Malignant Ventricular Ectopy Classification using Wavelet Transformation and Probabilistic Neural Network Classifier

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Abstract

Objective: The objective of this paper is to make a distinction between malignant ventricular Ectopic Electrocardiogram (ECG) signals from normal ones. Methods: The dataset is taken from MIT-BIH Physio bank ATM. The feature extraction has been done using the Discrete Wavelet Transformation (DWT) method. The experimental ECG signals have been decomposed till 5th level of resolution using daubechies wavelet of order 4 followed by computing various values. Based on the values, classification is performed using Probabilistic Neural Network (PNN) concept. Findings: This paper gives an independent approach for classifying malignant ventricular ectopy (MVE) ECG signals helping health care professionals. Application: The proposed method has been analyzed to be very effective in the classification of MVE ECG signals.

Keywords: Discrete Wavelet Transformation, Electrocardiograph, Malignant Ventricular Ectopic Beats, MIT-BIH Database, Probabilistic Neural Network

1. Introduction

For diagnosing the Cardiac disorders, several tests are used by cardiologists. Out of which ECG founds to be very popular. Recently, arrhythmias account for very serious heart disorder which can lead to sudden death also. Generally, arrhythmias are broadly categorized into two categories, first one is ventricular arrhythmia characterized as the abnormal heart rates arises in the lower chambers of the heart. This is one of the most hazardous cardiac diseases which increase the death rate. Other one is Supraventricular arrhythmias, recognized by rapid heart rhythms generated in the upper chambers of the heart called atria. Malignant ventricular arrhythmias are of 3 kinds: out-of-hospital Ventricular Fibrillation (VF), recurrent sustained ventricular tachycardia and torsades de pointes ventricular tachycardia in the long QT syndrome1. It occurs more with increasing age and creates problems in the functionality of ventricles.

The researchers have discussed about the effectiveness of Implantable Cardioverter Defibrillator (ICD)2 for decreasing the sudden death of arrhythmic patients. The authors of paper2 presented a detailed study on dealing patients having ventricular ectopic beats. This paper provides useful information for treating MVE patients. The objective of paper4 is to provide the clinical features and chromosomal background for analyzing the malignant arrhythmias by using six died patients and 51 live based on the magnetic resonance therapy and angiography. Results said, younger people are more attacked by this disease linking with chromosomes rather than older ones.

An echocardiography analysis was performed by the authors of paper5 for analyzing the effectiveness of ICDs and Cardiac Resynchronization Therapy (CRT) in treating Malignant Ventricular Tachyarrhythmia (MVT) patients. Paper6 shown the comparative study between four popular QRS detection algorithms i.e. Window pair, KNN, Slope vector and Dynamic Plosion index algorithm which is also an important factor in analyzing arrhyth-
mias. Paper\textsuperscript{7} discussed the issues related to patients having high risk of sudden cardiac death. This work shows the fact that the patients suffering from Malignant Ventricular Arrhythmias (MVA) retorts the antiarrhythmic drug treatment and quotes less rapid death rate in comparison to those who do not have this disorder. The results shown in paper\textsuperscript{8} presented the complicated MVA linking up with the mitral valve prolapsed syndrome treated by apridine therapy.

By analyzing the situation, there must be a strong need for unified approach that helps in differentiating between arrhythmic signals from normal ones. Although numerous methods have been developed during the last many years for making proper separation between ventricular and supraventricular arrhythmias, but no publication presented the classification of MVE beats using the methods adopted by the author of this paper. The research methodology adopted in this work is illustrated in Figure 1.

**2. Methods**

**2.1 Discrete Wavelet Transform**

The discrete wavelet technique is a multipurpose tool in the field of signal processing for solving the complex scientific and engineering problems\textsuperscript{9}. The wavelet filter analysis\textsuperscript{10} is based on two discrete words i.e. approximations and details. The approximation coefficients \( g(n) \) showing the components of high scale but low frequency while detail coefficients \( h(n) \) related to low scale components of high frequency of the original signal \( x \). The examined signal \( x \) is further analyzed through a chain of filters.

\[
Y[n] = (X \ast g)[n] = \sum_{k=-\infty}^{\infty} X[k]g[2n - k]
\]

\[
Y_{\text{low}}[n] = \sum_{k=-\infty}^{\infty} x[k]g[2n - k]
\]

**2.2 Probabilistic Neural Network**

A Probabilistic Neural Network (PNN) was announced by D.F. Specht in 1990 based on radial basis function neural network planned for the classification process based on Bayesian network\textsuperscript{12}. It consists four layers i.e. input layer, pattern layer, summation layer and output layer for performing the operations of feed forward neural network. The application of PNN is to perform discriminate analysis done by the kernel. This method is used basically in classification for training and testing the patterns of input and output data. PNN is very popular due to its fast training process and robust structure. Moreover, the learning of PNN\textsuperscript{13} classifier is very quick and depicts great success on numerous areas. On the basis of these features this is viewed as a supervised neural network\textsuperscript{14} capable to solve classification problems and pattern recognition. In this paper, we use PNN classifier for training and testing the data sets in order to obtain much faster and accurate classification analysis in comparison to any other feed forward multilayer network.

**3. Results and Discussion**

The functionality of suggested scheme is verified on varied range of ECG data (unhealthy and healthy) taken from the MIT-BIH database. The unhealthy ECG signals are taken from the malignant ventricular ectopy MIT-BIH database (vfdb) while healthy signals are taken from Fantasia Database (fantasia). The abnormal signals include 22 half hour ECG recordings who suffered from complicated MVA, whereas normal signals include 7 old (68-85 years) and 7 young (21-34) persons ECG recordings of length 120 minutes while watching fantasia movie. Figure 2 and

![Figure 1. Overall architecture of the proposed method](image)

![Figure 2. Approximation coefficients taken from unhealthy signal (MVE)](image)
3 shows approximate coefficients of unhealthy and healthy signals respectively while Figure 4 and 5 illustrates detailed coefficients of unhealthy and healthy persons respectively.

