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Multi-Threshold based Ambulatory ECG Signal Quality Assessment

Jing Huang[1,2], Xiao Liu[1,2,3], Jianxing Li[1,2],
Ying Ma[1,2], Fumin Zou[1,3], and Kan Luo[1,2,3]*

[1]Fujian University of Technology
33 Xueyuan Road, Fuzhou City 350118, Fujian Province, China

[2]Research and Development Center for Industrial Automation Technology of Fujian Province
33 Xueyuan Road, Fuzhou City 350118, Fujian Province, China

[3]Fujian Key Laboratory of Automotive Electronics and Electric Drive
33 Xueyuan Road, Fuzhou City 350118, Fujian Province, China
*Corresponding Author: luok@foxmail.com

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Abstract. *Signal quality assessment (SQA) is the key technology to reduce the false alarm rate and the risk of misdiagnosis by using useless signal. In the new generation wireless ambulatory ECG system, using SQA not only save resource and energy consumption but also improve the accuracy of diagnosis. Here, we present a multi-threshold based SQA method for front-end resource constrained node of ambulatory ECG system. By moving windows processing and noise detection, the proposed framework gives out the SQA perdition by threshold based fusion rules. Our noise detection operators include moving average filter, first-order forward difference, zero-crossing rate and autocorrelation coefficient, which can detect the noise of baseline drift, no-signal, power-line interference/muscle artefacts and high-frequency noise, etc.; The thresholds of fusion rules were optimized by a grid searching method. The performance of our method was tested with four practical 650s ECG signal. The prediction accuracy of Accepted/Rejected reaches up to 99.12%. Furthermore, the multi-threshold method was compared with other three SQA methods using the 2011 physioNet/computing in Cardiology challenge database. The experimental results indicate our SQA method has the characteristics of efficiency, non-adaptive signal processing and low computation complexity. It is suitable for using SQA application in resource-constrained ECG nodes.*
Keywords: Ambulatory ECG, Signal quality assessment (SQA), Real-time processing,

1. **Introduction.** Cardiovascular diseases (CVDs) have become the first death cause of human. According to the report of World Health Organization (WHO), 17.5 million people die from CVDs each year in worldwide, that accounting for 30% of all human deaths [1]. As a commonly used tool, Electrocardiogram (ECG) is a set of projected body surface electrical signal from the electrophysiological activity of heart [2], it is important for CVDs diagnosis. According to ECG, doctors can explore the insights of CVDs patients physiological and pathological phenomenon, and give proper medical treatment.

Due to the important role of ECG in clinical practices, many researchers continually study on the improvement of the traditional ECG instruments. Recent years, with the rapid development of wireless body sensor networks (WBSNs) and wearable techniques, many WBSNs-enabled ambulatory ECG monitoring devices have been developed, and they achieve convenience signal collection and accuracy diagnosis [3]. Such devices could be seamlessly integrated into patients life for heart status monitoring, satisfy the requirement in long-term monitoring and real-time feedback in mobile scenarios, and provide the possibility to avoid accidental adverse cardiovascular events during daily activity. However, most of the existing ECG devices need further improved to its ability of signal quality assessment (SQA), which is the major obstacle for accuracy decision of abnormal cardiac events. It is because ambulatory ECG is easily affected by motion and external environment, and its quality is much lower than that of rest ECG [4]. Misdiagnosis may cause by using the distorted ECG signals. Therefore, an efficient decision mechanism for usability of ECG signal becomes the key in ambulatory ECG system. If the standard of SQA for noisy identification is established, the system can adopt proper signal processing according to the noise level, such as dropping out or filtering, etc. The SQA saves the resource and energy due to the useless will not be processed or transmitted, and further reduces misdiagnosis [5].

