Hindawi Publishing Corporation
EURASIP Journal on Advances in Signal Processing
Volume 2007, Article ID 93195, 9 pages
doi:10.1155/2007/93195

Research Article

A Simple Method for Guaranteeing ECG Quality in Real-Time Wavelet Lossy Coding

Álvaro Alesanco and José García

Communications Technology Group, Aragón Institute of Engineering Research, University of Zaragoza, 50018 Zaragoza, Spain

Received 3 May 2006; Revised 19 October 2006; Accepted 17 December 2006

Recommended by David Hamilton

Guaranteeing ECG signal quality in wavelet lossy compression methods is essential for clinical acceptability of reconstructed signals. In this paper, we present a simple and efficient method for guaranteeing reconstruction quality measured using the new distortion index wavelet weighted PRD (WWPRD), which reflects in a more accurate way the real clinical distortion of the compressed signal. The method is based on the wavelet transform and its subsequent coding using the set partitioning in hierarchical trees (SPIHT) algorithm. By thresholding the WWPRD in the wavelet transform domain, a very precise reconstruction error can be achieved thus enabling to obtain clinically useful reconstructed signals. Because of its computational efficiency, the method is suitable to work in a real-time operation, thus being very useful for real-time telecardiology systems. The method is extensively tested using two different ECG databases. Results led to an excellent conclusion: the method controls the quality in a very accurate way not only in mean value but also with a low-standard deviation. The effects of ECG baseline wandering as well as noise in compression are also discussed. Baseline wandering provokes negative effects when using WWPRD index to guarantee quality because this index is normalized by the signal energy. Therefore, it is better to remove it before compression. On the other hand, noise causes an increase in signal energy provoking an artificial increase of the coded signal bit rate. Clinical validation by cardiologists showed that a WWPRD value of 10% preserves the signal quality and thus they recommend this value to be used in the compression system.

1. INTRODUCTION

ECG signal recording and further interpretation constitute the first tool for cardiopathy diagnosis. Almost all new ECG acquisition devices offer the possibility to digitally store the acquired ECG signals. Taking into account that a standard acquisition device usually works with a sampling frequency of 512 samples per second with a resolution of 16 bits and records 8 leads, the output information rate obtained is about 65 Kbit/s. Although the storage capacity in information systems as well as network bandwidth increases quickly, an efficient storage and transmission method is still required because it leads to an efficient use of the available resources. Moreover, this is specially critical in telecardiology systems, where the available network capacity could be scarce and/or expensive, such as in mobile or satellite communications.

ECG compression is a well-studied topic by the biomedical research community. In the last 15, years a great variety of compression algorithms has been presented. These methods can be roughly divided into two categories: direct methods and transform-based methods [1]. Direct methods treat the ECG samples directly in the time domain. Representative direct methods are AZTEC [2] and CORTES [3]. In transform-based methods, ECG samples are transformed into another domain in order to concentrate a large quantity of signal energy into a small number of coefficients, which afterwards are efficiently coded. Although many transforms have been used (KLT [4], DCT [5], etc.), the wavelet transform (WT) has attracted much attention in the last years [6, 7]. One of its main advantages is its simplicity. Computing the WT is very fast due to the existence of efficient algorithms. Another advantage is its versatility. Wavelet transform can use a great variety of mother functions and some of them adjust very well to the ECG morphology, leading to an efficient representation of the ECG signal in the wavelet domain. A deeper explanation of the wavelet transform can be found elsewhere [8].

In order to obtain relevant compression rates, wavelet compression has to be lossy. Because the power spectral density of the ECG signal has a smooth low-pass shape, the energy distribution at each scale of the WT is concentrated in a small number of coefficients. Moreover, the relevant WT coefficients appear very close in the order sequence within a wavelet scale and in the same position among scales. These properties can be exploited so as to obtain a high compression gain. In this way, the set partitioning in hierarchical trees (SPIHT) algorithm was proposed to be used for ECG signal compression [6]. SPIHT codes the wavelet coefficients exploiting the redundancies among wavelet scales. SPIHT algorithm has demonstrated its efficiency for ECG compression both in obtaining high compression gain with low distortion and computational simplicity, making it a good choice for real-time ECG transmission. Another interesting property is its scalability, not only for controlling the bit rate but also for controlling the distortion introduced in the coding process.

When working with lossy compression, much care must be taken with the distortion introduced in the coding process. The higher the compression rate, the better for transmission and storage purposes but the higher the signal distortion introduced. Two mathematical indices are commonly used to measure the distortion in the compressed ECG signal. The first one is the root mean square (RMS) error index, which is defined as follows:

$$\mathrm{RMS} = \sqrt{\frac{\sum_{n=1}^{N} \left(x[n] - \widetilde{x}[n]\right)^2}{N}}, \tag{1}$$

where $x[n]$ is the original signal, $\widetilde{x}[n]$ is the reconstructed signal, and N is the length of the signal block over which the RMS is calculated. The second one is the percentual RMS Difference (PRD) and it is defined as follows:

$$\mathrm{PRD} = \sqrt{\frac{\sum_{n=1}^{N} \left(x[n] - \widetilde{x}[n]\right)^2}{\sum_{n=1}^{N} x^2[n]}} \times 100(\%). \tag{2}$$

Nevertheless, neither PRD nor RMS indices is directly related to the clinical quality a cardiologist would appreciate when working with the compressed signals. For this reason, a more appropriate index should be used where the clinical quality was reflected while preserving the easy-to-compute property in order to have the possibility to be used in a real-time compression system. The wavelet-based weighted PRD measure (WWPRD) was introduced by Al-Fahoum [9], where it was shown that the correlation between the clinical quality (obtained with a direct survey conducted with cardiologists) and the new proposed index, WWPRD, is much higher than the correlation with the mathematical indices, for example, PRD index.

Since a highly distorted signal can be useless from a clinical point of view, a precise control in the distortion introduced (the quality of the reconstructed signal) is essential for a compression algorithm. In [10], a method for guaranteeing ECG quality using the SPIHT algorithm was also presented. However, due to its indirect way to estimate the distortion by using the Newton-Raphson technique to iteratively calculate the distortion, guaranteeing quality was complex. Besides, the index being guaranteed was PRD, which does not reflect a real clinical distortion.

In this paper we propose a simple method to guarantee the quality of reconstructed signal by thresholding the recently proposed index WWPRD, which reflects in a more accurate way the clinical distortion introduced by the coding process. The paper is organized as follows. A brief summary of SPIHT algorithm is presented in Section 2. In Section 3, the method for guaranteeing quality using the SPIHT is introduced. Extensive results using two different ECG databases as well as discussion of these results are provided in Sections 4 and 5, respectively. Finally, conclusions are presented in Section 6.

