International Journal of Applied Engineering Research ISSN 0973-4562 Volume 10, Number 14 (2015) pp 34410-34415

Chebyshev polynomials Transform for abnormalities detection using Artificial Neural Network classifier

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Abstract- Electrocardiogram (ECG) is the most widely used signal in clinical practice especially in monitoring and diagnostic of cardiovascular disease, it offers important information about health of patients and cardiologists.

In this paper, we proposed a technique to classify each heart beat of ECG into five classes: Normal beat, Paced beat, Left bundle branch block beat, Right bundle branch block beat and premature ventricular contraction beat using various neural classifiers. This system is based on mixture of temporal parameters and coefficients extracted after modelling of the ECG signal with the Chebyshev polynomial. Principal component analysis (PCA) is employed to reduce dimensions of input features and improve classification performance of neuronal classifiers, some recordings of MIT-BIH arrhythmia database ECG signals have been used for training and testing our classifiers. The experimental results demonstrate that the proposed feature extraction techniques show better performances compared to other based on temporal features only. The classifier performance is measured in terms of Sensitivity (Se), Specificity (SP) and correct classification (CC).

Keywords- ECG, neural classifiers, temporal parameters, Chebyshev polynomial, PCA, MIT-BIH arrhythmia database.

1. Introduction

A growing fraction of the population in developed countries is affected in recent years by cardiovascular disease. Considerable costs in research are spent for diagnosis and treatment of these diseases, the information about the functioning of the human heart come from a variety of sources. Most of this information comes through study, by using the most used techniques in clinical (for example measurement of ECG signal).

Electrocardiogram (ECG) plays a key role in monitoring and diagnostic of the patients. It offers important information about health of patients and cardiologists are able to recognize different heart diseases from the morphology and position of the ECG components.

Interpretation ECG wave is important to cardiac disease diagnosis, A typical ECG signal has three important parameters P, QRS, T, which characterize the cardiac activity (fig. 1.a), and a fourth parameter is the U wave [1, 2]. These waves correspond to the far field induced by specific electrical phenomena on the cardiac surface, The P wave is the result of slow moving depolarization of the atria. QRS complex which is made of Q, R and S waves shows ventricular depolarization. The T wave represents repolarization of the ventricles, and is longer in duration than depolarization [3].

For several decades, numerous techniques for ECG signal analysis and cardiac arrhythmia classification have been proposed to increase the accuracy of the system through mathematical methods. These methods include Wavelet Coefficient [2], selforganizing map [3], Autoregressive Modeling [4], RBF Neural Networks [5], and fuzzy c-means clustering techniques [6]. The revolution in computer science particularly artificial intelligence (AI) in recent years helps many researchers to developed several discriminative techniques for ECG beat classification such as artificial neural networks [7, 8, 9] or probabilistic neural networks [10]. Other work used the Kth nearest-neighbor rule [11, 12], genetic algorithms [13] and Support Vector Machines (SVMs) [13, 14, 15, 16].

The variation of the appearance of normal and abnormal ECG signals and inaccuracies in input feature vectors of the classifier caused by substantial overlapping of the frequencies of the P-wave, T-wave, QRS complex and the noise are major problems in the automatic classification of ECG beats [1]. For that, we searched to add new features to the temporal descriptors of ECG signal to ameliorate the classification algorithms.

In this paper, we presented six different multilayer neural networks MLPNNs, the first group of classifiers MLP contains the classifiers (MLP1, MLP2, and MLP3) uses as input features temporal descriptors extracted from ECG signal and the second group MLPC contains the classifiers (MLPC1, MLPC2, and MLPC3) uses as input features a mixture of temporal descriptors and Chebyshev polynomial coefficients retained after modeling ECG signal, the aim of using these models is for classifying heartbeats in five classes: Normal beat (N), Paced beat (PAC), Left bundle branch block beat (LBBB), Right bundle branch block beat (RBBB) and premature ventricular contraction beat (PVC), the difference between architect of proposed networks is in the number of neuron and the activation functions in each layer. The PCA method is used to reduce the vector features. ECG signals are obtained from the MIT-BIH cardiac arrhythmia database. To evaluate performance of the different MLPNNs, the Sensitivity (SE), Specificity (SP), and correct classification (CC) are calculated. High accuracies classifications were obtained by using the MLPNNs trained on mixture of temporal parameters and coefficients of modeling of the ECG signal with the Chebyshev polynomial.

