Adaptive Wavelet Discrimination of Muscular Noise in the ECG

P Augustyniak

AGH University of Science and Technology, Krakow, Poland

Abstract

The paper presents an adaptive time-frequency denoising algorithm. Main novelty is a running quasi-continuous scalo-temporal model of background activity built and subtracted from the ECG in order to yield a rectified representation of cardiac action.

Our algorithm is based on the P, QRS and T wave borders automatically detected in the ECG and uses the information on expected local signal bandwidth to determine time-frequency regions containing cardiac representation. The complement is assumed to contain only the background activity representation and thus these values can be picked-up directly to the time-scale model of noise.

The numerical tests performed with use of artificially noise-affected test signals reveal highly discriminative properties of the method. The amount of removed noise varies from 65% to 90% depending on input noise level.

1. Introduction

The ECG signal recorded in ambulatory or home care conditions is affected by the influence of extra-cardiac bioelectrical phenomena. These can hardly be avoided due to the variable recording conditions or due to the simultaneous activity of adjacent muscles. Noise removal techniques, being recently a hot topic of many research worldwide falls to one of the following categories: signal averaging [1], adaptive noise canceling [2] or wavelet-based noise reduction [3-6]. These techniques, however, assume particular conditions about noise stability and are not suitable for home care recordings when the broadband noise contribution varies in energy. The interest for an intelligent noise discrimination method grows with the common use of wearable devices for pervasive cardiac monitoring. The method is expected to yield a signal suitable for automated interpretation, even if the recorder is operated by untrained user in life-critical conditions.

The physiological background activity, despite its unavoidable character, shows a considerable extent of regularity that means also low variability of its statistical features. If the recording conditions are optimized for avoiding extracardiac cells stimulation, the Power Spectral Density and the temporal energy distribution of the noise may be considered as constant. These features, may be extrapolated from one time point to another and from one frequency band to another giving an impression of continuity, even if rarely or non uniformly sampled.

The documented electrical inactivity of the heart during the slow conduction of the stimulus in the Atrioventricular Node is a foundation of accurate measure of the noise level in the PR section of the ECG. This assumption is fairly fulfilled thanks to the central position of the AV Node close to the electrical center of the heart. In consequence, the baseline level is widely recognized reference point in the electrocardiogram. The RMS yields an accurate noise print, however it is accessible once per heartbeat only. Consequently, this approach has important limitations in a real application of ECG recordings:

- The baseline is short - (typically 60 ms) thus the measured noise spectrum starts at ca. 17 Hz.
- The baseline occurs once per heartbeat - thus the noise pattern is updated irregularly in long intervals.
- The baseline may not be present in rare cases such as: atrial flutter, fibrillation or premature R on T beats.

These limitations may be suppressed by a quasi-continuous noise model using maximum number of noise measurement samples beyond the baseline. The temporal distribution of diagnostic information in the discrete heartbeat representation and also the local ECG bandwidth are correlated with start- and endpoints of the P, QRS and T waves. This relationship, deduced from the physiological background of the electrocardiography, has been demonstrated with the use of statistical tools [2]. From the practical viewpoint, relying on these points is advantageous since their positions are computed by standard diagnostic software with the acceptable accuracy.

The time-frequency domain noise model is computed for each consecutive heartbeat with the use of individually detected wave borders and the general knowledge about the bandwidth of cardiac components expected locally. The noise model values in time-frequency are next subtracted from corresponding raw signal representation yielding a distilled ECG. This idea is the key point of our novel ECG-dedicated adaptive denoising algorithm.

