ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

IJARCCE

International Journal of Advanced Research in Computer and Communication Engineering

NCDSPICE 2016

National Conference on Digital Signal Processing, Information and Communication Engineering

Govt. Polytechnic College, Kasaragod

Vol. 5, Special Issue 4, November 2016

Screening and Prediction of Paroxysmal Atrial Fibrillation using Adaptive Neuro-fuzzy Classifier

Asha N D [1], Paul Joseph K [2]

HOD, Biomedical Engineering Department, EKNM Govt. Polytechnic College, Thrikkaripur, India[1]

Professor, Electrical Engineering Department, NIT, Calicut, India [2]

Abstract: Paroxysmal atrial fibrillation (PAF) is intermittent atrial fibrillation which is not present all the time. Atrial fibrillation (AF) is one of the prominent causes of stroke and its risk increases with age. This paper explains a method to screen the patients with PAF from the normal sinus rhythm patients using Heart Rate Variability (HRV) parameters and also the prediction of onset of PAF. The time domain, frequency domain and nonlinear parameters are estimated. Feature selection is done with the use of Linguistic Hedges (LH) of fuzzy set. The selected features are fed to an Adaptive Neuro-fuzzy Classifier (ANFC) for screening as well as prediction. The accuracy obtained for screening and prediction were 94% and 93.75% respectively. The sensitivity in both cases found to be 100%.

Keywords: Paroxysmal Atrial Fibrillation, Heart rate variability, Time domain, Frequency domain, Nonlinear, Linguistic Hedges, Adaptive Neuro-fuzzy Classifier.

I. INTRODUCTION

Atrial fibrillation (AF) is the one of most common sustained disorder of cardiac rhythm which is often associated with a high risk of morbidity and mortality from coronary failure, stroke and thromboembolic complications. The AF related disease affects the quality of life. Its risk increases with age [1]. AF can be classified into three grades: paroxysmal, persistent and permanent AF. The paroxysmal AF (PAF) can be a preceding sign of the persistent AF. Episodes of PAF can last from seconds to hours or even days, but will spontaneously revert to normal sinus rhythm. Persistent AF lasts for more than 7 days, but responds to cardioversion and permanent AF does not respond to cardioversion. AF increases 5-fold risk of stroke, and one in five of all strokes are attributed to this arrhythmia. Ischemic strokes along with AF are often fatal, and survived patients are left more disabled by their stroke and more likely to suffer a recurrence than patients with other causes of stroke. In effect, the risk of death for AF-related stroke is doubled and the cost of care is increased 1.5-fold [2]. If a patient has a stroke, the survival rate is higher if he or she was appropriately anti-coagulated, probably because the stroke is smaller and not as debilitating. It has been suggested that PAF is more predominant than persistent atrial fibrillation in stroke and transient ischemic attack patients [3]. However, short asymptomatic paroxysmal atrial fibrillation events may remain undetected by traditional methods of screening.

The studies of prediction of PAF are based on heart rate variability (HRV) and Electrocardiogram (ECG). The methods used for the study are time domain analysis, nonlinear analysis and spectral analysis of the data. The main findings reported in the literature which precede PAF onset are the increase of the number of Premature Atrial Complexes (PAC), decrease of complexity indices like Approximate Entropy (ApEn) and Sample Entropy (SampEn) and increase in the spectral energy of the HRV dynamics. Thong et al. [4] studied the number of PAC after an irregular RR interval, runs of atrial bigeminy and trigeminy, and the length of a short run of paroxysmal atrial tachycardia. They used 30- min ECG segment for analysis. It is reported that an increase in the activity detected by any of these three criteria is an indication of a forthcoming episode of PAF immediately after the end of the 30-min segment. The sensitivity and specificity of the study is found to be 89% and 91% respectively [5]. Zong et al. [6] studied the number and timing of PACs in the ECG episodes. They found that not only the number of PACs increases in each episode preceding PAF, but also these complexes mostly occur near the end of these episodes. They achieved a sensitivity of 79% for predicting the onset of PAF.

Several studies have been conducted based on the HRV analysis. Shin et al. [7] and Vikman et al. [8] used ApEn, SampEn and short-term scaling exponent 'α' of HRV data and found a statistically significant decrease before onset of PAF. Spectral analysis of HRV data reported in the literature reveals that spectral parameters change in low frequency (LF) and high frequency (HF) bands before

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

IJARCCE

International Journal of Advanced Research in Computer and Communication Engineering

NCDSPICE 2016

National Conference on Digital Signal Processing, Information and Communication Engineering

Govt. Polytechnic College, Kasaragod

Vol. 5, Special Issue 4, November 2016

PAF: an increase in the LF band or HF band and energy increase in both bands simultaneously during 5 min to up to 2 h HRV data distant from PAF [9—15]. Fioranelli et al. [12] also identified an energy increase in LF band and a decrease in the HF band. Hickey et al. [16] developed a technique based on a combination of autonomic tone and atrial ectopic beat occurrence. They have used the temporal correlation between LF and HF spectral components in the classification process. They observed that subjects with PAF are likely to have LF and HF components, which are highly correlated. Chesnokov [17,18] combined complexity and spectral analysis of the 30-min HRV segment and found that there is a statistically significant increase in the very low frequency (VLF) band, low frequency (LF) band, and high frequency (HF) band for the records immediately before PAF compared to distant ones, but the LF / HF ratio doesn't show much change. He also showed that complexity features like ApEn and SampEn, and short time fractal properties exhibit smaller values in episodes preceding PAF compared to distant ones. Lynn et al. [19] proposed an algorithm based on non-linear features calculated from return map and difference map of HRV signal. They reported a sensitivity of 64% for their prediction method.

