Lead Quality Monitoring for Detection of the Optimal Snapshot Time to Record Resting ECG

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Abstract

This study presents a multichannel ECG quality monitoring system, which continuously scans the leads' status (valid/lead-off) and quality (0-100%), according to the ECG components in the low, medium and high frequency bands. The system aims to detect the optimal moment to start the record of a 10s resting ECG within the 1st minute of signal acquisition – the earliest in time, the best in all leads' quality, named 'Optimal Snapshot Time' (OST) and 'Best Snapshot Quality' (BestSQ). The system compares the current leads' quality to an adaptive quality threshold (AQT) whose decreasing trend is trained on 375 ECGs. The validation over 267 ECGs in the test database shows that: 87.2% of the ECGs would be recorded with a quality ≥ 95%BestSQ; 33.1% at the optimal moment OST±2.5s; 29.3% would be started earlier due to their sufficient quality >AQT; 37.2% would be recorded with a delay >2.5s due to their compromised BestSQ, not reaching the AQT level in the vicinity of OST.

1. Introduction

The standard 12-lead resting electrocardiogram (ECG) recorded for 10s on a patient at rest in the supine position is one of the most widely used diagnostic tests in clinical routines of all kinds and for a wide range of diseases. The early starting of the ECG recording with sufficient ECG quality is essential for the patient's comfort and a prompt reliable diagnosis. However, the ECG signals are often contaminated by noise and artifacts that can manifest with similar morphologies as the ECG itself and affect the usability of the signals. Quantifying the noise in the ECG is not straightforward, partially due to the fact that there are many different types of noises and artifacts that can occur simultaneously, and partially because these noises and artifacts are often transient, and largely unpredictable in terms of their onset and duration.

The PhysioNet/Computing in Cardiology Challenge 2011 has addressed the development of methods for ECG quality assessment [1]. Most of the presented solutions apply simple procedures for: (1) detection of leads with constant voltage [2-12] and/or low amplitude [2,6-9,13]; (2) assessment of baseline wander and high-frequency noises by ECG filtering [2,8-10,12-14] or spectrum calculation [3,5,15]; (3) identification of steep and/or high amplitude artifacts [2,4-6,8,9,12] and assessment of the quality of QRS detection [3,4,10]. Some of the presented methods involve more complicated procedures, such as ECG reconstruction using QRS templates [14]; prediction of each ECG lead using other leads [13]; and cross correlation between leads and/or lead segments [7,16]. The algorithms for recognition of diagnostically useful ECGs combine the set of ECG measures in computationally efficient rule-based methods [2,4-15] or feed them in more sophisticated classifiers, such as: a quasi-linear combination between the Kth nearest neighbour rule and an ensemble of decision trees [16], linear discriminant analysis, Naive Bayes, support vector machine and multi-layer Perceptron artificial neural network [3].

This study aims to introduce an ECG quality monitoring system, which continuously scans the multi-lead ECG signal and automatically detects the optimal moment (the earliest in time, the best in ECG quality) to start the recording of a 10s resting ECG.

2. Methods

This study presents a real-time monitoring system of the quality of multichannel resting ECG that estimates the 'Global Quality' (0-100%) and the 'Global Status' (0/1) according to the state of all leads over the last 4s:

$$(1)\ \text{Global Quality} = \underset{i=1}{\overset{\text{Nb Leads}}{\text{median}}}(\text{Lead Quality}_i)$$

$$(2)\ \text{Global Status} = \underset{i=1}{\overset{\text{Nb Leads}}{\min}}(\text{Lead Status}_i)$$

, where

$$(3)\ \text{Lead Quality} = \frac{\text{Signal Level}}{\text{Signal Level} + \sum \text{Noise Levels}}.100\,,(\%)$$

$$(4)\ \text{Lead Status} = \begin{cases} 0 & \text{if the lead is 'off'} \\ 1 & \text{if the lead is 'valid'} \end{cases}$$

