An Adaptive Compression Algorithm for ECG Signals

Beatrice Arvinti*, Alexandru Isar** and Marius Costache*
* “Politehnica” University of Timisoara/Physical Foundations of Engineering, Timisoara, Romania
** “Politehnica” University of Timisoara/ Faculty of Electronics and Telecommunications, Timisoara, Romania
beatrice.arvinti@et.upt.ro, alexandru.isar@etc.upt.ro, marius.costache@et.upt.ro

Abstract— This paper presents a compression algorithm based on wavelets for electrocardiograms. Subband coding, an important feature of wavelet transforms, is exploited for the proposed method in order to enhance the compression ratio. The algorithm can be regarded as an adaptive one because several threshold levels are applied on the same signal. The results are accurate and the proposed compression system can be used to design a real-time remote monitoring system of the patient.

I. INTRODUCTION

Recent advances in technology enable the outspread of a relatively unconventional field of medicine: telemedicine. Remote monitoring systems have nowadays a powerful development, increasing the opportunity of a timely diagnosis of cardiac illnesses through constant monitoring of the patient in its home or working environment [1]. WLAN and WPAN technologies play an important role in the monitoring and transmission of clinically significant data, the patients being equipped with an ECG acquisition system which transmits the recorded data to a hospital for diagnosis (Fig. 1). There are several operations to be performed by the transmitter of a home monitoring system: sampling, quantization, baseline drift correction, denoising, compression, coding and modulation of the ECG signal.

Wavelet based techniques have become an alternative to standard signal analysis techniques based on Fourier analysis due to their good time-frequency representation of non-stationary signals, like biological signals. Sinusoidal functions used for the computation of the Fourier transform are replaced in wavelet analysis through dilations and translations of a basic function (1), called mother wavelets (MW), selected in accordance to the analyzed signal [2]:

\[ \psi_{a,b}(t) = \frac{1}{|b|^{1/2}} \psi \left( \frac{t-a}{b} \right), \quad a, b \in \mathbb{R}, \quad a \neq 0. \]

where \( a \) is a position parameter, \( b \) is a scale parameter and \( \psi(t) \) is the MW.

The aim of the proposed algorithm is the realization of a consistent compression ratio (CR) without loss of clinically significant information, so as to enable real-time monitoring and an easy implementation of the system. The system should be implemented either on a digital signal processor or a FPGA. In literature, wavelets have been used in compression applications ranging from speech compression [3] to image compression [4].

A high CR is necessary for the development of modern clinical systems which should be able to store and handle large quantities of data. The compression aims at a significant reduction of the volume (number of bits) of ECG signals, collected over a long period of time in order to enable their transmission to the hospital where the conditions to put a correct diagnosis are accomplished. Also, the MW necessary for the computation of the wavelet transform used in the compression algorithm has to be carefully chosen to improve the performance of the method. Generally, the quality of a compression method is appreciated using the rate-distortion theory [5]. Usually, the CR and the distortion factor of a signal are inversely proportional and thus a compromise has to be worked out for choosing the optimal CR.

Some results regarding the performance of wavelet based compression algorithms are reported in literature [6, 7]. The papers are proposed for comparison, as they are using examples from the same database (MIT-BIH Arrhythmia database) as our proposed algorithm. In [6], the ECG signal compression is performed using two types of filter banks, namely the Wavelet Packets (WP) and the Nearly–Perfect Reconstruction Cosine Modulated Filter Banks (N–PR CMFB). The Embedded Zerotree Wavelet (EZW) algorithm, proposed for image compression, has been applied to ECG signals and
refined to use WP and not the Discrete Wavelet Transform (DWT), discarding hierarchical relationships between wavelet coefficients. The input signal is decomposed applying a 2-channel reconstruction filter bank at both the low-pass and high-pass branch. The resulting binary tree is considered as a library of bases needed to represent the analyzed signal. The best base of every block is obtained through a pruning algorithm then the wavelet coefficients will be encoded with an EZW-based embedded algorithm. The number of bits necessary for representing the word that indicates the WP filter bank is calculated on account of the amount of possible bases. The encoding–decoding process stops when some target is reached, such as the compression ratio. An N–PR CMFB is a subclass of modulated M-channel maximally decimated filter bank. This algorithm is a simplification and does not take into account the zerotree algorithm when performing the compression.

