

## **ECG Signal Compression Using 2D Wavelet Foveation**

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### **Abstract**

*Foveation principles suggested by natural vision systems enable the construction of a proper mask that may modulate the coefficients given by the Discrete Wavelet Transform of an ECG record. The mask is spatially selective and provides maximum accuracy around specific regions of interest. Subsequent denoising and coefficient quantization are further combined with efficient coding techniques such as SPIHT in order to provide high compression ratios at low reconstruction errors. Experimental results reported on a number of MIT-BIH records show improved performances over existing solutions*

*Keywords: Foveation, 2D DWT, compression, ECG.*

### **1. Introduction**

ECG signal compression has been one of the major biomedical research topics during the last decades. Triggered by the availability of new theoretical tools, technological advances, and e-health initiatives, a plethora of original solutions have been reported and comparative tests on publicly available databases were conducted. Transform-based methods using a broad range of tools such as wavelet analysis, Discrete Cosinus Transform (DCT) or Principal Components Analysis (PCA) have been preferred over direct methods dealing with the raw ECG time series such as AZTEC or CORTES, and have been complemented by further signal processing stages based on optimal quantization and entropy encoding. Special attention has been paid to assessing the clinical quality of the lossy compressed data, hence specific distortion measures have been defined [1, 2, 3] in addition to the classical Euclidean ones.

One common aspect shared by many of the top performant compression methods refers to the use of the Discrete Wavelet Transform (DWT). It has been widely used in ECG signal analysis since this type of signals (short high-frequency impulses (R wave) superimposed on slowly varying waveforms (P, T, U waves), including artifacts and noise) favors processing tools with variable time-frequency resolution. Reported results indicate that DWT not only enables reliable identification of specific points and segments characterizing the ECG waveforms, but may also yield high compression ratios since most of the signal energy is concentrated in a limited number of significant coefficients.

An interesting line of research focuses on transforming the original one-dimensional ECG waveforms into 2D information, followed by further processing using various image processing tools. Examples include multiresolution analysis, vector quantization, and JPEG2000 coding. In this context, the present paper proposes a novel compression scheme inspired by natural vision systems, based on combining DWT analysis with the construction of a space-scale selective mask obtained following retina-like foveation principles [4].

Basically, foveation implements the design of the natural retina that provides variable spatial resolution: it has a very large number of cells in the central region (the fovea) and a continually decreasing number of cells towards its periphery. As a consequence, the details present in the original image are kept unaltered along the foveated region, while they smoothly disappear towards the margins of the visual field (anyway, in order to get a better picture of “interesting” regions in the inspected scene, the eyes successively switch between several distinct foveal points).

Using variable spatial resolution by means of foveation yields reduced data dimensionality, which may be exploited within a compression framework. Previous results have shown the possibility of treating foveation as an integral operator that may be conveniently approximated in order to provide a mask that will modulate the DWT coefficients of the analyzed signal, for both 1D and 2D cases [4]. As a consequence, the number of significant DWT coefficients will drop, and subsequent quantization will further decrease their number. Finally, the output data is obtained after applying a general-purpose lossless compression technique or more sophisticated methods especially efficient within the wavelet analysis framework such as EZW or SPIHT [5, 6].

Recent studies revealed that a cardiologist would spend most of the time inspecting specific regions along the ECG waveform [7], hence in order to preserve critical diagnose information we shall construct the mask by combining the contributions of several distinct foveal points, placed on the R peak, and the middle of the P and T waves, respectively. As such, we may preserve the durations, the amplitudes, and the shapes of clinically significant features that will ultimately contribute to assessing the quality of the compressed waveforms by means of various performance criteria such as Percent Root-Mean Square Difference (PRD), Compression Ratio (CR), or more sophisticated Weighted Diagnostic Distortion (WDD) measure [1]. It is interesting to note that some of the top performant segmentation procedures aiming at identifying the characteristic points of ECG signals have also been introduced within the wavelet analysis framework [8], although we may still consider complementary methods rooted in general pattern recognition theory that are able to detect specific regions-of-interest (ROI) [9, 10].

