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ECG Arrhythmia Classification Algorithms

Ashish Nainwal, Yatindra Kumar, Bhola Jha

***Abstract:** In last two decades lot of work is introduced on ECG classification. Authors took different database, features of ECG, class of data, learning and training algorithms to classify ECG signal. Normally class of data mentioned in source of database. Mainly three classification techniques which are discussed in this paper, these are support vectored machine (SVM), artificial neural network (ANN) and linear discriminate (LD). In this paper all the ECG classification based papers are analyzed and try to find out loophole and future challenges. This paper also discusses the different database of ECG signal.*

***Keywords:** ECG, ANN, SVM, LD, MIT-BIH.*

I. INTRODUCTION

ECG is the signal which is commonly used to diagnosis the cardiovascular diseases. These cardiovascular diseases can be classified in two classes. Morphological arrhythmia which is occurred due to the irregular single heart beat and rhythmic arrhythmia due to multiple irregular heartbeats. Sometimes only one heart beat is sufficient to detect the arrhythmia and sometimes it required large length of signal to detect arrhythmia. This duration may be one minute, one hours or one day. Once ECG signal is fetched from human body the signal processing can be done on this signal.

In signal processing the unwanted noises will be removed from raw ECG signal. This paper shows the survey of existing papers about on ECG features extraction and classification. Also discuss different types of arrhythmia which are detected in irregular ECG signal [1],[2],[3],[4],[5] .The block diagram of ECG classification is shown in Fig.1. The process of ECG signal classification divided into following steps.

1. Pre-processing of the ECG signal.
2. Extraction of ECG features.
3. Learning and classification.

For ECG classification different types of algorithms has been generated. Artificial neural network (ANN), support vector machine (SVM), linear distribution (LD) are the major algorithms. Authors modify theses algorithm to improve the classification of ECG signal.

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* Correspondence Author
Ashish Nainwal*, ECE department, Faculty of Engineering & Technology, Gurukul Kangri Vishwavidyalaya, Haridwar, India. Email: ashishnainwal86@gmail.com
Yatindra Kumar, Electrical Department, G B Pant Institute of Technology, Pauri Garhwal, India. Email: kyatindra@gmail.com
Bhola Jha, Electrical Department, G B Pant Institute of Technology, Pauri Garhwal, India. Email: bholajhaeee@gmail.com

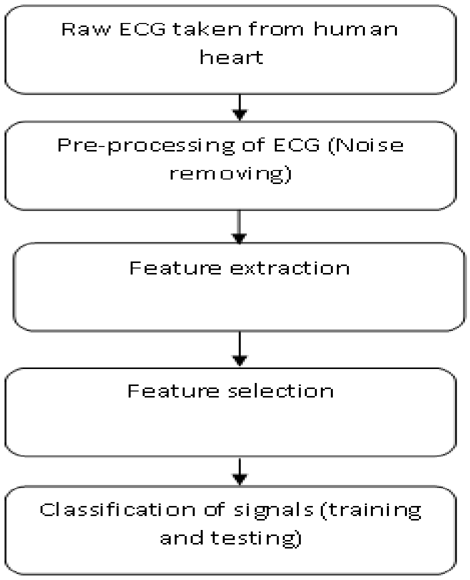

Fig 1. Process of ECG classification

II. THE ECG SIGNAL

ECG signal is the electrical activity of heart muscles. The pacemaker triggers the heart activity. The whole electric activity of heart is due to the action potential of cells. Such cells are located in the artia and ventricles. An action potential is transferred to one cell to another cell which produces the electric voltage. This activity of voltage transfer is shown on ECG signal [6] Fig.2.

