Ensemble Of Image Segmentation With Generalized Entropy Based Fuzzy Clustering

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Abstract—**Ensemble of image segmentation based on generalized entropy's fuzzy clustering is studied in this paper. Aiming at the generalized entropy's objective function in fuzzy clustering and introducing the spatial information into this objective function, we obtain an image segmentation algorithm ISGFCM based on neural network. Further, we introduce kernel into above objective function to obtain its kernel algorithm ISGKFCM. Then, we use ISGFCM and ISGKFCM as basis clustering algorithms, respectively, to generate many different image segmentation results and use 2SWC method to select some members of segmentation. And we use CSPA and its generalized method GCSPA to fuse some selected segmentation results. In experiment, three images are chosen to conduct some experimental study. Results show the effectiveness of presented method.**

Keywords-fuzzy clustering; image segmentation; generalized entropy; fusion

I. INTRODUCTION

Image segmentation is to partition the image into several independent, meaningful and semantically related regions. And it is a preliminary for image analysis and understanding. Its accuracy directly impacts the quality of image recognition and analysis as well as the final results. Thus, image segmentation has attracted more and more researchers' attention both in theory and practical application. So far, there exist many different image segmentation methods. Among them, clustering technique is commonly used one of image segmentation method. For example, Ahmed [1] proposed BCFCM by introducing spatial information to the objective function of fuzzy clustering. Afterwards, Chen et al. [2] improved BCFCM and proposed KFCM which replaced Euclidean distance with a Gaussian kernel-induced distance. Isa et al. [3] introduced the fuzzy moving k-means, adaptive moving k-means and adaptive fuzzy moving k-means algorithms to conduct image segmentation application. Gong et al. [4] employed a tradeoff weighted fuzzy factor and a kernel metric for image segmentation and Zhao et al. [5] proposed a kernel version of generalized fuzzy c-means clustering algorithm with spatial information. In addition, some researchers have focused on the image segmentation or fuzzy clustering based on entropy [6-8]. Liu et al. [9] used fuzzy entropy and grey relational analysis to solve the problem of noise sensitivity. In previous study, we introduced generalized entropy into fuzzy clustering and presented fuzzy clustering algorithm based on generalized entropy. Meantime, we consider a special case of objective function to solve image segmentation [10]. On the other hand, to improve performance of clustering algorithm, researchers began to study the cluster ensemble method. The concept of cluster ensemble was firstly proposed by Strehl and Ghosh [11], and they gave three consensus functions based on hyper-graph. Zhou et al. [12] proposed a clustering ensemble selection method based on mutual information. Fern et al. [13] proposed three clustering ensemble selection algorithms which are JC, CAS and Convex Hull, respectively. Hong et al. [14] proposed re-sampling based selective clustering ensembles. Later, Yu et al. [15] selected some subsets of features to obtain different clustering results. Moreover, Yang et al. [16] studied the cluster members weighting problem. In this paper, aiming at generalized entropy's fuzzy clustering, we study ensemble of image segmentation.

The rest of this paper is organized as follows. In section 2, we introduce related work for fuzzy clustering. In section 3, we introduce fuzzy clustering algorithm and its variant. In section 4, image segmentation with fuzzy clustering based on generalized entropy and the corresponding kernel algorithm are introduced. In section 5, ensemble approach for image segmentation is introduced. In section 6, some experimental results are given. In the last section, we draw some conclusions.

