# Fractal Feature Based ECG Arrhythmia Classification

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***Abstract*—We propose a method for the classification of ECG arrhythmia using local fractal dimensions of ECG signal as the features to classify the arrhythmic beats. The heart beat waveforms were extracted within a fixed length window around the R-peak of the signal and local fractal dimension is calculated at each sample point of the ECG waveform. The method is based on matching these fractal dimension series of the test ECG waveform to that of the representative ECG waveforms of different types of arrhythmia, by calculating Euclidean distances or by calculating the correlation coefficients. The performance of the classifier was tested on independent MIT-BIH arrhythmia database. The achieved performance is represented in terms of the percentage of correct classification ( found to be $99.49\%$ on an average). The performance was found to be competitive to other published results. The current classification algorithm proved to be a computationally efficient and hence a potential technique for automatic recognition of arrhythmic beats in ECG monitors or Holter ECG recorders.**

***Index Terms*—Beat classification, ECG arrhythmia, Fractal dimension**

## I. Introduction

The classification of electrocardiogram (ECG) into different disease categories is a complex pattern recognition task. Computer based classification of the ECG can achieve high accuracy and is potential of being a method for affordable mass screening for cardiac abnormalities. Long term (24 hours) ECG recording is needed for the identification of abnormal heartbeats and their manual editing is time consuming. In the last few decades, the application of mathematical models and statistical analysis for better interpretation of the physiologic-cardiac events has offered many solutions for fast automated recognition of diseased ECG signals. There are several published methods used to detect cardiac arrhythmia using heart rate variability [1], spectral analysis, time-frequency distribution [2]–[4] and nonlinear signal processing techniques [1], [5]. Classical techniques extract features, such as the QRS complex , R-R intervals [6], [7] and QRS frequency components for classification. Other techniques for computerized arrhythmia detection and classification employ QRS template matching by extraction of a complex set of ECG descriptors, including cross-correlation, frequency and temporal characteristics of QRS complex, for the recognition of ectopic beats [8].

The idea of self similar structures has occurred in mathematical research for a long time. It was Mandelbrot who gave this idea a firm theoretical background and coined such structures as fractals [9]. Broadly speaking, a fractal structure has the same statistics under all scales of magnification [9], [10]. After its inception, fractal and similar modeling techniques have been used in a wide spectrum of fields, starting from market analysis to the study of genome-sequences. Due to their ability of modeling nature more accurately, fractal modeling has proved to be an important tool in image analysis, especially in the field of texture modeling [11]. A recent work by one of the authors has proved the power of fractal dimension based approach in pattern recognition problems [12]. In the current work fractal modeling has been applied for neighboring samples of ECG signal segments to find the local fractal features. This in turn has been used in a template matching classifier to classify the ECG arrhythmia. To our knowledge, this is the first report describing ECG arrhythmia classification based on local fractal dimensions. The results are encouraging. The classification results obtained using the algorithm also have a good confidence level, as observed from the error-bar analysis of the classifier.

The rest of the paper is organized as follows. The next section gives a brief description of the database used in the classification exercises. The section next to it gives a background on fractals and fractal dimensions. After this the classification algorithms are described. The next section gives the results and analyzes them. The last section ends the paper with some conclusive remarks.

## II. ECG Database and Signal Preprocessing

The database used in the present work, is the ECG signals form the MIT-BIH Arrhythmia Database [13] available on Physionet website. The data has been recorded using two leads and at a sampling frequency of 360Hz. The proposed algorithm uses small segments of the waveform, each segment consisting of 200 samples. A fixed length window around the maximum peak of R-R interval, was applied to extract the heartbeat waveform. Not only QRS complex but also P and T waves were extracted using a window starting 50 samples before the R-peak point and ending 150 samples after the same point. This way there is no need for time alignment of the QRS waveforms. The ECG signals coming from different individuals, differ in their average power and base line. In order to compensate for these effects, power normalization is done on each segment before further processing.

After this preprocessing, the database consisted of 2316 segments of normal sinus beats (N), 240 segments of right bundle branch block beats (R), 171 segments of ventricular ectopic beats (V), 219 segments of left bundle branch block beats (L) and 45 segments of atrial premature beats (A).

