Dynamic Filtration of High-Frequency Noise in ECG Signal

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Abstract

Electromyographic (EMG) noise is constantly present in stress test electrocardiographic recordings, due to physical exercise. The aim of the study is to investigate a filter that suppress sufficiently the EMG noise, with minimal distortion of high frequency content of the QRS complex .

We studied 106 patients: age 63±10 years, 45 males. Digital 12-lead electrocardiograms (EC) were acquired during stress ECG test using veloergometer. Median recording duration of 7.08 minutes and a mean number of 669 RR intervals.

The considered EMG filter was tested, and the noise suppression out of QRS is at least 2.5 times higher than in QRS. A comparison with previous results in the same database for the analysis of QRS and T wave alternans, produced significant decrease of standard deviation of PCA index in QRS interval.

1. Introduction

Electromyographic (EMG) noise in the electrocardiogram (ECG) is caused by muscle activity or tension. The noise is present and observed in patients with uncontrollable tremors, in physical discomfort due to fear of ECG recordings, in an uncomfortable position of the body, in a "stress test" exercise, and others. The presence of EMG noise causes difficulties in the automatic ECG analysis and even in the visual interpretation.

A low-pass filter with a cutoff frequency of not less than 35 Hz is the standardized recommendation for noise suppression [1]. Its application leads to inadequate reduction of EMG noise together with the reduction of the amplitudes of the high frequency signal components, the Q, R and S pears of the QRS complex.

Several transform domain methods for EMG suppression have been proposed [2-4]. While showing good performance of the EMG reduction, in the most cases they implement costly computational operations. Other authors are using wavelets [5] and Hopfield neural networks [6].

A series of researchers are using the approximation filter of Savitzky and Golay (S&G) [7] with the use of different filtering coeficients in an attempt to improve the traditional compromise between efficient EMG noise suppression and maximal preservation of the ECG waveform:

- Christov and Daskalov [8] are using the S&G filter with dynamically varied number of samples and weighting coefficients, depending on the ECG signal slope;
- Gotchev et al. [9] are combining the dynamic approximation [8] inside the QRSs complex, with a trasform domain denoising outside them;
- Dotsinsky and Mihov are appling S&G filtering outside the QRSs [10]. Inside the QRSs they are usig comb filter, reducing this way the amplitudes of the Q, R and S peaks. The restoration of these aplitudes is further achieved by linearly-angular procedure [11]

The aim of the study is to construct a filter that suppresses sufficiently the EMG noise, with minimal distortions of the high frequency content of the QRS complex. We apply the S&G procedure, with a dynamic adjustment of the filtering window based on the amount of filtered noise inside and outside the QRS interval.

2. Methods and material

2.1. ECG database

We studied 106 patients: age 63±10 years, 45 males, 39 with diabetes mellitus (DM), 34 with positive stress test. Digital 12-lead electrocardiograms (ECG) were acquired during stress ECG test using veloergometer (GE Marquette Stress PC ECG Application) – 2-min stages 25W incremental workload.

2.2. High-frequency noise suppression

The proposed high frequency noise filtration is based on the method of S&G, with a dynamic change of the approximation window, in a function of the standard deviation of the residual noise inside and outside the QRS interval after filtration.

The first step consists of an automatic procedure to find an optimal identification of the QRS onset and offset by the analysis of all the acquired simultaneous leads., with the use of a specific algorithm based on interval analysis [12]. Three sets of leads were tested:

S_1: 8 independent leads

S_2: 12 standard leads

S_3: 15 leads (I,II,III,aVR,aVL,aVF,V1 to V6, X, Y, Z)

Two non-linear combined leads were compared in the identification problem, based on spatial differences ("spatial velocity", CL_SV) and product ("energy", CL_EN) of ECG intervals, for the considered set of leads:

$$CL\_SV_i = \Sigma_{j=1:L} (\text{abs} (X_{i-5,j} - X_{i+5,j}))$$

$$CL\_EN_i = \Sigma_{j=1:L} (\text{abs} (X_{i-5,j} - X_{i,j}) * (X_{i,j} - X_{i+5,j}),$$

where $X_{i,j}$ represents the i-th sample of the original j-th ECG lead, L is the number of leads in S_1 (8), S_2 (12), or S_3 (15), and the intervals i-5 and i+5 are chosen for the sampling frequency of 500 Hz.

