Bayesian Estimation for Cardiac Activity Reconstruction Using Clinical Data

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Abstract

Bayesian estimation provides a unique strategy that can be used to reconstruct non-invasively the cardiac activity from torso recordings while incorporating prior knowledge about the underlying cardiac sources.

This study investigates the accuracy of Bayesian estimation in localizing the origin of premature ventricular contractions (PVCs) for 10 patients. Surface recordings from 128 torso electrodes were captured before radiofrequency ablation. A training dataset containing simulated epicardial potentials, mimicking individual PVC, with 103 to 306 starting points per patient, was used as prior knowledge. All computations assumed homogeneous patient-specific torso models. Furthermore, the study investigates the effect of different training time intervals, ranging from 20% to 100% of the width of the QRS, on the accuracy of reconstruction in terms of localization error (LE).

Results showed accuracy variations among patients and training intervals. The 100% training time interval had the smallest mean LE (31.0 ± 16.1 mm) and median (25.3 mm), while the 60% interval had the highest mean LE (34.2 ± 16.6 mm) and the 20% interval had the highest median of LE (30.0 mm).

The study underscores Bayesian estimation's potential for cardiac activity reconstruction while investigating the impact of training time intervals on accuracy.

1. Introduction

The inverse problem of electrocardiography or Electrocardiographic Imaging (ECGI) non-invasively describes the cardiac electrical sources based on remote recordings on the torso surface [1]. Regularization, such as Tikhonov regularization, is required to handle the ill-posed nature of the inverse problem and enhance the accuracy of the reconstructed electrical activity [2].

Bayesian estimation facilitates the incorporation of prior information concerning unknown sources, specifically epicardial potentials for ECGI. By incorporating prior knowledge, Bayesian estimation enables the construction of prior distributions for unknown sources. The prior information, represented by the mean and covariance matrix, is derived from the training dataset constructed using either actual recordings or simulations. The posterior distribution, representing updated beliefs about the sources given observed data, is then derived through Bayes' theorem [3].

This study explores the accuracy of reconstructing cardiac activity through Bayesian estimation, using clinical data from patients experiencing spontaneous premature ventricular contractions (PVCs). Simulated heart potentials corresponding to single-pacing site ectopic beats are used as the training data required for estimating the prior statistical model. Additionally, it aims to enhance reconstruction accuracy by examining the impact of varying training intervals on the reconstruction. We hypothesized that using shorter time intervals would improve the accuracy of Bayesian estimates in detecting premature events, such as PVCs, when the onset of the heart's electrical activity is concentrated near the PVC origin.

2. Data and Methods

Data

A total of 10 patients (2 females and 8 males, with a mean age of 49 $\pm$ 17 years) from the Bratislava dataset [4] were used to localize the PVC source. Body surface potentials (BSP) were captured using the ProCardio 8 measuring system with 128 torso electrodes. To enhance signal quality, recorded signals were pre-processed to remove baseline drift and eliminate noise. The patient-specific 3D geometrical meshes representing the ventricles and torso were generated based on CT scan data. The origin of PVC was identified during the radiofrequency ablation procedure following BSP measurement. Additional details about the Bratislava dataset are available in [4].

Bayesian Estimation

The torso potentials $y(t)$ at a given time t are related to the epicardial potentials $x(t)$ through the formulation of the forward problem as

$$y(t) = Ax(t) + n(t),\ t = 1, \ldots, T \tag{1}$$

where A is a transfer matrix and $n(t)$ is the measurement noise. In the inverse problem, one would like to recom-

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pute the epicardial potentials x using measured torso potentials y. This can be also achieved by the Bayesian estimate defined as

$$\hat{x} = (A^T C_n^{-1} A + C_x^{-1})^{-1} (A^T C_n^{-1} y + C_x^{-1} \bar{x}). \quad (2)$$

Here, we assume that epicardial potentials x have a normal prior distribution with mean $\bar{x}$ and covariance C_x. Furthermore, we assume that noise n is independent and identically distributed with covariance $C_n = \sigma_n^2 I$ for $n \sim N(0, C_N)$. More details about the Bayesian estimate can be found in [3].

Transfer matrices A were calculated using the boundary element method for each patient, considering homogeneous torso models [5]. The measurement noise n was determined from torso potentials y for each patient individually. The noise was defined using the baseline signals.

