

## A Cluster Number Adaptive Fuzzy c-means Algorithm for Image Segmentation

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### **Abstract**

*Aiming at partitioning an image into homogeneous and meaningful regions, automatic image segmentation is a fundamental but challenging problem in computer vision. It is well known that Fuzzy c-means (FCM) algorithm is one of the most popular methods for image segmentation. However, the FCM-based image segmentation algorithm must be manually estimated to determine cluster number by users. In this paper, we propose a novel cluster number adaptive fuzzy c-means image segmentation algorithm (CNAFCM) for automatically grouping the pixels of an image into different homogeneous regions when the cluster number is not known beforehand. We utilize the Grey Level Co-occurrence Matrix (GLCM) feature extracted at the image block level instead of at the pixel level to estimate the cluster number, which is used as initialization parameter of the following FCM clustering to endow the novel segmentation algorithm adaptively. We cluster image pixels according to their corresponding Gabor feature vectors to improve the compactness of the clusters and form final homogeneous regions. Experimental results show that proposed CNAFCM algorithm not only can spontaneously estimate the appropriate number of clusters but also can get better segmentation quality, in compare with those FCM-based segmentation methods recently proposed in the literature.*

**Keywords:** *Image Segmentation, Fuzzy c-means, Estimation of Cluster Number, Composite Cluster Validity*

### **1. Introduction**

Image segmentation is one of the most difficult and challenging problems in a number of applications, and this low-level vision task is also one of the most crucial steps toward computer vision [1-3]. Classically, image segmentation is defined as an inverse problem which consists of achieving a compact region-based description of the image by decomposing it into meaningful or spatially multiple coherent regions, which are homogeneous with respect to one or more characteristics such as color or texture. From an implementation point of view, image segmentation can be treated as a clustering problem where the features describing a pixel correspond to a pattern, and each image region corresponds to a cluster. Therefore, many clustering algorithms, especially the fuzzy c-means algorithm (FCM), have widely been used to solve the segmentation problem and such a success chiefly attributes to introduction of fuzziness for the belongingness of each image pixel, which makes the clustering methods able to retain more information from the original image than the crisp or hard segmentation

methods (*e.g.*, K-means). The advantages of the FCM are its simply straightforward implementation, fairly robust behavior, applicability to vector data and the ability of uncertainty data modeling.

Nevertheless, most of the FCM-based image segmentation algorithms assume a prior knowledge of the cluster (region) number. While in many practical situations, the appropriate cluster number is unknown or impossible to determine, which has unneglectable impacts on the image segmentation quality. Therefore, how to automatically and accurately determine the cluster number to avoid over-segmentation or under-segmentation becomes a challenging task. To solve this problem, Li and Shen [4] proposed an algorithm called automatic modified fuzzy c-means cluster segmentation algorithm (AMFCM) that can automatically determine the optimal cluster number. However, the AMFCM algorithm requires iterative execution of the standard FCM with cluster number from 2 to maximum possible value until predefined optimal validation criteria is met, which will extremely increase the computational complexity. To improve the performance, an ant colony fuzzy c-means hybrid algorithm (AFHA) was proposed to overcome the FCM's sensitiveness to the initialization condition of cluster number in [5]. Essentially, the AFHA incorporated the ant system algorithm (AS) to the FCM to improve the compactness of the clustering results in the color feature space. However, its efficiency is still low due to computational complexity of the AS algorithm. To increase the AFHA's efficiency, an improved ant colony fuzzy c-means hybrid algorithm (IAFHA) was also introduced in [5]. Specifically, the IAFHA added an ant subsampling-based method to modify the AFHA. Although the IAFHA's efficiency had been increased, it still suffers from high computational complexity. Tan *et al.*, [6] presented a histogram thresholding fuzzy c-means hybrid (HTFCM) approach which applied the histogram thresholding technique to estimate optimal cluster number in an image. Then, the standard FCM algorithm was utilized to improve the compactness of the clusters forming those uniform regions based on color feature. The above algorithms assume that the input images mostly contain uniformly colored objects, which is typically not true for natural images. In fact, the texture feature reflecting the spatial patterns of pixels at image block level has strong links with the human perception and in many practical scenarios the color-alone feature at pixel level is not sufficiently robust to accurately describe the image content [7]. The cluster number estimation of those FCM-based algorithms, such as AFHA, IAFHA and HTFCM, only considers color feature at pixel level which means that they could not determine accurate cluster number for complex images, especially natural images.

