Choosing Electrogram Features for Predicting Catheter Ablation Outcomes in Persistent Atrial Fibrillation

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Abstract

The rate of successful outcomes of catheter ablation to treat persistent atrial fibrillation (persAF) using individual features including dominant frequency (DF), complex fractionated atrial fibrillation (CFAE), and rotors have been disappointing. We aim to identify the most important electrogram (EGM) features for successful ablations using a Random Forest (RF) classifier. A total of 3206 EGMs were collected using non-contact mapping catheter from 10 patients. 1490 EGMs were labelled as positive responses to ablation and 1716 EGMs as negative. Features were extracted from the three EGM signal domains (spectral, temporal and statistical) using time series feature extraction library in python. Five-fold cross validation (CV) was used for training and testing the classifier. A CV accuracy of 80.54% and F1 score of 78.23% were achieved for classifying the responses of EGMs to catheter ablation, with a sensitivity of 75.2% and specificity of 85.14%. RF showed potential for predicting the responses of EGMs to catheter ablation and finding the most important features. These features are the power spectral density (PSD) at 10Hz, the mean and the mean voltage of differences for spectral, statistical and temporal domains, respectively. This will further inform the further development of key features of EGMs for guiding catheter ablation in persAF.

1. Introduction

In clinical practice, atrial fibrillation (AF) is the most common sustainable arrhythmia, and uncoordinated activation of the atria is the main cause of such type of arrythmia. AF is relevant with the incidence of stroke, heart failure and the cardiac death in adults [1, 2], as the AF condition leads to blood clots in the atria due to the lack of effective atrial contraction in AF patients. AF therapy aims to restore the sinus rhythm. Medication has been used to regulate the heartbeat, but some AF patients continue to sustain AF in spite of medication treatment[3]. Catheter ablation is commonly employed to treat paroxysmal AF, but it is less effective for persistent AF (persAF), due to different mechanisms that initiate and maintain persAF [4]. Features using traditional methods such as DF [5], CFAE [6] and rotors [7] have not shown be sufficient to guide persAF ablation. Therefore, researchers have been searching for other features in EGMs to guide AF ablations. Features of EGMs represented by the power spectrum play an important role in treating the AF for the accepted frequency in human which is in the range between 3-15 Hz [5]. Voltage of the signals also has an impact to discriminate the regions that harbour the AF drivers. The low voltage regions in the atria are more dominant to harbour the AF [8-10]. Therefore, EGM features that are mentioned above might be good sites to terminate and enhance catheter ablation to treat the persAF. Machine learning techniques have been widely used to detect AF using ECG signals, but the utility of these techniques in raw EGMs classification based on positive or negative responses to catheter ablation has been explored for few works.

2. Materials and Methods

2.1. Dataset

The dataset was collected from 10 persAF patients undergoing left atrium (LA) catheter ablation for the first time. The high dominant frequency (HDF) regions were identified as described before [11]. The dataset was collected using non-contact basket mapping catheter using Ensite array, St. Jude Medical, 2048 nodes. EGMs were exported to the MATLAB platform and ablation was guided by DF. After the ablation process 4 out of 10 patients had AF termination (1 sinus rhythm and 3 flutters) before the pulmonary vein isolation (PVI). EGMs of up to 20 seconds were exported from all patients before ablation procedure to train and test the RF classifier.

 ISSN: 2325-887X DOI: 10.22489/CinC.2023.289

2.2. Data Labelling

The dataset was labelled based on AF cycle lengths (AFCL) criterion. The AFCL before and after ablation was calculated in a total of 51 locations (3206 EGMs) identified by HDF of 10 patients. Two classes of pre-ablation EGMs were considered as labels: positive and negative responses to catheter ablation. A positive response was identified by AF termination or AFCL increase (≥10ms), whereas negative response by AFCL decrease (≤10ms) [2] or AFCL unchange. A total of 3206 nodes were classified:1716 as negative and 1490 as positive responses.

2.3. Pre-processing

The 20 seconds of the collected EGMs were sampled at 2034.5Hz and then re-sampled to 512Hz to reduce the memory requirements for storage. QRST subtraction was performed to remove the effect of the far-field from the ventricle [12]. The middle window in Figure 1 shows the QRST subtraction process for EGM signal.

2.4. Feature Extraction

A total of 390 features were extracted from the EGMs using time series feature extraction library (TSFEL) [13]. This library is designed and implemented to be suitable for feature extraction from biomedical signals. The library extracted features from the EGMs in three domains (spectral, temporal and statistical). The extracted features from this library are shown in table 1.

2.5. Feature Selection

Feature selection process was performed to remove the features that are highly correlated and low variance. Pearson's correlation method with a threshold of 75% was used to remove the high correlated features. Low variance features were also removed with threshold of 0, where the EGM feature was removed from the feature set when the feature has exactly the same value for all EGM samples.

2.6. Feature Importance

A total of 32 features were resulted from the feature selection step. RF classifier was used to score of these features and then sequenced them based on their importance in the classification process. Figure 2 shows the features importance based on mean decrease in impurity (MDI) (Gini importance) criterion, which counts the times a feature is used to split a node, weighted by the number of samples it splits.

