Journal of Engineering Science and Technology
Vol. 7, No. 6 (2012) 744 - 755

A NOVEL APPROACH TO ARRHYTHMIA CLASSIFICATION USING RR INTERVAL AND TEAGER ENERGY

CHANDRAKAR KAMATH

Electronics and Communication Department,
Manipal Institute of Technology, Manipal, 576104, India
E-mail: chandrakar.kamath@gmail.com

Abstract

It is hypothesized that a key characteristic of electrocardiogram (ECG) signal is its nonlinear dynamic behaviour and that the nonlinear component changes more significantly between normal and arrhythmia conditions than the linear component. The usual statistical descriptors used in RR (R to R) interval analysis do not capture the nonlinear disposition of RR interval variability. In this paper we explore a novel approach to extract the features from nonlinear component of the RR interval signal using Teager energy operator (TEO). The key feature of Teager energy is that it models the energy of the source that generated the signal rather than the energy of the signal itself. Hence any deviations in regular rhythmic activity of the heart get reflected in the Teager energy function. The classification evaluated on MIT-BIH database, with RR interval and mean of Teager energy computed over RR interval as features, exhibits an average accuracy that exceeds 99.79%.

Keywords: Arrhythmia, Electrocardiogram (ECG), Nonlinear component, RR interval, Teager energy operator (TEO).

1. Introduction

Nowadays cardiac arrhythmias are the most common causes of mortality. Several techniques have been proposed to detect and identify different types of arrhythmia. Early diagnosis of the type of arrhythmia will facilitate proper treatment and thereby a prolonged life. These techniques usually extract features from raw electrocardiogram (ECG) signals to classify them. A good number of methods have been proposed and developed for analyzing ECG signals, each with advantages and disadvantages. However, most of them still require artificial assistance for improving the accuracy. The state of the cardiac health is also reflected in the instantaneous

Nomenclatures

ANE	Average nonlinear energy, V^2 or V^2rad^2
N	Number of samples in NE
NE	Nonlinear energy, V^2 or V^2rad^2
n	Integer index
x	Variable used to do the prediction
$x(n)$	Discrete time signal, V
y	Variable to be predicted
Greek Symbols	
ε	Error

(beat-to-beat) heart rate, which defined as the inverse of RR interval (interval between two R peaks) multiplied by 60. Heart rate variability (HRV), which is concerned with variation of RR interval from one beat to another, is a very popular non-invasive tool for assessing the functioning of autonomic nervous system, especially the sympathovagal balance. In the literature it is found that lot of research has gone into HRV analysis to investigate how the fluctuations in heart rate influence sympathetic and parasympathetic activities. However, not much is found where RR interval is used for arrhythmia classification. Traditionally HRV is evaluated using time domain measures (like, mean of RR intervals or its standard deviation), frequency domain measures (like, parametric and nonparametric methods for calculation of power spectral densities) or Poincaré plot indices as cited below.

Heart rate (HR) spectral analysis has been tried by Bruce Pomeranz et al. to assess the autonomic function [1]. They find that the low frequency fluctuations in supine position are mediated by parasympathetic nervous system. In standing position the low frequency fluctuations increase and are mediated by both sympathetic and parasympathetic nervous systems. However, in standing position the high frequency fluctuations decrease and are mediated by parasympathetic nervous system. Varoneckas has measured the level of autonomic HR control and sympathovagal balance using analysis of HR spectral components [2]. He also has assessed cardiovascular function and fatigue restoration cycle using HR Poincaré plots. King Leong et al. in a study of power spectrum of HRV found that the analysis leads to three spectral bands, namely, very low frequency (VLF), low frequency (LF) and high frequency (HF) [3]. They showed that the area under LF curve reflects cardiac sympathetic activity and that under HF reflects parasympathetic activity. Spectral measures, time domain measures and Poincaré plot measures have all been used to differentiate among different levels of obesity [4]. In their work it was found that all parameters reflecting parasympathetic tone (High frequency band, root mean square successive difference, proportion of successive normal-to-normal intervals, and scatter plot width) were significantly reduced in the case obese group compared to lean group. Gavin Sandercock et al. investigated the role of HRV in the prognosis for different modes of death in chronic heart failure [5]. They concluded from their findings that different HRV measurements predict different modes of death in chronic heart failure. Poincaré techniques to analyse HRV in infants in particular, congenital heart defects have been tried by Smith et al. [6]. They used SD1, SD2 and SD1/SD2, short term, long term, and randomness descriptors respectively, to characterise HRV and separate normal from those with congenital heart defects. In a new approach chaotic features of HR and its spectrum have been used by Guo-Qiang Wu et al. to evaluate health, aging, and heart failure [7]. They conclude that their approach is quantitatively superior to approximate entropy and other nonlinear methods. In the literature not much research is seen in the classification of ECG signal into different types of arrhythmia using HRV or RR interval signal. Some, using RR interval signal for classification, are quoted below.

