Discrete Wavelet-based Fuzzy Network Architecture for ECG Rhythm-Type Recognition: Feature Extraction and Clustering-Oriented Tuning of Fuzzy Inference System

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Abstract

The paper addresses a new QRS complex geometrical feature extraction technique as well as its application for supervised electrocardiogram (ECG) heart-beat type classification. Toward this objective, after detection and delineation of major events of the ECG signal via an appropriate algorithm, each QRS region and also its corresponding discrete wavelet transform (DWT) are supposed as virtual images and each of them is divided into eight polar sectors. Then, the curve length of each excerpted segment is calculated and is used as the element of the feature space. Afterwards, an appropriate fuzzy network classifier aimed for recognizing several heart-beat types is preliminarily designed. To propose a new classification strategy with adequate robustness against noise, artifacts and arrhythmic outliers, the fuzzy rules parameterization and determination stages were fulfilled using the fuzzy c-means (FCM) and the subtractive clustering techniques. To show merit of the new proposed algorithm, it was applied to 4 number of arrhythmias (Normal, Left Bundle Branch Block-LBBB, Right Bundle Branch Block-RBBB, Paced Beat-PB) belonging to 12 records of the MIT-BIH Arrhythmia Database and the average accuracy values Acc=94.58% and Acc=97.41% were achieved for FCM-based and subtractive clustering-based fuzzy-logic classifiers, respectively. To evaluate operating characteristics of the new proposed fuzzy classifier, the obtained results were compared with similar peer-reviewed studies in this area.

Keywords: *Feature Extraction; Curve-Length Method; Discrete Wavelet Transform; Fuzzy-Logic Classification; Subtractive Clustering; Fuzzy C-means Clustering; Arrhythmia Classification.*

1. Introduction

Signal processing and data mining tools have been developed to enhance the computational capabilities so as to help clinicians in diagnosis and treatment. The electrocardiogram (ECG) is a representative signal containing information about the condition of the heart. The shape and size of the P-QRS-T wave and the time intervals between various peaks contains useful information about the nature of disease afflicting the heart. However, the human observer cannot directly monitor these subtle details. Besides, since biosignals are highly subjective, the symptoms may appear at random in the timescale. The presence of cardiac abnormalities is generally reflected in the shape of ECG waveform and heart rate. Therefore, study of ECG

pattern and heart rate variability has to be carried out over extended periods of time, [1]. If according to any happening, the electro-mechanical function of a region of myocytes (constitutive cells of the heart myogenic muscle) fails, the corresponding abnormal effects will appear in the ECG which is an important part of the preliminary evaluation of a patient suspected to have a heart-related problem.

The general block diagram of the proposed heart arrhythmia recognition-classification algorithm including two stages train and test is shown in Fig. 1. According to this figure, first, the events of the ECG signal are detected and delineated using a robust wavelet-based algorithm [62-63]. Then, each QRS region and also its corresponding DWT are supposed as virtual images and each of them is divided into eight polar sectors. Next, the curve length of each excerpted segment is calculated and is used as the element of the feature space. An appropriate fuzzy network is then regulated using subtractive and the FCM clustering techniques. The proposed method was applied to 4 number of arrhythmias (Normal, LBBB, RBBB, PB) belonging to 12 records of the MIT-BIH database and the average value of accuracies Acc=94.58% and Acc=97.41% were achieved for fuzzy-logic classifiers based on the FCM and subtractive clustering techniques, respectively.

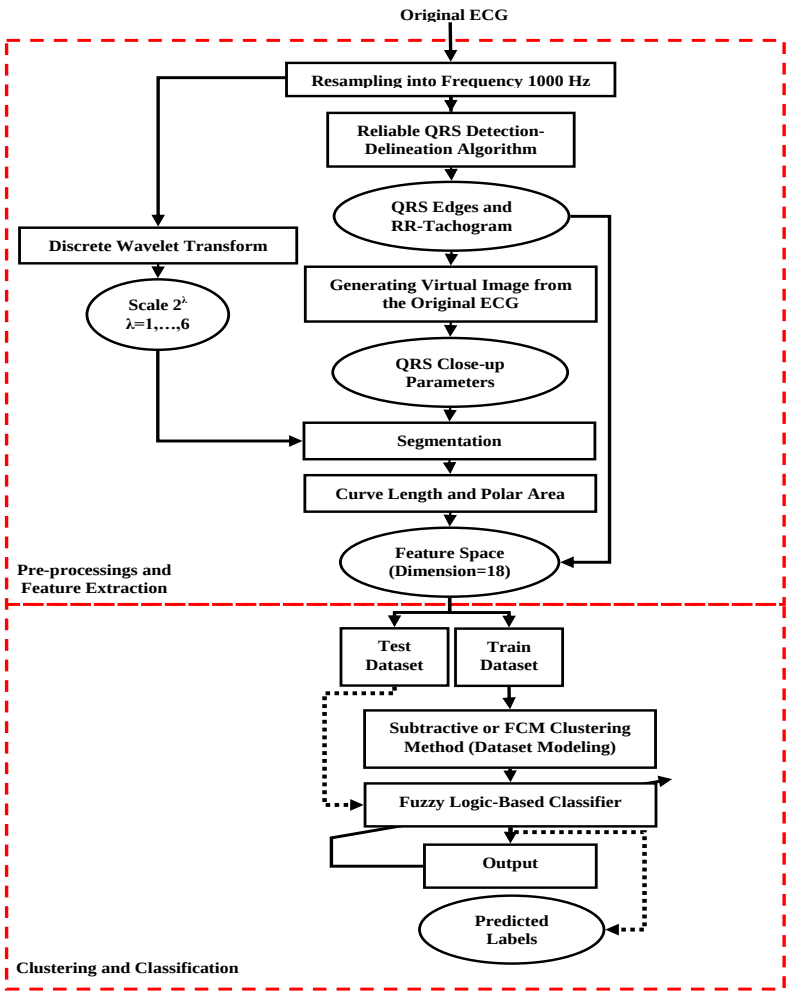

Figure 1. The general block diagram of an ECG beat type recognition algorithm supplied with the virtual image-based geometrical features

2. Previous Works

Based on a comprehensive literature survey among many documented works, it is seen that several features and extraction (selection) methods have been created and implemented by authors. For example, original ECG signal [17], preprocessed ECG signal via appropriately defined and implemented transformations such as discrete wavelet transform (DWT), continuous wavelet transform (CWT) [21], Hilbert transform (HT) [64], fast Fourier transform(FFT) [48-49], short time Fourier transform (STFT) [10], power spectral density (PSD) [51-52], higher order spectral methods [46-47], statistical moments [24], nonlinear transformations such as Liapunov exponents and fractals [43-45] have been used as appropriate sources for feature extraction. In order to extract feature(s) from a selected source, various methodologies and techniques have been introduced. To meet this end, the first step is segmentation and excerption of specific parts of the preprocessed trend (for example, in the area of the heart arrhythmia classification, ventricular depolarization regions are the most used segments). Afterwards, appropriate and efficient features can be calculated from excerpted segments via a useful method. Up to now, various techniques have been proposed for the computation of feature(s). For example mean, standard deviation, maximum value to minimum value ratio, maximum-minimum slopes, summation of point to point difference, area, duration of events, correlation coefficient with a pre-defined waveform template, statistical moments of the auto (cross) correlation functions with a reference waveform [32], bi-spectrum [46], differential entropy [37], mutual information [39], nonlinear integral transforms and some other more complicated structures [33-45] may be used as an instrument for calculation of features. After generation of the feature source, segmentation, feature selection and extraction (calculation), the resulted feature vectors should be divided into two groups “train” and “test” to tune an appropriate classifier such as a neural network, support vector machine or ANFIS, [30-40]. As previous researches show, occurrence of arrhythmia(s) affects RR-tachogram and Heart Rate Variability (HRV) in such a way that these quantities can be used as good features to classify several rhythms. Using RR-tachogram or HRV analysis in feature extraction and via simple if-then or other parametric or nonparametric classification rules [7-9], artificial neural networks, fuzzy or ANFIS networks [10-14], support vector machines [15] and probabilistic frameworks such as Bayesian hypotheses tests [16], the arrhythmia classification would be fulfilled with acceptable accuracies. Heretofore, the main concentration of the arrhythmia classification schemes has been on morphology assessment and/or geometrical parameters of the ECG events. Traditionally, in the studies based on the morphology and the wave geometry, first, during a preprocessing stage, some corrections such as baseline wander removal, noise-artifact rejection and a suitable scaling are applied. Then, using an appropriate mapping for instance, filter banks, discrete or continuous wavelet transform in different spatial resolutions and etc., more information is derived from the original signal for further processing and analyses. In some researches, original and/or preprocessed signal are used as appropriate features and using artificial neural network or fuzzy classifiers [17-25], parametric and probabilistic classifiers [26-28], the discrimination goals are followed. Although, in such classification approaches, acceptable results may be achieved, however, due to the implementation of the original samples as components of the feature vector, computational cost and burden especially in high sampling frequencies will be very high and the algorithm may take a long time to be trained for a given database. In some other researches, geometrical parameters of QRS complexes such as maximum value to minimum value ratio, area under the segment, maximum slope, summation (absolute value) of point to point difference, ST-segment, PR and QT intervals, statistical parameters such as correlation coefficient of a

assumed segment with a template waveform, first and second moments of original or preprocessed signal and etc. are used as effective features [29-35]. The main definition origin of these features is based on practical observations and a priori heuristic knowledge whilst conducted researches have shown that by using these features, convincing results may be reached. On the other hand, some of studies in the literature focus on the ways of choosing and calculating efficient features to create skillfully an efficient classification strategy [36-39]. In the area of nonlinear systems theory, some ECG arrhythmia classification methods on the basis of fractal theory [40, 41], state-space, trajectory space, phase space, Liapunov exponents [42-44] and nonlinear models [45] have been innovated by researchers. Amongst other classification schemes, structures based on higher order statistics in which to analyze features, a two or more dimensional frequency space is constructed can be mentioned [46, 47]. According to the concept that upon appearance of changes in the morphology of ECG signal caused by arrhythmia, corresponding changes are seen in the frequency domain, therefore, some arrhythmia classifiers have been designed based on the appropriate features obtained from signal fast Fourier transform (FFT), short-time Fourier transform (STFT), auto regressive (AR) models and power spectral density (PSD), [48-53]. Finally, using some polynomials such as Hermite function which has specific characteristics, effective features have been extracted to classify some arrhythmias [54, 55].

