ECG NOISE SUPPRESSION USING MORPHOLOGICAL OPERATORS AND ADAPTIVE ALPHA-TRIMMED MEAN FILTERING

V. Palodeto and J. L. B. Marques

Federal University of Santa Catarina/Electrical Engineering Department, Biomedical Engineering Institute, Florianópolis, Brazil

viviane@ieb.ufsc.br, jmarques@ieb.ufsc.br

Abstract: Electrocardiogram signals (ECG) are corrupted by many artefacts. Noise suppression is an important step for computational ECG analysis. To enable the clinical diagnosis, the processed signal must preserve the waves characteristics (morphology, amplitude and duration). This paper presents a hybrid approach to remove baseline drift and impulsive noise of the ECG using morphological operators and adaptive alpha-trimmed mean filter. Baseline line removal is performed by morphological operators and impulsive noise suppression is carried out by adaptive alpha-trimmed mean filtering. The algorithm developed is compared with other approaches which use morphological operators for noise suppression of ECG signals. Obtained results are satisfactory even when the signal is corrupted by a high noise level. Waves morphology is preserved after the filter processing.

Introduction

Electrocardiographic signals (ECG) are corrupted by many artefacts, mainly impulsive noise (caused by muscle activities and power line interference) and baseline drift (due to respiration and motion of the subject) [1].

Noise suppression is generally the first step performed in the signal processing of the ECG [2]. Artefact removal aims to produce a stable signal not only for subsequent automatic processing, but also for reliable visual interpretation [1]. Preserving the ECG waves characteristics (e.g. morphology, amplitude and duration) is important for clinical diagnosis.

A widely used approach for noise suppression is digital filtering [3], which is ineffective for reducing impulsive noise [1].

Alternatives to conventional linear processing are nonlinear operators such as median filtering and morphological operators [1].

Morphological operators have been used in the field of image processing and are known for their robust performance in preserving the characteristics of signal while suppressing the noise [4]. In [1, 5] is discussed a nonlinear filtering approach for noise suppression using morphological operators. However, this approach reduces the QRS complex amplitude.

The alpha-trimmed mean filters are nonlinear operators, which are used for the restoration of corrupted images and signals [6]. They are a good compromise between the median filter and the moving average filter, which are known to be the best for shorttailed noise types. The most significant feature of an alpha-trimmed mean filter is its robustness against impulses generated by an impulsive noise source [6].

In this work, we present a hybrid approach, designed by OMATF, for removing baseline drift and impulsive noise using morphological operators and adaptive alpha-trimmed mean filtering.

Materials and Methods

Mathematical Morphology, which is based on a set of operations, is mostly applied in image processing. However, it has been used in background normalization and noise suppression of biological signals, such as ECG [1, 5].

Morphological operators provide a nonlinear signal processing approach based on minimum and maximum operations [7]. There are two basic morphological operators: erosion and dilation. Erosion acts as a shrinking operator while dilation acts as an expansion operator.

Let f and k two discrete functions defined on F={0,1,...,N-1} and K={0,1,...,M-1}, respectively f:F→I and k:K→I, where I denotes the integers set.

The erosion of a function f by the structuring element k is denoted by $f \ominus k$ and it is defined as (1) [1]:

$$(f \ominus k) = \min_{n=0,..,M-1} f(m+n) - k(n) \quad \text{for } m=0,..., N-M \tag{1}$$

The dilation operation of f by k, $(f \oplus k)$, is defined as (2) [1]:

$$(f \oplus k) = \max_{n=m-M+1,...,m} f(n) + k(m-n) \quad \text{for } m=M-1,....N-1 \tag{2}$$

These operators usually are applied in tandem. Opening and closing are two derived operations defined in terms of erosion and dilation. Opening of a signal by a structuring element is defined as erosion followed by dilation. Closing of a data sequence is defined as dilation followed by erosion. Opening operation removes peaks from a signal. While, closing operation removes pits from a signal.

ISSN: 1727-1983

The length of the structuring element depends of the signal characteristics that must be preserved. Since the opening and closing operations are intended to remove peaks and pits, the structuring element must be designed such that ECG waves are not removed by these processes.

Considering that the duration of a wave as T sec., and the sampling rate as S Hz, the wave duration corresponds to TxS samples. So, in order to maintain this wave during the process the length of the structuring element must be less than TxS.

Alpha-Trimmed mean filters are widely used for restoration of signals and images corrupted by impulsive noise components [6].