Training Dataset

Prior information for the Bayesian estimation was acquired from a training set comprising simulated epicardial potential maps computed for individual PVC origins. This training data set was used to compute the mean $\bar{x}$ and covariance C_x.

Patient's simulations were computed for 103 up to 306 starting points (PVC origins) evenly distributed in a 10 mm grid through the endo-epicardial ventricular volume, as illustrated in Figure 1 A for patient P1. Each simulation was computed for the whole duration of PVC derived from recorded BSP. The training dataset was constructed by concatenating all epicardial simulations and it is defined as $X = [X_{PVC_1}, X_{PVC_2}, ..., X_{PVC_L}]$ where L is the total number of PVC simulations. The size of X_{PVC_i} corresponds to the number of nodes in the volume of the ventricular myocardium by the number of time frames.

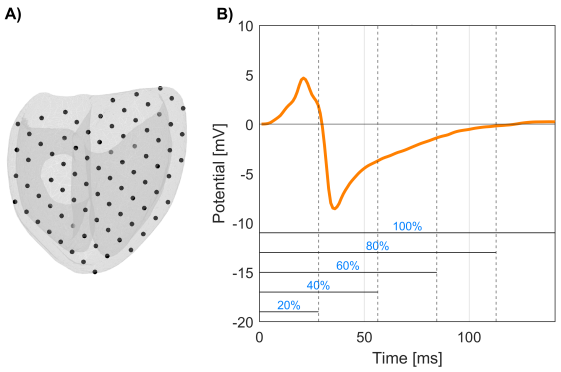

Figure 1. A) Starting points (black) for PVC simulations in patient P1. B) The time intervals selected for training depicted in the EGM of a specific starting node in the ventricular myocardium volume.

In this study, we examine the accuracy of the Bayesian estimate under varying training time intervals. Specifically, we assess intervals ranging from 20% of the total duration up to the entire duration of each test beat, incrementing in steps of 20% as shown in Figure 1 B for the electrogram (EGM) of one cardiac node.

Validation

The Bayesian estimate was used to reconstruct the epicardial potentials for all patients and all 5 training time intervals. The activation sequences were computed from the reconstructed potentials using a spatiotemporal method [6], and the origin of PVC was subsequently identified. The localization error (LE) was calculated by determining the Euclidean distance between the ablation point and the Bayesian estimate result. The ablation point was identified using the same heart model, which was used in the inverse solution. If multiple ablation points were present, the mean ablation point was considered for computing the localization error.

3. Results

The Bayesian estimate was calculated for 10 patients to localize the origin of a single PVC. Five training time intervals were used for each patient. Figure 2 illustrates the activation times (AT) for three different patients across all five training time intervals. Furthermore, it depicts the positions of the ablation point(s) and highlights the minimum of AT.

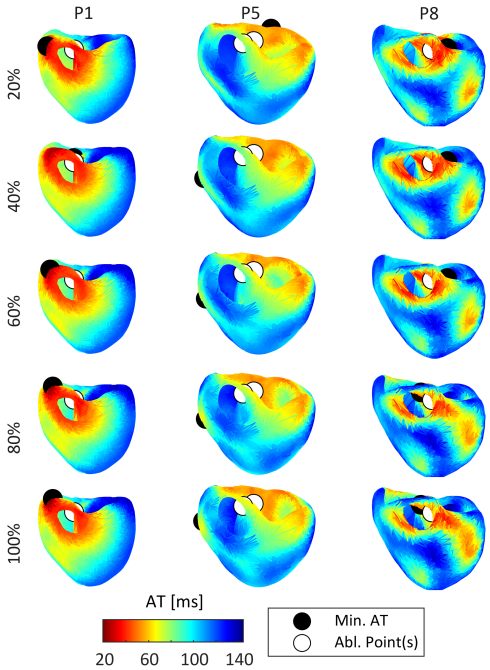

Figure 2. Activation times (AT) for 5 training time intervals for patients P1, P5 and P8. The ablation points are represented in white, while the minimal activation time (Min. AT) estimated from epicardial potentials is represented in black.

The LE was calculated for each patient and training time interval, as detailed in Table 1 and illustrated in Figure 3. The lowest mean LE of 31.0 ± 16.1 mm was observed for the 100% training time interval. Furthermore, the lowest median value of 25.3 mm was found for the 80% and 100% training time intervals. The smallest interquartile range (IQR) of 21.8 mm was found for the 20% training time interval, followed by 24.4 mm for the 100% training time interval. Figure 4 illustrates the distribution of LE values across each training time interval for all patients.

