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Local Activation Identification in Persistent Atrial Fibrillation Intracardiac EGM Signals for Automatic Spatio-temporal Dispersion Pattern Recognition

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Abstract—Atrial fibrillation (AF) is a common cardiac condition that predominantly affects the elderly population, presenting a significant risk factor for strokes and thus raising concerns in public health. Catheter ablation (CA) stands out as the most effective long-term treatment for persistent AF. A recently proposed novel CA approach is based on spatio-temporal dispersion (STD). This technique targets the STD patterns associated with active zones responsible for sustaining the arrhythmia. In this work we want to solve the peak detection problem, since it is a fundamental step for the automatic classification of STD patterns from multipolar electrograms (EGM). Instead of using machine learning models which lacks explainability, we want to understand the classification process performed at the block by interventional cardiologists in real time. The scenario is very challenging because the STD classification relies on visual peak detection to identify local activations, which are used to measure if STD does occur or not. We present our peak detector comparing it with eight different techniques from the state of the art. To extract peaks from real intracardiac EGM signals is difficult, most classical signal processing methods fail. We evaluate a total of nine techniques on the challenging scenario of real STD data. We analyze if the peaks are correctly identified, being part of the mathematical pipeline. Results show that identifying the peaks is a fundamental aspect to build the presented mathematical pipeline to overcome the STD classification problem, improving the classification accuracy with respect to previous works.

Index Terms—Persistent atrial fibrillation, arrhythmia, catheter ablation, peak detection, spatio-temporal dispersion, atrial electrogram (EGM).

I. INTRODUCTION

Atrial fibrillation (AF) is a common heart condition with a significant risk for stroke [1]. Catheter ablation (CA) stands as the most effective long-term treatment for persistent AF [2]. A novel CA approach focuses on spatio-temporal dispersion (STD) patterns identified visually by interventional cardiologists using the CARTO Pentaray[®] multielectrode mapping catheter (Biosense Webster, Irvine, CA, USA) [3]. While an ever-growing number of patients qualify for CA, determining the most effective ablation strategy for persistent AF remains a challenge [2]. The identification of STD patterns currently relies on visual interpretation by interventional cardiologists. The real-time data acquisition and labelling is prone to errors.

Offline relabeling is needed to improve data quality, but experts lack availability for this task and there are considerable variations in operator experience and learning curves, leading to inconsistencies in the process [4].

Machine learning (ML) is applied to address challenges where the creation of algorithms by human programmers would be economically unfeasible. ML methods involve constructing model from training data to predict classification labels [5]. The existing literature prompting the use of ML to guide the STD classification process lacks a comprehensive methodological analysis, and it is difficult to be interpreted by cardiologist in terms of explainability. A possible alternative approach seeks to model the interventional cardiologist's reasoning process, translating it into mathematical equations for the sake of explainability and accountability, using the data only for testing. We want to introduce a mathematical framework that can replicate the classification process that a cardiologist follows while performing the intervention and examining the atrial tissue doing electro-anatomical mapping. In this work we focus on the peaks' identification step of the procedure, which emerged as the starting point of the classification process. This is the starting point of the mathematical pipeline that we are developing and testing on a real dataset from Nice Pasteur University Hospital (CHU) labeled by experts during the intervention, and validated post procedure. This mathematical pipeline is layered on the peak identification step, which our results show to be a key point for a successful automatic classification. The ultimate objective is to validate the results of all the mathematical steps against the actual labels provided by experts. This validation will allow for the assessment of the mathematical decision support system's performance, providing insights into its accuracy and effectiveness in aiding cardiologists during ablation procedures.

II. METHODS

A. STD based catheter ablation of persistent AF

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. The STD patterns are identified manually at the block by interventional cardiologists looking at the 10-lead intracardiac EGM signals. This represents a substantial limitation to the standardization of EGM-based approaches with large operator differences in experience and learning curve profiles [3]. The data acquisition process relies on the communication between the cardiologist performing the intervention and the software engineer annotating the data in the CARTO electroanatomic mapping system (Biosense Webster). This is a challenging step, which unavoidably produces errors in the annotation process, and consequently in the data labels. Another important limitation concerns the differences existing between the real-time classification and the one performed offline after the intervention, not only for the above mentioned errors. The recorded samples are snapshots of 2.5 seconds, whereas the cardiologist has access not to a discrete timeline, but to a continuous flow of data. Data recorded are often noisy or unstable, while the cardiologist will look at the signal only when the catheter is properly placed and not moving, reducing noise, and fragmentation in the observed signals. Much information is missing in the offline labeling such as catheter position, patient history, adding difficulty. It is also important to remark that there is a strong imbalance between the two classes, STD patterns do not occur as often as non STD.

