Cardiac Arrhythmia Classification Using a Combination of Quadratic Spline-Based Wavelet Transform and Artificial Neural Classification Network.

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Keywords: Electrocardiogram, Wavelet Transform, Probabilistic Neural Network, Cardiac Arrhythmia, Digital Signal Processing.

Abstract.
The authors present the use of Wavelet Transform, using a quadratic spline function, and Probabilistic Neural Network (PNN) to classify 8 heartbeat conditions. The process consists of four mains stages. The first part consists of preprocessing and filtering selected ECG lead II (D II) data registers from the PhysioNet repository. The filtered signal is fed to a wavelet transform process using a quadratic spline function, to obtain a feature vector. The results are transferred to a Probabilistic Neural Network algorithm for heartbeat classification. Finally, the algorithm is tested with confusion matrices to determine classification accuracy. The algorithm yielded a 91.5%, 90.3% and 95.5% classification accuracy for auricular fibrillation, sinoauricular heart block and paroxysmal atrial fibrillation conditions respectively. The lower scores were obtained for premature atrial contraction and premature ventricular contraction conditions (75.5% and 69.9% respectively). However, considering the validation test conditions, the results suggest the algorithm is suitable for on-line classification of heartbeat conditions as part of a DSP-based Holter device.

1 Introduction

Cardiovascular disease prevails as one of the main causes of death worldwide. In turn tachyarrhythmic events are associated with a large percentage of sudden death cases [1]. Cardiac arrhythmia occurs intermittently which difficults early diagnosis. Amongst the clinical methods used for measuring cardiac activity the electrocardiogram (ECG) continues to be a cost-effective method for elucidating heart condition [2-3]: cardiac activity is recorded non-invasively by means of a set of electrodes attached to the thorax and/or limbs of the patient. The resulting data record is constituted by a sequence of waves the represent the propagation of impulses throughout the heart: P, Q, R, S, T and U waves (Fig. 1) and can be related to specific cardiac conditions.

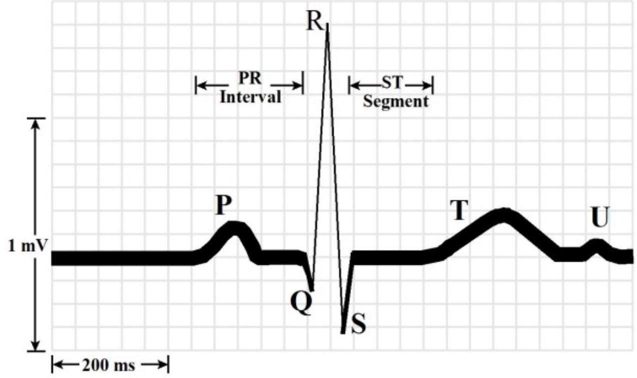

Fig. 1. Characteristic (normal) ECG signal.

1.1 Arrythmia

The term "arrhythmia" is associated with changes of frequency, rhythm or morphology of the ECG signal in comparison with normal ECG values. Diseases or disorders of the heart (cardiopathies) are reflected in the ECG signal [4]. In general, and in a very simplified manner, identifying arrhythmias from the ECG records involves 5 mains steps: measure heartbeat frequency, measure the time elapsed between consecutive R waves (RR interval), examine the P wave, measure the time interval between the P and R waves (PR interval), and measure the QRS complex duration and morphology.

1.2 Arrythmia classification

Although many of the physiological principles that originate the ECG signal are fairly well understood, in automatic analysis processes, it is difficult to determine exactly the beginning and the end of each component. After filtering, the first part of the arrhythmia classification process consists of delimiting each wave component. Many analysis methods directed towards automatic heartbeat classification have originated from QRS complex signal processing methods [5], because represents the most prominent feature of the ECG signal and bears great importance for diagnostic purposes. QRS complex delineation is another type of algorithms aimed at identifying peaks, beginning and end of P and T waves [6]. Amongst the methods used to obtain ECG signal components, the wavelet transform (WT) is a common choice.

