Cardiac Arrhythmia Recognition with Robust Discrete Wavelet-Based and Geometrical Feature Extraction via Classifiers of SVM and MLP-BP and PNN Neural Networks

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Abstract

Introduction: *An ECG signal has important information that can help for reflecting cardiac activity of a patient and medical diagnosis. Consistent or periodical heart rhythm disorders can result cardiac arrhythmias so classification algorithm for recognizing arrhythmias with satisfactory accuracy is necessary.*

Aims: *In this study, a robust wavelet based algorithm for detection and delineation of events in ECG signal is applied and then a new synthesis of MLP-BP and PNN neural networks for heart arrhythmia classification was described.*

Methods*: As a matter of fact any changes in the morphology of an ECG due to the arrhythmia are observed in time and frequency analysis so multi resolution analysis is applied for feature detection. First, noise and artifact is rejected by a discrete wavelet transform (DWT) and multi lead ECG is obtained. Then QRS complexes of signal is extracted and the signal is decomposed so corresponding DWT scales are segmented. Next curve length and high order moment order based feature extraction are calculated for each excerpted segment and elements of feature vector for regulating the parameters of classifiers are obtained. After generation of feature source and segmentation, Multi-Layer Perceptron-Back Propagation (MLP-BP) neural networks, Probabilistic Neural Network (PNN) and support vector machine (SVM) were designed and tuned and their results were compared.*

Results*: The proposed algorithm was tested to all 48 record of the MIT-BIH arrhythmia database and also the proposed topology of classifiers and its related parameters is optimized by searching of best value of parameters. The average value of accuracy of each classifier over all records of MIT-BIH for arrhythmias recognition is Acc=97.42, Acc=98.24 and Acc=97.42 for SVM, MLP and PNN classifiers respectively and also obtained results were compared with similar peer-reviewed studies in this subject.*

1. Introduction

Electrocardiogram (ECG) and related morphology and time scales of P-QRS-T cycles reflects the condition of the human heart and reveals hidden information on condition and behavior of heart. In totally, triggering of mechanical contraction of heart is depend to electrical activation where located in the heart right atrium. This electrical activation process is a intracellular calcium dependent which is known as excitation contraction coupling (ECC) that is happen in cellular scale [1,2]. In other hand in heart scales detail, there is another process which is known as mechanoelectric feedback (MEF). Generally in various abnormal conditions, ECC and MEF are altered from well function behavior state and then they lead to electromechanical dyssynchrony or dangerous arrhythmias [3, 4]. Interaction between electrical activity in sinus rhythm and normal activity of mechanical contraction or myocardial process is investigated in literatures by different researchers [5]. Also creation and detection of arrhythmia which is existed by malfunction in atrial and ventricular electrophysiology is an active research [6-7]. Increasing of accuracy and efficiency of computational signal processing methods for detection and classifications of arrhythmias is an ongoing research issue [8]. For improving detection of abnormalities in ECG signal different processing steps should be applied. In these approaches after removing of artificial noise and trends associated feature vectors are extracted and transformed these features into another spatial resolution and then feature space enhancement and recognition algorithm is designed [9]. For designing robust and efficient recognition system for arrhythmias, an exact and improved feature space and segmentation is needed [10]. Different feature extraction and classification approaches are proposed in literatures for detecting different arrhythmias. Some references like [11, 12] uses integration of PCA and ICA with statistical methods or correlation analysis. These approaches is applied for detection of some arrhythmias and efficiency of approach for detecting of another arrhythmias is reduced. Reference [13] is proposed a hybrid intelligent algorithm that was tested on the MIT-BIH arrhythmias database. This algorithm is used mamdani type fuzzy inference system that combined with two different multi-layer perceptron neural network. Also for improving accuracy some researchers is used multi paradigm approach that is based on integration of different computational approaches. Reference of [14,15] is used adaptive feature classification with modified support machines (SVMs) and least square support machines that is classified ECG beats to normal and PVC beats. Also k-means clustering approach for improving the recognition ability for high similar cases are proposed. Other references like [16, 17] is used adaptive wavelet approach with combing with machine learning approaches. Generally using this multi paradigm of approaches is enhanced the feature space and leads to the better classification.

In this paper a robust wavelet approach is used for delineation and segmentation of ECG features. Then, feature vectors for classifiers are gained 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 explained and it divided to three sections of pre-processing, features extraction for networks and arrhythmias recognition by three different classifiers. Also rhythm types with corresponded numeric codes is expressed. Then with predefined setting for networks the final classification accuracies for networks are plotted and compared. Finally in discussion section the performance of proposed approach against of different references are compared.

