International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 14 (2018) pp. 11501-11507

Diverenge Coding for Diagnosis of Atrial Fibrillation in ECG Signal Analysis

Upasani Dhananjay Eknath*, Dr. R.B. Ghongade

Bharati Vidyapeeth Deemed University College of Engineering, Pune, Maharashtra – 411030, India.

Abstract

Atrial fibrillation (AF) is a type of abnormal rhythm (arrhythmia) of the heart. In the ECG analysis, regressive models are used to detect the ECG features for AF detection. In the feature extraction process using regressive models, the ECG signal are processed for a regular time interval to extract the characteristic variation in ECG signal and develop a classification based on the variations observed in PQRST feature detection. The regression models are however time consuming due to recurrent coding and does not focus on the feature divergence issue. As the features extracted for different test subjects for the same observations vary, the divergence issue needs to be addressed to achieve an optimal solution in detection of AF. In this paper divergence problem using Bergman divergence approach is developed to achieve optimal recognition observations in ECG analysis. The proposed approach decomposes the patients' ECG signal into spectral bands. The obtained spectral bands are filtered and then processed for feature extraction. The SVM classifier is used for the classification of signal as Normal or AF detected.

Keywords: ECG, AF, Bergman Divergence etc.

INTRODUCTION

With the development of new technologies, the real time world is tending towards the process of automation. Various technologies have emerged in recent yearsin order to achieve higher processing efficiency, to improve the system performance and to obtain higher classification accuracy. In various applications the process of automation is also tending towards medical diagnosis. In the application of medical diagnosis the captured samples are passed to the processing unit and advance computational algorithms are executed to achieve the optimum results. In such applications, ECG processing in automated diagnosis is emerging. Cardiac activity is the most common physiological measure for the assessment of mental workload. An Electrocardiogram (ECG) is a cardiac measure that shows sensitivity towards variations in workload. The Electrocardiogram (ECG) essentially reads the electrical impulses that stimulate the heart to contract. It is the most useful tool to determine whether the heart is functioning normally or has been injured. ECG signal is compressed for effective utilization of the storage and easy transmission of the digitized ECG signals.

A typical ECG monitoring device generates a large amount of data in the continuous long-term (24-48 hours) ambulatory monitoring tasks. For good diagnostic quality, up to 12 different streams of data may be obtained from various sensors placed on the patient's body. The sampling rate of ECG signals varies from 125Hz to 500Hz, and each data sample may be digitized into 8 to 12 bits binary number. If lowest sampling rate of 125Khz with 8 bit encoding is used, ECD signal will generate approximately 7.5KB/minute and 450KB/hour. For a sampling rate of 500Hz and 12-bit encoding recording, it generates data at a rate of 540KB per minute and 30MB per hour. The data rate from 12 sensors totally will generate 12 times amount of data and it is very huge. Besides, recording over a period of time as long as 24 hours maybe needed for a patient with irregular irregular heart rhythms. During the process of compression or during the capturing process there are artifacts generated which would result in wrong interpretation. heart rhythms. During the process of compression or during the capturing process there are artifacts generated which would result in wrong interpretation.

