Noninvasive His-bundle Electrocardiogram: Toward Beat-to-Beat Electromyogram Noise Removal

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Abstract

EMG noise is a very impeding factor for beat-to-beat detection of His micropotentials in high-resolution ECG. Its reduction was attempted by a two-stage wavelet-domain Wiener filtering procedure. In the first stage, a pilot signal estimate was obtained by averaging a rather small number (~20) of successive beats synchronized to the R peak. In the second stage, this pilot signal together with EMG noise variance estimate, was used in the wavelet-domain Wiener filtering. The proposed noise suppression technique establishes a compromise between the need of beat-to-beat evaluation of the His potential and the noise-suppression-effective averaging. The algorithm shows adequate performance for records containing both moderate EMG and power-line interference, and for ECGs of sufficiently long P-Q interval (P-wave separated from Q-wave).

1. Introduction

His bundle electrocardiogram (ECG) is most widely used to assess Atrial-Ventricular (AV) conduction. More then 90% of the AV conduction defects can be defined by the His bundle ECG. A prolonged A-His interval or the absence of a signal from the His bundle indicates AV nodal location, while a prolonged His-V interval or the absence of a signal from the ventricles following a His signal indicates bilateral bundle location [1].

His bundle ECG is usually obtained by intra-cardiac recordings via a catheter positioned across the tricuspid valve adjacent to the His bundle.

In 1969 Scherlag *et al* [2] hypothesized that with sufficient ingenuity in the application of existing noise-reduction methods, together with the development of new methods for noise reduction, all based on a sufficient electrophysiological background, the His bundle signal eventually could be recorded from the surface of the body.

His-bundle micropotential amplitudes range from a few to less then 20 μV. They are commonly recorded with a high-resolution of 50-100 nV/bit analog-to-digital conversion with at least 1000 Hz sampling rate.

His potential analyses have depended mainly on signal averaging. Although this approach produces representative signals, the averaging process removes any beat-to-beat variations. However, beat-to beat variations may have important diagnostic value [3].

The presence of EMG contamination considerably impedes beat-by-beat His micropotentials acquisition from surface ECG. Therefore, we attempted beat-by-beat EMG noise removal from high-resolution ECGs.

Classical noise suppression methods, such as low-pass filtering and time-domain adaptive filtering, usually fail in removing white noise-like EMG signal in PQ segments, where they over-smooth very small-amplitude His potentials, or generate artefacts erroneously identified as His waves.

Alternatively, one can operate in a 'good' transform domain. 'Good' here means a decorrelating transform, compressing the signal features in a small number of significant coefficients. For signals accompanied with noise, where the signal is assumed to be highly correlated and noise is supposed to be uncorrelated, the good transform would lead to decomposition where most of the signal energy is concentrated in few significant coefficients, while the noise is spread almost uniformly over all transform coefficients with more significant influence on the smaller ones. By disregarding the coefficients bellow a selected threshold and after performing inverse transform, one can obtain a noise-free signal estimate [4]. The optimal decorrelation transform within this paradigm, the Karhunen-Loeve transform (KLT), is computationally prohibitive [5]. Other fast and with good decorellating properties transforms have been used instead. The wavelet transform is especially convenient because it offers the best time-frequency trade-off [4]. Ghael *et al* [6] have proposed to perform Wiener filtering in the wavelet domain. Since the wavelet transform tends to decorrelate the data, Wiener filter processes each coefficient inde-

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pendently, provided that the wavelet coefficients of the noise-free signal and the noise variance are known. In practice they are not and by using their estimates the wavelet-domain Wiener filtering becomes empirical [6].

Critical step in wavelet-domain Wiener filtering was to obtain an adequate noise-free signal estimate, needed for Wiener filter construction [6-8]. Wavelet-domain shrinkage by hard or soft threshold [9] has been used to obtain the needed signal estimate. For common ECG recordings this technique has been elaborated by taking into account the ECG signal morphology [7]. However, with this threshold technique there is a risk of introducing distortions or over-smoothing in the PQ interval, where the low-amplitude His wave should occur.