2. Material and Method

The development of the algorithm for the arrhythmias recognition can be divided into the following steps: ECG Signal pre-processing, construction of feature space for networks and feature classification for recognition of arrhythmias. The overall steps and structure of algorithm is plotted in fig.1. Also different rhythm types in MIT-BIH dataset with corresponding numerical code is plotted in table.1. For signal pre-processing step, discrete wavelet transform is applied and in order to decompose the ECG signal into different frequency bands, sequential high and low pass filtering is implemented and then the corresponding DWT at appropriate scales is retained. The next step after preprocessing of the ECG signal is detection of QRS complex key points and these points is detected and delineated in all 48 record of the MIT-BIH arrhythmia database and this is done before of feature vector extraction that is needed for neural networks. Afterwards, the geometrical indexing of each QRS complex is structured for feature extraction and then its basic related features such as second order statistical variance or curve length is extracted [18,19].

From this features measuring, high frequency components of ECG, existence of abnormalities like higher amplitude, disruption or ascending and descending in location of key points in complex is detectable and its features index is appropriate for constructing of feature space. After preparation and extraction of each features in all the MIT-BIH, the testing and target feature space and its related for normal and abnormal is provided for classification step. In this step three different neural networks model is applied and all network models is trained for recognition of arrhythmias. SVM have many applications in pattern recognition and data mining.

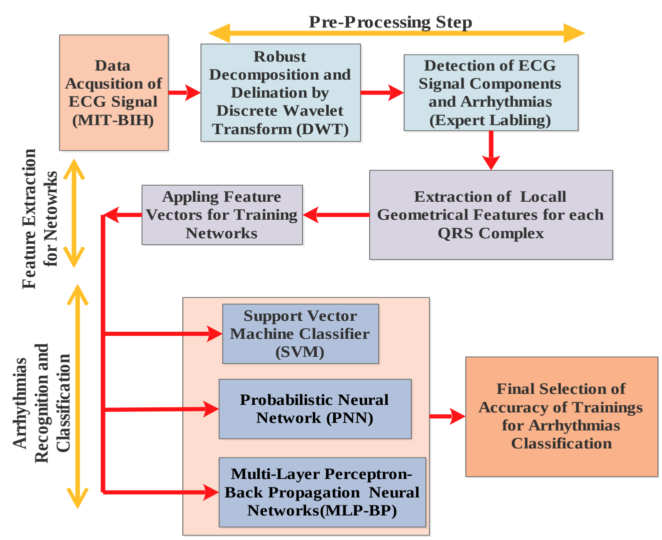


Fig. 1block diagram of the proposed ECG arrhythmias recognition algorithm

Table 1. Rhythm types with corresponded numerical code

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		

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]	100	98.35	98.78	**203**	[43, 126, 78, 86,97, 124, 81, 70]	93.94	95.96	94.02
101	[43, 78, 126, 124, 81,65]	99.73	99.73	99.73	**205**	[43, 78, 86,65, 70,126, 124]	98.70	98.50	98.02
102	[43, 47, 102,78, 86]	98.51	98.05	93.82	**207**	[43, 82, 86,76, 91, 33,93, 126, 124, 69,65]	94.71	96.40	94.82
103	[43, 78, 126, 65]	99.64	99.64	99.64	**208**	[43, 70,86, 78, 126, 124, 83,81]	95.70	97.44	93.31
104	[43, 47, 102,126, 81, 78, 86]	91.09	96.30	89.67	**209**	[43, 78, 65,124, 126, 86]	97.37	98.02	94.00
105	[43, 78, 86,126, 124, 81]	97.11	98.41	96.56	**210**	[43, 78, 86,70, 126, 97,124, 69]	96.81	97.20	96.63
106	[126, 43, 78, 86]	96.90	98.44	94.62	**212**	[43, 82, 78,126, 124]	97.91	97.37	98.28
107	[43, 47, 86,126]	100	100	99.30	**213**	[43, 78, 70,65, 86,97]	92.39	96.03	89.88
108	[43,78,86,120,126,65,124,70,106]	98.34	98.48	97.51	**214**	[43, 76, 86,126, 124, 81, 34, 70]	99.01	99.34	98.80
109	[43, 76, 70,86, 126]	100	99.60	98.61	**215**	[43, 78, 86,126, 65, 34, 70]	98.74	99.40	98.67
111	[43, 76, 126, 86]	100	99.65	99.65	**217**	[43, 47, 102,86, 78, 126, 124]	86.56	96.80	83.15
112	[43, 78, 126, 65]	100	99.60	99.70	**219**	[43, 78, 86,70, 34,65, 120]	98.15	98.80	97.06
113	[43, 78, 97]	100	100	99.87	**220**	[43, 78, 65,126]	99.15	97.57	98.18
114	[43, 78, 86,74, 70,124, 126, 65]	99.46	99.06	98.93	**221**	[43, 78, 86,126]	98.47	99.28	98.47
115	[43, 78, 126, 124]	100	100	100	**222**	[43, 78, 126, 65,106, 74]	83.43	88.86	84.48
116	[43, 78, 86,65, 126]	99.48	99.37	98.75	**223**	[43, 78, 86,65, 101, 70,126, 97]	93.16	96.10	99.01
118	[43, 82, 86,65, 120, 126]	98.25	98.14	97.39	**228**	[43, 78, 124, 86,126, 65, 34]	95.88	96.47	95.07
119	[43, 78, 86,126]	98.80	99.76	96.40	**230**	[43, 78, 126, 124, 86]	100	99.90	99.29
121	[43, 78, 126, 65,86]	100	100	99.60	**231**	[43, 82, 34,78, 120, 65,86]	98.38	99.37	98.00
124	[43, 82, 74,86, 70,65, 126, 106]	95.99	96.14	95.06	**232**	[43, 82, 65,126, 106]	97.92	97.80	96.41
200	[43, 86, 78,65, 126, 70]	94.10	96.13	94.51	**233**	[43, 86, 78,65, 70,124]	98.57	98.72	98.01
201	[43,78,97,106,86,120,65,74,126,70]	93.70	96.79	92.33	**234**	[43, 78, 126, 74,86]	99.54	99.54	96.46
202	[43, 78, 86,65, 124, 97, 70]	97.42	98.24	97.42	**Average**		**97.19**	**98.11**	**96.23**

