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High Specificity – a Necessity for Automated Detection of Lead Reversals in the 12–lead ECG

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Short running head: Automated detection of lead reversals

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Lead reversals in the 12–lead electrocardiogram (ECG) occur occasionally and this may lead to misdiagnosis and improper treatment[1–4]. The Left Arm / Left Foot (LA/LF) lead reversals are often difficult to detect and commonly used interpretation programs lack algorithms for their detection[2]. Recently a method based on artificial neural networks that detected LA/LF lead reversals was presented[2]. Thereafter Abdollah et al.[5] presented rule based criteria for the detection of LA/LF lead reversals and they reported a sensitivity of 90%, higher than that of the neural network, based on a data set of 70 recordings. However, the specificity level, which was very high using artificial neural networks, was not studied and discussed by Abdollah et al. The purpose of this study was to implement and test the Abdollah criteria on our large database of ECG recordings in order to obtain both sensitivity and specificity levels and to compare these levels with those achieved using artificial neural networks on the same database.

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A total of 11,423 ECGs, recorded for patients in the emergency department at the University Hospital in Lund, Sweden, during 1992–1993, were studied. The 12–lead ECGs were recorded using computerized electrocardiographs (Siemens Elema AB, Solna, Sweden). This study group was used in a previous study[2] where it was thoroughly scrutinized with respect to lead reversals and technically deficient ECGs. A total of 523 ECGs were excluded leaving 10,906 ECGs in the database. The Abdollah criteria[5] relies on P wave information and detectable P waves were only present in 9,072 of the recordings in our database. These 9,072 correctly recorded ECGs were then used to computationally generate an additional set of 9,072 ECGs with LA/LF lead reversal, by means of changing places of leads I and II, inverting lead III, and changing places of leads aVL and aVF. This process simulates exactly what would have been recorded if the leads had been interchanged on the patient. The final database consisted of 18,144 ECGs.

Averaged heart cycles were calculated and transferred to a computer for further analysis. ECG measurements used in the criteria and as inputs to the artificial neural networks were obtained from the measurement program of the computerized ECG recorders. The only measurement not presented directly by the measurement program was the occurrence of a positive terminal component of the P wave in lead III, which is part of the Abdollah criteria. This measurement was calculated as follows. The interval between the onset and the end of the P wave was divided into 15 parts of equal duration. The P wave in lead III was said to have a terminal positive component if the sum of the amplitudes in the last (15th) part were positive.

The Abdollah criteria[5] were based on the following two conditions:

Condition A: *P wave amplitude in lead I* $>$ *P wave amplitude in lead II.*

Condition B: *P wave in lead III has a terminal positive component*.

The criteria were then:

IF (condition A fulfilled) **OR** (condition B fulfilled)

THEN report LA/LF lead reversal.

The neural networks used in this study were multilayer perceptrons. A more general description of artificial neural networks can be found elsewhere[6]. Each network consisted of one input layer, one hidden layer, and one output layer. The latter encoded whether the ECG was recorded with the correct lead placement or not. The number of hidden neurons was 14. Different combinations of P, QRS, and T measurements were used as inputs for the neural networks, see Table I for details. A separate test set was used in order to assess the performance of the neural networks and to compare with the Abdollah criteria. The test set

TABLE I: Specification of the measurements used for the neural networks.

Neural network inputs
P−Axis*, QRS−Axis*, P sum# and T sum# in leads I, II, III, aVL, and aVF. (total of 14 inputs).

*QRS−Axis and P−Axis was presented as sin(axis$*\pi$/180) and cos(axis$*\pi$/180)
#P and T sum = maximal positive P (T) amplitude − |maximal negative P (T) amplitude|

was randomly selected from the full data set and contained 1/3 of the original data, leaving 2/3 of the data for training. A 5−fold cross validation scheme was used during the training in order to determine a suitable number of hidden neurons. Overtraining was avoided because of the large datasets and the relatively few number of parameters in the networks. After the number of hidden neurons was determined 15 networks were trained using the full training set but with different randomly selected initial weights. The average of the 15 individual network outputs was used to calculate the test results. In order to reach a very high specificity the neural networks was trained to identify ECGs with correct lead placement with highest possible accuracy. This was accomplished during the training session by means of presenting correctly recorded ECGs more often than the ECGs with LA/LF lead reversal. All calculations were performed using the JETNET 3.0 package[7].

The results for the neural networks and Abdollah criteria are presented in Table II. The sensitivity and specificity was 89.4% and 37.8% respectively, for the Abdollah criteria. The sensitivity of the neural network (99.4%) was significantly higher at the same level of specificity (P<0.001). Row 3 and 4 of Table II show the result for the two conditions of the Abdollah criteria separately. Condition A is the most important one, i.e. the comparing of the P wave amplitudes in the leads I and II. The neural network showed both higher sensitivity and specificity than Condition A. The neural network that was trained for high specificity (99.8%) detected 25.4% of the ECGs with lead reversals. Figure 1 shows two ECGs that were falsely detected as LA/LF lead reversals by the Abdollah criteria, but were classified as *correctly recorded* by the neural network.

