Wavelet Scattering Transform for Enhancing ablation Outcomes in Persistent Atrial Fibrillation

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Abstract

Introduction*: Several strategies have been used to target persistent atrial fibrillation (persAF) driver. However, no unique strategy has been proven effective in patients with persAF. Machine learning (ML) classifiers using features extracted from wavelet scattering transform (WST) might enhance the ablation outcomes.* ***Methods****: 51 high DF locations were ablated in 10 patients. 3206 non-contact electrograms (EGMs) were collected pre- and post-ablation using a balloon catheter. 1490 EGMs were labelled as positive ablation responses (AF termination or AF cycle length (AFCL) increased (≥10msec)), whereas 1716 EGMs were labelled as negative responses (AFCL increase (<10msec)) to catheter ablation. The WST technique was applied to extract features from EGMs after applying the QRST subtraction process. Several wavelet functions and dimensionality reduction methods were used. 10 ML classifiers were trained and tested by leaving EGMs of one patient out 10-fold cross-validation (CV).* ***Results****: The 10-fold CV overall accuracy, sensitivity, specificity, precision, F1_ score, AUROC, and balanced accuracy for the best scenario were using the Morlet function in WST, PCA, and the decision tree model with 78.91%, 81.21%, 76.92%, 75.34%, 78.17%, 0.76 and 79.07%.* ***Conclusions****: WST, with the help of PCA, played a significant role in predicting the responses of ablating the EGMs and their effect on AF termination and CL changes. The obtained results demonstrate the superiority of this method over our previous work.*

1. Introduction

Atrial fibrillation (AF) is the most common arrhythmia, affecting around 1-2% of the population. The risk of stroke is increased by around 5-fold in AF patients. Pulmonary vein isolation (PVI) is the cornerstone of ablation protocols for various types of AF [1]. Ablation strategies of persistent AF are more complicated and require ablation of additional sites in the atria, responsible for AF drivers. Several classical methods have been used to target the AF drivers, including dominant frequency (DF) [2], rotors [3], and complex fractionated atrial electrograms (CFAEs). However, the ablation outcomes using these methods have been suboptimal, and no ablation strategy has been verified in patients with persistent AF. Several signal processing techniques have been used to analyze the electrogram's characteristics for discriminating AF and non-AF signals. Most EGM analyses are based on Fourier transform (FT) analysis [4]. Due to the reciprocal relationship between the time and frequency resolution domains, an adapted version of the Fourier transform, known as the short-time Fourier transform (STFT), is considered for this effect [5]. STFT, which analyze the frequency content of signals over fixed-sized windows, has some limitations. Therefore, a wavelet transform (WT) is employed to analyze the frequency content of signals over different window sizes by using a wavelet function. A wavelet-based activation detector for more reliable computation of activation time of EGMs during the AF [6].

Deep learning techniques (e.g., convolutional neural networks (CNNs)) are used to extract features from raw signals or their time-frequency representations automatically. Hence, inspired from the large-scale deep learning algorithms on large datasets, we sought to have a better understanding of the deep network that utilizes some operations associated with CNNs [7, 8]. With its roots from CWT, wavelet scattering transform (WST) network extracts the frequency contents of the signals in an efficient way and produces coefficients/features that can be used as inputs to different machine learning classifiers. We used the WST technique to predict ablation outcomes in human persistent atrial fibrillation using non-contact electrogram signals.

2. Materials and Methods

The complete diagram for the proposed method, from data collection to outcomes, is shown in Figure 1.

2.1. Dataset Collection and Labeling

51 locations were identified in the left atrium of 10 persistent AF (persAF) patients as high dominant frequency (HDF) regions to guide the catheter during the ablation procedure. A total of 3206 non-contact electrogram (EGM) signals were collected from the ablating of these locations using an Ensite array mapping catheter (Abbot, USA) (Figure 1A). The EGM signals for an 18-second duration were collected pre- and post-ablations. The EGM signals were labeled by cardiologists from the Leicester Glenfield Hospital into two classes: a positive response to catheter ablation (AF termination or AF cycle length >=10ms), and a negative response (AFCL increased <10ms) [9]. Four out of ten patients had AF termination (three flutter and one sinus rhythm) before the PVI procedure.

2.2. AF Signal Processing

The collected signals were sampled at a rate of 2038.5 Hz and then resampled at 512 Hz to reduce processing time and memory allocation. A QRST complex subtraction process was applied to remove far-field effects resulting from ventricular activity, which can distort the true AF characteristics [10]. Lead I was used as a reference lead in the QRST removal process (Figure 1B).

