Peak-Based Spatio-Temporal Dispersion Classifier of Multipolar Intracardiac Electrograms in Persistent Atrial Fibrillation

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Abstract

Atrial fibrillation (AF) is a common cardiac condition that predominantly affects the elderly, posing a significant risk for stroke and raising public health concerns. Catheter ablation (CA) is the most effective long-term treatment for persistent AF. A novel CA approach based on spatio-temporal dispersion (STD) targets active zones that sustain the arrhythmia. STD detection relies on visual interpretation of multipolar electrograms (EGMs). Identifying local activations time shifting among leads is critical for determining the presence of STD. However, current literature advocating for the use of machine learning (ML) for STD classification lacks a thorough methodological analysis, reproducibility and is challenging for cardiologists to interpret. In this study, we present a new peak-based STD classifier using data solely for testing. This mathematical algorithm models the reasoning process of interventional cardiologists during STD-based CA, translating the manual classification process into signal processing operations to enhance explainability and interpretability. Results show that the peak-based classifier improves accuracy over previous methods.

1. Introduction

A major cause of stroke, atrial fibrillation (AF) is a common irregular heart rhythm that primarily affects the elderly population [1]. From 1990 to 2019, the prevalence of AF increased by 111.04% globally and reached 59.70 million cases [2]. AF is predicted to affect 6–12 million people in the USA by 2050 and up to 18 million in Europe by 2060. As the population continues to age, AF is becoming a significant and growing public health concern, taking epidemic proportions [3]. Despite promising emerging treatment options for this complex arrhythmia, an optimal solution is missing. It remains the last great frontier of cardiac electrophysiology, as the mechanisms behind its generation and perpetuation are still incompletely understood. Among possible treatments, catheter ablation (CA) is currently the most effective therapy in terms of long-term recurrence [1]. CA improves patients' quality of life by reducing dependence on medications and significant cognitive side effects [4]. A growing number of patients is eligible for CA, but determining the best ablation strategy remains elusive due to operator variability. Non-optimal CA approaches can result in AF recurrence, necessitating further interventions (redo).

A recent CA protocol is based on spatio-temporal dispersion (STD) pattern identification [5]. STD areas are defined as clusters of EGMs, either fractionated or non-fractionated, that display interelectrode time and space dispersion at a minimum of two adjacent bipoles such that activation spreads over more than the 50 % of the AF cycle length. STD patterns are manually identified by interventional cardiologists, who examine 10-lead intracardiac EGM signals [5]. This manual process presents a significant challenge to the standardization of EGM-based CA methods, as it is heavily influenced by the operator's experience and learning curve, leading to considerable variability. The data collection process relies on close communication between the cardiologist performing the intervention and the software engineer responsible for annotating the data within the CARTO Pentaray ® multielectrode mapping catheter (Biosense Webster, Irvine, CA, USA). This step, fundamental to conduct relevant studies, is inherently complex and prone to errors.

Current literature advocating for the use of machine learning (ML) in guiding STD identification often lacks thorough methodological analysis, reproducibility, and interpretability for cardiologists [5]. The training phase import bias from the data in the developed models, resulting not flexible as tailored on the specific protocol from the training set. To address these gaps, promote explainable solutions and help understanding the STD-based CA process, a mathematical algorithm is proposed in the present work. It models the cardiologists signal classification process during STD-based CA, translating their

decision-making into signal processing steps. Unlike current ML approaches, the mathematical framework does not rely on learning phases and data are used only for testing, ensuring reproducibility, and flexibility with the possibility of removing or adding any signal processing step in the pipeline. The ultimate goal is to validate the outcomes of the peak-based classification against the expert-provided labels. Real 10-lead intracardiac EGM data from Nice Pasteur University Hospital (CHU) were acquired by the CARTO Pentaray ® multielectrode mapping catheter (Biosense Webster, Irvine, CA, USA), and labelled by experts. The validation with real data enables the evaluation of the mathematical decision support system's performance, offering insights into its accuracy and effectiveness in assisting cardiologists during ablation procedures.

2. Methods

2.1. Problem statement

A real dataset was sourced comprising 53 persistent AF patients, more details in Sec. 3. This dataset is exclusively used for testing purposes. Let X denote the 2.5-second 10-lead intracardiac EGMs samples. The classification label y is binary, indicating either "STD" or "not STD", for each sample X. Our goal is, given input sample X, to accurately generate predictions for y.

2.2. Challenges

Notable difficulties lie in the discrepancies between real-time classification during the intervention and offline analysis post-intervention. While real-time data acquisition provides the cardiologist with a continuous stream of information, the recorded samples for offline analysis are limited to 2.5 seconds snapshots. Furthermore, during the intervention, the cardiologist views the signal only when the catheter is properly positioned and stable, thereby minimizing noise and fragmentation, whereas recordings are often noisy or unstable because of communication delays and small catheter movements. There is also a pronounced class imbalance, as STD patterns are significantly less common than non-STD patterns (details in Sec. 3), making the classification process more challenging.

2.3. Proposed mathematical pipeline for automatic STD classification

The development of the proposed mathematical pipeline (in Fig. 1) followed three main phases.

