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Real-time Signal Quality Assessment for ECGs Collected Using Mobile Phones

Chengyu Liu[1], Peng Li[1], Lina Zhao[2], Feifei Liu[1], Ruxiang Wang[1]

[1] School of Control Science and Engineering, Shandong University, Jinan, P.R.China
[2] Shandong Heng-Xin Inspection Technique Exploiture Center, Jinan, P.R.China

Abstract

Considering that the uncertainty noise produced the decline in the quality of ECGs, this paper proposed a real-time signal quality assessment method for ECGs collected using mobile phones. The method defines four "flags" to denote different type problems duo to the poor quality of ECGs: using flag1 to detect if there is a misplaced electrode; using flag2 to detect if there is a huge impulse; using flag3 to denote if there is a strong Gauss noise; and using flag4 to denote if there is a detector error of R-wave peaks by the template matching method. Then based on the values of four "flags", we calculate the single signal quality index (SSQI) for each ECG and the integrative signal quality index (ISQI) for twelve-lead ECGs. The range of ISQI is between 0 and 12 inclusively. High value of ISQI means good quality of the ECGs. Each ECG record would be assigned to two groups according to ISQI, acceptable and unacceptable group. We define two indices, Sensitivity and Specificity, to evaluate the validity of this paper's method and the results are 90.67% and 89.78% respectively.

1. Introduction

Recent years, using the mobile phone technology to collect and transmit electrocardiograms (ECGs) from rural patients for remote analysis by cardiologists at a city hospital has achieved rapid development. This technology is driven from the energetic efforts of Sana group and PhysioNet at MIT [1]. This has also inspired this year's PhysioNet/CinC challenge. However, noise and artefacts are inevitable in ECGs, and these problems contaminate the ECG signal quality. Poor ECG signal quality may induce an increased number of false alarms, degraded diagnostic performance, and an increased distraction and workload for clinical staff [2]. It is important therefore to establish quantitative method that can be used to demonstrate signal quality problem, especially for the real-time assessment.

Some assessment techniques of ECG signal quality have been proposed. The typical ones were summarized as follows: Allen J and Murray A mainly used the frequency measures to assess the ECG signal quality and effectively reduced the false alarms in coronary care unit (CCU) [2]; He T et al used independent component analysis (ICA) to enhance ECG signal quality by reducing the noise or artefacts [3]; Li Q et al proposed a robust heart rate estimation method by using signal quality indices and a Kalman filter and improved ECG signal quality in the intensive care unit (ICU) [4].

However, none of them was initially developed for mobile phone application. Besides, when using the mobile phone technology, the validity and reliability of ECG signal quality assessment are facing unprecedented challenge. The aim of this work was to develop a real-time signal quality assessment method for ECGs, which could easily implant on a mobile device. This method could tell whether or not the ECG signal is acceptable for subsequent analysis and tell why if it is unacceptable.

2. Methods

The challenge data are standard twelve-lead ECGs (leads I, II, II, aVR, aVL, aVF, V1, V2, V3, V4, V5, and V6) with full diagnostic bandwidth (0.05 through 100 Hz). The leads are recorded simultaneously for ten seconds [1]. We used training data (i.e. Set A) to design our algorithm since the reference quality assessments of Set A were provided to the participants. Different problems (such as misplaced electrodes, external interference, poor skin-electrode contact, and artifact resulting from patient motion) will occur in the original ECGs. Firstly, we classified these problems into four different types: 1) the straight line duo to the misplaced electrode; 2) huge impulse leading to the unconspicuous observation of other signals; 3) strong Gaussian noise; and 4) detector errors of R-wave peaks duo to the noise and artifact. These detector errors can be false negative (FN) when a real beat is missed caused by a low amplitude R-wave or strong noise, or false positive (FP) when a false beat is detected due to noise or a high amplitude T-wave [5]. Then we defined four "flags" to respectively denote these problems duo to the poor quality of ECGs. The meanings of the four "flags" are shown in Table 1. After that, the algorithms for detecting each of the four problems, i.e. calculating the values of "flags", were proposed. So every ECG lead has four "flags" values, which imply the ECG signal quality. We could use the "flags" to calculate the single signal quality index (SSQI) for each lead ECG. SSQI denotes that if the quality of the single ECG lead is adequate or not. At last, the integrative signal quality index (ISQI) for twelve-lead ECGs were calculated after SSQIs of all twelve ECGs obtaining. The flow chart of the method is shown in Figure 1.

