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Electrocardiogram Signal Forecasting using Iterated and Direct Methods Based on Artificial Neural Network

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Abstract—Electrocardiogram (ECG) is the electric activity of heart. It is widely used for the identification and prognosis of cardiovascular disease. In this paper forecasting of electrocardiography signal is presented using two forecasting methods i.e. iterated method and direct method. These methods are based on Backpropagation Neural Network (BPNN) Model. Comparison of these two methods has been presented. It is found that direct method outperform iterated method for forecasting of ECG signal. It is also found that mean square error (MSE) remains small in case of direct method for 3 steps ahead forecasting after that MSE increased rapidly. Clinical information in forecasted and actual signals are extracted by developing automatic ECG analyzer software. It is found that the clinical information was preserved in three steps ahead forecasting using direct method. It is concluded that neural networks have much potential for forecasting of ECG signal.

Keywords: Time Series Forecasting, Neural Network, Backpropagation, ECG, iterated forecasting, direct forecasting

1. Introduction

An electrocardiogram is a test that measures the electrical signals which control the rhythm of our heartbeat [1] [2]. Prediction of ECG signal has been used in many contexts. Among important unsolved problems of the present-day cardiology is the prediction of Ventricular Fibrillation (VF) and Ventricular Tachycardia (VT) [3]. Minija *et al.* [4] presented neural network based ECG segment prediction for classification of Ventricular Fibrillation. Ventricular Fibrillation is the process of chaotic contraction of cardiac fibers. During the fibrillation, blood is no longer pumped to the organism and death occurs if no immediate treatment is applied. Ventricular fibrillation can be terminated by means of heart defibrillation. Episodes of ventricular fibrillation most often are caused by myocardial infarction [5,6].

Al-Hujazi *et al.* [7] used prediction techniques for ECG data compression. Although digital storage media is not expensive and computational power has exponentially increased in last few years, the possibility of electrocardiogram (ECG) compression still attracts the attention, due to huge amount of data that has to be stored/transmitted. So instead of transmitting huge data, a small amount of data along with prediction algorithm can be transmitted. In this scenario, two issues are important. Firstly whether the forecasting algorithm forecasts well and secondly whether the clinical information in the ECG signals preserves.

Kautzner *et al.* presented the prediction of sudden death after acute myocardial infarction [8]. They found that depressed Heart Rate Variability (HRV) computed from short-term pre discharge ECG recordings obtained under standardized conditions is associated with an increased risk of sudden cardiac death. Such predictive power is substantially increased in combination with depressed left ventricular ejection fraction. This approach seems to be effective as a simple screening method to identify high risk subjects. HRV are determined by ECG so if ECG will predict accurately one can predict HRV [9].Various time series forecasting methods like Neural Network [10,11,12,13], embedding [14] ARIMA [15] Genetic Algorithm [16], Fuzzy Logics [16,17] and wavelets [18] can be used for forecasting of ECG signal. Neural Network has been proven to be a promising alternative to traditional techniques for nonlinear time series prediction. Backpropagation Neural Network, Kohonen Self-Organising Map (SOM) [19], recurrent neural network [20] and Generalized Regression Neural Network [21], are often used for time series prediction. Neural network can be used for supervised and unsupervised learning. They proved good for nonlinear function mapping. There are also some disadvantages of Neural Network. They are often considered as black box system. They are unable to manage imprecise or vague information, difficult to reach global minimum even by complex Backpropagation (BP) learning, rely on trial-and-errors to determine hidden layers and nodes.

Statistical methods such as ARIMA [15] have proven themselves to be relatively robust especially when generating short-run forecasts. ARIMA models outperform more sophisticated structural models in terms of short-run forecasting ability. Generally they are poor at predicting turning points, unless the turning point represents a return to a long-run equilibrium.

In this paper two methods are used, to forecast the ECG signal i.e. Iterated Method and Direct Method. These methods are based on Artificial Neural Network. Backpropagation algorithm was used to train and forecast the ECG signal. Section 2 gives the introduction to ECG signal. Forecasting model is explained in section 3. In section 4, forecasting methods are deseribed. The information about signal used in this paper is summarized in section 5. Introduction to ECG analyzer is given in section 6. Results are discussed in section 7. Conclusion is given in section 8 followed by references.

