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Fuzzy c-means clustering algorithm with a novel penalty term for image segmentation

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Fuzzy clustering techniques, especially fuzzy c-means (FCM) clustering algorithm, have been widely used in automated image segmentation. However, as the conventional FCM algorithm does not incorporate any information about spatial context, it is sensitive to noise. To overcome this drawback of FCM algorithm, a novel penalized fuzzy c-means (PFCM) algorithm for image segmentation is presented in this paper. The algorithm is formulated by incorporating the spatial neighbourhood information into the original FCM algorithm with a penalty term. The penalty term acts as a regularizer in this algorithm, which is inspired by the neighbourhood expectation maximization (NEM) algorithm and is modified in order to satisfy the criterion of the FCM algorithm. Experimental results on synthetic, simulated and real images indicate that the proposed algorithm is effective and more robust to noise and other artifacts than the standard FCM algorithm.

Keywords: image segmentation, fuzzy clustering, fuzzy c-means, expectation maximization.

1. Introduction

Image segmentation plays an important role in image analysis and computer vision, which is also regarded as the bottleneck of the development of image processing technology for until now there is no a technique that can handle all the segmentations of different types of image. The goal of image segmentation is partition of an image into a set of disjoint regions with uniform and homogeneous attributes such as intensity, colour, tone or texture, etc. Many different segmentation techniques have been developed and detailed surveys can be found [1–6]. According to Refs. 1, 3, and 4, 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.

Clustering is a process for classifying objects or patterns in such a way that samples of the same group are more similar to one another than samples belonging to different groups. Many clustering strategies have been used, such as the hard clustering scheme and the fuzzy clustering scheme, each of which has its own special characteristics. The conventional hard clustering method restricts each point of the data set to exclusively just one cluster. As a consequence, with this approach the segmentation results are often very crisp, i.e., each pixel of the image belongs to exactly just one class. 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. Due to the fuzzy, set theory [7] was proposed, which produced the idea of partial membership of belonging described by a membership function, fuzzy clustering as a soft segmentation method has been widely studied and successfully applied in image segmentation [10–17]. 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]. Although the conventional FCM algorithm works well on most noise-free images, it has a serious limitation, i.e., it does not incorporate any information about spatial context, which cause it to be sensitive to noise and imaging artifacts.

To compensate 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 [10–15]. Tolias *et al*. [10] proposed a fuzzy rule-based scheme called the rule-based neighbourhood enhancement system to impose spatial continuity by postprocessing on the clustering results obtained using FCM algorithm. In their another approach [11], spatial constraint is imposed in fuzzy clustering by incorporating the multi-resolution information. Noordam *et al*. [12] proposed a geometrically guided FCM (GG-FCM) algorithm based on a semi-supervised FCM technique for multivariate image segmentation. In their

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work, the geometrical condition information of each pixel is determined by taking into account the local neighbourhood of each pixel. Recently, some approaches [13–15] were proposed for increasing the robustness of FCM to noise by directly modifying the objective function. In Ref. 13, a new dissimilarity index that considers the influence of the neighbouring pixels on the centre pixel was presented to replace the conventional normed distance in the FCM algorithm. However, this method can handle only a small amount of noise [16]. In Ref. 14, a regularization term was introduced into the standard FCM to impose neighbourhood effect. Later, Li *et al.* [15] incorporated this regularization term into the adaptive FCM (AFCM) algorithm [17] to overcome the noise sensitivity of AFCM algorithm. Although this method is promising, it is computationally expensive that means more consuming time is needed during the computation.

In this paper, a novel fuzzy clustering method, called penalized FCM (PFCM) algorithm is presented for image segmentation. The penalty term takes the spatial dependence of the objects into consideration, which is inspired by the neighbourhood EM (NEM) algorithm [18] and is modified according to the criterion of FCM. The PFCM algorithm is then proposed by minimizing this new objective function according to the zero gradient condition, which can handle both the feature space information and spatial information during segmentation. The advantage of this algorithm is that it can handle small amount of noise and large amount of noise by adjusting a penalty coefficient. In addition, in this algorithm the membership is changed while the centroid computations are the same as in the standard FCM algorithm. Hence, it is easy to implement. Experiment results with different kinds of images show the method is effective and more robust to noise and artifacts in image segmentation than the traditional FCM algorithm without spatial constraints.

