Measurement of Noise in ECG Signals to Improve Automatic Delineation

Loriano Galeotti[1], Lars Johannesen[2,3], Jose Vicente[1], David G Strauss[1]

[1] Division of Physics, Office of Science and Engineering Laboratories, Center for Devices and Radiological Health, US Food and Drug Administration, Silver Spring, MD, USA
[2] Division of Pharmacometrics, Office of Clinical Pharmacology, Office of Translational Sciences, Center for Drug Evaluation and Research, US Food and Drug Administration, Silver Spring, MD, USA
[3] Department of Clinical Physiology, Karolinska Institutet and Karolinska University Hospital, Stockholm, Sweden

Abstract

Evaluation of quality in digital ECG recordings is of importance when analyzing data archives or for automatic patient monitoring. In these settings, using noisy signals may lead to incorrectly measured ECGs or triggering false alarms in patient monitoring. Empirically defined thresholds are usually employed to exclude noisy recordings.

We implemented a method to measure and correct the amount of noise in an ECG dividing it in three different categories: baseline wander, power-line and residual noise (e.g. muscular noise). To decide whether a signal is valid for its intended use (e.g. to measure T-offset), we characterized the amount of errors introduced on the ECG measurements as a function of the measured input noise

This method allows a generalized approach to evaluate ECG noise levels and to determine if ECGs are of sufficient quality for the intended use. We present an example showing how to select the noise limits to ensure a 10 ms maximum T-offset error using 74 ECGs (28 simulated and 46 real) and 213 different noise patterns. Using the same data we confirm the ability of the method to correctly measure the noise present in the signal.

1. Introduction

In order to improve the ECG data analysis process we implemented a method [1, 2] to measure and correct the amount of noise in an ECG by dividing it into three different categories (baseline wander, power-line and residual). This will allow improving the data quality by discarding the noisy recordings.

To decide whether a signal is valid for its intended use, e.g. to measure T-offset, we characterized the amount of errors introduced on the ECG measurements as a function of the measured noise.

This method will assist in analyzing large ECG databases by rejecting signals where noise would likely lead to unreliable measurements.

In automatic patient monitoring scenarios, the information about the types of noise can be used to help troubleshoot and solve common acquisition issues, allowing less trained operators to correct common recording problems (e.g. disconnected or poorly connected leads). This may be of particular importance to allow the use of smart monitoring devices in case of mass casualty incidents, where less trained caregivers can assist professional caregivers to monitor a large number of victims.

2. Methods

2.1. Noise removal and measurement

The ECG processing algorithm was described by Johannesen and Galeotti [1], and employs a method that allows the removal and measurement of the noise divided in three categories: baseline wander (changes in the baseline signal, principally due to respiration and electrode movement artefacts); power-line (due to the power distribution network) and residual noise (including noise arising from the myoelectric potentials of skeletal muscles due to patient movement).

The QRS complexes are detected using a nonlinear algorithm [3], and coarse location of QRS onset, median point and offset are identified. The signal average in a time window prior to the QRS onset (16 ms for 60 Hz countries, 20 ms for 50 Hz countries) is used as isoelectric point. The isoelectric points are interpolated using a cubic spline, representing the baseline wander noise [4]. The baseline wander noise is then measured (root-mean square or RMS through the 10 s segment) [5] and corrected by subtracting the noise signal from the ECG.

The ECG is segmented in beats and similarly, a 60 Hz (or 50 Hz, depending on the power line frequency used in the country where the ECG was recorded) sinusoid is fitted on the ECG segment (amplitude and phases are fitted on each beat, to allow for amplitude / phase changes on a beat-to-beat basis) [6], to represent the power-line noise that is measured (RMS), and subtracted to the ECG.

Beats are then grouped by similarity and their timings checked to exclude those of non-sinus origin. Dominant (most common morphology) beats are collected and aligned using the QRS median point identified previously, and then averaged to obtain a median beat. The average RMS difference between the dominant beats and the median beat constitutes the residual noise.

