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Image segmentation based on fuzzy clustering with neighborhood information

YONG YANG

School of Information Technology, Jiangxi University of Finance and Economics, Nanchang, P.R. China;
e-mail: greatyyy765@sohu.com

In this paper, an improved fuzzy *c*-means (IFCM) clustering algorithm for image segmentation is presented. The originality of this algorithm is based on the fact that the conventional FCM-based algorithm considers no spatial context information, which makes it sensitive to noise. The new algorithm is formulated by incorporating the spatial neighborhood information into the original FCM algorithm by *a priori* probability and initialized by a histogram based FCM algorithm. The probability in the algorithm that indicates the spatial influence of the neighboring pixels on the centre pixel plays a key role in this algorithm and can be automatically decided in the implementation of the algorithm by the fuzzy membership. To quantitatively evaluate and prove the performance of the proposed method, series of experiments and comparisons with many derivates of FCM algorithms are given in the paper. Experimental results show that the proposed method is effective and robust to noise.

Keywords: image segmentation, clustering, fuzzy *c*-means, membership function.

1. Introduction

Image segmentation is a key step toward image analysis and serves in the variety of applications including pattern recognition, object detection, and medical imaging [1], which is also regarded as one of the central challenges in image processing and computer vision. The task of image segmentation can be stated as the partition of an image into different meaningful regions with homogeneous characteristics using discontinuities or similarities of the image such as intensity, color, tone or texture, and so on [2]. Numerous techniques have been developed for image segmentation and a tremendous amount of thorough research has been reported in the literatures [3–5]. According to these references, the image segmentation approaches can be divided into four categories: thresholding, clustering, edge detection and region extraction. In this paper, a clustering based method for image segmentation will be considered.

Many clustering strategies have been used, such as the crisp clustering scheme and the fuzzy clustering scheme, each of which has its own special characteristics [6]. The conventional crisp clustering method restricts each point of the data set to exclusively just one cluster. However, in many real situations, for images, issues such as limited spatial resolution, poor contrast, overlapping intensities, noise and intensity inhomogeneities variation make this hard (crisp) segmentation a difficult task. Thanks to the fuzzy set theory [7], which involves the idea of partial membership described by a membership function, fuzzy clustering as a soft segmentation method has been widely studied and successfully applied to image segmentation [9–15]. Among the fuzzy clustering methods, fuzzy *c*-means (FCM) algorithm [8] is the most popular method used in image segmentation because it has robust characteristics for ambiguity and can retain much more information than hard segmentation methods [9, 10]. Although the conventional FCM algorithm works well on most noise-free images, it has a serious limitation: it dose not incorporate any information about spatial context, which cause it to be sensitive to noise and imaging artifacts.

To compensate for this drawback of FCM, the obvious way is to smooth the image before segmentation. However, the conventional smoothing filters can result in loss of important image details, especially boundaries or edges of image. More importantly, there is no way to rigorously control the trade-off between the smoothing and clustering. Other different approaches have been proposed [11–15]. TOLIAS and PANAS [11] proposed a fuzzy rule-based scheme called the rule-based neighborhood enhancement system to impose spatial continuity by post-processing the clustering results obtained using FCM algorithm. In their another approach [12], a spatial constraint is imposed in fuzzy clustering by either adding or subtracting a small positive constant to the centre pixel in a 3×3 window, depending on whether the most possible cluster assigned for the pixel in the 8-neighborhood is the same as or different to that of the centre pixel. NOORDAM *et al.* [13] proposed a geometrically guided FCM (GG-FCM) algorithm based on a semi-supervised FCM technique for multivariate image segmentation. In their work, the geometrical condition information of each pixel is determined by taking into account the local neighborhood of each pixel. Recently, some approaches [14, 15] were proposed for increasing the robustness of FCM to noise by directly modifying the objective function. In [14], a regularization term was introduced into the standard FCM to impose neighborhood effect. Later, ZHANG *et al.* [15] incorporated this regularization term into a kernel-based fuzzy clustering algorithm. Although the above two methods are claimed to be robust to noise, they are confronted with the problem of selecting the parameters that control the role of the spatial constraints. In addition, they are computationally complex.

