Using a new Time-Independent Average Method for Non-Invasive Cardiac Potential Imaging of Endocardial Pacing with Imprecise Thorax Geometry

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Abstract

Cardiac electrical imaging from body surface potentials is a technology with great potential for pre-procedure planning in the context of ventricular ablation, based on body surface measurements of arrythmic beats. Three clinically desirable properties of such an imaging system are the ability to localize endocardial as well as epicardial initiation sites, the ability to use fewer body surface leads than typical in a body surface mapping system , and the ability to maintain accuracy while limiting dependence on extensive anatomical imaging. At the same time,in the setting of premature ventricular beats, it is typically easy to obtain measurements of multiple beats with the same initiation site. Since sensitivity to measurement noise makes increased signal SNR desirable, multiple beats offer the possibility of improved accuracy. Here we compare standard ensemble averaging of the body surface measurements, reconstruction of individual beats followed by averaging of the results, and an averaging method developed by our group that is less sensitive to timing and propagation velocity variability from beat to beat, in the context of our recently reported method for endocardial pacing site localization using limited torso imaging. For a set of pacing site on the RV and LV endocardia of 3 subjects, we recorded multiple trials of 120 lead ECG and carried out inverse reconstructions using all three averaging methods. The reconstructed heart potentials were then used to estimate the pacing sites that were then validated against recorded pacing locations. The solutions from our time insensitive averaging method show improvement in localization accuracy over the solutions obtained with ensemble averaging, although the average of single-beat reconstructions results in better precision for most pacing sites.

1. Introduction

Ventricular ablation procedures for ectopic beat termination requires accurate localization of the focus of the ectopic beats insitu. This localization may take several attempts and extensive point-to-point mapping by the clinician, thus increasing the time of the intervention and with associated costs and risks. For this reason, these procedures could highly benefit from prior non-invasive localization of the critical sites that could lead to a reduced search area. A technology that could bring this benefits is cardiac electrical imaging, also called ECG imaging (ECGI). ECGI tries to estimate the underlying electrical distribution of heart surface potentials (HSPs) from the non-invasive body surface potentials (BSPs). Solving for the HSPs from BSPs is one variant of the inverse problem in electrocardiography, and requires a solution to the forward problem, that is a model of the relationship between HSPs and BSPs.

It is well known that this relationship depends only in geometry and conductivities and can be approximated to a high degree of accuracy by a static and linear function [1]. Thus, the solutions of the forward problem can be determined from detailed geometries of the torso and heart obtained from CT or MRI imaging. Once generated these geometries a BEM or FEM solver can approximate the solution of the forward problem, resulting in a forward transfer matrix (A). Thus, the relation between HSP (x) and BSP (y) becomes $y = Ax$.

However, because of the nature of the electrical propagation of potentials, the matrix A is ill-conditioned and thus the inverse problem is highly sensitive to noise in the measurements and to model error. In order to obtain meaningful inverse solutions, the inverse needs regularization [2]. There are many methods in the literature to regularize the inverse electrocardiography problem. Our group recently published a new method that uses a temporal spline approximation of the heart and body surface potentials and a transmural gradient regularization [3] and was shown to reconstruct endocardial as well as epicardial potentials in the context of a very limited set of CT slices, concentrated on the heart region, being available. In this study we use this spline-inverse method as an inverse solver for the HSPs.

When there are multiple beats with the same initiation site available, it is possible to obtain an ensemble average beat with increased SNR. However, variability in the sampling time and intra-beat velocity can introduce correlated noise that instead decreases SNR and with it introduces more error in the inverse solutions [4]. To overcome this limitation we propose to average heartbeats with a spline-based method that only uses the geometric properties of the heart potential while disregarding the time stamps. This method was first studied as a denoising technique for BSPs in [5] and is a natural extension of the spline-inverse method.

In this paper we will compare the differences in accuracy between traditional ensemble averaging of BSPs, our geometric averaging and ensemble average applied to the individual HSP solutions after applying the inverse procedure to each separate heartbeat in the ensemble. To do so, we will use the ventricle paced data previously used to validate the spline-inverse method [3] and the localization of the initial activation on the heart as reference to measure error.

2. Methods

Dataset

The dataset we used to compare the different averaging techniques consisted of BSP recordings from obtained during ventricular pacing on three volunteers with presumed healthy ventricles, performed, with appropriate human subject permission from Charles University Hospital in Prague, Czech Republic, in conjunction with standard atrial ablation procedures. Details of the experiment are in [3] but we summarize here.

During this intervention, the clinician paced the heart multiple times at several endocardial locations in both ventricles with a catheter-based device. The position of the pacing catheter was recorded using the CARTO XP electroanatomical mapping system while the BSP were recorded using an array of 120 ECG leads that also contained the standard 12 lead configuration as a subset. For the geometric model we fit generic torso and epicardial-endocardial ventricular heart surface geometries to limited axial X-Ray CT images of the volume containing the subjects heart. These geometries were then used to generate a mathematical forward model relating heart and body surface potentials. This dataset and geometry is freely available in the SCIRunData repository [6].

