A Novel Real-Time Multilead ECG Compression and De-Noising Method based on the Wavelet Transform

A Alesanco[1], S Olmos[1], R Istepanian[2], J García[1]

[1]Communications Technologies Group. Aragon Institute of Eng. Research. Univ. of Zaragoza, Spain
[2]Mobile Information and Network Technologies Research Centre (MINT). Kingston University, UK

Abstract

A new de-noising and compression method for ECG signals has been developed based on the wavelet transform. It has been designed for mobile telecardiology scenarios, where reliability as well as spectral efficiency are essential. The signal is segmented into beats and a beat template is subtracted to them. Beat templates as well as residual signals are coded with a wavelet expansion. De-noising and compression are achieved by selecting a subset of wavelet coefficients. The number of coefficients depends on the noise level. A SNR improvement about 5 dB was obtained. Compression performance has been tested using a subset of ECG records from MIT-BIH Arrhythmia database. For example, a compression ratio of 35 with a PRD as low as 3.6 % was achieved for record 119 .

1. Introduction

Nowadays, telecardiology is one of the most important fields in telemedicine. In the last years, there have been several telecardiology projects around the world [1]. Most of these projects dealt with prerecorded ECG signals which means that the transmission of ECG was off-line, normally using wired networks (i.e. telephone line) to transmit the signal. With the increasing popularity and accessibility of wireless communications, mobile telecardiology has become the natural substitute of wired telecardiology, offering mobility and remote area accessibility. A pioneer work in mobile telecardiology was performed in [2, 3] using a GSM network. The term mobile telecardiology references the telecardiology which uses wireless networks to transmit the ECG signal, both off-line (pre-recorded ECG signals) and on-line (real-time ECG signals). One of the problems a mobile telecardiology system has to face is the limited bandwidth available is this environment. Although third generation of mobile networks will increase considerably the available bandwidth, an efficient coding method will be required anyway, specially if one wants to use this resource to transmit other data, such as blood pressure, oxygen saturation, medical images, audio, video, etc. In this paper we present a new multilead ECG de-noising and compression method based on the wavelet transform, designed to work in a real-time transmission scenario: an ambulance carrying patients to a hospital.

2. De-noising and compression method

The de-noising and compression method is grouped in three stages:

- Preprocessing: baseline removal, beat detection and noise measurement.
- Template subtraction.
- Wavelet transform: coefficient selection and coding.

In Fig. 1 a general scheme of the method is shown.

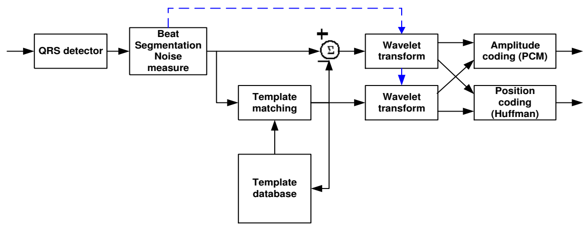

Figure 1. General Scheme of the method.

2.1. Preprocessing: baseline removal, beat detection and noise measurement

Firstly, the system removes the baseline of the acquired ECG signal. This process removes very low frequency components in the ECG which do not contain any clinical information and allowing to use the template subtraction method in a more efficient way.

For QRS detection we used a previously developed algorithm based on the wavelet transform [4]. The ECG is segmented into beat vectors aligned from QRS fiducial points. A beat is defined starting at 250 ms prior to its fiducial point. All beats have a dyadic length by completing the signal padding the last amplitude.

Noise power in each beat vector is estimated as the power remaining after high-pass filtering (cutoff frequency of 25 Hz) the repolarization interval (form 42 ms after QRS fiducial point to the beat end).

2.2. Template subtraction

Once the ECG signal has been segmented into beats, a beat template is subtracted to each beat. The method uses a dynamic template database which is created, modified and updated in real time using the new acquired beats. The first template stored in the database is the first available beat of the signal to be compressed. Then, for each new observed beat a correlation is performed between the observed QRS complex (defined from 100 ms prior the fiducial point to 100 ms after it) and the QRS complexes from the template database. The assigned template will be the one with largest normalized correlation coefficient, unless the correlation is poor (below a threshold) in which case a new beat template is created and added to the database with the observed beat vector. In order to take into account morphology changes, beat templates are updated after being used 10 times for beat subtraction. The new template is calculated as the running average of the current coded beat (as it will be reconstructed in the receiver) and the old template. Both the residual signal and the beat templates are coded by means of a truncated wavelet expansion.