In this paper, a novel improved FCM (IFCM) clustering algorithm for image segmentation is proposed. The algorithm is developed by incorporating the spatial neighborhood information into the standard FCM clustering algorithm by *a priori* probability. The probability is given to indicate the spatial influence of the neighboring pixels on the centre pixel, which can be automatically decided in the implementation of the algorithm by the fuzzy membership. The new fuzzy membership of the current centre pixel is then recalculated with this probability obtained from above. The algorithm is initialized by a given histogram based FCM algorithm, which helps to speed up the convergence of the algorithm. Experimental results with synthetic and real images show that the proposed method can achieve comparable results to those from many derivatives of FCM algorithm but with less computation time, which means the method presented in this paper is effective.

The outline of the paper is as follows. Section 2 describes the histogram based FCM (fast FCM) algorithm. The IFCM algorithm is presented in Sec. 3. Experimental results and comparisons are given in Sec. 4. Finally, some conclusions are drawn in Sec. 5.

2. Histogram based FCM algorithm

The fuzzy c-means (FCM) clustering algorithm was first introduced by DUNN [16] and later was extended by BEZDEK [8]. The algorithm is an iterative clustering method that produces an optimal c partition by minimizing the weighted within group sum of squared error objective function [17]:

$$J_{\mathrm{FCM}} = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik})^q d^2(x_k, v_i) \tag{1}$$

with the constraints:

$$u_{ik} \in [0, 1]$$

$$\sum_{i=1}^{c} u_{ik} = 1 \forall k$$

$$0 < \sum_{k=1}^{N} u_{ik} < N \forall i$$

where $X = \{x_1, x_2, \dots, x_n\} \subseteq R^p$ is the data set in the p-dimensional vector space, n is the number of data items, c is the number of clusters with $2 \le c < n$, u_{ik} is the degree of membership of x_k in the i-th cluster, q is a weighting exponent on each fuzzy membership, v_i is the prototype of the centre of cluster i, $d^2(x_k, v_i)$ is a distance measure between object x_k and cluster centre v_i. A solution of the object function J_{FCM} can be obtained via an iterative process, which is carried as follows:

$$v_i^{(b)} = \frac{\sum_{k=1}^{n} \left(u_{ik}^{(b)}\right)^q x_k}{\sum_{k=1}^{n} \left(u_{ik}^{(b)}\right)^q} \tag{2}$$

$$u_{ik}^{(b+1)} = \frac{1}{\sum_{j=1}^{c} \left(\frac{d_{ik}}{d_{jk}}\right)^{2/(q-1)}} \tag{3}$$

where b is the loop counter, d_{ik} is the distance measure between object x_k and cluster centre v_i, and d_{jk} is the distance measure between object x_k and cluster centre v_j. It can be seen that the standard FCM algorithm is an iterative operation, which calculates the centroids and membership function pixel-by-pixel when it is used for image segmentation. Thus, the convergence of the algorithm is very slow which makes it impractical for image segmentation. To cope with this problem, the gray level histogram of image is employed to the algorithm. Let us define the non-negative integrate set $G = \{L_{\min}, L_{\min} + 1, ..., L_{\max}\}$ as gray level, where $L_{\min}$ is the minimum gray level, $L_{\max}$ is the maximum gray level, therefore the grayscale is $L_{\max} - L_{\min}$. For image size $s \times T$, at point (s, t), $f(s, t)$ is the gray value with $0 \le s \le (S - 1)$, $0 \le t \le (T - 1)$. Let $\mathrm{His}(g)$ denote the number of pixels having gray level g. Therefore, the histogram function can be written as:

$$\mathrm{His}(g) = \sum_{s=0}^{S-1} \sum_{t=0}^{T-1} \delta\big(f(s, t) - g\big) \tag{4}$$

where $g \in G$, $\delta(0) = 1$ and $\delta(g \neq 0) = 0$. With this gray level histogram $\mathrm{His}(g)$, the new objective function of the fast FCM algorithm is now defined as:

$$J_q = \sum_{g=L_{\min}}^{L_{\max}} \sum_{i=1}^{c} (u_{ig})^q \mathrm{His}(g) d^2(g, v_i) \tag{5}$$

where u_{ig} represents the membership degree of the gray level g to cluster i, and with the following constraint:

$$\sum_{i=1}^{c} u_{ig} = 1, \forall g \tag{6a}$$

$$u_{ig} \in [0, 1], \forall i, g \tag{6b}$$

$$0 < \sum_{g=L_{\min}}^{L_{\max}} u_{ig} < n, \forall i \tag{6c}$$

Therefore, the above objective function (5) can be minimized using one Lagrange multiplier:

$$J = \sum_{g=L_{\min}}^{L_{\max}} \sum_{i=1}^{c} (u_{ig})^q \mathrm{His}(g) d^2(g, v_i) + \lambda \left(1 - \sum_{i=1}^{c} u_{ig}\right) \tag{7}$$

