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AN ADAPTIVE ACO-BASED FUZZY CLUSTERING ALGORITHM FOR NOISY IMAGE SEGMENTATION

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Abstract. *The fuzzy c-means (FCM) has been a well-known algorithm in machine learning/data mining area as a clustering algorithm. It can also be used for image segmentation, but the algorithm is not robust to noise. The possibilistic c-means (PCM) algorithm was proposed to overcome such a problem. However, the performance of PCM is too sensitive to the initialization of cluster centers, and often deteriorates due to the coincident clustering problem. To remedy these problems, we propose a new hybrid clustering algorithm that incorporates ACO (ant colony optimization)-based clustering into PCM, namely ACOPCM for noisy image segmentation. Our ACOPCM solves the coincident clustering problem by using pre-classified pixel information and provides the near optimal initialization of the number of clusters and their centroids. Quantitative and qualitative comparisons are performed on several images having different noise levels and bias-fields. Experimental results demonstrate that our proposed approach achieves higher segmentation accuracy than PCM and other hybrid fuzzy clustering approaches.*
Keywords: Unsupervised fuzzy clustering, Ant colony optimization, Image segmentation

1. Introduction.

Image segmentation plays an important role in image analyses, and is considered as one of the difficult and challenging problems in image processing technology [1, 27]. It is a process of partitioning an image into non-overlapped and consistent regions which are homogeneous with respect to some image property such as intensity, color, texture, and so on [9, 11]. Image segmentation has a wide range of applications such as image content analysis, object recognition, and computer-assisted medical diagnosis [5, 6]. In particular, it has become an increasingly important pre-processing step in medical image analysis. Related research has reported considerable progress over the past decade [5, 6, 7]. However, since in many cases images contain a significant amount of noise causing the segmentation difficult, we need a robust method to noise.

There are many approaches to image segmentation such as histogram-based methods, edge detection, region growing methods, split-and-merge methods, PDE-based methods and clustering methods [4]. Among them, we are interested in clustering based approaches, where each image pixel is assigned to a cluster such that all members in the same cluster are similar in the defined feature space. Once similar pixels are clustered together, the image can be segmented into distinct regions. The fuzzy c-means (FCM) has been one of the widely used clustering methods for image segmentation [12, 13]. Minimizing square of error, FCM produces good segmentation results for relatively easy images without estimating the density distribution of the image. Although FCM is a very useful image segmentation method, fuzzy data membership does not always correspond well to the actual degree of membership, and it is inaccurate in a noisy environment. To remedy such drawbacks of FCM, Krishnapuram and Keller proposed the possibilistic c-means (PCM) clustering [14]. PCM relaxes the column sum constraint of the fuzzy membership matrix in FCM and introduces a possibilistic partition matrix, which describes the degree of membership based on the typicalities of data points to their clusters. PCM with its possibilistic memberships is more robust to noise and outliers than FCM. However, by relaxing column sum constraint in FCM, PCM often causes the coincident clustering problem [10, 15]. Also, PCM is less but still sensitive to noise and the initialization of parameters such as the number of clusters and their centroids.

Recently, swarm-based heuristic approaches were combined with unsupervised fuzzy clustering to improve the overall clustering accuracy [24, 25, 26]. As one of such approaches, particle swarm optimization (PSO) was used to find the optimal cluster centers in advance, and then PCM was applied for image segmentation [19, 20]. These hybrid approaches work well, but they still have the coincident clustering problem of PCM. As another approach, Malisia and Tizhoosh [3] proposed an image binary segmentation method by adding pheromone information to original image pixels based on ant colony optimization (ACO) and clustering the image pixels with K-means algorithm. Also, Yu et al. [21] proposed a color image segmentation method which obtains the optimal initial cluster centers using ACO and then clusters the image data set with FCM. However, the proposed method is still sensitive to noise.