Yang et al. [20] developed another approach called Footprint analysis, to investigate heart rate dynamics before PAF and achieved a sensitivity of 57% for prediction of the onset of PAF. Mohebbi et al. [21] have done the recurrence quantification analysis of HRV and observed that there is significant change in the recurrence parameters. In another study Mohebbi et al. [22] used spectrum, bispectrum, and nonlinear features of the HRV signal. They noted that the frequency content and phase relations between frequency components of the HRV signal change before PAF events. H. Costin et al [23] used standard deviation of average five minute, the LF/HF ratio of the RR interval and morphologic variability (MV) of the ECG signal for PAF prediction. They found better accuracy for MV analysis than that obtained by means of HRV technique alone.

In this paper a more accurate screening and prediction of PAF is explained using time domain, frequency domain and nonlinear parameters of HRV. The database used for study is Atrial Fibrillation Prediction Data Base (AFPDB) and Normal Sinus Rhythm (NSR) database from Physionet. The objective of screening is to classify between normal individuals and PAF patients. A person whose is susceptible to PAF and normal most of the time can be identified using the screening method. Since the incidence of stroke is more in such person, it is able to start the anticoagulation therapy as early as possible. The prediction is done to identify onset patients from ordinary PAF patients. The screening and prediction is done using Adaptive Neuro-fuzzy Classifier.

II. MATERIALS AND METHODS

A. Database

The ECG data for analysis were taken from Physionet databases [24]. We used atrial fibrillation prediction database AFPDB and normal sinus rhythm database (NSRDB) with non-PAF heart rhythm. The AFPDB consisted of 30-min ECG segments immediately before PAF onset and segments at least 45 minute distance from any PAF occurrence. The records were taken from 25 subjects with documented PAF history. Each subject contains an odd numbered record name (p01, p03, . . ., p49) for the ECG segment distant from PAF event and even numbered record name (p02, p04, . . ., p50) for the ECG segment terminated immediately before PAF onset. The dataset consist of 40 NSRDB, 50 AFPDB training set have been downloaded from physionet. 5-min data are being used for the analysis. In the case of NSRDB the 5-min data are selected randomly but from AFPDB last 5-min data are used.

B. Pre-processing

The downloaded RR intervals are preprocessed to remove artifacts and nonstationarities in the time series. The nonstationarities are removed by the second order differencing of RR intervals. To resample the RR-interval, Cubic spline interpolation is used and the resampling frequency selected is 4Hz. Smoothness priors is used for removing the trend in which it is modelled as a linear observation model and the parameter estimation is done using regularized least means square estimate. The regularization parameter Lambda is taken as 500.

C. Feature Extraction

The features used for screening and prediction are time domain, frequency domain and nonlinear HRV parameters. The duration of data taken for analysis is 5-minutes. The data just before the occurrence of PAF is used for the analysis in the case of prediction.

1) Time Domain Analysis**:** The fluctuations in heart rate may be measured by a number of methods. Perhaps the simplest to perform are the time domain measures [25]. The simplest variables to calculate are the mean of NN interval (RR) and the standard deviation of the NN intervals (SDNN) the square root of variance. Since variance is mathematically equal to the total power of spectral analysis, SDNN reflects all the cyclic components responsible for variability in the period of recording. The mean HR and STD HR are the mean and standard deviation of HR which is (60/NN interval).The most commonly used measures derived from interval differences include RMSSD, the square root of the mean squared differences of successive NN intervals. NN50 is the number of interval differences of successive NN intervals greater than 50ms, and pNN50, the proportion

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

IJARCCE

International Journal of Advanced Research in Computer and Communication Engineering

NCDSPICE 2016

National Conference on Digital Signal Processing, Information and Communication Engineering

Govt. Polytechnic College, Kasaragod

Vol. 5, Special Issue 4, November 2016

derived by dividing NN50 by the total number of NN intervals. In addition to the above statistical measures, there are some geometric measures that are computed from the RR interval histogram. The HRV triangular index is obtained as the integral of the histogram divided by the height of the histogram which depends on the selected bin width. In order to obtain comparable results, a bin width of 1/128 seconds is used. Another geometric measure is the TINN which is the baseline width of the RR histogram evaluated through triangular interpolation.

2) Frequency domain Analysis: In the frequency-domain methods, a power spectrum density (PSD) is estimated for the RR interval series [25]. In HRV analysis, the PSD estimation is generally carried out using either FFT based methods or parametric AR modeling based methods. The advantage of FFT based methods is the easiness of implementation, while the AR spectrum yields improved resolution especially for short samples. In this paper, the power spectrum is computed by an AR modeling method. The order of the AR model is taken as 16 [3]. The Burg method is used to estimate the AR model parameters. The PSD of the AR model was computed by the equation:

$$PSD(f) = \frac{\sigma^2}{\left|1 + \sum_{k=1}^{P} a(k) e^{j2\pi fk}\right|^2} \quad (1)$$

where p= 16 and σ is the standard deviation of white noise. The generalized frequency bands in the case of short-term HRV recordings are the very low frequency (VLF, 0-0.04 Hz), low frequency (LF, 0.04 - 0.15 Hz), and high frequency (HF, 0.15 - 0.4 Hz) [25]. The frequency-domain measures extracted from the PSD estimate for each frequency band include peak frequencies, absolute and relative powers of VLF, LF, and HF bands, total power and LF/HF ratio.