Recently, different studies for ECG SQA have been investigated from various aspects. Most existing studies generate signal quality index (SQI) as a measure of SQA by analyzing and fusing the feature of signal, such as temporal and spectra features [10]. J.Y. Wang et al. evaluated the quality of the ECG signal by comparing the area of the continuous QRS waveform, the histogram and the cumulative histogram [6]. Langley et al. assessed the quality of ECG signal by adopting morphology features, which include saturation, amplitude, and slope, etc. [7]. Similarly, H.Xia et al. adopted a signal morphology based method [8]. Some scholars use machine learning method in ECG SQA[11]. Zhang, Y. et al. combined time-frequency features of the signal and an SVM classifier to class the quality of ECG, and achieved promising results [9]. Although improvement in identification usability accuracy of ambulatory ECG system using machine learning or SQI methods, most of them have great computation, that leads they are deployed in server-side. The data transmission of useless noised ECG signal between the front-end ECG node and back-end server is resource and energy wasting. At present, it is a challenge that there are few SQA algorithms for the resource constrained ECG nodes.

Motivated by this challenge, we proposed a multi-threshold based SQA algorithm for front node in ambulatory ECG system for accuracy identification the quality of signal under small computation. We combine windows moving average filter, first-order difference, zero crossing rate and autocorrelation operators to detect noisy; then the grid searching method was used to optimize the threshold of fusion rule; at last, the discriminant fusion rules give out the SQA prediction results. To verify the performance of the proposed method, we conducted experiments using practical four typical ECG signal segments.

2. **The framework of multi-feature threshold based SQA method.** Considering ECG signal is easily corrupted by noise, such as a baseline drift, muscle artefacts (MA), power line noise, Gaussian noise and impulse noise, it is possible to identify the signal quality level by using noise detection method. The overview of the proposed framework of multi-feature threshold ECG SQA method is shown in Fig.1. The framework includes three major steps. The first step is segmentation. The segmented frame is 2s length and with 50% overlap. The second step is noise detection. The frames are sequences feed into the operators. Then, the calculation results from baseline (BL), difference ($Diff$), zero crossing rate (ZCR) and autocorrelation (AC) operators are fed into the next fusion rules for making decision. In the third step, the algorithm gives out the SQA prediction by the rules. Furthermore, a grid searching method was used to optimize the thresholds of fusion rule.

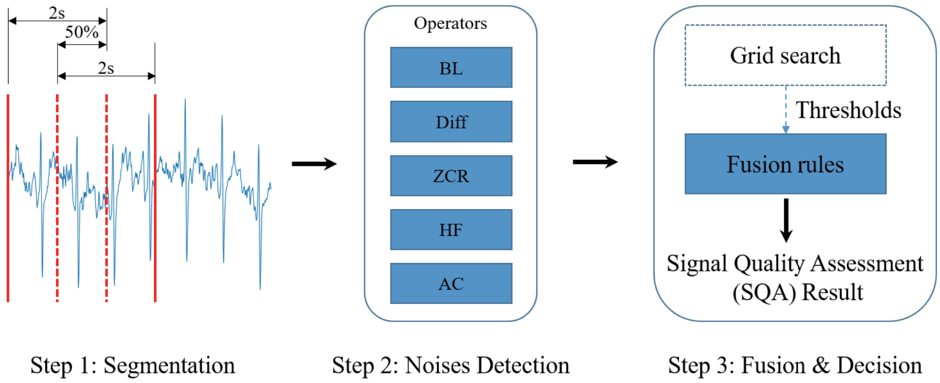

FIGURE 1. The framework of multi-feature threshold based ECG SQA method.

2.1. **Noise detection operators.**

(1) Baseline drift detection

Baseline (BL) drift is a common low-frequency noise in ECG signal. Here, we use a moving average filter to detect it. The window width of the filter is 1s, and with 50% overlap. The operator can be expressed as Eq. (1):

$$y(n) = \sum_{n=(-N/2)}^{N/2} x(n)/N \tag{1}$$

where $x(n)$ is the input ECG signal,$y(n)$is output, and $N$is the length of signal.

