Journal Of Harmonized Research (JOHR)

Journal Of Harmonized Research in Engineering
2(1), 2014, 208-216

ISSN 2347 – 7393

Review Article

A REVIEW PAPER ON ATRIAL FIBRILLATION ECG AND MALIGNANT VENTRICULAR ARRHYTHMIA ECG USING ANFIS

Dinesh Yadav, Deepak Bhatnagar

Computer Science and Engineering
Jhansi, India

Abstract:
Atrial fibrillation (AF) is an arrhythmia in which electrical activity in the atria is disorganized. Instead of the sinus node providing the normal electrical signals to the atrium, rapid circulating waves of abnormal electrical signals continuously stimulate the atrium. The atrial rate can exceed 400 beats per minute. During AF, electrical signals from the atrium constantly bombard the AV node. The AV node passes a large number of these rapid signals to the ventricles, which beat rapidly and irregularly. The ventricular rate can vary from 50 to 200 per minute, depending on the degree of AV conduction. In fact, the overall rate of the ventricles varies tremendously, depending on the age of the patient, the health of the AV node, and whether medications to slow AV conduction (such as calcium-channel blockers or beta blockers) are present. Ventricular arrhythmias occur more frequently with advancing age, severity of heart disease and ventricular hypertrophy. Malignant ventricular arrhythmias are following forms: out-of-hospital ventricular fibrillation (VF), recurrent sustained ventricular tachycardia in the long QT syndrome. Each condition has a high 1-year mortality rate. Potentially malignant ventricular arrhythmias are ventricular premature complexes (VPCs) of >10 per hour 10 to 16 days after acute infarction and repetitive VPCs. The most malignant arrhythmias occur with severely depressed ventricular function, but VPCs alone have independent prognostic significance. Benign ventricular arrhythmias occur in patients without known heart disease and do not require treatment. The exact effect of frequent and complex VPC in these patients needs further definition.
The ANFIS (Adaptive Neuro-Fuzzy Interface System) tool for detecting the normal and abnormal signal. Here the designed ANFIS model contained both approaches the neural network adaptive potential approach and the fuzzy logic qualitative approach. Hybrid method is used as an optimization method.

Keywords:- Adaptive Neuro-Fuzzy Interface System (ANFIS), Electrocardiogram (ECG) ,Artial Fibrillation, Malignant Ventricular

For Correspondence:
dineshyadav14@gmail.com
Received on: February 2014
Accepted after revision: March 2014

Introduction and Development in ECG Analysis

Electrocardiogram (ECG) monitoring and analysis is commonly conducted based on a visual inspection by a cardiologist. The observed features in this type of inspection are the signal periodical pattern and physical appearance. Neuro-fuzzy approach is one among the pattern recognition methods which has found its profound utilization in the ECG signal computer-aided diagnosis applications. From the signal processing prospective, ECG signal is noted for its non-linear, periodic, and dynamic signal characteristics. Such property has led to the employment of sophisticated mathematical and computational procedures in its analysis [1, 4]

Non-linearity of the ECG signal has made its clinical interpretation become not only difficult but also very much subjective. Therefore, the ability of a neuro-fuzzy system to recognize an ECG pattern will be of much use in clinical cardiac diagnosis. In the case of computer-aided diagnosis, the result is much more accurate if accompanied with other physiological parameters, such as temperature, heart rate, and blood oxygen saturation. Atrial fibrillation (AF) is an arrhythmia in which electrical activity in the atria is disorganized. Instead of the sinus node providing the normal electrical signals to the atrium, rapid circulating waves of abnormal electrical signals continuously stimulate the atrium. The atrial rate can exceed 400 beats per minute. During AF, electrical signals from the atrium constantly bombard the AV node. The AV node passes a large number of these rapid signals to the ventricles, which beat rapidly and irregularly. The ventricular rate can vary from 50 to 200 per minute, depending on the degree of AV conduction. In fact, the overall rate of the ventricles varies tremendously, depending on the age of the patient, the health of the AV node, and whether medications to slow AV conduction (such as calcium-channel blockers or beta blockers) are present. Ventricular arrhythmias occur more frequently with advancing age, severity of heart disease and ventricular hypertrophy. Malignant ventricular arrhythmias are following forms: out-of-hospital ventricular fibrillation (VF), recurrent sustained ventricular tachycardia in the long QT syndrome. Each condition has a high 1-year mortality rate. Potentially malignant ventricular arrhythmias are ventricular premature complexes (VPCs) of >10 per hour 10 to 16 days after acute infarction and repetitive VPCs. The most malignant arrhythmias occur with severely depressed ventricular function, but VPCs alone have independent prognostic significance. Benign ventricular arrhythmias occur in patients without known heart disease and do not require treatment. The exact effect of frequent and complex VPC in these patients needs further definition.

