.Segment = $\left\lfloor \dfrac{\text{length(ECG signal)}}{10 \times \text{Fs}} \right\rfloor$
2: **for** $i = 1 \rightarrow$ No.Segent **do**
3:   **if** Skew[i] ≥ 0 **then**
4:     **if** Skew[i] ≤ 2 and Per[i] < 0.7 **then**
5:       BAD $\leftarrow$ BAD + 1
6:     **else**
7:       $\widetilde{\mathbf{W}}$ = MODWT(ECG[i])
8:       $r[i]$=(11)
9:       **if** $r[i] \geq 50\%$ **then**
10:         GOOD $\leftarrow$ GOOD + 1
11:       **else**
12:         CONSIDER $\leftarrow$ CONSIDER + 1
13:       **end if**
14:     **end if**
15:   **end if**
16: **end for**

If the skewness is calculated at the previous stage, even though the "BAD" signal has a positive skewness value, the range of skewness values is still large even if there are a few cases of the "GOOD" signals that are positive because of the appearance of several long heartbeats. So by removing the upper outlier, we can narrow the value range of "BAD" signals and even change the value of "GOOD" signals that have a long heart duration to become negative, thereby making it easier to determine the threshold "GOOD" and "BAD".

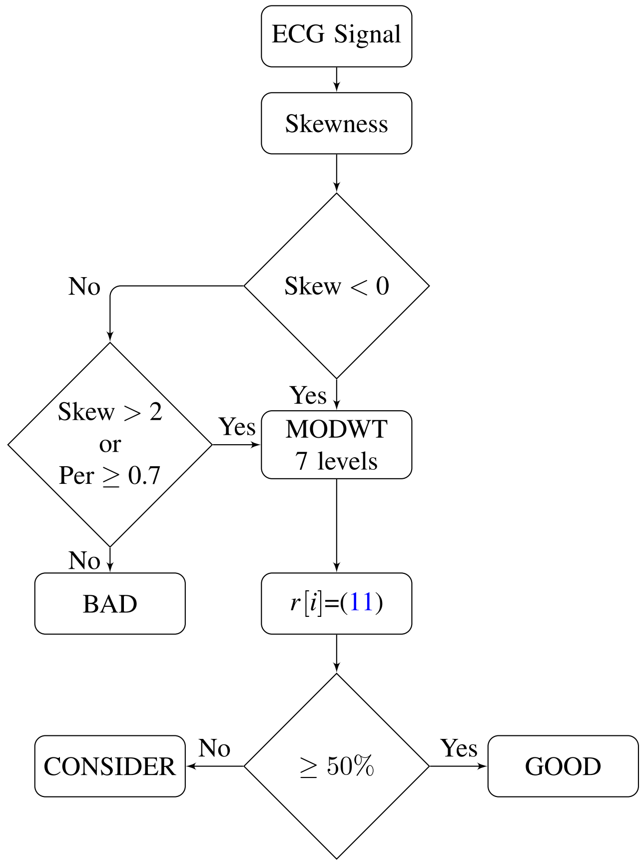


FIGURE 4. Flowchart of the Algorithm 2.

5) SKEWNESS CALCULATION

In statistic theory, skewness is a measure of the asymmetry of the probability distribution, and the skewness value can be positive, zero, or negative. This paper uses the skewness parameter to assess the quality of the ECG signal. The skewness of peak-peak interval has form

$$\mathrm{Skew} = \frac{1}{K}\sum_{k=1}^{K}\frac{(\mathrm{X}[k] - \overline{\mathrm{X}})^3}{\sigma^3}, \tag{7}$$

where K is the number of elements in set **X**, $\overline{\mathrm{X}}$ is the mean value, and σ is the standard deviation of set **X**. Set **X** contains the value of peak-peak intervals that applied the outlier elimination process.

The "BAD" signals are defined when skewness is positive skew or greater than 2. Thanks to the outlier elimination process, the skewness threshold for "BAD" signals can be defined in line 4 of Algorithm 2.

B. MAXIMAL OVERLAP DISCRETE WAVELET TRANSFORM

Until now, we have classified signals into "BAD" and "GOOD" categories. However, there is a potential risk of misclassifying anomalous heart signals containing useful information about abnormal heart activities such as "BAD". To address this, we have utilized the frequency domain, specifically MODWT. It decomposes signal into different sub-bands, and the ratio between these sub-bands can used to establish the "CONSIDER" class. Additionally, MODWT is suitable for our needs due to its low complexity when implemented on hardware, as evidenced in [28] and further exemplified in [29]. Besides, MODWT has several advantages when compared with Discrete Wavelet Transform (DWT)

- MODWT is a highly redundant, non-orthogonal transform. Unlike DWT which discards down-sampled data at each level of decomposition, MODWT retains this data, making it distinctive.
- DWT is typically employed for samples of size $2N$, $\forall\ N > 1$, whereas MODWT can be utilized for sample sizes of any value.
- Both transforms feature Multi-Resolution Analysis (MRA), but MODWT offers the advantage of transforming invariant. This means it can capture both the details and approximate coefficients of a signal, which shift along with the signal itself.

