Electroanatomic Mapping to determine Scar Regions in patients with Atrial Fibrillation

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Abstract—Left atrial voltage maps are routinely acquired during electroanatomic mapping in patients undergoing catheter ablation for atrial fibrillation. For patients who have prior catheter ablation when they are in sinus rhythm, the voltage map can be used to identify low voltage areas using a threshold of 0.2 - 0.45 mV. However, such a voltage threshold for maps acquired during atrial fibrillation has not been well established. A prerequisite for defining a voltage threshold is to maximize the topologically matched low voltage areas between the electroanatomic mapping acquired during atrial fibrillation and sinus rhythm. The results show that the proposed method is an improvement in specificity compared to the standard method. The same patient distorts the LVAs distribution. After adjusting to a lower threshold, as in (c), the LVAs on the AF map are restored to match the SR map.

Several studies have shown that the local atrial signal acquired during AF is lower than in SR. Thus, identifying LVA during EAM in AF should require a lower cutoff voltage [3]. However, determining a consistent threshold that can be applied to all patients remains challenging. A prerequisite is determining the best match of LVAs that can be obtained between the SR map and the AF map and thereby finding the best threshold to be applied on a patient-by-patient basis.

Problem Statement: Given a set of measurements during SR and AF for a patient, maximize the topologically matched LVAs between the derived SR and AF map and determine the best patient-specific cutoff voltage threshold.

In this paper, we demonstrate a method of deriving the AF map which is robust to noise and error in the measurements and improves the patient-specific sensitivity and specificity of matched LVAs in comparison to the standard method through the following contributions:

- Compute omni-directional bipolar voltages which are invariant to the orientation of the catheter, thus improving signal strength during AF.
- Apply Gaussian process regression (GPR) interpolation which improves the accuracy of LVA detection in regions of the atrium with lower measurement density.

II. BACKGROUND: STANDARD VOLTAGE MAP

Fig. 2 depicts the steps of deriving the current standard left atrial (LA) voltage map during catheter ablation of AF. Initially, as in (1), a 3D anatomical mesh is generated by manipulating a multi-electrode mapping catheter (Lasso or Pentaray) to different parts of the LA [4]. As the mesh is being created, recordings of 2.5 seconds of electrogram are collected at various locations around the endocardium. (2) shows the

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locations of all such sampled points on the LA mesh. The voltage value is interpolated to the remaining areas of the mesh to derive the final voltage map as shown in (3). The colors of the voltage map are based on a pre-specified cutoff threshold, where areas above the threshold are marked in magenta, and areas below the threshold are considered LVAs.

Fig. 2. Standard method of deriving voltage map. (1) Anatomical mesh is computed from catheter locations. (2) Bipolar voltages are computed from measurements of electrogram at points along the mesh. (3) The bipolar voltages are interpolated to the remainder of the mesh to derive the voltage map.

Fig. 3 shows that within the 2.5 seconds, a 300 ms time window is defined relative to the QRS peak, and the peak-to-peak voltage is computed within the time window.

III. ROBUST METHOD FOR VOLTAGE MAP DERIVATION

Our proposed robust method deriving the voltage map differs from the standard method in terms of two components: a) omni-directional bipolar voltage and b) GPR-based interpolation.

a) Omni-directional bipolar voltage: Fig. 4 shows a limitation of bipolar recording, the dependency on electrode orientation. If the bipolar placement is parallel to the isoelectric potential line, the bipolar recording will be zero, which does not reflect the local electric activity [5]. To reduce such dependency, we derive the omni-directional bipolar voltage. For each sample point, we select the unipolar electrogram recorded in the vicinity of the sample and compute all possible bipolar electrogram from this set. We approximate the omni-directional bipolar voltage as the largest bipolar amplitude from this set. Fig. 4 (1) Blue depicts the histogram of the voltages for a patient. Red shows how the corresponding voltages are amplified. In the tail portion, the voltages of some LVAs have increased above the threshold to be classified as healthy tissue. (2) and (3) exemplifies how the original red areas of voltage $\sim 0.06$ mV are enhanced into yellow and green areas of voltage $\sim 0.17$ mV.