(2) Difference operation

Difference ($Diff$) operator is commonly used to enhance the high-frequency components [12]. Here, we use the first-order forward difference to detect this type noise, and the formula of $Diff$ operator can be written as Eq. (2):

$$d(n) = \overline{x}(n) - \overline{x}(n-1) \tag{2}$$

where $\overline{x}(n)$ refers the rest signal,it is the original ECG signal $x(n)$removing the baseline, and $d(n)$is the output of the $Diff$ operator.

(3) Zero-crossing rate

There is spectra overlap between the QRS wave and high-frequency noise. Only using the difference operator is difficult to distinguish these two signals. To assist in the high-frequency noise identification, we introduce a new operator called zero crossing rate (ZCR) [13], which is defined as Eq. (3):

$$d(n) = \begin{cases} \frac{1}{2N+1}\sum_{n=(-N)}^{N} |sgn[d_l(n)] - sgn[d_l(n-1)]| & \text{for} \quad max(|d_l(n)| > th_{Diff}) \\ 0 & \text{for} \quad others \end{cases} \tag{3}$$

where th_{Diff} is a threshold of the ZCR operator, $sgn()$ represents a sign operation, its value is ± 1; $d_l(n)$ is the difference operation result of overlapping p points with the period of l.

$$d_l(n) = d[l+n], n = 0, 1, 2, ..., N-p-1 \tag{4}$$

The high-frequency (HF)operator can be obtained by further combining the $Diff$ and ZCR.

(4) Autocorrelation

Except baseline drift and high-frequency noise, ECG signals are usually corrupted by power line noise and muscle artefacts, which have periodic or limited bandwidth Gaussian random characteristics, respectively. Here, we adopted autocorrelation(AC)operators to detect this type noise [14]. The signal after difference processing is used for AC calculation. And the computation is during a moving window, which length is 1s and with 50%overlap. The operator of AC can be written as Eq. (5):

$$AC(n) = \frac{1}{N}\sum_{m=0}^{N-1} d(m) * d(m+n) \tag{5}$$

To adaptive different input signal, the result of AC operator in Eq. (5)is normalized to $[0, 1]$,and then feed into the fusion rules.

An example of 30s ECG noise detection using the proposed operators is shown in Fig.2.In the figure, it also marks out the gate output of BL, HF and AC with the optimized threshold. It can be seen from the figure that the proposed method can effectively detect baseline drift, high-frequency, power line noise and muscle artefacts. All computations are in a moving window. In order make the input and output signals have same length, a cubic spline interpolation [15] was used to resample the output of all operators.

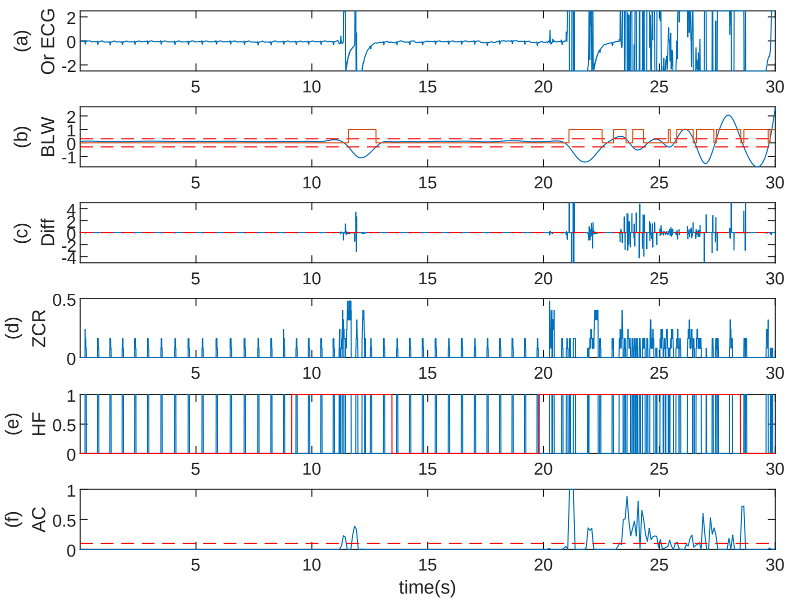

FIGURE 2. An example of 30s ECG noise detection using the proposed operators.(a)Original ECG; $(b) \sim (f)$ are the detection results correspond using BLW, $Diff$, ZCR, HF, AC operators,respectively.

