Coherence-Based Measure of Instantaneous ECG Noise

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Abstract

This paper presents a coherence-based method for estimation of spatial or temporal variability of leads quality in a multichannel ECG record. The method is dedicated to stress test or Holter analyzers and aimed at providing an objective criterion for local assessment of data reliability (e.g. ST-segment elevation or depression) in presence of variable noise.

The procedure starts with heartbeat segmentation followed by Fast Fourier Transform to the frequency domain. Consequently, autospectra and cospectra for each pair of signals are determined and the resulted coherence function is normalized and weighted by the noise spectrum (NS). Finally, a triangular matrix summarizes the coherence power and the ECG sections (beats or channels) are sorted accordingly to the value of Noise Estimate.

With average accuracy of noise estimate of 11.23% for regular and of 3.0% for NS-weighted coherence, the method is accurate enough for beat-to-beat noise tracking and for a reliable selection of best channel in a multichannel ECG record.

1. Introduction

Wearable systems for ubiquitous heart monitoring offer unprecedented patients' mobility often at a price of signal quality. If these acquisition tools are combined with automated ECG interpretation software, the reliability of the final outcome may potentially be affected. A good example is detection of ST-segment elevation or depression in a context of dynamic physical load during walk. These trends justify the research not only for improved interpretive algorithms, but also for accurate tools for assessment of ECG signal quality. Development of such tools was also in focus of Physionet Challenge in year 2011 [1-7].

Careful studies of the reported results and own experience of the Author concerning the bandwidth variability of the cardiac components in the ECG spectrum [8-10] led to the idea of using the similarity of band gap spectra (i.e. sections not containing cardiac components) between simultaneous signals from different leads or between consecutive heart beats of the same type in the given lead to select leads of best quality and to assess temporal changes of signal quality.

2. Materials and methods

2.1. Coherence as a representation of consequent events

The coherence is a frequency-domain measure of linear dependence between signals, as a function of frequency. Applied to a spectrum of ECG signal, the coherence helps to assess the contribution of additive random noise when its spectral distribution is uneven and different to the ECG spectrum. The particular interest of using the coherence is motivated by known variability of bandwidth of cardiac components. Consequently, the content of two highest octaves (i.e. 1/8 to 1/2 of the sampling frequency) may be interpreted as 'signal', particularly in proximity of the R wave, or as 'noise' otherwise.

Having two sections of the ECG signal $a(t)$ and $b(t)$ of the same length and the corresponding complex instantaneous spectra $A(f)$ and $B(f)$ we start with calculating the cross spectrum $S_{AB}(f)$ and the autospectrum $S_{AB}(f)$ using the formulas:

$$S_{AB}(f) = A^{*}(f) \cdot B(f) \tag{1}$$

and

$$S_{AA}(f) = A^{*}(f) \cdot A(f) \tag{2}$$

where * denotes a complex conjugate function.

Since most physical signals including the ECG are real valued, the imaginary component is not present and the resulting complex spectrum is an even function (i.e. symmetric with respect to the y-axis), and therefore the one-sided form $G_{AB}(f)$ is commonly used:

$$G_{AB}(f) = 0\ for\ f < 0) \tag{3a}$$

$$G_{AB}(f) = S_{AB}(f)\ for\ f = 0 \quad (3b)$$

$$G_{AB}(f) = 2 \cdot S_{AB}(f)\ for\ f > 0 \quad (3c)$$

Similar representation is also applied for autospectra. The real part of $G_{AB}(f)$ is known as the 'coincident spectrum' (or 'cospectrum'), while the imaginary part is termed the 'quadrature spectrum'.

The coherence is calculated from two autospectra and the cross spectrum by the formula:

$$\gamma^2(f) = \frac{|G_{AB}(f)|^2}{G_{AA}(f) \cdot G_{BB}(f)} \quad (4)$$

The value of coherence at each particular frequency can be interpreted as a squared correlation coefficient (expressing the degree of linear relationship between two signals), the autospectra correspond to the variances of both signals and the cross spectrum represents their covariance [11]. Although in case of perfectly linear relationships (such as between ECG leads) the coherence is expected to equal to unity, in real signals there is some random spread due to the added noise (fig. 1).