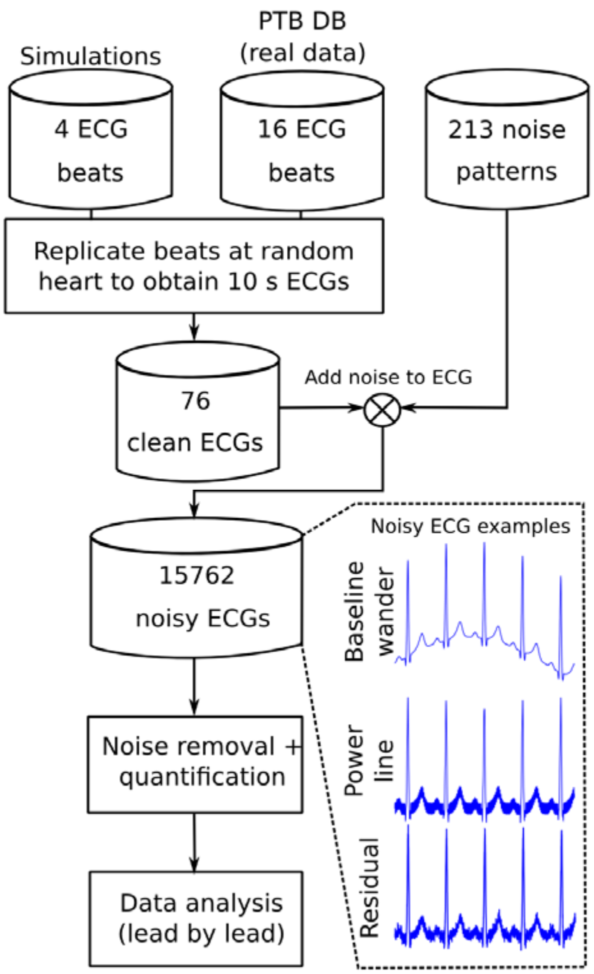

Figure 1. Flowchart illustrating noisy ECG.s creation and signal processing.

2.2. Creation of the clean ECG database

Figure 1 illustrates the procedure used to create and process the ECGs used in the analysis. Four beats were simulated using ECGSIM [7] to represent a normal and 3 different myocardial ischemia cases (anterior, inferior and right ventricle ischemia).

Additional ECGs were randomly selected from Physionet PTB-DB [8, 9]. To do that we used the processing tools previously described to identify in each ECG the section with higher mean heart rate stability, from where we extracted a median beat. The median beats were then evaluated visually and discarded if adjudicated as poor quality. We finally obtained 16 ECGs from the PTB-DB (2 normal, 12 myocardial infarct, 2 valvular disease). All signals were sampled at 1000 Hz with a minimum resolution of 0.5 uV.

To minimize heart-rate dependant effects, simulated and real median beats were then replicated at different random heart rates (from 60 to 90 beats per minute, adding a signal segment of the length needed to connect the end of the beats to the start of the following) to obtain segments of at least 10 seconds. In total we produced 74 clean ECGs (28 from simulations, 46 from real PTB-DB ECGs).

2.3. Artificial noise generation

Different values of artificial noise patterns were assessed for each of the noise categories. Noise amplitude values were randomized (uniform distribution) from 0 to a maximum for each noise category (3 mV for baseline wander, 5 mV for power-line, 0.3 mV for residual). The different maximum values were chosen in preliminary tests in order to have data in a meaningful range, taking into account the different impact on the ECG signal of the different noise types.

Baseline wander was simulated by interpolation of a cubic spline within a set of randomly placed points in time and amplitude. Each point was randomly placed within the 2/3rd central area of each beat with amplitude randomized (uniform distribution) between 0 and 3 mV.

Power-line noise was simulated as a 60 Hz sinusoid, which amplitude was uniformly randomly distributed between 0 and 5 mV.

Residual noise was simulated as white noise scaled by values uniformly randomly distributed between 0 and 0.3 mV.

A total of 213 different noise patterns were generated and added to each clean ECG, resulting in a total of 15762 noisy ECGs (Figure 1). The RMS difference between the ECGs before and after the addition of noise was stored, and will be referred as input noise, while the noise amounts measured by the various noise-removal stages will be referred as measured noise.

2.4. ECG annotation

The ECGs were processed using the ECGlib tools [2] to obtain a median beat and annotations (QRS onset and offset; T wave peak and offset). The median beats were low-pass filtered (25Hz) and annotated using a wavelet-based algorithm [10] for fiducial points delineation (e.g. QRS onset and offset) and a tangent method [11] for T-wave offset delineation.

2.5. Evaluation of noise measurements and maximum allowable noise

For each noisy ECG generated, the measured noise was compared to input noise. We evaluated the correlation between the input and measured noise using Pearson's correlation.

The goal of this work was to identify ECGs of sufficient quality for a certain analysis (e.g. locating fiducial points such T wave offset). Obviously the maximum allowable amount of noise depends on the specific application, so we defined a hypothetical case-study requiring the T offset measurement error within 10 ms.