In this paper, we propose a new hybrid clustering algorithm that incorporates ACO-based clustering into PCM, namely ACOPCM which is robust to noise. ACOPCM has three principal advantages:

1. ACOPCM automatically computes the appropriate number of clusters and their centroids by adopting ACO-based clustering without any pre-definition or assumption, which greatly affects the segmentation accuracy, cluster compactness, and coincident clustering problem of PCM.
2. Although existing hybrid swarm-based fuzzy clustering methods could not deal with the coincident clustering problem of PCM [19, 20], ACOPCM overcomes this problem using pre-classification pixel information derived from ACO-based clustering. The pre-classification pixels are composed of classified and unclassified ants (pixels). The former plays the role as base pixels for preventing coincident clusters, and the latter is classified by PCM.
3. In comparison of ACOPCM with other swarm-based hybrid fuzzy clustering methods, our algorithm is more robust especially to the high level of noise and bias-field in image segmentation.

This paper is organized as follows. In Section 2, we review related works to our research. Section 3 describes our proposed ACOPCM clustering algorithm in detail, and Section 4 shows comparison of our proposed algorithm with other unsupervised fuzzy clustering methods segmentation methods. Finally, Section 5 contains discussion and conclusion.

2. **Background.**

2.1. **FCM and PCM clustering algorithms.**

In unsupervised fuzzy clustering, FCM has been a well-known and widely used clustering method, since it was initially proposed by Ruspini [23] and improved by Dune [16]. The algorithm performs clustering by minimizing the objective function J_{FCM}, which as defined in Equation (1), is the weighted sum of squared errors within each cluster. Let N be the number of pixels, M the cluster number and m the weighted exponent (fuzzifier) that establishes the degree of fuzziness, and then the related optimization problem can be described as follows:

$$\min J_{FCM}(U,C) = \sum_{i=1}^{M}\sum_{j=1}^{N} \mu_{ij}^m d_{ij}^2 \tag{1}$$

$$\text{subject to } 0 \le \mu_{ij} \le 1, \sum_{i=1}^{M} \mu_{ij} = 1, \sum_{j=1}^{N} \mu_{ij} > 0,$$

where μ_{ij} is the membership degree of x_j (the intensity of pixel j) to c_i (the intensity of the cluster center i), and $U = [\mu_{ij}]_{M\times N}$ is the fuzzy partition matrix, $d_{ij} = \|c_i - x_j\|$ represents the intensity difference between the centroid of cluster i and the pixel j, and $C = \{c_1, c_2, \ldots, c_M\}$ is the set of intensities of cluster centers. The necessary conditions for minimizing J_{FCM} follow the update equations:

$$\mu_{ij} = \left(\sum_{k=1}^{M} \left(\frac{d_{ij}}{d_{kj}} \right)^{2/(m-1)} \right)^{-1}, \tag{2}$$

$$c_i = \frac{\sum_{j=1}^{N} \mu_{ij}^m \cdot x_j}{\sum_{j=1}^{N} \mu_{ij}^m}. \tag{3}$$

Note that FCM iteratively optimizes the objective function J_{FCM} by updating μ_{ij} and c_i until $\|U(t+1) - U(t)\| \le \varepsilon$ for some small positive number ε. Although FCM is a useful method in the image segmentation, membership of each data point does not always reflect well its actual membership to clusters, and may be inaccurate in a noisy environment. To improve this weakness, Krishnapuram and Keller proposed a new clustering algorithm, called possibilistic c-means (PCM) [14]. PCM relaxes the column sum constraint in FCM that the memberships of a data point over clusters sum to 1 for giving the low (or even no) membership of noise data, resulting in the related optimization problem described as follows:

$$\min J_{PCM}(U,C) = \sum_{i=1}^{M}\sum_{j=1}^{N} \mu_{ij}^m d_{ij}^2 + \sum_{i=1}^{M} \eta_i \sum_{j=1}^{N} (1-\mu_{ij})^m, \tag{4}$$