Taking the partial derivate of (7) with respect to u_{ig} and setting the result to zero yields:

$$u_{ig} = \left(\frac{\lambda}{q \,\mathrm{His}(g) d^2(g, v_i)}\right)^{\frac{1}{q-1}} \tag{8}$$

Since $\sum_{i=1}^{c} u_{ig} = 1, \forall g$, this constraint equation is then employed, yielding:

$$u_{ig}^{(b)} = \frac{1}{\sum_{j=1}^{c} \left[\frac{d(g, v_i)}{d(g, v_j)}\right]^{2/(q-1)}}, \forall i, g \tag{9}$$

Similarly, taking the Eq. (7) with respect to v_i and setting the result to zero, we have:

$$v_i^{(b+1)} = \frac{\sum_{g=L_{\min}}^{L_{\max}} \left(u_{ig}^{(b)}\right)^q \mathrm{His}(g) g}{\sum_{g=L_{\min}}^{L_{\max}} \left(u_{ig}^{(b)}\right)^q \mathrm{His}(g)}, \forall i \tag{10}$$

The new FCM algorithm now only operates on the histogram of the image. Hence, it is faster than the conventional version, which processes the whole data. However, it is important to note that even if this fast FCM algorithm is faster than the standard FCM algorithm, the results of the two algorithms are identical.

3. Improve fuzzy *c*-means algorithm

It is noted from (1) that the objective function of the traditional FCM algorithm does not take into account any spatial information, which means the clustering process is related only to gray levels independently of the pixels of image in segmentation. However, according to the theory of Markov random field (MRF) that most pixels belong to the same class as their neighbors, which means the class probability of a pixel depends on class memberships of its (spatial) neighbor clusters, in this way it can reduce the possible influence of noise and overlapping clusters [18]. Therefore, the limitation of the standard FCM algorithm makes it very sensitive to noise. The general principle of the technique presented in this paper is to incorporate the neighborhood information into the FCM algorithm during classification. Considering the influence of the neighboring pixels on the central pixel, the fuzzy membership function given in (3) can be extended to:

$$u_{ik}^* = u_{ik} p_{ik} \tag{11}$$

where $k = 1, 2, ... n$, n is the number of image data, and p_{ik} is the *a priori* probability of data point k belonging to cluster i, which can be automatically determined by the following neighborhood model. Hence, the objective function of the IFCM algorithm is changed as:

$$J_{\mathrm{IFCM}}^* = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik}^*)^q d^2(x_k, v_i^*) \tag{12}$$

Similar to that of histogram based FCM algorithm, the degrees of membership u_{ik}^* and the cluster centers v_i^* can be updated via:

$$u_{ik}^{*(b)} = \frac{p_{ik}}{\sum_{j=1}^{c}\left(\frac{d_{ik}}{d_{jk}}\right)^{2/(q-1)}} \tag{13}$$

$$v_i^{*(b+1)} = \frac{\sum_{k=1}^{n}\left(u_{ik}^{*(b)}\right)^q x_k}{\sum_{k=1}^{n}\left(u_{ik}^{*(b)}\right)^q} \tag{14}$$

The core idea now is to define the auxiliary variable p_{ik}, which is *a priori* information to guide the outcome of the clustering process. This paper proposed an adaptive method for determining this probability:

$$p_{ik} = \frac{\#N_k^i}{\#N_k} \tag{15}$$

where $\#N_k$ denotes the total number of points in the neighborhood of x_k and $\#N_k^i$ denotes the number of the neighboring points that belongs to cluster i after defuzzification. Here, the shape of the neighborhood is selected as an 8-neighborhood. Therefore, the *a priori* probability, p_{ik} is determined and updated during the clustering by converting the fuzzy partition matrix to a crisp partition matrix in this 8-neighborhood. In this paper, the defuzzification is carried out with the maximum membership procedure. The maximum membership procedure assigns object k to the class C with the highest membership:

$$C_k = \arg_i\{\max(u_{ik})\}, \quad i = 1, 2, ..., c \tag{16}$$

To prevent that our algorithm gets trapped in a local minima, the IFCM algorithm is initialized with the above fast FCM algorithm. Once the fast FCM is stopped, the IFCM algorithm continues with the values for the prototypes and membership values obtained from the fast FCM algorithm. The IFCM algorithm then iteratively updates its *a priori* probability, membership and centroids with these values. When the IFCM algorithm has converged, another defuzzification process takes place in order to convert the fuzzy partition matrix to a crisp partition matrix that is segmentation. Thus the IFCM algorithm is presented as follows:

Step 1: Set the cluster centroids v_i according to the histogram of the image, fuzzification parameter q ($1 \le q < \infty$), the values of c and $\varepsilon > 0$.