Arrhythmia classification using RR interval as a feature was tried by Tsipouras et al. [8]. A three RR interval sliding window classifies the middle beat into one of the five arrhythmic classes. The method when evaluated using MIT-BIH arrhythmia database exhibited an accuracy of 95.85%. In another work by the same authors the classification included four arrhythmic classes and six rhythm types [9]. With HRV as a base signal, Jacobson introduced the wavelet transform decomposition as a means of signal characterization for enhanced classification [10]. Using correlation coefficient and RR interval as feature vectors ECG beats were classified by Chiu et al. [11]. They found the method to be suitable for classification into premature atrial or ventricular beats. Tushar et al. employ curvilinearity of indices of HRV to identify congestive heart failure (CHF) patients from normal subjects [12]. Statistical parameters derived from RR interval signal have been used to classify arrhythmia [13]. But the analytical approach has lead to an accuracy of about 66% only. In another study by the same authors four nonlinear parameters, one from RR interval Poincaré plot, were considered for arrhythmia classification and the accuracy went up to 93.13% [14]. Khaled et al. [15], and Thuraisingham [16], have proposed a method using RR interval signal to distinguish CHF patients from normal subjects. Mahesh et al. have attempted to classify cardiac disease using HR signal [17]. Thalange et al. employ linear and nonlinear parameters to identify abnormalities like Creighton University Ventricular Tachyarrhythmia (CUVT), Malignant Ventricular Arrhythmia Ectopic Database (MVA) and ST Change (ST) [18]. Generalized discriminant analysis (GDA) reduced feature technique was tried by Yaghouby et al. to classify cardiac abnormalities using reduced features of heart rate variability signal. Nine linear and nonlinear features extracted from HRV are brought down to three using GDA [19]. Four types of cardiac arrhythmias including left bundle branch block, first degree heart block, supraventricular tachyarrhythmia and ventricular trigeminy were discriminated by neural network and reduced features with a very high accuracy of nearly 100%.

For more than three decades computer-aided systems have been used for the classification of ECG beats. In designing such systems the most important aspect is the integration of a suitable feature extractor and a pattern classifier. When we perform pattern classification, to meet higher accuracy it is not adequate if we have the best pattern classification system. It is found that performance of most classifiers degrades when some of the selected features are redundant. This can happen, for example, when selected features are correlated. The selected features must be capable of separating the classes at least to some useful degree. Otherwise they become irrelevant. It is important that the selected features must be screened for redundancy and irrelevancy. Also the number of extracted features must be small. Otherwise it will add on to a longer processing time. Hence it can be concluded that even the extracted feature vector set must be relevant, non-redundant (uncorrelated), significant and informative. Different methods can be used to extract diverse features from the same raw data. Therefore, many a time pattern classification turns out to be a problem of classification *with smallest number* of extracted features. In fact, the issue of selecting an optimal set of relevant features plays an important role in pattern classification.

