Neural Network Classification of Body Surface Potential Contour Map to Detect Myocardial Infarction Location

Sepideh Sabouri[1,3], Hamid SadAbadi[2,3], Nader Jafarnia Dabanloo[1,3]

[1] Faculty of Biomedical Eng., Science & Research Branch, Islamic Azad University, Tehran, Iran
[2] Department of Mechanical Engineering, Concordia University, Montreal, Qc, Canada
[3] Cardiovascular Research Group (CVRG), SRBIAU, Tehran, Iran

Abstract

This paper is the follow-up of our previous work presented for CinC/PhysioNet Challenge 2007 on the "electrocardiographic imaging of myocardial infarction". We have presented an automatic method for MI location detection by Neural Network classification of BSPM data.

Data used here contain BSPM signal of four patients and their actual infarcted segments (two training cases and two cases for test). By mapping Q-wave integral and QRS-complex integral on torso surface and applying four threshold-based rules, an abnormal area on the torso can be obtain. This detected abnormal area then is mapped to the heart segments. A NN classifier is used at final step.

The results expressed by parameter OS (overlapped segment) which is a value between 0 and 1, where 1 is a perfect match. The results for two test cases are $OS_{case\#3}$=0.7 and $OS_{case\#4}$=0.4 shows this mathematically simple method can predict the location of MI reasonably. However further works is needed to improve the results.

1. Introduction

Nowadays the standard 12-Lead ECG system is widely used for different cardiovascular arrhythmia detection as well as different heart diseases diagnosis and treatment. However, the limitations of this lead system are greatly discussed [1]. The main deficiency in the 12-lead approach is the lack of enough chest electrodes to monitor the entire heart surface. In fact, in this system only 6 chest electrodes are dedicated for this purpose which limits our information about pericardium especially in diagnosis of Myocardial Infarction (MI). The 12-lead conventional lead system suggested around 80 years ago by Wilson [2], to adapt different lead systems in a standard system. This standardization has many advantages. For instant, by using a standard lead system one can reliably compare the results in practical clinical application as well as research application in independent evolution of diagnosis algorithms.

Body Surface Potential Map (BSPM) is one of the most widely used and studied alternatives to the standard lead system. The number of electrodes in this approach is depend on the application and may vary among 32 to 219 [3] or more [4] to sample all electrocardiographic information as projected onto the torso surface.

The advantageous of using BSPM is clear, in that, localized abnormalities that are almost difficult to detect applying the 12-lead approach can be easily detected by using more electrodes [5]. BSPM have two major advantages comparing the formal 12-lead ECG includes: 1) to explore the entire chest surface 2) to be more sensitive in detecting local electrical abnormalities [6].

Because of the absence of comprehensive understanding of fundamental basic science of the ischemic heart disease, today, the application of BSPM in MI detection is increasing [7]. Finlay et al. [5] applied common features to the BSPM domain to discriminate between the normal electrode subsets and those with MI.

BSPM classification methods [8] like neural network (NN) are widely used as a powerful tool for classification of BSPM data in MI location detection [9].

Sun et al. [9] presented a NN-based method for classification of 32 normal subjects from 24 ischemia patients. They used the QRS integral maps as the selected feature, calculated for one cycle of each BSPM lead. Finally, by implying a two-layer feed-forward network they got 98% classification rate.

In this work, we introduce a simple but effective way to detect the location of MI by presenting a rule-based method, which uses a neural network classifier. For determining of the exact location of MI, the standard 17-segments left heart model (introduced by Cerqueira et. al [10]) is used.

The data used in this paper includes the 352 leads BSMP signals and expert analysis of gadolinium-enhanced MRI images (indicating the exact infarcted segments) of four MI patients. Two subjects used as training sets and two other cases used as test sets. They can be downloaded from CinC/Challenge 2007 website.

The first two training subjects used to infer some threshold based rules to discriminate between abnormal area and normal area on torso surface. Finally, by a neural network method, the proposed roles used to detect the infarcted segments of two test patients (two tests subject).

