# Classification and Prediction of Arrhythmias from Electrocardiograms Patterns Based on Empirical Mode Decomposition and Neural Network

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**Abstract.** Diagnosis of heart disease rests essentially on the analysis of the statistical, morphological, temporal, or frequency properties of ECG. Data analytical techniques are often needed for the identification, the extraction of relevant information, the discovery of meaningful patterns and new threads of knowledge from biomedical data. However for cardiovascular diseases, despite the rapid increase in the collection of methods proposed, research communities still have difficulties in delivering applications for clinical practice. In this paper we propose hybrid model to advance the understanding of arrhythmias from electrocardiograms patterns. Adaptive analysis based on empirical Mode Decomposition (EMD) is first carried out to perform signal denoising and the detection of main events presented in the electrocardiograms (Ecg). Then, binary classification is performed using Neural Network model. However in this work, the Ecg R-peak detection method, the classification algorithm are improved and the chart flow include a predictive step. Indeed, the classification outputs are used to perform prediction of cardiac rhythm pattern. The proposed model is illustrated using the MIT-BIH database, compared to other methods and discussed. The obtained results are very promising.

**Keywords:** ECG classification · Neural networks · Predictive models · Empirical mode decomposition · Arrhythmia

## 1 Introduction

An electrocardiogram (ECG) is a representation of the electrical impulses due to ionic activity in the heart muscles of the human heart (Fig. 5). And the analysis (statistical, morphological, temporal or frequency aspects of P, Q, R, S, T waves) of the ECGs shape is a key step during the investigation of symptoms related to heart anomalies [1]. An anomaly is an abnormality or irregularity


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that occurs when the behavior of the system is unusual and significantly different from normal previous behavior [3,21]. As heart disease is one of the leading cause of death around the world, the understanding of hearth anomalies is a main subject of research in the field of cardiac care and information processing [2]. For this purpose, many approaches have been proposed for anomaly detection, classification and prediction. Classical methods for anomalies detection use external probe [12,13] or internal components that periodically send heartbeats or store logs of relevant events when certain conditions occur [3]. The classification can be done through adaptive methods such as Harr descriptor, empirical mode decomposition and Neural Network models [1,2]. Unlike the detection and classification methods, the predictive approach gives indicators for possible abnormalities before the symptoms occur from historical data and an intelligent system [4,11]. The main approaches for prediction of anomalies are based on the statistics, information theory, data mining and machine learning (HMM, Bayesian networks, ARMA model, SVM) [3–5,17,21]. Several studies have shown the effectiveness of the statistical approach to machine learning and data mining [21]. Statistical techniques assume that data have predefined distributions and use the distribution gap to find an anomaly [4]. In this paper, we improved the model proposed in [1] for anomalies detection and ECG classification with empirical mode decomposition and neural network. The main contributions are the ECGs morphological properties taken as input during the classification and the predictive model based on heart rate frequency analysis. The proposed cardiac abnormalities prediction uses linear regression from the neural network outputs classifier. The results are illustrated using MIT-BIH database and discussed.

The body of the paper is organized as follows. First, Sect. 2 presents the architecture of our methodology, the basics of the empirical mode decomposition and the neural network classifier. Secondly, Sect. 3 describes the parameters extraction. Thirdly, Sect. 4 presents the classification method. Next, Sect. 5 describes the predictive model. Then, Sect. 6 shows and discuss the results obtained with our methodology. Finally, Sect. 7 draws conclusions and perspectives of work.

## 2 Model Presentation

The chart flow of the proposed classification and prediction approach for cardiac abnormalities is presented in the Fig. 1.

The inputs of our system (Fig. 1) are ECGs. For the MIT-BIH database, the each ECG includes three components: time samples, MLII signals and V5 signals. For the classification, we first extract the V5 signal, then denoise the signal through filtering and compute input parameters (Negative form, maximum amplitude, minimum amplitude, maximum width and minimum width) for the neural network classifier. The outputs of the classifier are then used during the prediction step. For this purpose, we first compute the ten previous heart rate, then we estimate the next heart rate to predict the existence or not of cardiac abnormality.