$$\text{subject to } 0 \le \mu_{ij} \le 1, \sum_{j=1}^{N} \mu_{ij} > 0.$$

In this case, μ_{ij} is defined as

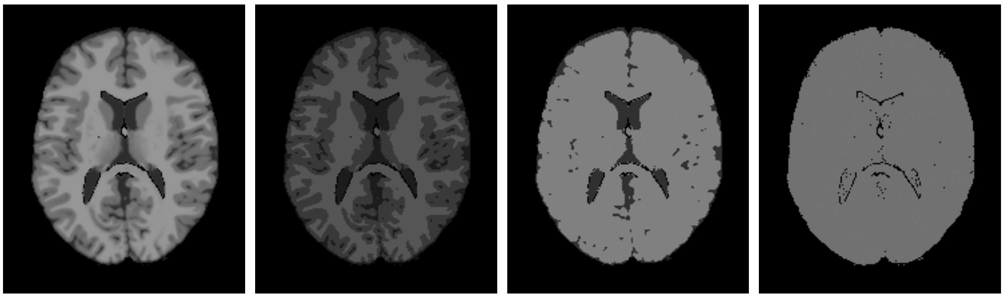
$$\mu_{ij} = \left(1 + \left(\frac{d_{ij}^2}{\eta_i} \right)^{1/(m-1)} \right)^{-1}, \tag{5}$$

where η_i is the scale parameter defined as

$$\eta_i = K \frac{\sum_{j=1}^{N} \mu_{ij}^m \cdot d_{ij}^2}{\sum_{j=1}^{N} \mu_{ij}^m}, \tag{6}$$

with $K > 0$ and in general $K = 1$.

PCM adopts possibilistic approach in which the membership value of a data represents possibility of a data belonging to a cluster. The possibilistic membership value is often interpreted as the typicality of a data point associated with each cluster rather than its relative memberships to the clusters in FCM. The advantage of PCM over FCM is robustness against outliers. However, by relaxing column sum constraint in FCM, PCM often causes the coincident clustering problem which generates identical clusters. Also, PCM is still fragile to the high level of noise and the initialization of parameters such as inappropriate the number of clusters and their centroids. Figure 1 shows such problems of PCM in brain image segmentation.



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

FIGURE 1. Segmentation problems of PCM (a) original simulated brain MR image (b) discrete anatomical model (ground truth) (c) segmentation result with inappropriate cluster centers (d) segmentation result with high level of noise (9% Gaussian noise)

2.2. **Ant colony optimization.** Mimickig real ants behavior, ant colony optimization (ACO) algorithm was first proposed by Dorigo et al. [17]. Since then, it has been applied successfully to a wide range of optimization problems such as Traveling Salesman Problem (TSP) [17], Quadratic Assignment Problem (QAP) [28], and Job Shop Scheduling (JSS) [2]. Recently, there have been attempts applying ACO to clustering problems [18, 22]. The key strength of ACO is in the direct communication among the individual ants based on pheromone amount and heuristic value, which is calculated by problem-dependent heuristic function that measures the trail quality.

In ACO, the path construction and pheromone update are the main steps. Let path (i, j) denote the path which connects node i to j. Each ant going from node i to j lays pheromone τ_{ij} on path (i, j). In the construction of a path solution, the ant chooses its path based on the following probability:

$$P_{ij} = \frac{\tau_{ij}^{\alpha}(t) \cdot \eta_{ij}^{\beta}(t)}{\sum_{s \in S} \tau_{ij}^{\alpha}(t) \cdot \eta_{ij}^{\beta}(t)}, \quad j \in S, \tag{7}$$

$$\tau_{ij} = \begin{cases} 1 & l_{ij} \leq r \\ 0 & \text{otherwise}, \end{cases} \tag{8}$$

where $\eta_{ij}(t) = r/l_{ij}$ denotes heuristic information at time t and l_{ij} is the intensity difference between i and j nodes (pixels), and $\tau_{ij}(t)$ denotes the pheromone concentration on path (i, j) at time t. The control parameters α and β explain the relative importance of pheromone versus the heuristic value, r is the clustering radius, and $S = \{s | l_{is} \leq r, s = 1, 2, \ldots, N\}$ is set of feasible nodes. After all ants have finished path construction, the quantity of pheromone is updated according to the following equation:

$$\tau_{ij}(t) = \rho \cdot \tau_{ij}(t) + \sum_{k=1}^{N} \Delta\tau_{ij}^{k}, \tag{9}$$

where ρ is the evaporation rate, N is the number of ants, and $\Delta\tau_{ij}^{k}$ is the amount of increased pheromone laid on path (i, j) by the k^{th} ant.