The compression method presented in [7] is based on the discrete symmetric wavelet transform and is using a spectrum estimator, the number of bits assigned to the quantizer being inversely proportional to the distortion of the output signal. An entropy coder, based on the Huffman coding is completing the system.

The structure of the paper is the following. In Section II are presented the basics for the Discrete Wavelet Transform (DWT) and its application in ECGs compression. Section III presents the proposed compression algorithm based on the DWT which was selected due to its sparsity and to the property of subband coding. In section IV are presented the simulation results and a visual comparison is performed between the original input ECG signal and the reconstructed signal after compression. Also, comparisons are performed with other ECG compression methods based on wavelets. In the last section some conclusions are drawn and further research directions established.

II. COMPRESSION ALGORITHMS

Several time–frequency methods are available for the decomposition and analysis of a given signal, like the Wigner-Ville Transform (WVT), Short Time Fourier Transform (STFT) or the DWT [8]. The DWT is preferred for the proposed algorithm because it is overcoming the limitations of other methods like, for example, a fixed analysis window length. Contrary to the STFT, the DWT allows the variation of the window length, enabling a different compression ratio for the low frequency and high frequency components of the analyzed ECG signal, an effect produced through the dilations and translations applied on the MW. This feature is important as the DWT concentrates the energy of the input signal into a small number of large valued wavelet coefficients, the others coefficients having small values. Considering only the large valued wavelet coefficients, an important compression ratio can be acquired without significant loss of clinical important information. The DWT has two features: the MW and the number of decomposition levels. The proposed compression algorithm is using the DWT aiming at the decomposition of the input ECG into wavelet coefficients, following the structure described in Fig. 2.

A finite impulse response (FIR) low-pass filter (with the impulse response \( LP_1 \)) and a FIR high-pass filter (with the impulse response \( HP_1 \)) are used for the computation of the approximation \( A_4 \) and detail \( d_4 \) wavelet coefficient sequences. The expression of \( LP_1 \) defines a so called scaling function and imposes the expression of \( HP_1 \) which defines the so called MW denoted by \( \psi \) in equation (1). Contrary to the Stationary Wavelet Transform (SWT), the DWT avoids redundancy of clinical irrelevant data through down-sampling by a factor of 2. The signal decomposition is realized on several levels, thus performing a multiresolution analysis (MRA) of the input signal. The spectrum of the coefficients \( A_1(n) \) occupies a low frequency band and the spectra of the coefficients \( d_1(n)-d_4(n) \) occupy some intermediary frequency bands. These bandwidths are distributed in the following order: \( A_4, d_4, d_3, d_2, d_1 \). So, the DWT coefficients are separated in subbands. For this reason the DWT can be seen as a subband coding transformation. An example of DWT decomposition is presented in Fig. 6. The main advantage of the wavelet transform upon the Fourier transform, for example, consists in the ability of performing a MRA of the analyzed signal. The DWT may be computed using several possible MWs, the best one being the one able to represent the ECG signal with the smallest number of significant wavelet coefficients. MWs with good time-frequency localization [9], like Daubechies20 (Db20) are preferred. The architecture of the acquisition chain proposed in this paper is presented in Fig. 3. The CR represents the ratio between the number of bits of the signal at the input of the compression system, \( B_{ECG} \) and the number of bits of the compressed signal \( B_{cECG} \). To ensure that through the reconstruction of the compressed signal there is little clinical relevant information lost, a measure of the distortions due to the compression algorithm has to be defined.

The distortions of the signal are measured using the Signal to Noise Ratio (SNR) defined as follows:

\[
SNR = \frac{\sum_{k=1}^{n} s^2(k)}{\sum_{k=1}^{n} (s(k) - \hat{s}(k))^2},
\]

where \( s \) represents the input signal having \( n \) samples and \( \hat{s} \) represents the signal obtained after compression and reconstruction. A simple to implement compression algorithm [10], based on the DWT uses a hard-thresholding procedure, considering all wavelet coefficients inferior to a given threshold as noise and rejecting them.