Table 1.Features extracted using TSFEL [13]

SPECTRAL DOMAIN	TEMPORAL DOMAIN	STATISTICAL DOMAIN
• FFT Mean Coefficients (#256)	• Absolute energy	• ECDF (#10)
• Fundamental Frequency	• Area Under the Curve	• ECDF Percentile (#2)
• Human Range Energy	• Autocorrelation	• ECDF Percentile Count (#2)
• LPCC (#13)	• Centroid	• Histogram (#10)
• Maximum Frequency	• Entropy	• Interquartile Range
• Maximum Power Spectrum	• Negative turning points	• Kurtosis
• Median Frequency	• Mean Absolute Difference	• Maximum
• MEL Frequency Cepstral Coefficients (#12)	• Mean differences	• Mean
• Power Bandwidth	• Median Absolute Difference	• Mean Absolute Deviation
• Spectral Centroid	• Median Difference	• Median
• Spectral Decrease	• Positive turning points	• Median Absolute Deviation
• Spectral Distance	• Peak to Peak Distance	• Minimum
• Spectral Entropy	• Signal Distance	• Root Mean Square
• Spectral Kurtosis	• Slope	• Skewness
• Spectral Positive turning points	• Sum Absolute Difference	• Standard Deviation
• Spectral Roll-off	• Total energy	• Variance
• Spectral Roll-On	• Zero Crossing Rate	
• Spectral Skewness	• Neighborhood peaks	
• Spectral Slope		
• Spectral Spread		
• Spectral Variation		
• Wavelet Absolute Mean (#9)		
• Wavelet Energy (#9)		
• Wavelet Entropy		
• Wavelet Standard Deviation (#9)		
• Wavelet Variance (#9)		
# Spectral features = 336	**#Temporal features = 18**	**# Statistical features = 36**
#Total features = 390		

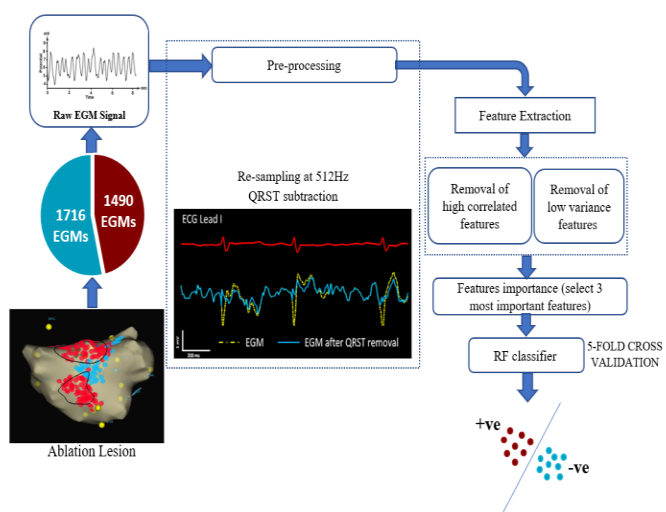


Figure 1. The complete diagram for the proposed method

2.7. RF Model Training

RF classifier was implemented using anaconda environment with python 3.8 for simulation. Five-fold cross validation technique was applied to a total of 3206 EGMs for training and testing the model. The classifier was trained using 80% (2565 EGMs) and tested on 20% (641 EGMs) of the dataset. The 3 most important features were selected to train and test the model, which can speed up the training process and also make them easier to analyse for guiding the ablation procedure. These features represented by FFT mean coefficient at 10Hz (PSD at 10 Hz) as the spectral domain feature, mean voltage of signal as a statistical domain feature and mean voltage of differences as the temporal domain feature. Grid search algorithm was applied to set and optimise the parameters' tunning as below:

- Max_depth = 5, and represents the number of splits for the decision tree in the RF trees is allowed to make. The number from 3-5 is good to prevent the overfitting of the RF classifier.
- N_estimators =10, and represents the number of trees in the forest.
- Criterion='gini', Gini was used as a criterion to evaluate the feature's importance.

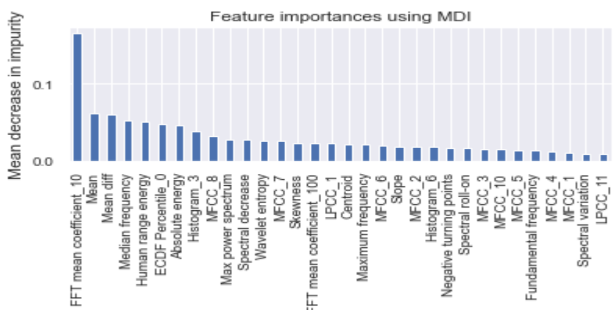


Figure 2. Importance of features based on MDI

3. Results and Discussion

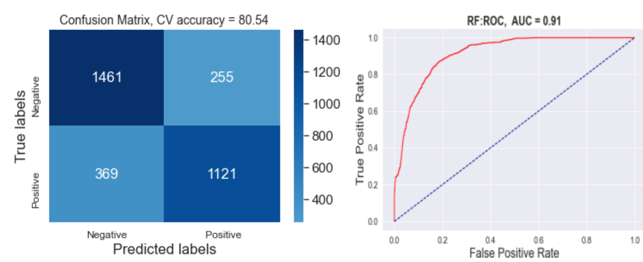
A RF classifier was used to classify the EGMs based on their positive or negative responses to catheter ablation. A total of 3206 labelled EGMs were used, with 2565 EGMs used as a train set, and 641 as a test set. The trained RF classifier achieved overall accuracy (5-fold-CV accuracy) of 80.54%.