2. SPIHT ALGORITHM

SPIHT was firstly presented in [11] as an efficient method for coding wavelet coefficients in image compression. In [6], the algorithm was introduced for ECG compression, obtaining very good results when being compared with other ECG compression methods.

The operation of the SPIHT method is here briefly explained. The principles of the SPIHT algorithm are partial ordering of the transform coefficients by magnitude with a set partitioning sorting algorithm, ordered bit plane transmission, and exploitation of self-similarity across different layers. By following these principles, the encoder always transmits the most significant bit to the decoder.

In a first step, coefficients are arranged in temporal orientation trees, which define the temporal relationship in the wavelet domain. The subset of subband coefficients c_i in the subset θ is said to be significant for m bit depth if $\max_{i\in\theta}\{|c_i|\} \geq 2^m$, otherwise it is said to be insignificant. If the subset is insignificant, a zero is sent to the decoder. If it is significant, a one is sent to the decoder and then the subset is further split according to the temporal orientation tree until all the significant sets are a single significant point. In this stage of coding, called the sorting pass, the indices of the coefficients are put onto three lists, the list of insignificant points (LIP), the list of insignificant sets (LIS), and the list of significant points (LSP). In this pass, only bits related to the LSP entries and binary outcomes of the magnitude tests are transmitted to the decoder. After each sorting pass, the significant coefficients for the threshold are gotten and then the mth most significant bits of every coefficient found significant in the previous pass are sent to the decoder. By transmitting the bit stream in this ordered bit plane way, the most valuable (significant) remaining bits are sent to the decoder. After the refinement pass, m is decreased by one, and the process continues until some condition is reached (in our implementation, this condition is the reconstructed signal distortion). Following the simple concept of an embedded scalar quantizer, the decoding process is straightforward once the encoded bits for wavelet coefficients are obtained.

3. GUARANTEEING QUALITY USING SPIHT

We assume that the original ECG block is defined by a set of sample values $s[i]$ where i is the sample order. The coding is actually done to the array

$$c = W(s), \tag{3}$$

where $W(\cdot)$ represents the wavelet transform and c is a vector containing the transform coefficients. In order to reconstruct the signal, the decoder initially sets the reconstruction vector $\tilde{c}$ to zero and updates its components according to the coded information. Hence, the decoder can obtain a reconstructed signal by using the inverse transform

$$\tilde{s} = W^{-1}(\tilde{c}). \tag{4}$$

The reconstruction distortion D is measured by the squared norm of the difference between the original vector and the reconstructed vector:

$$D(s - \tilde{s}) = \|s - \tilde{s}\|^2 = \sum_{i=1}^{N} \left(s[i] - \tilde{s}[i]\right)^2. \tag{5}$$

If we use the fact that the Euclidean norm is invariant to the wavelet transform (it is a unitary transformation), we can see that

$$D(s - \tilde{s}) = D(c - \tilde{c}) = \sum_{i=1}^{N} \left(c[i] - \tilde{c}[i]\right)^2. \tag{6}$$

Due to RMS and PRD, distortion indices are variants of the squared norm, it is easy to extrapolate these results to them:

$$D_{\text{RMS/PRD}} = \sqrt{\frac{\sum_{i=1}^{N} \left(c[i] - \tilde{c}[i]\right)^2}{F_N}}, \tag{7}$$

where F_N is the normalization factor with value N or $\sum_{i=1}^{N} c[i]^2$ for RMS and PRD, respectively. Thus, it is clear that the guarantee of reconstruction quality using PRD or RMS indices can be easily done by controlling the value of the coded coefficients.

The WWPRD index is defined as follows:

$$\text{WWPRD} = \sum_{j=0}^{j=N_L} w_j \text{WPRD}_j, \tag{8}$$

where N_L is the number of levels of the wavelet expansion which is taken equal to 5 as proposed in [9], w_j is the weight for the subband j and, WPRD_j is the PRD measure for each subband, which is defined as follows:

$$\text{WPRD}_j = \sqrt{\frac{\sum_{i=1}^{n_j} \left(c[i] - \tilde{c}[i]\right)^2}{\sum_{i=1}^{n_j} \left(c[i]\right)^2}} \times 100\%, \tag{9}$$

where $c[i]$ is an original coefficient within subband j and $\tilde{c}[i]$ is a reconstructed coefficient within subband j. In [9] two kinds of weights were proposed. Heuristic weights, which were assigned taking into account the distribution of ECG waves between scales [9]. The values of these weights are $w_{A5} = 6/27$, $w_{D5} = 9/27$, $w_{D4} = 7/27$, $w_{D3} = 3/27$, $w_{D2} = 1/27$, $w_{D1} = 1/27$. The WWPRD index calculated in this manner is called WWPRD_h. In the second version, data-dependent weights are introduced to consider the actual contribution of the subbands. The index calculated using these weights is denoted as WWPRD_w. The weights are calculated as follows:

$$w_j = \frac{\sum_{i=1}^{n_j} |c_j[i]|}{\sum_{j=0}^{N_L} \sum_{i=1}^{n_j} |c_j[i]|}. \tag{10}$$

Guaranteeing reconstruction quality both in PRD/RMS and WWPRD using the SPIHT algorithm can be achieved by stopping the coding process when the desired distortion is reached. To facilitate and speed up the task of calculating the squared norm between the original and the coded coefficients, a list of significant coded coefficients (LSCCs) is also introduced to the algorithm. Every time a bit is stored in the sorting or refinement pass, the list of coded coefficients is updated with the new value of the coefficient. In this way, the LSCC vector has two types of data: coded coefficients and coefficients that have a value equal to zero because the stopping condition has been reached before they are considered significant. In order to accelerate the process of calculating the error for RMS or PRD indices, (11) (which is derived directly from (7)) can be used

$$D_{\text{RMS/PRD}} = \sqrt{\frac{\sum_{i=1}^{N} c^2[i] + \sum_{i=1}^{N} \tilde{c}^2[i] - 2 \cdot \sum_{i=1}^{N} c[i] \cdot \tilde{c}[i]}{F_N}}. \tag{11}$$

Distortion indices (RMS and PRD) can be easily updated every time a new bit is added in the refinement pass by subtracting the term in the sumatories corresponding to the value of the coefficient before a new bit was added to the term corresponding to the coefficient's new value.

