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Recurrence quantification analysis as a tool for complex fractionated atrial electrogram discrimination

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Abstract— **Atrial fibrillation is the most encountered pathology of the heart rate. The reasons of its occurrence and its particular characteristics remain unknown, resulting from complex phenomena interaction. From these interactions emerges Complex Fractionated Atrial Electrograms (CFAE) which are useful for the ablation procedure. This study presents a method based on nonlinear data analysis, the Recurrence Quantification Analysis (RQA) applied on intracardiac atrial electrograms to detect CFAE particularities. The results obtained on areas previously tagged by a cardiologist show a good sensitivity to CFAE. Combination of RQA features offers a larger discrimination potential for future automated detection.**

I. INTRODUCTION

Complex Fractionated Atrial Electrograms (CFAE) have been proved to be involved in atrial fibrillation (AF) maintenance [1-3]. It seems at first that CFAE could result from reentrant activity induced by spiral waves (SW) on the cardiac substrate. The tracking and the radiofrequency (RF) ablation of those signals have become important steps in the praticist procedure of AF removal. Targeting CFAE areas is now part of the intervention in addition to the usual pulmonary veins isolation [4]. Ablation strategies focusing only on CFAE sites have shown great results on AF termination [5, 2]. Depending on the substrate configuration, (duration of the refractory period, presence of fibroblasts) CFAE can take many different forms and characteristics. Nowadays, cardiologists have learned to recognize CFAE visually. Therefore, this empirical recognition is not precise and the ablation process can be painful for the patients. It is worthwhile to qualify the CFAE properties more acurately in the atrial tissue.

A lot of analysis tools or descriptors are used in the literature to describe and classify intraatrial signals such as Dominant Frequency (DF) [6-9], Organisation (OI) and Regularity Index (RI) [8, 9], Entropy Index (EI) [10, 11], amplitude analysis [12], or Wavelet Transform (WT) [13]. Classification is an important step for the understanding of the underlying phenomena and their effect on the whole behaviour of the heart but also to predict the ablation procedure success. Several classifications have been proposed for those signals depending on their characteristics and embedding patterns [14, 15]. Used descriptors should be able to match the various aspects of CFAE and this makes computational identification difficult. Nowadays visual analysis is the most popular process to detect CFAE, this is the technique predominately used by the praticists. However, most of the time, visual classification is not possible and automatic classification could miss important signals. Tools that are able to classify types of CFAE are often made by a combination of descriptors. The complexity of these signals requires a multidimensional approach for a reliable identification.

The nonlinear dynamical techniques based on the concept of chaos, have been applied to many areas including the areas of medicine and biology [16-18]. In this work, using a recurrence property of the CFAE signals, some features are determined, allowing to detected several types of CFAE. Those descriptors are able to separate areas identified as CFAE from areas that are not significant for diagnosis.

Recurrence plots (RP), first introduced by [19] can be applied to time series data [20] in order to bring out temporal correlations in a manner that is instantly apparent to the eye. This technique has another important practical advantage in that it can be used to visualize nonstationary data, making it a useful analysis tool for physiological data [21] and driven systems [18] among other things, and it is quite robust to noise [22]. These plots disclose distance relationships between points on a dynamical system and provide a faithful representation of the time dependencies (correlations) contained in the data [19]. This includes the quantification of recurrence plots, like the Recurrence Quantification Analysis (RQA) [20] mainly based on statistical descriptions of these parallel line patterns, and it is useful to analyze time series with high levels of noise. Five features are extracted from RQA to characterise CFAE tagged signal. A presentation of the used database is made on section 2.A, then a description on the construction of recurrence plots is given in section 2.B . The section 3 shows some results corresponding to the recurrence plot analysis of different signals. A discussion and a conclusion section finishes this paper.

II. MATERIAL AND METHOD

A. Data presentation

Clinical data have been retrieved from ablation procedures; recordings were made using a Biosense Webster catheter model Thermocool. Data were digitized at 1 kHz frequency and with a 14 bits resolution, then filtered by the acquisition software with a bandpass (30Hz-300Hz). For each signal presented here, a cardiologist has validated and targeted areas identified and presented as CFAE. This database contains intracardiac signals from 20 patients suffering from paroxysmal or long-lasting atrial persistent fibrillation. Different types of CFAE signals are presented here that could belong to the different classes or grades described in the literature

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[14, 15]. Among the 20 samples subjected to analysis, 2 show a transition from AF to tachycardia after the site was ablated. The values given by quantifiers on those samples allow to observe differences between CFAE and non CFAE periods and yet to see the transition during AF termination (while the ablation process). Other signals contain periods of varying duration CFAE. One is an intracardiac recording of a sinusal rhythm activity. Each sample lasts 44 seconds, this duration is sufficient to observe the multiple transitions occurring during the recording.