2.3. Wavelet transform: coefficient selection and coding

Once the residual signal has been obtained, a wavelet expansion is applied to the multilead vector containing all the residuals from every lead. *Coiflet* wavelet was used as mother function. Compression and de-noising are achieved by selecting a subset of wavelet coefficients. The number of coefficients is selected according to signal and noise properties. It is well-known that white noise presents an uniform distribution in any domain while ECG signal power is concentrated in a small group of coefficients with low frequency. Thus, the signal-to-noise (SNR) can be improved by selecting the coefficients with largest amplitude. If the noise level is high, the number of WT coefficients must be decreased in order to avoid spending bit rate for noise coding [5]. The number of WT coefficients was selected in order to assure that the power of the rejected coefficients equals the noise power estimated in the preprocessing stage. Since a subset of coefficients has been removed, the de-noising process leads also to signal compression.

Amplitude as well as position of the WT coefficients must be coded for each multilead vector. Differential (first difference) Huffman coding is used for the coefficient position. The probability distribution function (PDF) used in the Huffman coder was learnt from a set of coefficient vectors. Adaptive PCM coding is used for coefficient amplitudes. The number of bits was chosen to assure a fixed quantization noise level.

3. Materials

In order to evaluate the performance of this new de-noising and compression method, we have used two databases. The first one is the MIT-BIH Arrhythmia database [6]. which has been extensively used to evaluate ECG compression methods. We have selected a subset of 6 signals (100, 103, 109, 111, 117, 119) of 10 minutes long. The sampling frequency of these signals is 360 Hz and they have a resolution of 11 bits per sample.

Since most of the signals that form the MIT database are already contaminated with noise, they are not suitable to evaluate the noise removal performance. We need noiseless ECG signals in order to add them white noise with a known power. For tah purpose we used an in-house noiseless database to evaluate the de-noising method. The signals of this database have 8 leads and have been acquired with a sampling frequency of 512 Hz and a resolution of 16 bit per sample.

4. Results

We have simulated the addition of different white noise power values to a clean ECG beat to test the de-noising method. After adding the noise, the method is applied to the beat. A subset of coefficients are set to 0 (discarded) following the power threshold criterion and afterwards the inverse wavelet transform is calculated to obtain the reconstructed signal. Results are shown in Fig. 2.

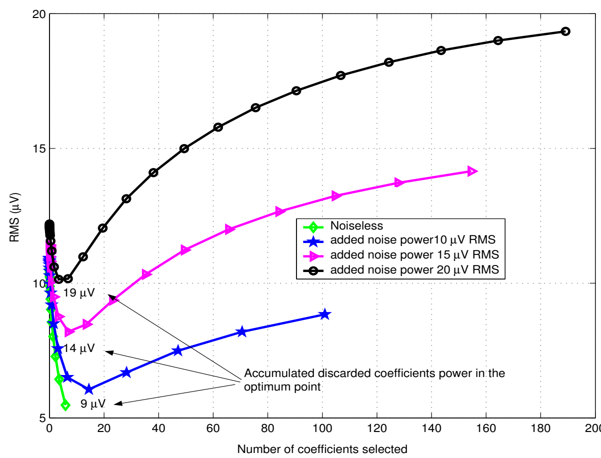

Figure 2. Optimum point for noise removal from an ECG signal.

To evaluate the distortion between the original beat and the reconstructed beat the Root Mean Square (RMS) value is considered. As it is shown in Fig. 2, the optimum number of coefficients is reached when the power of the discarded coefficients equals the power of the noise added. In this way, there is no advantage on setting the boundaries of the signal coefficients subset beyond the optimum value because if we add new coefficients, an increase in the reconstruction distortion will be obtained.

For de-noising purposes the best results are obtained when we set the threshold equals to the noise power value (estimated beat-to-beat in our system). Tab. 1 shows the results obtained applying the method for de-noise purposes. In the first column the RMS value of the noise is shown; the second one shows the mean noise estimated; the third and the fourth columns show the remaining noise level and the improvement in the SNR ratio respectively; finally, column five shows the compression ratio (CR) achieved in the de-noised signal. The de-noising performance is illustrated in Fig. 3.

Table 1. De-noising results

Added noise (μV RMS)	**Estimated noise**	**Output RMS error**	**ΔSNR (dBs)**	**CR**
10	9.8	5.9	4.6	54
20	19.1	10.1	5.9	74
30	28.4	14.4	6.3	90

The compression results obtained when the method is applied to the signals from the MIT database are shown in Tab. 2. It can be noticed that the performance depends on the ECG record being compressed. The best results are obtained when dealing with almost stationary ECG signals because the residuals to be coded have a lower entropy (for example in records 100 and 103). In Fig.4 an original ECG signal (record 109) and the corresponding reconstructed signal are shown. This signal block has been selected to show the performance of the method when dealing with ectopic beats.

