

# P-wave Analysis in Atrial Fibrillation Detection using a Neural Network Clustering Algorithm

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## Abstract

*Absence of P-waves in ECG records with irregular interbeat intervals (R-R) is a sign of Atrial Fibrillation (AF). Detection of P-waves in ECG beats or even average beats could be challenging if the artifact resembles a P-wave, or an actual P-wave is buried in the artifact. We developed a neural network algorithm to generate the ECG beat clusters in segments of the record. Beats with matching QRS complexes were clustered using Self-Organizing Map (SOM) technique and then cross-correlated to combine and generate the dominant clusters. This process helps to eliminate the abnormal or Artifact-corrupted beats. Fiducial points of the dominant average beat were measured by morphological techniques. If P-wave is detected in the average beat, it defines a smaller search window for individual beats to exclude the potentially false P-waves. A series of P-wave features determine the presence of P-wave throughout an ECG segment.*

*Our algorithm was tested on several datasets with annotated intervals for some cardiac rhythms. A decision tree ensemble of bagged trees classifier was developed and applied the P-wave and interbeat interval features, resulting in AF/non-AF classification with average  $F_1$  score of 96.0% in training subset and 95.6% in test subset of all records.*

## 1. Introduction

Atrial Fibrillation (AF) is the most common sustained cardiac arrhythmia associated with high rate of morbidity and mortality. AF is seen in about 1-2% of population and its prevalence is increasing rapidly [1,2]. Early detection and treatment of AF can prevent its subsequent complications such as stroke, heart failure, and sudden death [3].

Silent (asymptomatic) AF is associated with the same risk of cardiac diseases as symptomatic AF [4,5]. Unless identified incidentally in the patient's short ECG record, asymptomatic AF requires prolonged ECG monitoring with Holters or wearables which could be expensive and uncomfortable.

Several automated AF detection algorithms have been suggested in the past, however, automatic AF detection is still a challenging task, mostly due to its episodic nature.

Real-time data analysis techniques have been dramatically evolved in recent years because of the advent of powerful processors in personal computers and devices such as smartphones. Numerous machine learning and deep learning algorithms have been developed to analyze the increasing amount of data including real-time clinical measurements and physiological signals. Traditional machine learning algorithms analyze the data using a set of features designed by experts. Artificial neural networks utilizing deep learning methods, analyze a large set of data without the prerequisite to define a feature.

The 2016 European guidelines for the management of atrial fibrillation [6] recommends the diagnosis of AF in ECG by detecting its typical pattern which is completely irregular interbeat intervals between the beats with no distinguishable P-waves in an episode lasting at least 30 seconds.

In the AF detection studies, ventricular response has been analyzed using the interbeat intervals irregularity features including the interbeat statistical measures [7-8] and the entropy [9], while the atrial activity associated with the absence of P-waves is extracted from morphology [10] as well as wavelet analysis techniques [11].

In this study, we first utilized an unsupervised neural network algorithm to cluster the ECG beats of the same type and eliminate the abnormal or artifact-corrupted beats in the 30-sec segments of the ECG intervals annotated with the same rhythm. Secondly, we sought the potential P-waves in the cluster average beat and each beat in the dominant rhythm cluster, which in turn defined a set of atrial activity features applied to the classifier along with the ventricular activity (interbeat intervals) features. A decision tree ensemble classifier of bagged trees was used to detect the AF rhythm in the ECG segments and measure the classification performance.

The rest of the paper is organized as follows. In Section 2, we describe the algorithm and database, and discuss the details of the beat clustering, P-wave detection, feature extraction, and classification method. Section 3 presents the results. Section 4 provides the discussion and conclusions.

## 2. Method and Material

### 2.1. Algorithm

In this subsection we present our method in three parts. First, our neural network unsupervised clustering algorithm is explained. Dominant beat clusters are the outcome of this stage. We will then present our P-wave detection method. Last part is devoted to the feature extraction.

