Electrocardiographic Detection and Quantification of Acute Myocardial Ischemia with Dipole Modeling

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Abstract

Clinical electrocardiography is based on concept of a dipolar cardiac generator. This concept is not commonly used in quantitative analysis of the electrocardiograms (ECG). We applied dipole modeling and numerical field calculation in the detection of acute myocardial ischemia and for estimating the size of the resulting infarction.

Our data set consisted of 79 acutely ischemic patients and 84 controls. Dipoles were fitted to various ECG markers linearly derived from body surface potential mapping data. The best discriminating dipole parameter was sought in a leave-one-out manner. Size estimation was done by correlating the dipole parameters with CK-MB mass.

With the 12-lead ECG electrode layout, ST integral was the best marker in the whole patient set, and T integral in patients with myocardial infarction. In these both cases, the cosine of the sagittal angle was the best discriminating parameter. These parameters clearly outperformed the conventional ECG criteria in detection of ischemia.

1. Introduction

Acute ischemia is commonly detected with electrocardiography. In diagnostic use the 12-lead electrocardiogram (ECG) is the most common electrocardiographic method. Clinical electrocardiography and the 12-lead ECG are largely based on the concept of "heart vector". This vector can be modeled with a current dipole.

The electrocardiogram is typically visualized as time-voltage tracings of leads, and analyzed by comparing various time and amplitude ratios in and between the leads — not utilizing the dipole concept quantitatively. In this paper, we apply a dipole modeling method in detection of acute ischemia and estimation of the size of the resulting myocardial infarction.

2. Material and methods

2.1. Data set

We measured 123-channel body surface potential mapping (BSPM) from 79 acute ischemic patients and 84 healthy volunteers. The inclusion criteria for the patients were chest pain, alterations in the 12-lead ECG suggestive of myocardial ischemia, and / or elevation of myocardial enzymes (CK-MB mass and / or TnT). The initial ECG alterations did not necessarily fulfill the ST amplitude and contingency criteria defined in [1].

The measurements were carried out in the coronary care unit of Helsinki University Central Hospital within 12 hours from the onset of symptoms. In addition to BSPM and standard ECG and enzyme monitoring, the patients underwent various clinical imaging procedures, including coronary angiography. The patients were grouped according to the culprit coronary artery and presence of acute myocardial infarction (AMI). The culprit artery was specified in angiography (left anterior descending = LAD, left circumflex = LCX, or right coronary artery = RCA), and the AMI grouping was done according to the CK-MB mass maximum. The CK-MB value is known to correlate with the size of the myocardial infarction [2]. Basic patient information for all patient groups is displayed in Table 1. The BSPM data were obtained with BioSemi Mark 6 and Active Two biopotential amplifiers using disposable strip electrodes (Tyco Healthcare).

2.2. Preprocessing

The BSPM data were pre-processed semi-automatically: First, the baseline was removed with spline fitting. Beats that did not fit into acceptable RR interval (ectopic) were rejected. For each BSPM channel, beats with bad signal quality were detected with the aid of amplitude and noise criteria [3]. These bad signals were interpolated from other channels by minimizing the surface laplacian [4]. Finally, the beats were averaged according to a manually selected

Table 1. Patient characteristics and sensitivity (SE) of conventional Q wave classifier (see Section 3.1)

Group	N	N_f	Age	Q SE
All	79	22	61 ± 11	0.47
LAD	32	10	58 ± 10	0.53
LCX	10	1	56 ± 9	0.60
RCA	26	10	67 ± 12	0.38
AMI	68	18	61 ± 11	0.51
AMI LAD	28	8	58 ± 11	0.57
AMI LCX	8	0	57 ± 10	0.75
AMI RCA	22	9	66 ± 12	0.41

template [3].

The fiducial time points were detected automatically from the averaged signal. The mutual QRS complex onset and offset times were defined from the vector magnitude of the high-pass-filtered BSPM leads using signal envelopes and noise information. T wave apex and end were first defined for all BSPM channels as described in [3]. In further analysis, the median of these channel-specific time instants was used.