Step 2: Compute the histogram using (4).

Step 3: Compute the membership function using (9).

Step 4: Compute the cluster centroids using (10).

Step 5: Go to step 3 and repeat until convergence.

Step 6: Compute the *a priori* probability using (15) with the obtained results of membership function and centroids.

Step 7: Recompute the membership function and cluster centroids using (13) and (14) with the probabilities.

Step 8: If the algorithm is convergent, go to step 9; otherwise, go to step 6.

Step 9: Image segmentation after defuzzification using (16) and then a region labeling procedure is performed.

4. Experimental results

4.1. Comparisons

In this section, the results of the application of the IFCM algorithm are presented. The performance of the proposed method is compared with those of standard FCM algorithm [8], spatial FCM (SFCM) algorithm [14], and kernel-based fuzzy clustering (KFC) technique [15]. For all cases, unless otherwise stated, the weighting exponent $q = 2.0$ and $\varepsilon = 0.0001$. A 3×3 window of image pixels is considered in this paper, thus the spatial influence on the centre pixel is through its 8-neighborhood pixels. For the sake of simplicity, in all the examples, the parameter α in SFCM is set to be 0.7 and the parameters in KFC are set as: $\alpha = 0.7$, $\sigma = 150$. All the algorithms are coded in Microsoft Visual C++ Version 6.0 and are run on a 1.7 GHZ Pentium IV personal computer with a memory of 256 MB. In all the experiments, we found that since the IFCM algorithm is initialized by the proposed fast FCM algorithm, the algorithm converges after several iterations and consumes about 2 seconds.

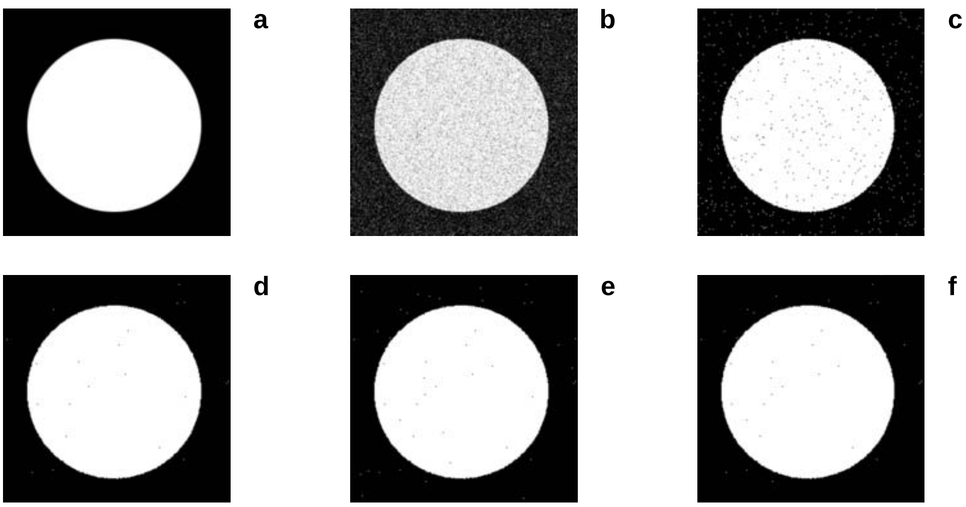

Fig. 1. Comparison of segmentation results on a two-class synthetic image. The original image (**a**), noisy image with SNR = 5 (**b**), FCM result (**c**), SFCM result (**d**), KFC result (**e**), IFCM result (**f**).

