Image Segmentation Method Using Fuzzy C Mean Clustering Based on Multi-Objective Optimization

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Abstract: Image segmentation is not only one of the hottest topics in digital image processing, but also an important part of computer vision applications. As one kind of image segmentation algorithms, fuzzy C-means clustering is an effective and concise segmentation algorithm. However, the drawback of FCM is that it is sensitive to image noise. To solve the problem, this paper designs a novel fuzzy C-mean clustering algorithm based on multi-objective optimization. We add a parameter \( \lambda \) to the fuzzy distance measurement formula to improve the multi-objective optimization. The parameter \( \lambda \) can adjust the weights of the pixel local information. In the algorithm, the local correlation of neighboring pixels is added to the improved multi-objective mathematical model to optimize the clustering center. Two different experimental results show that the novel fuzzy C-means approach has an efficient performance and computational time while segmenting images by different type of noises.

1. INTRODUCTION
As we all know, image segmentation is a complex problem in image processing, and it is also an important research topic in computer vision and pattern recognition applications. There are many methods of image segmentation. In the field of clustering, The standard fuzzy C-mean was deduced by Dunn in 1973 from the C mean algorithm, and then improved by Bezdek(1981). It has been proved to be an efficient framework for data clustering. This is an unsupervised clustering algorithm which has been successfully applied in the field of medical diagnosis, image analysis, target recognition. [1] However, the FCM algorithm is affected by the constraint condition of membership degree. In order to solve this problem, some researchers have carried on the noise pretreatment to the noisy image, and then use the FCM algorithm to reduce the noise influence.[2] This method will increase the computation time, at the same time, it will also produce unnecessary smoothing.[3] Some researchers have proposed that in the aspect of image processing, using the local information of pixels to modify the objective function of the standard FCM algorithm can reduce the impact of noise on clustering results. [4-6] The algorithm will also directly affect the choice of spatial information and the effect of segmentation time. This algorithm uses a more complicated method to update the cluster center.

Chen [7] et al. (2014) proposed a change form of FCM, called KSSCM, in which the local information was added to estimate the membership function and the original data was mapped to a high imensional Hilbert space. The use of local information can enhance the effect of segmentation, but also increase the computational complexity of the algorithm, which is mainly manifested in the operation time of iteration and the number of iterations. In 2011, Saha et al developed a new multi-objective optimization technique based on fuzzy clustering. [8] This technique uses multi-objective mathematical model to optimize the clustering centre in K dimensional fuzzy space.
We design a new clustering method named fuzzy clustering with multi-objective (MYFCM) in this paper. The sensitivity of the algorithm to noise can be reduced by replacing the single target of the FCM algorithm with the local multi-objective. This approach can reduce the sensitivity of the algorithm to noise, while also taking into account the computing speed advantage.

The main content of the paper is made up of the following four sections. Section 2 introduces the standard fuzzy C-means clustering method. We have improved the multi-objective optimization in Section 3. Next to the fourth section, we design an algorithm of image segmentation processing. Finally, two different experimental results and concluding remarks will be included.

2. FCM ALGORITHM

FCM is an efficient classification method which allows a section of data to belong to two or more clustering centre with a membership value. FCM tries to minimize the following objective function:

$$J_{FCM}(U,V,X) = \sum_{i=1}^{N} \sum_{j=1}^{c} u_{ij}^m d^2(x_i,v_j), 1 < m < \infty$$

(1)

Where $m$ ($m>1$) called the blur exponent. The vector $X = \{x_1, x_2, ..., x_n\}$ is consists of N pixels, the vector $V = \{v_1, v_2, ..., v_c\}$ is the centre of the cluster, $d^2(x_i,v_j)$ is defined as the Euclidean Distance of the object $x_i$ from the centre of $j$th cluster. The standard FCM algorithm assigns pixels to each cluster using fuzzy memberships, $u_{ij}$ is the degree of memberships.

