Assessment of Different Methods to Estimate Electrocardiogram Signal Quality

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Abstract

During the process of measurement, the ECG signal suffers from several noises, artifacts and interferences, which reduce its quality. Automatic signal quality estimation could permit indentify when the level of noise is high to avoid wrong ECG interpretation. With this aim, several methods have been proposed in the literature.

This work assesses eleven different methods for estimation of ECG signal quality available in literature. In addition, three new methods are proposed. These methods were evaluated in a simulated database containing ECGs with different types and levels of noise with SNR values ranging from -20 to 20 dB.

From all the quality estimators studied, one novel parameter: Kurtosis, gave the best performance overall the tests. It gave high correlation with the signal SNR (0.95±0.00) and high correlation with the output of a beat detector (Positive Predictivity=0.97±0.00) and high resolution in time (10 seconds of signal length). However kurtosis did not have a high dynamic range. Some methods require some knowledge about the ECG signal (like the position of the R peak) and therefore are not suitable for applications with high levels of noise.

1. Introduction

During the measurement of the ECG signal, noise, artifacts and interferences can reduce its quality significantly. ECG signal quality degrades specially during ambulatory monitoring when the level of activity is high and motion artifacts corrupt the signal making its interpretation difficult. Poor quality signals can result in false alarms, poor patient monitoring, imprecise measurement, and misleading analysis. Automatic control of ECG signal quality should be undertaken of a routine basis so that problems can be detected and corrected [1].

Several methods for estimation of signal quality are available in the literature. However, there is still a need to evaluate the accuracy of these estimators and to study their limitations.

The purpose of this work is to evaluate methods for estimating the quality of ECG signals in an objective way. Eleven methods available in literature were selected for this study. In addition, three new methods were proposed and evaluated on the same protocol.

2. Methods for ECG quality estimation

Eleven methods for ECG quality estimation existing in literature were implemented for evaluation. In addition, three novel methods were proposed and included in this evaluation study.

A. Methods existing in literature

- *Difference between the original signal and the aligned averaged signal (Average):* Noise is estimated as the difference between the original signal and the aligned averaged signal. Consequently the estimated SNR can be computed [2].
- *Karhunen-Loeve transform (KLT):* KLT is a transformation that reduces a large set of variables down to a smaller set. The smaller set of variables separates the information of the different sources (ECG and Noise). In this way, noise can be estimated and the SNR calculated [3].
- *Activity:* Defined as the variance of the signal [3].
- *Mobility:* Squared root of the ratio of the variance of the first derivative of the signal to the variance of the original signal [3].
- *Complexity*: Ratio of the mobility of the first derivative of the signals to the mobility of the signal itself [3].
- *Turns counts (TC):* Counting of the number of local minimums with amplitude higher than a threshold. The threshold was defined as 0.1mV [3].
- *Zero Crossing Rate (ZCR):* Counting of the number of times the signal change its amplitude from positive to negative values or vice versa. This value is then normalized dividing by the number of samples in the signal segment under study [3].
- *T-P interval average power divided by the QRS:* T-P interval average power divided by the QRS average power. This is calculated for every beat [4].
- *Cumulative mismatch histogram:* Mismatch values of consecutives QRS complex are stored as histograms for subsequent analysis generating a mismatch

histogram. Cumulative histograms are then calculated. The signal quality is determined based on how fast the cumulative histogram curves rise. The signals with higher quality will rise faster than the signals with lower quality [5].

- *First-Difference histogram*: The baseline is defined as the most common sample value during R-R periods. The sample value corresponding to the histogram peak was declared the baseline and the difference between consecutive baselines gives the baseline shift from beat to beat. Noise content is estimated from the first-difference histogram of R-R intervals. Noise contribution is one minus the frequency of occurrence of first differences with values around zero divided by the number of samples in the R-R interval [6].
- *Frequency content in six bandwidth and Out of range event (ORE):* Energy of the signal in six frequency bandwidths (0.05–0.25, 0.25–10, 10–20, 20–48, 48–52, and 52–100 Hz). ORE: counting of the number of times the signal go above or below a threshold. The threshold was defined as ±4 mV [7].

