CLASSIFICATION OF CARDIAC SIGNALS USING TIME DOMAIN METHODS

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ABSTRACT

Electrocardiography (ECG) deals with the electrical activity of the heart. The condition of cardiac health is given by ECG and heart rate. A study of the non-linear dynamics of ECG signals for arrhythmia characterization is considered. The statistical analysis of the calculated features indicate that they differ significantly between normal heart rhythm and the different arrhythmia types and hence, can be rather useful in ECG arrhythmia detection. The discrimination of ECG signals using statistical parameters is of crucial importance in the cardiac disease therapy. The four statistical parameters considered for cardiac arrhythmia classification of the ECG signals are the standard deviation of the NN intervals (SDNN), the standard deviation of differences between adjacent NN intervals (SDSD), the root mean square successive difference of intervals which are extracted from heart rate signals (RMSSD) and the proportion derived by dividing NN50 by the total number of NN intervals (pNN50). The inclusion of Adaptive neuro fuzzy interface system (ANFIS) in the complex investigating algorithms yield very interesting recognition and classification capabilities across a broad spectrum of biomedical problem domains. Using the computed statistical parameter classification was done using Analytical method and an accuracy of 66% was achieved. The ANFIS method was compared with Analytical method. ANFIS classifier was used for the classification and an accuracy of 94% was achieved which shows that ANFIS classifier is the best of the two methods compared.

Keywords: arrhythmia detection, ECG, heart rate, SDNN, SDSD, RMSD, NN50, pNN50, ANFIS.

1.0 INTRODUCTION

The electrical impulse conduction in the myocardium is related to the electrical properties of the cardiac cells. The ECG is a time varying signal reflecting the ionic current flow which causes the cardiac fibers to contract and subsequently relax.

2.0 ECG CHARACTERISTICS

The electrical signals described are measured by the ECG where each heart beat is displayed as a series of electrical waves characterized by peaks and valleys. An ECG gives two major kinds of information. First, by measuring time intervals on the ECG, the duration of the electrical wave crossing the heart can be determined and consequently we can determine whether the electrical activity is normal or slow, fast or irregular. Second, by measuring the amount of electrical activity passing through the heart muscle, a pediatric cardiologist may be able to find out if parts of the heart are too large or are overworked. The frequency range of an ECG signal is [0.05-100] Hz and its dynamic range is [1-10] mV. The ECG signal is characterized by five peaks and valleys labeled by successive letters of the alphabet P, Q, R, S and T. A good performance of an ECG analyzing system depends heavily upon the accurate and reliable detection of the QRS complex, as well as the T and P waves. The P wave represents the activation of the upper chambers of the heart, the atria while the QRS wave (or complex) and T wave represent the excitation of the ventricles or the lower chambers of the heart. The detection of the QRS complex is the most important task in automatic ECG signal analysis. Once the QRS complex has been identified, a more detailed examination of ECG signal, including the heart rate, the ST segment, etc., can be performed. Figure-1 shows ECG waveform characteristics and their corresponding positions in heart [1].

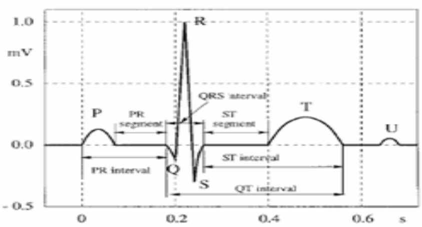

Figure-1. The ECG signal and its different components.

