Multichannel ECG Filtering: Source Consistency Filtering, Eigenfiltering and Traditional Methods

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Abstract

Noise reduction is a fundamental aspect of stress electrocardiogram (ECG) recording. In this setting, muscular noise represents the main antagonist to signal quality. A possible solution to muscle noise in stress ECG is to exploit the information redundancy in 12-lead recordings to reduce noise while preserving the ECG signal. Source Consistency Filtering (SCF) is a spatial redundancy filter that follows this principle.

In this paper, we compare the muscle noise rejection performance of conventional 25Hz and 40Hz low-pass filters (LPFs), the SCF and a method based on singular value decomposition (SVD) which exploits both the spatial and temporal correlation in the ECG signal.

Our results indicate that the SCF can afford a QRS complex distortion lower than that of a 40 Hz lowpass filter while still maintaining a high noise rejection. The QRS detection accuracy on the filtered ECG was comparable for all methods except for the SVD filter, which allowed a superior detection performance score in all the records.

1. Introduction

The interpretation of morphology and rhythm of the electrocardiogram is based on signals with good quality. While this is not an issue in resting ECG, noise rejection is required in Holter or stress ECG, as well as ECG recorded with wearable devices. The manifestations of noise in ECG may be divided in low frequency and high frequency noise [1]. High frequency noise is caused by powerline interference and skeletal muscle activity. For the former, stop band and nonlinear, sinusoid-based filters are established countermeasures [2]. Muscle noise represents a more complex interference, where the frequency content of the myographic potential is overlapping with the characteristic ECG band, typically from 5 to 100 Hz [3]. The most straightforward approach is to reduce excessive muscle noise is to low-pass filter the ECG signal. However, any low-pass filtering operation up to 100 Hz will inevitably distort the characteristic waves of ECG [4]. The choice of cut off frequency of the low-pass filter is then a compromise between noise rejection and wave distortion. As most of the frequency content of ECG waves lies under 40 Hz [5], 40 Hz low pass filters are commonly used in ECG stress recording devices.

Other muscle noise ECG filters have been proposed in the literature, with different properties of noise reduction, wave distortion, and computational complexity. Among the different techniques that have been proposed, we mention time-varying filters [6], filter banks [7], wavelets [8], warped polynomials [9], the Kalman filter [10], SVD-based eigenfilters [11] and the source consistency filter [12]. The general principle in many of these approaches is to adapt the noise rejection action to the local characteristics of the ECG signal. One way that this can be achieved is to take advantage of the information redundancy in 12-lead ECG, as the ECG signal is correlated between leads while noise typically is not. The source consistency filter and the SVD-based method rely on this assumption.

In this paper, we evaluate the source consistency filter with respect to the conventional low-pass filter. Additionally, we also propose an SVD-based method that takes into account both the spatial and temporal consistency of the signal, to further investigate the noise rejection potential of redundancy in 12-lead ECG.

2. Methods

The ECG signal recorded with electrodes can be considered as $\boldsymbol{y} = \boldsymbol{x} + \boldsymbol{\varepsilon}$, where $\boldsymbol{x}$ is the "true" ECG signal and $\boldsymbol{\varepsilon}$ is the noise term, When a noise reduction filter is applied to $\boldsymbol{y}$, the $\boldsymbol{\varepsilon}$ term is reduced while preserving the true signal $\boldsymbol{x}$. For this reason, in the filter evaluation we performed, we measured the performance of the different filters by comparing the difference between the filtered signal $H(\boldsymbol{y})$ and the real signal $\boldsymbol{x}$. In this work, we focused on muscle noise, *i.e.* we assume the $\boldsymbol{\varepsilon}$ term to represent only muscle noise.

2.1. Data

In order to obtain a true ECG signal $\boldsymbol{x}$, completely free of noise, we used the ECG simulator described in [13]. We synthesized 40, 5-minute long ECG records. In order to simulate the high-frequency muscle noise, we added bursts of gaussian white noise in the electromyographic frequency band, 5 to 70 Hz, thus obtaining the noise-corrupted $\boldsymbol{y}$ signals. The added noise was uncorrelated between leads, and frequency band limits varied from lead to lead. The SNR ratio of each burst of noise varied randomly from -10 to -1 dB. For the evaluation of QRS detection on filtered ECG, we also considered 40 real stress ECG recordings, where additional noise was added with the same method described above.

2.2. Low-pass filters

Two linear phase low-pass filters were considered as reference methods, with cut-off frequencies at 25 and 40 Hz, respectively.

2.2. Source-Consistency Filter

The source-consistency filter [12] takes advantage of the redundancy of spatial information in 12-lead ECG to preserve the true signal and reduce muscle noise, which is uncorrelated. In source-consistency filtering, the input signal $\boldsymbol{x}$ is high-pass filtered to remove most of the PQRST waves. The cut-off frequency of the high-pass filter in this study was set to 25 Hz. The 8 independent, high-pass filtered leads are estimated by least squares regression. The agreement between the high-pass filtered signal $\boldsymbol{h}$ and the estimated signal $\widehat{\boldsymbol{h}}$ is determined by consistency, c. Consistency modulates the filter output in a continuous way: $\boldsymbol{y} = \boldsymbol{x} - (c-1)\boldsymbol{h}$. Consistency is averaged in a window, which we set to 50 ms. The least squares regression coefficients for the estimation of $\boldsymbol{h}$ are calculated in the QRS portion of averaged ECG.