The ECG (Electrocardiogram) dynamic and nonlinear signal characteristic requires an accurate pattern recognition system. This paper describes the development of an ECG signal interpretation system, based on ANFIS nonparametric neuro-fuzzy approach. In 1887 Augustus D. Waller first published the electrocardiogram of human recorded with an electrometer.[3] He developed the lead system for ECG recording. In the cardiac cycle he identified five deflection points. After it there is huge data base is generated in terms of clinical and engineering aspects of electrocardiography. A very advanced electronic recorder is generated in last few decades. In the recent year a much compact ECG recorder are developed which we can wear for ECG recording. A W-ECG recorder is very popular now a day.

Heart defects are among the most common birth defects and the leading cause of birth defect-related deaths [4, 5]. Every year, about one out of 125 babies are born with some form of congenital heart defects [6]. The defect may be so slight that the baby appears healthy for many years after birth, or so severe that its life is in immediate danger. Congenital heart defects originate in early stages of pregnancy when the heart is forming and they can affect any of the parts or functions of the heart. Cardiac anomalies may occur due to a genetic syndrome, inherited disorder, or environmental factors such as infections or drug misuse [7, 4]. However, except for during labour, fetal electrocardiography has not proved an effective tool for imaging specific structural defects. Rather, fetal electrocardiography has been confined to more global issues such as general ischemia due to specific fetal positioning that chokes the umbilical cord [8]. The reason for this limitation is that the non-invasive fetal electrocardiogram (ECG) is contaminated by fetal brain activity, myographic (muscle) signals (from both the mother and fetus), movement artifacts and multiple layers of different dielectric biological media through which the electrical signals must pass. Now we have to define some existing technique for ECG signal analysis.

Literature of Survey: ECG

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 [9]. 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) [10]. 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 [11]. Task force (1996) gave guidelines for HRV including Heart rate variability-standards of measurement, physiological interpretation for clinical use [12]. Juha-Pekka Niskanen (2002) proposed the time domain methods for cardiac arrhythmia classification [13].Shahanaz ayub (2010) proprosed the method for fusion beats extaction from ECG using the neural network. The accuracy of the of the method was 96 % cascade feedforward method used [14]. Shahanaz Ayub and J P saini in 2011 proposed the method for detection of the beats from the ECG for classification of the abnormality using the cascade feed forward with 99.9% [15] Khandait Baeane in 2012 proposed the method for recognization of ECG abnormality using the neuro-Fuzzy approach with 98% accuracy[16]. R. Amandi, A. Shahbazi, A. Mohebi, M. Bazargan, Y. Jaberi, P. Emadi, and A. Valizade proposed method for detection of Automatic ECG Beat Tachycardia Using Artificial Neural Network 2012.[17] Nitin Kumar Sahu , Shahanaz Ayub and J P Saini proposed method for detection of normal and abnormal arrhythmia ECG signal using Adaptive Neuro-Fuzzy Interface System in 2013.[18]

QRS Detection Methods

Since cardiac cycle repeats according to heart rate hence it is assume that ecg signal is pseudo periodic signal. The components of cardiac cycles appear in a regular sequence P-QRS-T. PQ and ST segments are affected by variations in heart rate. The dominant feature of the cardiac cycle is R peak in QRS complex. It is distinctly find by from the sharp edges and high amplitude. Therefore the advantage of QRS complex in the ECG it is easy to locate even in the presence of low noise frequency. QRS detection is the basis for most of the ECG signal analysis approach. It is particularly useful in arrhythmia monitoring algorithms. The current heart rate can be determined by calculating the time period between two consecutive R peaks.

