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Detection of Frequently Overlooked Electrocardiographic Lead Reversals Using Artificial Neural Networks

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In the ECG recording situation, lead reversals occur occasionally.[1-3] They are often overlooked, both by the ECG readers and the conventional interpretation programs, and this may lead to misdiagnosis and improper treatment.[3,4] Artificial neural networks represent a computer based method[5,6] which have proved to be of value in pattern recognition tasks, e.g. ECG analysis[7-10]. They have showed high performance, exceeding that of two well known interpretation programs, detecting right/left arm lead reversals in the 12-lead ECG[1]. The left arm/left foot lead reversal is also clinically important and as some precordial lead reversals, do occur quite frequently. The purpose of this study was 1) to detect the left arm/left foot lead reversal and the five precordial lead reversals involving two adjacent leads with the help of artificial neural networks, 2) to compare the results with those of a widely used interpretation program concerning the precordial lead reversals.

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A total of 11,432 ECGs, recorded on patients in the emergency department at the University hospital in Lund during 1992-1993, were studied. The 12-lead ECGs were recorded using computerized electrocardiographs (Siemens-Elema AB, Solna, Sweden). Averaged heart cycles were calculated and transferred to a computer for further analysis. P, QRS, and ST-T measurements used in the criteria and as inputs to the artificial neural networks were obtained from the measurement program of the computerized ECG recorders.

Since artificial neural networks learn by training on a database of examples, it was crucial that no ECG with a lead reversal was presented to the network as an example of an ECG with correct lead placement. Therefore, great care was taken to exclude those ECGs from the database which showed signs of lead reversals or were technically deficient. Also pacemaker ECGs were excluded. The exclusion process comprised visual inspection by two experienced ECG readers and computer based methods using artificial neural networks.[1] ECGs with suspected lead reversals were verified in most cases by visually comparing the suspected ECG with an earlier or later recording from the same patient. A total of 523 ECGs were excluded leaving 10 906 ECGs in the database. (Table I)

The 10 906 correctly recorded ECGs were used to computationally generate six subsets of ECGs, each with one type of lead reversal. The left arm/left foot lead reversal was generated by means of changing places of lead I and II, inverting lead III and changing places of aVL and aVF (Figure 1). The five precordial lead reversals were generated by interchanging adjacent leads. This process yielded exactly the same ECGs that would have been recorded if the leads had been interchanged on the patient. Thus, the final material consisted of 76 342 ECGs, divided into seven groups.

A multilayer perceptron artificial neural network architecture[11] was used. A more general description of neural networks can be found elsewhere.[5] One neural network was used for each lead reversal. The neural networks consisted of one input layer, one hidden layer and one output layer. The latter consisted of one unit and encoded whether the ECG was recorded with correct lead placement or not. The hidden layer of the neural networks contained 7 (left arm/left foot lead reversal) and 4 (precordial lead reversal) neurons respectively. Different combinations of P, QRS, and ST-T measurements were used as inputs to the neural networks. The number of neurons in the input layer equals the number of input variables, in this study 22 for the left arm/left foot lead reversal and 16 for each of the different precordial lead reversals. Each network was trained and tested using the 10 906 ECGs with correct lead placement and 10 906 ECGs with the appropriate lead reversal.

For each lead reversal, the data set was divided into two parts: a training set and a test set. The training set was used to adjust the connection weights, whereas the test set was used to assess the performance. In order to get as reliable performance as possible, a cross validation procedure was used. The data set was randomly divided into equal parts, and each of the different parts was used once as a test set, while training was performed on the remaining parts of the data. We used 3-fold cross validation to decide when to terminate learning in order to avoid "overtraining" and 8-fold cross validation to train the networks and assess their performances. The performance was studied in the separate test set, and the results are the mean values from 10 different runs, i.e. each ECG was in the test set 10 times. During the training process the connection weights between the neurons were adjusted using the back propagation algorithm. In order to reach a very high specificity the networks were trained to identify ECGs with correct lead placement with highest possible accuracy. This was done during the training session by means of presenting these ECGs 300-500 times more often to the networks than the ECGs with a lead reversal. All calculations were done using the JETNET 3.0 package.[12]

The interpretation program developed at the Glasgow Royal Infirmary contains criteria for the detection of precordial lead reversals.[13] These criteria were applied to the correct ECGs and the ECGs with computer generated precordial lead reversals.The performances of the criteria were compared to those of the neural networks. There are no published criteria for the detection of left arm/left foot lead reversal.

