A New Method for Evaluating ECG Signal Quality for Multi-Lead Arrhythmia Analysis

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Abstract

A simple and computationally efficient new signal quality measure that is responsive to combinations of both physiological and non-physiological noise has been developed. The new signal quality measure is based on the use of the area differences between successive QRS complexes. The signal quality assessment for each lead is made on the basis of the characteristics of the statistical distribution of the area differences obtained over a period of time. The new signal quality measure was evaluated using the 44 non-paced patient records from the MIT-BIH two-channel arrhythmia database. Results presented in histogram and cumulative histogram plots showed that the signal quality can be accurately assessed using this new method. Of the total 44 non-paced records, the new method identified 22 records where one of the two leads had much better signal quality than the other lead. When this information was used for arrhythmia analysis, the averaged PVC false positive rate was 0.47% for leads that were selected by the new method, and 2.56% for leads that were not selected. These results clearly showed that the new signal quality measure developed can be used to accurately assess the ECG signal quality and can be incorporated easily into existing arrhythmia algorithms for performance improvement.

1. Introduction

With the development of advanced microprocessor technology and the related digital hardware, the use of multiple ECG leads for real-time arrhythmia analysis has quickly become a monitoring standard. Because of the availability of these new technologies, there has been an increasing interest in developing monitoring algorithms that can simultaneously process more than a single ECG lead. One of the key components in a multi-lead algorithm is the determination of which ECG channels should be included in the processing. Lead selection for a multi-lead monitoring algorithm is essential for the following reasons: (1) despite the increased amount of processing power available in the modern patient monitors, an ECG algorithm still has to share any processing resource with many other functions that these monitors perform, and, consequently, the amount of the processing resource allocated for the algorithm may therefore put a limit on the total number of ECG leads that such an ECG algorithm can process; (2) because many of the ECG leads are highly redundant, there is really no need to process all the available ECG leads all the time; (3) the advantage of processing one or more additional ECG leads can improve performance only if these additional leads exhibit high signal quality; in fact, using leads that have inferior signal quality will actually degrade algorithm performance rather than improve it.

Therefore it is important to develop a method of measuring the quality of the ECG signals. This signal quality measurement may be used in identifying which ECG leads are of high quality and thus should be selected for processing. In addition, this quality measure could also be used in determining the weighting of information from different ECG leads for QRS complex classification.

Clinical experience with current ECG-based monitoring algorithms has shown that noise has been the primary source of performance degradation for these algorithms. Noise that causes the degradation includes both non-physiological and physiological noise. Examples of non-physiological noise sources are 50/60 Hz line noise, baseline wander noise, electrode motion artifacts, and muscle artifacts. Examples of physiological noise are axis shift, QRS morphology variation, QRS amplitude variations, and atrial fibrillation/flutter.

