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Stability Analysis of QRS Features to Evaluate Signal Quality For Multi-lead QRS Dectection

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Abstract— **In automated ECG monitoring, QRS detection performance is dependent on noise measurements on individual leads. A new signal quality measurement based on stability analysis of QRS complex features has been developed to assess individual ECG lead quality. The new method was evaluated on the records of the MIT-BIH arrhythmia and NST databases. Results showed that the new signal quality measurement can be used to accurately assess ECG signal quality and can be easily incorporated into an existing multi-lead QRS detection algorithm for performance improvement.**

I. INTRODUCTION

Poor quality electrocardiograms (ECG) present challenges to accurate interpretation in patient monitoring. Clinical experience with current ECG-based monitoring has shown that the best performance can be achieved if the input is free from noise, and noise has been the primary source of performance degradation for ECG algorithms. Noise appearing on the ECG may be due to physiologic or non-physiologic sources. The most common noise is caused by skeletal muscle contraction/tremor, electrical interference and electrode movements. Failure to recognize and minimize artifact during monitoring may result in an incorrect detection of heart rate and arrhythmias which leads to false alarms and unnecessary clinician intervention.

Recently, the use of multiple ECG leads for real-time arrhythmia detection has become popular in patient monitoring. The key component in multi-lead algorithms is the determination of the lead quality of each processed ECG lead. The estimation of noise presence in ECG, on the other hand, will allow the ECG algorithm to either reject part or the entire ECG, or proceed for further analysis based on the magnitude of noise present in the ECG. There are a few techniques already implemented in patient monitoring to detect individual types of noise (mostly for high frequency noise, baseline wander, and low frequency noise).

Currently most methods for the detection and/or quantification of composite noise in ECG require accurate QRS detection for individual leads or one combined lead. The classic method to quantify signal quality of each lead is to represent ECG signal (P, QRS, T) morphology on template (aligned averaged signal) or modeling (KLT functions, wavelets, etc), and define the difference between the signal and the representation as the underlying residual noise in the ECG [1-3]. There are also some variations in noise definition. A mismatch histogram [4], based on the area difference between successive detected QRS complexes, and a index as T-P interval average power divided by the QRS average power [5] are proposed to be the noise metric.

The goal of this paper is to present a novel method that measures the quality for a given single lead by analyzing the stability of QRS complexes dynamically over a time window that is responsive to both non-physiological and physiological noise.

II. METHOD

Fig. 1 depicts the algorithm flow diagram of the stability analysis. The classical methods of determining the noise level of a given lead usually focus on the morphology features measurement of each individual QRS complex. The method described here focuses on the pattern similarity of QRS features for a group of QRS complexes. The key in this quantitative assessment of noise level is to check the pattern similarity of QRS complexes over a fixed time window beat by beat (complex by complex). If the pattern similarity level is high over a time period, the ECG signal quality is high. On the other hand, the low pattern similarity indicates noisy ECG signal.

Step 1: QRS Feature Representatives Selection.

As shown in Fig. 2, some features are used to delineate a QRS complex,

(a) h: The height of QRS
(b) w: The width of QRS

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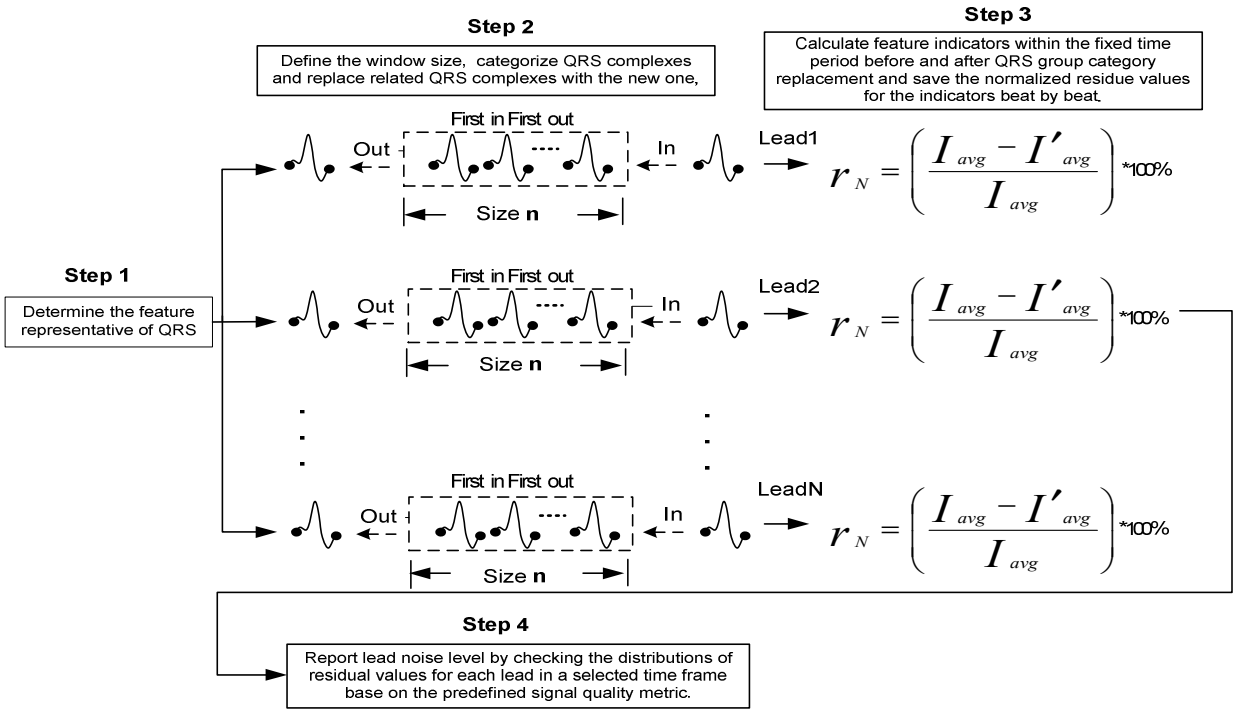

