Improving Automatic Detection of Acute Myocardial Infarction in the Presence of Confounders

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Abstract

Several ECG features are common electrocardiographic markers for manual interpretation of early repolarization (ER) and acute pericarditis (PCARD), both confounders for acute myocardial infarction (AMI). We hypothesized these features could improve automated AMI detection in the presence of ER and PCARD.

Method: The training set of ECGs included cardiologist reading of ER (n=147), PCARD (n=114), normal (n=239) and AMI (n=380). AMI was confirmed by reading infarct evolution in serial ECGs. The test set came from emergency department chest pain patients (n=1806). The reference was discharge diagnosis of AMI. Positive ECGs (n=1023) were both STEMI and NSTEMI. ECGs not meeting STEMI criteria by algorithm were excluded from both the test and training sets leaving 430 and 581 ECGs respectively. Two logistic regression AMI classifiers were compared, one using traditional features, another using traditional plus additional features to help detect ER and PCARD. Additional features included J-waves, notches, slurs, PQ segment depression, ST-T concavity, spatial QRS-T angle, and T-wave PCA ratio.

Results: As expected, the traditional ST-T features had the most discrimination power. However, the automatically-selected best features included T-wave PCA ratio and the mean anterior PQ segment depression. Total accuracy was higher for the additional feature classifier, 79% versus 70% .

Conclusion: Additional ECG features aimed at ER and PCARD may improve automatic AMI classification when STEMI criteria are met.

1. Introduction

There are many conditions that generate ST-segment elevation and can therefore be misinterpreted as ST-segment elevation myocardial infarction (STEMI) when symptoms of acute coronary syndromes (ACS) are present. Bundle branch blocks, acute pericarditis and benign early repolarization are often cited as conditions which must be carefully ruled out when STEMI is suspected.

J-waves, notches and slurs are frequently described ECG features for manual interpretation of early repolarization. Similarly, PQ-segment depression is a frequent marker of acute pericarditis. See Figure **1** for ECG examples of those features. Concave up ST-segment shape is commonly used to distinguish ischemic and non-ischemic ECGs in manual ECG interpretation. Although these features are regularly used in manual reading, they are not frequently discussed in automated ECG analysis.

In terms of manual reading, benign early repolarization is characterized by ST elevation, no reciprocal ST depression, upwardly concave ST segments, J-point deflections/notches/slurs, tall positive and peaked precordial T-waves and finally low ST/T ratio in lead V6 [1,2]. In manual reading, pericarditis is characterized by widespread ST elevation, concave up ST-segments, PQ-segment depression, concordant T-waves and PQ-segment axis opposite to P-wave axis [3]. In addition, significant Q-waves and reduced R-waves are features of AMI but not early repolarization or acute pericarditis.

Similarly, other ECG features are not used in manual interpretation because they cannot be estimated by eye; consequently, they cannot be validated manually. Some

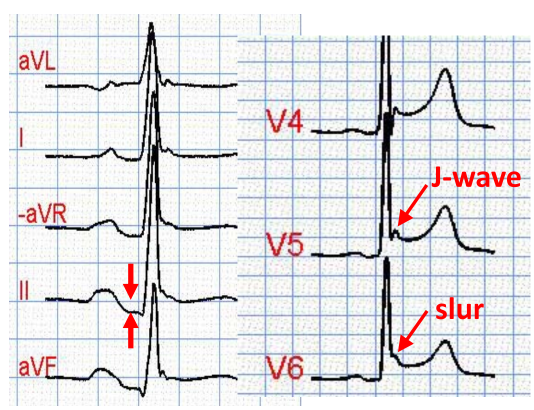

Figure 1. The left panel shows PQ segment depression in a case of acute pericarditis. The right panel shows examples of a J-wave and an R-wave slur characteristic of benign early repolarization.

of these derived ECG features which are linked to later coronary artery disease (CAD) are spatial QRS-T angle [4], and T-wave complexity [5].

We hypothesized that commonly used manual reading ECG features could help distinguish early repolarization, pericarditis and AMI. Note that since bundle branch blocks are usually considered separately, in this study, we address only narrow QRS ECGs.

2. Study population

Two separate databases were used for testing and training in this study. The training set was created by combining four separate data sets, early repolarization (n=147), pericarditis (n=114), normal (n=239) and AMI (n=380). In this case normal represents no significant abnormal pathology by ECG reading. The normal group contains ECGs with left ventricular hypertrophy (an abnormality) for example. AMI was confirmed by reading infarct evolution in serial ECGs. ECGs not meeting STEMI criteria by algorithm were excluded. The other groups were based on cardiologist reading of a larger hospital set.