2. Description of the implemented method

2.1 The proposed algorithm

The block diagram of the proposed algorithm is demonstrated in Fig. 1. It can be seen that the whole methodology is divided into four basic parts that is preprocessing, feature extraction, compression (reduction data) and classification.

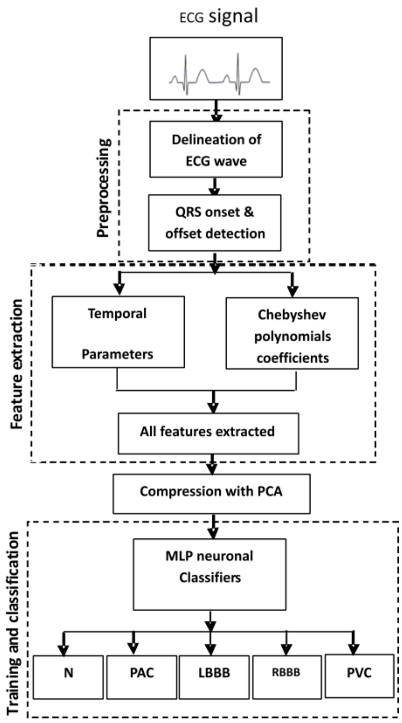

Fig.1. Block diagram of our automatic supervised classification algorithm.

2.2 Database

The collection database is the one of the most important task of signal processing. For our work, the MIT-BIH arrhythmia database in PhysioBank was used [18]. PhysioBank is a large and growing archive of well-characterized digital recordings of physiological signals and related data for use by the biomedical research community.

This database contains 48 ECG recordings, each containing 30 min segment selected from 24 hrs recordings of 48 individuals. Each ECG signal is passed through a band pass filter at 0.1–100 Hz and sampled at 360 Hz. The 44 records from MIT-BIH arrhythmia database are used for performance assessment. The different records used in this work are listed in Table.1.

Table 1. Distribution of the ECG records

Beats Type	MIT-BIH Arrhythmia Database Records
N	101, 103, 105, 115, 121, 122, 123, 202, 205,234
PAC	102, 104, 107, 217
LBBB	109, 111, 207, 214
RBBB	118, 124, 212, 231
PVC	119, 200, 208,233

2.3. Delineation and Extraction of features

The Electrocardiogram signals (ECG) can be seen as the periodization of a pattern composed of several successive waves rated P, QRS and T [18]. The delimitation of these waves for aim to detection of the characteristic waveforms and determination of peaks and limits of individual QRS complex, P and T waves which are very important for the medical interpretation of ECG signals .the work towards the automated delineation is started in the early 1960 [19,20].

The different waves and intervals measurement different waves illustrate in Fig. 2 were defined by using an algorithm reported in detail [21, 22, 23]. It includes the following basic steps: a High-pass filter, signal Empirical Mode Decomposition, QRS detection, QRS onset, T wave-end and P wave definition.

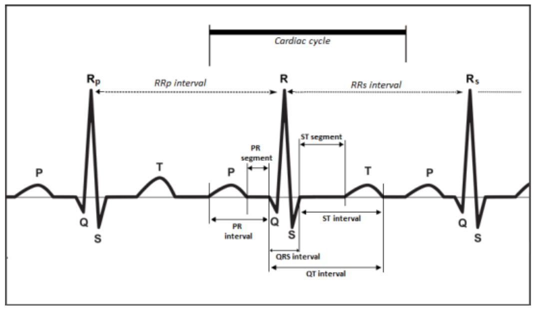

Fig.2. the most significant intervals of the ECG signal

1) Temporal Features

For each ECG heartbeat, a feature vector is extracted that represents some features of signals these features are described in table 2. In total, we used 10 temporals features for the experiments of feature selection.

