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Spatial Information Based Fuzzy Clustering Algorithm for Image Segmentation.

Deepthi P Hudedagaddi, and BK Tripathy*.

SCOPE, VIT University, Vellore, Tamil Nadu – 632014, India

ABSTRACT

Segmentation of images is one of the important techniques to obtain useful information from pixels in intermediate levels. In general, the fuzzy c-means approach (FCM) is highly effective for image segmentation. But traditional FCM fails to take spatial distribution of pixels in an image. Clusters are based on how pixels are distributed in feature space. This paper brings out the work done so far in incorporating the distribution of pixels according to their spatial information.

Keywords: spatial, fuzzy clustering algorithm, image segmentation.

***Corresponding author**

INTRODUCTION

Data mining is a popular technique to mine information from an enormous data set and make the best use of it. It also forms the analysis step of the knowledge discovery in databases (KDD). Knowledge discovery means to “develop something new”. Data mining includes four main divisions. They are Anomaly detection, Association, Classification, Clustering. Anomaly detection is the recognition of odd data records, that may be remarkable or data errors that involve further investigation. Association rule learning is the process to find the relationships between the variables. In this, relations are set up between the variables to create the new information that is needed for some purpose. Classification is the assignment of generalizing the known structure to apply to new data like in an e-mail process might attempt to categorize an e-mail as "legitimate" or as "spam". Clustering is a significant task in data analysis and data mining applications. It is the assignment of combination a set of objects so that objects in the identical group are more related to each other than to those in other groups (clusters). Cluster is grouping of elements which have the familiar characteristics.

Data Mining includes two types of learning sets, which are supervised and unsupervised learning.

a) Supervised Learning
   In supervised training, data has both input and the preferred results. It is the rapid and perfect technique. The accurate results are recognized and are given as part of input to the model through the learning procedure. Supervised models are neural networks, multilayer perceptron and decision trees.
b) Unsupervised Learning
   This technique is not provided with the accurate results during the training. This can be used to cluster the input information in classes on the basis of their statistical properties only. Unsupervised models are for dissimilar types of clustering, distances and normalization.

Clustering plays an important role in data analysis and data mining applications. It is the grouping of a set of elements so that elements in the same group are more identical to each other than to those in other groups. The elements of a cluster possess familiar characteristics. Cluster analysis can be done by finding similarities between data according to the characteristics found in the data and grouping similar data objects into clusters. A good clustering method will produce high superiority clusters with high intra-class similarity and low inter-class similarity. The superiority of a clustering result depends on equally the similarity measure used by the method and its implementation. Clustering technique’s superiority is calculated by its ability to find out some or all of the hidden patterns. Distance function can be used to measure similarity of a cluster. In data mining, there are some requirements for clustering the data. These requirements are interpretability, scalability, ability to handle dynamic data, discovery of clusters with arbitrary shape, able to deal with noise and outliers, insensitive to order of input records, high dimensionality, ability to deal with different types of attributes, minimal requirements for domain knowledge to determine input parameters, incorporation of user-specified constraints and usability. The types of data that are used for analysis of clustering are intervalscaled variables, binary variables, nominal, ordinal, and ratio variables, variables of mixed types [1]. The five types of clusters are used in clustering. The clusters are divided into these types according to their characteristics. The types of clusters are Well-separated clusters, Center-based clusters, Contiguous clusters, Density-based clusters and Shared Property or Conceptual Clusters. Many applications of clustering are characterized by high dimensional data where each object is described by hundreds or thousands of attributes. Typical examples of high dimensional data can be found in the areas of computer vision applications, pattern recognition, and molecular biology [8]. The challenge in high dimensional is the curse of dimensionality faced by high dimensional data clustering algorithms, basically means the distance measures become gradually more worthless as the number of dimensions increases in the data set. Clustering has an extensive and prosperous record in a range of scientific fields in the vein of image segmentation, information retrieval and web data mining.

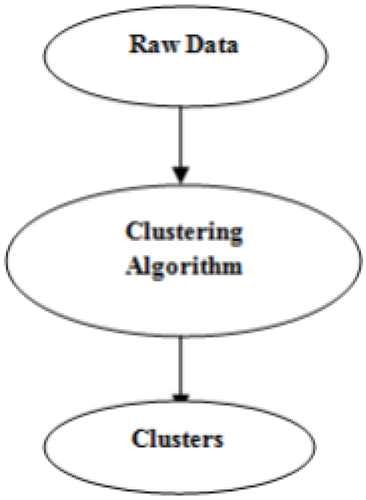

Fig 1: Stages of Clustering

Spatial clustering and analysis of these clusters plays an important role in quantifying geographic variation patterns. It is commonly used in disease surveillance, spatial epidemiology, population genetics, landscape ecology, crime analysis and many other fields, but the underlying principles are the same. Spatial data mining algorithms heavily depend on the efficient processing of neighbourhood relations since the neighbours of many objects have to be investigated in a single run of a distinctive algorithm.

