Comparison Between fuzzy C-Means Clustering (FCM) and geometrically guided condition Fuzzy C-Means clustering (ggc FCM)

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Abstract

This paper compare between the traditional fuzzy C-Means clustering FCM and a proposed technique approach to geometrically guided fuzzy clustering. A modified fuzzy C-Means clustering (FCM), is extended to incorporate a priori geometrical information from spatial domain in order to improve image segmentation. This leads to a new algorithm where the cluster guidance is determined by the membership values on neighboring pixels. The algorithm of FCM is tested on synthetic and real image to demonstrate the improved image segmentation compared to traditional FCM.

KEYWORDS: fuzzy C-means, Geometrically guided condition Fuzzy C-Means clustering, Conditional Fuzzy C-mean clustering, Fuzzy neighborhood, Edge preserving threshold, Defuzzification.

الخلاصة:

المقارنة بين تَجَمُّع التضبيب بواسطة الوسيط C مع التَجَمُّع التضبيب الهندسي الموجه المشرط بواسطة الوسيط C يتم في هذا البحث المقارنة بين تَجَمُّع التضبيب بواسطة الوسيط C (التقليدي) و مع نظرة تقنية مقترحة إلى التَجَمُّع التضبيب الهندسي الموجه المشرط بواسطة الوسيط C. أي ان التجمّعُ التضبيب بواسطة الوسيط C يمكن تطويره ليشمل عملية دمج معلوماتَ هندسيةَ أولية. ضمن المجالِ المكانيِ ليقوم بعملية تُحسّينَ تجزئية الصورةِ. هذا يُؤدّي إلى خوارزمية جديدة بدلا من خوارزمية تَجَمُّع التضبيب بواسطة الوسيط C (التقليدي) يعمل على التوجيه بتحديد المعلومات على شكل عنقودي بواسطة قيم

العضويةَ لنقاطِ الشاشة المتجاورة. إنّ خوارزميةَ تَجَمُّع التضبيب الهندسي الموجه المشرط بواسطة الوسيط C تم اختيارهاُ على الصورةِ الصناعيةِ و الصورة الحقيقيةِ لعَرْض تجزئة الصورةِ المُحسَّنِة بالمقارنة مع تَجَمُّع التضبيب بواسطة الوسيط تقليدي.

1. Introduction

The pattern recognition technique to segment a multivariate image is one of those technique, widely used in multivariate imaging, is fuzzy C-Mean clustering [1]. It is known as an unsupervised fuzzy clustering technique that use raw measurement data in order to reveal the underlying structure of the data and segment the image in regions with similar spectral properties. When FCM applied as a clustering technique in multivariate imaging, the relationship between pixels in the spatial domain is completely ignored. The partitioning of the measurement space depends on the spectral information only. When geometrical information is used during clustering process possible segmentation errors con be corrected during clustering by utilizing the information from spatial domain. Furthermore when two overlapping clusters in the spectral domain correspond to two different object in the spatial domain, usage of a priori spatial information can improve the separate of these two overlapping clusters. An example of multispectral image with overlapping spectral information are images produced by a computer based potato inspection system[1]. The inspection system uses standard 3-CCD color camera's for image capturing[2]. The obtained images are noise and contain overlapping spectra for certain similar colored defects. Without use of additional spatial information, the segmentation producer cannot discriminate between the similar colored potato defects. As a consequence, the classification procedure rejects the potato based on the wrong segmentation results. In order to add spatial information, a modification of the FCM algorithm is necessary because the traditional FCM is not suitable to add a priori information into the clustering process. Many modification and variant of FCM have been presented [2], where FCM is modified to search for s specific structure in the data e,g. lines ellipsoids. However, these algorithms impose a certain structure to the partition that they generate. In cases where spatial information is combined with spectral information, both techniques are used sequentially [3, 4, and 5]. In this paper the application the initial segmentation, which is performed by the spectral based FCM algorithm is followed by a spatial based algorithm which tries to correct the segmentation errors, which the algorithm cannot correct the errors the already presented segmentation results directly. In this paper modification of the unsupervised fuzzy clustering technique used called conditional FCM (c-FCM)[4,5], is utilized to guide the clustering process by an auxiliary variable(condition variable). The C-FCM algorithm uses auxiliary variable to influence the contribution of each object to the final position of the cluster prototype. The value of condition variable for each pixel is determined by the neighboring pixels in the spatial domain. This makes is possible to guide the clustering process based on spatial relationships. After each iteration step of the clustering process in the spectral domain, the condition of each pixel is updated. Influencing the segmentation results takes place during the segmentation process itself and not afterward. The determination of the condition is based on the memberships values of the neighboring pixels in the spatial domain. The Geometrically Guided conditional FCM swaps between the spectral domain and the spatial domain during the clustering process. A priori spatial information such as a certain shape or size of object in an multivariable image can now be used during clustering in order improve the segmentation result.

