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Adaptive Neuro-Fuzzy Inference System for Classification of ECG Signal

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ABSTRACT: The heart is one of the important parts of any human being. The heart produces electrical signals thus electrical signals are normally called as Electrocardiogram (ECG) signal. The Electrocardiogram signal is used for identifying the heart problems. Here Classification can perform by the ANFIS trained with the back propagation gradient descent method in combination with the least mean squares method. The ANFIS model is combined with the neural network adaptive capabilities and the fuzzy logic qualitative approach. The feature extraction process is done before classification. Four types of ECG beats (normal sinus rhythm, congestive heart failure or heart failure beat, ventricular tachyarrhythmia or tachycardia beat, and Atrial fibrillation beat) are obtained from the PhysioBank databases. These heart signals are classified by four ANFIS classifiers. To improve the diagnostic accuracy the fifth ANFIS classifier is used, it has the outputs of four ANFIS classifiers as input data. The objective of this project is to presents the application of adaptive neuro fuzzy inference system (ANFIS) model for classification of Electrocardiogram (ECG) signals.

KEYWORDS: Signal processing, Electrocardiogram (ECG), QRS Complex wave, adaptive Neuro fuzzy inference system (ANFIS), Fuzzy logic, neural network**.**

1. INTRODUCTION

The electrocardiogram (ECG) signal is the recording of the bioelectrical activities of the cardiac system. It provides valuable information about the functional aspects of the heart and cardiovascular system. Early detection of heart diseases/abnormalities can prolong life and enhance the quality of living through appropriate treatment. Therefore, numerous research and work analyzing the ECG signals have been reported for effective diagnostics, the study of ECG pattern and heart rate variability signal may have to be carried out over several hours. Thus, the volume of the data being enormous, the study is tedious and time consuming. Naturally, the possibility of the analyst missing (or misreading) vital information is high. Therefore, computer based analysis and classification of diseases can be very helpful in diagnostics. Conventional methods of monitoring and diagnosing electrocardiographic changes rely on detecting the presence of particular signal features by a human observer. Due to large number of patients in intensive care units and the need for continuous observation of such conditions, several techniques for automated electrocardiographic changes detection have been developed in the past 10 years to attempt to solve this problem. Such techniques work by transforming the mostly qualitative diagnostic criteria into a more objective quantitative signal feature classification problem. In the presented approaches, the analysis of the ECG signals for detection of electrocardiographic changes has been performed by using the autocorrelation function; frequency domain features, time frequency analysis, and wavelet transform [6]. Even though fairly good results have been obtained using such techniques, they seem to provide only a limited amount of information about the signal because they ignore the underlying nonlinear signal dynamics. In recent years, there has been an increasing interest in applying techniques from the domains of nonlinear analysis and chaos theory in studying the behavior of a dynamical system from an experimental time series such as ECG signals [2-6, 11].

Fuzzy set theory plays an important role in dealing with uncertainty when making decisions in medical applications. Therefore, fuzzy sets have attracted the growing attention and interest in modern information technology, production technique, decision making, pattern recognition, diagnostics, data analysis, etc. [1,2, 4, and 8]. Neuro-fuzzy systems are fuzzy systems which use Artificial neural networks (ANNs) theory in order to determine their properties (fuzzy sets and fuzzy rules) by processing data samples. Neuro-fuzzy systems harness the power of the two paradigms: fuzzy logic and ANNs, by utilizing the mathematical properties of ANNs in tuning rule-based fuzzy systems that approximate the way human process information. A specific approach in Neuro-fuzzy development is the adaptive Neuro-fuzzy inference System (ANFIS), which has shown significant results in modeling nonlinear functions. 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. Successful implementations of ANFIS in biomedical engineering have been reported, for classification [2-4] and data analysis.

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In this study, a new approach based on ANFIS was presented for classification of the ECG signals. The proposed technique involved training the four ANFIS Classifiers to the classify four classes of the ECG signals were used as inputs. The ANFIS Classifiers were trained with the back propagation gradient descent method in combination with the least squares method. The ECG signals (normal sinus rhythm, congestive heart failure / heart failure beat, ventricular tachyarrhythmia / tachycardia beat, and Arial fibrillation beat) were obtained from the PhysioBank database [21]. Each of the ANFIS Classifier was trained so that they are likely to be more accurate for one class of the ECG signals than the other classes. The predictions of the four ANFIS Classifiers were combined by the fifth ANFIS Classifier. The correct classification rates and convergence rates of the proposed ANFIS model were examined and then performance of the ANFIS model was reported. Finally, some conclusions were drawn concerning the saliency of features (inputs of the ANFIS Classifiers) on classification of the ECG signal.