3) Nonlinear Analysis: The nonlinear analysis of HRV assumes that the signal is chaotic. The parameters estimated are to quantify the chaotic nature of the HRV. The first step in nonlinear analysis is phase space reconstruction. It has two steps, the delay embedding and finding the embedding dimension of the signal. The delay embedding is done by considering the mutual information of the data. The embedding dimension is found by using the false nearest algorithm. The embedding dimension found to be 10 and time delay one. The parameters used for the analysis are Poincare´ plot parameters, Detrended fluctuation analysis (DFA), ApEn, SampEn and the recurrence plot parameters. The Poincare´ plot is a scatterplot of the current R-R interval plotted against the preceding R-R interval. The parameters estimated from Poincare´ plot are SD1, SD2 and SD12, the ratio between SD1 and SD2. SD1 measures the distribution of points perpendicular to the line of identity, whereas SD2 measures the dispersion on the line of identity [27].

HRV signal is a nonlinear non-stationary signal. Hence the analysis can be improved by detrending the signal. In DFA [28] analysis, the detrending of the signal is done by dividing the signal into small blocks and curve fitting is done by taking the least mean square error. The root-mean-square fluctuation of an integrated and detrended time series is measured at different observation windows and plotted against the size of the observation window on a log–log scale. The root-mean-square fluctuation of this integrated and detrended series is calculated using the equation:

$$F(n) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}[y(k) - y_n(k)]^2} \quad (2)$$

The fluctuation can be characterized by the short term scaling exponent ‘α1’($4 \le n < 11$) and long term scaling exponent ‘α2’ ($11 \le n \le N/4$) which is the slope of the line plotted between log [F (n)] to log (n).

ApEn[29] is defined as the logarithmic likelihood that the data patterns which are close to each other will remain close for the next comparison with a longer pattern. The more frequent and more similar patterns lead to the lower value of ApEn. Random signals will have higher values of ApEn. For an ‘N’ point dataset with ‘m’ embedding dimension and ‘r’ tolerance, the approximate entropy is given by

$$ApEn(m, r, N) = \frac{1}{N-m+1}\sum_{i=1}^{N-m+1}\ln[C_i^m(r)] - \frac{1}{N-m}\sum_{i=1}^{N-m}\ln[C_i^{m+1}(r)] \quad (3)$$

where is the correlation integral with ‘m’ data points. SampEn, improving ApEn quantifies the conditional probability that two sequences of ‘m’ consecutive data points that are similar to each other (within a given tolerance ‘r’) will remain similar when one consecutive point is included. There are two major differences between SampEn [31] and ApEn statistics. First, SampEn does not count self-matches. Second, SampEn does not use any template-wise approach when estimating conditional probabilities. To be defined, SampEn requires only that one template finds a match of length ‘m + 1’. The ‘m’ and ‘r’ are taken as two and (0.2*SD) respectively.

The recurrence plot is a visualization tool, which visualizes the recurrences of states in the phase space by a 2-dimensional plot. A recurrence is defined when the distance between two states i and j (points on the trajectory) is smaller than a threshold ε.

$$R_{i,j} = \Theta(\varepsilon_i - \|y(i) - y(j)\|),\ y(i) \in \Re^m, i, j = 1 \ldots N \quad (4)$$

where Θ is the Heaviside function, ‖ is Euclidean Norm.

In 1992, Zbilut and Webber [31] proposed to quantify the presence of patterns, like parallel lines of RPs, through

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

IJARCCE

International Journal of Advanced Research in Computer and Communication Engineering

NCDSPICE 2016

National Conference on Digital Signal Processing, Information and Communication Engineering

Govt. Polytechnic College, Kasaragod

Vol. 5, Special Issue 4, November 2016

statistical values and gave it the name 'Recurrence Quantification Analysis' (RQA). %REC quantifies the percentage of recurrent points falling within the specified radius. This variable can range from 0% (no recurrent points) to 100% (all points recurrent). The second recurrence variable is %determinism (%DET). %DET measures the proportion of recurrent points forming diagonal line structures. Diagonal line segments must have a minimum length defined by the line parameter, lest they be excluded. The name determinism comes from repeating or deterministic patterns in the dynamic. The third recurrence variable is maximum diagonal length LMAX, which is simply the length of the longest diagonal line segment in the plot, excluding the main diagonal line of identity (i = j). This is a very important recurrence variable because it inversely scales with the most positive Lyapunov exponent. Positive Lyapunov exponents gauge the rate at which trajectories diverge, and are the hallmark of dynamic chaos. Thus, the shorter the Lmax, the more chaotic (less stable) the signal is. The fourth recurrence variable Lmean is the average of diagonal line lengths which is larger than a minimum length. The fifth parameter entropy (ENTR), which is the Shannon information entropy of all diagonal line lengths distributed over integer bins in a histogram. ENTR is a measure of signal complexity and is calibrated in units of bits/bin. Individual histogram bin probabilities (Pbin) are computed for each non-zero bin and then summed according to Shannon's equation.

D. Adaptive Neuro-fuzzy classifier with linguistic hedges

Neuro-fuzzy systems are fuzzy systems, which use Artificial Neural Networks (ANN) in order to determine their properties by processing data samples. Neuro-fuzzy systems combine the power of the two paradigms: fuzzy logic and ANNs with the mathematical properties of ANNs in tuning rule-based fuzzy systems that approximate probably the same way human beings process information. A specific approach in neuro-fuzzy development is the adaptive neuro-fuzzy inference system (ANFIS). The ANFIS is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation [32]. Such framework makes the ANFIS modeling more systematic and less reliant on expert knowledge. In ANFIS, the membership function parameters are extracted from a data set that describes the system behavior. The ANFIS learns features in the data set and adjusts the system parameters according to a given error criterion [32]. Successful implementations of ANFIS in biomedical engineering have been reported, for classification [33-34] and data analysis [35].

