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# Classification of ECG Arrhythmias Using Adaptive Neuro-Fuzzy Inference System and Cuckoo Optimization Algorithm

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***Keywords:***

Adaptive neuro-fuzzy inference system, Cuckoo optimization algorithm, Electrocardiography, Wavelet transform.

***Abstract***

Accurate and computationally efficient means of classifying electrocardiography arrhythmias has been the subject of considerable research effort in recent years. This paper presents a hybrid method for automated diagnostic systems of electrocardiography arrhythmias. The proposed method includes three main modules including the denoising module, the classifier module and the optimization module. In the denoising module, the stationary wavelet transform is proposed for noise reduction of the electrocardiogram signals. In the classifier module, the adaptive neuro-fuzzy inference system is investigated. In adaptive neuro-fuzzy inference system (ANFIS) training, the vector of radius has an important role for its recognition accuracy. Furthermore, in the optimization module, the cuckoo optimization algorithm is proposed for finding optimum vector of radius. In the test stage, 3-fold cross validation method has been applied to the MIT-BIH arrhythmia database for evaluating the capability of the proposed method. The simulation results show that the proposed method has high recognition accuracy.

## 1. Introduction

Early detection of heart diseases is an important problem incardiology. In this regard, electrocardiography (ECG) provides vital clinical information and is widely used for diagnosis of heart pathologies [1, 2]. A correct diagnosis of a heart disease might require manual inspection of many hours of ECG heartbeats by expert physicians. This is tedious and time consuming with high possibility of missing critical information [3]. Therefore, automatic detection and classification systems which enable cardiologists to timely detect the cardiac diseases and institute appropriate intervention is very important since leading to an extended and enhanced quality of life for the patients [4, 5].

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Automatic classification of ECG data sets is critical for clinical diagnosis of cardiovascular diseases such as abnormal cardiac rhythm and arrhythmia. Therefore, practical ECG classifications is of great importance since a robust classification algorithm enhances the accuracy in diagnostics of cardiovascular diseases. As a result, ECG heartbeat classification has become an active area of research in the literature [6-17]. Although ECG heartbeat recognition has received much attention, providing a reliable and accurate recognition algorithm for abroad range of heart diseases is still a problem.

Artificial neural networks (ANN) have been widely applied for ECG classification. Most researchers [6-13] have used supervised ANNs, such as multi layer perceptron (MLP), radial basis function (RBF), and learning vector quantization (LVQ), in order to classify ECG signals. The advantage of neural network is that it is capable of handling noisy measurements requiring no assumption about the statistical distribution of the monitored data. It learns to recognize patterns directly through typical example patterns during a training phase. One disadvantage with neural network is the difficulty in understanding how a particular classification decision has been reached and also in determining the details of how a given pattern resembles with a particular class. In addition, there is no systematic way to select the topology and architecture of a neural network. In general, this has to be found empirically, whichcan be time consuming.

Some of the researchers used the support vector machine (SVM) for ECG classification [14-16]. Recently, SVMs have received increasingly attention, with remarkable results. However, the accuracy of an SVM is dependent on the choice of kernel function and the parameters (e.g. cost parameter, slack variables, margin of the hyper plane, etc.). Failure to find the optimal parameters for an SVM model affects its recognition accuracy [17].

Based on the published papers, there exist some important issues in the design of automatic ECG classification system which upon suitably addressed, lead to the development of more efficient classifiers. One of these issues is the denoising method. ECG recordings are often corrupted by large amounts of noise and artifacts that can be within the frequency band of useful cardiac data and can manifest with similar morphologies to the ECG waveform itself [18- 20]. Not only does the presence of noise and artifact interfere with the correct recognition of QRS, P and T waves of the ECG, but also increases the rate of false alarms for cardiac monitors. In the proposed method, we have used wavelet transform for the noise reduction. These denoising module is presented in Section 2.

Another issue is related to the choice of the classification approach to be adopted. The proposed method uses fuzzy rules for recognition task. In this approach, an expert system has been developed which has fuzzy rules obtained by the ANFIS. ANFIS represents the promising new generation of information processing systems. ANFIF is good at tasks such as pattern matching and classification, function approximation, optimization and data clustering, while traditional computers, because of their architecture, are inefficient at these tasks, especially pattern-matching tasks [21-25]. In the ANFIS training process, the radius of clusters has high efficiency on the performance of system. To this aim, the cuckoo optimization algorithm (COA) is chosen as an optimization technique for optimizing the ANFIS parameters [26]. This technique will improve the performance of ANFIS.

## 2. Proposed Method

The ANFIS model was developed using MATLAB Fuzzy Logic Toolbox (2015). A subtractive fuzzy clustering was generated to establish a rule base relationship between the input and output parameters. The data was divided into groups called as clusters using the subtractive clustering method to generate fuzzy inference system. In this study, the Sugeno-type fuzzy inference system was implemented to obtain a concise representation of a system's behavior with a minimum number of rules [27]. The linear least square estimation was used to determine each rule's consequent equation. A radius value was given in the MATLAB program to specify the cluster center's range of influence to all data dimensions of both input and output. If the cluster radius was specified a small number, then there will be many small clusters in the data that results in many rules. In contrast, specifying a large cluster radius will yield a few large clusters in the data resulting in fewer rules [28]. For example, if the data dimension is 3 (e.g., input has two columns and output has one column), radii = [0.5 0.4 0.3] specifies that the ranges of influence in the first, second, and third data dimensions (i.e., the first column of input, the second column of input, and the column of output) are 0.5, 0.4, and 0.3 times the width of the data space, respectively.Therefore, in this study COA-ANFIS is proposed to find the optimum vector of radius. Figure 1 shows a sample cuckoo. In this figure $p$ denotes the number of input-output variables.

$$\boxed{cuckoo = [radius_1, radius_2, \ldots, radius_p]}$$

**Figure 1.** Sample of cuckoo

## 3. Simulation Results

In this section, the performance of proposed classifier is evaluated. For this purpose, we have used the practical and real world data [29]. The used dataset contains 10000 examples of ECG signals. For this study, we have used 30% of data for training the classifier and the rest for testing.