The block diagram of the proposed approach is indicated in Figure 1. It includes a preprocessing module that splits the original waveform into separate single-beat segments, identifies the corresponding characteristic points, and performs a padding procedure in order to equalize the lengths of the individual segments to a common value (that should be chosen as a power-of-two to accommodate subsequent DWT analysis). For the 2D case, the single-beat segments should be arranged into a matrix format, and specific sorting procedures will be applied to fully utilize both intra- and inter-correlation between the lines [11, 12]. Based on the characteristic points provided by the preprocessing stage, a separate module computes a (multi-) foveation mask, the parameters of which are mainly influenced by the widths of the regions-of-interest. For the 1D case we have a distinct mask for each individual segment (based on its specific PQRST complex), whereas in the 2D case the number of foveation points will drop significantly, since a single region-of-interest may cover a group of single-beat segments. We subsequently perform DWT decomposition of the ECG segments and modulate the resulting coefficients by multiplying those with the corresponding mask. As a result, the number of (masked) DWT coefficients will decrease considerably, and their number may further be reduced after applying one of the available denoising procedures. In order to obtain the final compressed information we may choose between the following

alternatives: a) quantize the masked DWT coefficients and apply a general-purpose lossless or lossy procedure. Anyway, we should keep in mind that both the amplitudes and the positions of the remaining wavelet coefficients are to be stored. Additionally, we should also transmit a small overhead indicating the actual length of each single-beat segment, and its mean value; b) use an embedded scalar quantizer/compression method such as SPIHT that is especially suited to deal with wavelet-generated data (besides the original version of the algorithm we may even consider some of the recently introduced modified forms, available for both 1D and 2D cases [13, 14]). The reconstruction procedure should first decompress the coded information, then perform inverse DWT in order to yield a foveated waveform (or image) to be compared against the original data.

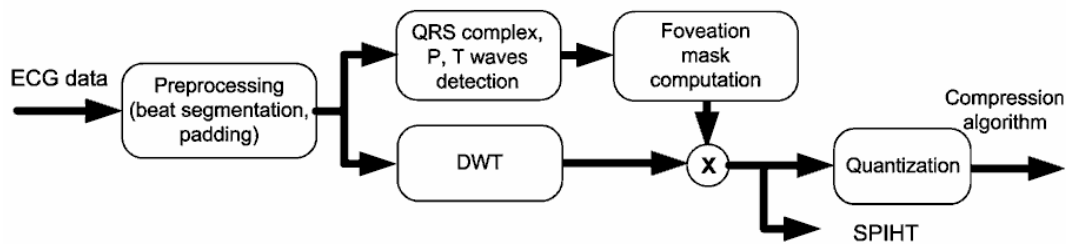


Figure 1. Block Diagram of The Wavelet Foveation Approach

There are a number of advantages of the proposed method, such as: a) the approximation error is spread non-uniformly along the analyzed waveform, exhibiting lower values around segments of critical clinical importance; b) since it is basically a wavelet-oriented approach it may benefit of existing highly performant compression techniques such as SPIHT. In this context, an additional advantage is given by the possibility of progressive-quality transmission (most significant bits are transmitted first, hence the major features of the received signal are readily observable, then it keeps continually improving) that may be highly desirable in critical, alarm-triggering situations; c) as pointed out later, the foveation operator may be realized by using lookup tables, and further simplified by considering binary approximations, thus greatly smoothing the progress of the implementation step.

## 2. Wavelet foveation

Going from a uniform resolution 1D or 2D signal to the fovea-like distribution exhibiting variable spatial resolution is called foveation. For the one-dimensional case, foveation of a signal has been modeled as space-variant smoothing according to [4]:

$$(Tf)(x) = \int_{-\infty}^{\infty} f(t) \frac{1}{w(x)} g \left[ \frac{t-x}{w(x)} \right] dt \quad (1)$$

where  $w: \mathbb{R} \rightarrow \mathbb{R}^+$  defines a weighting function and  $g: \mathbb{R} \rightarrow \mathbb{R}$  is a smoothing function. The weight  $w(x)$  is modeled as  $w(x) = \alpha|x - \gamma| + \beta$  and depends on three parameters:  $\alpha$  is the rate by which the resolution decreases,  $\gamma$  is the fovea (the point with the highest resolution), and  $\beta$  is the foveal resolution ( $\alpha$  and  $\beta$  must be non-negative). Since we are typically interested in processing the available information using multiple foveal points, the global weighting

function  $w(x)$  may be constructed from a set of individual ones  $\{w_1(x), w_2(x), \dots\}$  according to:

