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Recognition of ECG signals using wavelet based on atomic functions

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ABSTRACT

Heart disease is the principal cause of death across the globe and the ECG signals are used to diagnose it. The correct classification of this disease allows us the opportunity to apply a more focused treatment. ECG signals are fed into Automated Diagnosis Systems, and these systems use techniques like processing digital signals, machine learning, and deep learning. This paper shows the results when the sampling frequency of the ECG signals is resampled and proposes a new preprocessing stage. The new stage applies Wavelet based on Atomic Functions to eliminate the noise and baseline wander. The Wavelet based on Atomic Functions have demonstrated successful performances in computer science. The ECG signals are segmented into 1, 2, 5, and 10 s; these segmented signals are fed into the classifier stage. Our proposal was tested in four accessible public databases separately, and finally by gathering the databases. We were able to successfully differentiate between 11 types of ECG signals with an accuracy of 98.9%.

1. Introduction

Diverse heart disease affects the lives of millions, and this disease is the leading cause of death. As people get older, they have more probability of suffering heart disease. The United Nations calculated that the number of people aged 60 years would increase by 56% in 2030 [1]. The name of the medical test that detects heart abnormalities is electrocardiogram (ECG). The ECG measures the electrical activity of the heart through electrodes attached on the skin. The electrodes can be attached in different parts of the body; the most common configuration uses five electrodes [2]; other configuration uses ten electrodes [3]; these configurations measure the electrical

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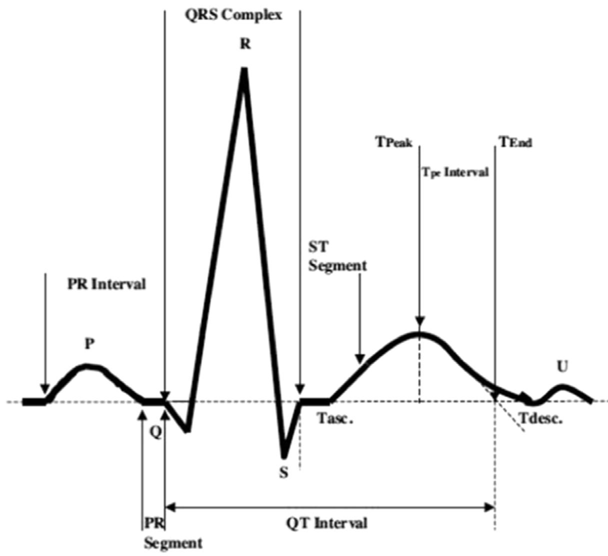


Fig. 1 – ECG of Normal Sinus Rhythm, Source [4].

signal. Different settings could be applied, so many kinds of leads could be created. The most common are; Lead I, Lead II, and Lead III.

Fig. 1 shows the ECG of Normal Rhythm; the waves on the ECG correspond electrical phenomena on the heart surface. P wave represents the Atrial depolarization. The QRS complex wave represents the Ventricular depolarization and the Atrial repolarization, while T wave represents the Ventricular polarization. When the electrical heart signals do not work correctly, the waveforms on the ECG change, then we know that an arrhythmia is present.

The term arrhythmia means any change in the electrical activity of the heart. This activity may happen fast, slowly, or erratically, thus the heart beats fast, slowly or erratically. Some people experiment in irregular heartbeats, which may feel like a racing heart or fluttering. Many arrhythmias are harmless, but if they occur in a damaged heart or they are severely abnormal, these arrhythmias could be dangerous. Arrhythmias consist of an early beat (premature contraction), slow beat (bradycardia), fast beat (tachycardia), and irregular beat (fibrillation or flutter).

The arrhythmias produce alterations on the ECG signal; in consequence, the ECG signals are the most common technique used to diagnose heart diseases. This technique could be complicated for humans; for example, in a complete ECG record, each beat has to be analyzed, sometimes the records last minutes, hours, or even days. After hours of analysis, human error may appear because of tiredness. For that reason, computational methods are an alternative to interpret the ECG signals.

Some years ago, several algorithms for ECG classification had been widely developed. The classical proposes consist of the next stages: Preprocessing, Segmentation, Feature extraction, and Classifier Algorithms. About the preprocessing stage, many techniques have been applied like FIR Digital Filter [5], Adaptive Filters [6], Multiadaptive Bionic Wavelet Transform [7], Nonlinear Bayesian Filters [8], among other things. The Segmentation stage uses techniques like Quad Level Vector [9], Neural Networks [10], Genetic Algorithms [11], Wavelet Transform [12,13], Filter Banks [14] among others. The feature extraction stage applies many algorithms, these are the most common: RR Interval [15,16], proposed Normalized RR Interval, ECG segments or ECG intervals [17], another features extraction algorithms are applied in time or frequency domain [18], Principal Component Analysis (PCA) [19,20], Kernel Principal Component Analysis (KPCA) [21], Independent Component Analysis (ICA) [22] among others techniques. The final stage uses techniques like Artificial Neural Network (ANN) [23], Support Vector Machine (SVM) [24], Linear Discriminant [25], Decision Trees [26], Nearest Neighbors [27], Clustering [28], Hidden Markov Models [29], Convolutional Neural Network (CNN) [1,30–33], inter alia.

