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Abstract. In image analysis, image segmentation performed an essential role to get detail information about image. Image segmentation is suitable in many applications like medicinal, face recognition, pattern recognition, machine vision, computer vision, video surveillance, crop infection detection and geographical entity detection in map. FCM is famous method used in fuzzy clustering to improve result of image segmentation. FCM doesn't work properly in noisy and nonlinear separable image, to overcome this drawback, Multi kernel function is used to convert nonlinear separable data into linear separable data and high dimensional data and then apply FCM on this data. NMKFCM method incorporates neighborhood pixel information into objective function and improves result of image segmentation. New proposed method used RBF kernel function into objective function. RBF function is used for similarity measure. New proposed algorithm is effective and efficient than other fuzzy clustering algorithms and it has better performance in noisy and noiseless images. In noisy image, find automatically required number of cluster with the help of Hill-climbing algorithm.

Keywords: Component: clustering · Fuzzy clustering · FCM · Hill-climbing algorithm · KFCM · NMKFCM · NMRBKFCM

1 Introduction

Image segmentation is a foremost topic for many image processing research. Image segmentation is acute and vital component of image examination system. It is method of subdividing image keen on different segment (collection of pixel). Segment consist set of similar pixel by using different properties of pixel like quality, shade, color, intensity, character text etc. The goal of method is to make simpler or variation of the presentation of an input image into more expressive and easier image to analyze. This method is performed using four approaches like Clustering, Thresholding, Region Extraction and Edge Detection. Clustering is approach to perform image segmentation on image. It is method of subdividing image into number of group and every image entity assign to group. Image entity allocate such that same entity fit to same group. Clustering perform by using two main approaches like crisp clustering and

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fuzzy clustering [2]. Crisp clustering is to process in which finding boundary between clusters. In this object belong to only one cluster. Fuzzy clustering has improved solution for this problem which is object fit to many groups. Fuzzy C-MEANS (FCM) has been used commonly as clustering technique for image segmentation. FCM be present method of clustering to which allow one object fits to two or more clusters. FCM is introducing fuzziness with degree of membership function of every object and range of membership function between 0 and 1 [3]. Aim of FCM is to minimize value of objective function and perform partition on dataset into n number of clusters. FCM provide better accuracy result than HCM in noiseless image. FCM is not working properly in noisy image and failed in nonlinear separable data, to overwhelm this drawback Kernel FCM (KFCM) has applied. Role of kernel is convert nonlinear separable data into linear separable data and low dimension into high dimensional feature space [4]. Propose Novel Kernel Fuzzy C-means (NMKFCM) algorithm which is to assimilate neighbor term in objective function and amend result over KFCM and FCM in noisy and noiseless image [5]. NMKFCM is very beneficial and useful method for image segmentation.

2 Clustering Algorithm

2.1 Fuzzy(Soft) Clustering Algorithm (FCM)

Aim of FCM has to curtail objective function [6]. The FCM algorithm is improved outcome over k-mean. In this method feature vector of dataset is subdivided into hard clusters. The feature vector is perfectly a participant of one group only. As an alternative of this method, the FCM has modified the situation. This method is allowed to feature vector for multiple membership positions to several group. FCM smartly handles with such problems by dealing with degree of membership function of feature vector which varies from 0 to 1. FCM is iterative clustering processes that generate ideal c partition by using abate weight inside the group, following formula for sum of square off error objective function Jm_{obj}.

$$J_{m_{obj}} = \sum_{x=1}^{P} \sum_{y=1}^{Q} U_{xy}^{m} d_{xy}^{2} \tag{1}$$

Where: Q: The number of forms in Z, P: The number of cluster, Uxy = The degree of association Z_x in the y^{th} cluster; d_{xy} = Distance unit between object Z_x and cluster center, W_y = The model of the center of cluster y, m: The weighting exponent on each fuzzy relationship.

The FCM emphases over decreasing objective function Jm_{obj} value and focus on the below constraints on U:

$$U_{xy} \in [0, 1],\ \mathrm{x} = 1, 2, 3, 4\ldots\mathrm{P},\ \text{number of forms.}$$
$$\mathrm{y} = 1, 2, 3, \ldots\mathrm{Q},\ \text{number of cluster}$$

$$\sum_{x=1}^{P} U_{xy} = 1, \mathrm{x} = 1, 2, 3, 4\ldots\mathrm{P}, \quad 0 < \sum_{x=1}^{P} U_{xy} < 1, \mathrm{y} = 1, 2, 3, \ldots\mathrm{Q}$$