In the first example, we generate a two-class synthetic image with gray levels 0 and 255 for background and foreground, respectively, and the image size is 256×256. The image was then corrupted by additive Gaussian noise such that the SNR = 5. Figure 1**a** is the original image and Fig. 1**b** is the degraded noisy images. Figure 1**f** shows the result of proposed method. The results of FCM, SFCM and KFC algorithms are displayed in Figs. 1**c**–1**e**, respectively. The results show that our approach can get comparable result as SFCM and KFC algorithms and outperforms the conventional FCM algorithm in the noisy situation. The number of misclassified pixels and the calculation time for different methods are counted during the experiments and listed in Tab. 1. It can be seen from Tab. 1 that the total number of the misclassification

Table 1. Number of misclassified pixels and calculation time for different methods.

	Methods			
	FCM	SFCM	KFC	IFCM
Misclassified number	549	23	46	33
Calculation time	1 s	2 s	14 s	2 s

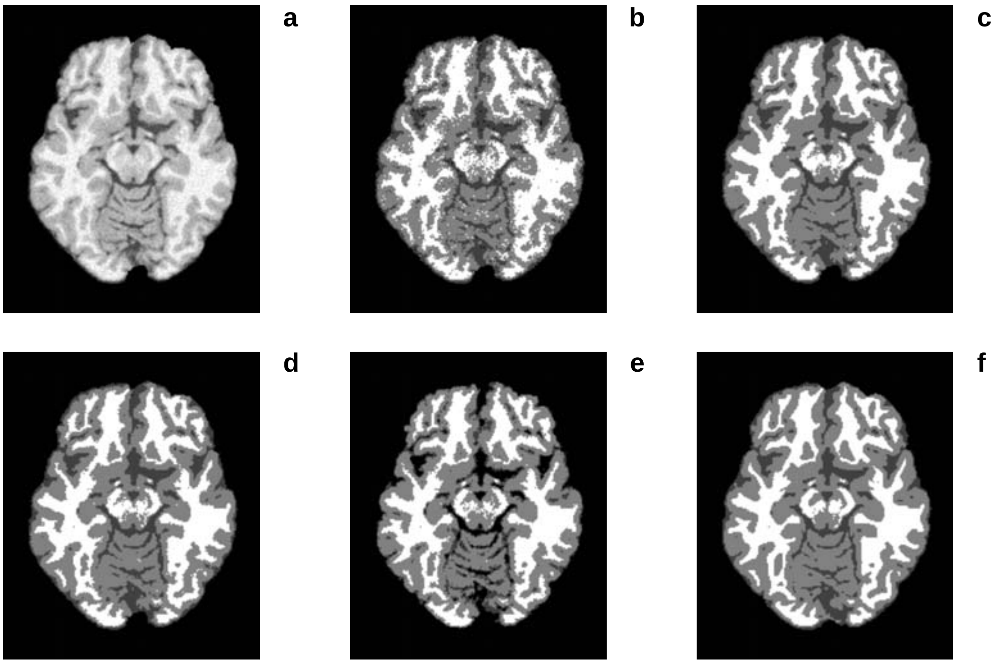

Fig. 2. Comparison of segmentation results on a MR phantom image corrupted by 5% Gaussian noise and no intensity inhomogeneity. The original images (**a**), FCM result (**b**), SFCM result (**c**), KFC result (**d**), IFCM result (**e**), ground truth (**f**).

pixels for the IFCM algorithm is less than those of FCM and KFC algorithms while a little more than that of the SFCM algorithm, and the misclassified number for FCM algorithm is about 17 times than that of the proposed method. Also, it is important to note from Tab. 1 that the calculation time for KFC is the longest in the four methods, and SFCM and IFCM algorithms cost almost the same time after convergence. The results presented in this example demonstrate that the incorporation of the spatial neighborhood information into the FCM algorithm can significantly improve the segmented results in the presence of noise and consume less time.

The second type example is a simulated magnetic resonance (MR) brain image obtained from the BrainWeb Simulated Brain Database [19]. This brain image was simulated with T1-weighted contrast, 1-mm cubic voxels, 5% noise and no intensity inhomogeneity. Before segmentation, the non-brain parts of the image such as the bone, cortex and fat tissues have been removed. The class number of the image was assumed to be four, corresponding to gray matter (GM), white matter (WM), cerebrospinal fluid (CSF) and background (BKG). Figure 2**a** shows a slice from the simulated data set, Figs. 2**b**–2**e** shows the segmentation results obtained by applying FCM, SFCM, KFC and IFCM algorithms, respectively and the ground truth is given in Fig. 2**f**. It is clearly seen that our segmentation result is much closer to the ground truth. The result of IFCM is almost identical to those of SFCM and KFC algorithms and is more homogeneous and smoother than that of the FCM algorithm, especially for WM. In this example, the calculation time for FCM is 1 s, for SFCM or IFCM it is 2 s, while for KFC it is 52 s.