Once the wavelet decomposition is complete, the following important statistical parameters are evaluated. Table 1 and 2 are presenting the calculated statistical values of unhealthy and healthy signal respectively.

- Mean: Computes the average values of the signal at various frequency levels.
- Median: Corresponds for taking the average for both DC and AC signals.
- Mode: Measures the most recurring value in a signal.
- Standard Deviation: For calculating the variations of signal at various levels.

The computed statistical values are likely to be fed into PNN classifier for training and testing. Authors of this paper are evaluating the performance of proposed method in terms of sensitivity, specificity, selectivity, and overall accuracy by using confusion matrix. Table 3 is showing statistical parameter values obtained by using the records taken from Malignant Ventricle Ectopy Database (MVE).

Table 1. Statistical parameter values obtained by using the records taken from malignant ventricular ectopy database (vfdb)

| Record No. | Mean    | Median   | Mode    | Standard Deviation |
|------------|---------|----------|---------|--------------------|
| 602        | 0.5182  | 0.4250   | 0.3500  | 0.5752             |
| 605        | 0.1678  | 0.1450   | 0.0900  | 0.1872             |
| 607        | -0.0614 | -0.0750  | -0.0650 | 0.4818             |
| 609        | -0.1281 | -0.0400  | 0.0200  | 0.8255             |
| 610        | -0.1293 | -0.0550  | -0.0200 | 0.6297             |
| 611        | -0.0245 | -0.1800  | -0.2900 | 0.8756             |
| 612        | 0.2791  | 0.3225   | 0.3650  | 0.1830             |
| 614        | 0.1979  | 0.1750   | 0.0450  | 1.3422             |
| 615        | -0.0208 | 0.0600   | 0.0800  | 0.8582             |
| 418        | -0.3798 | -0.3450  | -0.0100 | 0.4166             |
| 419        | -0.0987 | -0.0650  | 0.1900  | 0.4593             |
| 420        | -0.3650 | -0.3850  | -0.5000 | 0.2213             |
| 421        | -0.0874 | -0.1400  | -0.0800 | 0.6052             |
| 422        | -0.0444 | -0.0650  | -0.0600 | 0.3151             |
| 423        | -0.0838 | -0.0950  | -0.0600 | 0.1323             |
| 424        | 0.1379  | 0.1350   | 0.1550  | 0.1289             |
| 425        | 0.1379  | 0.1350   | 0.1550  | 0.1289             |
| 426        | 0.0208  | -0.0150  | -0.0400 | 0.1273             |
| 427        | -0.8591 | -0.7900  | -0.7350 | 0.2244             |
| 428        | 0.7518  | 0.7850   | 0.8400  | 0.1475             |
| 429        | -0.3273 | -0.3150  | -0.3200 | 0.0770             |
| 430        | -0.1858 | -0.1600  | -0.1600 | 0.1245             |

Table 2. Statistical parameter values obtained by using the records taken from Fantasia Database (fantasia)

| Record No. | Mean    | Median   | Mode    | Standard Deviation |
|------------|---------|----------|---------|--------------------|
| f1o01      | 8.4772  | 8.4480   | 8.4440  | 0.2804             |
| f1o02      | 8.1290  | 8.0600   | 8.0160  | 0.2815             |
| f1o03      | 8.1450  | 8.0520   | 8.0400  | 0.3827             |
| f1o04      | 8.1829  | 8.0880   | 8.0240  | 0.3433             |
| f1o05      | 8.0467  | 8.0040   | 7.9360  | 0.2973             |
| f1o06      | 8.1829  | 8.0880   | 8.0400  | 0.3433             |
| f1o07      | 8.1450  | 8.0520   | 8.0400  | 0.3827             |
| f1y01      | 8.2516  | 8.0920   | 8.1000  | 0.5101             |
| f1y02      | 8.1134  | 8.0160   | 7.9360  | 0.3717             |
| f1y03      | 8.0711  | 7.9160   | 7.8520  | 0.4736             |
| f1y04      | 8.1638  | 7.9880   | 7.9440  | 0.5212             |
| f1y05      | 7.9803  | 7.8920   | 8.1960  | 0.5909             |
| f1y06      | 8.1155  | 8.0560   | 8.0040  | 0.3037             |
| f1y07      | 8.1558  | 7.9600   | 7.9240  | 0.7280             |
Table 3. Comparison with other MVE detection attempts

| Method/Device                  | Sensitivity | Specificity | Selectivity | Accuracy    |
|-------------------------------|-------------|-------------|-------------|-------------|
| Cardioverter Defibrillators   | –           | –           | –           | 60.3%       |
| PNN (our method)              | 100%        | 92.85%      | 95.65%      | 97.22%      |

4. Conclusion

The proposed method is suitable for separating between normal and malignant arrhythmic patients. The combined approach of DWT with PNN has found to be very effective in classification of arrhythmic ECG signals. Out of 36 ECG signals, 22 are MVE (unhealthy) and rest 14 are normal ones. The result of the classification process is based on using the statistical values obtained by decomposition process of DWT. This technique has realized to be very beneficial in the proper detection of MVE arrhythmic patients. For experiments, the sample data have been taken from MIT-BIH Physio bank ATM. Our classification result shows sensitivity, specificity, selectivity and accuracy are 100%, 92.85%, 95.65% and 97.2% respectively.

5. References

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