B. Novel methods proposed

- *LMS adaptive filtering:* LMS adaptive filtering was used to remove the ECG signal and therefore estimate the noise content. A template of the clean ECG signal was used as reference input signal to the adaptive filter. Then SNR can be estimated.
- *Kurtosis*: Measure of the Gaussianity of a distribution [8]. As ECG signals are hyper-Gaussian, higher kurtosis values are associated with lower quality in the ECG.
- *Temporal Dispersion:* defined as:

$$\text{Dispersion} = \frac{\sum_1^{N-1}(n-\overline{n_x})\cdot X^2(n)}{\sum_1^{N-1} X^2(n)} \qquad (1)$$

where N is the number of samples contained in one period of ECG signal centered in the R-peak.

3. Methodology

3.1. Database

Simulated signals were created by adding different kind of noise to clean 12-standard lead ECG signals. Clean ECG signals were recorded from 5 healthy subjects while they were at rest. Signals were of 2-minutes length and were obtained with a sampling frequency of 4800Hz, using a generic biosignal acquisition system from g.Tec (g.USBamp). Five additive noises were simulated: 50Hz power-line interference, motion artifact, respiration interference, electro-surgical noise and electromyogram (EMG). Noises were scaled by multiplying the signals by a factor before adding them to the clean ECGs in order to obtain different levels of SNR. The SNR ranged from -20dB to 20dB with increasing steps of 1dB

3.2. Evaluation criteria

In order to evaluate the performance of the different methods, several parameters were calculated. Values are calculated for each SNR value and expressed in terms of mean and standard deviation (SD) over all SNR values.

A. SNR vs. Quality estimation

Correlation coefficient between the level of SNR and the quality estimation obtained was calculated at each SNR value.

B. Beat detection vs. Quality estimation

A beat detector algorithm [9] was used on the noisy signals in order to see the decrease in beat detection performance with the higher level of noise. Positive predictivity value (PPV) was calculated for each SNR. The correlation coefficient between the PPV and the quality estimator obtained from each method was computed.

C. Time resolution

The accuracy of the quality estimation of the different methods against the time length of the signal under analysis was also evaluated.

D. Dynamic range

The dynamic range of the different quality estimators was also studied. Input SNR values range from -20 dB to 20 dB were considered. The first derivate of the quality estimators calculated against the input SNR values was obtained and normalized. The dynamic range was obtained by identifying the values in the first derivative that are higher than 0.2 and lower than -0.2.

4. Results

4.1. SNR vs. Quality estimation

Different kinds of noises were added to clean ECG signals with 30 seconds-length. Noise was multiplied by a factor before addition in order to obtain an SNR value desired. The quality in the noisy signal was estimated using the quality estimation parameters under study. The SNR in the noisy signal was compared with the quality estimators by using the correlation coefficient in order to evaluate their performance. Results are summarized in table 1.

The quality estimator that had a higher correlation with the signal SNR was the Difference between the original signal and the aligned averaged signal (Average) with an average±SD of 1.00±0.00. From the novel parameters proposed in this paper, LMS adaptive filtering gave the highest correlation (0.99 ±0.00). In the contrary, mismatch gave the lower correlation (0.27±0.13).

Some of the quality estimators had a significantly different correlation depending on the kind of noise. For example, mobility had a correlation coefficient of 0.94±0.03 when only interference noise was added while when the only added noise was respiration the correlation coefficient was of 0.69±0.09. Other parameters, such as activity, gave similar correlation coefficients when the different kinds of noise were added separately.

Table 1. Correlation coefficients between SNR and Quality estimators

	Mean	SD	Pvalue
Literature proposals			
Activity	0.72	0.01	p<0.01
Average	1.00	0.00	p<0.01
Complexity	0.94	0.07	p<0.01
FDHistogram	0.86	0.03	p<0.01
KLT	0.98	0.01	p<0.01
Mismatch	0.27	0.13	0.16
Mobility	0.76	0.03	0.05
TP/QRSpower	0.87	0.03	p<0.01
TurnsCount	0.37	0.76	0.07
ZeroCrossing	0.71	0.50	0.09
Frequencycontent	0.85	0.01	p<0.01
Novel proposals			
Temp Dispersion	0.95	0.03	p<0.01
Kurtosis	0.95	0.00	p<0.01
LMS adapt filtering	0.99	0.00	p<0.01

4.2. Beat detection vs. Quality estimation

The output of a beat detection algorithm [9] was used to estimate the performance of the quality estimators. The decrement in the signal quality will be translated in a lower performance of the algorithm. Detections on the different levels of SNR were compared with annotations and PPV was calculated. The PPV for the noisy signal was compared with the quality estimators by using the correlation coefficient in order to evaluate their performance. Results are summarized in table 2.