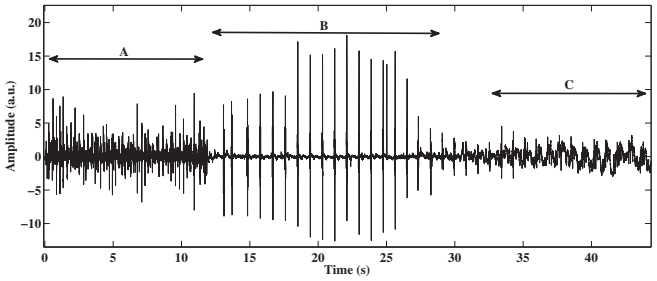

Fig. 1. Signal 1: Intracardiac signal from ablation procedure showing (A) CFAE, (B) RF ablation, and (C) tachycardia at once.

The left part of the signal 1, identified as CFAE has been tagged and validated by a specialist. This intraatrial electrogram is particularly interesting because ablation led to the termination of AF after a period of tachycardia. This example demonstrates the strong involvment of CFAE in AF.

In the used database, one can recognize signal corresponding to class II (complex pattern CFAE) (see Fig.2.a) or class IV (continuous electrical activity) (see Fig.2.b) according to the classification proposed by [15]. This database is representative of the diversity of signals defined as CFAE by the literature.

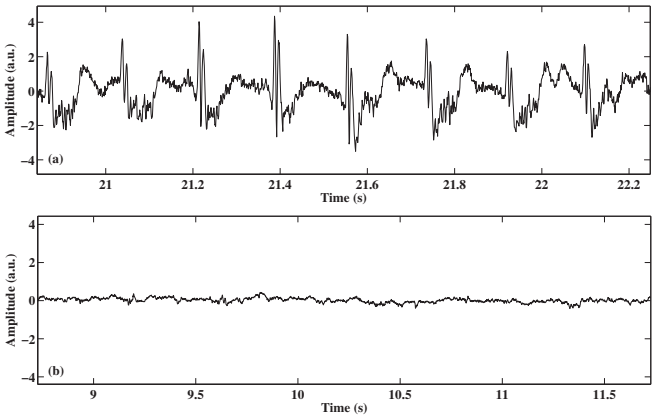

Fig. 2. (a) Intracardiac electrogram (signal 2) from ablation procedure showing a zoom of a CFAE with a pattern repetition. (b) Intracardiac electrogram (signal 3) showing a zoom of a CFAE type continuous electrical activity.

B. Recurrence plot and recurrence quantification analysis

The method of RP was first introduced to visualize the time dependent behavior of the dynamics of systems, which can be pictured as a trajectory $\overrightarrow{x_i} \in R^n (i = 1,...,N)$ in the n-dimensional phase space [19]. It represents the recurrence of the phase space trajectory to a certain state [23]. The main step of the visualization of the recurrence plot (RP) is the calculation of the recurrence matrix R (NxN),

$$R_{i,j} = \Theta(\alpha_i - \|\overrightarrow{x_i} - \overrightarrow{x_j}\|), \qquad i,j = 1,...,N, \qquad (1)$$

where α_i is a cutoff distance, $\|\cdot\|$ is a norm (in our case the Euclidean norm), and $\Theta(x)$ is the Heaviside function. The phase space vectors for one-dimensional time series S_i from observations can be reconstructed by using the Taken's time delay method, $\overrightarrow{x_i} = (S_i, S_{i+\tau}, ..., S_{i+(m-1)\tau})$ [24]. The dimension m can be estimated with the method of false nearest neighbors (theoretically, $m = 2n+1$) [24]. The cutoff distance α_i defines a sphere centered at $\overrightarrow{x_i}$. If $\overrightarrow{x_i}$ falls within this sphere, the state will be close to $\overrightarrow{x_i}$ and thus $R_{i,j} = 1$. In this paper a fixed α_i and the Euclidean norm are used, resulting in a symmetric RP. The binary values in $R_{i,j}$ can be simply visualized by a matrix plot with the colors black (1) and white (0). The lines and patterns in an RP give an idea of the recurrences in the system [19]. Indeed, there is always a main diagonal, because a system is always identical to itself at the same time. Non-principal diagonal lines represent moments in which the system state passes close to its initial value after a certain time. Vertical (and horizontal) lines represent, on the other hand, cases in which the system basically has not changed much. Quantifying the amount of time (or the probability, given by the average lengths and statistics of these lines) that the system spends in these regimes can be a useful (nonlinear) tool to analyze and characterize the dynamics of the system. Some authors have recently developed the Recurrence Quantification Analysis (RQA) to quantify an RP [16, 20, 22, 25, 26]. It yields the characterization of the time dependent behavior of these variables and, thus, it makes the identification of transitions in the time series possible. In this work, a computation of RQA parameters in small windows moving along the main diagonal of the RP is realized to reveal the characteristics of CFAE.

