ECG SIGNAL ENTROPY ASSESSMENT AND PR INTERVALS ALLOCATION IN MALIGNANT VENTRICULAR ARRHYTHMIAS

Shivani Patel, Hemant Amhia
Department of Electrical engineering, Jabalpur Engineering College, Jabalpur (Madhya Pradesh)

Abstract
The concept of pattern recognition refers to classification of data patterns and distinguishing them into predefined set of classes. The analysis ECG signal is an application of pattern recognition. The ECG signal generated waveform gives almost all information about activity of the heart. The ECG signal feature extraction parameters such as spectral entropy, Poincare plot exponent are used for study in this paper .This paper also includes artificial neural network as a classifier for identifying the abnormalities of heart disease.

Keywords: Artificial Neural Network, Electrocardiograph (ECG), Arrhythmia, feature extraction, Classification.
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I. INTRODUCTION

Electrocardiogram (ECG) is a nearly periodic signal that reflects the activity of the heart. A lot of information on the normal and pathological physiology of heart can be obtained from ECG. However, the ECG signals being non-stationary in nature, it is very difficult to visually analyze them. Thus the need is there for computer based methods for ECG signal Analysis [1]. A lot of work has been done in the field of ECG signal Analysis using various approaches and methods. The basic principle of all the methods however involves transformation of ECG signal using different transformation techniques including Fourier Transform, Hilbert Transform, Wavelet transform etc. Physiological signals like ECG are considered to be quasi-periodic in nature. They are of finite duration and non stationary [2]. Hence, a technique like Fourier series (based on sinusoids of infinite duration) is inefficient for ECG. On the other hand, wavelet, which is a very recent addition in this field of research, provides a powerful tool for extracting information from such signals [3].

Time-frequency analysis is a useful tool for many applications. The resulting representations separate input signals into their time-varying spectral components, suitable for applications such as in-depth scrutiny of the signal characteristics, or alternatively signal-to-noise enhancement by removing undesired content [4]. The ability of a given transform to depict the signal components such that they can be individualized in time or frequency is called resolution. The concept of resolution groups both the transform localization power (i.e. its intrinsic ability to distinguish between temporal and spectral information as defined by theoretical limitations) and the representation readability (i.e. any posterior processing done on the decomposition results for improving the separation of spectral components) [**1**]. The latter component includes any corrections to remove spectral leakage and smearing because finite-duration analysis windows are used within the transforms [4].

The Heisenberg uncertainty principle states that there is a limit in the precision with which certain complementary physical parameters can be known. By analogy to the Heisenberg uncertainty principle, the Gabor uncertainty principle states that spectral components cannot be defined exactly at any instant in time. In other words, one has either a high-localization in timing or frequency content but not both [**2**,**3**]. Some time-frequency transforms, such as the short-time Fourier transform (STFT), have fixed time-frequency localization, meaning that the unchanging length of the sliding analysis window results in the same time and frequency resolution at all analysed time instants of the signal. On the other hand, the continuous wavelet transform (CWT) varies the time length of its analysis operator (i.e. the length of the mother wavelet) in order to achieve a varying time-frequency localization. It uses long wavelets to analyse low frequencies precisely at the expense of limited time localization, and conversely short wavelets to ensure high time localization but limited information on frequency content [**3**,**4**].

The use of a finite-duration analysis window (operator) leads to spectral smearing and leakage [**5**], in essence introducing artefacts into the resulting time-frequency representation. This occurs because each analysis window (operator) introduces a convolution kernel which computes the weighted average of neighbouring points resulting in temporal and spectral smearing. This implies that a non-zero amplitude can be retrieved even if the true signal has no component at this time-frequency pair. The STFT and the continuous wavelet transform thus both suffer from finite localization as well as reduced readability due to spectral smoothing and leakage [**1**,**3**,**4**].

To enhance resolution, the synchrosqueezing transform (SST) applies three steps, namely (i) computation of the CWT to ensure varying time-frequency resolution, (ii) calculation of the instantaneous frequencies to enhance readability, and (iii) frequency reassignment to counter the effect of spectral smearing [**6**–**8**]. Computation of instantaneous frequencies enhances primarily readability but does not affect time-frequency localization as this is imposed by the Gabor uncertainty principle. The reassignment method computes the sphere of influence of each analysis window (operator) and reallocates the energy in the time-frequency plane to its centre of gravity in the time and frequency domains, thereby improving the readability of the time-frequency picture [**9**,**10**].