We hypothesize that a key characteristic of electrocardiogram (ECG) signal is its nonlinear dynamic behaviour and that the nonlinear component changes more significantly between normal and arrhythmia conditions than the linear component. This study gives an insight into capturing the nonlinear dynamics of the heart from the RR interval signal and exploits it in the classification of arrhythmia. The rationale behind choosing RR interval signal for analysis, rather than ECG itself, is RR interval signal is less susceptible to noise than the latter. The usual statistical descriptors used in RR interval analysis do not capture the nonlinear disposition of RR interval variability. We explore a novel approach to extract the features from nonlinear component of the RR interval time series using Teager energy operator (TEO) and classify the ECG signals into normal and various ventricular arrhythmia (left bundle branch block (LBBB), right bundle branch block (RBBB), premature-ventricular contraction (PVC) and paced beats), using *only two* features. Since Teager energy function accounts for the energy of the system that generated the signal and not the energy of the signal itself [20, 21], disturbances in the site and frequency of impulse generation and conduction path during the rhythmic activity of the heart manifest in the TEO energy function.

HRV analysis usually commences with the ventricular complex, QRS complex, which is the most significant wave. The normal QRS complex is due to the triggering from sino-atrial (SA) node and proper propagation through the conduction path in the ventricles. Under certain abnormal conditions it is found that triggering from ectopic centres and blocks in the conduction path change the course of the propagation front and lead to QRS complexes with wide and bizarre waveforms related to premature-ventricular contraction (PVC) and left and right bundle branch blocks (LBBB, RBBB) or ST segment elevation. Such complexes will not be related to a preceding P wave. In this case the signal energy gets spread over a longer duration in time domain.

A scatter plot of RR interval and mean of Teager energy function computed over RR interval reveals an excellent separation of the clusters for normal and arrhythmia signals. Further, it is found that the plot also shows an excellent separation among different arrhythmias. This brings out significant differences in the qualitative as well as quantitative analysis of the normal and pathological cases there by facilitating a better classification. Analysis of covariance (ANOCOVA) is performed to study the relationship between RR interval and mean of Teager energy, and how this relationship has changed from normal to arrhythmia. The resulting F-statistics and p-value show that the normal and various arrhythmic classes are distinctly different from one another. This further substantiates the discriminating capability of the selected features for classification of ECG beats. Finally the validation of the new approach is carried out on MIT-BIH database using ANN. The classification evaluated, with only two features, RR interval and mean Teager energy computed over RR interval, exhibits an average accuracy that exceeds 99.79%.

2. Methods and Materials

2.1. ECG records

In this study the ECG records used are from MIT-BIH database. The work involved 6 ECG records from normal sinus rhythm database and 6 ECG records from arrhythmia database. From each record the modified lead II was only considered for analysis. The resolution is 200 samples per mV. The sampling frequency of normal sinus rhythm data is 128 Hz and that of arrhythmia data is 360 Hz. A total of 13592 beats from MIT-BIH data base were analyzed. Out of these 11093 were normal beats from normal sinus rhythm data base and 2499 were arrhythmia beats from arrhythmia data base. The arrhythmia beats included 737 paced beats, 654 left bundle branch block (LBBB) beats, 456 right bundle branch block (RBBB) beats and 652 premature-ventricular contraction (PVC) beats.

2.2. R-peak detection

RR interval analysis usually begins with detection of QRS complex, in particular, R-peak and a good number of different methods have been proposed for *R*-peak detection over last decade [22-25]. In this work the R-peak detection algorithm uses the approach proposed by Benitez et al. [23]. The ECG signal is filtered to remove muscle noise and differentiated using a three-point central difference filter to remove base line drift, and motion artifacts. The differentiation suppresses lower amplitude P and T waves while enhances QRS complex. Hilbert transform is then applied to the differentiated ECG. The peaks of this processed signal exactly coincide with the time of occurrence of the R peaks. An adaptive threshold is used to detect the *R* peaks.

2.3. Teager energy operator (TEO) and nonlinear energy function

TEO is a non-linear energy tracking operator widely used in speech applications [26, 27]. An important property of TEO is that it is characterized by a time resolution that can track rapid changes in the energy (squared product of amplitude and frequency) of the signal. This is attributed to the fact that TEO operation is almost instantaneous as it uses only three samples and hence, is most suitable for real time applications. Thus besides energy, the operator can also track amplitude envelope and instantaneous frequency. Although the energy of any two tones at different frequencies, but equal amplitude, is same, the energy required to generate the two tones are different. The specialty of TEO is that it measures the energy of the system that generated the signal based on mechanical and physical considerations rather than the energy of the signal itself [20, 21]. Thus the advantage of using TEO is that it models the energy of the non-linear system that generated the ECG signal. Hence disturbances in impulse generation and conduction path get reflected in the Teager energy function.