Image segmentation is a process of dividing an image into different regions such that each region is nearly homogeneous, whereas the union of any two regions is not. It serves as a key in image analysis and pattern recognition and is a fundamental step toward low-level vision, which is significant for object recognition and tracking, image retrieval, face detection, and other computer-vision-related applications. Recently, many researchers have proposed various segmentation methods based on the new mathematic theories, such as threshold technique, the edge detection, the region growth, neural network and spatial clustering, etc.

Fuzzy C-means

Clustering algorithms are used to find groups in unlabeled data, based on a similarity measure between the data patterns (elements). This means that similar patterns are placed together in the same cluster. Fuzzy C-means algorithm has been proposed by Dunn [1] firstly in 1974 and extended by Bezdek [2] in 1981. The fuzzy cluster analysis has attracted more attention recently with introducing the fuzzy set theory. The main difference between fuzzy clustering and other clustering techniques is that it generates fuzzy partitions of the data instead of hard partitions. Therefore, data patterns may belong to several clusters, having in each cluster different membership values.

As a kind of unsupervised pattern recognition algorithm, FCM has been used in image segmentation broadly because of its simplicity and high efficiency. The traditional FCM algorithm uses the gray value as the only one feature in clustering and does not consider any spatial information, so it is very sensitive to the noise. In order to improve the robustness of the algorithm, many scholars have proposed kinds of methods. Some researchers have proposed KFCM which introduce the kernel function into FCM [3, 4, 5]. KFCM uses kernel distance to reshape Euclidean distance to improve the segmentation results and algorithm's efficiency. Many researchers introduce the spatial information into FCM [6-10], which incorporates the spatial information into the calculation of membership or the calculation of distance mostly.

SPATIAL INFORMATION

An important characteristic of an image is the high degree of correlation among the neighboring pixels. In other words, these neighboring pixels possess similar feature values, and the probability that they belong to the same cluster is great. This spatial relationship is important in clustering, but it is not utilized in a standard FCM algorithm. To exploit the spatial information, a spatial function is defined as:

$$h_{ij} = \sum_{k \epsilon NB(x_j)} u_{ik} \qquad (1)$$

where $NB(x_j)$ refers to the neighborhood pixels of x_j. . A 5x5 equally weighted mask centered on pixel x_j has been used for this purpose. The spatial function h_{ij} represents the degree of likeliness that x_j is in the i^{th} cluster. The value of the spatial function for a pixel is high for a particular cluster if most of the neighborhood pixels belong to the same cluster. It is included in the membership function as:

$$u'_{ij} = \frac{u_{ij}^{p} h_{ij}^{q}}{\sum_{k=1}^{c} u_{kj}^{p} h_{kj}^{q}} \qquad (2)$$

where p and q indicate the relative weightage of the initial membership and the spatial function respectively. In case of a noisy image, the spatial function reduces the number of misclassified pixels by taking the neighbouring pixels into account.

MODIFICATIONS OF FCM WITH RESPECT TO SPATIAL INFORMATION

FUZZY CLUSTERING WITH SPATIAL CONSTRAINTS FOR IMAGE THRESHOLDING[11]

Yong et.al proposed a spatially weighted fuzzy c means(SWFCM) which incorporated spatial neighbouring details into conventional FCM. They had realised that ambiguity and indistinguishable histogram are an issue in segmenting real world images and hence provided a solution fixing these issues. The principle of their technique is to incorporate the neighbourhood information into the FCM algorithm. In the standard FCM algorithm for a pixel $x_k \epsilon I$ where I is the image, the clustering x_k of with class i only depends on the membership value u_{ik} , for a noisy image, FCM is noise sensitive because the clustering process is related only to gray levels independently of pixels. Considering the influence of the neighboring pixels on the central pixel, they extended the fuzzy membership function to:

$$^{*}u_{ik} \;\; u_{ik}\, p_{ik} \qquad (3)$$

where k = 1, 2, ..., n (n is the number of image data) and p_{ik} is the probability of data point k belonging to cluster i, which is the spatial constraint and further referred to as the weight in this paper, which can be determined by the following neighborhood model. Thus the objective function of SWFCM was changed to:

$$J_q(U^*, V^*) = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik}^{*})^{q} d^2(x_k, v_i^{*}) \qquad (4)$$