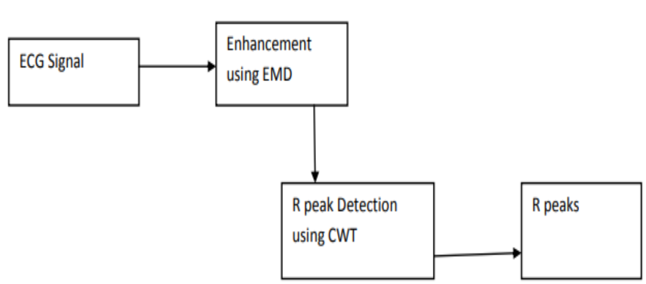


Fig 1.1 Block diagram.

Electrocardiogram (ECG) is a noninvasive technique that is used as a diagnostic tool for cardiovascular diseases [11]. ECG signal is widely used as a fundamental tool for the detection and diagnosis of heart disorders. ECG is the record of variation of bioelectric potential with respect to time as the human heart beats. It provides valuable information about the functional aspects of the heart and cardiovascular system. Since ECG is the most commonly recorded signal for the patient monitoring and examination process, it is important to be reliably and quickly detect the cardiac disorders. ECG can be recorded easily with the help of surface electrodes on the limbs or chest. It is considered a representative signal of cardiac physiology, useful in diagnosing cardiac arrhythmia [12]. Abnormality of the ECG shape is usually called arrhythmia. Arrhythmia is a common term for any cardiac rhythm that differs from normal sinus rhythm [13].Therefore, a powerful computer aided diagnosis (CAD) system is required for the early detection of cardiac abnormality [14].

II. EMPIRICAL MODE DECOMPOSITION

A new non-linear technique, called Empirical Mode Decomposition method, has recently been developed by N.E.Huang et al for adaptively representing non-stationary signals as sums of zero mean AM-FM components [6]. EMD is an adaptive, high efficient decomposition with which any complicated signal can be decomposed into a finite number of Intrinsic Mode functions (IMFs). The IMFs represent the oscillatory modes embedded in the signal, hence the name Intrinsic Mode Function. The starting point of EMD is to consider oscillations in signals at a very local level. It is applicable to non-linear and non-stationary signal such as ECG signal. An Intrinsic Mode function is a function that satisfies two conditions [15]:

(1) The number of extrema and the number of zero crossings must differ by at most 1.

(2) At any point the mean value of the envelope defined by maxima and the envelope defined by minima must be zero.

Sifting Process

Some of the assumptions made for decomposition are:

(1) The signal has at least two extrema: one maximum and one minimum [16].

(2) The characteristic time scale is defined by the time lapse between the extrema [17].

(3) If the signal has no extrema but has inflection points, then the signal can be differentiated one or more times to find the extrema. The basic principle of this method is to identify the intrinsic oscillatory modes by their characteristic time scales in the data empirically and then decompose the data. A systematic way to extract the IMFS is called the Sifting Process and is described below:

1. Identify all the extrema of x(t).
2. Interpolate between minima, ending up with a signal min (t) and similarly between extrema to give max (t).
3. Compute the average: e(t)= (min (t) + max (t))/2

III. RESEARCH MOTIVATION

An ECG is generated by a nerve impulse stimulus to the heart. The current is diffused around the surface of the body. The current at the body surface will build on the voltage drop, which is a couple of μV to mV with an impulse variation. Usually, this is a very small amplitude of impulse, which requires a couple of thousand times of amplification. Arrhythmias are caused by abnormalities in the conduction system of the heart. So, one of the most effective tools for arrhythmia diagnosis is the detection of ECG signals [18].

IV. SIGNAL CLASSIFICATION

Bio-signals are essentially nonstationary signals; they display a fractal-like self similarity. They may contain indicators of current disease or warnings about impending diseases. The indicators may be present at all times or may occur at random – in the time scale. However, to study and pinpoint anomalies in voluminous data collected over several hours is strenuous and time consuming. Therefore, computer based analytical tools can be very useful in diagnostics for in-depth study and classification of data over day long intervals [19].