From a more general perspective, foveation may be also treated as an integral operator [4]:

$$w(x) = \min\{w_1(x), w_2(x), \dots\} \quad (\mathbf{T}f)(x) = \int_{-\infty}^{\infty} k(x,t) f(t) dt \quad (2)$$

Considering a Gaussian smoothing function  $g(\cdot)$  as in Figure 2a, we give a contour plot of the kernel in Figure 2b. A number of important results have been established in [4] with direct application within the foveation framework. To start with, given a foveation operator  $\mathbf{T}$  with a weight function  $w(x) = \alpha|x|$ , and a smooth function  $g(x)$  with support on  $[-\alpha^{-1}, \alpha^{-1}]$ , we construct the matrix:

$$\theta_{j,m,k,n} = \langle \mathbf{T}\psi_{j,m}, \psi_{k,n} \rangle = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \psi_{j,m}(t) \psi_{k,n}(x) \frac{1}{|x|} g\left(\frac{t-x}{\alpha|x|}\right) dt dx \quad (3)$$

where  $\{\phi_{l_0,n}\}_{0 \leq n < 2^{l_0}} \cup \{\psi_{j,n}\}_{j \leq l_0, 0 \leq n < 2^{-j}}$  define an orthonormal wavelet basis ( $\psi_{j,n}(\cdot)$  and  $\phi_{l_0,n}(\cdot)$  represent scaled and translated versions of the mother wavelet  $\psi(\cdot)$  and scaling function  $\phi(\cdot)$ , respectively, and the notation  $\langle \cdot, \cdot \rangle$  defines the scalar product between 2 vectors). Matrix  $\theta$  may be interpreted as the two-dimensional DWT of the kernel function, as given in Figure 2c. The components of matrix  $\theta$  may be well approximated only by the diagonal elements  $\{\theta_{j,n,j,n}\}$ , based on the observation that these components exhibit rapid decay both along the main diagonal of matrix  $\theta$ , and off the diagonal (in fact, the speed of decay depends on the properties of the wavelet function, namely the regularity and number of vanishing moments). With reference to the example presented in Figure 2c, we illustrate the diagonal values of the transformation matrix in Figure 2d. Following the considerations above, the foveation operator  $(\mathbf{T}f)(x)$  gets a simpler form as [4]:

$$(\mathbf{T}f)(x) \approx \langle f, \phi_{l_0,0} \rangle \phi_{l_0,0} + \sum_{j=1}^{l_0} \sum_{n=0}^{2^j-1} \theta_{j,n,j,n} d_{j,n} \psi_{j,n} \quad (4)$$

where  $d_{j,n} = \langle f, \psi_{j,n} \rangle$  represent the one-dimensional DWT of  $f(t)$ . By denoting  $\mathbf{M} = \{\theta_{j,n,j,n}\}$  and interpreting it as a mask, we may compactly express the foveated waveform as:

$$(\mathbf{T}f)(x) = \mathbf{DWT}^{-1} \{ \mathbf{M} * \mathbf{DWT}(f) \} \quad (5)$$