LITERATURE REVIEW

Atrial fibrillation (AF) is the severe cardiac arrhythmia among population, with an increasing prevalence in the elderly (17% in people above 70 years) [1]. It is also one of the most frequent post-operative complications after cardiothoracic surgery (10-40%) [2], thus contributing to prolongation of hospitalization and to an increase of the related costs [3]. Although older age alone seems to be the strongest predictor for the development of AF [4, 5], in the last decades several studies have focused on finding algorithms able to predict AF by the analysis of surface electrocardiographic records. The importance of defining possible clinical predictors is even greater for patients undergoing post coronary artery bypass grafting (CABG)or other cardio surgical operations (e.g. aortic valve replacement). A risk stratification based on preoperative tests would be very useful either to optimize the prophylactic anti-arrhythmic treatment such as drugs or electrical pacing [6] in patients prone to develop postoperative AF shortening patient suffering and reducing costs associated to the hospitalization, or to limit drugs administration in low risk subjects. AF is the result of a fractionated atrial electrical activity mainly due to the shortening of atrial refractory period, which allows multiple wavelets pass through the atrial mass. If an obstacle in the conduction path exists, a subsequent phenomenon of re-entry of the electrical activation can lead to the arrhythmia. Since loss of atrial muscle and increased fibrous tissue are also consequences of the arrhythmia, AF can probably cause both molecular modifications of electrophysiological activity, and structural, functional, autonomic and metabolic alterations. These phenomena are known as atrial remodeling [7]. However, it is unclear whether these changes are the primary conditions to AF onset or if they are a consequence of atrial remodeling due to AF. According to the theory proposed in [8, 9], rapidly firing atrial ectopic foci can result in premature atrial complexes, in episodes of atrial tachycardia or AF, thus acting as starting triggers for the initiation of the arrhythmia on a predisposing abnormal substrate [10, 11]. A significant morbidity is strictly associated to AF. Several concomitant and underlying diseases, such as cardiomyopathy, affect patients with AF and a major risk for strokes or thromboembolic events must be taken into account. Management of patients with AF aims to restoration and maintenance of sinus rhythm, ventricular rate control, stroke prevention and concurrent disorders treatment [11]. A pharmacologic approach is usually pursued by administration of antiarrhythmic or anticoagulation drugs. Since each patient has a specific and peculiar drug-response it is difficult to predict which agent will be the most effective. A starting standard treatment is thus prescribed while selected therapy is established subsequently. A non-pharmacologic approach is recommended in patients showing drug resistance or intolerance but its modalities and options can differ depending on the arrhythmia conditions and severity. In CABG patients AF generally occurs 1-5 days after surgery with a peak incidence on day 2. It is usually self-limiting as its symptoms and effects fade within the first few days or weeks after operation. Patients developing post-CABG AF usually show no previous history of AF episodes. This probably means that the anatomic stresses developed as a result of surgery can trigger post-CABG AF on predisposing conditions [12, 13]. In [14] the classification of ECG signal to detect atrial fibrillation was suggested. The Approach developed an auto regressive model to achieve the objective of feature extraction. The coefficients are measured for regular time interval extracted through Burg's method. A KNN classier is used to detect the AF over different data length and classification is made over MIT-BIH AF database. The approach gives a simpler and optimal approach to AF detection, however the divergence in feature distribution among the features are not addressed. The divergence factor effects the variation detected in the ECG analysis. To achieve the objective, in this paper a divergence problem for ECG diagnosis with weighted Bergman divergence is suggested. To present the develop work, the rest of the paper is presented in 5 sections, where a basic detail to ECG signal and its analysis for AF is presented. The conventional modeling of auto regression model is suggested in section 3. Section 4 present the proposed approach of weighted divergence function, the experimental results are outlined in section 5. Section 6 present the conclusion of the developed work.

ECG SIGNAL REPRESENTATION

Atrial fibrillation (AF) is the severe cardiacarrhythmia. The persistent cases of AF cause palpitations, fainting, chest pain, or congestive heart failure and even stroke. To effectively treat or prevent AF, automated AF detection based on ECG monitoring is highly desirable. However, accurate detection of AF episodes based ECG signals is technically challenging. AF can easily go unnoticed as it does not show any severe symptoms, particularly in paroxysmal cases. In such cases, no obvious signs can be visually observed from the ECG signal shortly after or before an episode of AF. In general, ECG signal has frequency range from 0.05 to 100 Hz and its dynamic voltage range varies from 1mV to 10 mV. The ECG signal is characterized by five peaks and valleys labelled by the letters P, Q, R, S, T. In some cases we also use another peak called U. The key factor in analyzing ECG signal is QRS complex, T and Pwaves, hence we need to analyze it precisely. The P-wave represents the activation of the upper chambers of the heart, the atria, while the QRS complex and T-wave represent the excitation of the ventricles or the lower chamber of the heart. The detection of the QRS complex is the most important task in automated ECG signal analysis. Once the QRS complex has been identified a more detailed examination of ECG signal including Myocardial Infraction, ventricular hypertrophy, the abnormal heart rate, the ST segment etc. can be performed [3, 4]. In the normal sinus rhythm (i.e. normal state of the heart) the P-R interval is in the range of 0.12 to 0.2 seconds. The QRS interval is from 0.04 to 0.12 seconds. The Q-T interval is less than 0.42 seconds and the normal rate of the heart is from 60 to 100 beats per minute. So, from the recorded shape of the ECG, we can say whether the heart activity is normal or abnormal.