In this paper the Adaptive Neuro-fuzzy Classifier (ANFC) with Linguistic Hedges (LH) is used for feature selection as well as classification [36]. LHs are special linguistic terms by which other linguistic terms are modified. "Very", "more or less", "extremely" etc. are used as LHs. Let A be a linguistic term for input variable 'x' with MF $\mu_A(x)$. Then A^s is interpreted as a modified version of the original linguistic term is expressed as [36]

$$A^s \Rightarrow \left\{ (x, (\mu_A(x))^p) \middle| x \in X \right\} \quad (5)$$

where p is the linguistic hedge value of A.

The ANFC with LHs is based on fuzzy rules. In this paper, the proposed ANFC is based on zero-order Sugeno fuzzy model. The defuzzification method used is the weighted average operator. There are five layers in the architecture. The nodes in the same layer have the same type of node functions [36]. The membership layer fuzzifies the input with Gaussian, bell-shape, triangle or trapezoidal Membership functions (MF). In this study, Gaussian function is employed. The second layer is the power layer which estimates the powers of fuzzy sets with their LHs. The modified membership grade α_{ijs} is given by

$$\alpha_{ijs} = \left(\mu_{ij}(x_{sj})\right)^{p_{ij}} \quad (6)$$

where p_{ij} is the LH value of the i^{th} rule and j^{th} feature [36]. In third layer the degree of fulfillment of the fuzzy rule is determined. This is also called the firing strength of a rule. In layer 4 weighted outputs are calculated, and every rule can affect each class according to their weights. The defuzzification method used is the weighted average. If a particular rule controls a specific class, the weight between this rule output and that class will be bigger than the other class weights. The defuzzified output of s^{th} sample that belongs to k^{th} class is given by

$$O_{sk} = \sum_{i=1}^{U} \beta_{is} w_{ik} \quad (7)$$

where w_{ik} represents the degree of belonging to the k^{th} class that is controlled by the i^{th} rule and U is the number of rules [36]. On the next layer the normalization of the summed weight is performed. The class label of s^{th} sample is given by the maximum normalized value. The parameters {c, σ, p} of the network could be adapted by any optimization method. The scaled conjugate gradient (SCG) is used to tune the network parameters [37]. The SCG is a second-order supervised training and derivative based method. The weights w_{ik} are also adjusted using SCG training. The cost function that is used in the SCG method is determined by the least squares means of the difference between the target and the estimated class value.

E. Feature Selection using ANFC with linguistic hedges

Cetişli [38] introduced a fuzzy feature selection (FS) method based on the LH concept. This makes use of the LH value of fuzzy sets for feature selection [36, 38]. If the LH value of fuzzy set of any feature for a particular class

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

IJARCCE

International Journal of Advanced Research in Computer and Communication Engineering

NCDSPICE 2016

National Conference on Digital Signal Processing, Information and Communication Engineering

Govt. Polytechnic College, Kasaragod

Vol. 5, Special Issue 4, November 2016

is one, that feature is important for that class. Since the implementation is using binary values, a threshold has to be set for the LH, which is taken as 0.5 in this case. The LH above 0.5 is considered as 1 and below 0.5 is considered as 0. If the LHs values of features are close to one, these features are most important or relevant, and can be selected. On the contrary, if the LH values of features are close to zero, these features are not important, and can be discarded. Every class is defined by only one fuzzy classification rule for each feature. The program creates a feature selection and a rejection criterion by using power values of the features. There are two selection criteria, one is the selection of features that have the biggest hedge value for any class and the other is the selection of features that have a bigger hedge value for every class, because any feature cannot be selective for every class. For that reason, a selective function should be described from the hedge values of any feature as in Eq. (8) [38]:

$$P_j = \prod_{i=1}^{k} p_{ij} \qquad (8)$$

where Pj denotes the selection value of the jth feature, and K is the number of classes. The Feature selection and classification algorithms were discussed in detail in [38].