Table 2. Temporal features extracted from ECG signals

Designation	Description
R-R interval duration	Interval between two successive QRS
Q-R interval duration	Interval between R peak and the beginning of QRS complex
RS interval duration	Interval between the end of QRS complex and the peak R
QRS complex duration	Interval between the end and the beginning of the QRS complex
RR_S interval duration	Interval between the current R peak and the following R peak
RR ratio	$RR_{ratio} = RR_S/RR_p$
E_{QRS}	Energy of QRS complex
QT interval duration	Interval between T-end and the beginning of QRS complex
ST segment duration	Interval between the beginning of T wave and the end of QRS complex
ST interval duration	Interval between T-end and the end of QRS complex

2) Chebychev polynomial coefficients

The Chebyshev polynomials are the most used in solving the problems of interpolation and approximation in numerical analysis [24, 25]. These polynomials are orthogonal set of function recursively defined on the interval [-1, 1] in two kinds.

The Chebyshev polynomials of the first kind are defined by the recurrence relation $T_0(x) = 1$, $T_1(x) = x$, respectively

$$T_n(x) = 2xT_n(x) - T_{n-1}(x) \tag{1}$$

The first five Chebyshev polynomials for the first kind are:

$$T_0(x) = 1;\ T_1(x) = x;\ T_2(x) = 2x^2 - 1;\ T_3(x) = 4x^3 - 3x;\ T_4(x) = 8x^4 - 8x^2 + 1$$

The Chebyshev polynomials of the second kind are defined by the recurrence relation $U_0(x) = 1, U_1(x) = 2x$, respectively

$$U_{n+1}(x) = 2xU_n(x) - U_{n-1}(x) \tag{2}$$

The first five Chebyshev polynomials of the second kind are:

$$U_0(x) = 1;\ U_1(x) = 2x;\ U2(x) = 4x^2 - 1;\ U_3(x) = 8x^3 - 4x;\ U_4(x) = 16x^4 - 12x^2 + 1$$

Many other properties of Chebychev polynomials can be found in [26]

In this paper, we will use the Chebyshev polynomials of first kind to model ECG signal. In general, the signal g (t) becomes g(x) on the interval [-1, 1] and its series expansion Chebyshev polynomials given by:

$$g(x) = \sum_{n=0}^{\infty} C_{n,T} T_n(x) \tag{3}$$

The coefficients $C_{n,T}$ are calculated as follow:

$$\boldsymbol{C_{0,T} = \frac{1}{\pi}\int_{-1}^{1} \frac{g(x)}{\sqrt{1-x^2}} dx} \tag{4}$$

$$\boldsymbol{C_{n,T} = \frac{2}{\pi}\int_{-1}^{1} \frac{g(x)T_n(x)}{\sqrt{1-x^2}} dx\ si\ n \geq 1} \tag{5}$$

In this part of our work, an algorithm is implemented to model ECG signals through Chebyshev polynomials and extracted the coefficients of modeling, it consist of several steps as shown in fig.3, the ECG signal is first divided into blocks (segmentation), after a transposition of the signal in the domain of definition of the polynomial [-1, 1] to compute the coefficients for each signal segment. The decomposition of the ECG signals proposed so far segment the signal into blocks that coincide exactly with the cardiac cycle [27].

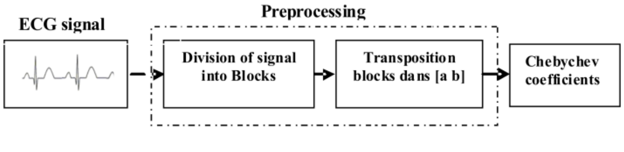

Fig.3. Modeling of the ECG signal with the Chebychev orthogonal polynomials

2.4. Principal component analysis (PCA)

The features extracted from each heart beat (temporal features and coefficients) create the feature vector includes most of the useful information. For the aim of reducing the database size as well as speeds up the inference procedure especially for a large database, different algorithms are proposed such as: Principal Component Analysis (PCA) [28], Association Rules (AR) [29], Rough Set theory [30], and Correlation-based feature subset selection (CFS) [31]. In this paper, the Principal Component Analysis (PCA) is used.