DWT of the signal $x[n]$ is decomposed into one approximate component and detailed components like (8), (9) with N is the number of samples, $\varphi_{j_0,k}(n)$ and $\psi_{j,k}(n)$ are functions of discrete variable x, respectively

$$W_{\varphi}(j_0,k) = \frac{1}{\sqrt{N}}\sum_{n} x[n]\varphi_{j_0,k}(n), \tag{8}$$

$$W_{\psi}(j,k) = \frac{1}{\sqrt{N}}\sum_{n} x[n]\psi_{j,k}(n). \tag{9}$$

Nevertheless, the partial DWT of the j^{th} level imposes a constraint on the sample size, necessitating it to be an integer multiple of $2^{j^{th}}$, which can lead to information loss in the signal. But MODWT would not, the MODWT at the j^{th} level is applicable to any sample size N and is created by eliminating reused values from the DWT through downsampling. The J_0 level comprises $J_0 + 1$ vectors:

$$[\widetilde{\mathbf{W}_1}, \widetilde{\mathbf{W}_2}, \ldots, \widetilde{\mathbf{W}_{J_0}}] \text{ and } \widetilde{\mathbf{V}_{J_0}}, \tag{10}$$

each of which has length N. Where, $\widetilde{\mathbf{W}_j}$ $(j = 1, 2, \ldots, J_0)$ represents the detail components, and $\widetilde{\mathbf{V}_{J_0}}$ corresponds to the approximate component. In this study, with a signal sampling rate of 250 Hz, a power ratio as expressed in (11) is computed to categorize the ECG signal's quality into distinct classes. This ratio is derived from the detail components to mitigate the influence of low-frequency noise that may appear in the approximate components.

This paper proposed a process that classifies signal quality into three levels: "BAD", "GOOD", and "CONSIDER". Algorithm 2 outlines the implementation of this process with a sampling rate of Fs = 250 [Hz] and a value of $J_0 = 7$. Figure 4 provides a more intuitive visualization of Algorithm 2.

$$r = \frac{\sum_{j=2}^{4} \mathrm{Var}(\widetilde{\mathbf{W}_j})}{\sum_{j=1}^{J_0} \mathrm{Var}(\widetilde{\mathbf{W}_j})}. \tag{11}$$

MODWT and skewness component work together on the refined ECG signal. The Skewness component simultaneously analyzes the asymmetry of the signal distribution to classify signals, while the MODWT method further classifies the signal quality based on frequency domain features. The combination of these two processes allows for a comprehensive understanding of the signal. The classification provided by MODWT and Skewness component together contribute to a robust detailed signal analysis and categorization.