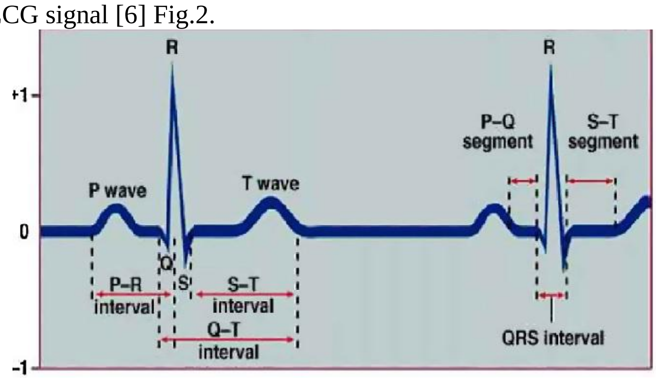

Fig. 2 ECG Signal

ECG signal is the depolarization and repolarisation of human heart cell. Atrial contraction (depolarization) define by the P wave atria depolarization is slow and small size so that P wave is slow and low amplitude wave. There is some propagation delay at the atriventricular (AV) node which results PQ segment of wave. Ventricular depolarization shows on QRS complex. ST segment is the plateau of action potential of ventricular myocyte.

T wave is the ventricular repolarisation [7]. 10 electrode systems are used to get the ECG signal form human heart Fig.3 [8]. Theses 10 electrodes are connected on different part of human body. One is connected with left arm (LA), one is on right arm (RA), one is on left leg (LL), one is on right leg (RL) and six electrodes are connected on the chest as shown in Fig. Right leg (RL) electrode is used as the reference for the other electrode. Now a day to measure the ECG signal different types of method and devices has been invented. Only single finger can provide ECG signal [9],[10],[11].

III. PREPROCESSING

When ECG signal is measured from the human heart it is affected by different types of noises. Without removing these noises there is no meaning of classification of ECG. There are different type of artefacts occurs in ECG signal. Due to ECG measuring electrode, human movement, interference with other frequency signals etc. power line interference, base line drift, electromyography (EMG) noise etc. are the main artifacts.

Base line drift and low frequency noise may be caused by breathing and coughing with very high movement of the chest in case of chest lead ECG system or in limb lead ECG acquisition system when an arm and leg movement happened. Power line interface is the most common artifacts in biomedical signals. It caused by the power line interference at 50Hz or 60Hz. This is periodic artifacts.

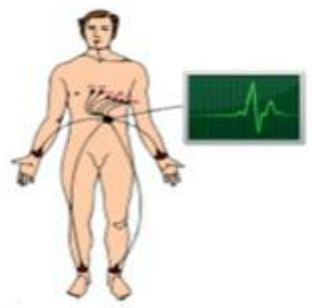

Fig. 3 10 Electrodes Configuration

Due to ECG instrumentation amplifier, catch the electromagnetic signal by the cables, recording device and other sources high frequency noise introduced in ECG signal.Lot of methods are used to remove these types of noises from ECG signal. De chazal et al. used median filter to remove base line drift. In last decade, many methods related to wavelaet transform are introduced to remove artifacts [12],[13],[14]. Wavelet transform is also used to remove base line wander proposed by Ye et al. [15]. Some authors used FIR filters for same purpose [16], [17], [18], [19], [20], [21], [22]. Bazi et al [23] introduced high pass filter to remove high frequency noise and notch filter to remove power line interference. Lin and young proposed second order low pass filter and median filter [24].

IV. FEATURE EXTRACTION

Effective classification of ECG signal is necessary to extract right features of signal. Features provide the information about the signal. Without this information it is not possible to classify the signal. Sometimes for particular arrhythmia we require some special features so it is important to know that which arrhythmia affects which feature of signal. There are different types of ECG feature like morphological feature, time domain feature, frequency domain feature, time and frequency domain feature etc. morphological features are defining the shape of ECG signal. It provides the amplitude and duration of P, Q, R, T, U wave. Morphological features are shown in below table