Advanced signal processing and learning methods have been applied to develop computational methods to recognize ECG signals. Researchers in the literature have applied one or more of the techniques previously mentioned. In Ref. [34] used a modified U-net model to perform analysis on ECG segments. The authors in Ref. [1] applied CNN to detect the ECG signals. In Ref. [35] preprocessed the ECG signal using a low-complex digital hardware implementation for arrhythmia detection. In Ref. [36] the features of the ECG signal are calculated using Welch's method and a discrete Fourier transform, in the Classifier stage, they use two genetic ensembles based on SVM. An automated system using a combination of CNN and long short-term memory (LSTM) for detection ECG signals is proposed by Ref. [33]. In Ref. [37] extracted the features of the ECG signal using the spectral power density then a machine learning algorithms were used. In Ref. [38] the apply to deep learning(1D-CNN) to detect 17 classes of cardiac arrhythmia. A 9-layer deep CNN to identify 5 different heartbeats in ECG signals is developed by Ref. [30]. In Ref. [31] a CNN structure comprises of four convolutional layers, four max pooling layers and three fully connected layers for the diagnosis of Coronary artery disease was proposed. In Ref. [32] presented a CNN to automatically detect the different ECG segments. The main features of the ECG signals are obtained through discrete wavelet transform, followed by principal component analysis on each decomposed level, the features were reduced through statistical analysis as an input to SVM in Ref. [39]. Arrhythmias detection algorithm that combines a number of ECG parameters using SVM is investigated in Ref. [40]. In Ref. [41] presented an automated method for using a single lead of ECG sensors using PCA, DWT, and SVM. In Ref. [42] the proposal applied PCA of segmented ECG beat, then these features were independently classified using neural network and LS-SVM. In Ref. [43] the authors applied an optimum support vector machine in which the dataset is reduced to 18 features using PCA. A summary of the approaches mentioned is presented in Table 1.

The approaches in the literature present the problem that the ECG signals have noise, the authors face the problem applying DWT or other filtering techniques. In this proposal, the signals were preprocessed to eliminate the noise and baseline wander using Wavelet based on Atomic Functions (WAF) due to it eliminates the noise better than the classic wavelets [44], then Z-score was applied to normalize the signals. After these signals were divided into segments, these

Table 1 – Summary.

Author, year	Database	Approach	Performance
Present Work	•MIT-BIH	Wavelet based on Atomic Function, Z-score, Decision Fine Tree	11 Classes
	•MIT-VFDB		10 s, Acc = 98.2%
	•Fantasia		5 s, Acc = 98.9%
	•St.-Petersburg		2 s, Acc = 97.4%
			1 s, Acc = 93.8%
Oh et al., 2019 [34]	•MIT-BIH	U-net	5 Classes, Acc = 97.3%
Achayra et al., 2018 [1]	•MIT-BIH	DWT, CNN	9 Classes, Acc = 93.18%
	•MIT-VFDB		
	•CUDB		
Pudukotai et al., 2018 [35]	•MIT-BIH	ADDHard	Acc = 97.28%
Plawiak, 2018 [36]	•MIT-BIH	Genetic ensemble, SVM	15 Classes, Acc = 93%
			17 Classes, Acc = 91%
Shu Lih Oh et al., 2018 [33]	•MIT-BIH	CNN and LSTM	5 Classes, Acc = 97.5%
Plawiak, 2018 [37]	•MIT-BIH	Evolutionary-Neural System	13 Classes, Acc = 95%
			15 Classes, Acc = 91%
			17 Classes, Acc = 90%
Yildirim et al., 2018 [38]	•MIT-BIH	1D-CNN	13 Classes, Acc = 95.2%
			15 Classes, Acc = 92.5%
			17 Classes, Acc = 91.3%
Achayra et al., 2017 [30]	•MIT-BIH	CNN	5 Classes, Acc = 94.03%
Achayra et al., 2017 [31]	•Fantasia	CNN, Z- score	2 Classes
	•St.-Petersburg		2 s, Acc = 94.95%
			5 s, Acc = 95.1%
Achayra et al., 2017 [32]	•MIT-BIH	CNN	4 Classes
	•CUDB		2 Sec, Acc = 92.5%
			5 Sec, Acc = 94.9%
Hamed et al., 2016 [39]	•VFDB	DWT, PCA	4 Classes, Acc = 96.89%
	•CUDB		
	•QTDB		
	•MIT-BIH		
Alonso-Atienza et al., 2014 [40]	•CUDB	Complexity, morphological, spectral features, SVM	2 Classes, Acc = 98.6%
Kaveh et al., 2013 [41]	•MIT-BIH	PCA, Discrete Wavelet Transform (DWT), SVM	Acc = 88.8%
Martis et al., 2013 [42]	•MIT-BIH	LS-SVM	5 Classes, Acc = 98.1%
Babaoglu et al., 2010 [43]	•Data Acquisition	PCA,SVM	Acc = 76.67%

segments long one second, two seconds, five seconds, and ten seconds. These segments were fed into the classifier stage to make the final decision. The rest of the paper is organized as follows: Section 2 is a summary of the databases, Section 3 is a description of the proposal, the experimental results are shown in Section 4, Section 5 provides the discussions, and finally, the conclusions.

2. Databases

The Databases used in this paper are obtained from 4 publicly available databases MIT-BIH [45,46], MIT-VFDB [45,47], Fantasia [45, 59] and St.-Petersburg INCART [3,45]. The summary of the four databases is shown in Table 2.

3. Proposed approach

This paper proposes to classify different ECG signals. To achieve this goal, we use different databases. First, the performance of each database is calculated according to the block diagram in Fig. 2. Next, the databases are gathered creating a new database. Then, the performance of the new database is calculated using the block diagram in Fig. 2 too. The block diagram of the proposed approach is shown in the next Figure. First, an ECG signal is fed into the preprocessing stage, which consists of WAF and Z-score. WAF eliminates noise and baseline wander, then Z-score is applied to remove the offset and the problem of amplitude scaling. Next, the preprocessed signals are segmented and concatenated according to the classes (The number of classes changes for each database). Next, the signals are resampled at frequencies lower than the original. Finally, the resulting signals are fed into the classifier stage to make the final decision. The following subsections provide a complete description of all stages of the proposed approach.