2.2. **Discriminant fusion rules and threshold parameters identification.** We designed series fusion rules for ECG SQA. The flowchart is shown in Fig. 3. It illustrates the logic flow of the proposed fusion rules. The scheme fuses the computation results of BL , $Diff$, ZCR, HF and AC, and gives out an Accepted or Rejected prediction. The first step of the scheme is BL computation; this is then followed by a comparison. If

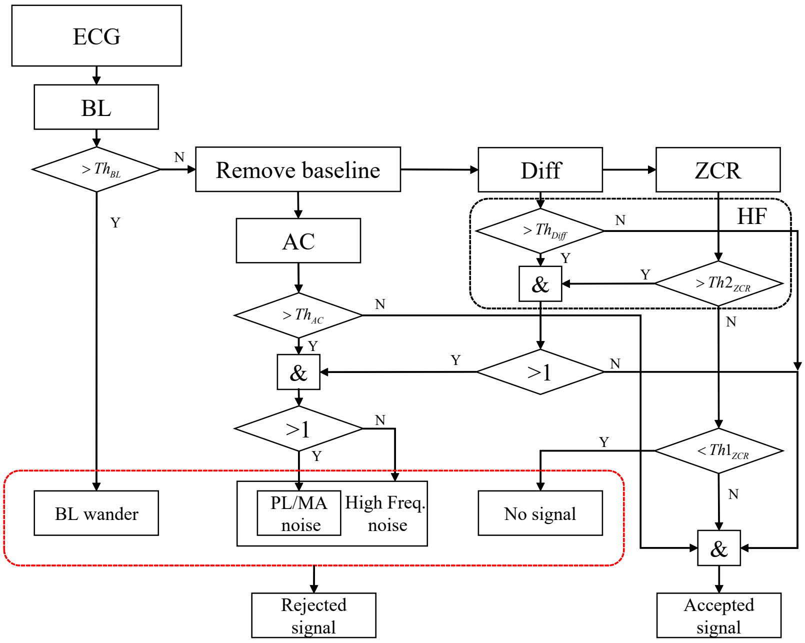

Figure 3. The fusion rules for ECG SQA.

the value of BL is greater than the threshold. Th_{BL}, the scheme generates a marker of baseline drift; otherwise, the algorithm filters the baseline of signal. Subsequently, the progressions are calculating the $Diff$, ZCR and AC, respectively. If the value of ZCR is smaller than $Th1_{ZCR}$, it indicates the segment contains no information, the algorithm marks it as no signal. The value of $Diff$ and ZCR are used to determine whether there was high-frequency (HF) noise in the signal segment, the detail processing of HF identification can be found in the Black dotted box of Fig.3. If $HF > 1$, it indicates that there is high-frequency noise in the signal. Next, it is a compassion between AC and Th_{AC} , If the value of AC greater than Th_{AC} , It can be concluded that the signal includes power line noise or muscle artefacts. Finally, the scheme gives out the comprehensive prediction. As long as any type of noise is detected, this segment of signal is classified as rejected. If the segment of signal passes all rules test, it is marked as accepted. The signal has good signal quality and can be used in further processing and analyzing.

The threshold optimization is a key of our method. The scheme will yield poor performance if inappropriate thresholds are used. The number of threshold in our proposed method is 5, and the range of thresholds can be estimated based on the prior statistical information of ECG signal in advance. Therefore, we adopt grid searching method [16] to optimize the thresholds. Four 650s manually annotated ECG signals was used as ground truth for threshold optimization. By minimizing the classification error between the prediction results and ground truth, the final selected $Th_{BL}, Th_{Diff}, Th1_{ZCR}, Th2_{ZCR}, Th_{AC}$ are 0.3, 0.05, 0.07, 0.3, and 0.1, respectively. Furthermore, in order to reduce the risk of wrong prediction, before and after a rejected marker, the 2s segments are recommended to mark as unacceptable.