II. RELATED WORK

As FCM algorithm has some shortcomings in the process of data clustering, some researchers have presented the improved FCM algorithms. They mainly combine FCM's objective function with entropy to get their clustering algorithm. In 1994, Karayiannis [6] used entropy to solve fuzzy clustering problem and proposed maximum entropy clustering algorithm. In this algorithm, the objective function is

$$J(\mu,v)=\tau\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}\log_2\mu_{ij}+\frac{1-\tau}{n}\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}\,\|x_j-v_i\|^2 .$$

In 1995, for uncertainty problem, the maximum entropy inference method was presented by Li et al [7]. Subsequently, they combined it with loss function between the point and the center to propose maximum entropy clustering algorithm. The objective function is

$$J(\mu,v)=\beta^{-1}\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}\log_2\mu_{ij}+\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}\|x_j-v_i\|^2 .$$

In 2000, Tran and Wagner [8] proposed fuzzy entropy clustering algorithm, which mainly uses objective function presented by Li. And in 2002, Wei and Fahn [17] proposed fuzzy bidirectional association clustering network and attempted to solve optimization problem with the following objective function using this network.

$$J(\mu,v)=\beta\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}\log_2\mu_{ij}+\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}^{m}\|x_j-v_i\|^2 .$$

It is regret that method presented by Wei et al. has some drawbacks. From the above given objective functions, we know that the objective function used in the entropy-based clustering algorithm is substantially very similar. To this end, we further study entropy based fuzzy clustering and give a unified model of fuzzy clustering as follows[10]:

$$J_G(\mu,v)=\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}{}^{m}\|x_j-v_i\|^2+\delta\sum_{j=1}^{n}(2^{1-\alpha}-1)^{-1}(\sum_{i=1}^{c}\mu_{ij}{}^{\alpha}-1),$$
$$\alpha>0,\alpha\neq1$$

where $\mu_{ij}=\mu_i(x_j)>0$ is degree of membership for x_j to ith cluster center v_i and $\sum_{i=1}^{c}\mu_{ij}=1$. μ is a matrix which is composed of all μ_{ij}'s (i=1,2,…,c; j=1,2,…,n), v is a vector whose component consists of cluster center v_i(i=1,2,…,c). In addition, we also give fuzzy clustering algorithm based on generalized entropy and its image segmentation algorithm by introducing spatial information. However, we only consider special case for unified objective function, namely m equal to α . To solve more general case, we study fuzzy clustering with the generalized entropy based on neural network [18] and fuzzy clustering ensemble algorithm [19]. Meanwhile, we also give a fast image segmentation algorithm based on clustering technique [20].

III. SPATIAL BIAS-CORRECTED FUZZY C-MEANS CLUSTERING

Clustering aims at categorizing data into groups or clusters such that the data in the same cluster are more similar to each other than to those in different clusters. One of commonly used methods is fuzzy c-means clustering (FCM). The fuzzy clustering problem is described as follows: Given that X={x_1,x_2,…,x_n} (n>1) is a finite data set, c is the number of cluster, m is fuzzy weight with 1<m<∞, v={v_i , 1≤i≤c} represents the cluster center, and μ={μ_{ij}, 1≤i≤c, 1≤j≤n} represents membership degree matrix, where μ_{ij} is the fuzzy membership degree from the data point x_j to center v_i. The objective function of FCM is written as

$$J(\mu,v)=\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}^{m}\|x_j-v_i\|^2, \qquad (1)$$

So fuzzy clustering is viewed as solving the following optimization problem:

$$\min_{\mu,v}\ J(\mu,v) \qquad s.t.\sum_{i=1}^{c}\mu_{ij}=1, 1\le j\le n .$$

Since FCM did not consider the spatial information of image, it is sensitive to salt and pepper noise and image artifacts. To overcome this drawback, Ahmed et al.[1] proposed BCFCM with the following objective function:

$$J_m^{BCFCM}(\mu,a)=\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}^{m}\|x_j-v_i\|^2+\frac{\beta}{N_R}\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}^{m}\sum_{x_r\in N_j}\|x_r-v_i\|^2 , \qquad (2)$$

where N_j represents the set of pixels that exist in a window around x_j and N_R is the cardinality of set N_j. Later, for reducing computation, Chen et al. [2] modified objective function (2) which is given as follows:

$$J_m^{CZ}(\mu,a)=\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}^{m}\|x_j-v_i\|^2+\beta\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}^{m}\|\bar{x}_j-v_i\|^2, \qquad (3)$$

In (3), when $\bar{x}_j$ is the mean of pixels within the window around x_j, J_m^{CZ} becomes objective function of BCFCM_S$_1$, and when $\bar{x}_j$ takes the median of the neighbors within the window, J_m^{CZ} turns to BCFCM_S$_2$. The effect of neighboring pixels is controlled by the parameter β .