Chosen quantifiers are the Recurrence Rate (RR) that is the percentage of recurrence points in a RP, the Trapping Time (TT) defined as the average length of the vertical lines, the Recurrence Time (RT) obtained by calculating the average vertical distance between recurrence structures, the Length, (L) given by the average length of the diagonal lines in a RP and the Entropy, (ENT) that is the Shannon entropy of the probability distribution of the diagonal line lengths in an RP. Details on their calculation is available in [27, 28].

III. Results

Data presented in section 2.A have been tested with tools above, the following shows examples of recurrence plot analysis and RQA analysis on intraatrial signals. First signal to be tested is the three states ones (signal 1) including a CFAE period, an ablation period and tachycardia at once (see Fig.3). This precious sample allows to initially assess the tools sensitivity.

A. Recurrence Quantification Analysis

Recurrence plot analysis is applied on every signal using a 2s shifting window giving a 1 second precision results. This

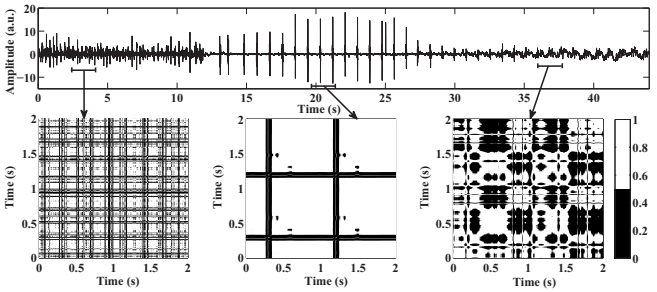

Fig. 3. Three steps of recurrence plot analysis from the 3 specifics moments of the signal 1. From left to right CFAE, RF ablation, tachycardia.

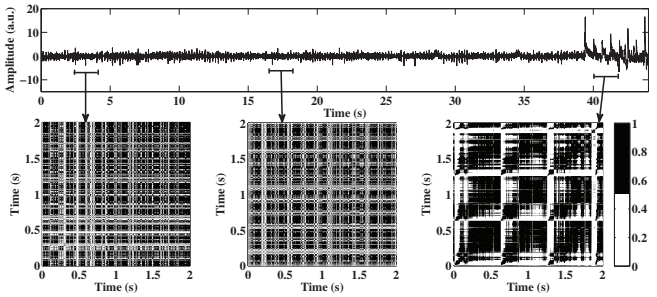

Fig. 4. Three steps of recurrence plot analysis from 3 specifics moments of the signal 4. The 2 first matrices represent CFAE periods, the third is the beginning of RF ablation.

graphical representation shows differences between CFAE sections and the rest of the signal. A threshold is applied to the recurrence matrix in order to display the recurrence within a particular phase distance. This one corresponds to the mean value of the recurrence matrix.It has been chosen after a comparison between different statistical parameters (mean, standard deviation, maximum or minimum....) because it allows the best discrimination values. Black points are representative of clone states in the phase portrait. Diagonal lines correspond to epochs where segments of the phase space trajectory run parallel. Recurrences matrices look quite similar for the CFAE periods in Fig.3 and Fig.4. State transitions are easily discernable from the recurrence matrices observation. To quantify the information embedded in this representation, one plots the five features listed above (RR, RT, L, ENT, TT). Fig.5 shows the evolution of those indexes among time for the signal 1 and the signal 4. All indexes shows a good sensitivity for the 3 parts of the signal. The CFAE periods represent the weakest values for RT, L and TT. The ablation part displays the highest values for 4 indexes and is easily identifiable, except for RT where the tachycardia part is high for signal 1. RT displays higher values for tachycardia than for CFAE, a combination of quantifiers is needed to distinguish tachycardia from ablation. These results suggest that it is possible to identify a certain type of CFAE in an intracardiac signal.