Objective function $\mathrm{J_{mobj}}$ defines a constrained optimization problem. Lagrange multiplier technique has applied for conversion of constrained to unconstrained problem. By using this calculates membership function and update cluster center separately.

$$U_{xy} = \frac{1}{\sum_{x=1}^{P} \left(\frac{d_{xy}}{d_{xl}}\right)^{\frac{2}{(m-1)}}} \tag{2}$$

$$\mathrm{x} = 1, 2, \ldots\mathrm{P \ and \ y}, \mathrm{l} = 1, 2, \ldots\mathrm{Q}$$

If $d_{xy} = 0$ then $U_{xy} = 1$ and $U_{xy} = 0$ for $x \neq y$
And calculate cluster center using following steps

$$W_y = \frac{\sum_{x=1}^{P} \left(U_{xy}\right)^m Z_x}{\sum_{x=1}^{P} \left(U_{xy}\right)^m} \tag{3}$$

2.2 Kernel Method

Kernel method is calculating the distance between two data points. The data points are plotted into a high dimensional space. They are openly separable using distance metric [7]. The existing work plans a way of incremental the correctness of the FCM by developing a kernel function in computing the distance of data point from the cluster centers. Radial basis kernel is used in distance to plot feature vector from the input space to a high dimensional space. The kernel function can be used in those algorithm which are exclusively be influenced by the dot product between two vectors. Linear algorithms are converted into decision-boundary algorithms when kernel function used. Those decision-boundary methods are corresponding to linear patterns functioning on the series of a feature space Ψ. Kernels are applied, the Ψ function does not essential to continually clearly computed. Kernel trick is general idea of the distance parameter that calculates distance between two data points. The pattern points are plotted into a high dimensional spaces in which pattern are clearly separable. Known unlabeled data set $Z = \{z_1, z2, z3 \ldots, z_n\}$ in the d-dimensional space R^d, let Ψ be a decision boundary mapping function from this response space to high dimensional feature space $\mathrm{H} : \Psi : R^d \rightarrow H_d, z \rightarrow \Psi(z)$. Dot product in the high dimensional feature pattern can be determined with the help kernel trick function $K_T(\mathrm{Z}_x, \mathrm{Z}_y)$ in the response space R^d.

$$\mathrm{K}_T(\mathrm{Z}_x, \mathrm{Z}_y) = \Psi(\mathrm{Z}_x).\Psi(\mathrm{Z}_y)$$

Consider the subsequent example. For $d = 2$ also the mapping function Ψ,

$$\Psi : R^2 \rightarrow H_d = R^3(\mathrm{Z}_{x1}, \mathrm{Z}_{y2}) \rightarrow (\mathrm{Z}_{x1}^2, \mathrm{Z}_{x2}^2, \sqrt{2\mathrm{Z}_{x1}, \mathrm{Z}_{x2}})$$

Then the dot product in the feature space H is measured as

$$\begin{aligned}
&\Psi(\mathrm{X}_i)\Psi(\mathrm{X}_j) \\
&= (\mathrm{Z}_{x1}^2, \mathrm{Z}_{x2}^2, \sqrt{2Z_{x1}Z_{x2}}) \cdot (\mathrm{Z}_{y1}^2, \mathrm{Z}_{y2}^2, \sqrt{2Z_{y1}Z_{y2}}) \\
&= ((\mathrm{Z}_{y1}^2, \mathrm{Z}_{y2}^2) \cdot (\mathrm{Z}_{y1}^2, \mathrm{Z}_{y2}^2))^2 \\
&= (\mathrm{Z}_x, \mathrm{Z}_y)^2 \\
&= K_T(\mathrm{Z}_x, \mathrm{Z}_y)
\end{aligned}$$

K-trick is the square of the dot product in the response phase. From the observation notice that this illustration used kernel idea function which determine the value of dot product in the feature pattern $\mathrm{H_d}$ without remarkably manipulative mapping function Ψ. Following are models of kernel idea function:

1. Polynomial Based K Trick-Function

$$K_T(\mathrm{Z}_x, \mathrm{Z}_y) = (\mathrm{Z}_x\mathrm{Z}_y + L)^2, \text{where } \mathrm{L} \geq 0, \mathrm{d} \in \mathrm{Q}$$

2. Gaussian Based K Trick Function

$$K_T(\mathrm{Z}_x, \mathrm{Z}_y) = \exp(-\frac{\left\|Z_x - Z_y\right\|^2}{2\sigma^2}), \text{where } \sigma > 0$$

