Adaptive Wavelets Applied to Automatic Local Activation Wave Detection in Fractionated Atrial Electrograms of Atrial Fibrillation

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Abstract

Catheter ablation is an effective therapy to treat atrial fibrillation (AF) whenever the proper atrial regions are targeted. Electro-anatomical mapping is commonly used for that purpose, thus facilitating the location of ablation targets. However, reliable mappings acquisition depends on an accurate detection of local activation waves (LAWs) from atrial electrograms (EGMs). This is currently a hand-made and time-consuming task performed during the intervention. In this work a novel algorithm to detect automatically LAWs is proposed. To deal with complex and fractionated recordings, the EGM is decomposed making use of a tailor-made wavelet function. Such a function is generated from the atrial activation providing the highest average correlation within the EGM. According to manual annotations provided by two experts from 21 EGMs, the algorithm identified 959 out of 970 available LAWs. Thus, for the whole database its average sensitivity, positive predictivity and accuracy were 99.18% ± 1.35%, 99.69% ± 0.66% and 98.90% ± 1.51%, respectively. These results suggest the method's reliability, being able to detect the LAWs and ignoring successfully non-atrial patterns, such as noise, artifacts or other baseline oscillations, which can often lead to false detections.

1. Introduction

Atrial Fibrillation (AF) is the most common cardiac arrhythmia, characterized by a rapid and uncoordinated atrial activation. The lifetime risk of developing AF affects $1-2\%$ of people in the developed world [1], increasing even more with the age [2]. Despite some progress in the earlier decades, the current therapy of this arrhythmia is still far from being satisfactory [1]. Recently, catheter ablation has emerged as the most effective tool to treat symptomatic and drug-resistant AF patients [3]. However, a successful application of this procedure requires an accuracy electro-anatomical guiding to locate those areas prone to be ablated [4].

To this respect, combining 3D anatomical maps of the atria with assessment of local activation waves (LAWs) has provided to be a powerful tool [5]. This kind of maps are normally performed by sequential point-by-point acquisition of coordinates and electrograms (EGMs). However, given that AF often presents complex activation patterns constantly changing on its on-going evolution [1], manual detection of LAWs from complex and fractionated EGMs is a challenging, very time-consuming and subjective task [6, 7]. Hence, automatic detection of LAWs has meant a significant advance in this context. It provides a more objetive and accuracy detection of LAWs, thus allowing to obtain more reliable and real-time atrial maps [4].

To date, a variety of algorithms to detect automatically LAWs can be found in the literature. Some of them [4, 8] are based on the widely used approach, proposed by Botteron & Smith, for the EGM preprocessing [9]. Others however make use of a correlation between the EGM and a mathematically constructed database of LAWs [5,10,11]. Nonetheless, all of them are still inaccurate when the EGM becomes highly complex and fractionated [5]. Interestingly, the Wavelet Transform (WT) has recently proven to be able to deal with this kind of EGMs [12, 13]. Indeed, Houben et al [12] improved their previous algorithm to detect LAWs by using this transform. Moreover, they have also proposed a novel WT-based method to detect ventricular activation waves [13]. However, in both cases the EGM was decomposed by only considering standard wavelet functions, such as the first derivative of a Gaussian waveform [12] or a quadratic spline [13]. Hence, the possibility of improving the LAW detection by using a wavelet function tailor-made for every EGM under study is here analyzed. The initial hypothesis lying on the idea that a waveform near the LAWs to be detected could highlight those masked by complex and nuisance non-atrial patterns.