Table 1. Meanings of the four “flags”

Flags	Meaning for the ECG	Values	
		1	0
Flag1	Is a straight line?	Yes	No
Flag2	Includes a huge impulse?	Yes	No
Flag3	Includes a Gaussian noise?	Yes	No
Flag4	Includes a detector error?	Yes	No

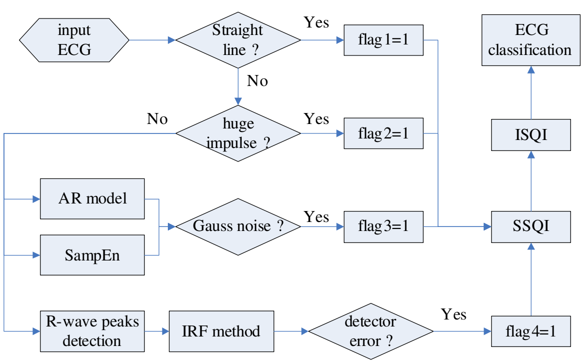

Figure 1. The flow chart of the method

2.1. Algorithm for detecting straight line

Because each ECG lead is sampled at 500 Hz and lasts for ten minutes, so the length of the ECG is 5000. Let $X=[x_1,x_2,\cdots,x_{5000}]$ denotes an ECG recording. Then X is divided in to five segments without overlap. The segment $X1_i$ is defined as follows:

$$X1_i=[x_{1000i+1},x_{1000i+2},\cdots,x_{x_{1000(i+1)}}] \qquad i=0,1,\cdots,4\,. \tag{1}$$

Subsequently, we calculated the differential sequence Y_i for each $X1_i$ and let σ_i denotes the standard deviation (SD) of Y_i. Set the threshold $r_{line}=1$. If σ_i is lower than r_{line}, it means that the amplitude of this segment $X1_i$ is almost changeless and this is most likely the misplaced electrode. Let N_{line} denotes the number that σ_i is lower than r_{line}. The flag1 is defined as follows:

$$\text{flag}1=\begin{cases}1 & N_{line}\ge 2\\ 0 & N_{\text{line}}<2\end{cases}. \tag{2}$$

Figure 2 shows the detections for straight line. The upper panel of Figure 2 (a) is ECG with misplaced electrodes and the one of (b) is normal ECG. The lower panels of Figure 2 are σ_i results responding to the ECG in the upper panels. If the misplaced electrodes happen, the ECG recording will almost be a straight line and it has few fluctuations. So σ_i is lower than r_{line}, while the result of normal ECG is higher than r_{line}. The value of flag1 accurately indicates this situation.

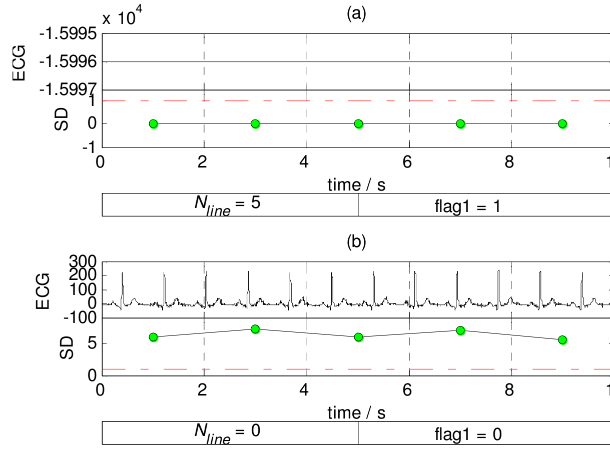

Figure 2. The detections for straight line, (a) ECG with misplaced electrodes, (b) normal ECG.