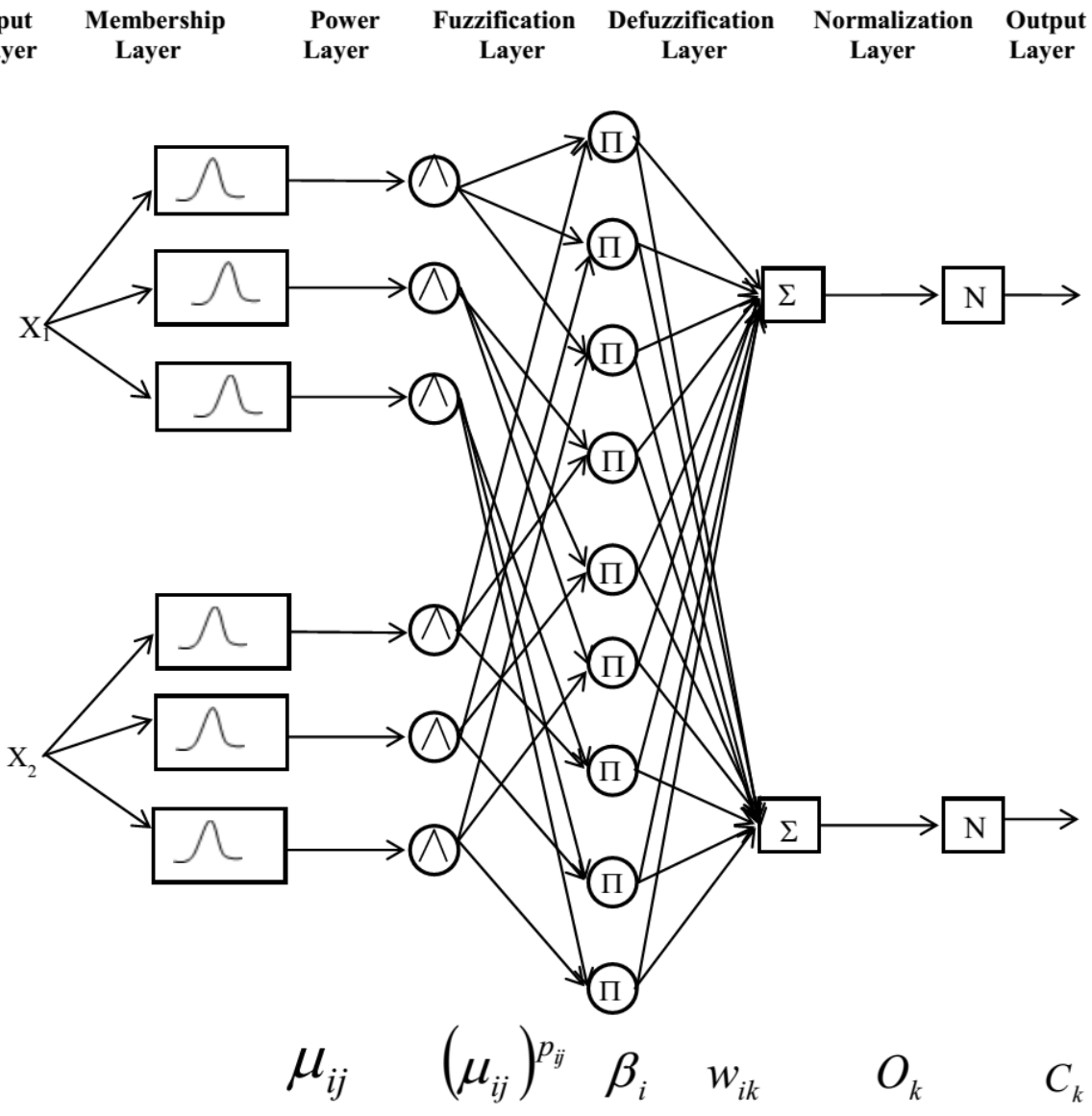

Figure 1 Structure of Adaptive Neuro-fuzzy classifier with linguistic hedges

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

IJARCCE

International Journal of Advanced Research in Computer and Communication Engineering

NCDSPICE 2016

National Conference on Digital Signal Processing, Information and Communication Engineering

Govt. Polytechnic College, Kasaragod

Vol. 5, Special Issue 4, November 2016

F. Statistical Analysis

The statistical analysis used in this case is Analysis of Variance (ANOVA). It is implemented in Microsoft Excel 2003® (Microsoft Corporation). Single-factor ANOVA is used here. The estimated parameters of NSR, PAF-normal and PAF-onset are entered into excel and the confidence level is taken as 95%. The p-values checked in each parameter to see the statistical significance. The mean and standard deviation also obtained from the analysis.

III. RESULTS

The RR-intervals are downloaded from physionet and pre-processing is done to remove noise. The estimated time domain parameters are given in Table I. The NSR means the normal sinus rhythm, PAF-normal consist of the odd numbered training set which is at least 45-minutes away from PAF occurrence and PAF-onset consists of the even numbered training set which is just before the occurrence of PAF. The results are given as mean± SD. The time domain like mean RR, mean HR was almost same for all the three cases. But this is not the case with STD RR, STD HR, pNN50, TINN etc. These values are more or less same for NSR and PAF-normal which indicates that time domain parameters shows present information.

The frequency domain parameters are shown in Table II.

Table I: The time domain parameters used as features and p-value of ANOVA test

Parameters	NSR	PAF-normal	PAF-onset	p-value
Mean RR	779.78±91.75	811.26±143.92	803.02±161.81	0.750
STD RR	33.36±11.62	37.03±19.91	72.38±38.05	1.00E-05
Mean HR	78.73±9.79	76.71±14.53	79.31±16.13	0.821
STD HR	4.27±1.55	4.74±4.11	10.39±8.19	0.001
RMSSD	30.64±19.26	52.06±31.89	96.8±58.8	0.00001
NN50	25.1±32.57	38.55±59.78	90.05±103.96	0.014
pNN50	6.97±9.54	9.61±12.89	21.83±22.04	0.009
Tri index	7.44±2.16	5.27±2.34	7.92±7.35	0.166
TINN	196.5±78.84	297.5±101.88	462.75±212.18	1.12E-06

The parametric method of estimation is used with AR model of order 16. Unlike time domain analysis, the frequency domain parameters show more similarity between PAF-normal & PAF-onset datasets. These values are very much different from NSR set. In the case of PAF patients more power is in the HF band and so the LF/HF ratio is always less than 1. But in the case of NSR more power is in the LF band. The HF band represents the vagal activity and as expected it to be more in the PAF patients. The LF band corresponds to sympathetic activity and vagal activity which is more in NSR which represents the normal condition of neural control.