2. Materials and methods

2.1. BSPM data preparation

In this paper, the behavior of two important ECG features affected by MI has been monitored on torso surface. These features include Q-wave integral and QRS-complex integral [11]. We call the consequent plots as "Q curve" and "QRS curve" respectively.

At the first step, the Q wave and R wave amplitude and location in each 352 lead has been extracted according to our previous work [12].

All 352 electrodes placed on torso surface, which contains anterior surface of thorax and posterior surface. The electrodes placed on torso surface on specific location. Then we assume vertical and horizontal lines on torso surface. Each horizontal and vertical line passes through specific electrodes. The horizontal and vertical lines definition and their layout are depicted in Fig. 1.

There are 17 horizontal and 32 vertical lines by this assumption. Note that the gular nodes are not considered here. X-axis corresponds to vertical lines position and Y-axis corresponds to horizontal lines as well.

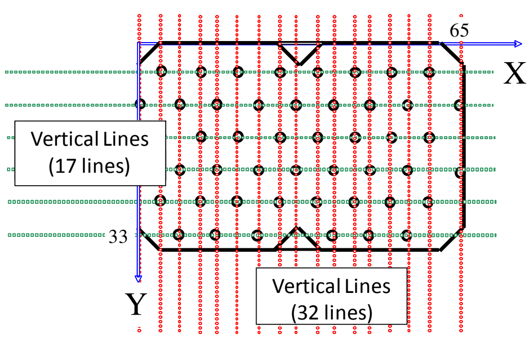

Figure 1. Schematic of on-torso horizontal and vertical line plane. The bold black line corresponds to torso surface

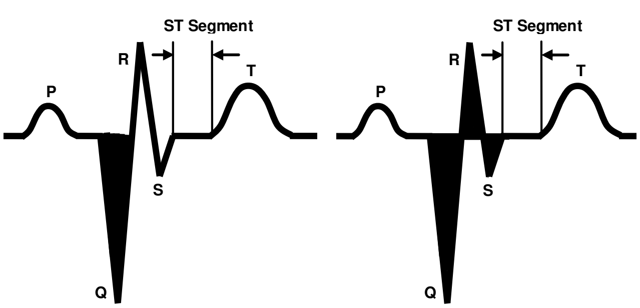

Figure 2. Definition of QRS-complex integral and Q-wave integral in a simplified model of ECG signal.

In the next step, the value of Q-wave integral and QRS complex integral are calculated for all 352 lead (first beat) as shown in Fig. 2 by using equations 1-2:

$$Q_{int} = \int_{Q-\text{wave onset}}^{Q-\text{wave offset}} V(x)dx = \sum_{x_{Q\ \text{onset}}}^{x_{Q\ \text{offset}}} V(x) \times \Delta x \qquad (1)$$

$$QRS_{int} = \int_{Q-\text{wave onset}}^{S-\text{wave offset}} V(x)dx = \sum_{x_{Q\ \text{onset}}}^{x_{S\ \text{offset}}} V(x) \times \Delta x \qquad (2)$$

Where V(x) is the voltage and x is the index. Then the variation of Q_{int} and QRS_{int}, corresponding to the electrodes that lie on a specific horizontal/vertical line, is plotted. The behavior of these curves changing based on the location of the infarcted segments accordingly. Fig. 3 shows Q curves and QRS curves for subjects #1 and #2.

We have used a 17-segments standard model of left ventricle (LV). This segmentation is depicted in Fig. 4.

Then we have estimated the boundaries of the left ventricle's segments using these presumed lines to make a connection between those lines and the LV segments. Knowing the location of the heart in the thorax showed in Fig. 5, we estimate the boundaries of the heart's segments based on the on-torso vertical lines. Fig. 4 illustrates these boundaries and their corresponding vertical lines.