The following procedure was repeated for each type of noise: for each lead of each noisy ECG the error in T offset annotation (time difference between the annotation on the noisy ECG and the one obtained on the clean ECG) was associated with the measured noise. The annotation errors were then sorted and grouped by measured noise (grouped in non-overlapping bins, each one containing 1000 measurements). The mean and 95% confidence interval (CI) were computed using MATLAB 8.0 (The MathWorks Inc., Natick, MA) on the T offset annotations for each bin, assuming the distributions were normal. The mean and 95% CI of each bin were then interpolated using a 4th order smoothed cubic spline. The intersection between the upper 95% CI interpolation and the pre-defined threshold (10 ms in our example) defined the maximum allowable noise, which may be conservatively rounded down for convenience of use.

3. Results

The evaluation of the noise measurements showed a very good correlation ($r>0.99$, $p<0.001$) between the input and measured noise amounts.

Evaluation of the maximum allowable noise is shown in figure 2. In each plot, the solid blue line represents the mean error vs. noise, while the dashed lines represent the upper and lower 95% CI. The red horizontal dotted line denotes the 10 ms maximum allowed annotation error. The maximum allowed noise (noise amount limit) is identified by the intersection of the dotted red line (maximum error) with the upper dashed line (upper 95% CI) and denoted by a vertical dotted green line.

We obtained a noise amount limit of 0.92 mV for baseline wander (figure 2A) and 0.10 mV for residual noise (figure 2B). Power-line noise does not intersect the annotation error threshold (figure 2C). This is probably due the combined effect of the power-line removal process and the low-pass filter included in the processing.

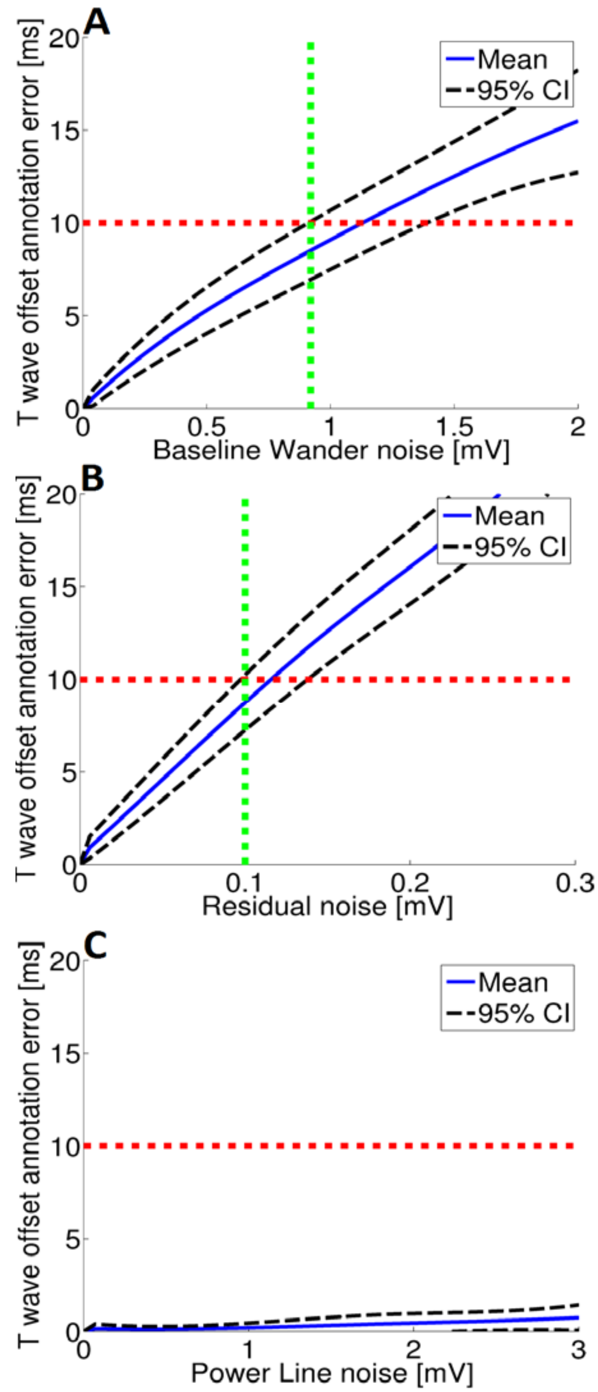

Figure 2. Mean and 95%CI of T offset annotation error vs. baseline wander (A), residual (B) and power-line (C) noise. The horizontal dotted lines represent 10 ms arbitrary noise limit and the vertical dotted lines mark its intersection with the upper 95% confidence interval. Plot limits were chosen to show ranges of interest.

4. Discussion

We implemented a method to reduce the noise in ECG signals and quantify the amount of noise within three categories (baseline wander, power-line and residual) to evaluate if a signal is of sufficient quality for the intended use.