Regarding WWPRD index, the process is quite similar to the previously explained process. WPRD_j values are stored from one step to another. Every time a bit is added to a coded coefficient, the corresponding WPRD_j value is updated. Because (9) is similar to (7), the same approach can be used, thus speeding up the process.

4. ECG DATABASES

In order to extensively test the method for guaranteeing quality, two different ECG databases have been used. The first one is the MIT-BIH Arrhythmia [12]. This ECG database consists of 48 two-lead ECG registers of 30-minute duration. The sampling rate is 360 samples per second with a resolution of 11 bits per sample. Although the database was originally created as standard test material for evaluation of arrhythmia detectors, this database is by far the most used database to test and compare ECG compression algorithms. The second ECG database is MIT-BIH compression [13]. It is composed of 248 two-lead ECG records of 20.48-second duration. The sampling rate is 250 samples per second with a resolution of

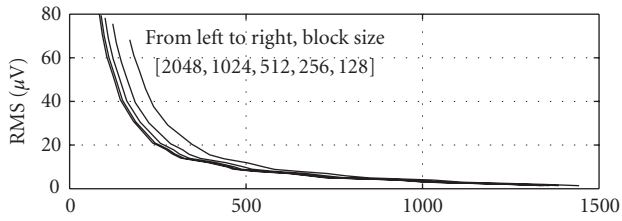


Figure 1: RD curves for different block lengths obtained for MIT-BIH compression database.

12 bits per sample. This database was created to pose a variety of challenges for ECG compressors, in particular for lossy compression methods. Despite of this fact, it is scarcely used to test the ECG compression algorithms, being relegated by MIT-BIH Arrhythmia.

5. RESULTS

In order to analyze the effects of baseline wandering when compressing ECG signals, results have been obtained for all the records in the databases both preserving and removing the baseline wandering. A simple method that can easily work in real-time operation has been used: a third-order low-pass Butterword filter with a cut frequency of 0.5 Hz used in the forward and backward directions to avoid phase distortion [14]. After the baseline is estimated, it is subtracted to the ECG signal. The selection of block length in the different databases follows the following criterion. Because real-time operation is required, it is not desirable that block length is excessively high. On the other hand, short blocks derive in lower compression rates than larger ones for the same distortion. Figure 1 illustrates this case for MIT-BIH compression database. It can be seen how as the block size increases, the performance also increases but there is a point beyond no significant gain can be achieved. As long as the block size is larger than the sampling frequency, the performance is not highly affected. Thus, block size is selected as the dyadic length two times up the sampling frequency (e.g., for MIT-BIH compression the sampling frequency is 250 thus the selected block size is 512). In this way, we obtain slightly better results than with the dyadic length just above the sampling frequency but without falling into excessive delay.

Although in the previous section methodologies for guaranteeing both PRD and WWPRD have been presented, we concentrate here only on the results for guaranteeing WWPRD since this index has been shown more important from a clinical point of view. The results of applying the method guaranteeing both WWPRD_h and WWPRD_w to the MIT-BIH Arrhythmia database are shown in Tables 1 and 2, respectively. The block size selected was 1024 samples. Results are given in the format of *mean* ± *standard deviation (SD)*. Values are calculated as follows. Three different WWPRD values were selected as targets (we call target to the desired distortion in the reconstructed ECG). Mean and SD values were calculated to the vector containing the results obtained block to block. This procedure is repeated for every record in the database. The mean value provided in the tables is the average of the mean value of each signal and the SD value is the average value of the sd for each signal (average statistics). Results obtained in the MIT-BIH Compression database are given in Tables 3 and 4 for WWPRD_h and WWPRD_w errors, respectively. Selected block size was 512 samples.

Table 1: Results when guaranteeing WWPRD_h in MIT-BIH arrhythmia. (WWPRD_h, WWPRD_w, and PRD expressed in %, RMS expressed in μV and bit rate in bps).

ECG with baseline				
Target		5%	10%	20%
Lead 1	WWPRD_h	4.99 ± 0.02	9.95 ± 0.06	19.84 ± 0.17
	WWPRD_w	4.12 ± 0.63	8.25 ± 1.22	16.14 ± 2.23
	PRD	2.27 ± 0.56	4.58 ± 0.98	10.19 ± 1.86
	RMS	9.96 ± 2.28	20.54 ± 4.1	46.48 ± 7.83
	Bit rate	698 ± 112	361 ± 63	192 ± 26
Lead 2	WWPRD_h	4.98 ± 0.02	9.96 ± 0.04	19.87 ± 0.14
	WWPRD_w	5.05 ± 1.04	9.83 ± 1.96	18.16 ± 3.46
	PRD	2.73 ± 0.83	4.8 ± 1.35	9.72 ± 2.48
	RMS	7.51 ± 1.74	13.95 ± 3.39	29.52 ± 6.9
	Bit rate	856 ± 109	494 ± 84	238 ± 43
ECG without baseline				
Lead 1	WWPRD_h	4.99 ± 0.02	9.96 ± 0.05	19.86 ± 0.15
	WWPRD_w	5.93 ± 0.64	11.66 ± 1.16	21.94 ± 1.89
	PRD	3.31 ± 0.67	6.53 ± 1.06	14.06 ± 1.71
	RMS	9.51 ± 2.1	19.28 ± 3.73	42.36 ± 6.92
	Bit rate	717 ± 110	374 ± 65	196 ± 27
Lead 2	WWPRD_h	4.99 ± 0.02	9.97 ± 0.04	19.88 ± 0.12
	WWPRD_w	7.51 ± 0.96	14.46 ± 1.81	25.94 ± 3.08
	PRD	4.67 ± 1.02	7.89 ± 1.48	15.27 ± 2.43
	RMS	7.2 ± 1.55	13.21 ± 3.02	27.34 ± 6.07
	Bit rate	875 ± 105	514 ± 85	247 ± 47

6. DISCUSSION

Results obtained for all the databases guaranteeing both WWPRD_h and WWPRD_w are very accurate in mean value with respect to the target and present a very low standard deviation. This fact demonstrates that the method for guaranteeing quality can be used with any type of ECG signal both with and without baseline.