IV. IMAGE SEGMENTATION WITH FUZZY CLUSTERING BASED ON GENERALIZED ENTROPY

The concept of entropy was first used in physics, and it was used to describe the atomic distribution of the degree of disorder. When system is more orderly and more determined, the value of the entropy is smaller. In 1948, Shannon proposed the concept of information entropy in information theory. Afterwards, some researchers introduced information entropy into clustering and proposed entropy-based clustering algorithm. The objective function for these clustering methods has following form:

$$J(\mu,v)=\alpha\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}\log\mu_{ij}+\eta\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}\|x_j-v_i\|^2 . \qquad (4)$$

For unifying fuzzy clustering algorithm based on entropy, in previous study[10], we gave the following objective function of fuzzy clustering based on generalized entropy and use Lagrange method to solve special case for objective function (5), namely m=α. We denote this algorithm as GFCM (Generalized entropy Fuzzy C-Means).

$$J_G(\mu,v)=\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}{}^{m}\|x_j-v_i\|^2+\delta\sum_{j=1}^{n}(2^{1-\alpha}-1)^{-1}(\sum_{i=1}^{c}\mu_{ij}{}^{\alpha}-1),\alpha>0,\alpha\neq1 . \qquad (5)$$

Considering that the above method for image segmentation is not sensitive to noise, spatial information is introduced into function (5). The above objective function (5) is become as

$$J_{GI}(\mu,v)=\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}^{m}\|x_j-v_i\|^2+\delta\sum_{j=1}^{n}(2^{1-\alpha}-1)^{-1}(\sum_{i=1}^{c}\mu_{ij}^{\alpha}-1)+\beta\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}^{m}\|\bar{x}_j-v_i\|^2,\alpha>0,\alpha\neq 1 \quad (6)$$

So, the optimization problem for fuzzy clustering based on generalized entropy is as follows:

$$\min J_{GI}(\mu,v)$$
$$s.t.\quad \sum_{i=1}^{c}\mu_{ik}=1,k=1,2,\cdots,n.$$

This optimization problem is solved using neural network in order to obtain degree of membership μ_{ij} and center of cluster v_i. Here, this algorithm is written as ISGFCM (Image Segmentation based on Generalized entropy Fuzzy C-Means).

To solve more complex problem, kernel is introduced into objective function (6). For this purpose, assuming that ϕ is a nonlinear mapping from the input space to the feature space, and K is a kernel function. Now, we replace $\|x_j-v_i\|^2$ in (6) with $\|\phi(x_j)-\phi(v_i)\|^2$ and write it as $J_{GIK}(\mu,v)$:

$$J_{GIK}(\mu,v)=\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}^{m}\|\phi(x_j)-\phi(v_i)\|^2+\delta\sum_{j=1}^{n}(2^{1-\alpha}-1)^{-1}(\sum_{i=1}^{c}\mu_{ij}^{\alpha}-1)+\beta\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}^{m}\|\phi(\bar{x}_j)-\phi(v_i)\|^2. \quad (7)$$

Here, we take Gaussian function as kernel function K, namely $K(x,y)=e^{-\|x-y\|^2/\sigma^2},\sigma>0$. As

$$\|\phi(x_j)-\phi(v_i)\|^2=K(x_j,x_j)+K(v_i,v_i)-2K(x_j,v_i)=2-2K(x_j,v_i),$$

Substituting it for (7) becomes

$$J_{GIK}(\mu,v)=2\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}^{m}(1-K(x_j,v_i))+\delta\sum_{j=1}^{n}(2^{1-m}-1)^{-1}(\sum_{i=1}^{c}\mu_{ij}^{m}-1)+\beta\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}^{m}(1-K(\bar{x}_j,v_i)). \quad (8)$$