In this paper, we focus on cluster number adaptive segmentation for computer vision applications. To overcome the aforementioned disadvantages of those FCM-based segmentation algorithms, a novel cluster number estimation module is added prior to the standard FCM algorithm to obtain optimal cluster number. In this estimation module, instead of processing at pixel level, the image is first divided into many small rectangular image blocks. We complete Gray Level Co-occurrence Matrix (GLCM) feature extraction and clustering at the block level to estimate optimal cluster number. The novel estimation module is based on the coarse image, which makes its execution time is very fast and could be ignored, basically. Moreover, in contrast to the initialization module of the IAFHA and HTFCM algorithm only employing color feature, GLCM texture feature allows us accurately to estimate cluster number. Then, in the FCM clustering, in contrast to the algorithms like FCM\_S [8, 9] that incorporate local spatial information in the objective function, Gabor filters [7, 10] are utilized for

feature extraction for each pixel. The parameters of the Gabor filter are specified by the frequency, the orientation of the sinusoid, and the scale of the Gaussian function. Therefore, the feature vector extracted for each pixel implicitly incorporate local orientations and spatial frequencies information. The proposed algorithm considers spatial information in the feature space instead of in the objective function, which makes the objective function quite simple. A large number of experiments were carried out to assess performance of the proposed segmentation algorithm, and experimental results have demonstrated that the CNAFCM algorithm could accurately determine cluster number and obtain better segmentation results (produce meaningful segmentation effectively) than those approaches such as AMFCM, AFHA, IAFHA and HTFCM.

## 2. The Standard FCM Algorithm

The FCM clustering algorithm was first introduced by Dunn [11] in 1973 and later extended by Bezdek [12] in 1981. This algorithm has been used as one of the popular clustering techniques for image segmentation in pattern recognition. In the FCM, each image pixel has certain membership degree associated with each cluster centroid. These membership degrees have values in the range  $[0,1]$ , indicating the strength of the association between that pixel and a particular cluster centroid. The FCM algorithm attempts to partition every image pixel into a collection of the  $K$  fuzzy cluster centroids by minimizing the weighted sum of squared error objective function  $J_m(U, C)$  [13]:

$$J_m(U, C) = \sum_{i=1}^N \sum_{j=1}^K u_{ji}^m d_{ji}^2 \quad (1)$$

subject to

$$\begin{aligned} \sum_{j=1}^K u_{ji}^m &= 1, \quad 1 < j < K \\ \sum_{i=1}^N u_{ji}^m &< N, \quad 1 \leq i \leq N \\ \sum_{i=1}^N \sum_{j=1}^K u_{ji}^m &= N \end{aligned} \quad (2)$$

where  $N$  is the total number of pixels in image,  $u_{ji}$  is the membership degree of  $i$ th pixel  $x_i$  to  $j$ th cluster centroid  $c_j$ ,  $m$  is the exponential weight of membership degree which controls the fuzziness of the resulting partition, and  $d_{ji} = \|x_i - c_j\|$  is the distance between  $x_i$  and  $c_j$ . It needs to be pointed out that the standard FCM algorithm would degenerate to hard c-means algorithm when  $u_{ji} \in [0,1]$  and  $m = 1$ . Let  $U_i = (u_{1i}, u_{2i}, \dots, u_{Ki})^T$  be the set of membership degree of  $x_i$  associated with each

cluster centroids, then  $U = (U_1, U_2, \dots, U_N)$  is the membership degree matrix and  $C = (c_1, c_2, \dots, c_K)$  is the set of cluster centroids.

The degree of compactness and uniformity of the cluster centroids greatly depend on the objective function of the FCM. In general, a smaller objective function of the FCM indicates a more compact and uniform cluster centroid set. Unfortunately, there is no close form solution to produce minimization of the objective function. To achieve the optimization of the objective function, an iteration process must be carried out by the FCM algorithm. The key steps of the FCM can be described in Table 1.

