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Development of ECG Arrhythmia Recognition from Category of Statistical Space and Discrete Wavelet Feature Extraction via Classifiers

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Abstract

Introduction: An important medical diagnostic technique to monitor and detect abnormalities in ECG signal is heart arrhythmias recognition. The physicians workload increases because of the high numbers of heart patients. As a result, a robust automated detection system is mandatory. On the other hand, consistent or periodical heart rhythms disorders with important information, which reflect cardiac activity, lead to cardiac arrhythmias, therefore arrhythmias recognition with acceptable accuracy is required.

Aims: In this study, a discrete wavelet-based algorithm for delineation of events in ECG signal is utilized and next a new fusion of MLP-BP and PNN neural networks for heart arrhythmia classification was defined.

Methods: Multi resolution analysis can be extracted from any changes in the morphology of an ECG signal into time and frequency analysis. Firstly, artifact and noise are excluded by a discrete wavelet transform (DWT). Secondly, multi lead ECG signal together with QRS complexes of signal is excluded. Finally, the ECG signal is decomposed, and consequently corresponding DWT scales are segmented. Next statistical features from reconstructed ECG segments are attained. Afterwards, curve length and high order moment order-based feature extraction is computed from ECG excerpted segment. Finally, elements of feature vector for modifiable the parameters of classifiers are utilized. Next, Multi-Layer Perceptron-Back Propagation (MLP-BP) neural networks, Probabilistic Neural Network (PNN) and support vector machine (SVM) were designed and adjusted and their results were compared.

Results: The proposed algorithm was verified to all 48 records of the MIT-BIH arrhythmia database. Also, the proposed topology of classifiers and their associated parameters is optimized by searching of the best value of parameters. The average value of accuracy of each classifier over all records of MIT-BIH for arrhythmias recognition is Acc=98.19, Acc=99.51 and Acc=97.53 for SVM, MLP and PNN classifiers correspondingly and obtained results were compared with similar peer-reviewed studies in this subject

Keywords: Arrhythmia Classification; ECG Feature Extraction; Statistical Methods; Wavelet Method

1. Introduction

Electrocardiogram (ECG) with associated time scales of P-QRS-T cycles described the status of the heart morphology and hidden information on condition of the heart. In general, activating of mechanical contraction of heart is related to electrical triggering where located in the heart right atrium. This electrical triggering process is an intracellular calcium dependent which is known as excitation contraction coupling (ECC) occurs in cellular scale [1, 2].

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In other hand in heart scales detail, there is another cellular process which is known as mechanoelectrical feedback (MEF). Generally, in numerous abnormal conditions, ECC and MEF are changed from well function behaviour state and next they lead to electromechanical dysynchrony or fatal arrhythmias [3, 4]. Communication between electrical activity in sinus rhythm and usual activity of mechanical contraction or myocardial process is examined in literatures by different researchers [5]. Also formation and finding of arrhythmia which occurred by malfunction in atrial and ventricular electrophysiology is an active research field [6-7]. Some reference like [8] suggest reliable estimation of the heart beat in contamination status for clear signal for better locating multi modal data coupling.

Increasing of exactness and effectiveness of computational signal processing methods for finding and classifications of arrhythmias is an ongoing research issue. For improving finding of abnormalities in ECG signal different processing steps should be used. In these approaches after eliminating of artificial noise and trends related feature vectors are takeout and transformed these features into another spatial determination and then feature space enhancement and recognition algorithm is calculated [9]. For designing strong and efficient recognition system for arrhythmias, a precise and enhanced feature space and segmentation is desirable and this stable noise extraction and modification is analysed and smoothed [10, 11].

Different feature space extraction and classification methods are suggested in literatures for detecting different arrhythmias. Some references like [12] applies mixing of PCA and ICA with statistical methods or correlation analysis.

These approaches are used wavelet analysis for detection of some arrhythmias and effectiveness of method for detecting of another arrhythmias is decreased. Reference [13] is offered a hybrid intelligent algorithm which was tested on the MIT-BIH arrhythmias database. This algorithm is applied Mamdani type fuzzy inference system that shared with two altered multi-layer perceptron neural network. Also for refining accuracy some researchers are used multi paradigm method that is related on integration of different computational methods.

Reference of [14,15] is applied adaptive feature organization with modified support machines (SVMs) which is classified ECG beats to normal and PVC beats. Also k-means clustering method for educating the recognition ability for high similar cases are suggested.

Other references like [16, 17] is utilized adaptive wavelet method with combing with machine learning approaches. Generally using this multi paradigm of methods is improved the feature space and cause to the better classification.

