Acute Myocardial Infarction: Analysis of the ECG Using Artificial Neural Networks

Mattias Ohlsson
Department of Theoretical Physics, Lund University
Lund, Sweden
mattias@thep.lu.se

Holger Holst and Lars Edenbrandt
Department of Clinical Physiology, Lund University
Lund, Sweden
holger.holst@klinfys.lu.se, lars.edenbrandt@klinfys.lu.se

Abstract

This paper presents a neural network classifier for the diagnosis of acute myocardial infarction, using the 12-lead ECG. Features from the ECGs were extracted using principal component analysis, which allows for a small number of effective indicators. A total of 4724 pairs of ECGs, recorded at the emergency department, was used in this study. It was found (empirically) that a previous ECG, recorded on the same patient, has no or very little effect on the performance for the neural network classifier.

1 Introduction

For patients attending the emergency department with chest pain, an early diagnosis of acute myocardial infarction is important because of the benefits of immediate and correct treatment. Different diagnostic methods have been studied, but the 12-lead ECG together with patient history is still the best method for early diagnosis of acute myocardial infarction.

The ECG diagnosis can be a difficult problem and misdiagnosis do occur. The use of a computer-based ECG interpretation program is therefore valuable in order to detect infarction ECGs. Artificial neural networks (ANN) is one computer-based method that has shown to be even better than experienced physicians in the ECG diagnosis, regarding myocardial infarction [1, 2].

In clinical practice the physician include in their ECG analysis a comparison between the current ECG and a previous one of the same patient, (if such one is available) as an aid in the decision making. The purpose of this study was to construct a neural network classifier for the diagnosis of acute myocardial infarction and to see if a previous ECG, recorded on the same patient, can increase classification performance.

2 Study Population

The study is based on patients who present to the emergency department of the University Hospital in Lund, Sweden during the period January 1990 - June 1997 and who had an ECG recorded and stored at that occasion. The 12-lead ECGs were recorded using computerized electrocardiographs (Siemens-Elema AB, Solna, Sweden). Each of these ECGs were analyzed as follows:

- (i) If the ECG was recorded on a patient who was admitted to the coronary care unit after the ECG recording, and was discharged with the diagnosis "acute myocardial infarction" and (ii) an earlier ECG recorded on the same patient was found in the ECG database of the hospital (not necessarily recorded at the emergency department).

then this pair of ECGs was defined as an *acute infarction* case. On the other hand:

- (i) If the ECG was recorded on a patient not suffering an "acute myocardial infarction" at that occasion and (ii) an earlier ECG recorded on the same patient was found in the ECG database of the hospital (not necessarily recorded at the emergency department).

then this pair of ECGs was defined as a *control* case. Only ECGs with severe technical deficiencies and pacemaker ECGs were excluded.

The acute infarction group consisted of 924 pairs of ECGs and the control group consisted of 3800 pairs of ECGs. A separate test group of 1000 pairs (200 infarctions and 800 controls) were randomly selected from the total set of 4724 ECGs.

3 Feature Extraction

3.1 12-Lead ECG

The digitized ECG consists of 12 leads where each lead represents one heart beat complex, approximately 1000 sample values long (1000 Hz). From each complex one extracts standardized measurements[1], that includes amplitudes, durations and areas. Figure (1) shows a generic ECG complex with P-, QRS- and T-waves. Common measurements are Q-, R-, S-amplitudes and sample values along the ST-segment. From a physiology point of view acute myocardial infarction cause changes in the ST-segment. We used the following measurements from each of the 12 leads:

1. Q-, R- and S-amplitudes.

2. QRS-area (area of the QRS wave).

[1]Computation of these measurements is performed by the recording software (Siemens Elema in our case).

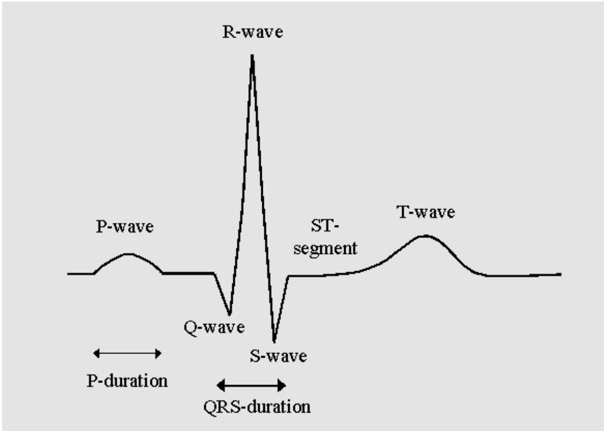

Figure 1: A generic ECG complex with a P- and QRS-wave followed by an ST-segment and an ending T-wave.

3. |ST-amplitude| / QRS-peek_to_peek (absolute value of the first ST amplitude divided by peek to peek amplitude of the QRS-wave).
4. ST-amplitudes (3 measurements taken from the start, 2/8 and 3/8 of the ST-segment).
5. ST-slope (the slope at the beginning of the ST-segment).
6. T-max (maximum of the T-wave).
7. T-min (minimum of the T-wave).

In total 144 measurements from each ECG were selected for further analysis.

For each patient there is two ECGs, the current and one previous ECG. Since the objective is to find out whether a previous ECG can help the classifier to determine acute myocardial infarction, we have two different datasets. The first consists of the current ECGs, i.e. the ECGs recorded at the emergency department. In the second dataset measurements of the difference between the current and the previous ECG have been added. The difference δ between each measurement α is simply taken as:

$$\delta_\alpha = \alpha_{\text{current}} - \alpha_{\text{previous}} \tag{1}$$

3.2 Principal Component Analysis

There is a high degree of correlation between measurements from the 12 leads. This correlation comes from the fact that 4 of the 12 leads are simple linear combinations of two other, e.g. lead II = lead I + lead III. There is also a natural correlation among some of the leads, because they are physically close to each other. The 144 original measurements can therefore be reduced to a smaller set of more "effective" variables. We used principal component analysis (PCA) to achieve this reduction.

