Quantitative Comparison of Two Cardiac Electrical Imaging Methods to Localize Pacing Sites

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Abstract

Electrocardiographic imaging (ECGI) is a technology with great potential to support pre-procedure planning for ablation interventions. However, since the inverse problem it tries to solve is ill-posed, it requires regularization to stabilize the solutions. There have been multiple approaches to attain this objective with different regularization techniques that impose spatial or temporal behaviour on the solution based on prior electrophysiological knowledge with softer or harder constraints. It is continuing research to determine which prior knowledge added is better suited in each situation and there is a need to compare different methods on the same dataset to resolve that question. Here we compare two temporal methods that lie at both sides of the softness/hardness imposition of the prior knowledge. In one hand the splines method by Erem et al. *imposes smoothness on the solution, while the cardiac isochrone positioning system (CIPS) forces the solutions to be step-function shaped in time. For this comparison we use the PSTOV dataset from the consortium on electrocardiographic imaging* `www.ecg-imaging.org` *which consists of body surface data during pacing at endocardial sites from subjects with healthy ventricles. The results show that on average CIPS performs better than the splines method, although there is too high a degree of variability within and across subjects and pacing locations to be able to predict which method performs better in an individual case.*

1. Introduction

Electrocardiographic imaging (ECGI) is a technology that tries to non-invasively image the electrical activity on the heart from electrocardiographic measurements on the body surface (BSP) and anatomical information about the heart and torso and which has a lot of potential in pre-procedure planning for ablation procedures. However, the ill-posedness of this problem makes the solutions obtained very sensitive to noise and modeling errors and thus require regularization of the iterative solution method based on prior knowledge.

Regularization methods can be classified as spatial or temporal, depending on the type of prior assumed, or as having softer or harder constraints, depending on how strict is the prior knowledge being imposed on the solution. Examples of these methods are Tikhonov regularization (spatial and soft), the spline method from Erem *et al.* (spatial + temporal and soft) or the cardiac isochrone positioning system (CIPS) (hard temporal + soft spatial) [1–4].

It is not trivial to determine a priori which method performs better for a specific patient ECG. Approaches that impose a strict temporal model on the solution are more resilient to the effects of ill-posedness, but they are more dependent on the model being an accurate description of the solution, while softer constraints may suffer from the opposite problems. Hence, it is necessary to thoroughly compare all methods across different datasets to determine in which situations it is preferable to implement one method or another.

Here we take a first step in that process and compare two temporal regularization methods with different approaches to soft/hard imposition of the constraints. On one hand, the splines method imposes smoothness on the solution through a spline interpolation whose parameters are learned from the BSP. On the other, CIPS restricts the transmembrane potential (TMP) temporal profile to be similar to a step function that arises at an unknown time. To compare these approaches, we use the PSTOV dataset, available at the consortium of electrocardiographyic imaging (CEI-`www.ecg-imaging.org`), which consists on a set of endocardial pacing experiments on human subjects.

2. Methods

In this section we briefly describe the methods used for this work. We do not intend to present a thorough description of the methods, for a more detailed description of those please refer to [2–4].

2.1. Splines

This method introduces a soft temporal prior that imposes smoothness on the inverse solutions. Its underlying assumption is that the temporal evolution of the heart surface potentials (EGM) follows a smooth curve in a high-dimensional space, —a 1D manifold— whose characteristics are similar to one observed on the BSP. To approximate this manifold on the BSP, this method fits a multi-dimensional spline that is independent of the time stamps of the potentials. Thus, the fitting recovers a set of knot points, which are potentials in themselves and characterize the shape of the curve, and the time warp, that determines the temporal interpolation of all the measured potentials on the spline. The use of splines to interpolate the potentials in time is especially useful since the parameters that fully determine the curve, the knot points ($\kappa_{y,i}$), are potential distributions in themselves, and thus can be used to solve for the equivalent knot points of the EGM ($\kappa_{x,i}$). Any ECGI method can be used as inverse solver; the current implementation of this method uses a 1rst order Tikhonov regularization that trades-off the least-squares fit of the error with the minimization of the spatial gradient of the potentials (Equation 1), where A is the forward matrix and D is an operator that approximates the spatial derivative of the potentials.

$$\min_{\kappa_{x,i}} \|\kappa_{y,i} - A\kappa_{x,i}\|_2^2 + \lambda \|D\kappa_{x,i}\|_2^2 \qquad (1)$$

After solving for the knot points on the heart, they are then used to recover the full temporal sequence of potentials with the time warp learned during the BSP fitting. This method is potential based —*i.e.* reconstructs the potential distribution on the heart—, thus, for it to recover the point of first activation, it is necessary to estimate the corresponding activation times. To do so, we use a spatio-temporal approach, which weights the minimum dv/dt of the heart potentials with their spatial gradient to favor solutions that follow the wavefront of activation. Finally, we smooth the resulting activation times on the heart as was described in [2]. We determine the point of first activation as the node with earliest estimated activation time.