3.1. *Preprocessing*

The acquisition of the ECG signals may contain noise. Discrete Wavelet Transform (DWT) is a computational technique for signal processing that allows getting electrical noise with Signal to Noise Ratio superior to Lock-In Amplifier equipment. For that reason, DWT based on Atomic Functions up(x) is applied to the ECG signals to remove the noise and baseline wander. Then Z-score is used to eliminate the offset and the problem of amplitude scaling into the signals. The Fig. 3 shows a comparison between the original signal and the preprocessed signal.

Table 2 – Database summary.

Database	No. Of Signals	Lead (s)	Lead used	Sampling Frequency (Hz)	ECG signal duration
MIT-BIH	48	I II	I	360	30 min
MIT-VFDB	22	I II	I	360	30 min
Fantasia	20	RESP ECG	ECG	250	120 min
St.-Petersburg INCART	75	I II III AVR AVL AVF V1-V6	I	257	30 min

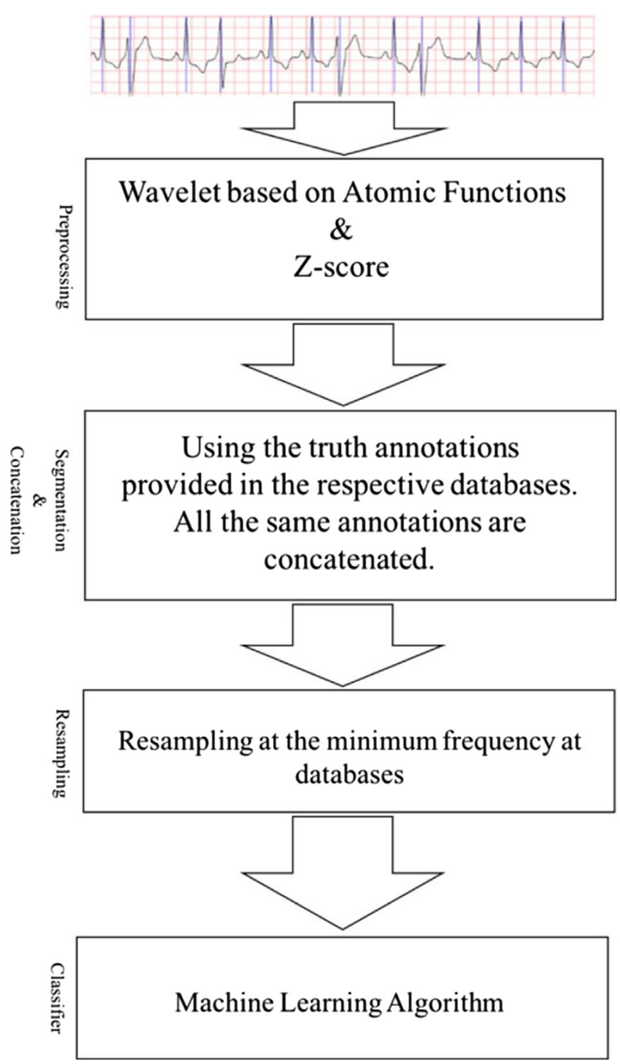


Fig. 2 – Block Diagram.

3.1.1. *Wavelet based on atomic functions*

In Ref. [44] presented a comparison between WAF with the classic Wavelets (Meyer, Daubechies, Symlet, among others). WAF presented the properties of multiresolution analysis and WAF had better time-frequency localization than the classics wavelets. A comparative analysis of denoising with WAF and classic wavelets was presented in Ref. [44], the WAF has the highest value of signal to noise ratio and the lowest relative error then the WAF due to it eliminates the noise better than the classic wavelets. WAF has successful performance when used in different tasks in computer science, for example, windowing radar processing, recognition of medical images, speech recognition, image processing, and super-resolution in image and video [48–51]. Given these facts, we applied WAF to filter ECG signals.

The Atomic Functions (AF) are the fundamental point to understand the Wavelet based on Atomic Functions. These functions are used in several applications in computer science like digital signal processing and pattern recognition. The AF are explained below; these functions are compactly supported infinitely differentiable solutions of differential equations with a shifted argument [48]:

$$L\,f(x) = \lambda \sum_{k=1}^{M} c(k)\, f(ax - b(k)), |a| > 1 \tag{1}$$

In Eq. 1, L is a linear differential operator with constant coefficients. In this paper, the Atomic Function up(x) is applied; this function is the most useful primitive function to create other AF [48]. Fig. 4 shows the function up(x), this function is represented in terms of the Fourier Transform for infinite convolution of rectangular impulses:

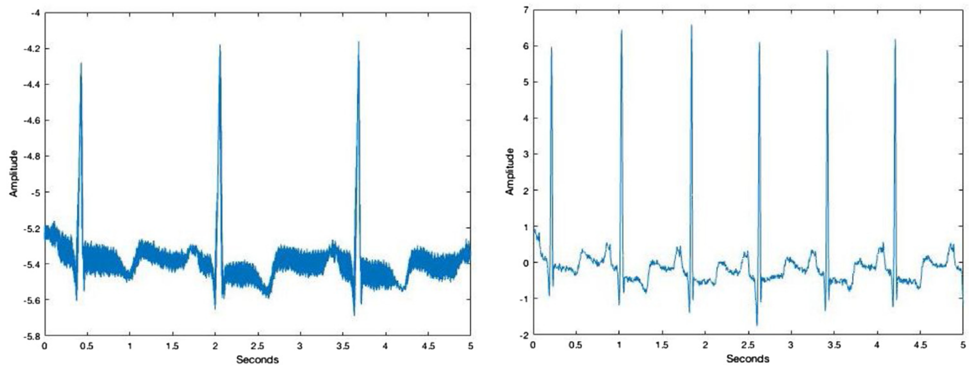
$$u\,p(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{jux} \prod_{k=1}^{\infty} \frac{\sin(u\,2^{-k})}{u\,2^{-k}}\, du \tag{2}$$