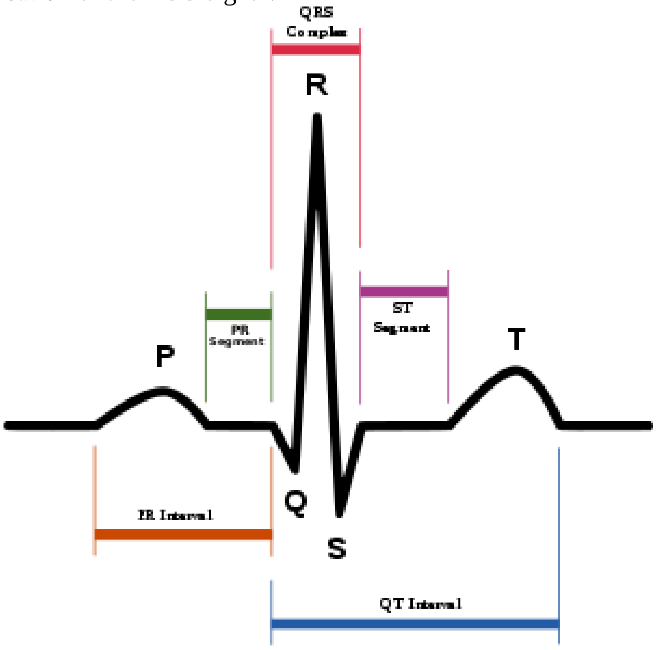

Figure 1: Schematic representation of normal ECG

II. MATERIALS AND METHODS

Decision making was performed in two stages: feature extraction and classification using the ANFIS classified trained with the back propagation gradient descent method in combination with the least squares method.

2.1. Data description:
PhysioBank database [21] is a large and growing archive of well-characterized digital recordings of physiologic signals and related data for use by the biomedical research community. PhysioBank currently includes databases of multi-parameter cardiopulmonary, neural, and other biomedical signals from healthy subjects and patients with a variety of conditions with major public health implications, including sudden cardiac death, congestive heart failure, epilepsy, gait disorders, sleep apnea, and aging. The databases of MIT-BIH normal sinus rhythm, MIT-BIH Atrial fibrillation were studied in this work. The waveforms of four different ECG beats (normal sinus rhythm, congestive heart failure / heart failure beat, ventricular tachyarrhythmia / tachycardia beat, and Arial fibrillation beat) considered in this study are shown in Fig. 3(a)–(d).

2.2. Adaptive Neuro-Fuzzy Inference System (ANFIS):
<u>Architecture of ANFIS:</u>
The ANFIS is a fuzzy model put in the framework of adaptive systems to facilitate learning and adaptation. Such framework makes the ANFIS modeling more systematic and less reliant on expert knowledge. To present the ANFIS architecture, two fuzzy if then rules based on a first order model are considered.

$$\text{Rule 1}: \quad \text{If } (x \text{ is } A_1) \text{ and } (y \text{ is } B_1) \text{ then } (f_1 = p_1 x + q_1 y + r_1)$$

$$\text{Rule 2}: \quad \text{If } (x \text{ is } A_2) \text{ and } (y \text{ is } B_2) \text{ then } (f_2 = p_2 x + q_2 y + r_2)$$

Where, x and y are the inputs, Ai and Bi are the fuzzy sets, fi are the outputs within the fuzzy region specified by the fuzzy rule, p_i, q_i and r_i are the design parameters that are determined during the training process. The ANFIS architecture to implement these two rules is shown in Fig. 4, in which a circle indicates a fixed node, whereas a square

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indicates an adaptive node. In the first layer, all the nodes are adaptive nodes. The outputs of layer 1 are the fuzzy membership grade of the inputs.

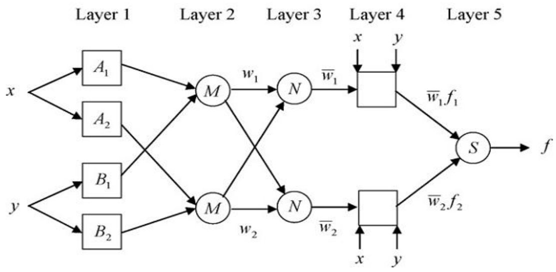

Figure 2: ANFIS architecture.