2.2. CIPS

This is a method with a highly restrictive model for the temporal behavior of the solution. It assumes that during depolarization on a healthy ventricle the temporal profile of the TMP is well represented by a continuous approximation of a step function. With this model, solving for the potentials on the heart simplifies to finding the moment at which this step function arises on each node of the heart surface —*i.e.* the activation times. CIPS solves for these unknowns with the non-linear least squares function in (Equation 2), where y(t) are the ECG measurements, u(t) is the step function shifted at the activation time (ρ) that corresponds to each node, A is the forward matrix that relates the two and L is the regularization matrix that approximates the Laplatian operator.

$$\min_{\rho} \|y(t) - Au(t-\rho)\|_2^2 + \lambda \|L\rho\|_2^2 \qquad (2)$$

This optimization problem can be solved with any iterative method. However, unfortunately, it has a large number of local minima that lead to unphysiological solutions of the inverse problem. CIPS overcomes this limitation with a physiologically guided initialization that uses a simplified model for activation on the heart. It uses the fastest-route algorithm on the heart to determine a sequence of activations that start at each individual node of the heart and picks the simulation with smallest fitting error with respect to the measured ECG to initialize the aforementioned optimization. This method directly solves for the activation times on the heart, thus to determine the point of first activation it is only necessary to select the node with earliest activation time.

3. Experiments and Results

To compare these two methods, we used the PSTOV dataset in the CEI website (`www.ecg-imaging.org`) that was first used in [2]. It consists on recordings from endocardial pacing experiments on 3 volunteers with healthy ventricles. The experiments were carried out with appropriate human volunteer subject permission from Charles University Hospital in Prague, Czech Republic, and in conjunction with standard atrial ablation procedures. In this experiment, the ventricles of each subject were stimulated multiple times at different locations in both left ventricle (LV) and right ventricle (RV). For each stimulation site the ECG was recorded using 120 electrodes on the body surface. The position of the stimulation catheter was recorded with the CARTO XP system and served as the ground truth. The heart geometries were obtained from an axial CT scan around the heart and a generic torso surface was fitted to the sections visible on the scans. No additional organs were segmented, thus using a homogeneous volume conductor model. More details on this dataset can be found in [2].

In this work, we used the recordings of each activation sequence individually to reconstruct the potentials on the

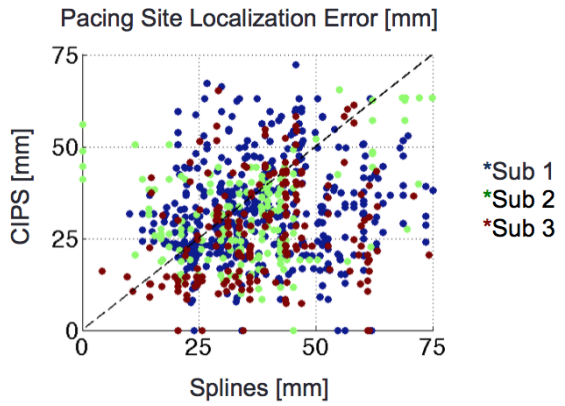

Figure 1: Scatter plot of the localization error (in mm) of both methods. Vertical axis indicates the localization error for CIPS and horizontal for splines. The color of each point indicates the subject: 1 in blue, 2 in green and 3 in red. The diagonal dashed line indicates identity.

heart with each method. To evaluate the error we compared the position of the earliest activation against the CARTO coordinates projected onto the nearest node on the heart. The results for the localization error of both methods can be found in the scatter plots from Figure 1. In this scatter plot, each axis represents localization error of each one of the two algorithms, thus points along the identity line (dashed diagonal line) indicate equal results, while points above or below indicate better results for splines or CIPS respectively. The distribution of the results reveals considerable variability across and within subjects, pacing location and method used. Both methods have a range of results from $15-20$ mm up to ~ 75 mm. However, CIPS has less density of results with higher error (≥ 50) mm, which on the scatter plot translates to a majority of points below the identity line.