1.3 Wavelet Transform

Performing the wavelet transform on a given signal can be considered as a lineal operation to obtain a time-frequency component representation at different scales. Consider Ψ(x) as a function of real or complex values in Hilbert space $L^2(R)$, where L represents the vector space of square-integrable functions and satisfies the admissibility condition so that (1):

$$\int_{-\infty}^{\infty} \psi(x)\ dx = 0 \tag{1}$$

One of the properties of the wavelet transform is that it can be scaled (2):

$$\psi_s(x) = \frac{1}{s}\psi\left(\frac{x}{s}\right) \tag{2}$$

The scale factor, s, dilates (s>0) or contracts (s<0) the wavelet function. Thus a continuous wavelet transform representation of function f(x) ϵ $L^2(R)$ is (3):

$$W_s f(x) = f(x) * \psi_s(x) = \frac{1}{s}\int_{-\infty}^{\infty} f(t)\left[\psi\left(\frac{x-t}{s}\right)\right] dt \tag{3}$$

where t is the translational factor, and corresponds to the time-domain convolution of f(x) and the basis function. From (3) the wavelet transform result depends on scale parameter s. In order to implement the wavelet transform on a computing device to operate on real data, it is necessary to use a fast discrete wavelet transformation. Given the scale factor $s=2^j$ where j ϵ **Z**, and **Z** is the set of all integers, yields the binary or dyadic wavelet transform [7]; assigning s to be multiples of two, results in a discrete binary wavelet transform implementation suitable for digital signal processing applications. The discrete wavelet transform of a digital signal f(n) can be calculated using (4) and (5):

$$s_2^j f(n) = \sum_{k\,\epsilon\,\boldsymbol{Z}} h_k s_2^{j-1} f(n - 2^{j-1}k) \tag{4}$$

$$W_2^j f(n) = \sum_{k\,\epsilon\,\boldsymbol{Z}} g_k s_2^{j-1} f(n - 2^{j-1}k) \tag{5}$$

where $s_2^j f(n)$ are approximation coefficients, $W_2^j f(n)$represent detail coefficients (2^j scale wavelet transform of f(n)) and n is the sample number. The terms $\{h_k, k\,\epsilon\,\boldsymbol{Z}\}$and $\{g_k, k\,\epsilon\,\boldsymbol{Z}\}$ correspond to low pass (H(W)) and high pass (G(W)) coefficients respectively. A number of wavelet functions for heartbeat classification are continuously reported, including the Haar wavelet (Fig. 2 A) [8], the Mexican hat wavelet (Fig. 2B) [9], the Morlet wavelet (Fig. 2C) [10] quadratic wavelet spline derived from a Gaussian function (Fig 2D) and combination of wavelet functions [11]. In particular, quadratic wavelets have shown acceptable time and frequency resolution when applied to ECG analysis [12], and suitability for implementation on dedicated processing hardware [13]. The quadratic wavelet used in this work to obtain the ECG fiducial marker and feature arrays, is derived from a Gaussian function (Fig. 2D) for compact support (6):