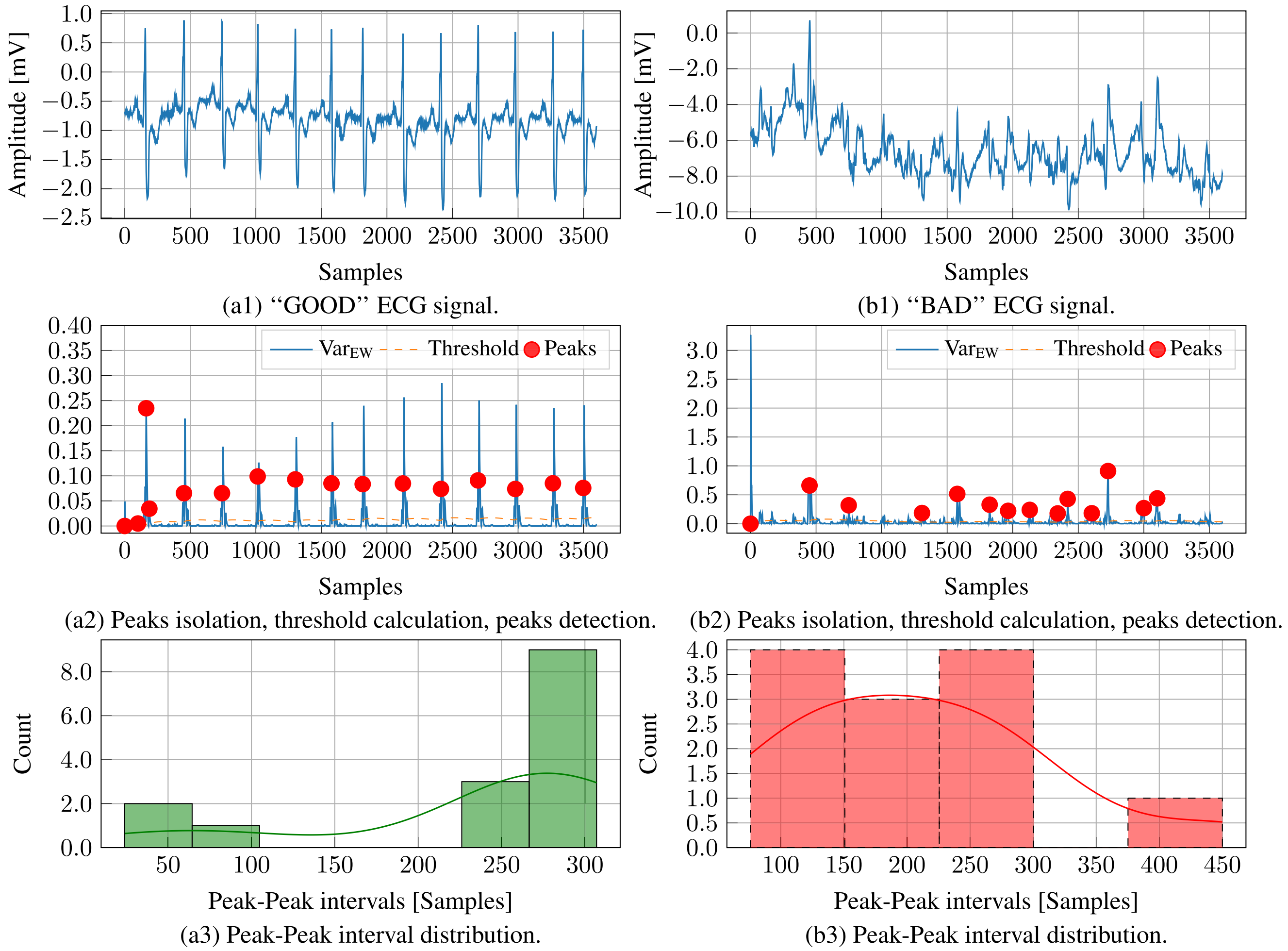
IV. EXPERIMENT RESULTS

A. DATABASES

Various ECG signals with different PQRST complexes and rhythms were collected to test the robustness of the proposed algorithm. The MIT-BIH Arrhythmia Database (MIT-BIHA) [30] is chosen to test the accuracy of the proposed SQI method and its independence from the type of ECG beat. The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings; the recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 [mV] range. The MIT-BIH Noise Stress Test Database (NST) [31] is used to evaluate the ability to detect the noise of the algorithm, which contains three different kinds of noise, which are Baseline Wander (BW), Motion Artifact and EMG artifact. The signals that added noise were taken from the MIT-BIHA. The noisy signal is generated by adding NST noise, beginning with ten seconds segments alternating with ten-second clean segments; the power of noise has the Signal-to-Noise Ratio (SNR) SNR $= -6, 0, 6, 12$, and 18 [dB]. In the NST database, signals at SNR $= 12$ [dB] and SNR $= 18$ [dB] were considered noise-free because the contribution of noise's power is extremely smaller than the signal's power. In contrast, signals at SNR $= 6, 0$, and -6 [dB] were considered noise.

Furthermore, to test the algorithm's ability for wearable ECG devices, the Physionet Challenge Database-2011 (C-2011) [32] is used. This database consisted of 1000 twelve-lead ECGs, and ECG signals were collected from a mobile phone, each lasting ten seconds and having a sampling rate of 500 samples per second and 16-bit resolution. The Physionet challenge was classified into acceptable and unacceptable quality ECG signals with 983 labels.

Additionally, this study incorporates the PhysioNet Challenge Database-2014 (C-2014) [33], which encompasses continuous, extended-term recordings obtained from bedside monitors or comparable apparatus. The intent of utilizing this database is to appraise the algorithm's precision in scenarios where ECG signals are captured during periods of sleep,



(a1) "GOOD" ECG signal.
(b1) "BAD" ECG signal.
(a2) Peaks isolation, threshold calculation, peaks detection.
(b2) Peaks isolation, threshold calculation, peaks detection.
(a3) Peak-Peak interval distribution.
(b3) Peak-Peak interval distribution.

FIGURE 5. Results of proposed Skewness method.

extending the evaluation beyond signals derived solely from daytime activities.

Conversely, the MIT-BIH Atrial Fibrillation Database (MIT-BIHAFib) [34] is harnessed to assess the algorithm's performance in scenarios involving ECG signals indicative of Atrial Fibrillation (AFib). AFib refers to an irregular and frequently accelerated heart rhythm, which can potentially result in severe consequences such as stroke, blood clots, and heart failure. Given the potential gravity of misdiagnosing this condition, accurate identification is paramount for safeguarding the patient's well-being.

Brno University of Technology ECG Signal Database with Annotations of P Wave (BUT-PDB) [35], this database was created by the cardiology team at the Department of Biomedical Engineering, Brno University of Technology, the database consists of fifty 2-lead ECG recordings, each recording is 2 minutes long with various types of pathology with annotated P waves. This database is useful to check the possibility of the algorithm with various P wave types, and this database is chosen because P-wave detection or PR interval is one of the essential things in the ECG analysis field. Furthermore, in a very noisy ECG signal, it may be highly challenging to detect P waves reliably and to measure PR intervals.

The Brno University of Technology ECG Quality Database (BUT-QDB) [36] serves as a resource to assess the robustness of our proposed method when applied to ECG recordings captured during routine daily activities. Those ECG signals were annotated into three class as follow: Class 1 indicates that ECG significant waveform (P wave, T wave, and QRS complex) are visible and their onsets and offsets can be detected reliably; Class 2 indicates that the noise level is increased and ECG significant points cannot be reliably detected, but the signal enables reliable QRS detection; Class 3 indicates that QRS complexes cannot be detected reliably and the signal is unsuitable for any further analysis. This database suitable for the purpose of evaluating the robustness of the algorithm to continuously recordings from wearable devices.

In the experimentation process, the WFDB toolbox [37] in Python is employed to resample the sampling rate of all databases to 250 samples per second. This resampling of the sample rate ensures equitable conditions for evaluating the efficacy of the proposed method across diverse databases.

TABLE 1. Performance of proposed SQI method.