QRS detection algorithm uses the high energy content of QRS complex that lie in 5 to 25 Hz band. The complex QRS detection algorithm used the application of neural network, hidden markov model and syntactic methods etc.[3]

In morphology based QRS detection approach morphological operators like opening and closing are used to enhance the particular shape of the QRS complex. Since QRS complex consist of positive and negative peaks hence it can be used in peak valley extractor for enhancing QRS complex and suppressed the other signal such as P and T as well as noise. In a curve length transform in which QRS complex detection is performed, the curved length is determined in terms of sum of Euclidean distances between the pairs of consecutive sample points in the ECG signal. The curve length of the ECG signal depends on the increments in the sample values and the sampling time of the ECG. For QRS detection the curve length of the ECG signal is evaluated in a window with the length matching with the widest possible QRS complex. When the window is in perfect alignment with the onset of QRS complex it produces the local maximum in the curve length feature and that is utilized for locating the onsets of the QRS complex. [3]

Beat Alignment

Certain measurements like levels of ST and T waves and morphology of P-QRS-T complex in the cardiac cycle are important for diagnosis of any abnormality. However , the presence of noise can hamper the readability of the ECG and hence can produce errors in estimating these cardiac parameters. There are various methods for alignment of ECG beats in the literature namely, the double level method, normalized integral method and matched filtering method etc. In the matched filter based technique a noise free ECG beat forms an impulse response of the matched filter. The local maxima in the output of the matched filter signal indicate positions of the alignment of the beat in the input ECG signal. This is similar to cross correlation based approach for beat alignment. The beat alignment is performed after searching for R peak. The first zero crossing after the R peak is marked as fiducial point for alignment. Any dc bias and slow baseline wander are to be removed to ensure that the zero crossing take place atb desired position. [3]

Reduction of Noise

It is clear that noise in the ECG signal can comes from various sources such as muscular activities 50/60 GHz powerline, skin stretching, electrode motion, movement of heart due to respiration etc. It is difficult to control the environment and prevent the interference due to some physiological events like breathing. There are several filtering approach s for reduction in noise. At every sample of the ECG signal the error produced by the difference between the constant reference and the filter weight multiplied by the previous input sample is used for updating the filter weight according to the least mean squares (LMS) algorithm.

Power line type of error is caused due to power line cords nearby and its effect can be minimized by moving away from such source of noise. Adaptive filtering techniques can be used for cancellation of power line and electromyography (EMG) interference. Here it should be noted that in many places the power line frequency may often deviate from the specified value. EMG noise is generated due to basically the activity muscular. The EMG signal seen on the skin surface is quite localized in nature. Due to this property the EMG interference in different ECG leads may be uncorrelated because the different leads are placed at different locations on the body. With this rationale an adaptive filtering technique has been proposed it suggests that for removal of the EMG from one particular lead of the ECG signal which acts as the primary input the signals from the orthogonal ECG leads can be used as the reference input of the adaptive filter. Thus by using multiple leads of ECG, the EMG interference can be suppressed using the adaptive cancellation technique. Apart from this, there are several other techniques used for calculating an estimate of the cardiac cycle by suppressing the noise. [3]

Different ECG Recorders

First holter proposed a wearable ECG recorder that record the ECG signal in analog form and transmit it through wireless link. It is useful in ambulatory applications. The wearable ECG (W-ECG) recorders are very light in weight (<80gm) and portable. Many of them are equipped with wireless transceivers, microprocessor with on board analysis algorithms for calculating cardiac parameters and displaying them on LCD displays. W-ECG used predefined ECG leads which are to be connected to the ECG electrodes that are placed on body. In the standard 12 lead ECG the primary leads are connected to the limbs and hence also referred as limb leads. However in ambulatory applications the limb lead may barricade the usual activities of the user and so that a modified electrode is used. In case of wearable ECG recorders the type of ECG electrodes should be easy to use, small size and able to provide reliable connection for long time. Disposable foam-pad Ag/AgCl electrodes fulfill all such requirements of W- ECG. Skin preparation prior to ECG recording is a standard practice in a hospital in order to reduce the artifacts. This involves removal of hair from the electrode sites, scrubbing of the sites with alcohol wipes and abrasion with abrasive pads. This can help for short term monitoring. [3]

