

## Detection of Atrial Fibrillation using Autoregressive modeling

K. Padmavathi\* and K. Sri Ramakrishna\*\*

\*Department of ECE, GRIET, India

\*\*Department of ECE, VRSEC, India

---

### Article Info

#### Article history:

Received Sep 14, 2014

Revised Dec 11, 2014

Accepted Dec 28, 2014

---

#### Keyword:

AR coefficients

Atrial Fibrillation

Burg method

KNN

MIT/BIH database

SVM

---

### ABSTRACT

Atrial fibrillation (AF) is the common arrhythmia that causes death in the adults. We measured AR coefficients using Burgs method for each 15 second segment of ECG. These features are classified using the different statistical classifiers: kernel SVM and KNN classifier. The performance of the algorithm was evaluated on signals from MIT-BIH Atrial Fibrillation Database. The effect of AR model order and data length was tested on the classification results. This method shows better results can be used for practical use in the clinics.

Copyright © 2015 Institute of Advanced Engineering and Science.  
All rights reserved.

---

### Corresponding Author:

K. Padmavathi

GRIET

Hyderabad, India

+91 9490014293

Email padma386@gmail.com

---

## 1. INTRODUCTION

Computerized electrocardiogram classification can help to reduce health care costs. ECG results indicate the presence of AF alarming the status of patient's heart. During AF, the hearts atria are quicker than normal beating. As the blood is not ejected completely out of atria, there might be chances of formation of blood clots in the atria resulting in increased risk of stroke. Electrocardiogram (ECG) is one of the useful tool for AF detection. AF can be detected by observing three main morphological features in the ECG as shown in Figure 1. They are

- P wave absence.
- Instead of P waves fluctuating waveforms (f-waves).
- Heart rate irregularity.

There are several methods to detect the features of AF [9]. Methods based on RR interval are proposed in [1], [2]. P wave based methods are presented in [1], [25]. The RR interval, P wave based methods have some limitations [8]. When the ECG changes quickly between rhythms or when Atrial Fibrillation takes place with regular ventricular rates, the methods based on RR interval fail in accurate detection [2]. Detecting the absence of P wave is difficult due to its small amplitude [25]. To study the atrial activity during AF, frequency domain techniques have been proposed in [22], [19], [21], [20]. Ventricular activity needs to be canceled before applying FFT. In presence of noise [20] this cancellation process may be difficult and involves high computation. Morphological features are difficult to detect because they change from patient to patient. From statistical features (AR features) we can easily classify AF signals. AR coefficients [24] are the simplest and best features for AF classification. This paper emphasizes on the use of AR modeling to discriminate between Non-AF and AF waves. Previous studies claim that, the usage of AR coefficient features yield better results than original time series features [24], [23].

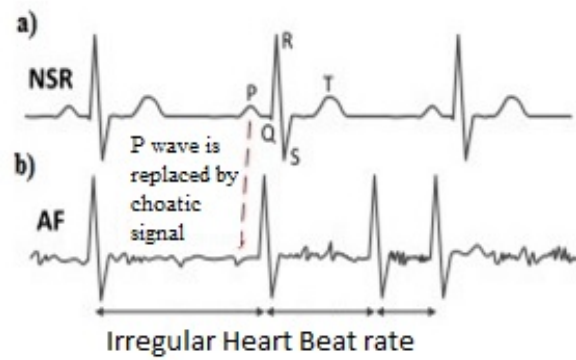


Figure 1. (a) Normal Synus Rhythm; (b) Atrial Fibrillation

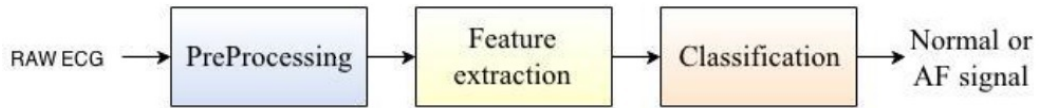


Figure 2. ECG Classification flow chart analysis

## 2. METHOD

### 2.1. Data

The proposed algorithm is estimated based on the data segments collected from MIT-BIH Atrial Fibrillation Database [16]. The AF classification flow diagram as shown in Table 1.