Principal component analysis (PCA) is mathematical technique used in signal processing , whose purpose is used the orthogonal transformation to transform a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components (PC).This transformation is bidirectional and no information is lost [32]. The result database constructed is used for learning and calculation of parameters of classifiers.

2.5. Description of the neural networks

Artificial Neural Network (ANN) is generally called neural network, is a computational model inspired by the functioning of the human brain with its organization of neurons and decision making processess [33]. It consists of simple but highly interconnected computing devices, each of which imitates the biological neuron. The ANN "learns" by adapting connections between its computational neurons to match input-output combinations.

There are different types of networks [34], the distinction between them is depending to the patterns of connection between the units and the propagation of data. The Multi-layer perceptron (MLP) [35] is the most commonly used neural network architecture and frequently used in biomedical signal processing [36].

In order to classify the heartbeat into five different classes: Normal beat (N), Paced beat (PAC), Left bundle branch block beat (LBBB), Right bundle branch block beat (RBBB) and premature ventricular contraction beat (PVC), various multi-layered perceptron neural networks (MLPNNs) are used namely: MLP1, MLPC1, MLP2, MLPC2, MLP3 and MLPC3. In table 3, the architecture of the different MLPs used, are be presented. In MLP structure, the features will be temporal descriptors extracted only in ECG signal. For MLPR, a mixture features between temporal descriptors and coefficients of modeling extracted from the ECG signal. As we can see in table 2, the difference between MLP1, MLP2 and MLP3 is the choice of the activation function in the hidden units. Same thing for the MLPC1, MLPC2 and MLPC3 topologies. The three-layer artificial neural networks are configured as follows: one input layer, 6 hidden layers (L=6) and one output layer with five neurons. Each hidden layer contains M neurons (See figure 4). Fifteen neurons for each hidden layer are used in MLP1, MLP3, MLPC1 and MLPC3 topologies, ten neurons in MLP2 and MLPC2.

Table 3. The topology of the different MLPNNs used

input neurons	hidden layers	Activation function	number of neutrons	output layers (Activation function)
Temporal features Mixture feature temporal/coefficients	6	$a = tansig(n)$	15	$a = tansig(n)$
Temporal features Mixture feature temporal/coefficients		$a = logsig(n)$	10	$a = logsig(n)$
Temporal features Mixture feature temporal/coefficients		$a = logsig(n)$	15	$a = tansig(n)$

Table 4. Performance analysis of the MLPC classifiers

types of beats/ classifiers	MLPC1			MLPC2			MLPC3		
	Accuracy (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)
NORMAL	99,4	98,99	99,50	99,90	99,50	100	99,20	100	99,01
PACED	99,6	100	99,50	99,90	100	99,87	98,80	97,96	99,00
LBBB	100	100	100	100	100	100	99,20	98	99,50
RBBB	99,6	99	99,75	99,80	99	100	99,20	96,15	100
PVC	99,7	99	99,87	100	100	100	99,10	97,51	99,49
Average	99,66	99.39	99.75	**99.92**	**99.70**	**99.97**	99.10	97.92	99.40

Table 5. Performance analysis of the MLP classifiers

types of beats/ classifiers	MLP1			MLP2			MLP3		
	Accuracy (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)
NORMAL	99,2	98,98	99,25	99,9	99,50	100	99,2	100	99,01
PACED	99,4	100	99,25	99,8	100	99,75	98,8	97,96	99,00
LBBB	100	100	100	100	100	100	98,9	97,48	99,25
RBBB	99,4	98,02	99,75	99,6	99	99,75	99	96,11	99,74
PVC	99,4	98,02	99,75	99,8	99,01	100	98,9	97,48	99,25
Average	99,48	99.00	99.60	**99.82**	**99.82**	**99.90**	98.96	97.81	99.25

3. Experimental Results and Discussion

The different MLPNNs evaluated on the different records in MIT-BIH arrhythmia database. The used of these classifiers were implemented in Mat lab 7.14 environment and tested on a common PC Pentium I5 Processer 2.5 GHz with 4 Go ram.