Database	Noise Type	Total	TP	FP	TN	FN	Se [%]	Pre [%]	Acc [%]
MIT-BIHA [30]	Noise-free	7618	7566	–	–	52	99.31	–	99.31
NST [31]	Noise & Noise-free	2533860	2004849	8431	400040	120540	94.32	99.58	94.91
C-2011 [32]	Noise & Noise-free	983	824	23	105	31	96.37	97.28	94.50
C-2014 [33]	Noise-free	970	970	–	–	0	100.0	–	100.0
MIT-BIHAFib [34]	Noise-free	77581	77262	–	–	319	99.59	–	99.59
BUT-PDB [35]	Noise-free	527	523	–	–	4	99.24	–	99.24
BUT-QDB [36]	Noise & Noise-free	35239	28434	194	5393	1218	95.89	99.32	95.99

B. PEAKS ISOLATION, THRESHOLD CALCULATION AND PEAKS DETECTION RESULTS

Figure 5 provides a comprehensive overview of the results generated by the proposed Skewness method. The step-by-step progression of the method's application to "GOOD" ECG signals is detailed in Fig. 5a. Within this, Fig. 5a1 displays the "GOOD" ECG signal, while Fig. 5a2 showcases the outcomes of the peak isolation, boundary calculation, and peak detection steps.

In Fig. 5a2, particular attention is drawn to the $\mathrm{Var}_{\mathrm{EW}}$ values, which exhibit high values at the R peak locations. The core concept of the proposed method hinges on the analysis of peak-peak intervals to assess the ECG signal. However, the challenge lies in precisely defining what constitutes a peak. If peaks are solely defined as samples with values exceeding those of their adjacent samples, this criterion is met by numerous points, particularly in the non-QRS regions. Consequently, the peak-peak intervals exhibit significant variability, rendering signal assessment arduous. Alternatively, assigning a fixed constant value to define peaks is problematic due to the dependence of ECG signal amplitude on multiple factors. Such a constant value might suit one ECG signal but prove unsuitable for another.

An adaptive boundary is introduced to address these issues to distinguish the impact of peaks in non-QRS regions while effectively identifying the R peaks in "GOOD" signal cases. The orange dashed line in Fig. 5a2 represents this adaptive boundary, computed using (2). This boundary effectively demarcates areas where $\mathrm{Var}_{\mathrm{EW}}$ values in non-QRS regions fall below the specified threshold. The utilization of Algorithm 1 with $\mathrm{Var}_{\mathrm{EW}}$ and the adaptive boundary as inputs yields the peaks represented by red circles in Fig. 5a2.

Furthermore, analogous processes are applied to "BAD" signals, exemplified in Fig. 5b1. These signals are crafted through a combination of "GOOD" ECG signals and noise signals sourced from the NST database with a signal-to-noise ratio (SNR) of −6 [dB]. Employing the same methodology as with "GOOD" signals, Fig. 5b2 illustrates the outcomes for the "BAD" signals.

C. SKEWNESS RESULTS

Drawing inspiration from the inherent randomness of noise, a notable observation arises: the occurrence of short peak-peak intervals tends to surpass that of more extended intervals. Leveraging this insight, the skewness of the peak-peak interval distribution emerges as a pivotal metric for defining signal quality.

This concept is visually demonstrated in Fig. 5a3 and Fig. 5b3, illustrating the distribution of peak-peak intervals for "GOOD" and "BAD" signals, respectively. The distribution shapes in these two scenarios exhibit skewed tails, albeit in opposite directions. Consequently, negative and positive skewness values serve as effective indicators for assessing "GOOD" and "BAD" signals.

D. PERFORMANCE OF PROPOSED SQI METHODS

The performance of the proposed method is evaluated by sensitivity (*Se*), precision (*Pre*) and accuracy (*Acc*), which were calculated as

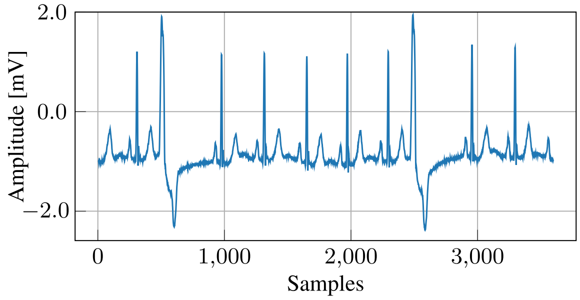
$$Se = \frac{TP}{TP + FN} \times 100\%, \tag{12}$$

$$Pre = \frac{TP}{TP + FP} \times 100\%. \tag{13}$$

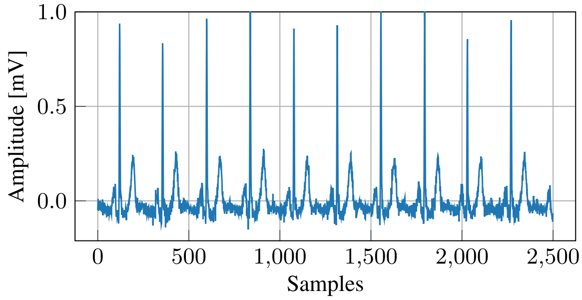
$$Acc = \frac{TP + TN}{TP + TN + FN + FP} \times 100\%. \tag{14}$$

where *TP* is the true positive that represents the correctly predicted segments. *FN* denotes the false negative, which means the signals were predicted to be "BAD" but were actually "GOOD". *FP* denotes the false positive, which means the signals were predicted to be "GOOD" but were "BAD".