2. Materials

The studied database consisted of 21 10 second-length endocardial EGMs. The recordings were obtained from both atria making use of a Navi-Star catheter (Biosense

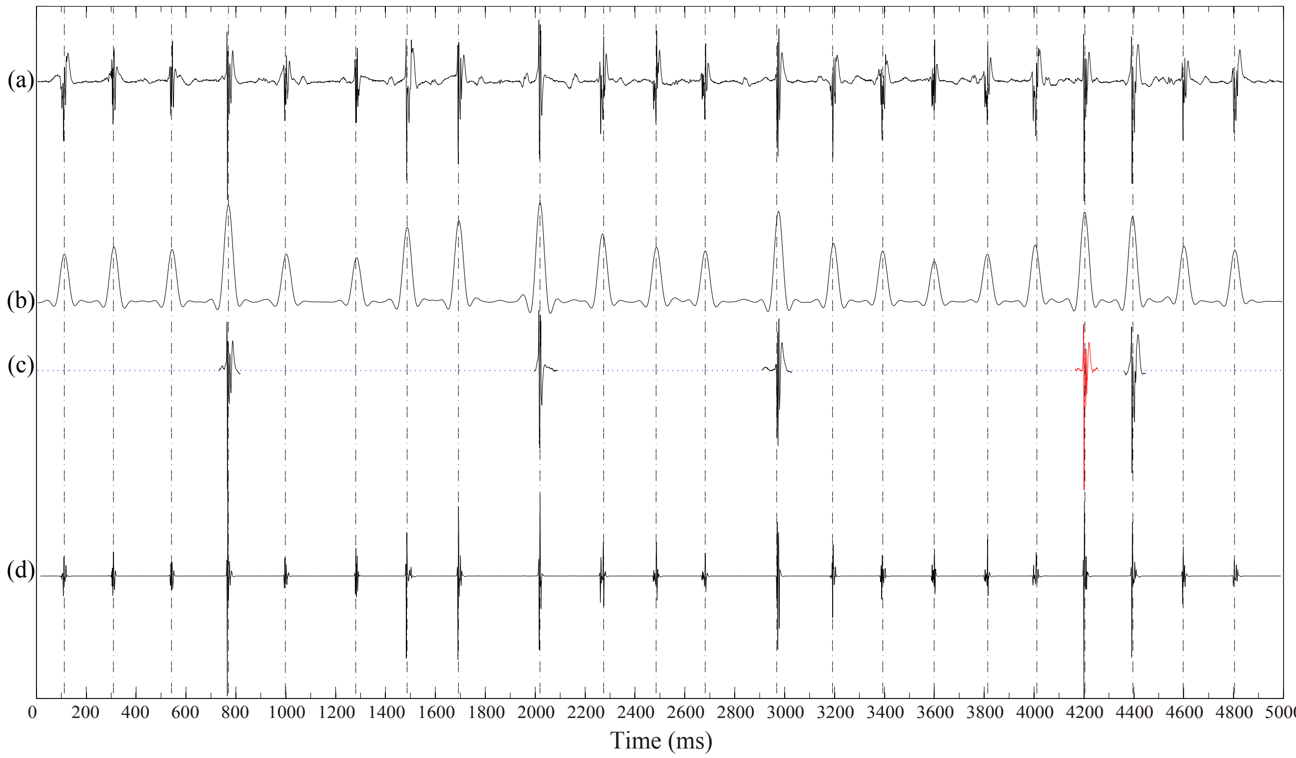

Figure 1. Graphical summary of the signals obtained by the proposed algorithm in their different steps: (a) Original EGM. (b) Signal resulting from the preprocessed EGM according to the Botteron's approach. (c) The five LAWs identified as potential candidates to be the MW. The finally selected LAW was marked in red. (d) Normalized signal from the first six wavelet scales finally used to detect the LAWs.

Webster, Inc., Diamond Bar, CA) and a sampling rate of 1 kHz. Their LAWs were manually marked by two experts blinded to the algorithm results.