Similar to FCM,degrees of membership u* and cluster centers v_i were updated.

$$(u_{ik}^{*})^{b} = \frac{p_{ik}}{\sum_{j=1}^{c} (\frac{d_{ik}}{d_{jk}})^{2/(q-1)}} \qquad (5)$$

and

$$v_i^{*(b+1)} = \frac{\sum_{k=1}^{n} [u_{ik}^{*\,(b)}]^{q}\, x_k}{\sum_{k=1}^{n} [u_{ik}^{*\,(b)}]^{q}} \qquad (6)$$

The core idea was to define the weight variable p_{ik} which is apriori information to guide the clustering process.

$$p_{ik} = \frac{\sum_{x_n \in N_k^i} 1/d^2(x_n, k)}{\sum_{x_n \in N_k} 1/d^2(x_n, k)} \qquad (7)$$

Where N_k is the data set of the nearest neighbours of central pixel *k*, and N_k is the subset of N_k composed of the data belonging to class *i*. After the a priori weight is determined, a new iteration step starts with this auxiliary variable p_{ik}. To prevent the SWFCM from getting trapped in local minima, the SWFCM algorithm is initialized with the above fast FCM algorithm. Once the FCM is stopped, the SWFCM algorithm continues with the values for the prototypes and membership values obtained from the fast FCM algorithm. When the algorithm has converged, a defuzzification process then takes place in order to convert the fuzzy partition matrix *U* to a crisp partition. A number of methods have been developed to defuzzify the partition matrix *U*, among which the maximum membership procedure is the most important. The procedure assigns object *k* to the class *C* with the highest membership.

With this procedure, the fuzzy images are then converted to crisp image. They called this method soft threshoding scheme contrary to conventional hard threshold scheme, which was been proven to be associated with loss of structure details on thresholding. Although a fuzzy thresholding method with FCM algorithm by finding the hard threshold at the intersection of both membership distributions, it is easily verified that this technique is almost equivalent to thresholding the image using the maximum membership procedure.

FUZZY C-MEANS CLUSTERING WITH SPATIAL INFORMATION FOR IMAGE SEGMENTATION[12]

Chuang et.al introduced a new segmentation method for FCM clustering. In a standard FCM technique, a noisy pixel is wrongly classified because of its abnormal feature data. Their method incorporated spatial information, and the membership weighting of each cluster was altered after the cluster distribution in the neighbourhood was considered. This scheme greatly reduces the effect of noise and biases the algorithm toward homogeneous clustering.

They said one of the important characteristics of an image is that neighbouring pixels are highly correlated. In other words, these neighbouring pixels possess similar feature values, and the probability that they belong to the same cluster is great. This spatial relationship is important in clustering, but it is not utilized in a standard FCM algorithm. To exploit the spatial information, a spatial function is defined in (1).

The clustering process is a a two-pass process at each iteration. The first pass is the same as that in standard FCM to calculate the membership function in the spectral domain. In the second pass, the membership information of each pixel is mapped to the spatial domain, and the spatial function is computed from that. The FCM iteration proceeds with the new membership that is incorporated with the spatial function. The iteration is stopped when the maximum difference between two cluster centers at two successive iterations is less than a threshold (Z=0.02). After the convergence, defuzzification is applied to assign each pixel to a specific cluster for which the membership is maximal.

They evaluated their results based on cluster validity functions. The representative functions for the fuzzy partition are partition coefficient V_{pc} and partition entropy V_{pe}.