2. ECG Signal

Whenever the heart starts systole, there is atrial contraction due to atrial depolarization, depicted by an upward deflection as P wave, which is relatively small amplitude equal to the mass of what is depolarized. P wave is followed by ventricular polarization that results in the form of Q, R, S waves. At the same time as ventricular polarization is in process, there is atrial repolarization masked within ventricular polarization and not normally seen. Ventricles start repolarizing after a plateau which results T wave upward deflection. A cycle of ECG signal has been shown in Figure 1.

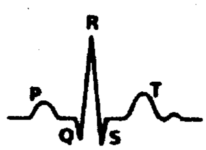

Figure 1: One Cycle of ECG

ECG signals are usually in the range of 1mV in magnitude and a bandwidth of about 0.05-100 Hz. Raw signal needs to be amplified and filtered. Electrical activity of the heart can be detected by placing small metal discs called electrodes on the skin. During electrocardiography, the electrodes are attached to the skin on the chest, arms, and legs. ECG monitoring machine records the ECG signal and prints it on the paper [30]. An ECG of a normal human is shown in Figure 2. [23].

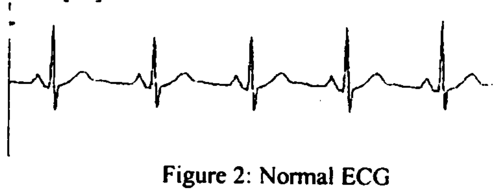

Figure 2: Normal ECG

2.1 *ECG SIGNAL PROCESSING*

A series of procedures are required that can extract useful information for the physician, enabling him/her to diagnosis concerning the pathophysiologic condition of the patient. We can also automate the diagnosis.

During ECG processing four different stages are required to implement. We must acquire the signal in its digital form and filter the signal. Main ECG characteristics like P wave, QRS complex, T wave, ST segment, PQ segment and others are detected. In order to complete the signal analysis stage some specific measurements to the above characteristics must be taken, like their amplitude and time duration. Using above characteristic automatic diagnosis can be done that can help the physician in reaching certain decisions.

From the above four ECG processing stages the first two (acquisition and filtering) have been studied thoroughly during the past two decades and the results were more than satisfactory. Various theories have been developed in the last couple of years that borrowed from Computer Science (Artificial Neural Network, Fuzzy Logic, and Pattern Recognition) and from Signal Processing (Wavelets, Nonlinear Analysis) for analysis and diagnosis. Mainly, they are being used to solve the problem of arrhythmia and ischaemia detection and recognition, two pathologic conditions that are very common and life threatening. Up till now, the research in this field has shown that computer methods can be efficient and can constitute a trustworthy tool in the diagnosis of ECG signal [24].

3. Forecasting Model

In this Paper, Backpropagation Neural Network model was used for training and forecasting.

3.1 Backpropagation Neural Network

Multilayer feed forward network consist of a set of sensory units (source nodes) that constitute the input layer, one or more hidden layers of computation nodes and an output layer of computation nodes. The input signal propagates through the network in a forward direction on a layer by layer basis. These neural networks are commonly referred as "Backpropagation Neural Network (BPNN)".

We train the multilayer network in a supervised manner with a highly popular algorithm, known as error-back propagation algorithm. This algorithm is based on error correction learning rule. BPNN has three distinctive characteristics. The model of each neuron in the network includes a non linearity at the output end. The important point is that the non linearity is smooth.

Network contains one or more layers of hidden neurons that are not part of the input or output of the network. These hidden neurons enable the network to learn complex tasks by extracting progressively more meaningful features from the input patterns. The network exhibits a high degree of connectivity determined by the synapses of the network. A change in the connectivity of the network requires a change in the population of the synaptic connections or their weights. It is through the combination of these three characteristics together with the ability to learn from experience through training that BPNN derives its computing power. But these characteristics are also responsible for making it difficult to undertake the study of the behavior of the network. The presence of distributed form of the non-linearity and the high connectivity to the network, make the theoretical analysis of the multilayer network difficult. The use of hidden neurons makes the learning process hard to visualize.

3.1.1 Backpropagation Training Algorithm

Backpropagation algorithm (Rumelhart and McClelland, 1986) is used in layered feed-forward ANNs. This means that the artificial neurons are organized in layers, and send their signals "forward", and then the errors are propagated backwards. A symbolic structure of BPNN is shown in Figure 3.