3.0 REVIEW OF LITERATURE

Cuiwei Li *et al.*, (1995) showed that with multi scale information in wavelets it is easy to characterize the ECG waves and the QRS complex. The difference from high P and T waves, noise, baseline drift and interference were recognized [2]. Senhadi *et al.*, (1995) compared wavelet transforms for recognizing cardiac patterns. The choice of the wavelet family as well as the selection of the analyzing function into these families have been discussed to the Daubechies decompositions provided by the spline wavelet (6 levels) and the complex wavelet (10 levels) [3]. Amara Graps (1995) showed that though D6 algorithm is more complex and has a slightly higher computational overhead but it picks up detail that is missed by the Harr wavelet algorithm, which is simpler than the former. D6 of Debauchees is similar in shape to QRS complex and their energy spectrum is concentrated around low frequencies

[4]. Task force (1996) gave guidelines for HRV including Heart rate variability-standards of measurement, physiological interpretation for clinical use [5]. Juha-Pekka Niskanen (2002) proposed the time domain methods for cardiac arrhythmia classification [6].

4.0 ECG FEATURE EXTRACTION

An ECG feature extraction system is based on the multi-resolution wavelet transform. ECG signals from Modified Lead II (MLII) are chosen for processing as the peaks of the R waves in signals from the ML II lead have the largest amplitudes among other leads. The result of applying two Daubechies wavelet filters (D4 and D6) of different length on the signal is compared. The wavelet filter with scaling function more closely similar to the shape of the ECG signal achieved better detection [4]. Db wavelet family is similar in shape to QRS complex and their energy spectrums are concentrated around low frequencies the signal is approximated by omitting the signal's high frequency components. The ECG signal and the details for eight wavelet scales are used which are scaled for better illustration. The detection of R peaks is shown in Figure-2.

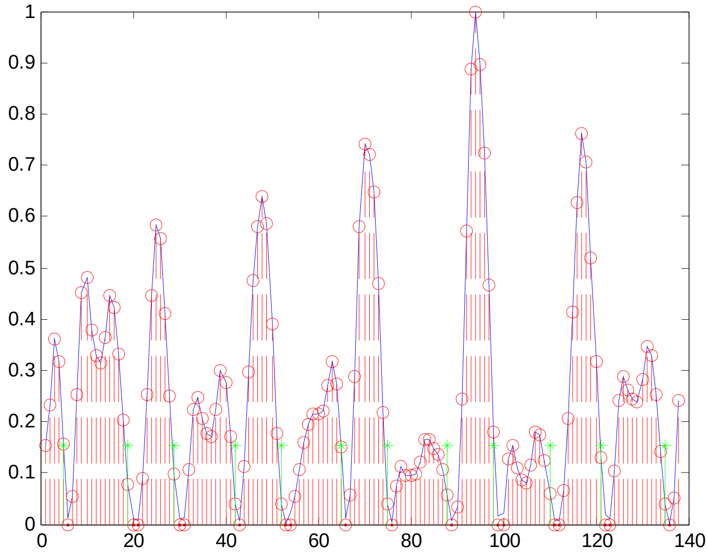

Figure-2. R peak detection.

5.0 ECG DATA USED

All the ECG data required for this work is used from American Institute of Physics, 1995, USA [7].

6.0 TIME DOMAIN ANALYSIS FOR ECG

Variation in heart rate may be evaluated by a number of methods. Perhaps the simplest to perform are the time domain measures. With these methods either the heart rate at any point in time or the intervals between successive normal complexes are determined. In a continuous ECG record, each QRS complex is detected, and the so-called normal-to-normal (NN) intervals (that is all intervals between adjacent QRS complexes resulting from sinus node depolarization), or the instantaneous hear rate is determined, Simple time-domain variables that can be calculated include the mean NN interval, the mean heart rate, the difference between night and day heart rate, etc. Other time-domain measurements that can be used are variation in instantaneous heart rate secondary to respiration, tilt, Valsalva manoeuvre, or secondary to phenylephrine infusion. These differences can be described as either differences in heart rate or cycle length. From the original R-R intervals, four standard measures parameters used in this work are:

1. The standard deviation of the NN intervals (SDNN).
2. The standard deviation of differences between adjacent NN intervals (SDSD)
3. The root mean square successive difference of intervals (RMSSD).
4. The number of interval differences of successive NN intervals greater than 50ms (NN50) used for the proportion derived by dividing NN50 by the total number of NN intervals (pNN50).