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 using a SVM classifier an optimal separating hyper plane (OSH) is obtained with consideration of minimal classification error and for high dimensional feature space the performance of this classifier is enhanced. The performance of SVM is compared with other neural networks such as probabilistic neural network and MLP in all MIT-BIH arrhythmia database. A probabilistic neural network (PNN) is a derived from statistical algorithm called kernel fisher discriminant analysis and Bayesian network.

And the differences between PNN and MLP in aspect of the topology of network is related to different layers that is called input and pattern layer and summation and decision layer. Neurons in input layer of PNN is saved the predictor variable value and this value is related to each neuron beside the target value and training data set is assigned to each neuron in hidden layer. This topology is more appropriate for classifying of high dimensional feature space and also its performance is compared to the MLP neural network. The parameters of classifiers are obtained with trial and error in order to optimizing the classification fitness function.

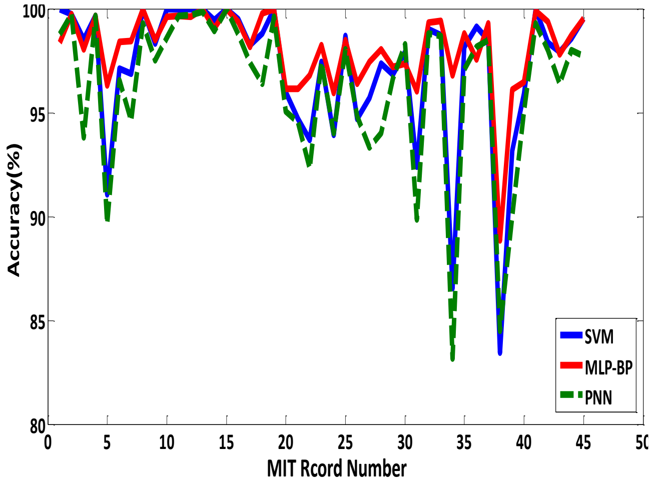
Topology of 2 layer MLP is developed with activation function of tangent sigmoid and logarithmic sigmoid for hidden and out layer and NHLN is set 20 with maximum epoch number (men) 500. For attaining satisfactory accuracy Key parameters for topology of SVM is tuned 20 and 0.0001 for c and γ respectively.

3. Results

In our algorithm in section of arrhythmias recognition SVM, MLP and PNN classifiers are implemented to all 45 MIT-BIH records. Accuracy of training with predefined topologies for classifiers are calculated for each records of all MIT-BIH datasets. Each records and related labeled arrhythmias with obtained results for accuracies of classifiers are shown in table2. According to table 2 the average accuracy of SVM, MLP and PNN is attained to 97.42, 98.24 and 96. 23, respectively.

4. Discussion and Conclusion

In this article, an approach was presented for ECG arrhythmia recognition using three classifiers which are SVM, MLP and PNN and employing all the 45 MIT-BIH recordings. For signal pre-processing, discrete wavelet transform was applied which decomposed ECG signal, after elimination of unnecessary bounds, the new denoised ECG time series was reconstructed. Afterwards, the ECG major events such Q, R and S-waves were delineated by which the second order statistical variance or curve length is extracted as feature for constructing of feature space. Then, the aforementioned networks were trained and tested by all the 45 MIT-BIH recordings. For evaluation of the proposed approach, 60% of all the data in MIT-BIH dataset are chosen for training of all MIT-BIH records is chosen for comparing of obtained results. References that is used the same database and through of classifiers and rest of data is used for evaluation.



`Fig. 2 Comparison of the obtained arrhythmias recognition accuracy of the three utilized classifiers

The obtained results are compared with other studies. The comparison is shown in table 3. Furthermore, 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.2. According to the figure the MLP classifier has better uniformly training and also discrimination power of SVM classifier is superior to PNN accuracy.

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=97.42 MLP-BP=98.24 PNN=96.23**

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