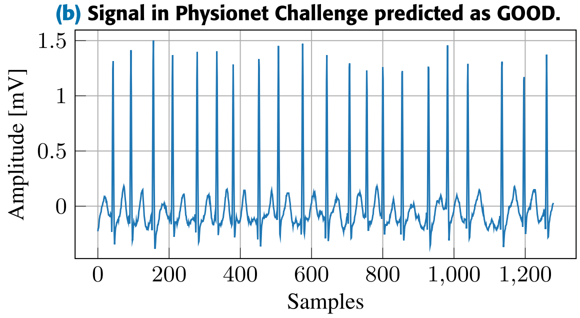
The TABLE 1 shows the performance of the proposed SQI method on different databases of ECG signals with various



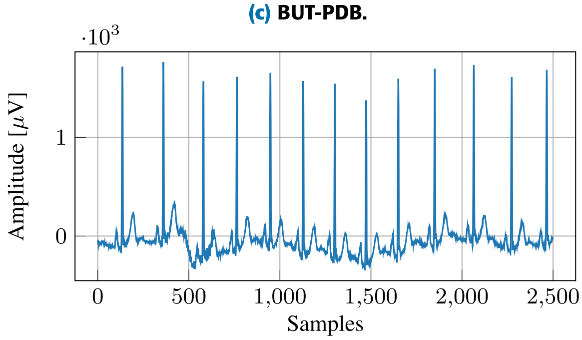
(a) MIT-BIHA database.



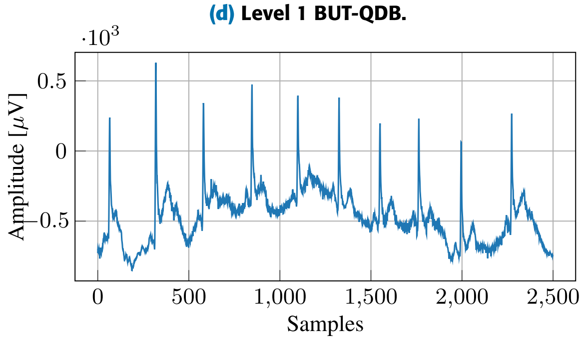
(b) Signal in Physionet Challenge predicted as GOOD.



(c) BUT-PDB.

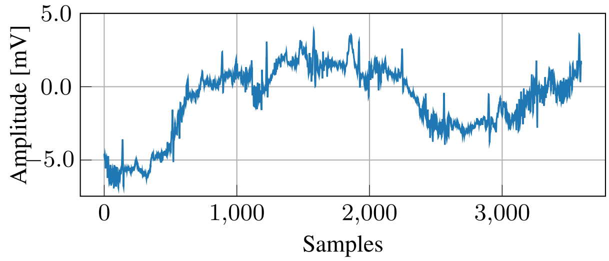


(d) Level 1 BUT-QDB.

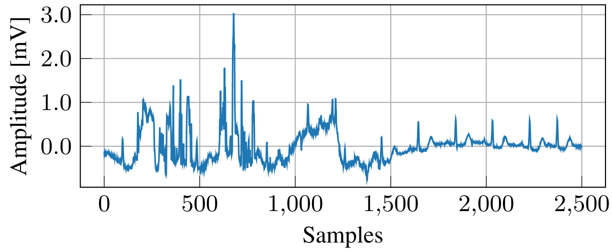


(e) Level 2 BUT-QDB.

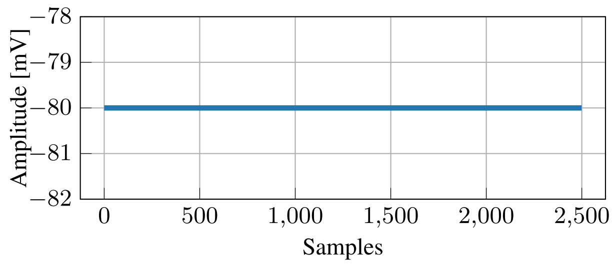
FIGURE 6. "GOOD" prediction results.



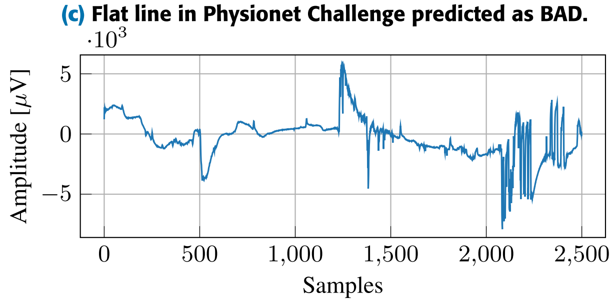
(a) MIT-BIH with MA + BW.



(b) Signal in Physionet Challenge predicted as BAD.



(c) Flat line in Physionet Challenge predicted as BAD.



(d) Level 3 BUT-QDB.

FIGURE 7. "BAD" prediction results.

noise types and levels. All of the databases prove the robustness of this method under different conditions.

- MIT-BIHA [30] and C-2014 [33] are suitable to evaluate when ECG signals are measured by hospital devices, bedside monitoring, or similar devices. It can be seen that the proposed method reaches a high sensitivity when ECG signals are collected from standard devices, $Se = 99.31\%$ and $Se = 100\%$ for MIT-BIHA and C-2014 database, respectively. This suggests that the method can achieve optimal performance when the signal quality is high, and the noise level is low.
- The MIT-BIHAFib [34], and BUT-PDB [35] databases are used to evaluate the robustness of the proposed method when ECG signals are particular types. This paper focuses on AFib and P waves because in the ECG analysis area, AFib and P waves are the hot research topic, and it has the ability to diagnose

TABLE 2. Percentage of GOOD and CONSIDER.