The idea of these validity functions is that the partition with less fuzziness means better performance. As a result, the best clustering is achieved when the value V_{pc} is maximal or V_{pe} is minimal. Disadvantages of V_{pc} and V_{pe} are that they measure only the fuzzy partition and lack a direct connection to the featuring property. Other validity functions based on the feature structure are available.

$$V_{pc} = \frac{\sum_j^N \sum_i^c u_{ij}^2}{N} \tag{8}$$

and

$$V_{pe} = - \frac{\sum_j^N \sum_i^c [u_{ij} \log u_{ij}]}{N} \tag{9}$$

A good clustering result generates samples that are compacted within one cluster and samples that are separated between different clusters. Minimizing V_{xb} is expected to lead to a good clustering.

$$V_{xb} = \frac{-\sum_j^N \sum_i^c u_{ij} \vee x_j - v_i \vee^2}{N * \left(min_{i \neq k} \left\{ \left\| v_k - v_i \right\|^2 \right\} \right)} \tag{10}$$

FAST AND ROBUST FUZZY C-MEANS CLUSTERING ALGORITHMS INCORPORATING LOCAL INFORMATION FOR IMAGE SEGMENTATION[13]

Cai et.al found Fuzzy c-means (FCM) algorithms with spatial constraints (FCM_S) have been proven effective for image segmentation. However, they still have the following disadvantages: (1) although the introduction of local spatial information to the corresponding objective functions enhances their insensitiveness to noise to some extent, they still lack enough robustness to noise and outliers, specially in absence of prior knowledge of the noise; (2) in their objective functions, there exists a crucial parameter α used to balance between robustness to noise and effectiveness of preserving the details of the image, it is selected generally through experience; and (3) the time of segmenting an image is dependent on the image size, and hence the larger the size of the image, the more the segmentation time. In this paper, by incorporating local spatial and gray information together, a novel fast and robust FCM framework for image segmentation, i.e., fast generalized fuzzy c-means (FGFCM) clustering algorithms, is proposed. FGFCM can mitigate the disadvantages of FCM_S and at the same time enhances the clustering performance. Furthermore, FGFCM not only includes many existing algorithms, such as fast FCM and enhanced FCM as its special cases, but also can derive other new algorithms such as FGFCM_S1 and FGFCM_S2 proposed in the rest of this paper. The major characteristics of FGFCM are: (1) to use a new factor S_{ij} as a local (both spatial and gray) similarity measure aiming to guarantee both noise-immunity and detail-preserving for image, and meanwhile remove the empirically-adjusted parameter α ; (2) fast clustering or segmenting image, the segmenting time is only dependent on the number of the gray-levels q rather than the size N(»q) of the image, and consequently its computational complexity is reduced from $O(NcI_1)$ to $O(qcI_2)$, where c is the number of the clusters, I_1 and I_2(< I_1, generally) are the numbers of iterations, respectively, in the standard FCM and our proposed fast segmentation method. The experiments on the synthetic and real-world images show that FGFCM algorithm is effective and efficient.

A MODIFIED FCM ALGORITHM FOR MRI BRAIN IMAGE SEGMENTATION USING BOTH LOCAL AND NON-LOCAL SPATIAL CONSTRAINTS[14]

Wang et.al presented a modified fuzzy c-means (FCM) algorithm for MRI brain image segmentation. In order to reduce the noise effect during segmentation, the proposed method incorporates both the local spatial context and the non-local information into the standard FCM cluster algorithm using a novel dissimilarity index in place of the usual distance metric. The efficiency of the proposed algorithm is demonstrated by extensive segmentation experiments using both simulated and real MR images and by comparison with other state of the art algorithms.

A novel modified FCM algorithm was proposed for overcoming the disadvantages of other methods. Our method incorporates both the local and non-local information into standard FCM clustering. The non-local means algorithm (NL-means) is first proposed by Buades et al. in [15] as an image denoising method. It tries to take advantage of the high degree of redundancy in image. In other words, they assumed that for every pixel in an image, we can find a set of samples with a similar neighbourhood configuration of it. Then the pixel under consideration could be influenced by the weighted averaging over these samples. The experiments show that the NL-means algorithm can deal with the noise of image successfully and geometrical edges in the image can be retained perfectly. However, just as point out in [15], due to the nature of the algorithm, the most favorable case for the NL-means is the textured or periodic case, because these two kinds of images have a large redundancy. For MRI brain images, because of the complicated structures, noise, blur in acquisition and the partial volume effect originating from the low sensor resolution, the images may contain exception, non-repeated details. Such details can be smoothed out by the NL-means algorithm. Especially for some fine tissue structures, there is no pixel with similar configuration could be found in the image or in a fixed “search window”. In order to prevent these details from being removed, the local constraint also should be considered.

