Automatic Detection of ECG Lead-wire Interchange for Conventional and Mason-Likar Lead Systems

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Abstract

Misconnection of ECG lead-wires can generate abnormal ECG and erroneous diagnosis. Existing methods for detecting lead-wire interchange were designed for ECG devices using conventional lead system. In this work we developed an automatic ECG cable interchange detection algorithm and compared the algorithm performance between conventional and Mason-Likar (ML) electrode placements. The algorithm was developed based on a decision tree classifier which uses beat morphology measurements that were obtained using Philips DXL ECG algorithm. The algorithm was evaluated for detecting limb cable interchanges on an independent database which included both conventional and ML ECG recordings for each subject (total 423 subjects). There was no statistically significant difference in terms of overall sensitivity and specificity. This morphology-based cable interchange detection algorithm showed similarly high performance for maintaining a low false positive rate for both lead systems. Therefore, in practice, the same algorithm may be used with either electrode placement without a need for a special configuration.

1. Introduction

Forty million ECGs are recorded annually in the United States. Electrode placement is considered one of the most important factors that determine ECG signal quality and misplacement can produce incorrect ECG abnormalities and thus generate erroneous diagnostic reports [1, 2]. Two different kinds of electrode placement errors are incorrect placement of the electrode relative to the anatomical landmarks, and connecting recording cables to the wrong electrodes which are placed on the anatomically correct locations. In this paper we are concerned with the latter, i.e. cable interchange error. Different criteria and algorithms have been proposed to detect cable interchange by analyzing the recorded ECG waveforms [1]. One major category involves the analysis of beat morphology which extracts a set of measurements from P, QRS, and T-waves and use these measurements to derive detection criteria [3-5]. Alternatively, novel methods have also been proposed which use the redundant information contained in the eight independent leads [6-7]. Such methods use the transformation or reconstruction of ECGs from the original lead system to an approximation and cable interchange is detected by comparing the original ECGs with transformed or reconstructed ECGs. Recent methods based on combining both morphology features and redundancy features show improved performance for the detection of cable interchange [8-9].

However, existing methods for detecting ECG cable interchange were designed for ECG devices using conventional 12-lead system with limb electrodes placed at conventional positions. For a wide range of ECG devices such as exercise and ambulatory devices, the Mason-Likar (ML) lead system [10-11] is often used. In the ML lead system, modified limb electrode positions are often used whereby the arm electrodes are placed at the infraclavicular fossae and the leg electrodes are placed on the lower abdomen rather than legs. This study aims to assess the performance of a novel morphology-based algorithm for detecting limb cable interchange under ML lead system. We compare the algorithm performance between conventional lead system and ML lead system using a unique validation database in which conventional ECG recording and ML ECG recording are available for each subject.

2. Methods

2.1. ECG databases

The development database included two population sources. One source was body surface potential maps recorded on a population including normal subjects, post-myocardial-infarction patients, patients with a history of ventricular tachycardia but no evidence of a previous myocardial infarction, and patients with a single-vessel coronary artery disease who underwent coronary angioplasty [12]. The second source was the Physionet PTB diagnostic ECG database [13-14] which includes both healthy control subjects and patients with various cardiac diseases including myocardial infarction, cardiomyopathy/heart failure, bundle branch block, dysrhythmia, myocardial hypertrophy, valvular heart disease, myocarditis, and other miscellaneous conditions. Consecutive 10-second snapshot ECGs were taken from each PTB recording. The ECGs from the development database used conventional limb electrode placement. The validation database came from a study population of patients with acute chest pain admitted to Lund University Hospital. For the validation database, there were 423 patients from which the ECGs in both conventional lead system and ML lead system were available for each patients. In total, there were 6272 ECGs from 1125 patients in the development database and 423 conventional ECGs and 423 ML ECGs from 423 patients in the validation database that were considered free of any cable interchange.

We investigated 2 common limb cable interchanges [3, 6] involving right arm (RA), left arm (LA), and left leg (LL). For each ECG, cable interchanges were simulated by effectively swapping the limb cables (LA-RA and RA-LL) by mathematical transform, which generated 2 additional ECGs from each original recording with no cable interchange.