The different neuronal networks were trained to obtain the final weights and biases by the trainlm algorithm; this algorithm uses standard numerical optimization techniques [37]. Three statistical indicators, correct classification (CC), Sensitivity (Se) and Specificity (Sp) have been used to evaluate the performance of the different MLPNN classification system. The performance parameters are calculated from the confusion matrix as follows. Sensitivity is defined as in (6), is a measure of the capacity of test the positive samples.

$$SE = \frac{TP}{TP+FN} \quad (6)$$

Specificity is defined as (7), is a measure of capacity of test the negative samples.

$$SP = \frac{TN}{TN+FP} \quad (7)$$

Accuracy is defined as (8).

$$\text{Accuracy}(CC) = \frac{TN+TP}{TP+TN+FN+FP} \quad (8)$$

Where TP is the number of true positive recognized beats, TN is the number of true negative recognized beats, FP is the number of false positive recognized beats, and FN is the number of false negative recognized beats. The overall average detection rate is defined as the percentage of recognized beats to the total number of tested beats.

The following tables 4and 5 shows the classification results performances of the six proposed networks with the overall architecture as shown in Table 3.

Table 6. comparative result of accuracy average of each MLPNN

Classifier	Accuracy (%)	Classifier	Accuracy (%)
MLP1	99.48	MLPC1	99.66
MLP2	**99.82**	**MLPC2**	**99.92**
MLP3	98.96	MLPC3	99.10

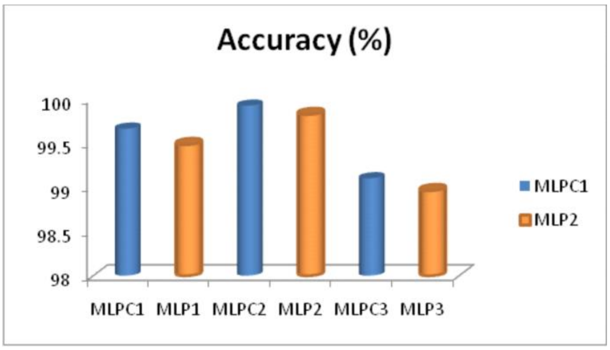

Fig. 4. Bar diagram of accuracy average of each MLPNN

According to the results illustrated in all tables, among different proposed MLPNNs, it was found that the classifier MLPC2 produced the best classification results performances.

As shown in table 6 and the figure 4, the classifiers of type MLPC gives good results compared to the other MLP classifiers. Also, we can see that MLP2 (CC=99, 82%) provides good classication performance comparatively with MLP1 and MLP3 (99,48% for MLP1 and 98.96% for MLP3). Likewise for the MLPC2 topology (CC=99,92%) where there is a more efficient classification compared to MLPC1 and

MLPC3 topologies (99,66% for MLP1 and 99.10% for MLP3). It involves that the right choice of the activation function and data features for each layer affect the recognition rate in the classifiers.

4. Conclusion

In this paper, a new approach based on neural networks for the automatic classification of ECG signal into five classes using two features extraction techniques such as temporal descriptors and Chebychev polynomial coefficients. As we have seen previously, the proposed scheme uses, various stages, including, signal processing step, feature extraction, PCA-based feature vector compression and finally training and classification. The aim is to identify the different classes of beat in ECG signal by using six different multi-layered perceptron neural classifiers namely: MLP1, MLPC1, MLP2, MLPC2, MLP3 and MLPC3. A comparative study was made between the six MLPs topologies presented in this work. The proposed classification algorithm is tested on MIT-BIH arrhythmia database from the universal MIT PhysioNet. We have shown that the classifier MLPC2 produced the best classification results performances describe both by the sensitivity, the specificity and correct classification parameters.