3. Methods

The continuous wavelet transform (CWT) is a time-frequency analysis to decompose a signal into different scales. Indeed, this tool characterizes a signal $x(n)$ in terms of translated and dilated versions of another signal $\psi(t)$, named *mother wavelet* (MW), by computing their correlation, i.e.,

$$CWT(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\psi^* \left(\frac{t-b}{a}\right) dt, \qquad (1)$$

a and b being the scale and translation parameters, respectively. A relevant advantage of this transform is that the MW can be chosen from a wide variety of predefined (or standard) functions to emphasize the most interesting properties of the signal under study. Nonetheless, when these functions are unable to highlight a specific pattern within the original signal, a MW can also be tailored [14]. Precisely, this option was here considered to improve the LAW detection from complex and fragmented EGMs. Thus, to extract a representative LAW pattern from every EGM, it was firstly preprocessed according to the Botteron's approach [9]. Then, the EGM was bidirectionally filtered with a 40–250 Hz band-pass FIR filter and its absolute value was obtained. Next, a 20 Hz low-pass bidirectional FIR filtering was used and the five points with the largest amplitude from the resulting signal were identified as LAWs, such as Figure 1 displays. Finally, each LAW was correlated with the whole signal, and the one providing the best average correlation was selected to act as MW.

However, in this last step the chosen waveform had to met the mathematical criteria described by eqs. (2), (3) and (4), where $\hat{\psi}(f)$ represents the Fourier transform of the MW and the admissibility constant C_g defines the range of frequencies covered by each employed scale a [14].

$$\int_{-\infty}^{+\infty} |\psi(t)|^2 dt \ < \ \infty, \qquad (2)$$

$$\hat{\psi}(f) = \int_{-\infty}^{+\infty} \psi(t) e^{-i(2\pi f)t} dt, \qquad (3)$$

$$C_g = \int_{0}^{+\infty} \frac{|\psi(t)|^2}{f} df < \infty. \qquad (4)$$

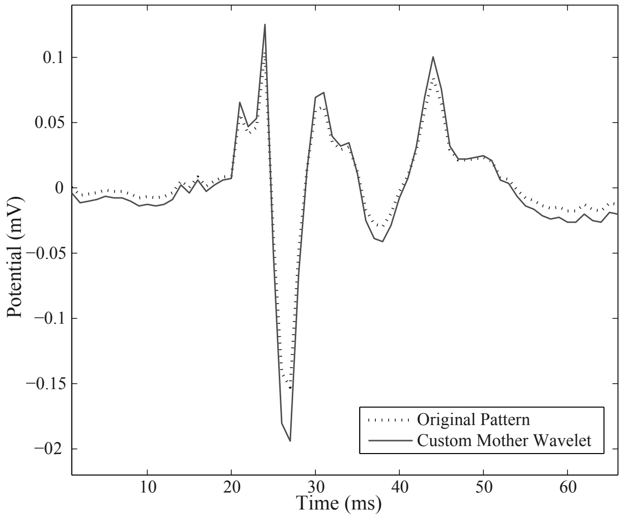

Figure 2. Graphical comparison between the obtained WM (solid line) and the selected LAW (dotted line) for a typical EGM. No relevant differences can be noticed between them.

Under these constraints, the selected pattern was approximated by a least squares optimization to be transformed into an admissible MW. Nonetheless, no significant alteration was observed for the obtained MW from every EGM, such as Figure 2 shows for a typical example.

The generated MW was then used to decompose the EGM into 16 stepwise scales. As can be observed from Figure 3, the wavelet coefficients energy resulted narrowly concentrated on the LAWs for every scale. Hence, although all of them could be used to detect LAWs, an exponentially weighted combination of the first six scales was considered for that purpose [12]. The resulting signal was normalized by using the original signal amplitude as a reference. Finally, an experimental threshold was set to discern between real LAWs and other complex patterns provoked by artifacts. It was adaptively modified to avoid the lack of LAWs. Thus, for every identified LAW its distance with the preceding wave was computed and, in case of this value was higher than 350 ms, the threshold was decreased to search for a LAW in between. Moreover, a 75 ms blanking period was also established around every detected LAW to prevent redundant marks.