- Modeling the cardiologist's reasoning to predict the classification label (STD or not STD): this step required long discussions with experts to analyze specific cases.

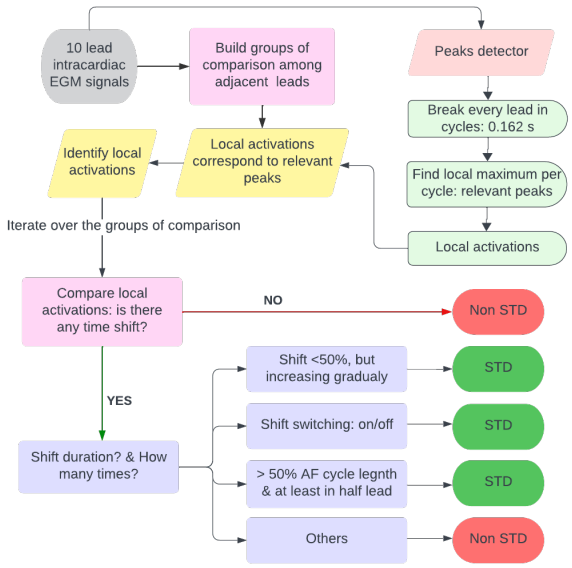

Figure 1. Mathematical peak-based STD classification pipeline.

- Translation into mathematical equations, modelling suitable signal processing operations: defining equations, systems, and conditions that represent the decision-making steps.
- Understanding and explanation: the outcome is not just a predictive model; it also provides insights into the decision-making process, enhancing its value for explainability.

Peak detection. As outlined in [5], a pivotal step in the STD classification of intracardiac EGMs is the detection of activation within AF cycles. STD definition hinges on the AF cycle length (AFCL) and the calculation of time delays between local activations of contiguous leads. Local activations correspond to peaks of higher amplitude in the signal track of a lead, mathematically defined as maxima. The AFCL, defined as the time between two successive atrial depolarizations, typically averages around 0.162 seconds over the persistent AF population [6]. The identification of local activations is difficult also for trained cardiologists. Identifying these local maxima automatically is even more challenging, especially given the considerable variability in amplitude across leads and the potential fragmentation of signals. A simple thresholding approach is insufficient, as even within the same lead the amplitude of local activations can vary significantly. As a first step, peaks (local activations) are identified within each lead. Peak detection is explained in [7], but it is summarized for completeness below.

1. *Signal transformation.* The signal $x(t)$ is first transformed to enhance the peaks' amplitude. This could in-

volve filtering or applying a mathematical transformation to make the peaks more prominent. Ideally we should select a filter that generalizes well across all sorts of variants found in real world data. As a starting point we implement a sinewave filter , considering 15 equi-spaced points in the interval $\left[\frac{\pi}{2}, \frac{3\pi}{2}\right]$:

$$f(t) = \begin{cases} \sin\left(\frac{\pi}{2} + \frac{t\pi}{14}\right) & t = 0, 1, \ldots, 14 \\ 0 & \text{otherwise} \end{cases}$$

Let us compute the cross-correlation between the raw signal and the sinewave filter. It is a measure of similarity, and it helps find where the sinewave filter matches the signal (i.e., the peaks), making those features more prominent. Let $\tilde{X}(t)$ represent the transformed signal, for time $t = [0, 2499]$, given by the cross correlation:

$$\tilde{X}(t) = \sum_{\tau=0}^{M-1} f(\tau) x(\tau + t)$$

where: t is the time index, M is the length of the filter ($M = 15$) and τ is the time shift applied to the filter.

2. *Single lead peak detection.* The number of peaks k can vary among leads, up to N. Given a sample composed by 10 leads, N is the minimum number of peaks in a single lead (one peak per cycle) across all leads. For $k = 1, \ldots, N$, the kth peak $\hat{X}_k$ is computed from the transformed signal $\tilde{X}(t)$, imposing a window interval of $T_{\text{AF}} = 162$ ms (average AF cycle) from the previous peak $\hat{X}_{k-1}$. Let us define $\hat{t}_k$ as the peak timing for the kth AF cycle and $\hat{t}_0 = 0$. The intervals are $I_k = [\hat{t}_{k-1}, \hat{t}_{k-1} + T_{AF}]$.

The detected peaks correspond to the local activations timing $\hat{t}_k$ within the lead. This entire process, to identify the time step of the maximum amplitude within each cycle k, can be estimated as:

$$\hat{t}_k = \arg\max_{t \in I_k} |\tilde{X}(t)|.$$

This process has to be iterated over the 10 leads independently, to identify all activation time steps.