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A neighborhood attraction depends on the location and features of neighboring pixels, is shown to improve the segmentation performance. The degree of attraction is optimized by a neural network. However, their method needs execute FCM twice to complete the segmentation. They proposed a novel modified FCM algorithm for overcoming the disadvantages of other methods. Their method incorporated both the local and non-local information into standard FCM clustering. The non-local means algorithm (NL-means) is first proposed by Buades et al. in [15] as an image denoising method. It tries to take advantage of the high degree of redundancy in image. In other words, they assumed that for every pixel in an image, we can find a set of samples with a similar neighborhood configuration of it. Then the pixel under consideration could be influenced by the weighted averaging over these samples. The experiments show that the NL-means algorithm can deal with the noise of image successfully and geometrical edges in the image can be retained perfectly. However, just as point out in [15], due to the nature of the algorithm, the most favorable case for the NL-means is the textured or periodic case, because these two kinds of images have a large redundancy. For MRI brain images, because of the complicated structures, noise, blur in acquisition and the partial volume effect originating from the low sensor resolution, the images may contain exception, non-repeated details. Such details can be smoothed out by the NL-means algorithm. Especially for some fine tissue structures, there is no pixel with similar configuration could be found in the image or in a fixed "search window". In order to prevent these details from being removed, the local constraint also should be considered. The membership value decides the segmentation results, and the membership value is determined by the distance measurement d_2.It can be deduced that the key to segmentation success is this measurement. In our proposed algorithm, the distance measurement influenced by local and non-local information is modified as follows:

$$D2(xj, vi) = (1 - \lambda j)d^2{}_l(xj, vi) + \lambda j d^2{}_{nl}(xj, vi)$$

where d_l stands for the distance measurement influenced by local information, and d_{nl} stands for the distance measurement influenced by non-local information, λ_j with the range from zero to one, is the weighting factor controlling the tradeoff between them.

A FAST AND ROBUST IMAGE SEGMENTATION USING FCM WITH SPATIAL INFORMATION[16]

Xiang et.al presented a novel FCM image segmentation scheme by utilizing local contextual information and the high inter-pixel correlation inherent. Firstly, a local spatial similarity measure model is established, and the initial clustering center and initial membership are determined adaptively based on local spatial similarity measure model. Secondly, the fuzzy membership function is modified according to the high inter-pixel correlation inherent. Finally, the image is segmented by using the modified FCM algorithm. Experimental results showed the proposed method achieves competitive segmentation results compared to other FCM-based methods, and is in general faster.

In the conventional FCM image segmentation algorithm, cluster assignment is based solely on the distribution of pixel attributes in the feature space, and does not take into consideration the spatial distribution of pixels in an image. We present a novel FCM image segmentation scheme by utilizing local contextual information and the high inter-pixel correlation inherent. Firstly, a local spatial similarity measure model is established, and the initial clustering center and initial membership are determined adaptively based on local spatial similarity measure model. Secondly, the fuzzy membership function is modified according to the high inter-pixel correlation inherent. Finally, the image is segmented by using the modified FCM algorithm.

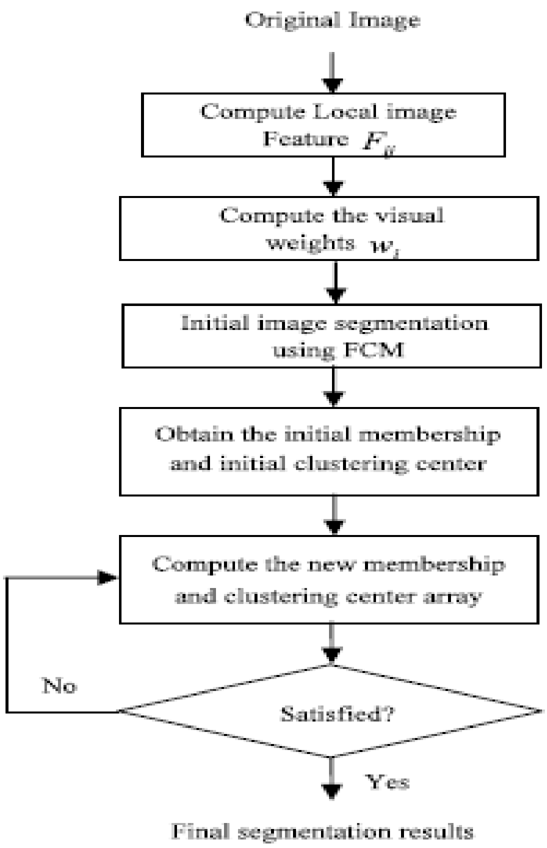

Fig 2: Fast and robust image segmentation using spatial information

The key steps of image segmentation can be described as follows.