The remainder of this paper is organized as follows. Section 2 briefly describes the theory of FCM and NEM algorithms. The PFCM algorithm is presented in Sec. 3. Experimental results and comparisons are given in Sec. 4. Finally, some conclusions are drawn in Sec. 5.

2. Preliminary theory

2.1. Fuzzy c-means clustering algorithm

The fuzzy c-means (FCM) clustering algorithm was first introduced by Dunn [19] and later 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 J_{FCM} [8]

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

where $X = \{x_1, x_2, \ldots, x_n\} \subseteq R^p$ is the data set in the p-dimensional vector space, 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 the 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:

- set values for c, q, and ε,
- initialize the fuzzy partition matrix ,
- set the loop counter $b = 0$,
- calculate the c cluster centres $\left\{v_i^{(b)}\right\}$ with $U^{(b)}$

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

- calculate the membership $U^{(b+1)}$. For $k = 1$ to n, calculate the following:, $I_k = \{i | 1 \le i \le c, d_{ik} = \|x_k - v_i\| = 0\}$, $\tilde{I}_k = \{1,2,\ldots,c\} - I_k$, for the k^{th} column of the matrix, compute new membership values, and if $I_k = \phi$, then

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

else $u_{ik}^{(b+1)} = 0$ for all $i \in \tilde{I}_k$ and , $\sum_{i \in I_k} u_{ik}^{(b+1)} = 1$, next k,

- if $\left\|U^{(b)} - U^{(b+1)}\right\| < \varepsilon$, stop; otherwise, set $b = b+1$ and go to step 4.

2.2. Neighbourhood EM algorithm

In order to incorporate the spatial dependence into the objects, a modified version of the conventional expectation maximization (EM) [20] algorithm has been proposed in [18]. In this approach, the maximum likelihood criterion is penalized by a term that quantifies the degree of spatial contiguity of the pixels supporting the respective components of the probability density function (pdf) model. The spatial structure of a given data set is defined by using the matrix $W = (w_{jk})$

$$w_{jk} = \begin{cases} 1 & \textit{if } x_j \textit{ and } x_k \textit{ are neighbors and } j \ne k \\ 0 & \textit{otherwise} \end{cases}. \tag{4}$$

The following term is then used for regularizing the maximum likelihood criterion

$$G(c) = \frac{1}{2}\sum_{j=1}^{n}\sum_{k=1}^{n}\sum_{i=1}^{c} c_{ij} c_{ik} w_{jk}, \tag{5}$$

where c is the number of classes and c_{ij} is the probability that x_j belongs to class i. This term characterizes the level of homogeneity of the partition. The more the classes contain adjacent elements, the greater this term is. Let us consider a simple case of a hard partition here, where each object belongs to a single class ($c_{ij} = 1$ if x_j belongs to class i, and $c_{ij} = 0$ otherwise). In this context, if all the objects belong to the same class, $G(c)$ will be maximal and if each object has neighbours which belongs to different classes, then $G(c)$ will be minimal, that is equal to 0. The new criterion of the NEM algorithm is obtained by optimising the weighted sum of two terms

$$U(c,\phi) = D(c,\phi) + \beta G(c), \tag{6}$$

where $D(c,\phi)$ is the log-likelihood function of EM algorithm, $\beta > 0$ is a fixed coefficient. Details about NEM can be found in Ref. 18. This algorithm is maximized to get the optimum results just as the same structure as the EM algorithm. Successful results have been reported for image segmentation using this algorithm.