2.2. Algorithm for detecting huge impulse

Given an ECG recording $X=[x_1,x_2,\cdots,x_{5000}]$, it is also divided in to ten segments without overlap. The segment $X2_i$ is defined as follows:

$$X2_i=[x_{500i+1},x_{500i+2},\cdots,x_{x_{500(i+1)}}] \qquad i=0,1,\cdots,10\,. \tag{3}$$

Set the threshold $r_{impulse}=1000$. If there is an element of $X2_i$ that higher than $r_{impulse}$, it means that this segment $X2_i$ has a huge impulse. Let $N_{impulse}$ denotes the number of $X2_i$ that contains one element higher than $r_{impulse}$ at least. The flag2 is defined as follows:

$$\text{flag}\,2=\begin{cases}1 & N_{impulse}\ge 1\\ 0 & N_{impulse}=0\end{cases}. \tag{4}$$

Figure 3 shows the results of ECG with huge impulse (upper panel) and ECG removing huge impulse (lower panel). The segment corresponding to one element is higher than $r_{impulse}$ is set to the mean value of the entire ECG (see the lower panel in Figure 3). The rest of ECG will to be processed normally.

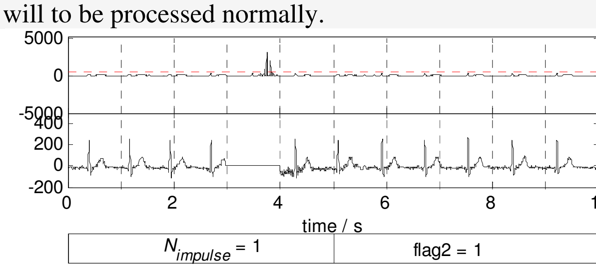

Figure 3. The ECG with huge impulse (upper panel) and ECG removing huge impulse (lower panel).

2.3. Algorithm for detecting Gaussian noise

In this section, we used two methods to detect if there is strong Gaussian noise consists in ECG recording. One method is the power spectrums using AR model [6]. The other is the complexity analysis using sample entropy (SampEn) [7]. When using AR mode, the power spectrums of X is divided into two major frequency components: signal-frequency (SF) component (0.05 through 40 Hz) and noise-frequency (NF) component (more than 40 Hz). If the noise becomes strong, the NF of X will enlarge, while the ratio of SF/NF will decline. At the same time, the complexity of X will also decline when the strong noise occurs, and the degressive SampEn denotes this change.

The ECG recording is divided in to ten segments without overlap using the same method of section 2.2. For each segment, the SF/NF and SampEn are calculated. The threshold of SF/NF set to be 1.5 and the threshold of SampEn set to be 0.7. The lower SF/NF or SampEn means the responding ECG segment maybe includes strong Gauss noise. The segment will be identified as a strong Gauss noise as long as both SF/NF and SampEn are lower than each threshold. Let N_{noise} denotes the number of the segment with strong Gauss noise. The flag3 is defined as follows:

$$\text{flag}\,3 = \begin{cases} 1 & N_{noise} \geq 3 \\ 0 & N_{noise} < 3 \end{cases}. \tag{5}$$

Figure 4 shows the results of SF/NF and SampEn for an ECG with strong Gauss noise (Figure 4 (a)) and a normal ECG (Figure 4 (b)). In each figure, the upper panel is ECG recording, the middle panel is the result of SF/NF, and the lower panel is the result of SampEn.