In our specific problem, the input signal is the 10-lead intracardiac EGM samples of 2.5 seconds X . The classification label y is binary: “STD” or “not STD”. Our aim is to effectively generate predictions for y . The function we call $\hat{f}(X)$ embodies the algorithm or model striving to emulate the logical reasoning employed by a cardiologist. In real-world scenarios, it is the cardiologist who determines the output label y , based on a logical thought decision-making process. The ML algorithm will associate to each sample X (input X has dimension 10×2500) to a predicted output \hat{y} . Instead of learning from data the classification label, without caring of the doctor reasoning steps, we want to model mathematically the reasoning of the cardiologist that brings to a certain classification. We start from the peak detection and local activation identification. Then we parameterize the decision process with a mathematical explicitly programmed model $\hat{f}(X)$, to achieve the final labelling $\hat{f}(X) = \hat{y}$. Figure 1 represents the most important steps of our pipeline.

B. Mathematical pipeline for automatic STD classification

We consider as input X the 10-lead EGM sample, we identify peaks, then we pass each sample through a system of conditions $\hat{f}(X)$ which contains the proper parameter to take the classification decision. The systems contains conditions regarding the number of peaks per lead, and the percentage of time shift among leads. Amplitude similarities between close peaks are computed (see Figure 1).

The mathematical pipeline uses local activations timing to automatically classify signals. Following the STD definition, AF activation time is compared per each cycle per adjacent

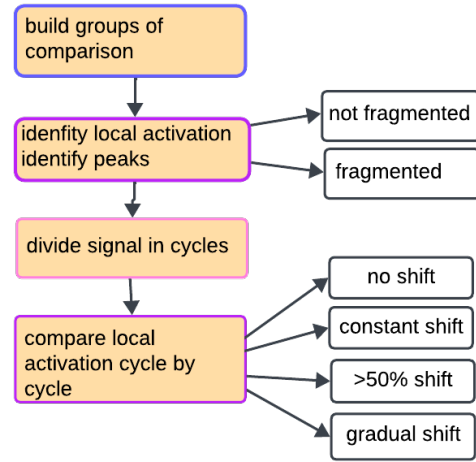


Fig. 1. Mathematical classification pipeline scheme.

lead to identify if STD occurs or not. The possible cases are: i) there is no time shift (no STD), ii) there is some time shift then: a) shift constant $> 50\%$ AF cycle length (STD), b) shift intermittent, appearing and disappearing in at least half signal (STD), c) gradually increasing shift up to $< 50\%$ (STD), d) others (no STD). Taking those information the pipeline will provide the label per each sample as final output \hat{y} , it will be the sample label.

C. Mathematical pipeline development process

Close collaboration with the experts is crucial in this case, as they play a pivotal role in identifying any disparities between their approach and the algorithm under development. A comparison is made between the human based supervised classification outcomes and the values generated by the mathematical algorithm. This comparative analysis will help ensure that the mathematical model aligns with the expert’s decision-making process. The mathematical pipeline development is based on three phases that we present below.

- Modeling the cardiologist’s reasoning: instead of trying to directly predict the classification label (e.g., “STD” or “not STD”), we aim to model the logical reasoning process that the doctor uses to arrive at that classification.
- Translation into mathematical equations: translate the cardiologist’s reasoning into a mathematical language, which involves defining equations, systems, and conditions that represent the logic used by the cardiologist to make their decision.
- Understanding and explanation: the result of this approach is not just a predictive model but also a model that explains the decision process. This can offer insights into why a particular classification is made and can be valuable for transparency, accountability, and potentially enhancing the decision-making process.