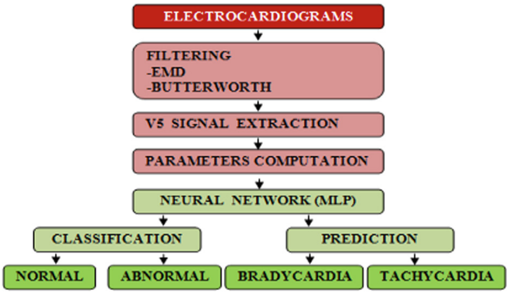


**Fig. 1.** Chart flow of the proposed classification and predictive approach.

### 2.1 Empirical Mode Decomposition

EMD decomposes iteratively a complex signal s(n) into components elementary AM-FM Types, called Intrinsic Mode Functions (IMFs) [10,16,18,20].

$$s(n) = r_k(n) + \sum_{k=1}^{K} imf_k(n) \tag{1}$$

Where $imf_k$ is the $k^{th}$ mode or IMF of the signal and $r_k$ is the trend residual. Figure 2 illustrates the empirical decomposition of ECG 100 [1].

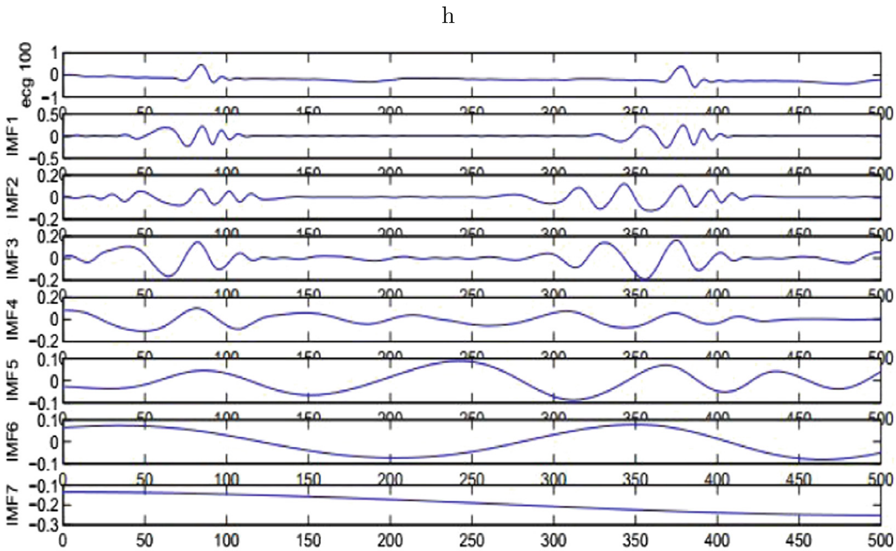


**Fig. 2.** Empirical mode decomposition of ECG 100 [1]

The sifting procedure generates a finite number of IMFs. The underlying principle of the EMD is to identify locally in the signal the fastest oscillations defined as the waveform interpolating the local maxima and minima. To do this, these last points are interpolated with a cubic spline to produce the upper and lower envelopes. The average envelope is subtracted from the initial signal and the same interpolation scheme is reiterated.

### 2.2 Neural Network

A neural network is a mathematical function, see Fig. 3 [1].

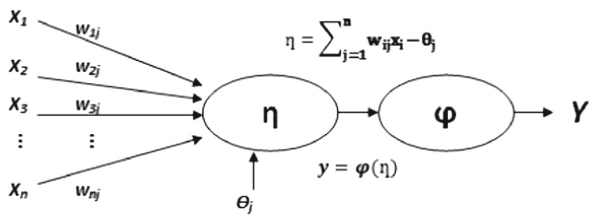


**Fig. 3.** Representation of an artificial neuron [1]. Inputs are multiplied by their weight. The products are added to give the weighted sum. The threshold of the node is subtracted from the weighted sum to determine the output of the node.

To set up a neural network, there must be defined input data, the activation function and the thresholds of the nodes. Each data (node) is associated with a weight. A neural network works as follows:

1. Computation of the weighted sum of the inputs and their weights;
2. Computation of the difference between the threshold and the weighted sum;
3. Computation of the image of the difference with the activation function.

In this paper, we propose a neural network composed of six nodes, corresponding to morphological properties of the complex QRS (negative form, maximum amplitude, minimum amplitude, maximum width, minimum width) and arrhythmia class. Figure 4 illustrated the network component.

## 3 ECG Patterns Detection

Intrinsic parameters are used for ECG patterns detection that can leads the classification that will be further performed. Indeed, statistical properties (mean, variance, standard deviation, energy and power) are often used as input parameters for classification [1]. However these parameters are global descriptors of data. Unlike statistical properties, morphological attributes allow local analysis. Thus, in this work, we used a set of morphological properties (negative form, maximum amplitude, minimum amplitude, maximum width, minimum width) of the complex QRS (Fig. 5) and the step activation function for classifying the ECG.