**Table 1. The Standard FCM Algorithm**

Steps	Algorithm Description
1:	Randomly initialize the fuzzy partition matrix $C^0$ , set the iteration terminating threshold $\epsilon$ to a small positive number in the range $[0, 1]$ and the number of iteration $q$ to 0.
2:	Calculate $U^q$ according to $C^q$ with Eq.(3)
3:	Calculate $C^{q+1}$ according to $U^q$ with Eq.(4)
4:	Update $U^{q+1}$ according to $C^{q+1}$ with Eq.(3)
5:	Compare $U^{q+1}$ with $U^q$ . if $\ U^{q+1} - U^q\  \leq \epsilon$ stop iteration. Otherwise, $q = q + 1$ , and repeat steps 3 to 4 until $\ U^{q+1} - U^q\  \leq \epsilon$ Finally, we can get the optimal membership matrix $U$ . Based on $U$ , we can get the final segmentation image.

$$u_{ji} = \frac{1}{\sum_{k=1}^K (d_{ji} / d_{ki})^{2/(m-1)}} \quad (3)$$

where  $1 \leq j \leq K$  and  $1 \leq i \leq N$ . It should be noted that if  $d_{ji} = 0$  then  $u_{ji} = 1$  and set others membership degrees of this pixel to 0.

$$c_j = \frac{\sum_{i=1}^N u_{ji}^m X_i}{\sum_{i=1}^N u_{ji}^m} \quad (4)$$

where  $1 \leq j \leq K$  and  $X_i$  is the multidimensional feature vector of  $i$  th pixel  $x_i$ .

### 3. Proposed Algorithm

#### 3.1. Basic Idea

As previously mentioned, the performance of the FCM-based segmentation algorithm is often affected by the cluster number which is manually initialized. Therefore, in this paper,

the core idea of our algorithm is to obtain a solution to overcome the FCM's sensitiveness to the cluster number by introducing a novel cluster number estimation module before the standard FCM clustering. The most important object in this estimation module is to accurately determine cluster number with minimal computation cost. Conventionally, feature vectors used in the FCM segmentation algorithm are usually extracted for each pixel. For an image with a typical size, hundreds of thousands of vector data will have to be processed if we directly do clustering at the pixel level. In fact, the notion of the region is well defined at the level of our visual perception, and the human eyes and brain are able to delineate regions that exhibit common spatial patterns, *i.e.*, texture. In a certain sense, an image can be roughly considered as the composition of several different regions. Therefore, the texture is useful for identifying object or region of interest, and the task to estimate the region number can be performed at the coarse level, *i.e.*, the image block level. In our work, the image block is a rectangular region with  $s = r \times r$  pixels and the standard FCM algorithm is employed to determine the optimal cluster number within the range of 2 to predefined maximum search value, which best suits a given image according to cluster validity index. Specifically, the Gray Level Co-occurrence Matrix (GLCM) texture feature of each block is used to estimate all possible homogenous regions in the image. Compared with the large number of pixels in an image, block-level representation of an image usually has only several hundreds of blocks. Therefore, we utilize the feature extracted at the block level instead of the pixel level resulting in reducing the computational cost of the clustering. The method provides an attractive way to estimate cluster number with minimal time cost in comparison with those approaches such as AMFCM, AFHA, IAFHA and HTFCM.

### 3.2. GLCM Texture Feature Extraction

Gray Level Co-occurrence Matrix was proposed in [14] by Haralick and is widely used for texture analysis. It estimates the second-order statistics related to image properties by considering the spatial relationship of pixels [15, 16]. The GLCM is created by calculating how often a pixel with the intensity value  $i$  occurs in a specific spatial relationship to a pixel with the value  $j$ . The major two steps are as follow:

The first step is to determine co-occurring probabilities of all pairwise combinations of quantized grey levels  $(i, j)$  in the fixed-size spatial window given two parameters which are the distance between the pixel pair  $d$  and their angular relation  $\theta$ .  $\theta$  is quantized in four directions ( $0^\circ$ ,  $45^\circ$ ,  $90^\circ$ , and  $135^\circ$ ). For rectangular  $r \times r$  image segment  $I(x, y)$ , gray levels  $i$  and  $j$ , the non-normalized GLCM  $P_{ij}$ 's are defined by:

$$P_{ij}(\theta, d) = \sum_{x=1}^r \sum_{y=1}^r C\{I(x, y) = i \wedge I(x \pm d\theta_0, y \mp d\theta_1) = j\} \quad (5)$$

where  $C\{\} = 1$  if the argument is true and  $C\{\} = 0$  otherwise. The  $\pm$  and  $\mp$  signs in Eq.(5) mean that each pixel pair is counted twice: once forward and once backward to make the GLCM diagonal symmetric. For each direction,  $\theta_0$  and  $\theta_1$  are shown in Table 2.