D. Proposed peak detector

We conducted an analysis of the classification protocol provided by our collaborator cardiologist. It is very important to start by reminding the original STD definition given in [6] on which the classification is based, which is summarized in the previous section. This served as the foundation for the initial set of conditions, needed to identify STD. The final phase involves translating these conditions and the others parameters considered by the cardiologist into mathematical code, to emulate his classification pipeline. Through this process we realized that a pivotal step in the STD classification process of intracardiac EGMs performed by cardiologists is the activation detection of the AF cycle. The STD definition is based on the AF cycle length and on the computation of time delays between lead activations of contiguous leads. The cycle length is defined as the time between two successive atrial depolarizations. The cycle length (on average 0.162 seconds) measurements encompass lead activation identification. The local activation identification process is automatic for trained cardiologist or human experts, but more difficult for machines. In fact, local activations are peaks of higher amplitude in the signal track of a lead in the intracardiac EGMs. Peaks are mathematically defined as maxima. Local activations can be seen as local maxima. The challenging part is to identify properly the local maxima, especially since amplitude may vary strongly among leads, and signals can be very fragmented. We cannot simply fix a threshold to identify the proper local maxima above all maxima, since even in the same lead the amplitude of local activation can vary significantly.

In this work we test different methods for peaks identification on our real dataset. In signal processing there are multiple methods assessed to identify peaks in a signal. In particular many were developed for detecting the R peaks in the electrocardiogram (ECG). Most detectors work with a threshold which moves the detection forward in time and use causal filters which delay the detection. Only a few detectors do actually a maximum detection. Most detectors cause a delay between the peak and its detection.

Transformation details: Before proceeding with our peak detection, we amplify the peaks to separate this feature from the rest of the signal and improve detection. A simple method is to apply filtering using template matching. Ideally, we should select a filter that generalizes well across all sorts of variants found in real world data. For simplicity's sake, we can implement a sinewave filter, considering v_i points for $i = 1, \dots, 15$ in the interval $[\frac{\pi}{2}, \frac{3\pi}{2}]$. The filter equation is $\sin(v_i)$. In Figure 2 we easily observe distinct peaks even under background noise. The filtered signal (in orange) is the computed cross-correlation between the raw signal (in blue) and the sinewave filter. This is often referred to as a convolution, which can also be considered as a measure of similarity between two signals. After the convolution, we have successfully amplified peaks and created some separation from the rest of the signal. After the filtering phase, we can detect peaks in our data. All local maxima can be identified by

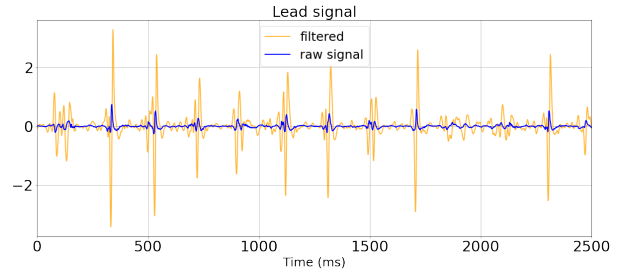


Fig. 2. Intracardiac EGM example lead number 1: filtering phase.

simple comparison of neighboring values and local activation are considered as peaks of interest, according to specific conditions determining a peak. The key point is to select proper parameters for peaks identification. A possibility is to fix a window and identify the absolute maximum per window. This window should have a length of time which correspond to the average cycle length. To define a cycle one first needs to identify local activations, which means peaks. We know on average cycle length for AF is 0.162 seconds [7] and we consider that value. We use the find peaks function from the Scipy python library [8] looking for the global maximum in each frame of 0.162 seconds per lead. This function takes a 1-D array and finds all local maxima by simple comparison of neighboring values. A peak or local maximum is defined as any sample whose two direct neighbors have a smaller amplitude. For flat peaks (more than one sample of equal amplitude wide) the index of the middle sample is returned (rounded down in case the number of samples is even). Smaller peaks are removed first until the condition is fulfilled for all remaining peaks. Using that detector we are able to identify correctly the highest peaks per window, and the local maxima in each entire lead. Sometimes also less relevant peaks are identified, which is not totally wrong since the objective it is also to identify peaks that the human eye would not notice at a first glimpse.

III. RESULTS

A. Study database

A real dataset has been acquired from Nice Pasteur University Hospital and meticulously labeled by domain experts during the intervention, and relabelled offline to avoid labelling mistakes. Remark that the peak identification step will be unsupervised, since the dataset does not contain peak information. We evaluate the effect of peak detection on the mathematical pipeline classification results. The dataset is composed by 430 samples, 112 STD and 318 non STD. Data are convoluted with sinus before being injected in the pipeline in our method, since the results benefit of a filtering step improving the ability of the detector to identify peaks. Data are used only for testing since this approach does not include any training phase.