Table 1. MIT-BIH Record Numbers

Normal Data	AF Data
16265, 16272, 16273,	04015, 04043, 04048,
16420, 16483, 16539,	04126, 04746, 04908,
16773, 16786, 16795,	04936, 05091, 05121,
17052, 17453, 18177,	05261, 04426, 06453,
18184, 19088, 19090,	06995, 07162, 07859,
19103, 19140, 19830.	0787, 07910, 08215,
	08219, 0837, 08405
	08434, 08455.

### 2.2. Noise Removal

The first step in our algorithm is dividing the signal into desired length. After segmentation, we considered each segment as a column of a matrix for compact notation and used sgolay filtering [15] to remove the baseline wander present in the signal as shown in Figure 3.

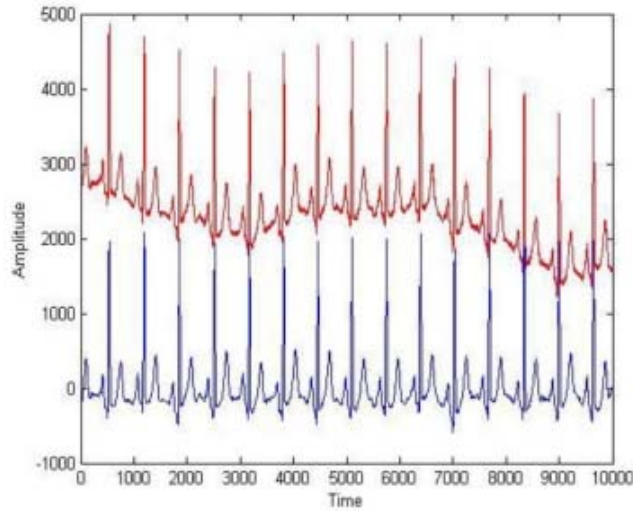


Figure 3. Up signal: Baseline noise signal, Down signal: Baselinewander removed signal

## 2.3. Feature Extraction

### 2.3.1. Computation of AR coefficients

Autoregressive model is based on the principle of linear prediction. In AR model [17] each sample is predicted based on the linear combination of previous samples. Let  $f_1, f_2, f_3, \dots, f_n$  be the time series. The  $p^{\text{th}}$  order autoregressive time series (written as AR(p)) of  $F(n)$  is given by the equation.

$$F(n) = \sum_{j=1}^p \alpha_j F(n-j) + \epsilon(n) \quad (1)$$

Where  $P$  is the model order  $\epsilon(n)$  is assumed to be white Gaussian noise with zero mean and variance  $\sigma^2$ . The AR model parameters  $\alpha_j$  are calculated using Yule-Walker, Burgs methods and the selected model order experimentally.

### 2.3.2. Yule-walker Method (YW)

$$\epsilon(n) = F(n) - \hat{F}(n) \quad (2)$$

$\hat{F}(n)$  is Predicted value  $\hat{F}(n)$

$$E = \sum_{n=1}^N (e(n))^2 = \sum_{n=1}^N (F(n) - \hat{F}(n))^2 \quad (3)$$

$$E = \sum_{n=1}^N (F(n) - \sum_{j=1}^p \alpha_j F(n-j))^2 \quad (4)$$

$\alpha_j$  is predicted to minimize error  $\epsilon(n)$ . Mean square value of the error will be minimum if  $\frac{\partial E}{\partial \alpha_j} = 0$

$$\sum_{j=1}^p \alpha_j R(j-i) = R(i) \quad (5)$$

$$R\alpha = r \quad (6)$$

$$\alpha = R^{-1}r \quad (7)$$

### 2.3.3. Burg's method

Input signal  $F(n)$ ,  $n=1, 2, \dots, N$ , and let us consider the backward and forward linear predictions of order  $k = 1, 2, \dots, m$

$$\hat{F}(n) = - \sum_{k=1}^m \alpha_m(k) F(n-k) \quad (8)$$

$$\hat{F}(n-m) = - \sum_{k=1}^m \beta_m(k) F(n-m+k) \quad (9)$$

where  $\alpha_m$  and  $\beta_m$  are the forward and backward prediction coefficients respectively  
 $f^t(n)[f(n); f(n-1), \dots, f(n-p)]$