2. Methods

The main assumption of our method is the extension of cardiac component-free region beyond the baseline borders. This extension is possible thanks to the uniform signal sampling and local variability of the cardiac component bandwidth. In order to correctly represent the high frequency QRS components and fulfill the sampling theorem, the sampling frequency is usually set to 500 or 1000 Hz. This value is much too high for other cardiac components occupying the majority of recording time. Knowing the expected cardiac component bandwidth one can use the gap above it to estimate the noise at least at high frequency on a scalo-temporal plane. Since the P, QRS and T waves are automatically determined with a high reliability, we found interesting to correlate the local bandwidth estimate with these waves, and not by the explicit time. As a result of long research, we found three possible sources of local bandwidth estimation in ECG:

- the study of physiological limitations, some processes (e.g. repolarization) could not be as fast as depolarization by their physiology described at a cellular membrane level,
- the analysis of database signals [7] with use of time-frequency decompositions such as wavelet transform,
- the analysis of expert perception of the ECG trace revealing local signal conspicuity and thus its relevance to the final diagnosis [8].

All these methods were found converging in their main results and the differences of the local bandwidth estimation methods are more subtle that the transform resolution. This is because the noise discrimination method uses a time-frequency domain arithmetic and consequently a reversible wavelet transform of a resolution limited by the uncertainty rule.

The heuristic function of local bandwidth expected at the time point n is expressed by a discrete function $f(n)$:

$$f : \forall n \in \{0,1,...N\} \rightarrow f(n) \in [0;0.5) \quad (1)$$

representing the local relative cut-off frequency. This function, using $k_1 ... k_5 \in \{0, 1, ...N\}$ as the representation of the standard positions of wave borders is projected to the local position of current heartbeat wave borders $h_1 ... h_5 \in \{0, 1, ...M\}$ for each point $i = 1...5$ (fig. 1):

$$\forall n \in [k_i, k_{i+1}], \forall m \in [h_i, h_{i+1}] \quad f'(m) = P^{S_i}(f(n)) \quad (2)$$

and the projection scale S_i varies from section to section:

$$S_i = \frac{h_{i+1} - h_i}{k_{i+1} - k_i} \quad (3)$$

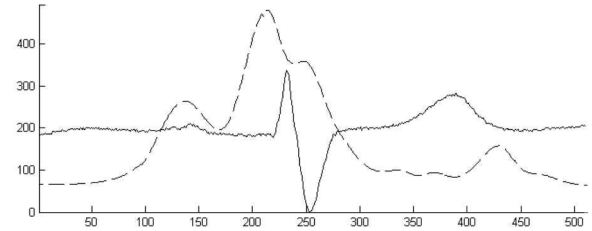

Figure 1. The example heartbeat (solid line) and the adapted bandwidth variability function (dashed line)

The time-frequency atoms of raw ECG representation are qualified as cardiac components only for scale j and time point m for which: $f'(m) > 2^{-j-1}$. Otherwise they are considered as extra-cardiac components (noise representation) and directly included in a basis of time-frequency noise model (fig. 2).

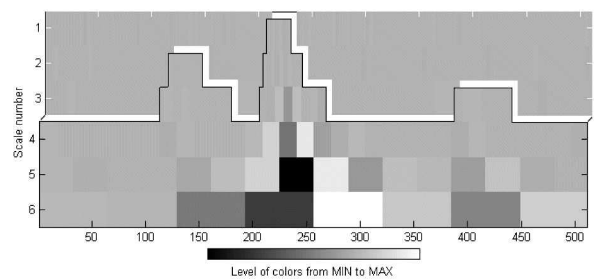

Figure 2. Splitting the time-frequency signal representation in the noise measurement region (above the local cut-off frequency) and the cardiac representation region (below).

In separate octaves N_j, $j \in \{1...3\}$, the noise measurement points are considered as non-uniformly sampled time series $N_j(\{n, v(n)\})$ and projected to the regular space [9] using the continuous function:

$$S_i(x) = a_i + b_i(x - x_i) + c_i(x - x_i)^2 + d_i(x - x_i) \quad (4)$$

$x \in [x_i, x_{i+1}]$, $i \in \{0, 1, ...n\text{-}1\}$ best fitted to the time series N_j, known as cubic splines interpolation.