Table- I: Morphological Features of ECG Signal

Feature	Ideal value	Variation(±)
P wave width	80ms	20ms
PQ interval	160ms	40ms
QRS complex width	100ms	20ms
QT interval	400ms	40ms
ST interval	120ms	20ms
Amplitude of P	0.115mV	0.05mV
Amplitude of QRS complex	1.5mV	0.5mV

In last decade the authors used different features for classification. Many authors use morphological features of ECG signal to classify the signal [13], [19], [21], [5], [25], [26]. RR intervals are one of the features which have a great capacity to classify heart beat of ECG signal. In some paper author only used RR interval for classification [27], [28], [29], [30]. QRS interval is also a good discriminating feature [31], [32]. Josh antonio et al. [33] and a. Nainwal et al. [34] take the wavelet decomposition of signal as a feature. Shameer faziludean et al. [35], Mehmet karuek et al. [32] finds the RR interval for classification. Himanshu gothwal et al. [36] calculates the heart rate as a feature. Xunde et al. [37], Shanshan chenet et al. [38] use dynamic features of ECG signal. Yu and chou [39] apply PCA for extraction of ECG features. Using large feature vector can make slow classification algorithm. The dimension of feature vector can be reduced using various techniques like principle component analysis (PCA)[40],[41],[42] or Independent component analysis (ICA) [43],[39],[25]. Some other different techniques are also introduced by authors, like Hermite transform [44], clustering [45], [46], [47], random projection [48], Lyapunov exponent [49], [50], projected and dynamic [38]. Another part of feature extraction is feature selection. It is not necessary that all the features of signal are important for classification. Feature selection reduced the number of features and increases the generalization power and the cost of computation of classification algorithm. Due to selection of features the training time of network is reduced [19].

V. CLASS OF DATA

Classification of signal is necessary to required class of data. Each paper does not used same class of data. Hari mohan rai et al. [51] makes two class of signal: normal and abnormal signal. Whole database divided in these two classes and then classify these databases into normal and abnormal signal.

Himanshu gothwal [36] uses six class of signal: Normal beat (N), premature ventricular contraction (PVC), fusion of ventricular and normal beat (F), atrial premature beat (A), right bundle beat(R) and fusion of paced and normal signal (F). Patricia Melia et al. [52] take the 15 class of data. K. Daqrouq et al. [53] implement their classification technique on four type of arrhythmias diseases.

VI. DATABASE

The main problem for researchers in biomedical field is database. Data base is the first step of ECG signal processing. MIT-BIH is one of the largest databases for biomedical signals as well as ECG signal [54]. Other data bases are:

1. EDB (the European society of cardiology)
2. AHA (the American Heart Association database)
3. CU (The Creighton sustained ventricular arrhythmia database)
4. NST (The Noise stress test database)

VII. CLASSIFICATION TECHNIQUES

There are two part of ECG classification of signal. One is the pre-processing, extraction of features and other is the learning and classification of signals. Here one set of features is used for machine learning and rest of set are for testing. The three most popular algorithms used for classification and got in literature survey are: support vector machine (SVM) [15], [55], [23], artificial neural network (ANN) [19], [56], [30] and linear discriminate (LD) [31], [57]. Most of papers are based on these three algorithms. Authors modify these methods to improve the accuracy and performance. In next section all three algorithms will be discussed.

A. Support vector Machine

Support vector machine is the most used classification method in survey for classification of different type of arrhythmia of heart. Shanshan chen et al. [38] used SVM with radial basis function signal. Various type of approach with SVM has been introduced like a SVM with artificial NN, with fuzzy theory [58], combined with genetic algorithm to make classifier [59] and SVM with least square method [60]. Alickovic and subasi [61] proposed a SVM classifier with combination of KNN, RBF and MLP. Ubeyli et al. [62] introduce multiclass SVM with error correcting output codes. De lannoy et al. [17] used SVM classifier with convex approximation of the balanced rate of classification for optimization.