There are a few known techniques for the detection of individual types of non-physiological noise (mostly, only for out-of-band noise such as 50/60 Hz noise, baseline wander, and high frequency muscle artifacts). However, there is no known technique for the detection of physiological noise. Furthermore, there are no known techniques for the detection and/or quantification of composite noise sources, be they strictly non-physiological, strictly physiological, or some combination of both. Therefore, the objective of this paper is to develop a single signal quality measure that is
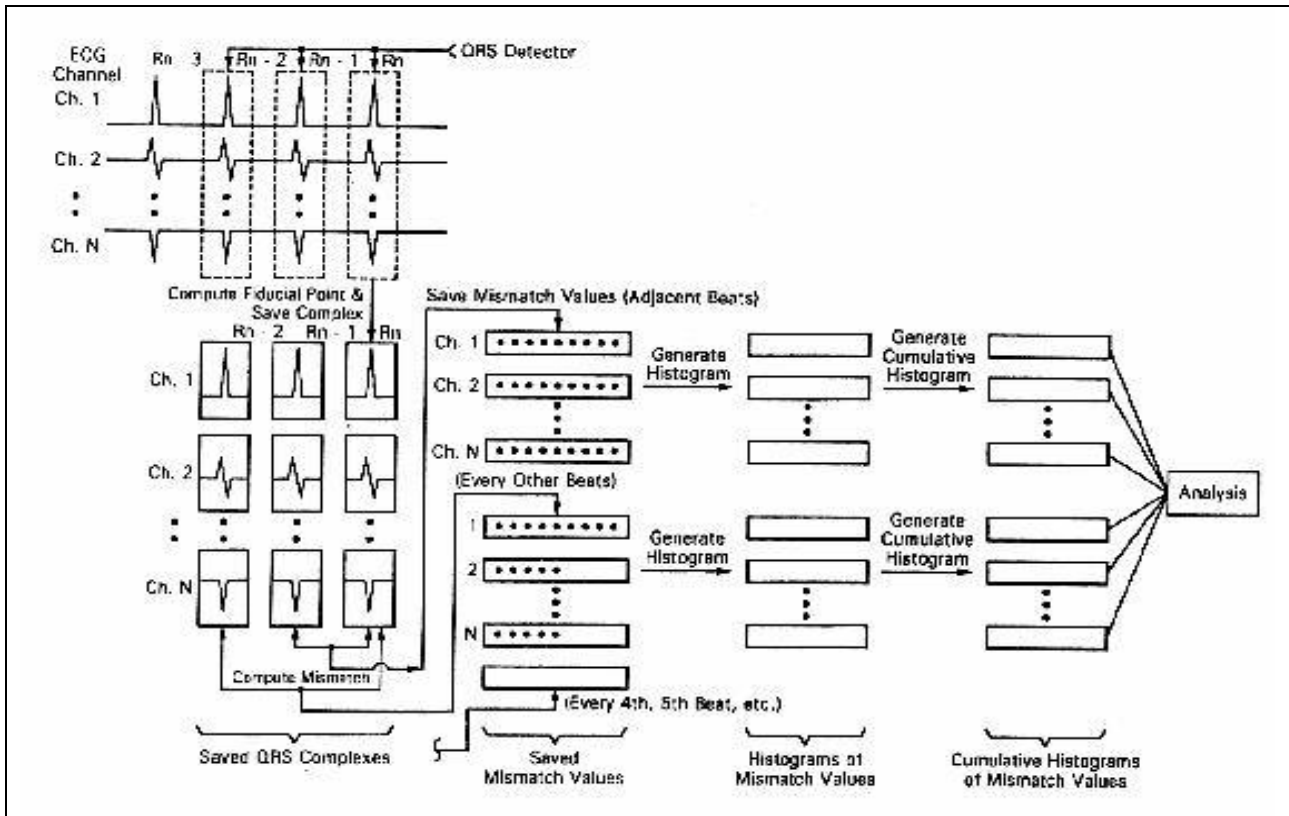
Figure 1. A high-level graphical schematic diagram of the new signal quality assessment algorithm

responsive to both non-physiological and physiological noise.

2. Method

The quantitative assessment of the noise contained in the ECG signal is achieved by the use of a mismatch indicator that combines various noise sources into a single metric. This metric is computed based on the area differences between successive QRS complexes (i.e., adjacent beats, every other beats, every third beats, etc.) When an ECG lead is essentially noise free, the area differences will be small. On the other hand, if the signal contains any significant amount of noise (whether from non-physiological or physiological sources) the area differences between successive QRS complexes will tend to be relatively large. By examining the area differences over a period of time, the signal quality associated with each ECG lead can be made on the basis of the characteristics of the statistical distribution of the calculated area differences. For signals that are relatively noise free, the distribution of the area differences will tend to be more tightly clustered with smaller values. Conversely, for signals that are relatively noisy, the distribution of the area differences

will tend to be more spread out and the calculated values will tend to be large.

The metric used for measuring the waveform area difference between two complexes X and Y is the normalized area difference as shown below:

$$\text{Mismatch} (X, Y) = \frac{\Sigma \, | \, X\,(i) - Y(i) \, |}{\Sigma \, | \, X\,(i) \, | + \Sigma \, | \, Y(i) \, |}$$

This metric is selected not only because it is more computationally efficient than the cross correlation function but also because it is sensitive to QRS amplitude variation. The value of the mismatch ranges from 0 to 1. When the two waveforms are identical, the mismatch value is 0. When the two waveforms are totally different (i.e., there is no overlap) the mismatch value is 1.0. In order to deal with integer values only, the mismatch value is arbitrarily scaled to a range from 0 to 512.

The high-level schematic diagram of an implementation of the new technique is shown in Figure 1, and the steps involved are described in the following:
QRS detection - All beats detected are saved and used in the subsequent signal quality analysis.

Fiducial point calculation – This is done so that a good starting point is provided to minimize the shifting required in the shifted mismatch computation.

Shifted mismatch computation – To ensure that the calculated area differences are due to true morphology variation rather than misalignment of the waveforms, the beats to be compared are shifted around the fiducial point to find the minimum mismatch value.

Generate mismatch histogram - The values of the area differences for successive beats over a period of time are stored as histograms for subsequent analysis.