Sensitivities and specificities of the neural networks and the conventional criteria for detection of lead reversals are presented in Table II. The networks used QRS and T wave measurements only as inputs (Table III). Adding P wave data to the input variables did not improve the performances of the networks. The specificities of the networks and the conventional criteria were very high for all the lead reversals. Also the sensitivities were generally high for the networks, ranging between 44.5% and 83.0%, while the sensitivities for the conventional criteria were much lower, ranging between 0.1% and 10.0%.

Figure 2-4 shows examples of ECGs which have been misinterpreted by the conventional interpretation program, due to lead reversals which was not detected. The ECGs presented in the figures belonged to the 208 ECGs with lead reversals found in the original database of 11 423 ECGs. The cases in the figures were all detected as lead reversals by the neural networks developed on the larger database.

The results clearly demonstrate that artificial neural networks can be used to detect lead reversals in the 12-lead ECG with very high specificity and mostly high sensitivity. Lead reversals were found in nearly 2% (208/11432) of the ECGs in this study, and considering that an estimated 300 million ECGs are recorded annually in the world, approximately 6 million of these may be recorded with a lead reversal. Most of them are not detected today, and this is especially true for the left arm/left foot lead reversal as well as some precordial lead reversals under study in this paper.

There were 208 ECGs with a lead reversal found in the database, and 194 belonged to one of the types under study in this paper (116) or to one of the lead reversals involving the right/left arm leads (47) or the right arm/foot leads (31), which have been studied earlier.[1,4]

These 8 types of lead reversals represent over 90 % of all the lead reversals found in our database, and this could probably be true for other settings too. The results from this and earlier studies, demonstrate that around 75% of these lead reversals could be detected by artificial neural networks, in combination with an algorithm for detection of the right arm/right foot lead reversal. There are many other types of lead reversal, and each of them may occur, although infrequently. Even though neural networks have not been developed for the specific detection of each of those different types, many of them would be detected by the networks developed for the most common lead reversals.

With a few exceptions, electrocardiography/cardiology textbooks do not cover lead reversals or their implications. The right arm/right foot lead reversal which is relatively common, as well as the lead reversals under study in this paper, are mostly not presented at all, while, e.g., the very rare right arm/left foot[14], left arm/right foot[15], and clockwise/counter clockwise[16] lead reversals have been described.

How could these neural networks be utilized in clinical routine? We propose that the electrocardiograph presents a warning, based on the neural network outputs, and advices the technician to check the cables. The recording is interrupted and no ECG complexes or ECG interpretation are presented. The technician must either then confirm that the leads are correctly placed or correct the leads before the recording can be completed. With this approach lead reversals could easily be corrected and a false detection by the neural networks would not cause much inconvenience.

Another approach is used in the computerized electrocardiographs today. A statement of suggested lead reversal is presented in the interpretation text. The leads affected by the possible lead reversal are disregarded in the interpretation, which therefore is incomplete. There are two disadvantages with this approach. First, the statement in the interpretation text could easily be missed by the technician in the recording situation. Second, a false detection by the interpretation program will result in an incomplete interpretation and the technician cannot change this when she has checked that the leads are correctly placed. Therefore, no (or almost no) false detections can be accepted using this approach, i.e. the specificity must be (almost) 100%.

If the specificity is not sufficiently high for the lead reversals, many of the ECGs reported as a case of lead reversal, would actually be a correctly recorded ECG. The positive predictive value, though, does not depend only on the specificity, but also on the sensitivity and prevalence for different lead reversals. Highest positive predictive value, 79%, has the precordial lead reversal which appeared most often in the database, the interchanging of leads V5/V6, although the specificity was the second lowest among the studied lead reversals.

Artificial neural networks can be used to recognize lead reversals in the 12-lead ECG at very high specificity, and the sensitivity was much higher than that of a conventional interpretation program. The neural networks developed in this and an earlier study for detection of lead reversals, in combination with an algorithm for the right arm/right foot lead reversal, would recognize around 75% of lead reversals encountered in clinical practice.

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Figure Legends

Figure 1 An ECG with left arm/left foot lead reversal (left) and the correctly recorded ECG on the same subject (right). This lead reversal can be simulated by relabeling of correctly recorded leads.