Fig. 1: Stability Analysis Algorithm Flow Diagram

(c) **ΔQRS**: The triangle area of QRS
(d) **ΔSS'T**: The area of ST-segment
(e) **d**: Peak direction of QRS peak
(f) **RR**: RR interval

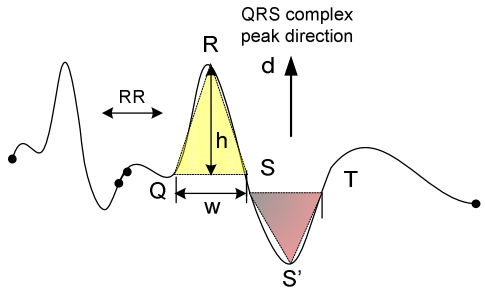

Fig. 2: Features for QRS complex

For simplicity, all the following description and results are based on two feature selection: the triangle area of ΔQRS (1) and the peak direction of the QRS complex.

$$\Delta\text{QRS} = \frac{1}{2} \cdot h \cdot w \qquad (1)$$

Where h is the height and w is the width of QRS complex.

Step 2: Determine the size **N** of continuous QRS complexes in the defined group, average each feature representative of all detected QRS complexes in the group. For instance, I_{avg} is the averaged feature representation of ΔQRS of all detected beats calculated as (2).

$$I_{avg} = \frac{1}{2} \cdot \left(\frac{\sum_{i=1}^{N} (h_i \cdot w_i)}{N} \right) \qquad (2)$$

As shown in Fig. 3, the QRS complexes group is categorized into two subgroups G1 and G2:

$$\forall QRS_i \in G1, \text{ If } \Delta\text{QRS} \geq I_{avg}$$

$$\forall QRS_j \in G2, \text{ If } \Delta\text{QRS} < I_{avg}.$$

Where $0 \leq i, j \leq \mathbf{N}$. **N** is the size of the group.

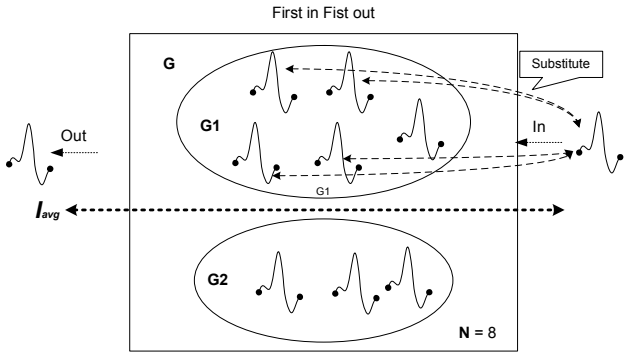

Fig. 3: QRS categorization and substitution

As shown in (3), the beats in the subgroup are replaced by the incoming beat with same characteristics of peak

direction and QRS triangle area.

$$\Delta_{QRS(i)} = \begin{cases} \Delta_{QRS(In)} & \text{If both the areas of } \Delta_{QRS(i)} \text{ and } \Delta_{QRS(In)} \le I_{avg} \text{ with the same peak direction} \\ & \text{Or} \\ & \text{If both the areas of } \Delta_{QRS(i)} \text{ and } \Delta_{QRS(In)} \ge I_{avg} \text{ with the same peak direction} \\ \Delta_{QRS(i)} & \text{Otherwise} \end{cases} \quad (3)$$

Where $QRS(In)$ is the latest detected QRS complex, $QRS(i)$ is the existing QRS complex in the group.

