Assessment of 12-lead ECG-based Noninvasive Electro-Anatomical Mapping Accuracy: Incorporating Fibrosis Data in Advanced Computational Algorithms

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Abstract

Restoring cardiac activation maps using a 12-channel ECG is a promising field in digital medicine with the potential to improve the management of cardiac disorders. This study examines the effect of incorporating detailed fibrosis data into the reconstruction of cardiac activation maps. Using retrospective data from 15 non-ischemic heart disease patients, we compared activation maps and ECGs generated with and without fibrosis information. The methodology involved solving the forward ECG problem using the eikonal equation and the lead field approach, followed by machine learning-based reconstruction. Accuracy was assessed using Spearman correlation coefficients and the mean absolute difference in local activation times.

Our results indicated that including fibrosis data enhanced the alignment of calculated ECGs with recorded signals, increasing the mean correlation coefficient from 0.74 to 0.78. However, this improvement was not statistically significant, indicating a limited impact on quantitative accuracy.

In conclusion, while fibrosis data aids in visualizing delayed activation areas, it does not significantly improve ECG-based map accuracy. Further research with larger datasets and advanced imaging is required to fully explore its clinical potential.

1. Introduction

Restoring cardiac activation maps using a 12-channel ECG is a promising area in digital medicine. This approach holds significant potential for enhancing physicians' ability to understand and predict the mechanisms underlying various cardiac disorders, as well as aiding in therapy planning and disease management [1–3]. Traditionally, these methods rely on medical imaging data to reconstruct the anatomy of the heart and ECG signals from the torso surface, generating a potential map on a geometric model of the heart [4, 5]. Recent studies have demonstrated a good correlation between noninvasive and invasive activation maps [4, 6, 7].

In this study, our objective was to improve previous methods of reconstructing activation maps from a 12-lead ECG [8] by incorporating detailed fibrosis information. The specific aims of this research are to investigate whether additional patient characteristics, such as the presence of complex fibrotic areas, can improve the accuracy of noninvasive activation maps. Examine the impact of fibrosis information on the accuracy of activation maps. Compare the differences in the results of methods that incorporate fibrosis data with those that do not.

By addressing these aims, we propose to provide a deeper understanding of how incorporating fibrosis information can enhance the accuracy and reliability of cardiac activation maps, thus improving diagnostic and therapeutic strategies in cardiac care.

2. Materials and Methods

2.1. Clinical data

This study utilized retrospective data from fifteen patients with a wide QRS complex (greater than 120 ms). The mean age was 59 ± 9.8 years, and 46.7% of the participants were male. Primary diagnoses included left bundle branch block (with typical or atypical ECG patterns) and non-ischemic cardiomyopathy.

The dataset included cardiac late gadolinium enhancement Magnetic Resonance Imaging (MRI), computer tomography (CT) data, and 12-lead ECG recordings. The 12-lead ECG recordings were digitized and processed to remove noise and artifacts. These signals were then mapped onto the surface of a torso model by aligning the positions of the ECG electrodes with the corresponding

points in the torso.

For each patient, a medical expert created a 3D patient-specific geometric model of the heart, torso, and lungs using automated segmentation of CT scans and a geometric model of the left ventricle (LV) and right ventricle (RV). Fibrotic regions were identified and manually segmented from the MRI images with gadolinium-enhancement using a threshold-based approach. This approach included three steps: LV boundaries segmentation, fibrosis segmentation at 5 standard deviations, and reconstruction of the three-dimensional model of LV with fibrotic regions. The segmented fibrosis was then incorporated into the geometric model of the heart. Segmentation of the MRI data was performed using 3D Slicer [9] software.

2.2. Merging CT and MRI geometry

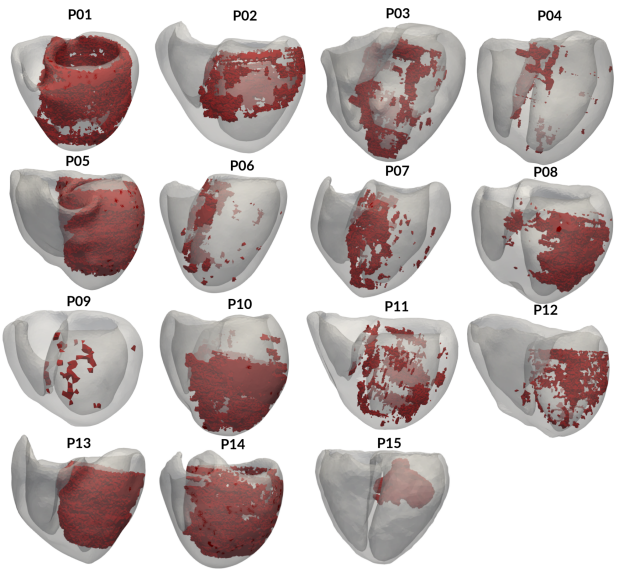

Figure 1. Personalized geometric models of ventricles from CT scans and fibrosis geometry from MRI scans. Ventricle and fibrosis geometries were manually merged.