The electrocardiogram (ECG) belongs to the category of bio-signals. It displays an apparent periodicity (approximately 60 bpm to 80 bpm in a healthy adult), but is not exactly periodic. The heart rate of a healthy individual is not a constant; even under serene conditions, it changes throughout the day, which can be directly monitored from the ECG. Disease and affliction influence heart rate, and therefore, the pattern and the range of heart rate variability would contain important information about the robustness of health, type of disease, etc. Therefore, classification based on the spread and pattern of this parameter can provide useful insight about the type and intensity of the affliction [20].

Many researchers have suggested various techniques including unconventional approaches, such as engineering diagnostic techniques, for determining patient conditions. A review of the literature in this area revealed that the application of artificial intelligence approaches (1) and neural networks (2,3) for automatic ECG analysis is being studied. In the work by van Gils et al (3), the back propagation (BP) and self-organizing map (SOM) neural network techniques were employed for classification purposes. Multimodal cardiovascular data were used as input to the neural network. Other approaches, like Bayesian and heuristic approaches (4), and Markov models (5) were also studied for classification purposes. In addition, ischemic episode detection using an artificial neural network trained with isolated ST-T segments has been developed by Frenkel and Nadal (6).

Several studies have presented the performance of neural network systems when used for the detection and recognition of abnormal ECGs (2) The use of neural network systems in ECG signal analysis offers several advantages over conventional techniques. The neural network can perform the necessary transformation and clustering operations automatically and simultaneously. The neural network is also able to recognize complex and nonlinear groups in the hyperspace. The latter ability is a distinct advantage over many conventional techniques. However, little work has been devoted to deriving better parameters for reducing the size of the network while maintaining good classification accuracy [21].

V. PROPOSED METHODOLOGY

Wavelet Transform

A fundamental goal of signal processing is to extract specific information from a given signal. For that reason signals are often transformed to different domains, expecting that the desired information can be read out easier [22]. One of these transformations is the so called wavelet transform (WT), which is introduced in the following. The subsequent sections present three major types of the WT, namely the continuous WT (CWT), the discrete WT (DWT) as well as the stationary discrete WT (SDWT). The aim of this section is to provide fundamental understandings of the concepts and to show how these three types differ. Explanations and graphics are mainly based on [12–15]. A Word about Wavelets Wavelets are described by real- or complex-valued wave forms, which have a definite beginning and end as well as a mean value of zero (Figure 2.3). Simply said, the WT of a signal is obtained by comparing the input signal with dilated and shifted versions of the unstretched wavelet, the so called mother wavelet. Due to their limited duration, wavelets are able to deal simultaneously with time and frequency and hence are suited to describe events that start and stop, as it is the case for non-stationary signals [23].

The Continuous Wavelet Transform (CWT) is used to decompose a signal into wavelets. Wavelets are small oscillations that are highly localized in time. While the Fourier Transform decomposes a signal into infinite length sines and cosines, effectively losing all time-localization information, the CWT's basis functions are scaled and shifted versions of the time-localized mother wavelet. The CWT is used to construct a time-frequency representation of a signal that offers very good time and frequency localization.

The CWT is an excellent tool for mapping the changing properties of non-stationary signals. The CWT is also an ideal tool for determining whether or not a signal is stationary in a global sense. When a signal is judged non-stationary, the CWT can be used to identify stationary sections of the data stream [24].

Mathematically, the continuous wavelet transform (CWT) computes the inner products of a continuous signal with a set of continuous wavelets according to the following equation:

$$WT_{u,a} = \langle s, \psi_{u,a} \rangle = \int_{-\infty}^{\infty} s(t)\psi^*_{u,a}(t)dt$$

where

$$\psi_{u,a} = \frac{1}{\sqrt{a}}\psi\left(\frac{t-u}{a}\right)$$

WTu,a is the resulting wavelet coefficients. ψu, a denotes a continuous wavelet, where u is the shift factor and a is the scale factor of the wavelet. ψ*u,a is the complex conjugate of ψu,a. For the continuous-time signal s(t), the scale factor must be a positive real number, whereas the shift factor can be any real number. If the continuous wavelet ψu,a meets the admissibility condition, you can use the computed wavelet coefficients to reconstruct the original signal s(t).

However, you seldom use the above integration to compute the CWT because of the following reasons:

The majority of real-world signals that you encounter are available as discrete-time samples. The analytical form of the signal s(t) usually is not accessible.