#### 2.1.1. Beat Clustering

We split the datasets of ECG records with expert-annotated rhythm intervals into 30-sec non-overlapping segments to generate a database of segments with known cardiac rhythms and fixed length. The intervals shorter than 30 seconds were discarded.

Using our QRS peak detection algorithm, we identified the QRS peaks in the 30-sec ECG segments to form a set of beats aligned at their QRS peaks.

We used a Self-Organizing Map (SOM) [12] neural network algorithm to cluster the aligned ECG beat with matching QRS complexes (200msec window around the QRS peak) in Matlab. A  $3 \times 3$  network of clusters was generated with each neuron containing a set of matched beats. Figure 1 shows an example of generating QRS-matched beat clusters corresponding to the neurons in the SOM network. Figure 2(a) shows the topology of SOM network of neurons (sample hits) in the same example with the number of matched beats on each neuron. Figure 2(b) shows the SOM neighbor distance map of the example where the direct neighbor connections are shown by lines between neurons. The color of the patches containing the connecting lines is proportional to the weight vector distance between adjacent neurons. Darker colors represent larger distances. Groups of similar neurons (beat clusters) are bonded by light patches, separated by darker patches from other groups of neurons.

Dominant cluster (with highest number of beats) is merged with other clusters if high correlation is measured between their average beats. In Figures 1 and 2(a), cluster 5 has highest number of beats and high correlation with clusters 3, 6, 7, 8, and 9. The method is applied to remaining clusters to find the secondary dominant cluster (cluster 1 in this example). The merged dominant cluster with non-ectopic rhythm is selected for analysis. Using this approach, Artifact-corrupted and abnormal beats are automatically excluded from the dominant cluster. Figure 3 shows (a) the dominant and (b) the subordinate average beats.

#### 2.1.2. P-wave Detection

Fiducial points of the dominant average beat were measured by morphological techniques after smoothing slightly by a 10-point moving average method. R-wave

peak was already found by our QRS detector. Q peak (if available) and  $Q_o$  (QRS onset) were determined by maximum vertical distance method.  $P_p$  (P-wave peak), if available, was then identified as the positive or negative prominent peak in a search window, then  $P_o$  and  $P_e$  (P-wave onset and end, respectively) were found by maximum vertical distance method with  $P_p$  at one end of the search line. Figure 4 shows an example of our P-wave detection method.

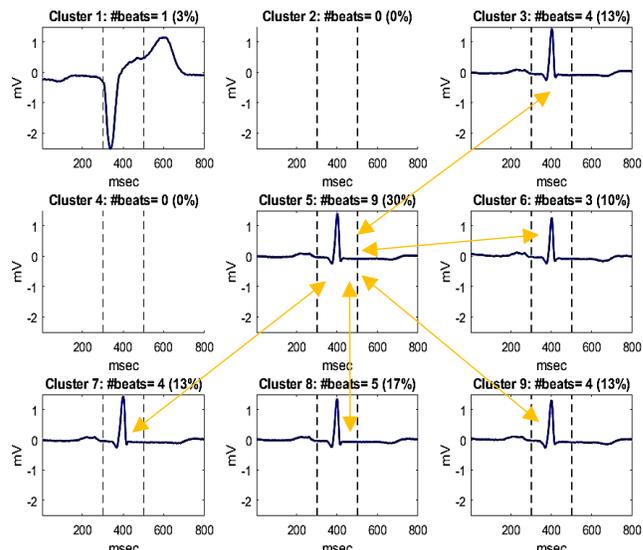


Figure 1. An example of clustering the beats by QRS matching and merging the highly-correlated cluster.

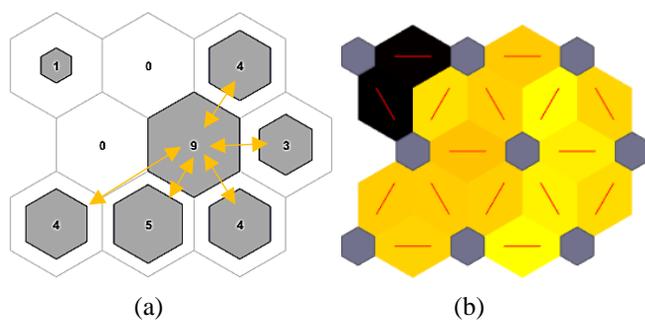


Figure 2. (a) Network topology, and (b) SOM neighbor distance map for the clusters in the example of Figure 1.