## III. Fractal and Fractal Dimension

Fractal is a mathematical model that defies the conventional measures, such as length and area. Fractals are most often characterized by their fractional dimension [14]. They are used to describe scale invariant random functions. Many methods have been devised to estimate the fractal dimension of time series waveforms, like power spectral analysis [15], range scaled analysis by calculation of Hurst exponent [16], box-counting method [17], Higuchi method [18], analysis by wavelet packets [19] etc. To estimate the fractal dimension of ECG signals we have used the power spectrum density (PSD) based algorithm.
The power spectrum of fractal process is given by the power law relationship of

$$S(f_n) \sim p f_n^{-\beta} \tag{1}$$

which yields

$$\log(S(f_n)) \sim \log(p) - \beta \log(f_n) \tag{2}$$

Here beta is the spectral index. The slope of the line fitting the $\log - \log$ plot of the power spectrum by a least square method in the linear frequency range gives the estimate of the spectral exponent $\beta$. Fractal dimension D characterize the complexity of a fractal curve in the time domain. The spectral index $\beta$ characterizes the power law relationship in the frequency domain. They are related by the following equation.

$$D = \frac{5-\beta}{2} \tag{3}$$

To find the fractal dimension of a curve, first an estimate of $\beta$ is obtained from the PSD curve. Then the fractal dimension D is found using the above expression.

## IV. Fractal feature based template matching classifier (FTMC)

The next step after the collection of ECG database and signal preprocessing, is to extract the fractal features of the signals. For that the local fractional dimension is calculated for each sample point in the signal by using the power spectral method described in the last section. A window of size $W$ is taken around each sample point, after which its fractional dimension is calculated using equations (1), (2) and (3). Fractional dimension at each point gives the fractal information about its neighboring values. Thus, an ECG signal waveform of 200 samples gets converted into a sample series of fractional dimensions of size $200-W$. Some representative ECG segments and their corresponding fractal dimension based templates (with $W = 15$) are given in the Appendix. In training phase, the above process is applied on each segment from the training dataset and the obtained fractal dimension series are saved as templates. In the test phase, each segment in the test dataset is first converted into its fractal dimension series based template and then is matched with the templates from the training phase.
For matching the templates from the test dataset to those from the test dataset, two methods are used. The first method consists of calculating the Euclidean distance between both the templates.

$$\text{Euclidean distance}(X_d) = \sqrt{\sum_{i=1}^{W}(x_i - y_i)^2} \tag{4}$$

Then the class giving the maximum match or minimum Euclidean distance, is declared as the class of the test ECG signal.
The second method consists of calculating the correlation coefficient between both the fractal dimension series based templates. This gives the degree of closeness between the two templates [20]. The maximum correlation coefficient gives the arrhythmia class of the test ECG signal. The correlation coefficient between two data series $X$ and $Y$ is given by [20]

$$r_{xy} = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n\sum x_i^2 - (\sum x_i)^2}\sqrt{n\sum y_i^2 - (\sum y_i)^2}} \tag{5}$$

The performance of the classification exercise is expressed in terms of the percentage rate of correct classification, error-bar with $3\sigma$ confidence bound and confusion matrix.

## V. Results and discussions

The amount of data for atrial premature beats (A) in the current dataset is very less (only 40 segments). Hence, this class was not included in most of the classification studies done in the current work. The types of arrhythmia for which the experiments are run are N, L, R and V. However, for the sake of completeness, the confusion matrix of table I also gives the performance of the classifier for atrial premature beats (A). Results from the current work will be presented in terms of three figures of merits, viz. error-bar results, absolute performance in terms of confusion matrix and performance with reduced training data.