1. Fuzzy C-means clustering

Give a set of n data patterns, $X = x_1,\ldots\ldots,x_n$, the FCM algorithm minimizes the weighted within group sum of squared error objective function J(U,V) figure 1:

$$J(U,V) = \sum_{K=1}^{n}\sum_{i=1}^{c} (U_{ik})^m \, d^2(x_k,v_j); \qquad (1)$$

where x_k is the k-th p-dimensional data vector, v_j is the prototype of the center of cluster i,u_{jk} is the degree of membership of x_k in the i-th, m is a weighting exponent on each fuzzy membership, mostly m=2 is used[4], $d^2(x_k,v_j)$ is a distance measure between object x_k and cluster v_j, n is the number of object and c is the number of clusters. A solution of the object function J(U,V) can be obtained via an iteration process where the degrees of membership u_{jk} and cluster centers vi are updated via[5]:

$$u_{jk} = \frac{1}{\sum_{j=1}^{c} (d_{jk}/d_{ij})^{2/(m-1)}} \qquad (2)$$

$$\sum^{n}_{k} u^{m}_{jk} x_k = 1 \qquad (3)$$

With the constrains

$$u_{jk \in (0,1)}, \ \sum^{c}_{i=1} u_{ik} \ \forall k, \ 0 < \sum^{n}_{k=1} u_{ik} > N \ \forall \ i$$

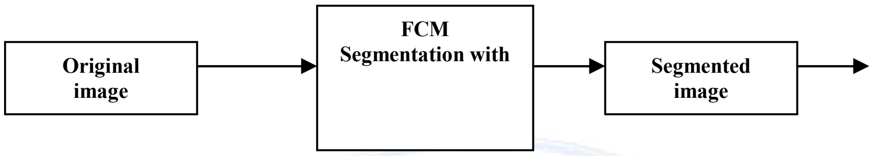

Figure (1): The principle of Conditional FCM

Algorithm(1) Fuzzy C-means Clustering

1. **input, x_k, v_j**
2. **Choose primary cancroids v_j (prototypes)**
3. **Compute the degree of membership of all feature vectors in all the Cluster compute (2)**
4. **Compute new cancroids V:**

$$V = \frac{\sum^{n}_{K=1} (U_{ik})^m x_k}{\sum^{n}_{k=1} (U_{ik})^m}$$

and update the memberships, u_{ik} to $u\hat{}_{ik}$ according goto step 2.

5. **if $\max_{ik} \| u_{ik} - u\hat{}_{ik} \| < l$ stop, otherwise go to step 3.**
6. **output $\max_{ik}$**

Figure (2): The principle of Conditional FCM

3. Conditional Fuzzy C-mean clustering

Clustering is usually seen as an unsupervised routing where no information about the underlying structure of the patterns is known. In cases where clustering is used and some labeled patterns (e.g edges) are available, it might be advantageous to use these labeled patterns to influence the clustering process. This fundamental are used in condition FCM, a FCM based clustering technique where the clustering is guided by an auxiliary variable to guide the outcome of the clustering process. For each labeled pattern X_k, an auxiliary matrix condition f_k exist, where $f_{k\ ranges}$ from (0,1). The update procedure for partition matrix U is now changed into see figure 2:

$$u_{ik} = \frac{f_k}{\sum_{j=1}^{c}(d_{ik}/d_{ij})^{2/m-1}} \qquad (4)$$

With the modified constraint

$$\sum_{i=1}^{c} u_{ik} = f_k \qquad (5)$$

For condition values f_k equal to 1, the partition update procedure is similar to the partition update procedure of the traditional FCM. A small value of the condition results in a low membership value. A low membership value minimizes the contribution of that particular object to the cluster center, if the condition is set to zero, the influence of that object to the procedure is neglected see figure 1. The algorithm of conditional Fuzzy C-mean clustering is the same FCM with addition auxiliary matrix condition f_k exist which $f_{k\ ranges}$ from (0,1) [6].

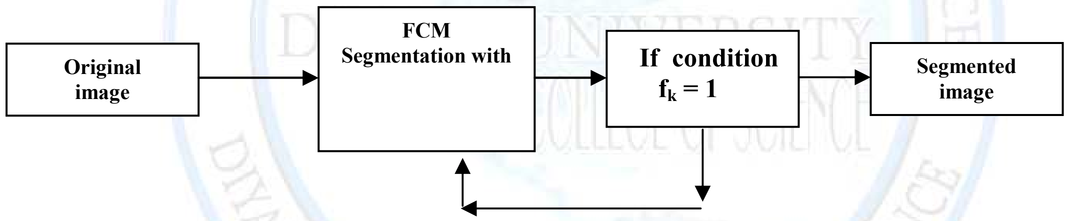

Figure (2): The principle of Conditional FCM

Algorithm(2) Conditional Fuzzy C-means Clustering

1. **input memberships, u_{ik}, f_k**
2. **Choose primary cancroids v_j (prototypes)**
3. **Compute the degree of membership of all feature vectors in all the Cluster**
4. **compute (4)**
5. **Compute new cancroids V:**

$$V = \frac{\sum_{K=1}^{n}(U_{ik})^m x_k}{\sum_{k=1}^{n}(U_{ik})^m}$$

and update the memberships, u_{ik} to $u\hat{}_{ik}$ according goto step 2.

6. **if $\max_{ik} \| u_{ik} - u\hat{}_{ik} \| < l$ go to 5**
7. **if $f_k = 1$ stop otherwise goto 3.**
8. **output f_k, $\max_{ik}$**

4. Geometrically guided condition Fuzzy C-Means clustering(ggc-FCM)

4.1. Principle of ggc-FCM

In case of clustering multivariate images with a traditional FCM algorithm, the spatial relationship between the pixels is not used during clustering. The construction of cluster prototypes is solely based on the distance in measurement space. The rational of ggc-FCM is to use spatial relationship during the construction of the cluster prototype. This means that both the spectral and spatial neighborhood of a pixel determine the contribution of a pixel to a cluster prototype. A spatial neighborhood window *W* around the pixel under consideration compare the majority class of the neighborhood pixel with the class of the pixel under consideration to indicate whether a pixel matches its neighborhood. This comparison is based on membership values and the results in a condition value for the pixel under consideration. The value of the condition indicates the similarity of the pixel compared to surrounding neighbors. The condition is high when surrounding pixels have similar membership values and the condition is low when surrounding pixels have deviate membership values. The condition procedure is not performed for each cluster. Only one cluster of the neighborhood majority has to be considered as this is most likely the cluster where the pixel will be assigned to in the defuzzification process. The cluster neighborhood is called *iMax* cluster and the membership values for this cluster determine the condition. Thus, the ggc-FCM algorithm swaps between the spectral domain and the spatial domain during clustering. To prevent false removal of edge pixels, an edge preserving threshold must be exceeded before the condition process is performed. The procedure to select value to remove spatial outliers and noise pixels, defuzzification procedure uses an *outlier threshold* to remove pixels with a condition value below this *outlier threshold* value see figure (3) [7,8].

