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Technical Note

Algorithm for EMG noise level approximation in ECG signals

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ABSTRACT

In this paper, we introduce an approach for Electromyogram (EMG) noise level approximation in Electrocardiogram (ECG) signals. The stationary wavelet transform (SWT) is used to find efficient translation-invariant approximation of EMG noise. This is accomplished in the form of reference signal extracted as an estimation of the signal quality vs. EMG noise. The reference signal is built and then normalized after considering different heart rates and rhythms which increases its robustness and reliability to give accurate results regardless of input signal rhythm. Additionally, four applications of the extracted reference signal are suggested in this paper.

For evaluation purposes both real EMG and artificial noises were used. The tested ECG signals are from MIT-BIH Arrhythmia Database Directory. The correlation coefficient between the added noise and the reference signal were computed for moving windows over the signal. Finally, the correlation between beats detection and reference signal was computed and presented. Reference signal gave high correlation with false positive values. Most false positives caused by EMG noise occur in intervals of greater amplitude reference signal and vice versa.

1. Introduction

The ECG contains very distinctive features which are essential for detection and interpretation of heart arrhythmias. However, automatic identification of these features is not a tractable problem, because of the presence of diverse non-cardiac contaminants that affect the ECG signal during acquisition process. These artifacts and noises are the main causes of imprecise delineation, and later classification of heartbeats which lead to false alarms and misleading analysis. Therefore, signal quality estimation and enhancement provide better detection and classification of heartbeats. Consequently, they reduce the number of false alarms found by analysis algorithms enabling more efficient analysis, especially for long term holter signals and for fetal ECG signals.

The main sources of contaminates are patient's electrodes motion artifacts, power line interference, baseline wander, and EMG noise caused by muscle tremors on the chest wall. Unlike power line interference and baseline drift, the EMG noise and patient-electrode motion artifacts are difficult to detect and eliminate using linear filtering, because of the non-stationary nature of these noises and the big overlaps on whole frequency bands of ECG and EMG signals [1–4].

2. Related work

Several methods for ECG signal quality estimation are presented in literature. Some of them are designed to work for all types of noises, while others are designed specifically for EMG noise detection and estimation. An automated algorithm for detecting EMG noise in large ECG data, based on the moving variance in the signal after suppressing of detected QRS complexes, is presented in [5].

Another method was introduced in [6] where authors present a residue-filtered method based on the averaging of successive aligned beats. They consider the difference be-tween the averaged beat and other beats the criteria of SNR, estimated from the ECG signal.

"Karhunen-Loeve" Transform (KLT) for ECG is one of the most robust methods for signal morphological representation and noise estimation [7]. Using a five term KL expansion of a 200 millisecond interval, which includes the QRS complex and part of the ST segment; authors represent morphology on ECG signal. The residual error of the representation is considered an estimate of the instantaneous noise content of the signal.

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This method and the residue filter method require finding the average beat. This depends greatly on the QRS complex delineation process, which is affected by noise amount and by beats morphology in the signal. Noise and different beats morphology (e.g. multiform PVC's MIT-BIH signals of 105 and 207) have a negative impact on the average beat reliability and its representative nature of other beats in the signal.

Authors in [8] introduced the ratio of T-P interval average power to QRS average power as a signal quality measure for each beat in the ECG signal. They propose this measure to select the best channel for detailed analysis. However, this method depends on the correct delineation of P and T waves and its results could be misleading when P and T waves are not detected precisely.

Kurtosis based quality measure was presented in [9] assuming that ECG signals are hyper-Gaussian. Therefore, Gaussianity of the signal amplitude distribution is computed and used, later, as quality estimation. Whereby, higher kurtosis values are associated with lower quality in the ECG signal and vice versa.

Two other methods were also proposed in [9]. First method uses *LMS* adaptive filtering. This method relies significantly on the reference signal used for filtering. The second method is temporal dispersion, which measures the dispersion of signal amplitude in intervals centered in *R* peaks.

Combination of the frequency content and signal amplitude was proposed in [19] to assess the ECG signal quality. Signal energy was computed in six different bandwidths (0.05–0.25, 0.25–10, 10–20, 20–48, 48–52, and 52–100 Hz), and on counting of the number of occurrences the signal exceeds a predefined threshold (out-of-range events).

In this paper, a new approach for EMG noise level approximation in the ECG signal is presented. The approximation of EMG noise is presented as a reference signal that indicates the signal quality vs. EMG noise in translation-invariance fashion.