$$f_m(n) = F(n) - \hat{F}(n) = \sum_{k=1}^m \alpha_m(k) F(n-k) \quad (10)$$

$$b_m(n) = F(n-m) - \hat{F}(n-m) = \sum_{k=1}^m \beta_m(k) F(n-m+k) \quad (11)$$

Where  $\alpha_m$  and  $\beta_m$  are the forward and backward prediction residuals. Note that  $\alpha_m = 1, \beta_m = 1$  by definition. The FIR prediction error filter or the lattice filter is given by the set of recursive equations

$$f_m(n) = f_{m-1}(n) + k_m b_{m-1}(n-1) \quad (12)$$

$$b_m(n) = k_m f_{m-1}(n-1) \quad (13)$$

$m=1,2,3,\dots,p$ . Where  $K_m$  are the reflection coefficients of the  $m^{\text{th}}$  recursion step. The initial values of the residuals are  $f_0(n) = b_0(n) = f(n)$

$$k_m = \frac{-2 \sum_{n=p+1}^N [f_{m-1}(n) + k_m b_{m-1}(n-1)]}{\sum_{n=p+1}^N [(f_{m-1}(n))^2 + b_{m-1}(n)^2]} \quad (14)$$

$$\alpha_m(k) = \alpha_{m-1}(k) + k_m \alpha_{m-1}(k-m) \quad (15)$$

$\alpha_m(0) = 1; \alpha_m(m) = k_m$ ,  
 where  $m=1$  to  $p$  and  $k=1$  to  $m$ .

All-pole prediction coefficients method excel in comparison to the autocorrelation method because they decrease the total prediction errors and the data sequence is not subjected to any window function. The advantage of the former method is that it is computationally efficient, stable and has high frequency resolution. The selection of the Autoregressive model order is of foremost importance in the classification of AF. The correct number of Autoregressive coefficients are determined using trial and error method. The coefficients of order 4, 8, 16 are used for our study.

## 2.4. Classification

The performance of two different classifiers SVM and k-NN are obtained with the AR coefficients as input.

### 2.4.1. Kernel Support Vector Machines (KSVM)

A kernel Support Vector Machine [26] is a supervised machine learning technique applicable for classification. It is an example for non-probabilistic binary linear classifier, established from Statistical Learning Theory [27]. It exhibits high accuracy and has capability to deal with high dimensional data sequences. The support vector machine makes use of pattern recognition among two point classes by Support Vectors (SV).

Kernels are functions that performs some mathematical operations on  $x_1, x_2$  depending on the selection of the kernel function.

$$x = \phi(x) \quad (16)$$

$$k(x_1, x_2) = \phi(x_1)\phi(x_2) \quad (17)$$

Gaussian kernel can be expressed as

$$k(x_1, x_2) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x_1 - x_2)^2}{2\sigma^2}} \quad (18)$$

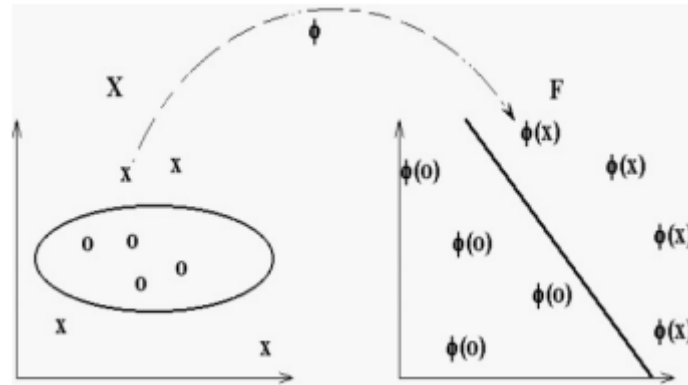


Figure 4. Kernel trick

Linear kernel can be expressed as

$$K(x_1, x_2) = \phi(x_1)\phi(x_2) \quad (19)$$

$$K(x_1, x_2) = x_1'x_2 \quad (20)$$

kernel functions can be applied to non-linear data so that non-linear features are converted into linear features as shown in Figure 4. By using kernel trick features can be represented in a high dimensional feature space. Linear classifier methods used to produce non-linear classification is the major advantage of kernels. As ECG is an one dimensional signal,  $x_1$  is  $x_2$  are the features of a two distinct ECG recordings. Linear and Gaussian kernels are applied on the ECG signal with SVM classifier.