2.3. Wavelet Scattering Transform

The wavelet scattering transform (WST) is a time-frequency analysis method. WST is commonly used in different biomedical applications due to its stability in the presence of local deformation [11]. The WST procedure is similar to a deep convolution network that iterates over three operators: complex wavelet transforms, a non-linear modulus operation | |, and a low-pass filter (averaging). Figure 1C shows the features extracted using WST for the two-levels tree structure. At the first layer of WST, the original signal $x(t)$ is convolved with the mother wavelet function ψ, which has a central frequency of λ. A non-linear modulus | | operator is applied to remove these oscillations. Lastly, a low pass filter ϕ is used to average the resultant convoluted signal. This process will be repeated for the other layers in WST to obtain the m scattering coefficients.

$$S_m x = \left| \left| x * \psi_{\lambda_1} \right| * \ldots \right| * \psi_{\lambda_m} \Big| * \varphi_J \qquad i = 1, 2, 3, \ldots, m \tag{1}$$

2.4. Wavelet functions

Morlet and Daubechies order 4 (bd4) were used as wavelet functions to extract the scattering features coefficients. Each wavelet has special characteristics for analyzing biomedical signals.

2.5. WST parameters

The WST technique requires setting several parameters to achieve meaningful results. The filter is designed to support a certain size (T) of the input signal. J and Q are the most important parameters used to control the frequency and scale of the wavelet transform. J represents the number of octaves used in decomposing the WST, and the Q parameter (also called 'quality factor') is the number of wavelets per octave of frequencies (dyadic scale). In this study, a wavelet scattering network was constructed using two layers. We set T = 9216 samples (18 seconds), Q1 = 10, and Q2 = 1 wavelet per octave at the first and second layers in the scattering network, and the J parameter was set to 3.

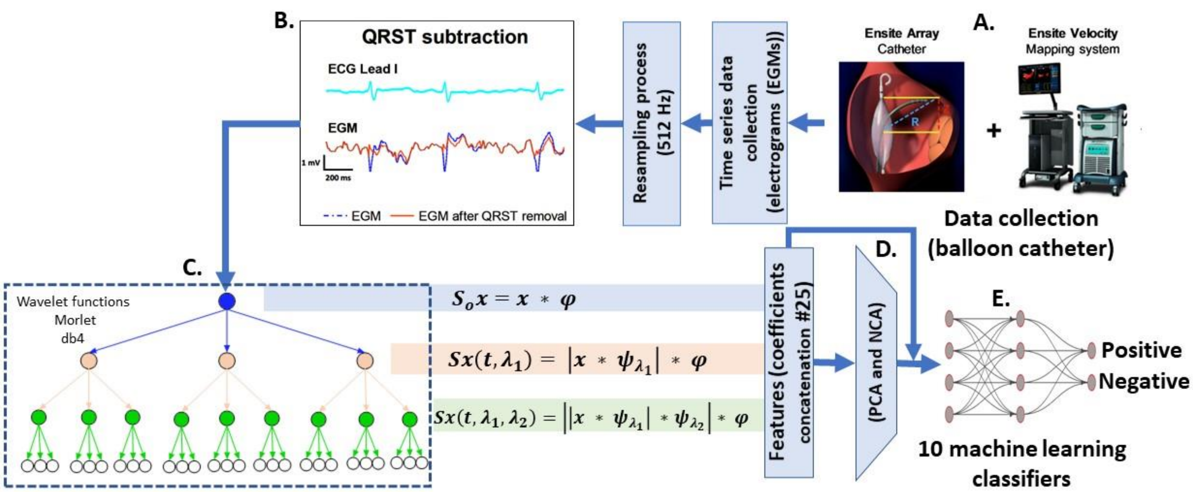

Figure 1 The pipeline for the proposed method using the WST technique.

2.6. Dimensionality reduction

Several dimensionality reduction (DR) techniques were used to reduce the number of features. Principal component analysis (PCA) and neighborhood component analysis (NCA) were used as supervised and unsupervised methods, respectively, to minimize the features in the feature vector (Figure 1D).

2.7. Machine learning models

Ten machine learning classifiers (random forest (RF), decision tree (DT), K nearest neighbors (KNN), AdaBoost, Gradient Boosting, Extra trees, support vector classifier (SVC), bagging and Bernoulli) were used for predicting the ablation outcomes based on the features from the WST and the reduction dimensionality methods PCA and NCA (Figure 1E).

3. Results and Discussion

Six scenarios were proposed to predict the ablation outcomes, as shown in Figure 2. A 10-fold leave EGMs one patient out cross validation (LEOPOCV) technique was used to assess the performance of each scenario. The best scenario was selected based on its performance in the metrics explained in Section 2.6. Scenario 2 (Morlet + PCA + decision tree model) showed the best performance with overall accuracy (ACC) of 78.91%, Sensitivity (SEN) of 81.21%, Specificity (SPC) of 76.92%, Precision (PPV) of 75.34%, F1_ score of 78.17%, AUROC of 0.76, and the balanced accuracy (BAC) of 79.07%. It can be seen that the metrics ranged from 76% to 79% for the highest performance classification (scenario 2) (Figure 3). The wavelet scattering-based Morlet function performed better than db4 in all scenarios. This might be because Morlet wavelets are well-suited for analyzing the time-frequency characteristics of non-stationary signals (such as EGM signals) by capturing both amplitude and phase information. Morlet wavelets offer a well-balanced time and frequency resolution for signals [12]. The algorithms based on decision trees work well with non-linear features; ML classifiers based on trees had the best performance among the others.