An interesting fact that can be noted is that the method is more accurate when working with low thresholds rather than high thresholds (the threshold is the target value to be guaranteed). This can be explained by the effect of magnitude of the bits being coded and their quantity. SPIHT algorithm starts storing the bits with highest value and as the threshold decreases, it continues storing bits with lower value. Because wavelet coefficients decrease with an exponential-like shape, as the magnitude of the bits decreases, there are much more bits available for coding (e.g., all the coefficients have bits of level 2^0). In this way, when trying to guarantee a low distortion, the number of bits needed is high and it can be adjusted

Table 2: Results when guaranteeing $WWPRD_w$ in MIT-BIH Arrhythmia. ($WWPRD_w$, $WWPRD_h$, and PRD expressed in %, RMS expressed in μV and bit rate in bps).

ECG with baseline				
Target		5	10	20
Lead 1	$WWPRD_w$	4.99 ± 0.01	9.95 ± 0.05	19.85 ± 0.14
	$WWPRD_h$	6.95 ± 1.09	13.55 ± 2.08	26.08 ± 3.62
	PRD	2.78 ± 0.4	5.77 ± 0.65	13.18 ± 1.06
	RMS	14.3 ± 3.26	30.52 ± 6.61	69.76 ± 14.08
	Bit rate	590 ± 115	320 ± 79	168 ± 37
Lead 2	$WWPRD_w$	4.99 ± 0.01	9.97 ± 0.04	19.88 ± 0.13
	$WWPRD_h$	6.16 ± 1.47	12.77 ± 3	25.63 ± 5.47
	PRD	2.73 ± 0.57	5.07 ± 0.82	11.13 ± 1.3
	RMS	9.34 ± 3.31	19.09 ± 7.09	43.98 ± 16.09
	Bit rate	816 ± 148	491 ± 123	244 ± 77
ECG without baseline				
Lead 1	$WWPRD_w$	4.99 ± 0.01	9.97 ± 0.03	19.89 ± 0.12
	$WWPRD_h$	4.42 ± 0.48	8.84 ± 0.91	18.26 ± 1.76
	PRD	2.89 ± 0.49	5.59 ± 0.83	12.51 ± 1.34
	RMS	8.97 ± 1.98	17.98 ± 3.97	40.59 ± 8.02
	Bit rate	801 ± 127	459 ± 97	227 ± 49
Lead 2	$WWPRD_w$	4.99 ± 0.02	9.98 ± 0.02	19.92 ± 0.09
	$WWPRD_h$	3.73 ± 0.57	7.61 ± 1.11	16.06 ± 2.29
	PRD	3.72 ± 0.75	5.81 ± 1.03	11.38 ± 1.59
	RMS	6.58 ± 1.68	11.92 ± 3.56	25.85 ± 7.82
	Bit rate	1035 ± 120	712 ± 121	387 ± 88

Table 3: Results when guaranteeing $WWPRD_h$ in MIT-BIH compression. $WWPRD_h$, $WWPRD_w$, and PRD expressed in %, RMS expressed in μV and bit rate in bps).

ECG with baseline				
Target		3%	6%	9%
Lead 1	$WWPRD_h$	4.97 ± 0.03	9.91 ± 0.09	19.75 ± 0.24
	$WWPRD_w$	5.36 ± 0.68	10.47 ± 1.24	19.93 ± 2.27
	PRD	3.33 ± 0.65	6.64 ± 1.15	14.01 ± 2.2
	RMS	9.36 ± 1.65	18.77 ± 3.09	40.05 ± 6.53
	Bit rate	530 ± 67	298 ± 45	167 ± 27
Lead 2	$WWPRD_h$	4.98 ± 0.03	9.93 ± 0.07	19.75 ± 0.23
	$WWPRD_w$	5.52 ± 0.84	10.62 ± 1.57	19.46 ± 2.68
	PRD	3.08 ± 0.7	5.84 ± 1.24	11.99 ± 2.3
	RMS	6.83 ± 1.23	13.23 ± 2.39	27.74 ± 5.01
	Bit rate	591 ± 76	330 ± 51	178 ± 28
ECG without baseline				
Lead 1	$WWPRD_h$	4.97 ± 0.04	9.93 ± 0.07	19.75 ± 0.23
	$WWPRD_w$	6.56 ± 0.61	12.65 ± 1.06	23.3 ± 1.75
	PRD	4.17 ± 0.66	8.15 ± 0.97	16.59 ± 1.58
	PRD	8.87 ± 1.53	17.66 ± 2.91	36.69 ± 6.11
	Bit rate	551 ± 65	311 ± 46	174 ± 29
Lead 2	$WWPRD_h$	4.97 ± 0.03	9.93 ± 0.07	19.77 ± 0.21
	$WWPRD_w$	7.26 ± 0.79	13.91 ± 1.43	24.82 ± 2.13
	PRD	4.42 ± 0.77	8.14 ± 1.16	16.11 ± 1.82
	RMS	6.53 ± 1.16	12.57 ± 2.26	26.02 ± 4.67
	Bit rate	610 ± 71	342 ± 51	181 ± 30

very well because of two factors: the magnitudes of the last bits are low and there are many bits available with low magnitude. On the contrary, as the threshold increases, so does the magnitude of the bits being discarded, making it more difficult to adjust exactly the distortion. In order to clarify this explanation, let ori = $[127, 60, 55, 5, 4, 3, 3, 2]$ be a vector containing the hypothetical WT coefficients of a subband of 8 samples. Let us also simplify the coding process assuming that bits are only dedicated to code amplitudes (we do not take into account bits to code other parameters in the algorithm). If we use one bit to code this vector, we would obtain cod = $[64, 0, 0, 0, 0, 0, 0, 0]$ as coded coefficient vector. The $WWPRD_j$ error for this subband between ori and cod vectors is 68.3. If we increase the number of bits used one by one, and the RMS error is calculated, we would obtain the sequence of possible errors that would be obtained when coding this hypothetical WT coefficients vector. This error sequence vector is shown here

$$\begin{aligned}&[68.3^{1\text{ bit}}, 57.9^{2\text{ bits}}, 46.0^{3\text{ bits}}, 32.0^{4\text{ bits}}, 26.5^{5\text{ bits}},\\ &20.5^{6\text{ bits}}, 14.5^{7\text{ bits}}, 11.6^{8\text{ bits}}, 8.8^{9,10\text{ bits}}, 7.7^{11\text{ bits}},\\ &7.3^{12\text{ bits}}, 6.0^{13\text{ bits}}, 5.0^{14\text{ bits}}, 4.2^{15\text{ bits}}, 3.8^{16,17\text{ bits}},\\ &3.3^{18,19,20\text{ bits}}, 2.7^{21\text{ bits}}, 2.0^{22\text{ bits}}, 1.5^{23\text{ bits}}, 1.3^{24,25\text{ bits}},\\ &1.1^{26\text{ bits}}, 0.9^{27,28\text{ bits}}, 0.7^{29\text{ bits}}, 0^{30,31,32\text{ bits}}].\end{aligned} \tag{12}$$

Superindices indicate the number of bits used to code the coefficients that have led to the shown error. It can be clearly seen how gaps between high values are higher than gaps between low values, explaining why it is possible to adjust better low error values.