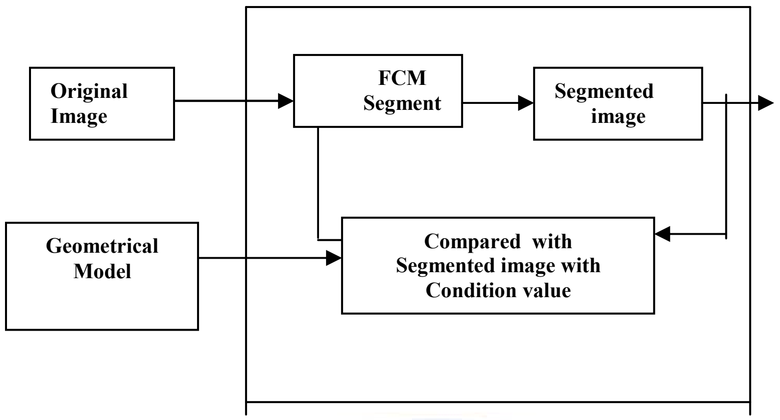

Figure (3): The principle of Conditional ggc-FCM which compared with FCM

4.2 FCM clustering on multivariate images

A multivariate image is a stack of congruent two-dimensional images of a single scene where each image in the stack is measured for a different variable, e.g wavelength. The number of rows (nr) and columns (nc) of the image define the horizontal and vertical dimension of the three-dimensional image stack and the number of variables (p), determines the height of the stack. It is usually necessary for practical reasons to rearrange this three stack of images into a two-dimensional matrix. All two-dimensional images are rearranged into a one-dimensional vector of nr x bc objects, called pixels. These rearranged images measured at p variables are combined to a two-dimensional data matrix Xnrnc,p. This rearranged of matrices is called unfolding and the reverse operation is called back-folding. The number of rows of the partition matrix U is equal to the number of rows of that matrix X. The columns of U are defined by c, the number of cluster. Back-folding a column of the U matrix with length nr x nc result in a two-dimensional image with nr rows and nc columns. The c columns of the partition matrix correspond to c back-folding images. The obtained images are called partition images and are used for the determination of the spatial neighborhood and the condition value of a pixel. Summarizing partition image i is the back-folding column i of partition matrix U and corresponds with cluster i[8].

4.3. Fuzzy neighborhood

The cluster with maximum sum of neighborhood membership values is considered to determine the condition of a pixel (iMax). To determine the majority class of neighborhood pixels, the membership values covered by the neighborhood window *W* are added for each partition image i. The partition image i with the highest sum of membership values within the window *W* is considered as the class the pixel under investigation belongs to. To obtain iMax, a vector sum-u_{rc} , consisting of membership summation within the window *W* for a given position(r,c) in the image is created:

$$\text{sum-}u_{rc} = (\text{ sum-}u_1 ,\ldots\ldots, \text{sum-}u_{c)} \text{ where sum-}u_{i\ r'c'\epsilon W} = \sum u_{r'c',i}\ ; \forall i = 1,\ldots,c \quad (6)$$

and the index of the sum-u_{rc} with the maximum sum-u_i is called iMax:

$$\text{iMax} = i \mid \max(\text{sum-}u_{rc}) \quad (7)$$

Where *W* is a neighborhood window with (odd) size s, $u_{r'c',i}$ is the degree of membership of neighbor pixel at partition (r′,c′) in the window *W* of partition image i. Now that the majority cluster iMax of the spatial neighborhood is know, the mean membership deviation Δm between the pixel under investigation and its neighbor in window *W* of the iMax cluster ifs determined:

$$\Delta m_{rc,iMax} = \frac{1}{s^2 - 1} \sum | u_{rc,iMax} - u_{r'c',iMax} | \quad (8)$$

Where $\Delta m_{rc,iMax}$ is the mean membership deviation for the pixel at position(r,c) of partition image iMax, $u_{rc,iMax}$ is the degree of membership of the center pixel in the window *W* of partition iMax. The final condition for a pixel located at position(r,c) in the center of the window *W* is obtained via multiplication of $\Delta m_{rc,iMax}$ with the membership value $u_{rc,iMax}$ with the membership value $u_{rc,iMax}$ of the pixel at position(r,c).

$$f_{rc} = \Delta m_{rc,iMa}\, u_{rc,iMax} \quad (9)$$

Where f_{rc} is the condition for the pixel at position(r,c). Multiplication of Δm with u_{rc} weakens the condition values in case of low values of u_{rc}. The result of this is that pixels with low membership values, are conditional more strongly than higher membership values[10].