Then the wavelets will be constructed based on atomic functions, the wavelet analysis defines an auxiliary function $\varphi(x)$, which is called scaling function. This function creates a collection of closes embedded subspaces $V_j \subset L^R(R)(j \in Z)$ producing multiresolution analysis, which has five properties, these properties has been studied in Refs. [12,52], following these properties are presented:

I. $\bigcup_{j \varepsilon Z} V_j = L^2(R)$

II. $\cap_{j \in Z} V_L = \{0\}$.

III. $f(x) \in V_j f(2x) \in V_{j+1}$.



(A) (B)

Fig. 3 – (A) Original, (B) preprocessed signals of MIT-BIH database.

IV. In this property exists a $\varphi(x) \in V_0$ then its shifts form a Riesz basis for V_0.

$\varphi(x)$ has a Fourier Transform $\varphi(\omega)$.

Then V_0 is the subspace of $L^2(R)$ created by the shifts of $\varphi(x)$. The functions $\varphi_n(x) = \varphi(x-n)$ form a Riesz basis V_0 if and only if Theorem 1 and Theorem 2 are true, these theorems has been studied in Ref. [52], following these Theorems are presented:

Theorem 1. The system $\{\varphi(x-n)\}_{n\in Z}$ obtained by the shifts of a function $\varphi(x) \in L^2(R)$ form a Riesz basis of $V_0 \subset L^R(R)$ if and only if there exist a positive constants A and B such that:

$$A \leq \sum_{n\in Z} |\varphi(\omega + 2\pi\omega)|^2 \leq B \tag{3}$$

Theorem 2. The functions $\varphi_n(x) = \varphi_n(x-n)$ form an orthonormal basis of $V_0 \in L^2(R)$ if and only if:

$$\sum_{n\in Z} |\varphi(\omega + 2\pi\omega)|^2 = 1 \tag{4}$$

In Ref. [26] proposed a function $\mathcal{X}(\omega) = |\varphi(\omega)|^2$ such that it shifts $\mathcal{X}_n(\omega) = \mathcal{X}_n(\omega + 2\pi n)$ satisfy the following equation:

$$\sum_{n\in Z} \mathcal{X}(\omega + 2\pi\omega) = 1 \tag{5}$$

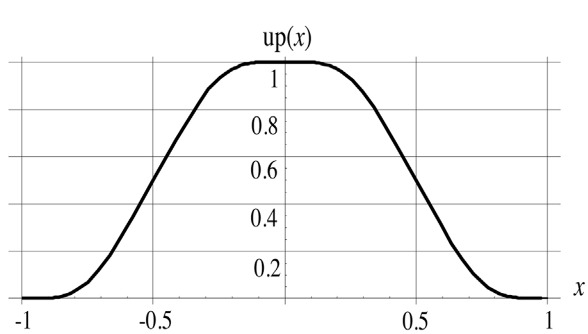


Fig. 4 – Plot of up(x), Source reference [48].

And the next conditions are satisfied:

$$supp(f(\omega)) = \left[\frac{-4\pi}{3}, \frac{4\pi}{3}\right] \tag{6}$$

$$f(\omega) = \begin{cases} 1\, if\ \omega \in \left[\frac{-2\pi}{3}, \frac{2\pi}{3}\right] \\ \frac{1}{2}\, if\ \omega = \pi \end{cases} \tag{7}$$

According to Refs. [48,52], in Eq. 9 a property of $up(\omega)$ is presented:

$$\sum_{n\in Z} up(\omega + n) = 1 \tag{9}$$

Next, the partial sum in the Eq. 10 is proposed [52] for the half of the function of support be lesser than or equal to the width of the flap top

$$up_1^{sum}(\omega) = up(\omega+1) + up(\omega) + up(\omega-1) \tag{10}$$

Then, the support of $up_1^{sum}(t) = [-2, 2]$ change to $up_2^{sum}(t) = [\frac{-4\pi}{3}, \frac{4\pi}{3}]$ [52].

$$up_2^{sum}(\omega) = up\left(\frac{3\omega}{2\pi} + 1\right) + up\left(\frac{3\omega}{2\pi}\right) + up\left(\frac{3\omega}{2\pi} - 1\right) \tag{11}$$

In Ref. [52] the Eq. 12 is applied to calculate the wavelet $up(\omega)$

$$\varphi(\omega) = up(\omega) = \sqrt{u} \tag{12}$$

Next, the Fourier Transform $\varphi(\omega)$ of $\varphi(x)$ is applied

$$\varphi(x) = \frac{1}{2\pi}\int_{-\infty}^{\infty} \varphi(\omega) e^{j\omega x} d\omega = \frac{1}{2}\int_0^{\frac{-4\pi}{3}} \varphi(\omega)\cos\omega x d\omega \tag{13}$$

Then according to Ref. [52] the Fourier Transform $\psi(\omega)$ is defined by the next equation:

$$\psi(\omega) = e^{\frac{j\omega}{2}} H_0\left(\frac{\omega}{2} + \pi\right)\varphi\left(\frac{\omega}{2}\right) = e^{\frac{j\omega}{2}}(\varphi(\omega - 2\pi) + \varphi(\omega + 2\pi))\varphi\left(\frac{\omega}{2}\right) \tag{14}$$

