Tuning Parameters of ANFIS Model Using Chaotic Particle Swarm Optimization Algorithm

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Abstract: In recent years, researchers have worked to find multiple methods to overcome the classification problems they encountered. In this paper, both the Chaotic Particle Swarm Optimization (CPSO) algorithm are connected with the Adaptive Fuzzy Inference System (AFIS) model, through two stages, the first stage, CPSO algorithm is used to tune parameters of the fuzzy inference system model. In the second stage, the fuzzy inference system model is constructed according to the optimum parameters that are found by the CPSO algorithm. The proposed CPSO-AFIS algorithm demonstrated efficacy and efficiency compared to the standard algorithm Adaptive Neuro Fuzzy Inference System (ANFIS).

1. Introduction:
When we classify a set of data using modern methods, we expect to obtain better results according to the available classifiers, and the examiner may not be able to use the classification in which he is not an expert, for example training the accuracy of parameters, and to obtain more accurate parameters, this is limited to use the expertise of the expert. Thus, there can be no complete realization that it is the best possible [1, 2].

Both the fuzzy system and the artificial neural network are the focus of researchers' attention, so the researchers worked to combine these two systems together to get one system called the Adaptive Nervous System for Fuzzy Inference (ANFIS). They obtained a system with distinctive characteristics that help overcome many of the problems (flexibility, speed, adaptability) that existed in both systems, so, they got better performance than the expert fog systems and the artificial neural network [3].

The focus of the researchers in (ANFIS) was to find a model capable of obtaining more accurate results through parameter training [4]. In spite of this improvement, sometimes we find there is a weak ability to find the best efficiency. Therefore, the swarm algorithms were used to make the system more efficient and accurate [5, 6].

The remnant of this paper is organized as follows: The chaotic map is presented in Section 2. The PSO in Section 3. ANFIS is presented in Section 4. The Proposed CPSO-AFIS algorithm is explained in Section 5. Section 6 covers the Experimental Results. Finally, in section 7, the conclusions are mentioned.

2. Chaotic Map:
Chaos theory used the mathematical approaches to improve both exploration and exploitation during the search for the optimal solution. The chaos is closely related to the study of the chaotic dynamic systems that are highly sensitive to the initial conditions, meaning that any small change in the elementary society
can have a major impact on the final results. Chaotic have random behavior, but providing chaotic behavior does not necessarily need randomness, and deterministic systems can also exhibit chaotic behavior without the need for randomness [2, 7].

2.1 Sine Map
The mathematical formula of this map is described in the following [8]:

\[ X_{n+1} = \frac{a}{4} \sin(\pi X_n) \]  

(1)

where \(0 < a \leq 4\).

3. Particle swarm optimization (PSO)
The PSO algorithm is a simulation of the behavior of groups of fish, insects and birds that fly in search of food through co-operation between group members, which was applied by Kennedy and Eberhardt 1995 [9]. The algorithm relies on a set of random values called particles. Each particle in the PSO is linked to the velocity and location of the object and can be modified. These particles move within the search space and the original algorithm of PSO is described as follows [10, 11]:

\[ v_{id} = v_{id} + c_1 \text{rand}() (p_{id} - x_{id}) + c_2 \text{rand}() (p_{gd} - x_{id}) \]  

(2)

\[ x_{id} = x_{id} + v_{id} \]  

(3)

where \(c_1\) and \(c_2\) are positive constants in Eq.(2), and \(\text{rand}()\) are two random functions (random numbers) in the range [0,1]. \(X_i = (x_{i1}, x_{i2}, ..., x_{iD})\) represents the ith particle , \(P_i = (p_{i1}, p_{i2}, ..., p_{iD})\) represents the best previous position (the position giving the best fitness value) of the ith particle.

The symbol \(g\) in Eq.(2) represents the index of the best particle among all the particles in the population, \(V_i = (v_{i1}, v_{i2}, ..., v_{iD})\) represents the rate of the position change (velocity) for particle i. The Eq. (2) explains how the velocity of the particles (birds, fish, insects, etc.) is updated dynamically and that Eq.(3) describes how the site is updated for particles [12, 13].

4. The Adaptive Neural Fuzzy Inference System (ANFIS)
Neural networks play an essential role when there is a sufficient number of inputs to conduct the training without prior knowledge of the nature of the entered data. As for fuzzy systems, there must be a full knowledge of the rules on which the problem is classified as it is represented by (IF-THEN) rules, which is the phrase for conditional statements expressed in the formula [14]:

IF \(X\) then \(Y\), where both \(X\) and \(Y\) are fuzzy sets.

The idea of ANFIS aims to integrate a neural network system with an adaptive fuzzy logic system, that is, we get a mysterious nervous system that combines the features of the neural network and the mysterious inference of the Sugeno type, which was developed in the early 1990s by Jean in order to reap the benefits available in both systems at the same time [5].

\[ \text{IF } X_n \text{ is } A_i \text{ AND } Y_n \text{ is } B_i \text{ THEN } F = P_i X_i + q_i X_n + r_i \]  

(4)

Figure 1. The adaptation ANFIS to conduct learning and training
Figure 2. The general structure of ANFIS

The first layer represents the process of fuzzing and determining the degree of membership for each entry. Usually, the organic grades within the first cycle are not appropriate and the reason for this is the random representation of these membership functions until the adjustment process is carried out, where these degrees are represented as follows [16]:

$$O_{i1} = \mu_{A_i}(X), \mu_{B_i}(Y)$$

The second layer is the nodes that are not adaptive as the rules are applied to them:

$$O_{i2} = \mu_{A_i}(X_1) \star \mu_{B_i}(Y_n)$$

The third layer, the excitation force on neurons is calculated through the normalization process and is as follows [17]:

$$\bar{w}_{i} = \frac{w_i}{\sum w_i}$$

This represents the output for the third layer and is symbolized by $O_3^i$.