Table 2. Compression ratio for different RMS error values and different MIT-BIH records.

Signal	**RMS 10 μV**	**20 μV**	**30 μV**	**40 μV**
100	CR = 9.8	35.5	81	170
103	CR = 9.3	38	83.5	157
109	CR = 4.9	14.1	25	40.3
111	CR = 3.5	16.1	37.4	67
117	CR = 6.4	30.3	80.4	158.6
119	CR = 5.7	15	25.3	42.6

5. Discussion

We have compared our results with those produced by other recent published ECG compressors (see Tab. 3). Only

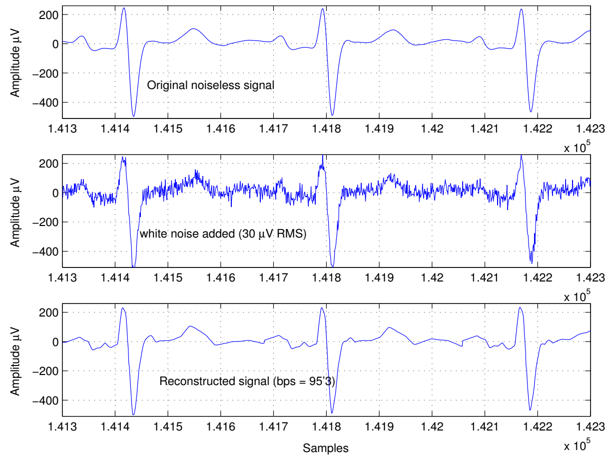

Figure 3. De-noising performance.

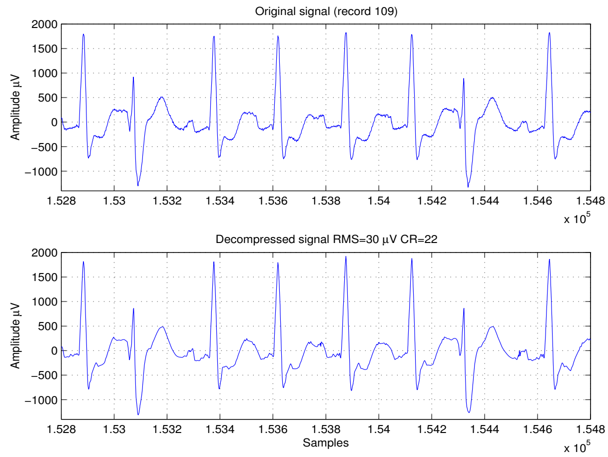

Figure 4. Comparison between original signal and reconstructed signal.

the first lead of the records has been considered to compare with them in equal conditions. The Percentual RMS Difference (PRD) error was used as distortion index [7].

Table 3. Comparison of the performance results with other compression methods.

Compression Method	**PRD (%)**	**CR**	**Signal**
Proposed	6	38.6	100
Proposed	6.6	46.8	100
Miaou [7]	6.6	43.4	100
Nygaard [8]	6	18.4	100
Proposed	3.6	103	117
Miaou [7]	3.6	39	117
Proposed	3.6	26.2	119
Miaou [7]	3.6	25.3	119

Miaou *et al* presented a compression method based on a vector quantizer (VQ) in the wavelet domain [7] .

As can be seen in Table 3, our algorithm has obtained higher compression rates for the same PRD and the three ECG records reported here. In [8] Nygaard *et al* proposed a time domain algorithm based on piece-wise linear approximation. The compression ratio achieved for record 100 was significantly smaller then the one obtained using our method.

Regarding the de-noising process, the method we use to evaluate the withe noise in the ECG signal seems to be very accurate, as it is shown in Tab. 1. The improvement in the SNR is very significant and the distortion that suffers the ECG signal is not high, as can be seen in Fig. 3.

6. Conclusions

In this work, we have proposed a multilead ECG coder based on the wavelet transform. The number of wavelet coefficients is selected according to the noise level estimated in the ECG in order to avoid spending data rate for noise coding. Amplitude and position of WT coefficients were coded with adaptive PCM and Huffman coders respectively. Compression results in MIT-BIH Arrhythmia database showed a better rate-distortion performance compared to previous coders

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Address for correspondence:

Álvaro Alesanco
Communications Technologies Group.
University of Zaragoza
C/María de Luna, 3
50018 Zaragoza
Spain

alesanco@unizar.es