The outputs of layers are as follows,

$$O_i^1 = \mu_{A_i}(x) \quad i = 1, 2 \qquad (1)$$

$$O_i^1 = \mu_{B_{i-2}}(y) \quad i = 3, 4 \qquad (2)$$

Where, $\mu_{A_i}(x)$, $\mu_{B_{i-2}}(y)$ Can adopt any fuzzy membership function. For example, if the bell-shaped membership function is employed, $\mu_{A_i}(x)$ is given by,

$$\mu_{A_i}(x) = \frac{1}{1 + ((x - c_i/a_i)^2)^{b_i}} \qquad (3)$$

Where ai, bi and ci are the parameters of the membership function, governing the bell-shaped functions accordingly.
In the second layer, the nodes are fixed nodes. They are labeled with M, indicating that they perform as a simple multiplier. The outputs of this layer can be represented as

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1, 2 \qquad (4)$$

Which are the so-called firing strengths of the rules.
In the third layer, the nodes are also fixed nodes. They are labeled with N, indicating that they play a normalization role to the firing strengths from the previous layer. The outputs of this layer can be represented as,

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2 \qquad (5)$$

Which are the so-called normalized firing strengths, In the fourth layer, the nodes are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial. Thus, the outputs of this layer are given by,

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i), \quad i = 1, 2 \qquad (6)$$

In the fifth layer, there is only one single fixed node labelled with S. This node performs the summation of all incoming signals. Hence, the overall output of the model is given by,

$$O_i^5 = \sum_{i=1}^{2} \bar{w}_i f_i = \frac{\left(\sum_{i=1}^{2} w_i f_i\right)}{w_1 + w_2} \qquad (7)$$

It can be observed that there are two adaptive layers in this ANFIS architecture, namely the first layer and the fourth layer. In the first layer, there are three modifiable parameters {ai, bi, ci}, which are related to the input membership functions. These parameters are the so-called premise parameters. In the fourth layer, there are also three modifiable parameters {pi, qi, ri} pertaining to the first-order polynomial.
2.3. Learning algorithm of ANFIS

The task of the learning algorithm for this architecture is to tune all the modifiable parameters, namely {ai, bi, ci} and {pi, qi, ri} to make the ANFIS output match the training data. When the premise parameters ai, bi and ci of the membership function are fixed, the output of the ANFIS model can be written as

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \qquad (8)$$

Substituting Eq. (5) into Eq. (8) yields:

$$f = \bar{w}_1 f_1 + \bar{w}_2 f_2 \qquad (9)$$

Substituting the fuzzy if–then rules into Eq. (9), it becomes

$$f = \bar{w}_1 (p_1 x + q_1 y + r_1) + \bar{w}_2 (p_2 x + q_2 y + r_2) \qquad (10)$$

After rearrangement, the output can be expressed as

$$f = (\bar{w}_1 x) p_1 + (\bar{w}_1 y) q_1 + (\bar{w}_1) r_1 + (\bar{w}_2 x) p_2 + (\bar{w}_2 y) q_2 + (\bar{w}_2) r_2 \qquad (11)$$

This is a linear combination of the modifiable consequent parameters p1, q1, r1, p2, q2 and r2. The least squares method can be used to identify the optimal values of these parameters easily. When the premise parameters are not fixed, the search space becomes larger and the convergence of the training becomes slower. A hybrid algorithm combining the least squares method and the gradient descent method is adopted to solve this problem. The hybrid algorithm is composed of a forward pass and a backward pass. The least squares method (forward pass) is used to optimize the consequent parameters with the premise parameters fixed. Once the optimal consequent parameters are found, the backward pass starts immediately. The gradient descent method (backward pass) is used to adjust optimally the premise parameters corresponding to the fuzzy sets in the input domain. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard back propagation algorithm.