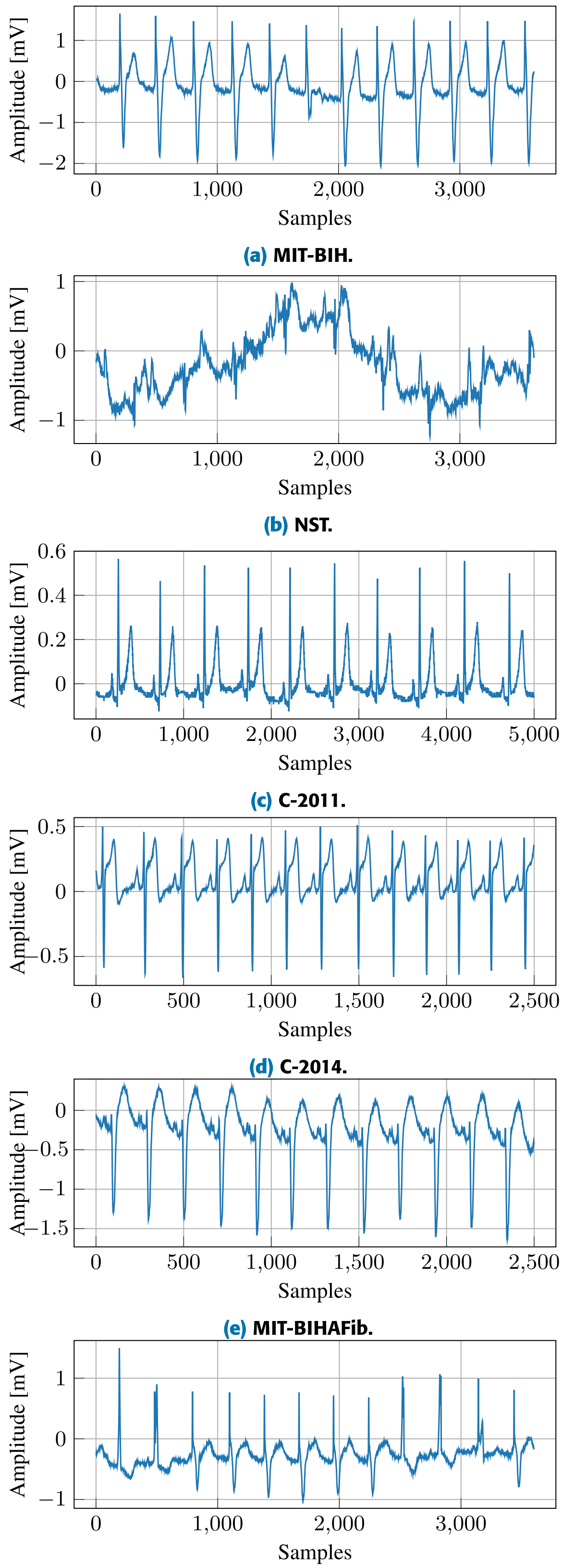
Database	GOOD [%]	CONSIDER [%]
MIT-BIHA [30]	72.00	28.00
NST [31]	56.00	44.00
C-2011 [32]	80.00	20.00
C-2014 [33]	100.0	0
MIT-BIHAFib [34]	85.00	15.00
BUT-PDB [35]	77.00	28.00
BUT-QDB [36]	9.85	92.15

dangerous diseases. It can be seen that the sensitivity under special ECG-type conditions still achieves high values with $Se = 99.59\%$ and $Se = 99.24\%$ for MIT-BIHAFib and BUT-PDB database, respectively.

- The NST [31], C-2011 [32], and BUT-QDB [36] databases are used to evaluate this method under noise-free and noisy conditions. The Se and Pre in the NST database reached 94.32% and 99.58%. Evaluating this method under daytime activities conditions, the C-2011 and BUT-QDB databases are used, $Se = 96.37\%$ and $Pre = 97.28\%$ for the C-2011 database and $Se = 95.89\%$ and $Pre = 99.32\%$ for BUT-QDB database. Besides, the Acc of all 3 data sets reached 94.91%, 94.50%, and 95.99% respectively.

Figure 6 shows the "GOOD" prediction results of the proposed method on various signal types. Figure 6a shows the signal of the MIT-BIHA database measured using conventional hospital devices, despite having multiple types of beat in the same signal, in this case, normal beat (N-type) and ventricular beat (V-type), the proposed method still predicts correctly. This result proves the proposed method's independence from various types of ECG beat, unlike the template matching method [13]. On the other hand, Fig. 6b shows the signal from C-2011 collected using mobile phones, which was labeled "GOOD" by qualified health experts, and the proposed method also predicts it to be "GOOD". In Fig. 6c, an ECG signal with a high heart rate is shown, which means that our method is also compatible with tachycardia signals. In Fig. 6d and Fig. 6e, is the signal measured while the patient is doing their casual activity, the proposed method can predict correctly despite the baseline wander and random noise, this is an important characteristic as we are aiming to apply our algorithm to wearable devices.