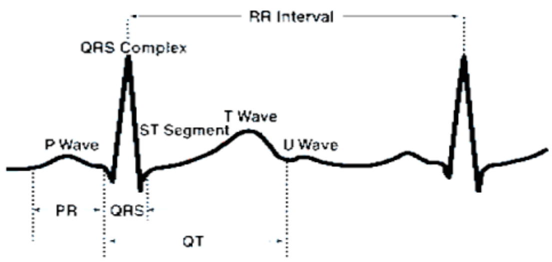

Figure 1. Standard ECG waves and intervals [7].

Figure 1 shows, the ECG signal showing the different intervals. The variations in the duration of P-wave has been used by physicians as a sign for abnormal atrial activities that could potentially lead to an AF signal. The RMS voltage of the filtered P-wave has also been reported as a good feature by many researchers [2]. Apart from these two, some other P-wave related parameters have been considered in the literature. The parameters associated with P-wave morphology are listed below:

1) P_amp : Amplitude of the P-wave.
2) P_ar : Area under the P-wave.
3) P_Wd : Width of the P-wave measured for a particular heart pulse.
4) P_dist : Time distance of the beginning of the P-wave till its maximum.
5) PR_dist : The distance from one P peak to the following R peak.

In order to get these parameters, each beat in the ECG is identified by detecting the R peaks. A time window is defined for the localization of the P-wave. If multiple P-waves are detected in the predefined time window, the average values are computed. In addition, some statistical measurements of these parameters have also been used. In [3], [4] minimum, maximum, mean and standard deviation of P_amp, P_ar, P_Wd, P_dist and PR_dist were taken as features for automated AF detection.

THE PROPOSED SYSTEM

Figure 2 shows the proposed system. The signal conditioner pre-processes the ECG signal. The ECG signal is further processed to feature extraction unit. The obtained features are given to learning architecture to create a feature data base. The extracted features of query signal are given to classifier during testing. Finally, the signal under testis classified as Normal or AF affected based on decision logic.

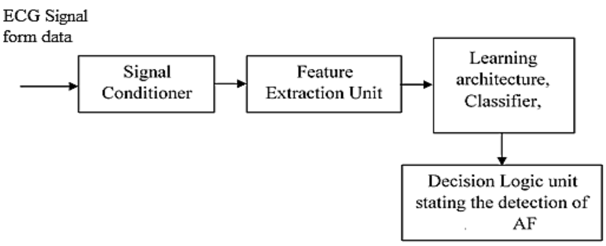

Figure 2. Proposed System

METHODOLOGIES

Autoregressive Modeling [14]

For the analysis of Atrial Fibrillation (AF), the MIT- BIH database is used. The database consist of 23 records of AF signals which are sampled as 250Hz, and 18 Normal sinus rhythms. To process the feature diagnosis an auto regressive model is used. The process computes the feature as a set of linear prediction model. This regression model is considered as a simultaneous clustering of more properties of the dataset. Auto- regression is used to produce a set of clusters of original data and also a set of clusters of their property. Unlike other clustering algorithms, Auto- regression also defines a clustering criterion and then optimizes it. In general, Auto-regression finds out the subsets of attributes and their properties simultaneously of a data matrix using a specified criterion. From the summarization point of view, Auto-regression provides significant benefits. Basically, there are two types of Auto- regression approaches, Block Auto-regression and Information Theoretic Auto- Regression (ITAR). Among the defined Auto- regression logic, the ITAR approach was proved to be optimal. The information theoretic Auto- regression was based on Burg's method. This ITAR tries to reduce the loss of information in the approximation of a data matrix X. The reduction in data loss can be minimized through a predefined distance called prediction function. Fora given Auto- regression model with (R,C) and a matrix approximation scheme P, a class of random variables which store the properties of attribute data matrix X is defined. The objective function tries to reduce the attributes loss on the approximation of $\hat{X}$ for an Auto- regression R, C. The burg's prediction information of X defined by [14]:

$$F_{\phi}(X) = -\sum_{k=1}^{m} a_m\,(k)(F(n-k) \qquad (1)$$

Here, the matrix approximation scheme is defined by the expected value and the divergence $d_{\phi}$for an optimal clustering as follows

$$(R, C) = \text{argmin}\ \ E[d_{\phi}(X, \hat{X})] \qquad (2)$$

Here, the Auto- regression was directly related with Euclidean distance and can be expressed as

$$d_{\phi} = (x_1 - x_2)^2 \qquad (3)$$

Here, the Auto- regression was evaluated by just calculating the Euclidean distance between the attributes magnitude values. The Euclidean distance will give the difference between the magnitudes of attribute values. Though this approach provides better diagnosis accuracy, it is almost equal to the diagnosis accuracy of sub-grouping approach. This approach does not consider the divergence of attribute properties. If the co-clustering is done by considering the divergence of attribute property, the diagnosing accuracy will be increased further. The complete detail about the proposed approach is given in next section.

Proposed Approach: Weighted-ITAR

The approach of conventional Auto- regression using ITAR was observed to be effective. However, in the approach of co-clustering operation following ITAR, the clustering is made based on the divergence factor of two observations (x_1, x_2). The divergence factor is computed using the Euclidian distance based approach. In this approach, two of the magnitudal components are compared to obtain a distance factor. The convergence is observed when the two observations satisfy a minimum divergence criterion. The approach results in an optimal co-clustering of data but the relational property of the data elements are not explored. Depending on the nature of occurrence, the data types are classified as discrete or variant data types. However the approach of ITAR does not consider this nature of attribute variation for clustering. Though the data type attribute results in proper defining of nature of variation for the observing attribute, a Euclidian approach is not appropriate in clustering. Hence in this proposed method, a weighted ITAR coding for co-clustering of data type is presented. The approach of co-clustering using weight factor is defined by allocating a weight value to the distinct class attributes in the sub cluster.

Let w_i be the allocated weight for each sub cluster C_i, where the sub cluster are derived using the method of medical and computer selected feature set, clustered using the data type property with 5 distinct class of effect,

$$C_i \in (H_0, S_1, S_2, S_3, S_4) \qquad (4)$$

Where the class attributes is defined as,

Table 1: Class Label Attribute to Distinct Classes Formed

Class Type (C_i)	Class Definition	% Affected	AF Condition	Associated Weight (w_i)
H_0	Normal	0%	Normal	1
S_1	Abnormal Type – 1	0-10%	Initial stage	2
S_2	AbnormalType – 2	10-30%	Abnormal – Low	3
S_3	AbnormalType – 3	30-60%	Abnormal – High	4
S_4	AbnormalType – 4	60-90%	Critical Stage	5

The allocated weights are assigned based on the severity of percentage of effect of each class attribute. The class with healthy condition is given weight '1', wherein class S_4 having severe effect is given a weight value of 5. In the process of mining the dataset for a information retrieval, the given query details are mined over the sub cluster dataset based on the medical oriented feature set and computer oriented feature sets, derived as outlined in previous section. To optimize the mining performance, co-clustering approaches were introduced. The ITAR based co-clustering was successfully been applied over MIT - BIH dataset, wherein the dataset is clustered into sub clusters based on the criterion of Bergman divergence Information$I_\emptyset(X)$, satisfying the convergence problem,

$$\arg\min(E[d_\emptyset(X,\tilde{X}])\qquad(5)$$

Where $X \in C_i$ and $\tilde{X}$is the new co-cluster formed for the sub clusterC_i. Here, $d_\emptyset$is defined as the divergence operator given by the Euclidian distance of the two observing element (x_1,x_2),