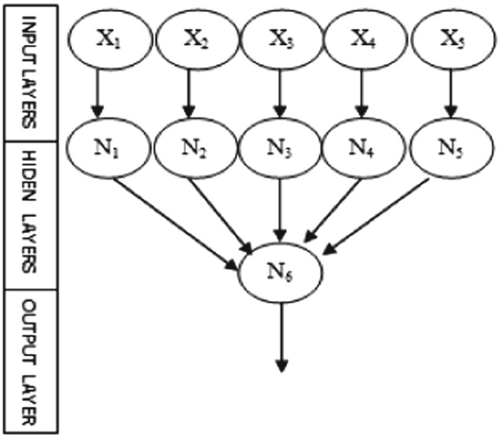


**Fig. 4.** Architecture of the neural network. The variables $X_1$ ... $X_5$ represent the morphological properties of the QRS complex, respectively the negative form, the maximum amplitude, the minimum amplitude, the maximum width and the minimum width. The variables $N_1$ .. $N_5$ represent the intermediate nodes. The Node $N_6$ determines the class of the signal.

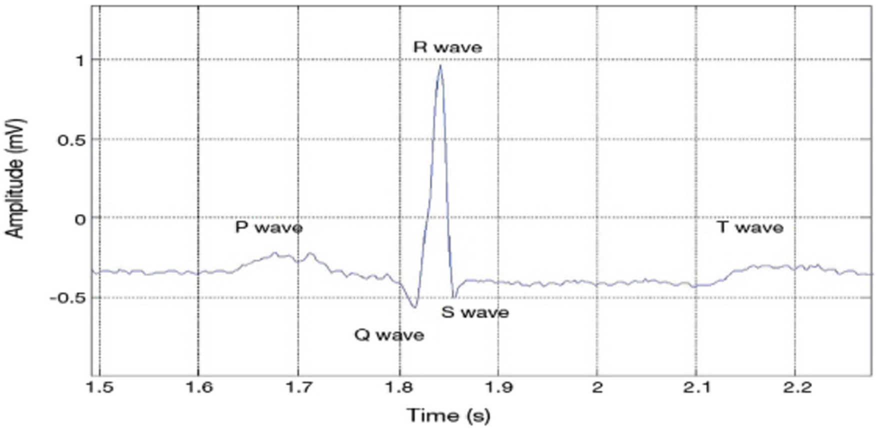


**Fig. 5.** Illustration of the morphological properties with ECG: P, Q, R, S and T waves represent a heartbeat [19].

### 3.1 Filtering

The signal are denoised using method based on empirical mode decomposition (EMD) and Butterworth filtering [1]. We subtract the first IMF ($IMF_1$) to eliminate the high frequency [10,18,20] and apply the Butterworth filter to smooth the signal [22]. The main operations are:

1. Inputs: ECGs
2. EMD based filtering

- Empirical mode decomposition (EMD);
- Remove the $IMF_1$;
- Subtract the $IMF_1$ from ECG.

3. Butterworth Filtering:
   - Compute the filter order;
   - Compute the filter coefficients;
   - Apply the filter.
4. Outputs: Denoised ECG.

### 3.2 Parameters Vector

The Algorithm 1 describe the detailed step processing of the morphological properties computation.

**Algorithm 1.** Parameters

function vecteur(s)
$e \leftarrow extrema(s)$
$l \leftarrow largeur(e)$
$a \leftarrow rdetecter(e)$
$n \leftarrow rnegative(e)$
$ln \leftarrow min(l)$
$lm \leftarrow max(l)$
$an \leftarrow min(a)$
$am \leftarrow max(a)$
$v \leftarrow [n, ln, lm, an, am]$
return v

- Algorithme 1 takes as input an ECGs and computes the maximums, the minimums of the widths and amplitudes of the QRS complexes. It detects a negative R-wave if it occurs and returns a parameters vector for the neural network.
- The extrema() function is used to compute the ECG local extrema (maximum and minimum).
- The function width() takes as input the ECG extrema, detects the waves (Q and S) and returns the QRS complex width.
- The rdetect() function takes as input the ECG extrema, computes the absolute maximum, uses a threshold of 75% of the absolute maximum to detect the R waves and returns the ECG R waves.
- The rnegative function() takes as input the ECG extrema, computes the absolute extrema (maximum, minimum, the ratio of the minimum and the maximum) and returns the index of a negative R wave if the ratio is greater than 0.75.