4.4 Edge preserving threshold

Edges may case a false of the mean membership deviation (Δm) if the window *W* is positioned at a transition between two images plans. The membership values of the pixels in the window *W* will deviate as the pixels in the window belong to different classes. As a result, edge pixels receive a low condition value. To prevent this, the procedure as describe above is extended with an extra threshold which must be exceeded before pixels are conditioned. With this extension, it is assumed that the mean membership deviation (Δm) is not caused by edge transition. This edge preserving threshold, further referred to as edge threshold, depends on the size of the window *W*. The edge threshold value is determined as follows:

$$\text{Edge threshold} = \frac{\text{Floor}(s/2)s}{S^2 - 1} \qquad (10)$$

Where s is the odd size of a squirt window *W*. For 3x3 widow, this value is 0.375 only when Δm exceeds the edge threshold value, the condition value is calculated. Pixels with a condition value below this edge threshold value keep their original condition value below the algorithm of Conditional ggc-FCM[11].

Algorithm (3) Conditional ggc-FCM

1. **input variables in Cluster compute Fuzzy C-means Clustering as it Algorithm.**
2. **Compute the degree of membership of all feature vectors in all the Cluster compute (4)**
3. **Compute new cancroids imax and**

$$0 < u_{rc} > 1$$
$$imax = \sum u_{rc} \text{ ; for all } i = 1,\ldots,c$$

and update the memberships, u_{rc} to $u_{r'c'}$,according

3. compute (8)

if $f_k = 1$ stop otherwise goto 4.

4. compute f_{rc} from (9)

5. calculate Edge threshold from (10)

6. if Δm > Edge threshold go to 3
Else go to 2.

7. output f_k, imax.

4.5. Defuzzification

Once the ggc-FCM procedure is stopped, the fuzzy matrix U must be defuzzified to a hard partition matrix to obtain a final classification of the pixels. Usually the procedure of maximum membership is used for the conversion. The procedure maximum membership will assign a class label to all pixels, even the pixels with extreme low condition values. This is undesirable as even spatial outline pixels with low condition values (f_{rc}) would be assigned to a class. Therefore pixels with a condition lower than a predefined threshold value, further referred to as outlier threshold are assigned to the reject class. Pixels assigned to the reject class have no contribution to the final position of any cluster prototype. The reject class is a collection of pixels with condition values below the outlier threshold. The reject class is not an extra class which is used during clustering with the ggc-FCM procedure; it is just an extra class during the defuzzification procedure. This outlier threshold procedure makes it possible to remove spatial value for the outlier threshold.

4.6. Determination of outlier threshold value

To determine the outlier threshold value, the coherence between Δm, u_{rc} and f_{rc} must be understood. According to equation 7, Δm depend on the membership values of neighborhood pixels and the membership value u_{rc} of the pixel under investigation. The range for Δm is [Edge Threshold,1] and the range for u_{rc} is [0,1]. As q=a result, the value for condition f_{rc} ranges from [0, Edge Threshold], according to equation 8. In case of defuzzification, this is also the range for the outlier threshold value. Combination of variables can be excluded beforehand of spatial outlier, which make it easer to select an optimal value for the outlier threshold. Discussed above the iMax cluster is considered which means that for this particular cluster the neighborhood pixels have high membership values. As a consequence of this, a spaial outlier pixel must have a low value for u_{rc} , otherwise a high value for Δm is not possible(equation 7). After all a high value for Δm is required to exceed edge threshold value. The above-mentioned constrain show that an optimal value for the outlier threshold is a combination of Δm and u_{rc} and in rang [0, u_{rc}]. To vrify this the situation as summarized in table 1[11,12].