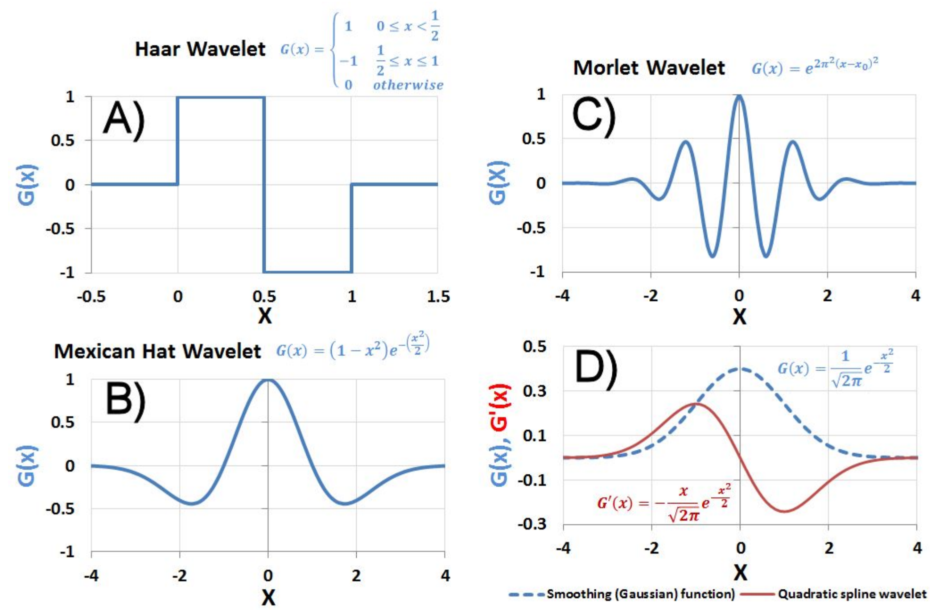

Fig. 2. Examples of reported wavelet functions used in ECG signal analysis. A) Haar, B) Mexican hat, C) Morlet and D) quadratic wavelets.

$$G(x) = \frac{x}{2\,\pi} e^{-\frac{x^2}{2}} \tag{6}$$

1.4 Probabilistic Neural Network (PNN).

Identifying single wave components is only one of the tasks involved in arrhythmia classification. The normal classification procedure continues by transferring the resulting feature array to some classifier. Thus, amongst the classifiers reported for arrhythmia classification are Artificial Neural Networks [14], Multi-layer perceptron [15], Radial Basis Functions [16], Fuzzy Network [17], Expert Systems [18], Support Vector Machine and Particle Swarm Optimization [19], Self-Organizing Maps [20] and Probabilistic Neural Network [21-22]. The PNN architecture is in essence a back-propagation network, but the activation function is derived from statistical data (i.e. exponential function) and can be considered as Parzen-based classifier that asymptotically approximates a Bayesian classifier (Fig. 3). The pattern and classes layers require supervised knowledge to correctly connect the each pattern layer node to the corresponding class layer node (*Sparsely Connected Layers*). The aim is to classify the n^{th} dimension feature vector X_i, according to some predefined class C_M. A common procedure normalizes the weights, W_N, as (8):

$$W_k = \frac{X_k}{\|X_k\|} \qquad k = 1,2, \dots N \tag{7}$$

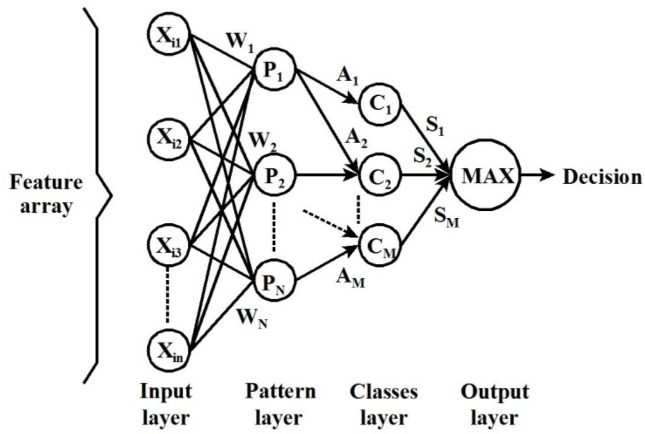

Fig. 3. Probabilistic Neural Network (PNN).

where W_k corresponds to the $P_k{}^{th}$ node, and $X_k \neq X_i$ is the training vector. The P_k pattern layer output, O_k, (9):

$$O_k = e^{\left(\frac{Z_k - 1}{\sigma^2}\right)} \tag{8}$$

where the width of the Gaussian function, σ, is selected to control the exponential activation function scale factor. O_k is the exponential kernel result operating over the dot product between the k^{th} training vector and the X_i vector to be classified, Z_k, (10):

$$Z_k = W_k^T \frac{X_i}{\|X_i\|} \tag{9}$$

The A_M functions are defined as (10):

$$A_{M_k} = \begin{cases} 1 & W_k \in C_M \\ 0 & otherwise \end{cases} \tag{10}$$

and the S_M array contains the equivalent proportional probability estimates (11):

