An Efficient Algorithm for Segmentation Using Fuzzy Local Information C-Means Clustering

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ABSTRACT - In this paper there is a variation of fuzzy c-means (FCM) algorithm is presented that provides image clustering. The proposed algorithm incorporates local spatial information and gray level information in a novel fuzzy way. The new algorithm is called fuzzy local information C-Means (FLICM). By using this algorithm we can overcome the disadvantages of the previous algorithms and at the same time enhances the clustering performance. The major characteristic of this FLICM is the use of a fuzzy local (both spatial and gray level) similarity measure, aiming to guarantee noise insensitiveness and image detail preservation. Furthermore, the proposed algorithm is fully free of the empirically adjusted parameters (a, λ_g, λ_s, etc.). Experiments performed on some synthetic and real images shows that this algorithm is effective and efficient, providing high robustness to noisy images.

Index Terms- Clustering, Fuzzy C-means, Fuzzy constraints, gray level constraints, image segmentation, and spatial constraints.

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I. INTRODUCTION

Image Segmentation is one of the first and most important tasks in image analysis and computer vision. In the literature, various methods have been proposed for object segmentation and feature extraction, described in references. However, the design of robust and efficient segmentation algorithms is still a very challenging research topic, due to the variety and complexity of images. Image segmentation is defined as the partitioning of an image into non-overlapped, consistent regions which are homogeneous in respect to some characteristics such as intensity, color, tone, texture, etc. The image segmentation can be divided into four categories: thresholding, clustering, edge detection and region extraction. In this paper, a clustering method for image segmentation will be considered.

Clustering is a process for classifying objects or patterns in such a way that samples of the same cluster are more similar to one another than samples belonging to different clusters. There are two main clustering strategies: the hard clustering scheme and the fuzzy clustering scheme. The conventional hard clustering methods classify each point of the data set just to one cluster. As a consequence, the results are often very crisp, i.e., in image clustering each pixel of the image belongs just to one cluster. However, in many real situations, issues such as limited spatial resolution, poor contrast, overlapping intensities, noise and intensity in homogeneities reduce the effectiveness of hard (crisp) clustering methods.

Fuzzy set theory [3] has introduced the idea of partial membership, described by a membership function. Fuzzy clustering, as a soft segmentation method, has been widely studied and successfully applied in image clustering and segmentation [4]-[9]. Among the fuzzy clustering methods, fuzzy c-means (FCM) algorithm is the most popular method used in image segmentation because it has robust characteristics for ambiguity and can retain much more information than hard segmentation methods [11]. Although the conventional FCM algorithm works well on most noise-free images, it is very sensitive to noise and other imaging artifacts, since it does not consider any information about spatial context.

To compensate this drawback of FCM, a preprocessing image smoothing step has been proposed. However, by using smoothing filters important image details can be lost, especially boundaries or edges. Moreover, there is no way to control the trade-off between smoothing and clustering. Thus, many researchers have incorporated local spatial information into the original FCM algorithm to improve the performance of image segmentation [5], [11], [14].

Fuzzy Local Information C-Means (FLICM) Clustering Algorithm
Motivated by individual strengths of FCM_S1, FCM_S2, EnFCM, and FGFCM and its variations, we propose, in this paper, a novel and robust FCM framework for image clustering called Fuzzy Local Information C-means (FLICM) clustering algorithm.

A. *Introducing the Fuzzy Factor*
All the methods described in the previous Section have yielded effective clustering results for images [12], [13], and [16], but still have some disadvantages.
1) Although the introduction of local spatial information enhances their insensitiveness to noise to some extent, they still lack enough robustness [18]-[20] to noise and outliers, especially in absence of prior knowledge of the noise.

2) There is a crucial parameter a (or) in their objective functions, used to balance between robustness to noise and effectiveness of preserving the details of the image. Generally, its selection has to be made by experience or trial and error experiments.

3) They are all applied on a static image, which has to be computed in advance. Details of the original image could be lost depending on the method used to generate the new image.

In order to overcome the above mentioned disadvantages a new factor in FCM objective function is needed. The new factor should have some special characteristics:

• To incorporate local spatial and local gray level information in a fuzzy way in order to preserve robustness and noise insensitiveness;

• To control the influence of the neighborhood pixels depending on their distance from the central pixel.

• To use the original image avoiding preprocessing steps that could cause detail missing.

• To be free of any parameter selection.