We modified the two-stage wavelet-domain Wiener filtering, adapting it for EMG noise suppression and micropotential recovery from high resolution ECG. A new method for obtaining the noise-free signal estimate, based on averaging of a limited number serial beats (10-20) is proposed. The method was tested on ECGs with added artificial His wave. The signal-to-noise ratio (SNR) and mean absolute error (MAE) were measured to assess the performance of the method and to establish its limitations.

The method was also tested with real three-channel ECG recordings where the third, intra-cardiac channel is used for verifying the detected His waves.

2. Methods

2.1. Wavelet-domain Wiener filtering

Consider a discrete signal **x** mixed with noise, assumed to be white Gaussian process **n**: **s=x+n**; **x, s, n** $\in R^N$. Wavelet-domain Weiner filtering denoising procedure can be described as follows [8]:

A preliminary noise-free signal estimate, called pilot signal, $\mathbf{x_e}$, is obtained from the discrete signal-noise mixture **s**. This pilot signal is transformed then to some appropriate domain, i.e. wavelet domain, acquiring the transform coefficient vector $\hat{\varsigma}$. The signal-noise mixture is transformed by the same wavelet transform, obtaining coefficients ξ. The noise variance $\hat{\sigma}$ is also adequately estimated. Both sets of transform coefficients $\hat{\varsigma}$, ξ and the noise variance $\hat{\sigma}$ are used to design an optimal, in the mean square error (MSE) sense, Wiener Filter H_{Wiener} [6]:

$$H_{Wiener}(j,k) = \frac{\hat{\varsigma}(j,k)^2}{\hat{\varsigma}(j,k)^2 + \hat{\sigma}(j)^2}, \quad (1)$$

where $k=1\ldots N/2^j$ is the coefficient's time position, and $j=1\ldots J$ is the coefficient's scale position for J decomposition levels.

The filtered coefficients are then obtained by a point-wise coefficient shrinkage, that is the transform domain Wiener filtering:

$$\xi_{WF}(j,k) = H_{Wiener}(j,k)\xi(j,k), \quad (2)$$

Finally, the denoised signal $\hat{\mathbf{x}}$ is obtained by inverse wavelet transform of the filtered coefficients ξ_{WF}.

The noise variance for each scale $\hat{\sigma}(j)$ is estimated using the wavelet coefficients of signal-noise mixture, representing regions outside the QRS complex [7].

The block diagram of the algorithm is shown in Figure 1.

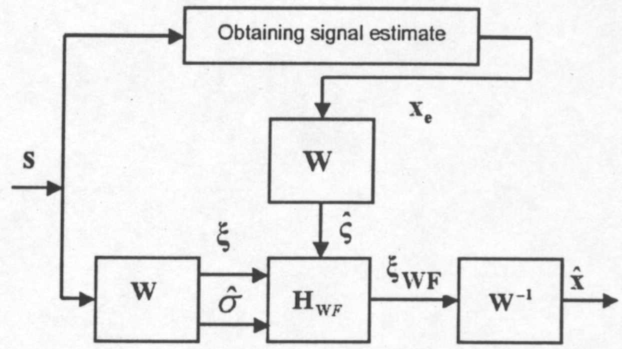

Figure 1. Two stage wavelet-domain Wiener filtering

2.2. Obtaining signal estimate

Preliminary wavelet transform with subsequent coefficients thresholding has been used so far, to obtain the pilot signal estimate [7-8]. However, similar technique is not applicable to the problem of micropotential recovery. His potentials are of small amplitudes and located in the P-Q interval near to the QRS complex. In transform domain they would be mapped into small-magnitude coefficients masked by the noise. Any shrinkage procedure will remove those coefficients and no His potential will occur in the signal estimate. Furthermore, shrinking coefficients near to the sharp QRS complex would cause pseudo-Gibbs oscillations that may be erroneously classified as His potentials. Hence, new technique for obtaining the signal estimate, preferably not threshold-based, should be used.

We suggest using an average of limited number (10-20) of serial beats as estimate. This estimate was obtained as follows: the ECG signal was divided into segments (beats) by detecting the R-peaks. If necessary, the power-line interference was removed by an appropriate method [10]. The pilot signal estimate, needed for the Wiener filtering procedure was obtained by averaging the successive beats, using the R peak as a fiducial point.

