Misplacement of the Left Foot ECG Electrode Detected by Artificial Neural Networks

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Abstract

Artificial neural networks (ANNs) have proved to be of value in pattern recognition tasks e.g. classification of electrocardiograms (ECGs). Electrocardiographic lead reversals are often overlooked by ECG readers, and may cause incorrect ECG interpretation, misdiagnosis and subsequent lack of proper treatment. A database of 11000 ECGs from an emergency department, which had been purified from technically deficient ECGs as well as ECGs with lead reversals were used in the study. The same database was used to generate by computer two subsets of 11000 ECGs, one consistent with right arm/left foot lead reversal and one with left arm/left foot lead reversal. After training, the networks detected 57.6 % of the ECGs with left arm/left foot lead reversal and 80.5 % of the ECGs with right arm/left foot lead reversal. The specificities were 99.97% and 99.95% respectively. The results show that ANNs can be trained to detect ECG lead reversals at very high specificity.

1. Introduction

Computer based interpretation programs have been developed during the last decades, and are now widely used and accepted by the medical community. Many ECG interpretation programs perform better than physicians who are not ECG experts and some of them are almost at par with trained ECG readers.[1] Both the average clinicians, experts and expert systems require correct data for a correct interpretation. Misplacements of electrodes during ECG recording is one situation which results in incorrect data. This may cause incorrect interpretations, misdiagnosis and subsequent lack of proper treatment.[2] Therefore interpretation programs contain criteria for the detection of the right/left arm lead reversal. These algorithms are known to have high specificity but rather low sensitivity, especially when P-waves are not detected. No other limb lead reversals are recognized by the commonly used interpretation programs.

ANNs can be used in pattern recognition tasks e.g. ECG analysis.[3-5] The sensitivity for the detection of the right/left arm lead reversal was significantly higher using ANNs, than for two well known rule based criteria, at comparable specificity.[6] The right arm/right foot lead reversal is almost as common as the right/left arm lead reversal. The resulting ECG pattern is very typical with almost a straight line in lead II. This pattern can be detected with simple criteria.[7] The left arm/left foot lead reversal is probably as common as the right arm/right foot lead reversal, but more difficult to detect. Most lead reversals are overlooked by the average physician, and even trained ECG readers often fail to recognize them.[7] The aim of this study was to develop methods for the detection of two limb lead reversals involving the left foot electrode; the right arm/left foot lead reversal and the left arm/left foot lead reversal.

2. Methods

2.1. Study population

The study was based on 11 423 ECGs recorded at the emergency department at the University hospital in Lund during 1992-93. A 12-lead ECG was recorded on subjects who presented at the department during this period and whose condition called for a stat ECG. All recordings were made digitally and average heart cycles were calculated. P, Q, R, and ST-T measurements were obtained using custom software.

Since the ANNs learn by training on examples, it was crucial that no ECG with lead reversal, or other technical deficiencies, was used as an example of a correctly recorded ECG. Great care was therefore taken to exclude all ECGs with limb lead reversals as well as technically deficient ECGs. Also pacemaker ECGs were excluded. The exclusion process comprised visual inspection by two trained ECG readers, as well as computer methods.

After the exclusions were made the study material consisted of 11 000 ECGs. These ECGs were used to computationally generate two more sets of ECGs, one each with a

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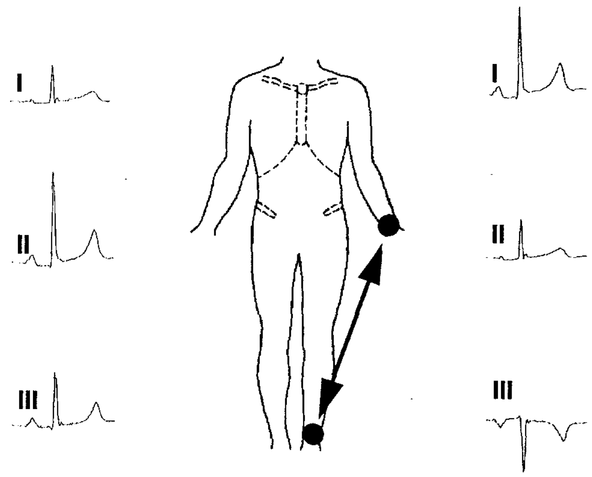

Figure 1. To the left a correctly recorded ECG and to the right the same ECG after a left arm/left foot lead reversal. The lead reversal is indicated by an arrow.

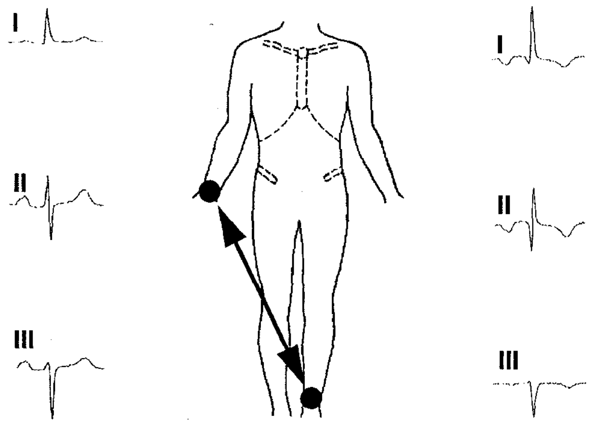

Figure 2. To the left a correctly recorded ECG and to the right the same ECG after a right arm/left foot lead reversal. The lead reversal is indicated by an arrow.

lead reversal involving the left foot electrode (Figures 1 and 2). The left arm/left foot lead reversal was generated by means of changing places of leads I and II, inverting lead III and changing places of aVL and aVF. To generate the right arm/left foot lead reversal, lead I and III changed places and polarity, lead II was inverted and aVR and aVF were interchanged. This generated exactly the same ECG that would have resulted if the lead reversal had been made in the recording situation. Thus, the final material consisted of 33 000 ECGs, divided into three subsets.