Table II: The Frequency domain parameters used as features and p-value of ANOVA test

Parameters	NSR	PAF-normal	PAF-onset	p-value
VLF peak	0.037±0.007	0.030±0.015	0.039±0.0000	0.0155
LF peak	0.077±0.014	0.107±0.046	0.12±0.034	0.0008
HF peak	0.195±0.076	0.274±0.079	0.253±0.09	0.0194
VLF power	156.1±130.83	67±47.86	292.55±532.5	0.0865
LF power	704.7±619.49	261.3±246.85	1239.5±1794.0	0.0252
HF power	188.9±148.49	681.75±624.54	2215±2413.24	0.0001
Total power	1050.8±757.36	1014.35±865.71	3760.1±4400.5	0.0016
VLF power%	15.37±7.48	9.39±8.03	6.74±4.25	0.0006
LF power %	63.77±14.55	25.98±13.87	29.13±13.04	0.0000
HF power%	20.73±14.1	64.1±20.47	63.69±15.66	0.0000
LF n.u	75.55±16.16	29.97±17.89	31.64±14.70	0.0000
HF n.u	24.29±16	69.44±17.64	67.88±14.7	0.0000
LF/HF ratio	4.99±3.379	0.534±0.433	0.54±0.38	0.0000

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

IJARCCE

International Journal of Advanced Research in Computer and Communication Engineering

NCDSPICE 2016

National Conference on Digital Signal Processing, Information and Communication Engineering

Govt. Polytechnic College, Kasaragod

Vol. 5, Special Issue 4, November 2016

In Table III, nonlinear parameters estimated are listed. There is a clear difference between NSR and PAF parameters except RQA parameters. The DFA parameters Alpha1 and Alpha 2 are almost same for PAF-normal &PAF-onset but it is much less compared to NSR which indicates that the fractal nature is reduced in PAF. The SD1, SD2, ApEn and SampEn are different for PAF-normal & PAF-onset.

In the first phase screening of patients as normal and PAF is done. The estimated 33 parameters are fed into an adaptive neuro-fuzzy classifier with NSR as 1 and PAF as 2. The data used for training are 20 NSR and 20 PAF datasets. For testing, 20 NSR and 30 PAF datasets are used. The classification was done with and without feature selection. The classification accuracy with all 33 parameters was 84% with sensitivity and specificity 84%. The feature selection was done with Linguistic Hedges with fuzzy set. The number of features selected was seven and the selected features are TINN, LF peak, HF power (%), LF (n.u), HF (n.u), LF/HF ratio and Lmax. A classification accuracy of 94% was obtained. The sensitivity and specificity was 100% and 88% respectively. The classification accuracy is increased as well as the complexity is reduced. Six clusters were used for classification. The performance errors were 1.26E-08 and 0.048185 respectively without and with feature selection.

Table III: The Nonlinear parameters used as features

Parameters	NSR	PAF-normal	PAF-onset	p-value
SD1	21.7±13.64	36.85±22.58	68.37±41.83	1.2E-05
SD2	40.77±13.64	36.67±18.20	68.05±42.64	0.001
SD1/SD2	0.55±0.29	0.99±0.27	1.08±0.49	3.9E-05
Lmean	14.6±11.86	21.75±13.78	32.99±36.95	0.056
Lmax	174±113.09	144.9±89.04	147.45±103.26	0.611
REC	37.36±12.98	54.85±22.54	53.17±26.16	0.022
DET	98.17±1.14	98.72±1.42	98.62±1.78	0.472
ENTR	3.266±0.45	3.54±0.53	3.55±0.69	0.207
ApEn	1.16±0.08	1.07±0.19	0.81±0.32	1.3E-05
SampEn	1.542±0.26	1.198±0.32	0.86±0.57	1.1E-05
Alpha1	1.24±0.31	0.59±0.24	0.61±0.28	1.4E-10
Alpha2	0.45±0.12	0.37±0.17	0.32±0.19	0.041

In the second phase, the prediction of PAF was done with the help of the same parameters. Here 35 dataset in the training set is used for training and 15 data are used for testing. Here also classification was done with and without feature selection. The classification accuracy for both cases found to be 93.75%. The sensitivity was 100% and specificity was 83.33% in both cases. But the number of selected features was only two and the selected features were pNN50 and ApEn. Thus the complexity of the network is much reduced for the same accuracy.

IV. DISCUSSION

In this study the screening and prediction of PAF are implemented. The classification between NSR and PAF as well as PAF normal and PAF onset is done. The features used are time domain, frequency domain and nonlinear parameters of HRV. The statistical analysis is done to verify the significance of each parameter. The length of the data used for the analysis was 5-min. An unidentified PAF may lead to stroke. A PAF patient during normal condition does not show any change in the ECG. Hence it is difficult to identify the persons with PAF. But our study showed that even though there is not much change in the time domain parameters of NSR and PAF patients, the frequency domain and nonlinear parameters show much difference that is sufficient enough to identify persons with PAF. It is observed that the normalized HF power is more in PAF patients whereas the LF power is more in NSR. The HF power corresponds to vagal activity and LF power mainly represents sympathetic activity. The vagal activity is high in PAF patients so that their HR is reduced. There is much difference in the ratio SD1/SD2 which is also an indication of sympathovagal balance. The analysis shows a clear difference in Alpha1 of DFA analysis which indicates that the reduction in the fractal nature of the HRV. The ApEn and SampEn also show variation between NSR and PAF.

Table IV: Result of screening of PAF

	Accuracy	Sensitivity	Specificity
Without FS	84 %	84%	84%
With FS using LHs	94%	100%	88%

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

IJARCCE

International Journal of Advanced Research in Computer and Communication Engineering

NCDSPICE 2016

National Conference on Digital Signal Processing, Information and Communication Engineering

Govt. Polytechnic College, Kasaragod

Vol. 5, Special Issue 4, November 2016

In the case of PAF normal and PAF onset patients, the time domain parameters show a clear difference between the two cases. The STD RR and STD HR show difference which indicates that the heart rate is more fluctuating just before the occurrence of PAF. TINN is also showing large variation between the two cases which reinforces the previous observation. In frequency domain analysis, the power in all the bands as well as the total power increased at the onset. But the percentage power as well as the normalized power remains almost same which indicates that the distribution of power in both cases is same. In the case of nonlinear analysis, Poincare parameters and entropies show the difference between both cases. ApEn and SampEn reduce during the onset. Alpha1 and alpha2 almost remain constant which indicates that the fractal nature is changed once the normal sinus rhythm is lost.