B. Artificial neural network

Artificial neural network is the replica of biological neural network. Typically, ANN consist input, output and hidden layer. Multilayer perceptron (MPL) and probabilistic neural network (PNN) are mostly used for arrhythmia classification in ANN architecture. PNN is most robust and efficient as compare to MPL. Mehmet Korurek et al. [63] proposed radial basis function based neural network to classify the ECG signal through QRS features. Feed forward neural network is another network which is widely used for classification. To improve the accuracy of classifier and reduced the training time of network hybrid neuro-fuzzy system is also introduced [63], [64],[45],[65]. Hari mohan rai et al. [51] proposed a three hidden layer network for classification. The transfer function of these layers is log sigmoid, radial basis function and linear transfer function respectively. Giiler and Ubeyli [62] proposed a combined neural network which has the good prediction accuracy.

C. Linear Discriminant Analysis

Linear discrimination a method used in pattern recognition, classification of signals to find the set of features that separates the different classes of signals. LDA calculates the highest possible difference between classes of data. This information helps to classify the signals. It is a statistic method based on the discriminant functions [66].Yogendra narain [67] used Linear discriminant to discriminant heartbeat and morphological features of signal. discriminant function is generated from the training data. Adjusting weight vector and bias the feature vectors are linearly separated. The criteria for calculating the weight vector varies according to the model adopted. In [31], maximum-likelihood is used to determine parameters of data. Roshan Joy [68] used LDA (Linear discriminate analysis), PCA (principal component analysis) and ICA (independent component analysis) to classify the ECG signals.

D. Other Techniques

Machine leaning and data mining algorithm such as decision trees [69], [70], [29], clustering [71], [72], nearest neighbors [73], [74], optimum path forest [75], rule based model [76], [77], [27], hidden markov models [78], [79], conditional random fields [22] and hyper box classification [80] are the other method for arrhythmia classification. Luz et al. [75] used optimum path forest classifier for classification. Mishra and raghav [81] introduced k nearest neighbor's algorithm to get promising results. Tsipouras et al. [76], [77] used the set of rules obtained by cardiologist for arrhythmic event. Clustering technology are mostly used with ANN. It improves the learning time of neural network [45]. In [82] ECG arrhythmia recognized by using hybrid model which contains neuro system, KNN and SVM.

There are some measures which are defined to check the performance of classification techniques.These are:
Sensitivity=TP/(TP+FN)
Positive Predictibility=TP/(TP+FP)
Negative Predictivity=TN/TN+FN
Specificity=TN/(TN+FP)
Accuracy= Correctly classified signals/Total number of signals Where TP is number of true positive, TN is number of true negative, FN is number of false negative and FP is number if false positive classification.

VIII. CONCLUSION AND FUTURE CHALLENGES

This Literature survey finds that most of paper used MIT-BIH arrhythmia database. MIT-BIH database is unbalanced. Another point we found that there is some limitation of database. We require some more databases for new results. To make new database is also a challenging task. Database also incorporates into standards like as AAMI standards to reach the students.

Most of the papers are focusing on accuracy of the classification; very less papers try to improve the training time and classification time of algorithms.

Hybrid network like neuro-fuzzy, GA neuro network, GA-fuzzy can improve the classification accuracy. Feature optimization can also help to improve the accuracy of classifier. Some new features of ECG signal can help in classification.