Much of the earlier work on TEO was carried out by Maragos and his co-workers [26-28]. The original Teager-Kaiser nonlinear energy (*NE*) for discrete time signal $x(n)$ is given by [28],

$$NE\{x(n)\} = x^2(n) - x(n-1)\, x(n+1) \tag{1}$$

The average nonlinear energy in time domain, *ANE*, is defined as

$$ANE = (\sum NE\{x(n)\}) \,/\, N \tag{2}$$

where the summation is carried out over N samples in NE. ANE, the mean of the Teager energy function provides a means for evaluating nonlinear dynamics of ECG signal in the time domain. In this study ANE is evaluated over each RR interval. This is used as one of the two features, the other being RR interval itself, in the scatter plot for classification.

2.4. Analysis of covariance (ANOCOVA)

ANOCOVA is a technique for analyzing grouped data, each group having a response (y, the variable to be predicted) and a predictor (x, the variable used to do the prediction). Using ANOCOVA, each y (mean of Teager energy) is modeled as a linear function of x (RR interval), with the coefficients of the line possibly varying from group to group. To study the relationship between RR interval and mean of Teager energy, and how this relationship has changed from normal to arrhythmia, 'separate line model' is tried for each class. MATLAB provides a statistical tool box to carry out this analysis. The results of this analysis are shown up in two tables, one for straight line coefficients and the second for test results, displaying F-statistics and p-value.

2.5. Neural networks for classification

To show the efficacy of selected features in separating classes scatter plots and ANOCOVA are used. However, since artificial neural networks have proved themselves as proficient classifiers and are particularly well suited for addressing non-linear problems we chose neural network. In this paper neural network is used as a classifier to identify if a given ECG beat belongs to normal class or one among the arrhythmia class based on the selected feature vectors. The two feature vectors will serve as inputs to the neural network and the class is the target. Given an input, the neural network is expected to identify if the beat is normal or arrhythmic (PVC, paced, LBBB, or RBBB). This is achieved through training the neural network by presenting previously recorded inputs and tuning the network to produce the desired targeted outputs.

Once the neural network is set up the samples are automatically divided into training, validation and test sets. The training set is used to teach the network. Training continues as long as the network continues improving on the validation set. The test set provides a completely independent measure of network accuracy.

To understand how the various procedures are applied to arrive at ECG classification, a flowchart is outlined in Fig. A-1 of *Appendix A*.

3. Results and Discussion

Figures 1 through 4 illustrate scatter plots used to show the qualitative results of the validity of appropriate choice of features and their impact on the separation of the beats into normal and one of the arrhythmic beats (PVC, paced, LBBB, or RBBB). These plots reveal an excellent separation of the features for normal from those of arrhythmia beats. A combined scatter plot of RR interval vs. mean of Teager energy for all types of beats is depicted in Fig. 5. A total of 13592 beats from MIT-BIH data base were analyzed. Out of these 11093 were normal beats from normal sinus rhythm data base and 2499 were arrhythmia beats from arrhythmia data base. The plot reveals an excellent separation of the features for normal from those of arrhythmia beats on visual inspection. There is also an excellent discrimination among different arrhythmia beats.

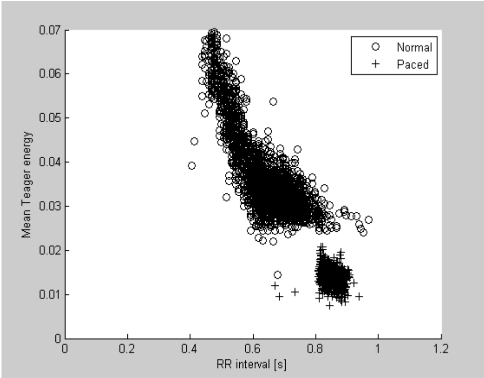

Fig. 1. Scatter Plot of RR Interval vs. Mean Teager Energy for Normal and Paced Beats. 'O' – Normal Beats and '+' – Paced Beats.

