Performance Evaluation in the Reconstruction of Body Surface Potentials from Reduced Lead Systems A Comparative Study of Lead Selection Algorithms

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Abstract

Several methods for optimal lead selection from multilead electrocardiographic recordings are analyzed. The non selected leads are reconstructed from the selected leads according to Least Squares Optimization and the performance is evaluated in terms of Mean Square Error of the derived potentials. The algorithms were tested on a database of 72 body surface potential recordings divided into four different patient groups. Each dataset was divided into a study and test subsets. Two experiments were carried out: (1) all steps are performed over the test dataset (ideal case) and (2) the lead selection and transformation matrix is carried out over the study dataset but the performance is evaluated over the test dataset (real case).

Our results show important reconstruction errors with either lead selection method and only increasing the number of leads reduces the error in reconstruction. However, if a reduced number of leads is to be selected outside the standard 12-lead ECG, the method proposed by Lux has been shown to be the best option.

1. Introduction

The 12-lead electrocardiogram (ECG) is the most extended non-invasive technique in cardiology, due its capability to assess reliably cardiac disorders in a simple and inexpensive manner. Despite the relatively high number of electrodes required to obtain the 12-lead ECG, the total amount of information provided by all them has been questioned [1, 2], and electrode repositioning has been suggested with the aim of improving the diagnostic information captured by the ECG.

The objective of the present study is to evaluate and compare two different lead selection algorithms from BSPM recordings that can be used in the future for the definition of specific lead sets. These approaches consist in selecting subsequent leads with the aim of obtaining as much representative information as possible of the global body surface potentials.

2. Materials

Our BSPM recording system has been described elsewhere [3]. Briefly, it consists on a commercial 64-lead recording system for biopotential measurements (Active One, Biosemi) sampled at 2048 Hz with a quantization of 1 μV/bit. Electrodes were distributed non-uniformly upon the chest, with 16 electrodes on the back and 48 on the anterior side, with a highest density at positions overlaying the heart.

One minute BSPM recordings were obtained from 72 patients admitted in the Hospital Clínico Universitario de Valencia. In order to have an homogeneous database, we selected 18 patients from each of the following groups: Control, Myocardial Infarction (MI), Bundle Branch Block (BBB) and Ventricular Hypertrophy (VH).

3. Methods

In order to proceed with the lead selection, a segment of 10 seconds of the potential signals of all patients within a group were concatenated, so that a new potential matrix (e.g. $\mathbf{X}_{\mathrm{BBB}}$) with a duration of 180 seconds was created for each of the groups. Furthermore, an additional matrix $\mathbf{X}_{\mathrm{global}}$ containing the potential signals of all patients in the database was generated to represent all groups. Finally, group potential signals containing only the QRS-complexes (e.g. $\mathbf{X}_{\mathrm{QRS}_{\mathrm{BBB}}}$), as well as an additional matrix containing only QRS-complexes of all patients were also created $\mathbf{X}_{\mathrm{QRS}_{\mathrm{global}}}$).

3.1. Lead selection

In this section, several methods for lead selection are described. Obviously, the best lead selection can be always

determined by evaluating all possible combinations and choosing the one that best matches the reconstruction of the remaining ECGs. With the aim of reducing the computational complexity, two suboptimal methods already proposed in previous studies and based on different criteria have been implemented [4, 5]. The results obtained with these methods will be also compared to the results that would be obtained using a selection of the conventional 12-lead ECG.

3.1.1. Method 1: Lux's Algorithm

This approach was proposed by Lux et al. in an early study [4], although this method is still being used by its authors. The criterion employed in the algorithm proposed in [4] is an iterative process where the lead that maximizes the information contained in the lead selection is added to the lead set from the previous iteration.