According to the present work, we can conclude that the used of Chebychev coefficients retained with the temporal features extracted from ECG and the right choice of the activation function for each layer greatly affects the recognition rate in the classifiers.

For this we believe that the proposed scheme can be served as an effective tool for cardiologists to diagnose heart diseases based on ECG signals.

Acknowledgements

This work was carried out in Biomedical Engineering laboratory from the University of Tlemcen.

References

[[1] N. Maglaveras, T. Stamkapoulos, K. Diamantaras, C. Pappas, M. Strintzis, ECG pattern recognition and classification using non-linear transformations and neural networks: a review, Int. J. Med. Inform. 52 (1998) 191–208.

[2] P. de Chazal, B.G. Celler, R.B. Rei, Using wavelet coefficients for the classification of the electrocardiogram, in: Proceedings of the 22nd Annual EMBS International Conference, Chicago IL, July 23–28, 2000.

[3] Marcel0 R. Risk, Jamil F. Sobh, J. Philip Saul, Beat Detection and Classification of ECG using self organizing maps, in: Proceedings – 19th International Conference – IEEEIEMBS, Chicago, IL. USA, October 30–November 2, 1997.

[4] N. Srinivasan, D.F. Ge, S.M. Krishnan, Autoregressive modeling and classification of cardiac arrhythmias, in: Proceedings of the Second Joint Conference Houston, TX, USA, October 23–26, 2002.

[5] Hafizah Hussain, Lai Len Fatt, Efficient ECG signal classification using sparsely connected radial basis function neural network, in: Proceeding of the 6th WSEAS International Conference on Circuits, Systems, Electronics, Control and Signal Processing, December 2007, pp. 412–416.

[6] Yuksel. Ozbay, Rahime. Ceylan, Bekir. Karlik, Integration of type-2 fuzzy clustering and wavelet transform in a neural network based ECG classifier, Expert Syst. Appl. 38 (2011) 1004–1010.

[7] T. Ince, S. Kiranyaz, M. Gabboudj, A generic and robust system for automated patient-specific classification of ECG signals, IEEE Transactions on Biomedical Engineering 56 (5)
(2009) 1415–1426.

[8] P. De-Chazal, R. Reilly, A patient adapting heartbeat classifier using ECG morphology and heartbeat interval features, IEEE Transactions on Biomedical Engineering 53
(12) (2006) 2535–2543.

[9] H. Mohan Rai, A. Trivedi, S. Shukla, ECG signal processing for abnormalities detection using multi-resolution wavelet transform and Artificial Neural Network classifier, ELSEVIER Measurement 46 (2013) 3238–3246 hhhh

[10] F. Melgani, Y. Bazi, Classification of electrocardiogram signals with support vector machines and particle swarm optimization, IEEE. Transactions on Information Technology in Biomedicine 12 (5) (2008) 667–677.

[11] I. Christov, G. Gomez-Herrero, V. Krasteva, I. Jecova, A. Gotchev, Comparative study of morphological and time–frequency ECG descriptors for heartbeat classification, Medical Engineering and Physics (28) (2006) 876–887.

[12] Y. Kutlu, D. Kuntalp, Feature extraction for ECG heartbeats using higher order statistics of WPD coefficients, Computer Methods and Programs in Biomedicine 105 (3) (2012) 257–267.

[13] A. Khazaee, A. Ebrahimzadeh, Classification of electrocardiogram signals with support vector machines and genetic algorithms using power spectral features, Biomedical Signal Processing and Control (5) (2010) 252–263.

[14] C.P. Shen, W.C. Kao, Y.Y. Yang, M.C. Hsu, Y.T. Wu, F. Lai, Detection of cardiac arrhythmia in electrocardiograms using adaptive feature extraction and modified support vector machines, Expert System with applications (39) (2012) 7845–7852. hhhh

[15] S.N. Yu, Y.H. Chen, Electrocardiogram beat classification based on wavelet transformation and probabilistic neural network, Pattern Recognition Letters (28) (2007) 1142–1150.

