Inverse Reconstruction of Epicardial Potentials Improved by Vectorcardiography and Realistic Potentials

Matthijs JM Cluitmans[1,2], Pietro Bonizzi[2], Joël MH Karel[2],
Paul GA Volders[1], Ralf LM Peeters[2], Ronald L Westra[2]

[1] Cardiovascular Research Institute Maastricht, Maastricht, The Netherlands
[2] Department of Knowledge Engineering, Maastricht University, Maastricht, The Netherlands

Abstract

The inverse problem of electrocardiography is to reconstruct electrical activity at the level of the epicardium from body-surface electrograms and a patient-specific torso-heart geometry. This is complicated by the ill-posedness of the inverse problem, making the reconstruction imperfect. Previously, we have shown that the use of realistic epicardial training electrograms can improve reconstruction quality in silico. Here, we apply this method in a patient and compare the resulting computed electrograms with intracardiac measurements. Additionally, we utilize a new method that yields further improvements by incorporating characteristics of vectorcardiographic information. Patient-specific vectorcardiographic optimization combined with training data created on a patient-specific heart improves morphologies of the reconstructed epicardial potentials. This underlines the need for constraints based on real patient-specific information in the regularization of the electrocardiographic inverse problem.

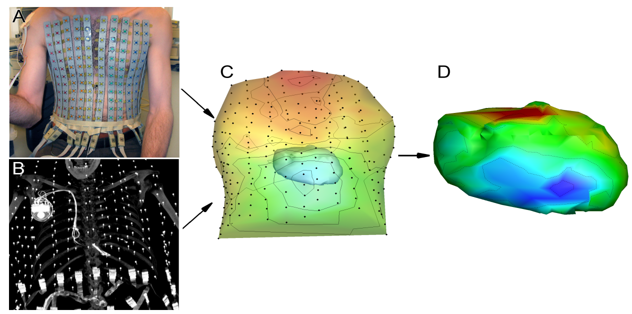

Figure 1. Inverse electrical heart activity reconstruction as applied in this paper. (A) Body-surface potentials are obtained with an extensive set of electrodes attached to the torso of the subject. (B) The location of the electrodes and of the outer heart-surface is determined from a CT scan. (C) The heart-torso geometry can be coupled with the measured body-surface potentials. (D) By applying inverse algorithms, the corresponding electrical heart activity can be reconstructed.

1. Introduction

Body-surface electrocardiograms (ECGs) are widely used to assess cardiac arrhythmias. However, these only reflect the attenuated and dispersed electromagnetic propagation of the heart's electrical activity to the body-surface. Direct, noninvasive assessment of electrical processes at the level of the heart muscle would be of great benefit to clinical practice. This can be achieved by solving the inverse problem of electrocardiography, which would yield electrical heart activity in terms of body-surface ECGs and the patient-specific torso-heart geometry, see Fig. 1.

During the last decades, much progress has been made in tackling the inverse problem of electrocardiography [1] and applications in humans appear with increasing frequency [2]. However, reconstruction of cardiac electrical activity remains imperfect. This is largely due to the ill-posedness of the inverse problem, meaning that small variations (e.g. noise) in the input data will yield large and unrealistic variations in the reconstructions. To cope with this problem, regularization is applied by incorporating additional constraints to arrive at more realistic solutions. Previously, we described the use of realistic training data to improve reconstructions [3]. Here, we apply this method in a patient and compare the resulting computed electrograms with intracardiac measurements. Additionally, we utilize a new method that yields further improvements by incorporating characteristics of vectorcardiographic patient-specific information.

2. Methods

2.1. The inverse problem of electrocardiography

In this study, we used a potential-based formulation to reconstruct heart-surface potentials (epicardial potentials).

This is described by the following forward problem:

$$Y_B = AY_H \quad (1)$$

in which Y_B represents the vectorized body-surface potentials (BSP), Y_H the vectorized heart-surface (epicardial) potentials, and A is the transfer matrix that contains the electromagnetic relation between those potential vectors. The transfer matrix is based solely on geometrical and conductivity properties of the torso and is usually determined from a patient-specific Computed Tomography (CT) scan.

In the inverse problem, the body-surface potentials Y_B and the transfer matrix A are assumed to be known. Due to the ill-posedness of the problem, direct solutions are very sensitive to noise. Hence, the solution will not depend continuously on the data [4]. By applying regularization schemes, the ill-posed nature of this problem can be restricted. In this study, we compare existing regularization schemes to our new proposed setup. This new approach is based on exploiting realistic training data and a vectorcardiographic representation to obtain improved reconstructions of heart-surface potentials.