3. Materials and Methods

3.1. The Discrete Wavelet Transform (DWT)

Generally, it can be stated that the wavelet transform is a quasi-convolution of the hypothetical signal $x(t)$ and the wavelet function $\psi(t)$ with the dilation parameter a and translation parameter b, as the following integration

$$W_a x(b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\,\psi\big((t-b)/a\big)dt, \;\; a > 0 \tag{1}$$

The parameter a can be used to adjust the wideness of the basis function and therefore the transform can be adjusted in several temporal resolutions. In Eq. 1, for dilation parameter “a” and the translation parameter “b”, the values $a = q^k$ and $b = q^k lT$ can be used in which q is the discretization parameter, l is a positive constant, k is the discrete scale power and T is the sampling period. By substituting the new values of the parameters “a” and “b” into the wavelet function $\psi(t)$, the following result is obtained

$$\psi_{k,l}(t) = q^{-k/2}\psi(q^{-k}t - lT);\; k,l \in Z^+ \tag{2}$$

The scale index k determines the width of wavelet function, while the parameter l provides translation of the wavelet function.

If the scale factor a and the translation parameter b are chosen as q=2 i.e., $a = 2^k$ and $b = 2^k l$, the dyadic wavelet with the following basis function will be resulted [76],

$$\psi_{k,l}(t) = 2^{-k/2}\psi(2^{-k}t - lT);\; k,l \in Z^+ \tag{3}$$

To implement the à trous wavelet transform algorithm, filters $H(z)$ and $G(z)$ should be used according to the block diagram represented in Fig. 2-a, [76]. According to this block

diagram, each smoothing function (SMF) is obtained by sequential low-pass filtering (convolving with $G(z)$ filters), while after high-pass filtering of a SMF (convolving with $H(z)$ filters), the corresponding DWT at appropriate scale is generated. In order to decompose the input signal x(t) into different frequency passbands, according to the block diagram of Fig. 2-b, sequential high-pass low-pass filtering including down-sampling should be implemented. The filter outputs $x_H(t)$ and $x_L(t)$ can be obtained by convolving the input signal $x(t)$ with corresponding high-pass and low-pass finite-duration impulse responses (FIRs) and contributing the down-sampling as

$$\begin{cases} x_L(t) = \sum_{k=-\infty}^{k=+\infty} g(k)\, x(2t-k) \\ x_H(t) = \sum_{k=-\infty}^{k=+\infty} h(k)\, x(2t-k) \end{cases} \tag{4}$$

$$t = 0,\ 1,\ldots,\ N-1$$

On the other hand, to reconstruct the transformed signal, the obtained signals $x_H(t)$ and $x_L(t)$ should be first be up-sampled by following simple operation

$$\begin{cases} x_L^*(2t) = x_L(t) \quad , \quad x_L^*(2t+1) = 0 \\ x_H^*(2t) = x_H(t) \quad , \quad x_H^*(2t+1) = 0 \end{cases} \tag{5}$$

$$t = 0,\ 1,\ldots,\ N-1$$

If the FIR lengths of the H(z) and G(z) filters are represented by L_H and L_G, respectively, then the reconstructing high-pass and low-pass filters are obtained as

$$\begin{cases} g^*(t) = g(L_G - 1 - t) \\ h^*(t) = h(L_H - 1 - t) \end{cases} \tag{6}$$

Then the reconstructed signal $x_R(t)$ is obtained by superposition of the up-sampled signals convolution with their appropriately flipped FIR filters as follow

$$x_R(t) = \sum_{k=-\infty}^{k=+\infty} h^*(k)\, x_H^*(t-k) + \sum_{k=-\infty}^{k=+\infty} g^*(k)\, x_G^*(t-k) \tag{7}$$

For a prototype wavelet $\psi(t)$ with the following quadratic spline Fourier transform,

$$\mathbf{\Psi}(\Omega) = j\,\Omega \left(\frac{\sin(\Omega/4)}{\Omega/4} \right)^4 \tag{8}$$

the transfer functions $H(z)$ and $G(z)$ can be obtained from the following equation

$$H(e^{j\omega}) = e^{j\omega/2}\left(\cos(\omega/2)\right)^3$$
$$G(e^{j\omega}) = 4je^{j\omega/2}\left(\sin(\omega/2)\right) \tag{9}$$

and therefore,

$$h[n] = (1/8)\{\delta[n+2] + 3\delta[n+1] + 3\delta[n] + \delta[n-1]\}$$
$$g[n] = 2\ \{\delta[n+1] - \delta[n]\} \tag{10}$$

It should be noted that for frequency contents of up to 50 Hz, the à trous algorithm can be used in different sampling frequencies. Therefore, one of the most prominent advantages of the à trous algorithm is the approximate independency of its results from sampling frequency. This is because of the main frequency contents of the ECG signal concentrate on the range less than 20 Hz [62-63]. After examination of various databases with different sampling frequencies (range between 136 to 10 kHz), it has been concluded that in low sampling frequencies (less than 750 Hz), scales 2^{λ} (λ=1,2,…,5) are usable while for sampling frequencies more than 1000 Hz, scales 2^{λ} (λ=1,2,…,8) contain profitable information that can be used for the purpose of wave detection, delineation and classification. In order to introduce a unified ECG rhythm-type recognition framework which is applicable for all sampling frequencies, the original signal in the core sampling frequency is mapped to a new trend with target sampling frequency 1 kHz. By this operation, once the parameters of the classification algorithm are properly regulated for the target sampling frequency, the algorithm can be implemented to the ECG data sampled at any rate. It should be noticed that this sampling frequency is the most profitable discretization rate among other rates. In this sampling frequency, features can be computed by application of dyadic scales 2^1 to 2^7. Also, for appropriate delineation of P-T waves, scales 2^3 to 2^5 can be implemented. As a summary, in table 1, approximate empirical inference for adoption of appropriate scales helping successful classification of P-QRS-T cycles, are presented.

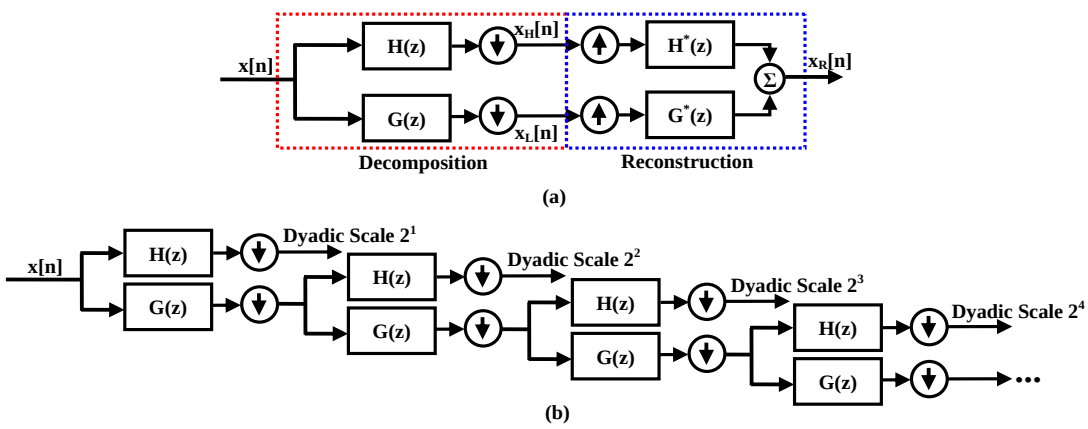

Figure 2. FIR filter-bank implementation to generate discrete wavelet dyadic scales and smoothing functions transform based on à trous algorithm. (a) one-step generation of detail coefficient scales and reconstruction of the input signal, (b) four-step implementation of DWT for extraction of dyadic scales.

Table 1. Appropriate dyadic scales versus sampling rate for successful classification of the heart-rhythm types. The results are based on empirical assessments.