2.4. Algorithm for detector error

The method of detecting the R-wave peaks was came from our recent work [8], which proposed an online detection procedure for R-wave peaks based on template matching. When R-wave peaks were detected, the fore-and-aft R-wave peaks formed the RR interval. If the signal quality is poor, the RR interval usually contains some detector errors (false negative and false positive, i.e. FN and FP). So it provides another approach to assess the ECG signal quality by analyzing the detector error of R-wave peaks. In this study, we use the impulse rejection filter (IRF) introduced by McNames *et al* (2004) to detect the errors in RR intervals [9]. The threshold of IRF is set to 2 just as the recommended value in [9]. Let N_{IRF} denotes the number of detector errors. The flag4 is defined as follows:

$$\text{flag}\,4 = \begin{cases} 1 & N_{IRF} \geq 1 \\ 0 & N_{IRF} = 0 \end{cases}. \tag{6}$$

Figure 5 shows the results of detector error for an ECG with FN (Figure 5 (a)) and an ECG with FP (Figure 5 (b)). In each figure, the upper panel is ECG recording, the middle panel is the RR intervals, and the lower panel is the result of IRF. It can be seen clearly that the value of IRF is higher than threshold 2 in the position of FN or FP. So IRF method can effectively detect the detector error in RR intervals.

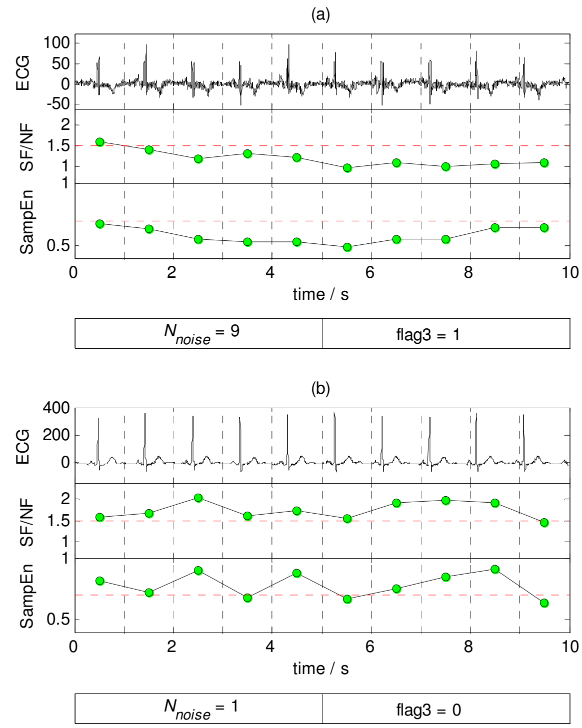

Figure 4. The results of the SF/NF and SampEn for, (a) an ECG with strong Gauss noise, and (b) a normal ECG.

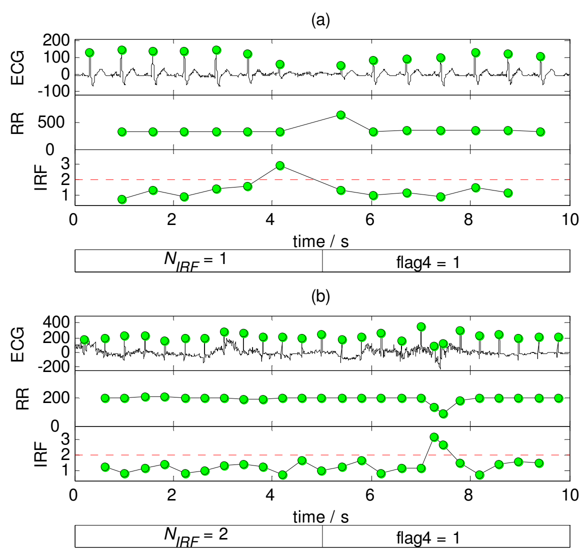

Figure 5. The ECG with huge impulse (upper panel) and ECG removing huge impulse (lower panel).

2.5. Single signal quality index (SSQI)

Using the flags calculated in section 2.1 to 2.4, SSQI of each ECG lead can be defined as follows:

$$\mathrm{SSQI} = 1 - flag1 - 0.2 \times (flag2 + 2 \times flag3 + flag4) - \alpha \text{ , (7)}$$

where α is a parameter and is calculated as follows:

$$\alpha = 0.05 \times (N_{impulse} + N_{noise} + N_{IRF}) \text{ .} \quad (8)$$

2.6. Integrative signal quality index (ISQI)

When the twelve SSQI of each ECG lead are obtained, then the ISQI for the twelve-lead ECGs is determined as follows:

$$\mathrm{ISQI} = \sum_{i=1}^{12} \max(\mathrm{SSQI}_i, 0) \text{ .} \quad (9)$$

If the ISQI of twelve-lead ECGs is more than 10, the ECGs are identified as the acceptable ECGs. Otherwise, the ECGs are identified as the unacceptable ECGs.