**Table 2.  $\theta$  Values for Different Directions**

$\theta$	$0^\circ$	$45^\circ$	$90^\circ$	$135^\circ$
$\theta_0$	0	1	1	1
$\theta_1$	1	1	0	-1

The second step is to apply statistics to the co-occurring probabilities. Statistics that identify some structural aspect of the arrangement of the co-occurring probabilities, which reflect some qualitative characteristic of the local image texture like smoothness or roughness, are applied to generate the texture feature vector. In our work, we calculate five GLCM texture features, which are used to form a feature vector: 1) contrast (CON); 2) homogeneity (HOM); 3) angular second moment (ASM); 4) entropy (ENT); 5) correlation (COR). Finally, each image block generates a feature vector to describe its texture characteristics.

### 3.3. Cluster Validity

For an unsupervised clustering scheme, the segmentation quality depends on determining the cluster number according to cluster validity index. Several well-known cluster validity indexes for evaluation of the cluster quality could be adopted. One of the most fundamental indexes is the mean squared error (MSE) that could be described as follows:

$$MSE = \frac{1}{N} \sum_{j=1}^K \sum_{i \in S_j} \|x_i - c_j\|^2 \quad (6)$$

It is quite clear from the concept of MSE that when cluster number is fixed, a good clustering algorithm should always generate results with small distortion. In other words, cluster centroids should be placed in such a way that they reduce the distances to data pieces as much as possible.

Another commonly used index is Bezdek's evaluation function  $V_{PC}$  [17], which is defined as follows:

$$V_{PC} = \sum_{i=1}^N \sum_{j=1}^K u_{ji}^2 / N \quad (7)$$

This cluster validity evaluation function essentially measures the fuzziness of a clustering result, properties of which were studied in [18]. A smaller  $V_{PC}$  value indicates a fuzzier result. Contrary, the larger the  $V_{PC}$  value, the better the clustering result. For a crisp partition,  $V_{PC}$  achieves maximum value of 1.

A more recent validity evaluation index is the Xie-Beni function [19], which is defined as follows:

$$V_{XB} = \frac{\sum_{i=1}^N \sum_{j=1}^K u_{ji}^2 \|x_i - c_j\|^2}{N \min_{\forall j \neq k} \|c_j - c_k\|^2} \quad (8)$$

According to Xie and Beni [19],  $V_{XB}$  should decrease monotonically when  $K$  is close to  $N$ . When  $V_{XB}$  shows a smaller value, the result is presumably a better partition.

In this work, the determination of the cluster number  $K_{opt}$  is carried out with combination of cluster validity index  $V_{PC}$  and  $V_{XB}$ .

### 3.4. FCM Clustering

Although the cluster number is appropriately estimated in cluster number estimation module, there still exists one problem to be resolved. For those FCM-based image segmentation algorithms such as AFHA, IAFHA and HTFCM, cluster assignment is based solely on the distribution of pixel attributes in the color feature space, and the spatial distribution of pixels in an image is not taken into consideration. The application of the FCM to complex scenes such as natural images will lead to over-segmented results since the spatial continuity is not enforced during the space partitioning process. The main approach is to introduce spatial constraints into the objective function of the FCM. Although the introduction of local spatial information to the corresponding objective functions solves the problem to some extent, it will also make the objective function more complicated at the same time, resulting in low efficiency.

As we know, a feature vector can be extracted at each pixel via computing its local properties. The feature of a pixel depends on a number of factors, such as the spatial relation among pixels, their scale, and orientation. In contrast to many conventional approaches, in this work, the spatial connectivity information between pixels is extracted and embedded in the multi-dimensional feature vector of each pixel. Specifically, Gabor filters with a large number of oriented band pass filters with adaptive filter size, orientation, frequency and phase have been used to extract spatial features of the pixels. As such, spatial connectivity is guaranteed since a definite spatial connectivity constraint has been imposed during feature extraction. For details about Gabor feature extraction, please refer to [20, 21]. Briefly, the standard FCM algorithm is used to cluster Gabor feature vectors of the pixels with the cluster number which has been estimated by the cluster number estimation module already, and then we label each pixel with its corresponding cluster to form final compact regions.