The following equation calculates the inverse Fourier Transform

$$= \frac{1}{\pi}\int_{2\pi/3}^{-8\pi/3} \varphi(\omega/2)\varphi(\omega - 2\pi)\cos\omega(x + 1/2)d\omega \tag{15}$$

The function $\psi(x)$ has the properties of wavelet, these properties has been studied and proved in Refs. [12,48,52], then the expression for wavelet coefficients is given by:

$$f_{j,n} = \int_{-\infty}^{\infty} f(x)\psi_{j,n}(x)dx \tag{16}$$

The wavelet analysis needs the auxiliary function $\varphi(x)$, this function was defined in the Eq. 13, this function is used to define the approximations:

$$\varphi_{j,n}(x) = 2^{-j/2}\varphi(x-n2^j/2^j). \tag{17}$$

In Eq. 17, $\varphi(x)$ satisfies the Eqs. 18–19

$$\int_{-\infty}^{\infty} \varphi(x)dx = 1 \tag{18}$$

$$\varphi(x) = \sqrt{2}\sum_{n\in Z} h_n\varphi(2x - n). \tag{19}$$

The Eq. 20 shows the Wavelet function

$$\psi_{j,n}(x) = 2^{-\frac{j}{2}}\psi\left(\frac{x - 2^j n}{2^j}\right), \tag{20}$$

In Eq. 17 satisfies the Eq. 21:

$$\psi(x) = \sqrt{2}\sum_{n\in Z} g_n\varphi(2x - n) \tag{21}$$

The wavelet transform uses two filters [12]. The first filter calculates the wavelet coefficients and the other filter applies the scaling function. The Eq. 22 provides an approximation of the signal and the Eq. 23 provides the detail signals:

$$W_L(n, j) = \sum_m W_L(m, j-1)h(m - 2n) \tag{22}$$

$$W_H(n, j) = \sum_m W_L(m, j-1)g(m - 2n) \tag{23}$$

$W_H(p, q)$ is the pth wavelet coefficient at the qth stage

$W_H(p, q)$ is the pth wavelet coefficient at the qth stage

In Eq. 22, $h(n)$ is the filter coefficient, it corresponds to the scaling function (low pass filter). The filter coefficient in the Eq. 23 is $g(n)$, it corresponds to the wavelet function (high pass filter) (Fig. 5).

3.1.2. *Z-score*

The Z-score [5] permits to compare signals when the statistical characteristics change; in this paper, each ECG signal has different statistical features. To analyze the ECG signals, Z-score is applied. We show how to calculate the Z-score of a vector using the Eqs. 24–26:

$$X = \frac{1}{N}\sum_{i=1}^{n} x_i \tag{24}$$

$$S = \sqrt{\frac{\sum_{i=1}^{n}(x_i - X)^2}{n-1}} \tag{25}$$

$$z_i = \frac{x_i - X}{S},\ i = 1, \ldots, n \tag{26}$$

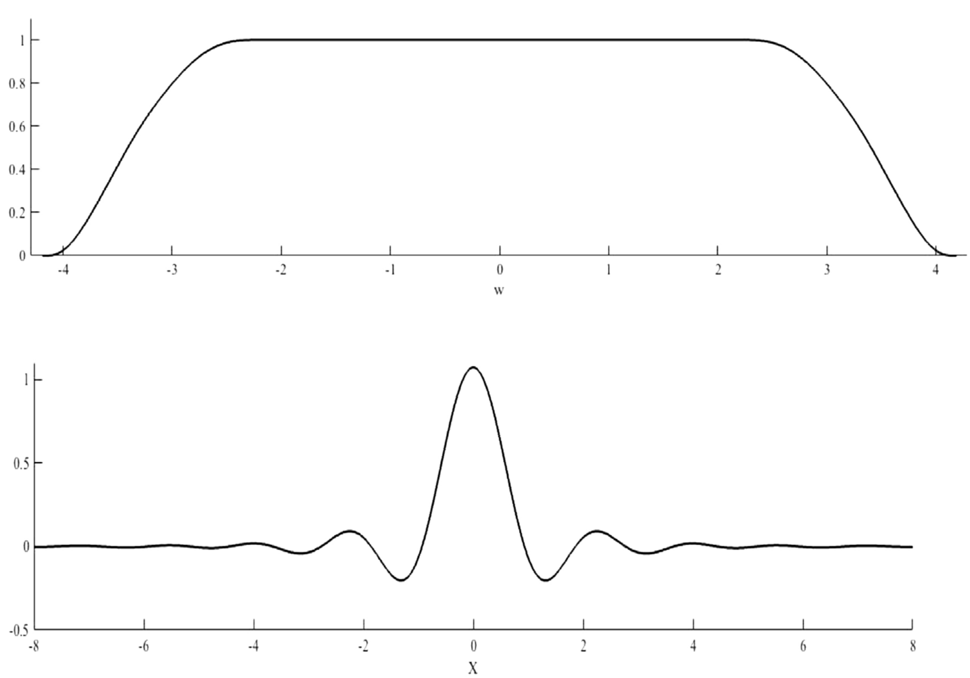


Fig. 5 – Upper $\varphi(\omega)$ for wavelet up(ω) *eq(12)*, Lower $\varphi(\mathbf{x})$ scaling function $\varphi(\mathbf{x})$ of up(ω) eq(13).