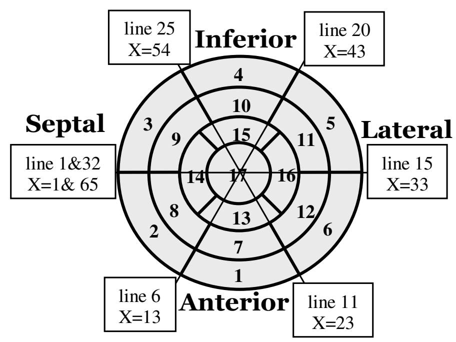

Figure 4. The relation between 17-segments boundaries and on-torso vertical lines in the circle of segments

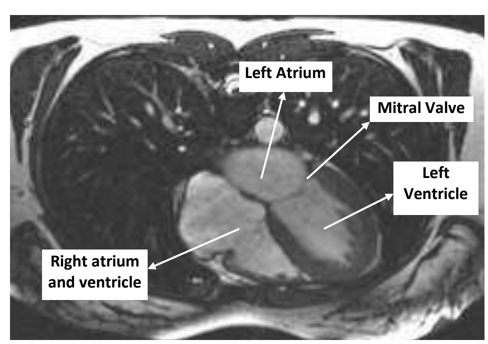

Figure 5. MRI image of the location of heart in the thorax

2.2. Predefined rules

We then examined Q curves and QRS curves (both vertical and horizontal lines) of cases #1 and # 2. The exact location of infarcted segments in these two training cases, are known based on expert analysis of their MRI image. Therefore, the X and Y position of boundaries of those infarcted segments are known as well. We then inferred some characteristics of these curves that can express the boundaries of infarct segments considering reported infarct segments. For instant two rules mentioned in the followings:

1- A region on Q curves of horizontal lines, which the value of Q integral is almost zero (by introducing threshold α) generally corresponds to the X position, of a region on "circle of segments" that their segments are infarcted. Fig. 6 illustrates this rule.

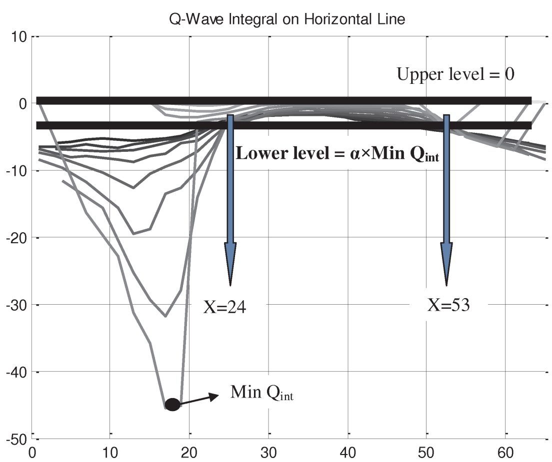

Figure 6. The threshold used for Q integral in case #1

2- The value of slope of Q integral curve in Vertical lines, when exceeding from a specific value is the Y position corresponds to the level of infarction. The level of infarction according to 17-segment model can be basal, mid-cavity of apical [10]. Equations 3 and 4 express this slope threshold (see Fig. 7):

$$\mathrm{Slope}^{\text{point x}}_{\mathrm{i^{th}\ line}} = \frac{\mathrm{QRS\,int}^{x+\Delta x}_{\mathrm{i^{th}\ line}} - \mathrm{QRS\,int}^{x}_{\mathrm{i^{th}\ line}}}{(x+\Delta x) - x} \qquad (3)$$

$$\left|\mathrm{Slope}^{\text{point x}}_{\mathrm{i^{th}\ line}}\right| \geq \alpha \,.\, \max \left|\mathrm{Slope}^{\text{point x}}_{\mathrm{i^{th}\ line}}\right|$$

$$\alpha \,.\, \max \left|\mathrm{Slope}^{\text{point x}}_{\mathrm{i^{th}\ line}}\right| = \text{threshold} \qquad (4)$$

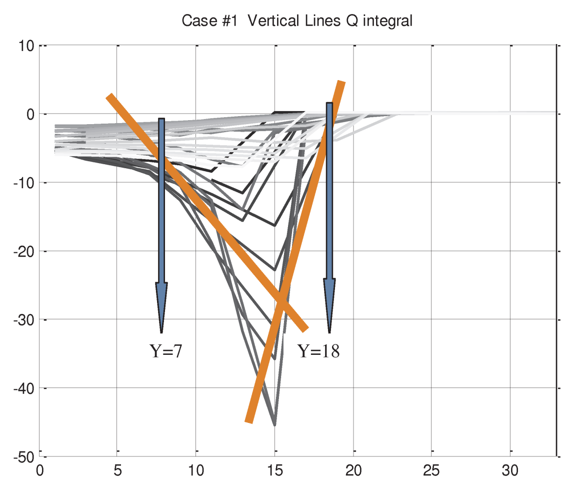

Figure 7. Determination of a region in vertical Q integral curve using their slopes and threshold method (case # 1)