$$S_M = \sum_{k=1}^{N} O_k \, A_{M_k} \tag{11}$$

1.5 WT/PNN reported results

There are indications that the use of algorithms based on WT for wave component identification and PNN for classification can be used for arrhythmia classification. Lin et al. [23] reported a high detection success rate (100%) for a single arrhythmia (Ventricular premature contraction) although the success rate diminishes (94%) when two or more arrhythmias are present. Ebrahimnezhad and Khoshnoud [21] reported 92.9% detection accuracy for four types of arrhythmias using PNN and linear predictive coefficients. Yu and Chen reported a 99% detection success rate for six heartbeat conditions [22]. In this work the authors present a QWT/PNN procedure, directed towards classifying eight heart beat conditions: normal sinus rhythm (N), auricular fibrillation (AF), premature atrial contraction (PAC), left bundle branch block (LBBB), right bundle branch block (RBBB), premature ventricular contraction (PVC), sinoauricular heart block (SHB) and paroxysmal atrial fibrillation (PAF).

2 QWT/PNN arrhythmia classification procedure

The arrhythmia classification method presented here conforms to the common principles of classification; a wavelet transform is used to determine a feature array which is transferred to a PNN classifier. However, in order to prepare the ECG it is necessary to conduct further pre-processing operations. Measured ECG signals regularly include various artifacts (Fig 3A).

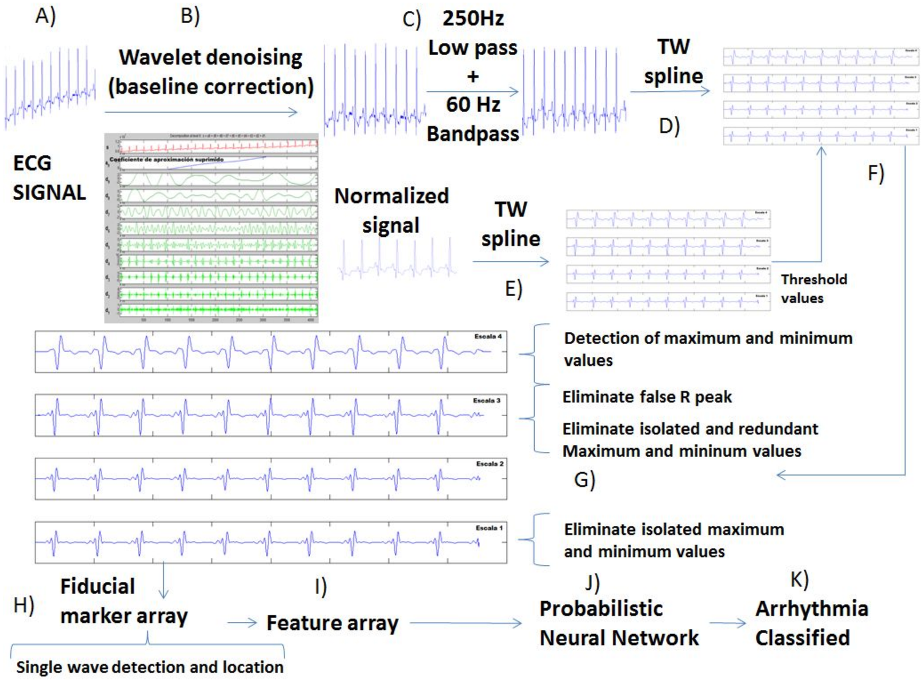

Fig. 4. Schematic diagram of the QWT/PNN arrhythmia classification process. A) The baseline of the original ECG signal B) is restored using a wavelet denoising process. C) The signal is filtered and D) transferred to the QTW section. E) A similar process is applied to the reference signal to obtain a set of threshold values. G) The QWT processed results in a set of H) fiducial markers and I) feature array. J) The PNN can then issue a result for K) arrhythmia classification.

For instance sweat, thorax movement (breathing) and patient activity result on poor electrode contact and displacement of the ECG signal from the baseline (isoelectric line). In order to restore the ECG baseline the process starts with a wavelet denoising operation (Fig 3B). The restored signal is then low-pass filtered to limit the bandwidth to 250 Hz, and band-reject filtered to reduce the effect of the mains (50 or 60 Hz, selectable) (Fig 3C). The filtered signal is then transferred to the QWT section (Fig. 3F). In a similar manner, the reference ECG signal is processed (Fig. 3E) to determine a set of threshold values (Fig 3F) as the basis to obtain the fiducial marker array (Fig 3H) and thus the feature array (Fig. 3I). The results are transferred to the PNN (Fig. 3J) which produces the arrhythmia classification results.