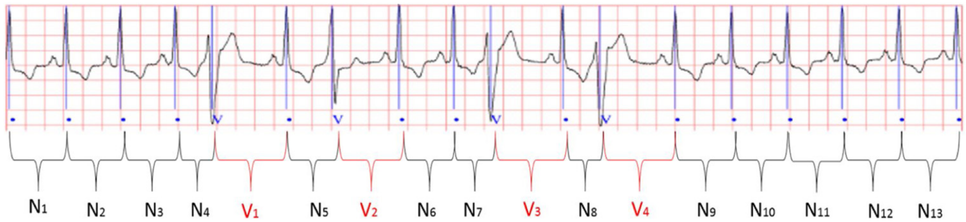


Fig. 6 – Record 221 MIT-BIH Database, 10 s.

Where X is the mean, S is the standard deviation and the z_i is the z-score of a data point x_i.

3.2. Segmentation & concatenation

The preprocessed signals are segmented and sorted according to the annotations provided in the databases. Fig. 6 shows an example of a recording of MIT-BIH database, which has two different types of ECG signals; Normal and Premature Ventricular Contraction. The different types of ECG signals are separated using the annotations of the database.

Then, we have the vector *Nb* and *P* for this recording, as shown in the Eqs. 27–28.

$$Nb = (N_1, N_2, N_3, N_4, N_5, N_6, N_7, N_8, N_9, N_{10}, N_{11}, N_{12}, N_{13}) \quad (27)$$

$$P = (V_1, V_2, V_3, V_4) \quad (28)$$

The full recordings for each Database are analyzed, each recording is segmented using the annotations as the previous Figure. Then, the vectors with similar annotations are concatenated. The different types of ECG signals for each Database are shown in Tables 3–7. Fig. 7 show illustrations of ECG signals.

3.3. Resampling

Table 2 shows the original frequency for each database; these databases have different sampling frequencies. Therefore, to ensure standardization across the databases, the ECG signals obtained from the BIH, VFDB, and St. Petersburg databases are downsampled to 250 Hz.

3.4. Classifier stage

This approach applies SVM and Decision Tree classifiers because they are the most popular algorithms in Machine Learning. Bellow a description of the classifiers used in this work is presented.

3.4.1. SVM

Support Vector Machine is used in applications like natural language processing, image and speech recognition and computer vision. The goal of SVM is to create an optimum hyperplane that enables the prediction of labels between two

Table 3 – BIH Database, Different types of ECG signals.

- Normal Beat
- Right Bundle Branch Block Beat
- Left Bundle Branch Block Beat
- Atrial Premature Beat
- Premature Ventricular Contraction
- Paced Beat
- Fusion of Paced and Normal Beat

Table 4 – VFDB Database, Different types of ECG signals.

- Normal Beat
- Atrial Fibrillation
- Ventricular Tachycardia
- Nodal A-V Junctional
- Supraventricular Tachyarrhythmia

Table 5 – Fantasia Database, Different types of ECG signals.

- Normal Beat
- Right Bundle Branch Block Beat
- Atrial Premature Beat
- Premature Ventricular Contraction

Table 6 – St. Peter Database, Different types of ECG signals.

- Normal Beat
- Right Bundle Branch Block Beat
- Atrial Premature Beat
- Premature Ventricular Contraction

Table 7 – New Database, Different types of ECG signals.

- Atrial Fibrillation (AB)
- Nodal A-V Junctional (NOD)
- Supraventricular Tachyarrhythmia (ST)
- Ventricular Tachycardia (SVTA)
- Normal Beat (N)
- Left Bundle Branch Block Beat (L4B)
- Right Bundle Branch Block Beat (R4B)
- Atrial Premature Beat (APB)
- Premature Ventricular Contraction (PVC)
- Paced Beat (PB)
- Fusion of Paced and Normal Beat (FPN)

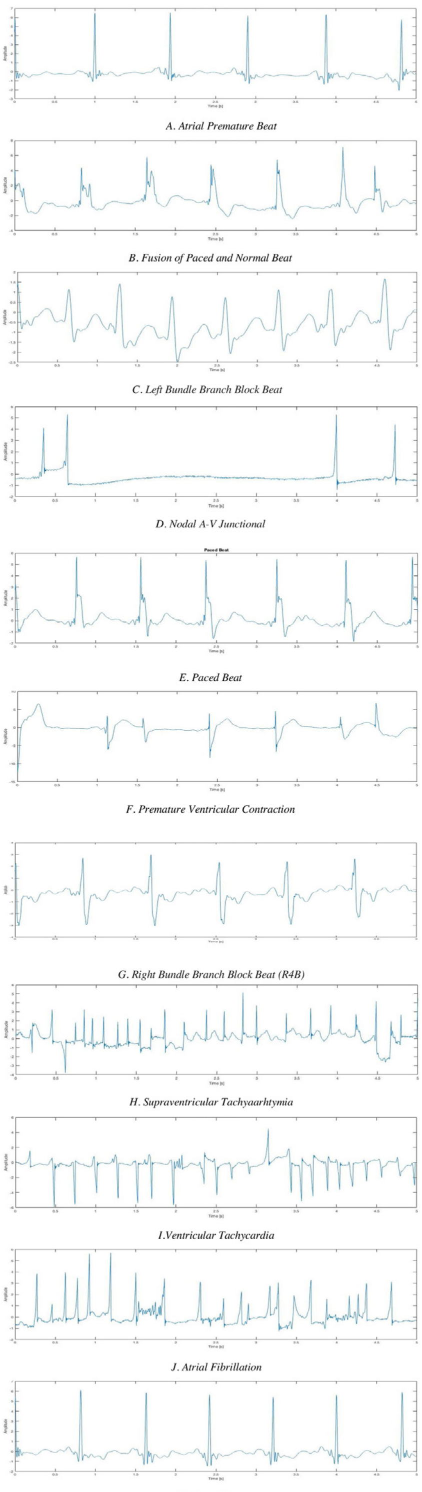


Fig. 7 – Illustrations of ECG samples.