Fig. 4. Benefits of using omni-directional bipolar voltages. (1) Bipolar voltages in AF (blue) are amplified (red), improving the signal. (2), (3) Regions of previously low voltage (red in (2)) are increased after computing omni-directional bipolar voltages (yellow in (3)).

b) Gaussian process regression based interpolation: If we model the endocardium as a surface and define the entire set of samples as, $D = \{x_n, y_n\}_{n=1}^N$, where inputs $X = \{x_n\}_{n=1}^N$ correspond to the locations on the mesh and $y = \{y_n\}_{n=1}^N$ are the voltage value at that location. Interpolating from these measured samples to the remainder of the mesh can be thought of as determining the estimates of the voltages at locations $X^*$. The two major sources of interpolation error are the low measurement density and measurement noise. Both of these can be accounted for by modeling them using a Gaussian process $GP(m(x), k(x,y'))$ [6], which is characterized by the mean $m(x)$ and the covariance $k(x,y')$ kernel functions. We assume the common zero mean function and use the squared exponential function $k(x,y') = \exp(-||x-x'||/(2\cdot l^2))$. Fig. 5(1) shows how the standard interpolation can result in regions that are classified as LVAs, due to interpolation error. (2) shows GPR-based interpolation can improve the boundaries of LVAs by considering the surrounding measurements.

For determining the optimum threshold, a search in the range of 0-0.45 mV is performed to maximize the product of sensitivity and specificity. Here, sensitivity $= \frac{TP}{TP+FN}$ and specificity $= \frac{TN}{TN+FP}$, where a true positive (TP) indicates that the corresponding face on the anatomical mesh is detected as a LVA and the true label is a LVA.

The proposed method of voltage map derivation was eval-
Fig. 6. Experimental setup. For each patient: From the SR map (1), LVA are determined (2) as well as the region of interest (3). Both (2) and (3) are topologically transferred to the AF map (4) and (5). (4) and (5) are intersected to obtain the true LVAs on the AF map (6). The optimal patient-specific threshold is determined by maximizing the product of sensitivity and specificity according to (8).

On average, our proposed method showed a sensitivity and specificity of 75.70% and 66.55%, respectively. This was a 3.00% improvement in the geometric mean compared to the standard method. Moreover, our proposed method exhibited a 7.88% improvement in sensitivity and a 0.30% improvement in specificity. ROC curves were obtained for each of the methods and the area under the curve was computed as shown in Fig. 7. Our proposed method showed an average of 3.91% improvement in terms of the area under the curve (AUC).

The overall evaluation process is depicted in Fig. 6. From the original data (1), we apply the standard 0.45 mV cutoff threshold on the SR map to identify regions of LVA (2). We select a region of interest (ROI) on the SR map (3), which consists of the posterior LA and pulmonary vein (PV) junctions. Both the LVA and the ROI is transferred to the AF mesh and intersected to form the final LVA on the AF map (4),(5),(6). Then result (7) is determined as shown in (8) in terms of sensitivity and specificity.

V. RESULTS AND DISCUSSION

A total of 46,589 data points were included in analysis, that was on average 6,656 data points for each of the 7 patients. Table I summarizes the results of evaluation for each patient.
case the combination of omni-directional bipolar voltages enhances the signal, and GPR-based interpolation filters such noise, preventing classification as LVAs.

In patient 7, our proposed method did not improve performance. Upon further inspection, we discovered that 90% of the ROI was LVA as shown in Fig. 9. This patient had undergone prior extensive surgical ablation and so had extensive areas of dense scar in the ROI, making discrimination difficult. Optimizing the threshold with a different criterion which accounts for this bias may result in a better outcome.