In each iteration, the following steps are carried out:
1. Estimation of non-selected leads $\mathbf{X}_{\{\mathbf{i_1},\ldots,\mathbf{i_N}\}}$ from the selected leads $\mathbf{X}_{\{\mathbf{j_1},\ldots,\mathbf{j_M}\}}$ in the previous iteration according to a least squares optimization approach. The estimated leads are represented as $\hat{\mathbf{X}}_{\{i_1,\ldots,i_N\}}$
2. Compute the error in the estimation $\mathbf{X_e}$ as a result of the difference between the reconstructed and true potentials.
3. Compute the covariance matrix ($\mathbf{C_e}$) of the residual signals $\mathbf{X_e}$.
4. For each of the non-selected leads compute an information index I that accounts for the global amount of information contained at each lead, which is defined as:

$$I(n) = \frac{\mathbf{c_n}\mathbf{c_n}^{\mathrm{T}}}{c_{nn}}, \tag{1}$$

where $\mathbf{c_n}$ is the vector corresponding to the coefficients in the n^{th}-row of $\mathbf{C_e}$, and c_{nn} is the diagonal coefficient in row and column n.
5. the electrode i_n that maximizes I is added to the reduced lead set.

This algorithm is initialized with $\hat{\mathbf{X}}_{\{\mathbf{i_1},\ldots,\mathbf{i_N}\}}$ being a zero $L \times K$ matrix and hence $\mathbf{X_e}$ being initially equal to $\mathbf{X}$, and is repeated until the desired number of electrodes is reached.

3.1.2. Method 2: van Oosterom's Algorithm

A new lead selection algorithm has been recently proposed in [5]. This algorithm iteratively adds to the lead set from the previous step the lead that maximizes a parameter α_M which aims to reflect the amount of information contained in a certain lead set. The parameter α_M is derived from the singular value decomposition (SVD) of the M selected leads $\mathbf{X}_{\{\mathbf{j_1},\ldots,\mathbf{j_M}\}}$, according to the following expression:

$$\alpha_M = \frac{\sigma_M}{\sigma_1}, \tag{2}$$

where σ_M and σ_1 are the smallest and largest singular values, respectively. According to [5], the larger α_M, the more information is contained in the lead set, and consequently the higher performance is achieved. This lead selection algorithm is an iterative procedure where (1) the lead i_n of the non-selected group is added to the M selected leads from the previous step, hence obtaining the potential matrices $\mathbf{X}_{\{\mathbf{j_1},\ldots,\mathbf{j_M},\mathbf{i_n}\}}$, for each n $1 \leq n \leq N$ (2) update $M = M + 1$ and compute α_M for each of those matrices. This provides an index α_M for each of the non-selected leads (3) the electrode i_n that maximizes α_M is selected and added to the lead set output in the previous iteration. This algorithm is repeated until the desired number of electrodes is reached.

3.1.3. 12-lead ECG

Unipolar leads that correspond to the 12-lead ECG were ordered with the objective of comparing the information of the 12-lead ECG with the information contained in the lead sets derived from the other selection methods. The sequence of leads: right arm, left leg, V_1, V_3, V_5, V_2, V_6, V_4 was chosen in an attempt of optimizing the information of every lead subset as it was done in the other methods of selection.

3.2. Evaluation of lead selections

In order to evaluate the lead sets that have been obtained by the different methods detailed in section 3.1 we derive non-selected leads and compare true recorded versus derived leads. The best lead set will be defined as the lead set that derives the rest of the leads more accurately.

Having the leads ordered as explained in section 3.1 we calculated derived as a linear combination $\mathbf{T}$ of selected leads by Least Squares Optimization. Derived leads were compared with true recorded leads by averaging the mean square error e_l over all leads:

$$\varepsilon_M = \frac{1}{L}\sum_{l=1}^{L} e_l. \tag{3}$$

Notice that $e_l = 0$ if lead l belongs to the selected leads.

In order to evaluate the performance of the algorithms, two experiments are performed. The first experiment refers to an ideal situation where the lead selection, the transformation matrix $\mathbf{T}$ and the parameter ε are computed for the test dataset. The second experiment refers to a real situation where neither the optimum lead system nor the optimum transformation matrix for the ECG segment under test are available, i.e. the test dataset. In this case, both

the reduced lead system and the transformation matrix are obtained from the study dataset.

4. Results

4.1. Evaluation of lead selections

The performance of each of the lead selection methods was tested according to the evaluation criteria defined in section 3.2. Evaluation was performed for each of the groups separately and also for a database containing patients from all groups in the study. As aforementioned, two different scenarios are investigated aiming to reflect the conditions in an ideal and a real case, respectively.