The degree of membership satisfies the following three conditions:

$$0 \leq u_{ij} \leq 1, \sum_{j=1}^{c} u_{ij} = 1, \sum_{i=1}^{N} u_{ij} \leq N, i = 1,2,\cdots,N \quad j = 1,2,\cdots,c$$

(2)

In the iterative process, the clustering centres and membership degrees are always updating, meanwhile, the value of objective function is closer to the minimum value. The membership matrix updates and the cluster centres by the following formula:

$$u_{ij} = \frac{1}{\sum_{i=1}^{N} \left( \frac{d_i}{d_{i,j}} \right)^{2/m-2}} = \frac{\sum_{i=1}^{N} u_{ij}^m x_i}{\sum_{i=1}^{N} u_{ij}^m}, \quad v_j = \frac{\sum_{i=1}^{N} u_{ij}^m x_i}{\sum_{i=1}^{N} u_{ij}^m}$$

(3)

Related research shows that the membership of the image cannot reflect the nature of the subordinate center in the noisy environment [9, 10] In order to overcome the shortcoming of FCM algorithm, we can use the local information of the data instead of the data, so as to reduce the negative impact of noise on the membership calculation. The calculation of membership matrix and clustering center is optimized by using multiple objects in the local region of the pixel.

3. MULTI-OBJECTIVE OPTIMIZATION

The FCM can be used in the classification of multidimensional data, the point and cluster center distance algorithm in FCM should be improved to adapt to the feasibility of this method. In order to reduce the sensitivity of the FCM image segmentation algorithm to the image noise, with a pixel as the center, to generate 6 dimensional pixel set, then using multi-objective optimization FCM algorithm to cluster the pixel set, achieve the purpose of image segmentation.

The text image X and the cluster centre V can be denoted as follows:

$$X = \{x_1,x_2,\ldots,x_N\}, \quad V = \{v_1,v_2,\ldots,v_c\}$$

(4)

Consider the 6-dimensional data $x_i$ by the following formula: $x_i = (x_{i,1}, x_{i,2}, x_{i,3}, x_{i,4,2}, x_{i,5,2}, x_{i,6,2})$

The j-th centre of cluster $v_j$ denoted as follows: $v_j = (v_{j,1,2}, v_{j,2,2}, v_{j,3,2}, v_{j,4,2}, v_{j,5,2}, v_{j,6,2})$

Sadi Nezhad presents a novel fuzzy clustering method based on multi-objective mathematical programming and an efficient fuzzy distance measurement [11] Taking into account the 6-dimensional data set, improved fuzzy distance measurement is formulated as follows.
\[ d^1_{i,j,p} = \lambda_p \text{Max}(0, v^1_{i,j,p} - x^1_{i,p}) \]
\[ d^2_{i,j,p} = \lambda_p v^2_{i,j,p} - x^2_{i,p} \]
\[ d^3_{i,j,p} = \lambda_p \text{Max}(v^3_{i,j,p} - x^3_{i,p}, x^3_{i,p} - v^3_{i,j,p}) \]  

(5)

The parameters \( \lambda_p \) is a weight coefficient of the distance measurement, \( \lambda_p \geq 0, \ i = 1,2,3, \ p = 1,2 \).

If the parameters \( \lambda_i = 1 \), that is, Sadi Nezhad gives a multi-objective fuzzy distance measurement.[11]

\[ d_{i,j} = (d^1_{i,i,i,j}, d^2_{i,i,j}, d^3_{i,i,j}, d^4_{i,i,j}, d^5_{i,i,j}) \]  

(6)

Then the membership values and the centre cluster are calculated as follows:

\[ u^m_{i,j} = \frac{1}{\sum_{p=1}^{3} \frac{1}{d^m_{i,j,p}}} \ k = 1,2,\ldots,c \ p = 1,2 \]  