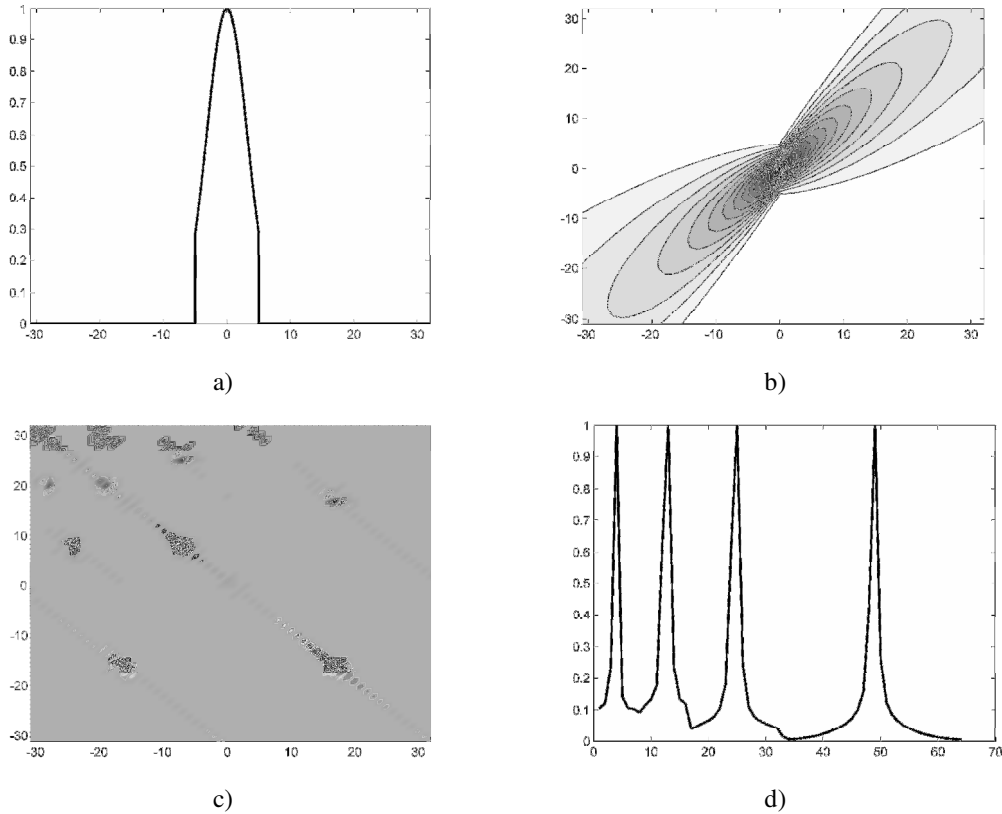


Figure 2. a) Gaussian-type smoothing function  $g(x)$ ; b) contour plot of the kernel function  $k(x, t)$  (darker pixels represent larger values); c) corresponding  $\theta$  matrix; d) diagonal entries of matrix  $\theta$

One interesting line of research that has attracted much attention recently relies on transforming the original one-dimensional ECG waveforms into 2D images, and thus enabling further coding techniques to use both interbeat and intrabeat correlations. As such, classical general-purpose compression methods such as JPEG2000 or wavelet-oriented solutions such as SPIHT or EZW have shown impressive performance improvements over one-dimensional cases [11-13]. Typically, the 1D-2D reshaping is based on special preprocessing procedures involving cut-and-align successive single-beat intervals [23] (complemented with constant value padding), or period normalization [24]. Various improvements of the basic approaches have also been proposed in order to increase the correlation between successive lines of the resulting image [11, 12].

The foveation principle previously introduced for the one-dimensional case may be generalized for the 2D case by considering a two-dimensional smoothing kernel [4]:

$$g_{x,y}(s,t) = \frac{1}{w(x,y)^2} g\left(\frac{s-x}{w(x,y)}, \frac{t-y}{w(x,y)}\right) \quad (6)$$

and a corresponding two-dimensional weight function  $w(x,y) = \alpha \|(x,y) - (\gamma_1, \gamma_2)\|_2 + \beta$ . Much similar to the 1D case, the kernel is also transformed via the (two-dimensional)

DWT, showing again rapid decay away from the foveal point. In order to obtain the actual expression of the mask, we should consider the following definitions for the two-dimensional wavelets [4]:

$$\begin{aligned}
 \Phi_{j,m,n}(x,y) &= \phi_{j,m}(x) \cdot \phi_{j,n}(y) \\
 \Psi^d_{j,m,n}(x,y) &= \psi_{j,m}(x) \cdot \psi_{j,n}(y) \\
 \Psi^v_{j,m,n}(x,y) &= \psi_{j,m}(x) \cdot \phi_{j,n}(y) \\
 \Psi^h_{j,m,n}(x,y) &= \phi_{j,m}(x) \cdot \psi_{j,n}(y)
 \end{aligned} \tag{7}$$