3. **Experimental results and discussion.** To evaluate the proposed scheme in terms of its efficacy at assessing ECG signal quality and low computation, experiments are carried out on a desktop computer (MATLAB 2017b, CPU i5-7400 @ 3.00 GHz, RAM 8.00 GB). Different from the signals used for the threshold optimization, Four 650s practical ECG signals were used to test the proposed algorithm. Since there are no obvious PL/MA

components within the test signal, in order to test the performance of PL and MA noise detection, In all four experimental signals, we manually added sinusoids (0.25 mV, 50 Hz) and Gaussian white noise ($= 0.15mV$) at 410 415s and 415 420s, respectively. Perdition accuracy and computation time are used as measures in the experiments. The proposed method was also tested in PhysioNet/Computing in Cardiology Challenge 2011 database for comparison of performance with other studies[7, 8, 9]. To quantify the SQA performance, the accuracy, sensitive and specificity are used as measures.

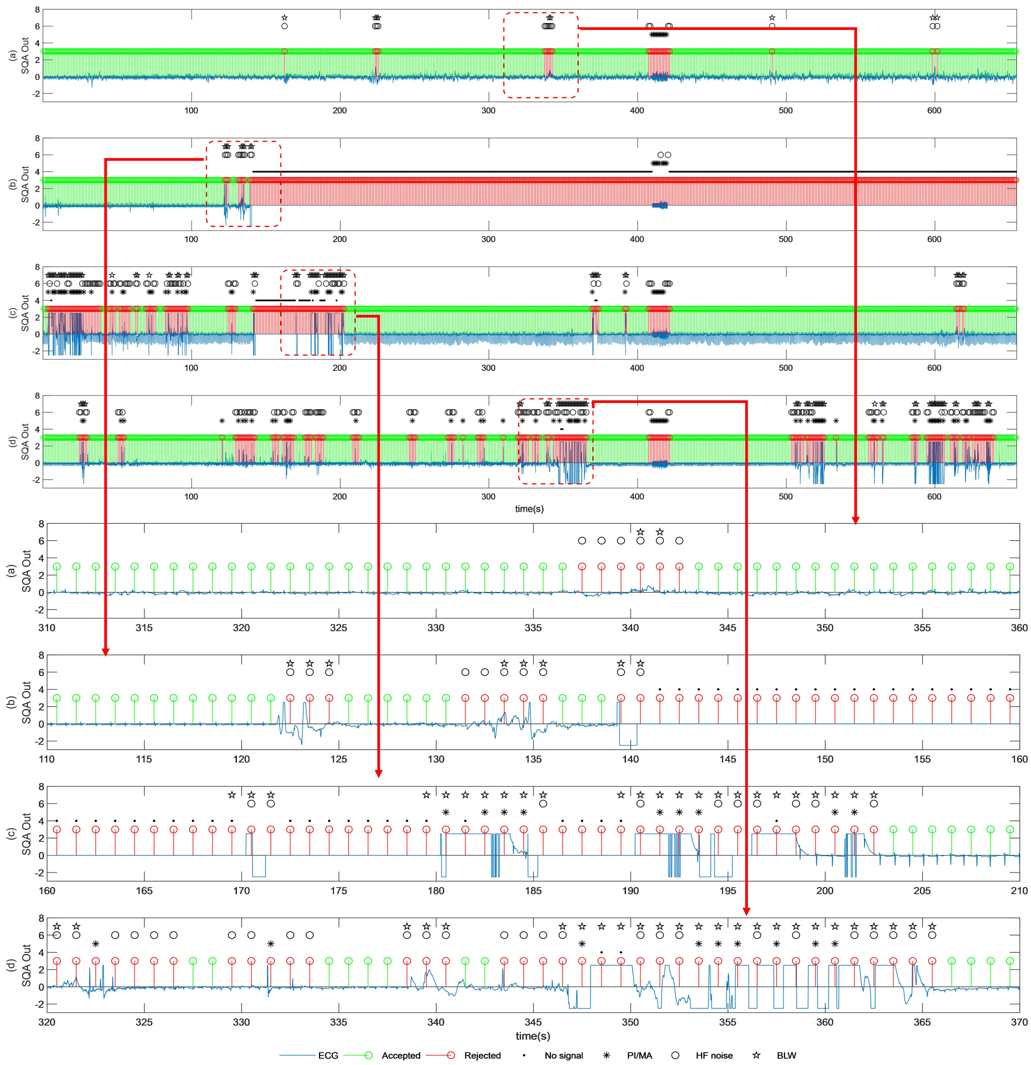

FIGURE 4. The SQA results of the four ECG signals. $(a) \sim (d)$ are the SQA results of four experimental signals.