B. Experimental results

In our method all local maxima are identified by simple comparison of neighboring values and local activation are con-

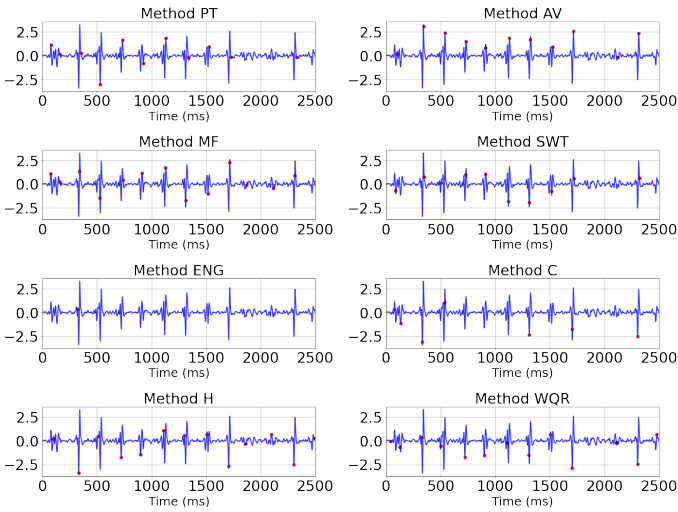


Fig. 3. Peak detection result with literature methods on lead number 5 of a 10 leads intracardiac EGM.

sidered as peaks of interest, according to specific conditions determining a peak. In Figure 3 it is possible to compare the peak detection performed by the methods from the literature in one out of the 10 leads of an EGM sample. This is a qualitative evaluation since a peak ground truth labelled by experts is missing. The methods, with their respective label in the title of the plots represented in Figure 3, are the following: Pan Tompkins detector (PT) [9], two Average detector (AV) [10], Matched filter detector (MF) [11], Stationary Wavelet Transform detector (SWT), Engzee detector (ENG) [12], Christov detector (C) [13], Hamilton detector (H) [14], QRS detector (QRS) [15]. The methods implementation has been taken from the python library `py-ecg-detectors` 1.3.5.¹

We can notice from Figure 3 that it is very hard to properly detect all the activations. Sometimes non relevant peaks are detected, and very relevant ones are missing. Figure 4 shows a 10-lead EGM sample where we performed our peak detection method on each lead. The lead number 5 is the same we showed in Figure 3 with the literature methods. The reader can see the peaks in red and compare their position among leads and observe how hard the labelling task must be.

To alleviate the lack of a quantitative evaluation for the peak detection we suggest to look at the results from our preliminary classification based on the peak identification step performed with our detector. In Figure 1 the steps of the mathematical pipeline are presented, in this work we focus on the final labelling and we will not consider any fragmentation index. Preliminary results of the mathematical pipeline under development are presented here to have quantitative key performance indicators (KPIs) of the improvements done with this new method which relies on our peak detection technique to identify local activations. Our chosen KPIs encompassed the F1 weighted score (F1), accuracy (Acc), area under the ROC curve (AUC ROC), positive predictive value (PPV),