Figure 1 shows the results obtained considering jointly all patient groups (control, MI, BBB and VH) divided into study and test sets. For 3 leads in an ideal case the reconstruction error was $55.3\mu V$ for method 1, $68.0\mu V$ for method 2 and $56.8\mu V$ for a subset of the 12-lead ECG, which increased up to $72.0\mu V$, $88.0\mu V$ and $66.6\mu V$, for method 1, method 2 and a subset of the 12-lead ECG, respectively under a real scenario (see table 1). With 8 leads in an ideal case, the errors in reconstruction are: $36.7\mu V$ for method 1, $44.5\mu V$ for method 2 and $39.6\mu V$ for the 12-lead ECG, which increased up to $42.9\mu V$, $52.1\mu V$ and $49.7\mu V$, for method 1, method 2 and the 12-lead ECG when the performance is evaluated in a real case (see table 2).

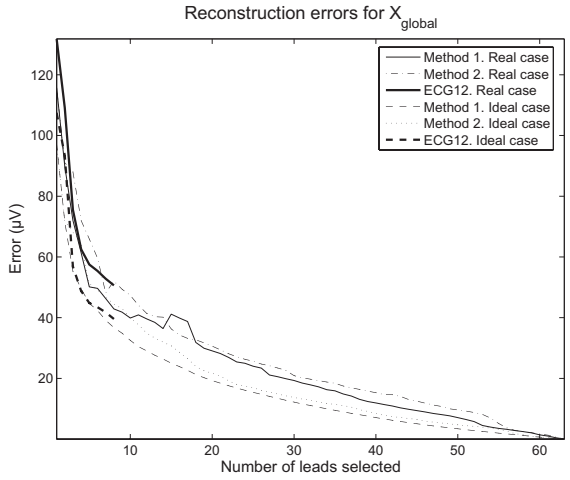

Figure 1. Error for limited lead sets on the whole ECG. Comparison of real and ideal case with both lead selection methods

As electrically inactive segments may influence the averaged error, we computed the errors for the QRS complex separately. In fact, the reconstruction errors over the QRS segment considering 8-lead sets and a real case increased up to $105.8\mu V$, $106.8\mu V$ and $130.1\mu V$ for method 1, method 2 and the 12-lead ECG (see tables 1 and 2 for more detailed information).

ECG segment	Method 1 Real	Method 1 Ideal	Method 2 Real	Method 2 Ideal	12-lead ECG Real	12-lead ECG Ideal
$\mathbf{X}_{\text{global}}$	72.0	55.3	88.0	68.0	66.6	56.8
$\mathbf{X}_{\text{QRS}_{\text{global}}}$	180.7	149.1	219.9	165.6	183.5	163.3
$\mathbf{X}_{\text{BBB}}$	122.7	82.8	262.7	107.9	109.3	102.1
$\mathbf{X}_{\text{QRS}_{\text{BBB}}}$	262.3	181.7	259.2	188.3	241.4	222.8

Table 1. Values (in μV) of ε_3 for 3-lead sets obtained from different lead selection methods and ECG segments.

ECG segment	Method 1 Real	Method 1 Ideal	Method 2 Real	Method 2 Ideal	12-lead ECG Real	12-lead ECG Ideal
$\mathbf{X}_{\text{global}}$	42.9	36.7	52.1	44.5	49.7	39.6
$\mathbf{X}_{\text{QRS}_{\text{g}}}$	105.8	76.3	106.8	94.8	130.1	99.6
$\mathbf{X}_{\text{BBB}}$	93.6	43.7	110.0	49.2	71.9	59.3
$\mathbf{X}_{\text{QRS}_{\text{BBB}}}$	172.3	93.5	160.0	102.1	144.8	109.6

Table 2. Values (in μV) of ε_8 for 8-lead sets obtained from different lead selection methods and ECG segments.

Error values for limited lead sets were calculated for the complete set of patients and for each group separately. Although for most groups, the performance was similar to the global performance, some differences could be observed in the BBB group, which presented lower performance than the rest of the groups. As an example, for method 1 considering 8 leads and a real case, the performance obtained for the BBB group decreased in comparison to the global ECG, with a reconstruction error of $93.6\mu V$ (see tables 1 and 2 for additional information regarding the results obtained with this patient group). Figure 2 shows the errors in reconstruction of the whole ECG of limited lead sets with an increasing number of selected leads for the BBB group. As can be observed in this figure, errors in the ideal case monotonically decrease as the number of leads increases, whereas this behavior can not be always reproduced in the real case (notice that it may occur that by adding a new lead the overall performance decreases).