The SQA analysis results of the four signal are illustrated in Fig.4. Except the original ECG signal, the figure also includes the markers of accepted prediction, rejected prediction and noise, such as power line noise, muscle artefacts, high-frequency noise, and baseline drift. We can observe that all no signal or saturated signals are identified; meanwhile, almost all baseline drifts and HF noise are accuracy marked out. Due to exiting spectra overlap among PL, MA and QRS-complexes, there are few high-frequency noises are classified as PL/MA. It can be found that part of manually added noise is predicted as HF during 410-420s. The visual comparison between prediction results and ground truth is shown in Fig.5, whose subfigures correspond to the four signals in Fig.4.

The predictions and ground truth are represented by circle symbols and star symbols, respectively. Compare with the ground truth, the average accuracy of Accepted/Rejected prediction reaches 99.12%. Overall, good performance in ECG SQA is achieved. It can be concluded that the proposed method has a great potential in SQA task.

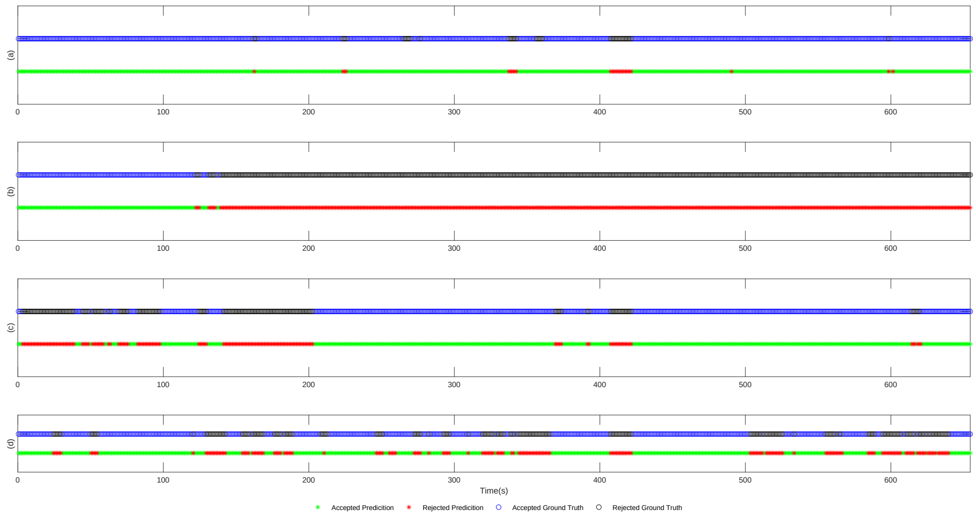

FIGURE 5. The visual comparison between prediction results and ground truth. $(a) \sim (d)$ are the results corresponded to the signals in Fig4. $(a) \sim (d)$.