Although only 8 leads are independent, three sets of leads S1, S2, S3 have been tested, because CL_EN and CL_SV are computed by non-linear transformation, with different behaviour inside and outside QRS. In the results section, the more appropriate set of leads will be defined for the delineation of the QRSon and QRSoff.

The S&G filter is based on the smoothing procedure applied on an interval of 2n+1 samples, defined by:

$$Y_i = 1/N \ \Sigma_{j=-n:+n} C_j * X_{i+j}$$

where X and Y represents the original and the filtered signal, n characterizes the approximation window of 2n+1 samples centered in the i-th sample, and C_j are weighted approximation coefficients:

$$C_j = 3 n^2 + 3 n - 1 - 5 j^2$$

and N is a normalization coefficient:

$$N = (2 n + 1) (4 n^2 + 4 n - 3) / 3$$

For n=7 the smoothing procedure reaches the recommended frequency of 35 Hz for the low-pass filtering of ECG signals. Higher values n>7 leads to a better suppression of EMG noise, but with certain signal distortion in the QRS complex, while n<7 leads to admissible ECG distortion, but it is not sufficient for EMG noise suppression. For these reasons, n varies in the range from 1 to 15.

The idea is to filter less inside the QRS and more outside for a minimal distortion of the high frequency informative content of the QRS complex.

For this purpose, the choice of n is performed dynamically, with the analysis of the difference between the original ECG signal and the filtered one (residual noise), and the standard deviation of residual noise inside QRS (std_RN_QRS) should be lower than outside QRS (std_RN_out). This constraint can be measured by the folloing ratio:

$$r\_in\_out = std\_RN\_out \ / \ std\_RN\_QRS,$$

where std_RN_QRS and std_RN_out are mean values inside and outside the QRS for the considered ECG interval.

Inside the QRS interval, n assumes its minimum value n_min in the range from 2 to 6, with a smooth transition towards outside the QRS, where it takes the maximum value (n=15). The filtering algorithm modifies n_min with decreasing values until the ratio r_in_out is >1. The critical point of this kind of filter is the distortion inside the QRS interval, and this is evident mainly with ECG signal with a low presence of high frequency noise. Fig 1.A reports a clean ECG signal, and the corresponding residual noise with n_min=3 (Fig 1.B), n_min=6 (Fig. 1.C) and a fixed window with n=15 (Fig. 1.D). The resulting ratio r_in_out are respectively equal to 2.85, 0.43 and 0.09.