4. Results

The proposed algorithm performance was evaluated in terms of sensitivity (*Se*) and positive predictive (P^+). Both metrics were defined as the ratio between the total of LAWs correctly classified and this number extended by false detections. Thus, whereas for *Se* false detections were the undetected LAWs, named as false negatives (FNs), for P^+ they were the points incorrectly marked as LAWs, named as false positives (FPs). The ratio between the number of LAWs correctly identified and its total, called accuracy (*Acc*), was also computed.

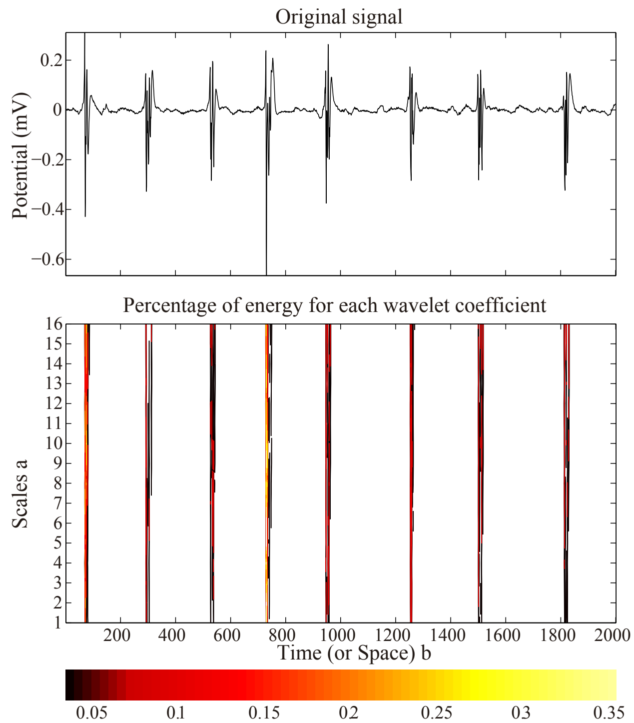

Figure 3. Wavelet energy distribution as a function of the time and scale for a typical EGM interval. As can be observed, the energy is narrowly concentrated on the LAWs for every scale.

Experts identified 970 LAWs from the analyzed database, the proposed algorithm being able to identify properly 959. Hence, it failed 11 detections, corresponding 3 to FPs and 8 to FNs, such that global values of *Se*, P^+ and *Acc* were 99.17%, 99.69% and 98.86%, respectively. In average for all the recordings, very similar values were also obtained: $Se = 99.18\% \pm 1.35\%$, $P^+ = 99.69\% \pm 0.66\%$ and $Acc = 98.90\% \pm 1.51\%$.

5. Discussion and conclusions

This work has introduced for the first time a novel algorithm to detect LAWs based on designing a customized MW for every EGM under analysis. The obtained results reported a high accuracy and a limited rate of erroneous detections when dealing with EGMs from different atrial areas. This behavior could be explained by the fact that the selected MW for each recording was able to highlight exclusively the LAWs, ignoring other non-atrial patterns. To this respect, Figure 1 shows how the algorithm only emphasized the atrial activations, minimizing the remaining areas among them. A proper detection of LAWs was then easier from this signal than from the obtained by the widely used Botteron's approach. In fact, noise, artifacts or other middle oscillations leading to false detections from the Botteron's approach were successfully avoided by the proposed algorithm.

Nonetheless, it should be mentioned that this method still uses the Botteron's approach as a initial step. However, it was only used to identify a clear and limited set of LAWs. Hence, because the main limitation for the Botteron's approach is the difficulty to discern automatically between noise and low amplitude atrial activations [4], this aspect does not restrict the proposed algorithm potential.

As a consequence, this algorithm could be a key first step to develop more reliable and accurate real-time anatomical maps, which could be helpful to improve the catheter ablation guiding as well as the current knowledge about AF mechanisms. Nonetheless, this pilot work must be extended to test the method with wider databases. Only in this way the robustness and repeatability of the obtained results could be validated.