TABLE 1. The of comparison of different SQA methods under the 2011 physioNet/computing in Cardiology challenge database

	Method	Feature	Results(%)		
			Acc.	Sen.	Spe.
Langley, P., et al. [7]	LTI method	Morphology features	85.7	-	-
Xia, H., et al. [8]	Multistage test method	Correlation, entropy, etc.	85.9	95.11	83.22
Zhang, Y., et al. [9]	SVM classifier	Seven features	92.2	77.94	98.09
Proposed method	Fusion rules decision	BL, Diff, ZCR, AC, etc.	77.35	89.33	73.87

For comparison of performance with the other three SQA methods, the proposed method also test in the 2011 physioNet/computing in Cardiology (PCinC) challenge database, which is an open access and annotated data for SQA evaluation. Considering an annotation interval of PCinC challenge database is 10s, we mark the signal as Unacceptable if low quality segment is detected. The comparison results are summarized in table1. The Accuracy, Sensitive and Specificity of our proposed method is 77.35%, 89.33% and 73.87%, respectively. Zhang, Y., et al proposed method achieved highest accuracy and specificity. However, the SVM classifier is hard to implement on a microcontroller. There are two points, which may cause unsatisfactory accuracy of our method in PCinC challenge database testing. Firstly, the samples of PCinC database are not used for training;

TABLE 2. Computation Time of the proposed method

ECG signal	Computation time (s)				
	BL	HF Diff+ZCR	AC	Fusion rule	All
Fig4.(a)	0.105	0.412	0.271	0.100	0.888
Fig4.(b)	0.097	0.401	0.269	0.107	0.874
Fig4.(c)	0.100	0.426	0.274	0.110	0.910
Fig4.(d)	0.101	0.425	0.270	0.104	0.900
Average	0.101	0.416	0.271	0.105	0.893
Std.	0.003	0.012	0.002	0.004	0.016

Secondly, due to the length of a frame is different from the time interval of an annotation, the output is not well matched the annotation, lead the accuracy is low. Moreover, the sensitive of 89.33% is achieved by our method, which indicate our scheme has good quality to detect noise.

To evaluate the computation complexity of proposed method, we analyzed the calculation time using four experimental signals, the results are summarized in table 2. The computation time of each operator and the fusion are counted and listed in each column of the table. The statistics of average value and standard deviation (Std.) are shown in the last two rows of the table. In our experimental platform, the computation time of the proposed algorithm is less than 1s when analyzing 650s ECG signal. The Std. values are not greater than 0.016, and they are stable. Such results indicate that the proposed method has the characteristics of low computation complexity and non-adaptive signal processing. During the calculation, the computation time of HF operator is the longest ones, which is because the HF operator consists of $Diff$ and ZCR. Similarly, the computation time of AC operator is close to 0.3s, because there is multiplication in this operation. Nevertheless, as a whole, the computational efficiency of proposed method is high. As shown in Eq.(1) $\sim$Eq.(5), the calculation only contains simple mathematical operations, such as subtraction, multiplication and comparison, which are fully supported by the hardware and instruction set of microcontroller. The computation complexity is O(n). These experimental results indicate that the proposed SQA method has low computational complexity, quick time response and less resource consumption. Since adopting a moving window, the algorithm can be used to process continuous-time signals. It can infer that the proposed algorithm is suitable for microcontroller based ECG acquisition node.

4. **Conclusions.** Signal quality assessment is the key technology for ambulatory ECG system. Establishing efficient SQA method not only gets system resource saving but also achieves accuracy of diagnosis improvement. In this study, we present a multi-threshold based SQA method for front-end resource constrained node of ambulatory ECG system. The framework adopts moving window processing. It combines the noise detection operators and threshold fusion rules, can efficiently predict the usability of the continue ECG signal and classify the major types of noise, such as baseline drift, no-signal, power-line interference/muscle artefacts. In the ECG signal SQA experiments, although distinguishing the PL/MA from the high-frequency noise still a challenge, the method achieves 99.12% accuracy of Accepted/Rejected prediction. The proposed method can be efficient used in ECG SQA application. Furthermore, due to the algorithm has the characteristics of non-adaptive signal processing and low computation complexity. The proposed multi-threshold SQA method is suitable using in resource-constrained ECG nodes.

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