Generate cumulative histogram – Cumulative histograms are derived from the histograms for subsequent signal quality analysis.

Signal quality analysis – The signal quality can be determined based on how fast the cumulative histogram curves rise. The signals with higher quality will rise faster than the signals with lower quality. Hence the order of the curves in the cumulative histogram automatically provides the ranking of the signal quality (the first curve on the left has the highest signal quality).

3. Results

Graphical Presentation - In this section, several examples are provided to demonstrate the ability of this new signal analysis technique in assessing signal quality. The test signals used are from the two-channel MIT-BIH database. In each example, the first 1minute of the two-lead ECG signals is shown in full disclosure plot, and followed by the histograms (shown on the left) and their corresponding cumulative histograms (shown on the right) of the mismatch values for the first 1, 3, 5, and 30 minutes of the ECG record. In each histogram plot, the vertical axis represents the actual number of beats, and the horizontal axis is the scaled mismatch number (range from 0 to 512). Results for the first ECG lead are plotted in dotted line, and the results for the second ECG lead are shown in solid line.

Record 209 (Figure 2) – For this record the 1st ECG lead is the preferred lead for automated arrhythmia analysis because the waveforms exhibit very little variation. The histogram plots accurately show that the 1st ECG lead is better because of the smaller mismatch values and fast rising cumulative histogram curve.

Record 119 (Figure 3) – For this record both leads exhibit good signal quality. However, due to the presence of bigeminy, the histogram plots generated from the mismatch values between every other beat (shown on the right) should be used instead of those obtained from the adjacent beats (shown on the left) for more accurate signal quality assessment. The overlapping curves accurately show that both leads have the same good quality for automatic analysis.

Record 203 (Figure 4) – For this record the 2nd ECG lead is not good for ventricular arrhythmia analysis due to the presence of atrial flutter/fibrillation waveforms. The cumulative histogram plots again accurately show that the 1st ECG lead is the preferred lead for analysis.
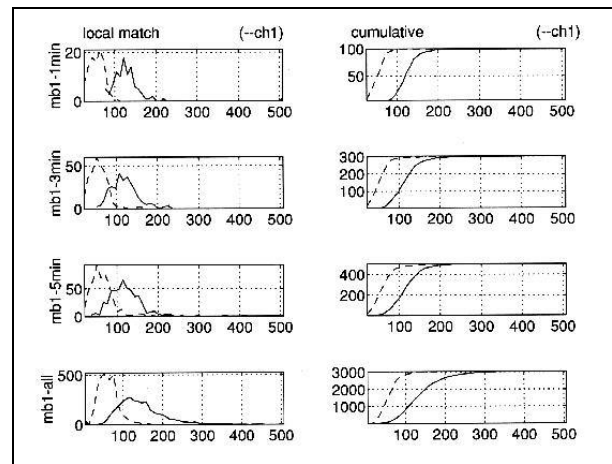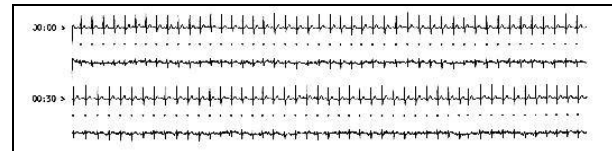

Figure 2. ECG signals and signal quality histogram plots for MIT-BIH Record 209.
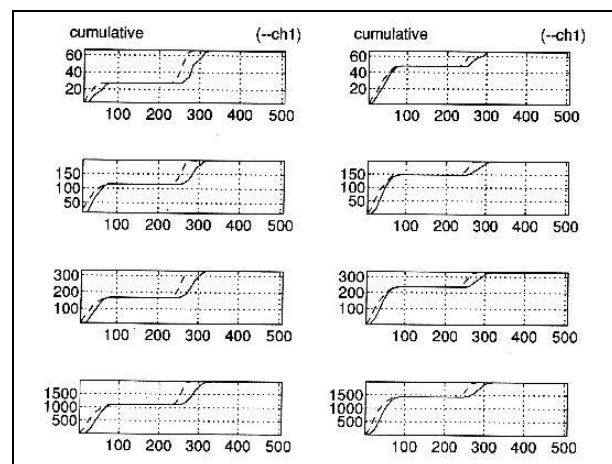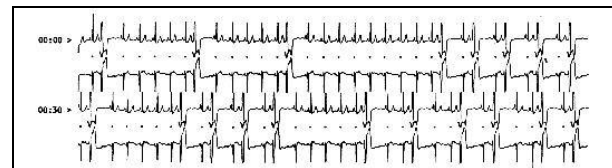