The manual merging of the ventricular and fibrosis models from the CT and MRI scans was performed in the Paraview software using the Transform filter. The results of merged personalized cardiac models for 15 patients including fibrotic regions are shown in figure 1. To measure the quality of model merging for ventricles from CT scans and fibrosis from MRI scans, we calculated the Hausdorff distance between endocardial LV surfaces from CT and MRI scans.

2.3. Electrophysiology model

We utilized a previously developed algorithm for non-invasive map reconstruction [8]. This approach involves solving the forward ECG problem and then using a machine learning (ML) algorithm to find the best-fit solution. The forward ECG problem was solved using the eikonal equation and the lead-field approach to simulate the potential distribution on the torso surface. To obtain different resulting activation maps and ECG signals, the forward problem was solved using a variety of conductivity and activation source parameters. Subsequently, an ML algorithm was applied to determine the cardiac activation map that best fits the observed ECG data. In this step, the ECG signals were transformed into latent space features using a convolutional variational autoencoder, and then the few closest solutions to the patient's ECG were identified using mean squared error between features in the latent space. The mean activation maps are considered as the resulting activation maps.

2.4. Fibrosis modeling

The presence of fibrosis was incorporated into the activation map calculations by adjusting the tissue conductivity in the fibrotic regions. During the reconstruction of the activation map, the conductivity parameters were constrained to $0.24m/s$ within the fibrotic zones and $0.36m/s$ within the gray zones. These boundaries were selected based on extensive data indicating the slowing of the excitation wave in fibrotic and gray zone regions as shown in numerous studies (e.g., [10]). This adjustment was implemented to more accurately reflect the electrical propagation characteristics of the heart in the presence of fibrosis.

2.5. Comparison metrics

We compared the computed activation maps and ECGs generated with and without the inclusion of fibrosis information. To evaluate the accuracy and consistency of ECGs and activation maps, we employed quantitative measures such as Spearman correlation coefficients and the mean absolute difference in local activation times.

To assess the statistical significance of the improvements observed after incorporating fibrosis information, we used the Wilcoxon test.

The activation map reconstruction and analysis processes were implemented using custom software developed in Python.

3. Results

A total of 15 patients with LBBB cardiac disorders were included in this study. The custom software developed for this study efficiently handled the reconstruction and analysis tasks. The average computation time to generate an activation map was approximately 15 minutes, which is suitable for clinical use. The pipeline for analysis is presented

in Figure 2. It starts with the segmentation of CT and MRI images and the alignment of the resulting geometries. The Mean Hausdorff distance between segmented CT and MRI endocardial LV surfaces was 1.10 ± 0.40 cm for 15 personalized models (at the same time, the average segment length of the 17-segment AHA model was 3.62 ± 0.99 cm). We then calculated two activation maps with and without fibrosis and compared the ECG and activation maps.

3.1. ECG validation

The reconstructed activation maps were validated by comparing the calculated ECG signals with the actual recorded ECG signals. The initial comparison showed a high mean correlation coefficient ($r = 0.74 \pm 0.06$, $p < 0.001$), indicating good agreement between the calculated and recorded ECGs.

When detailed fibrosis information was incorporated into the activation map reconstruction, the accuracy of the calculated ECG signals improved. The mean correlation coefficient increased to $r = 0.78 \pm 0.05$ ($p < 0.001$). This improvement demonstrates that including fibrosis data enhances the agreement between the calculated and recorded ECGs.

However, we found that the inclusion of fibrosis information did not result in a statistically significant difference (0.47, $p > 0.05$) between the correlation coefficients with and without fibrosis incorporation. This indicates that while the information about fibrosis can improve the visual and qualitative aspects of cardiac mapping, it may not be as crucial to the quantitative reproduction of ECG signals.

3.2. Effect of Fibrosis on Activation Maps

The inclusion of fibrosis information had a notable impact on activation maps. Regions with dense fibrosis exhibited altered activation patterns compared to non-fibrotic areas. This was particularly evident in patients with extensive fibrosis, where activation delays averaged $15 \pm 7ms$ in the fibrotic regions. In contrast, the activation times in non-fibrotic regions did not show significant changes.

The mean correlation coefficient between activation maps with and without fibrosis information was 0.91 ± 0.08, indicating that overall activation patterns were largely consistent, but significant fibrosis regions caused localized changes. This high correlation suggests that while the general activation map remains stable, the presence of fibrosis introduces important localized delays that are crucial to accurately representing the electrical activity of the heart.