The closed-form solution of the integration does not exist except for very special cases.

For these reasons, you usually select a set of discrete values for the scales and shifts of the continuous wavelets and then compute the CWT numerically [25].

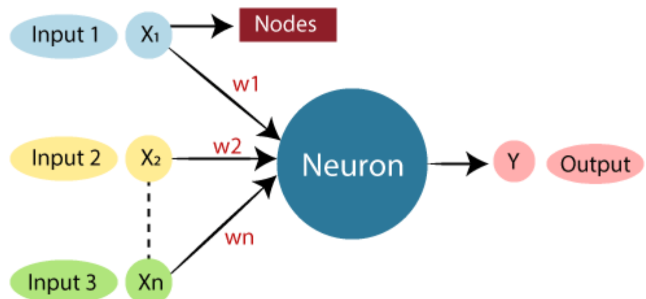
Use the WA Continuous Wavelet Transform VI to compute the CWT by specifying a set of integer values or arbitrary real positive values for the scales and a set of equal-increment values for the shifts.

Signal classification method-

The first neural network was introducing in 1943 by the neurophysiologist Warren McCulloch and logician Walter Pits. Artificial neural networks (ANNs) are biologically inspired networks that are useful in application areas such as pattern recognition, classification etc. . The decision making process of the ANN is holistic, based on the features of input patterns, and is suitable for classification of biomedical data. Typically, multilayer feed forward neural networks can be trained as non-linear classifiers using the generalized back propagation algorithm (BPA) [26] . The BPA is a supervised learning algorithm, in which a mean square error function is defined, and the learning process aims to reduce the overall system error to a minimum. The connection weights are randomly assigned at the beginning and progressively modified to reduce the overall system error. The weight updating starts with the output layer and progresses backward. The weight update is in the direction of 'negative descent', to maximize the speed of error reduction . The step size is chosen heuristically; in the present case, a learning constant q = 0.9 was chosen. For effective training, it is desirable that the training data set be uniformly spread throughout the class domains. The available data can be used iteratively, until the error function is reduced to a minimum. The ANN used for classification is shown in Fig. 1. The input layer consisted of nodes, and, in the subsequent hidden layers, process neurons with the standard sigmoid activation function were used. The output layer had three neurons, to divide the output domain into eight classes (000 to 111).

Artificial Neural Network Tutorial provides basic and advanced concepts of ANNs. Our Artificial Neural Network tutorial is developed for beginners as well as professions.

The term "Artificial neural network" refers to a biologically inspired sub-field of artificial intelligence modeled after the brain. An Artificial neural network is usually a computational network based on biological neural networks that construct the structure of the human brain. Similar to a human brain has neurons interconnected to each other, artificial neural networks also have neurons that are linked to each other in various layers of the networks. These neurons are known as nodes.



An **Artificial Neural Network** in the field of **Artificial intelligence** where it attempts to mimic the network of neurons makes up a human brain so that computers will have an option to understand things and make decisions in a human-like manner. The artificial neural network is designed by programming computers to behave simply like interconnected brain cells.

There are around 1000 billion neurons in the human brain. Each neuron has an association point somewhere in the range of 1,000 and 100,000. In the human brain, data is stored in such a manner as to be distributed, and we can extract more than one piece of this data when necessary from our memory parallelly. We can say that the human brain is made up of incredibly amazing parallel processors.

We can understand the artificial neural network with an example, consider an example of a digital logic gate that takes an input and gives an output. "OR" gate, which takes two inputs. If one or both the inputs are "On," then we get "On" in output. If both the inputs are "Off," then we get "Off" in output. Here the output depends upon input. Our brain does not perform the same task. The outputs to inputs relationship keep changing because of the neurons in our brain, which are "learning."

Characteristics Of ANN

- **Non Linearity:** The mechanism followed in ANN for the generation of the input signal is nonlinear.
- **Supervised Learning:** The input and output are mapped and the ANN is trained with the training dataset.
- **Unsupervised Learning:** The target output is not given, so the ANN will learn on its own by discovering the features in the input patterns.
- **Adaptive Nature:** The connection weights in the nodes of ANN are capable to adjust themselves to give the desired output.
- **Biological Neuron Analogy:** The ANN has a human brain-inspired structure and functionality.
- **Fault Tolerance:** These networks are highly tolerant as the information is distributed in layers and computation occurs in real-time.

