

Classifications Modification Based FCM with Spatial Information for Image Segmentation

Zhao Li, Xiaoming Zhou

Abstract Image segmentation is the foundation of computer vision and pattern recognition but is still a challenging problem. FCM has been used in image segmentation many years but its problem that is sensitive to noise still cannot be solved effectively. This paper proposes an improved algorithm that incorporates the spatial information and classification modification into the fuzzy C-means (FCM), which can overcome this shortcoming of the traditional FCM without increasing the computational complexity. In this algorithm, FCM will be used for initial segmentation, and then the classification of the element will be modified according to the dispersion of the class. After that, selective smoothing will be executed, which changes the gray value of the pixel according to the class its neighboring elements belong to. Finally, the image treated will be segregated again using FCM. As the experimental results shows, this algorithm can suppress noise efficiently and even can be used in image denoising. Moreover, the segmentation result of the uneven illumination image is also nice.

Keywords FCM, Image Segmentation, Spatial Information, Robustness.

1 Introduction

Fuzzy C-means algorithm has been proposed by Dunn [1] firstly in 1974 and extended by Bezdek [2] in 1981. As a kind of unsupervised pattern recognition algorithm, FCM has been used in image segmentation broadly because of its simplicity and high efficiency. The traditional FCM algorithm uses the gray value as the only one feature in clustering and does not consider any spatial information, so it is very sensitive to the noise[12].

In order to improve the robustness of the algorithm, many scholars have proposed kinds of methods. Some researchers have proposed KFCM which introduce the kernel function into FCM [3, 4, 5]. KFCM uses kernel distance to reshape Euclidean distance to improve the segmentation results and algorithm's efficiency. Many researchers introduce the spatial information into FCM [6-10], which incorporates the spatial information into the calculation of membership or the calculation of distance mostly. For example, the 8th reference and the 10th reference have add

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the 8-neighborhood information to the membership updating formula and the 7th reference defines the space similarity and uses the spatial information to calculate the distance of the class centre to the element. These improvements can reduce the sensitivity of the algorithm to noise to some extent but the calculation of the membership and the distance will become more complex so the computation will be heavier.

This paper proposes a new idea to introduce the spatial information, in which the image is processed by selectively smoothing based on the class the neighbourhood pixels belong to so the noise will be restrained but the edge information can be maintained. Because the calculation of the membership and the distance does not become more complex, the computational complexity does not increase..

2 The theory of FCM

FCM realize the optimal dividing of the sample set through minimizing the cost function[13]. Assuming that N elements will be divided into c classes, the cost function will be:

$$J = \sum_{i=1}^n \sum_{j=1}^c \mu_{ij}^m \|\vec{x}_i - \vec{v}_j\|^2, \quad \mu_{ij} > 0 \quad \sum_{j=1}^c \mu_{ij} = 1 \quad i = 1, 2, \dots, n \quad (1)$$

where \vec{x}_i is the eigenvector of the element i , \vec{v}_j is the class center of class j , μ_{ij} is the membership of the element i about the class j and m is the adjustment coefficient of which the value should be 1.5-2.5 according to the 11th reference and in this paper its value will be 2. FCM optimizes the cost function through updating the \vec{v}_j and μ_{ij} . According to the theory of Lagrange conditioned extreme value, the updating formula is:

$$\mu_{ij} = 1 / \left(\sum_{k=1}^c \left(\frac{\|\vec{x}_i - \vec{v}_j\|}{\|\vec{x}_i - \vec{v}_k\|} \right)^{\frac{2}{m-1}} \right) \quad (2) \quad v_j = \left(\sum_{i=1}^n \mu_{ij}^m \vec{x}_i \right) / \sum_{i=1}^n \mu_{ij}^m \quad (3)$$

When the two adjacent iterations of the cost function meet the formula: $|J_t - J_{t+1}| < \varepsilon$, where ε is a small positive number called allowable error, it is considered that the dividing is close to the optimal solution so the updating stops. Finally, classifications of elements are determined according to the maximum membership degree law.