Table 1. The LE in mm for each training time interval and patient along with the mean, standard deviation (STD), median, and interquartile range (IQR) for each training time interval.

Patient ID	20%	40%	60%	80%	100%
P1	30.9	11.0	29.2	27.8	27.8
P2	50.0	26.9	59.1	59.1	61.1
P3	20.9	20.0	21.2	22.8	21.6
P4	22.9	28.9	28.9	30.3	28.9
P5	55.8	59.8	59.4	59.4	56.4
P6	8.7	35.3	14.0	14.0	18.8
P7	39.4	46.1	43.2	18.4	18.4
P8	18.2	18.2	18.2	15.7	15.7
P9	29.1	54.1	45.9	52.5	38.7
P10	39.3	11.2	22.8	22.8	22.8
Mean	31.5	31.2	34.2	32.3	31.0
STD	14.7	17.4	16.6	17.9	16.1
Median	30.0	27.9	29.0	25.3	25.3
IQR	21.8	31.6	28.8	36.5	24.4

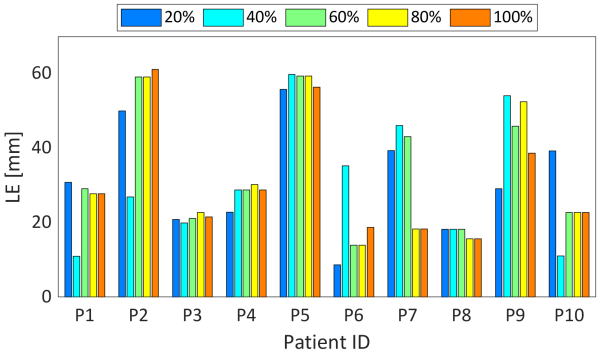

Figure 3. The LE in mm for each patient and each training time interval.

4. Discussion and Conclusion

In this study, the Bayesian estimate was used to localize the source of spontaneous PVC in a cohort of 10 patients from the Bratislava dataset [4], [7]. A training dataset

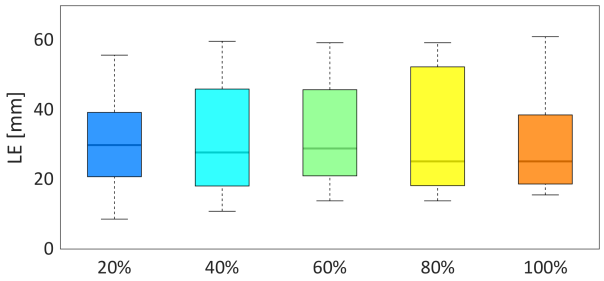

Figure 4. The distribution of LE values depicted as boxplot for each training time interval. The median is represented by the central line, while the lower and upper edges of the box represent the 25^{th} and 75^{th} percentiles, respectively.

was created using simulated epicardial potentials originating from multiple single PVC sources distributed across various regions of the myocardium. The training dataset was compiled using 20% to up to the entire duration of the QRS, aiming to examine the potential impact of training duration on the accuracy of the Bayesian estimate in localizing premature events such as PVC.

Figure 2 shows the AT obtained for each training time interval and three selected patients. Among these patients, two demonstrate good accuracy (P1 and P8), while one exhibits lower accuracy (P5) in estimating the origin of PVC. In P1, the minimum AT was found at the base of the right ventricle (RV), near the ablation point that was located in the right ventricle outflow tract (RVOT). For P8, the origin of the PVC was identified also in the the RVOT. Despite the small LE observed in patient P8, the Bayesian estimate results indicated the origin in the base of the left ventricle (LV). Patient P5 exhibited a lower accuracy in identifying the origin of the PVC. For P5, the ablation points were identified at the septum between RV and LV. However, the Bayesian estimate results consistently placed the origin of PVC on the endocardial layer in the RV-free wall for training time intervals ranging from 40%. Moreover, it's notable that the AT sequences appear scattered for patients P5 and P8, exhibiting multiple local minima. Enhancements in results could be achieved by refining the training dataset to encompass more information from the base of the ventricles, where PVC origins are often located [8]. Furthermore, using alternative methods to determine the minimal AT, such as those considering the size of regions with local minima, may also lead to improvements in accuracy.