So, the problem of generalized entropy fuzzy clustering based on the kernel is as follows:

$$\min J_{GIK}(\mu,v)$$
$$s.t.\quad \sum_{i=1}^{c}\mu_{ik}=1,k=1,2,\cdots,n. \quad (9)$$

Similarly, this optimization problem is solved using neural network in order to obtain degree of membership μ_{ij} and center of cluster v_i. Here, this algorithm is written as ISGKFCM (Image Segmentation based on Generalized entropy Kernel Fuzzy C-Means). If no spatial information is added to objective function, obtained algorithm is denoted as GKFCM (Generalized entropy Kernel Fuzzy C-Means).

It can be seen that in above algorithms, there are many parameters to be solved. For obtaining better clustering or segmentation result, one needs to choose the appropriate values of parameters. In reality, these values of parameters are very difficult to be found. For this reason, in the following, we use ensemble method for solving this problem in order to obtain better image segmentation.

V. ENSEMBLE OF IMAGE SEGMENTATION

Clustering ensemble mainly includes selection of members and their combination. For members of clustering ensemble, clustering results may be class labels or fuzzy memberships. In the past study, we use 2SWC method to study cluster ensemble problem [19]. In this paper, we choose 2SWC to further study ensemble of image segmentation. For integrity of paper, in the following, we simply introduce it. This algorithm mainly includes three parts: 1) Use some clustering algorithm to generate all clustering results. 2) Select many clustering members; 3) Use consensus method to combine these clustering members in order to obtain better clustering results. In the following, we introduce the last two steps in detail.

A. Selection with Clustering Ensemble Members

Suppose that there be M fuzzy clustering results. Let R_k be kth clustering result and μ_{ih} represents the membership for ith data sample attributing to the hth cluster ($0\leq i\leq n$, $1\leq h\leq c$). Thus, the presented measure function for each clustering result is defined as follows:

$$f_k=\sum_{i=1}^{n}\sum_{j=1}^{c-1}\sum_{l=j+1}^{c}|\mu_{i,j}-\mu_{i,l}|. \quad (10)$$

It can be seen that the larger value of f_k is, the harder the clustering result is. For selecting better clustering members, a threshold K_1 is introduced. If $f_k>K_1$ then we select this clustering member and put it into set S otherwise discard it. According to this method, we obtain p($p<M$) clustering ensemble members represented as matrix S, where S is a $n\times cp$ matrix. Next, we regard S as a hyper-graph G and select the more influential of the hyper-edge in the hyper-graph G. For this purpose, we define function L_g as follows:

$$L_g=\sum_{i=1}^{n}(-\mu_{i,g}\log(\mu_{i,g})), \quad (11)$$

where $\mu_{i,g}$ represents the gth feature for the ith data sample. Our purpose is to select some hyper-edges whose membership μ are more closer to 1 or 0. Then, we determine a threshold K_2. If $L_g<K_2$, then we select the gth clustering member and put it to matrix Q. After repeating this process, we obtain q features. Moreover, from (2) we know that the small value of the η_g is, the better feature is. Now, suppose that Q is a q ($1\leq q\leq p$) dimensional matrix. Let μ_g ($1\leq t\leq q$) represent each feature in matrix Q. Then Q can be expressed as $Q=[\mu_1\ \mu_2\ \ldots\mu_q]$,where μ_g ($1\leq g\leq q$) is column vector. And let L_g($1\leq g\leq q$) represent each feature value using (2) for matrix Q. To further determine each feature's role, we use L_g to weight each feature for matrix Q. According to the distribution principle, the smaller value of L_g is, the larger weight this feature is of. So we define the following weighting function

$$w_t=(1-\frac{L_t}{\sum_{t=1}^{q}L_t})\Big/\sum_{t=1}^{q}(1-\frac{L_t}{\sum_{t=1}^{q}L_t}). \quad (12)$$

Then the weighted fuzzy membership matrix Q can be expressed as $R=(w_1\mu_1\ w_2\mu_2\cdots w_q\mu_q)$.