3.3. Case Study

A case study of a patient with non-ischemic heart disease highlighted the practical benefits of incorporating information on fibrosis. As shown in Figure 2, the calculated ECG signals with fibrosis data demonstrate a better fit to the recorded ECGs compared to those without fibrosis data. The activation maps provided a detailed visualization and showed delayed activation areas, particularly in regions with fibrosis. A comparison of activation maps reveals distinct differences in activation patterns in the fibrosis regions, underscoring the importance of including fibrosis information to accurately reconstruct cardiac activation maps.

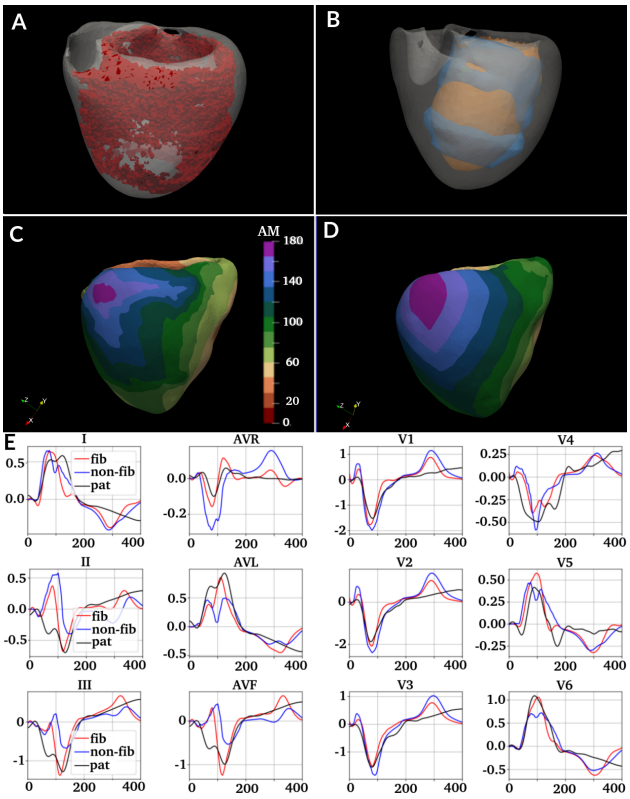

Figure 2. Patient 01. Reconstructed fibrosis geometry (A). CT reconstructed ventricular geometry and MRI reconstructed endocardial surface (B). Activation maps were reconstructed with fibrosis information (C) and without fibrosis information (D). Comparison of ECGs (E): clinical ECG signal (black lines), computed ECGs based on reconstructed activation maps with and without incorporated fibrosis (red and blue lines respectively).

4. Discussion and Conclusion

The findings of this study highlight the nuanced impact of incorporating fibrosis information in the reconstruction

of cardiac activation maps from 12-lead ECGs. Although integrating detailed fibrosis data improved the alignment of the calculated ECG signals with the recorded ECGs, the mean correlation coefficient increased from 0.74 to 0.78, this improvement is not statistically significant according to the Wilcoxon test. This suggests that while information on fibrosis can improve certain qualitative aspects of activation maps, its impact on the quantitative accuracy of ECG reproduction may be limited. Similar results were achieved in Lopez-Perez et al. [11], where similar ECG signals were obtained with and without inclusion of fibrosis, but inclusion of fibrosis in the model was very important for the analysis of ventricular tachycardia.

The case study of a patient with non-ischemic heart disease illustrates the practical benefits of this approach. The activation maps that included fibrosis information not only matched the recorded ECGs more closely but also revealed distinct activation patterns within the fibrotic regions. These patterns, characterized by delayed activation, are critical for understanding the underlying electrophysiological changes associated with fibrotic tissue.

However, several limitations need to be addressed in future research. First, the retrospective nature of the study and the limited sample size may affect the generalizability of the findings. Expanding the dataset to include a larger and more diverse patient population would enhance the robustness of the results. Secondly, the accuracy of the fibrosis segmentation from MRI images relies heavily on the threshold-based approach, which might not capture all nuances of fibrotic tissue. Advanced imaging techniques and more sophisticated segmentation algorithms could further improve the fidelity of fibrosis incorporation.

In conclusion, incorporating detailed fibrosis information into the reconstruction of cardiac activation maps from 12-lead ECGs enhances the accuracy and provides valuable insight into the electrophysiological behavior of the heart, particularly in fibrotic regions. This approach holds promise in improving the diagnostic and prognostic capabilities in the management of cardiac disorders, paving the way for more personalized and precise treatment strategies. Further research and technological advances are needed to overcome current limitations and fully realize the potential of this methodology in clinical practice.

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