One interesting result which can be analyzed on these tables is the effect of the baseline wandering in ECG compression. When $WWPRD_h$ is guaranteed in ECGs with baseline, the rate is lower than the rate without baseline for the same $WWPRD_h$. On the other hand, this increase in the rate is much higher when guaranteeing $WWPRD_w$. Since both $WWPRD_h$ and $WWPRD_w$ are normalized by the energy of the subband, if baseline wandering is high, the energy of the lower subband will be high, provoking that both WWPRD thresholds can be achieved using a lower amount of bits. The reason why $WWPRD_w$ suffers a higher increase compared with $WWPRD_h$ is related to the way the weights are calculated for each index. Baseline frequencies are placed in $A5$ subband. When guaranteeing $WWPRD_h$, $A5$ subband weight is constant and takes a value of 6/27. On the other hand, when guaranteeing $WWPRD_w$, $A5$ subband weight depends on the energy in the subband. If baseline is present, the energy of $A5$ subband will increase, compared to the energy when baseline is removed. Thus, $A5$ weight will increase its value when guaranteeing $WWPRD_w$ and baseline is present. Since $A5$ weight will represent an important percentage of all

Table 4: Results when guaranteeing $WWPRD_w$ in MIT-BIH compression. $WWPRD_w$, $WWPRD_h$, and PRD expressed in %, RMS expressed in μV and bit rate in bps).

ECG with baseline				
Target		5	10	20
Lead 1	$WWPRD_w$	4.98 ± 0.01	9.94 ± 0.05	19.81 ± 0.15
	$WWPRD_h$	4.79 ± 0.69	9.72 ± 1.36	20.31 ± 2.8
	PRD	3.09 ± 0.37	6.26 ± 0.64	13.8 ± 1.11
	RMS	8.94 ± 1.73	18.27 ± 3.53	40.34 ± 7.5
	Bit rate	558 ± 77	313 ± 57	169 ± 32
Lead 2	$WWPRD_w$	4.98 ± 0.01	9.95 ± 0.04	19.81 ± 0.17
	$WWPRD_h$	4.9 ± 0.89	10.17 ± 1.86	21.63 ± 3.78
	PRD	2.78 ± 0.41	5.43 ± 0.72	12.12 ± 1.23
	RMS	6.68 ± 1.42	13.49 ± 3.09	30.4 ± 6.84
	Bit rate	623 ± 92	350 ± 72	175 ± 37
ECG without baseline				
Lead 1	$WWPRD_w$	4.98 ± 0.01	9.95 ± 0.04	19.84 ± 0.13
	$WWPRD_h$	3.87 ± 0.4	7.97 ± 0.73	16.81 ± 1.41
	PRD	3.28 ± 0.47	6.4 ± 0.76	13.76 ± 1.26
	PRD	7.3 ± 1.38	14.63 ± 2.81	31.84 ± 5.95
	Bit rate	655 ± 69	396 ± 59	210 ± 36
Lead 2	$WWPRD_w$	4.98 ± 0.01	9.96 ± 0.04	19.86 ± 0.12
	$WWPRD_h$	3.53 ± 0.43	7.31 ± 0.82	15.62 ± 1.66
	PRD	3.29 ± 0.52	5.96 ± 0.85	12.43 ± 1.42
	RMS	5.28 ± 1.1	10.2 ± 2.31	22.13 ± 4.96
	Bit rate	746 ± 80	478 ± 74	250 ± 45

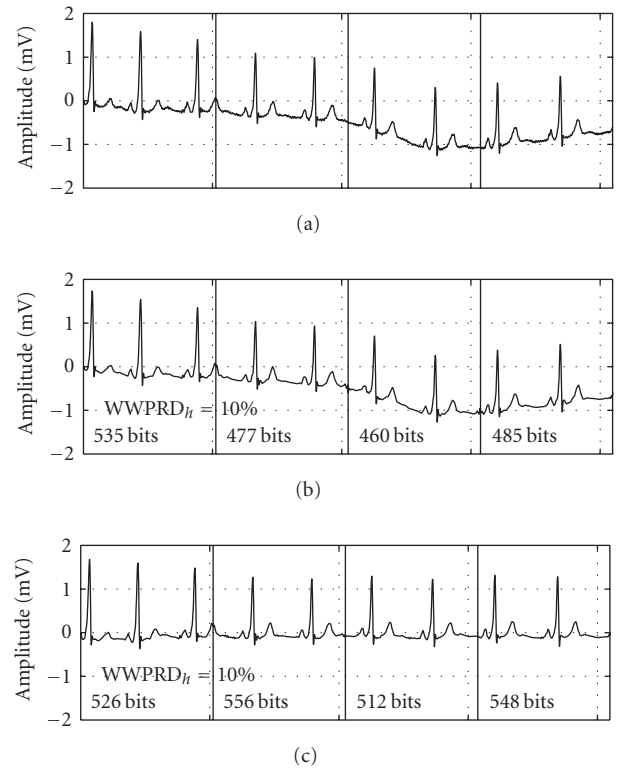


Figure 2: Effects on compression quality due to baseline wandering. (a) Original signal. (b) Reconstructed signal with baseline wandering. Target $WWPRD_h$ = 10%. (c) Reconstructed signal without baseline wandering. Target $WWPRD_h$ = 10%.