B. Generalized Consensus Method

To deal with matrix R, we generalize the consensus function presented by Strehl and Ghosh[11]. In the following, we mainly expend hyper-graph partitioning algorithm CSPA. That is to say clustering result with clustering member is degree of fuzzy membership. For simplicity, we write it as GCSPA. After using this function to process the feature of the matrix R, METIS algorithm is used to obtain the final clustering result.

In the following, we give the detailed ensemble algorithm and denote it as 2SWC[19].

Step 1 Initialize threshold K_1 and K_2.

Step 2 Choose a base clustering algorithm and use it to generate M clustering members (clustering results).

Step 3 Calculate f_k using (10) for all clustering members. If $f_k > K_1$, then we select this clustering member and add it into matrix S.

Step 4 Use (11) to compute L_g for all columns. If $L_g < K_2$, then we select this feature and put it to matrix Q.

Step 5 Utilize above computational results to compute w_t in order to obtain matrix R.

Step 6 Use the GCSPA and METIS algorithm to combine the selected clustering members in order to get final clustering result.

VI. EXPERIMENTS

In the following, we mainly study ensemble of image segmentation using fuzzy clustering based on generalized entropy which include ISGFCM and ISGKFCM. We choose three images which are Cameraman, Coins and Lena, respectively, to conduct the experiment, where Lena image is downloaded from Internet and the others are built-in-matlab. All images are set with size 72×72 pixels. In order to facilitate the expression, we make the following definition. FCM based on generalized entropy is expressed as GFCM, and the corresponding kernel form is shorten as GKFCM. In addition, their ensemble methods are denoted as EGFCM and EGKFCM, respectively. Similarly, ensemble methods for ISGFCM and ISGKFCM are written as EISGFCM and EISGKFCM, respectively. The fused method directly using CSPA is shortening as ‘h’, and their generalized approach is shorten as ‘f’.

In experiment, we use basis clustering algorithm GFCM, GKFCM, ISGFCM and ISGKFCM to generate 19 clustering results, respectively. Then, using 2SWC method chooses some members from above clustering results. And CSPA and its generalized method are used to fuse above clustering results. The ensemble of segmentation results is shown in Fig. 1 to Fig. 3, where subfigure a is original image and subfigures from *b* to *i* are ensemble of image segmentation using h-EGFCM, f-EGFCM, h-EGKFCM, f-EGKFCM, h-EISGFCM, f-EISGFCM, h- EISGKFCM and f- EISGKFCM, respectively.

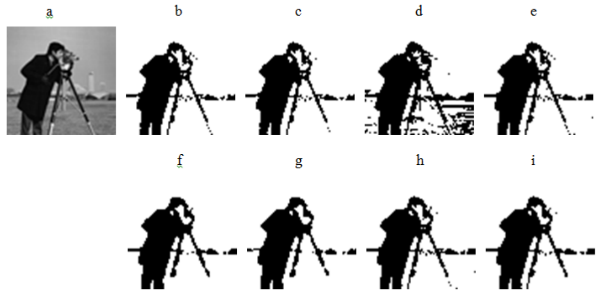

Figure 1. Segmentation results on Cameraman image using different method.

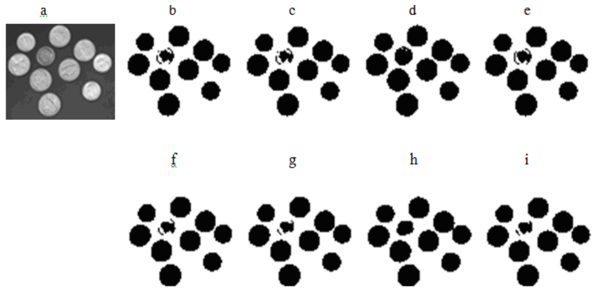

Figure 2. Segmentation results on Coins image using different method.

