

Cepstral Based Approach for Online Quantification of ECG Quality in Freely Moving Subjects

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Abstract

We present an algorithm for assessing the ECG signal quality in real time. The algorithm is designed for small systems with low computational power.

The method estimates the ECG cepstrum on a running window of 10 s and calculates the power of the highest peak in the “quefreny” band of the mean cardiac interval (between 0.25 and 2.0 s). If the ECG is corrupted by noise, the power of this cepstral peak is just a fraction of the total power. The ECG quality index (QI) is defined as ratio between the power of the cepstral peak and the total cepstral power. Examples with ECG of different signal quality from different leads illustrate the method. Moreover, two overnight ECG recordings were analyzed by setting the threshold for ECG acceptability at $QI > 0.40$. ECG signals were classified acceptable for 99.8% and 60% respectively of the recordings time. These percentages were similar to those scored visually by an expert operator (100% and 67% respectively).

1. Introduction

Recent advancements in sensors technologies are making it possible to monitor physiological signals and behavioural data unobtrusively for long periods. This and the parallel progress of ambient intelligence (i.e., information technologies for acquiring knowledge about a monitored environment and for reacting automatically to its events) open new scenarios for ambient-assisted living applications.

An example of these applications is the *Ambient Aware Assistance* (ACUBE) project (1), aimed at developing a smart environment for elderly or disabled people in nursing homes. ACUBE consists of three computational levels. The lower level is a sophisticated sensing architecture for collecting physiological and behavioural data. This includes long-term ECG recordings obtained by wearable devices based on textile sensors (2). The

second level consists of processing algorithms to recognize specific events (like anomalies in heart rate variability), while the upper level represents the “system intelligence” to operate decisions in support of medical and assistance staff. In such applications, it is highly advisable that the sensing device itself provides information on the quality of the recorded signals. This avoids that higher computing levels analyse meaningless data or operate decisions on the base of unreliable information.

To address this issue, we developed an algorithm for online quantification of ECG signal quality in the context of ambient-assisted living applications. The algorithm is designed for running on microprocessors with low computational power, and for working with any ECG derivation. In case of multi-lead recordings, the algorithm should be able to recognize the best lead allowing to temporarily exclude leads which become too noisy because of changes in posture or activity levels.

The algorithm is based on the cepstral analysis of ECG for quantifying periodic patterns with period in the physiological range of the R-R interval. This paper describes the algorithm and illustrates its performances by applying it to segments of ECG recordings with different signal quality.

2. Cepstral based assessment of ECG signal quality

In case of high signal-to-noise ratios, an ECG segment of few beats appear as “quasi-periodic” function, with period equal to the inverse of the heart rate, $1/f_{HR}$. This means that the Fourier spectrum is mainly composed by harmonics at multiples of the fundamental frequency f_{HR} .

This spectral pattern is lost if high levels of noise corrupt the ECG. Therefore the proposed algorithm evaluates the quality of the ECG recording by verifying whether its Fourier spectrum is composed by a series of spectral peaks spaced at multiples of the mean heart rate.