3. Proposed Adaptive ACO-Based Fuzzy Clustering Algorithm.

3.1. Initialization of tentative cluster centers. In general, ACO can effectively handle the optimization and clustering problems due to the parallel searching capability. On the other hand, it is well-known to suffer from high computational complexity for a large amount of data. Since each ant (i.e., an image pixel) should estimate the distances and the amount of pheromone on the connected paths, the running cost of ACO can be quite high in the image segmentation. Also, to achieve high-quality segmentation, we need the appropriate number of clusters and their centroids in the clustering algorithm. Commonly, we have assumed or manually determined the relevant number of clusters by investigating the image grayscale histogram. However, the outcomes could not guarantee the optimum.

In order to reduce the time complexity of ACO and obtain the more correct number of clusters, we roughly choose the tentative number of clusters based on pixel intensity statistics as the preprocessing step. The procedure of obtaining pixel statistics is described below.

: Determine the tentative initial number of clusters and their centroids.

- Make M' divisions with 256 gray levels and assign image pixels to each division, the set of divisions $S = \{s_1, s_2, \ldots, s_{M'}\}$ contains assigned image pixels. When $|s_k|$ is larger than some threshold, let $V = \{v_1, v_2, \ldots, v_{M'}\}$, calculate v_h by the following equation.

$$v_h = \frac{1}{|s_k|} \sum_{j \in d_k} x_j, \quad j = 1, 2, \ldots, N, \tag{10}$$

where M' is the number of divisions, and N is the number of pixels in an image.

The time complexity of ACO is approximately $O(N^2)$, but with the above preprocessing step, obtaining the tentative cluster number M', the time complexity of ACO is reduced to approximately $O(N)$ [18, 21]. The tentative initial cluster centers should be more compact and optimal through the proposed ACOPCM.

3.2. The ant colony-possibilistic c-means hybrid algorithm. PCM has a strong inherent capability for local search, but it is likely to obtain local optima when the inappropriate initial number of the clusters and centroids are used. They substantially affect the overall segmentation accuracy and cluster compactness, and also decide the parameter η_i of PCM which affects the final segmentation result.

In this paper, we adopt the ACO-based clustering to provide the appropriate number of clusters and centroids automatically, thereby mitigating the problem of getting trapped in local optima of PCM. Through the ACO-based clustering, the tentative initial cluster centers could be more compact and optimal, as illustrated in Figure 2.

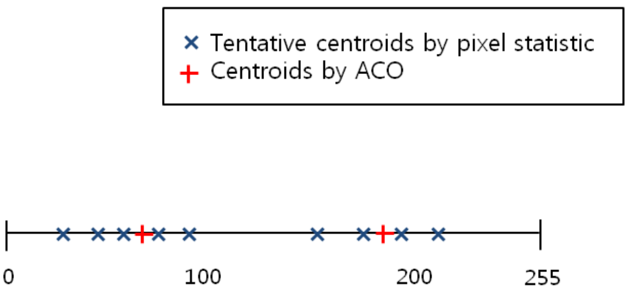
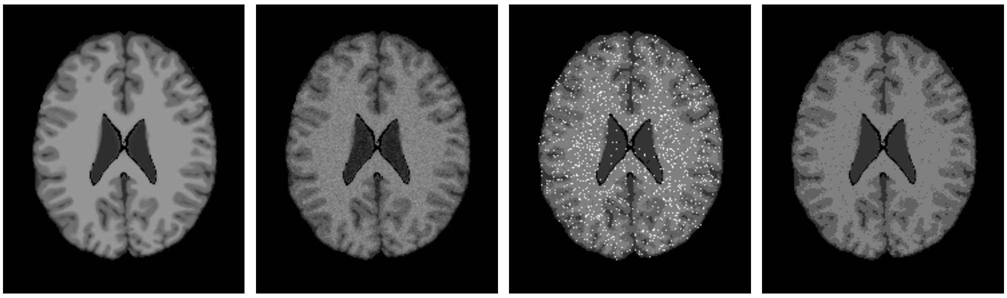


Figure 2. Illustration of cluster centers



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

FIGURE 3. Illustration of pre-classified ants (a) original simulated MR image (b) original simulated MR image with 7% Gaussian noise (c) pre-classified ants image derived from ACO (d) segmentation result of ACOPCM

