www.jmss.mui.ac.ir

Discriminant Analysis Between Myocardial Infarction Patients and Healthy Subjects Using Wavelet Transformed Signal Averaged Electrocardiogram and Probabilistic Neural Network

Ahmad Keshtkar[1,2], Hadi Seyedarabi[3], Peyman Sheikhzadeh[1], Seyed Hossein Rasta[1,2]

[1]Department of Medical Physics, Faculty of Medicine, Isfahan University of Medical Sciences, Isfahan, Iran, [2]Department of Biomedical Engineering, Faculty of Advanced Medical Sciences, Tabriz University of Medical Sciences, Tabriz, Iran, [3]Department of Electrical and Computer Engineering, University of Tabriz, Tabriz 51666, Iran

Submission: 12-02-2013 Accepted: 04-10-2013

ABSTRACT

There are a variety of electrocardiogram based methods to detect myocardial infarction (MI) patients. This study used the signal averaged electrocardiogram (SAECG) and its wavelet coefficient as an index to detect MI. Orthogonal leads signals from 50 acute myocardial infarction (AMI) and 50 healthy subjects were selected from the national metrology institute of Germany (PTB diagnostic database). They were filtered and discrete wavelet transformed was exerted on them. Four conventional features and two new features introduced in this study were extracted from SAECG and its wavelet decompositions. Finally for data classification, probabilistic neural network were used. This method was able to detect and discriminate AMI patients from healthy subjects using the probabilistic neural network, which shows 93.0% sensitivity at 86.0% specificity with 89.5% accuracy. This technique and the new extracted features showed good promise in the identification of MI patients. However, the sensitivity and specificity is comparable with other findings and has high accuracy although we extracted only 6 features.

Key words: *Discrete wavelet transform, electrocardiogram, myocardial infarction, probabilistic neural network*

INTRODUCTION

The conventional methods for the detection of MI and its discrimination from healthy people were based on the check and study of ST segment, T direction, Q pathologic on conventional electrocardiogram (ECG). Using of wavelet transform in ECG signals to reveal more details has been developed for last 10 years. The analysis of vectorcardiogram (VCG) features, which is extracted from orthogonal leads has also been used for myocardial infarction (MI) detection, since the orthogonal leads give us more and helpful information about ventricles.[1]

There are many studies about MI patients' detection using different methods. Hurd *et al*. 1981 first used VCG and ECG simultaneously for detection of MI patients.[1] Eriksson *et al*. 1997 also studied patients with left and right bundle branch block using VCG in order to diagnose MI.[2] Papaloukas *et al*. 2002 studied ST segment and T wave using artificial neural network.[3] Toledo *et al*. 2009 proposed an analysis of high-frequency QRS components to identify cardiac ischemia.[4] Dehnavi *et al*. 2011 using VCG and neural network identified ischemic patients with %86 accuracy.[5] Furthermore, recently Correa *et al*. 2013 extracted new features and showed that combination of conventional and new extracted features is high sensitive in detection of MI patients.[6]

Our study was based on signal averaged electrocardiogram (SAECG) and its wavelet decomposition as a new method in detection of MI patients. During the procedure, multiple ECG tracings were obtained over a period of approximately 20 min evaluating several hundred cardiac cycles to detect subtle abnormalities that increased risk for cardiac arrhythmias. These subtle abnormalities are usually undetectable on a conventional ECG. The late potentials (LP) in cardiac disease such as ventricular tachycardia were studied using SAECG.[7,8] We assumed this technique is sensitive to detect the acute myocardial infarction (AMI) and gives more information than conventional ECG. SAECG uses orthogonal leads such as VCG.

MATERIALS AND METHODS

Real electrocardiographic signals provided by "PhysioNet" database were used to develop our algorithm in the technique. We chose "PTB diagnostic ECG database[9] with

Address for correspondence:
Dr. Seyed Hossein Rasta, Department of Medical Physics, Faculty of Medicine, Tabriz University of Medical Sciences, Tabriz 51666, Iran.
E-mail: s.h.rasta@abdn.ac.uk

a sampling frequency of 1 kHz, resolution of 16 bit with 0.5 μV/LSB and total duration of about 2 min. Each ECG was made by 15 leads: The 12 conventional and 3 orthogonal (Frank leads). The study population consisted of 100 cases each with three orthogonal signals (Vx, Vy, Vz) from the Frank leads. In this study, 50 normal controls with no history of MI and 50 patients with AMI were included. MI patients from PTB 15 lead diagnostic database were AMI patients.