So, we introduce the novel fuzzy factor G_{ki} defined as

$$G_{ki} = \sum_{\substack{j \in N_i \\ i \neq j}} \frac{1}{d_{ij}+1} (1 - u_{kj})^m \|x_j - v_k\|^2$$

(1)

Where, the ith pixel is the center of the local window (for example, 3x 3), K is the reference cluster and the i th pixel belongs in the set of the neighbors falling into a window around the ith pixel. (Ni). $d_{i,j}$ is the spatial Euclidean distance between pixels i and j ,u_{kj} is the degree of membership of the jth pixel in the kth cluster, m is the weighting exponent on each fuzzy membership, u_k and is the prototype of the center of cluster .It is easy to see that the factor G_{ki} is completely free of using any parameter that controls the balance between the image noise and the image details. The control of this balance is automatically achieved by the definition of the fuzziness of each image pixel (both spatial and gray level). Also, by using, d_{ij} the factor G_{ki} makes the influence of the pixels within the local window, to change flexibly according to their distance from the central pixel. Thus, more local spatial information can be used. It is worth indicating that the shape of the local window used in our experiments is square, but also, windows with other shapes such as diamond or circle can easily be adapted to the algorithm. As a whole, G_{ki} reflects the damping extent of the neighbors with the spatial distances from the central pixel. In contrast, the parameter a(or λ) in FCM_S, EnFCM, FGFCM, and their variants, is globally taken as a constant and, thus, it is relatively difficult to vary adaptively with different spatial locations or distances from the central pixel. Moreover, there is no need of preprocessing steps to apply the algorithm, as it will be shown in the following. The important role of G_{ki} during the application of the algorithm will also be shown in the following subsection.

B. General Framework of FLICM

By using the definition of G_{ki}, we now propose a robust FCM framework for image clustering, named Fuzzy Local Information C-Means (FLICM) clustering algorithm. It incorporates local spatial u_{ki} and v_k gray level information into its objective function, defined in terms of

$$J_m = \sum_{i=1}^{N} \sum_{k=1}^{c} \left[u_{ki}^m \|x_i - v_k\|^2 + G_{ki} \right].$$

(2)

The two necessary conditions for J_m to be at its local minimal extreme, with respect to u_{kj} and v_k are obtained as follows:

$$u_{ki} = \frac{1}{\sum_{j=1}^{c} \left(\frac{\|x_i - v_k\|^2 + G_{ki}}{\|x_i - v_j\|^2 + G_{ji}} \right)^{1/m-1}}$$

$$v_k = \frac{\sum_{i=1}^{N} u_{ki}^m x_i}{\sum_{i=1}^{N} u_{ki}^m}.$$

(3,4)

Thus, the FLICM algorithm is given as follows.

Step 1. Set the number C of the cluster prototypes, fuzzification parameter m and the stopping condition.

Step 2. Initialize randomly the fuzzy partition matrix.

Step 3. Set the loop counter $b = 0$

Step 4. Calculate the cluster prototypes using (4).

Step 5. Compute membership values using (3).

Step 6. If $max \{U^{(b)} - U^{(b+1)}\} < \xi$, Then stop, otherwise, set $b = b+1$ and go to step 4.

When the algorithm has converged, a defuzzification process takes place in order to convert the fuzzy partition matrix U to a crisp partition. The maximum membership procedure is the most important method that has been developed to defuzzify the partition matrix. This procedure assigns the pixel to the class C with the highest membership.

$$C_i = \arg_k \{\max\{u_{ki}\}\}, \quad k = 1, 2, \ldots, c.$$

(4)

It is used to convert the fuzzy image achieved by the proposed algorithm to the crisp segmented image. The measure used in the FLICM objective function is still the Euclidean metric as in FCM, which is computationally simple. Moreover, differently from FCM, FLICM is robust because of the introduction of the factor G_{ki} which can be analyzed as follows.

The noise tolerance and outliers resistance property, completely relies on the definition of G_{ki} as it is seen is automatically determined rather than artificially set, even in the absence of any prior noise knowledge. Two basic cases which describe the performance of the algorithm when outliers are present in the window will be presented in the following. As it will be shown the G_{ki} of the noise-corrupted pixels within a window will be kept to similar value to the central pixel ignoring the influence of the noise. The G_{ki} value will adaptively change in every

iteration, converging to the central pixel's value and thus preserving the insensitiveness to noise and outliers.