Even though this algorithm provides the appropriate initialization of parameters, it does not solve the coincident clustering problem of PCM. To overcome the problem, we apply pre-classified ants (pixels) derived from the ACO-based clustering to PCM. The pre-classified ants are composed of the classified and unclassified ants. The classified ants are clustered by the ACO-based clustering utilizing its strong capability to converge to the global optimum. All classified ants with the centroid information belong to each cluster set. The remaining members are defined as unclassified ants. When we carry out PCM, the classified ants are assigned to the image and play a key role as base pixels in preventing the coincident clustering problem, and the unclassified ants will be positioned into any discovered cluster by means of PCM. The classified ants are shown as their centroid value and the unclassified ants are shown as white pixels, as illustrated in Figure 3(c). Figure 3(d) shows the proposed ACOPCM overcomes coincident clustering problem, and stably segments the brain MR image.

The proposed ACOPCM algorithm is described in Algorithm 1.

4. **Experiment.** In this section, we investigate the performance of the proposed algorithm on the three images: simulated, real brain MR image and cameraman image. The system parameters are set as $\alpha = 0.4$, $\beta = 2$, $\rho = 0.9$, $\lambda = 0.35$, $T = 30$, $M' = 9$, $\varphi = 20$, $r = 20$ as analyzed in [21], and the weighting exponent m in PCM is set to 1.5. Experiments were done in Matlab 7.11.

To evaluate the segmentation results, we adopt the Jaccard similarity index (SI), which is defined for the tissue class k as:

$$J^k(s_g, s_r) = \frac{|s_g^k \cap s_r^k|}{|s_g^k \cup s_r^k|}, \tag{11}$$

where s_g^k is the pixel set of the ground truth of class k, and s_r^k is the pixel set of segmentation results of class k using a given algorithm. When the value of $J^k(s_g, s_r)$ approaches to 1, the segmentation results become closer to the ground true.

First, our algorithm is tested on simulated brain MR images, which are provided by McConnell Brain Imaging Centre of the Montreal Neurological Institute, McGill University*. They offer a large number of different synthetic brain MR images with Gaussian

*http://www.bic.mni.mcgill.ca/brainweb/.

Algorithm 1 ACOPCM clustering

Input: Image data $I \in \Re^{N \times 1}$
Output: Segmented image

Initialize the tentative cluster center v_h by Equation (10), V is the set of cluster centers.
Q_h is the ant(pixel) set that contains the members of v_h.
$t = 0$
repeat
  $t = t + 1$
  For each ant j in I, calculate its distance l_{hj} to every v_h.
  If $l_{hj} = 0$, the probability $P_{hj} = 1$. Otherwise, if $l_{hj} \leq r$, calculate P_{hj} by Equation (7).
  If $P_{hj} \geq \lambda$, assign the ant to Q_h, and update the pheromone by Equation (9). Otherwise, leave the ant into the unclassified ants set waiting for next iteration.
  Refresh the cluster centers using the following equation:

$$v_h = \frac{1}{|Q_h|} \sum_{j \in Q_h} x_j. \tag{11}$$

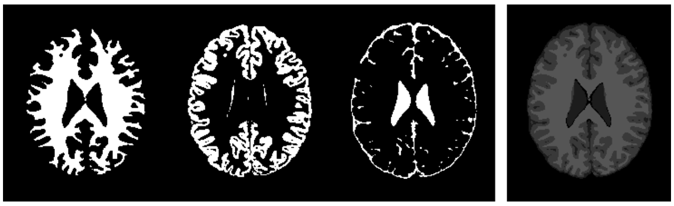
  Calculate the distance between cluster centers. If the distance is less than the given threshold T, merge the clusters and refresh the cluster centers by Equation (11).
until $\|V(t+1) - V(t)\| < \varphi$.
Assign the value of v_h to its members(classified ants) and remain unclassified ants.
Set the cluster number $M = |V(t+1)|$ and the cluster centers $C = V(t+1)$.
Initialize posssibilistic partition matrix $U = [\mu_{ij}]_{M \times N}$, estimate η_i by Equation (6).
$z = 0$
repeat
  $z = z + 1$
  Calculate cluster centers $C(z+1)$ by Equation (3).
  Update possibilistic memberships of pixels $U(z+1)$ by Equation (5).
until $\|U(z+1) - U(z)\| < \varepsilon$.
Segment image by matrix U which is based on the majority membership to a cluster.

noise levels varying from 0% to 9% and bias-fields (intensity inhomogeneities) from 0% to 40%, including an anatomical model of the normal brain, which can serve as the ground truth for analyzing segmentation performance. Knowing this information, we can assess the performance of the different algorithms quantitatively.