Database Sampling Frequency <Hz>	Suitable Scales for QRS Feature Extraction	Suitable Scales for P-T Features	Sensitivity of Classification Algorithm to Parameters
128	2^1-2^2	2^1-2^2	High-undesirable
250	2^1-2^2-2^3	2^1-2^2	High-undesirable
360	2^1-2^2-2^3	2^2-2^3-2^4	Medium-undesirable
500	2^1-2^2-2^3-2^4	2^3-2^4	Medium-undesirable
≥1000	2^1-….-2^7	2^3-2^4-2^5	Robust-desirable

3.2. Fuzzy Network

Fuzzy logic means approximate reasoning, information granulation, computing with words and so on. Ambiguity is always present in any realistic process. This ambiguity may arise from the interpretation of the data inputs and in the rules used for description of the relationships between the informative attributes. Fuzzy logic provides an inference structure that enables the human reasoning capabilities to be applied to artificial knowledge-based systems. Fuzzy logic provides mathematical background for emulation of certain perceptual and linguistic attributes associated with human cognition, whereas the science of neural networks provides a new computing tool with learning and adaptation capabilities.

3.2.1 Fuzzy Inference System: Fuzzy inference systems (FIS) are also known as fuzzy rule-based systems, fuzzy model, fuzzy expert system, and fuzzy associative memory. This is a major unit of a fuzzy logic system. The decision- making is an important part in the entire system. The FIS formulates suitable rules and based upon the rules the decision is made. This is mainly based on the concepts of the fuzzy set theory, fuzzy IF–THEN rules, and fuzzy reasoning. FIS uses "IF. . . THEN. . . " statements, and the connectors present in the rule statement are "OR" or "AND" to make the necessary decision rules. The basic FIS can take either fuzzy inputs or crisp inputs, but the outputs produced by it are almost always fuzzy sets. Fuzzy inference system consists of a fuzzification interface, a rule base, a database, a decision-making unit, and finally a defuzzification interface. A FIS with five functional block described in Fig. 3.

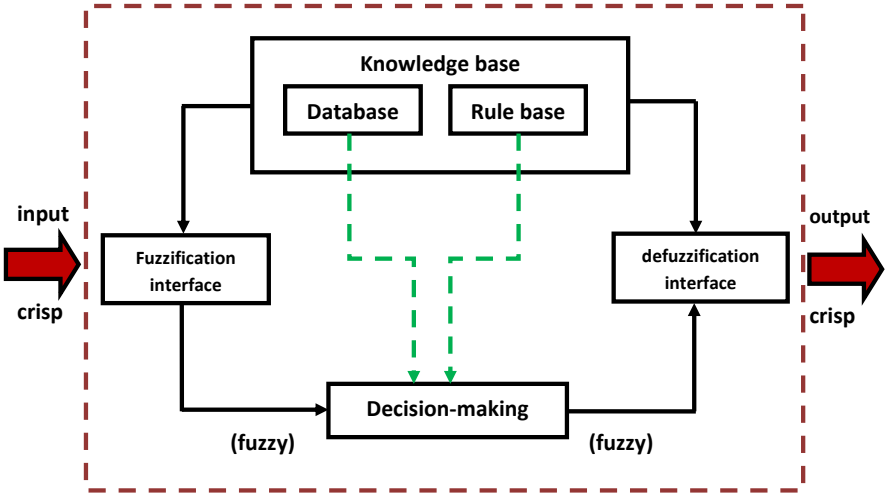

Figure 3. Fuzzy InferenceSsystem

3.3. Clustering

Data clustering is considered as an interesting approach for finding similarities in data and putting similar data into groups. Clustering partitions a data set into several groups such that the similarity within a group is larger than that among groups. Most of the data collected in many problems seem to have some inherent properties lending themselves to natural groupings. Nevertheless, finding these groupings or trying to categorize the data is not a simple task for humans unless the data is of low dimensionality (two or three dimensions at maximum). Clustering algorithms are used extensively not only to organize and categorize data, but are also useful for data compression and model construction. By finding similarities in data, one can represent similar data with fewer symbols for example. Also if we can find groups of data, we can build a model of the problem based on those groupings. Clustering techniques are used in conjunction with radial basis function networks or fuzzy modeling primarily to determine initial location for radial basis functions or fuzzy if-then rules. There are different clustering techniques such as k-means clustering, fuzzy c-means clustering, subtractive clustering, histogram adaptive smoothing and mountain clustering, (Jang, 1993 [71]).

3.3.1. Subtractive Clustering: If there is no clear idea how many clusters there should be for a given set of data, subtractive clustering is a fast, one-pass algorithm for estimating the number of clusters and the cluster centers in a set of data. Consider a collection of n data points in an m-dimensional space. Without loss of generality, the data points are assumed to have been normalized within a hypercube. Since each data point is a candidate for cluster centers, a density measure at data point $\mathbf{x}_i$ is defined as:

$$D_i = \sum_{j=1}^{n} \exp\left(-\frac{\left\| \mathbf{x}_i - \mathbf{x}_j \right\|^2}{(r_a/2)^2} \right) \tag{11}$$

Where r_a is a positive constant. Hence a data point will have a high density value if it has many neighboring data points. The radius r_a defines a neighborhood; data points outside this radius contribute only slightly to the density measure. After the density measure of each data point has been calculated, the data point with the highest density measure is selected as the first cluster center. Let x_{c1} be the point selected and D_{c1} its density measure. Next the density measure for each data point x_i is revised by the formula

$$D_i = D_i - D_{c1} \exp\left(-\frac{\left\| \mathbf{x}_i - \mathbf{x}_{c1} \right\|^2}{(r_b/2)^2} \right) \tag{12}$$

where r_b is a positive constant. Therefore, the data points near the first cluster center x_{c1} will have significantly reduced density measures, thereby making the points unlikely to be selected as the next cluster center. The constant r_b defines a neighborhood that has measurable reductions in density measure. The constant r_b is normally larger than r_a to prevent closely spaced cluster centers; generally r_b is equal to 1.5 r_a. After the density measure for each data point is revised, the next cluster center x_{c2} is selected and all of the density measures for data points are revised again. This process is repeated until a sufficient number of cluster centers are generated.

When applying subtractive clustering to a set of input-output data, each of the cluster centers represents a prototype that exhibits certain characteristics of the system to be

modeled. These cluster centers would be reasonably used as the centers for the fuzzy rules' premise in a zero-order Sugeno fuzzy model, or radial basis functions in a Radial Basis Function Network (RBFN). For instance, assume that the center for the i-th cluster is c_i in an M dimension. The c_i can be decomposed into two component vectors p_i and q_i, where p_i is the input part and it contains the first N element of c_i; q_i is the output part and it contains the last M - N elements of c_i. Then given an input vector x, the degree to which fuzzy rule i is fulfilled is defined by

$$\mu_i = \exp\left(-\frac{\|n-\mathbf{p}_i\|^2}{(r_a/2)^2}\right) \tag{13}$$

This is also the definition of the i-th radial basis function if we adopt the perspective of modeling using RBFNs. Once the premise part (or the radial basis functions) has been determined, the consequent part (or the weights for output unit in an RBFN) can be estimated by the least-squares method. After these procedures are completed, more accuracy can be gained by using gradient descent or other advanced derivative-based optimization schemes for further refinement, (Jang, 1993 [71]).

3.3.2 Fuzzy C-means Clustering: Fuzzy C-means clustering (FCM), also known as fuzzy ISODATA, is a data clustering algorithm in which each data point belongs to a cluster to a degree specified by a membership grade. FCM partitions a collection of n vector Xi, i = 1, ..., n into c fuzzy groups, and finds a cluster center in each group such that a cost function of dissimilarity measure is minimized.

FCM employs fuzzy partitioning such that a given data point can belong to several groups with the degree of belongingness specified by membership grades between 0 and 1. To accommodate the introduction of fuzzy partitioning, the membership matrix U is allowed to have elements with values between 0 and 1. However, imposing normalization stipulates that the summation of degrees of belongingness for a data set always be equal to unity:

$$\sum_{i=1}^{c} u_{ij} = 1, \quad \forall j = 1,\ldots,n. \tag{14}$$

The cost function (or objective function) for FCM is defined as:

$$J(U, c_1,\ldots,c_c) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c}\sum_{j}^{n} u_{ij}^m d_{ij}^2, \tag{15}$$

where u_{ij} is between 0 and 1.c_i is the cluster center of fuzzy group i; $d_{ij} = \|c_i - x_j\|$ is the Euclidean distance between i-th cluster center and j-th data point; and m $\in [1,\infty)$ is a weighting exponent. The necessary conditions for Equation (15) to reach a minimum can be found by forming a new objective function J as follows:

$$\begin{aligned}\bar{J}(U, c_1,\ldots,c_c,\lambda_1,\ldots,\lambda_n) &= J(U, c_1,\ldots,c_c) + \sum_{j=1}^{n} \lambda_j \left(\sum_{i=1}^{c} u_{ij} - 1\right) \\ &= \sum_{i=1}^{c}\sum_{j}^{n} u_{ij}^m d_{ij}^2 + \sum_{j=1}^{n} \lambda_j \left(\sum_{i=1}^{c} u_{ij} - 1\right),\end{aligned} \tag{16}$$

where λ_j, j=1 to n, are the Lagrange multipliers for the n constraints in equation (14). By differentiating $\bar{J}(U, c_1, \ldots, c_c, \lambda_1, \ldots, \lambda_n)$ with respect to all its input arguments, the necessary conditions for Equation (15) to reach its minimum are:

$$c_i = \frac{\sum_{j=1}^{n} u_{ij}^m x_j}{\sum_{j=1}^{n} u_{ij}^m}, \tag{17}$$

and

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}} \right)^{2/(m-1)}}. \tag{18}$$

The FCM algorithm is simply an iterated procedure through the preceding two necessary conditions. In a batch-mode operation, FCM determines the cluster centers c_i and the membership matrix U using the following steps:

Step 1: Initialize the membership matrix U with random values between 0 and 1 such that the constraints in Equation (14) are satisfied.