The uniform representation of the noise, extended to the cardiac component area, is then obtained by sampling the $S_i(x)$ at the time points m (fig. 3):

$$N'_j(m) = \sum_m S_i(x) \cdot \delta(x - mT) \quad (5)$$

As the scale number increases, the contribution of cardiac representation groves and below 32 Hz ($j > 3$), the reliable measurement of noise is never possible since the, bandwidth is entirely occupied by the representation of cardiac activity. Therefore a noise extrapolation based on the first three scales coefficients is used to estimate the noise print in lower frequencies. This extrapolation uses the second-order polynomials:

$$N'(k,j) = a_{k,j} \cdot j^2 + b_{k,j} \cdot j + c_{k,j} \qquad (6)$$

generated by all atoms of embedded trees originating from the considered coefficient. Therefore, the estimation of the noise level at a given time point k on the scale j is based on three average values $M_j(k, i)$ of all corresponding atoms $s(n, i)$ on each of the first three scales (fig. 4):

$$M_j(k,i) = \frac{1}{2^{j-i}} \sum_{n=2^{j-i}k}^{2^{j-i}(k+1)-1} s(n,i) \qquad (7)$$

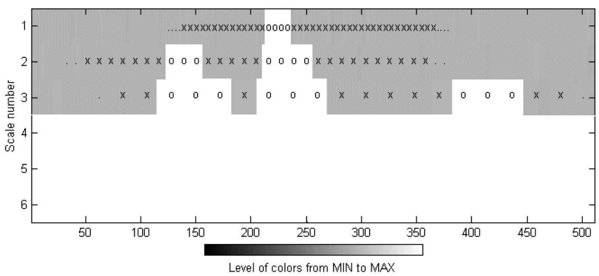

Figure 3. Distribution of noise measurement and interpolation samples on each scale. The missing values 'o' are estimated from the previous and subsequent measured values 'x'.

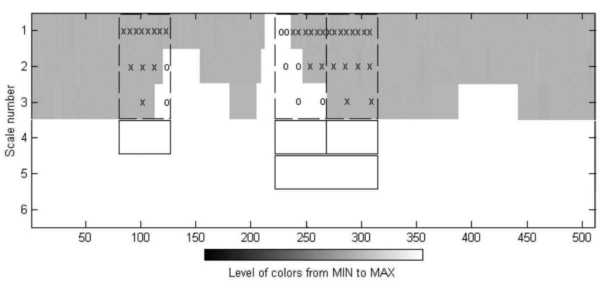

Figure 4. Extrapolation of noise values to low frequency bands with averaging of the noise print in the time domain

The time-frequency ECG background activity model contains partially measured and partially computed atoms of noise N' matching exactly the time-frequency plane of the raw signal. In respect of noise discrimination, it is interesting to continue the processing in the time-frequency domain instead of recovering the time-domain noise pattern. The values of time-frequency atoms in the noise model $N'(j, m)$ are subtracted from the values of the corresponding atoms in the representation of the raw signal $R(j, m)$:

$$D(j,m) = R(j,m) - N'(j,m) \qquad (8)$$

This operation yields a modified time-frequency plane representing the distilled cardiac signal $D(j, m)$. This plane is then fed to the inverse wavelet transform, which produces the time-domain ECG signal with discriminated noise.

3. Results

The ECG-dedicated adaptive wavelet discrimination of muscular noise was tested for the efficiency against CSE Multilead Database signals accompanied by reference segmentation points and against mathematically synthesized artificial signals. Three noise patterns:

- poor electrode contact (abrupt baseline changes),
- electromagnetic interference (sinus wave, 60 Hz),
- muscle fibrillation (high frequency noise)

were re-sampled from the MIT-BIH Noise Stress Database (12 bit, 360 Hz) [10], normalized to four test levels 50%, 20%, 10% and 5% (corresponding to -3dB, -7dB, -10dB and -13 dB SNR) and mixed with the original ECG.

The measure of noise discrimination efficiency was the PRD ratio representing how far the noise-contaminated and distilled signal is close to the original. The CSE-originated signals could not be considered as noise-free and because the tested algorithm discriminates equally the intrinsic and mixed noise, the distilled version was not expected to converge to the original. Therefore the CSE signals were used for testing the model adaptivity to local ECG changes (tab.1), while tests with artificial signals provide a proper estimate of noise discrimination efficiency (tab. 2).