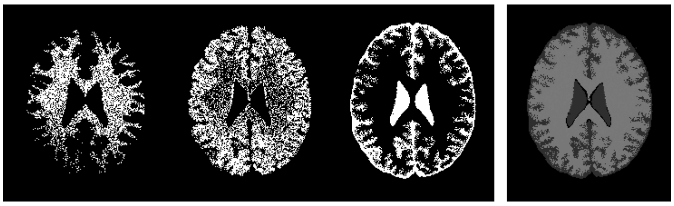
In this experiment, we use the 96th brain region slice of the simulated T1-weighted brain MR image (Figure 4). To graphically show the segmentation results, we employ this image with 9% noise and 40% bias-field (see Figure 4(a)). Figure 4(b) shows the discrete anatomical structure consisting of white matter (WM), gray matter (GM), cerebrospinal fluid (CSF) and the total region. Figures 4(c)-4(e) display segmentation results with PCM, ACO+FCM [21], and ACOPCM. From those figures, we can recognize the proposed ACOPCM achieves better segmentation accuracy than other methods.

Figure 5 shows the SI comparison of several methods on the simulated brain image with 7% and 9% noise, and 40% bias-field, where we can see that our ACOPCM algorithm achieved best segmentation results. Particularly, in Figure 5(b), the SI results of PCM and PSO+PCM [19] deteriorated due to the coincident clustering problem and the high level of noise. On the other hand, our ACOPCM overcame those difficulties and obtained

(a)



(b)

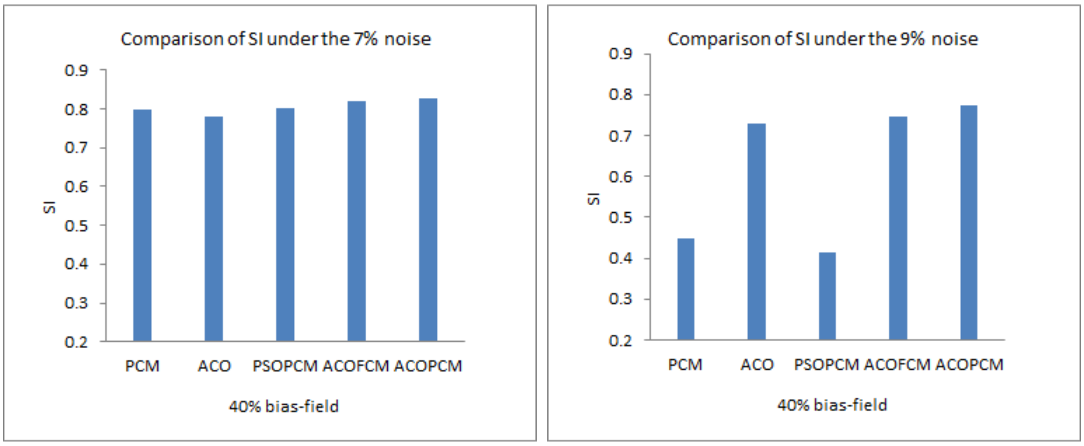


(c)

(d)

(e)

Figure 4. Segmentation results of simulated brain MR images (a) original image with 9% noise and 40% bias-field (b) discrete anatomical model(from left to right) WM, GM, CSF, and total segmentation (c) results of PCM (d) results of ACO+FCM (e) results of ACOPCM



(a) (b)

Figure 5. Comparison of segmentation results (a) SI results with the 7% noise and 40% bias-field (b) SI results with the 9% noise and 40% bias-field