Also, to quantitatively evaluate the performance of the four algorithms, tests were realized on the above brain MR phantom images containing 3%, 5%, and 7% noise with no intensity inhomogeneity. Figure 3 shows the segmentation accuracy

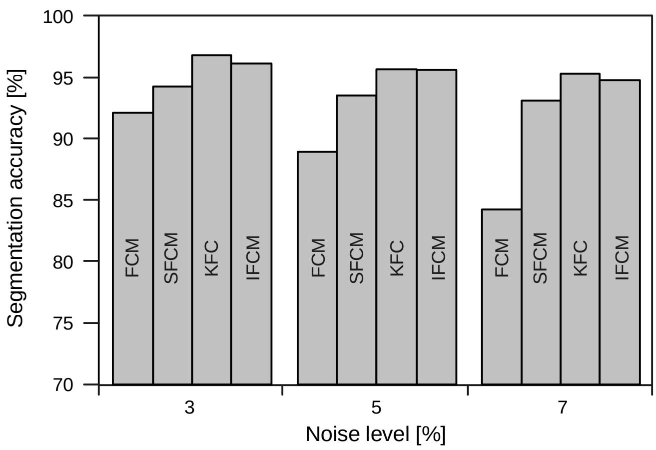

Fig. 3. Segmentation accuracy of different methods on brain phantom MR images under different levels of noise.

of applying these algorithms to the images with different levels of noise. Here, the segmentation accuracy (SA) is defined as:

$$\text{SA} = \frac{\text{Number of correctly classified pixels}}{\text{Total number of pixels}} \times 100\% \tag{17}$$

It can be seen from Figure 3 that as the noise level increases, the SA of FCM degrades rapidly. However, the modified algorithms such as SFCM, KFC and our proposed IFCM algorithms can all handle the problem caused by noise and can get higher SA even under the noise of 7%. Overall, the KFC and IFCM algorithms produce almost identical results, which are a little better than that of the SFCM algorithm. However, from the above analysis, it should be noted that the KFC algorithm needs more computational time than IFCM algorithm.

In the last examples, there is a real-world standard test image named *cameraman* without adding any type of noise. In this experiment, the class number *c* is set to be 2. The original image is shown in Fig. 4**a**. The results of segmentation by applying different methods to the image are presented in Figs. 4**b**–4**e**, respectively. Here, the calculation time for FCM is less than 1s, for SFCM or IFCM it is less than 2 s, while for KFC it is more than 17 s. As can be seen, the four algorithms can well extract the object from the background in each image. However, it is important to note that the proposed method performs the best for the segmentation with more homogeneous regions and with least spurious components and noises particularly in the grass ground area of *cameraman*. The results presented here can prove that our method is capable