3. Penalized FCM algorithm

It is noted from Eq. (1) that the objective function of the traditional FCM algorithm does not take into account any spatial information, this means the clustering process is related only to grey levels independently on pixels of image in segmentation. This limitation makes FCM to be very sensitive to noise. The general principle of the technique presented in this paper is to incorporate the neighbourhood information into the FCM algorithm during classification. In order to incorporate the spatial context into FCM algorithm, the objective function of Eq. (1) is penalized by a regularization term, which is inspired by the above NEM algorithm and modified based on the criterion of FCM algorithm. The new objective function of the PFCM is defined as follows

$$\begin{aligned} J_{PFCM} &= \sum_{k=1}^{n}\sum_{i=1}^{c}(u_{ik})^q d^2(x_k,v_i) \\ &+ \gamma \sum_{k=1}^{n}\sum_{j=1}^{n}\sum_{i=1}^{c}(u_{ik})^q (1-u_{ij})^q w_{kj} \end{aligned}, \tag{7}$$

where w_{kj} is defined as Eq. (4). The parameter γ (≥ 0) controls the effect of the penalty term. The relative importance of the regularizing term is inversely proportional to the signal-to-noise (SNR) of the image. Lower SNR would require a higher value of the parameter γ, and vice versa. When $\gamma = 0$, J_{PFCM} equals J_{FCM}. The major difference between NEM algorithm and PFCM algorithm is that the penalty term in the NEM is maximized to get the solutions while in the PFCM it should be minimized in order to satisfy the principle of FCM algorithm. Besides, the penalty term in the PFCM algorithm has the weighting exponent to control the degree of fuzziness in the resulting membership function contrary to the penalty term in the NEM algorithm that is crisp. This new penalty term is minimized when the membership value for a particular class is large and the membership values for the same class at neighbouring pixels is also large, and vice versa. In other words, it constrains the pixel's membership value of a class to be correlated with those of the neighbouring pixels.

The objective J_{PFCM} function can be minimized in a fashion similar to the standard FCM algorithm. An iterative algorithm for minimizing Eq. (7) can be derived by evaluating the centroids and membership functions that satisfy a zero gradient condition. The constrained optimization in Eq. (7) will be solved using one Lagrange multiplier

$$\begin{aligned} \eta_q &= \sum_{k=1}^{n}\sum_{i=1}^{c}(u_{ik})^q d^2(x_k,v_i) \\ &+ \gamma \sum_{k=1}^{n}\sum_{j=1}^{n}\sum_{i=1}^{c}(u_{ik})^q (1-u_{ij})^q w_{kj} + \lambda\left(1-\sum_{i=1}^{c}u_{ik}\right) \end{aligned}. \tag{8}$$

Taking the partial derivate of Eq. (8) with respect to u_{ik} and setting the result to zero yields

$$\left[\begin{aligned} \frac{\partial \eta_q}{\partial u_{ik}} &= q(u_{ik})^{q-1} d^2(x_k,v_i) \\ &+ \gamma q(u_{ik})^{q-1}\sum_{j=1}^{n}(1-u_{ij})^q w_{kj} - \lambda \end{aligned}\right]_{u_{ik}=u_{ik}^*} = 0. \tag{9}$$

Solving for u_{ik}^*, we have

$$u_{ik}^* = \left(\frac{q\left(d^2(x_k,v_i) + \gamma\sum_{j=1}^{n}(1-u_{ij})^q w_{kj}\right)}{\lambda}\right)^{-1/(q-1)} \tag{10}$$

Since $\sum_{l=1}^{c} u_{lk} = 1, \forall k$, this constraint equation is then employed, yielding

$$\sum_{l=1}^{c}\left(\frac{q\left(d^2(x_k,v_l) + \gamma\sum_{j=1}^{n}(1-u_{lj})^q w_{kj}\right)}{\lambda}\right)^{-1/(q-1)} = 1. \tag{11}$$

Solving λ from Eq. (11), we have

$$\lambda = \frac{q}{\left(\sum_{l=1}^{c}\left(\frac{1}{d^2(x_k,v_l) + \gamma\sum_{j=1}^{n}(1-u_{lj})^q w_{kj}}\right)^{1/(q-1)}\right)^{q-1}}. \tag{12}$$

Combing Eqs. (12) and (10), the zero-gradient condition for the membership estimator can be written as

$$u_{ik}^* = \frac{1}{\sum_{l=1}^{c}\left(\frac{d^2(x_k,v_i)+\gamma\sum_{j=1}^{n}(1-u_{ij})^q w_{kj}}{d^2(x_k,v_l)+\gamma\sum_{j=1}^{n}(1-u_{ij})^q w_{kj}}\right)^{1/(q-1)}}. \quad (13)$$