Figure 2 The interpretation program reported ectopical atrial rythm in this ECG with left arm/left foot lead reversal (left). Also note that no Q waves are present in the inferior leads. The ECG with correct lead placement (right) shows sinus rhythm and a healed inferior myocardial infarction.

Figure 3 To the left an ECG with a left arm/left foot lead reversal with ST depressions in the inferior leads. To the right the ECG with correct lead placement. There are ST elevations in the inferior leads, consistent with acute myocardial injury.

Figure 4 To the left an ECG with a reversal of V1/V2. This gives an impression of loss of R wave amplitude and septal ST changes suggesting ischemic heart disease, according to the interpretation program. To the right the ECG with correct lead placement. The lead reversal was not detected by the interpretation program that incorporates conventional criteria for detection of near-neighbour lead reversals, but found by the neural network.

Table I: Reasons for exclusion of ECGs (n=11 423).

Reason for exclusion	Number of ECGs excl		
Lead reversals			**208**
Left arm/left foot	12		
V1/V2	3		
V2/V3	16	116	
V3/V4	6		
V4/V5	11		
V5/V6	68		
Right/left arm	47		
Right arm/right foot	31		
Other lead reversals	14		
Pacemaker ECG			**197**
Technically deficient ECG			**118**
Total			**523**

Table II: Sensitivities and specificities of artificial neural networks and conventional criteria.

	Artificial Neural Networks		Conventional Criteria	
Lead Reversal	**Sensitivity**	**Specificity**	**Sensitivity**	**Specificity**
Left arm/left foot	57.6 %	99.97 %	-	-
V1/V2	80.6 %	99.94 %	4.0 %	99.95 %
V2/V3	44.5 %	99.87 %	9.3 %	100 %
V3/V4	77.5 %	99.95 %	10.0 %	100 %
V4/V5	83.0 %	99.95 %	4.7 %	100 %
V5/V6	73.2 %	99.88 %	0.1 %	100 %

Table III: Measurements used in the neural networks trained to detect lead reversals.

Lead reversal	Measurements
Left arm/left foot	Q, R, and S amplitudes in I, II, III, aVL, and aVF *T sum in I, II, III, aVL, and aVF #QRS axis
V1/V2	Q, R, S, and T amplitudes in V1-V4
V2/V3	R, S, and T amplitudes in V1-V4 QRS area in V1-V4
V3/V4	R, S, and T amplitudes in V2-V5 QRS area in V2-V5
V4/V5	R, S, and T amplitudes in V3-V6 QRS area in V3-V6
V5/V6	Q, R, S, and T amplitudes in V3-V6

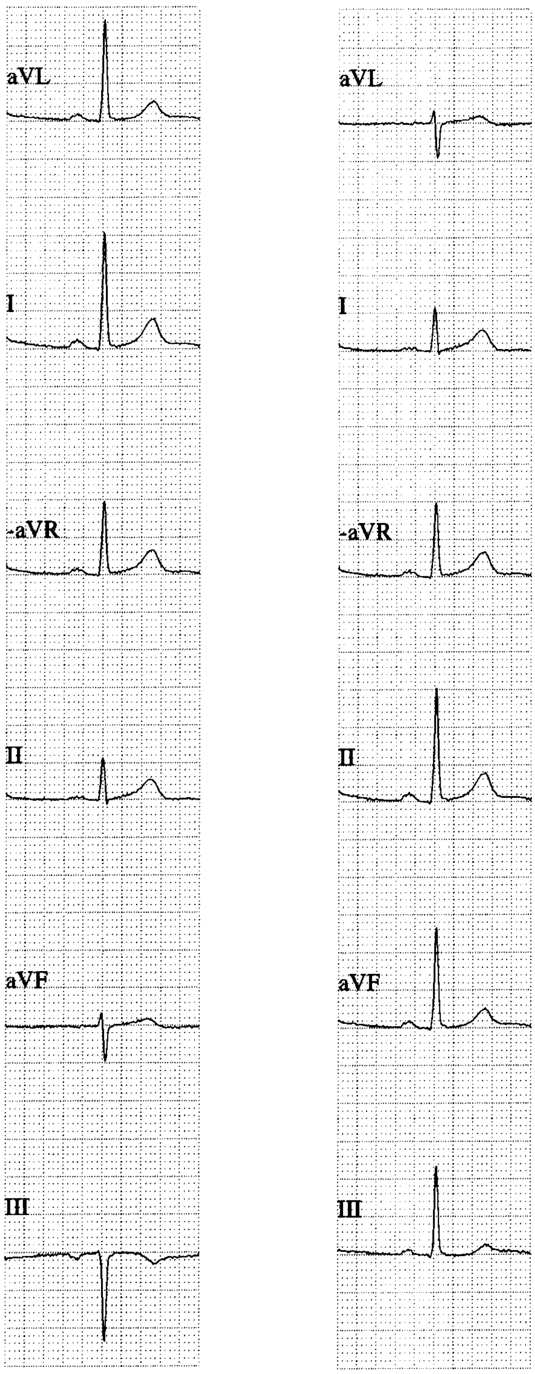
*T sum = maximal positive T amplitude – |maximal negative T amplitude|