The expression of the foveated image is approximated as:

$$\begin{aligned}
 (T^{fov}\mathbf{I})(x,y) &= \int_{R^2} \mathbf{I}(s,t) g_{x,y}(s,t) ds dt = \\
 &= \langle \mathbf{I}, \Phi_{l_0,0,0} \rangle \Phi_{l_0,0,0} + \sum_{k,m,n,j} c^k_j[m,n] d^k_j[m,n] \Psi^k_{j,m,n}
 \end{aligned} \tag{8}$$

where  $\{d^k_j[m,n]\}$  define the two-dimensional DWT transform of the original (constant resolution) image  $\mathbf{I}$  along the diagonal, vertical, and horizontal directions, respectively, and the masking coefficients  $\{c^k_j[m,n]\}$  approximate the dominant (diagonal) entries of the transformed kernel. These coefficients may be computed as follows [4]:

$$c^k_j[m,n] = \begin{cases} c_j[r] \cdot b_j[r], & \text{if } k = v \\ b_j[r] \cdot c_j[r], & \text{if } k = h \\ c_j[r] \cdot c_j[r], & \text{otherwise} \end{cases} \tag{9}$$

where  $r = \sqrt{m^2 + n^2}$ ,  $c_j[m]$  is the one-dimensional mask computed as in equation (3), and coefficients  $b_j[n]$  approximate the scalar product  $\langle \phi_{j,m}, T^{fov}(\phi_{j,m}) \rangle$ . As a consequence, we only need to keep two one-dimensional masks and compute the two-dimensional mask as indicated in equation (9).

### 3. Experimental results

We have performed extensive computer simulations in order to validate the compression performances of the foveation approach. Tests were conducted using 10-minute long signals extracted from a number of records in the MIT-BIH Arrhythmia database [25], namely records 100, 101, 102, 103, 105, 106, 115, 117, 119, 202, 209, and 212. The data is sampled with 360 Hz, and is represented with 11 bits resolution. The records first undergo a preprocessing step that is merely driven by the 2D experiments. Specifically, we automatically detected the characteristic points of the ECG waveforms using the wavelet-based procedure introduced in [8]. It relies on an important theoretical result reported by S. Mallat that illustrates the possibility of characterizing the local shape of irregular structures by means of the evolution of DWT local maxima along successive dyadic scales [26]. A number of several such modulus-maxima based approaches have been reported [8], showing

remarkable performances on several publicly available databases. Basically, a multiscale decomposition is first performed on the given ECG record, and afterwards the presence of min-max pairs of coefficients is identified on successive distinct resolution scales. Only pairs that are present on all scales are selected and further processed, the rest are treated as parasitic and eliminated, with the additional benefit of removing also many sources of noise and/or artifacts. We begin by first detecting the R peaks, since they yield modulus maxima with highest amplitudes. This enables the segmentation of the original ECG record into individual single-beat signals. In fact, following the procedure in [11], we cut the raw data at every 130th sample before each R peak in order to avoid large variations between the edge values. Next, we apply mean-padding of the individual beats to obtain a common length for all the segments by augmenting them with an appropriate number of constant values given by the average amplitude of each segment. The common length is given by the next power-of-two of the longest original single-beat segment in order to accommodate the data to the subsequent DWT processing (more specifically, the common length was set to 512 samples). The next step consists in detecting the onset and final points of the T and P waves, respectively, using the same modulus-maxima approach described earlier. Although the method has been used with remarkable success in practical applications, we should nevertheless note that the performances of this strategy rely on existing medical experience that provides statistical information on average segments durations, refractory periods, and typical artifacts. For the 2D case, individual (mean-padded, length equalized) segments are assembled into a square matrix to be foveated, as in Figure 3. Following [11, 12], we increase the correlation between successive rows of the image by performing a sorting procedure. We experimented with both period length sorting as in [11], and complexity sorting as in [12], and obtained better results with the later approach.