In this paper a wavelet approach is applied for segmentation of ECG features. Then, feature vectors for neural networks are utilized and testing and training data for MLP-BP neural networks and PNN is extracted. The structure of this paper is as follows.

First overall structure of algorithm is described and it divided to four. Also rhythm types with corresponded numeric codes are stated. Therefore, with predefined setting for networks the concluding classification accuracies for networks are plotted. Finally, in discussion section the performance of proposed approach against of different references are compared.

2. Material and Method

The steps of the algorithm can be separated into the following steps: pre-processing of the ECG signal, construction of feature space and feature classification for defining of the ECG arrhythmias.

The overall steps and structure of algorithm is plotted in Fig.1. Similarly different rhythm types in MIT-BIH dataset with equivalent numerical code is plotted in table.1.

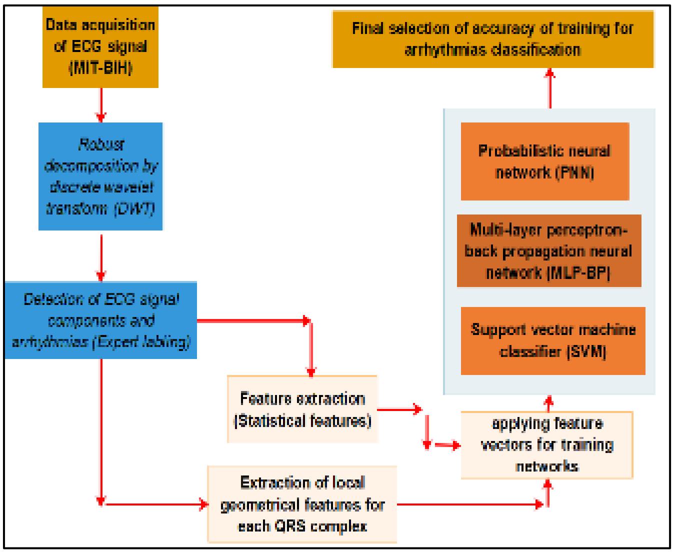

Figure 1 Block diagram of the proposed ECG arrhythmias

Table 1 Rhythm types with corresponded numerical code recognition algorithm

Numeric code	Rhythm	Numeric code	Rhythm
70	Fusion of Ventricular and Normal Beat	102	Fusion of Paced and Normal Beat
74	Nodal(junctional)Permature Beat	106	Nodal(junctional)Escape Beat
76	Left Bundle Branch Block Beat	120	Non-Conducted P-Wave(Blocked APC)
78	Normal Beat	124	Isolated QRS-Like Artifact
81	Unclassifiable Beat	126	Change in Signal Quality
82	Right Bundle Branch Block Beat	33	Ventricular Flutter Wave
83	Supraventricular Premature Ectopic Beat	34	Comment Annotation
86	Premature Ventricular Contraction	43	Rhythm Change
91	Start of Ventricular Flutter/Fibrillation	47	Paced Beat
93	End of Ventricular Flutter/Fibrillation	65	Atrial Premature Beat
97	Aberrated Atrial Premature Beat	69	Ventricular Escape Beat
101	Atrial Escape Beat		

2.1. Discrete wavelet transform (DWT)

For signal pre-processing step, discrete wavelet transform is employed and in hope to extract the ECG signal into different frequency bands, sequential high and low pass filtering is applied and consequently, the corresponding DWT at appropriate scales is recollected.

The Specific structure of wavelet bases may be appreciated by considering generation of an orthonormal wavelet basis for function $g \in l^2(R)$ (the space of square integral real functions). The approach of Daubechies is the most often adopted in applications of wavelets in statistics, mutually orthonormal, functions or parent wavelets: the scaling function, φ (sometimes referred to as the father wavelet), and the mother wavelet, ψ .

$$\varphi_{j0k}(t) = 2^{j_0/2}\varphi(2^{j_0}t - k)$$
$$\varphi_{jk}(t) = 2^{j/2}\varphi(2^{j}t - k) \qquad (1)$$
$$j = j_0, j_0 + 1, \ldots, k \in Z$$