2.2. Spatiotemporal Eigenfilter

The ECG at each lead is autocorrelated, and cross-correlated with the ECG at each other lead. Conversely, muscle noise affecting each lead is typically poorly autocorrelated and not cross-correlated with the noise affecting the other leads. In turn, noise is not cross-correlated with the ECG signals. The proposed spatiotemporal eigenfiltering (STEF) method for the extraction of ECG from noisy signals exploits both these autocorrelation and cross-correlation differences. The signal is decomposed and reconstructed with few eigenvalues, which account for almost all signal information.

The STEF method combines the auto and cross-correlation information by applying the singular values and singular vectors decomposition the matrix $\boldsymbol{A}$

$$\boldsymbol{A} = \begin{bmatrix} x_1^0 & \dots & x_1^w \\ \dots & \dots & \dots \\ x_1^{N-w} & \dots & x_1^N \end{bmatrix} \dots \begin{bmatrix} x_L^0 & \dots & x_L^w \\ \dots & \dots & \dots \\ x_L^{N-w} & \dots & x_L^N \end{bmatrix}$$

where x_k^i refers to the sample of the input signal $\boldsymbol{x}$ of lead k at time i, N is the length in samples of the ECG signal to be filtered, L are the independent leads and w is the temporal embedding window size. In other words, the matrix Y is built by concatenating 8 Hankel matrices, one for each ECG lead. Each Hankel matrix is individually built by repetition of a single lead translated in time up to a number of samples w.

The matrix $\boldsymbol{A}$ is decomposed by SVD, thus resulting in

$$\boldsymbol{A} = \boldsymbol{U}\boldsymbol{S}\boldsymbol{V}^{\mathrm{T}}$$

where the columns of $\mathbf{U}$ are the left singular vectors, the columns of $\boldsymbol{V}$ are the right singular vectors and $\boldsymbol{S}$ is a diagonal matrix of singular values. SVD is thus applied to a matrix in which each ECG signal appears w times. The signal is reconstructed by first setting to zero the singular values after the p-th one, where $p = 8$ was determined empirically. The corresponding singular value matrix, $\boldsymbol{S}_r$, has only $p \leq q$ of the original $q = wL$ singular values. The reconstructed $\boldsymbol{B}$ matrix is given by

$$\boldsymbol{B} = \boldsymbol{U}\boldsymbol{S}_r\boldsymbol{V}^{\mathrm{T}}$$

The reconstructed, filtered signal $\boldsymbol{x}_r$ is obtained by averaging the cross diagonals of $\boldsymbol{B}$ for each lead k:

$$\boldsymbol{B}(k) = \begin{bmatrix} b_k^0 & \dots & b_k^w \\ \dots & \dots & \dots \\ b_k^{N-w} & \dots & b_k^N \end{bmatrix}$$

The singular values and vectors are calculated in the initial phase of the stress ECG recording, where the noise power is much lower than the ECG power. The eigenvectors associated with the largest singular values take into account the changes that occur with the highest correlation on the wL signals (including cross-correlation and autocorrelation). Since the ECG is commonly much more cross-correlated and autocorrelated than noisy components, the first eigenvalues will account for the signal components.

3. Results

We evaluated the filtering accuracy of the considered methods with three metrics, shown in Table 1, Table 2 and Table three. The first metric is the mean error between the noise-free simulated ECG $\boldsymbol{x}$ and the filtered signal $H(\boldsymbol{y})$. The second metric is the mean error for QRS complexes only, which was calculated on 100ms long windows centered on each QRS complex.

Table 1. Mean average error between clean ECG and filtered ECG. The error is averaged between all records and all independent leads.

Algorithm	Global error MAE, µV	QRS error MAE, µV
No filter	98.08	12.01
25 Hz LPF	44.42	9.57
40 Hz LPF	70.16	8.94
SCF	53.11	**8.23**
STEF	**37.36**	10.51

While the lowest overall error was achieved with the STEF method, SCF achieved the lowest QRS complex distortion. The third metric of filtering performance we report is the average, minimum, and maximum F1 score of QRS detection, shown in table 2.

Table 2. Mean QRS detection F1 score for all simulated records. Minimum and maximum values are reported in the brackets.

Algorithm	QRS detection, F1 Mean (min – max)
No filter	0.970 (0.749 – 1.000)
25 Hz LPF	0.973 (0.762 – 1.000)
40 Hz LPF	0.969 (0.749 – 1.000)
SCF	0.970 (0.756 – 1.000)
STEF	**0.997 (0.980 – 1.000)**

QRS detection performance was calculated for each independent ECG lead as a measure of QRS signal distortion. The STEF method allowed superior QRS detection performance in all leads, even in the worst cases.