3 Experimental test procedure

The availability of arrhythmia databases has contributed to development of ECG signal processing algorithms. In particular the MIT /BIH database [24] has proved and invaluable tool [25] for testing arrhythmia classification methodologies. The method presented in section 2, was coded in MATLAB and tested using seventeen 30-minute ECG lead II (D II) data registers from the PhysioNet repository: 100, 101, 103, 105, 106, 118, 119, 201, 202, 203, 205, 207, 209, 210, 213, 215 y 219. The algorithm operates over 6-second data blocks. The wavelet coefficients were selected to fit four scale bandwidths (Table 1). Table 2 describes the parameters used for feature extraction.

Table 1. Bandwidth correspondence to scale levels used

Scale	Bandwidth
2^1	31 to 94 Hz.
2^2	16 to 39 Hz.
2^3	8 to 26 Hz.
2^4	4 to 12Hz.

Table 2. Parameters for feature extraction

Parameter	1st beat	....	Nth beat
Number of P waves	0,1,2....	....	0,1,2....
P wave polarity	-1 negative, 1 positive 0 more than 1 P wave	....	-1 negative, 1 positive 0 more than 1 P wave
QRS duration	Time (s)	....	Time (s)
PR interval	Time (s)	....	Time (s)
Position of R	Referenced to the beginning of the segment	....	Referenced to the beginning of the segment
RR interval	Time (s)	....	Time (s)
HR	Beats / minute	....	--
Global rhythm	0 abnormal, 1 normal	....	---

Classes are assigned per type of heartbeat condition: auricular fibrillation (AF)=1, normal sinus rhythm (N) = 2 , premature atrial contraction (PAC)=3, left bundle branch block (LBBB)=4, right bundle branch block (RBBB)=5, premature ventricular contraction (PVC)=6, sinoauricular heart block (SHB)=7 and paroxysmal atrial fibrillation (PAF)=8.

4 Results

Single wave identification is based on detection of maximum and minimum values and zero crossing detection with respect to the isoelectric line [26]. Fig. 4 shows a typical wave identification result over a six second period. Table 3 shows a summary of the results used to feed the PNN.

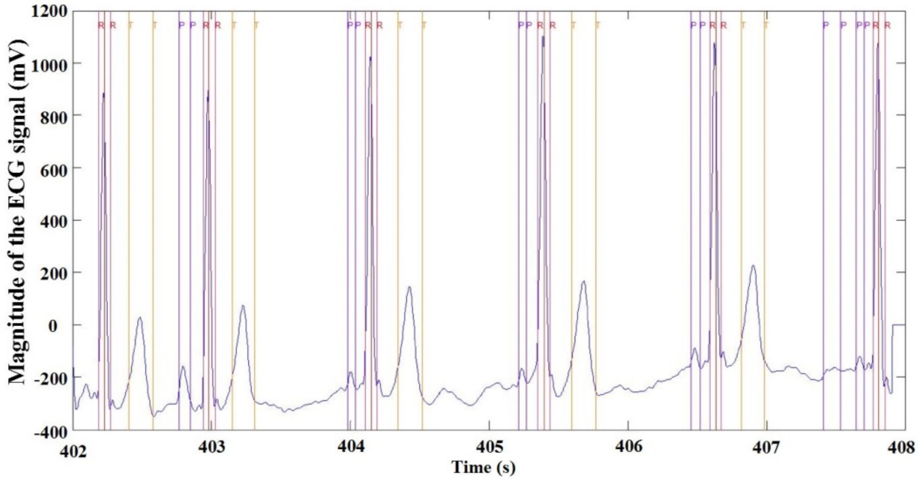

Fig. 4. Example result from the wave identification process (record 202).