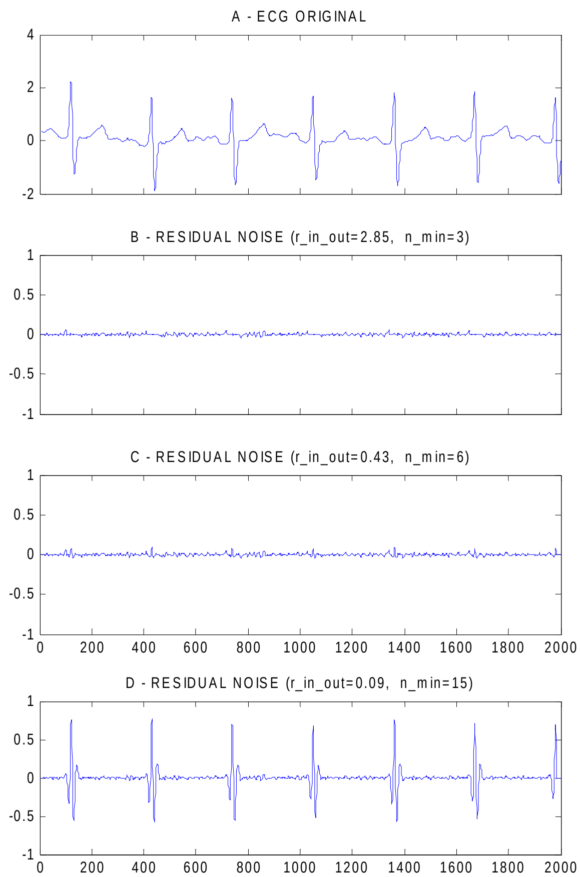

Fig. 1. Example of clean ECG signal (A) and residual noise obtained by the proposed dynamic filtration with different n_min values inside the QRS interval; n_min=3 (B), n_min=6 (C), and with a fixed window n=15 (D).

In this work, the heuristic value of r_min=2.5 has been chosen in order to limit distortion effects in the QRS complex. In this way, the filtering window does not depend on the amplitude of the ECG signal in the different leads, rather by the characteristics of the residual noise inside and outside the QRS complex.

As a consequence, in absence of high-frequency noise, the filtering activity in QRS is not significant.

3. Results

A set of 106 patients have been considered for this study, and the ECG stress test signals were examined. This dataset contains ECG recording with a median duration of 7.08 minutes, and a mean number of 699 RR intervals. The automatic identification procedure for the detection of QRS onset and offset is tuned/optimized considering the two kinds of combined leads (CL_EN and CL_SV), and considering 8 (S1), 12 (S2) or 15 (S3) leads.

The optimal solution of the identification problem is consisting mainly by finding the derived ECG signal with the most discriminant power between inside and outside QRS interval. For this purpose, the different combined leads (CL_SV, CL_EN) with the three sets of leads (S1, S2, S3) were compared in order to find the more appropriate combination. This is performed minimizing the number of QRS candidates that will be recognized as false positive QRS interval in a successive step, with the objective of the simplest pattern recognition procedure.

Table 2 reports some characteristics of the optimization procedure for QRS identification.

Table 2. Results of the automatic QRS identification procedure.

comb lead	n leads	false candidates	%
CL_EN	15	299	0.40%
CL_EN	8	467	0.63%
CL_EN	12	550	0.74%
CL_SV	8	578	0.78%
CL_SV	15	622	0.83%
CL_SV	12	1117	1.50%
CL_EN/CL_SV	15/8	196	0.26%

The procedure for QRS identification produced the lower number of false candidates using 15 leads and spatial energy (paired sign test, $p<0.001$). The use of the results of two methods (favoring the one with the lower number of false candidates) can produce a more efficient combined algorithm (n=196, 0.26%).

The High-frequency noise filter, based on the method of Savitzky-Golay with a dynamic adjustment of the filtering window (n) inside the QRS interval in relation to the residual noise, has been tested to all the ECG signals of the database of 106 patients.

Fig. 2.A illustrates an example of ECG signal (lead V3) with presence of evident high-frequency noise. The proposed method apply a high-frequency filter with decreasing values of filtering widow (n) inside the QRS interval, until the ratio between the standard deviation of the residual filtering noise outside and inside QRS interval is higher than 2.5.

In this case values of n_min=6 inside the QRS interval produce a ratio r_in_out=2.99. Fig. 2.B reports the behavior of the filtering window (n) parameter computed by the proposed method, and Fig. 2.C shows the corresponding residual noise. Fig. 2.D reports the case of using a constant filtering window (n_min=15), and the resulting residual noise is characterized by a ratio r_in_out=0.29.