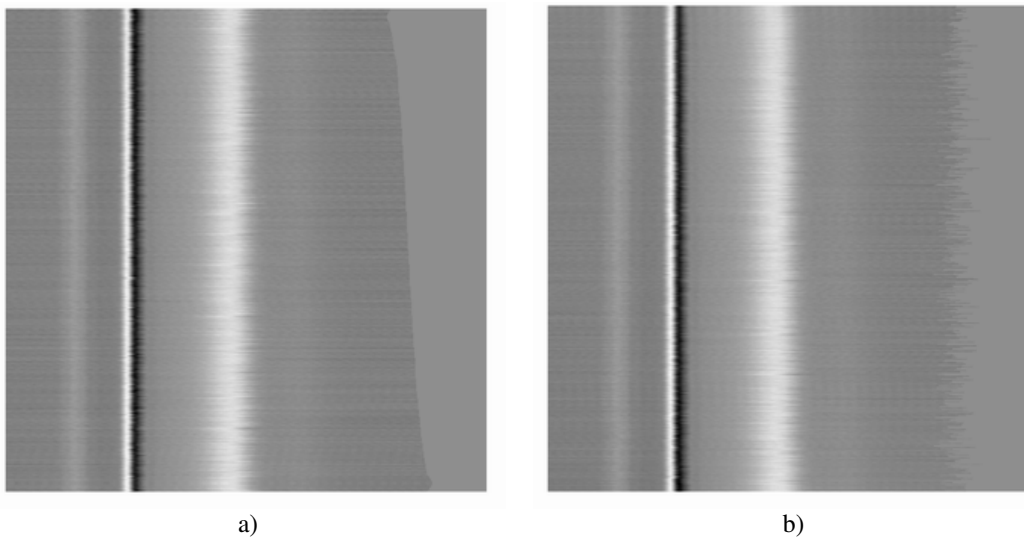


Figure 3. Preprocessing procedures for the 2D case (record 117):  
a) period sorting; b) complexity sorting

DWT was performed using a biorthogonal basis, namely 7/9 Villesanor type [18], that proved optimal according to previous studies [16, 17]. The  $\alpha$  parameter controlling the foveation rate was chosen inversely proportional with the width of the QRS complex, and the

P and T waves, respectively. The values of the  $\beta$  parameter controlling the foveal resolution was selected at a common value of 1 for all the foveal points.

The compression performances were computed in terms of the Percent Root-Mean Square Difference (PRD) and the Compression Ratio (CR) defined as follows:

$$PRD = \sqrt{\frac{\sum_{i=1}^N (x[i] - \hat{x}[i])^2}{\sum_{i=1}^N x^2[i]}} \times 100 \quad [\%] \quad (10)$$

$$CR = \frac{N_{bits}^{original}}{N_{bits}^{compressed}}$$

where  $x$  denotes the original signal and  $\hat{x}$  the compressed version.  $N_{bits}$  defines the total number of bits used to encode the original and the compressed signal, respectively. We have further compressed the masked wavelet coefficients using both a general purpose compression algorithm, namely the Lempel-Ziv coding strategy implemented in the gzip tool [27], and the wavelet-oriented SPIHT algorithm [5]. In the former case, we first quantized the amplitudes of the coefficients using a 8-bit scalar quantizer (the compressed information includes both the amplitudes of the masked wavelet coefficients and their positions). As regarding the SPIHT algorithm, we used the code developed by the authors of the original method to deal with the 1D case (code available at <http://www.cipr.rpi.edu/research/SPIHT/>). For the 2D case we used the MATLAB Wavelet Toolbox, ver. 4.3.