Similarly, taking Eq. (8) with respect to v_i and setting the result to zero, we have

$$v_i^* = \frac{\sum_{k=1}^{n}(u_{ik})^q x_k}{\sum_{k=1}^{n}(u_{ik})^q}, \quad (14)$$

which is identical to that of FCM because in fact the penalty function in Eq. (7) does not depend on v_i. Thus, the PFCM algorithm is given as follows:

PFCM algorithm

Step 1. Set the cluster centroids v_i, fuzzification parameter q, the values of c and ε.

Step 2. Calculate membership values using Eq. (13).

Step 3. Compute the cluster centroids using Eq. (14).

Step 4. Go to step 2 and repeat until convergence.

When the algorithm has converged, a defuzzification process then takes place in order to convert the fuzzy partition matrix U to a crisp partition. A number of methods have been developed to defuzzify the partition matrix U, among which the maximum membership procedure is the most important. The procedure assigns the object k to the class C with the highest membership

$$C_k = \arg_i\{\max(u_{ik})\}, \; i = 1,2,\ldots,c. \quad (15)$$

With this procedure, the fuzzy images are then converted to crisp image that is segmentation.

4. Experimental results

In this section, the results of the application of the PFCM algorithm are presented. The performance of the proposed method is compared with that of the standard FCM algorithm. For all cases, unless otherwise stated, the weighting exponent $q = 2.0$, $\varepsilon = 0.0001$, and $\gamma = 400$ where the parameter γ is selected experimentally in order to give appropriate results. 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. It is important to note the intensity value of all the images given below ranges [0,255], and if the image is noisier, a larger parameter γ is then needed.

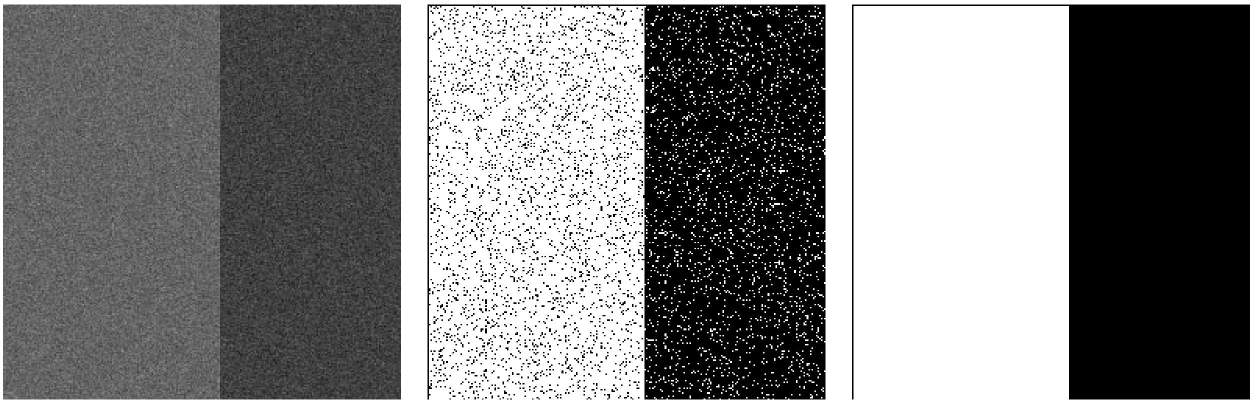
To evaluate the performance of the proposed approach, tests were first realized on two synthetic images. First, we generate a simple two-class synthetic image, whose intensity values are 100 and 60, respectively, and the image size is 256×256. The image is then corrupted by 5% Gaussian noise, which means the signal to noise (SNR) is 100/5 = 20. The original image is shown in Fig. 1(a) and the results of FCM and PFCM are given in Figs. 1(b) and 1(c), respectively. As it can be seen, without spatial information constraints, FCM algorithm cannot even separate the two classes, while PFCM algorithm correctly classifies the image into two parts without any noise existing in the segmented regions. Second, a multiple-class synthetic image has been created, in which the intensity values are 0, 255, and 128, respectively, and the image size is 256×256. Additive 10% Gaussian noise was then added to the image. To get a better insight, the image is segmented by FCM and PFCM into three corresponding classes with intensity values 255, 0, and 128, representing class 1, class 2, and class 3, respectively.

