Cycle Length Estimation Using Accurate Adaptive Detection of Local Activations in Atrial Intracardiac Electrograms

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Abstract

The normal electrical potential propagates throughout the atria periodically. During atrial arrhythmias its propagation is modified because the substrate is not homogeneous and new sources of punctual electrical activity appear. The periodic behavior of activation remains predominant, but becomes local in different parts of the atria. It is characterized by cycle length (CL) which measures the frequency of activation and can be computed from intracardiac bipolar electrograms (EGM) recorded by a mapping catheter during the catheter ablation procedure. The CL value of different mapped zones is an extremely important resource for physicians when performing persistent Atrial Fibrillation (AF) ablation because it helps to identify pathological zones and define the ablation strategy. Thus, a reliable estimation of the CL of atrial tissue is essential. The complexity of this task stems from the large variability in EGM morphology influenced by multiple wavefronts, fragmentation and added noise. In this work, we propose a cycle length estimator that can process the complex mapping signals recorded during atrial arrhythmias ablation and reliably provide the frequency of their periodic activity.

1. Introduction

The cycle length (CL) is a measure for the characterization of the electrical activity of the heart substrate, serving to guide catheter ablation. It is measured in milliseconds and generally reflects the time during which a full cycle of relaxation and contraction of studied heart tissue occurs. Recent research revealed that zones of acute termination of persistent Atrial Fibrillation (AF) during catheter ablation demonstrated rapid activity [?]. Furthermore, the relative difference between activation frequencies of mapped zones and those from reference catheter (e.g. from coronary sinus) helps to make a judgment of the studied substrate. Thus, a reliable estimation of the cycle length of atrial tissue during the mapping phase is essential.

The local electrical activity is often generated by several neighboring sources with different characteristics resulting in bipolar electrograms (EGM) with high variability of wave morphology and amplitude, making the accurate analysis of CL a challenging issue. During the mapping phase, the slow conduction zones generate fragmented and low voltage electrical signals, whose activation period is difficult to interpret. In addition, intracardiac recordings are known to be influenced by added noise.

A large amount of research work has been done in the field of signal processing applied to cardiac signals. All methods proposed in previous related works on CL estimation of electrocardiogram (ECG) and intracardiac EGMs can be divided into two groups:

1. Frequency based approaches as Fast Fourier Transform (FFT) or autocorrelation study. These methods consequently study power spectral density to extract the most prepotent components considered as the dominant frequency of the studied signal. They are known to be highly sensitive to the variability of the activation intervals, complex fractionation and potential phase change [?].
2. Different adaptive thresholding methods based on amplitude-based detection of atrial activations reflect the recent tendency in the research field of computational cardiology and prove to be more robust to the disorganized origin of AF intracardiac signals [?]. All of them apply different preprocessing techniques. As the preprocessing significantly influences the studied signal, its choice has to be treated with high importance.

In this work, we took into account all these considerations and proposed an algorithm that can deal with complex mapping signals of atrial arrhythmias and reliably estimate the frequency of their periodic behavior. We define the concept of cycle length within the context of local activity of atria as the time interval between two consecutive local activations waves (LAWs) on the recorded intracardiac EGMs. The adopted method aims to mimic human appraisal of the periodic activity: detect the activations equidistantly separated from each other within the studied batch. CL measures are then assessed as the gaps between these active segments.

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2. Methodology

2.1. Dataset and Metrics

Intracardiac bipolar EGMs were obtained using different mapping catheters introduced via the right femoral vein and guided by an electroanatomical navigation system during 40 AF ablation procedures at the Saint-Joseph Hospital in Marseille. They were extracted from General Electric CardioLab recording system (USA) with a sampling frequency of 977 Hz. Two physicians were asked to choose several batches of both normal and complex bipolar mapping signals and measure the CL of their periodic activity. The final test set D_1 consists of 38 AF segments from 8 patients ($3.21s \pm 0.9$) and 21 segments from AT rhythm from 7 patients (of average length $4.92s \pm 1.7$). An additional dataset D_2 was kept aside to optimize numeric parameters of the algorithm. It consists of 82 AF mapping segments from 15 patients (of average length $2.75s \pm 0.7$) and 21 AT segments from 10 patients ($4.82s \pm 1.19$). No patient from this cohort appears in the test set D_1.

