Classification of Inverse Solutions to Two Dipoles

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Abstract

The aim of the simulation study was to identify cases in which an inverse solution to two dipoles characterizes the existence of two simultaneous lesions with changed repolarization.

Difference STT integral body surface potential maps computed for 48 single lesions and 96 pairs of lesions were used as the input data for an inverse solution to two dipoles. Additional noise with signal to noise ratio (SNR) 20, 30 and 40dB was applied to the input data. The inverse solution was obtained as several pairs of dipoles. 23 characteristics of the solution were used as features for the quadratic variant of the Fisher discriminant analysis that should distinguish the inverse solutions that correctly identify 2 lesions from those yielding incorrect results or corresponding to a single lesion.

The mean localization error in cases of correct results was 1.2±0.8cm regardless of the SNR. If eight most informative features were used, the sensitivity of the classification method was from 97 to 89% and the specificity from 94 to 84% for input maps with SNR from 40 to 20dB.

The inverse solution to two dipoles together with the proposed classification of obtained results yields the identification of 2 simultaneous lesions without the need of some a priori information about the number of lesions.

1. Introduction

The inverse solution using two dipoles was suggested in [1] for localization of two simultaneous lesions which can occur in patients with ischemic heart disease and atherosclerosis. It was supposed that each lesion can be represented by one dipole. As it is known, such inverse solution is ill-posed [2] and the obtained resulting pair of dipoles may not be the proper representative of the location of the pair of lesions. The additional question in such a computation is 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 pair of dipoles.

In this simulation study groups of inverse results were computed for each case. Then various characteristics of the resulting dipoles were specified and used as discriminating features enabling to recognize the correct inverse solutions representing the two lesions and to distinguish them from other solutions obtained either for one lesion or obtained as incorrect identification of the two simultaneous lesions.

2. Material and methods

The body surface potential maps (BSPMs) were simulated for several cases with presence of one lesion or pair of lesions in the modeled ventricular myocardium. Each lesion was modeled as an area with changed repolarization properties of action potentials.

For each case with one lesion or pair of lesions the inverse solution was computed and some characteristics of the solution as well as the correctness of the solution were evaluated.

The characteristics were then used as discriminating features in classification task to recognize correct identification of two lesions.

2.1. Forward and inverse solution

In the analytically defined geometrical model of heart ventricles small lesions with changed repolarization were modeled as part of a sphere or part of an ellipsoid located in the myocardium. Six positions of the lesions (anterior, inferior and posterior; each subendocardial and subepicardial) typical for stenosis of one of the three main coronary vessels were defined [3]. 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 lesion were created. The changed repolarization within each lesion was modeled by shortening the myocytes' action potential duration by 20%. To simulate two simultaneous lesions representing the two-vessel disease, twelve position combinations of pairs of ischemic lesions were modeled considering eight different lesion 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 [4].

As it was shown in [5] 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:

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

The equivalent integral generator (EIG) computed by the inverse solution was a pair of dipoles as described in [1]. 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 from 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, not only the pair with minimal RMSDIF value, but all pairs of dipoles with RMSDIF fulfilling the condition (2) were taken into account for further analysis:

$$RMSDIF \leq minRMSDIF + 0.01 \quad (2)$$

The visual inspection of the inversely obtained groups of dipole pairs revealed the differences between the solutions. The correct results locating two lesions were usually stable, situated in two restricted areas of the modelled ventricle, while the incorrect results or the results for single modeled lesion were scattered in larger area of the ventricle as it is illustrated in Figure 1.

Therefore 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 [6]. The gravity center of each cluster was then considered as representative of the position of one modeled ischemic lesion.

The modeled left ventricle was divided into three parts, (anterior, inferior and posterior), each representing the corresponding positioning of modeled lesion. 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 including the results obtained from DIMs computed for single lesions were considered incorrect (Figure 1). The groups of correct and incorrect results served as classes in the following discriminant analysis.

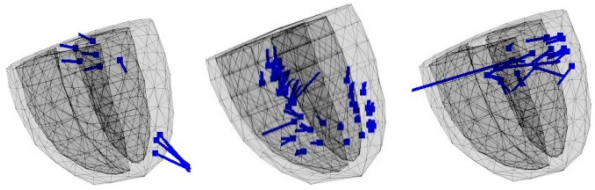

Figure 1. The examples of the groups of resulting dipoles obtained by the inverse solution with two dipoles. From left to right: Correct solution for the case with two modeled lesions, incorrect solution for two modeled lesions, a solution for the case with one modeled lesion.

2.2. 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 twenty three different characteristics of the clusters of dipoles were specified and tested as possible features for a two class discrimination analysis. In the first class there were the inverse solutions correctly representing two modeled lesions, while in the second class there were the incorrect solutions for two modeled lesions together with the solutions for single modeled lesions.

Quadratic variant of the Fisher discriminant analysis was applied on the data [7]. 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 [8]. 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 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

3.1. Forward and inverse solution

The DIMs were computed for 48 cases with one lesion and 96 cases with two lesions in the modeled myocardium. Gaussian random noise with zero mean was added to each DIM by two ways and three levels of noise were studied corresponding to SNR of 20, 30 and 40 dB. For each noise level thirty noise realizations were generated.

First random noise (N1) was applied directly on the DIM's values and can represent the errors in measured signals processing such as wrong baseline correction or bad skin to electrode conductivity conditions.

Second random noise (N2) was applied to positions of electrodes on modeled thorax and represents the differences between assumed and real placement of electrodes. The extent of electrodes misplacement was chosen to simulate the values of SNR 20, 30 and 40 dB in DIMs. Such noise corresponded to electrodes misplacements 1.1±1.0 cm, 0.4±0.4 cm and 0.1±0.1 cm respectively.