Table- II: Performance evaluation of different algorithms

S. No	Paper	No of classes	Features Extract	Classifier	Accuracy (%)
1	Kandala Rajesh et al., (2017) [83]	5	sample entropy, coefficient of variation, singular values, and band power of IMF(intrinsic mode function) of ECG features	sequential minimal optimization-support vector machine	99.20
2	Josh Antonio et al., (2017) [33]	8	Wavelet decomposition	DSP based wavelet transform	92.74
3	Shameer Faziludeen et al., (2016) [35]	2	RR interval	evidential k nearest neighbors (EKNN)	-
4	Xunde Dong et al., (2017) [37]	5	Dynamic features	deterministic learning	97.78
5	Shanshan Chen et al., (2017) [38]	15	projected and dynamic features	SVM	98.46
6	Santanu Sahoo et al., (2015) [84]	4	QRS complex features	neural network (NN) and support vector machines (SVM) classifier	96.67
7	Patricia Melin et al., (2016) [78]	15	Fiducial points detection and segmentation of cycles	Modular neural network , LVQ	99.16
8	Rashid Ghorbani Afkhami et al., (2015) [28]	5	RR interval, Higher Order Statistical Features, Mixture Modeling Features	-	99.70
9	K. Daqrouq et al., (2014) [53]	4	wavelet packet transform	Probabilistic NN (PNN)	97.92
10	Barbara Mali et al., (2014) [85]	2	ECG parameters, Time domain HRV parameters, Nonlinear HRV parameters, frequency domain HRV parameters.	MATLAB tool	99.45
11	Manu Thomas et al., (2015) [86]	5	Wavelet coefficients	ANN	94.64
12	Shirin Shadmand et al., (2016) [87]	5	Hermit function coefficient, temporal feature	BBNN(Block based neural network)	97
13	Hari Mohan Rai et al., (2013) [51]	2	Morphological features, Wavelet coefficients	ANN	94.7
14	Himanshu Gothwal et al., (2011) [36]	6	heart rate, QRS complex	FFT-ANN (BPN)	98.48
15	Mehmet Korurek et al., (2010) [32]	6	QRS width, QRS height, RR interval	RBFNN	Se=96.251%, Sp=99.104%
16	A. De Gaetano et al., (2009) [88]	2	RRR interval	Feed forward NN	Se=98%,Sp=99%
17	Eduardo Jose da S. Luz et al., (2012) [75]	5	Wavelet coefficients, LDA RR interval	SVM,ANN	Se=84%,Sp=72%
18	Inan Guler et al., (2005) [89]	4	Wavelet coefficients	Combined-NN	96.94
19	Mohamed I. Owis et al., (2002) [49]	5	Morphological features	K-NN	86.67
20	Philip de Chazal et al., (2004) [31]		ECG intervals, morphological	Weighted LD	83
21	Soria et al., (2009) [16]		Morphological ,RR intervals	Weighted LD	90
22	Zhang and Luo (2014) [20]		Wavelet coefficients, RR interval, morphological features	Combined SVM	87