2.2. Neural network

A multilayer perceptron architecture was used.[8] A more general description of ANN could be found elsewhere.[9] The ANNs consisted of three layers; one input layer, one hidden layer and one output layer. The number of neurons in the input layer depended on the number of input variables. There were 22 for both types of reversal but the variables were different. There were 7 hidden neurons in the network structure when training and testing for the left arm/left foot lead reversal, and 9 hidden neurons in the network used for the right arm/left foot lead reversal. The output layer contained one neuron. The output unit encoded whether an ECG was correctly recorded (output value=0) or with a lead reversal (output value=1).

The database was divided into two parts, a training set and a test set. The training set was used to adjust the weights in the neural network, and the test set was used to assess its performance. To get as reliable performance as possible, K-fold cross validation was used i.e. the database was randomly divided into K different parts. Training was performed on K-1 parts and the remaining part constituted the test set. All the K different parts were once used as a test set. We used 8-fold cross validation for training and testing the network and 3-fold cross validation to decide when to terminate learning in order to avoid "overtraining".

A backpropagation algorithm was used for adjusting the connection weights during the training process. All calculations were done using the JETNET 3.0 package.[10]

3. Results

The networks for detection of left arm/left foot lead reversal had a sensitivity of 57.6% at a specificity of 99.97%. The networks for detection of right arm/left foot lead reversal had a sensitivity of 80.5% at 99.95% specificity. At a specificity of 99.90%, the sensitivity was 88.9%. The use of P-wave measurements did not improve the performance. No comparison was made with other interpretation programs, since no algorithm for those limb lead reversals has been published.

4. Discussion

The number of ECGs recorded in the world increases steadily. Probably around 300 million ECGs are recorded annually in the world, using computer-based interpretation programs.

It is of great importance that the ECG data presented to the reader or the interpretation program are correct. Therefore great effort has been invested in optimizing the technical quality of the ECG recording. One area where quality

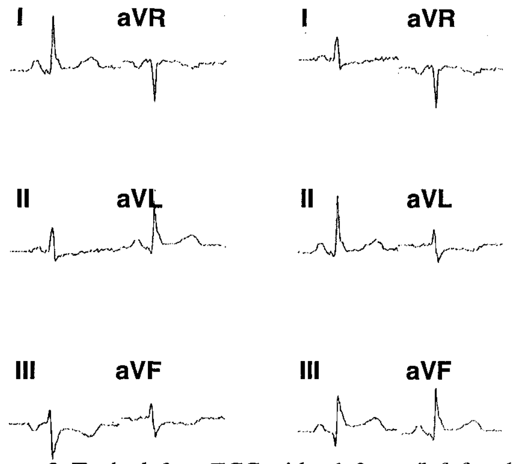

Figure 3. To the left an ECG with a left arm/left foot lead reversal and to the right the same ECG correctly recorded. Note the ST depression in the inferior leads of the left ECG which correponds to ST elevation in the correctly recorded ECG.

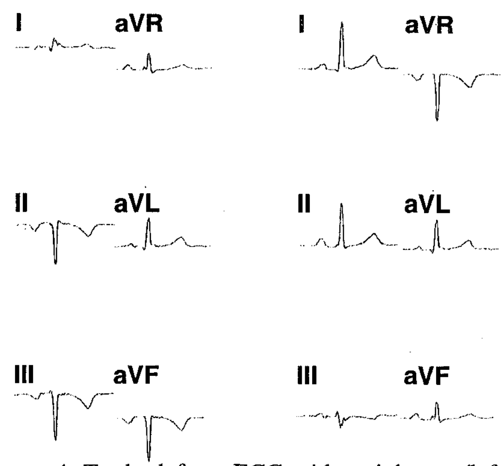

Figure 4. To the left an ECG with a right arm/left foot lead reversal and to the right the same ECG correctly recorded. Note the inferior Q waves in the left ECG which are not present in the correctly recorded ECG.

control has not been improved, is detection of electrode misplacement/lead reversals in the 12-lead ECG. The only limb lead reversal algorithm that, to our knowledge, is used today, is the one for detecting the right/left arm lead reversal.

In the material investigated in this study, there is evidence of 1% limb lead reversals. If this figure is regarded as typical, the number of ECGs with a limb lead reversal is 3 million in the world each year. Most of these are undetected today and sometimes they cause diagnostic errors.

Figure 3 shows an ECG which was interpreted as having ST-changes in the inferior and lateral leads, but no infarction suspected. This was a case of left arm/left foot lead reversal. The correctly recorded ECG was interpreted as having inferior ST-elevation with suspected acute myocardial injury. Figure 4 shows another example where a lead reversal may cause diagnostic errors. This ECG was interpreted by an interpretation program as having an inferior infarction and ectopic atrial rythm, but the correctly recorded ECG is normal. In the clinical situation the physicians, who were not ECG experts, agreed with the incorrect interpretation.

Some of the lead reversals are extremely difficult to detect even for trained ECG readers, and this may be one reason why there are no other algorithms than for the left/right arm lead reversal in the interpretation programs. Since some of the lead reversals are relatively infrequent, there is demand for very high specificity, and this is difficult to achieve with reasonably high sensitivity for rule based criteria.

Artificial neural networks have opened a new and powerful way of developing new strategies for detecting lead reversals. The results in this study showed that most lead reversals can be detected at a very high specificity, almost 100%. There are no data to compare with, but since the interpretation programs used today find practically none of these lead reversals, the results are interesting for those who take interest in ECG interpretation.

Acknowledgments

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