$$d_\emptyset(x_1,x_2) = (x_1,x_2)^2\qquad(6)$$

Clustering based on the consideration of coefficient magnitudes results in co-clusters based on the observing values, the relational property among the values and the severity of the class values are however not been considered. As observed, continuous data types are more effective in decision deriving than the discrete data type, so an inclusion of type factor and integrating the co-clusters based on the class attribute leads to finer co-clustering of the dataset. In consideration to the stated approach, the weighted co-clustering computes an aggregative weight value of each of the class label (w_i) given as,

$$W = \sum_{i=1}^{n} w_i\qquad(7)$$

Where, w_i is the weight value assigned to a class attribute for n sub classes under observation. While considering a co-clustering of each class, the aggregated weight value is computed, and the co-clustering limit of $\frac{W_C}{N}$ is set. Where, $W_c$is the total weight values assigned to each class attribute.

$$W_c = \sum_{i=1}^{N} w_i\qquad(8)$$

Where N is the number of classes.

The convergence problem is then defined by,

$$\arg\min(E[d_\emptyset(X,\tilde{X})] \Rightarrow (\min(W) > \frac{W_C}{N})\qquad(9)$$

The solution to the convergence problem, is here defined by two objectives, with minimum estimated divergence based on Euclidian distance, subjected to the condition having a minimum aggregated weight value lower than half of the total class weight value. A limit of $\frac{W_C}{N}$ is considered, to have a co-clustering objective of minimum similar elements entering into a class, without breaking the relational property among the observing attribute. The process of the proposed weighted ITAR (W-ITAR) approach is illustrated as follows:

Let, C_1,C_2,C_3,C_4,C_5 be a sub cluster derived from the selection approach of medical and computer oriented selection process with data type attribute. The associated weight for each of the class be W_1,W_2,W_3,W_4,W_5 assigned with the value of $\{1,2,3,4,5\}$. For this set of dataset, to apply weighted co-clustering process the following step of operations are applied,

Step 1: The Bergman divergence for the two observing element is computed using (6).

Step 2: For each divergence, $d_\emptyset(x_1,x_2)$, the convergence criterion defined by (5) is computed.

Step 3: The aggregative sum weighted value for the observing class is then computed using (7).

Step 4: The convergence criterion is then checked for the obtained aggregated weight value following (9).

Step 5: The above steps are repeated for all sub classes to co-cluster.

In the considered case, the total weight

While co-clustering the elements of the entire sub class is obtained by,

$$W_c = \sum_{i=1}^{N} w_i = 15.$$

Now, for the clustering of two sub classes, $C_1,C_2$and C_1,C_4, the aggregative weight sum is obtained as,

$$W_{12} = 3\text{and } W_{14} = 6.$$

Considering convergence problem of (9), the limiting value is 15/5 = 3.

In this case $W_{14} > \frac{W_c}{N}$ hence not clustered in the same group, even though the divergence criterion is satisfied. This results in co-clustering of sub-classes with highest similarity into one class. As, could be observed, class-1 and class-4 are of more dissimilarity than class 1and 2. The allocated weight values governed the class relation and the limiting of the total weight value which prevents the wrong clustering of the sub-class. The operational algorithm for the suggested weighted co-clustering approach is as illustrated.

EXPERIMENTAL RESULTS

This section illustrates the details about the result analysis. The performance of proposed approach is verified through accuracy. The accuracy of the proposed approach is measured using the standard confusion metrics. The metrics are listed as True Positive (TP), False Positive (FP), True Negative (TN), False negative (FN). The complete analysis was carried out on all the classes of patients listed above such as Normal (0), Abnormal Type 1 (1), Abnormal Type 2 (2), Abnormal Type 3 (3) and Abnormal Type 4 (4). TP denotes the Effective people correctly identified as effective, FP denotes the Normal people incorrectly identified as effective, TN denotes Normal people correctly identified as Normal and finally FN denotes Effective people incorrectly identified as Normal. The accuracy is calculated by the following mathematical expression,

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{10}$$

Where,

TP = True Positive (Correctly Identified)

FP = False Positive (Incorrectly Identified)

TN = True Negative (False, Correctly Identified)

FN = False Negative (False, Incorrectly Identified)