### A. *Error bar Calculation:*

Classification performance of a classifier expressed in terms of percentage of correct classification, can many times be misleading. Because, classifiers are sensitive to the training and test dataset used. With a small change in the training and test dataset, the performance of classifier can change. An efficient classifier's performance is expected not only to be high but also to change as little as possible with a change in the training and test datasets. Error-bar study gives information about how reliable is the classifier's performance. For this the classification exercise is run repeatedly with different choices of training and test datasets. However, the amount of data in training and test datasets are kept constant. Let $P_{cci}$ represent the probability of correct classification (in percentage) for a certain class of signal for the $i^{th}$ iteration. Then the estimated mean value of the probability of correct classification $P_{ccm}$ for that class is given by:

$$P_{ccm} = \frac{1}{N}\sum_{i=1}^{N} P_{cci} \tag{6}$$

Here $N$ is the total number of iterations run. The estimated standard deviation of the probability of correct classification $P_{ccad}$is given by:

$$P_{ccad} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_{cci} - P_{ccm})^2} \tag{7}$$

In comparing the results, the mean value of performance was plotted along with an error bar of width thrice the standard deviation.

As has been discussed, there are two methods of template matching used in the current work based on Euclidean distance and correlation coefficient. The error-bar plots of FTMC based on both these methods are presented in figure 1. Both in terms of absolute performance and in terms of error-bar analysis the Euclidean distance based FTMC proved to be the better choice. The Euclidean distance based FTMC also took less computational time than the correlation coefficient based FTMC. Hence, to keep the analysis pithy, all the further results will be presented for the Euclidean distance based FTMC only.

Another information of interest is the window size $W$ using which the local fractal dimension is calculated. The figure 2 shows the change in the performance of the Euclidean distance based FTMC with different window sizes ($W$). The indices in X-axis represent the window size and in Y-axis represent the classification performance in terms of percentage of correct classification for each type of arrhythmia used in the database. It can be stated here that the computing time increases with increasing $W$. $W = 15$ was found to be an optimal choice for $W$, and has been used to obtain the results presented in the rest of the paper.

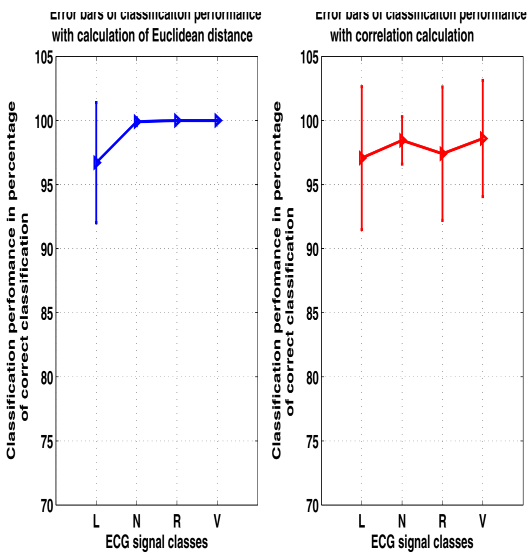


Fig. 1. Classification performance for Euclidean distance and correlation coefficient based FTMC, along with the corresponding error bars

## B. Absolute performance and confusion matrix:

There are five different classes of arrhythmia taken into consideration in this work. Correspondingly there will be five probabilities of correct classification. While dealing with the absolute performance of the FTMC, a complete information is obtained by analyzing the confusion matrix for the classification task. It gives the number of times a signal has been correctly classified and also the number of times it has been misclassified as some other type of arrhythmia. The confusion matrix also gives an idea about which class may act as a confuser for another given class. Table I gives the confusion matrix for the Euclidean distance based FTMC.

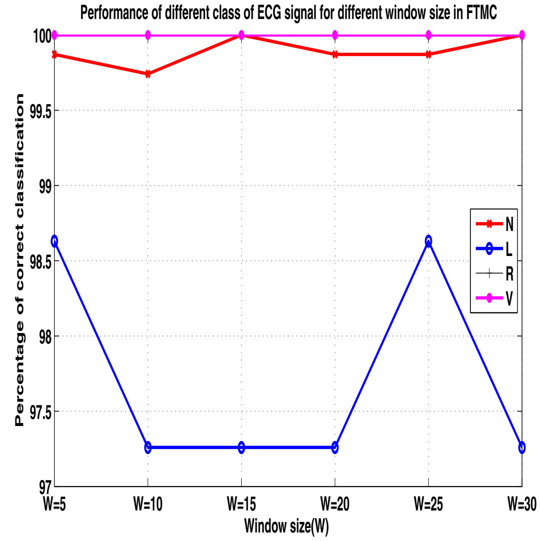


Fig. 2. Performance of different classes of ECG signals for different window size in the Euclidean distance based FTMC (curves of R and V are overlapping)