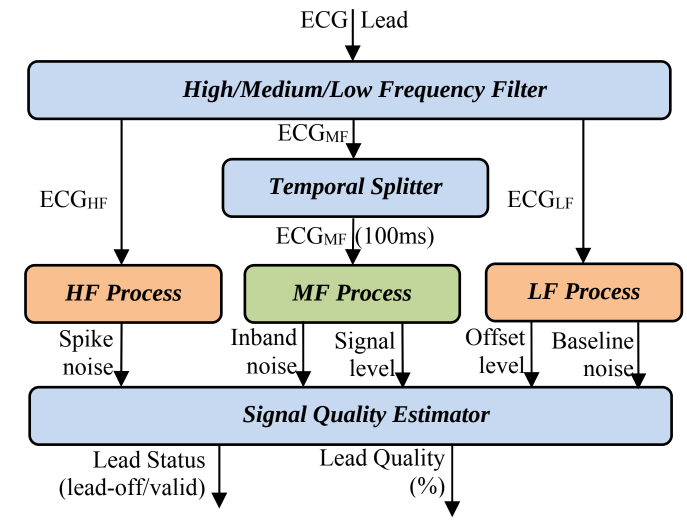

Figure 1. Block-diagram of the designed lead quality monitoring system.

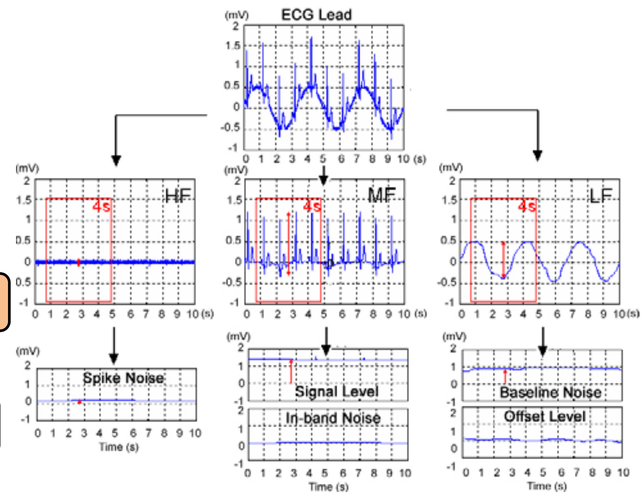

Figure 2. Example of ECG lead split to HF/MF/LF bands and estimation of Signal level and different noise levels.

The 'Lead Status' and 'Lead Quality' are scanned for each lead within sliding 4s intervals by calculating the Signal level and several noise levels from the filtered ECG signal in the high, medium and low frequency bands (see the diagram in Figure 1 and the example in Figure 2):

- High frequency (HF) components are used for estimation of Spike noises;
- Medium frequency (MF) components are further separated by a temporal splitter that derives the maximum and minimum peak-to-peak amplitudes in sliding windows of 100 ms. These signals are used for the calculation of the Signal level and In-band noises (e.g. powerline interference);
- Low frequency (LF) components represent the DC Offset level and the Baseline noise.

The binary output of the ECG quality monitoring system, named 'Snapshot Status' (0/1) enables the start of the resting ECG recording. It is activated (set to 1) only when the 'Global Status'=1 (i.e. all leads are 'valid') and the minimal 'Global Quality' for all samples within the last 10s, named 'Snapshot Quality' (SQ) exceeds a predefined or adaptive quality threshold (QT or AQT):

$$(5)\ \text{Snapshot Quality} = \begin{cases} \min\limits_{i=0}^{10\text{sec}}(\text{Global Quality}_i) & \text{if Global Status} = 1 \\ 0 & \text{otherwise} \end{cases}$$

$$(6)\ \text{Snapshot Status} = \begin{cases} 1 & \text{if SnapshotQuality} > \text{QT} \\ 0 & \text{otherwise} \end{cases}$$

The training process optimizes the QT value in function of time, aiming to set 'Snapshot Status'=1 closest to the first instant within the 1st minute after beginning of the recording when the maximal SQ is reached. This instant is named 'Optimal Snapshot Time' (OST) to record resting ECG at its best quality. The accuracy for detection of OST is tested with fixed QT and adaptive QT, as defined in section Results.

3. ECG databases

The study involves recordings from an own ECG database collected from chest pain patients at the Emergency Department of the University Hospital Basel:

- ECG recordings – a number of 542 standard 12-lead ECG signals, duration of 5 minutes. The total database is divided to independent datasets for training (375 ECGs) and testing (267 ECGs);
- ECG device – SCHILLER CS-200 Excellence, 1000 Hz sampling rate, 1 µV amplitude resolution.