3. Method

In order to illustrate our approach a flow diagram is presented in Fig. 1. The first block in the flow diagram is the Stationary Wavelet Transform (SWT), which is applied on the ECG signal to find the signal details. Afterwards, the most likely QRS complexes are detected using multi-resolutional analysis (MRA). The corresponding zero-crossings, peaks and valleys of QRS complexes are excluded from any later computation. Then, the remaining zero-crossings, peaks and valleys in the wavelet details at scale 2^2 are used to build the array of zero-crossing, peaks, and valleys A_{zpv}. This is illustrated in Fig. 2. Next step is to smooth the formed array A_{zpv}. The resulted signal after smoothing is considered as non-normalized approximation of EMG noise. Finally, two thresholds $\sigma 1$ and $\sigma 2$ are used in the normalization of the resulted smooth signal. The thresholds were found after the analysis of several recordings with different cardiac activities which helps to globalize this method for all ECG signals.

3.1. Wavelet transform of ECG signal

In order to capture time-scale variations of the ECG signal, wavelet transform (WT) is used. The WT of signal $x(t)$ is defined as

$$W_a x(b) \frac{}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\psi(\frac{t-b}{a})dt, \quad a > 0, \tag{1}$$

where $\psi(t)$ is the mother wavelet, a is positive and defines the scale, and b defines the shift and could be any real number. Mallat in [11] shows that in case the mother wavelet is derivative of a smoothing function $\theta(t)$, the wavelet transform equation could be written as

$$W_a x(b) - a(\frac{d}{db}) \int_{-\infty}^{+\infty} x(t)\theta(t-b)dt \tag{2}$$

We can conclude from (2) that zero-crossings (when $W_a x(b) = 0$) correspond to the inflection points of $x(t)\theta(t-b)$. So, they indicate the location of signal sharp variation points at each scale a [10]. Therefore, finding these points in the details of wavelet transform is equivalent to finding sharp changes in the ECG signal which is our ultimate goal, since sharp changes are most likely originated by noise. The noisy signal could be written as

$$x(t) = x'(t) + n(t), \tag{3}$$

where $x'(t)$ stands for the clean signal, and $n(t)$ stands for the EMG and other high-frequency noises. Replacing (3) in (2) allows us to rewrite Eq. (2) as

$$\begin{aligned} W_a x(b) - a(\frac{d}{db}) \int_{+\infty}^{-\infty} x'(t)\theta(t-b)dt \\ -a(\frac{d}{db}) \int_{+\infty}^{-\infty} n(t)\theta(t-b)dt. \end{aligned} \tag{4}$$

Two unknown variables are in (4), the wavelet coefficients of the clean signal $x(t)$ and wavelet coefficients of noise $n(t)$. Thus, estimating the coefficients of signal directly means to estimate the noise coefficients. We will be dealing with this in details in our study.

In our method we use the quadratic Spline wave proposed by Mallat in [11]. As the Spline wave is an anti-symmetric wavelet, the points of maximum slopes of amplitude variations in the ECG signal will correspond to local minima and maxima in the WT details, while the ECG signal local minima and maxima will be associated with zero-crossings at different scales [10,11]. To overcome the lack of translation-invariance of discrete version of wavelet transform (DWT), we use stationary wavelet transform (SWT) which allows us to perform a time-invariant multi-resolutional analysis using the "algorithme à trous" approach [12].

3.2. Extraction of zero-crossings, peaks, and valleys

From the spectrum of ECG signal waves with the EMG noise introduced in [2] and frequency responses of Spline wavelet decomposition filters introduced in [11,12], it is clear that scale 2^2 of SWT contains most of high-frequency components of QRS complexes, as well as EMG noise [10,11,13].

Having in mind what zero-crossings represent in SWT details, we can say that finding zero-crossings in this scale is equivalent to finding sharp changes corresponding to waves with high frequencies in the ECG signal. However, zero crossings in wavelet details give only position information but do not differentiate small amplitude fluctuations from important discontinuities [10,11,14]. Thus, we suggest the use of local minima/maxima in the wavelet details in addition to zero-crossings. This provides sufficient representation of the corresponding signal changes, originated by both heart electrical activity and by EMG and high-frequency contaminants.

Since our main goal is to extract the EMG noise only, multi-resolutional analysis is used to find and exclude from zero crossings, and local minima/maxima points that are most likely corresponding to QRS complexes. The residual signal is then considered as rough estimation of non-signal containments coefficients in the wavelet details.