Segmentation by Incremental Clustering

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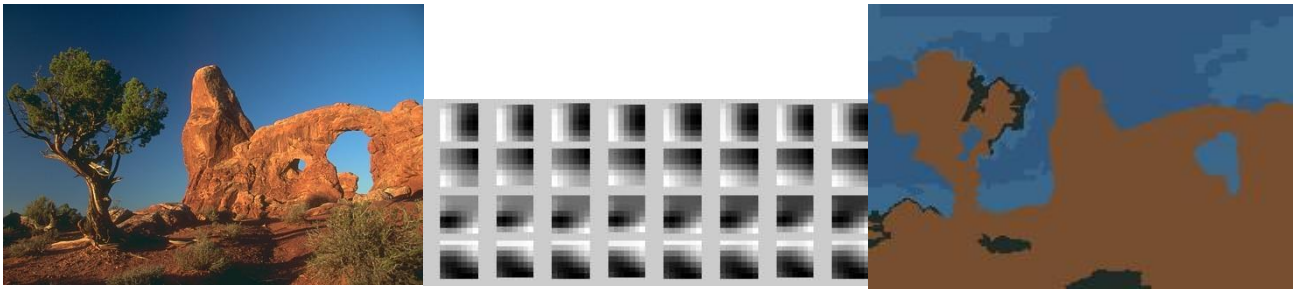


a. Input image b. Clusters c. Segmentation

Figure 1: Segmentation by incremental clustering

ABSTRACT
A method for unsupervised segmentation by incremental clustering is introduced. Inspired by incremental approach and correlation clustering, clusters are added and refined during segmentation process. Correlation clustering is to keep away from pre-definition for number of clusters and incremental approach is to avoid re-clustering that is needed in iterative methods. The Gaussian spatial kernel is involved like a part of similarity function to cover local image structure. Cluster representative is updated efficiently to satisfy the old and new similarity constraints rather than re-clustering the entire image. Experimental results are discussed and show that the algorithm requires reasonable computational complexity while gaining a comparable or better segmentation quality than standard methods.

General Terms
Pattern Recognition, Algorithms

Keywords
Incremental Clustering, Correlation Clustering, Unsupervised Segmentation

1. INTRODUCTION
Image segmentation refers to a field of image processing that aims to partition an image into disjoint regions. The overriding objective is to generate homogeneous regions and difference of their neighboring in respect to some characteristics such as color, intensity, or texture. Clustering approach is widely used for image segmentation. It is the search of clusters such that objects within the same cluster are similar while objects in different clusters are distinct in some feature space. Here, the clustering provides similarity measurement of image regions in segmentation process.

Interest in the image segmentation by clustering has increased significantly among the research community to the varied and important applications of segmentation. Some of the key clustering include: k-Mean [01], [02], [03], EM [04], Mean-shift [05], [06] and Graph-cut [07].

There is a popular task in clustering algorithms to pre-define the number of clusters. Inadequate pre-selection of the number of clusters may lead to bad clustering outcome. This also may make the algorithms insufficient for batch processing of big image databases. There has been some work by Dempster et al. [08] to bridge this gap by providing the Expectation-maximization (EM) algorithm which is a general-purpose maximum likelihood algorithm for missing-data problems, has been applied to estimate the parameters of mixture models. However, speed of convergence of the EM algorithm is dependent on the amount of overlap among the mixture components and is sometimes very slow [09], [10].

Correlation clustering [11], [12] is a data mining method for clustering that does not require a bound on the number of clusters that the data is partitioned into. Thus, the method divides the data into the optimal number of clusters based on the similarity between the data points. On the other hand, incremental clustering [13], [14], [15] is approach to refine clusters dynamically.

This work continues with the incremental clustering approach, the correlation clustering, and in particular applies the approaches for image segmentation. A new incremental clustering based segmentation algorithm is presented in this paper. In the proposed method, the number of clusters is not predefined and clusters are added during clustering process. Therefore, the number of clusters is increased incrementally but it's constrained by a max number. The distance function for similarity measurement is based on Gaussian distribution [16] to cover partially local image structure.

In fact, the proposed approach is fast, non-iterative, simple to implement. Please refer to figure 1 for an example of image segmentation by the incremental clustering algorithm. Fig. 1a shows the original image. Four clusters which are added and updated in clustering process are displayed in fig. 1b and segmentation result is demonstrated in fig. 1c.