For some fixed $j_0 \in Z$, where Z is set of integers. The $2^{j/2}$ term maintains unity norm of the basis function at various scales and j and k are the scaling and translation parameters, respectively. A unit increase in j in (1) has no effect on scaling function (φ_{j0k} has a fixed width), but packs oscillations of ψ_{jk} into half the width (doubles its scale or resolution). A unit increase in k in (1) shifts the location of both φ_{j0k} and ψ_{jk}, the former by a fixed amount (2^{-j0}) and the latter by an amount proportional to its width (2^{-j}). Given the wavelet basis, a function $g \in l^2(R)$ is then represented in a corresponding wavelet series as

$$g(t) = \sum_{k \in Z} c_{j0k}\varphi_{j0k}(t) + \sum_{j=j_0}^{\infty}\sum_{k \in Z} w_{jk}\psi_{jk}(t) \quad (2)$$

with $c_{j0k} = \langle g, \phi_{j0k} \rangle$ and $w_{jk} = \langle g, \psi_{jk} \rangle$ (where $\langle .,. \rangle$ isthe standard l² inner product of two functions: $\langle g_1, g_2 \rangle = \int_R g_1(t) g_2(t) dt$

The wavelet expansion (2) represents the function g as a series of successive approximations.Given a vector of function value $g = [g(t_1), g(t_2), \ldots, g(t_n)]^T$ of equally spaced points t_i, the DWT of g is given by:

$$d = Wg \qquad (3)$$

where d is an $n \times 1$ vector comprising both discrete scaling coefficients $u_{j0,k}$ and discrete wavelet coefficients $d_{j,k}$ and W is an orthogonal n×n matrix associated with orthonormal wavelet basis chosen. Both $u_{j0,k}$ and $d_{j,k}$ are related to their continuous counterparts $c_{j0,k}$ and $w_{j,k}$ via the relation ships $c_{j0,k} \approx u_{j0,k} / \sqrt{n}$ and $w_{j,k} \approx d_{j,k} / \sqrt{n}$ .The factor $\sqrt{n}$ arises because of the difference between continuous and discrete orthonormality conditions [1-2].Fig. 2 illustrates sturcture of DWT in high and low frequency and the red rectangle related to the approximation part [22].

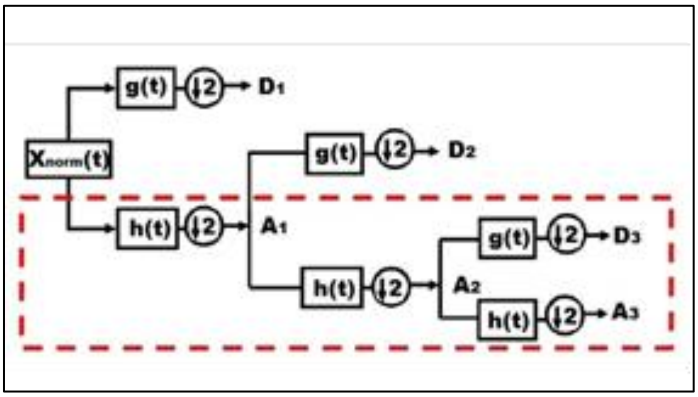

Figure 2 Structure of DWT in low and high frequency

2.2. Statistical features

The next step after preprocessing the ECG signal is finding of QRS complex key points and these points are spotted and delineated in all 48 records of the MIT-BIH arrhythmia database and this is completed before of feature vector extraction that is desired for neural networks.

The statistical features which are used in this paper are as follows.

- Mean: it is the average of a set of numbers and realized as the ratio between sum of these numbers and the number of elements in the set.
- Standard deviation: the amount of variation of a given data is computed by using this measure.
- Skewness: it is the sum of the numbers in the dataset distribution divided by the number of values in the distribution.
- Variance: let us define a set of random number X and its mean X^{-}. Variance defines how far X are spread out from X^{-}.

2.3. Geometrical features for each QRS complex

The geometrical indexing of each QRS complex is organized for feature extraction. Next, its basic associated features such as second order statistical variance or curve length are extracted [18, 19].

From these features measuring, high frequency components of ECG, presence of abnormalities like higher amplitude, disruption or ascending and descending in position of key points in complex is measureable and its features index is suitable for constructing of feature space [23]. After research and extraction of each feature in all the MIT-BIH, the testing and target feature space and its associated for normal and abnormal is provided for classification step.

2.4. Geometrical features for each QRS complex

In this stage three different neural networks model is used. All network models is trained for recognition of arrhythmias.