#### 2.4.2. K-Nearest Neighbour (KNN)

In the K-nearest neighbors rule, a new vector  $y$  of a new class is classified based on the distance from nearest mean vector. The distance from vector  $y$  and the centroid of the  $m^{th}$  cluster  $z_l$  is calculated as the Euclidean distance

$$S_m = \sqrt{\sum_{l=1}^n (y_l - z_l^m)^2} \quad (21)$$

$m$  is the cluster index,  $n$  is the number of the parameters used and  $l$  the parameter index. Vector  $y$  can be classified in to class  $k$  at which  $s_m$  is minimum. We selected the value of  $k$  as 1.

### 3. RESULTS

The 5,15 and 30 second length sequences from each recording are considered and AR coefficients are calculated. The effect of model order on classification results is investigated. For the SVM and K-NN classifiers, 280 recordings are given for training (2/3 of total recordings) and 93(1/3 of total recordings) are given for testing. Three modeling orders are used to differentiate the proposed method with other methods. Classification accuracies for different model orders and different lengths are shown in 2 to 4 Tables. The results of these methods are shown in Tables 2 to 4. It is evident that the burg's method with KNN classifier shows best results among the two classifiers irrespective of the length of data sequence for model order 8.

### 4. CONCLUSION

In this paper the use of AR modeling for Atrial Fibrillation arrhythmia detection is examined. A comparison of the performance of SVM and kNN classifiers on signals from MIT-BIH Atrial Fibrillation Database is depicted. Analysis effect of various model order's for different data segment lengths is performed. Among the two classifiers KNN with Burg's method achieved the best results. The minimum misclassified segments were achieved in 5, 15, 30 second segments for the model order 8, which proves to be the best classification obtained. Burg's method shows good results for short data segments with SVM classifier, Yule Walker method shows good results for data segments of length 30 seconds for model order 6 with KNN classifier. Selecting the model order and segment length depends on the required precision and availability of the computational resources. This algorithm can be used for real time detection of AF signals. The former procedures for feature extraction such as ventricular activity cancellation and detection of R peak, which are tedious in nature can be eliminated.

Table 2. Classification for Model order 4

Data length	Accuracy			
	YW+SVM	Burg+SVM	YW+KNN	Burg+KNN
5 Sec	76.9	92.3	46.1	38.4
15 Sec	92.3	76.9	92.3	92.3
30 sec	92.3	92.3	76.9	76.9

Table 3. Classification for Model order 6

Data length	Accuracy			
	YW+SVM	Burg+SVM	YW+KNN	Burg+KNN
5 Sec	76.9	92.3	53.8	61.5
15 Sec	84.6	100	69.2	92.3
30 sec	92.3	100	100	92.3

Table 4. Classification for Model order 8

Data length	Accuracy			
	YW+SVM	Burg+SVM	YW+KNN	Burg+KNN
5 Sec	76.9	92.3	84.6	100
15 Sec	84.6	100	84.6	100
30 sec	92.3	100	92.3	100

### REFERENCES

- [1] M. Mohebbi H. Ghassemian. Detection of atrial fibrillation episodes using svm. 30th Annual International Conference. IEEE; 2008. p. 177-180.
- [2] G.B. Moody, R.G. Mark. A new method for detecting atrial fibrillation using rr intervals. *Computers in Cardiology*; vol. 10: 1983. p. 227-230.
- [3] L. Schamroth. An introduction to electrocardiography. *Academic medicine*; vol 39: 1964. p. 977.
- [4] H. Chatterjee, R. Gupta, and M. Mitra. A statistical approach for determination of time plane features from digitized ecg. *Computers in biology and medicine*; vol. 41: no. 5. 2011. p. 278-284.
- [5] S. Banerjee and M. Mitra. Application of cross wavelet transform for ecg pattern analysis and classification. *IEEE transactions on instrumentation and measurement*; vol. 63: 2014. p. 326-333.
- [6] M. Mitra and R. Samanta. Cardiac arrhythmia classification using neural networks with selected features. *Procedia Technology*; vol. 10: 2013. p. 76-84.
- [7] S. Bhattacharyya. Classification of right bundle branch block and left bundle branch block cardiac arrhythmias based on ecg analysis. 2012.