6.1. Statistical methods

From a series of instantaneous heart rates or cycle intervals, particularly those recorded over longer periods, traditionally 24 hours, more complex statistical time-domain can be calculated. These may be divided into two classes (a) those derived from direct measurements of the NN intervals or instantaneous heart rate and (b) those derived from the differences between NN intervals. These variables may be derived from analysis of the total ECG recording or may be calculated using smaller segments of the recording period.

ARPN Journal of Engineering and Applied Sciences

6.1.1. Standard deviation of the NN intervals

The simplest variable to calculate is the SDNN that is the square root of variance. Since variance is mathematically equal to total power of spectral analysis, SDNN reflects all the cyclic components responsible for variability in the period of recording. In many studies, SDNN is calculated over a 24 hours period and thus encompasses both short-term high frequency variation, as well as the lowest frequency components seen in a 24-hours period, as the period of monitoring decreases, SDNN estimates shorter and shorter cycle lengths. It should also be noted that the total variance of HRV increases with the length of analyzed recording. Thus on arbitrarily selected ECGs, SDNN is not a well defined statically quantity because of its dependence on the length of recording period. Thus, in practice, it is inappropriate to compare SDNN measures obtained from recordings of different durations. However, durations of the recordings used to determine SDNN values (and similarly other HRV measures) should be standardized. A short-term recording are used in this work. Calculation of standard deviation is shown in equation 1.

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \overline{x})^2}\,, \quad (1)$$

Where $\{x_1, x_2, \ldots, x_N\}$ is the sample and $\overline{x}$ is the mean of the sample. The denominator $N-1$ is the number of degrees of freedom in the vector $(x_1-\overline{x}, \ldots, x_N-\overline{x})$.

6.1.2. Standard deviation of differences between adjacent NN intervals

The most commonly used measures derived from interval differences include the standard deviation of differences between adjacent NN intervals. Calculation of standard deviation is show in equation 1.

6.1.3. Root mean square successive difference of intervals

The most commonly used measures derived from interval differences include the square root of the mean squared differences of successive NN intervals. Calculation of root mean square is show in equation 2.

$$x_{\mathrm{rms}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} = \sqrt{\frac{x_1^2 + x_2^2 + \cdots + x_n^2}{n}} \quad (2)$$

The rms for a collection of n values $\{x_1, x_2, \ldots, x_n\}$ is shown in equation 2.

6.1.4. Proportion- pNN50

The number of interval differences of successive NN intervals greater than 50ms (NN50) is calculated. It is used for the proportion derived by dividing NN50 by the total number of NN intervals (pNN50).
All the four statistical parameters are computed for the entire database [7].

7.0 ARRHYTHMIA CLASSIFICATION

Arrthymia considered for the purpose of this study were classified into eight categories, namely

(i) Left bundle branch block (LBBB).

(ii) Normal sinus rhythm (NSR).

(iii) Pre-ventricular contraction (PVC).

(iv) Atrial fibrillation (AF).

(v) Ventricular fibrillation (VF).

(vi) Complete heart block (CHB).

(vii) Ischemic dilated Cardiomyopathy (ISCH).

(viii) Sick sinus syndrome (SSS) [8].

Table-1. Range of input parameters for classification model.

Class	SDNN	SDSD	RMSSD	pNN50(%)
LBBB	30.6±11.48	32.8±6.17	32.5±6.17	4.41±2.18
NSR	28.7±25.32	32.2±24.5	31.9±24.2	7.01±11.6
PVC	432.0±8.91	714±156.1	708±152.0	40.8±18.14
AF	254.85±57.48	467.9±155.65	466.4±155.21	48.4±0.73
VF	22.4±14.066	31.0±22.23	30.9±22.17	7.52±13.03
CHB	81.4±49.47	99.9±67.95	99.8±67.92	12.5±14.8
ISCH	103.2±151.79	3.73±5.46	140.7±24.62	2.48±3.83
SSS	274.85±74.69	369.08±87.7	368.81±87.62	35.1±10.3

8.0 ANALYTICAL CLASSIFIER

The four statistical parameters computed for the ECG data are used for this method of classification. A program was written for the classification based on the range of the input parameters given in Table-1. The program was evaluated for the database and overall accuracy was computed and tabulated in Table-2. An accuracy of 65.62% was achieved. The output of a sample signal is shown in Figure-3.