Figure 3. ECG signals and signal quality histogram plots for MIT-BIH Record 119.
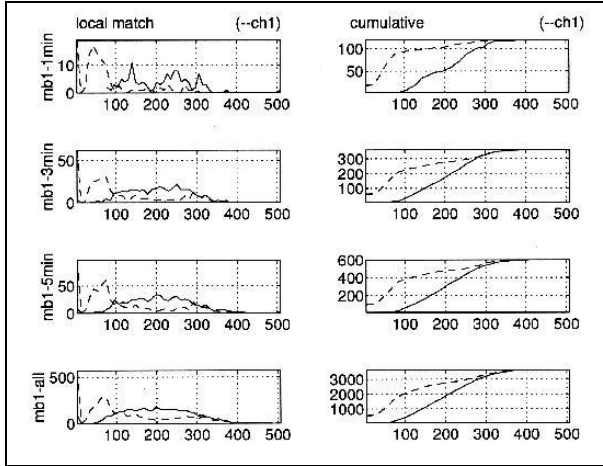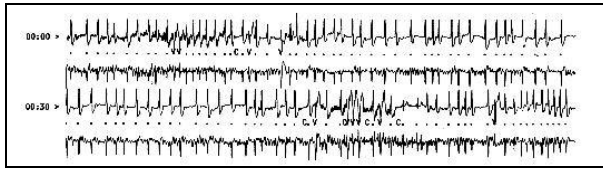
Figure 4. ECG signals and signal quality histogram plots for MIT-BIH Record 203
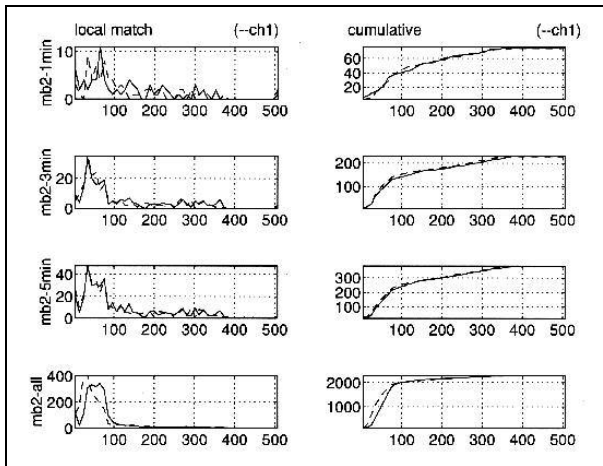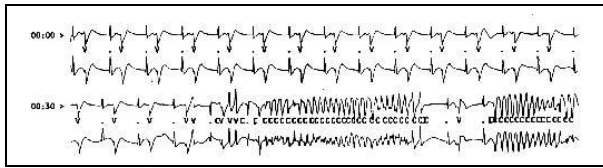

Figure 5. ECG signals and signal quality histogram plots for MIT-BIH Record 207.

Record 207 (Figure 5) – This example shows that despite the presence of ventricular bigeminy, and episodes of VT and ventricular flutter, the heavily overlapping cumulative distribution curves indicate that both ECG leads have good signal quality for analysis.

From these examples it is clear that the new signal quality assessment algorithm can be used to accurately assess the quality of the ECG signals.

Arrhythmia Performance - As a further example to show the potential value of this method in arrhythmia detection performance improvement, all 44 non-paced records from the MIT-BIH database were processed for each lead independently by an arrhythmia algorithm running in single-lead mode. False positive rates for PVC detection for each record were then generated. Using the new signal quality measure algorithm, a total of 22 records were identified to have one lead exhibited much better signal quality than the other lead. For these 22 records, the averaged PVC false positive rates for both the single leads selected as better quality and the leads not selected were separately computed. The results are presented in Table 1 below. From these results it is clear that as expected the leads that are identified by this new algorithm as the signals with higher quality provide much better performance (lower false positive rate on PVC detection) than those leads that are not selected.

	Leads selected	Leads not selected
Averaged PVC Detection False Positive Rate	0.47%	2.56%

Table 1. Arrhythmia performance improvement summary

4.   Conclusion

A simple and computationally efficient new signal quality measure that is responsive to combinations of both physiological and non-physiological noise has been developed. The usefulness of this technique in quantifying the signal quality has been demonstrated. These results clearly showed that the new signal quality measure developed can be used to accurately assess the ECG signal quality and can be incorporated easily into existing arrhythmia algorithms for performance improvement.

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