weights, the effect of baseline wandering increasing the energy and lowering the number of bits required to guarantee a desired distortion will be amplified thus provoking a higher increase in rate when guaranteeing $WWPRD_h$, where the weight is constant. These effects are clearly shown in Figures 2 and 3 for $WWPRD_h$ and $WWPRD_w$, respectively. Figures 2(a) and 3(a) present the same original ECG signal. It has been included two times for clarity. They represent the first 4 blocks (512 samples per block) of record 12 936_01 from MIT-BIH compression database. Figures 2(b) and 3(b) show, respectively, the reconstructed signal when the $WWPRD_h$ and $WWPRD_w$ target distortions are selected to be 10%. For each block, the number of bits needed to obtain the desired goal is shown. In Figures 2(c) and 3(c), the reconstructed signals when the baseline has been removed before compression are presented when guaranteeing $WWPRD_h$ and $WWPRD_w$, respectively. It can be noticed how the bit rate needed to guarantee both $WWPRD_h$ and $WWPRD_w$ decreases as the variations of the baseline wandering increase when baseline is not removed although this effect is more acute when guaranteeing $WWPRD_w$ as discussed earlier. This could be damaging for the clinical quality of the reconstructed signal since the quality decreases for the same WWPRD. On the other hand, if the baseline wandering has been removed prior to compression, the clinical quality of the signal is higher block to block (see Figures 2(c) and 3(c)). Because guaranteeing PRD is less bit demanding when the baseline wandering is high (as it happens in blocks three and four), this is translated into a loss of quality in the reconstructed signal for the same WWPRD. Decreasing the distortion threshold to assure a higher quality in order to avoid the effects of the baseline wandering is not an optimal solution since the increase in bit rate in those blocks with low baseline wandering would not be justified if with less bits an acceptable quality can be achieved. Guaranteeing WWPRD when compressing a signal with baseline has a negative effect because the real fact is that the quality is not uniform through the blocks, being lower when the baseline wandering is high, as it has been shown both in Figures 2 and 3. This effect is much more acute when guaranteeing $WWPRD_w$.

Another interesting found fact is the bit rate variability of the transmission rate compared with the variability of the error. This is shown in Figures 4(a) and 4(c) which represent the error obtained block to block for lead 1 of record 101 from MIT-BIH Arrhythmia database when guaranteeing $WWPRD_h$ (target 10%) and $WWPRD_w$ (target 10%) without baseline, respectively. It can be seen, as expected, that the achievement of the goal is very accurate. Figures 4(b)

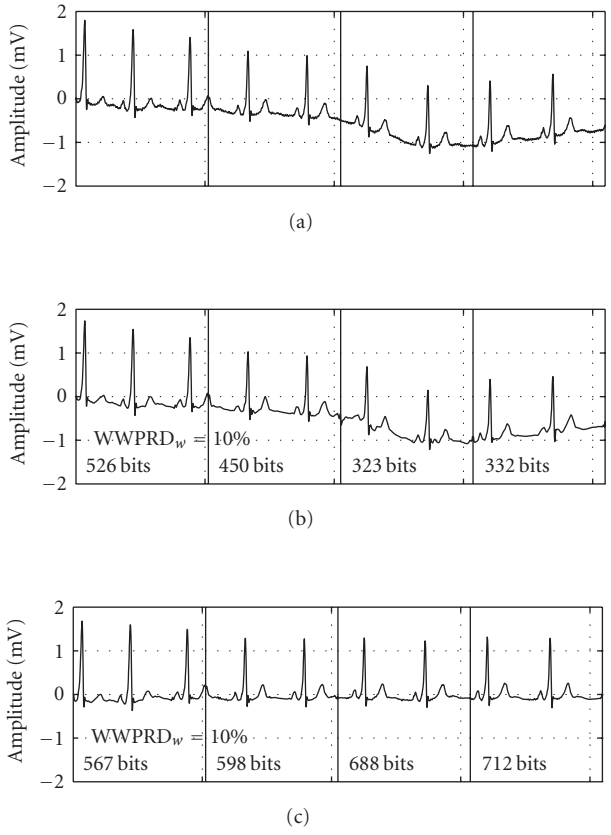


Figure 3: Effects on compression quality due to baseline wandering. (a) Original signal. (b) Reconstructed signal with baseline wandering. Target WWPRD$_w$ = 10%. (c) Reconstructed signal without baseline wandering. Target WWPRD$_w$ = 10%.

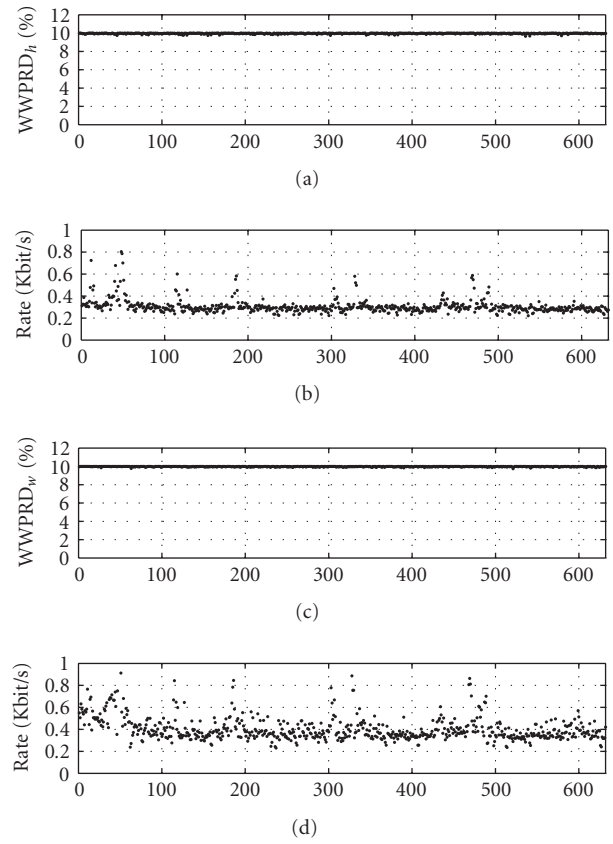


Figure 4: Quality results for record 101 of MIT-BIH Arrhythmia database is expressed block to block. (a) Target WWPRD$_h$ = 10%. (b) Rate for target WWPRD$_h$ = 6%. (c) Target WWPRD$_w$ = 10%. (d) Rate for target WWPRD$_w$ = 10%.

and 4(d) show the evolution of the rate block to block when guaranteeing WWPRD$_h$ (target 10%) and WWPRD$_w$ (target 10%), respectively. In both cases, the variability of the rate is high but it can be appreciated how this variability when guaranteeing WWPRD$_w$ is higher than when guaranteeing WWPRD$_h$. Variability in block energy explains the variability in the rate achieved for both WWPRD$_h$ and WWPRD$_w$. Blocks with high energy (e.g., those where two QRS are located) need more bits to guarantee the desired quality compared with those blocks with low energy. The higher variability in WWPRD$_w$ compared with WWPRD$_h$ is explained taking into account the way the weights are calculated. Fixed weights used in WWPRD$_h$ compensate the effects caused by energy variability, thus lowering the variability in transmission rate. On the other hand, energy-dependent weights used in WWPRD$_w$ amplify these effects thus provoking a high transmission rate variability. Besides the natural variability of the signal energy there exists another source of energy for a block; noise. Record 101 presents blocks with a high noise, which can be easily recognized in Figures 4(b) and 4(d) due to their high transmission rate. Thus, the high increase in transmission rate is dedicated to code the extra energy introduced by noise. To prevent this problem, in [15] an automatic compression system that adjusts its threshold to the noise energy was introduced. It was based on a beat segmentation strategy instead of block segmentation. Clinical evaluation showed that the method provides very good quality in the reconstructed signals from a clinical point of view while preventing the data rate to increase dramatically due to noise.