In this work, we have presented a method for deriving the voltage map during AF and comparing it to voltage maps acquired during SR. Our method computes omni-directional bipolar voltages from the measurements and utilizes GPR-based interpolation to derive the voltage map. Evaluation on the test cohort showed that, in general, the method improved

The patient-specific sensitivity and specificity in determining LVAs of the AF map compared to the standard method, though some exceptions exist. This improvement in matched areas between the maps is significant and has important practical implications as clinicians interpret voltage maps according to the areas and not by the individual point measurements. More accurate information about LVA distribution is helpful to clinicians in planning ablation strategies for patients who require repeat catheter ablation for arrhythmia recurrences.

Immediate future work is to apply the method over a larger cohort. In a practical clinical setting, patient-to-patient variability may need to be accounted for in the criterion. Overall, the results provide evidence that the proposed method improves the detection of LVAs in AF maps. Because of the robustness to measurement noise and interpolation error, the proposed method could lead to a more consistent criterion.

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### TABLE II

| Patient | Sens. | Sens. | GM | Spec. | Spec. | Voltage Threshold | Sens. | Sens. | GM | Spec. | Spec. | Voltage Threshold | ΔSens. | ΔSpec. | ΔGM | ΔSpec. |
|---------|-------|-------|----|-------|-------|-------------------|-------|-------|----|-------|-------|-------------------|--------|--------|----|--------|
| 1       | 76.18 | 63.56 | 69.58 | 0.72 | 0.26 | 84.92 | 70.74 | 77.51 | 0.85 | 0.23 | 42.53 | 11.40 | 11.40 | 0.30 | 11.60 |
| 2       | 54.87 | 57.64 | 56.24 | 0.57 | 0.32 | 72.72 | 47.49 | 58.77 | 0.61 | 0.11 | 32.53 | 17.89 | 71.48 | 62.66 | 17.89 |
| 3       | 77.38 | 71.48 | 74.37 | 0.80 | 0.16 | 91.22 | 69.59 | 79.67 | 0.86 | 0.15 | 17.89 | 71.48 | 71.48 | 62.66 | 17.89 |
| 4       | 79.52 | 78.08 | 78.80 | 0.85 | 0.26 | 85.42 | 77.07 | 81.14 | 0.89 | 0.30 | 7.42 | 1.29 | 7.42 | 1.29 | 7.42 |
| 5       | 58.08 | 66.88 | 62.32 | 0.67 | 0.36 | 69.24 | 56.71 | 62.66 | 0.66 | 0.38 | 19.21 | 15.21 | 57.64 | 57.64 | 15.21 |
| 6       | 80.61 | 74.64 | 77.57 | 0.83 | 0.32 | 72.87 | 83.41 | 77.96 | 0.85 | 0.21 | -9.60 | 11.75 | 50.00 | 50.00 | 11.75 |
| 7       | 70.24 | 52.57 | 60.77 | 0.63 | 0.10 | 53.54 | 60.87 | 57.09 | 0.61 | 0.17 | -23.78 | 15.79 | 50.00 | 50.00 | 15.79 |
| Average | 70.98 | 66.41 | 68.52 | 0.73 | 0.22 | 75.70 | 66.55 | 70.69 | 0.76 | 0.22 | 7.88 | 0.30 | 7.88 | 0.30 | 7.88 |
| Std     | 10.49 | 9.19  | 8.87  | 0.11 | 0.11 | 12.72 | 12.54 | 10.65 | 0.13 | 0.09 | 18.96 | 13.32 | 5.54  | 5.54  | 13.32 |

**Fig. 8.** Example of improved result: Patient 1, baseline vs proposed method.

**Fig. 9.** Patient 7. Baseline vs proposed method. Poor performance can be attributed to the dominance of LVAs in the ROI, thus penalizing specificity.

**Fig. 9.** Patient 7. Baseline vs proposed method. Poor performance can be attributed to the dominance of LVAs in the ROI, thus penalizing specificity.