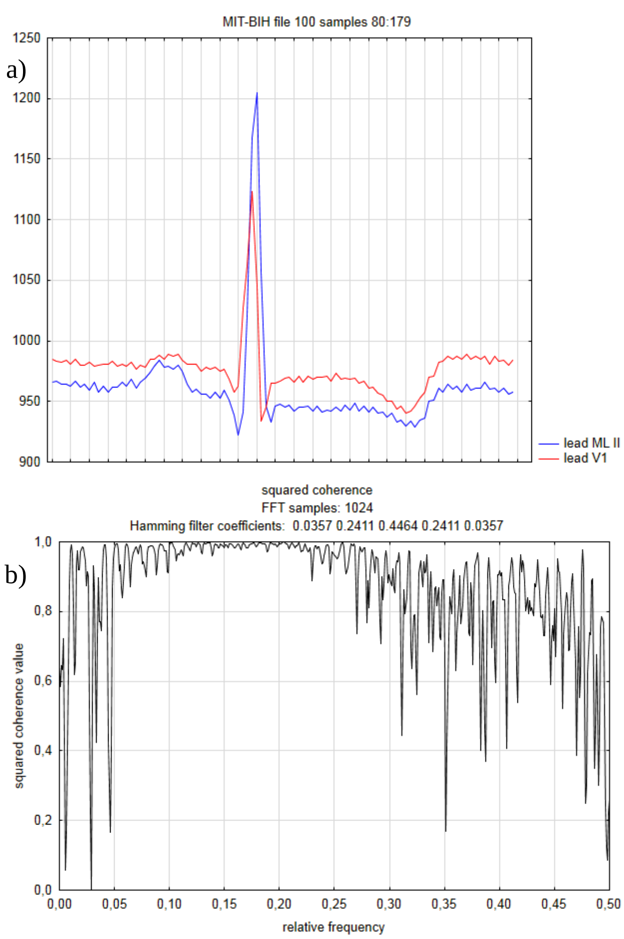

Fig. 1. Example of coherence between two ECG leads a) one beat from MIT-BIH database, b) coherence plot.

Therefore, assuming that the noise is the only factor influencing the coherence, the latter is used to estimate the signal quality. The Signal-to-Noise Ratio (SNR) may thus be expressed as a ratio of coherent to non-coherent power:

$$SNR = \frac{\gamma^2}{1-\gamma^2} \quad (5)$$

The use of frequency domain noise estimate is beneficial in case of signals with a bandwidth of predictable variability. In ECG the variance of frequency components may be interpreted as related to signal quality or as a sign of changes of diagnostic features (such as VLP). Our interpretation is based on a Standard ECG Bandwidth (SEB) allowing for separation of noise and possibly cardiac components in time-frequency plane with regard to R peaks and other fiducial points in ECG (fig. 2) [12]. Calculation of these points with use of any medical purpose-built procedure and fitting of the SEB function yields accurate estimation of the noise spectrum (NS) along with the coherence for any desired section of the signal.

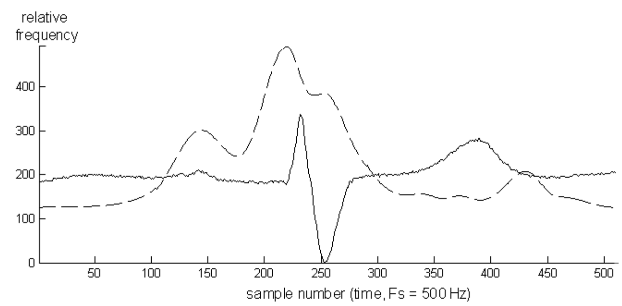

Fig. 2. An example ECG signal (solid line, CSE Ma001, lead I) and corresponding Standard ECG Bandwidth (dashed line) fitted to the positions of fiducial points.

2.2. Implementation details

In many practical applications the coherence is calculated with the Fast Fourier Transform (FFT) followed by multiplication or division of vectors of respective spectra. Such approach makes the coherence calculations very efficient in DSP-based systems.

The proposed procedure starts with heartbeat segmentation followed by the FFT to the frequency domain. The spectra were then filtered with a Hamming 5-tap filter to compensate for spectrum leakage and yield a smoother Power Spectral Density (PSD) function. Consequently, autospectra and cospectra for each pair of signals are determined and the resulted coherence function is normalized and optionally weighted by the NS. For the reason of assessment of the contribution from NS-based weighting, two variants of the algorithm were implemented. Finally, the triangular matrix summarizes the coherence power and the ECG sections (recorded simultaneously form leads) are sorted accordingly to the value of Noise Estimate. The scheme of lead quality ranking is presented in fig. 3.