The network receives inputs by neurons in the input layer, and the output of the network is given by the neurons on an output layer. There may be one or more intermediate hidden layers. The backpropagation algorithm uses supervised learning, which means that we provide the algorithm with examples of the inputs and outputs we want the network to compute, and then the error (difference between actual and expected results) is calculated. The idea of the backpropagation algorithm is to reduce this error, until the ANN learns the training data. The training begins with random weights, and the goal is to adjust them so that the error will be minimal.

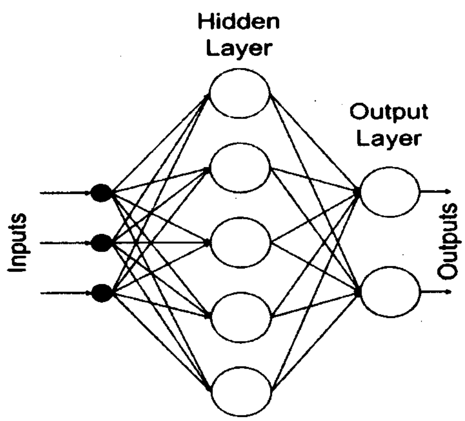

Figure 3: BPNN symbolic Structure

The network receives inputs by neurons in the input layer. The product-sum of all the inputs of neurons of preceding layer and their corresponding weights are calculated. The product of bias and its weight is also added in it.

$$net_j = bias * W_{bias} + \sum_k I_{pk} W_{jk} \qquad (1)$$

From eq. (1) net_j is used to calculate the output of neuron as follows:

$$O_{pj}(net_j) = \frac{1}{1+e^{-\lambda net_j}} \qquad (2)$$

The output neuron error signal δ_{pj} is given by

$$\delta_{pj} = (T_{pj} - O_{pj}) O_{pj} (1 - O_{pj}) \qquad (3)$$

The hidden neuron error signal δ_{pj} is given by

$$\delta_{pj} = O_{pj}(1 - O_{pj}) \sum_k \delta_{pk} W_{kj} \qquad (4)$$

Where δ_{pk} is the error signal of a post-synaptic neuron k and W_{kj} is the weight of the connection from hidden neuron j to the post-synaptic neuron k. Compute weight adjustments ΔW_{ji} by

$$\Delta W_{ji} = \eta \delta_{pj} O_{pj} \qquad (5)$$

Apply weight adjustments according to

$$W_{ij} = W_{ij} + \Delta W_{ij} \qquad (6)$$

4. Forecasting Methods

4.1 *Iterated Method*

In iterated Method Multi-input single output architecture is used. Multi-inputs are given input to neural network while single output was used as target. After training of ANN to desired value of mean square error (MSE) this model is used to forecast the future values recursively. Let x_1, x_2, x_3, ...x_n are input then in first iteration x_{n+1} will be output in second iteration x_2, x_3, x_4......... x_n, x_{n+1} will be input and x_{n+2} will be out put.

4.2 *Direct Method*

In this method multiple input multiple out put architecture is used. After training the network with Backpropagation algorithm the forecasted values are obtained by multiple inputs. Let x_1, x_2 ....x_{200} was input to the network x_{201}, x_{202}..................x_{400} were the forecasted value in second step x_{201}, x_{202}.....x_{400} was input and x_{401}, x_{402}.......x_{600} will be output.

5. ECG Signals Selection

Six ECG signals have been selected. One ECG signal is of healthy subject, other ECG signals are from those patients who have cardiac problems of Premature Ventricular Complexes (PVC), Atrial Premature Contraction (APC) and Bundle Branch Block (BBB). These signals are obtained from MIT-BIH Arrhythmia Database Directory [29]. The ECG wave forms are shown in Figure 4.

Figure 4: Selected ECG signals

The details about these ECG Signals are shown in Table (1).

Table 1: ECG Signals

Sr. #	M/ F	Age	Cardiac Problems
1	-	-	Non
2	M	69	PVC, APC
3	F	24	PVC
4	M	63	PVC
5	F	23	PVC, Ventricular trigeminy
6	F	32	Sinus arrhythmia, BBB

5.1 *Cardiac Problems Associated with Selected ECGs*

Details about these cardiac problems are given below.

5.1.1 Premature Ventricular Complexes

Premature Ventricular Complexes are caused by a spontaneous electrical impulse arising in the ventricle. This impulse occurs earlier than the normal impulse would (hence it is "premature.") Sometimes the presence of PVCs indicates an inherent electrical instability in the heart, and therefore indicates an increased risk of sudden death [25].

