Longitudinal Analysis of EGM Dynamics near Ablation Points in Idiopathic Ventricular Arrhythmia

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Abstract

Idiopathic ventricular arrhythmias pose a challenge due to unclear underlying mechanisms. This study analyzes electrogram (EGM) data from three patients who underwent radiofrequency ablation (RFA), using feature extraction and dimensionality reduction to characterize signals near ablation sites. Findings show regions with similar EGM morphology do not always correspond spatially within the heart, and features like FFT coefficients and ECDF percentiles significantly correlate with effective ablation sites. These markers could improve ablation accuracy, enhancing outcomes for idiopathic ventricular arrhythmia.

1. Introduction

Idiopathic ventricular arrhythmias (IVAs) are arrhythmias originating from the ventricles without structural heart disease, posing significant management challenges. Radiofrequency ablation (RFA) is often employed when drug therapies fail, necessitating accurate identification of the effective ablation point within the heart tissue to terminate the arrhythmia [1].

Electroanatomical mapping, utilizing unipolar and bipolar electrograms (EGMs), is essential in this process. The unipolar signal measures the voltage difference between the catheter tip and a distant reference point, usually a virtual electrode on the chest, providing a broad perspective on the electrical activity, including far-field signals. Conversely, the bipolar signal, representing the voltage difference between two closely spaced electrodes on the catheter, offers a more localized view by reducing the influence of distant electrical sources. The bipolar signal's reduced sensitivity to far-field signals makes it valuable for identifying the precise site of abnormal electrical activity, while the unipolar signal is crucial for pinpointing the exact origin of the electrical impulse. The clear negative deflection in a sharp unipolar signal indicates the origin of the impulse, which is vital for accurately localizing the arrhythmogenic focus [2].

Despite the utility of these signals, identifying the effective ablation point remains a complex challenge. The interpretation of EGM signals involves assessing various morphological features, with considerable variability depending on the specific tools and techniques used. Moreover, established guidelines are not always definitive, leading to a reliance on clinician expertise and potentially inconsistent outcomes.

To address these challenges, this study investigates the identification of effective ablation points by analyzing patterns and features within EGM signals. We extracted biomarkers from EGMs using a feature extraction library used by Qaqos et al. to caracterize EGMs [3], which provides a comprehensive set of functions specifically tailored for EGM analysis. Our selection of biomarkers was informed by the work of Sorgente et al., who introduced the concept of negative concordance patterns in unipolar and bipolar signals. Sorgente et al. proposed this pattern as a criterion for localizing the effective ablation point, suggesting that the presence of a sharp negative deflection in the unipolar signal, alongside a corresponding pattern in the bipolar signal, could indicate the optimal site for ablation [2].

In addition to these biomarkers, we conducted a longitudinal analysis of the EGM data using multiple kernel learning (MKL), a technique that has been effectively employed by Sergio Sanchez-Rodriguez et al. [4] to characterize the latent space of biomedical signals. MKL allows for the integration of multiple features, facilitating a more nuanced analysis of signal dynamics over time. We also drew inspiration from Mariana Nogueira's work [5], which utilized longitudinal analysis to uncover underlying pathophysiological mechanisms in nonstandardized stress echocardiography.

By combining these advanced techniques and insights,

our goal is to identify distinctive patterns and features in EGM signals that reliably correlate with effective ablation sites, ultimately improving the precision and success of RFA procedures in idiopathic ventricular arrhythmias.

2. Methods

2.1. Patient Data Collection

Data were collected from three patients who underwent radiofrequency ablation for idiopathic ventricular arrhythmia. The dataset included electrocardiogram (ECG) and EGM signals from multiple points within the heart, as well as a label indicating the effective ablation point. The collection process followed clinical procedures, ensuring high-quality data acquisition.

2.2. Signal Preprocessing and Marker Extraction

Following the methodology outlined by Sorgente et al. [2] and Delacretaz et al. [6], we identified key markers in the EGM signals: the R peak, the onset of the QRS complex, the onset of activation in both unipolar and bipolar signals, and the point of maximum deflection in the unipolar signal. To achieve this, we utilized the ECG segmentation tool developed by Jimenez-Perez et al. [7]. This tool allowed for the precise segmentation of beats corresponding to premature ventricular contractions (PVCs), as shown in figure 1. We focused on a region of interest extending from the R peak up to 300 ms before, as this interval is most likely to contain the markers of interest. Trends in the signal derivative were analyzed to accurately identify these markers, an example of this implementation can be seen in figure 2.