STD detection. According to the STD definition, the AF activation time, corresponding to peak timing, has to be compared across each cycle for adjacent leads to determine whether STD is present or not. Two adjacent leads are denoted L_i and L_j for $i, j = 1, \ldots, 10$ (one lead per bipole). Let $\hat{t}_{k,i}$ and $\hat{t}_{k,j}$ represent the activation times (peak times) at the kth cycle for leads L_i and L_j, respectively, estimated following the steps above. The time shift between the two leads for the kth cycle is computed as the timing difference:

$$\Delta t_{k(i,j)} = \left|\hat{t}_{k,i} - \hat{t}_{k,j}\right|.$$

The possible scenarios are:

Table 1. Mathematical pipeline KPIs on the tested labelled real dataset

F1	Acc	AUC	PPV	Sens	NPV	Spec
0.65	0.60	0.65	0.38	0.55	0.80	0.65

- Some time shift: cases a, b, c below.

a) Constant shift greater than 50% of the AF cycle length, in consecutive frames in at least half of the lead. The condition $\Delta t_{k(i,j)} > \frac{T_{\text{AF}}}{2}$ has to be True consecutively $N/2$ times.

b) Intermittent shift that appears and disappears in at least half of the signal. The condition $\Delta t_{k(i,j)} > \frac{T_{\text{AF}}}{2}$, alternates True and False values.

c) Gradually increasing shift up to less than 50% of the AF cycle length, in at least half of the lead. The conditions below have to be True at least $N/2$ times.

$$0 < \Delta t_{k(i,j)} < \frac{T_{\text{AF}}}{2} \quad \text{and} \quad \Delta t_{k(i,j)} < \Delta t_{k+1(i,j)}.$$

- No relevant time shift and other cases: $\Delta t_{k(i,j)}$ does not satisfy any of the above conditions.

3. Results and discussion

A total of 430, 10-leads intracardiac EGM samples were recorded and then exported from the software. To ensure accuracy, the samples were relabeled offline, resulting in 112 STD and 318 non-STD samples. Each EGM recording spans 2.5 seconds and is sampled at 1000 Hz. The success of the peak detection and the parsing is crucial to obtain a correct classification. Figure 2 presents in red the peak detection on a 10-lead EGM sample before the classification results. The pipeline, utilizing the steps outlined in this work, compares the timing of these peaks across the leads. The classification results of the mathematical pipeline are presented in Table 1. The key performance indicators (KPIs) encompass the F1 weighted score (F1), accuracy (Acc), area under the ROC curve (AUC), positive predictive value (PPV), sensitivity (Sens), specificity (Spec), and negative predictive value (NPV). The proposed peak-based classifier reached a weighted F1 score of 0.65 while the ML result on the same dataset was 0.430 in [8].

4. Conclusion

The proposed method introduces a new reproducible and interpretable mathematical pipeline to classify STD intracardiac EGM signals. This algorithm models the reasoning process of the cardiologist, step by step. First peaks are identified. Then the mathematical pipeline provides the sample classification label, outperforming in terms of F1 score our previous results of ML based STD classification

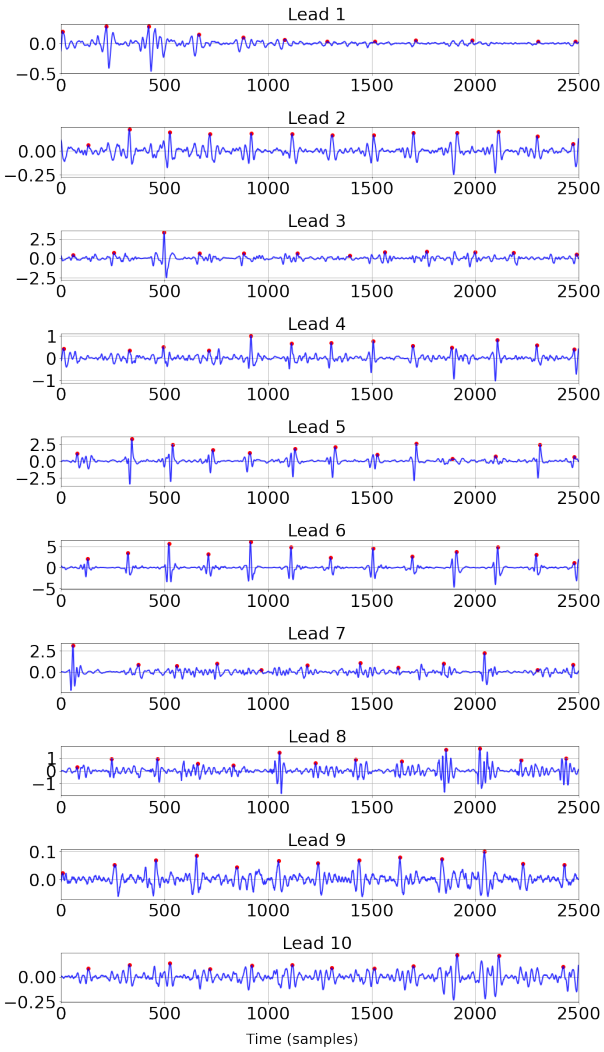

Figure 2. Peak detection resulting from our automatic method in a 10-lead intracardiac EGM sample.

on the same dataset. There are challenges associated with this approach, including the complexity of translating human reasoning into mathematical equations and the need for expertise with the STD identification problem. It may also require different cohorts data to be tested properly. To evaluate the performance of the detector, it would be beneficial to have peaks labelled by cardiologist instead of the automatic detection only. In this work we focus on the final labelling and we do not consider any fragmentation index.

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