2. OUTLINE OF PAPER
The organization of the paper is as follows. The prior work is presented in section 3. Proposed method and experimental results are shown in section 4 and 5 accordingly, where a comparative study is done. Discussion and future work are in section 6 and 7. Finally a conclusion is given in section 8.

3. PRIOR WORK

In order to gain a better understanding of the article goals and approach it is helpful to first briefly outline some traditional segmentation clustering methods including incremental clustering.

k-Means clustering algorithm was developed by J. MacQueen [01] and then by J. A. Hartigan and M. A. Wong [02]. The method is simple and fast. It's necessary to pick-up k - the number of clusters. Mean of each cluster from its member is re-computed. If no mean has changed more than some ε, then stop.

Fuzzy c-means clustering (FCM) [17] is more natural than hard clustering. Objects on the edges between several clusters are not forced to fully belong to one of the clusters, but rather are assigned partial membership. FCM and bilateral filter [18] is applied for image segmentation [19].

Mean shift segmentation [05], [06] is a nonparametric clustering technique, which does not require prior knowledge of the number of clusters. The mean of the data in search window is re-computed in each iteration and the search window is centered at the new mean location. Repeat this until convergence. The algorithm is calculation intensive. Graph cut segmentation [07] is a graph-based approach that makes use of efficient solutions of the max flow/mincut problem between source and sink nodes in directed graphs. This generic framework can be used with many different features and affinity formulations thought high storage requirement and time complexity.

Most clustering methods request re-calculation in feature space through iteration loops for clustering data. Incremental clustering provides a process of incremental classification that aim at refining the partial classification in an iterative way, where features are progressively evaluated [20].

An incremental clustering algorithm for data mining was developed by Ester et al. Algorithm DBSCAN in [13] is a density-based and partition clustering. Hierarchical agglomerative clustering (HAC) or Hierarchical cluster analysis (HCA) is presented in [14], [15] for cluster analysis which seeks to build a hierarchy of clusters. An incremental clustering algorithm is proposed in [21] with changing the radius threshold value dynamically. The algorithm restricts the number of the final clusters and reads the original dataset only once. Next, images in [22] can be segmented by incremental iterative clustering where a gravitational function is defined in feature space to manage clustering process.

There are some specific problems of incremental k-Means including the seeding problem, sensitivity of the algorithm to the order of the data, and the number of clusters. Static and dynamic single-pass incremental k-Means procedures are presented in [23] to overcome these limitations. Other incremental version of the k-Means algorithm is shown in [24] that involves adding cluster centers one by one as clusters are being formed. An incremental partitioning based k-Means clustering is addressed in [25]. It is applied to a dynamic database where the data may be frequently updated.

Expectation conditional maximization (ECM) [26] and α-EM algorithm [27] were developed from EM by Fraley al. [28]. These methods can be applied to estimate the number of clusters using mixture models.

4. INCREMENTAL CLUSTERING

Given an RGB image presented by an *M*-dimension function of space:

$$u:\Omega\to\Re^N, u(x):=(u_1(x),..u_M(x)),\ x\in\Omega\in\Re^2 \quad (1)$$

$$u_i:\Omega\to\Re, i=1,..,M \quad (2)$$

Our goal is to perform clustering the input image into clusters:

$$C=\{c_j, j=1,..k\} \quad (3)$$

by building membership function f that maps pixels x_i to c_j

$$f(x_i):\Omega\to C \quad (4)$$

Denote $s(x)$ - a spatial frame of the size $\tau\times\tau$ with center in x

$$s(x)=\begin{bmatrix} \dots & \dots & \dots \\ & \dots & \\ \dots & \dots\ x\ \dots & \dots \\ & \dots & \\ \dots & \dots & \dots \end{bmatrix} \quad (5)$$

Mark $u_\tau(x)$ for the extraction of $u(x)$ in a frame of the size $\tau\times\tau$ with center in x

$$u_\tau(x)=f(s(x))=\begin{bmatrix} \dots & \dots & \dots \\ & \dots & \\ \dots & \dots\ u(x)\ \dots & \dots \\ & \dots & \\ \dots & \dots & \dots \end{bmatrix} \quad (6)$$