• Case 1: The central pixel is not a noise and some pixels within its local window may be corrupted by noise. An example illustrated in Fig. 1 depicts this situation, in which a 3 X 3 window was used. This window was extracted from the noisy image (marked with a rectangle) shown on the left of the top row of the Fig. 1. It is clearly shown that after five iterations the algorithm converges and the cor- responding membership values of the noisy, as well as of the no-noisy pixels converge to a similar value, ignoring the noisy pixels Fig. 1(a)–1(d)]. The neighboring pixels, where their corresponding windows are intercovered, are examined as well. Generally, in such cases, the gray level values of the noisy pixels are far different from the other pixels within the window, and thus the factor G_{ki} balances their membership values. Therefore, the combination of the spatial and the gray level constraints incorporated in the G_{ki} suppress the influence of the noisy pixels, and, hence, the algorithm becomes more robust to outliers.

• Case 2: The central pixel is corrupted by noise, while the other pixels within its local window are homogenous, not corrupted by noise. Such an example is clearly demonstrated in Fig. 2. Again a 3 X 3 window was used, which was extracted from the noisy image (marked with a rectangle) shown on the left of the top row of the Fig. 2. It is shown that after five iterations the membership value of the noisy (central) pixel converges to a similar to neighboring pixels membership value, ignoring in this way the potential influence by noise, as shown in Fig. 2(d). Generally, in such cases the factor G_{ki} balances the membership value of the central pixel taking into account the spatial, as well as the gray level of the no-noisy neighboring pixels in a fuzzy manner. Thus, the proposed method becomes more robust to outliers, since the membership value of the central pixel is not influenced by noise. The above two examples just give some intuitive illustrations about the robustness of our algorithm. The enhancement of its robustness to noise and outliers is based on the incorporation of the G_{ki} with fuzzy spatial and gray level localities constraints (18).

Another issue that is worth to point out is the denoising potential of the proposed method in comparison to other methods. FCM_S1 uses a mean-type filtering, so it is relatively suitable for noisy images corrupted by Gaussian noise, whilst FCM_S2 uses a median-type filtering, and as a consequence, it is relatively suitable for images corrupted by impulsive noise. Also, in both cases, the final effectiveness of ignoring the noise in clustering relies on the value of the parameter. Thus, it is generally hard to choose the proper method (FCM_S1 or FCM_S2) and the optimal parameter for good clustering results. On the other hand, FGFCM is independent of the noise type, but its clustering results depend also on parameter.

Parameter has a relatively small value range, and one can reach more easily than FCM_S1 and FCM_S2 the correct parameter. But its selection still needs experience or usage of the trial-and-error method. Compared with FCM_S1, FCM_S2 or FGFCM, FLICM is independent of the type of the noise and completely free of any parameter selection or use. Its denoising performance is shown in the experimental results section.

The factor G_{ki} also seems to preserve more image information. It incorporates both local spatial and gray level relationship the local spatial relationship changes adaptively according to spatial distances from the central pixel. The local gray level relationship not only varies automatically according to different gray level difference between the pixels over an image, but also is dependent on their fuzzy membership values. Thus, the value of G_{ki} varies from pixel to pixel, as well as from iteration to iteration within a neighborhood window, which likely preserves more information than using the same values for each pixel and iteration. Therefore, FLICM adopting G_{ki} seems able to preserve more image details than the other methods. The major characteristics of the FLICM are summarized below:
• It provides noise-immunity.
• It preserves image details.
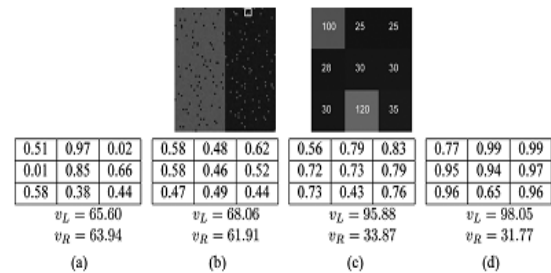• It is free of any parameter selection.

Fig. 1. 3 X 3 window with noise (marked with a rectangle in the initial image), their corresponding membership values and the cluster centers (v_L and v_R). (a) The initial membership values, (b) after one iteration, (c) after three iterations, (d) after five iterations.
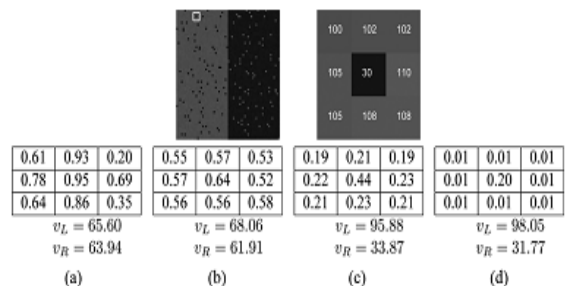

Fig. 2. 3 X 3 window with noise (marked with a rectangle in the initial image), their corresponding membership values and the cluster centers (v_L and v_R). (a) The initial membership values, (b) after one iteration, (c) after three iterations, (d) after five iterations.