1. Set the number of c of the cluster prototypes, initialize randomly those prototypes and set ε > 0 to a very small value. (In this paper, we set c = 2, m = 2, ε = 0.0001.)
2. Compute the local image feature F_{ij} for all neighbor windows over the image.
3. Compute the visual weights w_i for the pixel *i* over the image.

$$w_i = \sum_{j\in\Omega_i} \left(F_{ij} \cdot g(x_j, y_j)\right) \Big/ \sum_{j\in\Omega_i} F_{ij}$$

   where Ω_i represents a square window centered on pixel i in the spatial domain (for example, 5×5). $g(x_j, y_j)$ is gray value of the pixel j, (x_j, y_j) is a spatial coordinate of the pixel $_j$. F_{ij} denotes local image feature.

4. Segment the image using equations in step 3, the membership and clustering center array are obtained after the convergence as initial parameters

$$\mu_k(x_i, y_i) = \frac{(w_i - v_k)^{-2/m-1}}{\sum_{j=0}^{c-1}(w_i - v_j)^{-2/m-1}}$$

$$v_k = \frac{\sum_{i=0}^{q-1} r_i \mu_k(x_i, y_i)^m w_i}{\sum_{i=0}^{q-1} r_i \mu_k(x_i, y_i)^m}$$

   Here, r_i is the number of the pixels having the gray value equal to i, and $\sum_{i=0}^{q-1} r_i$ = M × N.

5. Compute the new membership and clustering center array using Eqs. In step 4 based on initial membership and clustering center results.
6. Repeat Step 5 until the following termination criterion is satisfied $|V_{new} - V_{old}| < \varepsilon$
   Then, the finial segmentation result is obtained.

1.6 IMAGE SEGMENTATION USING SPATIAL INTUITIONISTIC FUZZY C MEANS CLUSTERING[17]

Tripathy et. al proposed the intuitionistic fuzzy c means with spatial information(sIFCM).This was an extension to Chang's work.

The sIFCM algorithm is given as follows:

1. Provide the initial values for the centroids v_i where i =1,…,c
2. Compute the membership function as follows:

   $$u_{ij}=\frac{1}{\sum_{k=1}^{c}\left(\frac{||x_j-v_i||}{||x_j-v_k||}\right)^{\frac{2}{m-1}}}$$

   for all i = 1,…,c and j = 1,…,N
3. Compute the hesitation value as:

   $$\pi_{ij}(x)=1-u_{ij}(x)-(1-u_{ij}(x))/(1+\lambda u_{ij}(x))$$

   for all i = 1,…c , λ >0 and j = 1,…,N
4. Compute the membership function as:

$$\mu'_{ik}=\mu_{ik}+\pi_{ik}$$

   for all i = 1,…c and j = 1,…,N
5. Calculate the spatial function as

   h_{ij} = $\sum_{k\epsilon NB(x_j)} u_{ik}$

   for all i = 1,…c and j = 1,…,N
6. Compute the new membership function which incorporates the spatial function as:

   h_{ij} = $\sum_{k\epsilon NB(x_j)} u_{ik}$

   for all i = 1,…c and j = 1,…,N c
7. Set u_{ij} = u_{ij}" for all j = 1,…,N and i = 1,…c
8. Calculate the new centroids as follows:

$$v_i=\frac{\sum_{j=1}^{N}u_{ij}^{m}x_j}{\sum_{j=1}^{N}u_{ij}^{m}}$$

   for i=1,..,c
9. If $|u_{ij}(new)-u_{ij}(old)| <\in$ then stop, otherwise go to step 2.

They used DB and D indices are used to measure the cluster quality in addition to the evaluation metrics used by Chung et.al[8,9].Speckle noise of mean 0 and variance 0.04 had been induced in the image. FCM, sFCM has been applied to the image. V_{pc} and V_{pe} is calculated.

Two other cluster validity functions used are the Davies-Bouldin (DB) index and the Dunn (D) index. The DB index is defined as the ratio of sum of within-cluster distance to between-cluster distance. It is formulated as given

$$DB=\frac{1}{c}\sum_{i=1}^{c}\max_{k\neq i}\left\{\frac{S(v_i)+S(v_k)}{d(v_i,v_k)}\right\} \quad \text{for } 1<i,k<c \qquad (13)$$

The aim of this index is to minimize the within cluster distance and maximize the between cluster separation. Therefore a good clustering procedure should give value of DB index as low as possible.

