Identification of Two Lesions with Local Repolarization Changes Using Two Dipoles in the Inverse Solution

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Abstract. *In the simulation study the method for inverse identification of two distinct simultaneous lesions with changed repolarization in the ventricular myocardium is described. The inverse localization of two lesions was obtained from the difference STT integral body surface potential maps (DIMs). The DIMs corresponding to 48 single lesions and 96 double lesions were simulated on the surface of an inhomogeneous torso using a numerical model of the ventricles. It was supposed that the double lesions can be represented by two dipoles. Twenty three characteristics of the obtained inverse solution were specified and used as the features in a discriminant analysis that should distinguish the inverse solutions that correctly identify two lesions from those yielding incorrect results or corresponding to single lesion.*
The mean lesion localization error in cases with two lesions was 1.2 cm. For optimally selected subset of 7 features the quadratic discriminant analysis with cross-validation and feature selection yielded an overall double lesion classification error smaller than 12% for input ECG data with added noise if the signal to noise ratio was above 20 dB.

Keywords: Difference Integral Maps, Lesions with Changed Repolarization, Clusters of Results, Added Noise, Discriminant Analysis

1. Introduction

In patients with ischemic heart disease and atherosclerosis one, two or more simultaneously occluded coronary arteries can be present. For inverse localization of single small lesions with changed repolarization the inverse solution to one dipole was suggested in [1]. Analogically for two lesions, the inverse solution to two dipoles was proposed and described in [2]. In such a computation the additional problem arises whether we need the a priori information about the number of lesions or we are able to determine the number of lesions (one or two) from the properties of the obtained two resulting dipoles.

In this study various characteristics of the inverse solution to two dipoles were proposed and tested as discriminating features enabling to recognize the correct inverse solutions representing two lesions with changed repolarization and to distinguish from the other results obtained either for one lesion or incorrectly identifying two simultaneous lesions.

2. Subject and Methods

Simulation of Surface ECG and Inverse Localization of Local Ischemic Lesions
In the geometrical model with analytically defined heart ventricles small lesions with changed repolarization were modeled as part of a sphere or part of an ellipsoid located in the subendocardial or subepicardial myocardium as it is described in [1]. The changed repolarization within each lesion was modeled by shortening the myocytes' action potential duration by 20%. Six positions of the lesions typical for stenosis of one of the three main coronary vessels were defined. The lesions varied in size (from 0.1 to 6.1% of the modeled ventricular volume) and in shape (eight variations for each position). Together 48 variations of single lesions were created. To simulate two simultaneous lesions representing the two-

vessel disease, twelve combinations of pairs of ischemic lesions were modeled considering eight different shapes, resulting together in 96 pairs of modeled lesions. The mean mutual distance between the centers of the lesions was 5.6 cm.

To compute body surface potential maps (BSPMs) corresponding to normal ventricular activation and to activations with modeled lesions, the cardiac generator was inserted into an inhomogeneous torso model with lungs and ventricular cavities. BSPMs in 64 points representing the positions of measuring electrodes on the body surface were computed by the boundary element method [3].

As it was shown in [4], the local repolarization changes are reflected in difference integral maps (DIMs) computed by subtraction of STT integral maps obtained during normal activation from STT integral maps obtained during activation of the ventricular model with local ischemia. To mimic the real measurements, three levels of random noise with zero mean and normal distribution were added to the input DIM. The noise levels were characterized by the signal-to-noise ratio (SNR), expressed in dB and defined as:

$$SNR = 20log_{10}\frac{rms(DIM)}{rms(noise)} \quad [\text{dB}] \qquad (1)$$

For each input DIM, three levels of noise were added corresponding to SNR of 20, 30 and 40 dB. For each noise level thirty noise realizations were generated.

Because two simultaneous lesions were searched in this study, the equivalent integral generator (EIG) computed by the inverse solution was a pair of dipoles as described in [2]. Possible locations of the inversely estimated dipoles representing the modeled lesions were in 168 predefined points evenly distributed throughout the modeled ventricular volume. The mean distance between the neighboring predefined positions was approximately 1 cm. The inverse solution with two dipoles was computed from DIMs simulated for two modeled lesions as well as for one modeled lesion.

The best pair of dipoles was selected according to the criterion of minimal relative residual error RMSDIF (in the range 0 to 1) between the input DIM and the map generated by particular EIG. The value of RMSDIF was computed for all possible pairs of inversely estimated dipoles and characterized the quality of the obtained inverse solution. To observe the stability and reliability of the results, all pairs of dipoles with RMSDIF fulfilling the condition (2) were taken into account for further analysis:

$$RMSDIF \leq \min RMSDIF + 0.01 \qquad (2)$$

The modified K-means clustering method based on Euclidean distance between the dipoles was applied on all analyzed dipoles in the group to divide them into two clusters by an iterative algorithm [5]. The gravity center of each cluster represented the position of one modeled ischemic lesion.

The modeled left ventricle was divided into three parts, each representing the volume supplied by one of the three main coronary vessels. The cluster of dipoles was considered a correct representative of the modeled lesion if more than 2/3 of the cluster's members belonged to the corresponding part of the ventricular model. The results obtained from the DIMs computed for two simultaneous lesions were considered correct if both clusters correctly denoted the positions of the modeled lesions. All other results as well as results obtained from DIMs computed for single lesions were considered incorrect. The groups of correct and incorrect results served as classes in the following discriminant analysis.