5.1.2 Atrial Premature Contraction

Atrial Premature Contraction (APC) originates within the atrial myocardium but outside the sinoatrial node. The APC occurs before the next expected sinus discharge, it maybe conducted normally through the atrioventricular node and ventricles, or it can be partially or completely blocked. The cause of APC is not fully known. An increased rate of premature contractions has been observed prior to the onset of atrial fibrillation and has been associated with lung and thyroid diseases [31].

5.1.3 Bundle Branch Block

Bundle Branch Block occurs when one of the bundle branches becomes diseased or damaged, and stops conducting electrical impulses; that is, a bundle branch becomes "blocked." The main effect of a bundle branch block is to disrupt the normal, coordinated and simultaneous distribution of the electrical signal to the two ventricles [25].

6. ECG Analyzer

The forecasting of ECG signal is useful only if the clinical information preserves in forecasted signal. To extract clinical information we developed a software using MATLAB which extracts clinical information. We used this software to extract height of R-wave and depth of Q and S waves. We also extract the time information i.e. at which time these peak produces in actual and forecasted signal. This software is also capable of finding RR-intervals in ECG signal. Table 5 shows the height/depth of QRS waves while table 4 shows the time at which these waves produced.

7. Results and Discussion

Iterated method gives small MSE in training data set but does not provide stable forecasting. The clinical information does not preserve in forecasting by this method. MATLAB ® is used for training and forecasting. The MSE for testing and forecasting data parts are given in Table 2. The forecasted and actual signals of 200 steps ahead are shown in figure 5. It can be see from figure 5 that forecasting signal shows the trend in the actual signal but it loses important clinical information. The MSE in testing data set was 0.0068, but in forecasted signal it was 0.0585. It shows that MSE raises 8.6 times in forecasted data set then that of actual.

Table 2: Mean Square Error (Iterated Method)

Sr. No.	Data Set	MSE (Testing)	MSE (Forecasted)
1	Normal	0.0227	0.0319
2	100	0.0064	0.0532
3	106	0.0040	0.0139
4	107	0.0028	0.0902
5	208	0.0019	0.1043
6	212	0.0032	0.0572
Average		**0.0068**	**0.0585**

In direct method average MSE was 1.11e-005 in testing part and 1.30e-004 in forecasted part for first three steps ahead forecasting. This graph shows that the MSE for all the data sets is negligible for three steps ahead forecasting. In direct method three steps mean 1200 data points because we used output vector of length 400. The clinical information was preserved for these 1200 data points. The ECG analyzer (described above) was used to extract Q, R, and S waves information in actual and forecasted signals in direct method case. In Table 5 R_H, is the height of R waves while S_D and Q_D, are depth of Q and S waves respectively. Table 5 shows that there is no significant difference between height/depth of these waves in forecasted and actual signal. It is also important clinical information that at what time these Q, R, S waves produces, for this purpose again ECG analyzer is used to extract time information these results are summarized in Table 4. Again we found that for three cycles ahead forecasting of direct method the time information in forecasted signal preserves well.

After finding the efficiency of direct method we used direct method recursively and ten steps ahead forecasting obtained. It was found that MSE raises abruptly after three steps. The graph of MSE vs. steps of forecasting is shown in figure 7. After ten steps the mean square error was about 0.2 but no clinical information was preserved.

Table 3: Mean Square Error (Direct Method)

Sr. No.	Data Set	MSE (Testing)	MSE (Forecasted)
1	Normal	9.5923e-007	1.9589e-004
2	100	9.8270e-007	1.8437e-005
3	106	9.9853e-006	3.9669e-004
4	107	2.6038e-005	3.2773e-005
5	208	9.9999e-006	3.9618e-005
6	212	1.8447e-005	9.3836e-005
Average		**1.11e-005**	**1.30e-004**