Literature of Survey: ANFIS

In most fuzzy systems, fuzzy rules were obtained from the human expert. However, every expert does not want to share his knowledge and there is no standard method that exists to utilize expert knowledge. As a result, ANNs were incorporated into fuzzy systems to be able to acquire knowledge automatically by learning algorithms. The learning capability of the NNs was used for automatic fuzzy if then rules generation (Czogala and Leski 2000). The connection of fuzzy systems with an ANN is called neuro-fuzzy, NF, systems. Like in NNs where knowledge is saved in connection weights, it is interpreted as fuzzy if then rules in NF systems. The most frequently used NN in NF systems is radial basis function neural network, RBFNN in which each node has radial basis function such as Gaussian and Ellipsoidal. Their popularity is due to the simplicity of structure, well-established theoretical basis and faster learning than in other types of NNs. Also, there are many developed fuzzy neural networks (FNN) as NF algorithms in literature. Adaptive network based fuzzy inference system, ANFIS, is one of them. It is type of RBFNN.

Jang (1992) proposed to use the ANFIS architecture to improve the performance of the fuzzy controllers. The performance of the fuzzy controller relies on two important factors: knowledge acquisition and the availability of human experts. For the first problem, Jang proposed the ANFIS to solve the automatic elicitation of the knowledge in the form of fuzzy if then rules. For the second problem, that is how the fuzzy controller is constructed without using human experts; a learning method based on a special form of gradient descent (back propagation) was used. The proposed architecture identified the near optimal membership functions and the other parameters of a controller rule base for achieving a desired input-output mapping. The back propagation type gradient descent method was applied to propagate the error signals through 15 different time stages to control the plant trajectory. The inverted pendulum system was employed to show the effectiveness and robustness of the proposed controller.

In 1992, Uchikawa et. al. presented a fuzzy modeling method using fuzzy neural networks, FNNs, with the back propagation algorithms. They proposed three types of NN structures of which the connections weights have particular meanings for getting fuzzy inference rules for tuning membership functions. These structures are categorized into FNNs and these different types FNNs realize three different types of reasoning.

Rao and Gupta (1994) described the basic notions of biological and computational neuronal morphologies and the principles and architectures of FNNs. Two possible models of FNN were given. In first one, the fuzzy interface provides an input vector to a multilayered network in response to linguistic statements. Then the NN can be trained to yield desired output. In the second scheme, a multilayered NN drives the fuzzy inference mechanism. It was pointed out that using FNN approaches having the potential for parallel computation could eliminate the amount of computation required.

In another paper, Uchikawa et. al. (1995) presented a new design method of adaptive fuzzy controller using linguistic rules of fuzzy models of the controlled objects. FNNs identify fuzzy models of nonlinear systems automatically with the back propagation algorithm in this method. Authors also presented a rule-to-rule mapping method for describing the behavior of fuzzy dynamical systems. Using this methodology, first, the control rules are modified by considering rule-to-rule transitions. After that, designed controller was implemented with another FNN. The adaptive tuning of the control rules was done using the fuzzy model of the controlled object by utilizing the derivative 16 value from the fuzzy model. A second order system was simulated to show the feasibility of the proposed design method.

Aoyama et. al. (1995) proposed a FNN employed in IMC scheme for SISO nonlinear process. The control-affine model was described identified from transient and steady state data using back propagation in this scheme. Inverse of the process is obtained through algebraic inversion of the process model to use as a controller. Two highly nonlinear process; CSTR and pH neutralization processes were studied. In the CSTR, effluent concentration was controlled using the coolant flow rate. In pH neutralization, manipulating the base flow rate controlled the effluent pH. The proposed strategy was compared to a conventional PID controller for set point and disturbance changes. The results showed that controller performance was significantly better than PID controller.

A methodology for batch process automation using reinforcement learning was presented Martinez and Wilson (1997). In this study, an autonomous controller continuously learned to implement control actions that can drive the process state very close to desired one with near optimal performance. Fuzzy QLearning algorithm was proposed to build the controller. This methodology was exemplified using a batch process involving simultaneous reaction and distillation.