There was a high degree of correlation between the measured noise and the input noise. This is of primary importance for the error estimation process, which is based on the measured noise.

We showed with an example how the noise amplitude can be used to predict the accuracy of measurements such as the T wave offset. This information can be used in different real-world situations.

In case of post-hoc analysis of ECG databases, such as the FDA ECG Warehouse, it is possible to discard a priori the noisy ECGs that may otherwise lead to wrong measurements, polluting the data results.

In real time patient monitoring, a noisy signal likely to produce an erroneous measurement can be treated properly to avoid the generation of false alarms, potentially decreasing “alarm fatigue” [12].

The division of the noise into different categories allows the implementation of automatic troubleshooting algorithms, thus potentially enabling untrained caregivers to solve common recording issues. This could be useful in case of mass casualty incidents.

Furthermore, the process can be used to select the best settings for a signal processing setup (i.e. filtering frequencies) by running the noise performance analysis using different processing settings and identifying the settings that are less sensitive to the noise.

The cases when an annotation is undetected (missed) were excluded from the analysis. In our hypothetical scenarios, these cases should be handled properly, using a different data segment of better quality when possible. Further analyses will be conducted to characterize the influence of noise on missed detection and the effect of the distribution of noise across leads.

The proposed method can be used to establish specific noise thresholds for different ECG analysis algorithms and devices, making possible to identify ECGs of poor quality to improve post-hoc data analysis, reduce the false alarm rate in monitoring devices, and help untrained caregivers to solve simple acquisition problems.

Acknowledgements and disclaimer

This project was supported in part by FDA’s Critical Path Initiative, FDA’s Office of Women’s Health, and appointments to the Research Participation Program at the Center for Drug Evaluation and Research and Center for Devices and Radiological Health administered by the Oak Ridge Institute for Science and Education through an interagency agreement between the U.S. Department of Energy and the U.S. Food and Drug Administration.

The opinions presented here are those of the authors. No official support or endorsement by U.S. Food and Drug Administration is intended nor should be inferred. The mention of commercial products, their sources, or their use in connection with material reported herein is not to be construed as either an actual or implied endorsement of such products by the U.S. Department of Health and Human Services.

References

[1] Johannesen L, Galeotti L. Automatic ECG quality scoring methodology: mimicking human annotators. Physiological measurement 2012;33(9):1479-89.

[2] Johannesen L, Vicente J, Galeotti L, Strauss DG. ECGlib: Library for Processing Electrocardiograms. . Computing in Cardiology 2013;in press.

[3] Paoletti M, Marchesi C. Discovering dangerous patterns in long-term ambulatory ECG recordings using a fast QRS detection algorithm and explorative data analysis. Computer methods and programs in biomedicine 2006;82(1):20-30.

[4] Meyer CR, Keiser HN. Electrocardiogram baseline noise estimation and removal using cubic splines and state-space computation techniques. Computers and biomedical research, an international journal 1977;10(5):459-70.

[5] Vaglio MIL, Gates G, Badilini F. Use of ECG quality metrics in clinical trials. Comput Cardiol 2010;37:505.

[6] Bazhyna ACI, Gotchev A, Daskalov IK, Egiazarian K. Powerline interference suppression in high resolution ECG. Computing in Cardiology 2003;30:561-4.

[7] van Dam PMOT, van Oosterom A. ECGSIM: interactive simulation of the ECG for teaching and research purposes. Computing in Cardiology 2010;37:841-4.

[8] Bousseljot R KD, Schnabel, A. Nutzung. Nutzung der EKG-Signaldatenbank CARDIODAT der PTB über das Internet. Biomedizinische Technik 1995;40(1):317.

[9] Goldberger AL, Glass L, Hausdorff JM, Ivanov PCh, Mark RG, Mietus JE, Moody GB, Peng C-K, Stanley HE. PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals. Circulation 2000 101(23):e215-e20

[10] Martinez JP, Almeida R, Olmos S, Rocha AP, Laguna P. A wavelet-based ECG delineator: evaluation on standard databases. IEEE Trans Biomed Eng 2004;51(4):570-81.

[11] Qiuzhen XaSR. New algorithms for QT dispersion analysis. Computers in Cardiology 1996.

[12] Cvach M. Monitor alarm fatigue: an integrative review. Biomedical instrumentation & technology / Association for the Advancement of Medical Instrumentation. 2012;46(4):268-77.

Address for correspondence.

Loriano Galeotti
10903 New Hampshire Avenue Building 62 RM 1111
Silver Spring, Maryland, 20993, USA
Loriano.galeotti@fda.hhs.gov