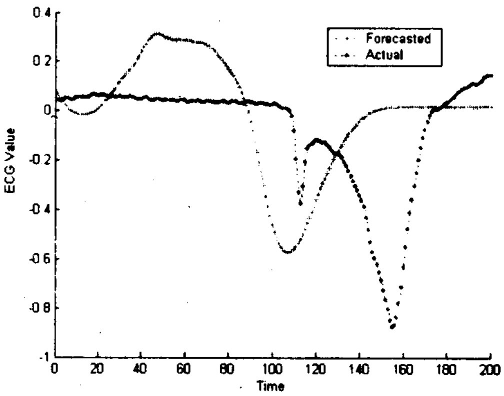

Figure 5: ECG forecasting Iterated Method

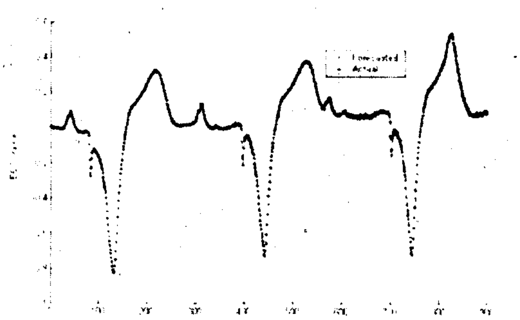

Figure 6: ECG forecasting Direct Method

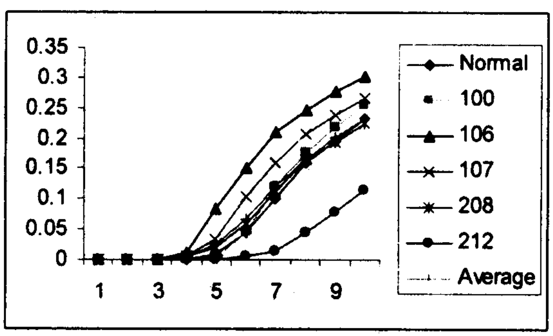

Figure 7: MSE verses forecasting steps Direct Method

Table 4: Time at which QRS Waves produced in actual and forecasted signals

Data Set	Cycle	Actual			Forecasted		
		Q_T	R_T	S_T	Q_T	R_T	S_T
100	1	250	260	359	250	260	358
	2	552	562	660	552	562	663
	3	859	870	971	859	870	1157
106	1	269	276	284	269	276	284
	2	407	586	645	407	586	644
	3	972	986	994	926	937	995

Table 5: QRS Waves Height/Depth in Actual and Forecasted Signal

Data Set	Cycle	Actual		
		Q_D	R_H	S_D
100	1	-0.4253	0.4170	-0.4253
	2	-0.4336	0.7697	-0.4336
	3	-0.5000	0.7261	-0.5000
106	1	-0.0895	0.5208	-0.0895
	2	-0.0192	0.3962	-0.0192
	3	-0.1342	0.3578	-0.1342
Forecasted				
100	1	-0.4250	0.4183	-0.4250
	2	-0.4388	0.7257	-0.4388
	3	-0.5297	0.6614	-0.5297
106	1	-0.0902	0.5221	-0.0902
	2	-0.0183	0.3983	-0.0183
	3	-0.1987	0.3520	-0.1987

8. Conclusion

The forecasting of ECG signal has been carried out using neural network based two methods i.e. iterated method and direct method. The direct method shows much better results as compared to iterated method. For evaluation of preservation of clinical information. ECG analyzer has been developed. It is found that clinical information preserves in case of direct method. It is also found that as we increase the forecasting domain the MSE raises abruptly after 3 steps ahead forecasting.

In future the prediction of ECG signal can be evaluated by mixture of algorithms like neuro-fuzzy, neuro-genetic approaches.

References:

[1] BC Health Guide web address http://www.bchealthguide.org/kbaltindex.asp

[2] Cardiovascular Disease Annotated Bibliography, Chapter 8:
http://www.fhcrc.org/phs/cvdeab/chpt08.html

[3] R. Myerburg, A. Interian, R. Mitrani *et al.* *Frequency of Sudden Cardiac Death and Profiles of Risk.* American Journal of Cardiology 80(5B) (1997). p. 10F-19F.

4] Minija Tamošiunaite , Šarunas raudys. *A Neural Network Based on ECG ST Segment Prediction Accuracy for Classification of Ventricular Fibrillation*, The 2nd International Conference on Neural Network and Artificial Intelligence, Belarusian State University of Informatics and Radioelectronics, Belarus

[5] A. Gomes, S. Winters. Late Potentials in the Post-Infarction Period: Correlation with the Ejection Fraction, Holter Monitoring, and Inducability of Ventricular Tachycardia. High-Resolution Electro-cardiography, N. El-Sherif, G. Turitto (eds.). Futura Publishing Co. NY, 1992. pp. 371-390.

[6] I. Bl··žaite, J. Brazdžionyte, J. Blužas, *A. Mickevičiene. Signal-averaged Electrocard- iogram. Pecularities of the First and Recurrent Myocardial* Infarction, Journal of the Hong Kong College of Cardiology 5(2) (1997). p. 119-125.