### 3.5. Pseudo Code

The outline of the proposed segmentation algorithm, which automatically clusters the pixels of an image into different homogeneous regions when the cluster number is not known beforehand, is illustrated in Table 3:

## 4. Experimental Results

In this section, a large number of experiments were carried out to assess the performance of the proposed cluster number adaptive FCM-based image segmentation algorithm (CNAFCM), and the results were summarized. The aim of these experiments is to test the accuracy of the CNAFCM algorithm for image segmentation with respect to the correct identification of perceptual regions in the synthetic and natural images. Since HTFCM developed by Tan and Isa [6] adopts similar approach with AMFCM, AFHA, IAFHA and outperforms them, we mainly tested the performance by comparing the results returned by the proposed CNAFCM algorithm against those returned by the well-established HTFCM algorithm.

#### 4.1. Experiments Performed on Synthetic Images

Since the ground truth data associated with complex natural images is difficult to estimate and its extraction is highly influenced by the subjectivity of the human operator, we performed the experiments on synthetic images where the ground truth is unambiguous. To evaluate whether segmentation algorithm can accurately estimate the cluster (region) number, we executed the CNAFCM and HTFCM algorithm on five sets of synthetic images from the VisTex database [22], respectively. Each of the five sets of images contains 6 synthetic images, and each synthetic image has four or five regions which are filled with texture image according to layouts shown in Figure 1. Some synthetic images (*i.e.*, the first set of synthetic images) are given in Figure 2, the others were omitted due to space limitation. The experimental data summarized in Table 4 and Table 5 indicate that the proposed algorithm with texture extraction and composite evaluation index working at image block level offers more accurate estimation of the region number substantially, while estimations given by color-based HTFCM algorithm are almost wrong. It means that our approach could obtain better segmentation results by producing a fewer number of regions as well as providing more homogeneous segmented region. The main reason behind this was that, in some cases, regions in synthetic images may be composed of two colors or even more resulting in over-estimation of region number when using HTFCM algorithm.

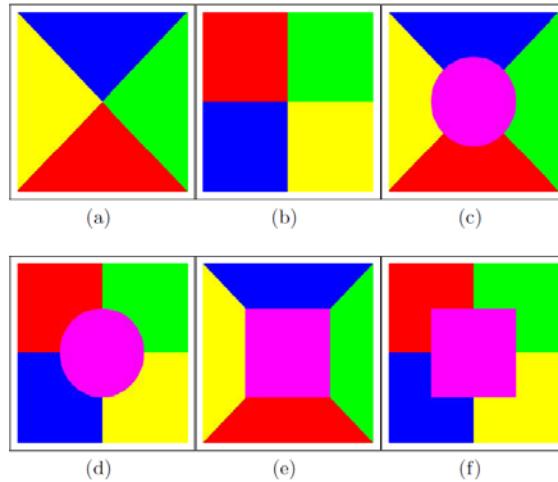
**Table 3. Cluster Number Adaptive Fuzzy c-means Algorithm**

Steps	Algorithm Description
	Maximal search cluster number $K_{max}$
1	Divide the input image into image blocks with height $r$ and width $r$ .
2	Extract GLCM feature vector $f_B^j$ for each image block and obtain data set $F_B = \{f_B^j\}_{j=1}^Z$ , where $Z$ is the number of image blocks.
3	For $k = 1$ to $K_{max}$ Do the standard FCM clustering on $F_B$ , and calculate cluster validity index $V_{PC}^k$ and $V_{XB}^k$ . End for
4	According to $V_{PC}^k$ and $V_{XB}^k$ , determine the optimal cluster number $K_{opt}$ .
5	Apply the Gabor filter to extract texture feature $f_P^i$ for each pixel and obtain set $F_P = \{f_P^i\}_{i=1}^N$ , where $N$ is the number of pixels.
6	Do standard FCM clustering on $F_P$ again with cluster number $K_{opt}$ .