The ANN has 3 main layers:

- **Input Layer:** The input patterns are fed to the input layers. There is one input layer.
- **Hidden Layers:** There can be one or more hidden layers. The processing that takes place in the inner layers is called "hidden layers". The hidden layers calculate the output based on the "weights" which is the "sum of weighted synapse connections". The hidden layers refine the input by removing redundant information and send the information to the next hidden layer for further processing.
- **Output Layer:** This hidden layer connects to the "output layer" where the output is shown.

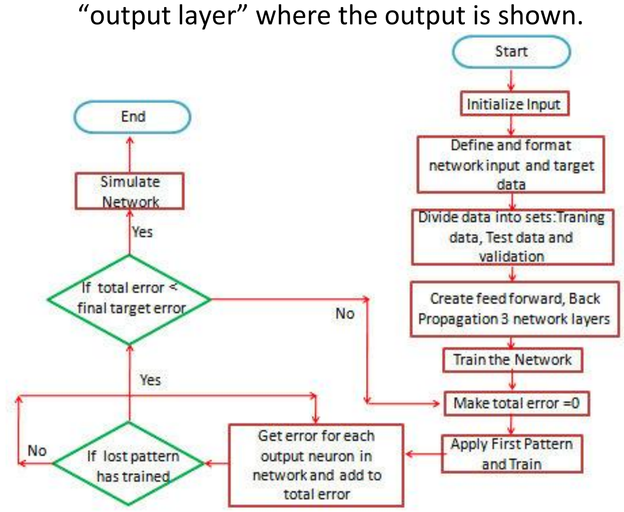


Fig. 5.1 Flow chart of ANN.

Disease Classification using ANN

For the purpose of this study, the cardiac disorders were classified into eight categories, namely (i) left bundle branch block (LBBB) (ii) normal sinus rhythm (NSR) (iii) preventricular contraction (PVC) (iv) atrial fibrillation (AF) (v) ventricular fibrillation(VF) (vi) complete heart block (CHB) (vii) ischaemic/dilated cardiomyopathy (viii) sick sinus syndrome (SSS). The ANN classifier was fed by three parameters derived from the heart rate signals. They were spectral entropy, Poincare plot geometry and largest Lyapunov exponent (LLE).

VI. RESULT AND SIMULATION

The diagram in fig. 5.1explains the overall methodology for detection and classification of arrhythmias in this work. The overall block diagram consists of signal preprocessing, QRS detection, feature extraction and ANN (Artificial Neural Network) signal The first step is the measurement of acquisition period, which requires a wide range of the ECG signal collection including different abnormalities. The data could be collected from real subjects in the future, but it is presently available from the database. The second step is QRS detection which to corresponds to the period of ventricular contraction or depolarisation. The third step is to find the smallest set of features that maximize the classification performance of the next step. ECG feature extraction is mainly used in this step.

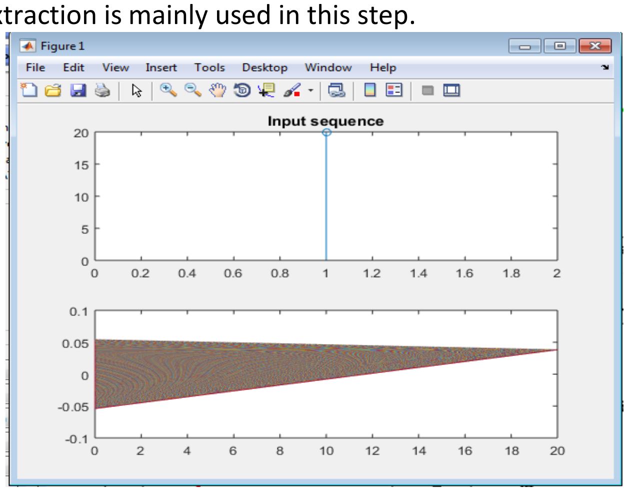


Fig.6.1. Signal DCT input sequence.