Step 2: Calculate c fuzzy cluster centers c_i,i = 1,... , c, using Equation (17).

Step 3: Compute the cost function according to Equation (15). Stop if either it is below a certain tolerance value or its improvement over previous iteration is below a certain threshold.

Step 4: Compute a new U using Equation (18). Go to step 2.

The cluster centers can also be first initialized and then the iterative procedure carried out. No guarantee ensures that FCM converges to an optimum solution. The performance depends on the initial cluster centers, thereby allowing us either to use another fast algorithm to determine the initial cluster centers or to run FCM several times, each starting with a different set of initial cluster centers, (Jang, 1993 [71]).

4. The Fuzzy Classification Algorithm: Design, Implementation and Performance Evaluation

When fuzzy inference technique (such as Mamdani or Sugeno methods) is implemented for supervised classification of a hypothetical feature space, the major problem is to appropriately determine the parameters of inference base membership functions. This section of manuscript includes details describing the QRS detection-delineation, geometrical feature extraction, FCM and subtractive clustering techniques aimed for enhanced supervised classification of heart rhythm types. For determining the fuzzy classifier membership functions parameters, two different clustering techniques called as FCM and subtractive were applied. Numerous assessment indicated that the subtractive clustering technique yields more

accuracy and robustness relative to FCM-based tuning strategy in cases of arrhythmic outliers and disturbing circumferential effects.

4.1. QRS Geometrical Features Extraction

4.1.1. ECG Events Detection and Delineation: In this step, QRS complexes are detected and delineated. Today reliable QRS detectors based on Hilbert [64, 65] and Wavelet [62, 63] transforms can be found in literature. In this study, an ECG detection-delineation method with the sensitivity and positive predictivity Se = 99.95% and P+ = 99.94% and the average maximum delineation error of 6.1 msec, 4.1 msec and 6.5 msec for P-wave, QRS complex and T-wave, respectively is implemented [62]. By application of this method, detecting the major characteristic locations of each QRS complex i.e., fiducial, R and J locations, becomes possible.

4.1.2. Detected QRS Complex Geometrical Features Extraction [77]: In order to compute features from the detected QRS complexes either normal or arrhythmic via the proposed method, first a reliable time center should be obtained for each QRS complex. To find this point, the absolute maximum and the absolute minimum indices of the excerpted DWT dyadic scale 2^4 using the onset-offset locations of the corresponding QRS complex, are determined. It should be noted that according to comprehensive studies fulfilled in this research, the best time center of each detected QRS complex is the mean of zero-crossing locations of the excerpted DWT (see Fig. 4).

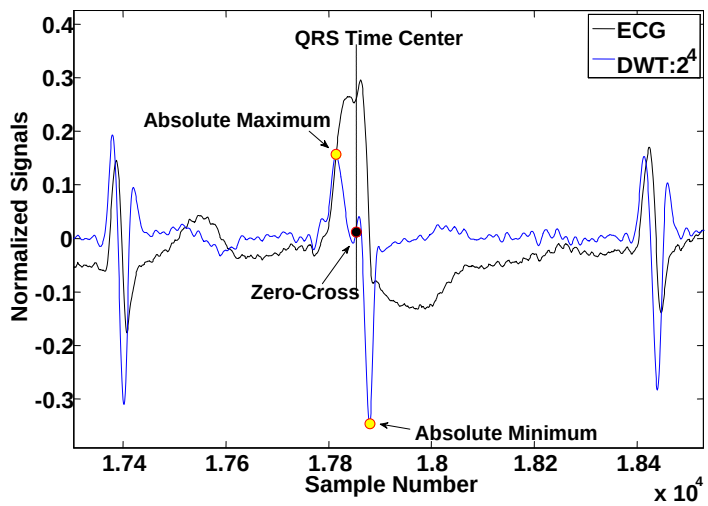

Figure 4. Determination of the time center of a detected QRS complex using excerpted DWT scale 2^4

To make a virtual close-up from each detected QRS complex, a rectangle is built on the complex with following specifications:

- The left-side mid-span (longitudinal direction) of the rectangle is the fiducial location of the QRS complex.
- The maximum absolute vertical distance of the complex from the fiducial point is the half of the rectangle height.

- The center of rectangle is the time-center of the QRS complex.
- The right-hand abscissa of the rectangle is the distance between QRS time center and its J-location.

Afterwards, Each QRS region and also its corresponding DWT are supposed as virtual images and each of them is divided into eight polar sectors. Next, the curve length of each excerpted segment is calculated and is used as element of the feature space, (therefore, for each detected QRS complex, 16 features are computed). The quantity curve-length of a hypothetical time series x(t) in a window with length W_L samples can be estimated as

$$M_{CL}(k) \approx \frac{1}{F_S} \sum_{t=k}^{k+W_L-1} \sqrt{1+\left[\left(x(t+1)-x(t)\right)F_S\right]^2} \tag{19}$$

Where, F_s is sampling frequency of the time series x(t). The curve length is suitable for measuring the duration of the signal $x(t)$ events, either being strong or being weak. Generally, the M_{CL} measure indicates the extent of flatness (smoothness or impulsive peaks) of samples in the analysis window. This measure allows the detection of sharp ascending/descending regimes occurred in the excerpted segment [63].

In Fig. 1, the general block diagram of the ECG beats annotation algorithm with the proposed QRS geometrical feature space is illustrated. A generic example of a holter ECG and its corresponding 2^4 DWT dyadic scale with the virtual images of the complexes provided for feature extraction as well as two quantities obtained from the RR-tachogram are shown in Fig. 5.

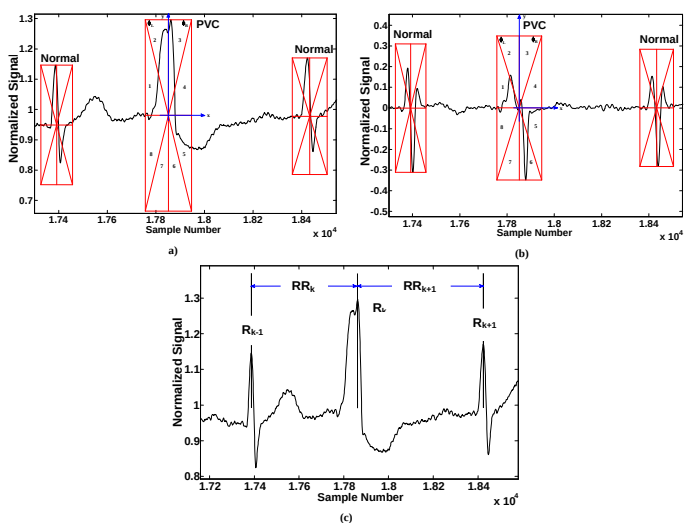

Figure 5. Extraction of the geometrical features from a delineated QRS complex via segmentation of each complex into 8 polar sectors by generating of a virtual image from the complex. (a) original ECG, (b) DWT of the original ECG and (c) RR-interval.

4.2.1 Design of Fuzzy Classifier Based on the FCM Clustering: In this step a sugeno fuzzy network with 12 rules is generated based on the FCM clustering technique. In table 2, the

details associated with the used database for generating fuzzy network and its testing, are shown.

In Fig. 6 membership function for one of the inputs is shown. In Fig. 7, the rule-viewer is depicted. Obtained confusion matrix and result of this method can be viewed in table 3.

Table 2. The name of selected MITDB records with their rhythm type contents

Record	Normal		LBBB		RBBB		PB	
	Number of Beats for generating fuzzy network	test	Number of Beats for generating fuzzy network	test	Number of Beats for generating fuzzy network	test	Number of Beats for generating fuzzy network	test
100	100	100	0	0	0	0	0	0
102	0	0	0	0	0	0	100	100
103	100	100	0	0	0	0	0	0
107	0	0	0	0	0	0	100	100
109	0	0	100	100	0	0	0	0
111	0	0	100	100	0	0	0	0
118	0	0	0	0	100	100	0	0
124	0	0	0	0	100	100	0	0
212	0	0	0	0	100	100	0	0
214	0	0	100	100	0	0	0	0
217	0	0	0	0	0	0	100	100
234	100	100	0	0	0	0	0	0
Total	300	300	300	300	300	300	300	300

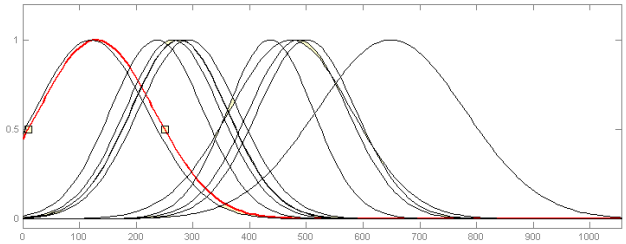

Figure 6. Membership functions for 15th feature space element. The corresponding parameters of the MFs were determined by application of the FCM method.