Table 2 The exhausted results of MIT/BIH arrhythmia database records

Record	Rhythm codes	SVM	MLP_BP	PNN	Record	Rhythm codes	SVM	MLP_BP	PNN
100	[43, 78, 65,86]	99	97.35	99.78	203	[43, 126, 78, 86,97, 124, 81, 70]	95.94	97.96	95.02
101	[43, 78, 126, 124, 81,65]	99.73	99.83	99.73	205	[43, 78, 86,65, 70,126, 124]	98.70	99.50	98.02
102	[43, 47, 102,78, 86]	98.21	98.55	93.82	207	[43, 82, 86,76, 91, 33,93, 126, 124, 69,65]	95.71	94.40	96.82
103	[43, 78, 126, 65]	99.74	99.44	99.64	208	[43, 70,86, 78, 126, 124, 83,81]	97.70	99.44	98.31
104	[43, 47, 102,126, 81, 78, 86]	91.69	96.40	89.67	209	[43, 78, 65,124, 126, 86]	97.37	99.02	94.00
105	[43, 78, 86,126, 124, 81]	97.11	98.41	95.56	210	[43, 78, 86,70, 126, 97,124, 69]	96.81	92.20	96.63
106	[126, 43, 78, 86]	96.90	98.44	94.62	212	[43, 82, 78,126, 124]	98.91	97.37	98.28
107	[43, 47, 86,126]	100	100	99.30	213	[43, 78, 70,65, 86,97]	92.39	99.03	89.88
108	[43,78,86,120,126,65,124,70,106]	98.44	98.78	97.81	214	[43, 76, 86,126, 124, 81, 34, 70]	98.01	96.34	98.80
109	[43, 76, 70,86, 126]	100	99.70	98.61	215	[43, 78, 86,126, 65, 34, 70]	98.46	99.40	98.67
111	[43, 76, 126, 86]	99	99.65	99.65	217	[43, 47, 102,86, 78, 126, 124]	86.56	96.89	83.15
112	[43, 78, 126, 65]	100	99.60	99.70	219	[43, 78, 86,70, 34,65, 120]	98.45	98.78	97.06

113	[43, 78, 97]	100	100	99.87	220	[43, 78, 65,126]	99.35	97.44	98.18
114	[43, 78, 86,74, 70,124, 126, 65]	99.66	99.86	98.93	221	[43, 78, 86,126]	98.56	99.28	98.47
115	[43, 78, 126, 124]	100	100	99	222	[43, 78, 126, 65,106, 74]	83.93	88.96	84.48
116	[43, 78, 86,65, 126]	99.68	99.87	98.85	223	[43, 78, 86,65, 101, 70,126, 97]	93.26	96.20	99.01
118	[43, 82, 86,65, 120, 126]	98.65	98.64	97.79	228	[43, 78, 124, 86,126, 65, 34]	95.68	96.67	95.07
119	[43, 78, 86,126]	98.80	99.96	96.40	230	[43, 78, 126, 124, 86]	100	96.90	99.29
121	[43, 78, 126, 65,86]	100	100	98.60	231	[43, 82, 34,78, 120, 65,86]	99.38	99.77	98.00
124	[43, 82, 74,86, 70,65, 126, 106]	95.99	97.14	96.06	232	[43, 82, 65,126, 106]	97.62	97.87	96.61
200	[43, 86, 78,65, 126, 70]	94.10	98.13	94.51	233	[43, 86, 78,65, 70,124]	98.56	98.62	98.61
201	[43,78,97,106,86,120,65,74,126,70]	94.70	96.79	92.33	234	[43, 78, 126, 74,86]	99.56	99.56	96.66
202	[43, 78, 86,65, 124, 97, 70]	98.92	99.24	97.23	Average		98.19	99.51	97.53

SVM is used in many applications like pattern recognition and data mining. Generally let x={$(x_i|y_i)$} for i=1…n be an n training space where x_i is a sample of input feature space and y_i is a class label of output space. By applying a SVM classifier an ideal separating hyper plane (OSH) is attained with consideration of minimal classification error and for high dimensional feature space the precise of algorithm is enhanced. The performance of SVM is compared with other neural networks such as probabilistic neural networks and MLP in all MIT-BIH arrhythmia databases.

A probabilistic neural network (PNN) is a derivative from statistical algorithm named kernel fisher discriminant analysis and Bayesian network. The modifications between PNN and MLP in characteristic of the topology of network is associated to different layers that is called input and pattern layer and summation and decision layer.

Neurons in input layer of PNN neural classifier is kept the predictor variable value and this value is associated to each neuron beside the target value and training data set, which is assigned to each neuron in hidden layer. This topology is more suitable for classifying high dimensional feature space and its performance is compared to the MLP neural network. The parameters of classifiers are gained with trial and error to optimize the classification fitness function.