2.2. Realistic training data as reconstruction basis

Traditional regularization methods incorporate mathematical or physical information to arrive at a better inverse solution. A novel approach is to use electrophysiological information as well. We previously investigated this idea in a small simulation study, where details of this method can be found [3]. In short, this method incorporates the following steps:

1 Epicardial training potentials $Y_H^{\#}$ are simulated on the patient's digitized heart surface as determined from CT scan. To create a diverse training set, we used the FitzHugh-Nagumo action potential model [5] to simulate multiple beats, originating from different, randomly chosen locations on the heart surface.
2 Singular Value Decomposition (SVD) of the training potentials yields $Y_H^{\#} = USV^{\mathrm{T}}$, with U and V containing the left and right singular vectors, respectively, and S containing the singular values σ_i [6]. In this case, the columns of U represent a spatial basis for the set of realistic heart-surface potentials. Due to the descending ordering of singular values, the first columns of U are more important for representing the training data, and truncation may be applied to arrive at a smaller spatial basis. A condensed basis will be beneficial as it leaves fewer possibilities for ill-posed influences that could result in unrealistic solutions. Therefore, we truncate U to a suitably small basis U_t consisting of only the first t components.
3 An existing regularization method (such as the Generalized Minimal Residual (GMRes) method [7]) is used to obtain reconstructed epicardial potentials $\hat{Y}_H$ from body-surface potentials Y_B and the transfer matrix A.
4 Next, these epicardial potentials are projected onto the realistic basis U_t, yielding the final reconstruction of epicardial potentials $\bar{Y}_H$.

As a novel approach, we propose a new step between steps 3 and 4, in which the reconstructed epicardial potentials are optimized in a patient-specific way before projection onto the realistic basis. To achieve this optimization, we aim to match the vectorcardiographic characteristics of the reconstructed epicardial potentials with those of the measured body-surface potentials.

2.3. Vectorcardiographic optimization of epicardial potentials

Starting from $\hat{Y}_H$ in step 3, this set is beat-by-beat analyzed with SVD to select the primary orthogonal components that contain the most information, (Z_H^{ℓ}), with superscript $(\cdot)^{\ell}$ indicating the ℓ^{th} cardiac beat:

$$\hat{Y}_H^{\ell} = U_H S_H V_H^{\mathrm{T}} \Rightarrow Z_H^{\ell} = \sqrt{n}(V_H^{(p)})^{\mathrm{T}}$$

with n the number of observations and p the number of orthogonal components preserved. This yields a cardiac dipole in a virtual orthogonal space. A similar procedure is applied to the 12-lead ECG (Y_{12}, which was recorded simultaneously with Y_B) to obtain an orthogonal p-dimensional approximation of the surface potentials (Z_B^{ℓ}):

$$Y_{12}^{\ell} = U_{12} S_{12} V_{12}^{\mathrm{T}} \Rightarrow Z_B^{\ell} = \sqrt{n}(V_{12}^{(p)})^{\mathrm{T}}$$

We choose to apply this procedure to Y_{12} instead of Y_B to exploit a different ensemble of surface information, but it would also be possible to apply this procedure to Y_B directly.

Both sets of dipoles represent the same electrical heart activity. However, the initial heart-surface potentials $\hat{Y}_H$ were influenced by ill-posedness and their dipole might not match the dipole of the body-surface potentials. To compensate for this mismatch, a beat-to-beat regularization of the reconstructed heart-surface electrograms $\hat{Y}_H$ is obtained by aligning the corresponding intracardiac dipole Z_H^{ℓ} with the body-surface dipole Z_B^{ℓ}, exploited as a reference. This is achieved by means of a statistical signal model which accounts for morphological differences between the intracardiac dipole loop and body-surface dipole loop in terms of: scaling, modeled by the positive scalar α; an orthogonal transformation, modeled by the $(p \times p)$ orthonormal matrix R; time synchronization (due to possible differences between Y_{12} and Y_B), modeled by a shift matrix J_τ, with τ being an integer time shift, such that $\tau = \Delta \times F_s$, with Δ the maximum time synchronization error allowed and F_s the sampling frequency [8]. This model optimizes the reconstructed heart-surface potentials to match the information in the measured body-surface potentials that might have been lost due to ill-posedness. Thus, the regularized epicardial dipole is modeled by:

$$\tilde{Z}_H^\ell = \alpha R Z_H^\ell J_\tau$$

Parameters α, R, and τ are estimated by solving the following minimization problem:

$$\epsilon^2_{\min} = \min_{\alpha,R,\tau} ||Z_B^\ell - \alpha R Z_H^\ell J_\tau||_F^2 \tag{2}$$

where $||\cdot||_F$ denotes the Frobenius norm, which for a generic matrix C is $||C||_F^2 = \mathrm{tr}(\mathrm{C}^\mathrm{T}\mathrm{C})$; note that R, α and τ also depend on ℓ. [8] This minimization cannot be achieved in a closed-form solution [9] and it is then performed by first finding the estimates of α and R by fixing τ. The minimization with respect to τ is then solved by a grid search in the interval $[-\Delta; \Delta]$. Estimates of α and R are obviously computed for all values of τ. In order to include the time synchronization step, it is necessary to add 2Δ samples to the intracardiad dipole loop Z_H^ℓ, such that $Z_H^\ell = (p \times n + 2\Delta)$. The time shift matrix J_τ which corrects for misalignment in time between the intracardiac dipole loop and the body-surface dipole loop is then defined by:

$$J_\tau = [\mathbf{0}_{\mathbf{n}\times\mathbf{\Delta}-\tau} \;\; \mathbf{I}_{\mathbf{n}\times\mathbf{n}} \;\; \mathbf{0}_{\mathbf{n}\times\mathbf{\Delta}+\tau}]^\mathrm{T}$$

In this framework, it can be shown that the estimate of R can be found in analogy to the context of rotation of subspaces [10], and is given by:

$$\hat{R}_\tau = U_\tau V_\tau^\mathrm{T}$$

where U_τ and V_τ^T are found by calculating the SVD of $Z_B^\ell J_\tau^\mathrm{T} (Z_H^\ell)^\mathrm{T}$. The estimate of α is then:

$$\hat{\alpha}_\tau = \frac{\mathrm{tr}(\mathrm{J}_\tau^\mathrm{T}(\mathrm{Z}_\mathrm{H}^\ell)^\mathrm{T}\hat{\mathrm{R}}_\tau^\mathrm{T}\mathrm{Z}_\mathrm{B}^\ell)}{\mathrm{tr}(\mathrm{J}_\tau^\mathrm{T}(\mathrm{Z}_\mathrm{H}^\ell)^\mathrm{T}\hat{\mathrm{R}}_\tau^\mathrm{T}\mathrm{Z}_\mathrm{H}^\ell\mathrm{J}_\tau)}$$

Finally, the regularized epicardial beat is obtained as follows:

$$\tilde{Y}_H^\ell = \frac{1}{\sqrt{N}} U_H^{(p)} S_H^{(p)} \tilde{Z}_H^\ell \tag{3}$$

Note that this represents the global optimum of Eq. (2). Differently from [8, 9], no average beat is defined in this procedure, neither for Z_H^ℓ nor for Z_B^ℓ, to preserve a detailed representation of each cardiac loop.

Following the vectorcardiographic optimization of reconstructed heart-surface potentials, we project these onto the realistic basis as descriped in step 4 to obtain the vectorcardiographic optimized and projected final reconstruction of epicardial potentials $\bar{Y}_H^\ell$ for the ℓ^{th} beat.

2.4. Clinical validation data

Test and validation data were obtained from a patient in the Maastricht University Medical Center (MUMC+, Maastricht, The Netherlands). Data collection consisted of three recordings: 1) Extensive body-surface potential recordings; 2) A CT-scan; 3) Intracardiac lead recordings. Body-surface potential recordings Y_B were obtained with 256 electrodes attached to the torso of the patient, at a sampling frequency F_s of 2048Hz. Recordings include native rhythm (with a left bundle branch block morphology, LBBB), and pacing by implanted pacemaker (pacing both right and left ventricles). A CT scan was obtained with the electrodes still attached to the patient's torso. A geometry was created from the electrode positions (representing the body-surface) and the outer heart-surface. The conductor volume was assumed to be homogeneous. A transfer matrix A relating the electrical activity at the heart-surface to the body-surface was computed with methods available from the SCIrun software repository [11] (see Fig. 1).