Dagli et. al. (1997) combined the Dynamic Neural Networks, DNN, with the Fuzzy Associative Memory, FAM, that determines the performance of the controller by evaluating the error (e) and derivative of the error (Δe) of the system to find a better model for nonlinear control problems. The proposed model consisted of three major parts: action network, ANW, critic network, CNW and fuzzy membership adjustment procedure. ANW was the main controller of the model generates the control signal of the system. The CNW was used as the 17 FAM. The output of the CNW was sent to ANW to adjust the weight matrices of the DNN. CNW was composed of the fuzzifier, the rule base and deffuzifier. Fuzzy membership adjustment procedure was used to improve the quality of the output network. The proposed model was tested in chemical and real processes.

Peng and Chen (1999) developed an intelligent control system for the direct adaptive control of chemical processes in the presence of unknown dynamics, nonlinearities and uncertainties. They constructed a Neuro-Fuzzy Controller (NFC) with an equivalent four-layer connectionist network. With a derived learning algorithm, fuzzy rules and membership functions were updated adaptively by observing the process output error. A shape tunable NN with back propagation algorithm was also suggested as the estimator in order to provide a reference signal to the controller. The proposed algorithm was implemented to direct adaptive control of an open loop unstable nonlinear CSTR. Comparisons were performed with a static fuzzy controller.

Belarbi et. al. (2000) proposed a FNN that learns rules of inference for a fuzzy system through classical back propagation. The network was trained off-line in a closed loop simulation to design Fuzzy Logic Controller (FLC). Another network was used as a design model in order to back propagate the error signal. Controller rules were extracted from the trained network to build the rule base of the FLC. The framework was applied to the estimation and control of a batch pulp digester. The Kappa number, the controlled variable, which cannot be measured online was estimated with same type of FNN through the measurements of the batch temperature and concentration of the alkali. Although the FLC was quite simple with nine rules, simulation results showed good degree of robustness in the face of parameter variations and changes in operating conditions.

Leiviska et. al. (2001) used linguistic equations (fuzzy models) and NN models in prediction of Kappa number in the continuous digester. Actual prediction data was collected from a continuous digester house. It included the extraction flow measurements and reactive index, temperature in the extraction flow, and the measurement of Kappa number from an online device after digester. Then the data was divided into training and testing data. ANFIS was used as one of the fuzzy model and gave the best performance in other fuzzy models.

Castillo and Melin (2001) used an ANFIS methodology in electrochemical process. The problem in battery manufacturing was to find how much the current could be increased without causing battery to explode due to the increase in temperature and at the same time minimizing the time of loading. Since ANFIS can be used to adapt the membership functions and consequents of the rule base according to the historical data of the problem, ANFIS was used as fuzzy controller in this research. Fuzzy logic toolbox of MATLAB was used with 5 membership functions and first order Sugeno function in the consequents. ANFIS controller input and output were temperature and electrical current, respectively. They found that, the ANFIS methodology gave better results than manual, conventional and fuzzy control methods.

In another study of adaptive FNN, Hancheng et. al. (2002) used the ANFIS to extract fuzzy rules from experimental data for material property modeling. Prediction of tensile strength based on compositions and microstructure was aimed. Hence, back propagation NNs used in literature needed large amount of training data in order to acquire high learning precision, and had a poor generalization capability and obtaining experimental data was also expensive, authors tried to use ANFIS. To verify the generation of the model, 38 available patterns were divided into two categories: a training set of 29 cases and a test 19 of 9 cases. All the membership functions of the input variables were of the Gaussian type, and parameters sub-spaces were determined by using *K*-means clustering of the training data set, 20 rules being obtained. Inputs to the ANFIS were the carbon equivalent, the graphite flake size, and the micro hardness of the matrix, the amount of austenite dentrite and the eutectic cell. Output was the tensile strength. The results were compared with multiple statistical analyses, fuzzy regression and the generalized regression network and ANFIS showed good learning precision and generalization.

Sarimveis et. al. (2002) presented a new fast and efficient method for training RBFNN to model nonlinear dynamical MIMO discrete-time systems. The proposed training methodology was based on a fuzzy partition of the input space and combines self-organized and supervised learning. According to the algorithm, first, the centers of the nonlinear units were determined. Then, the widths of Gaussian functions were calculated. Finally, the connection weights between the hidden and the output layers were computed, by solving a simple quadratic optimization problem, which minimized the errors between the desired and predicted outputs. The developed RBF network models were used to predict the concentration and temperature in CSTR and Kappa number in a continuous pulp digester. The most important advantage of proposed algorithm was the ability to determine the network structures and parameters using a very limited computational time.