IV. EXPERIMENTAL RESULTS

In this section, we show the performance of the proposed method by presenting numerical results and examples on various synthetic and real images, with different types of noise and characteristics. Furthermore, we compare the efficiency and the robustness of FLICM with six fuzzy algorithms FCM_S1, FCM_S2, EnFCM, FGFCM_S1, FGFCM_S2, FGFCM, and two well-known non fuzzy algorithms, k-means [21] and hierarchical clustering based on the SLINK algorithm [22]. The denoising performances of the above nine algorithms were compared with respect to the optimal segmentation accuracy (SA), where SA is defined as the sum of the correctly classified pixels divided by the sum of the total number of pixels [9]

$$SA = \sum_{i=1}^{c} \frac{A_i \cap C_i}{\sum_{j=1}^{c} C_j} \qquad (5)$$

Where c is the number of clusters represents the set of pixels belonging to the ith class found by the algorithm, while C_i represents the set of pixels belonging to the ith class in the reference segmented image.

In our numerical experiments, we generally choose the parameters to be λs =3, ε =0.00001 and N_R= 8 (a 3 X 3 window centered on each pixel, except the central pixel itself) [16]. First, we apply these algorithms to a synthetic test image (Fig. 3(a): 128 X 128 pixels, two classes with two gray level values taken as 20 and 120) corrupted by different levels of Gaussian, Uniform and Salt & Pepper noise, respectively. The number of clusters is set equal to c =2. Also, parameter λg is set equal to λg = 6.0 for FGFCM and its variants (obtained by searching the interval of [0.5, 6] with respect to SA). The parameter a is chosen equal to a = 4.2 in all the algorithms FCM_S1, FCM_S2 and EnFCM [12], which is obtained by seeking the interval [0.2, 8]. Fig. 3 illustrates the clustering results of a corrupted by gaussian noise (20%) image. FGFCM_S1 [Fig. 3(f)], FGFCM_S2 [Fig. 3(g)], FGFCM [Fig. 3(h)], k-means [Fig. 3(i)], and SLINK [Fig. 3(k)] are respectively affected by the noise to different extents, which indicates that these algorithms lack enough robustness to the gaussian noise. Visually, FCM_S1 [Fig. 3(c)], FCM_S2 [Fig. 3(d)], and EnFCM [Fig. 3(e)] remove most of the noise, but still their results are not satisfactory enough. On the other hand, FLICM [Fig. 3(k)] removes almost all the added noise achieving satisfactory results, fact that is verified by the segmentation accuracy (SA) results shown in Table I.

Table I gives the average segmentation accuracy results of the nine algorithms on the specific synthetic image corrupted respectively by different noises with different levels. Each experiment has been performed using five different random initializations and the typical one has been assumed as the result. performance than FCM_S type, EnFCM, FGFCMs, and non fuzzy algorithms, presenting robustness to all considered kind of noises against to the other eight algorithms.
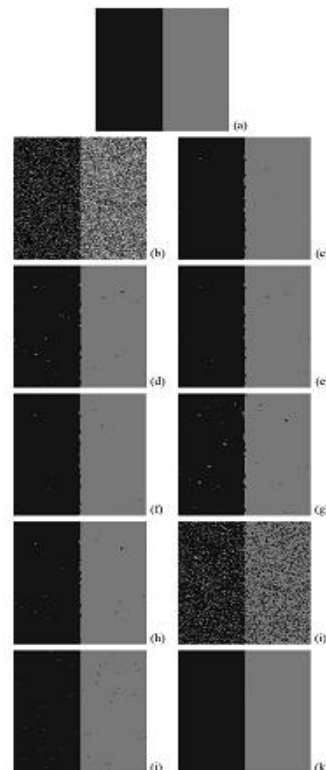

Fig. 3. Clustering of a synthetic image. (a) Original image, (b) the same image with gaussian noise (20%), (c) FCM_S1 result, (d) FCM_S2 result, (e) EnFCM result, (f) FGFCM_S1 result, (g) FGFCM_S2 result, (h) FGFCM result, (i) k-means result, (j) SLINK result, and (k) FLICM result.