The previously described test set came from emergency department chest pain patients (n=1806) [6]. The patient selection was based on the availability of discharge diagnosis of AMI or not AMI. This was the AMI reference. Positive AMI ECGs (n=1023) included both STEMI and NSTEMI. The other classifications used in the training set, early repolarization, acute pericarditis and normal, were not annotated in the test set.

The test set came from 7,710 emergency department chest patients collected over 36 months. 1102 patients had an ICD9 discharge diagnosis of 410.XX for acute MI. 1853 patients were ruled out for acute MI, but only 796 had clinical data available. After excluding 13 patients for missing ECG (n=7) and corrupted ECG (n=6), the total negative acute MI set was 783. When positive and negative cases were combined, and after exclusions (LBBB (n=60), not meeting ST elev criteria (n=1235), QRS duration > 130ms (n=81)), 430 patients remained in the test set.

3. Methods

The ECG data sets made up of 12-lead 10-second ECGs (500 samples per second, 5μV resolution) were analysed by the Philips DXL algorithm to obtain standard measurements such as ST-segment (measured at J-point plus 20ms) and T-wave amplitudes. Derived measurements included ST to T-wave amplitude ratio and the number of leads with ST elevation or depression. Selvester QRS score for estimation of MI size was used to summarize Q-wave and reduced R-wave features of AMI [7]. We call these the traditional features.

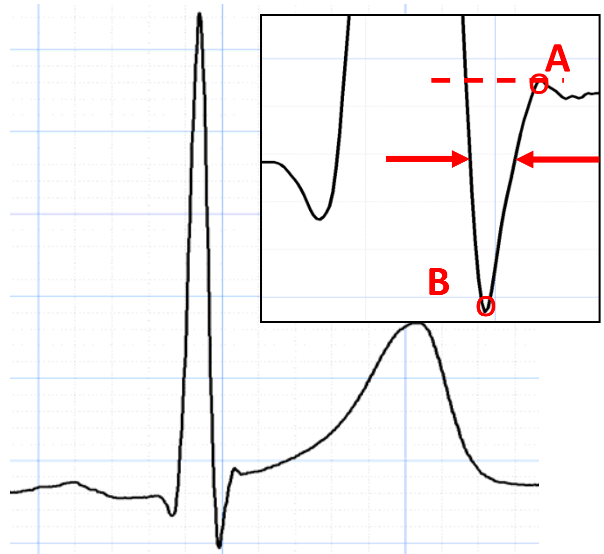

Figure 2. Measurement of J-wave and J-point notch. The J-point notch is detected first by finding local extrema A and B, next by measuring the duration (between red arrows) down 80uV from point A. The duration must be less than 20ms to be called a notch.

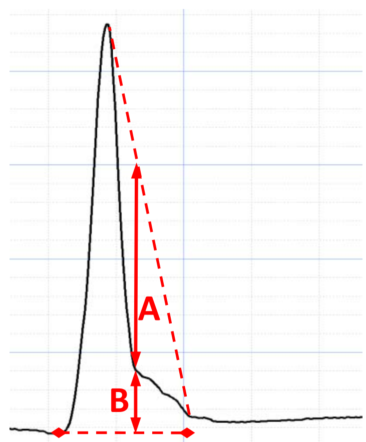

Figure 3. Measurement of J-point slur. The location of line segment A in time is chosen to maximize the distance between waveform and the line connecting R-wave peak and J-point.

Additional features included detection of the J-waves, notches and slurs common in early repolarization and measurement of PQ-segment deviation by the difference in amplitude between P-wave onset and QRS onset. Figure **1** shows the method for detecting J-waves and J-point notches. The method for measuring J-wave slurs can be found in Figure **3**. Abnormal repolarization was additionally measured by spatial QRS-T angle, T-wave principal component analysis (PCA) ratio (round T-wave vector loops), rotation direction of T-wave loops (clockwise or counter clockwise) and concavity of the

Figure 4. Measurement of ST-segment concavity. Concavity is measured as the maximum distance between the dotted line connecting J-point and T-wave peak and the waveform. This distance is normalized to the T-wave amplitude to create a relative measurement.

segment from J-point to T-wave peak (see Figure **4**).

Two logistic regression AMI classifiers were designed, one using traditional features, and the other using traditional plus additional features mentioned above. Both classifiers used forward step-wise feature selection on the training set to choose the 8 best representative ECG features. The basis for the logistic regression design was the function mnrfit, part of the Matlab^{TM} Statistics package (MathWorks, Natick, Massachusetts).

3.2. Statistical methods

Classifier performance was assessed by calculating sensitivity (SE), specificity (SP), positive predictive value (PPV), negative predictive value (NPV), total accuracy (ACC) and odds ratio (OR) defined as the ratio of positive likelihood ratio and negative likelihood ratio. Total accuracy and odds ratio are both single number measures of accuracy.

4. Results

The features summarized in Table 1 were selected in the forward step-wise feature selection in the logistic regression classifier design when additional features were available. The features at the top of the list were chosen first so they have the highest impact on performance.