[16] Z. Zidelmal, A. Amirou, D. Ould-Abdeslam, J. Merckle , ECG beat classification using a cost sensitive classifier, ELSEVIER. Computer methods and Programs in Biomedicine (2013) 570–577 titre1685

[17] R. Mark and G. Moody, "MIT-BIH Arrhythmia Database," 1997, http://ecg.mit.edu/dbinfo.html.

[18] B.-U. Kohler, C. Hennig, and R. Orglmeister, "The principles of software QRS detection," IEEE Eng. Med. Biol. Mag., vol. 21, no. 1, pp. 42–57,2002.

[19] Friedemann W. S., and Hubert V. P., Automatic Recognition of Electrocardiographic Waves by Digital Computers. Circulation Research, v.9, pp. 1138-1143, 1961.
[20] Willems J. L. , A review of computer ECG analysis: Time to evaluate and standardize. Crit. Rev. Med. Inform., v.1 n.2, pp.167-207, 1986.
[21] Z.E. Hadj Slimane, F. Bereksi Reguig, A real-time QT interval detection algorithm, Journal of Mechanics in Medicine and Biology 8 (2) (June 2008)251–263.
[22] Zine-Eddine Hadj Slimane, Amine Nait-Ali. QRS complex detection using Empirical Mode Decomposition. Digital Signal Processing. Digital Signal Processing 20 (2010) 1221–1228.
[23] M. Bachir, Z.E. Hadj Slimane. A real-time interval measurement algorithm. 2nd International Conference on Signal, Image, Vision and Their Applications (SIVA'13), November 18-20, 2013, Guelma, Algeria.
[24] N. BAKHVALOV "Méthodes Numériques" ; Edition MIR 1976.
[25] Cambridge University Press Numerical Recipes in C: The Art of Scientific Computing", (ISBN O-521-43108-5), 1988-1992
[26] G. Szegö "Orthogonal polynomials", American Mathematical Society, Vol. 23, fourth edition 1975.
[27] W. Philips, G. De Jonghe "Data compression of ECG's by highdegree polynomial approximation", IEEE Transactions on Biomedical Engineering, Vol. 39, N° 4, pp. 330-337, 1992.
[28] D. Calisir, and E. Dogantekin, A new intelligent hepatitis diagnosis system: PCA LSSVM, Expert Systems with Applications, vol. 38, pp. 10705-10708, 2011.
[29] M. Karabatak, and M. C. Ince, An expert system for detection of breast cancer based on association rules and neural network, Expert Syst Appl, vol. 36, no. 2, pp. 3465-3469, 2009.
[30] H. L. Chen et al. A support vector machine classifier with rough set based feature selection for breast cancer diagnosis, Expert Syst Appl, vol. 38, no. 7, pp. 9014-9022, 2011.
[31] M. A. Hall, Correlation-based Feature Subset Selection for Machine Learning, Hamilton, New Zealand, 1998.
[32] Jolliffe IT. Principal Component Analysis. Springer Series in Statistics 2002. New York: Springer.
[33] MACY, R. B.,pandya, A. S. Pattern Recognition with Neural Networks in C++.Florida: CRC Press LLC, 1996.
[34] SANDHYA SAMARASINGHE. Neural Networks for Applied Sciences and Engineering : From Fundamentals to Complex Pattern Recognition. AUERBACH, September 12, 2006, ISBN-10:084933375X.
[35] R.P. Lippmann, An introduction to computing with neural nets, IEEE ASSP Magazine April (1987) 4–22.
[36] A.S. Miller, B.H. Blott, T.K. Hames, Review of neural network applications in medical imaging and signal processing, Med. Biol. Eng. Comput. 30 (1992) 449–464.
[37] H. Demuth, M. Beale and M. Hagan, (2006) Neural network toolbox For Use with MATLAB.

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