Table 1. The average difference of denoised and original database signals for most frequent patterns of continuous noise.

noise pattern	PRD [%]			
	50	20	10	5
poor electrode contact	47	13	4.7	2.7
electromagnetic interference	17	4.3	1.3	0.95
muscle fibrillation	14	2.3	1.0	0.85

Table 2. The average difference of denoised and original synthesized signals for most frequent patterns of continuous noise.

noise pattern	PRD [%]			
	50	20	10	5
poor electrode contact	46	11	4.3	2.1
electromagnetic interference	17	4.3	1.3	0.95
muscle fibrillation	10	1.4	0.71	0.33

The dynamics of noise model adaptation was also tested with use of modulated noise. Two modulations were used:

- sine modulation simulating the muscular activity (fig 5, tab. 3),
- square modulation simulating a sudden occurrence of noise (fig. 6, tab. 4).

In order to avoid any correlation with the ECG, the modulating function uses frequency constantly increasing in a range from 1 to 10 Hz.

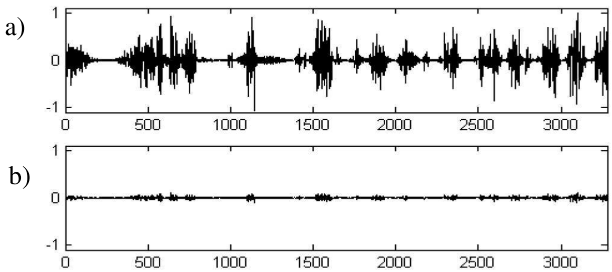

Figure 5. Result of the denoising test with the use of sinus-modulated noise (a) added noise pattern, (b) remaining noise.

Table 3. The average difference of denoised and original synthesized signals for patterns of sinus-modulated noise.

noise pattern	PRD [%]			
	50	20	10	5
poor electrode contact	47	13	4.5	2.4
electromagnetic interference	17	4.4	1.4	1.1
muscle fibrillation	11	1.6	0.78	0.37

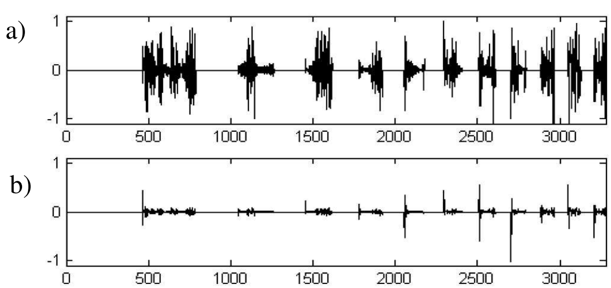

Figure 6. Result of the denoising test with the use of square-modulated noise (a) added noise pattern, (b) remaining noise.

Table 4. The average difference of denoised and original synthesized signals for patterns of square-modulated noise

noise pattern	PRD [%]			
	50	20	10	5
poor electrode contact	47	16	5.7	3.9
electromagnetic interference	23	9.1	4.4	1.9
muscle fibrillation	19	4.7	2.1	1.2

4. Discussion and conclusions

A new ECG-dedicated method for noise modeling and discrimination was developed and tested. The noise discrimination efficiency for static and sinus-modulated signals were 11.6 dB and 11.1 dB respectively and falls to 6.5 dB due to the inaccuracy of model adaptation when a noise step occurs in a section where the full bandwidth is used by cardiac components. The time-frequency noise model is quasi-continuous and adapts to the physiological changes of muscular activity. The use of the standard bandwidth function allows the user to define his or her own profile of interest and even to adapt the method to other signals of variable information density.

Acknowledgements

Scientific work supported by the Polish State Committee for Scientific Research resources in years 2004-2007 as a research project No. 3 T11E 00127.

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Address for correspondence

Piotr Augustyniak
30, Mickiewicza Ave. 30-059 Krakow Poland
august@agh.edu.pl