4.1 Similarity Measurement

Given a clusters c_j and a pixel x_i, their similarity function can be described in L-norm of difference between $\mu_\tau(c_j)$ and $u_\tau(x_i)$:

$$d(x_i,c_j)=\left\|u_\tau(x_i)-\mu(c_j)\right\|^L, j=1,..k \quad (7)$$

Here $\mu(c_j)$ is representative of cluster c_j - a matrix with size $\tau\times\tau$. Most clustering algorithms represent clusters by their centroid and use an Euclidean distance in building them. This may produce generally a hyper-spheric cluster shape, therefore makes them unable to obtain the real image structure [29]. The function $d(x_i,c_j)$ is in Euclidean metric when $L=2$. In this case, all positions in the frame $\tau\times\tau$ with center in x are equal. So, in order to capture local image structure better, the function $d(x_i,c_j)$ may involve Gaussian kernel G for spatial distance:

$$G_\sigma(x,y)=\frac{1}{\sigma\sqrt{2\pi}}\exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right) \quad (8)$$

This kernel can play weighting role for the similarity function:

$$d(x_i,c_j)=\frac{1}{W_{x_i}}\sum_{y\in s(x_i)}G_{\sigma_s}(x_i,y)*\left\|u_\tau(y)-\mu(y)\right\|^1 \quad (9)$$

where W_{x_i} is normalization factor:

$$W_{x_i}=\sum_{y\in s(x_i)}G_{\sigma_s}(x_i,y) \quad (10)$$

Note that $L=1$ is used in (9). The similarity function is applied like the base of cluster assignment for pixel x_i:

$$f(x_i) := c_* = \arg\min_{C_j \in C}(d(x_i, c_j)) \quad (11)$$

4.2 Algorithm

The incremental clustering (IC) based segmentation algorithm proceeds by user initially selecting input image u, frame size τ, similarity threshold λ, spatial deviation σ and maximum number of clusters $k_{\max}$. Let the set of clusters empty at the beginning:

$C=\emptyset, k=0.$ (12)

For each $x_i \in \Omega, i = 1..n$ the algorithm takes the following steps:

Step 1. Computing the memberships:

Find distance from x_i to existing clusters by the similarity function (9, 10):

$$d(x_i, c_j), j = 1,..k \quad (13)$$

If exists cluster *(k>0)* and $\min_{c_j \in C}(d(x_i, c_j)) <= \lambda$ then assign membership for x_i:

$$f(x_i) := c_* = \arg\min_{C_j \in C}(d(x_i, c_j)) \quad (14)$$

Else

Step 2. Add new cluster:

if number of clusters $k <= k_{\max}$, add a new cluster to C:

$$c_{j+1}, \mu(c_{j+1}) := u_\tau(x_i), C := C \cup C_{j+1} \quad (15)$$

and assign membership of x_i to the cluster:

$$f(x_i) = c_* := c_{j+1} \quad (16)$$

else assign membership of x_i to cluster c_* found by (14)

Step 3. Updating representative for the cluster c_*

$$\mu(c_*) = 1/numel(c_*) \sum_{x \in c^*} u_\tau(x) \quad (17)$$

where *numel* is short for number of elements.

Turn to step 1 until all pixels were clustered./.

Note that averaging representative by (17) requests saving historical $\mu_\tau(c_j)$. Rather than reserve space for this, averaging operation may have iterative form: averaging value is updated by the value of new member:

$$\mu(c_*) := \frac{\mu(c_*) * (numel(c_*) - 1) + u_\tau(x)}{numel(c_*)} \quad (18)$$

4.3 Computational Complexity

Let n is the number of pixel x. Earlier we showed that the operation (18) doesn't require $\mu_\tau(c_j)$ and the IC algorithm has space complexity $O(\tau\sigma k_{\max} n)$. In case to store $\mu_\tau(c_j)$ by (17), the space complexity is $O(\tau\sigma n \log n)$.

Time complexity is $O(\tau\sigma k_{\max} n)$. The algorithm takes as much time as big $\tau, \sigma, k_{\max}$ and n. In experiments described in next section our preference for these parameters are

$$\tau = 3, \sigma = 3, k_{\max} = 3,4,5 \quad (19)$$

5. EXPERIMENTS

Figure 2 shows an example of cluster update in time series during clustering image 3096.jpg from BSDS500 [30] with $k_{\max} = 3$. Clustering the same image with $k_{\max} = 8$ produced historical clusters displayed in figure 3.

Probabilistic Rand Index (PRI) [31], [32] is selected for segmentation quality measurement in our experiments. Each segmentation result was compared with all three human segmentation samples and get PRI as average of RIs [31].