We also calculated QRS detection on real, annotated stress ECG data, where simulated noise (section 2.1) was added to the real noise already present.

Table 3. Mean QRS detection F1 score for real ECG records with added simulated noise. Minimum and maximum values are reported in the brackets.

Algorithm	QRS detection, F1 Mean (min – max)
No filter	0.994 (0.766 – 0.999)
25 Hz LPF	0.995 (0.774 – 0.999)
40 Hz LPF	0.994 (0.760 – 0.999)
SCF	0.994 (0.776 – 0.999)
STEF	**0.998 (0.989 – 1.000)**

These results were obtained with MATLAB. The QRS detection method we used is described in [14]. We also show an example of filter output (red) superimposed to real noisy ECG (black) in Figure 4. This plot was obtained from a real 12-lead stress ECG recording without adding simulated noise, and lead II is shown for each of the four filters.

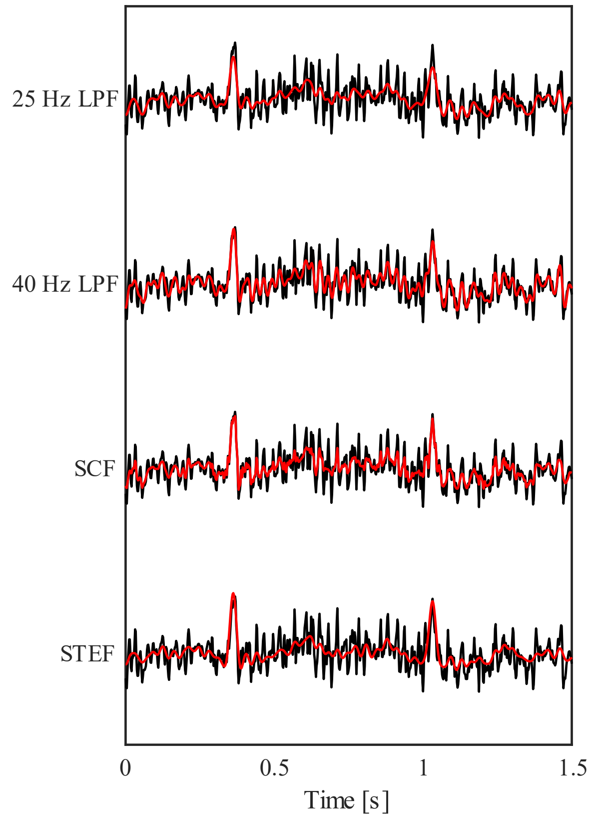

Figure 1. Example of real muscle noise filtering from stress ECG. The same lead II of a real noisy ECG recording is shown. The black signal is unfiltered ECG, the red signal is the filtered output for the four methods we considered.

4. Discussion and conclusion

The different characteristics of the filters we considered in this evaluation can be highlighted in Figure 4. The 40 Hz filter is able to preserve most of the QRS complex amplitude, but muscle noise is still partially present in the output. The 25 Hz filter smooths both the noise and the upward tip of the QRS complex. The SCF appears as a compromise between the two, where he filtering action is modulated by the consistency between leads. In windows where consistency is high, *i.e.* around a QRS complex, the output is unfiltered. When consistency equals zero the output is effectively a 25 Hz low-pass filter, which is the minimal cut-off frequency we set. Lastly, the STEF filter shows a remarkable ability to maintain a stable baseline even in the presence of loud noise. However, we can also note a distortion of QRS complex, not caused by frequency cut-off, but from the inexact reconstruction of the subspace of the $p < M$ eigenvectors instead.

Regarding the source consistency filter, we showed how the minimal cut-off frequency we set to 25 Hz translates to a QRS distortion comparable to that of a 40 Hz filter. The muscle noise spectra extends below 25 Hz, however further lowering the minimal frequency cut-off of the SCF may include excessive QRS complex energy in the least squares estimation. This, in turn, would render the solution unstable due to excessive correlation between the high-pass filtered leads. The other fundamental parameter of the SCF method is the consistency function, which is averaged on a window. Further study on the consistency function and the window size could possibly improve the noise rejection and wave preservation characteristics.

The STEF method we introduced reached the lowest overall filtering error, although with a QRS distortion greater than the SCF. Additionally, QRS detection performance on ECG records filtered with this method was the highest in all leads, thus demonstrating the ability of this filter to take full advantage of information redundancy to extract ECG from bursts of high intensity noise. We speculate that the method may fail to recover the ECG when the structure of the interdependence between the leads changes over time during the stress test. For this reason, a evaluation on ischemic events is required. In addition, the effect of low-frequency artifacts and channel loss on filtering performance should also be investigated.

The major limitation of this work is indeed the simplistic noise model we adopted, which is filtered gaussian white noise. Future developments of this work should also focus on more realistic noise simulation algorithms.

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