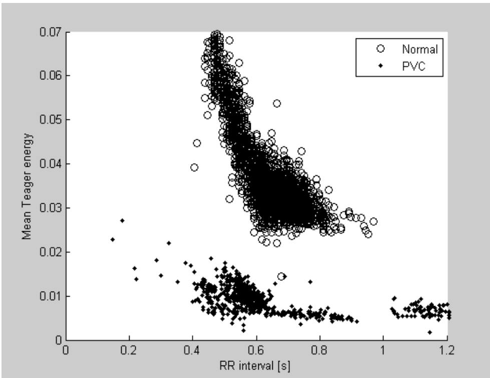

Fig. 2. Scatter Plot of RR Interval vs. Mean of Teager Energy for Normal and PVC Beats. 'O' – Normal Beats and '.' – PVC Beats.

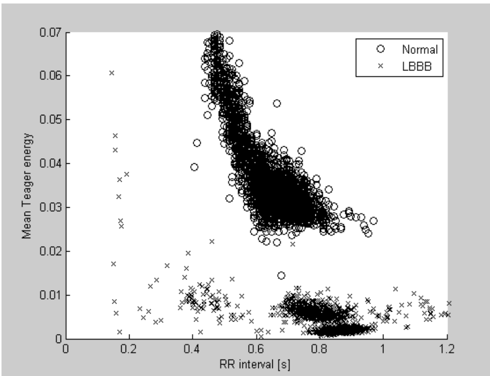

Fig. 3. Scatter Plot of RR Interval vs. Mean of Teager Energy for Normal and LBBB Beats. 'O' – Normal Beats and 'x' – LBBB Beats.

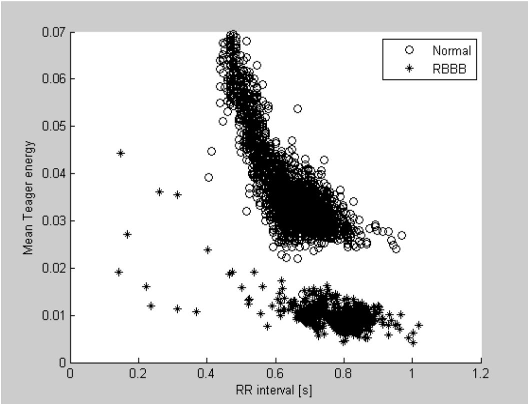

Fig. 4. Scatter Plot of RR Interval vs. Mean of Teager Energy for Normal and RBBB Beats. 'O' – Normal Beats and '*' – RBBB Beats.

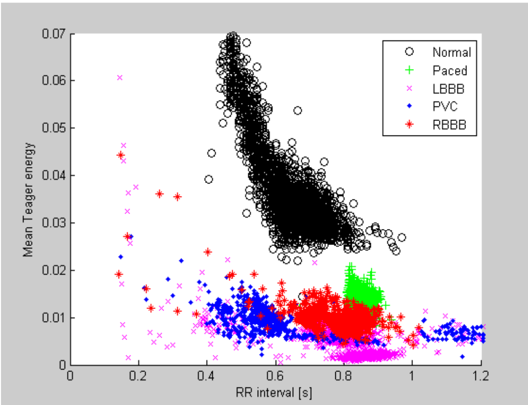

Fig. 5. A Combined Scatter Plot of RR Interval vs. Mean of Teager Energy for Different Types of Beats. 'O' – Normal Beats; '+' – Paced Beats; '.' – PVC Beats; 'x' – LBBB Beats; '*' – RBBB Beats.

To substantiate the discriminating capability of the selected features for classification of ECG beats we use the ANOCOVA and the resulting plot is depicted in Fig. 6. The coefficients of the five straight lines, one for each ECG class, appear in the Table 1 titled ANOCOVA coefficients. It can be seen that the slopes are roughly -0.0247, with a small deviation for each group. The separate lines that fit the different ECG classes are described by the following equations.

$$
\begin{aligned}
&\text{Normal: } y = (0.0303+0.0674) + (-0.0247-0.0695)\,x + \varepsilon \\
&\text{Paced : } y = (0.0303-0.0216) + (-0.0247+0.0232)\,x + \varepsilon \\
&\text{LBBB : } y = (0.0303-0.0194) + (-0.0247+0.0169)\,x + \varepsilon \qquad (3)\\
&\text{RBBB : } y = (0.0303-0.0081) + (-0.0247+0.0090)\,x + \varepsilon \\
&\text{PVC : } y = (0.0303-0.0183) + (-0.0247+0.0203)\,x + \varepsilon
\end{aligned}
$$

Table 1. ANOCOVA Coefficients.