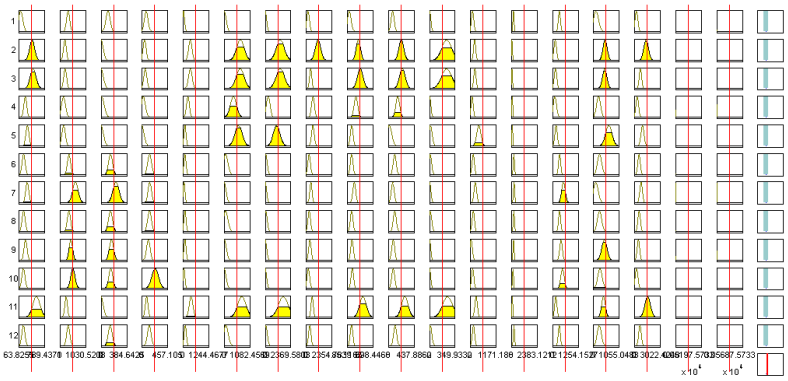

Figure 7. The rule-viewer of fuzzy classifier obtained by application of FCM clustering technique.

Table 3. (a) The confusion matrix of the fuzzy classifier based on the fuzzy c-means (FCM) clustering for the selected MITDB records

	Normal	LBBB	RBBB	PB
Normal	272	22	3	3
LBBB	5	284	10	1
RBBB	2	5	289	4
PB	2	2	6	290

(b) result of fuzzy classifier based on the FCM clustering

	Normal	LBBB	RBBB	PB
Sensitivity (%)	90.66	94.66	96.33	96.66
Positive Predictivity (%)	96.79	90.73	93.83	97.31
Accuracy (%)	94.58			

4.2.2 Design of Fuzzy Classifier Based on Subtractive Clustering: For generating fuzzy network based on the subtractive clustering, the value of radius (r_a) (as mentioned in section B.3.1) is chosen to be 0.8 obtained after several experiments. With this value as the radius, 7 fuzzy rules are obtained. The used database for this part is similar to previous section. In the case of subtractive clustering, similar to the FCM-based fuzzy classification network, the membership function for one of the input and the corresponding rule-viewer are depicted in Figs.8 and 9. Also the obtained confusion matrix and the obtained results of this method are shown in table 4. In Fig. 10, the error rate diversities of two FCM-based and subtractive clustering-based fuzzy classifiers are demonstrated.

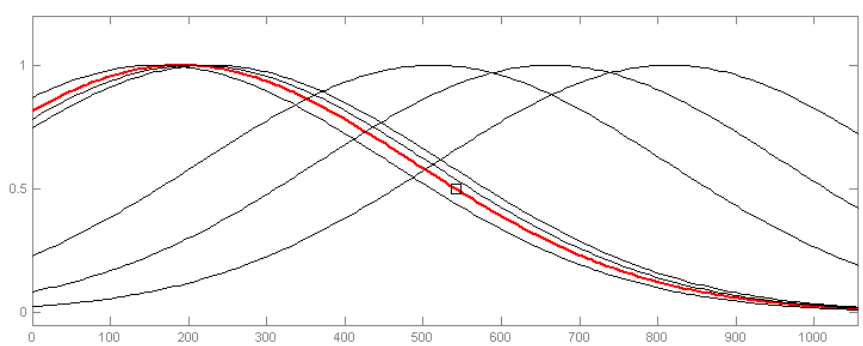

Figure 8. Membership functions for 15th feature space element. The corresponding parameters of the MFs were determined by application of the subtractive clustering method.

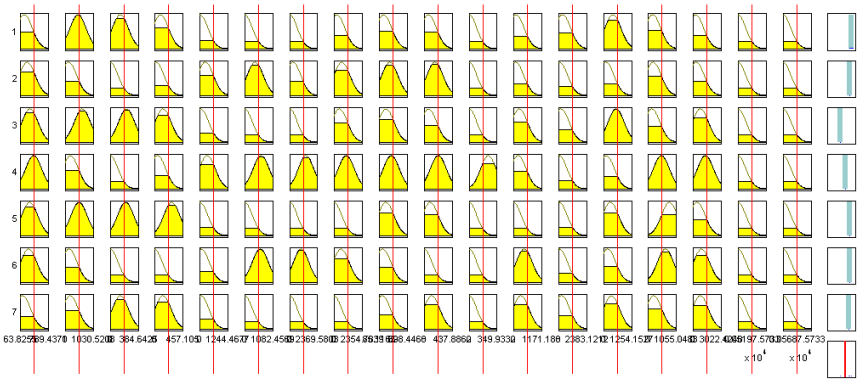

Figure 9. The rule-viewer of fuzzy classifier obtained by application of the subtractive clustering technique.

Table 4. (a) The confusion matrix of the fuzzy classifier based on subtractive clustering for the selected MITDB records

	Normal	LBBB	RBBB	PB
Normal	299	1	0	0
LBBB	2	289	9	0
RBBB	0	1	296	3
PB	8	3	4	285

(b) result of fuzzy classifier based on subtractive clustering

	Normal	LBBB	RBBB	PB
Sensitivity (%)	99.66	96.33	98.66	95
Positive Predictivity (%)	96.76	98.29	95.79	98.95
Accuracy (%)	97.41			

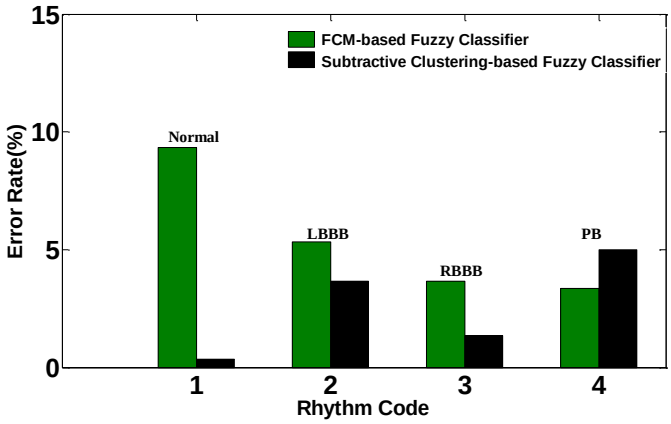

Figure 10. Error-rate diversity analysis for justification of adopting the superior clustered fuzzy-rule by application of the FCM and subtractive clustering techniques.

4.3. Arrhythmia Classification Performance Comparison with Other Works

In the final step, in order to show the marginal performance improvement of the proposed arrhythmia classification algorithm, the method is assessed relative to other high-performance recent works. The result of comparison of the proposed method and other works is shown in table 5.

Table 5. Summary of the Previous Studies

Authors	Method	Signal	Dataset	Accuracy
B. Anuradha and V.C.Veera Reddy [79]	Feature Extraction: Spectral Entropy, Poincare Plot Geometry, Largest Lyapunov Exponent and Detrended Fluctuation Analysis Classification: Fuzzy	ECG	233 Beats from MIT-BIH Used for Testing	93.13
Osowski and Linh [73]	Feature Extraction: Cumulants of the Second, Third and Fourth Order Classification: Fuzzy Hybrid Neural Network	ECG	7185 Beats from MIT-BIH; 4035 Training-3150 Testing [Normal: 2250, APB: 658, LBBB: 1200, PVC: 1500, RBBB: 1000, VF: 472, VE: 105]	96.06
N.Kannathal and C.M. Lim [14]	Feature Extraction: Largest Lyapunov Exponent, Spectral Entropy, Poincare Geometry Classification: ANFIS	RR interval	600 Dataset from MIT-BIH; 320 Training-280 Testing; 10 Classes	94
Linh and Osowski [78]	Feature Extraction: Hermite Coefficients Classification: ANFIS	ECG	7279 Beats from MIT-BIH; 3611 Training-3668 Testing; [Normal: 2344, LBBB: 1250, RBBB: 1050, PVC:1400 APB:658,VE:105, VF: 472]	96
Dokur and Olmez [67]	Feature Extraction: Discrete Wavelet Transform Classification: Intersecting Spheres Network	ECG	3000 Beats from MIT-BIH; Normal, LBBB, RBBB, P, p, a, VE, PVC, F, f: 300 from Each Category; 1500 Training-1500 Testing	95.7
Hu et al. [74]	Feature Extraction: PCA in 29 Points from QRS, Instantaneous and Average RR-Interval, QRS Complex Width Classification: Mixture of Experts (SOM, LVQ)	ECG	25 min from Each Record in MIT-BIH 200 Series Excluding Records 212, 217, 220, 222 and 232 [Normal: 43897, PVC: 5363]	95.52
Tsipouras et al. [30]	Feature Extraction: RR-Interval Classification: Knowledge-based System	RR-interval signal	30000 Beats from MIT-BIH [N,P, f, P, Q, LBBB, RBBB: 25188, PVC, F: 2950 , APB, a, J, S: 1213, e, j, n, VE: 265, VF: 384]	95.85
This study	Feature Extraction: Geometrical Properties Obtained from Segmentation of Each Detected-Delineated QRS Complex Virtual Image as well as RR-Tachogram Classification: The Fuzzy Classifier based on FCM and Subtractive Clustering Techniques	ECG	2400 Beats from MIT-BIH; 1200 Modeling-1200 Testing [Normal: 600, LBBB: 600, RBBB: 600, PB:600]	97.41

5. Conclusion and Future Works

In this study, a new heart arrhythmia classification algorithm based on a new QRS complex geometrical feature extraction technique as well as an appropriate choice from each beat RR-tachogram was described. In the proposed method, first, the events of the ECG signal were detected and delineated using a robust wavelet-based algorithm. Then, each QRS region and also its corresponding DWT were supposed as virtual images and each of them was divided into eight polar sectors. Next, the curve length of each excerpted segment was calculated and

was used as the element of the feature space. To propose a new classification strategy with adequate robustness against noise, artifacts and arrhythmic outliers, the fuzzy rules parameterization and determination stages were fulfilled using the FCM and the subtractive clustering techniques. The proposed method was applied to 4 number of arrhythmias namely as Normal, LBBB, RBBB4, PB belonging to 12 number of the MITDB (records with 100, 102, 103, 107, 109, 111, 118, 124, 212, 214, 217 and 234 codes in the database) and the average value of Acc=97. 41% was achieved showing marginal improvement in the area of the heart arrhythmia classification. To evaluate performance quality of the new proposed fuzzy classifier, the obtained results were compared with several similar studies in this area. In the unsupervised classification techniques aimed for regulation of the fuzzy inference system membership functions, a dominant problem is to assign automatically the best number of input-output memberships by sequentially minimizing a suitable cost function. The future research stream pursuing this research is concentrated to solve this problem.