Let {x(i),x(i-1),...,x(i-n+1)}, where n=2N+1 be a set of n sample signal values observed in a window, W_i. These values are arranged in ascending order (3),

$$x_{(1)}(i) \leq x_{(2)}(i) \leq \ldots \leq x_{(n)}(i) \tag{3}$$

such as $x_{(1)}(i)$ is the minimum, $x_{(n)}(i)$ is the maximum, and $x_{(N+1)}(i)$ is the median of the above set of signal values. The output of the alpha-trimmed mean filter, $y(i;\alpha)$ is (4) [6]:

$$y_n(i;\alpha) = \frac{1}{n-2(\alpha n)} \cdot \sum_{j=(\alpha n)+1}^{n-(\alpha n)} x_{(j)}(i) \tag{4}$$

Hence, the alpha-trimmed mean filter performs like a moving average filter when α value is close to 0, and like a median filter when α is close to 0.5.

The main design problem of the alpha-trimmed mean filter is to select the better value of α for a given noise type. However, this selection may not be possible when the noise is not known or varies with time [6]. For these cases, has to be developed an adaptive filter that changes the α value according to some characteristics of the signal.

The proposed approach uses two steps to process the ECG signal: 1-) removal baseline drift and 2-) impulsive noise suppression. Figure 1 illustrates a block diagram of this approach.

The structuring element used, which is symmetric and parameterized, was created as describes in (5), (6) [1]. Considering a structuring element k of length 2N, for n=0,1,...,N:

$$k(n) = h \times \left(1 - e^{-\alpha n}\right) \tag{5}$$

and for n= N+1,...,2N:

$$k(n) = k(2N - n) \tag{6}$$

Impulsive noise suppression is performed by adaptive alpha-trimmed mean filters. The α values are defined based on signal information. The adaptive process used is described as follow (7):

$$y(i) = \begin{cases} m(\alpha_1) & : \text{if } H(i) \leq \tau_1 \text{ or } H(i) \geq \tau_2 \\ m(0) & : \text{otherwise} \end{cases} \tag{7}$$

where m is the alpha-trimmed mean filter, H(i) is information about sample i, which is defined in the equation (8), α_1 and α_2 are the alpha value applied, and τ_1 and τ_2 are thresholds fixed according to the characteristics of the signal.

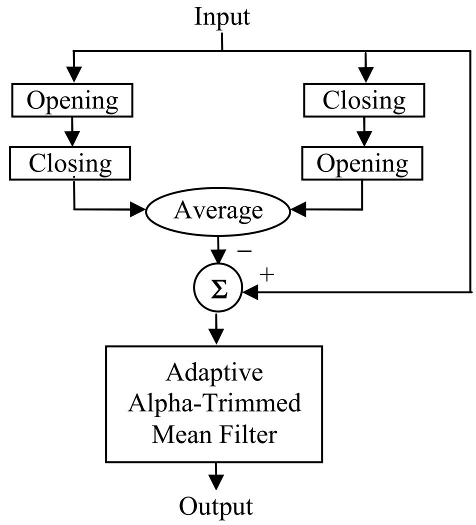

Figure 1: Block diagram of the algorithm. In the first step, after the opening and closing operations, the baseline is obtained. The baseline drift is subtracted from the input. After, the alpha-trimmed mean filtering is applied for impulsive noise suppression.

When the onset of a QRS peak is detected, the α value used is α_1 (7), such as the alpha-trimmed filter considers few samples near of the sample i. Otherwise, the alpha-trimmed filter performs like a moving-average filter.

QRS peaks detection was adapted from an algorithm described in [8]. The first derivative is calculated for each signal point using the formula (8):

$$H(i) = X(i+1) - X(i-1) \tag{8}$$

The thresholds τ_1 and τ_2 (7) are defined, respectively as a fraction of the minimum and maximum values of the derivative array.

To analyze the algorithm performance for noise suppression were realized experiments divided in two classes. A first series of experiments were performed using a simulated ECG signal added to impulsive noise and baseline drift. The simulated signal (noise-free) is modelled as described in [9]. This model has a software version implemented in MATLAB, named ECGSYN, which is freely available in [10]. Impulsive noise and baseline drift were modelled using the equations (9), (10), as described in [1].

The impulsive noise is described as a mixture of Gaussian noise that has the following probability distribution function (9):

$$P_i(y) = (1-\varepsilon) \cdot \phi\left(\frac{y}{\sigma_1}\right) + \varepsilon \cdot \phi\left(\frac{y}{\sigma_2}\right) \tag{9}$$

 ISSN: 1727-1983

where $\phi(y)$ is the probability distribution function of a Gaussian random variable with zero mean and unit variance.