As expected, the traditional features had the most discrimination power. The traditional features made up the first 6 chosen in the step-wise selection when additional features were available. However, 2 of the 8 automatically-selected best features came from the additional set. Of the additional features, T-wave PCA ratio (a.k.a. T-wave loop roundness) was chosen first in the step-wise feature selection followed by mean PQ-segment depression in leads V1 – V4.

Trad+Add	description
latSTdepr	Average ST depression in leads I, aVL, V5 and V6
MI size	Selvester QRS score
infSTelev	Average ST elevation in leads II, III and aVF
sgVcgSTmag	Maximum magnitude of the ST-segment in the sagittal plane
frVcgTmag	Maximum magnitude of T-wave loop in the frontal plane
latSTelev	Average ST elevation in leads I, aVL, V5 and V6
T_PCAratio	Ratio of the first and second T-wave principal components
antPQdepr	Average PQ segment depression in leads V1-V4

Table 1. Order of forward stepwise selection of traditional and additional ECG features for classification of AMI, PCARD, ER and normal.

The statistical measures for the performance of the two classifiers on the test set are reported in Table 2.

Features	SE	SP	PPV	NPV	ACC	OR
Traditional	71	68	88	43	70	5.3
Traditional & additional	85	61	87	56	79	8.5

Table 2. Performance of AMI detection on the test set by the classifiers using only traditional or traditional and additional features.

The additional feature classifier had higher sensitivity and lower specificity, nearly equal PPV and higher NPV when compared to the traditional feature classifier (see Table **2**). The single number measures of accuracy, odds ratio and total accuracy were both higher for the additional feature classifier.

4. Discussion

As we hypothesized, use of the additional features commonly used in manual reading of early repolarization and pericarditis does improve detection of acute MI. We would expect the number of early repolarization and pericarditis ECGs mistakenly called AMI to be reduced due to better criteria for the ST confounders. In this way, we would expect the number of false positives to be reduced without much impact on the number of false negatives. However, our results show the opposite. We see improvement in sensitivity, i.e. fewer false negatives. This observation can be explained by the nature of our experiment. We used statistical techniques to train the classifiers. Without intervention, such techniques work to reduce overall error rate not just one specific type of error. The best overall error reduction was achieved by reducing false positives but mostly false negatives. This reduction in false negatives can be seen in the increased sensitivity.

Our hypothesis relates to commonly used ECG features for early repolarization and pericarditis in manual reading but we included many other features as well. The purpose of adding other repolarization features beyond the ones used for manual reading was to allow comparison between features.

As with other fundamental ECG measurements, there is not a consensus on the definition of a J-wave, J-point notch or J-point slur [8]. Since many papers point to J-waves, notches and slurs as a feature of early repolarization, we refined our detection criteria to emphasize the detection in early repolarization at the expense of detection for similar features in pericarditis, acute MI and normal ECGs. For that reason, our criteria include a requirement for ST elevation or flat ST but not ST depression. Another commonly used criterion to emphasize early repolarization not employed here is location of J-waves/notches/slurs in leads V4 through V6.

One interesting aspect of the results is the high value of Selvester QRS score (MI size) to classify AMI. Selvester score was the second feature chosen. Only one other feature had better discriminating ability. Of course absence of pathologic Q-waves is important to separate AMI, ER, and PCARD, but Q-waves are not stressed as a feature in discussions of manual reading. Selvester score being chosen as the second feature demonstrates its high importance for AMI detection in the presence of early repolarization and pericarditis. Again, it must be emphasized that ST deviation does not carry the weight it usually does because all ECGs in the test and training data sets met STEMI criteria.

AMI detection was more sensitive using the additional features. As shown in Table **3**, it appears that the additional feature classifier was more sensitive to the other groups as well. The total number of classifications outside of AMI, i.e. pericarditis, early repolarization or normal, was much greater for the additional feature classifier, 113 versus 24. The traditional feature classifier could not specify a classification for the large number of cases represented by the “other” column. Since we do not have annotation on the test set outside of AMI, we cannot comment on the accuracy of the early repolarization or normal classifications even for positive acute MI cases because these ECGs could have ST deviation due to ER but not ST deviation due to ischemia/infarction.

A) truth\ traditional	AMI	PCARD	ER	normal	other
AMI	232	7	4	5	78
Not AMI	33	0	7	1	63

B) truth\ trad&add	AMI	PCARD	ER	normal	other
AMI	276	13	25	12	0
Not AMI	41	6	44	13	0

Table 3. Test set confusion matrix for the traditional (panel A) and traditional & additional (panel B) feature classifiers.

5. Conclusion

Additional ECG features aimed at early repolarization and acute pericarditis may improve automatic AMI classification when STEMI criteria are met.

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