A Vector Cardiographic Based Method To Determine the Culprit Artery in Acute Coronary Syndrome

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Abstract

In this study we present a vectorcardiographic method to identify the culprit artery in acute coronary syndrome (ACS) in a study population of 860 patients with single vessel disease who underwent percutaneous coronary intervention (PCI). This method takes, in addition to the classical STEMI definition of J point elevation > 100 μV, also features of the QRS complex and the T wave into account.

Comparing this method with published algorithms we found, in our data set, an improvement in specificity and sensitivity using QRS axis elevation, QRS-T angle and T axis azimuth in the transverse plane. Extending this method to the ever increasing amount of patients with non-STEMI ACS who underwent PCI, we also found a beneficial effect of inclusion of QRS and T-wave feature on sensitivity and specificity.

1. Introduction

The ECG is a very important diagnostic tool early in the assessment of acute coronary syndrome (ACS). It is often the first tangible evidence that the patients' symptoms are, indeed, caused by ACS, through an occlusion of any of the coronary arteries RCA (right coronary artery), LAD (left anterior descending artery) or LCX (left circumflex artery). Although the culprit artery (CA) can only be unequivocally determined by TCA (transluminal coronary angioplasty) a number of algorithms have been proposed (for an overview, see 1) that indicate which artery is involved. These algorithms are based on the elevations of the ST segments in the 12 leads of the standard ECG, ST Elevation Myocardial Infarction (STEMI). Over the past decade, an increasing number of patients showing no ST elevation in any of the 12 leads (termed NSTEMI, Non STEMI) underwent PCI. In this study we aim to develop a reliable algorithm for identification of the CA based on ECGs showing STEMI and extend that algorithm to include NSTEMI ECGs.

2. Methods

For this study we selected ECGs from patients with single vessel disease and Thrombolysis In Myocardial Infarction (TIMI) flow grade zero who underwent Percutaneous Coronary Intervention (PCI). The occluded segment was identified according to the 16-segment model used by the AHA. (1-4 and 16 = RCA, 6-10 = LAD, 11-15 = LCX). All ECGs used in this study were taken up to 3 hours prior to the intervention and electronically recorded on GE MAC, Dräger Multiview, Philips Intellivue or Physio Control machines. For the purpose of this study they were subsequently stored in a Dräger Megacare VF 3.1 database. Since the majority of the ECGs was supplied in a non-Megacare format we devised a template file into which the raw signal data (12 leads x 10 s x 500 samples/s) was stored and subsequently imported into the Megacare system. The Megacare system was then used to reanalyze the newly imported ECG and to calculate the measurement matrix. Also, all ECGs used in this study were exported from the Megacare database and converted to an ASCII file (csv format, 8 independent leads I, II, V1-V6) of 5000 samples per lead. The ASCII file was used as import for 'BEATS' (2), a custom made Matlab program (the Mathworks, Natick, MA, USA) that, in short, uses the method of Kors et al (3) to convert the 8 ECG leads to a Vector Cardiogram (VCG) with X pointing horizontally to the left, Y pointing vertically down, and Z pointing towards the back of the patient, according to the AHA standard. Position of the onset QRS, J point and end of T wave were determined for each complex except for those deselected by the user. These values were stored along with a baseline corrected signal of the 8 independent leads.

Another Matlab program, 'FEATS', was then used to extract 106 different features for each QRS-T complex from the baseline corrected ECG, amongst which: vector magnitude, azimuth, elevation and X, Y and Z amplitudes for the QRS complex, the T wave, the J point + nn ms (with nn ranging from 0 to 80 ms), the spatial QRS-T

angle and the ventricular gradient. Azimuth was defined as the angle of the vector with the X-axis in the XZ plane, elevation was defined as the angle of the vector with the XZ plane.

Exclusion criteria: LBBB, RBBB, ventricular pacing, poor signal quality, obvious right precordial placement of the electrodes C3-C6, or any ECG that could not be completely reanalyzed by the Megacare system. Of the initially 1036 available ECGs 860 were included giving a learning set and a test set of 430 ECGs each. Of each of the 16 segments equal amounts (+/- 1) were present in the 2 sets. Since some segments were underrepresented, ECGs could not matched according to patient demographics. If needed, both sets were subdivided into sets containing STEMI or NSTEMI ECGs only.

STEMI was defined as an elevation of the J-Point of at least 100 µV (200 µV for V1-V2) in 2 or more of the consecutive leads aVL, I, -aVR, II, aVF, III or V1-V6 for use with the Tierala algorithm or as an elevation of the J-Point of 100 µV or more for the vector cardiographic leads X and Y and an elevation of 200 µV or more for lead Z.

Selection of best performing features: We considered best performance as maximal combined sensitivities and specificities for all 3 arteries, expressed as Index of Merit (IM), defined as % sensitivity + % specificity - 100 [4].

For each of the 106 features 3 histograms, corresponding to the 3 CA's, were constructed from the test set.