Table-2. The results of the two classifiers.

Type Of signal	No. of data sets used for testing	Output Of Analytical method	Output Of ANFIS classifier	Accuracy (%) Analytical method	Accuracy (%) ANFIS classifier
LBBB	4	3	4	75	100
NSR	7	5	7	71.42	100
PVC	4	2	3	50	75
AF	3	2	2	66.66	66.66
VF	5	4	5	80	100
CHB	3	1	3	33.33	100
ISCH	3	2	3	66.66	100
SSS	3	2	3	66.66	100
Total	32	21	30	65.62	93.75

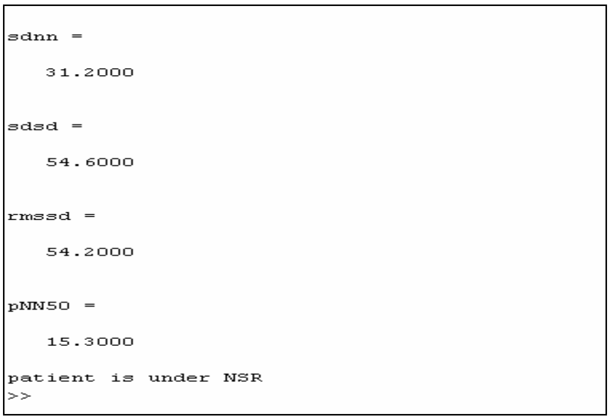

Figure-3. The output of analytic classifier.

9.0 ANFIS CLASSIFIER

Both neural networks and fuzzy logic are universal estimators. They can approximate any function to any prescribed accuracy, provided that sufficient hidden neurons and fuzzy rules are available. Recent results show that the fusion procedure of these two different technologies seems to be very effective for the systems identification. Gradient descent and Back propagation algorithms are used to adjust the parameters of membership functions (fuzzy sets) and the weights of defuzzification (neural networks) for fuzzy neural networks. ANFIS applies two techniques in updating parameters. The ANFIS is a FIS implemented in the framework of an adaptive fuzzy neural network. It combines the explicit knowledge representation of a FIS with the learning power of ANNs [9]. The objective of ANFIS is to integrate the best features of fuzzy systems and neural networks. The advantage fuzzy a set is the representation of prior knowledge into a set of constraints to reduce the optimization research space is utilized. The adaptation of back propagation to structured network to automate fuzzy control parametric tuning is utilized from NN. For premise parameters that define membership functions, ANFIS employs gradient descent algorithm to fine-tune them. For consequent parameters that define the coefficients of each equation, ANFIS uses the least-squares method to identify them. This approach is thus called hybrid learning method since it combines gradient descent algorithm and least-squares method. To achieve good generalization toward unseen data, the size of the training data set should be at least as big as the number of modifiable parameters in ANFIS. Functionally there are almost no constrains on the node functions of an adaptive network except for the requirement of piecewise differentiability [10]. The neurons in ANFIS have different structures.

- The Membership function is defined by parameterized soft trapezoids (Generalized Bell Functions).
- The rules are differentiable T-norm usually product.
- The Normalization is by Sum and arithmetic division.
- Functions are linear regressions and multiplication with $\overline{w}$, that is, normalized weights ω, and Output (Algebraic Sum).

Hybrid systems are a growing research area in medical applications. This system overcomes some of the major drawbacks of conventional expert systems such as the consultation with human experts for knowledge acquisition.

The four statistical parameters are used as input for the ANFIS classifier.