TABLE I

CONFUSION MATRIX FOR EUCLIDEAN DISTANCE BASED FTMC ($W = 15$)

| Train / Test | A | L | N | R | V | Performance (in percentage) |
|---|---|---|---|---|---|---|
| A | 27 | 1 | 2 | 0 | 0 | 90.00 |
| L | 0 | 144 | 2 | 0 | 0 | 98.61 |
| N | 0 | 0 | 1544 | 0 | 0 | 100 |
| R | 0 | 0 | 0 | 160 | 0 | 100 |
| V | 0 | 0 | 0 | 5 | 109 | 95.41 |

$$\text{Total Performance} = \frac{\sum_{Category}\text{correctly classified beats}}{\text{Total beats}} = \frac{1984}{1994} = 99.498\% \tag{8}$$

This performance is comparable to the best performances found in the open literature [21], and is better than the results presented in many other works [22], [23].

## C. Performance with reduced training set:

ECG measurement involves human subjects and hospital conditions. This makes the collection of exhaustive amount of real-life data both time taking and costly. Hence, a practical ECG signal classifier will be expected to perform with limited amount of training dataset. This section gives the result regarding the performance of the FTMC algorithm with reduced amount of training data. Figure 4 describes the trend of how FTMC behaves with reduced amount of training data. The indices on X-axis represent the reduction factor (p) defined by following equation and indices on Y-axis represent the classification performance in percentage of correct classification.

$$p(\text{Reduction factor}) = \frac{\text{no of test signals}}{\text{no of training signals}} \quad (9)$$

Except for the arrhythmia of type L, the performance remains

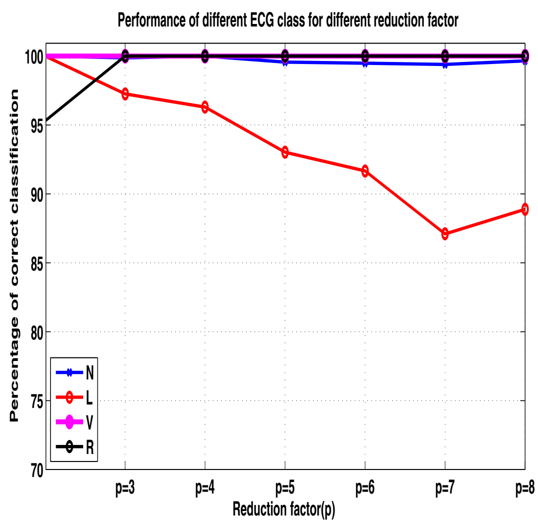


Fig. 3. Classification performance for different reduction factor

almost unchanged with the reduction in training dataset.

## VI. Conclusions

We have developed a local fractal feature based template matching method for the classification of ECG arrhythmia. This is based on extracting local fractal dimension information from the ECG signal and matching that with the templates of representative ECG signals for different types of arrhythmia. It was observed that the classifier's performance is optimal when the local fractal dimension is calculated for each 15 samples ($W = 15$) and the matching is done using the Euclidean distance as the figure of merit. The performance for individual arrhythmia came extraordinary good with $100\%$ correct prediction for normal and right bundle branch block beats, $95.4\%$ correct prediction for ventricular ectopic beats and $98.6\%$ correct prediction for left branch block beats. In addition, the percentage of beats misclassified as normal beats in these categories was $0\%$. The false alarm cases were also very less, i.e. only 4 normal beats were misclassified as arrhythmic. It has long been speculated that biological signals can best be modeled using fractal models. The current algorithm tries to exploit this and uses the local fractal dimensions. It avoids complicated computations by applying estimations over the samples only around the QRS wave rather than comparing all P-QRS-T waves. It saves computational time as it does not need time alignment for signals. The overall good recognition results, optimistic errorbar characteristics, and limited immunity to reduction in training dataset shows the potentialities of the current recognition algorithm. With some fine-tuning the FTMC algorithm can prove to be a preferable quasi real-time operating technique and can be used for the automatic recognition of ECG arrhythmia in ECG monitors or ECG Holters. This will be the future endeavor of the authors.