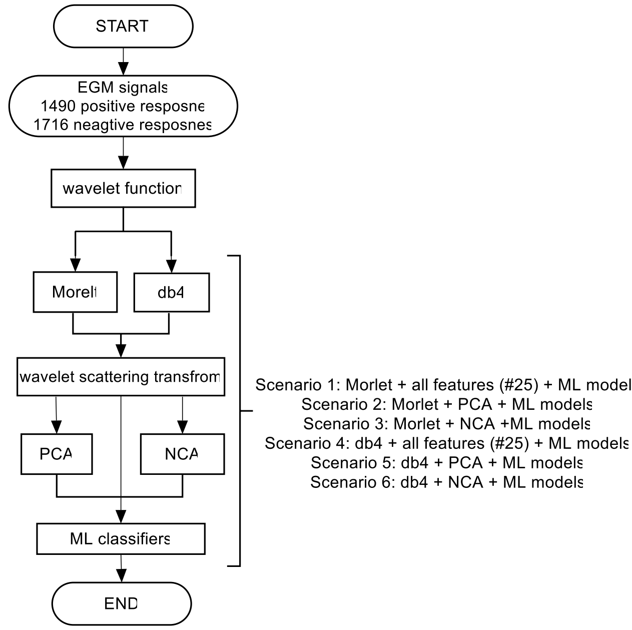

Figure 2 Flowchart of the proposed 6 scenarios

To assess the performance of the best scenario (Scenario 2), a confusion matrix (CM) was used to display the number of positive and negative classifications. Figure 4 shows the CM and the receiver operating characteristics (ROC) for scenario 2. It can be seen that the second scenario had a good balance of TP and TN values. Therefore, to achieve the highest-performance model for predicting the EGM responses to the ablation procedure, it is essential to consider the PCA as a DR method and the DT model as an ML classifier. The proposed WST method boasts an advantageous characteristic of the EGM signals: invariance to both dilation and translation. A comparison was made between the proposed method and our previous work [13], showing the superiority of this approach.

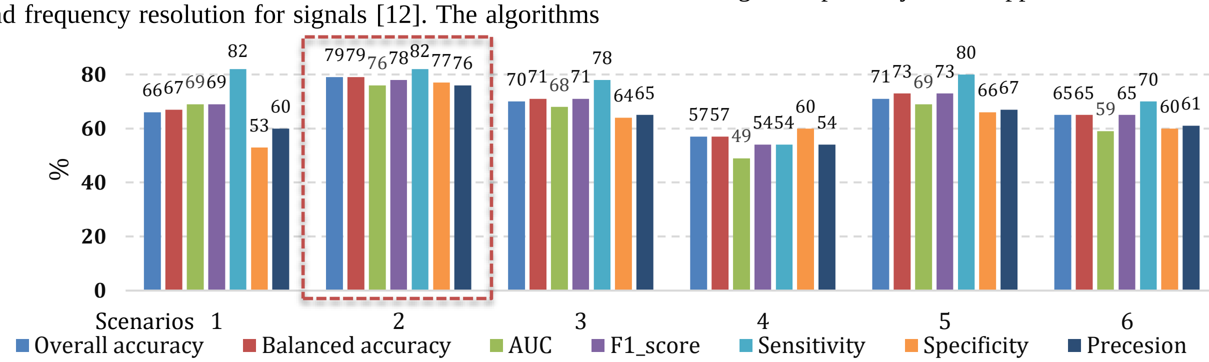

Figure 3 performance comparisons of the 6 scenarios

Table 1 Comparison of the proposed method with our previous work

Features type	Best model	Overall accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1_score (%)	Balanced accuracy (%)	AUC
Three signal domains [13]	DT	75.22	76.5	74.5	72.3	74.34	75.5	0.73
Proposed method (scenario 2)	**DT**	**78.91**	**81.21**	**76.92**	**75.34**	**78.17**	**79.07**	**0.76**

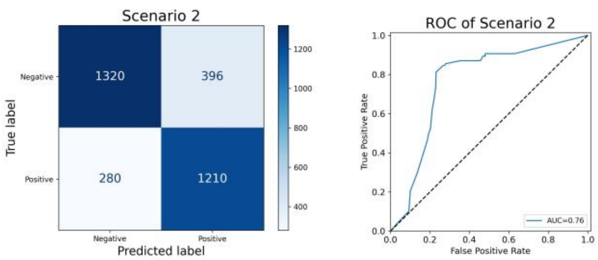

Figure 4 CM and ROC for scenario 2

4. Conclusions

WST, with the help of the PCA technique, played a significant role in predicting the responses of ablating the EGMs and their effect on AF termination and CL changes. Scenario 2 using WST features, Morlet as wavelet function, PCA and DT as classifier had the highest performance over others with overall accuracy (ACC) of 78.91%, Sensitivity (SEN) of 81.21%, Specificity (SPC) of 76.92%, Precision (PPV) of 75.34%, F1_ score of 78.17%, AUROC of 0.76, and the balanced accuracy (BAC) of 79.07%. Scenarios with the Morlet function and PCA technique showed the highest performance compared to using db4 and NCA techniques. A comparison between the proposed method and our previous work [13] shows the superiority of this method in predicting the ablation outcomes.

Acknowledgments

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