Figure 3. Segmentation results on Lena image using different method.

In addition, to show anti-noise performance for different method, we add salt and pepper noise to three images. The experimental results are shown in Fig. 4 to Fig. 6.

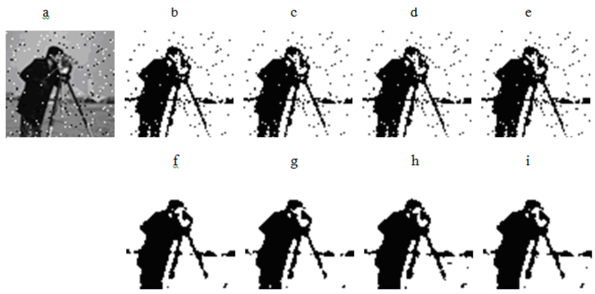

Figure 4. Segmentation results on added noise Cameraman image using different method.

From the ensemble results above, we see that when using basis clustering algorithms GFCM, GKFCM, ISGFCM and ISGKFCM, their ensemble results does not have obvious difference. However, when images to be segmented have noise, ensemble result of ISGFCM and ISGKFCM is superior to that of GFCM and GKFCM. Moreover, in experiment, we also study ensemble of image segmentation using fast image segmentation technique and obtain similar segmentation results. However, this method takes less time compared with above method.

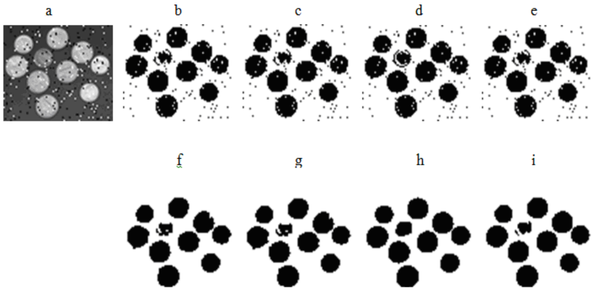

Figure 5. Segmentation results on added noise Coins image using different method.

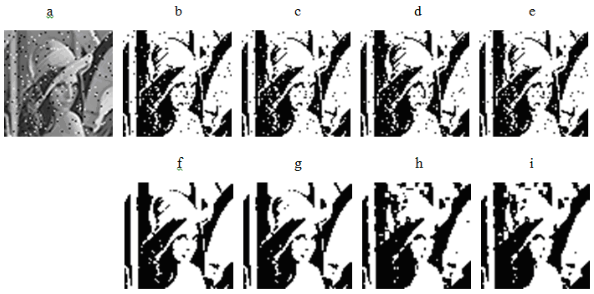

Figure 6. Segmentation results on added noise Lena image using different method.

VII. CONCLUSIONS

In this paper, we mainly study ensemble of image segmentation based on generalized entropy's fuzzy clustering. Aiming at the generalized entropy's objective function in fuzzy clustering and introducing the spatial information into this objective function, we obtain an image segmentation algorithm ISGFCM based on neural network. Further, we introduce kernel into above objective function to obtain its kernel algorithm ISGKFCM. By using basis clustering algorithms ISGFCM and ISGKFCM to generate many different segmentation results, 2SWC is used to select some members of segmentation. Then, we use CSPA and its generalized method GCSPA to fuse selected segmentation results. For the convenience of comparison, we also study ensemble of GFCM and GKFCM. Experimental results show the effectiveness of presented method. In future, we further study image segmentation algorithm based on generalized entropy, its fused method and its fast image segmentation method.

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REFERENCES

[1] M. N. Ahmed, S. M. Yamany, N. Mohamed, A. A. Farag, T. Moriarty, "A modified fuzzy c-means algorithm for bias field estimation and segmentation of MRI data," IEEE Transactions on Medical Imaging, vol. 21, no. 3, pp. 193-199, 2002.