The results for each patient and training time interval are summarized in Table 1 and depicted in Figure 3. For certain patients, like P3 and P8, the accuracy remains relatively stable across various training time intervals. However, for others, such as P7 and P9, the accuracy fluctuates more. Additionally, certain patients achieved good accuracy, such as P3 and P8 with LE values below

25 mm, while others, like P2 or P5, exhibited higher LE exceeding 50 mm. The training dataset was constructed using simulated epicardial potentials from various origins. However, simulations were not conducted for the ablation point, resulting in a model error calculated as the distance between the ablation point and the nearest simulation point. The mean model error was 6.3 mm $\pm$ 2.9 mm, with the lowest model error of 2.3 mm for P2 and the highest 11.9 mm for P6. This model error may influence the results of the Bayesian estimate. In the future, it would be intriguing to explore whether incorporating simulation data for the ablation point into the training dataset leads to improvements.

The distribution of LE values for each training time interval is depicted in Figure 4. Variation in mean LE was observed between training time intervals, with higher mean LE associated with longer training time intervals such as 60%. However, the lowest mean LE was observed for 100% training time interval. Furthermore, an increase in the STD of LE was observed with longer training times, indicating greater variability. Analyses of median and IQR further illustrated fluctuations between training time intervals. The lowest median was observed for 80% and 100% training time intervals. Considering the relatively small mean, median, and IQR, selecting a 100% training time interval seems like a good choice for the Bayesian estimate. However, if one prefers to save computational time when constructing a training dataset or would like to obtain preliminary results quickly, opting for a shorter time interval is an option. Nevertheless, these results were obtained for a limited number of patients and based on the assumption of a homogeneous torso model. The research [7] indicates disparities in localization accuracy between homogeneous and inhomogeneous torso models for potential-based methods. Therefore, in the future, we plan to conduct a similar analysis using an inhomogeneous torso model.

The inverse solutions were calculated using Tikhonov regularization on the same dataset as used in the study. These results are summarized in [7]. The mean LE of 31.0 ± 16.1 mm achieved with a 100% training time interval was lower than the LE of 37.6 ± 17.8 mm reported for the same dataset using an inverse solution with Tikhonov regularization. This work suggests that the Bayesian estimate can be used to localize the origin of PVC with improved accuracy to the Tikhonov regularization. However, both methods have their benefits and drawbacks. Bayesian estimation's ability to provide statistical performance analysis tools and to include prior knowledge enhances the interpretability and reliability of estimations. However, its reliance on prior information can be also a limitation, as obtaining such information may be challenging. Tikhonov regularization offers a straightforward approach to address the ill-posedness of the inverse problem but may oversmooth solutions due to parameter tuning. The choice between the methods depends on factors like input data characteristics, computational efficiency, and the required output parameters.

Overall, this study underscores the potential of Bayesian estimation to reconstruct the electrical activity of the heart and to localize the origin of ectopic activity such as PVC.

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References

[1] Rudy Y, Messinger-Rapport B. The inverse problem in electrocardiography: solutions in terms of epicardial potentials. PubMed 1 1988;16(3):215–68.

[2] Tikhonov AN, et al. Numerical methods for the approximate solution of ill-posed problems on compact sets. Dordrecht: Springer Netherlands, 1995; 65–79.

[3] Serinagaoglu Y, Brooks D, Macleod R. Improved performance of bayesian solutions for inverse electrocardiography using multiple information sources. IEEE Transactions on Biomedical Engineering 2006;53(10):2024–2034.

[4] Svehlikova J, et al. The importance of ecg offset correction for premature ventricular contraction origin localization from clinical data. Measurement Science Review 2022; 22(6):246–252.

[5] Barr RC, Ramsey M, Spach MS. Relating epicardial to body surface potential distributions by means of transfer coefficients based on geometry measurements. IEEE Transactions on Biomedical Engineering 1977;BME-24:1–11.

[6] Erem B, et al. Using transmural regularization and dynamic modeling for noninvasive cardiac potential imaging of endocardial pacing with imprecise thoracic geometry. IEEE Transactions on Medical Imaging 2014;33(3):726–738.

[7] Serinagaoglu Y, et al. Comparison of dipole-based and potential-based ECGI methods for premature ventricular contraction beat localization with clinical data. Frontiers in Physiology 6 2023;14.

[8] Iwai S, et al. Right and left ventricular outflow tract tachycardias: Evidence for a common electrophysiologic mechanism. Journal of Cardiovascular Electrophysiology 2006;17(10):1052–1058.

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