To predict the CA in an ECG the height in each of the 3 the histograms was calculated and multiplied by values found for the other features under consideration.

For optimization, a set of 9 randomly chosen features was used; 2 QRS-related features, 5 ST-related features and 2 T-wave related features and the IM was calculated. This procedure was repeated 1000 times and each time an improvement in IM was found the selected features were saved. The above procedure in itself was repeated 100 times and the single feature participating most often in the calculation of the 10% best IM values was considered to be a key feature. This feature was then fixed in the next iteration along with one less randomly chosen feature, until 5 key features had been determined.

Additionally, we used the commonly accepted fact that any ST elevation which is maximal in V2, V3 or V4 points to involvement of the LAD. We slightly adapted the method described by Tierala [5] to determine this involvement: ST elevation in V2-V4 is larger than any ST elevation in the limb leads and/or in V5 or V6, thus excluding V1 from the calculations.

In order to compare our results with published performances, we calculated for each ECG the CA using the algorithm developed by Tierala [5], since this algorithm performed slightly better than the algorithm of Fiol [6] in our data set (1). For these calculations we used the values for the ST elevation as given by the Megacare system.

3. Results

We analyzed 860 ECGs, 475 from Groningen, 296 from Rotterdam and 89 from Leiden. Patient age was 66 ± 25 years, 75% male. The percentage of NSTEMI ECGs was 39%.

Table 1 lists the distribution of the different segments and arteries over the learning and test sets.

First, the overall performance of the Tierala algorithm was determined by calculation of the Index of Merit (IM), table 2. Running this algorithm on the learning set and the test set separately gave only slight differences (< 2%). These values are in good agreement with our previously presented results based on a smaller data set [1].

Table 1. Distribution of segments and culprit arteries

Segment number	1	2	3	4	16	RCA
Amount in Learning set	53	68	32	6	5	164
Amount in Test set	54	68	32	6	4	164
Segment number	6	7	8	9	10	LAD
Amount in Learning set	99	74	7	13	1	194
Amount in Test set	98	74	8	12	1	193
Segment number	11	12	13	14	15	LCX
Amount in Learning set	27	15	24	6	0	72
Amount in Test set	27	15	25	5	1	73

Table 2. Performance of the Tierala algorithm on the combined learning and test sets, subset of 525 STEMI ECGs.

	Spec	Sens	IM
RCA	91	88.5	79.5
LAD	92.4	88.8	81.2
LCX	96.9	32	28.9

Table 3 shows the results using our algorithm on the STEMI ECGs. The best performing features as determined from the learning set were, in order of importance: J point azimuth, maximal ST vector elevation in the J point to J+80 ms range, QRS axis elevation, QRS-T angle and T axis azimuth. The integrals of the histograms of these 5 features are given in figure 1. Major differences, compared to those of table 2 were an increased sensitivity for LCX and a decreased specificity for RCA, with an average IM of 66.3

Table 3. Performance of our algorithm on the test set (subset of 265 STEMI ECGs)

	Spec	Sens	IM
RCA	81.5	88.9	70.4
LAD	96.5	85.7	82.2
LCX	96.4	50	46.4

If the determination of the key features is restricted to NSTEMI ECGs only, similar features are found to be important, albeit giving a lower average IM: 43.5. Again J point azimuth and maximal ST vector elevation in the J point to J+80 ms range are performing best, but now with additionally the maximal QRS vector magnitude in the Y direction the QRS-T angle in the sagittal plane and the mean QRS vector magnitude.