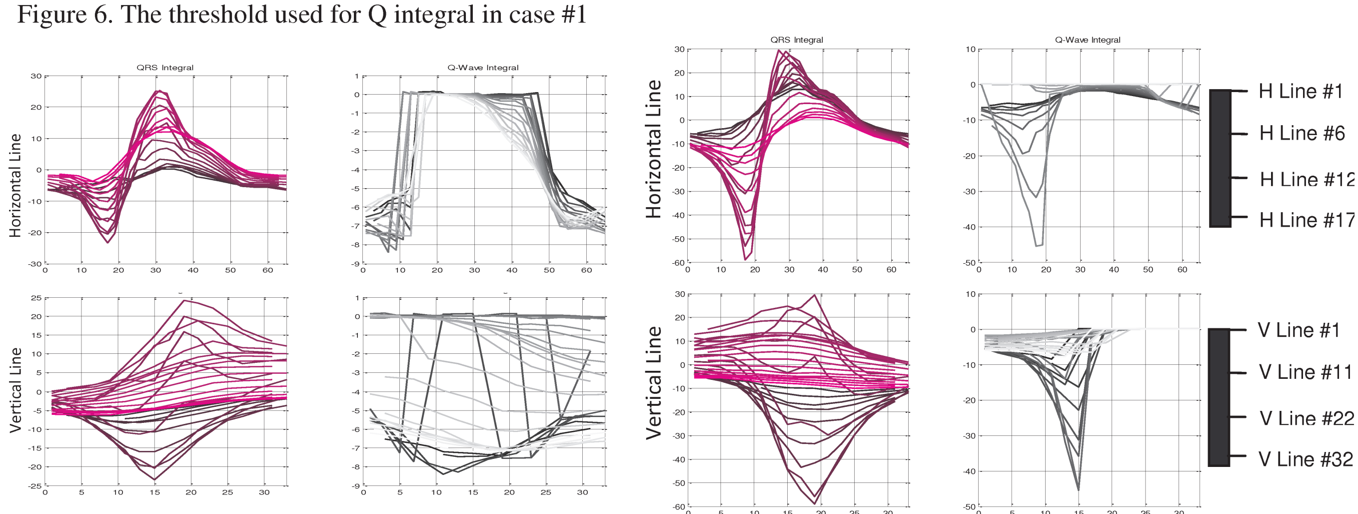

Figure 3. The Q curves and QRS curves for subject #1 (right) and #2 (left) used for training:
(Two upper figures) the curves for horizontal lines (horizontal plots)
(Two lower figures) the curves for vertical lines (vertical plots)

2.3. Neural network

Here, we have four different rules. After determining of the different ranges due to each rule, the data are arranged in a special way into a vector, to be used as an input for the neural network. For each training subject, the input vector has eight elements. The number of output is equal 17 heart segments. In each subject, for those elements with infarction, the magnitude is 1, and for those segments with no infarction, the magnitude is put as zero. After the determination of input and output data, we designed the appropriate feed forward Neural Network.

Based on the above explanation, the neural network has 8 neurons on its input layer and 17 neurons in its output layer. Only one hidden was used and the number of neurons in this layer was selected in a varied fashion from 3, 5, 6, 7 and 9. After training the networks with these varied numbers of hidden neurons, it was observed that using 7 neurons resulted in the best network performance. Fig. 8 shows NN diagram.