3 The description of this paper's algorithm

3.1 The modification of the classification

The traditional FCM algorithm uses the maximum membership degree law to determine the classification of the elements without considering the elements' distribution of each class. If the elements' distribution of class j is more dispersed than other class, there may be a element i which belongs to the class j but is a little far to the class center so its membership about the class j μ_{ij} may not be the maximum among the $\mu_{ik}, (k = 1, 2, \dots, c)$. Under this condition the maximum membership degree law will make the wrong classification.

To solve this problem, in this paper, the classification of the elements that comes from the FCM cluster result will be modified according to the dispersion degree of the class. $C(i)$ is defined as the class that element i belongs to, so when element i belongs to class j , $C(i) = j$.

Calculating the membership' mean of every class:

$$\mu_j = \sum_i \delta(j - C(i))\mu_{ij} / n_j \quad (4), \text{ where } n_j \text{ is the number of elements belonging}$$

to class. j

Calculating the membership' variance of every class:

$$\sigma_j = \sum_i \delta(j - C(i))(\mu_{ij} - \mu_j)^2 / n_j \quad (5), \text{ where } \delta(i) = 1 \text{ when } i = 0, \text{ and}$$

$\delta(i) = 0$ when $i \neq 0$.

Calculating the percentage of the total variance that every class's variance ac-

$$\text{counts for: } p_j = \sigma_j / \sum_{i=1}^c \sigma_i \quad (6)$$

Defining a threshold for every class: $f_j = \mu_j(1 - p_j)^\alpha$, where α is the adjusting factor that is negatively correlated with the number of the classes and in this paper $\alpha = 3$.

The modification of the classification will follow the criterion below:

It's assumed that element i belongs to class j . If $\mu_{ij} > f_j$, the classification will not be changed. If $\mu_{ij} \leq f_j$, the formula $d_{ij} = \mu_{ij} - f_j, (j = 1, 2, \dots, c)$ (7) will be calculated and element i will be divided to the class of which the d_{ij} is minimum. This modification makes the samples move from the class less dispersed to

the class more dispersed.

3.2 Selective smoothing based on spatial information

The traditional FCM algorithm uses the gray value as the only one feature to clustering and ignores the spatial information of the pixel. The classification of the pixel will be wrong when adding some noise so the traditional FCM is very sensitive to the noise, and the segmentation results has poor continuity.

This paper proposes a new idea to introduce the spatial information. This algorithm executes selective smoothing to the image according to the classification of the neighborhood pixel which can restrain the noise but maintain the edge information.

The specific process is described below:

After the modification of the classification, it's assumed that pixel i belongs to class j . The $n * n$ neighborhood of pixel i will be searched so it can be found that the class k has the most neighborhood pixels and the class m has the second most neighborhood pixels.

1. If, nothing will be done.
2. If $j = m$ and $k - m < t$, where $t > 0$ is a adjustable parameters and is positively correlated with n , nothing will be done.
3. If $j \neq k$ and $j \neq m$, the gray mean of the neighborhood pixels that belong to class k will be assigned to pixel i .
4. If $j = m$ and $k - m \geq t$, the gray mean of the neighborhood pixels that belong to class k will be assigned to pixel i .

In this paper, $t = 2$, $n = 3$.

The function of the second step is to avoid executing smoothing to the edge so the edge information can be maintained.

3.3 The whole process of the algorithm

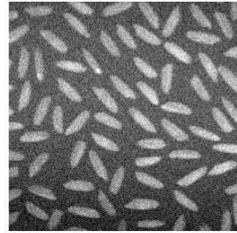
step1: Using FCM for initial segmentation based on the maximum membership degree law

step2: Modifying the classification of the pixels

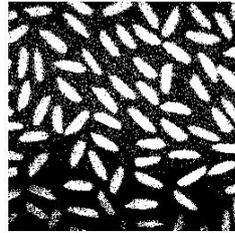
step3: Executing selective smoothing to the image according to the classification of the neighborhood pixels

step4: Using FCM for final segmentation based on the maximum membership degree law