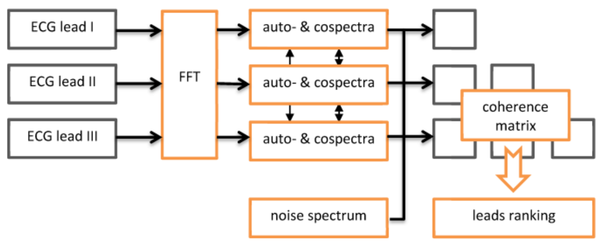

Fig. 3. Scheme of lead quality ranking procedure.

Besides the selection of the best (i.e. minimum noise) lead, the proposed procedure may also be used for tracking of changes of signal quality in a given lead. In this case the coherence of sections from the same lead corresponding to the subsequent heart beats is calculated and assessed.

3. Tests and results

3.1. Testing conditions

The proposed method was tested with the CSE Multilead Database [13] (12 bit, 500 Hz) and the artificially added muscular noise from the MIT-BIH Database (12 bit, 360 Hz) [19], resampled to 500 Hz and mixed with the signal at the level ranging from -30 dB to 0 dB RMS. The noise patterns were representative for muscle fibrillation (a clipping-free sections were selected).

Accordingly to the two purposes the procedure was designed to, we carried out two sets of experiments differing by noise mixing. In a channel selection test, the noise was increasingly added to different ECG channels of a multilead record and the proper channel ranking was assessed. In a noise tracking test the added noise was modulated with time and the proper value of noise level was checked at each heartbeat report.

In each test two variants of the algorithm were compared in order to assess the possible contribution of NS-based weighting. The NS was calculated separately using the record fiducial points provided in CSE Database. For this purpose, the signal section containing the ECG with added noise was transformed to time-frequency domain in order to separate the possible cardiac and noise components [8]. The inverse transform was made uniquely for the noise component, and then the FFT and subsequent Hamming filtering yield a smooth PSD of the noise in a specific section. This function was used to weighting of the coherence values in frequency domain.

3.2. Test results

The accuracy of noise estimate was assessed with two variants of algorithm differing by optional inclusion of NS-based weighting. The results for best channel selection scenario (i.e. coherence between simultaneous leads) are presented in table 1.

Table 1. Accuracy of the Noise Estimate (best channel selection scenario).

noise level	regular	NS-weighted
-30	-23.1	-28.1
-25	-21.8	-23.7
-20	-19.1	-20.8
-15	-14.0	-15.2
-10	-8.81	-10.2
-5	-4.33	-5.15
0	+0.71	-0.21

The results for tracking the changes of signal quality scenario (i.e. coherence between consecutive heart beats) are presented in table 2.

Table 2. Accuracy of the Noise Estimate (tracking the changes of signal quality scenario).

noise level	regular	NS-weighted
-30	-22.4	-24.8
-25	-20.8	-21.4
-20	-18.5	-19.1
-15	-14.7	-15.4
-10	-9.21	-9.23
-5	-4.74	-4.87
0	+0.33	-0.15

4. Discussion

With average accuracy of noise estimate of 11.2% for regular and of 3.0% for NS-weighted coherence the method is accurate enough for beat-to-beat noise tracking and reliable selection of best channel in a multichannel ECG record.

Although the a priori knowledge on the noise spectrum is not mandatory, it significantly improves the performance. In the range -20 to -10 dB, the accuracy of Noise Estimate is nearly 3 times higher due to NS weighting. For lower levels of added noise, main source of Noise Estimate inaccuracy is the presence of intrinsic noise in CSE Database records, however NS weighting still significantly improves the accuracy. For levels above -10dB, the added noise dominates other sources of incoherence and thus the Noise Estimate is accurate even without weighting. Shortening the length of time epoch decreases the accuracy of noise estimation, and thus the interval corresponding to one heartbeat seems to be reasonable in aspect of assessment of ECG data reliability.

Comparing the performance of the proposed method in best channel selection and tracking the changes of signal quality scenarios, we found that in the latter case the accuracy of Noise Estimate is lower. This can be explained by beat-to-beat variations of the ECG resulting in lower values of coherence even between pure signals. In this case NS weighting procedure helps in distinguishing between cardiac variations-related incoherence (suppressed by weighting) and contribution from noise.

For the test purpose it was assumed that CSE Database examples contain purely cardiac components. In fact real ECG recordings already contain the noise of various origins and adding artificial noise yields an inaccurate result. Since the measurement procedure considers both noise sources in a similar way, the resulting figure is not expected to exactly match the added noise level.

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