The performance of the proposed work is evaluated by calculating the parameters: Sensitivity, Specificity, Recall, Precision and F-Measure. The parameters are defined and calculated as:

The sensitivity is measured as the ratio of True Positive (TP) to the sum of True Positive (TP) and false negative (FN).

$$Sensitivity = \frac{TP}{TP+FN} \tag{11}$$

The specificity is measured as the ratio True Negative (TN) to the sum of True Negative (TN) and false positive (FP).

$$Specificity = \frac{TN}{TN+FP} \tag{12}$$

Precision is the ratio of TP to sum of TP and FP while recall is the ratio of TP to sum of TP and FN. The following expressions give precision and recall measurements

$$Recall = \frac{TP}{TP+FN} \tag{13}$$

$$Precision = \frac{TP}{TP+FP} \tag{14}$$

F-measure is the combined measure of precision and recall. F-measure is also called as balanced F-score, the expression is as

$$F\_measure = \frac{2*Recall.Precision}{Recall+Precision} \tag{15}$$

ALGORITHM: W- ITAR:

The algorithm using W – ITAR is described briefly below:

Output *: Co_cluster classes* (CC_i)

Method M₀:

1. for each type attribute,

2. Compute sub-clusters, C_i € *(linear, variant selected Features)*

Where i, is the class attributes =1 to 5 for considered 5 classes.

3. Cluster the selected attributes from class C_i *based on passed data type,*

4. C_{ico}*=1; if, data type attribute = 'continuous'*

5. C_{ico}*=0;if data type attribute = 'discrete'*

6. Formulate updated cluster, $C_{iupdt} = C_i \cap C_{ico}$, *where i=1to*

7. Perform Co-clustering over C_{iupdt} *using w_co_clustering:M₁.*

Method M_1: W_co-clustering *(C_{iupdt}, w_i)*

1. *Allocate weight (w_i) to each C_{iupdt} $C_{iupdt} \Leftrightarrow w_i$*
2. *Compute Bergman Divergence using Euclidean Distance, $d_{\emptyset}(x_1, x_2) = (x_1 - x_2)^2$*
3. *Compute Bergman Index, $I_{\emptyset}(X) = E(\log\left(\frac{X}{E(X)}\right))$*

   Where $I_{\emptyset}(X)$ is Bergman Index, satisfying the criterion, $\arg\min(I_{\emptyset}(X))$
4. *Compute aggregated weight, W, defined by,*

$$W = \sum_{i=1}^{n} w_i$$

where i is the sub cluster, selected by Bergman divergence criterion,

5. *Compute the limiting bound value W_c defined by,*

$$W_c = \sum_{i=1}^{N} w_i$$

Where N is total number of sub clusters.

6. *Applying the weight convergence criterion, $\arg\min(E[d_{\emptyset}(X,\tilde{X})] \Rightarrow (\min(W) > \frac{W_C}{N})$*

The sub-cluster are co-clustered. end M_1, end M_0,end

Table 2. Percentage Accuracy Comparison for ECG Signal of time 12 Hours

Parameter	Class / Method	Normal	ABN Type 1	ABN Type 2	ABN Type 3	ABN Type 4
Accuracy (%)	ITAR [15]	76	77	78	79	79
	W-ITAR	85	82	84	82	80
Sensitivity (%)	ITAR [14]	89	89	89	89	89
	W-ITAR	92	87	89	87	91
Specificity (%)	ITAR [14]	74	65	68	61	68
	W-ITAR	89	79	89	82	81
Recall (%)	ITAR [14]	87	82	80	86	88
	W-ITAR	91	93	98	90	89
F-Measure(%)	ITAR [14]	89	86	90	84	80
	W-ITAR	95	90	92	89	88
CT (sec)	ITAR [14]	0.75	0.66	0.78	0.7	0.74
	W-ITAR	0.4	0.55	0.43	0.5	0.63

CONCLUSION

A new approach of feature representation for AF diagnosis based on the relational property of the data attributes and type values is presented. In the mining process for heart disease analysis, the clustering operation based on data type property of continuous and discrete is used. The sub-cluster formation results in optimal data clusters with AF features selection, in consideration with its type property. The type property is observed to be a significant observation in appropriate clustering of dataset, and shown a higher performance in classification accuracy. The weighted co-clustering over this sub-cluster improves the performance accuracy in consideration to class type values assigned to each class level.