The inverse solution was computed for each modeled position of one lesion or two lesions for each noise and each level of noise, i.e. 180 solutions for particular position of lesion or pair of lesions. For each solution the group of resulting pairs of dipoles was divided to two clusters. The percentage of obtained correct solutions decreased for lower SNR as it is shown in Table 1.

Table 1. The amount of the obtained correct solutions from all cases with modeled two lesions.

SNR	40 dB	30 dB	20 dB
N1	85.8%	86.4%	80.2%
N2	86.0%	85.6%	79.0%

The localization error of the inverse solution for cases with two lesions was evaluated as the distance between the gravity center of the modeled lesion and the gravity center of the nearer cluster of inversely estimated dipoles and is summarized in Table 2.

Table 2. The mean localization error of correct and incorrect inverse solutions for cases with modeled two lesions.

Localization error [cm]				
	Noise N1		Noise N2	
SNR	Correct r.	Incorrect r.	Correct r.	Incorrect r.
40 dB	1.2±0.8	2.4±0.9	1.2±0.8	2.2±0.9
30 dB	1.2±0.8	2.5±0.9	1.2±0.8	2.4±1.0
20 dB	1.2±0.8	2.7±1.2	1.2±0.7	2.5±1.2

3.2. Classification of the inverse results

For each inverse solution the group of resulting dipoles was obtained which was divided to two clusters and 23 characteristics of them were computed.

The classification of the results was then performed for identification of correct results representing two simultaneous lesions. As it can be seen from the Figure 2 the sensitivity of the classification increased rapidly from 72- 82% up to 89 - 97% in dependence of SNR when the best eight discriminating features were used in dependence of SNR. The inclusion of additional features increased later the sensitivity, but only slightly. The specificity did not change significantly in dependence of the number of features or the noise N1, N2 and varied from 84% to 94%.

The sensitivity and specificity curves were similar regardless of the noise or SNR of the input maps.

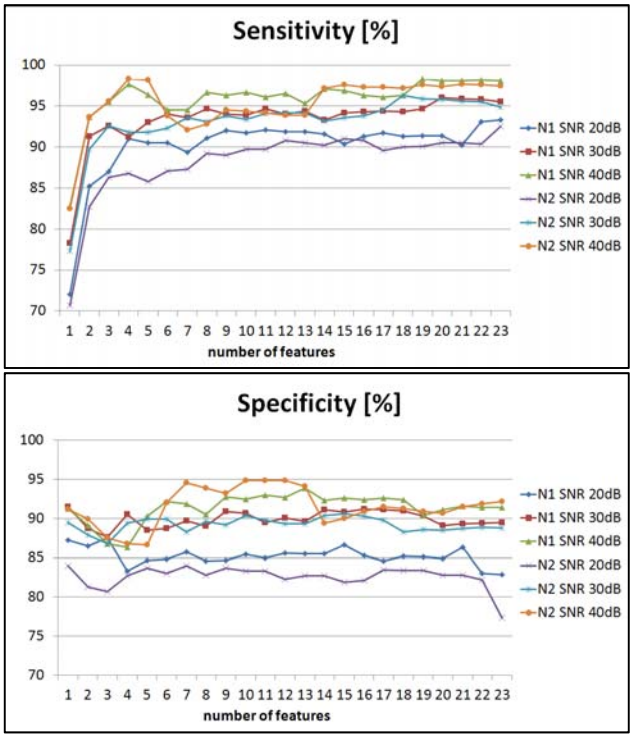

Figure 2. Sensitivity and specificity of the classification of correct results for the inverse solution with two dipoles for noise N1 and N2 in input DIMs and 3 levels of noise (20, 30 and 40 dB resp.).

4. Discussion

The application of the random noise to the electrode positions revealed quite large sensitivity of the input DIMs to this type of noise because the misplacement of about 1cm caused the SNR 20 dB. This fact consequently

influenced the localization error of the inverse solution as it was shown also in [9]. In our study it is reflected in lower number of correct inverse solutions (Table 1). Therefore the knowledge of the real positions of measuring electrodes seems to be very important for successful inverse solution.

The inverse solution with two dipoles was suggested as proper constraint instead of regularization for cases with two small lesions in comparison to multiple dipoles approach in inverse problem. However, due to the ill-posedness of the problem there were achieved only 80-85% of correct solutions.

The stable value of the localization error for correct solutions regardless of the noise level can be explained by the use of the same rule for selection of correct results. The moderate increase of the localization error for incorrect results with bigger noise is probably caused by higher instability of these solutions.

The quantification of the properties of inverse solutions and their use in the classification method allowed distinguishing the correct solutions representing two simultaneous lesions with changed repolarization. The use of eight selected features gave the sensitivity of the classification more than 90 % for 5 out of 6 simulated noise levels. 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. Next features characterized the mutual angle of the average dipoles of each cluster, standard deviations of projections of dipoles positions to the line joining the centers of clusters, their maximal and minimal values and standard deviation of angles of the dipoles in the cluster.

The identification of two simultaneous lesions was performed without the a priori information about the number of lesions because in the classification the incorrect solutions for two lesions were together with the solutions for single modeled lesion in the same class, while in the other class there were only correct results for two modeled lesions.

5. Conclusion

To study the stability and reliability of the inverse solution for identification two lesions, the groups of inversely estimated pairs of dipoles were investigated.

The proposed specification of their features together with proper classification method is promising for quantification of reliability of the inverse solution.

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