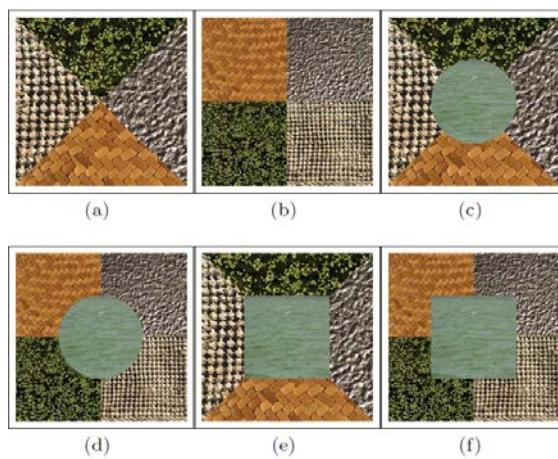
As we know in advance the layouts for synthetic images, the segmentation accuracy of the CNAFCM algorithm can be easily estimated by calculating the following quantitative index:

$$QI = \frac{\sum_{i=1}^C S_i \cap S_i^{ref}}{\sum_{i=1}^C S_i \cup S_i^{ref}} \quad (9)$$

where  $S_i$  represents the set of pixels belonging to the  $i$ th region found by the proposed algorithm and  $S_i^{ref}$  represents the set of pixels belonging to the  $i$ th region in the segmented ground truth image. In fact,  $QI$  is a fuzzy similarity measure, indicating the degree of equality between  $S_i$  and  $S_i^{ref}$ , and the larger the  $QI$ , the better the segmentation is. To evaluate the segmentation errors between the ground truth and the segmented results numerically, we tabulate a quantitative comparison in Table 6 for the third image in the each set of synthetic images (a total of five images). The experimental data depicted in Table 6 show that the quantitative index errors are acceptable.



**Figure 1. Segmentation Layouts for Synthetic Images**



**Figure 2. The First Set of Synthetic Images used in our Experiments**

**Table 4. Number of Regions Estimated by HTFCM with Histogram Thresholding Estimation**

Set No	Pattern No					
	1	2	3	4	5	6
1	5×	5×	6×	6×	6×	7×
2	4	6×	6×	6×	6×	5
3	5×	5×	7×	6×	5	6×
4	5×	5×	6×	6×	6×	6×
5	4	5×	6×	6×	5	5
Ground Truth	4	4	5	5	5	5

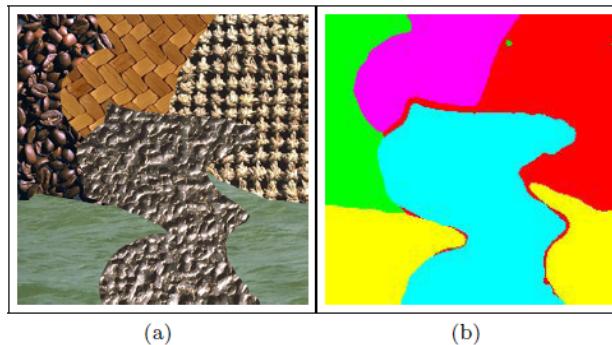
In order to verify the discrimination power of our segmentation approach in the more general case, it was also applied to a synthetic test image with different regions separated by irregular boundary. The result depicted in Figure 3 is very satisfactory even in the case of divided region.

**Table 5. Number of Regions Estimated by CNAFCM Algorithm with Composite Evaluation Criterion**

Set No	Pattern No					
	1	2	3	4	5	6
1	4	4	5	5	5	5
2	4	3	5	5	5	5
3	4	2×	5	5	5	5
4	2×	5×	5	4×	5	5
5	4	4	4×	5	5	5
Ground Truth	4	4	5	5	5	5

**Table 6. Comparison of Segmentation Errors (%)**

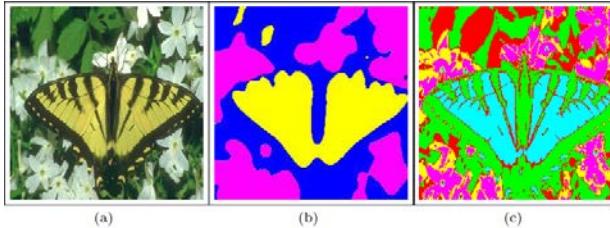
	Synthetic image				
	Set 1	Set 2	Set 3	Set 4	Set 5
Accuracy(%)	96.90	91.82	96.50	93.82	94.19