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10.0 CLASSIFICATION USING ANFIS

The classification of cardiac arrhythmia using ANFIS uses GBELLMF generalized bell curve membership function. GBELLMF (X, PARAMS) returns a matrix, which is the generalized bell membership function evaluated at X. PARAMS are a 3-element vector that determines the shape and position of this membership function (MF). The generalized bell function is shown in Figure-4 depends on three parameters a, b, and c as given by:

$$f(x,a,b,c)=\frac{1}{1+\left|\frac{x-c}{a}\right|}2b \qquad (3)$$

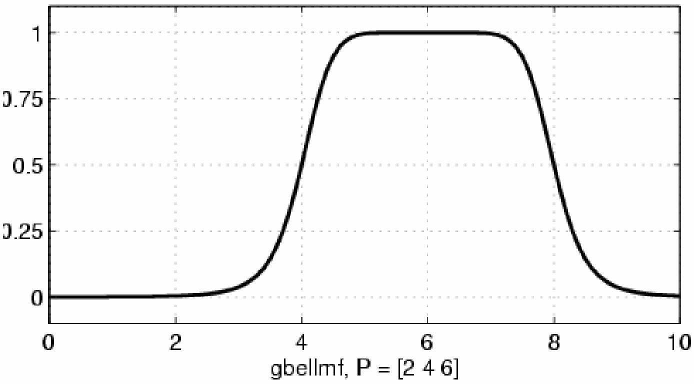

Figure-4. Generalized bell membership function.

The membership functions (MFs) of SDNN, SDSD, RMSSD and pNN50 are plotted. .As an example the MFs of SDNN is shown in Figures-5 and 6.

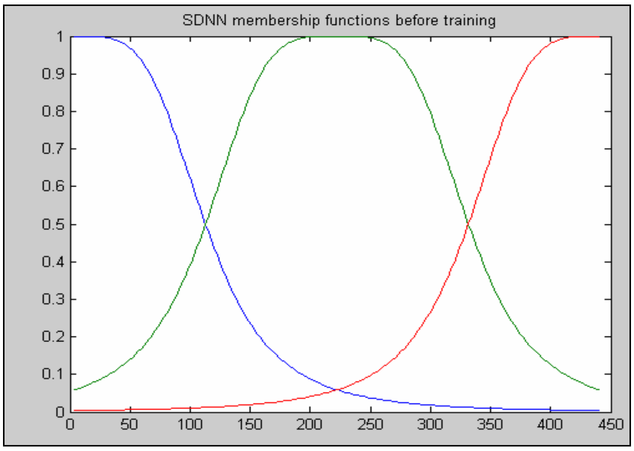

Figure-5. SDNN membership function before training.

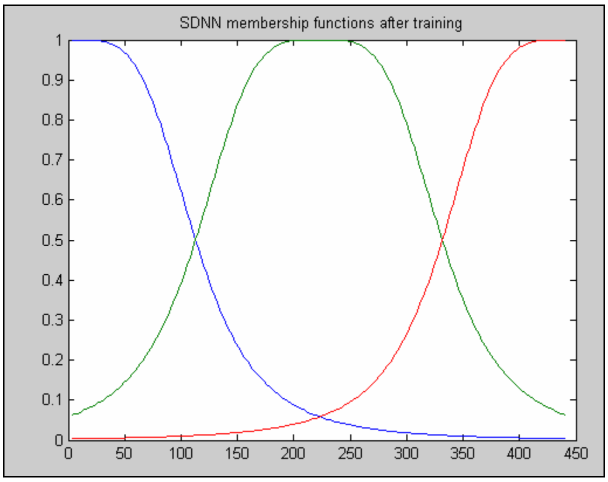

Figure-6. SDNN membership function after training.