Figure 4 shows effect of parameter $k_{\max}$ for clustering 3096.jpg. Original image is displayed in fig 3a. Human segmentation samples are shown in fig 3e, 3i, 4m. They are used like reference objects for the PRI estimation. Calculation time (*t*) is measured by sec (*s*). Segmentation by clustering for the image was performed also by k-mean [01], [02] and Fuzzy c-means clustering (FCM) [17]. IC algorithm gave the best PRI=0.833 and time t= 6.039 (fig. 4d) for $k_{\max} = 3$. Statistics of PRI for image 3096.jpg is shown in figure 5.

Figure 5 presents clustering results for some other BSDS images when $k_{\max} = 3,4$. Statistics from experiment on all BSDS images is presented in figure 7a, where average PRI for FCM, KM, IC are 0.353, 0.429 and 0.465 accordingly. Thus, this showed that IC improved PRI, though it takes more time than k-Mean (see fig. 7b).

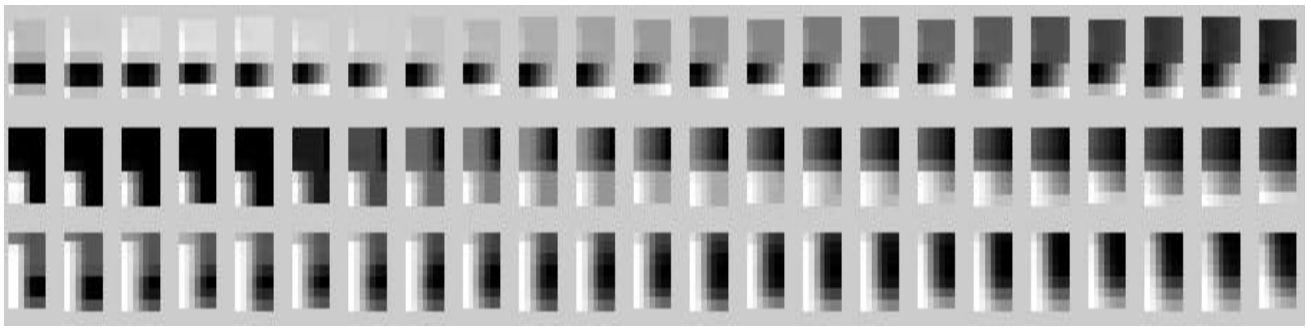


Figure 2: Incremental clusters in case k_{max}=3 for segmentation of image 3069.jpg