The 'Best Snapshot Quality' (BestSQ) and 'Optimal Snapshot Time' are annotated for each recording in the database. For this purpose, an automatic analysis is run to measure the maximal SQ and its first time of occurrence within the first minute after start of the recording.

4. Results and discussion

The example in Figure 3 illustrates the quantification of different noises when present in the ECG lead, so that the estimation of the enhanced spike noise (middle) and baseline noise (bottom) results in deterioration of the 'Lead Quality' from 97% to 84% and 56%, respectively.

The statistical evaluation of the SQ in function of time over the training database (Figure 4) shows:

- The non-outlier range of all ECGs exceeds:
  - SQ>65% within the first 10s.
  - SQ>75% within the first minute;
- At least half of the ECGs:
  - exceed SQ>80% within the first minute;
  - do not exceed SQ>85% till the end of the recording (5 min);
- Almost no ECGs exceed SQ>90% till the end of the recording (5 min).

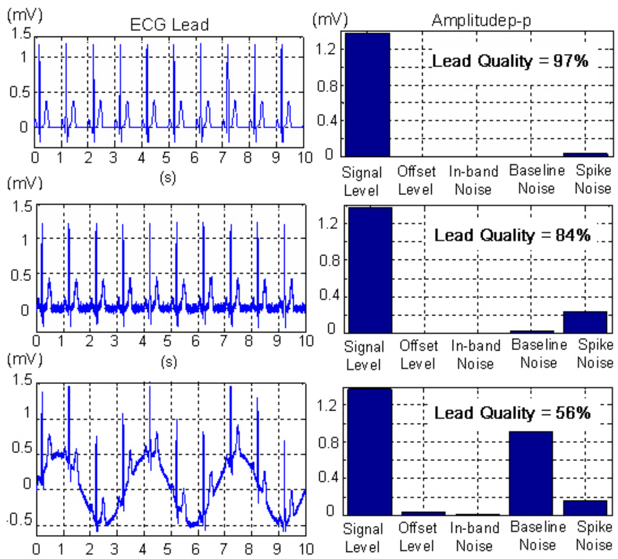

Figure 3. Example of ECG signal – noise-free (top), HF noise (middle), baseline wander (bottom), and the corresponding estimation of the large Signal level (all), Spike noise (middle) and baseline noise (bottom).

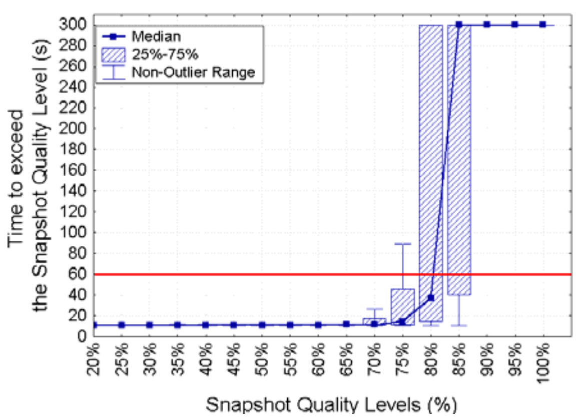

Figure 4. Box-plot distribution of the time to exceed fixed SQ levels in the training database. The maximal time is set to 300 seconds if a specific SQ level is not reached till the end of the ECG recording.

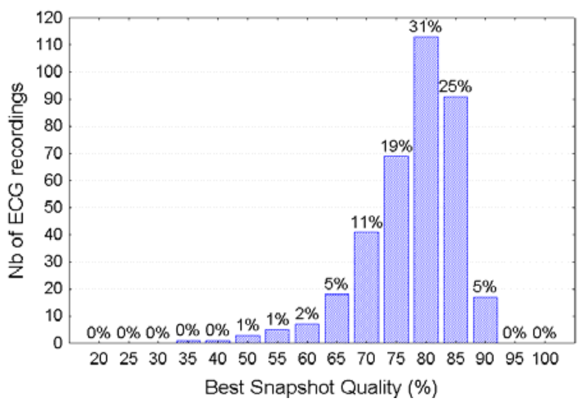

Figure 5. Histogram of the BestSQ according to the annotations in the training database.