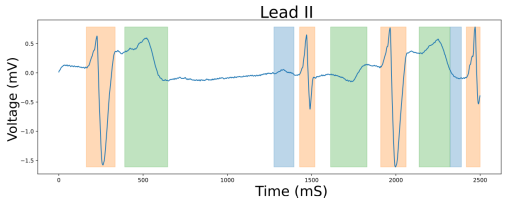

Figure 1. Segmented ECG record. Orange regions represent the QRS complex, blue regions the P wave, and green regions the T wave. The premature ventricular contraction (PVC) beat is located around the second 2.

2.3. Feature Extraction and Dimensionality Reduction

To apply Multiple Kernel Learning (MKL), we used only the unipolar and bipolar EGM signals. Stimulation

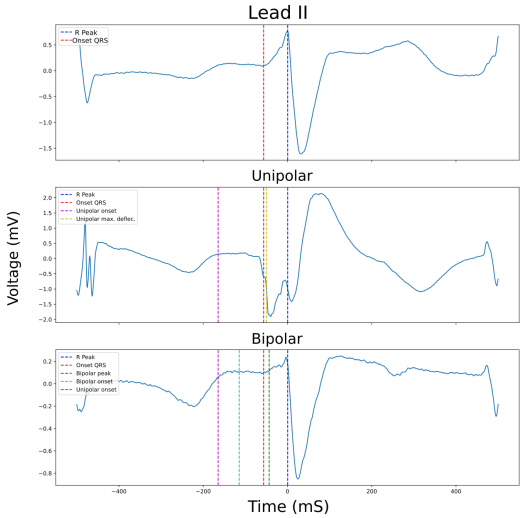

Figure 2. Region of interest with biomarkers. The time axis is centered on the R peak of the premature ventricular contraction (PVC) beat, showing ±400 ms. The lines indicate the biomarkers for each lead. In red, the onset of the QRS complex, in blue, the R peak, in magenta, the unipolar onset, in yellow, the unipolar maximum deflection, in turquoise, the bipolar onset, and in green, the first peak in bipolar.

points used for mapping were excluded from the analysis, and outliers were removed using the Isolation Trees algorithm. The MKL implementation from Jimenez-Perez et al. [8] was then applied to generate the output spaces for each patient, an example of which can be seen in figure 3.

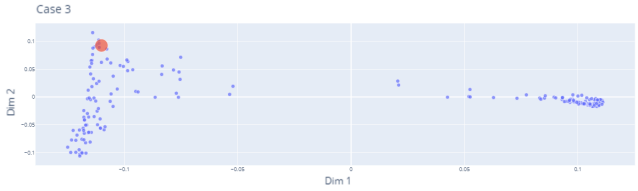

Figure 3. Example of output space. All the points are distributed along the space according to their similarity. The red point corresponds to the effective ablation point.

For feature extraction, we employed the Time Series Feature Extraction Library (TSFEL) [9] as described by Qaqos et al. [3, 10]. This library allowed us to extract a wide range of features from the EGM signals, including time-domain, frequency-domain, and statistical features. Given the high dimensionality of the resulting feature space, we applied principal component analysis (PCA) to reduce the data to two dimensions. This enabled us to visu-

alize the signal distribution and identify patterns that could indicate the effective ablation point.

2.4. Longitudinal Analysis and Statistical Evaluation

We generated the output space for each patient separately, focusing on analyzing the progression of EGM signals in relation to the effective ablation point. By examining the 10 nearest points to the effective ablation point in the output space, we evaluated signal morphology changes and their relationship to anatomical proximity.

3. Results

Due to space constraints, we present detailed analyses for one patient.

3.1. Nearest Points to the Effective Ablation Point

We analyzed the 10 points nearest to the effective ablation point in the output space.

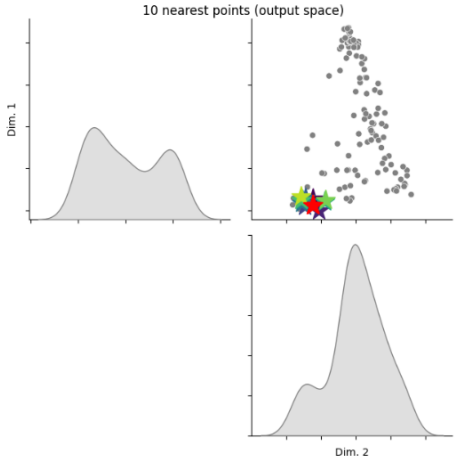

Figure 4. Output space with the nearest points to the effective ablation point.

- **Bipolar Signals:** Minimal changes were observed, except for the furthest points.
- **Unipolar Signals:** Morphological changes appeared closer to the effective ablation point. Notably, all points lacked a peak at the start of the unipolar signal and exhibited a low voltage, high-frequency pattern before the bipolar signal onset.