Topology of 2 layer MLP is established with activation function of tangent sigmoid and logarithmic sigmoid for hidden and out layer and NHLN is set 20 with maximum epoch number (men) 550. For attaining satisfactory accuracy Key parameters for topology of SVM is tuned 23 and 0.00011 for c and γ respectively.

3. Results

In our algorithm in section of arrhythmias recognition SVM, MLP and PNN classifiers are applied to all 45 MIT-BIH records. Correctness of training with predefined topologies for classifiers are computed for each records of all MIT-BIH datasets. Each records and related labeled arrhythmias with attained results for accuracies of classifiers are shown in table 2. According to table 2 the average accuracy of SVM, MLP and PNN is reached to 98.19, 99.51 and 97. 53, respectively.

4. Discussion

In this paper, discrete wavelet transform, for signal pre-processing, was used which decomposed ECG signal, after elimination of needless bounds. Next, the new denoised ECG time series was restored. Thereafter, the ECG major events such Q, R and S-waves were delineated. Next, the second order statistical variance or curve length is extracted as feature for constructing of feature space. Also, statistical features are extracted for applying to the different classifiers. Then, the above-mentioned networks were trained and verified by all the 45 MIT-BIH recordings.

For assessment of the proposed approach, 60% of all the data in MIT-BIH dataset are elected for training. References that are applied to the same database and through of classifiers and rest of data is utilized for evaluation.

The results obtained are compared with other studies. The comparison is shown in table 3. Besides, for making logical decision for comparison of performance of each classifier, accuracy percentage for recognition of arrhythmias for each record of MIT-BIH is plotted in Fig. 3. According to the figure the MLP classifier has better uniform training and discrimination power of SVM classifier is superior to PNN accuracy.

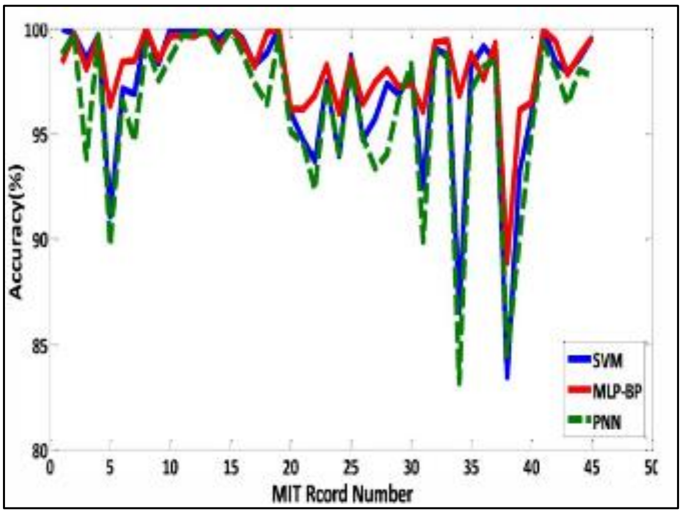

Figure 3 Comparison of the obtained arrhythmias recognition accuracy of the three utilized classifiers

Table 3 Comparison of the results of the MIT-BIH dataset

Author	Method	Dataset	Accuracy
Simon & eswaran(1997)	Decision based neural network	MIT-BIH	96.03
Valtino X. et al (1999)	Multi rate signal processing for feature extraction, filter banks	MIT-BIH	97.56
Langerholm et al. (2000)	Hermite functions and self-organizing maps	MIT-BIH	98.49
Guleri and ubeyli (2007)	FCM-PCA-MLP neural network	MIT-BIH	99
Jalal. A et al. (2009)	QRS complex key points, Genetic-SVM with linear and polynomials	MIT-BIH	93.46
This study	Geometrical feature extraction and SVM,MLP-BP and PNN classifier	MIT-BIH	SVM=98.19 MLP-BP=99.51 PNN=97.53

5. Conclusion

In this paper, an approach was presented for ECG arrhythmia recognition utilizing three classifiers which are SVM, MLP and PNN and engaging all the 45 MIT-BIH recordings. Also, discrete wavelet transform is used for preprocessing and development of ECG better perfect way to delineate and differentiate the restored and needless data like a huge time series harmonic data. For assessment of the proposed approach, 60% of all the data in MIT-BIH dataset are elected for training and a mix of neural networks method are trained and classified with each other in which other references has better output expert decision. In the next studies, the overlap of time series of ECG and better fusion training can be inspired from this paper.

Compliance with ethical standards

Disclosure of conflict of interest

We do not have any conflict of interest to be disclosed.

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