3. Results and discussion

We use the ECGs of Set A to test the validity of the method proposed in this paper. There are 773 acceptable ECGs and 225 unacceptable ECGs in all. For the convenience of the expression, we define four symbols to denote the identification results. Let $A1$ denotes the amount that the unacceptable ones are falsely identified as the acceptable ones; $A2$ denotes the amount that the unacceptable ones are truly identified as the unacceptable ones; $N1$ denotes the amount that the acceptable ones are truly identified as the acceptable ones; $N2$ denotes the amount that the acceptable ones are falsely identified as the unacceptable ones. Afterward, two indices, Sensitivity and Specificity, are defined to evaluate the validity of the method as in equations (10) and (11). The results of classification and indices are shown in Table 2. As can be seen from Table 2, Sensitivity and Specificity are respectively 90.67% and 89.78%. The method proposed in this paper exhibits a fine performance for the ECG signal quality assessment.

$$\mathrm{Sensitivity} = A2 / (A1 + A2) \times 100\% \text{ ,} \quad (10)$$

$$\mathrm{Specificity} = N1 / (N1 + N2) \times 100\% \text{ .} \quad (11)$$

Table 2. The results of classification and indices

Classification				Indices (%)	
A1	*A2*	*N1*	*N2*	Sensitivity	Specificity
21	204	694	79	90.67	89.78

4. Conclusions

We have developed a real-time signal quality assessment method for ECGs collected using mobile phones. Firstly, the method integrated several algorithms to calculate SSQI: 1) the algorithms to detect two types extreme situations: straight line and huge impulse; 2) the algorithm based on the analysis of AR model; 3) the algorithm based on the analysis of SampEn; 4) the template matching method to detect the R-wave peaks; 5) the IRF method to detect the errors in R-wave peaks detection. Then we calculated ISQI for twelve-lead ECGs based on twelve SSQIs. The analysis of Sensitivity and Specificity validated the fine performance of the method.

Acknowledgements

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References

[1] http://physionet.org/challenge/2011/

[2] Allen J, Murray A. Assessing ECG signal quality on a coronary care unit. Physiological Measurement 1996; 17: 249-258.

[3] He T, Clifford G, Tarassenko L. Application of independent component analysis in removing artefacts from the electrocardiogram. Neural Computing & Applications 2006; 15: 105-116.

[4] Li Q, Mark RG, Clifford GD. Robust heart rate estimation from multiple asynchronous noisy sources using signal quality indices and a Kalman filter. Physiological Measurement 2008; 29: 15-32.

[5] Liu CY, Liu CC, Shao P, et al. Comparison of different threshold values r for approximate entropy: application to investigate the heart rate variability between heart failure and healthy control groups. Physiological Measurement 2011; 32: 167-180.

[6] Burr RL, Cowan MJ. Autoregressive spectral models of heart rate variability: Practical issues. Journal of Electrocardiology 1992; 25: 224-233.

[7] Richman JS, Moorman JR. Physiological time-series analysis using approximate entropy and sample entropy. American Journal of Physiology - Heart and Circulatory Physiology 2000; 278: H2039-H2049.

[8] Li P, Liu CC, Zhang M, et al. A Real-Time QRS Complex Detection Method. Acta Biophysica Sinica 2011; 27: 222-230.

[9] McNames J, Thong T, Aboy M. Impulse rejection filter for artifact removal in spectral analysis of biomedical signals. 26th Annual International Conference of the IEEE IEMBS 2004; 145-148.

Address for correspondence.

Chengyu Liu
School of Control Science and Engineering
17923 Jingshi Road, Jinan, P. R. China 250061
Tel: +86-159-53148364
E-mail: bestlcy@sdu.edu.cn.