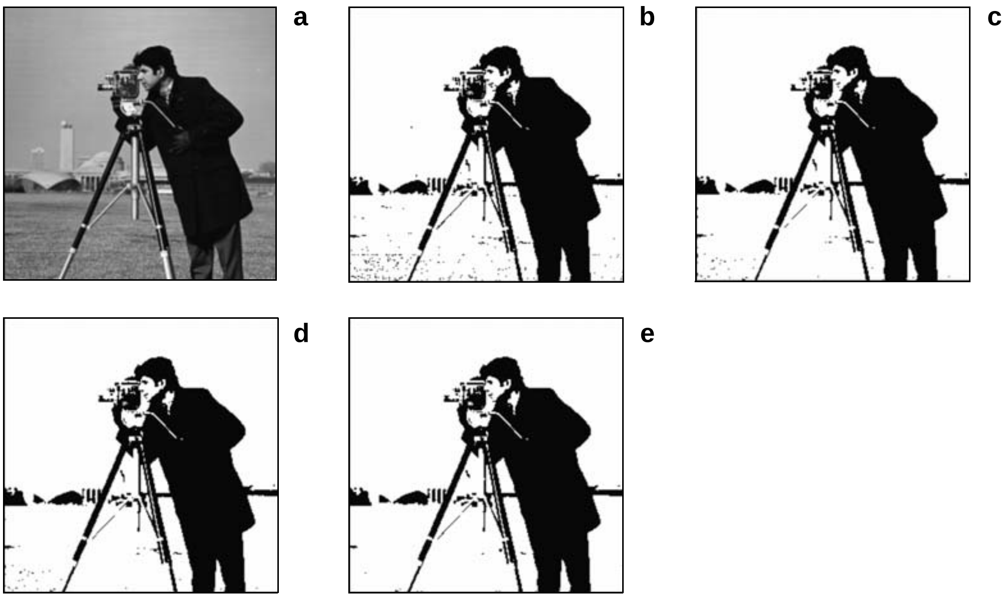

Fig. 4. Comparison of segmentation results on a real standard image named *cameraman*. The original image (**a**), FCM result (**b**), SFCM result (**c**), KFC result (**d**), IFCM result (**e**).

T a b l e 2. Uniformity value of the four algorithms on the *cameraman* image.

Methods	σ_O^2	σ_B^2	σ_T^2	U
FCM	425	679	3942	0.71994
SFCM	388	704	3942	0.72298
KFC	382	703	3942	0.72476
IFCM	362	711	3942	0.72780

of coping with not only noises but also artifacts in the image. In addition, to better evaluate the performance of these four algorithms, quantitative comparisons are carried out in the following. Since there is no ground truth or reference segmentation for this kind of image, we employ the concept of uniformity as in ref. [20] to compare the segmentation results. The uniformity of a segmentation result is defined by:

$$U = 1 - \frac{\sum_{i=1}^{S} \sigma_i^2}{K} \tag{18}$$

where S is the number of classes, σ_i^2 is the within-class variance of the i-th class, and K is a normalization factor which can limit the maximum value of the measure to 1. Here, we set $K = \sigma_T^2$ as its original formal [21], and σ_T^2 denotes the total gray-level variance of the image. If the pixels in each class spread widely, the uniformity value is small. Therefore, a better segmentation will cause the uniformity value bigger [20]. Table 2 shows the results of the uniformity values of the four algorithms, σ_O^2 denotes the variance of the object and σ_B^2 denotes the variance of the background. Form Tab. 2, we can find that the proposed IFCM algorithm gets the highest uniformity value in the four algorithms, while the original FCM algorithm gets the lowest uniformity value. The quantitative comparisons given here can again indicate that our method is effective and robust to noise and artifacts.

4.2. Discussion

As can be seen from the above experiments, one can observe in some situations that perhaps the IFCM algorithm cannot get identical results to those of SFCM and KFC algorithms. But, it should be noted that both the SFCM algorithm and the KFC algorithm rely on the parameter α, which means that if the parameter α in the SFCM algorithm or the KFC algorithm is set larger, less misclassified pixels could be obtained. However, until now there is no criterion for these two algorithms to choose appropriate parameters to control the trade-off between minimizing the standard FCM objective function and obtaining smooth membership functions. In other words, if α is set too large, more smooth regions can be yielded; however some detailed information such as boundaries or edges could be lost in this case. On the contrary, if α is set too small, more noise will still exist. Different to both SFCM and KFC algorithms, our method presented in this paper is fully adaptive without introducing any parameter to control the trade-off between the smoothing and segmentation. Perhaps it is not the ideal fuzzy based algorithm for image segmentation, but it is an effective method.

5. Conclusions

To overcome the noise sensitiveness of conventional FCM clustering algorithm, this paper presents a novel IFCM algorithm for image segmentation. The main contribution of this algorithm is to incorporate the spatial neighborhood information into the standard FCM algorithm by *a priori* probability. The probability can be automatically decided in the algorithm based on the membership function of the centre pixel and its neighboring pixels. Our approach is carried out without introducing any additional parameters, thus the algorithm is adaptively implemented. As we employ a fast FCM algorithm to initialize the IFCM algorithm, the algorithm converges after several iterations. A variety of images, including synthetic, simulated and real images were used to compare the performance of FCM, SFCM, KFC and IFCM algorithms. Experimental results show that the proposed method is effective and more robust to noise and other artifacts than the conventional FCM algorithm in image segmentation.