Two measures are defined for assessment of the OST detection accuracy:

(1) *RecOnTime* (%) – the percentage of ECGs which are triggered on time, i.e. the triggering instant appears in the vicinity of the annotated OST±2.5s.

(2) *RecBestSQ* (%) – the percentage of ECGs which would be recorded at their best quality, i.e. with triggered SQ>95% of their annotated BestSQ.

The training process scans the range of fixed quality thresholds (FQT), applied in equation (6), searching for the solution with maximized common optimization criterion (*OptCrit*), which takes at equal weight both *RecOnTime* and *RecBestSQ:*

OptCrit (%) = (RecOnTime + RecBestSQ)/2 → *Max.*

Figure 6 shows the training trends of *RecOnTime, RecBestSQ* and *OptCrit* in function of FSQ levels with well recognized *OptCrit* maximum for FQT=75%, providing 32% of the ECGs recorded at the optimal moment and 65% of the ECGs recorded at their best snapshot quality.

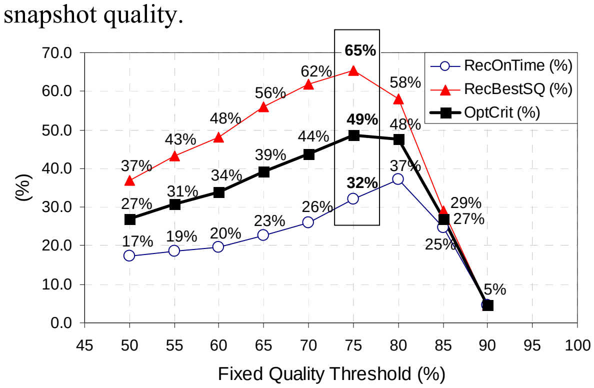

Figure 6. Training process of FQT.

An adaptive quality threshold (AQT) is also designed, following the median and quartile range statistics in Figure 4 that clearly indicates: longer time is required to get higher SQ levels, distributed in the range 75-85%. Besides, this range covers the annotated BestSQ in about 75% of all ECGs (Figure 5). The AQT design follows the principle for setting an initial high threshold, which allows immediate ECG acquisition after the first 10s if the signal quality is sufficient and to slowly decrease this threshold, aiming to record the ECG with the best possible quality within the 1st minute. The AQT time-trend (Figure 7) is trained by iterative adjustment of the threshold levels over time, aiming at maximized *OptCrit* on the training database.

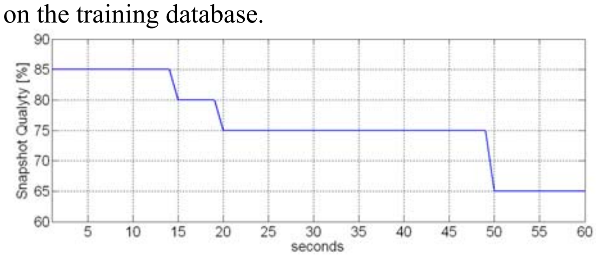

Figure 7. Time trend of the optimal AQT.

Table 1. Performance of the optimal AQT for OST detection on the training and test datasets.

Dataset	RecBestSQ (%)	RecOnTime (%)	RecEarly (%)	RecLate (%)
Training	**87.2**	**39.2**	29.1	30.4
Test	**87.2**	**33.1**	29.3	37.2

The optimal AQT design (Figure 7) is found to decrease from 85% down to 65% within the 1st minute of ECG acquisition. The optimal AQT performs better than the optimal FQT=75%: *RecOnTime* by 7% points (39% vs. 32%); *RecBestSQ* by 22% points (87% vs. 65%), considering the training results in Table 1. The same AQT performance with improved *RecBestSQ* is also confirmed on the independent test dataset. In Table 1, two additional measures are defined for a detailed study of the percentage of ECGs which are not triggered on time, including *RecEarly* and *RecLate* for the cases triggered earlier than OST-2.5s and later than OST+2.5s, respectively. It should be noted that the sum of the percentages (*RecEarly* + *RecOnTime* + *RecLate*) < 100% because the ECGs which have quite compromised quality and do not reach the AQT level till the end of the recording do not have OST detected and thus not counted.