#QRS axis was presented as sin(axis • _/180) and cos(axis • _/180)

Summary

Artificial neural networks can be used to recognize lead reversals in the 12-lead ECG at very high specificity, and the sensitivity is much higher than that of a conventional interpretation program. The neural networks developed in this and an earlier study for detection of lead reversals, in combination with an algorithm for the right arm/right foot lead reversal, would recognize around 75% of lead reversals encountered in clinical practice.

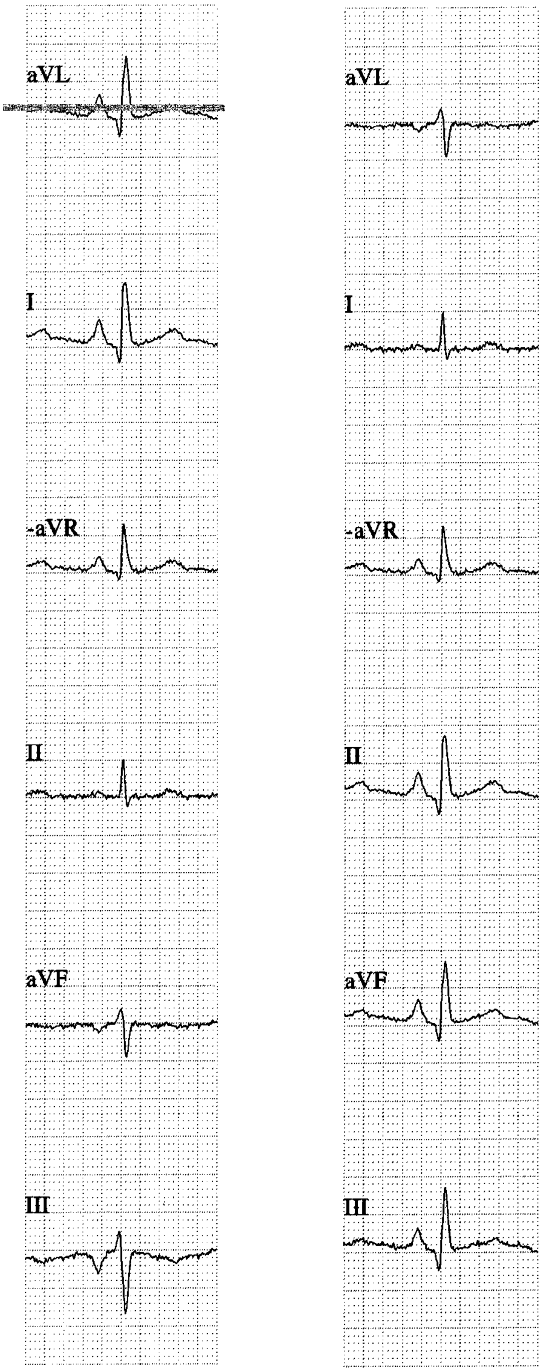
Figure 1



Left arm/foot lead reversal

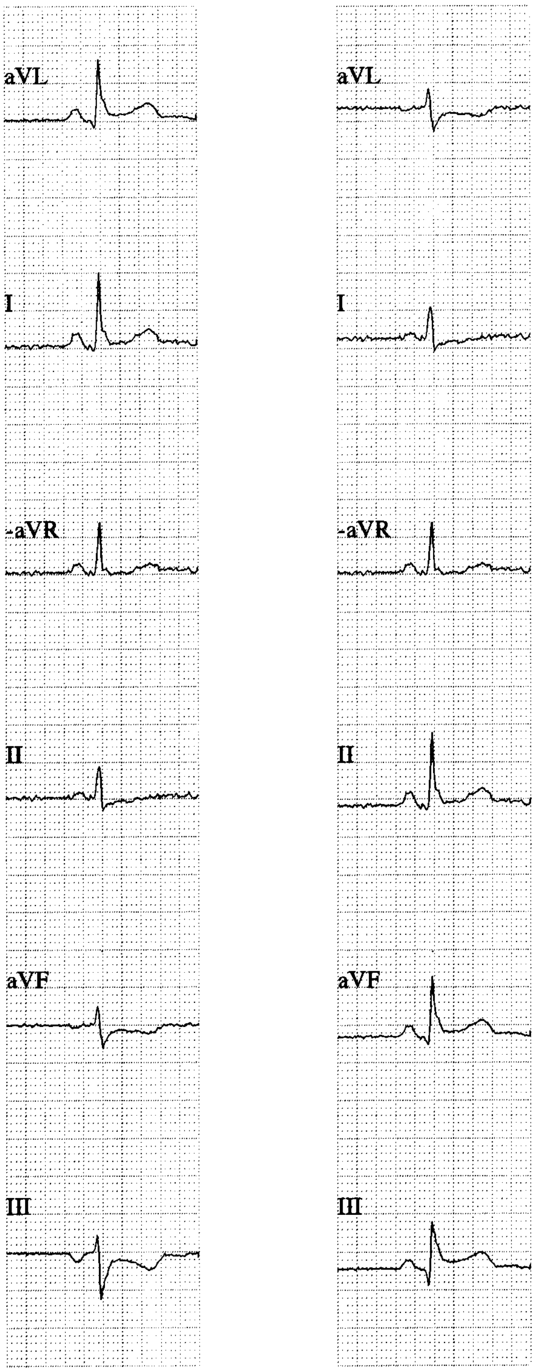
Correct lead placement

Figure 2



Left arm/foot lead reversal **Correct lead placement**

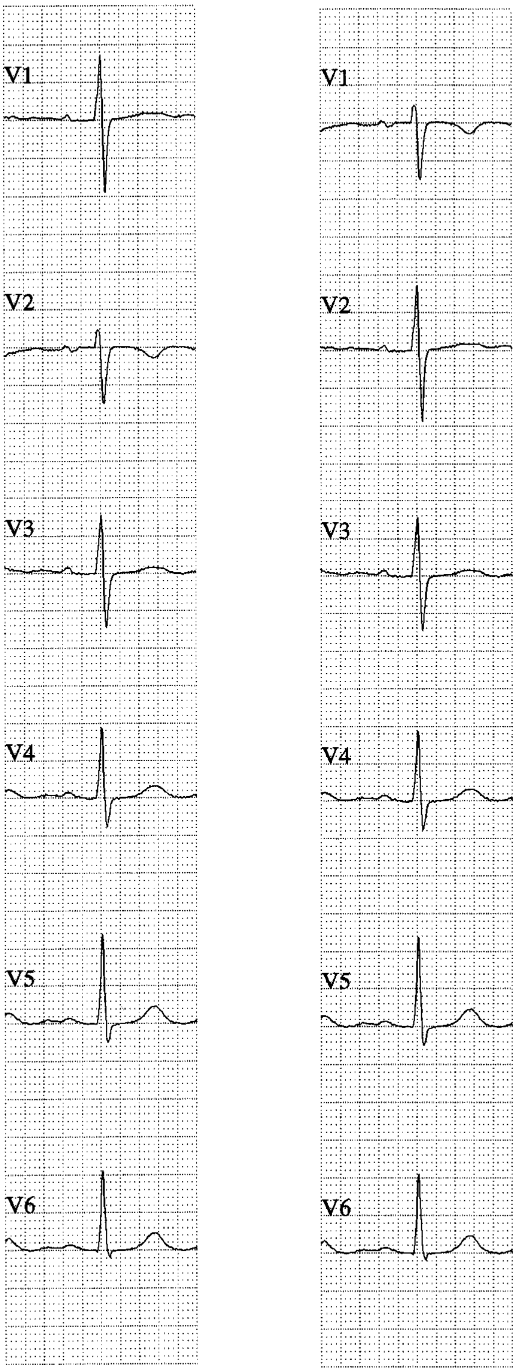
Figure 3



Left arm/foot lead reversal

Correct lead placement

Figure 4



V1/V2
lead reversal

Correct lead
placement