**Figure 3. The Synthetic Image with Different Textures Separated by Irregular Boundary and its Segmentation Result**

#### 4.2. Experiments Performed on Natural Images

In this subsection, the segmentation results are evaluated visually. As we know, although synthetic test images are best for verifying the possibilities and limits of an algorithm, segmentation of natural images is a reliable evaluation indicator for image segmentation algorithms. In order to evaluate CNAFCM's performance with respect to the identification of perceptual homogenous regions, we have tested the proposed CNAFCM segmentation algorithm on a large number of complex natural images databases (*i.e.*, Berkeley [23]), which includes images characterized by nonuniform textures, fuzzy borders, and low image contrast. For instance, we have compared our segmentation results with the ones by the color-based segmentation algorithm, *i.e.*, HTFCM. Figure 4 illustrates the result, the same image was always been used in other literature, so the reader may compare to those methods. From the result, it can be observed that the different regions produced by CNAFCM algorithm are well segmented and the shape of objects in the images is preserved. However, it can also be observed that the regions produced by HTFCM algorithm are mixed together (caused by over-estimation of regions), which can not preserve the shape of objects in the images and makes it difficult to detect and recognize objects in the high-level vision applications.



**Figure 4. Natural Image from the Berkeley Database and Segmentation Results. a) Original Image; b) Using Proposed Algorithm; b) Using HTFCM Algorithm**

#### 5. Conclusion

Automatic image segmentation is always a fundamental but challenging problem in computer vision. To segment the pixels in image space, the most straightforward idea is first to obtain a coherent or robust clustering result on the pixels' feature space, then each pixel is labeled with the cluster that contains its feature vector. It is well known that the standard FCM algorithm is one of the most popular clustering-based methods for image segmentation. However, the cluster number must be known in advance when using the FCM algorithm. The cluster number estimation module of the previous algorithms such as AFHA, IAFHA and HTFCM only consider color feature at pixel level which means that they could not determine accurate cluster number for complex images, especially for natural images. In this paper, we present a novel cluster number adaptive fuzzy c-means algorithm. The highlight is the utilization of image blocks instead of pixels in the cluster number estimation module. We extracted GLCM texture feature at the image block level and employed the standard FCM algorithm for estimating the cluster number. The method provides an attractive way to estimate cluster number with minimal time cost in comparison with those algorithms such as AMFCM, AFHA, IAFHA and HTFCM. On the basis of Xie-Beni and Bezdek criterions, we proposed a combined validity criterion to find the cluster number. Experiments show that proposed algorithm based on GLCM feature extraction and composite cluster validity criterion could be enough to effectively estimate the cluster number of the images in most cases. In fact, the texture feature reflecting the spatial patterns of pixels at image block level

has strong links with the human perception. Therefore our new approach is robust to accurately describe the image content in many practical scenarios. Nevertheless, future work should take other cluster validity criterions into account for specific application requirements. Besides, we are considering on how to standardize GLCM features used in this paper, and this could make it robust to estimate the cluster number. We try to make the proposed algorithm more suitable for segmentation of natural images without a priori knowledge about the content in the computer vision applications.