When evaluating a compression methodology it is very important to evaluate the compressed signals from a clinical point of view. For this reason, we have carried out a simple simiblind test taking into account 10 records selected from each ECG database randomly, where cardiologists were asked to compare the compressed signals at different WWPRD values with the original ones. The values selected for both WWPRD$_h$ and WWPRD$_w$ were 5%, 10% and 20%. Figures 5 and 6 show an example of original and compressed signals when guaranteeing record 12936_01 from MIT-BIH compression database for WWPRD$_h$ and WWPRD$_w$, respectively. Cardiologists expressed that they would choose a threshold of 10% in both WWPRD indices in order to give the same diagnosis and to feel comfortable working with the compressed signals.

To evaluate the execution times of the coding and decoding processes we have used 8-lead ECG records since usually the maximum number of leads an ECG signal can present is 8 (extra leads are calculated from the original 8).

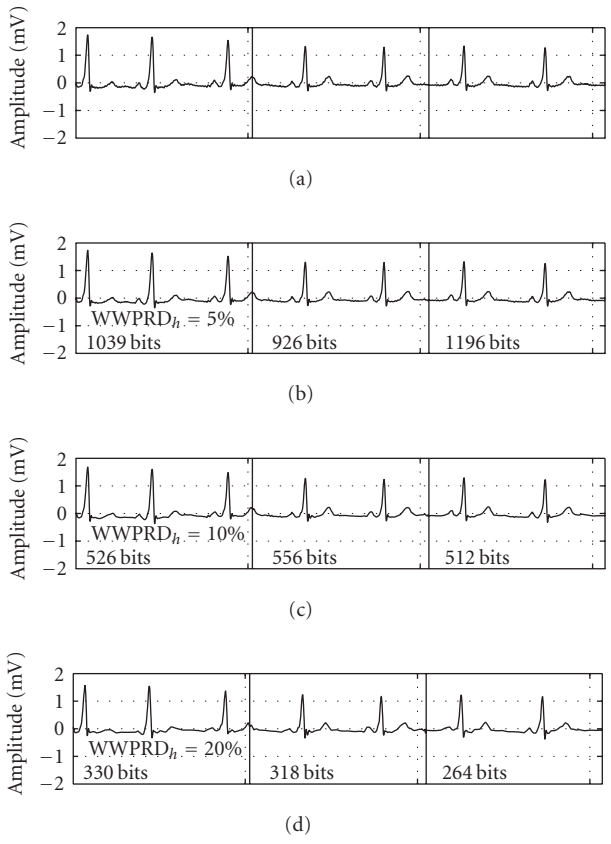


Figure 5: (a) Original signal. (b) Reconstructed signal when guaranteeing WWPRD$_h$ = 5%. (c) Reconstructed signal when guaranteeing WWPRD$_h$ = 10%. (d) Reconstructed signal when guaranteeing WWPRD$_h$ = 20%.

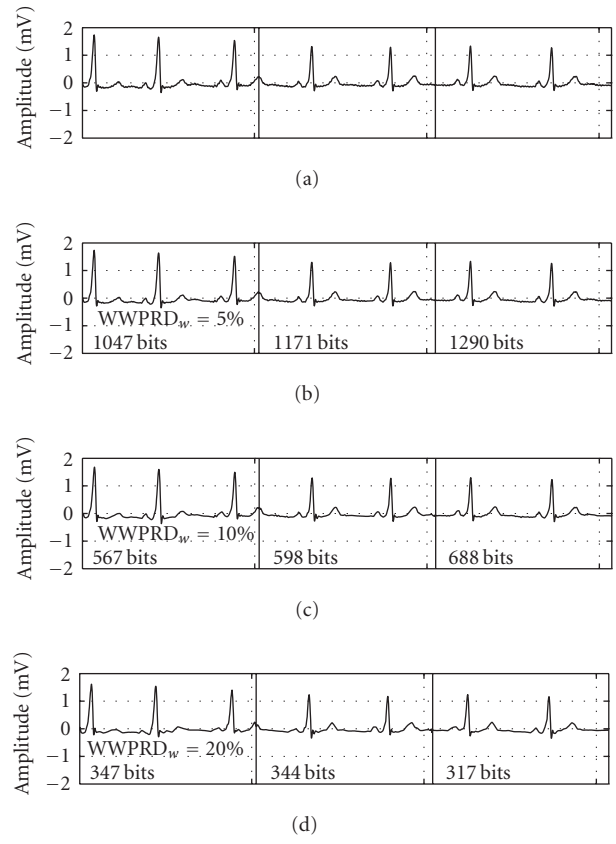


Figure 6: Original signal. (b) Reconstructed signal when guaranteeing WWPRD$_w$ = 5%. (c) Reconstructed signal when guaranteeing WWPRD$_w$ = 10%. (d) Reconstructed signal when guaranteeing WWPRD$_w$ = 20%.

Table 5: Maximum execution times for the coding and decoding processes in different PCs.

PC characteristics	Coding	Decoding
Pentium IV 2.8 GHz 1 GB RAM	8 ms	3 ms
Pentium II 300 MHz 256 MB RAM	90 ms	29 ms

We have created 8-lead records from those of the MIT-BIH Arrhythmia replicating both leads 4 times. Each record of the database was coded/decoded separately as it would be done in a real-time operation. Target distortion was set up to 0 because it represents the most operation demanding case. Average execution times were obtained for the database and the maximum times among them are reported in Table 5. Results are given in milliseconds required to code 1 second of original signal.

Results of Table 5 clearly show that even for a PC with a Pentium II 300 MHz processor with 256 MBytes of RAM there is no problem for achieving real-time functionality. The programming language used for the coder was C because of its efficiency.