The full benefit of the foveation approach is obtained in the 2D case, since we not only exploit both intra-beat and inter-beat correlations, but we may also decrease significantly the number of foveal points, since each point would extend its “region of influence” in both coordinates. Within this context, we will exploit the observation at the end of Section 3, by using distinct  $\alpha$  parameters to define the weighting functions (and corresponding one-dimensional masks) along the horizontal and vertical coordinates. More specifically, while we keep the idea of choosing the  $\alpha$  parameter along the horizontal direction inversely proportional to the durations of the foveal segments (QRS complex, and the P and T waves, respectively), we will set the  $\alpha$  parameter along the vertical direction inversely proportional to the number of selected foveal points. As such, we may obtain a uniform covering of the foveal regions using a small number of actual foveal points. Comparative analysis with existing reported data is indicated in Table 1 for records 100, 117, and 119, showing improved performances. The dimensions of the images in all cases is 512x512 pixels, and number of foveation points was 16. End-effects were tackled by performing symmetric extensions along both coordinates.

In Figure 4a are evidenced the regions-of-interest defined by the QRS complex, P and T waves, respectively, along with the actual positions of the foveal points, whereas in Figure 4b we present the shape of the two-dimensional mask centered on the selected foveal points, showing uniform coverage of the clinically significant regions.



Examples of original and compressed waveforms, along with corresponding error sequences are indicated in Figure 5, showing the preservation of useful diagnostic information.

Table 1. Performance comparison with existing methods for the 2D case

Method	Record	CR	PRD [%]
Lee et al [23]	100	24:1	8.10
Chou et. al [11]	100	24:1	4.06
Filho et. al [12]	100	24:1	3.47
Foveation + SPIHT	100	20:1	0.52
Filho et. al [12]	117	24:1	1.64
Filho et. al [12]	117	13:1	1.07
Filho et. al [12]	117	8:1	0.75
Chou et. al [11]	117	13:1	1.18
Bilgin et. al [28]	117	8:1	0.86
Foveation + SPIHT	117	32:1	0.51
Foveation + SPIHT	117	17:1	0.29
Foveation + SPIHT	117	9.5:1	0.18
Bilgin et. al [28]	119	21.6:1	3.76
Filho et. al [12]	119	20.9:1	1.78
Filho et. al [12]	119	10:1	0.93
Chou et. al [11]	119	10:1	1.03
Foveation + SPIHT	119	20:1	0.49
Foveation + SPIHT	119	12:1	0.28

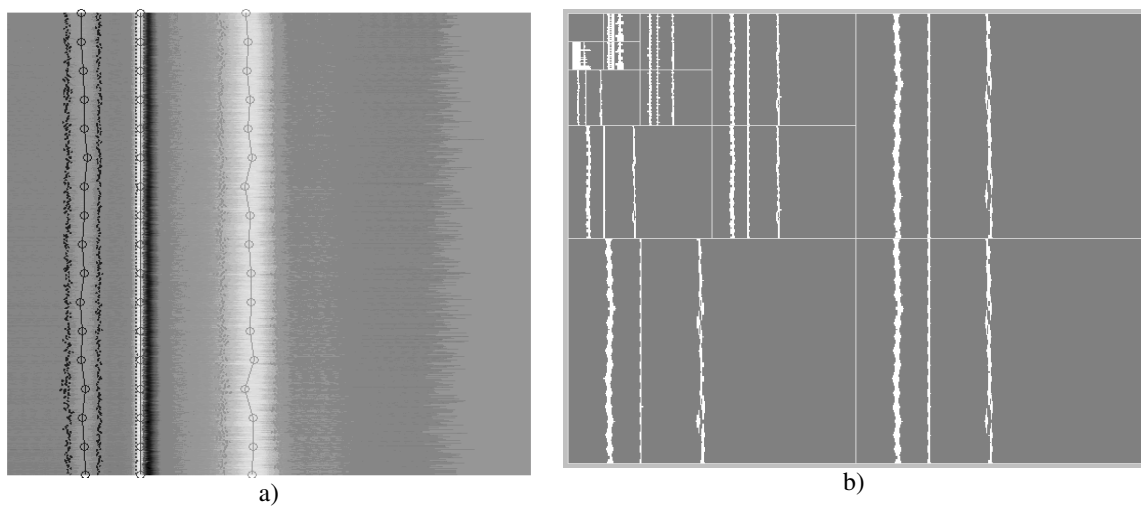


Figure 4. Wavelet foveation for the 2D case: a) Continuous line: onset and final points of the P waves, QRS complexes, and T waves, respectively; Circle line: foveal points; b) Foveation mask uniformly covering the regions-of-interest