On the contrary, Fig. 7 provides a comprehensive view of the prediction outcomes for "BAD" signals achieved through the proposed method across various signal types. Fig. 7a demonstrates a signal affected by both MA and BW noise, characterized by an SNR of approximately −6 [dB]. This result serves as compelling evidence of the method's capability to identify signals influenced by diverse forms of noise. A similar outcome is depicted in Fig. 7b, where the proposed



(a) MIT-BIH.
(b) NST.
(c) C-2011.
(d) C-2014.
(e) MIT-BIHAFib.
(f) BUT-PDB.

FIGURE 8. "CONSIDER" prediction results.

method accurately detects a "BAD" signal. It's worth noting that this algorithm consistently predicts results with 100%

accuracy when the signal represents a flat line, exemplified in Fig. 7c. Finally, in Fig. 7d, the signal collected during a patient's routine activities is heavily overshadowed by noise, resulting in the method categorizing it as "BAD" due to the pronounced dominance of noise over the ECG signal.

TABLE 2 provides a comprehensive overview of the percentages attributed to the classifications of "GOOD" and "CONSIDER" when applying MODWT. A notable observation is the variability in the occurrence of the "CONSIDER" class across different databases. The "CONSIDER" class is helpful for predicting whether an ECG signal is a special rhythm, and Fig. 8 shows the "CONSIDER" class in different databases. Figure 8a, b, c, d, e and f show the various of ECG signal's shape, these signals have in common is that they all have T-wave signals that are louder than usual, which usually occurs when the patient is ischemic. In addition, other T waveforms represent different pathologies. In Fig. 8f, the T wave of the QRS complex overlaps and disappears the P wave of the QRS complex immediately after it, which is highly likely to signal a heart disease. The reason for calling this "CONSIDER" class is because there is still some noise in the signal, as shown in Fig. 8b.

E. PERFORMANCE COMPARISON

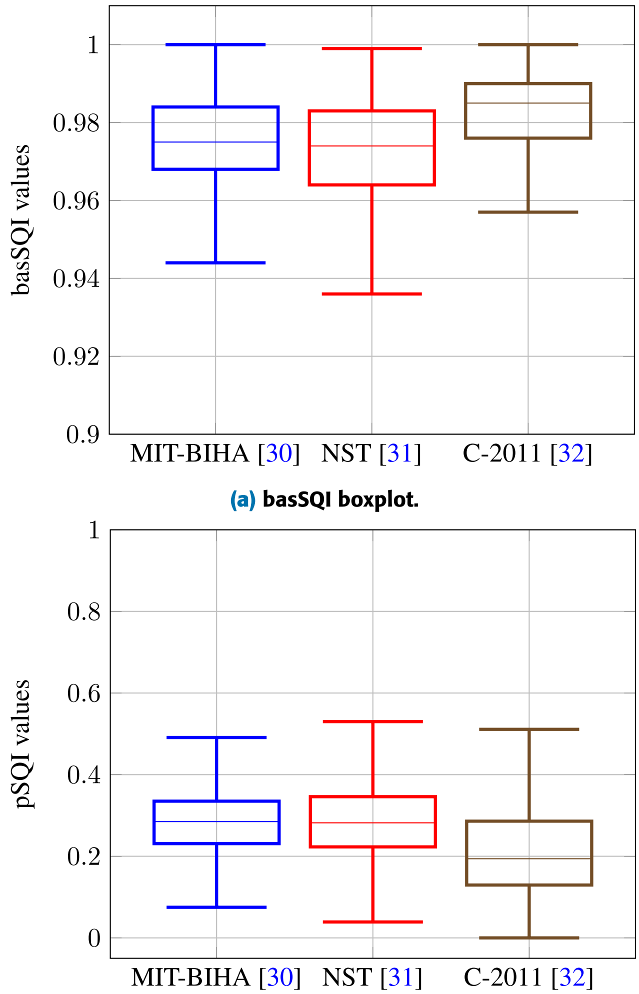
To compare with the proposed algorithm, this paper performs two frequency-domain methods, basSQI, and pSQI [38]. The basSQI is the relative power in the baseline defined in (15). The pSQI is the ratio of power spectral density in the QRS energy band to that in the overall energy band defined in (16). Where $P(f)$ is the power spectrum of the ECG signal.

$$\text{basSQI} = 1 - \frac{\int_0^1 P(f)\,df}{\int_0^{40} P(f)\,df}, \tag{15}$$

$$\text{pSQI} = \frac{\int_5^{15} P(f)\,df}{\int_5^{40} P(f)\,df}. \tag{16}$$

However, the values of basSQI and pSQI make it impossible to grade the quality of signals into different levels. C-2011 [32], MIT-BIHA [30], and NST [31] databases are used to consider a threshold of basSQI and pSQI in three scenarios: C-2011 for both noise and noise-free signals in one database, MIT-BIHA for noise-free signals, and NST for noise signals with SNR = −6 and 0 [dB]. Figure 9a and Fig. 9b show values of basSQI and pSQI methods, respectively. It can be seen that the range of values of all three scenarios is similar for both basSQI and pSQI. Especially in MIT-BIHA and NST databases, values of basSQI and pSQI do not have too many differences, so it is hard to grade signals as "GOOD" or "BAD" if these methods are used.