3.1 CM and ROC

The confusion matrix (CM) for the trained RF classifier is shown in Figure 3a. This figure shows the number of true positive and negative responses in comparison with the total number of EGMs responses. It can be seen that the trained classifier achieved an overall accuracy 80.54% using 5-fold CV technique, whereas it performed 75.2%, 85.14% and 78.23% for a sensitivity, specificity and the F1_score, respectively. Receiver operating characteristics (ROC) and the area under the curve (AUC) for the positive class are shown in Figure 3b. It can be noticed that the AUC for the trained classifier was 0.91.

3.2 Statistical Feature Analysis

The unpaired t-test was used to analyse the 3 most important features. Unpaired t-test using Welch's correction were applied to analyse the binary RF model. Figure 4 shows the mean and the standard deviation for the 3 most important features. The mean of PSD at 10Hz for the positive and negative classes were 0.0018±0.0013 and 0.0015±0.0024. The mean voltages were 0.011±0.036 and 0.027±0.055, while the mean differences were $-2.2\times10^{-6}\pm5.5\times10^{-5}$ and $1.5\times10^{-5}\pm6.8\times10^{-5}$, respectively. P-value for the two classes was <0.0001. These results support the recent findings that PSD of EGMs has an impact for successful ablation [5]. In this work, EGM regions that responded positively to catheter ablation have higher PSD at 10Hz, and also atrial regions with low voltage and high frequency are more likely to harbour AF drivers [8, 9]. Low voltage areas in left atrial are the marker for presence of fibrosis areas [10]. Therefore, it is noticed that the features of the positive class were different from those of the negative class. This indicates that atrial regions responsible for AF exhibit distinct characteristics compared to non-AF regions.



(a) (b)

Figure 3. CM and ROC for the trained RF classifier

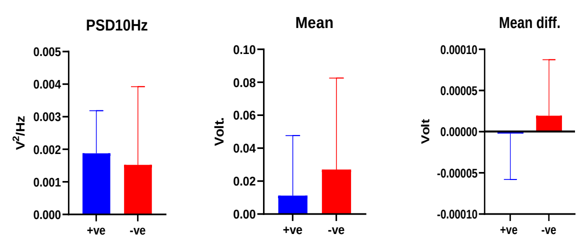


Figure 4. The bar graph of 3 most important features.

4. Model Employment and Limitations

The RF trained model applied to all data points (2048) including the nodes/EGMs that are not ablated for predicting the responses of EGMs to catheter ablation. Figure 5 shows the 3D geometry of 10 patients. The left atrium of all patients is color-coded by the prediction of RF model, whereas the color-coded dots are the actual ablation responses. The limitation of this work represents by the number of patients. Therefore, more patients with more ablation lesion dataset would assist to enrich the trained classifier with more knowledge for classification of EGMs responses for inter-patients' differences.

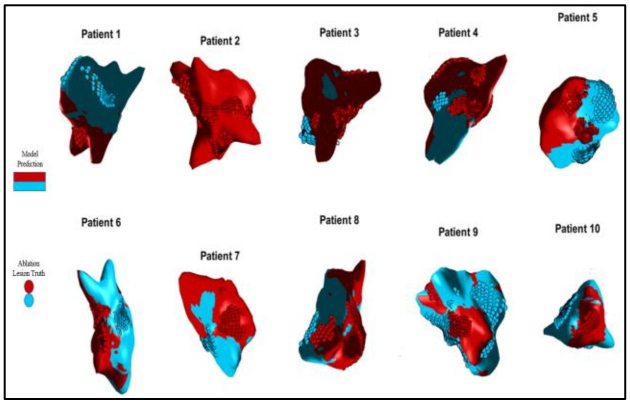


Figure 5. The 3D geometry of left atrium of 10 patients

5. Conclusions

This paper aims to identify the most important features associated to the initiation and maintenance of persAF from three EGM signal domains (spectral, temporal and statistical). Twenty seconds of EGM duration were used in the proposed method. Features based on three EGM domains were extracted from each signal. The importance for each feature was calculated based on mean decreased in impurity. The most important features using RF classifier represented by PSD for spectrum frequency 10Hz for spectral domain, mean voltage for the statistical domain and mean voltage of differences for the temporal domain of the signals. These important findings may suggest that targeting the sites with these features might lead to an improvement of the success rate of catheter ablation for treating the persAF. The accuracy of trained RF classifier based on these features was 80.54%.

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