Various linear ECG markers were calculated from the BSPM data. The markers contained both instantaneous maps (for example, the T apex amplitude) and integral maps (over various parts of the QRS complex and ST-T wave).

For further analysis, 12-lead data were reconstructed from the BSPM data. Virtual limb electrodes were placed on shoulders and left hip, and marker values at those points were interpolated from the BSPM values. Conventional Q wave criteria for established myocardial infarction were evaluated automatically from the 12-lead data according to directions in [1].

2.3. Field calculation

The cardiac electric field was modeled with quasi-static Maxwell equations [5], which lead to the Poisson equation

$$\nabla \cdot (\sigma \nabla \phi) = \nabla \cdot \vec{J}_{\mathrm{p}}, \tag{1}$$

where σ is conductivity and $\vec{J}_{\mathrm{p}}$ the primary current density. The Poisson equation was converted with the Green formulas [6] to the surface integral form, which was then discretized with the boundary element method (BEM). The potential was modelled with linearly varying nodal basis functions, and the residual was weighted with the point collocation technique [7]. The element matrix was inverted using the matrix deflation [8], resulting in

$$\Phi = \vec{F}\Phi^{\infty}, \tag{2}$$

where Φ (and Φ^{∞}) contain values of the potential (and infinite medium potential) at all N nodes of the element model. The Dalhousie standard torso was used as the volume conductor model. Internal conductivity differences were not taken into account, but anisotropic skeletal muscle layer was approximated with the "torso extension" method [9].

In order to calculate the potential of a current dipole $\mathrm{D}(\vec{r}_{\mathrm{D}}, \vec{Q})$ (placed at $\vec{r}_{\mathrm{D}}$, dipole moment $\vec{Q}$), a lead field matrix [10] was formed: First, calculate the potential of orthogonal unit dipoles placed in $\vec{r}_D$ with

$$\vec{L}_x = \Phi_{\mathrm{D}}(\vec{r}_{\mathrm{D}}, \vec{e}_x) = \vec{F}\Phi^{\infty}_{\mathrm{D}(\vec{r}_{\mathrm{D}}, \vec{e}_x)}, \tag{3}$$

and similar formulas for $\vec{L}_y$ and $\vec{L}_z$. Then form the matrix

$$\vec{L}_f = (\vec{L}_x\ \vec{L}_y\ \vec{L}_x), \quad \dim(\vec{L}) = (N, 3). \tag{4}$$

Now the potential of the dipole $\mathrm{D}(\vec{r}_{\mathrm{D}}, \vec{Q})$ is calculated as

$$\Phi = \vec{L}_f \vec{Q}. \tag{5}$$

In inverse modeling the potential has to be known at the electrode positions. The electrode-setup specific lead field matrix is formed by choosing only those rows of the L_f that correspond to those mesh nodes, where the electrodes are located. Thus we end up at a lead field matrix L with dimensions $N_e \times 3$, where N_e is the number of electrodes.

Estimation of the equivalent current dipole (ECD) was divided in two steps: The dipole position was sought iteratively with the Nelder–Mead simplex search [11]. For each test dipole position $\vec{r}_{\mathrm{D}}$, the locally optimal dipole moment was calculated by pseudo-inverting the lead field matrix $\vec{L}$ defined in $\vec{r}_{\mathrm{D}}$:

$$\vec{Q} = \vec{L}^{+}\Phi_{\mathrm{meas}}, \quad \vec{L}^{+} = (\vec{L}^{\mathrm{T}}\vec{L})^{-1}\vec{L}^{\mathrm{T}}. \tag{6}$$

The dipole position optimization aimed at maximizing the goodness of fit G:

$$G = 1 - \frac{|\Phi_{\mathrm{meas}} - \Phi_{\mathrm{calc}}|^2}{|\Phi_{\mathrm{meas}}|^2}. \tag{7}$$

2.4. Dipole analysis

The dipole fitting was performed for both BSPM and 12-lead markers. For BSPM data the dipole analysis was carried out with both freely moving and fixed dipoles. With 12-lead data we used only fixed dipoles. From the dipole moment vectors, the following parameters were calculated:

- x, y, and z components of the dipole moment vector $\vec{Q}$: $Q_{\mathrm{x}}, Q_{\mathrm{y}}, Q_{\mathrm{z}}$
- Length of the dipole moment vector: Q
- Lengths of the projections of $\vec{Q}$ in frontal, transversal, and sagittal planes: $Q_{\mathrm{f}}, Q_{\mathrm{t}}, Q_{\mathrm{s}}$.
- Directional cosines between the coordinate axes and the afore-mentioned projections: $\cos_{\mathrm{f}}$, $\cos_{\mathrm{t}}$, $\cos_{\mathrm{s}}$

2.5. Statistical comparisons

Discrimination testing for each dipole parameter between patients and controls was done with the receiver operating characteristic (ROC) curve and leave-one-out cross-validation: First, one case was left out of the data set. From the rest of the set, a ROC curve was formed, and the optimal discrimination point was found by maximizing the product of sensitivity (SE) and specificity (SP) in this teaching set. Then the test case was classified. The procedure was repeated, until all the cases were tested. Sensitivity and specificity in the cross-validation set were then calculated from the classification results.

Dependency between dipole parameters and the CK-MB mass was assessed with the Pearson correlation coefficient R. Confidence intervals for R were estimated nonparametrically with bias-corrected and accelerated bootstrap technique (BCa) [12].

3. Results

3.1. Detection

Results for the best discriminating parameters between the patient groups and controls are shown in Tables 2 and 3. The results in Table 2 were obtained with the BSPM set and a moving dipole model — the method with the most data and no a priori assumptions about dipole position or moment. In these results the best overall ECG marker for discriminating between the patients and controls was the T apex amplitude. LAD cases were best classified with the sagittal cosine of the QRS first quarter dipole, and LCX cases with the frontal projection amplitude of the QRS second quarter dipole. For RCA cases the best discrimination was obtained with T wave parameters. The classification results of the RCA cases were worse than those of the culprit left coronary arteries.

In the results presented in Table 3, the scenario was simplified and the degrees of freedom of the source were reduced: the data of nine electrodes were used for defining the three dipole components, and the dipole position was set to the midpoint of left venticle in the Dalhousie model. With this setup, the classification results were slightly better than with the previous one, except for the RCA patients. The best marker was, however, different for each group. The fixed dipole method was also applied to BSPM data, but the results are not presented here in detail. Overall, the good markers were similar to those of the 12-lead set, and the discrimination results resembled those obtained with the moving dipole. The repolarization parameters performed relatively better with the fixed dipole methods than with the moving dipole method.

Sensitivities of the conventional Q criterium are displayed in Table 1. Specificity of the Q criterium was 0.82.

Table 2. Detection results with the full BSPM electrode set and a moving dipole source

Group	N	Marker	D. para	SE	SP
All	79	T apex	Q_{x}	0.71	0.83
LAD	32	QRS 1 / 4	$\cos_{\mathrm{s}}$	0.72	0.94
LCX	10	QRS 2 / 4	Q_{f}	0.70	0.93
RCA	26	ST 1 / 2	Q_{x}	0.62	0.93
AMI	68	T apex	Q_{x}	0.74	0.83
AMI LAD	28	QRS 1 / 4	$\cos_{\mathrm{s}}$	0.82	0.94
AMI LCX	8	QRS 2 / 4	Q_{f}	0.88	0.93
AMI RCA	22	T apex	$\cos_{\mathrm{t}}$	0.73	0.83

Table 3. Detection results with the 12-lead electrode set and a fixed dipole source

Group	N	Marker	D. para	SE	SP
All	79	ST	$\cos_{\mathrm{f}}$	0.72	0.83
LAD	32	T apex	$\cos_{\mathrm{f}}$	0.78	0.93
LCX	10	ST80 int	Q_{s}	0.80	0.90
RCA	26	QT	Q_{x}	0.69	0.86
AMI	68	T	$\cos_{\mathrm{f}}$	0.69	0.92
AMI LAD	28	QRS 1 / 4	$\cos_{\mathrm{s}}$	0.79	0.94
AMI LCX	8	T	Q_{x}	0.88	0.93
AMI RCA	22	ST60 int	$\cos_{\mathrm{t}}$	0.68	0.89