The baseline drift was modelled as (10) [1]:

$$b(n) = B + m \cdot n + A \cdot \cos\left(2\pi.\frac{n}{N} + \phi\right) \tag{10}$$

where B is a bias value, N controls the severity of the baseline roll and m controls the degree of upward or downward drift.

These artefacts were added to the simulated signal as follows (11):

$$r(n) = s(n) + i(n) + b(n) \tag{11}$$

where r(n) is the noisy signal, s(n) is the noise-free simulated ECG, i(n) is the impulsive noise component, and b(n) is the baseline drift [1].

Two metrics were applied to measure the algorithm performance: d_2 (root-mean-squared difference between two signals [1]) and SNR (signal-to-noise ratio, denoted in dB [10]). Assuming s the simulated ECG signal and n the output of the process of filtering the noisy signal, d_2 was defined as (12) [1]:

$$d_2(s,p) = \left(\frac{1}{L}\sum_{i=1}^{L}\left|s(i) - n(i)\right|\right)^{1/2} \tag{12}$$

where L is the sample number of the signals.

The SNR is defined as (13) [11]:

$$\mathrm{SNR} = 10 \cdot \log_{10}\left(\frac{S_\sigma}{N_\sigma}\right) \tag{13}$$

where S was the noise-free ECG, N was the processed signal, and X_σ was defined as (14):

$$X_\sigma = \sum_{l=0}^{L}\left(X(l) - \mu_x\right)^2 \tag{14}$$

where μ_x was the mean of the signal X.

Others experiments using the developed algorithm were performed using acquired ECG and ECG data from the MIT-BIH arrhythmia database. Real ECG had 240Hz sampling rate, while data archives from MIT-BIH database had, generally, sampling rate of 360Hz.

Results

Figure 2 presents the performance of two algorithms for processing a simulated ECG signal added to noise: IMABNECG [3], which uses only morphological operators, and OMATF. Artefacts (impulsive noise and baseline drift) were generated as described, equations (8) and (9), using for the baseline drift m=0.8, A=500 and N=1000; and for the impulsive noise using ε=0.2, σ_1=65 and σ_2=650.

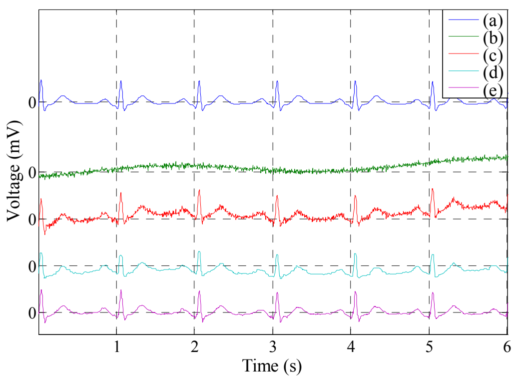

Figure 2: (a) Noise-free simulated ECG; (b) noise generated adding baseline drift and impulsive noise; (c) Noise-free ECG added to noise; (d) noise suppression performed by IMABNECG; (e) noise suppression performed by OMATF.

A single heart beat is detailed in Figure 3. The simulated noise-free ECG, the simulated ECG signal added to noise and the OMATF output are overlapped.

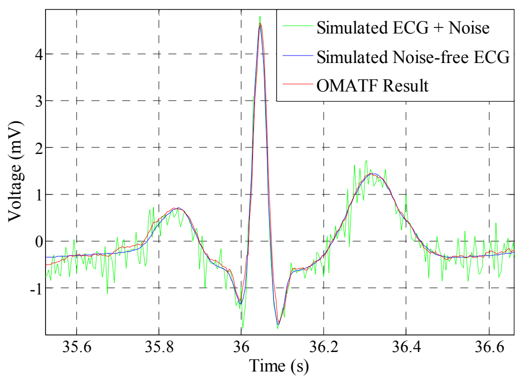

Figure 3: Detailed heat beat from simulated ECG overlapped with the signal added to generated noise and the OMATF output.

The comparison in Table 1 considers the algorithm INSBNECG described in [1], IMABNECG implemented in [3] as an improved version of INSBNECG and OMATF. The parameters: ε, σ_1 and σ_2 define the level of impulsive noise [1]. As σ_1 and σ_2 increases, the noise amplitude increases. The frequency of impulsive noise occurrence increases as ε increases.

Table 1: Performance comparison of the algorithms noise suppression at different impulsive noise levels (**I:** ε=0.1 σ_1=2 σ_2=20; **II:** ε=0.2 σ_1=65 σ_2=650; **III**: ε=0.3 σ_1=70 σ_2=700).