Adaptive Network Based Fuzzy Interface System (ANFIS):

In our work adaptive Neuro-fuzzy interface tool for training and testing the database, here ANFIS is an adaptive network which uses neural network topology and fuzzy logic together; ANFIS uses the characteristics of both methods. The combination of both methods removes the some disadvantage of both the method.

Actually, ANFIS is like a fuzzy inference system but in ANFIS feed-forward back propagation to minimize the error. Mamdani type and Takagi-Sugeno type is commonly used system in ANFIS .In our analysis, we use zero-order Takagi-Sugeno fuzzy inference system.

The ANFIS first introduced by Jang in 1993, It is a model that maps inputs through input membership Functions (MFs) and associated parameters, and then through output MFs to outputs. The initial membership functions and rules for the fuzzy inference system can be designed by employing human expertise about the target system to be modeled. ANFIS can then purify the fuzzy if–then rules and membership functions to describe the input–output behavior of a complex or multi-dimensional system. Jang describe that even if human proficiency is not available than it is possible to naturally set up practical membership functions(MFs) and uses the neural training process to create a set of fuzzy if–then rules that estimated a desired data set.

References

[1] Jang, J.S.R., Sun, C.T., and Mizutani, E., *Neuro-Fuzzy and Soft Computing*, Prentice-Hall International, 1997.

[2] *Fuzzy Logic Toolbox, User Guide*, Version 2, The MathWorks Inc., 2002.

[3] S. Chaudhuri et al., Ambulation Analysis in Wearable ECG, DOI: 10.1007/978-1-4419-0724-0_2, Springer Science + Business Media, LLC 2009.

[4] Congenital Heart Defects. March of Dimes. 2005. [Online]. Available: http://www.marchofdimes.com/professionals/14332_1212.asp.

[5] Minino AM, Heron MP, Murphy SL, Kochanek KD. Deaths: Final data for 2004. National Vital Statistics Reports. Aug, 2007.

[6] Congenital Heart Defects in Children Fact Sheet. American Heart Association; 2008. [Online]. Available: http://www.americanheart.org/children.

[7] Pajkrt E, Weisz B, Firth HV, Chitty LS. Fetal cardiac anomalies and genetic syndromes. Prenat Diagn. Dec, 2004. pp. 1104–1115. [Online]. Available: http://dx.doi.org/10.1002/pd.1067.

[8] Zuckerwar A, Pretlow R, Stoughton J, Baker D. Development of a piezopolymer pressure sensor for a portable fetal heart rate monitor. IEEE Trans Biomed Eng. 1993;40(no. 9):963–969.

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

[10] 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.
[11] Amara Graps. 1995. An Introduction to Wavelets. IEEE Comp.Sc. and Eng. 2(2).
[12] 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.
[13] 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.
[14] Shahanaz Ayub and J.P. Saini "Fusion beats extraction from ECG using neural network based soft computing techniques" Advances in Applied Science Research, 2010, 1 Pelagia Research Library ISSN: 0976-8610.
[15] Shahanaz Ayub and J.P. Saini, "ECG classification and abnormality detection using cascade forward neural network", International Journal of Engineering, Science and Technology, Vol. 3, No. 3, 2011, pp. 41-46.
[16] P.D.Khandait * Dr. N.G. Bawane Dr. S.S. Limaye S.P.Khandait "Efficient ECG Abnormalities Recognition Using Neuro-Fuzzy Approach" International Journal of Advanced Research in Computer Science and Software Engineering ISSN: 2277 128X Volume 2, Issue 4, April 2012.
[17] R. Amandi, A. Shahbazi, A. Mohebi, M. Bazargan, Y. Jaberi, P. Emadi, and A. Valizade "Automatic ECG Beat detection Tachycardia Using Artificial Neural Network" World Academy of Science, Engineering and Technology 71 2012.
[18] Nitin Kumar Sahu , Shahanaz Ayub and J P Saini "detection of normal and abnormal arrhythmia ECG signal using Adaptive Neuro-Fuzzy Interface System" International Journal of Advanced Research in Computer Science and Software Engineering ISSN: 2277 128X Volume 3, Issue 11, November 2013.