Inverse Problem

As mentioned above, to solve the inverse problem we used an algorithm that described in [3]; code is available online in the Forward/Inverse Toolkit of SCIRun [7]. Again we describe briefly and refer the reader to [3] for details.

Our algorithm imposes spatio-temporal regularization. The temporal assumption is that the BSPs and HSPs during a heartbeat each traverse a (distinct, but closely related) smooth curve in a high-dimensional space, in which the potential at each electrode represents a different dimension. With this assumption, the algorithm approximates this curve by fitting a high-dimensional spline to the measured BSPs. This fitting minimizes the average distance to the interpolated curve in the high dimensional space of all samples of the BSPs, disregarding the actual time stamps associated with each sample. The resulting spline is determined by its knot points — which are potential distributions themselves — and its time warp — the projection of each sample to the interpolated curve. The algorithm assumes, based on the fact that the BSPs and HSPs are related by a spatial PDE but with no temporal mixing, assumes the temporal position of the knot points is invariant on the heart and the body and thus calculates the inverse solution of each knot point using a Tikhonov inverse. Key to obtaining endocardial potentials is a regularization term that minimizes the volumetric (transmural) gradient in the heart. Finally, the HSPs are reconstructed creating a new spline with the inverse knot points and the time warp. More details on this inverse method can be found in [3].

Averaging Methods

In order to compare the distinct averaging methods, we averaged the recorded BSPs during QRS across multiple pacings at the same site and then fed the averaged BSPs as input to the inverse method. The averaging methods we compared were the ensemble average and a spline-based average. Also, with the objective of comparing with single beat inverses, we ensemble averaged the HSPs obtained after inverse solutions computed on all individual beats.

The standard method for averaging is the ensemble average which calculates the mean BSP for each time instance across all recordings. With the assumption of having at least partially uncorrelated additive noise, this method should always increase SNR. However, if other variability such as changes in intra-beat velocity are present, this method will introduce correlated noise that may strongly affect the inverse solutions.

A different approach to use a spline-based method, which is a natural extension of the spline-inverse method. In the inverse algorithm the curve in high-dimensional space is assumed to be the same for all heartbeats produced with the same activation pattern. Thus, in the spline-based *averaging*, the curve fitting was done by fitting across all available recordings from a single pacing site at once. This procedure is robust to variability in timing since the spline fitting is done independently of time stamps, while it also attenuates noise present in individual beats.

Validation

Validating results in inverse electrocardiography is not straightforward. Since the potentials of interest are usually inaccessible, there is no ground truth to compare the solutions to the inverse algorithms. However, this paced dataset provides a unique situation to test the validity of the reconstructed HSPs, by comparing initial activation sites extracted from the inversely-computed potentials to CARTO measurements of the pacing locations.

We used the algorithm described in [8] to estimate the node corresponding to the earliest activation site from the computed potential distribution and then calculated localization error as the distance (in mm) between that node and the CARTO-reported pacing location.

3. Results

To compare the overall error of the two BSP averaging methods, spline-based and ensemble, and the ensemble average of reconstructed HSPs, we show a histogram of the localization error in Figure 1. In it we observe that the distribution of the error is similar for all three averaging types. Most of the error centered around the mean at around 35mm although its distribution spreads to over 80mm for some pacing sites. In the case of inverse solutions using data restricted to the standard 12 lead measurements, the error distributions are similar but shifted to higher error, which was to be expected given the reduction in the number of leads.

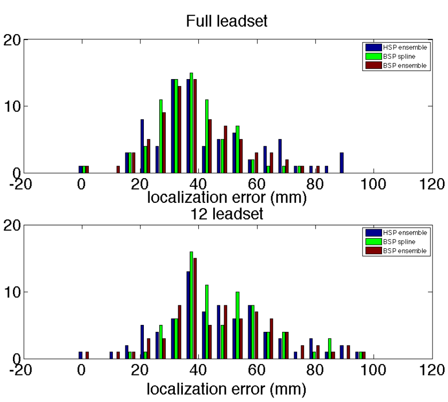

Figure 1. Histogram of the localization error for all 3 subjects. The bar colors correspond to the different averages: HSP ensemble (red), BSP ensemble (blue) and BSP spline-based (green). Above inverse with full lead set, below inverse with 12 lead set.