Table 1:Upper and Lower bounds for Δm and u_{rc}

No.	Δm	u_{rc}	f_{rc}
1	1	0	0
2	Edge Threshold	0	0
3	Edge Threshold	1	Edge Threshold

Situation 1 is typical for spatial outlier, a high value for Δm which indicate the deviation between the center pixel and its neighbor, is accompanied with a low value for u_{rc} which indicate a low cluster membership for the current cluster iMax. Since the resulting f_{rc} value is low, these spatial outlier can be removed with a low value for the outlier Threshold. Situation 2 and 3 indicate that the center pixel is not a convincing spatial outlier(Δm = Edge Threshold), as the center pixel and its neighbor deviate just enough for Δm to exceed the Edge Threshold value, situation 2 is more or less the opposite of situation 1, which describe a typical spatial outlier. This makes situation 2 not likely to occur in case of a spatial outlier. A pixel with $u_{rc} = 1$ as shown in situation 3, is also not a spatial outlier. To explain this, the combination of high neighborhood membership values(due to the iMax cluster) and a high value for u_{rc} already indicates that the pixel is not an outlier. In case of a spatial outlier, a maximum value for $u_{rc} = 0.5$ is expected because it is unlikely that a $\Delta m \geq$ Edge Threshold is accompanied with $u_{rc} > 0.5$ (see equation 7) The value of $u_{rc} = 0.5$ is the turning point where, in case of the iMax cluster, a transition takes place from outlier yo no outlier. Therefore for situation 3, the maximum of u_{rc} is considered as being 0.5 in case of spatial outlier. The corresponding value of the f_{rc} is than a proper value for the outlier threshold.

$$\text{Outlier threshold} = \text{Edge Threshold} * 0.5 \qquad (11)$$

The result of application are shown to verify this value of the outlier threshold.

5. Experiment

In this application will take experiment of removal of spurious pixels in synthetic image, and improvement of the ggc-FCM compared to traditional FCM, experiment have been carried out. The algorithm is tested on synthetic and real multivariate (RGB) images and the result are compared with the of the traditional FCM. In all experiment the fuzzy partition is converted to a crisp partition by applying the procedure of maximum membership. In case of ggc-FCM this procedure is extended with the outlier threshold.

The artificial image (140x70 pixels) consist of two squares of similar color (R=150,G=50,B=50) on different background color(R=125,G=75,B=50). To verify that the outcome of the clustering result is not influenced by unequal cluster sizes, which is a know pitfall of FCM the amount of foreground pixels (5000) is in balance with the amount of background pixels(4940). The image is contaminated with Gaussian noise to simulate cluster overlap. The standard deviation of the noise varied in range from $\mu=0,\sigma=0$ to $\mu=0,\sigma=15$, resulting in 16 experiments in which the outcome of the traditional FCM was compared with ggc-FCM. For both FCM and ggc-FCM, the number of cluster(c) is set to 2 and the Euclidian distance measure is used. In case of ggc-FCM a 3x3 window contains the a priori spatial knowledge of spurious single pixels. The outlier threshold is set to $0.375*0.5 = 0.1875$. The number of rejected and misclassified pixels are counted and the results are shown in table (2) and table (3). figures (4) and figures (5) show the corresponding segmented images.

6. The Result

Multivariate image with FCM algorithm the spatial information is not used during clustering. The graph in figure 4 shows the partitioning of the measurement space with traditional FCM algorithm. The graph shows that the foreground cluster and the background cluster are identified easily. However if the segmented image is considered the foreground object are contaminated with background pixels and vice versa. Due to the added noise, background pixels have shifted to the foreground cluster and foreground pixels have shifted to the background cluster. As the traditional FCM uses no information from the spatial domain, this result is to be expected. Table 2 summarizes the clustering results with standard FCM for 16 different noise levels. None of the pixels are rejected during standard FCM clustering. The #FALSE column indicates the number of misclassified pixels. The table shows that the number of misclassification increases when the noise variance increases due to be increasing cluster overlap.