classes (the labels are −1 and +1). Considering X as data points and the separating hyperplane defined in the Eq. 29.

$$W^T X + w_0 = 0 \tag{29}$$

Where W is the vector of coefficient of X and w_0 is the vector of coefficient of x_0

$$g(x_i) = +1;\ if(W^T x_i + w_0 > 0) \tag{30}$$

$$g(x_i) = -1;\ if(W^T x_i + w_0 < 0) \tag{31}$$

The objective of training an SVM model is to find the W and w_0 so that the hyperplane separates the data. Therefore, it is an optimization problem as present in the following equation:

$$minimize\left(\frac{1}{2}\|W\|^2\right) allowing\, g(W^T x_i + w_0 \geq 1)\ i\ =\ 1, 2, \ldots N \tag{32}$$

The Lagrangian method is used to solve the optimization problem, then the next equations show the solution:

$$\sum\nolimits_{\alpha_t} g(\alpha_t \langle x, x_t \rangle + w_0 > 0)\, implies\, g = +1,\ t = 1, 2, \ldots, N \tag{33}$$

$$\sum\nolimits_{\alpha_t} g(\alpha_t \langle x, x_t \rangle + w_0 < 0)\, implies\, g = -1,\ t = 1, 2, \ldots, N \tag{34}$$

In the Eqs. 33 and 34, α_t are the Lagrange Multipliers and $\langle x, x_t \rangle$ are the scalar product of support vector x and vectors x_t. The Fine Gaussian kernel was used as shown in the Eq. 35 at the place of scalar product of the Eqs. 33 and 34 for non linear separation:

$$G(x_i, x_j) = e^{\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right)} \tag{35}$$

$$\sigma = \frac{\sqrt{p}}{4}, \tag{36}$$

We have 11 types of ECG signals so we applied a scheme of the SVM to multiclass problem. A study of methods for multiclass SVM is given in Ref. [53, 60], we selected the "one versus one" method. This method consists in selecting different classes of the database and training binary classifiers to distinguish them.

3.4.2. *Decision tree*

A Decision Tree has the advantage of the implementation simplicity; these classification models have the shape of a tree. The result is a tree with nodes and leaves. A decision tree breaks down the database into shorter subset. The Decision Tree starts from a root node. The internal nodes have ingoing and outgoing edges while that the leaves just have nodes with ingoing edges. The data navigate from the root node to a lead, where finally the data is classified.

$$L = \{(x_n, y_n),\ n = 1, \ldots, N\} \tag{37}$$

The training database is defined in the previous equation, the database has N patterns, vector x is a vector and y is the class. After training the Decision tree, a new pattern propagates through the tree then the pattern assigns to the class in which the leaf belongs. In this work Fine Tree decision is applied, it has many leaves to make subtle distinctions between classes; the maximum number of splits is 100. An overview of decision tree is presented in Ref. [54].

4. Training & testing

In this paper, 10-fold cross-validation is performed to evaluate the proposed approach. We use 90% of the signals to training the approach; the other 10% is used to test the method. The ECG signal samples, after the preprocessing step, were directly fed to the classifier stage. The results are shown in Tables 8–11 use as classifier Fine Gaussian SVM [53,55,56], and the results shown in Table 12 use Fine Gaussian SVM and Fine tree [54,57].

5. Results

In this section, the results for the databases are shown in Tables 8–11, Table 12 shows the results when the previous databases were combined. Tables 8–12 show the results when the ECG signals were segmented (1 s, 2 s, 5 s, and 10 s), and these signals were resampled, starting with the original sample frequency and gradually decreasing to 250 Hz. The frequency 250 Hz ensures standardization between databases. Tables 3–7 show different ECG signals for each database, the ECG signals used were 10 min long per each type. In Table 8, 70 min of recordings are analyzed, 50 min of records are analyzed in Table 9, Tables 10–11 show the results when 40 min of recordings were analyzed. Finally, Table 12 shows the results when 110 min of records are examined. Tables 8–11 use Fine Gaussian SVM as a classifier; meanwhile, Table 12 uses Fine Gaussian SVM and Fine Tree as classifier. Finally, Table 13 shows the per-class performances of the 11 different types of ECG signals in a matrix confusion using Fine Tree as classifier.

Table 8 – Results for BIH Database, 7 different types of ECG signals.

Frequency [Hz]	Pattern size			
	10 s	5 s	2 s	1 s
360	99.4%	99%	98.8%	98.2%
350	98.6%	98%	99.1%	98.4%
300	98.6%	98.8%	99.2%	99.4%
250	97.6%	99.2%	99.5%	98.7%

Table 9 – Results for VFDB Database, 5 different types of ECG signals.

Frequency [Hz]	Pattern size			
	10 s	5 s	2 s	1 s
360	99.7%	99.9%	99.9%	99.9%
350	99.7%	99.8%	99.9%	99.8%
300	99.9%	99.9%	99.8%	99.9%
250	99.8%	99.7%	99.7%	99.7%

Table 10 – Results for St. Peter Database, 4 different types of ECG signals.

Frequency [Hz]	Pattern size			
	10 s	5 s	2 s	1 s
257	99.8%	99.7%	99.9%	99.9%
250	99.8%	99.7%	99.9%	99.9%

Table 11 – Results for Fantasia Database, 4 different types of ECG signals.

Frequency [Hz]	Pattern size			
	10 s	5 s	2 s	1 s
250	99.7%	99.8%	99.9%	99.9%

Table 12 – Results for New Database, 11 different types of ECG signals.