The stages of the proposed method have shown in summary in a general diagram [Figure 1].

Filtering and Preprocessing

The ECG signals were preprocessed in two following stages to reduce low/high frequency noises and the artifacts caused by power line interface.

- Removing DC component and the low frequency oscillation and also remaining in interested bandwidth limit, 4th order High-pass and a 5th order Low-pass bidirectional Butterworth filters with cut-off frequencies of 25 Hz and 300 Hz respectively[7,10] were used in ECG signal
- Removing power line interface noise, a narrow band noise centered 50 Hz frequency, 50 Hz notch filter were created by the filter design toolbox of MATLAB software version 7.11.0, Math works Inc., Natick, MA.

Signal Averaged ECG

Signal averaged electrocardiography is a technique to detect low signals in microvolts range, by improving signal to noise ratio. Relocation of the positions of leads in patients causes to change in their waveform. Thus choosing a low noise segment of the signal and calculating the maximum autocorrelation between it and other its segments, QRS complexes could be found. The average of these segments gives an informative QRS complex with minimum noise.

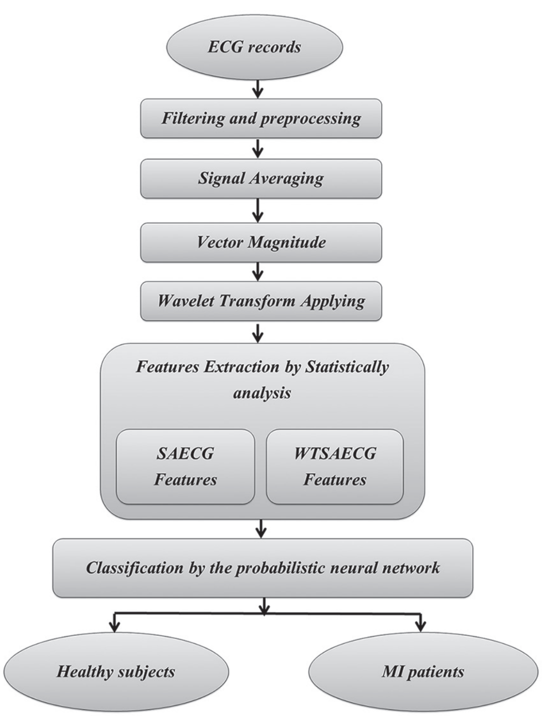

Figure 1: General diagram of proposed method

Averaging

Averaging for SAECG can be used either temporal or spatial by three pairs of orthogonal bipolar leads X, Y, Z. To record SAECG, 150-300 beats are sufficient in the most of cases. The most famous signal averaging method that has been used in the literatures is signal time averaging that includes averaging for several consecutive QRS complexes in the time domain. This method will not work properly unless the QRS complex replicated exactly.

To obtain an averaged signal it must be generally analyzed and fragmented into QRS complexes with different cycles to form an averaged single QRS complex. The ventricular premature beats signals, unusual conduction beats or beats with detected noises were identified and excluded from the processing system. An automatic model recognition algorithm using several primary QRS complexes were utilized to generate a new pattern. Using this pattern, the next beat was analyzed in terms of the appropriateness of the pattern and selected if it was fit in the pattern. Finally, the selected beats along signal were averaged.[11]

Vector Magnitude

The filtered signals for the three leads were combined into a VM which quantifies the energy measured by the three bipolar leads.[7] VM is defined as:

$$\mathrm{VM} = \sqrt{X^2 + Y^2 + Z^2} \tag{1}$$

where $X(t)$, $Y(t)$ and $Z(t)$ are the SAECG of the three leads that is shown in Figure 2.

Wavelet Decomposition Analysis

Wavelet transform that is widely used in biomedical applications converts a signal into a different form of signals in time and frequency domains simultaneously. This conversion reveals the characteristics that are hidden in the original signal. The wavelet basis function is small and has an oscillating wavelike characteristic that has its concentrated energy in time.