Term	Estimate	Std. Err.	T	Prob>|T|
Intercept	0.0303	0.00036	84.64	0
Normal	0.0674	0.00072	93.01	0
Paced	-0.0216	0.00044	-49.47	0
LBBB	-0.0194	0.00058	-33.38	0
RBBB	-0.0081	0.00113	-7.17	0
PVC	-0.0183	0.00047	-38.86	0
Slope	-0.0247	0.00047	-52.45	0
Normal	-0.0695	0.00108	-64.39	0
Paced	0.0232	0.00053	43.56	0
LBBB	0.0169	0.00072	23.56	0
RBBB	0.009	0.00145	6.20	0
PVC	0.0203	0.0006	33.96	0

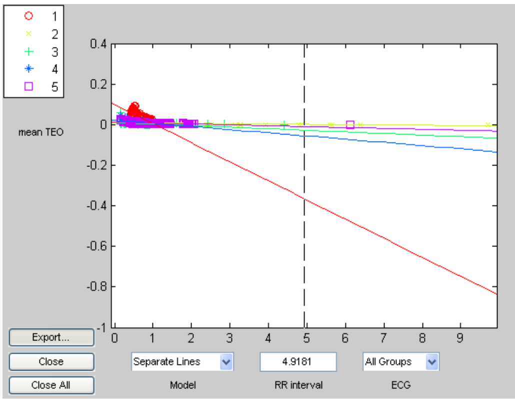

Fig. 6. ANOCOVA Analysis of Different ECG Classes.

Although the straight lines have nearby slopes, the interaction index = ECG × RR interval in Table 2. expresses the difference in slopes. This is confirmed by a large F-statistic = 1295.8 and a very small p-value = 0. This implies that the slopes are significantly different and so also the different ECG classes. Figure 7 illustrates multiple comparisons of slopes which again confirm that all classes (normal and four types of arrhythmia) are distinctly different.

In practice a variety of classifiers are available. However, as explained earlier for want of a better classifier we resorted to neural network. The same ECG records from MIT-BIH were used, among which 11093 were normal beats and 2499 were arrhythmia beats. In the testing phase out of 498 normal beats 2 were incorrectly classified as abnormal beats and out of 465 arrhythmia beats all were rightly classified as arrhythmia beats. The results exhibited an average accuracy that exceeded 99.79%.

Table 2. Anova Test Results.

Source	d.f.	Sum Sq	Mean Sq	F	Prob>F
ECG	4	1.15156	0.28789	11015.82	0
RR interval	1	0.01998	0.01998	764.46	0
ECG×RR interval	4	0.13548	0.03387	1295.98	0
Error	6479	0.16932	0.00003		

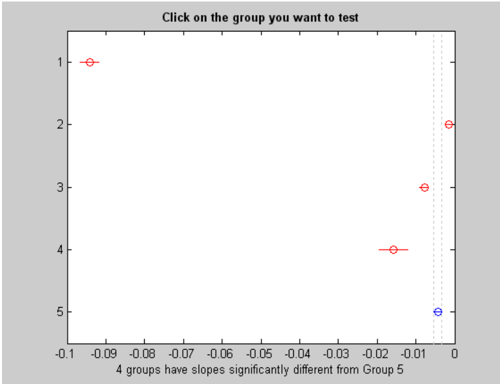

Fig. 7. Multiple Comparisons of Slopes.

4. Conclusions

A novel approach to extract nonlinear component of RR interval signal and its efficacy in the classification of arrhythmia is discussed. The classification accuracy achieved through only two features, RR interval and mean Teager energy, is comparable to that obtained by others using a large number of parameters. Further, since Teager energy can track rapid changes in energy, instantaneous amplitude and instantaneous frequency of the signal, there is scope for new descriptors which can capture nonlinear dynamics, to be defined. This in turn can enhance both diagnostic and prognostic indicators of the cardiovascular problems.