To provide a clearer view of how the localization error of each pacing site changes when averaging HSPs or BSPs, we show in Figure 2 a histogram of the change of error between ensemble average in HSPs and the two other averaging techniques in BSPs. This change is shown as $\Delta Error_{spl} = Error_{spline} - Error_{HSP}$ and $\Delta Error_{ens} = Error_{ensemble} - Error_{HSP}$. Thus, negative independent variables in the histogram indicate improvement when using BSP averaging while positives values indicate a loss of performance. In these histograms it is clearer that, on average there is not much change between averaging BSPs or HSPs. It is possible that the inverse method is already smoothing out the solutions leaving most results unchanged and, although there are some pacing sites that do benefit from BSP averaging, other cases show an increase of error such that the overall mean gain is close to 0mm. An exception is subject 3, which shows an larger improvement in localization error for several pacing sites when averaging BSPs and, as a result, a much better mean increase than in the other two subjects. Overall, the error improvement plots indicate that the spline-based averaging produces a slightly better improvement than ensemble averaging. However, even though the distribution of localization error improvement for both BSP averages are around the origin, the ensemble average shows a much tighter concentration at 0mm, indicating that its results do not differ much from the ensemble average at HSP. On the other hand, the error change produced with the spline-based average has more variance and some pacing sites shows a big improvement when this algorithm is applied.

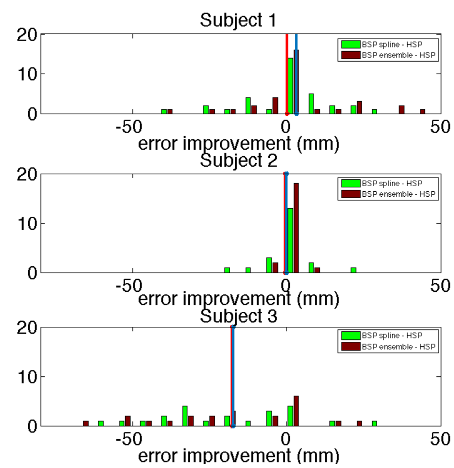

Figure 2. Histogram of the localization error improvement of the BSP averages with respect to HSP average in each subject for the full leadset inverse. The bar colors correspond to the comparison: BSP-spline with HSP-ensemble (green) and BSP-ensemble with HSP-ensemble (blue). The vertical lines indicate the average improvement for BSP-spline with HSP-ensemble (red) and BSP-ensemble with HSP-ensemble (blue). Each row represents a different subject.

Figure 3 shows the same error improvement histogram but this time for the inverses taken on the standard 12 lead configuration. In this case, the ensemble average on BSP shows much less change with respect to the HSP average, the distribution is highly concentrated in $\Delta Error_{ens} = 0$mm. A possible explanation is that the inverse solutions for datasets limited to the standard 12 lead need more regularization to compensate for the missing information. Thus, the resulting HSPs are smoother and less sensitive to input noise. For the spline-based average, we observe that, as in the full leadset solutions, it shows a little better performance than the BSP ensemble average and the distribution of ΔErr_{spl} has longer tails, with a little bias towards negative values.

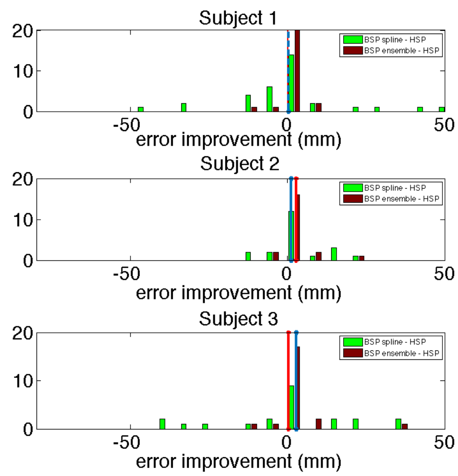

Figure 3. Histogram of the localization error improvement of the BSP averages with respect to HSP average in each subject for the 12 leadset inverse. The bar colors correspond to the comparison: BSP-spline with HSP-ensemble (green) and BSP-ensemble with HSP-ensemble (blue). The vertical lines indicate the average improvement for BSP-spline with HSP-ensemble (red) and BSP-ensemble with HSP-ensemble (blue). Each row represents a different subject.

4. Conclusions

Our results indicate that averaging BSPs prior to calculating the inverse solutions lead to results that were similar or at times slightly better than the solutions obtained from ensemble averaging of the inverse solutions taken individually. When averaging BSPs, we did not see difference between ensemble average and spline-based average for most cases. Since our spline algorithm is non-linear, and the regularization is carried out independently for each inverse solution computed, it is not obvious that this would be the case. Also, even considering the small improvement in the localization accuracy of averaging BSPs compared against HSPs, the gains in computation speed due the reduction of number of inverse solves needed make averaging a desirable step in when solving the inverse problem.

A clinically interesting feature are the inverse solutions taken on standard 12 lead recordings. For these cases we observed less of an effect of the averaging algorithm on the localization error. We speculate that this is related to the typically higher influence of the regularization term in inverses with reduced number of measurements.

More work is needed to determine under which specific situations these averaging methods perform better or worse and what metrics can be see to discern which one is better without advance knowledge of the correct location as we had here from the CARTO measurements.

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