The parameters given by the output of Algorithm 1 are used as input for the cardiac abnormalities prediction (Algorithm 2).

**Algorithm 2.** Heart Rate

function frequence(e)<br>
$s \leftarrow e(2,:)$<br>
$sp \leftarrow abs(s)$<br>
$l \leftarrow length(s)$<br>
$r \leftarrow []$<br>
$m \leftarrow max(sp)$<br>
**for** $i \leftarrow 1$ *to* $l$ **do**<br>
    $q \leftarrow sp(i)/m$<br>
    **if** $q \geq 0.50$ **then**<br>
        $r \leftarrow [r, s(i)]$<br>
    **end if**<br>
**end for**<br>
$fc \leftarrow length(r)$<br>
return fc

The function frequence() (Algorithm 2) takes the extremum of an ECG, counts the number of R waves and returns the heart rate and the number of beats per minute.

## 4 Classification

The classification involves two functions: the network function and the classifier function. The implemented neural network uses H(x), the step activation function with a threshold (s) for each parameter: $H(x) = 0\ si\ x < s\ and\ H(x) = 1\ si\ x \geq s$. The parameters are negative form, minimum width, maximum width, minimum amplitude and maximum amplitude which are respectively associated to the following thresholds 0, 0.06, 0.10, 0.5 and 2.5 [9]. The network function is composed of six neurons. It takes as input a parameters vector and returns zero (0) for normal or one (1) for abnormal. The classifier iterates the network function and detects an anomaly when there is [9]:

1. a negative R wave;
2. a minimum width is less than 0.06;
3. a maximum width is greater than 0.10;
4. a minimum amplitude is less than 0.5;
5. a maximum amplitude is greater than 2.5.

This proposed process improves the classification method proposed in [1] by 6.25%. The improvement is due to the use of the morphological parameters on the one hand and the step function on the other hand. The morphological parameters allow to perform local analysis with defined thresholds.

## 5 Abnormalities Prediction

The detection and prediction of anomalies are very important in monitoring the patients and ensure a good patient care. Several techniques exist for the detection and prediction of cardiac abnormalities. In this section, prediction based on linear regression [8] is presented. A linear regression model can be described by Eq. (2):

$$\begin{aligned} y &= a + bx \\ a &= \bar{y} - b\bar{x} \\ b &= \frac{\sum(x-\bar{x})(y-\bar{y})}{(x-\bar{x})^2} \end{aligned} \tag{2}$$

where, $y$ is the estimated frequency and $x$ the prediction horizon. The frequency prediction is done through the following steps:

1. Computation of the 10 previous heart rates;
2. Estimation of the next heart rate;
3. Classification of the estimated cardiac frequency with a network of neurons;
4. Prediction of a cardiac abnormality (Tachycardia or Bradycardia).

The prediction base is constructed by extracting the samples from last 10 min and computing the corresponding heart rates. The cardiac frequency is estimated using the Algorithm 3.

**Algorithm 3.** Prediction Method

function predire(dfc,t)<br>
$y \leftarrow dfc$<br>
$x \leftarrow 1 : 10$<br>
$mx \leftarrow mean(x)$<br>
$my \leftarrow mean(y)$<br>
$n \leftarrow 0$<br>
$d \leftarrow 0$<br>
**for** $i \leftarrow 1$ *to* 10 **do**<br>
    $n \leftarrow n + (i - mx) * (y(i) - my)$<br>
    $d \leftarrow d + (i - mx) * (i - mx)$<br>
**end for**<br>
$b \leftarrow n/d$<br>
$a \leftarrow my - b * mx$<br>
$fcp \leftarrow a + b * t$<br>
return fcp

The function (Algorithm 3) takes ten previous frequencies and $t$ (horizon prediction). It estimates the heart rate at $t$ (prediction horizon). When the estimated heart rate is less than 50 beats per minute, Bradycardia is predicted [7]. And when the estimated heart rate is higher at 100 beats per minute, tachycardia is predicted [7].