Mean absolute error (MAE) and root mean square relative error (RMSRE) were chosen to evaluate the estimation of cycle length on signals from D_1. Batches where the absolute error exceeded 15% were reviewed with physicians to detect whether they arise from the annotation errors or the algorithm was really mistaken.

2.2. Algorithm

The algorithm takes consecutive mapping signal batches of 1500 ms as input. The main goal is to retrieve a correct segmentation (called further S) on separate LAWs ($s_i \in S$). Once periodically distant s_i are found, the CL can be computed as the difference between their positions. To do so, a preprocessing (see **??**) of signals was designed to facilitate LAWs detection. Then, thresholded extrema are detected on preprocessed signal and are subsequently clustered into separate s_i (**??**). Finally, the post processing of initial segmentation is done to deal with missed or overly detected activations according to the designed condition of periodicity (**??**). The final cycle length is computed in ms as the difference between reference positions chosen within each LAW.

All numeric parameters are computed relatively to the distribution of signal's values in order to make the algorithm robust to potential distribution shifts (e.g. with a new signal source). They were optimized using D_2.

2.2.1. Preprocessing

As mentioned above, the preprocessing step is a crucial step as the correctly done cleaning of the signal, emphasizing the real atrial activity and simplifying difficult fragmented parts, can significantly improve its further interpretation by automated estimation. Our suggested preprocessing consists of the removal of baseline wander and high frequency noise reduction.

Baseline wander removal is done by use of a Butterworth highpass filter with a cut-off frequency set to 10 Hz.

High frequency noise reduction is based on the discrete wavelet transform thresholding introduced by Donoho [**?**]. The idea of the method is that the energy of the signal is higher than the energy of the noise, thus it could be suppressed. The signal is decomposed into low-frequency approximation and high-frequency detail components with wavelet Daubechies 8 (see figure **??**). An adaptive thresholding based on the estimation of the noise variance is applied on each level's detail. Everything beneath the threshold is set to zero and higher energy values are preserved as originated from the signal's content. In the end, the signal is composed again by inverse wavelet transform with suppressed noise components.

2.2.2. Initial LAWs segmentation

Firstly, a detection of extrema using an adaptive threshold is employed on preprocessed signal batch. Initially, the threshold is set to 0.95 percentile of values in studied batch. Then, the obtained extrema are clustered into activations using kernel density estimation with a Gaussian window of bandwidth 10 [**?**]. Onsets o_i and ends e_i of segments $s_i \in S$, where the density is higher than zero, are chosen as the borders of sought LAWs. A reference position $r_i \in [o_i, e_i]$ (often called local atrial time LAT) is chosen within each s_i. The onset, the argmax and the mass center within s_i were tested as r_i [**?**] and the argmax which showed the best performance was retained. The similarity of relative differences $\delta r = r_i - r_{i-1}$ in the batch is a good marker whether periodic (equidistantly separated) activations were correctly found. Thus, a measure of ratio variability RV was developed in order to monitor if the segmentation satisfies a periodic condition and if any post processing is needed. The ratio variability is computed as:

$$RV(S) = \frac{\max_i(\delta r_i) - \min_i(\delta r_i)}{\frac{\sum_i (\delta r_i)}{n}}$$

and is invariant to the absolute value of the signal. If found segments are not equidistantly separated, RV is high. While they behave periodically, it is close to 0.