3. Radial Base K-Function

$$K_T(\mathrm{Z}_x, \mathrm{Z}_y) = \exp\left(-\frac{\sum\left|Z_x^v - Z_y^v\right|^w}{\sigma^2}\right), \text{where } \sigma, \mathrm{v}, \mathrm{w} > 0$$

4. Tangent K Trick-Function

$$K_T(\mathrm{Z}_x, \mathrm{Z}_y) = 1 - \tanh\left(-\frac{\left\|Z_x - Z_y\right\|^2}{\sigma^2}\right), \text{where } \sigma > 0$$

2.3 Novel Modified Kernel FCM Algorithm (NMKFCM)

Novel modified kernel fuzzy method is assimilating neighborhood pixel value in objective function. NMKFCM algorithm is modified version of KFCM. NMKFCM which incorporate neighborhood pixel value using 3×3 or 5×5 window and introduce this value in objective function [1, 8]. In this '$\propto$' parameter is trained for control weight of neighbor's term which is achieved greater value with intense of image noise. Range of $\propto$ value lies within 0 to 1, if percentage of noise is low then choose value of $\propto$ between 0 and 0.5 and percentage of noise is higher then choose value of $\propto$ 0.5 and 1.0. NMKFCM is an iterative process which minimizes value of objective function with neighborhood term [9]. In this objective function introduce window around pixel and $\propto$ parameter.

$$J_{NMKFCM_{obj}}(\mathrm{U},\mathrm{W}) = \sum_{y=1}^{Q}\sum_{x=1}^{P} U_{xy}^{m}(1-\mathrm{K}_T(\mathrm{Z}_x,\mathrm{W}_y))\left(\frac{N_R - \alpha\sum_{k\in N_i} U_{yk}}{N_R}\right) \tag{4}$$

Where: NR: The cardinality, Ni: Collection of neighbors of pixel Zi, $\mathrm{K_T}$ is Gaussian k trick-Function. Objective function $\mathrm{Jnmkm_{obj}}$ describes a constrained optimization problem. Objective function is going to change constrained optimization problem into decision-boundary optimize problematic by applying Lagrange multiplier method.

Update membership function U_{ij}:

$$U_{xy} = \left(\frac{((1-\mathrm{K}_T(\mathrm{Z}_x,\mathrm{W}_y))(\frac{N_R-\alpha\sum_{l\varepsilon N_i} U_{yl}}{N_R}))^{-\frac{1}{m-1}}}{\sum((1-\mathrm{K}_T(\mathrm{Z}_x,\mathrm{W}_y))(\frac{N_R-\alpha\sum_{l\varepsilon N_l} U_{kl}}{N_R}))^{-\frac{1}{m-1}}}\right) \tag{5}$$

Update Cluster center $\mathrm{W_j}$:

$$W_y = \frac{\sum_{y=1}^{Q} U_{xy}^{m} K_T(\mathrm{Z}_x,\mathrm{W}_y)\mathrm{Z}_x}{\sum_{x=1}^{P} U_{xy}^{m}(\mathrm{Z}_x,\mathrm{W}_y)} \tag{6}$$

NMKFCM work very well in neighborhood pixel information.

2.4 Novel Modified Radial Base Kernel Fuzzy C-Means Algorithm

Novel modified Radial Base kernel fuzzy method is assimilating hesitation degree and RBF kernel function into FCM clustering algorithm. Novel modified kernel FCM algorithm which incorporate neighborhood value into objective function. To determine correct value of α is experimentally hard and range of $\propto$ value differs image by image. NMRBKFCM is worked on similarity of dataset value so accuracy increases as compare to NMKFCM approach. Similarity measure is applied to measure the degree of matching between two objects. In this objective function, introduce hesitation function and RBF:

$$J_{RBNKFCM_{obj}}(\mathrm{U},\mathrm{W}) = 2\sum_{x=1}^{Q}\sum_{y=1}^{P} U_{xy}^{m}(1-\exp(-\frac{\sum\left|Z_x^v - Z_y^v\right|^w}{\sigma^2})) \tag{7}$$

Where v, w is greater than 0, It is nominated as kernel width and It has integer positive number, U_{xy}^{m} is membership function, $\prod_x$ is hesitancy degree.

$\prod_x$ Defined as: $\prod_x = \frac{1}{N}\sum_{K=1}^{N}\prod_{xk}, k \in N[1,\mathrm{N}]$

Where we have to calculate $\prod_{xk}$:

$$\prod_{xk} = 1 - U_{xk} - W_y \tag{8}$$

This value is introduced into objective minimize function to maximize the dataset pattern in the class. This method used for decrease entropy of histogram of image. Objective function $\mathrm{J_{RBNKFCM}}$ describes a constrained optimization problem. Objective function is going to change constrained optimization problem into decision-boundary optimize problematic by applying Lagrange multiplier method.