[7] E. Al-Hujazi and H. Al-Nashash, *ECG data compression using Hebbian Neural Network*, Journal of Medical Engineering and Technology, , Vol. 20, No. 6., p.p. 211-218, 1996.

[8] Kautzner J, St'ovicek P, Anger Z, Savlikova J, Malik M. Utility of short-term heart rate variability for prediction of sudden cardiac death after acute myocardial infarction, Acta Univ Palacki Olomuc Fac Med 1998;141:69-73

[9] Solange Akselrod, David Gordon, F. Andrew Ubel, Daniel C. Shannon, Clifford A. Barger, and Richard J. Cohen, *Power spectrum analysis of heart rate fluctuation: A quantitative probe of beat-to-beat cardiovascular control*. Science, vol. 213, no. 4504, pp. 220–222, July 1981.

[10] Tim Sauer, *Time Series Prediction by Using Delay Coordinate Embedding, pp202-204.* Time Series Prediction: Forecasting the Future and Understanding the Past, Eds. Weigend and Gershenfeld, Addison-Wesley, 1993

[11] S. Bengio, F. Fessant, and D. Collobert. *A Connectionist System for Medium-Term Horizon Time Series Prediction.* In International Workshop on Applications of Neural Network to Telecommunications, Stockholm, Sweden, 1995.

[12] F. Fessant, S. Bengio, and D. Collobert. On the Prediction of Solar Activity Using Different Neural Network Models. Annales Geophysicae, 1995.

[13] F. Fessant, S. Bengio, and D. Collobert. *Use of Modular Architectures for Time Series Prediction.* Neural Processing Letters, 1995.

[14] Tim Sauer, *Time Series Prediction by Using Delay Coordinate Embedding. pp175-196.* Time Series Prediction: Forecasting the Future and Understanding the Past, Eds. Weigend and Gershenfeld, Addison-Wesley, 1993

[15] Peter J. Brockwell, Richard A. Davis, *Introduction to Time Series Forecasting. pp 198-202*, 2nd Edition, Springer 2003

[16] A. Abraham, B. Nath, *A Neuro-Fuzzy Approach for Forecasting Electricity Demand in Victoria.* Applied Soft Computing Journal, Elsevier Science, Volume 1 /2, 2001, pp. 127-138

[17] Song, Q. and Chissom, B.S. *New Models for Forecasting Enrollments: Fuzzy time series and neural network approaches.* Paper presented at the meeting of the American Educational Research Association, Atlanta, GA. 1993

[18] Geva, A. (1998). ScaleNet—Multiscale Neural-Network Architecture for Time Series Prediction. IEEE Transactions on Neural Network, 9(5), 1471-1482

[19] Amaury Lendassei, Michel Verleyseni, Eric de Bodt, *et al. European Symposium on Artificial Neural Network 1998. Bruges (Belgium).* April 1998, D-Facto Publications (Brussels), ISBN 2-9600049-8-1

[20] C. Lee Giles, Steve Lawrence, A. C. Tsoi, Noisy Time Series Prediction using a Recurrent Neural Network and Grammatical Inference, Machine Learning, Volume 44, Number 1/2, July/August, pp. 161–183, 2001.

[21] Specht, D.F, "*A Generalized Regression Neural Network*", IEEE Transactions on Neural Network, 2, Nov. 1991, 568-
576, 1991.

[22] BC Health Guide web address http://www.bchealthguide.org/kbaltindex.asp

[23] ECG signal wave form online available http://www.physionet.org/cgi-bin/chart?database=apnea-ecg&tstart=&width=medium

[24] Medical Technology and Software development unit:
http://medlab.cs.uoi.gr/pages_en/research/ecg.htm

[25] Heart Disease web site, http://heartdisease.about.com/library/weekly/aa011501a. [illegible]

[26] Working to prevent Sudden Cardiac Death by promoting a better understanding of Arrhythmias through education and research web site, [illegible] irregular [illegible] .htm

[27] Heart disease web site,, [illegible] library [illegible]

[28] MATLAB and SIMULINK for Technical Computing: [illegible] mathworks.com

[29] MIT-BIH Arrhythmia Database Directory http://www.physionet.org/[illegible]

[30] Cardiology Services at Hendricks Regional Health, http://www.hendrickshospital.org/ourservices/cardiology.htm

[31] Arrhythmias: An Introduction, http://www.understandingpad.com/