When $RV(S)$ is higher than 0.5, found segments are not behaving periodically meaning that some activations may be missing. In this case, the explained segmentation on LAWs is redone by lowering the threshold for extrema to 0.9 percentile, resulting in segments set $\hat{S}$ which has a higher or equal number of found segments. $\hat{S}$ is retained if

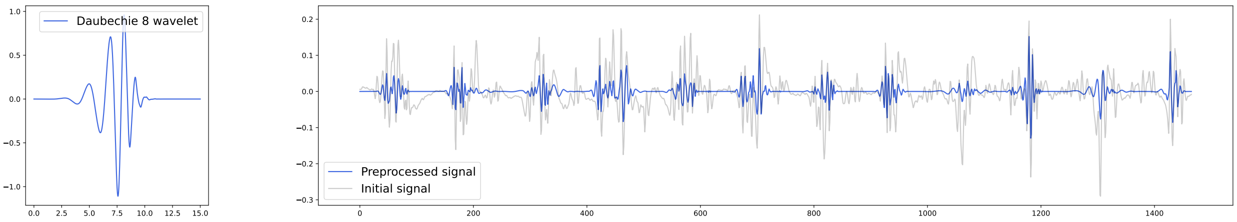

Figure 1. Left panel: Daubechies 8 wavelet. Right panel: example of preprocessed mapping signal. Note that emphasized isoelectric line activations are much more distinguishable than in the initial signal.

$RV(\hat{S}) \le RV(S)$, i.e. yielding an improved segmentation as LAWs are expected to be periodic.

Still, if $RV(\hat{S})$ remains high, the post-processing explained in the next section is applied.

2.2.3. Post-processing of segments

Suggested post-processing consists of three steps applied successively, the first one deals with segments s_i, two latter ones with intervals δr_i. It is controlled by RV of obtained at each step segmentation S_i as follows: if S_i reduces the variability in terms of periodicity, i.e. $RV(S_i) \le RV(S_{i-1})$, S_i is retained for the further step.

The post-treatment of segments S was designed to treat cases when even after the preprocessing no isoelectric line separates correctly two distinct activations resulting into one prolonged segment s_i. If any segment s_i is longer than two times the average length of activations of the signal, it is divided into two separate ones.

The post-treatment of intervals $\delta r = r_i - r_{i-1}$ consists of the adaptive search of missed activations in highly distant intervals and a merge of neighboring activations for the overly close ones. To do this, all found intervals δr_i are clustered into 3 groups, assuming there could be too short (Δ_s), real (Δ_r) or too long ones (Δ_l).

- Too long intervals $\delta r_i \in \Delta_l$ are consequentially retreated by searching the missing activations with the same procedure explained in 2.2.2 but on the initial signal without removed high frequency noise. The hypothesis is that missing activations are mostly related to lost amplified activity after preprocessing. If an activity is found within the treating interval δr_i, it is added to the segments if RV reduces. Groups Δ_s, Δ_r, Δ_l are recomputed. Maximum 3 attempts are allowed.
- The segments of short intervals $\delta_i \in \Delta_s$ are merged into one if $\min\limits_{i,\delta_i \in \Delta_s} \delta r_i \le \frac{\max\limits_{j,\delta_j \in \Delta_r} \delta r_j}{2}$. After each merge, Δ_s, Δ_r, Δ_l are recomputed. Maximum 3 attempts are allowed.

If the final RV is higher than 0.6 the segmentation is considered as periodic and the final CL is estimated as the median of intervals between reference positions.

3. Results and Discussion

As explained in 2.1, the test set comprises 38 AF and 21 AT mapping segments. Each time segment contains several bipolar recordings from mapping catheter, the periodic ones were annotated with CL value by two physicians as in the operating room: an interval is chosen, its length is measured in ms and divided by the number of activations. Dividing further each segment by non overlapping batches of 1500 ms provides us with a large number of signal samples (listed in the Table **??**) to compute metrics.

3.1. Metrics

Table 1. Metrics by rhythm computed on D_1.

	AF	AT
MAE (ms)	5.38 ± 5.2	2.9 ± 4.64
RMSRE	3.85	1.73
Number of outliers ($\ge 15\%$)	5	13
Number of aperiodic predictions	7	10
Total number of signal batches	196	440

After the review with physicians, it turned out that 2 out of 5 AF outliers revealed erroneous annotations (white noise), 2 had segments with prolonged activations, thus, the CL is ambiguous, and the last represents a real error. 13 AT signals, where the error $\ge 15\%$, were highly corrupted with ventricular far field activity and their activations behaved as double potential, resulting in estimated CL value twice the annotated one. The case of double potential represents a known limitation of the approach, see section 3.2 for more details.