Similar to the DB index the D index is used for the identification of clusters that are compact and separated. It is computed by using

$$\mathrm{Dunn} = \min_i \left\{ \min_{k \neq i} \left\{ \frac{d(v_i, v_k)}{\max_l S(v_l)} \right\} \right\}$$
$$\text{for } 1 < k, i, l < c \qquad (14)$$

It aims at maximizing the between-cluster distance and minimizing the within-cluster distance. Hence a greater value for the D index proves to be more efficient[18].

A brain MRI image of dimensions 225x225 was used for proving their results. The number of clusters, c=3. The results of MRI image with speckle noise is shown below.

Fig 3: MRI image- speckle noise

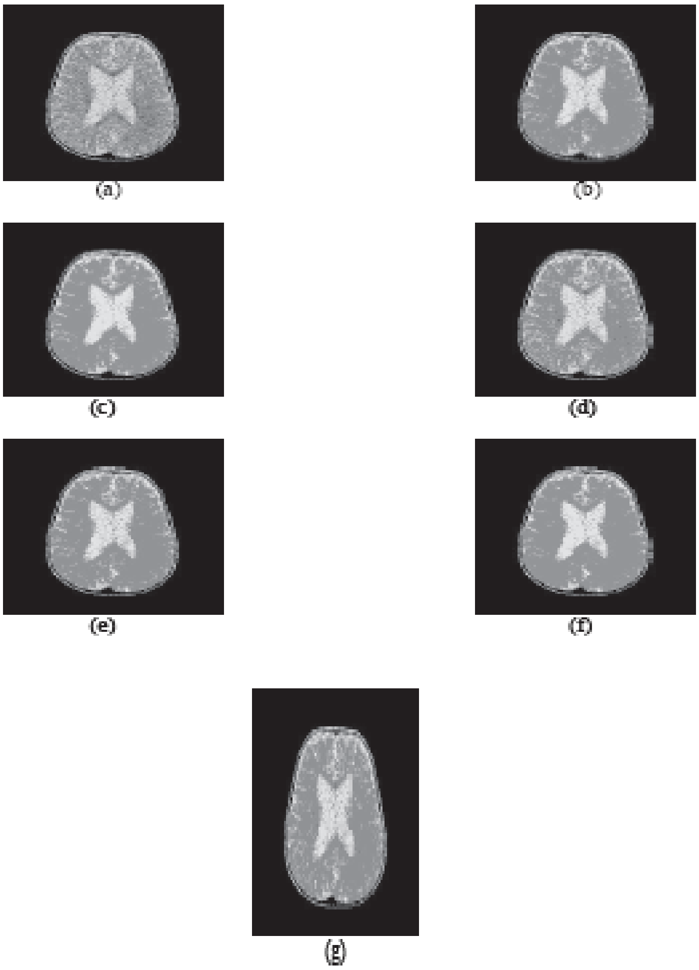

Fig 4: Image segmentation of noisy image. (a) FCM. (b) sFCM1,1. (c) $sFCM_{1,2}$.(d) $sFCM_{2,1}$. (e) $sIFCM_{1,1}$. (f) $sIFCM_{1,2}$. (g) $sIFCM_{2,1}$

TABLE 1: CLUSTER EVALUATION RESULTS ON THE IMAGE WITH SPECKLE NOISE

METHOD	RESULTS ON THE NOISY IMAGE			
	V_{pc}	V_{pe}	DB Index	D Index
FCM	0.6975	2.8195×10^{-4}	0.4517	3.4183
$sFCM_{1,1}$	0.7101	5.9541×10^{-9}	0.4239	3.6734
$sFCM_{2,1}$	0.6922	7.7585×10^{-12}	0.4326	3.4607
$sFCM_{1,2}$	0.6874	4.2711×10^{-12}	0.4412	3.6144
$sIFCM_{1,1}$	0.7077	1.1515×10^{-08}	0.4254	3.6446
$sIFCM_{2,1}$	0.7135	8.1312×10^{-13}	0.4276	3.7472
$sIFCM_{1,2}$	0.713	4.6770×10^{-13}	0.4393	3.4968

In case of the image with speckle noise, the results are more visible. Standard FCM algorithm fails to cluster the image appropriately as spurious blobs and spots contribute to misclassification. Increasing the parameter q, which is the degree of the spatial function, modifies the membership function to accommodate spatial information to a greater degree, and produces better results. The table below shows the performance of the different techniques applied on the noisy image.