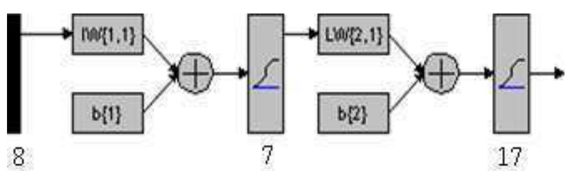

Figure 8. Schematic diagram of the ANN used in here

A forward multilayer perceptron (MLP) type of an artificial neural network was used in this paper. The function for the performance index used in the network training was the Mean Square Error (MSE).

3. Results

The NN results of two test subjects are the estimated infarcted elements. These results are compared to a gold standard that consists of expert analysis of MRI data. Given the estimated and standard sets of infarct segments, "overlap" (SO) can be defined as the number of segments in both sets divided by the number of segments in either set (a value between 0 and 1, where 1 is a perfect match).

This method is based on the work that already presented in CinC PhysioNet Challenge 2007 [13]. However, now the method becomes automatic.

Our first results using very rough thresholds, overall result was OS = 0.7. By adjusting the thresholds, we achieved the following results for each subject (Tab. 1).

Table 1. Result of the method for subjects #3 and 4

Case No.	Estimated Infarcted Segment	SO
3	16 15 12 11 10 5 6 4	0.7
4	15 14 11 10 9 5 4 3	0.4

4. Discussion and conclusions

In this paper, we addressed an innovative automatic method for detection of MI location using BSPM data implying a threshold base method and NN classifier. The results show the proposed method can estimate the location of both cases medially. It seems that the method has some problems in estimation of MI in case #4.

Future works can focused on implying other ECG parameters such as T wave amplitude, QRS complex duration, and R wave amplitude on on-torso lines to detect the location of infarcted area more precisely.

References

[1] Carley SD, Review of the use of additional leads for the early electrocardiographic diagnosis of acute MI. Emergency Medicine 2003(15):143-154.

[2] Wilson FN, ECG that represent the potential variations of a single electrode. American Heart Journal 1934(9):447-58.

[3] Hoekema R, et. al., On selecting a Body Surface Mapping Procedure. Journal of ECG, 1999, 32(2):93-101.

[4] Fady Dawoud, et. al.,, Using inverse electrocardiography to image myocardial infarction, reflecting on the 2007 PhysioNet/CinC Challenge, J ecg, 2008; 41(6): 630-635.

[5] Dewar D Finlay, et. al.,, Mining for diagnostic information in body surface potential maps: A comparison of feature selection techniques, Biomed Eng Online 2005; 4(51);1-14.

[6] Luigi De Ambroggi, et.al., Clinical use of BSPM in cardiac arrhythmias, Dept. Cardiology, clinico San Donato, Italy.

[7] Sippens-Groenewegen A, et. al., BSP of ectopic left and right ventricular activation. QRS spectrum in patients without structural heart disease. Circl, 1990; 82: 879-96.

[8] H Zheng, et. al., Supervised Classification Models to Detect the Presence of Old MI in Body Surface Potential Maps, Computers in Cardiology 2006;33:265−268.

[9] Sun, G. et. al., Classification of normal and ischemia from BSPM by NN approach, Engineering in Medicine and Biology Society, 1988. Proceedings of the International Conference of the IEEE, 1988, 3;1504 - 1505.

[10] M.D. Cerqueira, et.al., Standardized Myocardial Segmentation and Nomenclature for Tomographic Imaging of the Heart, Circulation 2002; 105, 539-542.

[11] Robert S. MacLeod, et. al., Effects of Heart Position on the Body-surface Electrocardiogram, J ECG, 2000; 33,229-37.

[12] A. Ghaffaria, et. al., A new mathematical based QRS detector using continuous wavelet transform, Computers & Electrical Engineering, 2008; 34(2): 81-91.

[13] SadAbadi, H., et. al., "Variation of ECG features on torso plane: An innovative approach to myocardial infarction detection", Computers in Cardiology, 2007; pp. 629 - 632.

Address for correspondence.

Nader Jafarnia Dabanloo

Faculty of Biomedical Engineering, Science & Research Branch, Islamic Azad University (SRBIAU), Tehran, Iran
Phone: +98-21-4447 4321
n_jafarnia@yahoo.com, jafarnia@srbiau.ac.ir