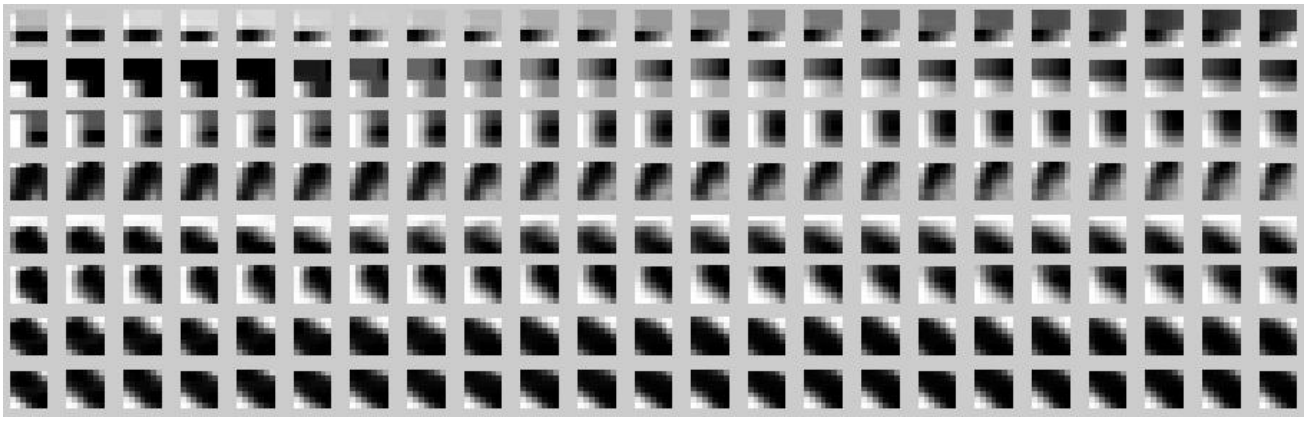
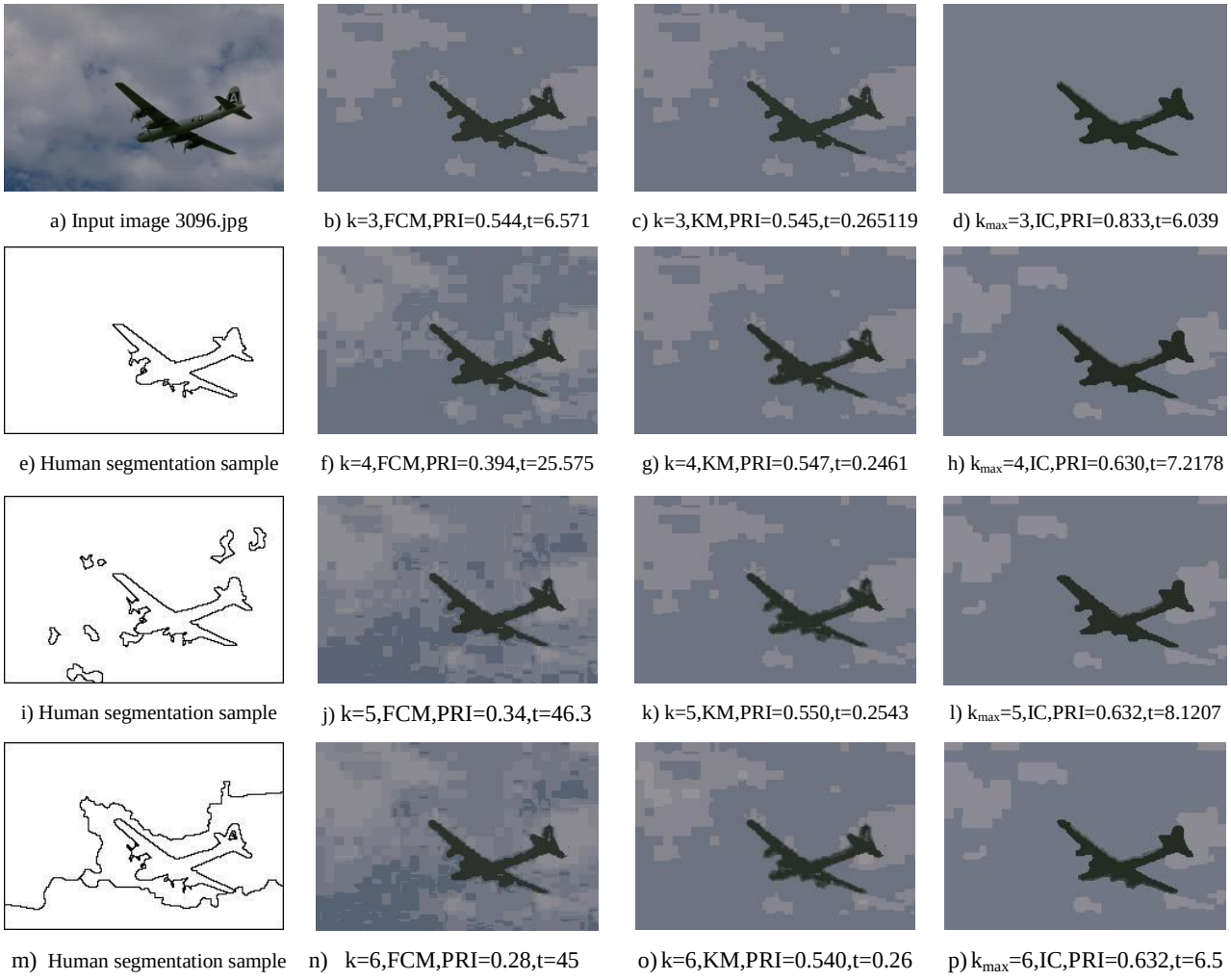


Figure 3: Incremental Clusters in case k_{max}=8 for segmentation of image 3069.jpg



a) Input image 3096.jpg b) k=3,FCM,PRI=0.544,t=6.571 c) k=3,KM,PRI=0.545,t=0.265119 d) k_{max}=3,IC,PRI=0.833,t=6.039

e) Human segmentation sample f) k=4,FCM,PRI=0.394,t=25.575 g) k=4,KM,PRI=0.547,t=0.2461 h) k_{max}=4,IC,PRI=0.630,t=7.2178

i) Human segmentation sample j) k=5,FCM,PRI=0.34,t=46.3 k) k=5,KM,PRI=0.550,t=0.2543 l) k_{max}=5,IC,PRI=0.632,t=8.1207

m) Human segmentation sample n) k=6,FCM,PRI=0.28,t=45 o) k=6,KM,PRI=0.540,t=0.26 p) k_{max}=6,IC,PRI=0.632,t=6.5