Errors calculated for the BBB group and within the QRS complex can be observed in figure 3. These errors were higher than the errors for the QRS segment in the database containing all groups and also higher than the errors computed over the whole segment of the BBB group. Considering 8 leads in a real case, the errors obtained with method one were $172.3\mu V$ (see tables 1–2 for more detailed information).

5. Discussion and conclusions

As it can be inferred from the previous section, with the methods proposed, we can obtain lead sets that differ from one lead selection method to another and also from one patient set to another even for patients from the same group. From the results shown in the previous section, it can be stated that the method 1 (ie, Lux's method) is the one that

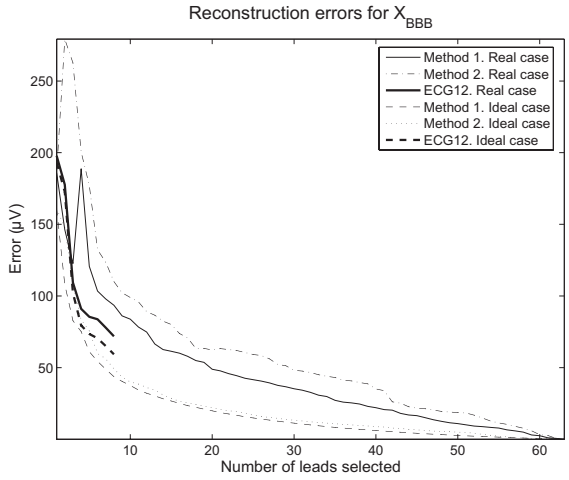

Figure 2. Error for limited lead sets on the whole ECG for the BBB group. Comparison of real and ideal case with both lead selection methods

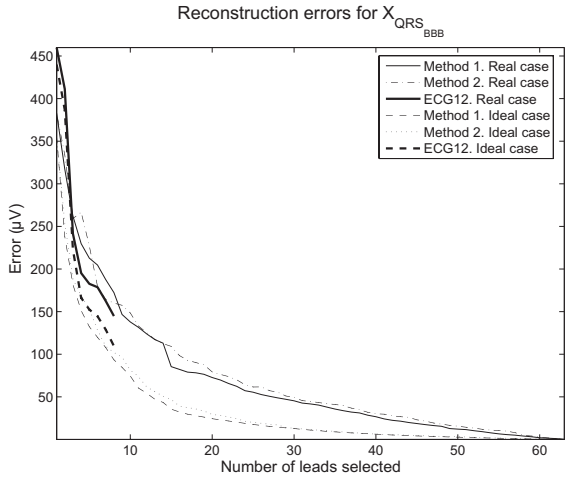

Figure 3. Error for limited lead sets on the QRS complex for the BBB group. Comparison of real and ideal case with both lead selection methods

achieves best performance in all groups and all ECG segments both for the real and the ideal case, whereas with the leads from method 2 and subsets of the 12-lead ECG, the error values are slightly higher.

The error values obtained in the ideal scenario would reflect the lower bounds that can be achieved by each of the methods. Nevertheless, the performance decreases significantly under a real scenario, where the optimum lead set and the optimum reconstruction matrix for the patient under analysis are unknown and, hence, are estimated from the study database. This performance decrease in the real case is mainly due to the fact that the linear matrix that reconstructs non-selected leads from selected leads is not the optimum one as well, since it may be different for each patient. Indeed, the error is not always monotonically decreasing as the number of leads increases in a real context.

As observed, the performance in the group of patients suffering from BBB are much poorer than with the rest of the patient groups, probably because electrical activations in this arrhythmia exhibit more heterogeneous dipole directions than during normal ventricular activation.

Another aspect to emphasize is that, if a limited number of electrodes are to be selected (e.g. 9 electrodes as in the case of the 12-lead ECG), the errors in reconstruction are significant (around $50\mu V$ within the whole ECG and $100\mu V$ for the QRS complex). From these results it can be derived that ECG signals can only be approximated, but not accurately reconstructed from a linear combination of a limited number of signals. Therefore, our recommendation is to include as many leads as possible, specially in those arrhythmias with diagnostic information at the level of several μV. Nevertheless, in the case that the lead system is limited to 9 electrodes, we consider that the 12-lead ECG is appropriate, at least for the database employed in this study.

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