Table V: Summary of result of prediction

	Accuracy	Sensitivity	Specificity
Without FS	93.75 %	100%	83.33%
With FS using LHs	93.75%	100%	88.33%

This study shows that these features are good markers to discriminate the PAF patients from normal individuals. The prediction of PAF onset is also possible with these features. The screening of PAF patient is very important since one of the major causes of stroke is PAF. When the patient is under control, the ECG will be normal and so PAF is unidentified. But just by taking 5-min HRV the PAF can be identified. The sensitivity of screening was 100% whereas specificity was 88% which is high compared to existing methods. The prediction method also uses only 5-min data and the sensitivity and specificity is high.

During the study we observed that as the number of clusters increases in fuzzy classification up to seven the accuracy was also increasing. But the consistency of the result was less compared to lesser clusters. The number of clusters used in our study is six. By considering other parameters like instantaneous power and instantaneous frequency the result may improve to 100% accuracy with more consistent result.

V. CONCLUSION

The present day technology of pacing for preventing the onset of atrial arrhythmias needs accurate predictors of these arrhythmias. During a regular check-up of a person with 5-min of ECG, it is capable to distinguish the risk of PAF which may lead to permanent AF as well as stroke. This study presents an answer to the above problems. The time domain, frequency domain and nonlinear parameters are used for the screening and prediction with only 5-min data. The ANFIS with linguistic hedges produced a good performance for the screening and prediction. The feature selection using LH also found to be a good choice for this application. With a bare minimum of two features, we could predict the risk of PAF which assumes great significance in the context of online prediction.

REFERENCES

1. Furberg, C. D., Psaty, B. M., Manolio, T. A., Gardin, J. M., Smith, V. E., & Rautaharju, P. M. (1994). Prevalence of atrial fibrillation in elderly subjects (the Cardiovascular Health Study). The American journal of cardiology, 74(3), 236-241.
2. Camm, A. J., Kirchhof, P., Lip, G. Y., Schotten, U., Savelieva, I., Ernst, S., & Folliguet, T. (2010). Guidelines for the management of atrial fibrillation, The Task Force for the Management of Atrial Fibrillation of the European Society of Cardiology (ESC). European heart journal, 31(19), 2369-2429.
3. Bollmann, A., & Lombardi, F. (2006). Electrocardiology of atrial fibrillation. Engineering in Medicine and Biology Magazine, IEEE, 25(6), 15-23.
4. Thong, T., McNames, J., Aboy, M., & Goldstein, B. (2004). Prediction of paroxysmal atrial fibrillation by analysis of atrial premature complexes. Biomedical Engineering, IEEE Transactions on, 51(4), 561-569.
5. Moody, G., Goldberger, A., McClennen, S., & Swiryn, S. (2001). Predicting the onset of paroxysmal atrial fibrillation: The Computers in Cardiology Challenge 2001. In Computers in Cardiology 2001 (pp. 113-116). IEEE.
6. Zong W., Mukkamala R., & Mark, R. G. (2001). A methodology for predicting paroxysmal atrial fibrillation based on ECG arrhythmia feature analysis. In Computers in Cardiology 2001 (pp. 125-128). IEEE.
7. Shin, D. G., Yoo, C. S., Yi, S. H., Bae, J. H., Kim, Y. J., Park, J. S., & Hong, G. R. (2006). Prediction of paroxysmal atrial fibrillation using nonlinear analysis of the RR interval dynamics before the spontaneous onset of atrial fibrillation. Circulation journal: official journal of the Japanese Circulation Society, 70(1), 94.
8. Vikman, S., Mäkikallio, T. H., Yli-Mäyry, S., Pikkujämsä, S., Koivisto, A. M., Reinikainen, P., & Huikuri, H. V. (1999). Altered complexity and correlation properties of RR interval dynamics before the spontaneous onset of paroxysmal atrial fibrillation. Circulation, 100(20), 2079-2084.
9. Herweg, B., Dalal, P., Nagy, B., & Schweitzer, P. (1998). Power spectral analysis of heart period variability of preceding sinus rhythm before initiation of paroxysmal atrial fibrillation. The American journal of cardiology, 82(7), 869-874.
10. Huang, J. L., Wen, Z. C., Lee, W. L., Chang, M. S., & Chen, S. A. (1998). Changes of autonomic tone before the onset of paroxysmal atrial fibrillation. International journal of cardiology, 66(3), 275-283.
11. Fioranelli, M., Piccoli, M., Mileto, G. M., Sgreccia, F., Azzolini, P., Risa, M. P., & Puglisi, A. (1999). Analysis of heart rate variability five minutes before the onset of paroxysmal atrial fibrillation. Pacing and clinical electrophysiology, 22(5), 743-749.
12. Bettoni, M., & Zimmermann, M. (2002). Autonomic tone variations before the onset of paroxysmal atrial fibrillation. Circulation, 105(23), 2753-2759.
13. Amar, D., Zhang, H., Miodownik, S., & Kadish, A. H. (2003). Competing autonomic mechanisms precedethe onset of postoperative atrial fibrillation. Journal of the American College of Cardiology, 42(7), 1262-1268.
14. Tomita, T., Takei, M., Saikawa, Y., Hanaoka, T., Uchikawa, S. I., Tsutsui, H., & Kubo, K. (2003). Role of autonomic tone in the initiation and termination of paroxysmal atrial fibrillation in patients without structural heart disease. Journal of cardiovascular electrophysiology, 14(6), 559-564.