Figure 4: Example of k-Mean, FC, IC for k=1,2,3..6 on image 3069.jpg of BSDS

PRI/number of clusters	KM	FCM	IC
3	0.511	0.437	0.833
4	0.435	0.401	0.630
5	0.402	0.399	0.632
6	0.397	0.386	0.632
7	0.400	0.315	0.631
8	0.405	0.326	0.635

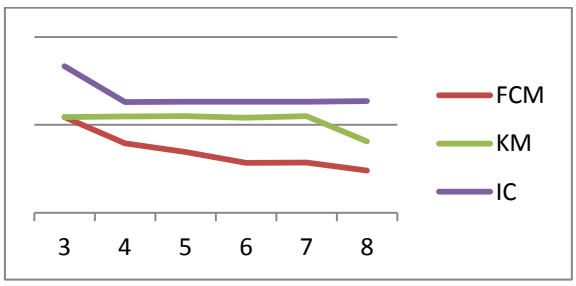
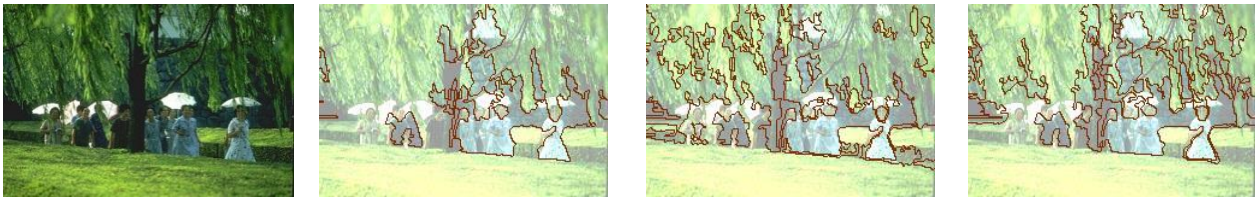
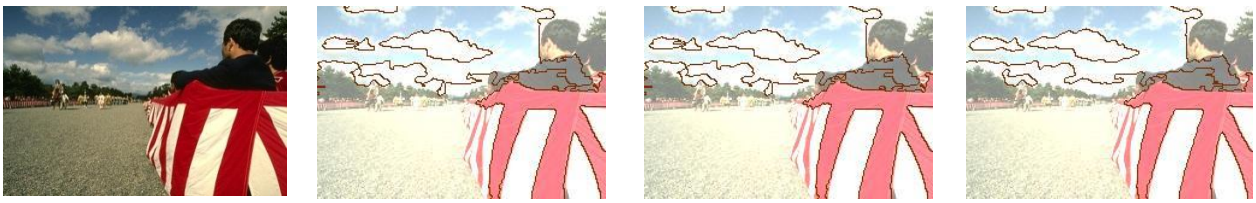


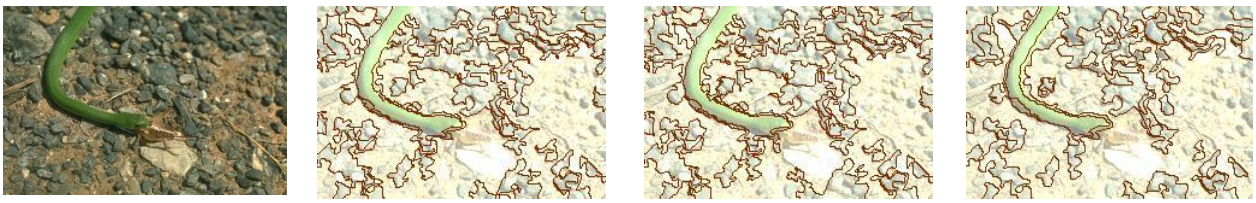
Figure 5: Statistics of PRI for experiments of k-Mean, FCM, IC on all BSDS color images



a) 65033.jpg, k=3 b) KM,PRI=0.660,t=0.145020 c) FCM,PRI=0.430,t=4.24573 d) IC,PRI=0.668,t=5.616285