The independent test-validation of the real-time ECG quality monitoring system with AQT (Table 1) shows that: 87.2% of the ECGs would be recorded with a quality ≥ 95%BestSQ; 33.1% of the ECGs would be recorded at the optimal moment OST±2.5s; 29.3% of the ECGs would be started earlier due to their sufficient quality, exceeding the AQT before reaching BestSQ; 37.2% of the ECGs would be recorded with a delay >2.5s due to their compromised BestSQ, which is not sufficient to exceed the AQT level in the vicinity of OST but delayed until the descending AQT falls below the current SQ.

5. Conclusions

This study presents an ECG quality monitoring system which enables the start of multichannel ECG recording, following the principle: the earliest in time, the best in quality, where the quality of each lead is estimated from the low, medium and high frequency ECG content. The starting of the ECG recording is enabled in real-time when: (1) all leads become 'valid'; (2) the lead quality of the median quality lead exceeds a predefined threshold for at least 10s. Fixed and adaptive thresholds are optimized, aiming to maximize the percentage of ECGs which are triggered on time or recorded at their best quality. The best performing adaptive threshold is dropping from 85% down to 65% within the 1st min, with about 87% of the ECGs recorded at their best quality. This makes the presented ECG quality monitoring system suitable to trigger the recording of 10s resting ECG, which is a widely used diagnostic test in clinical routines.

References

[1] Silva I, Moody G, Celi L. Improving the quality of ECGs collected using mobile phones: The PhysioNet/Computing in Cardiology Challenge 2011. Computing in Cardiology 2011; 38:273-6.

[2] Langley P, Di Marco L, King S, Duncan D, Di Maria C, Duan W et al. An algorithm for assessment of quality of ECGs acquired via mobile telephones. Computing in Cardiology 2011; 38:281-4.

[3] Clifford G, Lopez D, Li Q, Rezek I. Signal quality indices and data fusion for determining acceptability of electrocardiograms collected in noisy ambulatory environments. Computing in Cardiology 2011; 38:285-8.

[4] Hayn D, Jammerbund B, Schreier G. ECG quality assessment for patient empowerment in mHealth applications. Computing in Cardiology 2011; 38:353-6.

[5] Liu C, Li P, Zhao L, Liu F, Wang R. Real-time signal quality assessment for ECGs collected using mobile phones. Computing in Cardiology 2011; 38:357-60.

[6] Moody B. Rule-based methods for ECG quality control. Computing in Cardiology 2011; 38:361-3.

[7] Xia H, Garcia G, McBride J, Sullivan A, DeBock T, Bains J et al. Computer algorithms for evaluating the quality of ECGs in real time. Computing in Cardiology 2011; 38:369-72.

[8] Jekova I, Krasteva V, Dotsinsky I, Christov I, Abächerli R. Recognition of diagnostically useful ECG recordings: Alert for corrupted or interchanged leads. Computing in Cardiology 2011; 38:429-32.

[9] Jekova I, Krasteva V, Christov I, Abächerli R. Threshold-based system for noise detection in multilead ECG recordings. Physiol Meas 2012; 33:1463-77.

[10] Johannesen L. Assessment of ECG quality on an Android platform. Computing in Cardiology 2011; 38:433-6.

[11] Ho Chee Tat T, Xiang C, Thiam L. Physionet Challenge 2011: Improving the quality of electrocardiography data collected using real time QRS-complex and T-wave detection. Computing in Cardiology 2011; 38:441-4.

[12] Chudacek V, Zach L, Kuzılek J, Spilka J, Lhotska L. Simple scoring system for ECG quality assessment on Android platform. Computing in Cardiology 2011;38:449-51.

[13] Noponen K, Karsikas M, Tiinanen S, Kortelainen J, Huikuri H, Seppänen T. Electrocardiogram quality classification based on robust best subsets linear prediction error. Computing in Cardiology 2011; 38:365-8.

[14] Starc V. Could determination of equivalent dipoles from 12 lead ECG help in detection of misplaced electrodes. Computing in Cardiology 2011;38:445-8.

[15] Zaunseder S, Huhle R, Malberg H. CinC Challenge - Assessing the usability of ECG by ensemble decision trees. Computing in Cardiology 2011; 38:277-80.

[16] Kalkstein N, Kinar Y, NaÕaman M, Neumark N, Akiva P. Using machine learning to detect problems in ECG data collection. Computing in Cardiology 2011; 38:437-40.

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