The fourth layer in this layer, the fuzzing process is reversed, meaning results are easy to read and understand. Where this process takes place as follows [18]:

$$O_3^i = Y_i = \bar{w}_i F_i = \bar{w}_i (p_i X_1 + q_i X_2 + r_i)$$

where $p_i$, $q_i$, and $r_i$ are the parameters of the model in a given order because they deal with the part that was then in the ambiguity area.

The fifth layer, this layer represents the final output of the system (ANFIS) as it consists of one node and represents the sum of the outputs of the nodes in the previous layers. The calculation is as follows:

$$O_5^i = \sum_i y_i = \sum_i \bar{w}_i F_i = \sum_i \bar{w}_i(p_i X_1 + q_i X_2 + r_i)$$

The learning algorithm in ANFIS uses a hybrid learning, as it combines the two methods of rapid regression and the method of estimating the least squares, and the training in each epoch goes through two phases: the forward direction phase and the back direction phase [18, 19].

5. The Proposed Algorithm CPSO-AFIS

The proposed CPSO-AFIS method consists of two basic stages. In the first stage, the Chaotic Particle Swarm Optimization Algorithm (CPSO) is used to determine the optimum parameters of the Fuzzy Inference System (FIS) in the Sugeno model. In the second stage, a FIS model is created according to the optimal parameters that were found by the CPSO algorithm, where these optimal parameters are entered into the inference system and the ideal model is formed according to the dataset used. The proposed CPSO-AFIS method has been tested on three different datasets and classified according to the Mean Squared Error (MSE) criteria.
Step1: Set the initial parameters of FIS and PSO algorithm.

Step2: Initialization a chaotic sine map with the initial point (x=0.7).

Step3: Create FIS of Sugeno model using optional parameters.

Step 4: Set the initial velocities and positions using, Eq. (2) and Eq. (3)

Step 5: Evaluate dataset by fitness function.

Step 6: Set iteration i from 1 to max of iteration.

Step 7: Update velocity and position according to Eq. (2) and Eq. (3).

Step 8: When i≤ Max_iteration stop satisfied and return get the best parameters of FS.

Step 9: Insertion of the optimal parameters of FIS into the Sugeno model.

Step 10: Calculate the MSE criterion for the proposed CPSO-AFIS method.

6. Experimental Results

The proposed algorithm CPSO-AFIS is evaluated, and its interest is compared with the ANFIS model. In order to verify the effectiveness of the CPSO-AFIS algorithm for classification problems, we selected 3 different classification datasets from the literature. These datasets were obtained from the UCI repository [20]. Table 1 shows the comprehensive description of data sets.

| Dataset      | # Samples | # Features |
|--------------|-----------|------------|
| Data1=Iris   | 150       | 4          |
| Data2=Engine | 1199      | 2          |
| Data3=Thalasemia | 150    | 10         |

The training and testing dataset for the CPSO-AFIS algorithm, achieved the best MSE, for instance, in Data1, the MSE of the testing dataset is 4.2444e-2 by the FMI-BPSO which is lower than 5.1314e-2 by ANFIS.
Table 2: The MSE of training and testing for datasets.

| Datasets | Methods    | MSE of Training | MSE of Testing |
|----------|------------|-----------------|----------------|
| Data1    | CPSO-AFIS  | 3.5362e-2       | 4.2444e-2      |
|          | ANFIS      | 4.5146e-2       | 5.1314e-2      |
| Data2    | CPSO-AFIS  | 3.9281e-4       | 3.7042e-4      |
|          | ANFIS      | 4.6159e-4       | 4.6821e-4      |
| Data3    | CPSO-AFIS  | 8.0337e-3       | 7.5253e-3      |
|          | ANFIS      | 8.4832e-3       | 7.547e-3       |

The execution comparison shows that, compared to the ANFIS model, the proposed algorithm, CPSO-AFIS, has an obvious advantage in terms of MSE of the classification and the ANFIS is worse than CPSO-AFIS through the three datasets.

Figure 3. Represents the comparison of MSE between CPSO-AFIS & ANFIS in Data1.
Figure 4. Represents the comparison of MSE between CPSO-AFIS & ANFIS in Data2.

Figure 5. Represents the comparison of MSE between CPSO-AFIS & ANFIS in Data3.

7. Conclusion
In this paper, the CPSO-AFIS method was proposed between the chaotic Particle Swarm Optimization Algorithm (CPSO) of type Sine map and Fuzzy Inference System (FIS) of type Sugeno model to improve the classification performance of the datasets in Table 1. The results of the proposed CPSO-AFIS method were compared with the results of ANFIS through the Table2 and Figures (3-5) and the experimental results from the datasets in Table2 indicate that the proposed CPSO-AFIS method has a classification performance that is higher than the ANFIS through MSE criteria.

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