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References

[1] KIM J., FISHER J.W., YEZZI A., CETIN M., WILLSKY A.S., *A nonparametric statistical method for image segmentation using information theory and curve evolution*, IEEE Transactions on Image Processing **14**(10), 2005, pp. 1486–1502.
[2] DONG G., XIE M., *Color clustering and learning for image segmentation based on neural networks*, IEEE Transactions on Neural Networks **16**(4), 2005, pp. 925–936.
[3] HARALICK R.M., SHAPIRO L.G., *Image segmentation techniques*, Computer Vision, Graphics and Image Processing **29**(1), 1985, pp. 100–132.
[4] PAL N.R., PAL S.K., *A review on image segmentation techniques*, Pattern Recognition **26**(9), 1993, pp. 1277–1294.
[5] PHAM D.L., XU C., PRINCE J.L., *Current methods in medical image segmentation*, Annual Review of Biomedical Engineering **2**(1), 2000, pp. 315–338.
[6] WEINA WANG, YUNJIE ZHANG, YI LI, XIAONA ZHANG, *The global fuzzy c-means clustering algorithm*, [In] Proceedings of the World Congress on Intelligent Control and Automation, Vol. 1, 2006, pp. 3604–3607.
[7] ZADEH L.A., *Fuzzy sets*, Information and Control, Vol. 8, 1965, pp. 338–353.
[8] BEZDEK J.C., *Pattern Recognition with Fuzzy Objective Function Algorithms*, Plenum Press, New York 1981.
[9] BEZDEK J.C., HALL L.O., CLARKE L.P., *Review of MR image segmentation techniques using pattern recognition*, Medical Physics **20**(4), 1993, pp. 1033–1048.

[10] FERAHTA N., MOUSSAOUI A., BENMAHAMMED K., CHEN V., *New fuzzy clustering algorithm applied to RMN image segmentation*, International Journal of Soft Computing **1**(2), 2006, pp. 137–142.

[11] TOLIAS Y.A., PANAS S.M., *On applying spatial constraints in fuzzy image clustering using a fuzzy rule-based system*, IEEE Signal Processing Letters **5**(10), 1998, pp. 245–247.

[12] TOLIAS Y.A., PANAS S.M., *Image segmentation by a fuzzy clustering algorithm using adaptive spatially constrained membership functions*, IEEE Transactions on Systems, Man and Cybernetics, Part A **28**(3), 1998, pp. 359–369.

[13] NOORDAM J.C., VAN DEN BROEK W.H.A.M., BUYDENS L.M.C., *Geometrically guided fuzzy C-means clustering for multivariate image segmentation*, [In] Proceedings 15-th International Conference on Pattern Recognition, Vol. 1, 2000, pp. 462–465.

[14] AHMED M.N., YAMANY S.M., MOHAMED N., FARAG A.A., MORIARTY T., *A modified fuzzy C-means algorithm for bias field estimation and segmentation of MRI data*, IEEE Transactions on Medical Imaging **21**(3), 2002, pp. 193–199.

[15] ZHANG D.Q., CHEN S.C., PAN Z.S., TAN K.R., *Kernel-based fuzzy clustering incorporating spatial constraints for image segmentation*, [In] Proceedings of International Conference on Machine Learning and Cybernetics, Vol. 4, 2003, pp. 2189–2192.

[16] DUNN J.C., *A fuzzy relative of the ISODATA process and its use in detecting compact well-separated clusters*, Journal of Cybernetics **3**(3), 1973, pp. 32–57.

[17] PAL N.R., PAL K., KELLER J.M., BEZDEK J.C., *A possibilistic fuzzy c-means clustering algorithm*, IEEE Transactions on Fuzzy Systems **13**(4), 2005, pp. 517–530.

[18] TRAN T.N., WEHRENS R., HOEKMAN D.H., BUYDENS L.M.C., *Initialization of Markov random field clustering of large remote sensing images*, IEEE Transactions on Geoscience and Remote Sensing **43**(8), 2005, pp. 1912–1919.

[19] COLLINS D.L., ZIJDENBOS A.P., KOLLOKIAN V., SLED J.G., KABANI N.J., HOLMES C.J., EVANS A.C, *Design and construction of a realistic digital brain phantom*, IEEE Transactions on Medical Imaging **17**(3), 1998, pp. 463–468.

[20] CHANG C.C., WANG L.L., *A fast multilevel thresholding method based on lowpass and highpass filtering*, Pattern Recognition Letters **18**(14), 1997, pp. 1469–1478.

[21] DU-MING TSAI, *A fast thresholding selection procedure for multimodal and unimodal histograms*, Pattern Recognition Letters **16**(6), 1995, pp. 653–666.

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