![Figure 2. A four-level filter bank for the DWT.](image-url)
III. PROPOSED COMPRESSION ALGORITHM

The proposed compression algorithm consists in two phases. The first phase of the proposed compression algorithm consists in the computation of the DWT of the ECG which must be compressed. Contrary to the algorithm described at the end of the previous section, the threshold will not have a fixed value, but it will be dependent on the current subband. For each subband we will calculate the standard deviation of the coefficients and we will fix the threshold as an appropriate fraction of the standard deviation. The second phase of the proposed compression algorithm consists in an adaptive quantization. Looking at Fig. 6, we can notice that the coefficients of the DWT belonging to different subbands have different magnitudes. The coefficients $A_4$ have the biggest magnitudes followed by coefficients $d_4$, $d_3$, $d_2$ and $d_1$. If we select a quantization level which allows the representation of all coefficients on an imposed number of bits then the binary representations of the values $d_4$, $d_3$, $d_2$ and $d_1$ will begin with some zeros. To prevent this disadvantage, we can quantize the values of those coefficients using a reduced number of bits. The number of bits necessary for the quantization of each of those sequences of coefficients can be evaluated by dividing the maximal value of the sequence $A_4$ to the maximal values of the sequences $d_4$, $d_3$, $d_2$ and $d_1$.

IV. SIMULATION RESULTS

The simulations of the compression system which represents the subject of this paper use as input signal ECGs from the MIT-BIH ECG database, which are acquired using a sampling frequency of 360 Hz and an analog to digital conversion (ADC) on 11 bits.

We have used the database already mentioned for enabling a performance comparison with the results presented in [10]. The same ECG as in [10], namely 102, has been used and the result obtained applying the proposed compression algorithm is illustrated in the following. In Fig. 4 are presented both the original ECG (first diagram) and the signals obtained after denoising (second diagram), [11] and baseline correction (third diagram) [12]. A zoom has been made on seven beats of the signals in Fig. 4, for enabling a better insight and the corresponding results can be seen in Fig. 5.

The first phase of the compression algorithm supposes the computation of the DWT of the signal obtained after denoising and baseline correction. The coefficients, obtained starting from the DWT of the ECG 102, are represented in Fig. 6. Next, the different subbands are identified, as can be seen in Fig. 6. We notice the approximation coefficients $A_4$ and four detail subband coefficients $d_4$, $d_3$, $d_2$ and $d_1$. Next, each detail subband is treated independently. The standard deviations of each detail subband, $sd_k, k=1...4$, are computed and the corresponding thresholds $t_k$ are selected.
We have applied the following rule for the selection of the thresholds: $t_k = 0.25 s_d$. Thus the detail wavelet coefficients are filtered using hard thresholding filters with different threshold values. The next step of the proposed compression algorithm consists in the determination of the number of bits necessary for each signal subband. The approximation coefficients have been quantized on 11 bits in order to keep the resolution of the original ECGs from the MIT-BIH database. Thus, 11 bits are used for the approximation coefficients and for the first detail coefficients subband. The number of bits necessary for the binary representation of the detail wavelet coefficients from the other subbands depends on the selection of the MW, as can be seen in Table I. For the MW Db20 (10 vanishing moments), for the second detail subband are necessary only 10 bits, for the third subband 9 bits and for the last detail subband only 7 bits. Thus is realized a compression ratio of 7.79, higher than the maximum compression ratio obtained in [10], equal with 5.46 for the same input ECG. The reconstructed signal is obtained applying the inverse DWT (IDWT) to the sequence of quantized wavelet coefficients.

In Fig. 7 have been represented both the original and the reconstructed signal and no visible distortions can be perceived.

![Figure 6](image1)

**Figure 6.** The sequence of wavelet coefficients showing the approximation coefficients and the four subbands of detail coefficients.

![ECG after denoising and baseline correction](image2)

**Figure 7.** Zoom on seven beats of the original ECG signal (data 102) and the reconstructed signal.

![ECG after compression and reconstruction](image3)