2.2. Algorithm development

The detection and classification algorithm uses the morphology measurements. The Philips DXL ECG algorithm was used to automatically extract morphology features including P-wave frontal axis, P-wave clockwise vector loop rotation direction, QRS frontal axis, QRS clockwise vector loop rotation direction, R-wave amplitude and T-wave amplitude from lead I and lead II. The P-wave features were only used when the ECG had consistent beat-to-beat PR interval and did not show atrial fibrillation or atrial flutter. Using the development database, a decision tree [15] was designed to classify each set of measurements to no interchange, LA-RA interchange, and RA-LL interchange. Pruning was used to reduce the complexity and over-fitting of the decision tree. Considering the low prevalence of cable interchange in the clinical setting, a cable interchange detection algorithm should be configured with high specificity in order to prevent generating many false positive notifications. Therefore, during the algorithm development, the decision tree model was trained by assigning unequal prior probability according to the prevalence of cable interchanges for each output class to favor specificity over sensitivity.

2.3. Statistical analysis

Algorithm performance was evaluated in terms of sensitivity and specificity from a confusion matrix. To calculate the individual sensitivity and specificity for each cable interchange, that particular cable interchange was defined as a positive event while the other cable interchange and no cable interchange were defined as a negative event thereby reducing the size of the confusion matrix to 2-by-2. Considering that there were 2 types of individual cable interchanges, the algorithm performance was also evaluated in terms of overall sensitivity and specificity, in which we defined either type of cable interchanges as a single positive event. We calculated the statistical significance based on the 95% confidence interval (CI) of the difference in the performance ratios (sensitivity and specificity) as recommended by Altman et al [16].

3. Results

3.1. Measurements from conventional ECG and ML ECG

Table 1 summarizes the difference in morphology measurements between conventional ECGs and ML ECGs. Compared with conventional ECGs, the ML ECGs have a shift towards a more vertical position of both the P-wave frontal axis (mean shift of 18 degree, excluding the cases with atrial fibrillation or atrial flutter) and the QRS-wave frontal axis (mean shift of 20 degree). There are also considerable individual variations such as large amplitude difference between conventional ECGs and ML ECGs. As a consequence of the QRS frontal axis shift, the R-wave amplitude for lead I decreases while the R-wave amplitude for lead II increases in ML ECGs.

Table 1. Comparison of morphology measurements between conventional ECGs and ML ECGs

Measurement	Conventional	ML
	Mean±SD	Mean±SD
P-wave frontal axis (º)	40±39	58±39
QRS frontal axis (º)	13±48	33±56
Lead I R amp (µV)	826±370	573±294
Lead II R amp (µV)	646±376	945±536

Figure 1 and Figure 2 show scatterplots of QRS frontal axis and P-wave frontal axis for conventional ECGs and ML ECGs respectively. Different colors represent no interchange and different types of cable interchanges. Comparing Figure 1 with Figure 2, the distribution of different types of cable interchanges and no interchange within this 2D plane is similar between conventional ECGs and ML ECGs. For both conventional ECGs and ML ECGs, overlap between no interchange and LA-RA interchange is smaller than the overlap between no interchange and RA-LL interchange which indicates it is easier to separate LA-RA interchange from no interchange than to separate RA-LL interchange from no interchange. Therefore, in order to reduce false positive cases, more RA-LL interchange cases within the overlap region would be considered as negative cases, and this explains the slightly decreased sensitivity of detecting RA-LL interchange.

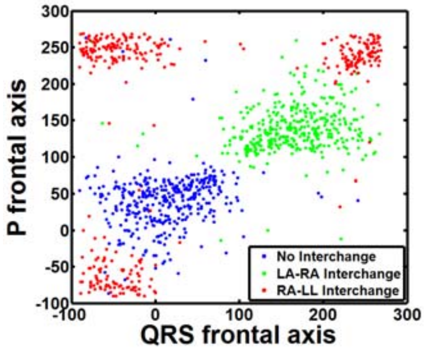

Figure 1. Scatterplot of QRS-wave frontal axis and P-wave frontal axis for conventional ECGs.

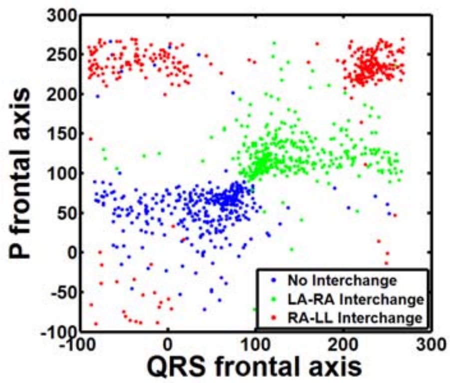

Figure 2. Scatterplot of QRS-wave frontal axis and P-wave frontal axis for ML ECGs.