Using the sIFCM approach produces even more desirable results. For the noisy image, all sIFCM techniques perform better than the corresponding sFCM counterparts and the standard FCM with the exception of $sIFCM_{1,1}$. These methods reduce the number of spurious spots and blobs and produces a segmented image with a much better homogeneity. Smoother segmentation is achieved by taking a higher value of the parameter q but it may blur some of the finer details. For MRI image induced with speckle noise, $sIFCM_{2,1}$ produces the best cluster validation results. Its DB and D scores are found out to be 0.4276 and 3.7472 respectively whereas the corresponding scores for $sFCM_{2,1}$ are 0.4326 and 3.4607 respectively.

CONCLUSION

The modification of fuzzy c-means to incorporate spatial information has provided a new arena of research. This is near to a paradigm shift in image segmentation where noise is an integral part of it. The various algorithms developed so far has been successful in providing better results than the traditional clustering algorithms. The simple idea of that the neighbourhood pixels also have similar properties has been exploited by researchers for assigning a pixel into a cluster. With the introduction of several other rough and fuzzy based hybrid algorithms, this field puts forth new challenges for researchers.

REFERENCES

[1] Dunn J C, J. (1974). A fuzzy relative of the ISODATA process and its use in detecting compact well-separated clusters. J Cybern, 32-57. 2.

[2] Bezdek J C, J. (1980). A Convergence Theorem for The Fuzzy ISODATA Clustering Algorithm. IEEE PAMI, 1(2), 1-8

[3] Girolami M, J. (2002). Mercer kernel-based clustering in feature space. IEEE Transactions on Neural Networks, 13(3), 780-784.

[4] 4. Shen H, Yang J, Wang S, etal, J. (2006). Attribute weighted Mercer kernel based fuzzy clustering algorithm for general non-spherical datasets. Soft Comput, 10(11), 1061-1073.

[5] Zhang D Q, Chen S C, J. (2003). Clustering incomplete data using kernel-based fuzzy c-means algorithm. Neural Process Lett, 18(3), 155-162.

[6] Zhang Aihua (2004) The Research of Image Segmentation Based on Fuzzy Clustering. PhD thesis, Huazhong University of Science and Technology, Wu Han, China.

[7] Yi Yufeng, Gao Liqun, Guo Li, J. (2012). Similar Class Merging Based FCM for Image Segmentation. Journal of Northeastern University(Natural Science), 33(7), 930-933.

[8] Yang Yue, Guo Shuxu, Ren Ruizhi, J. (2012). Modified kernel-based fuzzy cmeans algorithm with spatial information for image segmentation. Journal of Jilin University (Engineering and Technology Edition), 41(2), 283-287.

[9] Li Yanling, Shen Zhi, J. (2009). Fuzzy C-means algorithm based on the spatial information for image segmentation. J. Huazhong Univ. of Sci. & Tech. (Natural Science Edition), 37(6), 56-59.

[10] Shen Xuanjing, He Yue, Zhang Bo, J. (2012). FCM With Spatial Information and Membership Constrains for Image Segmentation.JOURNAL OF BEJTING UNIVERSITY OF TECHNOLOGY, 38(7), 1073-1078.

[11] Yang, Yong, Chongxun Zheng, and Pan Lin. "Fuzzy clustering with spatial constraints for image thresholding." Optica Applicata 35.4 (2005): 943.

[12] Chuang, Keh-Shih, et al. "Fuzzy c-means clustering with spatial information for image segmentation." computerized medical imaging and graphics 30.1 (2006): 9-15.

[13] Cai, Weiling, Songcan Chen, and Daoqiang Zhang. "Fast and robust fuzzy c-means clustering algorithms incorporating local information for image segmentation." Pattern Recognition 40.3 (2007): 825-838.

[14] Wang, Jianzhong, et al. "A modified FCM algorithm for MRI brain image segmentation using both local and non-local spatial constraints."Computerized medical imaging and graphics 32.8 (2008): 685-698.Buades A, Coll B, Morel J-M. A non-local algorithm for image denoising. In CVPR 2005:60–5.

[15] Wang, Xiang-Yang, and Juan Bu. "A fast and robust image segmentation using FCM with spatial information." Digital Signal Processing 20.4 (2010): 1173-1182

[16] .Tripathy, B. K., Avik Basu, and Sahil Govel. "Image segmentation using spatial intuitionistic fuzzy C means clustering." Computational Intelligence and Computing Research (ICCIC), 2014 IEEE International Conference on. IEEE, 2014.