(7)

\[ v^k_{i,j,p} = \frac{\sum_{i=1}^{N} u^m_{i,j} x^k_{i,p}}{\sum_{i=1}^{N} u^m_{i,j}} \ k = 1,2,\ldots,c \ p = 1,2 \]  

(8)

4. FUZZY C MEAN CLUSTERING BASED ON MULTIOBJECTIVE OPTIMIZATION

Let \( I = [i_{i,j} \ i = 1,2,\ldots,m \ j = 1,2,\ldots,n] \) denotes \( m \times n \) matrix of the original image. The vector \( x_i \) is generated by the neighborhood of the pixels in the text image \( I \). The vector \( x_i \) can be simply expressed as:

\[ x_i = (i_{p,q}, i_{p-1,q}, i_{p+1,q}, i_{p,q+1}, i_{p,q-1}) \]  

(9)

The text image \( X \) is composed of the above vector. Meanwhile, the parameters \( \lambda^t \) in (6) are defined as follows:

\[ \lambda^t_1 = \frac{i_{p-1,q} + i_{p+1,q} + i_{p,q+1} + i_{p,q-1}}{i_{p,q}} \]
\[ \lambda^t_2 = \frac{i_{p-1,q} + i_{p+1,q} + i_{p,q+1} + i_{p,q-1}}{i_{p,q}} \]
\[ \lambda^t_3 = \frac{i_{p-1,q} + i_{p+1,q} + i_{p,q+1} + i_{p,q-1}}{i_{p,q}} \]
\[ \lambda^t_4 = \frac{i_{p-1,q} + i_{p+1,q} + i_{p,q+1} + i_{p,q-1}}{i_{p,q}} \]
\[ \lambda^t_5 = \frac{i_{p-1,q} + i_{p+1,q} + i_{p,q+1} + i_{p,q-1}}{i_{p,q}} \]  

(10)

The parameter is used to adjust the weights of the neighborhood of the pixels in fuzzy distance measurement, and the effect of noise on the clustering segmentation method is reduced. There is a brief description of the clustering segmentation method. The text image \( X \) is composed of the above vector. Meanwhile, the parameters \( \lambda^t \) in (5) are defined as follows:

Step 1: Initialize the 6-dimensional data \( X \) set of the original image using (9), set the value of \( \varepsilon \);
Step2: Initialize the membership function \( U = [u_{i,j}] \);
Step3: Calculate the centers vectors using (8);
Step4: Calculate the fuzzy distance using (5) and (6), \( d_{i,j} = (d^1_{i,i,j}, d^2_{i,i,j}, d^3_{i,i,j}, d^4_{i,i,j}, d^5_{i,i,j}) \);
Step5: Update the membership function \( U' = [u'_{i,j}] \) using (5).
Step6: If \( \|U' - U\| < \varepsilon \) then Stop; otherwise \( U = U' \), and return to step 3;
5. CONCLUSION

This experiment is based on the matlab7.0 programming environment. In order to prove the superiority of our algorithm in dealing with noisy image segmentation problems, experiments are carried out on three kinds of images: Gauss noise, salt and pepper noise. The results show that the MYFCN algorithm has a better effect on the image segmentation and the computation speed compared with other clustering algorithms.

5.1. Text Contrast Test

We first compare the proposed algorithm with other algorithms proposed so far, including standard FCM algorithm, ENFCM algorithm [12] and KSSCM algorithm [7]. The experimental results can be used to compare the segmentation effect, the number of iterations, the computation time and the computational complexity of various algorithms. In all the examples used in this section, the parameters used in algorithm are set to $m=2$, $c=2$ and $\varepsilon = 10^{-5}$.

In the process of image segmentation, we employ the rate of pixel misclassification as the measurement tools for the performance of the segmentation method. In this paper, we employ misclassification error (ME) measure. ME can be simply expressed as: [13]

$$ME = 1 - \frac{B_0 - B_f}{B_0 + F_0} \cdot \left| B_0 - F_f \right|$$

(11)

Where $B_0$ and $F_0$ have been defined as the background and background area pixels of the test image, respectively, $B_f$ and $F_f$ denote the foreground and foreground area pixels in the test image.