Step 3: Recalculate the averaged feature representative I'_{avg} of the new subgroups in (4).

$$I'_{avg} = \frac{1}{2} \cdot \left(\frac{N1 \cdot h(in) \cdot w(in) + \sum_{i=0}^{N2} h_i \cdot w_i}{N} \right) \quad (4)$$

Where **N1** is the number of QRS in G1 that are replaced by $QRS(in)$ and **N2** is the size of G2. $h(in)$ is the height and $w(In)$ is the width of $QRS(In)$. h_i is the height and w_i is the width for $QRS_i \in G2$. Where $0 \le i \le$ **N2** and **N1** + **N2** = **N**.

The averaged feature representative I_{avg} is normalized for each QRS complex (or beat) in (5).

$$r_N = \left(\frac{I_{avg} - I'_{avg}}{I_{avg}} \right) \cdot 100\% \quad (5)$$

Step 4: Analyze and report signal noise level.

As shown in Fig. 4, if the signal is clean the QRS complex pattern is stable for the group (at least for a short period time window). The distribution range of r_N is close to zero. A high weight for clean signal is assigned to the processed lead for this time period. If the signal is not stable, the QRS complex pattern is unstable, and distribution range of r_N is far away from zero. A weight for the low quality of signal is assigned to the processed lead for this time period.

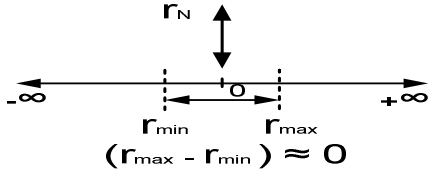

Fig. 4 Distribution range of r_N for clean signal.

III. RESULTS

In this section, three examples are provided to demonstrate the ability of this new signal analysis technique to assess signal quality and its application in multi-lead QRS detection. The test signals used are from the two-channel MIT-BIH, AHA and NST (The Noise Stress Test Database) databases. The tests are done against different clinical situations e.g. normal, noise and arrhythmia.

Let r_N = 100 (or -100) if $r_N \ge 100$ (or $\le$ -100). In each distribution plot of r_N, the vertical axis represents the percentage of r_N (range from -100 to 100%), and the horizontal axis is the scaled time frame.

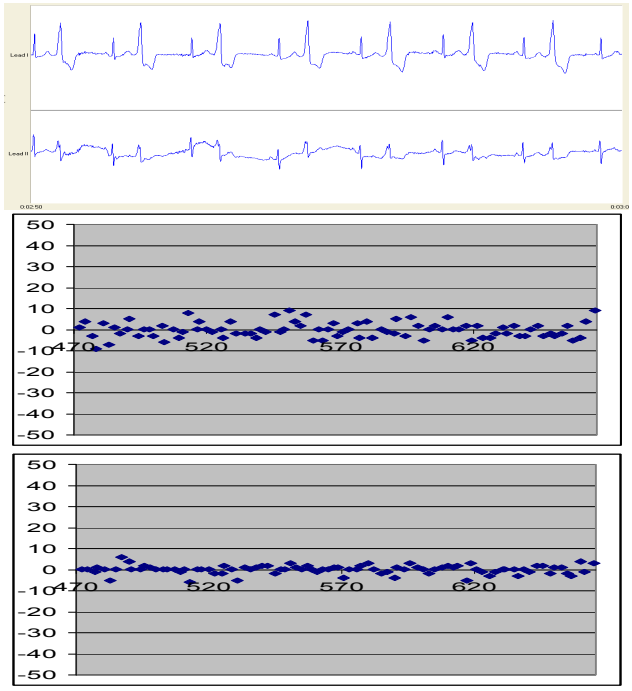

Fig. 5: 1 minute raw signal and algorithm results of lead 1 and lead 2 in AHA Record 4209.

Fig. 5 illustrates 1 minute (between 02:20 and 03:20) of 2 channels of ECG waveform (partially raw signal in upper plot and related r_N distribution in lower plots) in AHA Record 4209. For this time period, despite the presence of ventricular bigeminy the algorithm shows that both leads have good signal quality most of time by giving the low radios of r_N for both leads. This shows that the algorithm has good performance under the regular arrhythmia events.