**Figure 8.** Zoom on five beats of the original ECG signal 117 (up) and the reconstructed ECG signal (bottom).

### Table I. The results of performed simulations

<table>
<thead>
<tr>
<th>MW</th>
<th>CR</th>
<th>SNR</th>
<th>No. bits</th>
<th>No. bits</th>
<th>No. bits</th>
</tr>
</thead>
<tbody>
<tr>
<td>Db4</td>
<td>7.76</td>
<td>22.87</td>
<td>11</td>
<td>10</td>
<td>8</td>
</tr>
<tr>
<td>Db6</td>
<td>7.76</td>
<td>23.09</td>
<td>10</td>
<td>10</td>
<td>8</td>
</tr>
<tr>
<td>Db8</td>
<td>7.76</td>
<td>23.20</td>
<td>10</td>
<td>10</td>
<td>8</td>
</tr>
<tr>
<td>Db10</td>
<td>7.78</td>
<td>23.60</td>
<td>11</td>
<td>10</td>
<td>7</td>
</tr>
<tr>
<td>Db12</td>
<td>7.78</td>
<td>23.46</td>
<td>11</td>
<td>10</td>
<td>7</td>
</tr>
<tr>
<td>Db14</td>
<td>7.78</td>
<td>23.59</td>
<td>10</td>
<td>10</td>
<td>7</td>
</tr>
<tr>
<td>Db16</td>
<td>7.78</td>
<td>23.97</td>
<td>10</td>
<td>9</td>
<td>7</td>
</tr>
<tr>
<td>Db18</td>
<td>7.79</td>
<td>24.20</td>
<td>10</td>
<td>9</td>
<td>7</td>
</tr>
<tr>
<td>Db20</td>
<td>7.79</td>
<td>24.36</td>
<td>10</td>
<td>9</td>
<td>7</td>
</tr>
</tbody>
</table>

The selected MW belongs to the Daubechies family of compactly supported mother wavelets having the maximum number of vanishing moments for a given support length composed by 45 elements and in Table I is illustrated the variation of the CR with the selection of the MW. We notice the increase of the CR and SNR with the increase of the number of vanishing moments of the MW.

To perform a comparison with the methods proposed in [6] and in [7], the proposed algorithm has been applied to the element denoted by 117 in the selected database and, for the mother wavelets Db20, a CR of 7.82 for a SNR of 20.60 has been obtained (Fig. 8). The results are comparable with the results presented in [6], where a CR of 7.7 has been obtained. In [7], the CR is ranging from 4.1 to 7.9, but the distortions are higher with the increase of the CR. For the proposed adaptive compression algorithm, no distortion of the original signal can be perceived (see Fig. 8).

### V. Conclusion

The paper presents an easy to implement compression method for ECG signals based on wavelets. To avoid errors in the diagnosis of an electrocardiogram, errors which could lead to serious consequences, upon the input signal has been firstly applied a denoising and a baseline drift correction method, proposed in [11] and [12]. A wavelet based compression algorithm, obtained in preliminary researches [10], has been improved and presented in this paper. An adaptive quantization has been chosen for the present paper. The selection of an
appropriate threshold for the hard-thresholding of the wavelet coefficients from each detail subband followed by an adaptive quantization are effective measures of increasing the compression ratio without loosing clinically significant information. A visual comparison, like in any hospital environment, has been performed between the original and the reconstructed signal to validate the proposed method. The proposed compression method is very fast. It can be further improved on the basis of the following observation. A great number of wavelet coefficients become equal with zero after the hard-thresholding. Their binary representation could be realized with a number of bits smaller than 7. In fact, it is sufficient to code only their positions. For the coding of the positions of the nulls wavelet coefficients we propose a run-length encoding (RLE) [3], which is a fast coding method based on the substitution of identical symbols in a sequence.

The proposed method shows comparable results with the method described in [6], where the waveforms were obtained with the N-PR CMFB based compressor. The performances of ECG compression when using WP were poorer than the ones obtained with the DWT or N-PR CMFB. As a conclusion, a CR close to 8 is comparable to other compression ratios mentioned in literature [6, 7]. The advantage of the DWT based method consists in its reduced computational effort and in its adaptive character.

Further research direction is the replacement of the DWT, which is not shift invariant, with other wavelet transforms, as for example the hyperanalytic wavelet packets transform, better suited for the ECGs compression. We also intend to ask a cardiologist to perform an authorized visual checking of our compression results.

ACKNOWLEDGMENT

This work was partially supported by the strategic grant POSDRU/88/1.5/S/50783, Project ID50783 (2009), co-financed by the European Social Fund – Investing in People, within the Sectoral Operational Programme Human Resources Development 2007-2013 and partially by a grant of the Romanian Research Council (CNCSIS) with the title “Using Wavelets Theory for Decision Making” no. 349/13.01.09.

REFERENCES