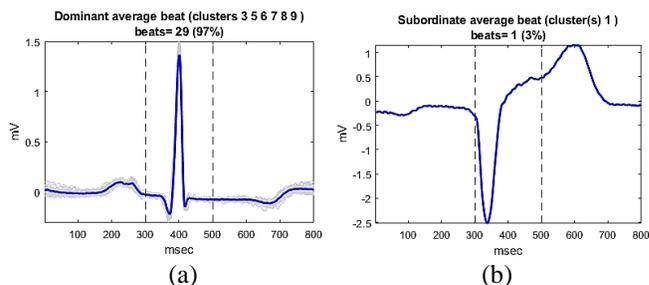


Figure 3. (a) Dominant average beat by merging clusters 3, 5, 6, 7, 8, and 9, and (b) the subordinate average beat from the single PVC, in the example of Figure 1.

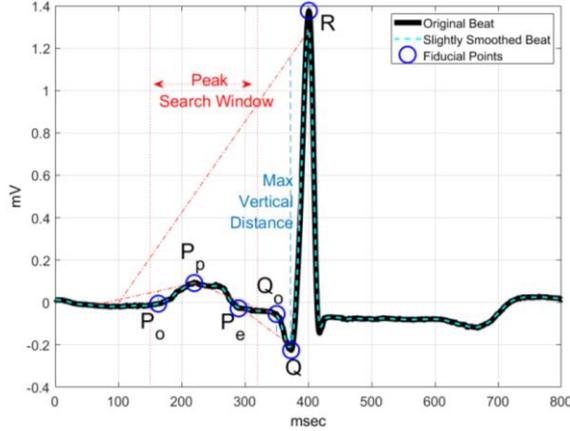


Figure 4. An example of our P-wave detection method.

To find a peak in each beat in the dominant cluster, the same technique is applied, however, an existing P-wave in dominant average beat will apply a smaller peak search window and helps to exclude the potentially false P-waves.

### 2.1.3. Feature Extraction

The atrial activity features bearing P-wave characteristics are associated with presence or absence of consistent P-waves in a 30-sec segment of ECG recording while the ventricular response features define irregularity of the beats.

#### *Atrial activity features (n=12):*

- Mean and standard deviation of the following measures within the segment: PR interval, P-wave duration, P-wave onset-peak duration, P-wave amplitude (peak-onset)
- Number of P-waves detected in segment
- Presence/absence of potential P-wave in average beat
- Mean and standard deviation of the correlation of P-waves in average beat with each beat in the segment.

#### *Ventricular response features (n=12):*

- Median, standard deviation, sample entropy, and Shannon entropy of each of the following measures: NN-intervals, absolute value of the differences of the NN intervals, absolute value of the second differences of the NN intervals.

### 2.1.4. Classifier

Classification was performed between AF records and non-AF records including normal sinus rhythm (NSR) and some P-wave-bearing arrhythmias such as sinus bradycardia (SB), LBBB, RBBB, and ectopic rhythms (bigeminy and trigeminy) with normal beats used in the feature extraction.

We designed a decision tree ensemble classifier with bootstrap aggregation (bagging) with 50 decision trees. Positive event was the AF rhythm detection in segments. Each rhythm class in each database was randomly split into

80% training data and 20% test data. We used 5-fold cross-validation for performance evaluation of the training data. Important features were evaluated for training data.

## 2.2. Database

Our algorithm was tested on several datasets with annotated intervals for some cardiac rhythms. Each 30-sec segment in these intervals was resampled to 1000 Hz. Only first lead was used in a multi-lead record.