Classification of the Inverse Results

The presented inverse method always gives the result with two dipoles or two clusters of dipoles regardless of the original situation (one lesion or two lesions) from which the input

DIM was computed. Therefore 23 different characteristics of the clusters of dipoles were specified and tested as possible input features for a two class discriminant analysis.

Quadratic variant of the Fisher discriminant analysis was applied on the data [6]. Then a cross-validation technique in a form of repeated random sub-sampling validation was applied. In 1000 trials, 80 % of available data was randomly chosen for training and remaining 20 % for validation. Classification rule was obtained during the training. Resulting classification rates were obtained as a mean rate of false positives, false negatives and their average. Greedy forward selection algorithm was used by adding the best feature in each round [7]. Starting from one feature with the least classification error, subset of features was built by consecutive steps. The most appropriate feature from the remaining set of features was added during each step in order to form the next dimension of the feature space. The optimal number of features for separation of correct results for two lesions from the results for single lesions or incorrect results for two lesions was searched.

3. Results

The localization error was evaluated from the DIMs computed for two lesions in the modeled heart as the distance between the gravity center of the modeled lesion and the gravity center of the closer cluster of inversely estimated dipoles (Table 1).

Table 1. Summary for the inverse solutions using two dipoles from DIMs computed for two simultaneous lesions in the modeled ventricular myocardium.

Signal to noise ratio [dB]	40	30	20
Percentage of correct results [%]	85.8	86.4	80.2
Localization error of correct results [cm]	1.2±0.8	1.2±0.8	1.2±0.7

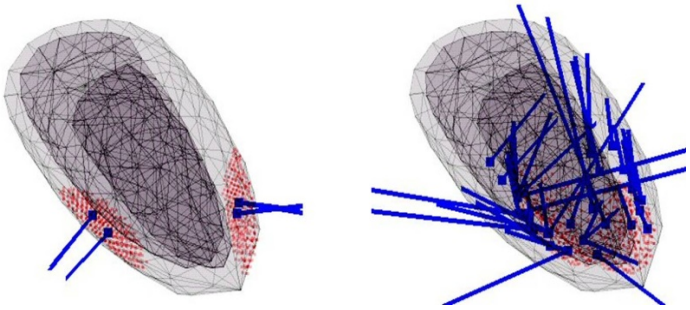

Fig. 1. Examples of groups of analyzed inversely estimated pairs of dipoles from input DIMs computed for two simultaneous lesions. Left – correct result, right – incorrect result. Dotted areas indicate the positions of modelled lesions.

From the graph in Fig. 2 it implies that the mean classification error decreased rapidly when the first two discriminating features were used. Adding more features to the classification decreased the mean error only slightly. The best two features were the same for all levels of noise. The best feature was the ratio between the mutual distance of clusters and the standard deviation of positions of dipoles in the clusters. The second best feature was the minimal value of the standard deviation of angles of the dipoles in the cluster. The optimal number of features (seven) was chosen as the number of features when the rate of false positives and false negatives were similar in each level of noise.

For SNR from 40 to 20 dB, if only two features were used, the sensitivity of the double lesion identification was from 94 to 85 % and the specificity was from 86 to 89%. If seven most informative features were used, the sensitivity was from 94 to 89% and the specificity from 92 to 86%.

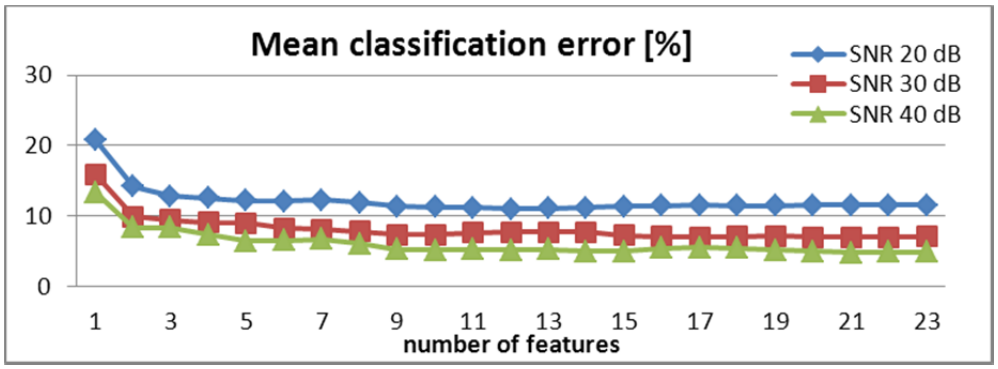

Fig. 2. The average classification error depending on the number of used features.

4. Discussion and Conclusions

As it can be seen from the obtained results, using the proposed inverse solution it was possible to correctly identify two simultaneous lesions with changed repolarization in more than 80% of simulated input data with the SNR not lower than 20dB. The localization error of correctly identified lesions was not influenced by the added noise.

The presented analysis of the obtained inverse solutions and their subsequent classification allowed distinguishing of the reliable results from the incorrect results and from results for input data corresponding to single lesions.

The inverse solution with two dipoles together with the proposed analysis and classification of obtained results yields the identification of two simultaneous lesions with the sensitivity and specificity higher than 85% for input data with added noise with SNR not lower than 20dB without the need of some a-priori information about the number of lesions.

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