The discrete wavelet transform (DWT) has been used for analyzing, decomposing and compressing the ECG signals. It generates coefficients based on the correlation between the wavelet of certain scales and the original signal. A signal using DWT may be characterized by a number of

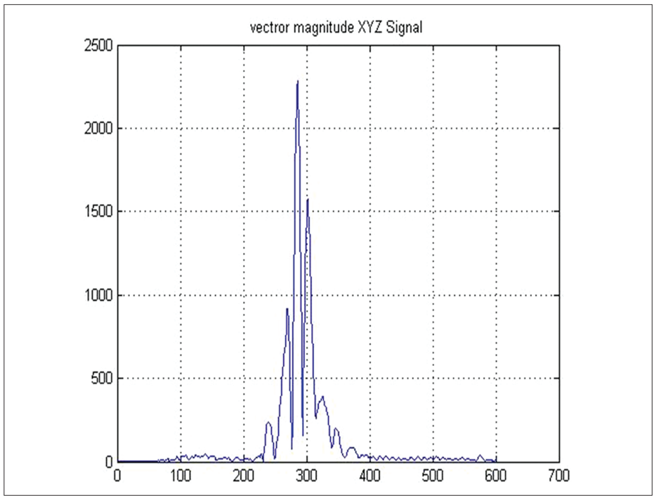

Figure 2: Example of vector magnitude of three orthogonal electrocardiogram leads

wavelet coefficients produced by distinct scales. Carrying out of DWT for the discrete time series might be called discrete-time continuous wavelet transform. It corresponds to a multi-resolution analysis, which can decrease the redundancy of each filtered signal, so the processing algorithm can be applied effectively to a small subset of the original signal. Basic wavelets are characterized by symmetry, orthogonality and compact support.

Besides the mentioned properties, shape matching is alternative to wavelet selection. In this study, we used "Coiflet" wavelet as basic wavelet that is orthogonal and has shape matching with signal averaged curve feature [Figure 3]. This wavelet has better detection for ECG[12] and insures minimum signal degradation. It provides a convenient technique for QRS extraction[13] and widely used in data compression.[14] Furthermore, this was used for cardiac arrhythmia classification algorithms.[15,16]

Statistical Analysis

Data are expressed as the mean ± standard deviation and statistical analysis was performed using the independent *t*-test for paired variables. $P < 0.05$ was considered to be significant. Statistical software that used in this paper was Statistical Package for the Social Sciences version 16.0.0., SPSS Inc., Chicago.

Feature Extraction

Feature extraction from SAECG

In this section, three features are extracted from SAECG without applying wavelet transform:

QRS-d feature is the time duration of a filtered QRS from onset to offset in time (sample), this is a conventional feature.

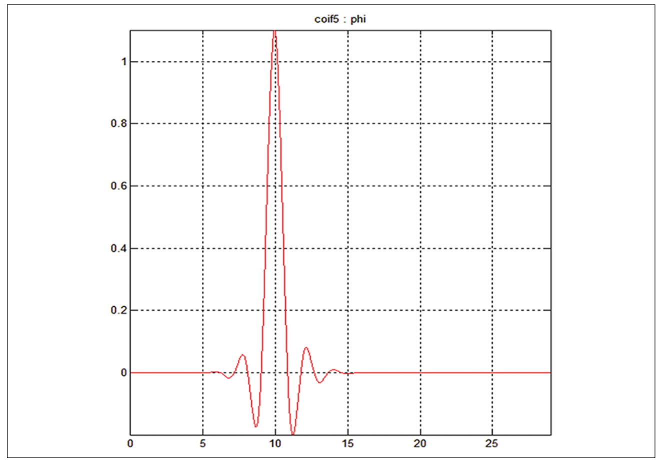

Figure 3: Scaling function for Coif5

Maxpeak is calculated by voltage of the maximum peak of a signal in SAECG.

Smooth muscle is smoothness magnitude of the curve in SAECG, which as a new feature was used in this study. Our purpose was to check the smoothness of signal that shows a significant difference between MI and healthy group. After extraction of this feature from two groups' data, they statistically were analyzed to confirm our assumption.