Prior to the PCA the 144 variables were grouped into the 7 groups listed above. The PCA was then applied to each of these smaller datasets separately. Figure (2) shows the eigenvalues of the covariance matrix, normalized so that the largest is one, for each group of variables. Clearly, there exists a large degree

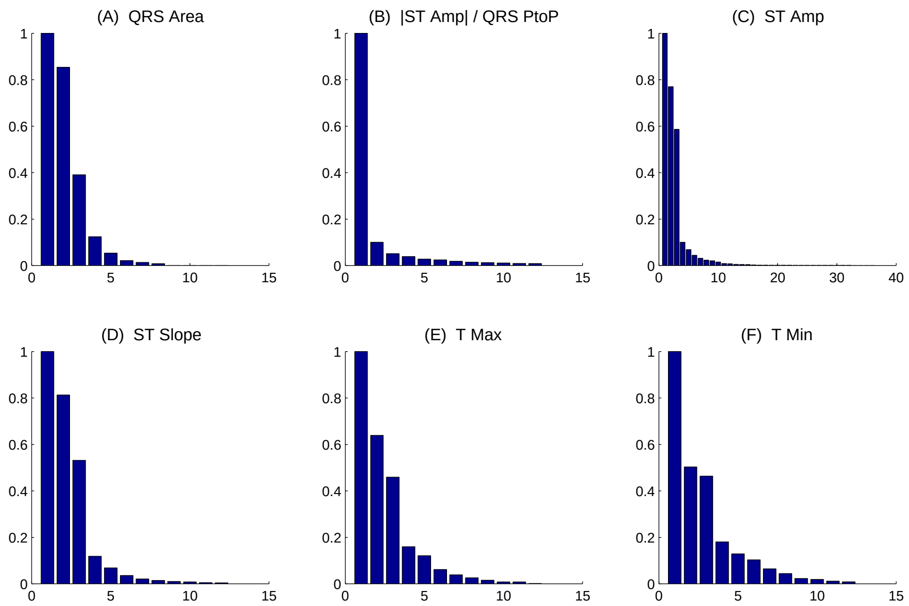

Figure 2: Principal component analysis of the measurements from the dataset of current ECGs. The plots show the (normalized) eigenvalues of the covariance matrix for the variables i group 2-7.

of (linear) correlation between the measurements within each group. As can be seen in figure (2B) the 12 measurements |ST-amplitude| / QRS-peek_to_peek can in practice be reduced to a single variable. The PCA analysis of dataset with differences between the current and the previous ECG shows a similar behavior with large linear correlations. Table (1) summarizes the variables used as inputs for the neural network classifiers.

4 Artificial Neural Networks

Feed-forward ANN have turned out to be a very powerful approach for classification problems. A general introduction to the subject can be found in ref. [3]. We used a standard multilayer perceptron architecture with one hidden layer of 10 nodes. The output layer consisted of one neuron that coded

	Number of PCA components	
	Current ECG dataset	Difference dataset
QRS-amplitudes	2	0
QRS-area	1	0
|ST-amplitude| / QRS-peek_to_peek	1	1
ST-amplitudes	4	3
ST-slope	2	0
T-max	3	1
T-min	3	1
Total	16	6

Table 1: Summary of the variables used as inputs to the neural networks.

whether the patient suffered from acute myocardial infarction (1) or not (0). A summed-square error function was used together with a Langevin extension [4] of the backp-propagation updating rule. Langevin updating consists of adding a random Gaussian component to the gradient, which has the effect of speeding up the minimization procedure. In order to avoid over-training a weight elimination [5] regularization term was used, i.e.

$$E \to E + \nu \sum_i \frac{w_i^2}{\tilde{w}^2 + w_i^2} \tag{2}$$

where $\tilde{w}$ was set to 1. The sum over weights does not include the threshold weights since they should not be part of the regularization.

The ν parameter was set using a 5-fold cross-validation scheme on the training set. Finally, a committee of 20 networks was trained on the full training set using this ν. The classification performance on the test set was calculated using the average output of the committee.

5 Results

Table (2) presents the result of the networks on the test set. It it presented in terms of the area under the *receiver-operating characteristic* (ROC) curve. The area for the networks trained on the data set with only the current ECGs is 0.84. The networks trained with information from two ECGs for each patient, i.e. both the current and the previous ECG, got a area under the ROC curve of 0.85. Although slightly higher than the network without this information a statistical analysis gives a p-value of 0.29. There are of course many ways of representing the difference between two ECGs. The one employed in this paper did not appear to increase classification performance i.e. a previous ECG does not help (or at least not significantly) the classifier for the task of diagnosing acute myocardial infarction.

Dataset	Number of inputs	Area under the ROC curve
Current ECGs	16	0.84
Current ECGs + previous ECGs	22	0.85

Table 2: Performance of the network committee on the test set.

6 Conclusion

A neural network classifier were constructed to detect acute myocardial infarction, using the 12-lead ECG. Key indicators were extracted with principal component analysis on common measurements of the ECG. When diagnosing an acute myocardial infarction ECG a previously recorded one (if available) is often used as a reference. The presence of such a previous ECG appears to have little effect on the performance of the network classifier.

7 Acknowledgments

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