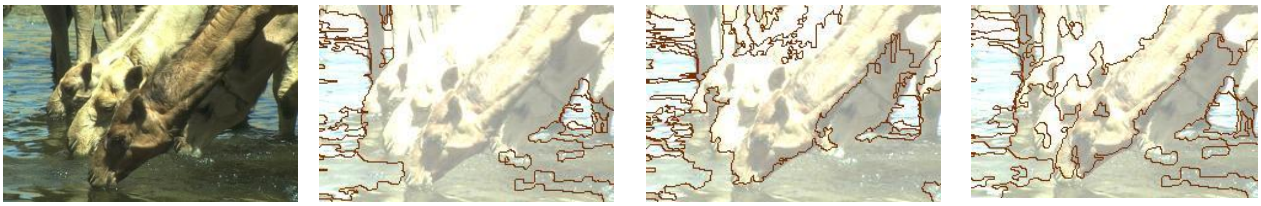


e) 145086.jpg, k=3 f) KM,PRI=0.459,t=0.120240 g) FCM,PRI=0.459,t=1.32993 h) IC,PRI=0.463,t=4.189168



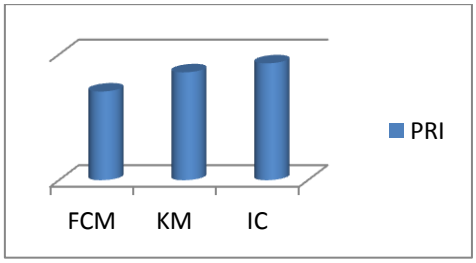
i) 175043.jpg, k=3 j) KM,PRI=0.412,t=0.130742 k) FCM,PRI=0.404,t=3.01356 l) IC,PRI=0.455,t=4.123928

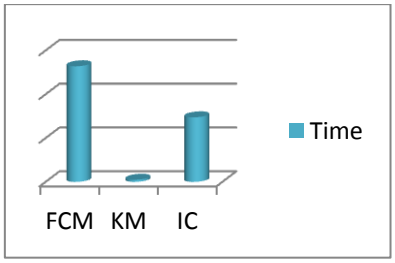
m)160068.jpg, k=4 n) KM,PRI=0.331,t=0.124054 o) FCM,PRI=0.326,t=5.19268 p) IC,PRI=0.372,t=5.105848



q) 16077.jpg, k=4 r) KM,PRI=0.579,t=0.230228 s) FCM,PRI=0.398,t=19.1578 t) IC,PRI=0.469,t=5.166366

Figure 6: Example of k-Mean, FCM, IC on 6 BSDS images.





	FCM	KM	IC
PRI	0.353	0.429	0.465

a.

	FCM	KM	IC
Time	13.196	0.239	7.365

b.

Figure 7: PRI and Time Complexity by FCM, KM and IC from BSDS experiments.

6. DISCUSSION

The IC algorithm does clustering incrementally by only one round of checking pixels of input image. As similarity function works on $\tau \times \tau$-size frame, it takes more time than k-Mean. In order to have the best representative frame for cluster, the frame must be full size. It means that pixels inside input image having full neighbours for the $\tau \times \tau$-size frame should be considered first to create all necessary cluster representatives. Other pixels laying on borders of input images will be checked later, just for membership assignment. As big as spatial deviation σ and frame size τ, the local structure is considered in similarity function, but gets more computing time. Our practical preference for σ and τ is 3.

The similarity threshold λ has close association to the final number of clusters k. As less λ, clusters are added as more frequently and final number of clusters reaches as quickly the $k_{\max}$. So the similarity threshold may be taken from experimental statistics for optimal solution.

7. FUTURE WORK

The need for similarity measurement is essential for segmentation by clustering. Though IC method utilizes local neighborhood information in the measurement but some parameter selection requires specific consideration for better result. Fuzzy set [17] could be a solution for getting solution for the case and it may help to ameliorate clustering process.

8. CONCLUSION

In this paper, aiming at producing image segmentation, a new algorithm is proposed to generate clusters incrementally. Similarity function with Gaussian spatial kernel is applied to manage membership assignment. Clusters are created due to necessary and cluster representative is updated every time when having a new member for a cluster. Our algorithm is a fully automatic method with optional parameter selection for more flexibility. The algorithm works well on various examples. A careful evaluation by statistics on BSDS shown that algorithm requires reasonable computational complexity while gaining a comparable or better segmentation quality than standard methods.

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