TABLE I
Segmentation Accuracy (SA %) of nine algorithms on synthetic images.

	Gaussian			Uniform			Salt & Pepper		
	8 %	10 %	15 %	8 %	10 %	15 %	8 %	10 %	15 %
FCM_S1	99.28	98.34	97.21	99.98	99.49	96.54	99.60	99.45	99.10
FCM_S2	99.71	99.34	98.04	99.98	99.76	95.67	99.62	99.53	99.46
EnFCM	99.30	98.36	97.25	**99.99**	99.52	96.26	99.60	99.45	99.10

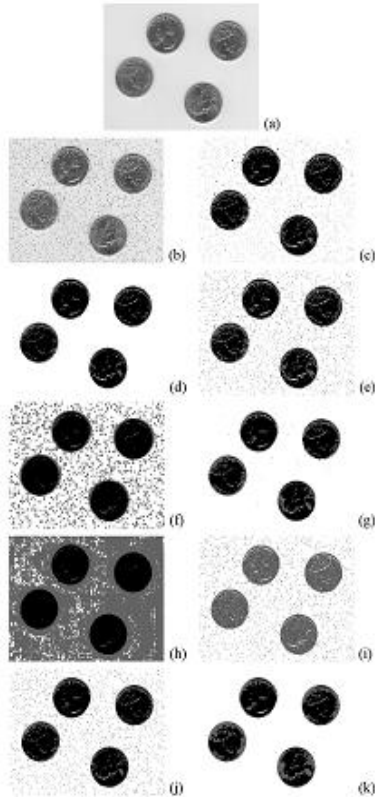| FGFCM_S1	97.58	97.51	97.04	97.65	97.61	96.41	97.66	97.51	97.34
FGFCM_S2	99.81	99.43	97.72	99.92	99.78	94.25	74.90	74.89	74.88
FGFCM	98.62	98.48	97.60	98.68	98.56	95.92	88.12	86.69	83.33
k-means	92.08	88.96	79.93	82.88	81.55	80.01	92.82	92.78	91.31
SLINK	99.77	99.22	98.49	81.92	68.05	57.92	99.29	99.17	98.68
FLICM	**99.89**	**99.64**	**98.95**	99.98	**99.89**	**98.74**	**99.9.3**	**99.91**	**99.90**

Fig. 4. Clustering of a synthetic image. (a) Original image, (b) the same image with gaussian noise (30%), (c) FCM_S1 result, (d) FCM_S2 result, (e) EnFCM result, (f) FGFCM_S1 result, (g) FGFCM_S2 result, (h) FGFCM result, (i) k-means result, (j) SLINK result, and (k) FLICM result.

TABLE II
Comparison Scores (R %) of nine algorithms on various images.

	Gaussian	Uniform	Salt & Pepper
FCM_S1	85.09	92.54	80.68
FCM_S2	86.50	93.12	80.05
EnFCM	86.72	92.37	80.77
FGFCM_S1	84.71	83.90	77.82
FGFCM_S2	85.19	83.33	73.09
FGFCM	86.01	63.07	64.32
k-means	76.56	79.08	67.96
SLINK	84.10	83.83	79.05
FLICM	87.94	95.18	83.58

Furthermore, we apply the nine clustering algorithms to the real image eight [23] [Fig. 4(a)], contaminated with salt & pepper [Fig. 4(b)]. The clustering results are shown in Fig. 4(c)–4(k). The parameters selected for this experiment are c = 3, a = 1.8 and λg = 6.0. It is clearly illustrated in Fig. 4(c)–4(j) that FCM_S1, FCM_S2, EnFCM, FGFCM, and its variants and the two non fuzzy algorithms, are all influenced by the noise to different extents, which indicates that these algorithms lack enough robustness to the salt & pepper noise, while the proposed method FLICM [Fig. 4(k)] can basically eliminate the effect of the noise. It is also worth noting that the selection of the parameters *a* and λ has been performed by trial-and-error method selecting those with the smallest optimal segmentation accuracy (SA) error.