References

1. Pomeranz, B.; Macaulay, R.J.; Caudill, M.A.; Kutz, I.; Adam, D.; Gordon, D.; Kilborn, K.M.; Barger, A.C.; Shannon, D.C.; Cohen, R.J.; and Benson, H. (1985). Assessment of autonomic function in humans by heart rate spectral analysis. *AJP - Heart and Circulatory Physiology*, 248(1), H151-H153.
2. Varoneckas, G. (1999). Analysis of heart rate variability during sleep as a tool for assessment of cardiovascular adaptability and fatigue in sleep-wake cycle. *RTO HFM workshop*, 22(1), 22-27.
3. Leong, K.S.; Mann, P.; Wallymahmed, M.; Macfarlane, I.A.; and Wilding, J.P.H. (2000). Abnormal heart Rate Variability in adults with growth hormone deficiency. *Journal of Clinical Endocrinology & Metabolism*, 85(2), 628-633.
4. Rabbia, F.; Silke, B.; Conterno, A.; Grosso, T.; De Vito, B.; Rabbone, I.; Chiandussi, L.; and Veglio, F. (2003). Assessment of cardiac autonomic modulation during adolescent obesity. *Obesity Research*, 11(4), 541-548.
5. Sandercock, G.R.H.; and Brodie, D.A. (2006). The role of heart rate variability in prognosis for different modes of death in chronic heart failure. *Pacing and Clinical Electrophysiology* (*PACE*), 29(8), 892-904.
6. Smith, R.L.; Wathen, E.R.; Abaci, P.C.; Von Bergen, N.H.; Law, I.H.; Dick II, M.D.; Connor, C.; and Dove, E.L. (2009). Analyzing heart rate variability

in infants using nonlinear Poincaré techniques. *Computers in Cardiology*, 36, 673-676.

7. Wu, G.-Q; Arzeno, N.M.; Shen, L.-L.; Tang, D.-K.; Zheng, D.-A.; Zhao, N.-Q.; Eckberg, D.L.; and Poon, C.-S. (2009). Chaotic signatures of heart rate variability and its power spectrum in health, aging and heart failure. *Plos one*, 4(2), 1-9.
8. Tsipouras, M.G.; Fotiadis, D.I.; and Sideris, D. (2002). Arrhythmia classification system using RR-interval duration signal. *Computers in Cardiology,* 29, 485-488.
9. Tsipouras, M.G., Fotiadis, D.I.; and Sideris, D. (2005). An arrhythmia classification system based on the RR-interval signal. *Artificial Intelligence in Medicine*, 33(3), 237-250.
10. Jacobson, M.L. (2003). Analysis and classification of physiological signals using wavelet transforms. *ICECS 2003, Proceedings of the* 2003 10th *IEEE International Conference on Electronics, Circuits and Systems*, 2, 906-909.
11. Chiu, C.-C.; Lin, T.-H.; and Liau, B.-Y. (2005). Using correlation coefficient in ECG waveform for arrhythmia detection. *Biomedical Engineering applications, Basis and Communications*, 17(3), 147-152.
12. Thakre, T.P.; and Smith, M.L. (2006). Loss of lag-response curvilinearity of indices of heart rate variability in congestive heart failure. *BMC Cardiovascular Disorders*, 6(27), 1-10.
13. Anuradha, B.; Suresh Kumar, K.; and Veera Reddy, V.C. (2008). Classification of cardiac signals using time domain methods. *ARPN Journal of Engineering and Applied Sciences*, 3(3), 7-12.
14. Anuradha, B.; and Veera Reddy, V.C. (2008). Cardiac arrhythmia classification using fuzzy classifiers. *Journal of Theoretical and Applied Information Technology*, 4(4), 353-359.
15. Khaled, A.S.; Owis, M.I.; and Mohamed, A.S.A. (2006). Employing time-domain methods and Poincaré plot of heart rate variability signals to detect congestive heart failure. *International Journal of Bioinformatics and Medical Engineering* (*BIME*), 6(1), 35-41.
16. Thuraisingham, R.A. (2009). A classification system to detect congestive heart failure using second-order difference plot of RR intervals. *Cardiology Research and Practice*, Article ID 807379, 1-7.
17. Mahesh, V.; Kundaswamy, A.; Vimal, C.; and Sathish, B. (2010). Cardiac disease classification using heart rate signals. *International Journal of Electronic Healthcare*, 5(3), 211-230.
18. Thalange, A.V.; and Mergu, R.R. (2010). HRV analysis of arrhythmias using linear–nonlinear parameters. *2010 International Journal of Computer Applications*, 1(12), 71-76.
19. Yaghouby, F.; Ayatollahi, A.; and Soleimani, R. (2009). Classification of cardiac abnormalities using reduced features of heart rate variability signal. *World Applied Sciences Journal*, 6(11), 1547-1554.
20. Quatieri, T.F. (2004) *Discrete-time speech signal processing, principles and practice.* Pearson Education (Singapore) Pte. Ltd.