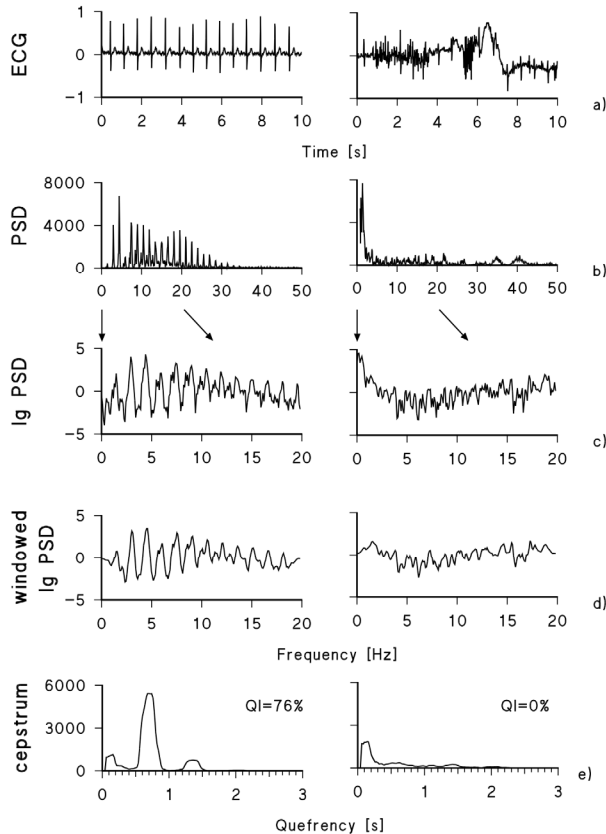


Figure 1. Illustration of the algorithm. The method is applied on running windows of 10 s (panels a). FFT spectra are estimated (panels b), log-transformed between 0 and 20 Hz (panels c), smoothed and windowed (panels d). In absence of noise (left), the log-spectrum appears as a damped oscillation producing a dominant cepstral peak at the *quefreny* of the mean R-R interval (panel e). This structure may be lost in case of noise (right panels). The quality index, QI, is the ratio between the power of the main cepstral peak (if present) and the total cepstral power.

The algorithm is based on the evaluation of the power Cepstrum of the ECG (3;4). The Cepstrum of a signal $x(t)$ is the power spectrum of the logarithm of its power spectrum. Since the power spectrum of $x(t)$ can be expressed as the squared magnitude of the Fourier Transform, FT , of $x(t)$, i.e., $PSD(f) = |FT\{x(t)\}|^2$, similarly the power Cepstrum of $x(t)$ can be expressed as $CPS(t) = |FT\{\log(PSD(f))\}|^2$.

The cepstral analysis is useful to quantify how close the ECG spectrum resembles a sequence of equispaced peaks. In fact, after the calculation of the logarithm of the ECG spectrum, the sequence of peaks at multiples of f_{HR} Hz (the mean heart rate) appears smoothed and more similar to a damped oscillation with period f_{HR} Hz. If the log-spectrum is treated as a new signal, the role of the time variable t is played by the frequency variable f . The power spectrum of such a frequency-domain signal can be

estimated and will show a peak corresponding to the oscillation with period f_{HR} Hz. Since the signal is function of a frequency variable in Hertz, its spectrum (i.e., the power cepstrum), is function of a temporal variable, in seconds, called “quefreny”. Therefore, the sequence of equispaced peaks in the ECG spectrum will result in a main cepstral peak centred on the $1/f_{HR}$ quefreny. The proposed algorithm is based on these properties and is illustrated in figure 1.

The first step is to calculate the ECG power spectrum (FFT after Hann data windowing) over a running window of 10 seconds. The example of figure 1 (panel b, left) clearly shows the sequence of equispaced peaks characterizing the power spectra of ECG waveforms. The peak amplitude decrease starting from frequency higher than 20 Hz. Therefore cepstral analysis is performed only on the portion of the ECG spectrum where the peaks amplitude remains roughly constant, i.e., up to 20 Hz.

The second step is to calculate the log spectrum and to linearly detrend it. The sequence of log-transformed peaks appears as a damped oscillation (panels c, left). The spectrum is smoothed by a moving average of order 3 and data windowed (10% cosine-taper, panels d).

Finally the FFT spectrum is calculated obtaining the power cepstrum. In the example of figure 1 (panels e), the cepstrum is plotted between 0.05 and 3 seconds. The lower limit is defined by the length of the input signal, $PSD(f)$. Since the spectrum is limited to 20 Hz, cepstral components at quefrenies lower than $1/20=0.05$ s cannot be resolved. The cepstrum (panels e, left) shows a main peak occurring at 700 ms, corresponding to the mean R-R interval. When noise importantly affect the ECG signal (figure 1, panel a, right) the typical spectral pattern is lost (panel b, right) and no oscillations appear in the log spectrum (panels c and d, right). Consequently, also a dominant spectral peak in the physiological band of the mean R-R interval does not appear (panels e, right).

To quantify numerically the ECG signal quality, we defined a quality index, QI, as the ratio between the power of the main cepstral peak and the total cepstral power between 0.05 and 3 s. The main cepstral peak is identified as the highest peak in the physiological band where the mean R-R interval is expected to fall, i.e., between 0.25 and 2 s. Its power is calculated by integrating the cepstrum over a quefreny band centred on the maximum and ample ± 0.3 s. The QI index may range between 0 (lowest quality) and 1 (highest quality).

A test evaluates whether the maximum cepstral peak in the physiological band can be actually considered the genuine peak produced by the mean R-R interval. A threshold equal to the third percentile of the peak is calculated. If the cepstrum overcrosses this threshold one and only one time in the physiological band (0.25-2 s), then the peak is assumed to be the true peak associated to the mean R-R interval. If the test is not passed, the peak is discarded and QI is set at 0.