In order to measure the smoothness of function *y*(t) over an interval [0, n] by Eq. (2), where t is the number of samples (time) and *f*(t) is the signal amplitude (voltage):

$$\text{Curve smoothness} = \sum_{t=0}^{t=n} (y''(t))^2 \ \text{ or } \int_0^n (y''(t))^2 \qquad (2)$$

This equation was normalized to the maximum peak in all cases to obtain comparable criteria.

The extracted features from wavelet transformed SAECG

Three other features after applying wavelet transform were extracted:

MaxMin: Numerical differences between maximum and minimum peak on wavelet decomposed signal. Maxhist: Maximum value of the histogram for wavelet decomposed signal. Number of disarrangement points (NDP): Takayama *et al*.[17] exerted continues wavelet transform on one orthogonal lead for hypertrophy cardiomyopathy patients and extracted signal distortion feature. NDP is disarrangement criteria for wavelet decomposed signal (number of positive and negative peaks). In this paper, this feature was extracted with wavelet transformed SAECG (WTSAECG) from 3 pair leads from MI patients and healthy subjects. Furthermore, statistical analysis was performed using independent sample *t*-test to check results. Other features that did not show a significant difference between two study groups were removed from our study.

Classification by the Probabilistic Neural Network

Probabilistic neural network is based on radial basis function and it may be used for classification problems. The classification of an input pattern was determined by the largest value of a posteriori class probability density function (PDF). Unknown probability densities can be estimated using a set of training samples (normalized to parzen model that has shown in Eq. (3): Unit length) in a

$$f(x)=\frac{1}{m_c}\frac{1}{(2\pi\sigma^2)^{d/2}}\sum_i \exp(\frac{z_i-1}{\sigma^2}) \tag{3}$$

where x is the feature vector of the input sample, m_c is the number of training patterns in class c, σ is the smoothing parameter, d is the number of features, and $Z_i = y_i \times x$, with y_i representing the training pattern of each sample in class c. The smoothing parameter σ is computed from $\sigma^2 = Gm_c^{-F}$, where $F = \frac{1}{d}$ and G is determined through experimental probabilistic neural network (PNN) classifications of the data in which G is allowed to vary. The value of G is taken from running PNN that provides the highest classification accuracy.

The accuracy of the PNN classification somewhat depends on the accuracy of this PDF approximation. A very large value of smoothing parameter ($\sigma \rightarrow \infty$) produces an estimation that is Gaussian in spite of the true underlying distribution. A very small value of smoothing parameter ($\sigma \rightarrow 0$) produces an estimation that has distinct modes corresponding to the locations of each training sample. However, classification accuracy has not been significantly changed by small changes in σ. The PNN configuration for a two-class problem is displayed in Figure 4.

The input units distribute the features of the samples being classified by the neural network. The pattern units produce the dot product ($Z_i = y_i \times x$) and perform the neuron activation function (the exponentiation). The output for each class from the pattern units are summed in the appropriate summation units. Finally, the output class is determined by the highest value of the PDF estimates.[18]

For this study, 80 samples were selected for training through 100 samples and 20 samples for testing. To obtain significant result, k-fold cross validation method was used. This method is also known as rotational method. Basically, k-fold cross method is derived from the cross-validation method that is used to measure and compare the learning algorithm. The cross-validation process is repeated k times (the folds), with each of the k subsamples used exactly once as the validation data. The k results from the folds then could be averaged to produce a single estimation. Furthermore different results were obtained by changing in the spread of radial basis function factor in the network and suitable spread was evaluated so the best sensitivity, specificity and accuracy were selected.

RESULTS

After using wavelet transform in decomposition of SAECG in five levels, second detail level were selected because of the apparent features for comparison study between two groups. Figure 5 shows this apparent features, for example MI patients' wavelet coefficient is disordered than healthy people.