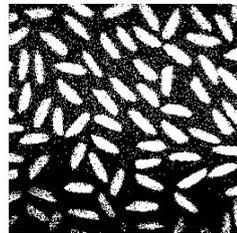
4 Evaluation and experiment



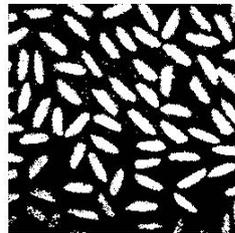
(a) Gaussian noise image



(b) FCM

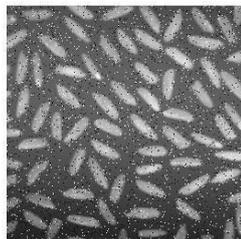


(c) KFCM

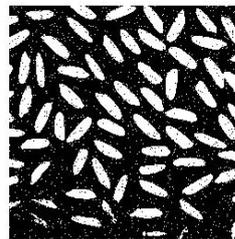


(d) proposed algorithm

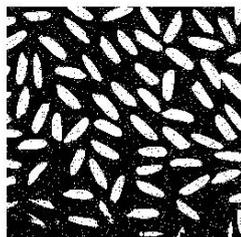
Fig. 1 experiment results of the rice image with Gaussian noise



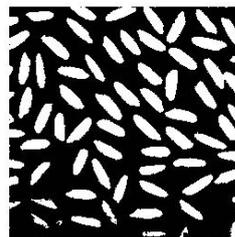
(a) salt and pepper noise image



(b) FCM

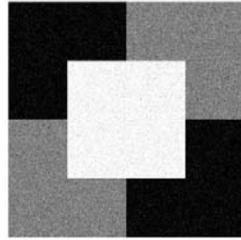


(c) KFCM

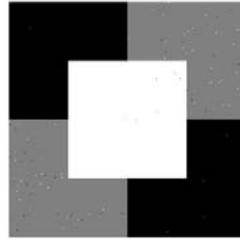


(d) proposed algorithm

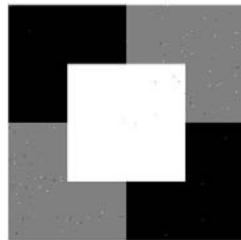
Fig. 2 experiment results of the rice image with salt and pepper noise



(a) Gaussian noise image



(b) FCM

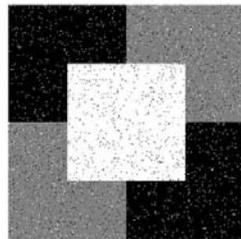


(c) KFCM

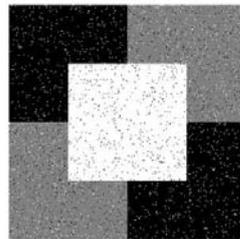


(d) proposed algorithm

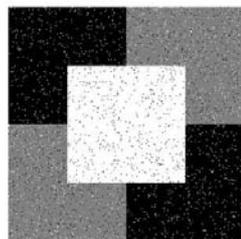
Fig. 3 experiment results of the synthetic image with Gaussian noise



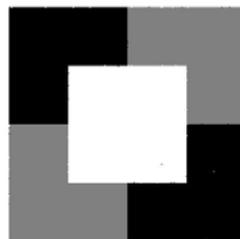
(a) salt and pepper noise image



(b) FCM



(c) KFCM



(d) proposed algorithm

Fig. 4 experiment results of the synthetic image with salt and pepper noise

Due to space limitation, this paper only uses FCM and KFCM for contrast with the proposed algorithm. Subjective evaluation and objective evaluation will be

used as a standard to evaluate the effectiveness of the algorithm. The former displays the segmentation results directly while the latter uses the correct segmentation rate as a standard.

Fig. 1(a) is the rice image polluted by the Gaussian noise of which the mean is 0 and the variance is 400. The segmentation results of Fig. 1(a) are showed in Fig. 1(b)-(d). Fig. 2(a) is the rice image polluted by 5% salt and pepper noise. The segmentation results of Fig. 2(a) are showed in Fig. 2(b)-(c). Through comparing, it is found that the segmentation results of the proposed algorithm have the better continuity and the noise also has been restrained well.