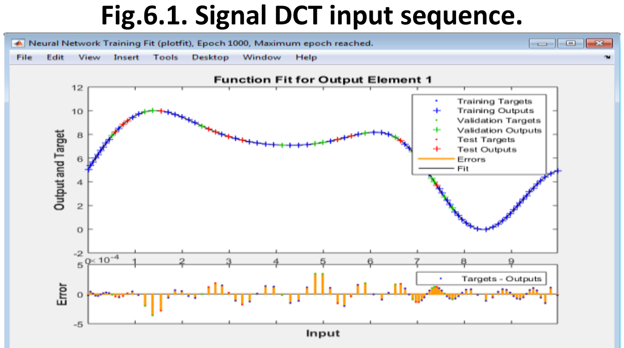


Fig.6.2 Entropy Prediction.

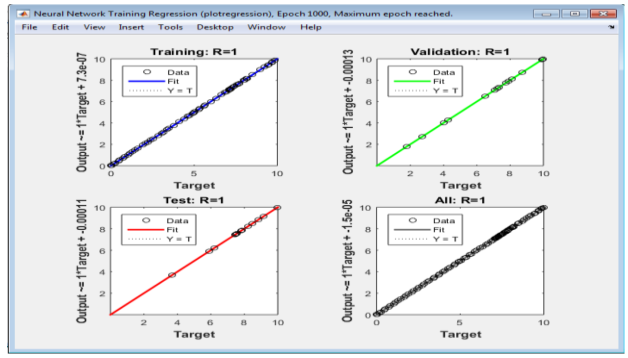


Fig.6.3 Regression Curve for given signal classification.

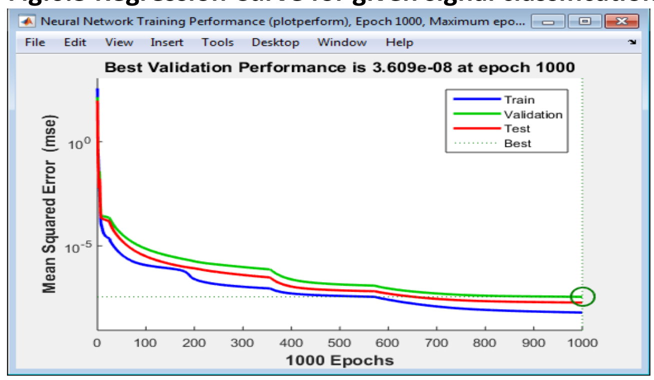


Fig.6.4 Entropy Prediction Error Occurred.

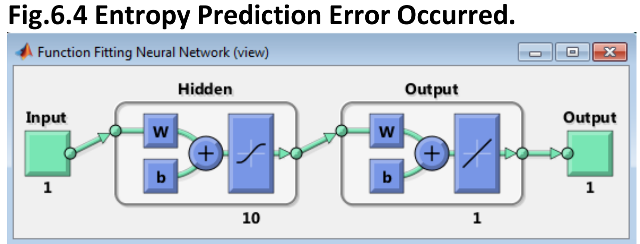


Fig.6.5 Layers.

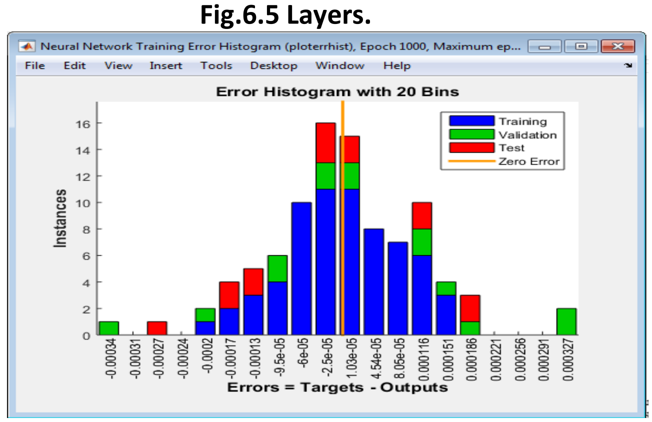


Fig.6.6 MSE variation.

VII. CONCLUSION

In this paper, several neural network-based classifiers were assessed and deployed to automatically classify normal and ischemic ECGs. These classifiers were trained using the polyspectrum patterns and features extracted from the higher-order spectral analysis of normal and ischemic ECG signals. These input patterns are Gaussian noise-free and contain both amplitude and phase information. The highest classification rate was obtained using the polycoherence index slices as input features, with the Extended Delta-Bar-Delta learning rule and two hidden layers. In the presented work, the use of slices from higher-order statistics shows its strength in analysing and classifying nonlinear ECG dynamics.

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