Update membership function U_{xy}:

$$U_{xy} = \frac{\left(\frac{1}{(1-\mathrm{K}_T(\mathrm{Z}_x,\mathrm{W}_y))}\right)^{-\frac{1}{m-1}}}{\sum_{y=1}^{Q}\left(\frac{1}{(1-\mathrm{K}_T(\mathrm{Z}_x,\mathrm{W}_y))}\right)^{-\frac{1}{m-1}}} \tag{9}$$

Update Cluster center W_j:

$$W_y = \frac{\sum_{x=1}^{P} U_{xy}^{m}\cdot K_T(\mathrm{Z}_x,\mathrm{W}_y)\cdot Z_x}{\sum_{x=1}^{P} U_{xy}^{m}\cdot K_T(\mathrm{Z}_x,\mathrm{W}_y)} \tag{10}$$

Algorithm

$\mathrm{J_{RBNMKFCMOBJ}}$ can be obtaining through an iterative process, which is achieved by following steps:

Input

1. Z = $\{Z_1, Z_2 \ldots Z_N\}$, Object Pattern,
2. Q, 2 $\leq$ Q $\leq$ y, y is numeral of cluster,
3. Set value of Ɛ, it is stopping criteria parameter,
4. Initialize membership function U_{xy} using data set and cluster,
5. Calculate initial cluster center W0 = (w01, w02 … w0Q).

Output

$\mathrm{W_y} = \{\mathrm{W_0}, \mathrm{W_1}, \mathrm{W_2} \ldots \mathrm{W_y}\}$, Final center of clusters.

STEP:

1. Set loop counter s = 0
2. Calculate C cluster center W_y^s with U^s by using Eq. 10
3. Calculate membership function U^{s+1} by using Eq. 9
4. If $\{U^s - U^{s+1}\} < \varepsilon$ then stop, then fix r = r + 1 and move to step number 4.

3 Hill–Climb Algorithm

Hill-climb algorithm is used to determine number of cluster for image segmentation. Clustering approach is used unsupervised model for number of cluster. Hill-Climb algorithm is used to identify required number of cluster for image segmentation. Recognition of salient image region is beneficial for many applications like histogram and segmentation of image, image retrieval. This dilemma is attempted by plotting pixels into various feature patterns. Saliency is calculated as the local contrast of image area with respect to neighborhood of many scales [10]. In this evaluate space among the average feature vectors of pixel with respect to image sub region and average feature vector of neighborhood pixel. At a known scale, divergence based saliency value $c_{i,j}$ for a pixel at position (i, j) in image is calculated as the space S between regular vectors of pixel features of inner region R1 and outer region R2.

$$C_{ij} = S[(\frac{1}{r_1}\sum_{x=1}^{r_1} V_p), (\frac{1}{r_2}\sum_{y=1}^{r_2} V_q)] \tag{11}$$

Where r_1 and r_2: number of pixels in *R1* and *R2* respectively, v: vector of feature components correlated to a pixel. S: Euclidean space if v is a vector of uncorrelated feature elements, Mahalanobis space: elements of the vector are associated.

In experiment, CIELab color distance is used RGB images for generate feature vectors like color and luminance. Meanwhile accepted variances in CIELab color distance are nearly Euclidian, s in Eq. (12).

$$C_{ij} = \|V1 - V2\| \tag{12}$$

Where v1 = [L1; x1; y1]T and v2 = [L2; x2; y2]T: average vectors for regions R1 and R2. Add saliency values across the scales to determined final saliency plan as discussed below:

$$m_{ij} = \sum\nolimits_S C_{ij} \tag{13}$$

Hill-climbing method is understood as search window run across the space of the s-dimensional histogram to discover the leading bin from window.

4 Experimental Result

Fuzzy clustering methods are performing segmentation on real image, medical image and synthetical image. In medical image open source dataset is available which can used for experiment performance. Real image is captured image by various devices. In this work only .BMP and .jpeg format is used for execution purpose.