3. Applications on ECG data segments

To evaluate its performances, the algorithm has been applied on segments of ECG signals from different leads, with different heart rates and different signal-to-noise ratios.

Effects of mean heart rate. To evaluate whether the algorithm is sensitive to the mean heart rate, we compared two ECG segments recorded in young healthy volunteers during supine rest and during an incremental exercise test at the cycloergometer. ECG was derived from the II Einthoven lead sampled at 200 Hz. The two selected ECG segments were characterized by markedly different heart rates (160 bpm during exercise and 48 bpm at rest), nevertheless their signal quality appeared similarly high by visual inspection.

Results of cepstral analysis are shown in figure 2. Confirming visual analysis, the quality index was the same for the two recordings. In fact, both the cepstra were characterized by a main peak falling within the physiological quefreny band (0.25-2.0 s). The cepstral shapes, however, differed markedly because the main peaks fell at the two extremes of the physiological bands, reflecting the marked difference in the mean R-R interval.

Automatic selection of the best lead and identification of lead disconnection. The proposed method was also designed for automatically selecting the best lead for heart rate variability analysis in case of multi-lead recordings. To evaluate whether this goal can be achieved, we analysed a multilead ECG recording in a healthy volunteer during different activities, which included periods of supine rest and light physical exercise on an arm ergometer. The ECG was recorded by the Einthoven 3-lead system, and sampled at 200 Hz. The

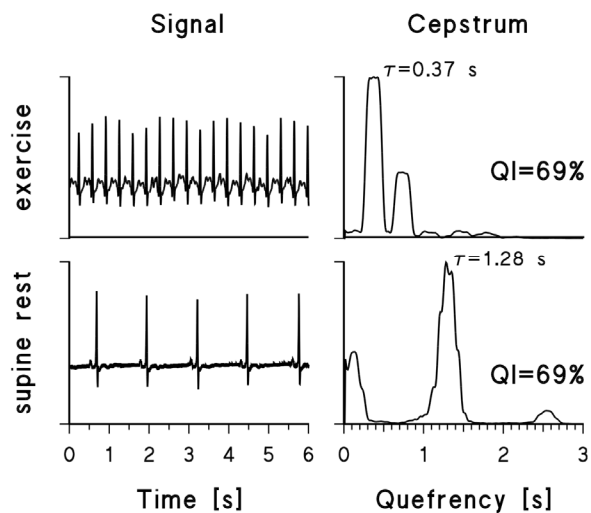


Figure 2. Application on ECG recorded in healthy volunteers during high load exercise (upper panel, heart rate around 160 bpm) and during supine rest (lower panels, heart rate around 48 bpm); τ is the *quefreny* of the main peak.

running assessment of QI indicated that during supine rest the signal with the best quality was recorded from lead I. However, during exercise lead I resulted to be more affected by the muscular noise produced by arms movements, and lead III became the lead with the best signal quality in terms of QI. This classification was confirmed by visual analysis of the original ECG data (figure 3).

Similarly, the method could also detect the disconnection of an ECG electrode. This event was in fact associated to the disappearance of the main cepstral peak for two of the three leads (figure 4).