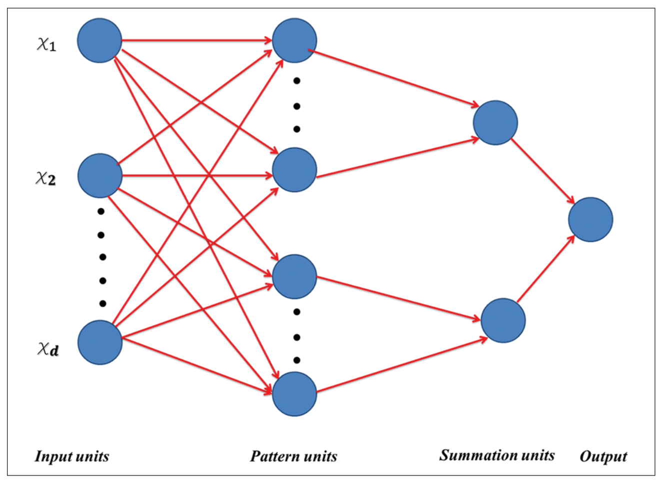

Figure 4: Architecture of probabilistic neural network

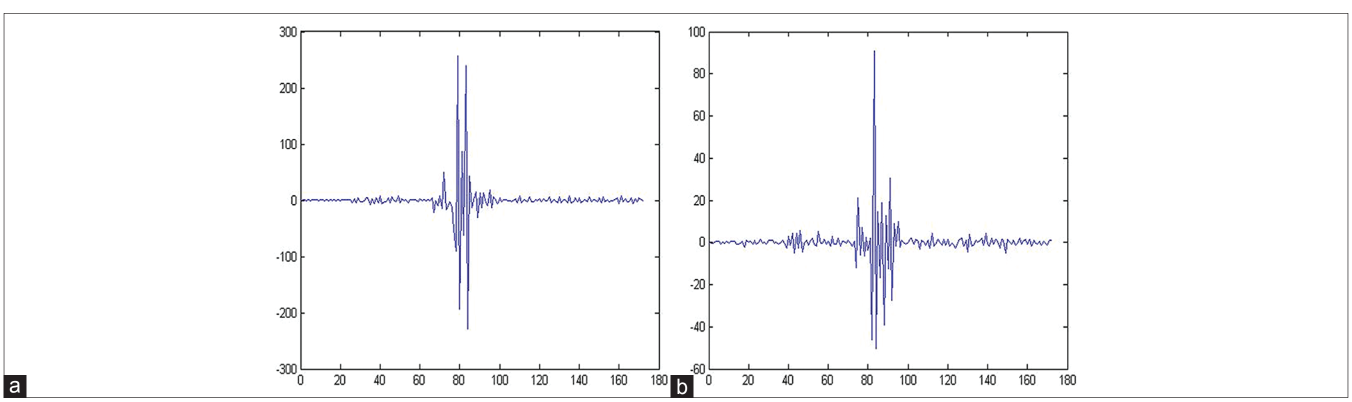

Figure 5: Wavelet transformed signal for control (above) and myocardial infarction (below), there is a significant discrimination in form, distortion and amplitude of peaks for two groups

Analyzing the results using independent *t*-test for extracted features showed significantly difference between two groups ($P < 0.05$). In addition, the filtered QRS complex in MI group was longer than it in the healthy group (183.9 ± 40.1 vs. 156.9 ± 18.6, $P < 0.001$). Maximum value of the peak in healthy people was higher than it in MI patients (821.1 ± 279.2 vs. 485.7 ± 142.1, $P < 0.001$). Signal smoothness value in MI patients was more than it in healthy people (0.2 ± 0.12 vs. 0.12 ± 0.03, $P < 0.001$). The distortion criteria in MI patients was greater than it in the control group (37.6 ± 9.6 vs. 33.4 ± 7.3, $P = 0.016$). Furthermore, maximum value of signal histogram in MI patients was greater than it in the control group (34.5 ± 5.3 vs. 30.6 ± 2.7, $P < 0.001$). Numerical differences between the maximum and minimum of the peak on wavelet decomposed signal in the healthy group were more than that in MI patients (182.3 ± 71.7 vs. 135.4 ± 58.4, $P = 0.001$). All these features comparison between two groups are shown in Table 1.

This paper used 10-fold cross validation and also True positive, False positive, True negative, False negative, Sensitivity, specificity and accuracy were calculated for each fold so then averaged for 10 folds. The Classification results for 10-fold are shown in Table 2.

Finally, confusion matrix for the results was calculated that is shown in Table 3.

