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 EGM features for successful ablations using a Random Forest (RF) classifier. A total of 3206 EGMs (nodes) were collected using non-contact mapping catheter of 10 patients for 20 seconds duration using (Ensite array, St Jude Medical) system. 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 domain) using time series feature extraction library (TSFEL) in python. The three most important features were selected for this classification. Five-fold cross validation (CV) was used for training and testing the classifier, where 80% of data were used as training, and 20% as testing. A CV accuracy of 80.54% and F1 score of 78.23% were achieved for identifying and classifying the responses of EGMs to catheter ablation, with a sensitivity of 75.2% and specificity of 85.14%. RF classifier showed potential for predicting the responses of EGMs to catheter ablation and finding the most important features of EGMs. These features are the power spectral density (PSD) of spectrum frequency at 10 Hz, the mean voltage and mean voltage of differences for spectral, statistical and temporal EGM signal domains, respectively. This will further inform the further development of key features 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 than others [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. Material 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.

2.2. Data Labelling

The dataset was labelled based on 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 increased by ≥10ms [2], whereas negative response by AFCL decrease of <10ms or unchanged. A total of 3206 nodes were classified:1716 as negative and 1490 as positive response.

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 TSFEL. 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 with low variance. Pearson's correlation technique with a threshold of 75% was used to remove the high correlated features. Only one feature was retained from two features that were correlated by ≥75%. 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.

Table 1. Features extracted based on bio signal domain

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

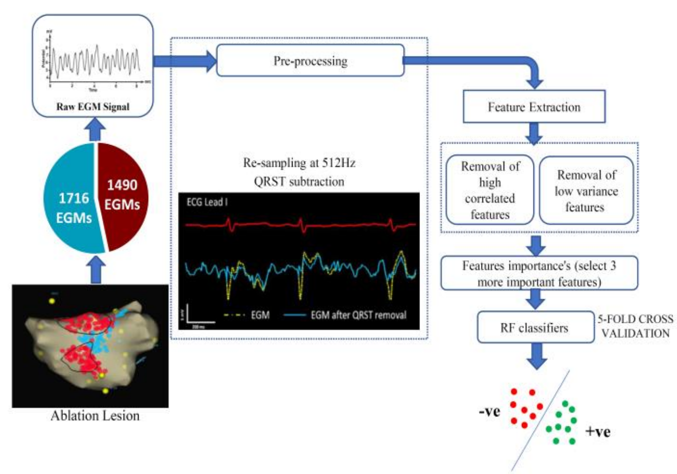


Figure 1. The complete diagram of data collecting, labelling, pre-processing and analysis techniques.

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 (Gini importance) criterion, which counts the times a feature is used to split a node, weighted by the number of samples it splits.

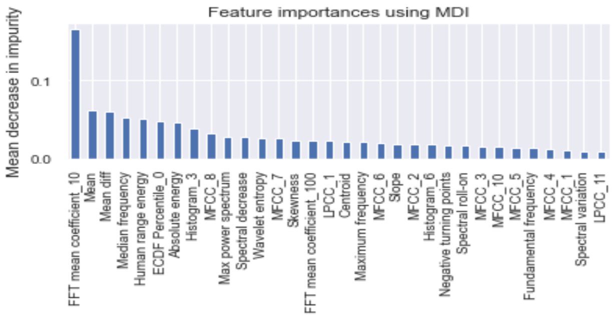


Figure 2. Importance of features based on MDI

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% (2956 EGMs) and tested on 20% (640 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 10 Hz (PSD of spectrum frequency at 10 Hz) as the frequency 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.

3. Results and Discussion

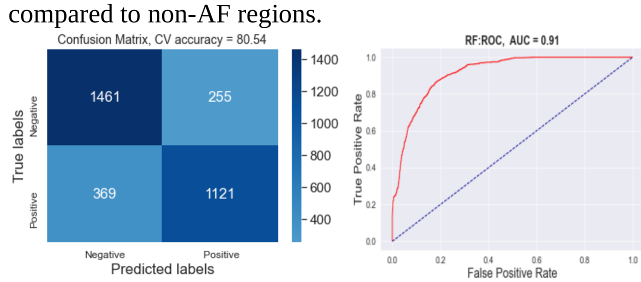
A RF classifier was used to classify the EGMs based on their positive or negative responses to catheter ablation. A total of 3206 labelled EGMs were used, with 2965 EGMs used as a train set, and 641 as a test set. The trained RF classifier achieved overall accuracy (5-fold-CV accuracy) of 80.54%.

3.1 CM and ROC

The confusion matrix (CM) for the trained RF classifier is shown in Figure 3. 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 4. 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 for the binary RF model classification. Figure 4 shows the mean and the standard deviation for the 3 most important features. The mean of PSD of spectrum frequency at 10 Hz 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 $1.5\times10^{-5}\pm6.8\times10^{-5}$. P-values for the two classes are <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 PSD at 10 Hz, 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

2.8. Model Employment and Limitation

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 to catheter ablation for inter-patients' differences.

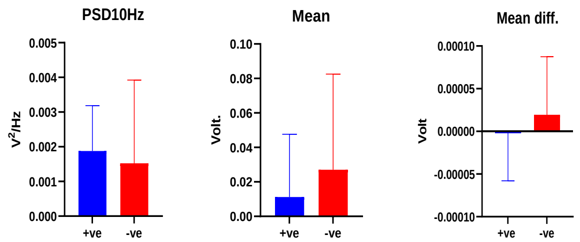


Figure 4. The bar graph of 3 most important features.

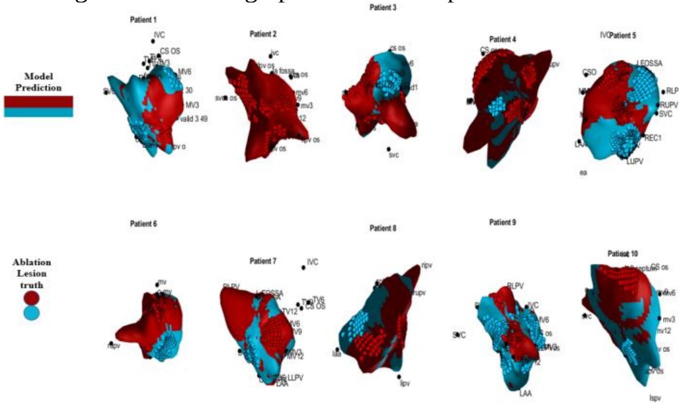


Figure 5. The 3D geometry for all 10 patients showing the prediction and actual EGMs.

4. 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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