Table 2: Clustering results for FCM algorithm of 16 measurement at different noise levels

No.	Noise variance	#foreground pixels	#reject	#FALSE	#background	#reject	#reject
1	0	5000	0	0	4940	0	0
2	1	5000	0	0	4940	0	0
3	2	5000	0	0	4940	0	0
4	3	5000	0	0	4940	0	0
5	4	5000	0	0	4940	0	0
6	5	4999	0	1	4939	0	1
7	6	4993	0	7	4935	0	5
8	7	4972	0	28	4916	0	24
9	8	4934	0	66	4873	0	67
10	9	4879	0	121	4838	0	102
11	10	4794	0	206	4765	0	175
12	11	4704	0	296	4685	0	255
13	12	4628	0	372	4595	0	345
14	13	4555	0	445	4511	0	429
15	14	4458	0	542	4450	0	490
16	15	4377	0	623	4344	0	596

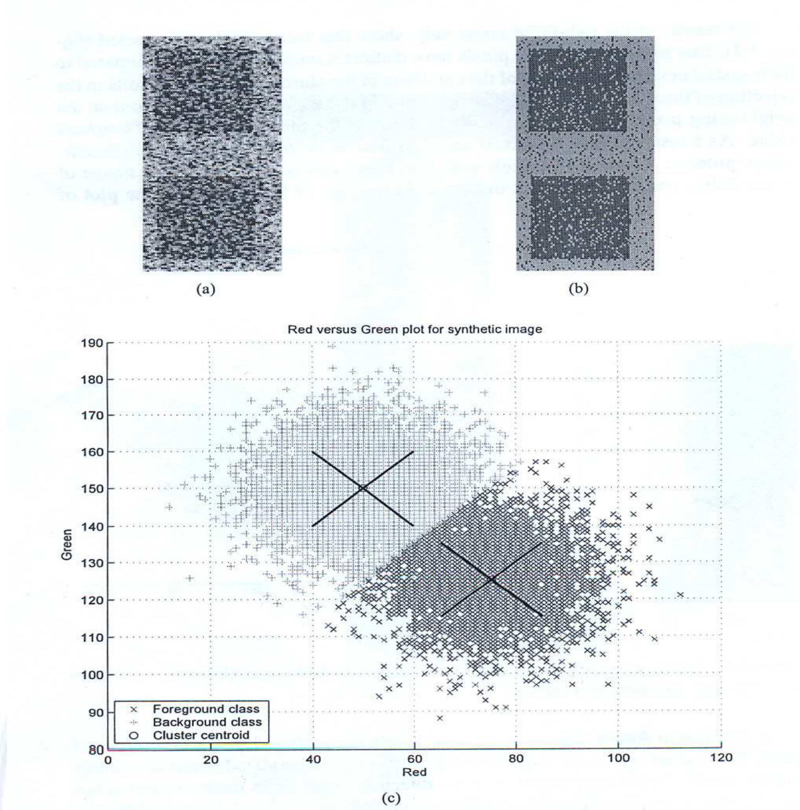

Figure 4: Results of traditional FCM (a)Original image contaminated with Gaussian noise(μ=0,σ=10);(b) segmented image;(c) Red versus green plot colore, cross hair represents the center of a cluster.

The result of the ggc-FCM model conversely, show that some pixels are rejected (figure 5). Due to the noise, these pixels have distinct membership values compared to their spatial neighbor. The use of the condition in the clustering process result in the rejection of these isolated pixels. The condition of those pixels, which is based on the neighboring pixels in the spatial domain., is below the predefined outlier threshold value. As a result of this, the are classified to the reject class in de defuzzification process. The rejected pixels appear as black pixels in the classified image of figure 5(a) and as small black diamonds in the plot figure 5(b). The plot of figure 5(b) also shows that these rejected pixels are scattered in the measurement space. The segmented image in figure5(a) shows that the rejected pixels are mostly isolated pixels. This demonstrates that the rejection of pixels in measurement space is solely determined by the geometrically based condition. Table 3 summarizes the clustering results with ggc-FCM for 16 different noise levels. Due to the increasing cluster overlap, the number of rejected pixels and the number of misclassifications increasing when the noise variance increases. Comparing the results of traditional FCM in table 2 and the results of ggc-FCM in the table 3 shows that clustering with ggc-FCM results in less misclassified. Table 3 also shows that ggc-FCM rejects pixels even when no or little noise added to the image. The number of rejected pixels matches with number of foreground corners. The 4 corners pixels of the two squares are rejected. To prevent this, a higher edge threshold value must be chosen. However the consequence of a higher edge threshold is that less misclassified pixels will be detected as they will not exceed the edge threshold. In this particular, the number of rejected corner pixels is far less than the number of missed misclassified pixels would be.