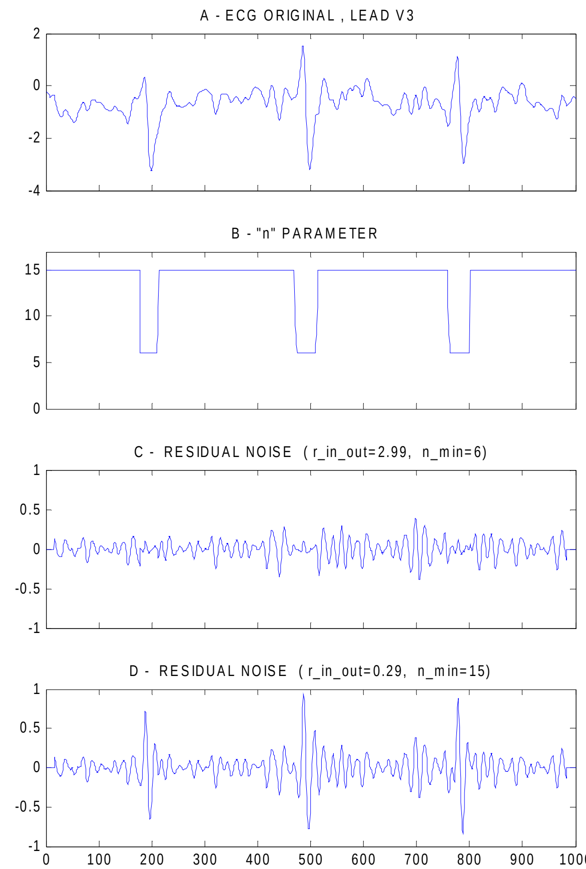

Fig. 2. High-frequency noise filtration of ECG signal with EMG noise (lead V3). A. Original ECG signal; B. window filter n parameter. C. Residual noise with the proposed method (n_min=6). D. Residual noise with fixed window (n=15).

Figure 3.A reports an interval of ECG signal of the same patient (lead V3) with no visual presence of high frequency noise. In this case the optimal filter is reached with n_min=3 inside QRS (Fig. 3.B), which produces the residual noise of Fig. 3.C characterized by a ratio r_in_out=2.94. The use of a constant filtering window

produces the residual noise reported in Fig. 3.D, characterized by a ratio r_in_out=0.07, and in which the distortion effect in the QRS complex is evident.

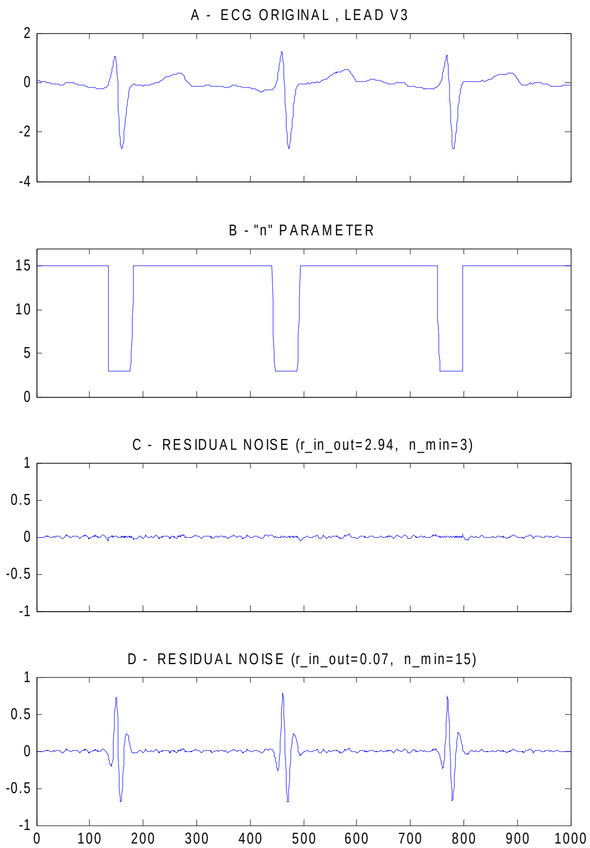

Fig. 3. High-frequency noise filtration of ECG signal without EMG noise (lead V3). A. Original ECG signal; B. window filter n parameter. C. Residual noise with the proposed method (n_min=3). D. Residual noise with fixed window (n=15).

4. Conclusions

The High-frequency noise filter, based on the method of Savitzky-Golay with a dynamic adjustment of the filtering window inside the QRS interval has been proposed and tested. A comparison with previous results in the same database for the analysis of QRS and T wave alternans, produced significant decrease of standard deviation of PCA index in QRS interval.

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