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TABLE II: Results for the Abdollah criteria, the Conditions A and B separately and for the neural networks. Neural network 3 refers to a network trained for high specificity.

	Sensitivity	**Specificity**
Abdollah Criteria	89.4%	37.8%
Neural network (1)	99.4%	37.8%
Condition A	77.9%	78.7%
Condition B	49.0%	48.5%
Neural network (2)	92.5%	93.7%
Neural network (3)	25.3%	99.8%

Abdollah et al. reported a sensitivity for the detection of LA/LF lead reversals of 90%, based on a study of 70 ECGs. The sensitivity was found to be very similar (89.4%) in this study, which was based on a much larger database (9,072 ECGs). However, Abdollah et al. did not study the specificity and in this study it was found to be as low as 37,8%. This is too low to be of any clinical use. In an earlier study[2] 12 ECGs with LA/LF lead reversal were found in a database of more than 11,000 recordings. Criteria with low specificity applied to lead reversals with such a low prevalence will result in a large dominance of false positive detections compared to true positive detections. For example, if the Abdollah criteria were applied to 10,000 ECGs 10 of approximately 11 LA/LF lead reversals would be detected but more than 6000 correctly recorded ECGs would falsely be detected as LA/LF lead reversals. In general, methods detecting rare events, must have a high specificity, otherwise the number of false positive classifications will be high (low positive predictive value) and discussions of the level of sensitivity is almost of no interest. A high sensitivity could always be archived at a cost of a low specificity and vice versa.

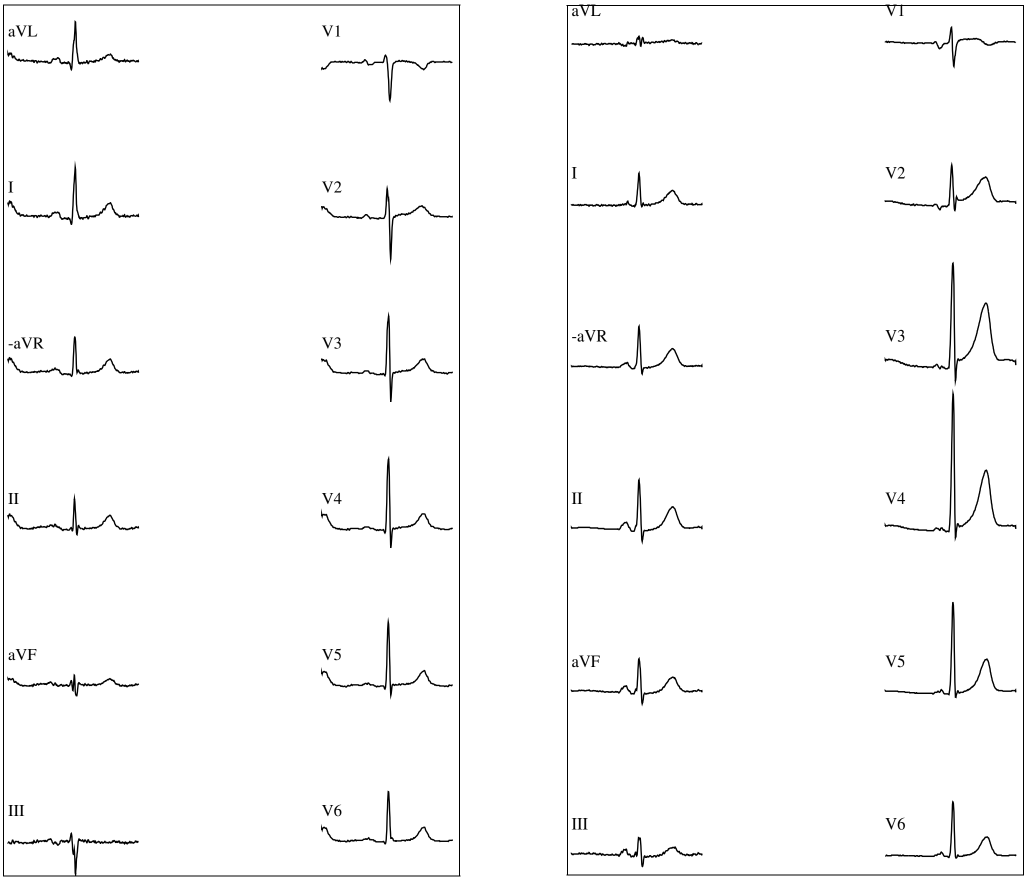

Figure 1 (Left) A correctly recorded ECG that was detected as a LA/LF lead reversal by the Abdollah criteria. The condition A was fulfilled, i.e. *P wave amplitude in lead I* > *P wave amplitude in lead II.* The ECG was correctly classified by the neural network. (Right) A correctly recorded ECG that was detected as a LA/LF lead reversal by the Abdollah criteria. The condition B was fulfilled, i.e. *P wave in lead III has a terminal positive component*. The ECG was correctly classified by the neural network.

Conclusion. Artificial neural networks can detect the most common lead reversals with sensitivities which, to our knowledge, no rule base criteria has achieved at comparable high specificities. The sensitivity of the Abdollah criteria was 89.4% but the specificity was very low. At this low specificity the artificial neural network was significantly better.

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