References

[1] U.R. Acharya, “Advances in Cardiac Signal Processing ,”Springer Publishing, 2007.

[2] A. Ghaffari, M. Atarod, M. R. Homaeinejad, Y. Ahmady, R. Rahmani, "Detecting and Quantifying T-wave Alternans Using the Correlation Method and Comparison with the FFT-based Method," 34th Annual Conference of Computers in Cardiology (CinC), September 14-17 2008, Bologna, Italy.

[3] A. Ghaffari, M. R. Homaeinezhad, M. Akraminia, M. Atarod, and M. Davaeeha, "Detecting and Discriminating Premature Atrial and Ventricular Contractions: Application to Prediction of Paroxysmal Atrial Fibrillation," 35th Annual Conference of Computers in Cardiology (CinC), September 13-16 2009, Lake City-Utah, USA.

[4] A. Ghaffari, M. R. Homaeinezhad, M. Akraminia, M. Atarod, and M. Davaeeha, "Detecting and Quantifying T-Wave Alternans in Patients with Heart Failure and Non-Ischemic Cardiomyopathy via Modified Spectral Method," 35th Annual Conference of Computers in Cardiology (CinC), September 13-16 2009, Lake City-Utah, USA.

[5] A. Ghaffari, M. Atarod, M. R. Homaeinejad, R. Rahmani, "On-Line Identification of the Heart Hemodynamic Parameters via the Discrete-Time Kalman-Bucy Filter Using Invasive Noisy Blood Pressure Waveform Observations," 34th Annual Conference of Computers in Cardiology (CinC), September 14-17 2008, Bologna, Italy.

[6] A. Ghaffari, M. R. Homaeinezhad, Y. Ahmadi, and M. Rahnavard, "An Open-Source Computer Model for Visualization of Artificial Abnormal Multi-Lead Electrocardiographic Phenomena," World Journal of Modelling and Simulation, In-Press, 2009.

[7] M. G. Tsipouras, D. I. Fotiadis, D. Sideris, "An arrhythmia classification system based on the RR-interval signal," Artificial Intelligence in Medicine (2005) 33, 237-250.

[8] M. Nilsson, P. Funk, E. M.G. Olsson, B. von Scheele, N. Xiong, "Clinical decision-support for diagnosing stress-related disorders by applying psychophysiological medical knowledge to an instance-based learning system," Artificial Intelligence in Medicine (2006) 36, 159-176.

[9] P. de Chazal, R. B. Reilly, "A Patient-Adapting Heartbeat Classifier Using ECG Morphology and Heartbeat Interval Features," IEEE Transactions on Biomed. Eng., Vol. 53, No. 12, Dec. 2006.

[10] M. G. Tsipouras, D. I. Fotiadis, "Automatic arrhythmia detection based on time and time-frequency analysis of heart rate variability,"Computer Methods and Programs in Biomedicine (2004) 74, 95-108.

[11] Sung-Nien Yu, Kuan-To Chou, "Integration of independent component analysis and neural networks for ECG beat classification," Expert Systems with Applications 34 (2008) 2841-2846.

[12] S. N. Yu, K. T. Chou, "Selection of significant independent components for ECG beat classification," Expert Systems with Applications 36 (2009) 2088–2096.

[13] U. R. Acharya, M. Sankaranarayanan, J. Nayak, C. Xiang, T. Tamura, "Automatic identification of cardiac health using modeling techniques: A comparative study," Information Sciences 178 (2008) 4571–4582.

[14] N. Kannathal, C.M. Lim, U. Rajendra Acharya, P. K. Sadasivan, "Cardiac state diagnosis using adaptive neuro-fuzzy technique," Medical Engineering & Physics 28 (2006) 809–815.

[15] F. Melgani, Y. Bazi, “Classification of Electrocardiogram Signals With Support Vector Machines and Particle Swarm Optimization,” IEEE Transactions on Information Technology in Biomedicine, Vol. 12, No. 5, 667-677, 2008.

[16] S. N. Yu, K. T. Chou, "A switchable scheme for ECG beat classification based on independent component analysis," Expert Systems with Applications 33 (2007) 824–829.

[17] Y. Ozbay, R. Ceylan, B. Karlik, "A fuzzy clustering neural network architecture for classification of ECG arrhythmias,"Computers in Biology and Medicine 36 (2006) 376–388.

[18] S. Osowski, T. Markiewicz, L. Tran Hoai, "Recognition and classification system of arrhythmia using ensemble of neural networks," Measurement 41 (2008) 610–617.

[19] R. Ceylan, Y. Uzbay, B. Karlik, "A novel approach for classification of ECG arrhythmias: Type-2 fuzzy clustering neural network," Expert Systems with Applications 36 (2009) 6721-6726.

[20] K. Polat, S. Sahan, S. Gune, "A new method to medical diagnosis: Artificial immune recognition system (AIRS) with fuzzy weighted pre-processing and application to ECG arrhythmia," Expert Systems with Applications 31 (2006) 264–269.

[21] Chia-Hung Lin, Yi-Chun Du, Tainsong Chen, "Adaptive wavelet network for multiple cardiac arrhythmias recognition," Expert Systems with Applications 34 (2008) 2601–2611.

[22] C. Wen, T. C. Lin, K. C. Chang , C. H. Huang, "Classification of ECG complexes using self-organizing CMAC," Measurement 42 (2009) 399-407.

[23] A. Ebrahimzadeh, A. Khazaee, "Detection of Premature Ventricular Contractions Using MLP Neural Networks: A Comparative Study," Measurement (2009), doi: 10.1016/j. measurement. 2009. 07. 002.

[24] P. de Chazal, M. O’Dwyer, R. B. Reilly, "Automatic Classification of Heartbeats Using ECG Morphology and Heartbeat Interval Features," IEEE Transactions on Biomed. Eng., Vol. 51, No. 7, Jul. 2004.

[25] O. T. Inan, L. Giovangrandi, G. T. A. Kovacs, "Robust Neural-Network-Based Classification of Premature Ventricular Contractions Using Wavelet Transform and Timing Interval Features," IEEE Transactions on Biomed. Eng., Vol. 53, No. 12, Dec. 2006.

[26] M. Wiggins, A. Saad, B. Litt, G. Vachtsevanos, "Evolving a Bayesian classifier for ECG-based age classification in medical applications," Applied Soft Computing 8 (2008) 599-608.

[27] A. Bartolo, B. D. Clymer, R. C. Burgess, J. P. Turnbull, J. A. Golish, M. C. Perry, "An Arrhythmia Detector and Heart Rate Estimator for Overnight Polysomnography Studies," IEEE Transactions on Biomed. Eng., Vol. 48, No. 5, May 2001.

[28] K. Polat, S. Gunes, "Detection of ECG Arrhythmia using a differential expert system approach based on principal component analysis and least square support vector machine," Applied Mathematics and Computation 186 (2007) 898–906.

[29] Y. C. Yeh, W. J. Wang, C. W. Chiou, "Cardiac arrhythmia diagnosis method using linear discriminant analysis on ECG signals," Measurement 42 (2009) 778–789.

[30] M. G. Tsipouras, C. Voglis, D. I. Fotiadis, "A Framework for Fuzzy Expert System Creation-Application to Cardiovascular Diseases," IEEE Transactions on Biomed. Eng., Vol. 54, No. 11, Nov. 2007.

[31] I. Christov, I. Jekova G. Bortolan, "Premature ventricular contraction classification by the *K*th nearest-neighbours rule," Physiol. Meas. 26 (2005) 123–130.

[32] F. A. Minhas, M. Arif, "Robust electrocardiogram (ECG) beat classification using discrete wavelet transform," Physiological Measurement, 29 (2008) 555–570.

[33] V. Chudacek1, G. Georgoulas, L. Lhotska, C. Stylios, M. Petrık, M. Cepek, "Examining cross-database global training to evaluate five different methods for ventricular beat classification," Physiol. Meas. 30 (2009) 661–677.

[34] T. P. Exarchos, M. G. Tsipouras, C. P. Exarchos, C. Papaloukas, D. I. Fotiadis, L. K. Michalis, "A methodology for the automated creation of fuzzy expert systems for ischaemic and arrhythmic beat classification based on a set of rules obtained by a decision tree," Artificial Intelligence in Medicine (2007) 40, 187-200.