# 6 Results and Discussion

## 6.1 Data Description

For the learning, testing, evaluation and validation of our classifier, we use the ECG of the MIT-BIH Arrhythmia database [1,15]. It is a waveform and class completed references databases of physionet.org. It is composed of 48 signals recorded on a half-hour. The MIT-BIH Arrhythmia database ECG can be downloaded from physionet.org. It is a set of 48 data files, 48 annotations files and 48 head files. The files have 64800 items including 21600 samples (time), 21600 MLII signals and 21600 V5 signals.

We considered 70% of ecg for learning and 30% for testing and evaluation. The learning base is composed of 33 ecg including 19 ecg normal and 14 ecg abnormal. The test base is composed of 15 ecg including 6 abnormal ecg and 9 ecg normal. Our goal, during testing, is to be able to detect all abnormal ECGs.

## 6.2 Classification and Prediction

We first use dual filtering based on the EMD and the Butterworth filter during the preprocessing step. Then, we compute the classification parameters (Table 1) and estimate the heart rate (Table 3) for the prediction. We have computed the parameters for the Forty-eight (48) ECG signals from the MIT-BIH database. Table 1 shows, as exemple, the parameters of the five ECG signals (100, 102, 104, 106 and 108).

**Table 1.** Characteristic vectors for the classification

| ECG | FORME NEGAT | LARG MIN | LARG MAX | AMPLIT MIN | AMPLIT MAX |
|---|---|---|---|---|---|
| 100 | −0.5860 | 0.0660 | 0.1270 | −0.5860 | 0.7350 |
| 102 | −3.3040 | 0.1310 | 0.5550 | −3.3040 | −3.0240 |
| 104 | −0.9310 | 0.0500 | 0.4330 | −0.9310 | 0.8870 |
| 106 | −0.4280 | 0.0560 | 0.0950 | −0.4280 | 0.5220 |
| 108 | −2.3600 | 0.1610 | 0.3000 | −2.3600 | −1.8170 |

**Table 2.** The performance indices

| Classifier | TP | FP | TN | FN | Ac | Se | Sp | Pp |
|---|---|---|---|---|---|---|---|---|
| SPNNC [1] | 5 | 1 | 2 | 7 | 47% | 42% | 22% | 83% |
| This work | 6 | 0 | 4 | 5 | 67% | 55% | 44% | 100% |

For evaluating the performance of the classifier, we have computed the standard familiar metrics [6,14] like Accuracy (Ac), Sensitivity (Se), Specificity (Sp), Positive Predictivity (Pp) using True Positive (TP), True Negative (TN), False Negative (FN) and False Positive (FP). Compared (Table 2) to our previous work [1], we see an improvement in all performance indices, particularly anomaly detection, represented by the positive predictivity (Pp).

**Table 3.** Frequencies estimated for the prediction

| ECG | FC 1 | FC 2 | FC 3 | FC 4 | FC 5 | FC 6 | FC 7 | FC 8 | FC 9 | FC 10 | FC ESTIMÉE |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 100 | 17 | 46 | 4 | 35 | 7 | 51 | 363 | 110 | 56 | 113 | 163.26 |
| 101 | 185 | 107 | 186 | 283 | 110 | 140 | 67 | 13 | 95 | 83 | 44.06 |
| 118 | 36 | 51 | 40 | 82 | 36 | 59 | 74 | 47 | 83 | 52 | 69.40 |

We have computed and estimated the frequencies for the forty-eight (48) ECG signals from the MIT-BIH database. We compute ten heart rates for the forty-eight ECG and we estimated their heart rates. In Table 3, we gave the example of the three cases of estimation of the cardiac frequency. The estimated frequencies will be given as parameters of the neural network to predict a cardiac anomaly.

Table 3 contains the ten heart rates and the estimated frequency of three ECG signals (100, 101 and 118). For ECG 100, the estimated heart rate is 163.26. This frequency predicts tachycardia. The frequency 44.06 predicts a bradycardia for the ECG 101. And ECG 118 is predicted normal by the frequency 69.40.

## 7 Conclusion

In this work, we proposed an approach based on empirical mode decomposition (EMD), the neural network and linear regression for classification and prediction of cardiac abnormalities. The main contributions are the ECGs morphological properties taken as input during the classification and the predictive model based on heart rate frequency analysis. The output of our approach gives promising results for the classification and prediction of cardiac abnormalities such as tachycardia and bradycardia. In future works, the predictive model will be combined with a stochastic model to better understand the behavior of ECG signals.

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