The TABLE 3 provides a comprehensive overview of performance comparisons across distinct SQI methodologies, furnishing a visual foundation for assessing SQI algorithms; these findings were referred from [23] and [39]. Sensitivity is prioritized for assessment in the healthcare context because the purpose of SQI is to minimize misprediction of good signals, which can cause loss of important information used to diagnose disease. However, accuracy is also a metric used to evaluate the method; a good method is when the trade-off between *Se* and *Acc* is reasonable. The results show that when considering the noise-free set, our method achieves the highest results (up to 99.31%) when considering the noisy data set, our method also gives the best results. This demonstrates that our method effectively distinguishes between good and bad signals, with minimal risk of overlooking good signals. Thus, it is well-suited for applications requiring signal quality assessment. For datasets with both types of signals, our method does not achieve the highest results yet remains acceptable with $Se = 96.37\%$, compared to the top performance by Liu et al. [40] at 97.67%. However, in terms of accuracy (*Acc*), our method outperforms all others, boasting a score of 95.10%, whereas Liu et al. achieved only 93.09%.



(a) basSQI boxplot.
(b) pSQI boxplot.

FIGURE 9. basSQI and pSQI boxplots.

V. DISCUSSION AND FUTURE WORKS

The experimental outcomes underscore the efficacy of the proposed method in terms of sensitivity and accuracy, both

TABLE 3. Performance comparison between SQI methods.

First author and year of publication	Signal Type	Se [%]	Acc [%]
Clifford (2011) *et al.* [42]	Noise-free	91.17	N/M
	Noise	81.01	N/M
Hayn *et al.* (2012) [14]	Noise-free	79.74	N/M
	Noise	73.92	N/M
Orphanidou *et al.* (2015) [13]	Noise-free	78.94	N/M
	Noise	69.36	N/M
Athif *et al.* (2017) [43]	Noise & Noise-free	91.20	91.10
Huerta *et al.* (2020) [44]	Noise & Noise-free	90.37*	87.77*
Xie *et al.* (2021) [45]	Noise & Noise-free	96.24*	N/M
Liu *et al.* (2021) [41]	Noise & Noise-free	**97.67**[a]	93.09
Tai *et al.* (2023) [46]	Noise-free	96.73	N/M
	Noise & Noise-free	96.81	92.98
Proposed SQI method	Noise-free	**99.31**[b]	–
	Noise	**97.69**[c]	–
	Noise & Noise-free	96.37	**95.10***[a]

[a] : The highest value in Noise & Noise-free.
[b] : The highest value in Noise-free.
[c] : The highest value in Noise.
* : The average value.
N/M: Not mentioned in article.

for noise-free and noisy signals. The assessment encompasses diverse databases serving various purposes, including standard devices like hospital equipment and static devices from MIT-BIH and C-2014 databases for medical use. The MIT-BIHAFib and BUT-PDB databases are considered for pathologies assessment, while the NST, C-2011, and BUT-QDB databases are employed for noise evaluation. Notably, ECG signals from wearable devices during daytime activities in the C-2011 and BUT-QDB databases enable the robustness evaluation of the proposed method for wearable application.

In the context of this study, the sensitivity index takes precedence, as the absence of accurate "GOOD" signals could lead to diagnostic information loss. In contrast to alternative methods like Hamilton-Tompkins, R-peak and noise amplitude temporal features, high-order statistical SQI, and amplitude difference variance-based SQI, the newly proposed method exhibits significantly heightened sensitivity in classifying signal quality. Implementing this method can potentially curtail server-related costs in post-processing and extend the battery life of wearable devices in pre-processing by exclusively transmitting signals that meet the requirement.

The "CONSIDER" class should be classified as "GOOD" and "BAD" in the future by a suitable algorithm. Besides, developing prototypes on microcontrollers and Field Programmable Gate Arrays (FPGA) is demanded to evaluate feasibility and power consumption accurately. The "CONSIDER" class should be classified as "GOOD" and "BAD" in the future by a suitable algorithm. Besides, developing prototypes on microcontrollers and Field Programmable Gate Arrays (FPGA) is demanded to evaluate feasibility and power consumption accurately.

VI. CONCLUSION

In this paper, we've introduced a novel method designed for evaluating ECG signal quality by using skewness and MODWT analysis, utilizing EWVM to mitigate the influence of low-frequency noise alongside an adaptive threshold for peak identification inspired by the stochastic nature of noise. This enables signal classification into "GOOD", "BAD", and a new "CONSIDER" level, which is indicative of potential heart conditions like ischemia. This method is shown to be independent of ECG beat types, and robust against noise and artifacts while being compatible with wearable devices. Evaluation across various noise levels results in $Se = 99.31\%$ on noise-free, $Se = 97.69\%$ on noisy, and $Se = 96.37\%$ on the combination of the two signals. Evaluation of various ECG databases results in high sensitivity and accuracy, notably, $Se = 100\%$ for C-2014 and $Acc = 99.58\%$ for NST, this shows its superior sensitivity and accuracy compared to methods like template matching or other SQIs. Beyond its immediate benefits, this method is promising for enhancing wearable ECG device performance, extending battery life, reducing costs, and improving heart disease diagnosis. Additionally, future directions encompass exploring machine learning integration to further improve its adaptability and overall performance.

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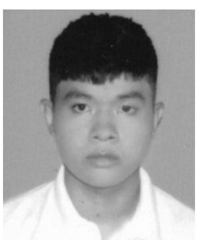

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