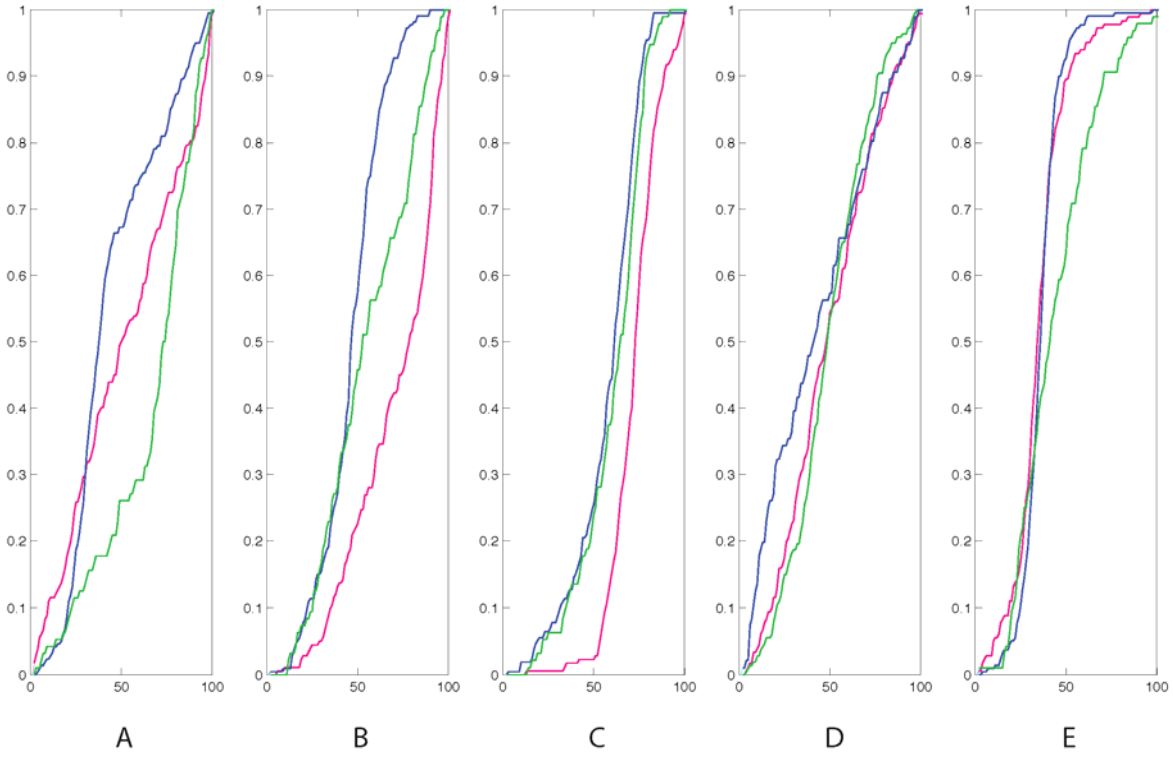

Figure 1. Integrals of the histograms for the best performing features that were derived from the STEMI learning set. Panel A: J Point azimuth. B: Maximal elevation in the J+0 - J+80 ms interval. C: QRS axis elevation. D: QRS-T angle in the transverse plane. E: T axis azimuth. LAD = blue, RCA = red, LCX = green line

4. Discussion

We have shown that including features other than the ST elevation, like QRS axis elevation, T axis azimuth and QRS-T angle can be of additional value in the determination of the CA. Of course, the ST segment information was of paramount importance; indeed, the first 2 key features determined in the iterative process were ST related. As can be seen from figure 1, the J Point azimuth and the maximal elevation in the J-J+80 interval happen to give the largest separations between the red and green lines representing the RCA and the LCX. Also note that the separation between the line representing the LAD and the other two arteries is less important because we used the VCG-independent method to determine involvement of the LAD: maximal elevation in V2-V4. Other features that seemed to give a good separation between the RCA and the LCX upon visual inspection were often closely related to the features mentioned above. We found, e.g. the QRS axis in the frontal plane having same properties as the QRS axis elevation.

The Tierala and also the Fiol algorithms have the advantage of being much simpler than our vector cardiographic method and their method can possibly be applied by a trained observer without consulting a rule book or a computer. However, the method presented here has the advantage that it may yield better specificities and sensitivities to pinpoint the CA and that it can be applied to NSTEMI ECGs as well, whereas the Tierala algorithm is not designed for NSTEMI ECGs, as we have shown in a previous study [1]. It should be noted, however, that by reducing their criteria for ST elevation form 100 to 50 μV and applying these values in their algorithm will result in an increase of specificity and sensitivity (unpublished results) that approaches the method described here for the NSTEMI ECGs.

References

[1] van der Putten NHJJ, Rijnbeek PR, Dijk WA, van Herpen G, Maan AC, Lipton JA, Kors JA. Validation of electrocardiographic criteria for predicting the culprit artery in patients with acute myocardial infarction. Computing in Cardiology 2010; 37:21-24

[2] Man S, Maan AC, van der Wall EE, Schalij MJ, Swenne CA. BEATS, an interactive Research Oriented ECG Analysis System. Computing in Cardiology 2010; 37: 1007-1010

[3] Kors JA, van Herpen G, Sittig AC, van Bemmel JH. Reconstruction of the Frank vectorcardiogram from standard electrocardiographic leads: diagnostic comparison of different methods. Eur Heart J 1990, 11(12):1083-1092

[4] Hanssen AW, KuipersWJA. On the relationship between the frequency of rain and various meteorological parameters (with reference to the problem of objective forecasting). Koninklijk Nederlands Meteorologisch Instituut. Mededelingen en Verhandelingen 1965;81:2-15

[5] Tierala I, Nikus KC, Sclarovsky S, Syvänne M, Eskola M. Predicting the culprit artery in acute ST-elevation myocardial infarction and introducing a new algorithm to predict infarct-related artery in inferior ST-elevation myocardial infarction: correlation with coronary anatomy in the HAAMU trial. J Electrocardiol. 2009;42:120-7.

[6] Fiol M, Cygankiewicz I, Carillo A, Bayes-Genis A, Santoyo O, Gomez A et al. Value of electrocardiographic algorithm based on “ups and downs” of ST in assessment of a culprit artery in evolving inferior wall acute myocardial infarction. Am J Cardiol. 2004;94:709-14.

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