Table 3. Summary of the example test results

	Heartbeat					Feature array
Parameter	**1st**	**2nd**	**3rd**	**4th**	**5th**	
# of P waves	1	1	1	1	2	**3**
P polarity	1	1	1	1	0	**7**
QRS duration	0.0840	0.0840	0.0920	0.0840	0.0840	**1**
PR Interval	0.1760	0.1280	0.1360	0.1320	0.1200	**1**
R location	0.9800	2.1480	3.3920	4.6280	5.8040	
RR Interval	0.7520	1.1680	1.2440	1.2360	1.1760	
HR	1					
Rythm	0					**0**

The feature array is transferred to the PNN which produces the probability for each arrhythmia. The results are used to issue a classification confidence factor, CF (12):

$$\text{CF}= 1 - e^{-\frac{(P_1-P_2)}{P_2}} \tag{12}$$

where P_1 is the highest probability and P_2 is second highest probability. Table 4 shows a summary of the classification results, indicating detection of premature auricular contraction with a 100% confidence factor.

Table 4. Summary of classification results for the example data set.

Heartbeat condition	PNN output	Confidence factor CF
AF	1.2983e-04	
N	1.4244e-14	
PAC	99.9999	100%
LBBB	3.8343e-15	
RBBB	1.2438e-19	
PVC	5.7963e-16	
SHB	6.1052e-285	
PAF	4.3960e-190	

The analysis process is repeated for all records using 6-second contiguous data sets. A confusion matrix is used to show the classification score of a particular class, referenced to the rest of classes (Table 5).

Table 5. Classification results (confusion matrix)

	AF	N	PAC	LBBB	RBBB	PVC	SHB	PAF
AF	**91.5%**	1.8%	2.8%	1.3%	0.0%	1.5%	0.0%	1.1%
N	0.7%	**96.8%**	1.6%	0.3%	0.0%	0.2%	0.4%	0.0%
PAC	9.9%	5.3%	**75.5%**	0.0%	0.7%	4.0%	4.6%	0.0%
LBBB	0.0%	0.0%	0.0%	**91.1%**	7.8%	0.6%	0.6%	0.0%
RBBB	1.7%	0.0%	0.9%	7.3%	**86.6%**	3.4%	0.0%	0.0%
PVC	3.9%	9.7%	13.5%	0.0%	1.2%	**69.9%**	1.9%	0.0%
SHB	0.0%	9.7%	0.0%	0.0%	0.0%	0.0%	**90.3%**	0.0%
PAF	0.0%	0.0%	4.5%	0.0%	0.0%	0.0%	0.0%	**95.5%**

When a single arrhythmia is present in the test signal, the classification accuracy is high. However, when there is more than one arrhythmia condition present, the classification accuracy degrades. The lower scores were obtained for premature atrial contraction and premature ventricular contraction conditions (75.5% and 69.9% respectively). However, the algorithm yielded a 91.5%, 90.3% and 95.5% classification accuracy for auricular fibrillation, sinoauricular heart block and paroxysmal atrial fibrillation conditions respectively.

5 Conclusions

In comparison with previous reported works, the confusion matrix tests the classification accuracy and suggest decreased accuracy, but may reflect a more realistic result. When two or more arrhythmia conditions are present in the test signal the accuracy decreases considerably. For instance, PVC resulted difficult to detect due to a small RR interval; the effect is also related to AF. A factor that may have influenced the low detection scores, is the reduced number of data set used for training. Thus there is room for improvement by increasing the number of training data sets. The six-second ECG data length was selected bearing in mind algorithm implementation on dedicated DSP hardware; it is necessary to investigate the effectiveness and robustness of the algorithm for different amounts of data. The inherent nature of the digital signal processing operations involved suggest that the method is suitable for implantation on a portable ECG data acquisition devices. Coding the algorithm in MATLAB allows rapid functional verification. However, it is necessary to develop the appropriate code, optimized for specific DSP hardware. Nevertheless, it was shown that the procedure presented here can perform ECG classification on signals where there is more than a single arrhythmia condition.

6 Acknowledgments

The authors acknowledge the financial support from *Secretaria de Educación Pública* through *Direccion General de Educación Superior Tecnologica (SEP-DGEST)* to carry out this work.

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