Table 4. Correlation coefficients R between dipole parameters and the CK-MB mass

Group	Marker	D. para	R	CI(R)
All	QRS 2 / 4	$\cos_{\mathrm{t}}$	-0.58	[-0.78, -0.26]
LAD	QRS 2/ 4	$\cos_{\mathrm{t}}$	-0.88	[-0.94, -0.78]
LCX	QT	$\cos_{\mathrm{t}}$	-0.80	[-0.98, -0.38]
RCA	ST60 int	$\cos_{\mathrm{s}}$	-0.42	[-0.90, 0.05]
AMI	QRS 2 / 4	$\cos_{\mathrm{t}}$	-0.56	[-0.77, -0.22]
AMI LAD	QRS 1 / 4	$\cos_{\mathrm{t}}$	-0.87	[-0.94, -0.77]
AMI LCX	QT	$\cos_{\mathrm{t}}$	-0.73	[-0.99, -0.05]
AMI RCA	QRS 3 / 4	$\cos_{\mathrm{t}}$	-0.49	[-0.84, 0.04]

In all the groups, our dipole parameters gave considerable better sensitivities and as good or better specificities than the Q criterion.

3.2. Size quantification

The best correlations (with 95% confidence intervals) between dipole parameters and the CK-MB mass are displayed in Table 4. In general, cosine of the transversal projection of the second QRS quarter dipole correlated best with CK-MB. For LAD cases this correlation was very good, also in terms of the confidence interval. For LCX cases, QT integral was the best marker with correlations ranging up to - 0.8. However, this correlation had a large CI, extending in AMI cases to almost zero. In RCA cases the CI crossed the zero line; these correlations are not statistically significant.

4. Discussion

With the moving dipole, the ST segment and T wave markers performed best in general patient categories. In the groups with culprit left coronary arteries, the BSPM results with the moving dipole model are in good correspondance with coronary anatomy and the normal depolarization sequence: the first quarter of the QRS complex reflects depolarization of the anterior myocardium, where LAD is located. Respectively, typical LCX region and the second quarter of the QRS correspond well.

With the fixed dipole all groups were best detected with ST or T parameters. The QRS parameters performed well only with the AMI LAD cases of the 12-lead set. The difference in optimal markers between moving and fixed dipole methods can be explained by the fundamental difference of the methods: the moving dipole method tries to locate the focal, dipolar source, but the fixed dipole — especially with limited electrode set — is only capable of some kind of spatial characterization of the potential. The moving dipole model is thus expected to perform better with localized sources, and initial parts of the depolarization wavefront fall into that category better than the more diffuse depolarization phase. But, in the detection task the moving dipole does not bring advantage compared to the fixed dipole model; actually the results of the fixed dipole methods were slightly better.

The detection results with the reconstructed 12-lead data were better than those of the BSPM data. This at first surprising result can be explained by the simplicity of the source model and the electrode positioning: In the 12-lead layout six of the nine electrodes are close to the heart and thus sensitive to local potential sources. In our BSPM layout, the relative amount of electrodes close to the heart is smaller; hence the far field components have major role in the dipole fitting, and we are essentially modeling the true dipolar part of the body surface potential. Also the method for reconstructing the 12-lead ECG may have a role: the virtual limb leads were created from the BSPM data using the same thorax surface model that was used in the field calculation.

Comparing to the results obtained with the conventional Q wave criteria, the methods presented here perform clearly better. In interpreting and comparing the results it is, however, important to keep in mind that our dipole results are from a cross-validation set, and the results of the conventional criteria are from a true test set. However, the authors do not believe that the large differences in results could be explained by this set difference.

5. Conclusions

This study shows that dipole modeling can bring additional information to quantitative ECG analysis. With methods presented here, an equivalent dipole can be derived from small leadsets, for example, electrodes of the 12-lead ECG. The dipole derived from reconstructed 12-lead ECG data discriminated well between healthy controls and patients with acute ischemia or infarction.

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