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## References

- [1] G. P. Tellaeché, X. P. Burgos-Artizzu and A. Ribeiro, "A computer vision approach for weeds identification through support vector machines", *Applied Soft Computing*, vol. 11, no. 1, (2011), pp. 908-915.
- [2] D. Weinland, R. Ronfard and E. Boyer, "A survey of vision-based methods for action representation, segmentation and recognition", *Computer Vision and Image Understanding*, vol. 115, no. 2, (2011), pp. 224-241.
- [3] J. Blasco, N. Aleixos and E. Molto, "Computer vision detection of peel defects in citrus by means of a region oriented segmentation algorithm", *Journal of Food Engineering*, vol. 81, no. 3, (2007), pp. 535-543.
- [4] Y. Li and Y. Shen, "An automatic fuzzy c-means algorithm for image segmentation", *Soft Computing*, vol. 14, no. 2, (2009), pp. 123-128.
- [5] Z. Yu, O. C. Au, R. Zou, W. Yu and J. Tian, "An adaptive unsupervised approach toward pixel clustering and color image segmentation", *Pattern Recognition*, vol. 43, no. 5, (2010), pp. 1889-1906.
- [6] K. S. Tan and N. A. M. Isa, "Color image segmentation using histogram thresholding fuzzy c-means hybrid approach", *Pattern Recognition*, vol. 44, no. 1, (2011), pp. 1-15.
- [7] D. E. Ilea and P. F. Whelan, "An adaptive unsupervised segmentation algorithm based on color-texture coherence", *IEEE Trans. Image Process.*, vol. 17, no. 10, (2005), pp. 1926-1939.
- [8] M. Ahmed, S. Yamany, N. Mohamed, A. Farag and T. Moriarty, "A modied fuzzy c-means algorithm for bias field estimation and segmentation of MRI data", *IEEE Trans. Med. Imag.*, vol. 21, no. 3, (2002), pp. 193-199.
- [9] S. Chen and D. Zhang, "Robust image segmentation using FCM with spatial constraints based on new kernel-induced distance measure", *IEEE Trans. Syst., Man, Cybern.*, vol. 34, no. 4, (2004), pp. 1907-1916.
- [10] D. A. Clausi and H. Deng, "Design-based texture feature fusion using Gabor filters and co-occurrence probabilities", *IEEE Trans. Image Process.*, vol. 14, no. 7, (2005), pp. 925-936.
- [11] J. C. Dunn, "A fuzzy relative of the isodata process and its use in detecting compact, well separated cluster", *Cybernetics*, vol. 3, no. 3, (1973), pp. 32-57.
- [12] Bezdek, "Pattern Recognition with Fuzzy Objective Function Algorithms", Plenum Press, New York, (1981).
- [13] S. S. Reddi, S. F. Rudin and H. R. Keshavan, "An optimal multiple threshold scheme for image segmentation", *IEEE-SMC*, vol. 14, no. 4, (1984), pp. 611-665.
- [14] R. M. Haralick, K. Shanmugam and I. Dinstein, "Textural features for image classification", *IEEE Trans. Syst., Man, Cybern.*, vol. SMC-3, no. 6, (1973), pp. 610-621.
- [15] L. K. Soh and C. Tsatsoulis, "Texture analysis of SAR sea ice imagery using gray level co-occurrence matrices", *IEEE Trans. Geosci. Remote Sens.*, vol. 37, no. 2, (1999), pp. 780-795.
- [16] Clausi and B. Yue, "Comparing co-occurrence probabilities and markov random Fields for texture analysis", *IEEE Trans. Geosci. Remote Sens.*, vol. 42, no. 1, (2004), pp. 215-228.
- [17] J. C. Bezdek, "Cluster validity with fuzzy sets", *Cybernet . Syst.*, vol. 3, no. 3, (1974), pp. 58-73.
- [18] N. R. Pal and J. C. Bezdek, "On cluster validity for the fuzzy c-means model", *IEEE Trans. Fuzzy Syst.*, vol. 3, no. 3, (1995), pp. 370-379.
- [19] X. L. Xie and G. A. Beni, "Validity measure for fuzzy clustering", *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 13, no. 4, (1991), pp. 841-847.
- [20] J. F. Khan, R. R. Adhami and S. M. A. Bhuiyan, "A customized Gabor filter for unsupervised color image segmentation", *IEEE Trans. Geosci. Remote Sens.*, vol. 27, no. 4, (2009), pp. 489-501.

- [21] J. Daugman, "Uncertainty relations for resolution in space, spatial frequency, and orientation optimized by two-dimensional visual cortical filters", *Journal of the Optical Society of America*, vol. 2, no. 7, (1985), pp. 1160-1169.
- [22] Media Lab., Mass. Inst. Technol., Cambridge, MA. Vision Texture (Vistex)Database. Available: <http://vismod.media.mit.edu/vismod/imagery/VisionTexture/vistex.html>
- [23] D. Martin, C. Fowlkes, D. Tal and J. Malik, "A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics", *Proceedings of the Eighth International Conference On Computer Vision*, Vancouver, Canada, (2001) July 7-14, pp. 416-425.

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