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## VII. Appendix

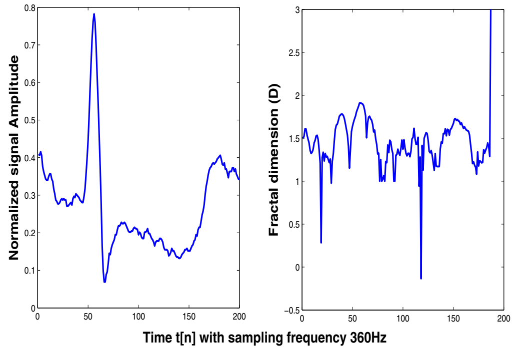


Fig. 4. The ECG signal and their fractal dimensions (*Normal sinus beats)*

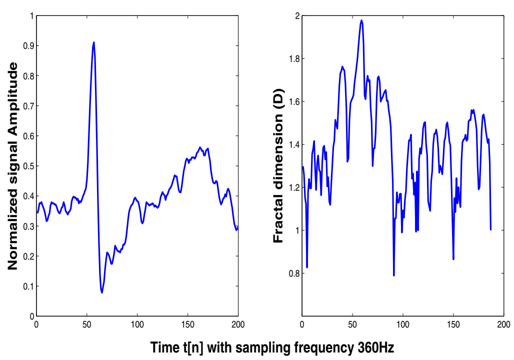


Fig. 5. The ECG signal and their fractal dimensions (*Atrial premature beats)*

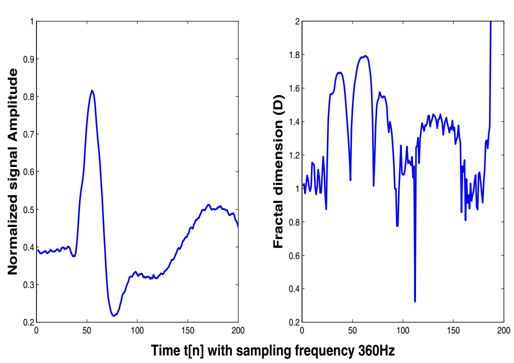


Fig. 6. The ECG signal and their fractal dimensions (*Left bundle branch block beats)*

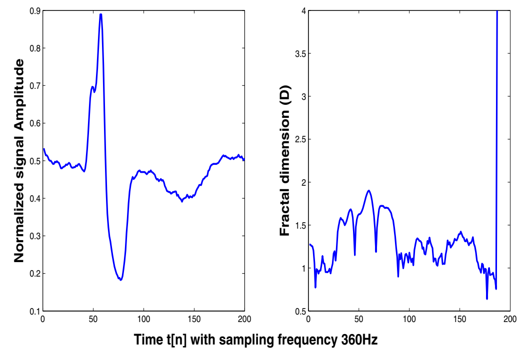


Fig. 7. The ECG signal and their fractal dimensions (*Right bundle branch block beats)*

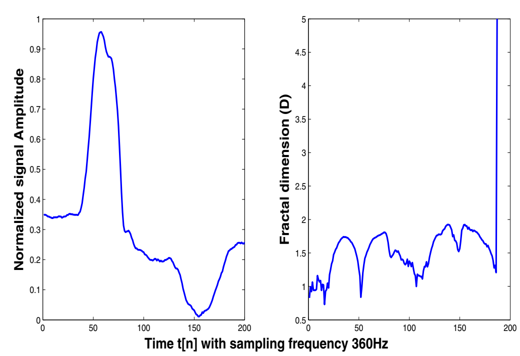


Fig. 8. The ECG signal and their fractal dimensions (*Ventricular ectopic beats)*