III. RESULTS AND DISCUSSION

Selection of the ANN inputs is the most important component of designing the neural network based on pattern classification since even the best Classifier will perform poorly if the inputs are not selected well. Input selection has

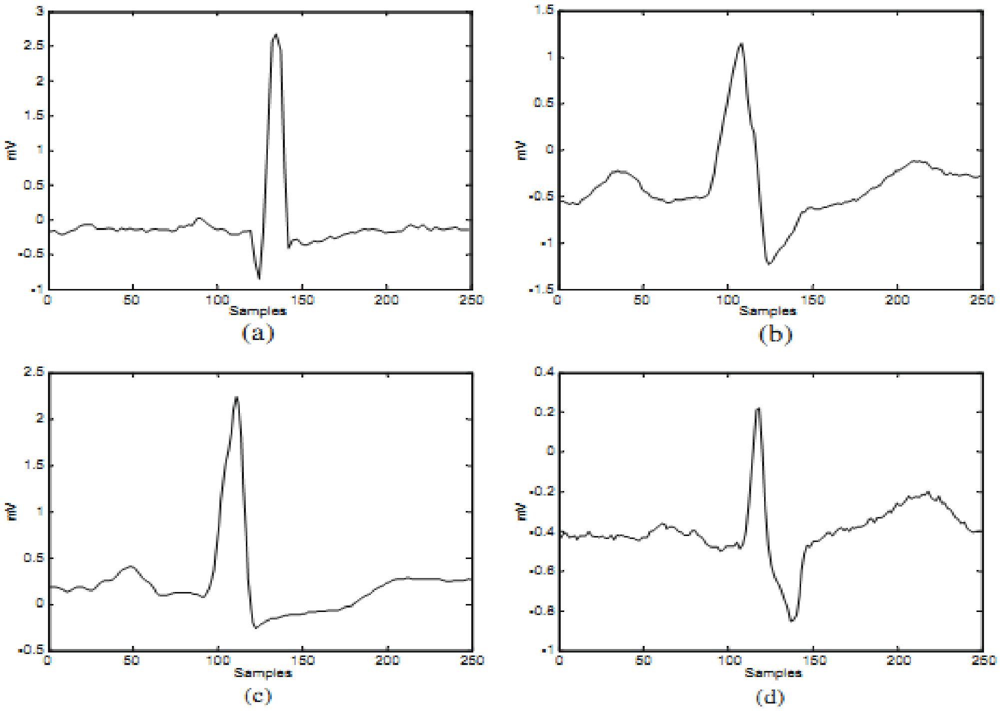

Figure 3: Sample Waveforms of the ECG beats (a) normal beat, (b) congestive heart failure beat, (c) ventricular tachyarrhythmia beat, and (d) Atrial fibrillation beat.

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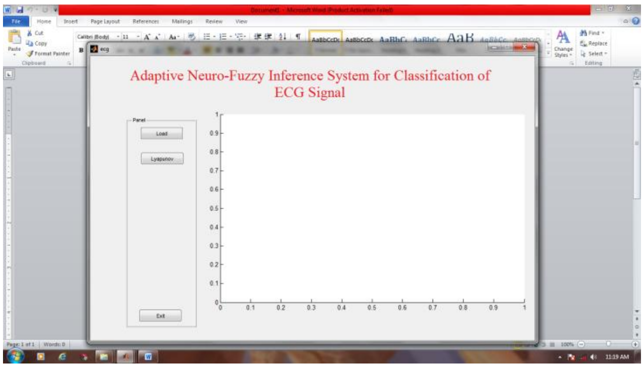
two meanings: (1) which components of a pattern, or (2) which set of inputs best represent a given pattern.
High-dimension of feature vectors increased computational complexity and therefore, in order to reduce the dimensionality of the extracted feature vectors (feature selection), statistics over the set of the ANFIS were used. The following statistical features were used in reducing the dimensionality of the extracted feature vectors representing the signals under study:

1. Normal sinus rhythm,
2. Congestive heart failure/ heart failure.
3. Ventricular tachyarrhythmia/tachycardia and
4. Atrial fibrillation beat.

The feature vectors were computed by the usage of the MATLAB software package. The four ANFIS Classifiers were trained with the back propagation gradient descent method in combination with the least squares method when four features (dimension of the extracted feature vectors) representing the ECG signals were used as inputs. Samples with target outputs normal sinus rhythm, congestive heart failure / heart failure beat, ventricular tachyarrhythmia / tachycardia beat, and Arial fibrillation beat were given the target values obtained. To improve classification accuracy, the fifth ANFIS Classifier (combining ANFIS) was trained using the outputs of the four ANFIS Classifiers as input data. The fuzzy rule architecture of the ANFIS Classifiers was designed by using a generalized bell-shaped membership function defined in Eq. (3).