Figure 2 shows the histogram of the difference between results between splines and CIPS. Negative results indicate improvement for CIPS and positive for splines. In it, it is clearer that on average CIPS performs better than splines. The mean variation is of ~ 5 mm of improvement with CIPS, which attains improvements of 20 mm for a substantial number of recordings. Nevertheless, there is a noticeable number of recordings for which the splines method solves the inverse problem with more accuracy.

4. Discussion

The results obtained in this comparison show that both methods obtain solutions in a similar range of localization error, although on average, CIPS is better at detecting the location of initial activation on the heart. However, the high variability observed within and across different subjects, locations and methods makes it hard to predict with a reasonable degree of certainty which method is to perform better on an individual recording.

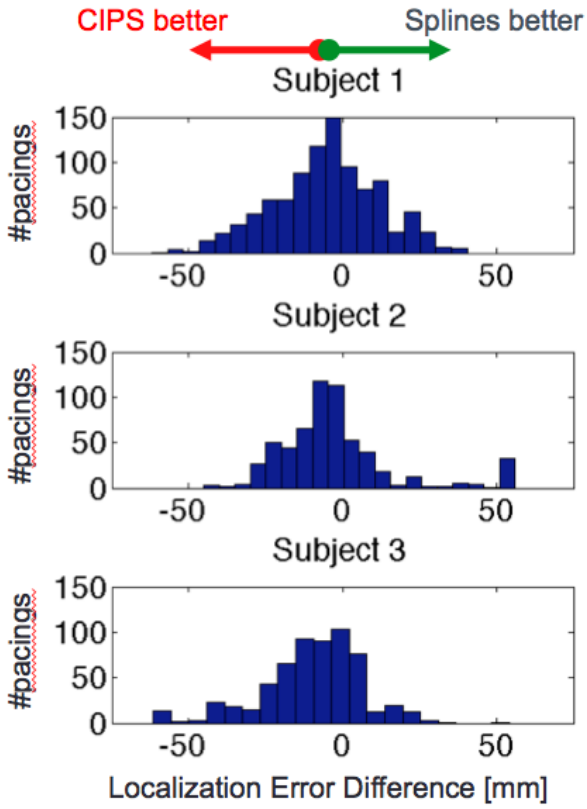

Figure 2: Histogram of difference between localization error (in mm) for splines minus CIPS for each subject. Negative values indicate smaller localization errors for CIPS and positive values smaller errors for the splines method.

There are multiple factors that need to be considered when analyzing these results. First, these experiments were carried out on subjects with healthy ventricles, which fits the basic assumption of CIPS. The presence of scar or ischemia on the myocardium would affect CIPS more than the splines, thus it would be necessary to add such examples in a more extensive testing experiment as in [5]. Second, the used homogeneous volume conductors pose a major challenge to both inverse solution methods, as the omission of blood cavities and lungs create modeling errors which influence the results of the inverse procedures. Including these additional inhomogeneities might improve the solutions obtained with both inverse methods. Another challenge from this dataset that should be considered is the uncertainty introduced in the registration of the CARTO locations onto the heart geometry. This procedure might be adding unrealistic errors in the ground truth for both methods. Finally, the spline method is a potential based

method and it does not resolve for activation times. Hence it requires of a further estimation of these, which is not a solved research problem and is bound to introduce error in the solutions.

5. Conclusions

We compared two temporal regularization methods that differ on the softness/hardness of their constraints. In one case, the spline method only imposes smoothness on the solutions, while CIPS restricts those to behave as a step function. The experiments carried out in human data from pacing experiments show that, on average, CIPS performs better than the splines method. However, there is a high degree of variation in the results obtained across and within methods that does not allow to determine which method is to perform better for an individual recording.

Acknowledgements

This work was supported in part by NIH grant P41GM103545. The authors also gratefully acknowledge CEI for prvoding the data and S. Havranek and J. Simek, from the Second Department of MedicineDepartment of Cardiovascular Medicine, First Faculty of Medicine, Charles University in Prague and General University Hospital in Prague, Czech Republic, as well as D. Wichterle, from the Department of Cardiology, Institute for Clinical and Experimental Medicine-IKEM, Prague, Czech Republic for its collection

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