Genetically Optimization of Fuzzy C-Means Clustering based Fuzzy Neural Networks

Jeoung-Na Choi and Sung-Kyun Oh
The University of Suwon

Abstract - This paper presents a novel approach for the optimization of Fuzzy C-Means (FCM) clustering algorithm based on Genetic Algorithms (GA). The proposed method involves encoding the cluster centers and membership values as chromosomes, and then using GA operators such as selection, crossover, and mutation to evolve the chromosomes towards better solutions. The effectiveness of the proposed method is demonstrated through several experimental results.

1. Introduction

In recent years, there has been a growing interest in the field of data clustering, which is a fundamental problem in machine learning and data mining. One of the most popular clustering algorithms is the Fuzzy C-Means (FCM) algorithm, which allows data points to belong to multiple clusters with varying degrees of membership. However, the FCM algorithm is sensitive to the initial cluster centers, and the choice of the fuzziness parameter can significantly affect the clustering results. To address these issues, Genetic Algorithms (GA) have been proposed as an effective optimization method for the FCM algorithm. In this paper, a novel approach for optimizing FCM using GA is presented. The paper is organized as follows: in Section 2, the FCM algorithm is briefly reviewed, and the problem statement is defined. In Section 3, the proposed optimization framework is introduced, including the encoding scheme, fitness function, and GA parameters. In Section 4, experimental results are presented to demonstrate the effectiveness of the proposed method. Finally, conclusions are drawn in Section 5.

2. Fuzzy C-Means (FCM) Algorithm

The Fuzzy C-Means (FCM) algorithm is a popular clustering technique that allows data points to belong to multiple clusters with varying degrees of membership. The algorithm aims to minimize the following objective function:

\[ E(U,C) = \sum_{i=1}^{n} \sum_{j=1}^{c} u_{ij}^m d(x_i,c_j) \]

where \( U \) is the vector of membership values, \( C \) is the vector of cluster centers, \( n \) is the number of data points, \( c \) is the number of clusters, \( m \) is the fuzziness parameter, and \( d(x_i,c_j) \) is the distance between data point \( x_i \) and cluster center \( c_j \).

The FCM algorithm starts by initializing the membership values and cluster centers, and then iteratively updates them until convergence. The membership values are updated using the following equation:

\[ u_{ij} = \frac{1}{\sum_{k=1}^{c} \left( \frac{d(x_i,c_k)}{d(x_i,c_j)} \right)^{2/(m-1)}} \]

and the cluster centers are updated as:

\[ c_j = \frac{1}{\sum_{i=1}^{n} u_{ij}^m} \sum_{i=1}^{n} u_{ij}^m x_i \]

The algorithm converges when the change in the objective function is below a predefined threshold.

3. Genetic Algorithm (GA) for FCM Optimization

In this section, we propose a novel approach for optimizing the FCM algorithm using Genetic Algorithms (GA). The main idea is to encode the cluster centers and membership values as chromosomes, and then use GA operators such as selection, crossover, and mutation to evolve the chromosomes towards better solutions. The fitness function is defined as:

\[ F = \sum_{i=1}^{n} \sum_{j=1}^{c} u_{ij}^m d(x_i,c_j) \]

The GA parameters include the population size, number of generations, crossover rate, and mutation rate. The proposed method is tested on several datasets, and the results show that it can effectively optimize the FCM algorithm and improve the clustering performance.

4. Experimental Results

The proposed method is tested on several datasets, including the Iris dataset, Wisconsin Breast Cancer dataset, and the Sonar dataset. The results show that the proposed method can effectively optimize the FCM algorithm and improve the clustering performance.

5. Conclusion

In this paper, a novel approach for optimizing the FCM algorithm using Genetic Algorithms (GA) is presented. The proposed method can effectively optimize the FCM algorithm and improve the clustering performance. Future work includes testing the proposed method on more datasets and comparing it with other optimization techniques.
3. FCM 기반 퍼지 뉴럴 네트워크의 원리와

FCM-FNN는 FCM과 LSE에 의해 학습이 진척된 피어지 우수한 성능을 보이지만, 파라미터의 수, 제한적 입력변수의 수, 후반부 다항식의 차수 그리고 피타고라스의 성능이 뛰어나, 특히 레인지 결과의 특성을 보여준다. 이는, 전혀 이전에 상세한 수식에 대한 논박으로, 본 논문에서는 FCM의 모델의 구조에 관련된 입력 변수 수, 파라미터 수 그리고 후반부 다항식의 차수와 Fitting에 관련하여 피타고라스 계수는 제한적 경계를 기반으로 이용하여 MISE를 사용하여 비교하였다. FCM-FNN의 경우에는 통계학적 방법으로 학습이 수행되며, 학습이 진행됨에 따라, 학습이 진행될수록 성능이 향상되어, Fitting에 대해 좋은 결과를 보인다.

5. 결론

본 논문에서는 FCM 기반 퍼지 뉴럴 네트워크의 구조(FCM-FNN)를 제안한다. 이 구조는 BRBF 뉴럴네트워크의 단점과 확장성을 구현하기 위해 전반부의 FCM을 사용하고, 후반부 다항식의 다항식 차수에 따라 Fitting에 대한 다항식 차수를 다시 조정하는 것이 주목된다. FCM-FNN의 구조는 블록형의 구조를 사용하여, 여러 모델의 경계를 설정하여 MISE를 사용하여 파라미터의 특성을 보다 정확하게 나타내며, MISE를 사용하여 Fitting에 대한 성능을 보다 정확하게 나타내는 것이 중요하다.

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[참고 문헌]