A few months after this procedure, pseudo-unipolar electrograms were recorded with the implanted pacemaker from an epicardial lead in the left ventricle (LV) and an endocardial lead in the right ventricle (RV). These recordings were obtained for a paced beat and a native beat. Although the recordings were not obtained simultaneously with the other data sets, the corresponding 12-lead ECG was comparable for those beats. Therefore, these recordings were used for validation purposes, although their pseudo-unipolar characteristics prevent exact morphological comparison to reconstructed unipolar electrograms.

3. Results

Figure 2 shows the results for two different types of beats on two different locations (right ventricle and left ventricle), where we decided by experimenting to fix regularization parameters p and t to 7. As can be seen, electrograms reconstructed with the GMRes method are able to reconstruct the first part of the QRS complex correctly, but seem to miss the second deflection in that complex. When vectorcardiographic optimization is applied as well, this deflection shows up more pronounced. Subsequent projection on the realistic basis gives further improvements and stabilizes the solution.

Also when looking at the ability to determine the pacing location from the reconstructed electrograms, the results are improved by the proposed technique. For the paced beat, GMRes reconstructs a location of first activation 92 mm from the known pacing location. With vectorcardiographic optimization, this improves to 37 mm, and further projection on the realistic basis yields a mismatch of only 22 mm.

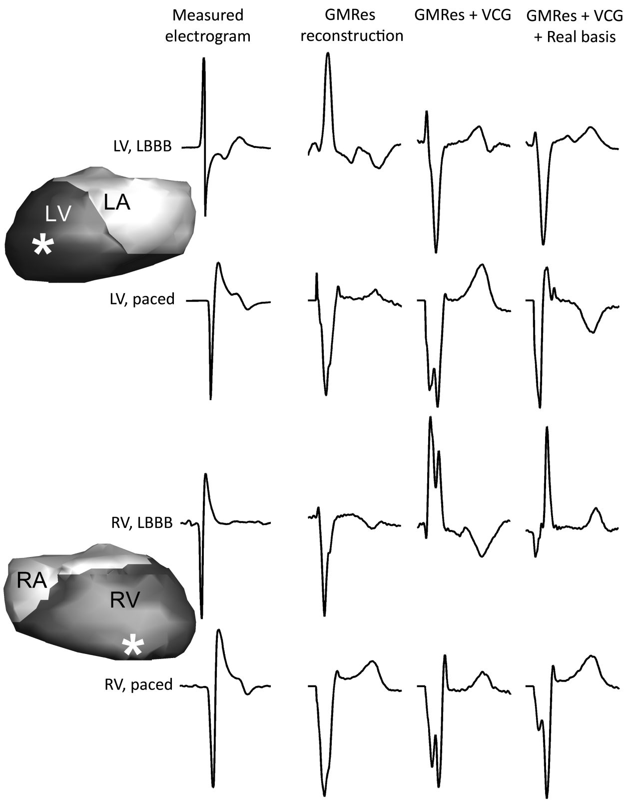

Figure 2. Electrograms on a patient's heart, measured via pacemaker leads (left column) and non-invasively reconstructed from body-surface potentials (other columns). The reconstructed electrograms are regularized with the Generalized Minimal Residual method only (GMRes), with GMRes and subsequent vectorcardiographic optimization (GMRes+VCG), and with subsequent projection on a realistic basis (GMRes+VCG + Real Basis).

4. Conclusions

In this study, we investigated electrocardiographic inverse problem regularization by patient-specific vectorcardiographic optimization and subsequent projection onto a basis obtained from realistic simulated training data. Comparison with actual intracardiac beats from a patient shows that epicardial beat reconstruction is improved with respect to GMRes only, notably for recovering previously missed deflections and decreasing the mismatch when detecting the pacing location. The physiological meaningfulness of these reconstructions was also confirmed by experts.

One limitation is that some of the deflections appearing in the GMRes regularized electrogram seem to become less pronounced when applying the proposed method. Therefore, care should be taken when applying our method too rigorously; this can be alleviated by convenient tuning of the vectorcardiographic optimization dimension p and the realistic basis dimension t. How to automatically determine these parameters is still an open question.

In conclusion, this study underlines the need for constraints based on patient-specific information to achieve a physiologically meaningful regularization of the electrocardiographic inverse problem. We have shown that a patient-specific vectorcardiographic approach combined with training data created on a patient-specific heart shows potential to fulfill this need.

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Address for correspondence:

Matthijs JM Cluitmans

Department of Knowledge Engineering, Maastricht University, P.O. Box 616, 6200 MD Maastricht, The Netherlands
m.cluitmans@maastrichtuniversity.nl