21. Kaiser, J.F. (1990). On a simple algorithm to calculate the 'energy' of a signal. *Proceedings of International Conference Acoustics, Speech, and Signal Processing ICASSP*-90, 381-384.
22. Friesen, G.M.; Jannett, T.C.; Jadallah, M.A.; Yates, S.L.; Quint, S.R.; and Nagle, H.T. (1990). A Comparison of the noise sensitivity of nine QRS detection algorithms. *IEEE Transactions on Biomedical Engineering*, 37(1), 85-98.
23. Benitez, D.S.; Gaydecki, P.A.; Zaidi, A.; and Fitzpatick, A.P. (2000). A new QRS detection algorithm based on the Hilbert transform. *Computers in Cardiology*, 27, 379-382.
24. Kohler, B.-U.; Henning, C.; and Orglmeister, R. (2002). The principles of software QRS detection. *IEEE Engineering in Medicine and Biology*, 21(1), 42-57.
25. Yimman, S.; Hinjit, W.; Desyoo, P.; Bholsithi, W.; and Dejhan, K. (2004). Wavelet packet transform applications on QRS detection. *Proceedings of the Fourth IEEE International Symposium on Signal Processing and Information Technology*, 445-448.
26. Maragos, P.; Quatieri, T.F.; and Kaiser, J.F. (1990). Detecting nonlinearities in speech using an energy operator. *Proceedings of the 1990 IEEE Digital signal processing workshop*, 1-2.
27. Maragos, P.; and Potamianos, A. (1995). Higher order differential energy operators. *IEEE Signal processing letters*, 2(8), 152-154.
28. D'Alessandro, M.; Esteller, R.; Vachtsevanos, G.; Hinson, A.; Echauz, J.; and Litt, B. (2003). Epileptic seizure prediction using hybrid feature selection over multiple intracranial EEG electrode contacts: A report of four patients. *IEEE Transactions on Biomedical Engineering*, 50(5), 603-615.

Appendix A

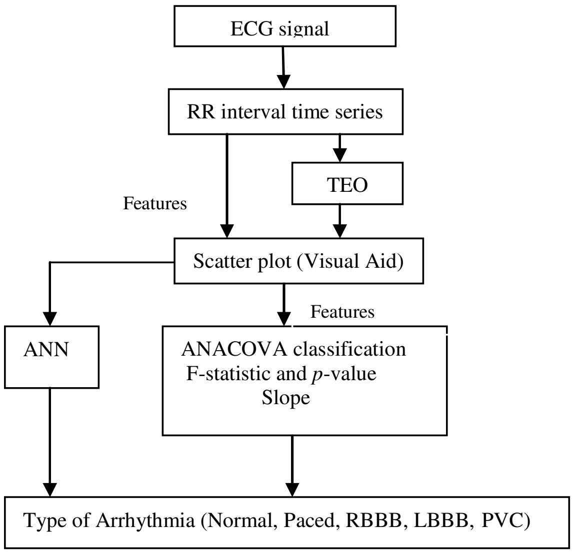

Fig. A-1. Flowchart to Show How the Various Procedures are Applied to Classify ECG Signals.