Each ANFIS Classifier was implemented by using the MATLAB software package (MATLAB version 7.0 with fuzzy logic toolbox). The ECG signals were divided into two separate data sets the training data set and the testing data set. The adequate functioning of the ANFIS depends on the sizes of the training set and test set The training data set was used to train the ANFIS model, whereas the testing data set was used to verify the accuracy and the effectiveness of the trained ANFIS model for classification of the four classes of ECG signals. The steps of parameter adaptation of each ANFIS are shown in Fig. 4. The step size is decreased (by multiplying it with the component of the training option corresponding to the step size decrease rate) if the error measure undergoes two consecutive combinations of an increase followed by a decrease. The step size is increased (by multiplying it with the increase rate) if the error measure undergoes four consecutive decreases.

Feature saliency provides a means for choosing the features, which are best for classification. Therefore, in this study changes of the final (after training) membership functions with respect to the initial (before training) membership functions of the input parameters were examined. Membership function of each input parameter was divided into three regions, namely, small, medium, and large.



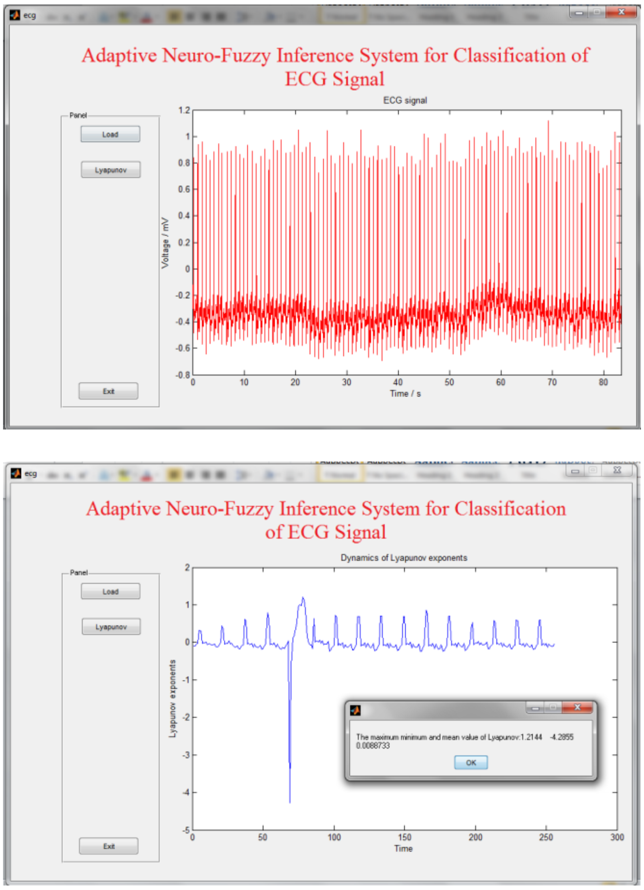


Figure 4: Output Waveforms of the ECG Signal.

IV. CONCLUSIONS

This paper presented a new application of ANFIS for classification of the ECG signals. Fuzzy set theory plays an important role in dealing with uncertainty when making decisions in medical applications. Using fuzzy logic enabled us to use the uncertainty in the Classifier design and consequently to increase the credibility of the system output. The four ANFIS Classifiers were used to classify four classes of ECG signals when the QRS complex of the ECG signals were used as inputs. The predictions of the four ANFIS Classifiers were combined by the fifth ANFIS Classifier. The presented ANFIS model combined the neural network.

Some conclusions concerning the saliency of features on classification of the ECG signals were obtained through analysis of the ANFIS. The classification results and statistical measures were used for evaluating the ANFIS. The total classification accuracy of the ANFIS model was 93%. The obtained results demonstrated that the proposed ANFIS model can be used in classifying the ECG signals by taking into consideration the misclassification rates.