As the annotation process mimics the operating room workflow (i.e. appreciating the number of LAWs within a set time interval), the annotations of CL are susceptible to inter-annotator variability and measurement errors. In order to take into account the order of magnitude while interpreting results, we asked five experts of used annotation tool to measure CL on same five signal batches. The mean of standard deviations is equal to 5.66 ms.

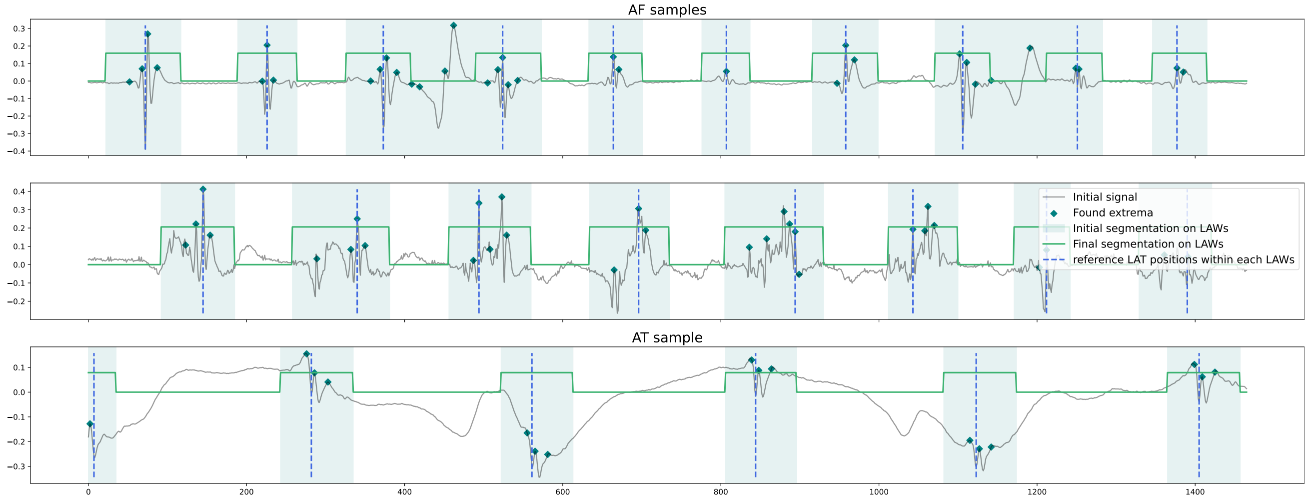

Figure 2. Visualization of outputs of all steps of the algorithm.

3.2. Discussion

The suggested algorithm demonstrated high performance of accurately chosen metrics on the dataset annotated by experts and showed strong potential for use during AF catheter ablation. Suggested preprocessing proved to be effective for interpretability of signals by diminishing noise components and emphasizing atrial activity. It enhances the adaptive segmentation on LAWs performing with high precision.

The algorithm was initially designed for rapid rhythms. The method processes non-overlapping batches of 1500 ms and a buffer of the same length was implemented to keep references from previous batch. Thus, if a CL is $\geq 3s$, there would be either one or no activation in the batch and no period would be found. However, this limitation can be simply lifted by optimizing the buffer allocation while adapting to slow rhythms.

As the method is based on adaptive amplitude-based thresholding search of activations without considering morphology, an over detection of activations in the case of equidistant double potential waves or ventricular far field artifacts could appear. In the first case, even if the interpretation of the real CL value is ambiguous, the risk could be mitigated by clustering the segments based on morphology or frequency spectrum. In the case of corruption with ventricular far field complexes, even if it is not common in AF mapping signals, its suppression might be considered.

4. Conclusion

The method provides a reliable estimation of CL of bipolar mapping signals that could significantly improve existing clinical workflow of catheter ablation of AF. In this work, the CL estimator was optimized for rapid rhythms, nevertheless thanks to generic design of amplitude-based research of periodic activity, the method can be adapted to all types of rhythms.

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