7. CONCLUSIONS

In this paper, a simple and efficient method for guaranteeing reconstructed ECG quality in real time has been presented. Compression is based on performing the wavelet transform to blocks of the original ECG signal and wavelet coefficients are efficiently coded using the SPIHT algorithm. The list of significant coded coefficients (LSCCs) is introduced to the original algorithm so as to control the quality in an easy manner. Extensive tests have shown the accuracy of the method not only obtaining the desired target in mean but also with a low standard deviation value. It has also been shown that baseline wandering could produce a disturbing effect in real quality when guaranteeing WWPRD due to the normalization performed by the signal energy in the calculation of this index. These effects are much more acute when guaranteeing WWPRD$_w$ rather than WWPRD$_h$ due to the way the weights are calculated. Hence, it is recommended to remove baseline wandering before compression. Noise in ECG signals increases the bit rate due to the extra energy introduced. In order to prevent this effect, an adaptive approach that varies the threshold should be used. Cardiologists reflect that they will feel comfortable working with a WWPRD of 10%. Real-time tests performed have shown that the algorithm is very

fast thus having no problem to work in a real-time environment. Even for a low-capacity PC, execution times keep below 100 ms per second for an 8-lead ECG signal.

ACKNOWLEDGMENTS

This work was supported by Project TSI2004-04940-C02-01 from Comisión Interministerial de Ciencia y Tecnología (CICYT) and Fondos Europeos de Desarrollo Regional (FEDER), Project FIS PI051416 from Fondo de Investigación Sanitaria (FIS), and VI Framework Programme: IST-27142 PULSERS II IP.

REFERENCES

[1] S. M. S. Jalaleddine, C. G. Hutchens, R. D. Strattan, and W. A. Coberly, "ECG data compression techniques—a unified approach," *IEEE Transactions on Biomedical Engineering*, vol. 37, no. 4, pp. 329–343, 1990.

[2] J. R. Cox, F. M. Nolle, H. A. Fozzard, and G. C. Oliver Jr., "AZTEC: a preprocessing program for real-time ECG rhythm analysis," *IEEE Transactions on Biomedical Engineering*, vol. 15, no. 2, pp. 128–129, 1968.

[3] J. P. Abenstein and W. J. Tompkins, "A new data-reduction algorithm for real-time ECG analysis," *IEEE Transactions on Biomedical Engineering*, vol. 29, no. 1, pp. 43–48, 1982.

[4] S. Olmos, M. Millán, J. García, and P. Laguna, "ECG data compression with the Karhunen-Loève transform," in *Proceedings of Computers in Cardiology*, pp. 253–256, Indianapolis, Ind, USA, September 1996.

[5] N. Ahmed, P. J. Milne, and S. G. Harris, "Electrocardiographic data compression via orthogonal transforms," *IEEE Transactions on Biomedical Engineering*, vol. 22, no. 6, pp. 484–487, 1975.

[6] Z. Lu, D. Y. Kim, and W. A. Pearlman, "Wavelet compression of ECG signals by the set partitioning in hierarchical trees algorithm," *IEEE Transactions on Biomedical Engineering*, vol. 47, no. 7, pp. 849–856, 2000.

[7] M. L. Hilton, "Wavelet and wavelet packet compression of electrocardiograms," *IEEE Transactions on Biomedical Engineering*, vol. 44, no. 5, pp. 394–402, 1997.

[8] C. Chui, *An Introduction to Wavelets*, Academic Press, London, UK, 1992.

[9] A. S. Al-Fahoum, "Quality assessment of ECG compression techniques using a wavelet-based diagnostic measure," *IEEE Transactions on Information Technology in Biomedicine*, vol. 10, no. 1, pp. 182–191, 2006.

[10] S.-G. Miaou and C.-L. Lin, "A quality-on-demand algorithm for wavelet-based compression of electrocardiogram signals," *IEEE Transactions on Biomedical Engineering*, vol. 49, no. 3, pp. 233–239, 2002.

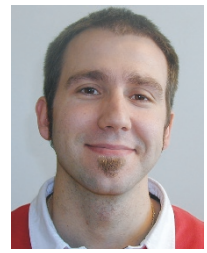
[11] A. Said and W. A. Pearlman, "A new, fast, and efficient image codec based on set partitioning in hierarchical trees," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 6, no. 3, pp. 243–250, 1996.

[12] G. B. Moody and R. G. Mark, "The MIT-BIH arrhythmia database on CD-ROM and software for use with it," in *Proceedings of Computers in Cardiology*, pp. 185–188, Chicago, Ill, USA, September 1990.

[13] G. B. Moody, R. G. Mark, and A. L. Goldberger, "Evaluation of the 'TRIM' ECG data compressor," in *Proceedings of Computers in Cardiology*, pp. 167–170, Washington, DC, USA, September 1988.

[14] L. Sörnmo and P. Laguna, *Biomedical Signal Processing in Cardiac and Neurological Applications*, Elsevier, San Diego, Calif, USA, 2005.

[15] Á. Alesanco, S. Olmos, R. S. H. Istepanian, and J. García, "Enhanced real-time ECG coder for packetized telecardiology applications," *IEEE Transactions on Information Technology in Biomedicine*, vol. 10, no. 2, pp. 229–236, 2006.



Álvaro Alesanco was born in Ezcaray, Spain, in 1977. He received the Master's degree in telecommunications engineering from the University of Zaragoza (UZ), Zaragoza, Spain, in 2001. He is currently Assistant Professor of communication networks in the telematics engineering area in UZ. He is also a Visiting Researcher at Mobile Information and Network Technologies Research Center, Kingston University, Kingston upon Thames, London (United Kingdom). He has undergone different research stages working on telemedicine in Australia and United Kingdom. His research interests are ECG and echocardiography video coding and transmission in wireless e-health environments.

José García was born in Zaragoza, Spain, in 1971. He received the M.S. degree in physics and the Ph.D. degree "with honors" from the University of Zaragoza (UZ), Zaragoza, Spain, in 1994 and 1998, respectively. He is with the Department of Electronics Engineering and Communications in the Polytechnic Center of UZ. He is currently an Associate Professor in the telematics engineering area and a Member of the Aragón Institute of Engineering Research (I3A). He is the founder and responsible of the Telemedicine Group in the I3A. He is Recipient, Investigator, and Coinvestigator of research grants from the *Ministry of Science and Technology* and the Sanitary *Research Funds* in the area of telemedicine applications and networks. His work is also supported by major industrial and mobile companies such as *Telefónica Móviles* in the area of wireless communications for health. He has undergone different research stages in USA, Sweden, and Austria. He has published more than 50 refereed international journal and conference papers, mostly in the areas of wireless telemedicine and biomedical signal processing. He is also a Reviewer of several journals on the topic. His research interests are in telemedicine, biomedical signal processing for transmission, wireless communications, and other related topics.