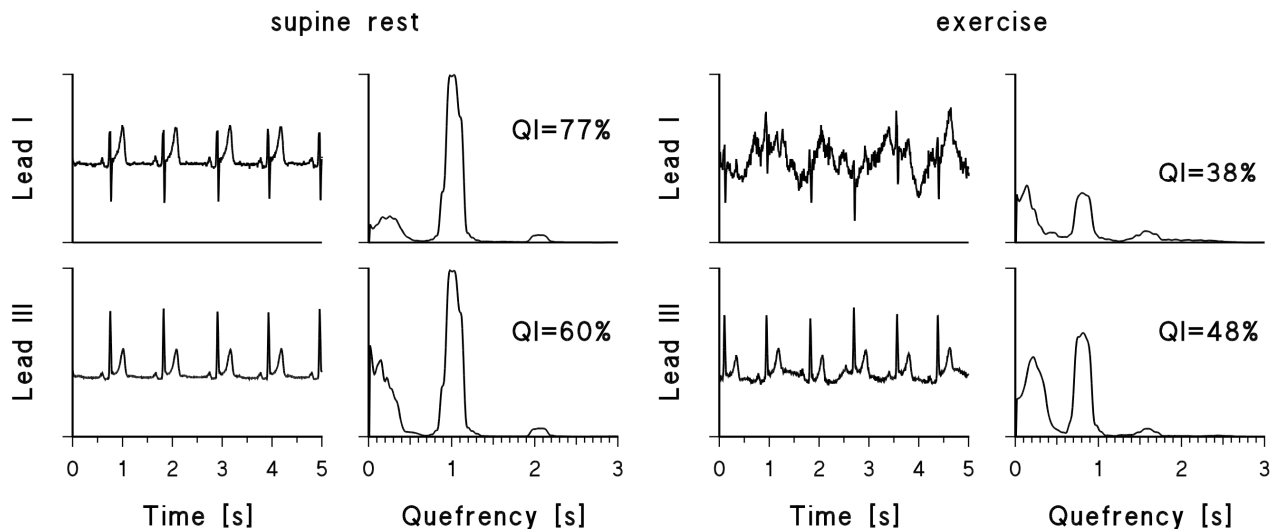


Figure 3. Identification of the ECG lead with best signal quality. Panels show ECG from I and III Einthoven leads and their cepstra in the same subject during supine rest and exercise. Lead I has the highest QI during supine rest but during exercise it is more prone to muscular noise than lead III, as quantified by the dramatic fall in QI.

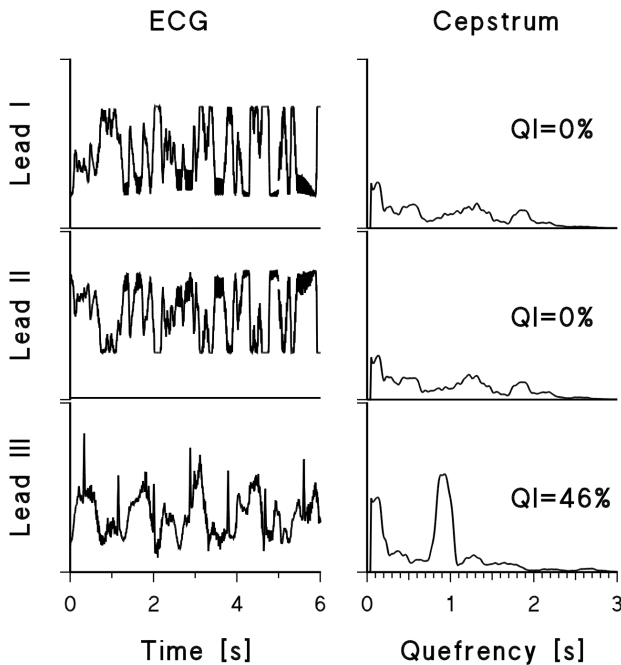


Figure 4. Effects of electrode disconnection on ECG cepstra from 3-lead Einthoven recording: the main cepstral peak associated to the mean R-R interval disappears in two of the three leads.

Application on polysomnographies. The method was also applied to automatically evaluate the quality of two ECG recordings in healthy subjects sleeping at night. Recordings were obtained with the wearable MagIC device (2) at sea-level (subject 1) and at 6800 m asl on a camp on Mt Everest (subject 2: see details in (5)).

The quality of the two recordings was scored visually by an expert operator who classified segments of 30 s of data as “acceptable” or “not acceptable” for HRV analysis. Then, the same classification was performed automatically by the algorithm over a running window of 10 s, by setting an acceptability threshold at $QI > 0.40$.

The algorithm classified of acceptable quality 99.8% (subject 1) and 60% (subject 2) of the tested signals. These percentages were similar to those obtained scoring the signal quality visually (100% and 67%).

4. Conclusions

The proposed algorithm is based on simple computing procedures which allow its implementation on small

electronic devices. This makes it possible the real-time assessment of ECG signal quality at the “sensor-level”, by the same recording devices.

Despite its computational simplicity, the method seems to provide scores of ECG signal quality reasonably similar to those provided by expert operators after visual classifications. The examples illustrated in this work support the use of the proposed method for automatically switching to the best lead in multi-lead applications in freely moving subjects, and for associating reliability scores to the information sent to higher computational levels in ambient intelligence systems.

Acknowledgements

The research was funded by the Provincia Autonoma of Trento, call for proposal Major Projects 2006 (project ACube).

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