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References

[1] Fuster V, Rydén LE, Cannom DS, Crijns HJ, Curtis AB, Ellenbogen KA, Halperin JL, Kay GN, Le Huezey JY, Lowe JE, et al. 2011 ACCF/AHA/HRS focused updates incorporated into the ACC/AHA/ESC 2006 Guidelines for the management of patients with atrial fibrillation: a report of the American College of Cardiology Foundation/American Heart Association Task Force on Practice Guidelines developed in partnership with the European Society of Cardiology and in collaboration with the European Heart Rhythm Association and the Heart Rhythm Society. Journal of the American College of Cardiology 2011;57(11):e101–e198.

[2] Heeringa J, van der Kuip DA, Hofman A, Kors JA, van Herpen G, Stricker BHC, Stijnen T, Lip GY, Witteman JC. Prevalence, incidence and lifetime risk of atrial fibrillation: the Rotterdam study. European heart journal 2006; 27(8):949–953.

[3] Calkins H, Kuck KH, Cappato R, Brugada J, Camm AJ, Chen SA, Crijns HJG, Damiano Jr RJ, Davies DW, DiMarco J, et al. 2012 HRS/EHRA/ECAS Expert Consensus Statement on Catheter and Surgical Ablation of Atrial Fibrillation: recommendations for patient selection, procedural techniques, patient management and follow-up, definitions, endpoints, and research trial design. Europace Apr 2012; 14(4):528–606.

[4] Ng J, Sehgal V, Ng JKY, Gordon D, Goldberger JJ. Iterative method to detect atrial activations and measure cycle length from electrograms during atrial fibrillation. Biomedical Engineering IEEE Transactions on 2014;61(2):273–278.

[5] Treo EF, Cervantes DO, Ciaccio EJ. Automated detection and mapping of electrical activation when electrogram morphology is complex. Biomedical Signal Processing and Control 2013;8(1):41–49.

[6] Ng J, Kadish AH, Goldberger JJ. Effect of electrogram characteristics on the relationship of dominant frequency to atrial activation rate in atrial fibrillation. Heart Rhythm 2006;3(11):1295–1305.

[7] Verheule S, Tuyls E, van Hunnik A, Kuiper M, Schotten U, Allessie M. Fibrillatory conduction in the atrial free walls of goats in persistent and permanent atrial fibrillation. Circulation Arrhythmia and Electrophysiology 2010;3(6):590–599.

[8] Faes L, Ravelli F. A morphology-based approach to the evaluation of atrial fibrillation organization. IEEE Engineering In Medicine And Biology Magazine 2007; 4(26):59–67.

[9] Botteron GW, Smith JM. A technique for measurement of the extent of spatial organization of atrial activation during atrial fibrillation in the intact human heart. Biomedical Engineering IEEE Transactions on 1995;42(6):579–586.

[10] Houben RP, de Groot NM, Lindemans FW, Allessie MA. Automatic mapping of human atrial fibrillation by template matching. Heart Rhythm 2006;3(10):1221–1228.

[11] Lin YJ, Lo MT, Lin C, Chang SL, Lo LW, Hu YF, Chao TF, Li CH, Chang YC, Hsieh WH, Chung FP, Tsao HM, Chang HY, Huang NE, Chen SA. Nonlinear analysis of fibrillatory electrogram similarity to optimize the detection of complex fractionated electrograms during persistent atrial fibrillation. J Cardiovasc Electrophysiol Mar 2013;24(3):280–9.

[12] Houben RP, De Groot N, Allessie M, et al. Analysis of fractionated atrial fibrillation electrograms by wavelet decomposition. Biomedical Engineering IEEE Transactions on 2010;57(6):1388–1398.

[13] Alcaine A, Soto-Iglesias D, Calvo M, Guiu E, Andreu D, Fernández-Armenta J, Berruezo A, Laguna P, Camara, et al. A wavelet-based electrogram onset delineator for automatic ventricular activation mapping. Biomedical Engineering IEEE Transactions on 2014;61(12):2830–2839.

[14] Misiti M, Misiti Y, Oppenheim G, Poggi JM. Wavelets and their Applications. John Wiley & Sons, 2013.

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