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

IJARCCE

International Journal of Advanced Research in Computer and Communication Engineering

NCDSPICE 2016

National Conference on Digital Signal Processing, Information and Communication Engineering

Govt. Polytechnic College, Kasaragod

Vol. 5, Special Issue 4, November 2016

15. Vincenti, A., Brambilla, R., Fumagalli, M. G., Merola, R., & Pedretti, S. (2006). Onset mechanism of paroxysmal atrial fibrillation detected by ambulatory Holter monitoring. Europace, 8(3), 204-210.
16. Hickey, B., Heneghan, C., & De Chazal, P. (2004). Non-episode-dependent assessment of paroxysmal atrial fibrillation through measurement of RR interval dynamics and atrial premature contractions. Annals of Biomedical Engineering, 32(5), 677-687.
17. Chesnokov, Y. V., Holden, A. V., & Zhang, H. (2007). Screening patients with paroxysmal atrial fibrillation (PAF) from non-PAF heart rhythm using HRV data analysis. In Computers in Cardiology, 2007 (pp. 459-462). IEEE.
18. Chesnokov, Y. V. (2008). Complexity and spectral analysis of the heart rate variability dynamics for distant prediction of paroxysmal atrial fibrillation with artificial intelligence methods. Artificial intelligence in medicine, 43(2), 151-165.
19. Hickey, B., & Heneghan, C. (2002, September). Screening for paroxysmal atrial fibrillation using atrial premature contractions and spectral measures. In Computers in Cardiology, 2002 (pp. 217-220). IEEE.
20. Lynn, K. S., & Chiang, H. D. (2001). A two-stage solution algorithm for paroxysmal atrial fibrillation prediction. In Computers in Cardiology 2001 (pp. 405-407). IEEE.
21. Mohebbi, M., & Ghassemian, H. (2011). Prediction of paroxysmal atrial fibrillation using recurrence plot-based features of the RR-interval signal. Physiological Measurement, 32(8), 1147.
22. Mohebbi, M., & Ghassemian, H. (2012). Prediction of paroxysmal atrial fibrillation based on non-linear analysis and spectrum and bispectrum features of the heart rate variability signal. Computer methods and programs in biomedicine, 105(1), 40-49.
23. Costin, H., Rotariu, C., & Păsărică, A. Atrial Fibrillation Onset Prediction Using Variability of ECG Signals.
24. Physionet NSR and AFDB database. http://www.physionet.org /physiobank/database [accessed June, 2013].
25. Camm, A. J., Malik, M., Bigger, J. T., Breithardt, G., Cerutti, S., Cohen, R. J., & Singer, D. H. (1996). Heart rate variability: standards of measurement, physiological interpretation and clinical use. Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology. Circulation, 93(5), 1043-1065.
26. Boardman, A., Schlindwein, F. S., Rocha, A. P., & Leite, A. (2002). A study on the optimum order of autoregressive models for heart rate variability. Physiological measurement, 23(2), 325.
27. Karmakar, C., Khandoker, A., Gubbi, J., & Palaniswami, M. (2009). Complex Correlation Measure: a novel descriptor for Poincaré plot. Biomedical engineering online, 8(1), 17.
28. Peng, C. K., Havlin, S., Stanley, H. E., & Goldberger, A. L. (1995). Quantification of scaling exponents and crossover phenomena in nonstationary heartbeat time series. Chaos: An Interdisciplinary Journal of Nonlinear Science, 5(1), 82-87.
29. Pincus, S. M. (1991). Approximate entropy as a measure of system complexity. Proceedings of the National Academy of Sciences, 88(6), 2297-2301.
30. Richman, J. S., & Moorman, J. R. (2000). Physiological time-series analysis using approximate entropy and sample entropy. American Journal of Physiology-Heart and Circulatory Physiology, 278(6), H2039-H2049.
31. Zbilut, J. P., Giuliani, A., & Webber, C. L. (1998). Recurrence quantification analysis and principal components in the detection of short complex signals. Physics Letters A, 237(3), 131-135.
32. Jang, J. S. (1993). ANFIS: adaptive-network-based fuzzy inference system. Systems, Man and Cybernetics, IEEE Transactions on, 23(3), 665-685.
33. USHER, J., CAMPBELL, D., VOHRA, J., & CAMERON, J. (1999). A Fuzzy Logic-Controlled Classifier for Use in Implantable Cardioverter Defibrillators. Pacing and clinical electrophysiology, 22(1), 183-186.
34. Güler, İ., & Übeyli, E. D. (2005). A modified mixture of experts' network structure for ECG beats classification with diverse features. Engineering Applications of Artificial Intelligence, 18(7), 845-856.
35. Virant-Klun, I., & Virant, J. (1999). Fuzzy logic alternative for analysis in the biomedical sciences. Computers and Biomedical Research, 32(4), 305-321.
36. Cetisli, B. (2010). Development of an adaptive neuro-fuzzy classifier using linguistic hedges: Part 1. Expert Systems with Applications, 37(8), 6093-6101.
37. Møller, M. F. (1993). A scaled conjugate gradient algorithm for fast supervised learning. Neural networks, 6(4), 525-533.
38. Cetisli, B. (2010). The effect of linguistic hedges on feature selection: Part 2. Expert Systems with Applications, 37(8), 6102-6108.