Figure 2(a) shows the test degraded noisy images. The results of FCM algorithm and PFCM algorithm are displayed in Figs. 2(b) and 2(c), respectively. We observed that the three regions are well brought out by these two algorithms. However, with the FCM algorithm, the segmentation result still has much noise especially in class 1 and class 3, while the result used by PFCM algorithm is less speckled and smoother. The number of misclassified pixels with the two methods is counted during the experiments and it is listed in Table 1. It can be seen from Table 1 that the total number of misclassification pixels for the FCM algorithm is nearly 63 times than that of the proposed method. These two examples can demonstrate the incorporation of the spatial neighbourhood constraints into the FCM algorithm can significantly improve the segmented result in presence of noise.

Table 1. Number of misclassified pixels with FCM and PFCM methods for Fig. 2(a).

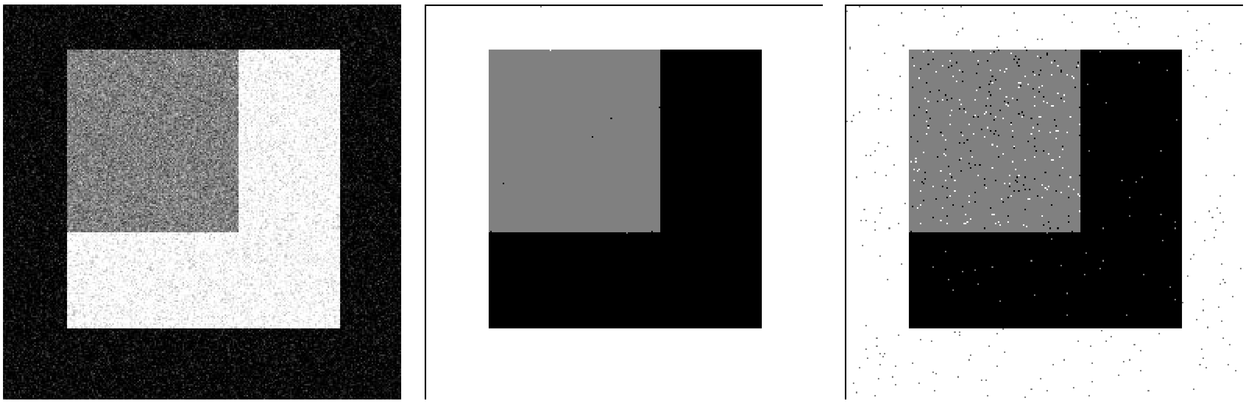
Segmentation method	FCM	PFCM
Class 1	185	1
Class 2	42	1
Class 3	337	7
Total	564	9

The second type of example is a simulated magnetic resonance (MR) brain image obtained from the BrainWeb Simulated Brain Database [21]. This brain image was simulated with T1-weighted contrast, 1-mm cubic voxels, 7% noise, and no intensity inhomogeneity. Before segmentation, the non-brain parts of the image such as the bone, cortex and fat tissues should be removed. The class number of the image was assumed to be four, corresponding to grey matter (GM), white matter (WM), cerebrospinal fluid (CSF) and background (BKG). The parameter γ is set to be 500 in this experiment. Figure 3(a) shows a slice from the simulated data set, Figs. 3(b) and 3(c) show the segmentation results obtained by applying FCM and PFCM, respectively, and the ground truth is given in Fig. 3(d). It is clearly seen that our