NMKFCM method is improved result of image segmentation as compare to FCM and KFCM. NMRBKFCM is also improved segmentation result over other fuzzy clustering algorithm. The performance of NMKFCM method is evaluated by using parameter like CAR, Runtime and Number of iteration. H/W requirement for this experiment is Intel Celeron processor M 1.7 GHz, OS is Microsoft Windows XP, 512-MB memory and the platform is MATLAB 6.5. Clustering Accuracy Rate (CAR) is used to evaluate performance of clustering method. CAR defined in below formula [11]

$$CAR = \left| \frac{A_{xy} \cap A_{ref}}{A_{xy} \cup A_{ref}} \right| \tag{14}$$

Where A_{xy}: set of pixel fitting yth cluster found by xth method and A_{refj}: set of pixel fitting to the jth cluster in the reference segmented image. By using this formula calculate accuracy rate.

Medical Image:

We apply fuzzy clustering algorithms to medical image and Add 2%, 5% and 10% salt and pepper noise into real image. Hill-climbing algorithm automatically determines cluster number 17 is used in image segmentation. In NMKFCM choose $\propto$ value from 0 to 0.5 for less noisy image and for noisier image choose $\propto$ value from 0.5 to 1, $N_R = 8$ (Figs. 1 and 2).

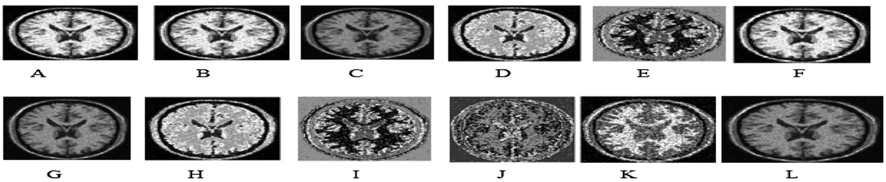

Fig. 1. Medical image

Input image (A) FCM (B) KFCM (C) NMKFCM (D) NMRBKFCM (E) 2% Noise FCM (F) 2% Noise KFCM (G) 2% Noise NMKFCM (H) 2% Noise NMRBKFCM (I) 5% Noise FCM (J) 5% Noise KFCM (K) 5% Noise NMKFCM (L) 5% Noise NMRBKFCM (Table 2).

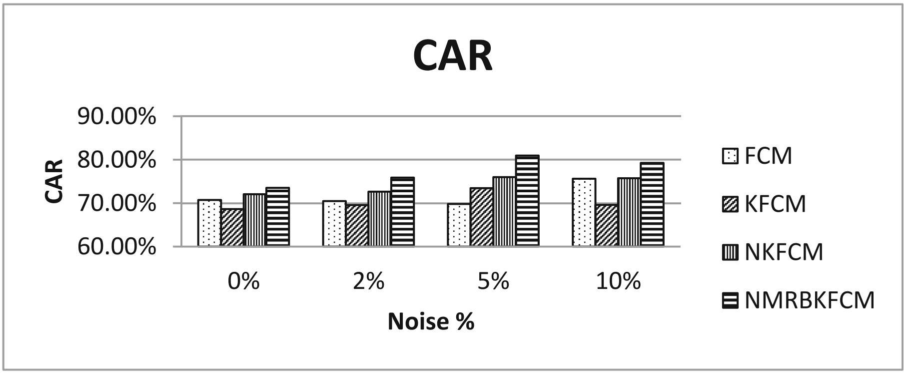

Fig. 2. Comparison between fuzzy clustering algorithms using CAR value from Table 1

Table 1. Comparison with fuzzy clustering algorithms using Cluster Accuracy Rate

NOISE%	FCM	KFCM	NKFCM	NMRBKFCM
0%	70.7439%	68.6309%	72.0572%	73.5222%
2%	70.4721%	69.5362%	72.6506%	75.8815%
5%	69.8048%	73.467%	76.0044%	80.9542%
10%	75.6375%	69.6031%	75.7221%	79.2545%

Table 2. Comparison between FCM, KFCM, NMKFCM, NMRBKFCM using runtime period for 0% noise

Method	Runtime in second
FCM	4.2755 s
KFCM	5.2075 s
NMKFCM	4.2084 s
NMRBKFCM	4.1123 s

5 Conclusion

Proposed algorithm gives efficient image segmentation than FCM and KFCM fuzzy clustering algorithms. Proposed method improves the segmentation performance by incorporating the effect radial base kernel function and hesitation degree. Proposed algorithm has determined automatically required cluster number for image segmentation. There are several things that could be done in the future as the continuation of this work. At firstly, in noisy image propose algorithm which can be determined automatically cluster number but this number is not useful for image segmentation because proposed algorithm has been generated cluster for noisy pixel so image segmentation could not be effective as compare to noiseless pixel. Secondly choosing of optimal factor α is still main issue, proposed algorithm assign value of optimal factor α randomly. In future work, add other kernel function into FCM objective function.

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