Table 1. Segmentation evaluation of simulated T1-weighted brain MR images

	Noise Level	7%			9%		
Class	Bias-Field	0%	20%	40%	0%	20%	40%
PCM	CSF	0.826	0.839	0.807	0.516	0.501	0.482
	GM	0.762	0.779	0.741	0.361	0.334	0.355
	WM	0.86	0.871	0.847	0.47	0.409	0.542
ACO [18]	CSF	0.763	0.779	0.673	0.621	0.664	0.671
	GM	0.741	0.746	0.738	0.679	0.625	0.69
	WM	0.884	0.889	0.847	0.802	0.824	0.787
PSO+PCM [19]	CSF	0.836	0.839	0.815	0.534	0.519	0.482
	GM	0.768	0.779	0.747	0.356	0.349	0.335
	WM	0.86	0.871	0.847	0.399	0.409	0.472
ACO+FCM [21]	CSF	0.828	0.827	0.805	0.738	0.737	0.736
	GM	0.79	0.797	0.767	0.687	0.697	0.685
	WM	0.878	0.885	0.864	0.811	0.817	0.805
ACOPCM	CSF	0.855	0.856	0.831	0.794	0.74	0.793
	GM	0.79	0.80	0.772	0.707	0.684	0.709
	WM	0.878	0.889	0.869	0.825	0.824	0.823

the better segmentation results. The detailed segmentation results under various noise levels and bias-fields are presented in Table 1.

In the second experiment, we test and compare the results on a real brain MR image. Figure 6 presents the comparison of segmentation results for the image corrupted by 10% Gaussian noise [8]. Figure 6(a) shows the original test image, Figure 6(b) shows the artificially corrupted image, and Figures 6(c)-6(f) present the results from PCM, PSO+PCM, ACO+FCM and our ACOPCM. Our proposed algorithm obtained the better segmentation result compared to other methods without any coincident clustering problem.

Our final test was carried out on the cameraman image. To apply the proposed algorithm to the test image, we set the parameters as $T = 70$ and $m = 2.0$ for PCM.

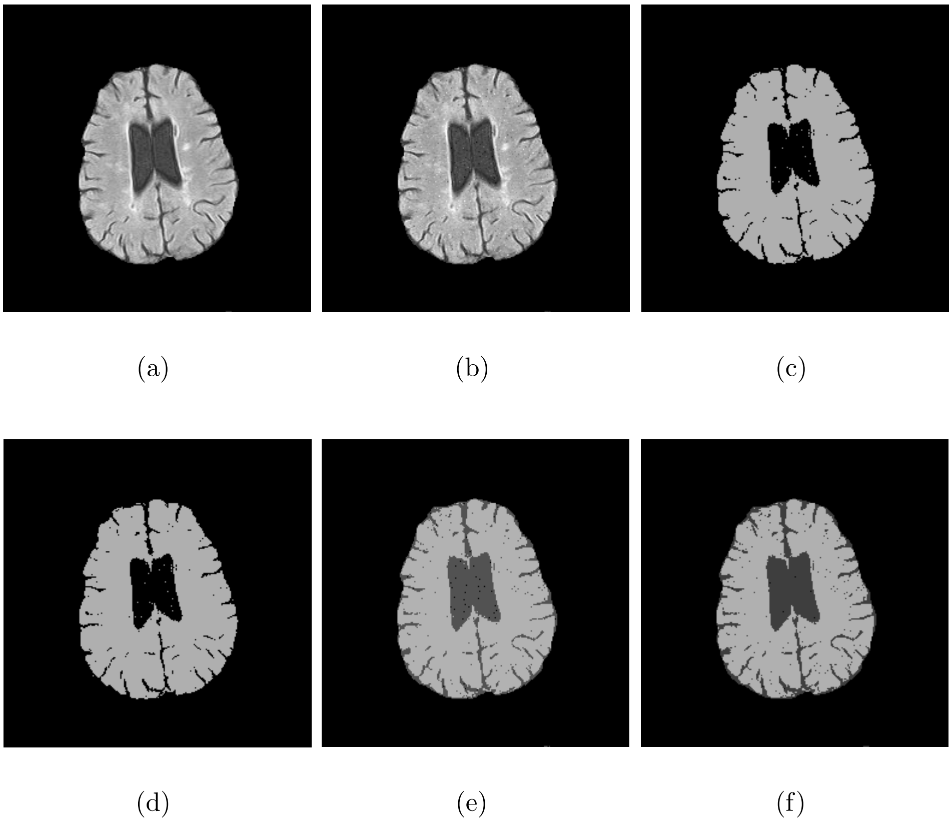
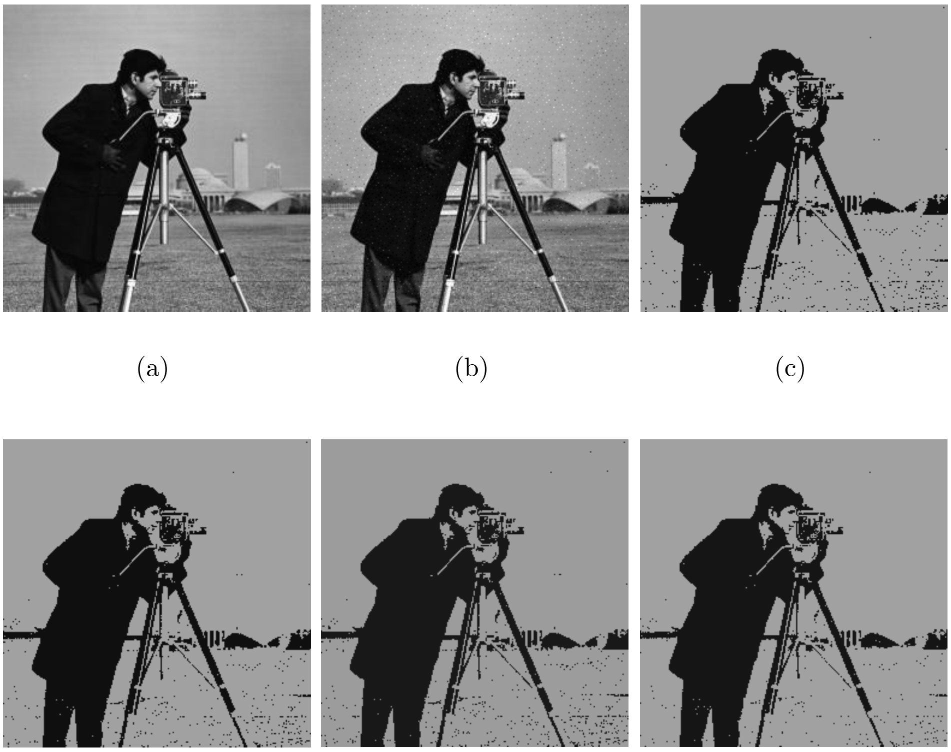