[2] S. C. Chen, D. Q. Zhang, "Robust image segmentation using FCM with spatial constraints based on new kernel-induced distance measure," IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, vol. 34, no. 4, pp. 1907-1916, 2004.

[3] N. A. M. Isa, S. A. Salamah, U. K. Ngah, "Adaptive fuzzy moving k-means clustering algorithm for image segmentation," IEEE Transactions on Consumer Electronics, vol. 55, no. 4, pp. 2145-2153, 2009.

[4] M. Gong, Y. Liang, W. Ma, "Fuzzy c-means clustering with local information and kernel metric for image segmentation," IEEE Transactions on Image Processing, vol.22, no. 2, pp. 573-584, 2013.

[5] F. Zhao, L. Jiao, H. Liu, "Kernel generalized fuzzy c-means clustering with spatial information for image segmentation," Digital Signal Processing: a review journal, vol. 23,no. 1,pp. 184-199, 2013.

[6] N. B. Karayiannis, "MECA: maximum entropy clustering algorithm," Proceedings of the Third IEEE Conference on Fuzzy Systems, vol. 1, pp. 630-635, 1994.

[7] R. P. Li, M. Mukaidono, "A maximum-entropy approach to fuzzy clustering," Proceedings of IEEE International Conference on Fuzzy Systems, vol. 4, pp. 2227-2232, 1995.

[8] D. Tran, M. Wagner, "Fuzzy entropy clustering," The Ninth IEEE International Conference on Fuzzy Systems, San Antonio, US, pp. 152-157, May 2000.

[9] Y. Y. Liu, W. B. Liu, Z. Y. Z, "Image segmentation method based on fuzzy entropy and grey relational analysis,"Proceeding of the Fourth International Conference on Image and Graphics, pp. 372-376, 2007.

[10] K. Li, H.Y. Ma, and Y. Wang, "Unified model of fuzzy clustering algorithm based on entropy and its application to image segmentation," Journal of Computational Information Systems, vol.7,Issue 15, pp.476-483, 2011.

[11] A. Strehl, J. Ghosh, "Cluster ensemble-a knowledge reuse framework for combining multiple partitions," Journal on Machine Learning Research(JMLR),vol.3,pp.583-617, 2002.

[12] Z. H. Zhou, W. Tang, "Cluster ensemble", Knowledge-Based Systems, vol.19, pp.77-83, 2006.

[13] X. Fern , W. Lin, "Cluster ensemble selection," Journal Statistical Analysis and Data Mining,vol.1,Issue 3,pp.128-141,2008.

[14] Y. Hong, S. K Wong, H. L. Wang, Q. S. Ren, "Resampling-based selective clustering ensembles," Pattern Recognition Letters, vol.30, pp.298-305, 2009.

[15] Y. Yang and K. Chen, "Temporal data clustering via weighted clustering ensemble with different representations," IEEE Transactions on Knowledge and Data Engineering, vol.23,no. 2, pp.307-320, 2011.

[16] Z. Yu, H. S. Wong, J. You, Q. M. Yang, H. Y. Liao, "Knowledge based cluster ensemble for cancer discovery from biomolecular data," IEEE Transactions on Nanobio Science, vol.10,no.2,pp.76-85, 2011.

[17] C. Wei and C. Fahn, "The multisynapse neural network and its application to fuzzy clustering," IEEE transactions on neural networks, vol. 13,no. 3, pp. 600-618, 2002.

[18] K. Li, P. Li, "A fuzzy clustering algorithm with the generalized entropy based on neural network," Journal of Computational Information Systems, vol.9, no. 1, pp.353-360, 2013.

[19] K. Li, P. Li, "A selective fuzzy clustering ensemble algorithm," International Journal of Advanced Computer Research, vol.3,Issue 13,pp.1-6,2013.

[20] K. Li, Y. Wang, "A fast image segmentation based on clustering technique," IPASJ International Journal of Information Technology, vol. 2, Issue 6, pp. 8-13, 2014.