	I		II		III	
Approach	**d_2**	**SNR**	**d_2**	**SNR**	**d_2**	**SNR**
INSBNECG	0.086	6.7	0.085	6.58	0.086	6.38
IMABNECG	0.062	12.2	0.073	9.83	0.075	8.88
OMATF	0.051	15.7	0.053	14.2	0.061	11.4

ISSN: 1727-1983 © 2005 IFMBE

Figure 4 shows the noise level significance determined by the parameters used in Table 1.

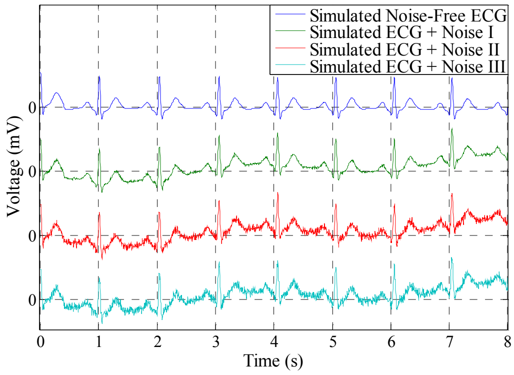

Figure 4: Different noise levels described in Table 1.

Experiments with acquired ECG and data from the MIT-BIH database presented satisfactory results. Figure 5 shows an overview of the OMATF processing applied in a real ECG. Removed impulsive noise, baseline drift and filtered signal are shown.

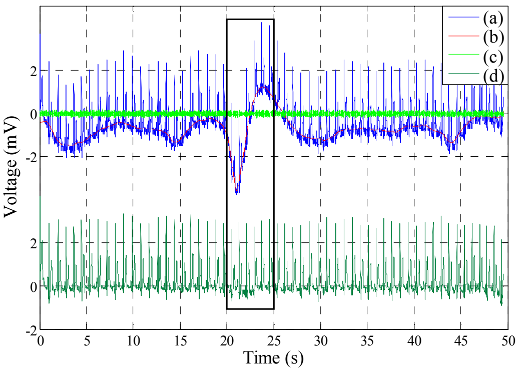

Figure 5: Noise suppression in an acquired ECG. (a) Acquired ECG signal; (b) Baseline drift; (c) Removed impulsive noise; (d) Filtered signal by OMATF.

Figure 6 shows a zoom of Figure 5.

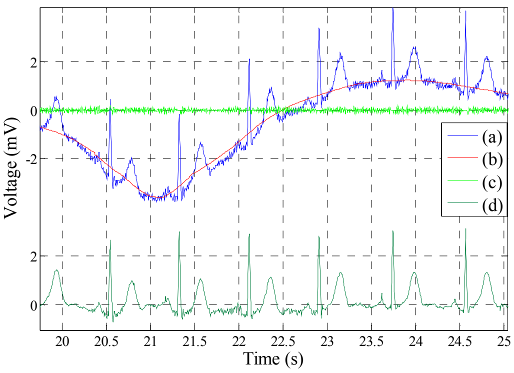

Figure 6: Zoom of Figure 5.

A single beat detailed analysis from Figure 5 is provided in Figure 7. For overlapping the processed and acquired ECG, the baseline was subtracted from the original signal. Figure 7 shows the efficiency of OMATF in preserving waves morphology and maintaining the peaks amplitudes.

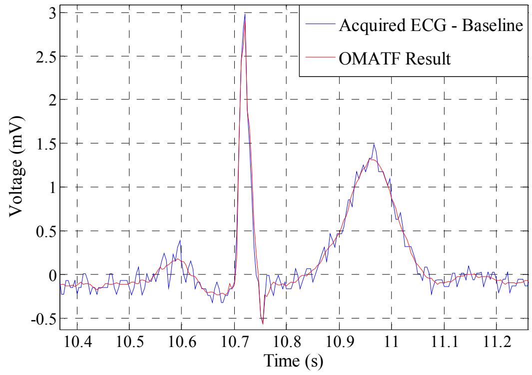

Figure 7: Detailed heart beat extracted from Figure 5. The acquired ECG is denoted by a blue line, and the ECG after filtering by OMATF by a red line.

Discussion

Others nonlinear operators were tested, such as median filtering. Although, the results were unsatisfactory, the attenuation was higher than observed in IMABNECG [3] and OMATF results.