DISCUSSION

In this study, we used signal averaged ECG and its wavelet coefficient with probability neural network to detect MI patients and applied 2 min orthogonal leads signals to obtain SAECG form, while the time was shorter than other SAECGs' methods that were used in LP detection. As a result saving time was an advantage of our method. In addition by comparing conventional ECG (using 10 electrodes), our technique used seven electrodes that was another advantage for this method.

The diagnostic methods of MI are commonly used in clinical practice, including ECG, blood enzymes, computer imaging, chest X-ray, and cardiac catheterization etc., However clinicians are interested to use noninvasive, fast, cheap and high precision methods for diagnosis. ECG with different electrode positions such as conventional electrodes position or orthogonal electrodes position has many benefits. By using computer and mathematical models in cardiology, the infarction diagnosis is rising.

This technique using a new method in MI patient's detection is more sensitive than the previous works[2,3,5,6] but is comparable in Specificity and accuracy with them. Finally, comparing our results with those recently reported by others[5,6] can be concluded that our method based on 6 features shows good performance. Dehnavi *et al*.[5] based on 22 features obtains Sen = 70% and Spec = 86%, Correa *et al*.[6] based on 8 VCG features obtains Sen = 88.5% and Spec = 92.1% in comparison, our method using only 6 features achieves Sen = 93.0% and Spec = 86.0%. The results of our study and some of other previous works are presented in Table 4.

Table 1: Statistical analysis of six selected features listed in order expressed in text by mean±standard deviation

Feature	Healthy (n=50)	MI (n=50)	P value
QRS-d	156.9±18.6	183.9±40.1	<0.001
Maxpeak	821.1±279.2	485.7±142.1	<0.001
SM	0.12±0.03	0.2±0.12	<0.001
MaxMin	182.3±71.7	135.4±58.4	0.001
Maxhist	30.6±2.7	34.5±5.3	<0.001
NDP	33.4±7.3	37.6±9.6	0.016

All the features are normalized to a QRS complex. QRS-d – Time duration of a filtered QRS from onset to offset in time; Maxpeak – Voltage of the maximum peak of a signal in SAECG; SM – Smoothness magnitude; MaxMin – Numerical differences between maximum and minimum peak on wavelet decomposed signal; Maxhist – Maximum value of histogram for wavelet decomposed signal; NDP – Number of disarrangement points; MI – Myocardial infarction; P<0.05

Table 2: Tabular analysis of k (10) folds cross-validation method for all folds

*Fold no.	FP	TN	TP	FN	Sen	Spec	Acc
1	0	10	10	0	1	1	1
2	0	10	10	0	1	1	1
3	1	9	10	0	1	0.9	0.95
4	1	9	9	1	0.9	0.9	0.9
5	2	8	9	1	0.9	0.8	0.85
6	2	8	9	1	0.9	0.8	0.85
7	2	8	9	1	0.9	0.8	0.85
8	2	8	9	1	0.9	0.8	0.85
9	2	8	9	1	0.9	0.8	0.85
10	2	8	9	1	0.9	0.8	0.85
Total	14	84	93	7	Average=0.93	Average=0.86	Average=0.895

*TP – True positive; FN – False negative; FP – False positive; TN – True negative; Sen – Sensitivity; Spec – Specificity; Acc – Accuracy

Table 3: Confusion matrix for all data

Predicted actual	MI	Healthy	Total (%)
MI	TP=93	FN=7	Sen=93.0
Healthy	FP=14	TN=84	Spec=86.0
			Acc=89.5

MI – Myocardial infarction; TP – True positive; FN – False negative; FP – False positive; TN – True negative; Sen – Sensitivity; Spec – Specificity; Acc – Accuracy

Table 4: The results of various methods in detection of MI patients using ECG and VCG

Method	Extracted features	Sen %	Spec %	Acc %
Eriksson *et al*.[2]	QRS vector analysis	-	-	71 and 78
Papaloukas *et al*.[3]	ST-T segment analysis	90	90	-
Dehnavi *et al*.[5]	22 VCG features	70	86	86
Correa *et al*.[6]	8 VCG features	88.5	92.1	90
Our method	6 WTSAECG features	93.0	86.0	89.5

