SEPARATING CARDIAC AND MUSCULAR ECG COMPONENTS USING ADAPTIVE MODELLING IN TIME-FREQUENCY DOMAIN

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The paper presents an adaptive time-frequency denoising algorithm. Other denoising methods use a very general probability-based noise model and as general-purpose algorithms rarely consider the a priori knowledge about the signal. Main novelty of the proposed algorithm is the 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 adapts the general information on expected local signal bandwidth to each particular heartbeat. This leads 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. For the remaining part of scalo-temporal surface the noise is interpolated with cubic splines in each scale independently and than extrapolated to lower scales. 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% (SNR increased by 6.5 dB and 11.6 dB respectively) depending on input noise level. The time-frequency noise model is quasi-continuous and adapts to the physiological changes of muscular activity using maximum available real data points. The use of the standard bandwidth function is arbitrary for the ECG, but allows the user to adapt the method to other signals of variable information density.

INTRODUCTION

The ECG signal recorded in unstable conditions (e.g. ambulatory or home care) suffers from the influence of extra-cardiac bioelectrical phenomena. Due to the simultaneous activity of adjacent muscles this influence can hardly be avoided with use of technical measures. Classical noise removal techniques assume noise stability and since in home care recordings the broadband noise contribution varies in energy, this requirement is not fulfilled. Particular interest for an intelligent noise discrimination method comes from the common use of wearable devices and telemedicine. In these applications, the recorder is expected to yield a signal suitable for automated interpretation, even if operated by untrained user.

The documented electrical inactivity of the heart during the slow conduction of the stimulus in the Atrioventricular Node is a foundation of commonly performed measurement of the noise level in the PR section of the ECG [1]. 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. Unfortunately, this approach has important limitations in a real application of ECG recordings: short duration of the baseline limiting the bandwidth, and rare, irregular occurrence of the baseline.

The background activity, despite its unavoidable character, is limited by the rules of electrophysiology and thus predictable to a considerable extent. Main idea of our proposal is to divide the cardiac-originated components and the background electrophysiological signs in a time-frequency plane. The domain allows setting maximum number of noise measurement points and only few gaps has to be filled with use of interpolation or extrapolation in order to obtain a quasi-continuous noise model. Finally, the noise model is subtracted from the original signal yielding rectified ECG record. Such approach considers local variability of background activity, variability of the heart rate and favorites the measured noise information over the estimates.

MATERIALS AND METHODS

Local bandwidth of the ECG

The typical sampling frequency of 500 or 1000Hz corresponds to relatively short QRS complex and is much too high for other cardiac components occupying the majority of recording time. The gap above the expected cardiac component bandwidth and the Nyquist frequency is used to measure the noise level at high frequency on a scalo-temporal plane. Because of different nature of particular components of heart evolution (the P, QRS and T waves), we found interesting to correlate the local bandwidth estimate with these waves, and not by the explicit time. Fortunately, the waves can be determined automatically with acceptable reliability by the software.

Local bandwidth of the ECG was estimated by the analysis of expert perception of the ECG trace revealing local signal conspicuity and thus its relevance to the final diagnosis [2], however our research show other approaches converging to similar results. The heuristic function of local bandwidth expected at the time point n is expressed by a discrete function $f(n)$:

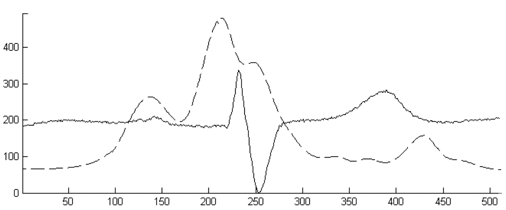
$$f : \forall n \in \{0,1,\ldots N\} \rightarrow f(n) \in [0; 0.5)$$

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

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

with projection scale S_i varying from section to section:

$$S_i = \frac{h_{i+1} - h_i}{k_{i+1} - k_i}$$



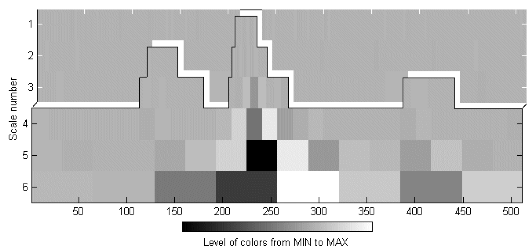


Figure 1 a) The example heartbeat (solid) and the adapted bandwidth variability function (dashed). b) Corresponding time-frequency signal representation divided in the noise measurement region (above the local cut-off frequency) and the cardiac representation region (below).

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

Towards the noise model continuity

In separate octaves N_j, $j \in \{1...3\}$, noise measurement points are considered as non-uniformly sampled time series $N_j(\{n, v(n)\})$ and projected to the regular space [3] using the continuous function: $x \in [x_i, x_{i+1}]$, $i \in \{0, 1,....n\text{-}1\}$ 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. 2a):

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 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. 2b):

Discrimination of modeled noise in the ECG

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 $R(j, m)$:

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

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.

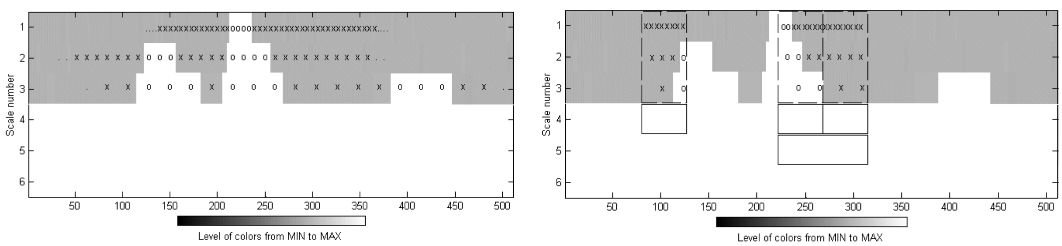


Figure 2. (a) Distribution of noise measurement and interpolation samples in first three scales. (b) Extrapolation of noise values to low frequency bands with averaging of the noise print in the time domain. Missing values 'o' are estimated from adjacent measured values 'x'.

RESULTS

The ECG-dedicated adaptive wavelet discrimination of muscular noise was tested with CSE Multilead Database signals accompanied by reference segmentation points and with and with synthesized noise-free ECG. Both kinds of signals were mixed with MIT-BIH Noise Stress Database (resampled from 360 Hz), normalized to four test levels 50%, 20%, 10% and 5% (corresponding to -3dB, -7dB, -10dB and -13 dB SNR) and with mathematically synthesized noise representing three patterns:

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

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 tests with artificial signals provide a proper estimate of noise discrimination efficiency (tab. 1).

The dynamics of noise model adaptation was also tested with use of sinus-modulated noise. In order to avoid any correlation with the ECG, the modulating function uses frequency constantly increasing in a range from 1 to 10 Hz.

Table 1. The average difference of denoised and original synthesized signals for patterns of static and sinus-modulated noise.

noise pattern	PRD [%]							
	static noise				modulated noise			
	50	20	10	5	50	20	10	5
poor electrode contact	46	11	4.3	2.1	47	13	4.5	2.4
electromagnetic interference	17	4.3	1.3	0.95	17	4.4	1.4	1.1
muscle fibrillation	10	1.4	0.71	0.33	11	1.6	0.78	0.37

DISCUSSION

A new ECG-dedicated method for noise modeling and discrimination was developed and tested. The noise discrimination efficiency for static and sinus-modulated signals was 11.6 dB and 11.1 dB respectively. The time-frequency noise model is quasi-continuous and adapts to the physiological changes of muscular activity.

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