Besides, we also applied the same nine algorithms on the same image (eight [23]), as well as on a number of other images (e.g., Figs. 3–5). All the test images were corrupted by Gaussian, Uniform and Salt & Pepper noise at different levels: 3%, 5%, 8%, 10% to 35% with step 5%. Parameters for FCM_S1, FCM_S2 and EnFCM, as well as parameter λg for FGFCM and its variants were selected by performing the trial-and-error method and

Choosing those that maximizing the quantitative index shown in (23). These results (Table II) can lead us to the conclusion drawn from the experimental results on the synthetic image. Each experiment has been performed using five different random initializations and the typical one has been assumed as the result.

Table II illustrates the clustering comparison of the nine algorithms calculating their scores using the following quantitative index [16], [24]:

$$r = \sum_{i=1}^{c} \frac{A_i \cap C_i}{A_i \cup C_i} \qquad (6)$$

Where, C is the number of clusters, A_i represents the set of pixels belonging to the *i*th class found by the algorithm, while C_i represents the set of pixels belonging to the *i*th class in the reference segmented image. Index r is in fact a fuzzy similarity measure, indicating the degree of equality between A_i and C_i, and the larger the r is, the better the clustering is. Furthermore, Fig. 6 shows some clustering results on real images [25]. The left column shows the initial images, while the right column depicts the clustering results as they were obtained by the proposed algorithm.

The algorithm has been applied to each image using five different random initialization and every time the result was the same, that is, the one presented in Fig. 6. Figs. 3–6 and Table II illustrate that FLICM outperforms the other eight algorithms, which can attribute that the introduction of factor G_{ki} guarantees relative insensitivity both to noise and outliers.

Finally, Fig.5 illustrates the average computational cost for each of the nine algorithms compared above. Each image size has been tested to five different images with random initializations and the cluster number varying from 2 to 5. The methods in the figure are presented in computational time descending order. The quickest method is FGFCM_S1, while the slowest is the SLINK. The proposed method is quite computational consuming, but this drawback is compensated for its very good performance as it was shown above. Furthermore, the proposed algorithm is easily programmed, since it does not contain any complicated programming part. All experiments were performed on a Pentium IV (3 GHz) workstation under Windows XP Professional without any particular code optimization.
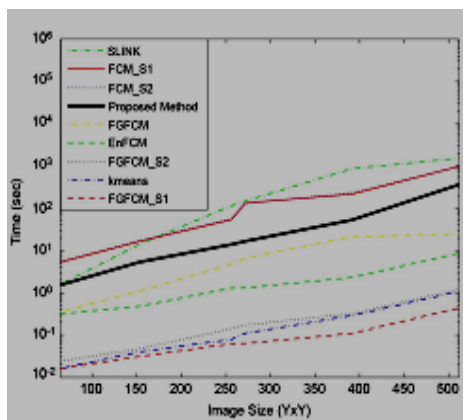

Fig. 5. Computational cost (in seconds) of nine clustering algorithms.

Since, the computational cost above presented is heavily influenced by the programming style, we also present a quick complexity analysis for all the tested algorithms. Taking into account the time complexity of the original FCM, which is $O(nc)$ is the histogram's length and is the number of clusters), it is easily deduced that the total complexity of all FCM variations have the same complexity with a small variation depending on the preprocessing step each algorithm uses. On the other hand, the SLINK method has a complexity of $O(n^2)$, while the complexity for algorithms FCM_S1, FCM_S2 and the proposed one is $O(HWc)$, where H and W are the dimensions of the image under consideration.

V. CONCLUSION

In this project, a novel robust fuzzy local information c-means (FLICM) algorithm for image clustering was introduced. The proposed algorithm can detect the clusters of an image overcoming the disadvantages of the known FCM algorithms and their variants. This is achieved by incorporating local spatial and gray level information. The FLICM introduces a new factor G_{ki} as a local (spatial and gray) similarity measure which aims to guarantee robustness both to noise and outliers. Also, the algorithm is relatively independent of the type of the added noise, and as a consequence, in the absence of prior knowledge of the noise, FLICM is the best choice for clustering. This is also en- forced by the way that spatial and gray level image information are combined in the algorithm; the factor combines in a fuzzy manner the spatial and gray level information, rendering the algorithm more robust to all kind of noises, as well as to outliers. Furthermore, all the other fuzzy c-means algorithms for image clustering exploit, in their objective functions, a crucial parameter a (or λ), which is used to balance the robustness and effectiveness of ignoring the added noise. This parameter is mainly determined empirically or using the trial-and-error method. The FLICM is completely free of any parameter determination, while the balance between the noise and image details is automatically achieved by the fuzzy local constraints, enhancing concurrently the clustering performance.

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