FIGURE 6. Segmentation results of real brain MR image (a) real brain MR image (b) noisy image with 10% Gaussian noise (c) result of PCM (d) result of PSO+PCM (e) result of ACO+FCM (e) result of ACOPCM

Figure 7(a) shows the original cameramen image, and Figure 7(b) shows the noisy image with 10% Gaussian noise. Figures 7(c)-7(f) then present the results for PCM, PSO+PCM, ACO+FCM and our ACOPCM. From the figure, the our approach produced the improved segmentation results for noisy image compared to other methods. With different levels of noise, we got the same trend as with 10%. The trend of the results is quite similar to those in the above two experiments.

5. **Conclusion.** PCM has been suggested for systematically handling the major problem of FCM; that is, noise sensitivity. Notwithstanding this strength, it still has two drawbacks: its performance mainly depends on the initialization of cluster centers, and occasionally deteriorates due to the coincident clustering problem.

To overcome those drawbacks, we proposed a new hybrid clustering algorithm that incorporates ACO-based clustering into PCM (ACOPCM) especially for the noisy image segmentation. The proposed ACOPCM solves the problems by adaptively selecting the parameters such as the appropriate number of clusters and their centroids, and employing the pre-classified pixel information to solve the coincident clustering problem of PCM. Quantitative and qualitative comparisons were performed on brain MR and cameraman images with different noise levels. From the test, we found our clustering algorithm obtained better segmentation accuracy than the conventional PCM and hybrid fuzzy clustering approaches.



(a) (b) (c)

(d) (e) (f)

FIGURE 7. Segmentation results of cameraman (a) original cameraman image (b) noisy image with 10% Gaussian noise (c) result of PCM (d) result of PSO+PCM (e) result of ACO+FCM (f) result of ACOPCM

In the future work, since the system parameters of ACOPCM which are chosen empirically impact on the segmentation result, we will find the optimal parameters and apply to the various kinds of real-world images.

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