- [8] K. Tateno and L. Glass. A method for detection of atrial brillation using rr intervals. in *Computers in Cardiology 2000; IEEE*. 2000. p. 391-394.
- [9] B. Weng, J.J. Wang, F. Michaud, and M. Blanco Velasco. Atrial fibrillation detection using stationary wavelet transform analysis. in *Engineering in Medicine and Biology Society; EMBS 2008. 30th Annual International Conference of the IEEE. IEEE*. 2008. p. 1128-1131.
- [10] A. Grinsted, J. C. Moore, and S. Jevrejeva. Application of the cross wavelet transform and wavelet coherence to geophysical time series. *Nonlinear processes in geophysics*; vol. 11: no. 5/6. 2004. p. 561-566.
- [11] M. Ibn Ibrahimy, R. Ahsan, and O.O. Khalifa. Design and optimization of levenberg marquardt based neural network classifier for emg signals to identify hand motions. *Measurement Science Review*; vol. 13: no. 3. 2013. p. 142-151.
- [12] G. Singh and C. Singh. Estimation of coherence between ecg signal and eeg signal at different heart rates and respiratory rates. *IJIET*; vol. 1: no. 5. 2012. p. 159-163.
- [13] L.S. Sarraf, J.A. Roth, and K.M. Ropella. Differentiation of atrial rhythms from the electrocardiogram with coherence spectra, *Journal of electrocardiology*; vol. 35: no. 1. 2002. p. 59-67.
- [14] G. Baselli, S. Cerutti, S. Civardi, D. Liberati, F. Lombardi, A. Malliani, and M. Pagani. Spectral and crossspectral analysis of heart rate and arterial blood pressure variability signals. *Computers and Biomedical Research*; vol. 19: no. 6.1986. p. 520-534.
- [15] C. Zheng, M. Zhou, and X. Li. On the relationship of non parametric methods for coherence function estimation. *Signal Processing*; vol. 88: no. 11.2008. p. 2863-2867.
- [16] R. Doe. (2000, Jun.) Ecg data base@ONLINE. Available: <http://www.physionet.org>
- [17] J.G. Proakis. Digital signal processing principles algorithms and application. *Pearson Education India*; 2001.
- [18] P.D. Welch. The use of fast fourier transform for the estimation of power spectra: a method based on time averaging over short, modified periodograms. *IEEE Transactions on audio and electro acoustics*; vol. 15: no. 2. 1967. p. 70-73.
- [19] J. Ng, J.J. Goldberger. Understanding and interpreting dominant frequency analysis of af electrograms. *Journal of cardiovascular electrophysiology*; vol.18 (6): 2007. p. 680 - 685.
- [20] M. Stridh, L. Sornmo, C.J. Meurling, S. B. Olsson. Characterization of atrial fibrillation using the surface ecg. *time-dependent spectral properties*; Biomedical Engineering. *IEEE Transactions on*, vol.48 (1):2001.p. 1927.
- [21] J. Suri, J. A. Spaan, S. M. Krishnan, et al. *Advances in cardiac signal processing*. Springer; 2007.
- [22] M. Stridh, L. Sornmo. Shape characterization of atrial fibrillation using time-frequency analysis. in *Computers in Cardiology IEEE*; 2002.p. 1720.
- [23] Q. Xi, A.V. Sahakian, S. Swiryn. The effect of qrs cancellation on atrial fibrillatory wave signal characteristics in the surface electrocardiogram. *Journal of electro cardiology*; vol. 36(3): 2003. p. 243-249.
- [24] D. Ge, N. Srinivasan, S.M. Krishnan. Cardiac arrhythmia classification using autoregressive modeling. *Biomedical engineering*; online 1 (1): 2002. p.5.
- [25] S.A. Guidera, J.S. Steinberg. The signal-averaged p wave duration: a rapid and noninvasive marker of risk of atrial fibrillation. *Journal of the American College of Cardiology*; vol. 21(7): 1993. p. 1645-1651.
- [26] Wenjuan Zeng. Support Vector Machines Application Research in Pattern Classification. *TELKOMNIKA Indonesian Journal of Electrical Engineering*; Vol. 13(1): 2015.
- [27] Pan Wentao, Peng Zhaoqin, Caochun Li Bo. Applying SVM for Foot Pressure Pattern Classification. *TELKOMNIKA Indonesian Journal of Electrical Engineering*; vol. 12(4): 2014. p. 2753-2761.