[35] I. Christov, G. Bortolan, "Ranking of pattern recognition parameters for premature ventricular contractions classification by neural networks," Physiol. Meas. 25 (2004) 1281–1290.

[36] K. Polat, S. Kara, A. Güven, S. Günes, "Usage of class dependency based feature selection and fuzzy weighted pre-processing methods on classification of macular disease," Expert Systems with Applications 36 (2009) 2584–2591.

[37] H. Liu, J. Sun, L. Liu, H. Zhang, "Feature selection with dynamic mutual information," Pattern Recognition 42 (2009) 1330 - 1339.

[38] N. Abe, M. Kudo, "Non-parametric classifier-independent feature selection," Pattern Recognition 39 (2006) 737 – 746.

[39] H. Peng, F. Long, C. Ding, "Feature Selection Based on Mutual Information: Criteria of Max-Dependency, Max-Relevance, and Min-Redundancy," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 27, No. 8, Aag. 2005.

[40] Chia-Hung Lin, Yi-Chun Du, T. Chen, "Nonlinear interpolation fractal classifier for multiple cardiacarrhythmias recognition," Chaos, Solitons and Fractals 42 (2009) 2570–2581.

[41] Y. Wang, Y. Zhu, N. V. Thakor, Y. Xu, "A Short-Time Multifractal Approach for Arrhythmia Detection Based on Fuzzy Neural Network," IEEE Transactions on Biomed. Eng., Vol. 48, No. 9, Sep. 2001.

[42] R. Rohani Sarvestani, R. Boostani, M. Roopaei, "VT and VF classification using trajectory analysis," Nonlinear Analysis, In-Press, 2009.

[43] K. Nopone, J. Kortelainen, T. Seppanen, "Invariant trajectory classification of dynamical systems with a case study on ECG," Pattern Recognition 42 (2009) 1832 - 1844.

[44] R. J. Povinelli, M. T. Johnson, A. C. Lindgren, F. M. Roberts, J. Ye, "Statistical Models of Reconstructed Phase Spaces for Signal Classification," IEEE Transactions on Signal Processing, Vol. 54, No. 6, Jun. 2006.

[45] M. I. Owis, A. H. Abou-Zied, A. M. Youssef, Y. M. Kadah, "Study of Features Based on Nonlinear Dynamical Modeling in ECG Arrhythmia Detection and Classification," IEEE Transactions on Biomed. Eng., Vol. 49, No. 7, Jul. 2002.

[46] S. N. Yu, Y. H. Chen, "Noise-tolerant electrocardiogram beat classification based on higher order statistics of subband components," Artificial Intelligence in Medicine (2009) 46, 165-178.

[47] L. Khadra, A. S. Al-Fahoum, and S. Binajjaj, "A Quantitative Analysis Approach for Cardiac Arrhythmia Classification Using Higher Order Spectral Techniques," IEEE Transactions on Biomed. Eng., Vol. 52, No. 11, Nov. 2005.

[48] I. Christov, G. Gomez-Herrero, V. Krasteva, I. Jekova, A. Gotchev, K. Egiazarian, "Comparative study of morphological and time-frequency ECG descriptors for heartbeat classification," Medical Engineering & Physics 28 (2006) 876–887.

[49] Chia-Hung Lin, "Frequency-domain features for ECG beat discrimination using grey relational analysis-based classifier," Computers and Mathematics with Applications 55 (2008) 680–690.

[50] Szi-Wen Chen, "A Two-Stage Discrimination of Cardiac Arrhythmias Using a Total Least Squares-Based Prony Modeling Algorithm," IEEE Transactions on Biomed. Eng., Vol. 47, No. 10, Oct. 2000.

[51] S. Kar, M. Okandan "Atrial fibrillation classification with artificial neural networks," Pattern Recognition 40 (2007) 2967 - 2973.

[52] M. Stridh, L. Sörnmo, C. J. Meurling, S. B. Olsson, "Sequential Characterization of Atrial Tachyarrhythmias Based on ECG Time-Frequency Analysis," IEEE Transactions on Biomed. Eng., Vol. 51, No. 1, Jan. 2004.

[53] I. Jekova, G. Bortolan, I. Christov, "Assessment and comparison of different methods for heartbeat classification," Medical Engineering & Physics 30 (2008) 248–257.

[54] M. Lagerholm, C. Peterson, G. Braccini, L. Edenbrandt, L. Sörnmo, "Clustering ECG Complexes Using Hermite Functions and Self-Organizing Maps," IEEE Transactions on Biomed. Eng., Vol. 47, No. 7, Jul. 2000

[55] W. Jiang, S. G. Kong, "Block-Based Neural Networks for Personalized ECG Signal Classification," IEEE Transactions on Neural Network, Vol. 18, No. 6, Nov. 2007.

[56] A. S. Al-Fahoum, "IH combined wavelet transform and radial basis neural networks for the classifying life threatening cardiac arrhythmias," Medical, Biological Engineering and Computing, 37 566–73, 1999.

[57] K. Minami, H. Nakajima, T. Toyoshima, "Real-time discrimination of ventricular tachyarrhythmia with Fourier transform

neural network," IEEE Transactions on Biomedical Engineering 46 179-85, 1999.

[58] G. K. Prasad, J. S. Sahambi Classification of ECG arrhythmias using multi resolution analysis and neural networks Conf. Convergent Technologies Bangalore, India, 2003.

[59] Y. H. Chen, S. N. Yu, "Subband features based on higher order statistics for ECG beat classification," 29th Annual International Conference of IEEE Engineering in Medicine and Biology, 1859-1862, 2007.

[60] I. Guler, E. D. Ubeyli, "A modified mixture of experts network structure for ECG beats classification with diverse features," Engineering Applications of Artificial Intelligence, 18 845-56 2005.

[61] I. Guler, E. D. Ubeyli, "ECG beat classifier designed by combined neural network model," Pattern Recognition 38 199-208, 2005.

[62] A. Ghaffari, M. R. Homaeinezhad, M. Khazraee, M. Daevaeiha, “Segmentation of Holter ECG Waves via Analysis of a Discrete Wavelet-Derived Multiple Skewness-Kurtosis Based Metric,” Annals of Biomedical Engineering, Springer Publishing, 38 (4) ,1497-1510, 2010.

[63] A. Ghaffari, M. R. Homaeinezhad, M. Akraminia, M. Atarod, and M. Daevaeiha, “A Robust Wavelet-based Multi-Lead Electrocardiogram Delineation Algorithm,” Medical Engineering & Physics, 31(10):1219–1227, 2009.

[64] D. Benitez, P. A. Gaydecki, A. Zaidi, A. P. Fitzpatrick, "The use of the Hilbert transform in ECG signal analysis," Computers in Biology and Medicine, Vol. 31 pp. 399–406, 2001.

[65] A. Ghaffari, M. R. Homaeinezhad, M. Atarod, M. Akraminia, "Parallel Processing of ECG and Blood Pressure Waveforms for Detection of Acute Hypotensive Episodes: A Simulation Study Using a Risk Scoring Model," Computer Methods in Biomechanics and Biomedical Engineeing, Taylor & Francis Publishing, In-Press, 2009.

[66] S. N. Yu, Y. H. Chen, "Electrocardiogram beat classification based on wavelet transformation and probabilistic neural network," Pattern Recognition Letters 28 1142–50, 2007.

[67] Z. Dokur, T. Olmez, E. Yazgan, "Comparison of discrete wavelet and Fourier transforms for ECG beat classification," Electronic Letters. 35 1502-4, 1999.

[68] Douglas C. Montgomery, George C. Runger, "Applied Statistics and Probability for Engineers," Third Edition, John Wiley & Sons, 2003.

[69] G. B. Moody, R. G. Mark, "The MIT-BIH Arrhythmia Database on CD-Rom and Software for it," The Proceeding of Computers in Cardiology, pp. 185-188, 1990.

[70] Christopher M. Bishop, "Pattern Recognition and Machine Learning," Springer Publishing, 2006.

[71] J. S. R. Jang, "ANFIS: Adaptive-Network-Based Fuzzy Inference System," IEEE Trans. Systems, Man, Cybernetics, 23(5/6):665-685, 1993.

[72] Z. Dokur, T. Olmez, “ECG beat classification by a hybrid neural network,” Computer Methods and Programs in Biomedicine, 81, 154-167, 2001.

[73] S. Osowski, T. H. Linh, “ECG beat recognition using fuzzy hybrid neural network,” IEEE Transactions on Biomedical Engineering, 48, 1265-1271, 2001.

[74] Y. Z. Hu, S. Palreddy, W. J. Tompkins, “A patient-adaptable ECG beat classifier using a mixture of experts approach,” IEEE Transactions on Biomedical Engineering, 44, 891, 900, 1997.

[75] M. G. Tsipouras, D. I. Fotiadis, D. Sideris, “Arrhythmia classification using the RR-interval duration signal,” The proceeding of the Computers in cardiology Conference, 485-488, 2002.

[76] Stephane Mallat, “A Wavelet Tour of Signal Processing,” Academic Press, 1999.