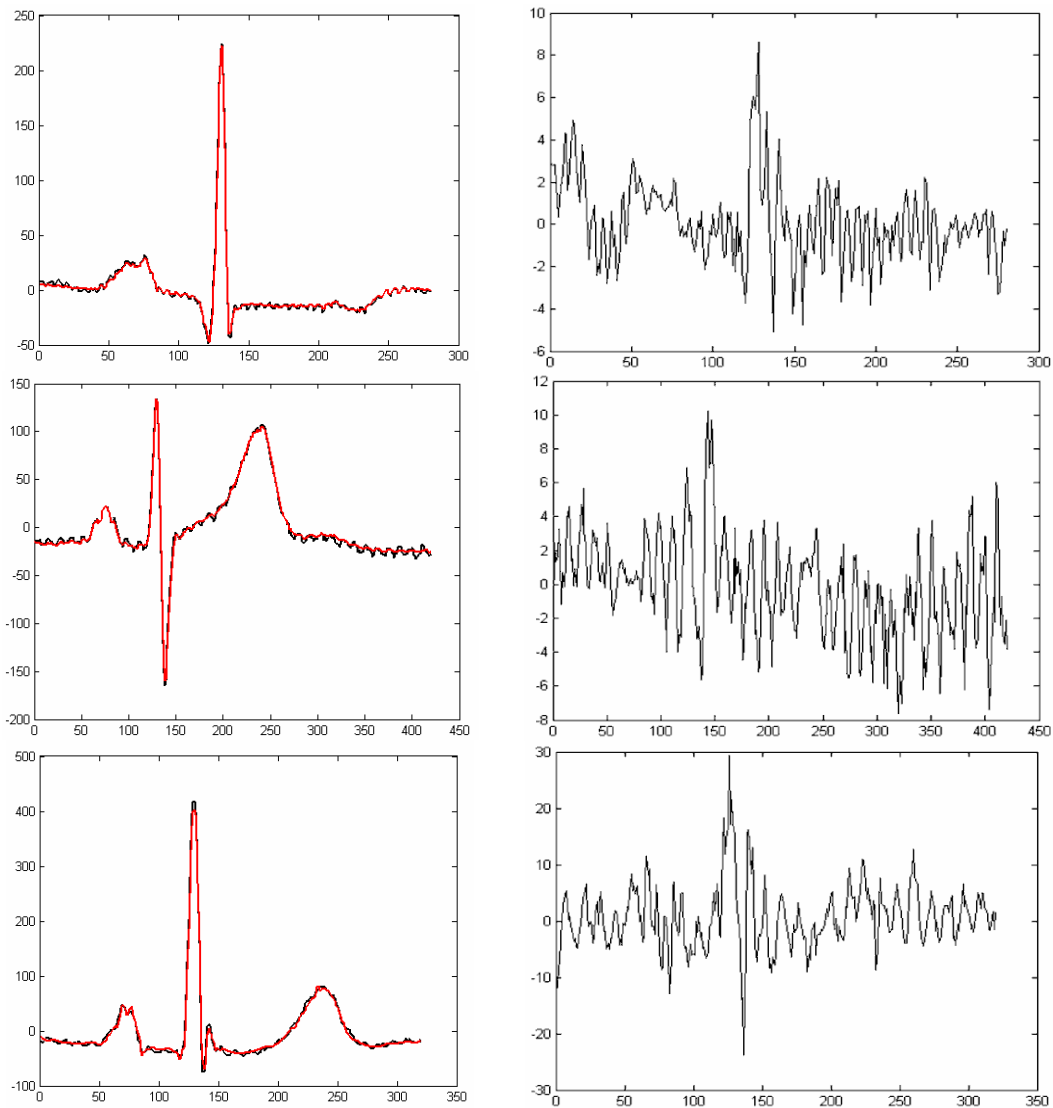


Figure 5. Left – Original (black) and foveated waveforms (red); Right – error sequences. From first to last row, the records under study are 100, 117, and 119.

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