Classifier	Pattern size			
	10 s	5 s	2 s	1 s
SVM Fine Gaussian	95.8%	96.7%	95.2%	96.1%
Decision Tree	98.2%	98.9%	97.4%	93.8%

6. Discussion

This paper faces the problem of recognizing different ECG signals. The proposed approach uses ECG signals (1 s, 2 s, 5 s, and 10 s). We used the databases MIT-BIH, MIT-VFDB, Fantasia, and St Peter. These databases are prevalent in the literature. The results in Tables 8–9 show that if the ECG signals are resampled, the accuracies oscillate in a maximum of 1.3%, as we can see in Table 8 when the 10 s signals were analyzed. If the sampling frequency is reduced, the number of samples per signal are reduced too. This means lower computational cost, so classification techniques like CNN could be applied in less time. For example, when 10 min of signal is analyzed at a frequency of 360 Hz, the signal has 216,000 samples, but if this signal is resampled at 250 Hz, then the number of samples decreases to 150,000. This fact reflects a change in performance, as shown in Tables 8 and 9. When the ECG signals are resampled, they are dropping a bit of information. This allows the classifier to make a decision. In future work, it is possible to make a study of the loss information suffered by each ECG signal when it is resampling.

Tables 9–11 show the results when, at the maximum, 5 types of ECG signals are analyzed. Table 12 shows the results of 11 types of ECG signals, for which the maximum accuracy is 96.7% using Fine Gaussian SVM. When Fine Decision Tree is applied, the accuracy goes up to 98.9%.

Table 1 shows our results in bold font, and we can see that the results are better than previous reported works which used different techniques like CNN, SVM, Z-score, Genetic Ensemble, LSTM, Evolutionary Neural System, DWT-Daubechies, and PCA, among others.

Table 13 – Confusion Matrix of 11 different types of ECG signals using Fine Tree in pattern size of 5 s.

Confusion Matrix	AB	APB	FPN	L4B	NOD	N	PB	PVC	R4B	ST	SVTA
AB	98%		<1%	<1%	<1%	<1%	1%		<1%		
APB	<1%	99%			<1%			<1%			
FPN			99%					<1%	<1%		
L4B	<1%		<1%	99%	<1%			<1%			
NOD			<1%	<1%	99%						
N	<1%		<1%			99%	<1%	<1%			
PB	<1%	<1%			1%		98%	<1%			
PVC	<1%			<1%	<1%	<1%	1%	98%			
R4B		<1%				<1%			99%		
ST										100%	
SVTA											100%

For example, Kaveh et al. [41] 2013 used DWT-Daubechies and SVM; and the reported accuracy is 88.8%. Our proposal improves on that accuracy by 10.1%. Acharya et al. [1] 2018, applied DWT-Daubechies and CNN, and the reported accuracy was 93.18. Our proposal improves on that accuracy by 5.72%. Plawiak et al. [37] 2018 recognized, 17 classes with an accuracy of 90%, 15 classes with an accuracy of 91%, and 13 classes with an accuracy of 95%. Our proposal improves on that result by 8.9%, 7.9% and 7.6%, respectively.

Oh et al. [34] 2019 applied U-net, their accuracy was 97.3%. Our proposal improves the accuracy by 1.6%.

This paper proposes the Wavelet based on Atomic Functions in the preprocessing stage; this function is the principal distinctness. Atomic Functions are widely used in computer science [49–52,58]. Kravchenko et al. [49] compared the atomic functions with classic ones; and the atomic functions exceeded the classic ones. This paper compares the results to other papers which used DWT-Daubechies, as shown in the results in Table 1, the accuracy is better when the Wavelet based on Atomic Functions is applied. In a future exhaustive comparison between WAF and Classical Wavelets can be explored.

We use four databases. The accuracies are similar between databases. Unfortunately, the databases are small, so our approach was not robust enough, this is a limitation in this work. This work has the limitation that recognizes 11 ECG signals, other authors [36–38] recognize 17 ECG signals. In a future work, our proposal could apply to recognize 17 ECG signals. In the future work the approach would be more robust if we use bigger database and the classifier stage use a CNN. Finally, our approach could be applied to other biological signals to identify variations.

7. Conclusion

This paper introduces the Wavelet based on Atomic Functions in the preprocessing stage to classify different ECG signals. The results are compared to other reported works; which used classic Wavelet in the preprocessing scene. The proposal recognizes up to 11 kinds of ECG signals with an accuracy of 98.9%.

The results show that it is possible to reduce the sample frequency without considerable losses in accuracy, which means lower computational cost. Then, classification techniques as CNN could be applied in less time. If these techniques are useful; then they could recover the lost accuracy when the signal is resampling.

The accuracies of our approach could be improved by bigger ECG databases and techniques like CNN. Our approach could be applied to detect anomalies in other biomedical signals.

Disclosure of potential conflicts of interest

We declare that we do have no commercial or associative interests that represent a conflict of interests in connection with this manuscript. There are no professional or other personal interests that can inappropriately influence our submitted work.

Research involving human participants and/or animals

This article does not contain any studies with human participants or animals performed by any of the authors.

CRediT authorship contribution statement

Andres Hernandez-Matamoros: Conceptualization, Data curation, Visualization, Software, Writing - original draft. **Hamido Fujita:** Acquisition, Supervision, Visualization, Formal analysis, Methodology, Writing - review & editing. **Enrique Escamilla-Hernandez:** Software, Validation. **Hector Perez-Meana:** Project administration, Funding, Writing - review & editing. **Mariko Nakano-Miyatake:** Investigation, Writing - review & editing.

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