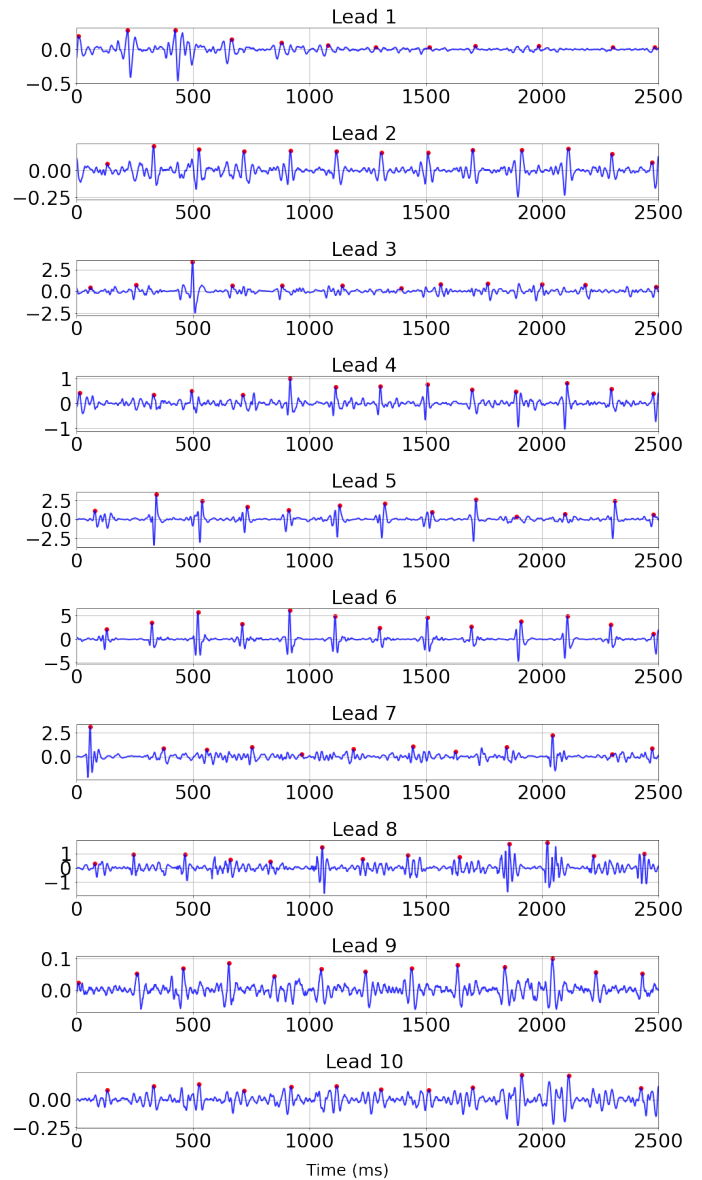


Fig. 4. Peak detection result of our method in the entire sample (10-lead intracardiac EGM).

TABLE I
MATHEMATICAL PIPELINE KPIs ON THE TESTED LABELLED REAL DATASET

F1 score	Acc	AUC ROC	PPV	Sens	NPV	Spec
0.574	0.549	0.510	0.270	0.429	0.746	0.592

sensitivity (Sens), specificity (Spec), and negative predictive value (NPV). In Table I all KPIs are presented. This manually implemented classifier reached a weighted F1 score of 0.57 which is better than the previous developed ML methods for the STD classification in [5], which had a value of 0.430. Also many details in the math pipeline can be improved, bringing a margin for further improvements in future works.

¹<https://pypi.org/project/py-ecg-detectors/>

IV. DISCUSSION

We considered peak detection algorithms from the literature. State of the art methods for peaks detection [9]- [15] have been tested on real intracardiac EGM data and compared with our technique, on top of the proposed mathematical pipeline. They all fail dramatically with our data which is very noisy and fragmented, as shown in one example in Figure 3. Thanks to the windowing technique which breaks the signal in 0.162 seconds frames, our method is able to identify peaks as global maximum in each window, and then going back to the entire signal, it can identify local activation also in very fragmented leads. This peak identification technique is an important step for the mathematical pipeline which provides the sample classification label, outperforming in terms of F1 score our previous results of STD classification on the same dataset.

V. CONCLUSION

The method proposed in this contribution introduces the bases for a shift from traditional supervised machine learning, which focuses on predicting classification labels based on input data, to a more explanatory or interpretable mathematical pipeline. We aim to understand and model the reasoning process of the cardiologist. This approach falls within the realm of interpretability and explainability and can be valuable in since it is important to understand why a particular decision is taken for clinical practice. The peak identification method presented is an important step for our mathematical pipeline, which is able to better follow the cardiologist classification criteria for evaluating 10-lead intracardiac EGM signals recorded during the CA intervention.

There are challenges associated with this approach, including the complexity of translating human reasoning into mathematical equations and the need for extensive domain expertise. It may also require a large amount of high-quality data to accurately capture the cardiologist's decision-making process. It would be beneficial to have peaks labelled by a cardiologist, even though in very fragmented signal the human ground truth may be less correct with respect to the peaks that we can compute since the human eye can be wrong when peaks are very close in amplitude.

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