REFERENCE

[1] Chih-Chun Chia, James Blum, ZahiKaram, Satinder Singh, Zeeshan Syed, “Predicting Postoperative Atrial Fibrillation from Independent ECG Components”, Association for the Advancement of Artificial Intelligence, 2014.

[2] L. Clavier, J. Boucher, R. Lepage, J. Blanc, and J. Cornily, “Automatic p-wave analysis of patients prone to atrial fibrillation,” Medical and Biological Engineering and Computing, vol. 40, pp. 63–71, 2002.

[3] E. Ros, S. Mota, F. Fernandez, F. Toro, and J. Bernier, “ECG characterization of paroxysmal atrial fibrillation: Parameter extraction and automatic diagnosis

algorithm," Computers in Biology and Medicine, vol. 34, no. 8, pp. 679 – 696, 2004.

[4] B. Pourbabaee and C. Lucas, "Automatic detection and prediction of paroxysmal atrial fibrillation based on analyzing ecg signal feature classification methods," in 2008 Cairo International Biomedical Engineering Conference, CIBEC 2008, Cairo, Egypt, 2008.

[5] B. Hickey, C. Heneghan, and P. De Chazal, "Non-episode-dependent assessment of paroxysmal atrial fibrillation through measurement of RR interval dynamics and atrial premature contractions," Annals of Biomedical Engineering, vol. 32, no. 5, pp. 677 – 687, 2004.

[6] D. Kim, Y. Seo, W. R. Jung, and C.-H. Youn, "Detection of long term variations of heart rate variability in normal sinus rhythm and atrial fibrillation ecg data," in International Conference on BioMedical Engineering and Informatics, BMEI 2008, vol. 2, Sanya, Hainan, China, 2008, pp. 404 – 408.

[7] N. Kikillus, M. Schweikert, and A. Bolz, "Identifying patients suffering from atrial fibrillation during atrial fibrillation and non-atrial fibrillation episodes," in IFMBE Proceedings, vol. 22, Antwerp, Belgium, 2008, pp. 1349 – 1352.

[8] N. Kikillus, G. Hammer, S. Wieland, and A. Bolz, "Algorithm for identifying patients with paroxysmal atrial fibrillation without appearance on the ecg," in Annual International Conference of the IEEE Engineering in Medicine and Biology - Proceedings, Lyon, France, 2007, pp. 275 – 278.

[9] N. Kikillus, G. Hammer, N. Lentz, F. Stockwald, and A. Bolz, "Three different algorithms for identifying patients suffering from atrial fibrillation during atrial fibrillation free phases of the ecg," in Computers in Cardiology, vol. 34, Durham, NC, United states, 2007, pp. 801 – 804.

[10] Y. Chesnokov, A. Holden, and H. Zhang, "Screening patients with paroxysmal atrial fibrillation (paf) from non-paf heart rhythm using hrv data analysis," in Computers in Cardiology, vol. 34, Durham, NC, United states, 2007, pp. 459 – 462.

[11] N. Lentz, N. Kikillus, and A. Bolz, "A screening method to detect atrial fibrillation with symbolic dynamics," in IFMBE Proceedings, vol. 25, no. 4, Munich, Germany, 2009, pp. 1464 – 1467.

[12] Steinberg JS, Zelenkofske S, Wong SC, Gelernt M, Sciacca R, Menchavez E. Value of the P wave signal-averaged ECG for predicting atrial fibrillation after cardiac surgery. *Circulation* 1993;88:2618-22.

[13] Stafford PJ, Kolvekar S., Cooper J. Signal averaged P wave compared with standard electrocardiography for prediction of atrial fibrillation after coronary artery bypass grafting. *Heart* 1997;77:417-22.

[14] K.Padmavathia, K.Sri Ramakrishna, "Classification of ECG signal during Atrial Fibrillation using Autoregressive modeling", Procedia Computer Science 46 (2015) 53 – 59.