When morphological operators are applied to impulsive noise suppression, there is a reduction in the QRS amplitude. The attenuation is due to structuring element length, which is created to remove the impulsive noise. The structuring element acts over the QRS complex as if it was impulsive noise. Thus, the peaks of the QRS complexes are attenuated in the same way that the impulse noise.

In OMATF algorithm, the length of the structuring element, the length of the window (used in alpha-trimmed mean filter) and the α_l value are dependent on sampling rate of the signal. So, these parameters are set according the signal sampling rate.

The QRS detection algorithm used in OMATF is simple and not very robust. However, considering the baseline drift removal carried out in the algorithm first step, the QRS peaks generally will correspond to the maximum and minimum values. Furthermore, the intencion is to detect points that are parte of the QRS complex, instead the peaks.

Instead the other nonlinear operator mentioned above, the adaptive alpha-trimmed mean filter removed the impulsive noise without attenuation. Since, its adaptive process applies another α value when the higher frequencies of the QRS complex, which must be preserved, are detected.

ISSN: 1727-1983 © 2005 IFMBE

Conclusions

A hybrid approach was presented (denoted by OMATF) to ECG noise suppression was presented using morphological operators and adaptive alpha-trimmed mean filtering.

The OMATF approach performance was firstly demonstrated (Figures 2 and 3) using a simulated ECG signal added to noise and comparing the simulated noise-free ECG with OMATF results (Table 1). In this case, the algorithm presented satisfactory results, even with high noise level.

Furthermore, the noise suppression was performed in a real acquired ECG signal (Figures 5, 6 and 7). Baseline removal and impulsive noise suppression were satisfactory and efficient, when it is considered the large amount of artefacts presented in the acquired ECG signal.

Our approach shows to be robust to different levels of noise and artefacts. The signal morphology is preserved and there is no attenuation of the QRS amplitude.

Acknowledgements

We wish to thanks to CAPES and CNPq for the VP M.Sc. scholarship and JLBM research grant and scholarship.

References

[1] CHU, C. H., DELP, E. J. (1989): ‘Impulsive Noise Suppression and Background Normalization of Electrocardiogram Signals Using Morphological Operators’, IEEE Trans. Biom. Eng., **36**, pp. 262-273

[2] PAHLM, O., SORNMO, L. (1985): ‘Data Processing of Exercise ECG´s’, IEEE Trans. Biom. Eng., **32**, pp. 708-713

[3] ASLE, J. A., SCHILDER, T. S. (1985): ‘Removal of Baseline Wander and Power-Line Interference from the ECG by an Efficient FIR Filter with a Reduced Number of Taps’, IEEE Trans. Biom. Eng., **32**, pp. 1052-1060

[4] MARAGOS, P., SCHAFER, R. W. (1987): ‘Morphological Filters- Part 1: Their Set-Theoretic Analysis and Relations to Linear Shift-Invariant Filters’, IEEE Trans. Acoust. Speech. Signal Processing, **36**, pp. 1153-1169

[5] SUN, P., WU, Q. H., WEINDLING, A. M., FINKELSTEINS, A., IBRAHIM, K. (2003): ‘An Improved Morphological Approach to Background Normalization of ECG Signals’, IEEE Trans. Biom. Eng., **50**, pp. 117-121

[6] ÖTEN, R., FIGUEIREDO, R. J. P. (2004): ‘Adaptive Alpha-Trimmed Mean Filters under Deviations from Assumed Noise Model’, IEEE Trans. on Image Processing, **13**, pp. 627-639

[7] SERRA, J. (1982): ‘Image Analysis and Mathematical Morphology’, (Academic, New York)

[8] FRIESEN, G. M., JANNETT, T. C., JADALLAH, M. A., YATES, S. L., QUINT S. R., NAGLE, H. T. (2003): ‘A Comparison of the Noise Sensitivity of Nine QRS Detection Algorithms’, IEEE Trans. on Biom. Eng., **37**, pp. 85-98

[9] MCSHARRY, P. E., CLIFFORD, G., TARASSENKO, L., SMITH, L. (2003): ‘A Dynamical Model for Generating Synthetic Electrocardiogram Signals’, IEEE Trans. on Biom. Eng., **50**, pp. 289-294

[10] ECGSYN - A realistic ECG waveform generator, Internet site address: http://www.physionet.org/physiotools/ecgsyn/

[11] AFONSO, V. X., TOMPKINS, J. W., NGUYEN, T. K., MICHLER, K., LUO, S. (1996): ‘Comparing Stress ECG Enhancement Algorithms’, IEEE Eng. Med. Bio. Mag., **15**, pp. 37-44

ISSN: 1727-1983 © 2005 IFMBE