The quality estimator that had a higher correlation with the beat detector PPV was the novel parameter Kurtosis (0.97±0.00). From the quality estimators existing in the literature, Frequency content in six bandwidth and ORE with 0.92±0.07 gave the best correlation. Turns Count gave the lowest correlation coefficient (0.21±0.48).

Table 2. Correlation coefficients between PPV and Quality estimators

	Mean	STD	Pvalue
Literature proposals			
Activity	0.85	0.28	p<0.01
Average	0.60	0.24	p<0.01
Complexity	0.58	0.14	p<0.01
FDHistogram	0.37	0.17	p<0.01
KLT	0.50	0.20	p<0.01
Mismatch	0.22	0.20	p<0.01
Mobility	0.67	0.25	0.20
TP/QRSpower	0.79	0.28	0.07
TurnsCount	0.21	0.48	p<0.01
ZeroCrossing	0.29	0.37	0.04
Frequencycontent	0.92	0.07	p<0.01
Novel proposals			
Temporal Dispersion	0.67	0.26	p<0.01
Kurtosis	0.97	0.00	p<0.01
LMS adaptive filtering	0.67	0.26	p<0.01

4.3. Time resolution

In order to evaluate the time resolution of the different quality estimators, signals lengths from 5 to 120 seconds were considered. The signal length that gave the highest average correlation coefficient with the SNR was identified as the best one for each quality estimator. Results are summarized in table 3.

Table 3. Signal length that gave the highest correlation with SNR signal.

	Signal length (seconds)
Literature proposals	
Activity	15
Average	30
Complexity	15
FDHistogram	30
KLT	60
Mismatch	30
TP/QRSpower	15
TurnsCount	5
ZeroCrossing	5
Frequencycontent	10
Novel proposals	
Temporal Dispersion	40
Kurtosis	10
LMS adaptive filtering	15

The quality estimation methods of Turns Count and Zero Crossing needed the lowest signal length (5 seconds) in order to achieve the highest correlation with SNR. In the contrary KLT needed 60 seconds to get its highest correlation with the SNR.

4.4. Dynamic range

The dynamic range of the quality estimators was also studied in order to evaluate their working range on the input SNR. The parameter value calculated over the signal SNR was obtained. The first derivative was calculated in order to obtain the slope of the parameter response. When the first derivative had a value below -0.2 or higher than 0.2 it was considered that the parameter was varying when the SNR was varying. Results are summarized in table 4.

Some quality estimators, such as KLT, Average and LMS adaptive filtering, had a variation on the whole SNR range considered. In the contrary, Activity, Mobility, TP/QRSpower and Frequency content parameters had a low SNR dynamic range.

Table 4. Dynamic range.

Low DR	**Middle DR**	**High DR**	**whole SNR**
Activity	TurnsCount	FD Histog	KLT
Mobility			Average
TP/QRS	TempDisper.	ZeroCross	LMS adapt
FreqContent	Kurtosis		filtering

5. Conclusions

This work evaluates the performance of several quality estimators existing in the literature. A simulated dataset was used by adding added artificial noise to clean ECGs. Different kinds of noise and SNR levels were considered. In addition, novel parameters are also proposed to estimate signal quality in ECGs.

The quality estimation parameters that had the highest correlation with the signal SNR were Average or KLT method from the literature, and LMS adaptive filtering method from the novel proposals. The highest correlation with a beat detection algorithm response was obtained by Kurtosis and Frequency content methods.

Time resolution of the methods was also investigated. Turns Count and Zero Crossing, had the highest time resolution with 5 seconds while KLT needed 60 seconds to give its best performance.

Dynamic range of the parameters was also investigated. KLT, Average and LMS adaptive filtering gave a response on the whole SNR range studied.

It was found that Kurtosis was the quality estimator that gave the best performance overall the tests. It had a high correlation with the signal SNR (0.95±0.00) and high correlation with beat detection PPV (0.97±0.00) and high resolution in time (10 seconds). However kurtosis did not have a high dynamic range.

As a limitation of the study, it is important to note that some quality estimators (for example, Average or T-P interval average power divided by the QRS) need some information from within the ECG (such as position of the QRS complex) in order to be calculated. This is not always possible since for low signal quality it might not be possible to have an accurate QRS detection.

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