3.2. Algorithm performance

Table 2 and Table 3 summarize the performance of the cable interchange detection algorithm for conventional ECGs and ML ECGs, respectively. The differences in overall sensitivity and specificity are not statistically significant. There is also no statistical difference in sensitivity for either LA-RA or RA-LL cable interchange. The statistical test did not show a significant difference in specificity for RA-LL interchange, although revealed a marginally significant difference for specificity of LA-RA interchange.

4. Discussion

Existing methods for detecting ECG cable interchange were designed and optimized for ECG devices using lead system with limb electrodes placed at conventional positions. However, exercise and ambulatory ECG devices often use the ML lead system with modified limb electrode placement. In this study, we propose a new method for detecting ECG cable interchange using morphology measurements and compare the algorithm performance using a database with both conventional ECGs and ML ECGs. With this database, we showed that there was no statistically significant difference in terms of overall sensitivity and specificity, as well as the sensitivity for individual limb cable interchange between the conventional and ML lead systems. The results indicate that this morphology-based cable interchange detection algorithm showed similarly high performance for maintaining a low false positive rate for both lead systems and therefore, in practice, the same algorithm may be used under either electrode placement without a need for a special configuration.

Table 2. Summary of performance for conventional ECGs

	Overall	LA-RA	RA-LL
Sensitivity (%)	85.6	91.3	72.8
Specificity (%)	97.9	97.9	97.5

Table 3. Summary of performance for ML ECGs

	Overall	LA-RA	RA-LL
Sensitivity (%)	86.5	88.9	75.9
Specificity (%)	98.1	96.5	98.5

From clinical and practical point of view, an algorithm with high specificity and low false positive rate is preferred because of the low prevalence of lead-wire interchange [3, 6]. Therefore, the algorithm was configured to maintain a very high overall specificity. Even with a high specificity configuration, the algorithm was still able to achieve high overall sensitivity and individual sensitivity for each type of limb cable interchanges. In addition, this algorithm could also be configured to achieve different performance under other scenarios when a very high sensitivity is required, at the cost of slightly decreased specificity.

Consistent with a study of impact of modified electrode placement [11], we noticed the shift of frontal axis for both P-wave and QRS-wave towards more vertical positon for ML ECGs. This might explain the slight difference in terms of sensitivity between conventional ECG and ML ECG for individual limb cable interchange (LA-RA interchange has higher sensitivity in conventional ECGs and RA-LL interchange has higher sensitivity in ML ECGs). However, as shown in the scatterplot of P-wave frontal axis and QRS-wave frontal axis, the distribution of different types of cable interchanges and no interchange is similar between conventional ECGs and ML ECGs. The statistical analysis also showed no difference in terms of individual sensitivity for both LA-RA interchange and RA-LL interchange. This is because other than frontal axis, we also included clockwise frontal vector loop rotation direction in the classifier, which is less affected by the change of lead system.

In this study, we did not investigate LA-LL interchange, or interchange between precordial cables. The LA-LL interchange was not considered because experts felt that serial ECGs were required for reliable detection of the LA-LL interchange; in other words, even an expert cannot dependably detect LA-LL interchange using only a single 10-second snapshot. The detection of precordial cable interchanges for conventional electrode placement has been previously addressed [7, 9]. It is noticed that electrode placement for ML lead system affects more on the frontal plane yet less on the horizontal plane; and therefore we believe performance difference for detecting precordial cable interchanges should be small between conventional lead system and ML lead system. We also did not investigate interchanges between arm and right leg (active ground). These right leg cable interchanges cannot be simulated by swapping the waveforms from 12-lead ECG and need specific databases for development and validation. There are some commonly used criteria (e.g., flat line on limb lead II or III) that could be used to visually detect the cable interchange between arm cable and right leg cable [17]. Future studies can be conducted when such specific databases are available.

5. Conclusion

In conclusion, the present study demonstrates that our novel algorithm is capable of detecting cable interchanges with high sensitivity while maintaining low false positive rate for both conventional lead system and ML lead system. Therefore, in practice, the same algorithm may be used under either lead system without a need for a special configuration. The flexibility of algorithm may have wide application for assisting automated ECG analysis for more accurate diagnosis of cardiac diseases in exercise and ambulatory ECG devices.

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