Table3: Clustering results for ggc-FCM of 16 measurement at different noise levels

No.	Noise variance	#foreground pixels	#reject	#FALSE	#background	#reject	#reject
1	0	4992	8	0	4940	0	0
2	1	4992	8	0	4940	0	0
3	2	4992	8	0	4940	0	0
4	3	4992	8	0	4940	0	0
5	4	4992	8	0	4940	0	0
6	5	4991	8	1	4939	0	1
7	6	4982	10	5	4933	5	2
8	7	4961	31	8	4914	16	10
9	8	4922	57	21	4860	61	19
10	9	4863	100	37	4829	74	37
11	10	4776	163	61	4751	144	45
12	11	4676	219	105	4668	196	76
13	12	4606	251	143	4565	244	131
14	13	4528	299	173	4488	267	185
15	14	4430	330	240	4425	333	182
16	15	4346	379	275	4318	357	265

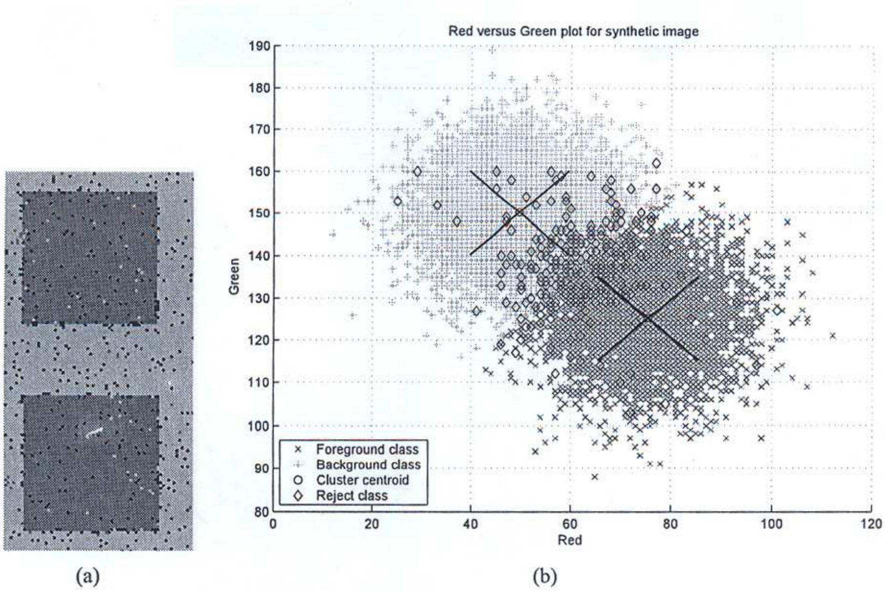

Figure 5: Results of gge-FCM. (a) segmented image; (b) Red versus Green, the cross hair represents the center of a cluster.

7. Conclusion

This paper shows the traditional FCM applied as a clustering technique in multivariate imaging, the relationship between pixels in the spatial domain is completely ignored and the partitioning of the measurement space depends on the spectral information only. The use of ggc-FCM clustering as a multivariate image segmentation process clearly shows improvement above clustering with traditional FCM. The addition of a priori information from the spatial domain makes it possible to intervene in the clustering process and guide the clustering. A window of variable size is sufficient to store a priori spatial information about spurious pixels or small objects. The optimal value for outlier threshold can be determined. As a result no additional parameters setting are required for ggc-FCM compared to traditional FCM The result of the ggc-FCM conversely, show that some pixels are rejected, due to the noise which are classified to the reject class in de defuzzification process, these pixels have distinct membership values compared to their spatial neighbor, where in FCM pixels are no rejected.

12. Reference

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