[77] M. R. Homaeinezhad, H. Najjaran Toosi, A. Ghaffari, M. Tahmasebi, M. M. Daevaeiha, “Long-Duration Ambulatory Holter ECG QRS Complex Geometrical Templates Extraction by Non-Parametric Clustering of the QRS Virtual Close-up Extracted Feature Space,” The Proceedings of the Computing in Cardiology Conference, Belfast, UK, September, 24-27, 2010.

[78] Tran Hoai Linh, Stanislaw Osowski, Maciej Stodolski, “On-Line Heart Beat Recognition Using Hermite Polynomials and Neuro-Fuzzy Network, “On-Line Heart beat recognition using Hermite polynomials and neuro-fuzzy network,” IEEE Transactions on Biomedical Engineering, 52, 1224-1231, 2003.

[79] Mrs. B.Anuradha, V.C.Veera Reddy, “cardiac arrhythmia classification using fuzzy classifiers,” Journal of Theoretical and Applied Information Technology, 4, 353-359, 2008.

APPENDIX: The Matlab Implementation of the Discrete Wavelet Transform

In Fig. A.1, the frequency response of several DWT dyadic scales for two sampling frequencies 500 Hz and 1000 Hz is illustrated. From Fig. A.1, it can be seen that in sampling frequency 500 Hz, the dyadic scale 2^4 holds approximately all required ECG components while in sampling frequency 1000 Hz, in scale 2^5 all major components are preserved.

In Fig. A.2, several dyadic scales obtained via application of à trous DWT to an arbitrary holter record, are illustrated. As it can be seen, by increment of the dyadic dilation parameter 2^{λ}, the high-frequency fluctuations of the transform induced by measurement noises are

diminished. The pseudo code associated with Eqs. 4 to 9 can be written in Matlab format as follows

```
%=====================================================================
% Matlab Implementation of "a' Trous "Discrete Wavelet Transform
% CardioVascular Research Group- CVRG, Department of Mechanical Engineering,
% K. N. Toosi University of Technology, June-2008.
% L: Decomposition level (Dyadic Scale 2^L)
% x: Original Signal
INITIALIZE;
lx = length(x);                          % Data length
DWTL = x;                                % Initialize output
%=====================================================================
% calculating filter outputs for the inputted levels
for i = 1 : L
 h = 1/8*[1 zeros (1, 2^ (i-1)-1) 3 zeros(1,2^(i-1)-1) 3 zeros(1,2^(i-1)-1)
1];
 g = 2*[1 zeros (1, 2^ (i-1)-1) -1];
 Hlen = floor (length (h)/2);
 Glen = floor (length (g)/2);
 lpf = conv(DWTL,h);                   % Lowpass FIR filter
 hpf = conv(DWTL,g);                   % Highpass FIR filter
 lpf = lpf(Hlen : lx + Hlen-1);        % Removing extra points
 hpf = hpf(Glen : lx + Glen-1);
 DWTL(1 : 2*lx) = [lpf hpf];
end,

DWT = hpf;
%======================== End of Code ==============================
```

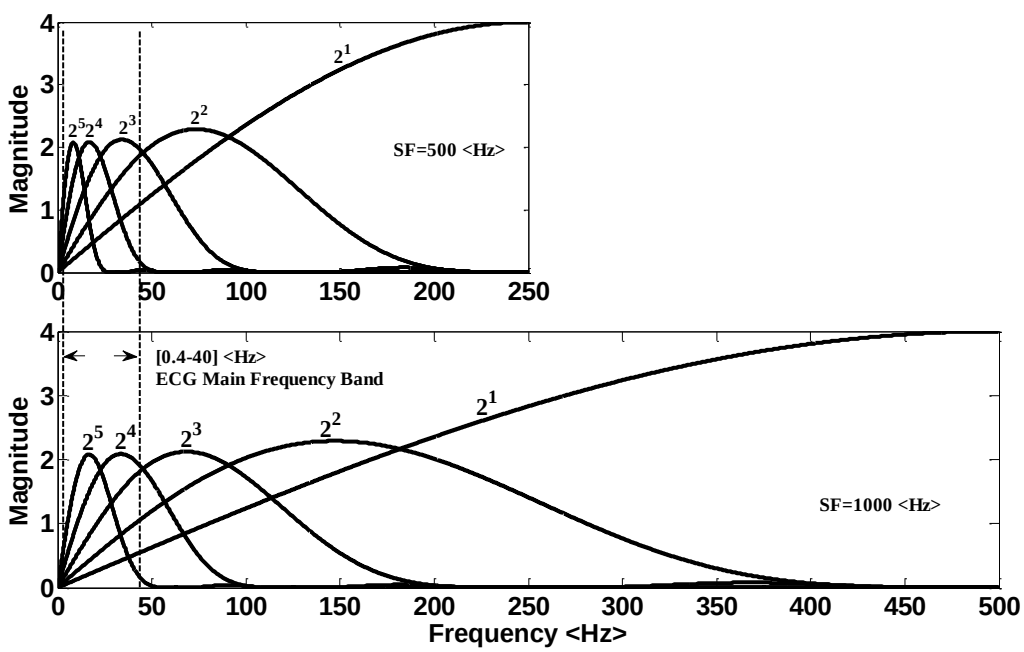

Figure A.1. Frequency response of the several DWT scales for two sampling frequencies (top) 500 Hz and (bottom) 1000 Hz.

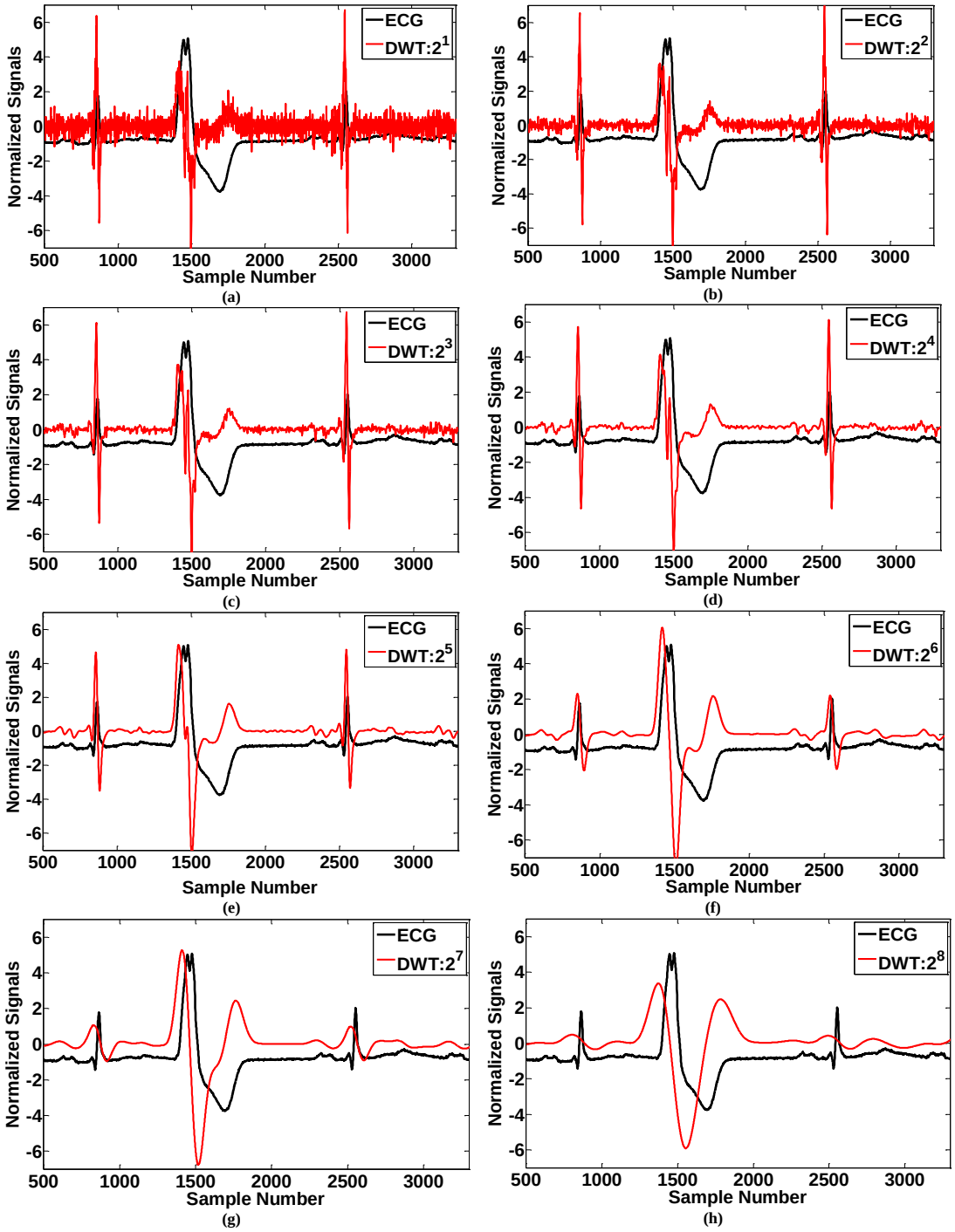

Figure A.2. Illustration of several DWT dyadic scales 2^{λ} obtained from application of a trous filter bank to an arbitrary record of high-resolution holter data for (a) λ=1, (b) λ=2, (c) λ=3, (d) λ=4, (e) λ=5, (f) λ=6, (g) λ=7, (h) λ=8.

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