23	Huang et al., (2014) [90]		RR interval	SVM	Se=93, PP=90.9
24	Ubeyli et al., (2007) [62]	4	Discrete wavelet transform	SVM, ECOC	99
25	Kumar and kumaraswamy, (2013) [30]	3	RR intervals	RBF, MLP,IOAW-FFNN	92
26	YU and chou, (2008) [91]	8	ICA, RR intervals	BPNN,PNN	98
27	Kim et al., (2009) [42]	6	PCA, RR intervals	ELM	98
28	Mishra and Raghav,(2010) [88]	6	Local fractal dimension	Nearest Neighbor	89
29	Chen et al., (2014) [89]	6	RR intervals	NN, SVM	100
30	Alickovic and subasi, (2015) [61]	5	AR	kNN, RBF, SVM, MLP	99
31	De lannoy et al. (2010) [17]		Morphological features, ECG intervals, HOS	Weighted SVM	83
32	Mar et al., (2011) [19]		Statistical features, morphological, temporal features	MLP, Weighted LD	89
33	Tsipoures et al., (2007) [77]	4	RR intervals	Fuzzy Expert System	96
34	Sarfraz et al., (2014) [43]	11	QRS power, RR intervals	ICA coefficients, BPNN	99
35	Mehmet, (2004) [63]	4	Wavelet, High order statistics cummulants	kNN	98
36	Lanata et al., (2011) [74]	6	Higher order statistics	kNN, Mixture of Gaussian	85
37	Tran et al., (2014) [93]	7	Hermite basis function,RR intervals	Ensemble of classifiers	98
38	Zhang et al., (2014) [21]		ECG intervals and segments, RR intervals, morphological features	Combined SVM	86
39	Minhas and Arif, (2008) [94]	6	PCA, RR intervals, Wavelet	kNN	99
40	Abdelhamid Daamouche et al.(2012) [95]	8	Wavelet transform	particle swarm optimization, SVM	Se=91,Sp=96.14,Pp=74.26
41	Sucharita Mitra (2006) [96]	3	Morphological features	a rule-based rough-set decision system	95.8
42	Miad Faezipour (2010) [97]	2	QRS complex	repetition-based packet-processing techniques	97.42
43	Swati Banerjee (2014) [98]	2	QRS complex	Cross Wavelet transform	97.6
44	Tamer O lmez et al. (2003) [99]	10	Wavelet transform	GA with Neural Network	98
45	Yeh et al. (2012) [100]	5	Morphological ,RR interval, Qualitative feature selection	Clustering	94
46	Wang et al. (2013) [101]	8	PCA ,LDA	PNN	99
47	Wang G et al. (2018) [102]	4	Morphological & temporal features	Recurrent Neural Network (RNN)	99.8
48	Mathews M S et al. (2018) [103]	5	R-R Interval, heartbeat, morphological	Deep Learning Neural Network (DNN)	95
49	Sannino et al.(2018) [104]	2	Temporal Features	DNN	99.68
50	Dikar A et al.(2018) [105]	8	Morphological & statistical features	Genetic Algorithm Wavelet Kernel Extreme Learning Machine(GA-WK-ELM)	95

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AUTHORS PROFILE

Ashish Nainwal received his BTech in Electronics and Communication Engineering from the DIT University (formerly known as Dehradun Institute of Technology), Dehradun, India in 2009 and MTech in Digital Signal Processing Engineering from the G.B. Pant Institute of Engineering & Technology, Pauri Garhwal, India, in 2011. He is currently pursuing his PhD degree at the G.B. Pant Institute of Engineering & Technology, Pauri Garhwal, India. He is working as an Assistant Professor in the Faculty of Engineering and Technology, Gurukul Kangri Vishwavidhalaya Haridwar, Uttarakhnad, India. His research interests are biomedical signal processing and image processing.

Dr. Yatindra Kumar received his BE in Electronics and Communication Engineering in 1999 from the G.B. Pant Engineering College Pauri-Garhwal, Uttarakhand, India, MTech in Control and Instrumentation from the Motilal Nehru National Institute of Technology (formerly MNREC), Allahabad, Uttar Pradesh in 2002 and PhD from the Indian Institute of Technology, Roorkee, India in 2014. Currently, he is an Associate Professor in the Electrical Engineering Department at G.B. Pant Institute of Engineering & Technology Pauri-Grahwal Uttarakhand (An Autonomous College of Government of Uttarkhand). He has published some ten research papers in international and national journals and conferences. His areas of interest are digital signal and image processing, biomedical signal processing, machine learning and cognitive analysis.

Dr. Bhola Jha received his Bachelor of Science in Electrical Engineering from the Muzaffarpur Institute of Technology (MIT), Bihar, India in 1998, MTech degree from the Jawaharlal Institute of Engineering and Technology (JNTU), Kakinada, Hyderabad, Andhra Pradesh, India in 2004 and PhD from the Osmania University (OU), Hyderabad, Andhra Pradesh, India in 2013. He has rich experience of about 16 years in teaching and research. He is currently working as an Associate Professor in the G.B. Pant Institute of Engineering & Technology, Pauri-Garhwal, Uttarakhand, India. He is a life member of Solar Energy Society of India (SESI) and Indian Society for Technical Education (ISTE). His research interests include machine modelling, drives and control, non-conventional energy sources, power system analysis, transients, signal analysis, etc.