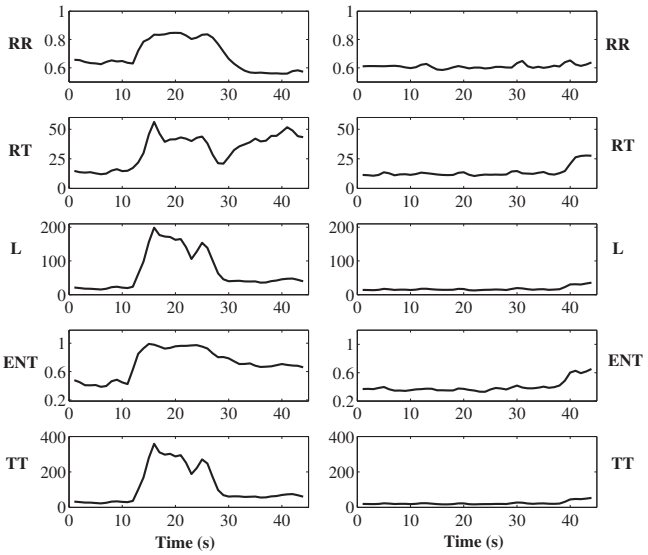

Fig. 5. RQA values among time for signal 1 (left column) and signal 4 (right column) with a one second precision.

B. Classification of intracardiac electrograms using RQA features

These 5 indexes are applied on the clinical database composed of 20 signals. In order to explore the differencies between the CFAE parts and the rest of the signal, coordinates of the tag are used to differentiate the RQA values of CFAE. Fig.6 shows the indexes median values for both CFAE and

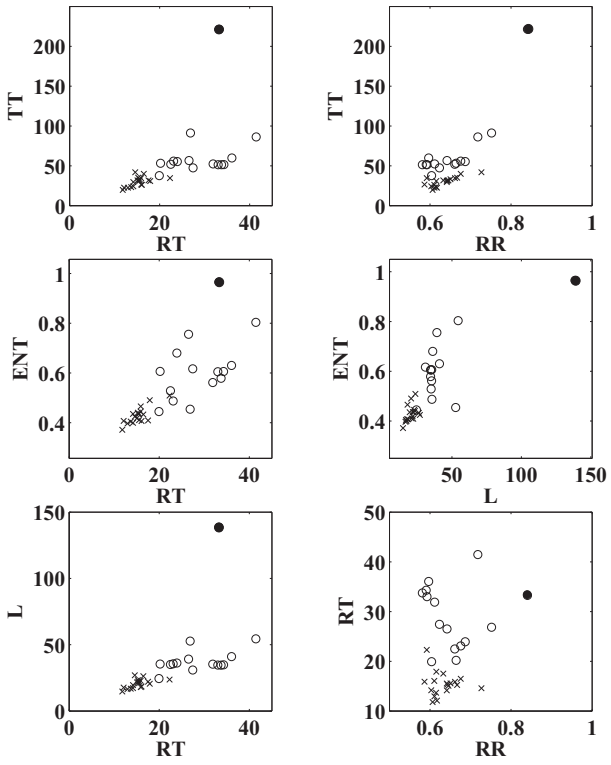

Fig. 6. The 6 RQA values representations from the 5 features for the 20 signal database crosses for CFAE, circles for nonCFAE.

nonCFAE parts in each of the 20 signals tested. The database includes several signals containing only CFAE. One signal shows a full sinus rhythm activity, it is indicated on plots by the black circle. The chosen representation brings out the sensitivity of each index to the areas of interest. Previous observations are confirmed with Fig.6 where CFAE values remains the weakest. The repartition of both CFAE and nonCFAE classes in the plots makes it possible to consider an automatic detection process. Some parts tagged as CFAE are surrounded by nonCFAE samples, this can be explained by the inaccuracy of the visual tagging. Acurate reading of these plots reveals that the majority of tagged CFAE parts displays identifiable values. It also appears that values from the sinus rhythm signal are represented well beyond others, suggesting that RQA analysis has the possibility to detect the end of fibrillation.

IV. Conclusion and discussion

This work presents an analysis tool applied for CFAE indentification. It is based on recurrence plot analysis and recurrence quantification analysis. Features are extracted from the recurrence matrix that show some of the signal nonlinear characteristics. Each signal of the clinical database has been tagged by a cardiologist to highlight the CFAE areas. Depending on the indexes, CFAE is well identified. Last part of this work shows that median RQA values from CFAE part stay within typical range for the tagged parts. Combine the RQA features improves the discrimination potential of this method by covering a wider range of recurrence properties. The tagging sessions occurred after the AF removal interventions, making it harder for the specialist to recognize areas of interest being out of the context. Furthermore, the temporal resolution of the algorithm induces imprecision at the tag boundaries. Those reasons could explain the misclassified signals. The proposed method does not offer yet a better detection than the specialist as it relies on its expertise. However, we believe that RQA analysis can allow automated detection and classification of CFAE electrograms and that it can be part of an AF removal standardization process. Descriptors are presented by pairs but larger combinations are possible using multidimensional representations such as neural network for more accurate results. With a larger clinical database RQA might also differentiate the several CFAE classes presented in literature.

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