Measure the time complexity (TC) of the algorithm with the time needed for an iteration operation, that is, the total computation time (TCT) divided by the number of iterations (NI). From the following figures and table data show that the algorithm in this paper is better performance in segmentation of the image than three other algorithms.

![Figure 1. Original image A, B, C](image)

![Figure 2. Segmentation result of image A, B, C](image)

![Figure 3. Segmentation results of the image A: results by the Gauss noise (4%) image, FCM, ENFCM, KSSCM and MYFCM respectively](image)

**Table 1.** The performance comparison of four different algorithms in Figure A

| Algorithm | NI  | TCT (s) | ME     | TC   |
|-----------|-----|---------|--------|------|
| FCM       | 21  | 0.945   | 0.043  | 0.045|
| ENFCM     | 14  | 1.552   | 0.0051 | 0.111|
| KSSCM     | 18  | 2.346   | 0.0025 | 0.130|
| KSSCM     | 5   | 0.891   | 8.7097e-004 | 0.178|
Figure 4. Segmentation results of the image B: results by the Gauss noise (6%) image, FCM, ENFCM, KSSCM and MYFCM respectively.

Table 2. The performance comparison of four different algorithms in Figure B

| Algorithm  | NI | TCT (s) | ME    | TC    |
|------------|----|---------|-------|-------|
| FCM        | 20 | 0.937   | 0.054 | 0.047 |
| ENFCM      | 13 | 1.220   | 0.0021| 0.094 |
| KSSCM      | 14 | 1.806   | 0.0017| 0.129 |
| KSSCM      | 5  | 0.793   | 9.0033e-004 | 0.159 |

Figure 5. Segmentation results of the image C: results by the Salt-pepper noise image, FCM, ENFCM, KSSCM and MYFCM respectively.

Table 3. The performance comparison of four different algorithms in Figure C

| Algorithm  | NI | TCT (s) | ME    | TC    |
|------------|----|---------|-------|-------|
| FCM        | 17 | 0.578   | 0.102 | 0.034 |
| ENFCM      | 11 | 0.978   | 0.067 | 0.094 |
| KSSCM      | 15 | 1.232   | 0.008 | 0.082 |
| KSSCM      | 6  | 0.512   | 0.003 | 0.085 |

In Figure 1, there are three original images A, B, C, and in Figure 2 are the corresponding ideal segmentation result. It can be seen from the Figure 3-5 that the algorithm in this paper has relatively good segmentation results. The data provided in Table 1-3 shows that our algorithm has very good results in terms of the time complexity (TC), the total computation time (TCT), misclassification error (ME) and the number of iterations (NI).

5.2. Text Noise Immunity

The second kind of experiment is to test the anti-noise ability of the algorithm. Add ten different levels (0.01, 0.03, 0.05, 0.07, 0.09, 0.13, 0.17, 0.21, 0.25) of Gauss noise to figure A, and then use different methods to do the segmentation. Figure 6 show that the ME distribution map of different methods. It is obvious that the proposed algorithm in the Gauss noise level below 13%, it is very good, compared to the other three algorithms.
**Figure 6.** The ME distribution map of different methods. The horizontal axis represents the noise level, and the vertical axis represents the ME value.

We add a parameter $\lambda$ to the fuzzy distance measurement formula to improve the multi-objective optimization. The parameter $\lambda$ can adjust the weights of the pixel local information. The improved multi-objective optimization mathematical model is applied to the FCM algorithm, so that the new FCM algorithm (MYFCM) has a good processing effect, which can be obtained from Tables. In order to further illustrate the influence of image noise on the algorithm, we do anti-noise test to prove the effect of the algorithm in noisy image processing.

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