11.0 RESULTS AND CONCLUSIONS

The results of Analytical classifier are at the acceptable level. The classifier is able to differentiate between normal and abnormal ECG. This is a crucial step in cardiac signal analysis. To improve the classification rate ANFIS was used as classifier. ANFIS model is most suitable for the tasks to which there is least or limited knowledge about input variables and rules. The ANFIS classifier can be a diagnostic tool to aid the physician in the analysis of heart diseases. The results show that the proposed method is effective for classification of cardiac arrhythmia with an overall accuracy of 93.75% as shown in Table-2. The results conclude that it is possible to classify the cardiac arrhythmia with the help of ANFIS. The advantage of the ANFIS classifier is its simplicity and ease of implementation. The impact of the input features

ARPN Journal of Engineering and Applied Sciences

plays an important role on the final decision process. The algorithm supports the implementation of the expert's knowledge and optimized the system easily. The outputs of ANFIS are shown in Figures-7 and 8. The proposed method gives a framework to detect more arrhythmia using ANFIS method for the classification.

```
Start training ANFIS ...

   1      1.98652
   2      1.9865
   3      1.98651
   4      1.98649
   5      1.98649
   6      1.98651
   7      1.98651
   8      1.98653
   9      1.98658
  10      1.9865
  11      1.98653
  12      1.98655
  13      1.98654
  14      1.98656
  15      1.98659
  16      1.98664
  17      1.98661
  18      1.98655
  19      1.98659
  20      1.98656

Designated epoch number reached --> ANFIS training completed at epoch 20.


p =

    3.0196

cardiac arrhythmia is
AF
```

Figure-7. The output of ANFIS classifier.

```
Step size decreases to 0.005259 after epoch 480.
 481      1.04074
 482      1.04076
 483      1.04074
 484      1.04073
 485      1.04075
 486      1.04073
 487      1.04069
 488      1.04067
 489      1.04058
Step size increases to 0.005785 after epoch 489.
 490      1.04054
 491      1.04045
 492      1.04044
 493      1.04047
 494      1.04044
 495      1.04044
 496      1.04029
Step size decreases to 0.005207 after epoch 496.
 497      1.04031
 498      1.04031
 499      1.04026
 500      1.04028

Designated epoch number reached --> ANFIS training completed at epoch 500.


p =

 -6.2158e+003

cardiac arrhythmia is
```

Figure-8. The misclassified output of ANFIS classifier.

REFERENCES

[1] Joseph J. Carr and John M. Brown. 2001. Introduction to Biomedical Equipment Technology. Pearson Education Inc.

[2] Cuiwei Li, Chongxum Zheng and ChangfengTai. 1995. Detection of ECG characteristic points using wavelets transforms. IEEE Transactions on Biomedical Engineering. 42(1): 21-28.

[3] Senhadi, L., Carrault, G., Bellanger, J.J., and Passariello, G. 1995. Comparing Wavelet Transforms for Recognizing Cardiac Patterns. IEEE Engineering in Medicine and Biology Magazine, Publication. 14(2): 167-173.

[4] Amara Graps. 1995. An Introduction to Wavelets. IEEE Comp.Sc. and Eng. 2(2).

[5] Task force of the European society of cardiology and the North American society of pacing and electrophysiology. 1996. Heart rate variability-standards of measurement, physiological interpretation, and clinical use. 93(5): 1043-1065.

[6] J. Niskanen, M. Tarvainen, P. Ranta-aho, P. Karjalainen. 2004. Software for advanced HRV analysis. Computer Methods and Programs in Biomedicine. 76(1): 73-81.

[7] Sprott J. C. and Rowland. 1995. Chaos data analyzer: the professional version. (American Institute of Physics, USA), www.sportt.physics.wisc.edu.

[8] Sokolow Maurice, McIlroy Malcolm B. and Cheitlin Melvin D. 1990. Clinical Cardiology (Lange Medical Book). London: Prentice Hall International, UK.

[9] Jang Roger JS. 1993. ANFIS-Adaptive-network-based neuro-fuzzy inference systems. IEEE Transactions on Systems, Man, and Cybernetics. 20(3): 665-685.

[10] Jang JSR, Sun C T and Muzutani E. 2007. Neuro-Fuzzy and Soft Computing-A computational approach to learning and machine intelligence. Pearson Education Inc.