Fig. 6 illustrates the overall performance of algorithm for 1 minute and 15 seconds (between 08:15 and 09:35)

MIT BIH Record 203 (raw signal in upper plot and related r_N distribution in the second and third plots). For this time period, the presence of artifact waves caused

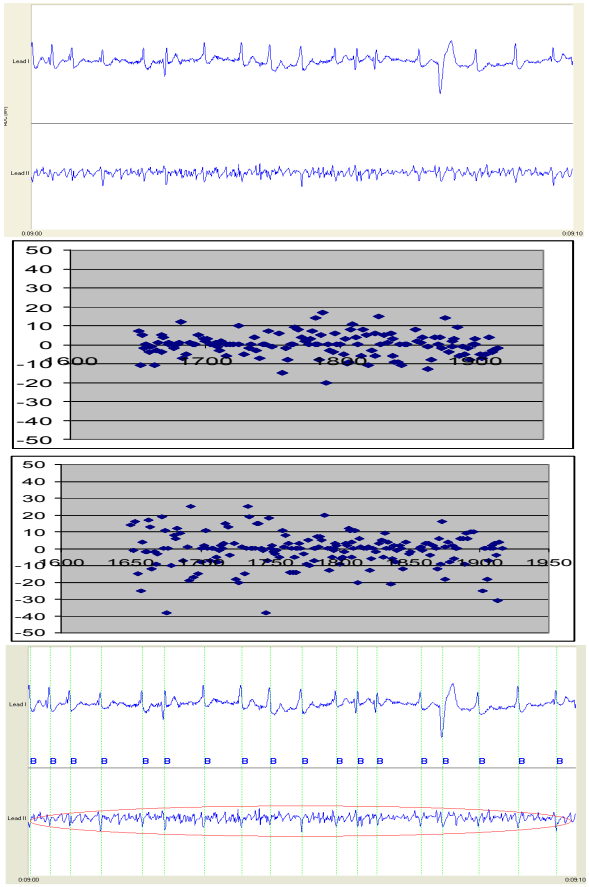

Fig. 6: 1 minute and 15 seconds' raw signal and algorithm results of lead 1 and lead 2 in MIT BIH Record 203.

the noise level in lead 2 to be significantly higher than lead 1, illustrated by measuring the distribution range of r_N for both leads. The lead 1 is selected for arrhythmia analysis (lead 2 is disabled). The third plot shows the results for QRS complexes position identification.

Fig. 7 illustrates the overall performance of algorithm for 1 minute (between 13:10 and 14:10) NST Record 119e06 (raw signal in upper plot and related r_N distribution in the second and third plots). For this time period, the presence of artifact waves caused the noise level in lead 2 to be significantly higher than lead 1, illustrated by measuring the distribution range of r_N for both leads. The lead 2 is selected for arrhythmia analysis (lead 1 is disabled). The third plot shows the results for QRS complexes position identification.

IV. CONCLUSION

A new signal quality measure that is responsive to composite noise has been developed for ECG lead quality assessment during QRS detection. The usefulness of this technique in qualifying the signal quality has been demonstrated. These results showed the new signal quality measure can be used to accurately assess the ECG signal quality and can be easily incorporated into an existing multi-lead QRS detection algorithm for performance improvement.

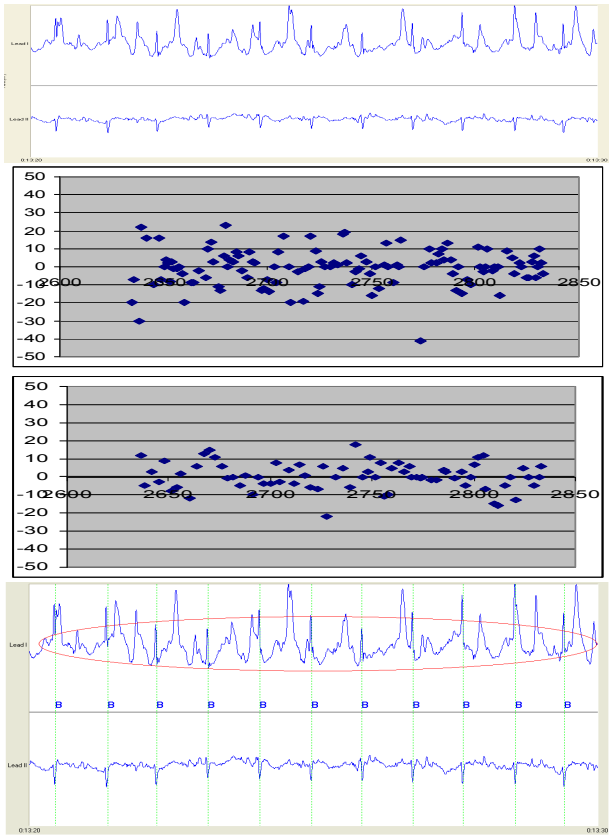

Fig. 7: 1 minute raw signal and algorithm results of lead 1 and lead 2 in NST Record 119e06.

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