Fig. 3(a) is the synthetic image polluted by the Gaussian noise of which the mean is 0 and the variance is 400. The segmentation results of Fig. 3(a) are showed in Fig. 3(b)-(d). Fig. 4(a) is the synthetic image polluted by 5% salt and pepper. Fig. 4(b)-(d) is the segmentation results of Fig.4(a). Correct segmentation rate of the synthetic image has been show in Table.1. From the experimental results we can see correct segmentation rate of this paper's algorithm is higher than the other two algorithms especially to the Gaussian noise, the correct segmentation rate reaches 100%.

Table 1 The contrast of the correct rate

	FCM	KFCM	PROPOSED ALGORITHM
GAUSSIAN NOISE	99.86	99.88	100%
SALT AND PEPPER NOISE	96.60	96.60	99.93%

5 Conclusion

This paper proposes an improved algorithm that incorporates the spatial information and classifications modification into FCM. This algorithm will modify the pixel's classification according to the dispersion degree of the class, then executes selective smoothing to the image according to the classification of the neighborhood pixel and finally executes secondary segmentation to the image treated. The experimental results show that this algorithm can restrain the noise efficiently, and because it does not incorporate the spatial information into the calculation of membership or distance, its computational complexity is close to the FCM, but its effects is better than FCM.

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Reference

1. Dunn J C, J. (1974). A fuzzy relative of the ISODATA process and its use in detecting compact well-separated clusters. *J Cybern*, 32-57.
2. Bezdek J C, J. (1980). A Convergence Theorem for The Fuzzy ISODATA Clustering Algorithm. *IEEE PAMI*, 1(2), 1-8.
3. Girolami M, J. (2002). Mercer kernel-based clustering in feature space. *IEEE Transactions on Neural Networks*, 13(3), 780-784.
4. Shen H, Yang J, Wang S, et al, J. (2006). Attribute weighted Mercer kernel based fuzzy clustering algorithm for general non-spherical datasets. *Soft Comput*, 10(11), 1061-1073.
5. Zhang D Q, Chen S C, J. (2003). Clustering incomplete data using kernel-based fuzzy c-means algorithm. *Neural Process Lett*, 18(3), 155-162.
6. Zhang Aihua (2004) The Research of Image Segmentation Based on Fuzzy Clustering. PhD thesis, Huazhong University of Science and Technology, Wu Han, China.
7. Yi Yufeng, Gao Liqun, Guo Li, J. (2012). Similar Class Merging Based FCM for Image Segmentation. *Journal of Northeastern University(Natural Science)*, 33(7), 930-933.
8. Yang Yue, Guo Shuxu, Ren Ruizhi, J. (2012). Modified kernel-based fuzzy c-means algorithm with spatial information for image segmentation. *Journal of Jilin University (Engineering and Technology Edition)*, 41(2), 283-287.
9. Li Yanling, Shen Zhi, J. (2009). Fuzzy C-means algorithm based on the spatial information for image segmentation. *J. Huazhong Univ. of Sci. & Tech. (Natural Science Edition)*, 37(6), 56-59.
10. Shen Xuanjing, He Yue, Zhang Bo, J. (2012). FCM With Spatial Information and Membership Constrains for Image Segmentation. *JOURNAL OF BEIJING UNIVERSITY OF TECHNOLOGY*, 38(7), 1073-1078.
11. Pal N R, Bezdek J C. J. (1995). On Cluster Validity for The Fuzzy c-means Model. *IEEE Fuzzy Systems*, 3(3), 370-379.
12. Xu Xiaoli (2012) Research of Image Segmentation Algorithm Based on Clustering Analysis. PhD thesis, Harbin Engineering University, Ha Erbing, China.
13. Sergios Theodoridis, Konstantinos Koutroumbas, M. (2006). *Pattern Recognition*. Bei Jing: China Machine Press.