VCG – Vectorcardiogram; WTSAECG – Wavelet transformed signal averaged electrocardiogram; MI – Myocardial infarction; ECG – Electrocardiogram; QRS – QRS complex; ST – S and T wave

Detection of MI patients with ECG has three parameters, a significant Q wave for necrosis, ST segment elevation for injury and inverted T wave for ischemia. In AMI, it is usual for T to be inverted or ST elevation be seen. T inverted detection (ischemia) is easy to identify rather than ST elevation because of its feature. However, after a short time it returns to its original state and depends upon two other parameters. Because of averaging three pairs of orthogonal leads, our method has more information about cardiac electrical changes rather than one conventional lead. Furthermore, we used wavelet coefficient that was included more information about ventricles that were hidden in conventional method/or it were difficult to detect.

CONCLUSION

Based on the results of this study, we can be concluded that our technique has shown significant performance in MI patient detection. However, the sensitivity and specificity is comparable with other findings[2,3,5,6] and has high accuracy although we extracted only 6 features.

Briefly, the proposed technique, based on signal averaged ECG and WTSAECG and new extracted features using probabilistic neural network may well be used for more accurate identification of MI patients.

ACKNOWLEDGMENTS

The authors acknowledge the financial support of Faculty of Medicine, Tabriz University of Medical Sciences, Iran, for this study. With special thanks to Shabnam Afkari and Dr. Fariborz Akbarzadeh for invaluable comments.

REFERENCES

1. Hurd HP 2nd, Starling MR, Crawford MH, Dlabal PW, O'Rourke RA. Comparative accuracy of electrocardiographic and vectorcardiographic criteria for inferior myocardial infarction. Circulation 1981;63:1025-9.
2. Eriksson P, Andersen K, Swedberg K, Dellborg M. Vectorcardiographic monitoring of patients with acute myocardial infarction and chronic bundle branch block. Eur Heart J 1997;18:1288-95.
3. Papaloukas C, Fotiadis DI, Likas A, Michalis LK. An ischemia detection method based on artificial neural networks. Artif Intell Med 2002;24:167-78.
4. Toledo E, Lipton JA, Warren SG, Abboud S, Broce M, Lilly DR, *et al*. Detection of stress-induced myocardial ischemia from the depolarization phase of the cardiac cycle – A preliminary study. J Electrocardiol 2009;42:240-7.
5. Dehnavi AR, Farahabadi I, Rabbani H, Farahabadi A, Mahjoob MP, Dehnavi NR. Detection and classification of cardiac ischemia using vectorcardiogram signal via neural network. J Res Med Sci 2011;16:136-42.
6. Correa R, Arini PD, Valentinuzzi ME, Laciar E. Novel set of vectorcardiographic parameters for the identification of ischemic patients. Med Eng Phys 2013;35:16-22.
7. Simson MB. Use of signals in the terminal QRS complex to identify patients with ventricular tachycardia after myocardial infarction. Circulation 1981;64:235-42.
8. Couderc JP, Chevalier P, Fayn J, Rubel P, Touboul P. Identification of post-myocardial infarction patients prone to ventricular tachycardia using time-frequency analysis of QRS and ST segments. Europace 2000;2:141-53.
9. Goldberger AL, Amaral LA, Glass L, Hausdorff JM, Ivanov PC, Mark RG, *et al*. PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. Circulation 2000;101:E215-20.
10. Raimon J, Laguna P, Caminal P. Filtering techniques for ventricular late potentials analysis. Proceedings of the IEEE 14th Annual International Conference, November 1992; Engineering in Medicine and Biology Society; p. 545-6.
11. Jané R, Rix H, Caminal P, Laguna P. Alignment methods for averaging of high-resolution cardiac signals: A comparative study of performance. IEEE Trans Biomed Eng 1991;38:571-9.
12. Abi-Abdallah D, Chauvet E, Bouchet-Fakri L, Bataillard A, Briguet A, Fokapu O. Reference signal extraction from corrupted ECG using wavelet decomposition for MRI sequence triggering: Application to small animals. Biomed Eng Online 2006;5:11.
13. Istepanian RS, Hadjileontiadis LJ, Panas SM. ECG data compression using wavelets and higher order statistics methods. IEEE Trans Inf Technol Biomed 2001;5:108-15.
14. Rajoub BA. An efficient coding algorithm for the compression of ECG signals using the wavelet transform. IEEE Trans Biomed Eng 2002;49:355-62.
15. Khadra L, al-Fahoum AS, al-Nashash H. Detection of life-threatening cardiac arrhythmias using the wavelet transformation. Med Biol Eng Comput 1997;35:626-32.
16. al-Fahoum AS, Howitt I. Combined wavelet transformation and radial basis neural networks for classifying life-threatening cardiac arrhythmias. Med Biol Eng Comput 1999;37:566-73.
17. Takayama H, Yodogawa K, Katoh T, Takano T. Evaluation of arrhythmogenic substrate in patients with hypertrophic cardiomyopathy using wavelet transform analysis. Circ J 2006;70:69-74.
18. Bankert RL. Cloud classification of AVHRR imagery in maritime regions using a probabilistic neural network. J Appl Meteorol 1994;33:909-17.