The number of beats in the averaging procedure was subject to compromise between more efficient noise suppression and detection of the beat-to-beat His wave varying position in he P-Q interval.

3. Experimental results

High-resolution ECG recordings were used, of 16.3 s. duration. The number of leads and electrode locations were selected for each patient, in order to achieve good His wave signal. The files consisted of 10-25 time-consecutive epochs. Our example experiment was performed on a patient with 16x16.3 s. records file. Three leads were simultaneously recorded (two from the body-surface and one intracardiac) with 1000 Hz sampling rate and 100 nV/bit resolution. The surface ECGs were acquired from two bipolar chest leads, roughly similar to Frank X and Y frontal plane leads.

A moving average filter was applied to eliminate the powerline interference and to suppress the EMG noise. As this filter practically eliminated the His waves as well, artificially generated His waves with varying (1-3 ms) phase positions were added to the P-Q segment of every beat (Figure 2a). True EMG noise recorded by the same equipment and with varying energy was added as well (Figure 2b). This experiment allowed applying the proposed denoising method (Figure 2c), using different number of beats in the averaging procedure, with the purpose to determine the best number of averaged beats.

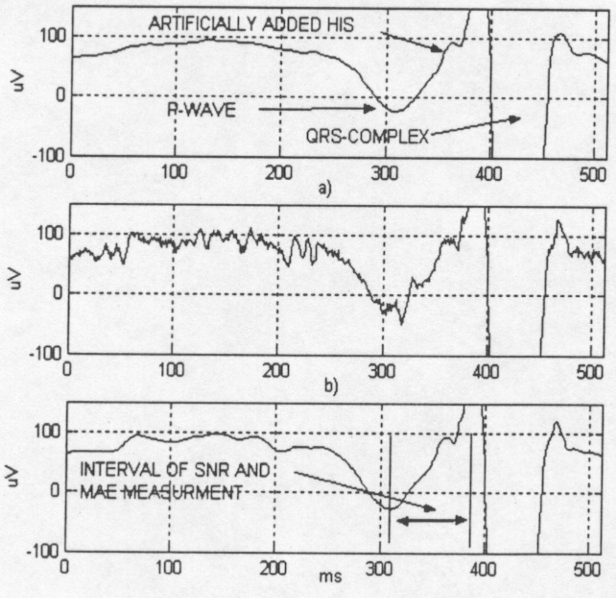

Figure 2. a) Artificial His-bundle added in the P-Q interval before each QRS complex; b) EMG noise mixed with the entire record; c) Processed signal.

The algorithm performance has been assessed by the mean absolute error (MAE) and by the signal-to-noise ratio (SNR). They were calculated along P-Q segment at two stages (see Figure 2): as differences between the initial noise-free and the contaminated signals (denoted as input SNR and input MAE) and as differences between the initial and the restored signals (denoted as output SNR and output MAE). The obtained results are summarized in Table 1 for number of averaged beats changing from 10 to 30.

For a number of averaged beats smaller then 10 the EMG noise was insufficiently suppressed in the pilot signal, making it too noisy for the Wiener filtering performance. For a number of averaged beats higher than 20 the EMG noise was suppressed to an acceptable level and the performance was stabilized. No additional improvement was found with increasing the number of beats. Furthermore, for beats more than 30, the averaged beat was slightly over-smoothed. Less clear His potential was obtained with varying its position.

Table 1. SNR and MAE for the signal before and after denoising procedure, for different number of averaged beats.

Input signal		Number	Output signal	
SNR,dB	MAE, μV	of beats	SNR, dB	MAE, μV
9	234.4	30	15.04	155.7
9	234.4	20	14.91	156.8
9	234.4	15	14.80	157.5
9	234.4	10	14.67	158.5
12	169.8	30	17.08	118.0
12	169.8	20	16.99	118.7
12	169.8	15	16.89	119.3
12	169.8	10	16.76	120.1
15	124.7	30	18.86	91.27
15	124.7	20	18.81	91.54
15	124.7	15	18.73	92.04
15	124.7	10	18.61	92.88
18	93.5	30	20.30	72.67
18	93.5	20	20.27	72.70
18	93.5	15	20.23	72.97
18	93.5	10	20.12	73.70

His potentials became visually recognizable when MAE<80, equivalent to SNR>20 dB. These output measures were achievable with input SNR higher than 15 dB. For signals with lesser input SNR, the performance of the algorithm was questionable.

