

## Chapter 4

# Arrhythmia ECG Beats Classification Using Wavelet-Based Features and Support Vector Machine Classifier

**Chandan Kumar Jha**

*Indian Institute of Technology Patna, India*

**Maheshkumar H. Kolekar**

*Indian Institute of Technology Patna, India*

### ABSTRACT

*Abnormal behavior of heart muscles generates irregular heartbeats which are collectively known as arrhythmia. Classification of arrhythmia beats plays a prominent role in electrocardiogram (ECG) analysis. It is widely used in online and long-term patient monitoring systems. This chapter reports a classification technique to recognize normal (N) and five arrhythmia beats (i.e., left bundle branch block [LBBB], right bundle branch block [RBBB], premature ventricular contraction [V], paced [P], and atrial premature contraction [A]). The technique utilizes features of heartbeats extracted by the wavelet multi-resolution analysis. The feature vectors are used to train and test the classifier based on the support vector machine which has been emerged as a benchmark in machine learning classifier. It accomplishes the beat classification very efficiently. ECG records of the MIT-BIH arrhythmia database are utilized to acquire the different types of heartbeats. Performance of the proposed classifier outperforms the contemporary arrhythmia beats classification techniques.*

### INTRODUCTION

In recent years, the incidence and prevalence of cardiovascular diseases (CVD) have gained an expanding growth. As per the recent report of WHO, the overall death rates due to CVD have decreased but the burden of heart diseases still remains at peak (Martis *et al.*, 2013). Among many complications of CVD, atrial and ventricular arrhythmias are one of them which occur due to the abnormal electrical activity

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## Arrhythmia ECG Beats Classification

of heart muscles. Abnormal behavior of heart muscles generates different abnormal cardiac rhythms which are collectively known as arrhythmia. Ventricular fibrillation and flutter are some arrhythmia types which are life-threatening. It results in medical emergencies lead to cardiac arrest, hemodynamic collapse and sudden cardiac death (Huikuri *et al.*, 2001).

The electrical activity of heart muscles could be monitored non-invasively using Electrocardiogram (ECG). Due to the small amplitude and duration, it is difficult to interpret the concealed information present in the ECG data. Therefore, a computer-assisted diagnostic tool could help the physicians in their practice and interpretation. The computer-assisted diagnosis tools can play a major role in the cardiovascular disease management (Hadhoud *et al.*, 2006). These tools are based on many classifiers such neural network (Gutiérrez-Gnecchi *et al.*, 2017), support vector machine (Übeyli, *et al.*, 2007; Kolekar *et al.*, 2015), deterministic learning (Dong *et al.*, 2017), hidden Markov model (Liang *et al.*, 2014; Dash *et al.*, 2017), Bayesian network (de Oliveira *et al.* 2011; Kolekar *et al.*, 2015; Kolekar *et al.*, 2011), linear discriminant analysis (Yeh *et al.*, 2009) etc. These classifiers are widely used for arrhythmia beat classification. A classifier based on the generalized linear model and the auto-regressive model was developed in (Ge *et al.*, 2002) which claims 93.2% classification accuracy for six types of arrhythmia beats. A neuro-fuzzy technique with Hermite coefficients was used in (Linh *et al.*, 2003) to classify ECG beats with 96% accuracy. In (Martis *et. al.*, 2009), a Gaussian mixture model-based classification scheme was proposed for normal and abnormal ECG with 94% accuracy. An automated screening tool based on support vector machine classifier was proposed in (Martis *et al.*, 2012) to distinguish normal and abnormal ECG beats with 95.6% accuracy.

In Table 1, different arrhythmia beats classifiers and features they used are shown. Generally, classifiers used in computer-assisted diagnosis tools use temporal, morphological, statistical and spectral features (Mar *et al.*, 2011, de Chazal *et al.*, 2006) of ECG beats for proper classification. First, a minicomputer system (Fancott *et. al.*, 1980) was developed in 1980 for 24 h monitoring of heart patients. This system utilized the temporal features of ECG to classify three types of beats. The morphological and RR-interval based features of ECG were used in (Melgani *et al.*, 2008) to distinguish normal and five arrhythmia beats using particle swarm optimization. A higher order spectral features based classification scheme for

Table 1. Different arrhythmia beats classifier and features

| Literature                    | Classifier                           | Features                        | Classes |
|-------------------------------|--------------------------------------|---------------------------------|---------|
| Acir <i>et al.</i> , 2005     | Least-square SVM                     | Temporal + spectral             | 6       |
| Melgani <i>et al.</i> , 2008  | SVM                                  | Temporal + morphological        | 6       |
| Chua <i>et al.</i> , 2009     | SVM                                  | Higher order spectral           | 5       |
| Kutlu <i>et al.</i> , 2012    | Neural network                       | Higher order statistics         | 5       |
| Martis <i>et al.</i> , 2013   | SVM                                  | Spectral+PCA                    | 5       |
| Martis <i>et al.</i> , 2013   | Least-square SVM                     | Spectral+PCA                    | 5       |
| Mert <i>et. al.</i> , 2014    | Decision tree                        | Temporal                        | 6       |
| Khalaf <i>et al.</i> , 2015   | SVM                                  | Spectral correlation            | 5       |
| Thomas <i>et al.</i> , 2015   | Artificial neural network            | DWT + morphological             | 5       |
| Shadmand <i>et al.</i> , 2016 | Optimized block based neural network | Hermite coefficients + temporal | 5       |
| Li <i>et al.</i> , 2017       | Regression neural network            | Morphological                   | 5       |

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