How to cite this article: Keshtkar A, Seyedarabi H, Sheikhzadeh P, Rasta SH. Discriminant Analysis Between Myocardial Infarction Patients and Healthy Subjects Using Wavelet Transformed Signal Averaged Electrocardiogram and Probabilistic Neural Network. J Med Sign Sens 2012;3:195-225-31.

Source of Support: Tabriz University of Medical Sciences, **Conflict of Interest:** None declared

BIOGRAPHIES

Ahmad Keshtkar received his BSc in Applied Physics from Shahid Beheshti University and MSc in Medical Physics from Tarbiat-e-Modarres University. He started his academic work from 1991 in Tabriz University of Medical Sciences, Faculty of Medicine as medical physics instructor. He started his MSc module courses from 1998 and then PhD programme at the Medical Physics and Engineering Department in the University of Sheffield in UK. Then, he graduated on 2003 and continued his academic activity with PhD in Tabriz University of Medical Sciences, Medical Physics Department as assistant professor. Keshtkar was chosen as Head of Medical Physics Department from 2005 and Head of Medical Engineering Department from 2011 and he is Associate professor now. His PhD programme was in characterizing the human urinary bladder using Electrical Impedance Spectroscopy to find a minimally invasive technique. He had assessed the feasibility of detecting the bladder and esophagus abnormalities using this technique and improving a novel technique now by designing and constructing the Iranian first Electrical Impedance Spectroscopy System. Ahmad Keshtkar is a Member of Iranian Association of Medical Physicists (IAMP) and a member of International Society For Electrical Bio-impedance (ISEBI); www.isebi.org.

E-mail: mpp98ak@hotmail.com

Hadi Seyedarabi received B.S. degree from University of Tabriz, Iran, in 1993, the M.S. degree from K.N.T. University of technology, Tehran, Iran in 1996 and Ph.D. degree from University of Tabriz, Iran, in 2006 all in Electrical Engineering. He is currently an associate professor of Faculty of Electrical and Computer Engineering in University of Tabriz, Tabriz, Iran His research interests are image processing, computer vision, Human-Computer Interaction, facial expression recognition and facial animation.

E-mail: seyedarabi@yahoo.com

Peyman Sheikhzadeh received the B.S degree in Physics from Urmia University and M.S. degree in Medical Physics from Tabriz University of Medical Science. Now he is PhD student in Medical Physics in Tehran University of Medical science. His research interests are Medical Imaging, Signal and Image processing

E-mail: psh82@yahoo.com

Seyed Hossein Rasta graduated in applied physics at the University of Mashhad and soon afterwards went to the University of Tehran, Institute of Biophysics and Biochemistry where he completed an MSc (course and thesis) in Molecular Biophysics in 1993. He then worked in RcSTIM of Tehran University of Medical Sciences. He joined the academic board of the Tabriz University of Medical Sciences as a lecturer in 1996, lecturing biophysics in medicine. He was awarded a PhD scholarship by TUMS and so studied Medical Physics and Bioengineering field at University of Aberdeen and graduated in 2008. He was then appointed assistant professor of Medical Physics in TUMS. He collaborates as honorary postdoc researcher with University of Aberdeen. He works on developing of medical imaging methods and medical image/signal processing.

E-mail: s.h.rasta@abdn.ac.uk