The signal progression of these points, as shown in Figure 5, illustrates the changes in signal morphology as one moves closer to the effective ablation point in the output space.

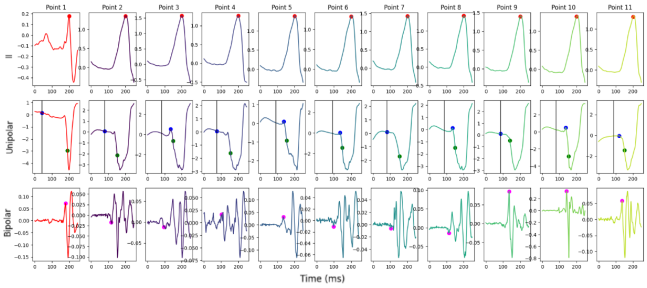

Figure 5. Progression of the nearest points to the effective ablation point in the output space.

3.2. Anatomically Closest Points

We also analyzed the 10 anatomically closest points to the effective ablation point.

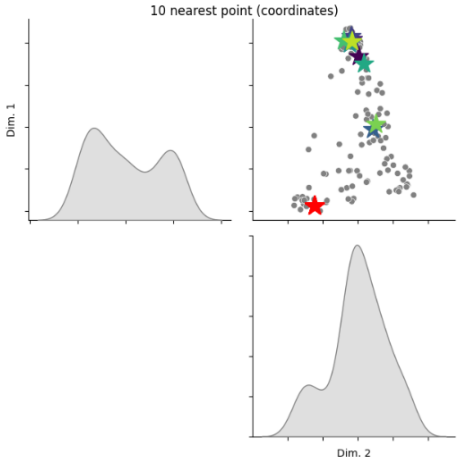

Figure 6. Output space with the anatomically nearest points to the effective ablation point.

- **Unipolar Signals:** Displayed high similarity across points.
- **Bipolar Signals:** Varied significantly. The anatomical proximity did not correlate with signal similarity, as points were spread throughout the output space, indicating that signals from anatomically close regions are not necessarily alike.

The progression of these signals is illustrated in Figure 7, showing how signal morphology changes with anatomical proximity.

3.3. Signal Progression Along Axes

Progression analysis along the X and Y axes of the output space revealed:

- **Y Axis:** Showed more signal variability.
- **X Axis:** Signals, especially unipolar, tended to maintain their morphology.

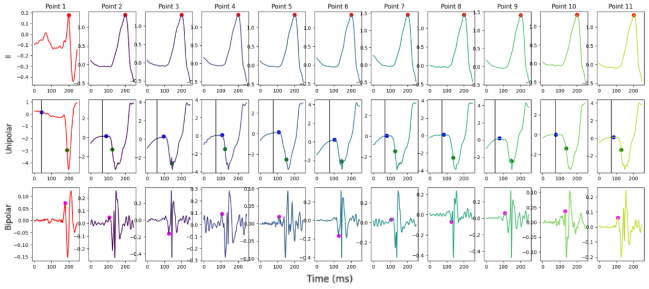

Figure 7. Progression of the anatomically nearest points to the effective ablation point in the output space.

3.4. Statistical Analysis of Biomarkers and Features

• **Biomarkers:** Showed low overall correlation with signal distribution in the output space. For example, precocity (time between bipolar onset and R peak) had a mean correlation of 0.13, and the unipolar deflection feature had a correlation of 0.075.

• **TSFEL Features:** The highest correlations were observed for FFT mean coefficients (0.3 for the third window, 0.296 for the second window) and ECDF percentile (0.28). While FFT features exhibited some spatial patterning in the output space, ECDF and biomarkers did not show clear patterns.

4. Discussion

The results highlight that anatomical proximity does not consistently correlate with signal similarity, emphasizing the need for improved EGM interpretation methods. The stability of unipolar signals suggests their reliability in identifying arrhythmogenic substrates, supporting their combined use with bipolar signals for more accurate ablation point identification.

The low correlation between biomarkers and the output space indicates that relying solely on these markers may not suffice. A multi-faceted approach that incorporates additional EGM features and possibly anatomical data is necessary for optimal results. TSFEL feature analysis shows promise, although further refinement is needed to capture missing information.

5. Conclusion

This study demonstrates the potential of advanced signal processing techniques to improve the identification of effective ablation points in idiopathic ventricular arrhythmia. Combining traditional biomarkers with additional EGM features and anatomical data may enhance RFA accuracy. Future work should validate these findings in larger cohorts and explore integrating more data sources to refine the identification process.

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