The first dataset is PhysioNet MIT-BIH Arrhythmia database [13,14] with the long recordings from 48 patients, originally sampled at 360 Hz. The second dataset is European ST-T Database [15,16], collected from 79 ambulatory patients collected at 250 Hz. The third dataset is AHA database with 154 recordings recorded at 250 Hz [17]. The fourth dataset is the PhysioNet/CinC Challenge 2017 training dataset [18] collected from AliveCor ECG recording devices, consisting of 8,528 ECG recordings from 9 to 60 seconds in length with the original sample rate of 300 Hz. We excluded the ‘others’ and ‘noisy’ classes of the challenge dataset as they did not fit in our AF/non-AF classification. Table 1 shows the number of segments in each rhythm class for all datasets.

Table 1. Number of the 30-sec segments for each annotated rhythm in the datasets

Rhythm		Dataset				
		MIT-BIH	European	AHA	CinC 2017	
AF		223	28	-	744	
Non-AF	SR	1,577	-	-	4,967	
	Arrhythmia	SB	60	29	-	-
		LBBB	15	-	-	-
		RBBB	5	-	-	-
	Ectopic	Bigeminy	26	1	342	-
		Trigeminy	12	2	108	-

## 2. Results

Different combinations of rhythm classes and datasets were tested using our AF/non-AF classifier. Training performance was evaluated by a 5-fold cross-validation on 80% of all data, while test performance was measured on the remaining 20%. Table 2 shows the training and test classifier performance for the combination of MIT-BIH, European, and AHA datasets, versus the CinC challenge 2017 dataset, as well as all datasets combined.

Assessment of the important features shows that in the CinC challenge 2017 dataset, ventricular response features are more important, leading with the Shannon entropy of the differences of NN intervals. Atrial activity features are more important in the group of the other three datasets with P-wave amplitude as the most important feature. Shannon entropy of differences of the NN intervals is the most important feature in classification of all datasets combined.

Table 2. AF/non-AF classifier performance.

Datasets		SE (%)	SP (%)	PPV (%)	NPV (%)	F1 NonAF (%)	F1 AF (%)	F1 Total (%)	Acc (%)
MIT-BIH+ European+ AHA	Train.	98.0	99.9	99.0	99.8	99.8	98.5	99.2	99.7
	Test	93.9	100.0	100.0	99.3	99.7	96.8	98.3	99.4
CinC Challenge 2017	Train.	88.4	99.0	93.1	98.3	98.7	90.7	94.7	97.6
	Test	87.2	98.7	90.9	98.1	98.4	89.0	93.7	97.2
All datasets	Train.	91.4	99.3	94.7	98.8	99.0	93.0	96.0	98.3
	Test	90.4	99.2	94.2	98.7	99.0	92.2	95.6	98.2

### 3. Discussion and Conclusions

We performed a successful classification of AF/non-AF rhythms in four datasets containing AF, NSR, and Several arrhythmia records. Using a beat clustering neural network algorithm helped us to exclude the abnormal, dissimilar, or artifact-corrupted beats. Our P-wave detection method found the fiducial points in all beats and the average beat of the dominant cluster, and atrial activity features were defined based on the location/amplitude of these points.

We observed that the classification performance was lower for CinC challenge 2017 dataset versus the combination of other three datasets. The important features in the challenge dataset were also different from the other datasets: Ventricular response features versus atrial activity features, respectively. These differences could be due to the lower signal quality in the challenge records where the QRS-peak detection resulting in NN-interval is more robust than P-wave detection, as well as the difference in rhythm annotation, and difference in the record selection methods.

In this work, we aimed to study the contribution of features defined by P-waves and NN-intervals. Adding more features would increase the AF/non-AF classification performance and make the classification of other arrhythmias possible. Also, signal quality analysis was out of the scope of this study.

The rhythm classes in the datasets were unbalanced in number of records and biased towards the NSR rhythms. Addition of more records with AF and other Non-AF rhythm classes would result in a more robust classification.

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