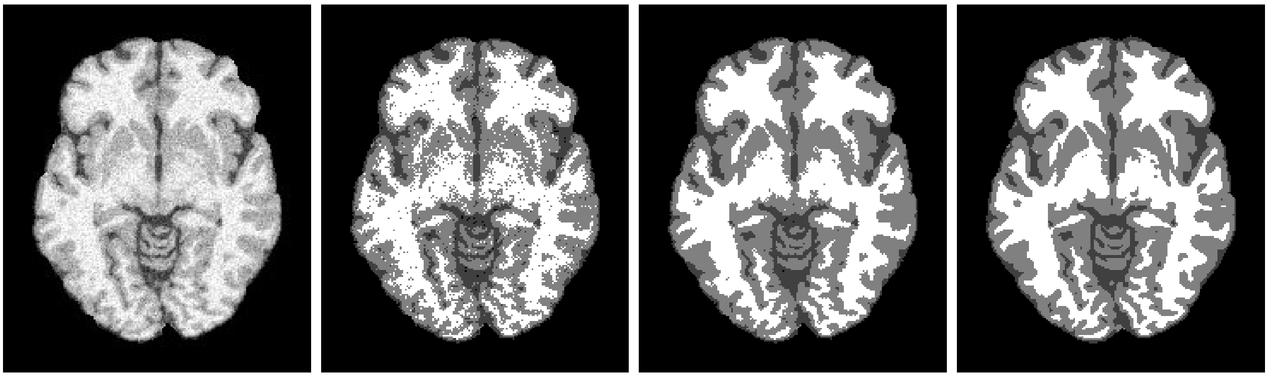
(a) (b) (c)

Fig. 1. Comparison of segmentation results on a two-class synthetic image corrupted by 5% Gaussian noise: the original image (a), FCM result (b), and PFCM result (c).



(a) (b) (c)

Fig. 2. Comparison of segmentation results on a three-class synthetic image corrupted by 10% Gaussian noise: the original image (a), FCM result (b), and PFCM result (c).



(a) (b) (c) (d)

Fig. 3. Comparison of segmentation results on a MR phantom corrupted by 7% Gaussian noise and no intensity inhomogeneity: the original images (a), FCM results (b), PFCM results (c), and ground truth (d).

segmentation result is much closer to the ground truth. The result of PFCM is more homogeneous and smoother than that of the FCM algorithm, especially for WM, which again indicates that our method is effective and robust to noise. To measure the segmentation accuracy, we also apply the quantitative evaluation of performance by using the overlap metric criteria [22]. The overlap metric is a measure for comparing two segmentations that is defined for a given class assignment as the sum of the number of pixels that both have the class assignment in each segmentation divided by the sum of pixels where either segmentation has the class assignment. Larger metric means more similar for results. The overlap metrics of WM, GM, CSF, and BKG are given in Table 2. As it can be seen from Table 2, the overlap metrics of WM and GM have been increased greatly with our method, compared to those of the conventional FCM algorithm.

Fig. 4. Comparison of segmentation results on real standard images named Lena and cameraman, (a) the original images, (b) FCM results, and (c) PFCM results.

In the last examples, there are two groups of real standard test images, which are named Lena and cameraman, respectively. These images are introduced without adding any type of noise. In both experiments, the class c number is set to be 2. The original images are shown in Fig. 4(a), where the top is Lena and the bottom is cameraman. The results of the FCM algorithm and PFCM algorithm are presented in Fig. 4(b) and 4(c), respectively. As it can be seen, both the FCM and PFCM algorithms can well extract the object from the background in each image. However, it is important to note the proposed method performs better for the segmentation with more homogeneous regions such as the face, the shoulder and the cap of Lena, 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 of coping with not only noises but also artifacts in the image.

Table 2. Overlap metrics with FCM and PFCM methods for Fig. 3(a).

Segmentation method	WM	GM	CSF	BKG
FCM	0.896	0.868	0.876	0.989
PFCM	0.977	0.931	0.894	0.991

5. Conclusions

We have presented a novel penalized fuzzy c-means (PFCM) algorithm that is able to incorporate both local spatial contextual information and feature space information into the image segmentation. The algorithm is developed by modifying the objective function of the standard FCM algorithm by a penalty term that takes into account the influence of the neighbouring pixels on the centre pixels. A variety of images, including synthetic, simulated and real images were used to compare the performance of FCM and PFCM 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. It should be emphasized that if the algorithm performs on an image with higher contamination intensity, a larger parameter γ should be set in order to provide better result. Future work will focus on adaptively deciding the penalized parameter of this algorithm as well as compensating for the intensity inhomogeneity while segmenting the image data.

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