Furthermore, we have done several experiments for evaluating the proposed method. All of the obtained results are the average of 50 independent runs. The ECG signals considered in three groups: normal, premature ventricular contractions (PVC) and other arrhythmias.

### 3.1. Performance Without Optimization

First, we have evaluated the performance of the recognizer without optimization. Table 1 shows the recognition accuracy of the different systems. From Table 1, it can be seen that ANFIS with row data achieves recognition accuracy of 94.26%. Its performance increases with using denoised signals value up to 97.14%.

**Table 1.** Recognition accuracy of the recognizer without optimization

| Classifier | Input | Number of fuzzy rules | Recognition accuracy (%) |
|---|---|---|---|
| ANFIS | Row data | 276 | 94.26 |
| ANFIS | De-noised signal | 27 | 97.14 |

### 3.2. Performance With Optimization

Next, we have applied COA to find the optimum vector of radius. The control parameters of COA are listed in Table 2. Table 3 shows the obtained results using proposed method. From this table it can be found that the recognition accuracy is increased up to 99.27%. It can be seen that the optimization improves the performance of recognizer significantly. The highest recognition accuracy (99.27%) is achieved with only nine fuzzy rules.

**Table 2.** Coefficient values in the COA

| Parmameter | Value |
|---|---|
| Number of Cuckoos | 40 |
| Minimum number of eggs | 2 |
| Maximum number Of eggs | 5 |
| Number of clusters | 2 |
| Maximum number Of Cuckoos | 200 |
| $\alpha$ | 30 |
| $\lambda$ | 0.05 |
| Maximum iteration | 100 |

**Table 3.** Recognition accuracy of the recognizer with optimization

| Classifier | Input | Number of fuzzy rules | Recognition accuracy (%) |
|---|---|---|---|
| COA-ANFIS | Row data | 144 | 97.38 |
| COA-ANFIS | Denoised signal | 12 | 99.27 |

In order to indicate the details of the recognition for each pattern, the confusion matrix of the recognizer is shown by Table 4. The values in the diagonal of confusion matrix show the correct performance of recognizer for each pattern. In other words, these values show that how many considered patterns are recognized correctly by the system. The other values show the mistakes of the system. For example, look at the third row of this matrix. The value of 99.00% shows the percentage of correct recognition of other arrhythmias and the value of 1.00% shows that this type of arrhythmia is wrongly recognized with PVC arrhythmia. In order to achieve the recognition accuracy of the system, it is needed to compute the average value of that appears in diagonal.

**Table 4.** Confusion matrix for best result

| | Normal | PVC | Other |
|---|---|---|---|
| Normal | 100 | 0 | 0 |
| PVC | 0 | 98.5 | 1.5 |
| Other | 0 | 1 | 99 |

### 5.3. Comparison With Different Classifier

The performance of the proposed classifier has been compared with other classifiers for investigating the capability of the proposed classifier, as indicated in Table 5. In this regard, probabilistic neural networks (PNN) [30], radial basis function neural network (RBFNN) [30] and MLP neural network with different training algorithm such as: back propagation (BP) learning algorithm [30] and with resilient propagation (RP) learning algorithm are considered [30]. They comprise parameters which should be readjusted in any new classification. Furthermore, those parameters regulate the classifiers to be best fitted in for classification task. In most cases, there is no classical method for obtaining the values of them and therefore, they are experimentally specified through try and error. It can be seen from Table 5 that the proposed method has better recognition accuracy than other classifiers.

**Table 5.** Comparison the performance of proposed classifier (COA-ANFIS) with other classifiers.

| Classifier | Recognition accuracy (%) |
|---|---|
| PNN | 96.16 |
| RBF | 98.73 |
| MLP (BP) | 95.21 |
| MLP (RP) | 98.35 |
| COA-ANFIS | 99.27 |

## 4. Conclusion

ECG which reveals the rhythm and function of the heart is an important non-invasive clinical tool for cardiologists to diagnose various heart diseases. In the past decades, many automatic ECG arrhythmia classification systems have been developed using computational intelligence techniques. In this research, we proposed a method for ECG classification based on wavelet transform and ANFIS. Based on the experimental results, this paper recommends the use of proposed system (COA-ANFIS) for ECG classification.The complexity of the recognition system is very low in comparison with other works. The highest level of accuracy obtained by ANFIS using unprocessed data was 94.26%. The proposed method improves the accuracy up to 97.14% by using approximation coefficients of wavelet transform as the classifier inputs. Furthermore, optimizing the structure of the ANFIS and using approximation coefficients of wavelet transform as the input of the present optimized classifier, significantly improves the accuracy of the proposed system up to 99.27%.

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