REFERENCES

1. Elif Derya Übeyli, "Recurrent neural networks employing Lyapunov exponents for analysis of ECG signals" Expert Systems with Applications 37 (2010) 1192–1199.
2. Rahime Ceylan, Yuksel ozbay, Bekir Karlik, "A novel approach for Classification of ECG arrhythmias: Type-2 fuzzy clustering neural network" Expert Systems with Applications 36 (2009) 6721–6726.
3. Yuksel ozbay, Gulay Tezel, "A new method for Classification of ECG arrhythmias using neural network with adaptive activation function" Digital Signal Processing 20 (2010) 1040–1049.
4. Yun-Chi Yeh , Wen-June Wang, Che Wun Chiou, "A novel fuzzy c-means method for classifying heartbeat cases from ECG signals" Measurement 43 (2010) 1542–1555.
5. "Majid Moavenian, Hamid Khorrami , A qualitative comparison of artificial Neural Networks and Support Vector Machines in ECG arrhythmias Classification" Expert Systems with Applications 37 (2010) 3088–3093.
6. "Majid Moavenian, Hamid Khorrami , "A comparative study of DWT, CWT and DCT transformations in ECG arrhythmias Classification" Expert Systems with Applications 37 (2010) 5751–5757.
7. Engin Avci, Ibrahim Turkoglu, "An intelligent diagnosis system based on principle component analysis and ANFIS for the heart valve diseases" Expert Systems with Applications 36 (2009) 2873–2878.

ISSN 2278 - 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering
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8. Assaleh, K, "Extraction of Fetal Electrocardiogram Using Adaptive Neuro-Fuzzy Inference Systems" Biomedical Engineering, IEEE Transactions on Volume:54, Issue: 1 Digital Object Identifier: 10.1109/TBME.2006.883728 Publication Year: 2007, Page(s):59-68 Cited by: 2.
9. Ataollah Ebrahim Zadeh, Ali Khazaee, Vahid Ranaee, "Classification of the electrocardiogram signals using supervised classifiers and efficient features" computer methods and programs in biomedicine 99 (2010) 179–194.
10. Abarbanel, H. D. I., Brown, R., & Kennel, M. B. (1991) "Lyapunov exponents in chaotic systems: Their importance and their evaluation using observed data" International Journal of Modern Physics B, 5(9), 1347–1375.
11. Acır, N. (2005) "Classification of ECG beats by using a fast least square support vector machines with a dynamic programming feature selection algorithm" Neural Computing & Applications, 14(4), 299–309.
12. Umut Orhan, Mahmut Hekima, Mahmut Ozer, "EEG signals classification using the K-means clustering and a multilayer perceptron neural network model" Expert Systems with Applications 38 (2011) 13475–13481.
13. Mehmet Korürek, Ali Nizam, "Clustering MIT–BIH arrhythmias with Ant Colony Optimization using time domain and PCA compressed wavelet coefficients" , Digital Signal Processing 20 (2010) 1050–1060.
14. Marie-Francoise Lucas, Adrien Gaufriau, Sylvain Pascual, Christian Doncarli, Dario Farina, "Multi-channel surface EMG Classification using support vector machines and signal-based wavelet optimization" Biomedical Signal Processing and Control 3 (2008) 169–174.
15. Amit K. Mishra, Shantanu Raghav, "Local fractal dimension based ECG arrhythmia Classification" Biomedical Signal Processing and Control 5 (2010) 114–123.
16. Clodoaldo A.M. Lima, Andre L.V. Coelho, "Kernel machines for epilepsy diagnosis via EEG signal Classification: A comparative study" Artificial Intelligence in Medicine 53 (2011) 83– 95.
17. Raymond R. Bond, Dewar D. Finlay, Chris D. Nugent, George Moore, "A review of ECG storage formats" international journal of medical informatics 80 (2011) 681–697.
18. Gharaviri, Ali; Teshnehlab, Mohammad; Moghaddam, H. A, "Ischemia detection via ECG using ANFIS" Engineering in Medicine and Biology Society, 2008. 30th Annual International Conference of the IEEE Digital Object Identifier: 10.1109/IEMBS.2008.4649368 Publication Year: 2008, Page(s): 1163 – 1166.
19. Khaled Assale, "Adaptive Neuro-Fuzzy Inference Systems for Extracting Fetal Electrocardiogram" Signal Processing and Information Technology, 2006 IEEE International Symposium on Digital Object Identifier: 10.1109/ISSPIT.2006.270782 Publication Year: 2006, Page(s): 122 – 126.
20. A.L. Goldberger, L.A.N. Amaral, L. Glass, J.M. Hausdorff, P.Ch.Ivanov, R.G. Mark, J.E. Mietus, G.B. Moody, C.K. Peng, H.E. Stanley, PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals, Circulation 101 (23) (2000) e215–e220 (Circulation Electronic Pages <http://circ.ahajournals.org/cgi/content/full/101/23/e215>).
21. Data's obtained from the PhysioBank database:
22. http://www.physionet.org/physiobank .