These observations were confirmed by experiments with real ECG from another patient, using three body-surface leads. In this case, the initial SNR with the EMG noise variance, estimated in the 'flat' signal areas, varied in the range of 12 ÷ 19 dB. For signals containing moderate noise (SNR=15 dB or higher) the method yielded good results, proven by the reference intra-cardiac signals. An example is given in Figure 3. Together with the EMG noise, the input signal contains some powerline interference, which was removed using a time-subtraction method [10]. The remaining EMG noise resulted in initial SNR close to 15 dB. The processed His (Figure 3d) is far better recovered then the averaged wave (Figure 3c) It can be seen in Figure 3e that the time location of the His wave in the processed ECG correspond to that of the intra-cardiac His potential.

4. Discussion

We applied two-stage wavelet-domain Wiener filtering for beat-to-beat EMG noise suppression, aimed at His micropotential detection. The procedure used a noise variance and a well-estimated pilot (noise-free) signal, obtained by averaging a relatively small number (~20) of successive beats, referenced to the R peak. The averaging signal moderately suppressed the noise around the His potential and did not introduce distortions. We consider this an important result of this first step. We relied further to wavelet-domain Wiener filtering for efficient noise suppression and detecting beat-to-beat His wave changes. Hence, our noise suppression technique establishes a compromise between the need for beat-to-beat evaluation of the His potential and noise-suppression averaging.

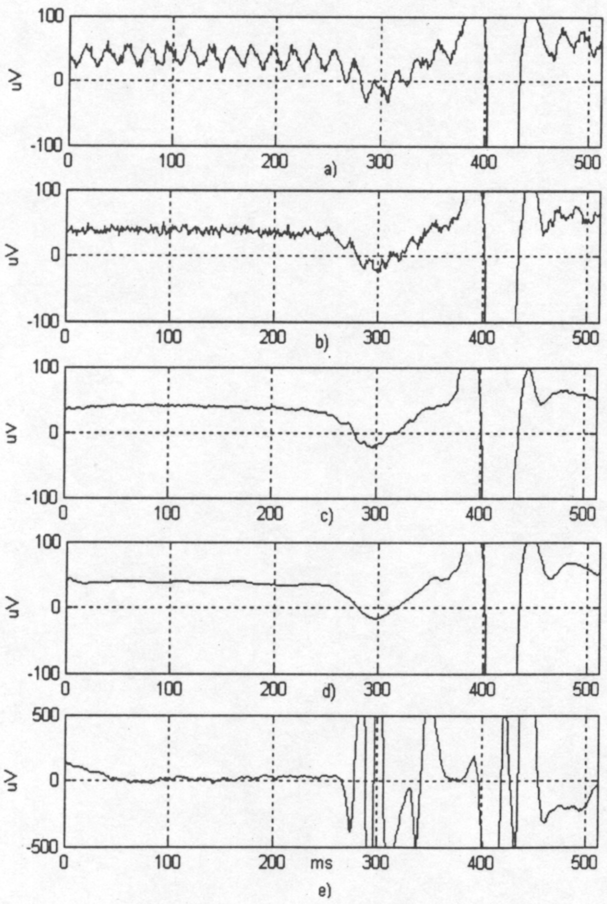

Figure 3. Beat-to-beat noise removal wavelet-domain Wiener filtering, (a) Body-surface ECG - Lead 2, (b) Lead 2 after power-line interference removal, (c) Averaged ECG over 20 beats prior to the current one, used as pilot estimate in the Wiener filtering, (d) signal processed by the WDWF method, (e) intra-cardiac reference signal for the same region.

The method was evaluated with real signals, recorded simultaneously from body surface and with intra-cardiac electrodes. The method yielded acceptable results in cases with initial SNR, calculated along the P-Q interval, higher than 15 dB.

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