# A Robust Fuzzy Local Information C-Means Clustering Algorithm

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***Abstract*—This paper presents a variation of fuzzy c-means (FCM) algorithm that provides image clustering. The proposed algorithm incorporates the local spatial information and gray level information in a novel fuzzy way. The new algorithm is called fuzzy local information C-Means (FLICM). FLICM can overcome the disadvantages of the known fuzzy c-means algorithms and at the same time enhances the clustering performance. The major characteristic of 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 ($a, \lambda_g, \lambda_s$, etc.) incorporated into all other fuzzy c-means algorithms proposed in the literature. Experiments performed on synthetic and real-world images show that FLICM algorithm is effective and efficient, providing robustness to noisy images.**

***Index Terms*—Clustering, fuzzy c-means, fuzzy constraints, gray level constraints, image segmentation, spatial constraints.**

## 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 [1] and [2]. 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 nonoverlapped, 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 inhomogeneities 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 [10] 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 in [9], [12], and [13]. 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].

Tolias and Panas [5] developed a fuzzy rule-based scheme called the ruled-based neighborhood enhancement system to impose spatial constraints by postprocessing the FCM clustering results.

Noordam *et al.* [6] proposed a geometrically guided FCM (GG-FCM) algorithm, a semi-supervised FCM technique, where a geometrical condition is used determined by taking into account the local neighborhood of each pixel.

Pham [15] modified the FCM objective function by including a spatial penalty on the membership functions. The penalty term leads to an iterative algorithm, which is very similar to the original FCM and allows the estimation of spatially smooth membership functions.

Ahmed *et al.* [9] proposed FCM_S where the objective function of the classical FCM is modified in order to compensate the intensity inhomogeneity and allow the labelling of a pixel to be influenced by the labels in its immediate neighborhood. One disadvantage of FCM_S is that the neighborhood labelling is computed in each iteration step, something that is very time-consuming.

Chen and Zhang [12] proposed FCM_S1 and FCM_S2, two variants of FCM_S algorithm in order to reduce the computational time. These two algorithms introduced the extra mean and median-filtered image, respectively, which can be computed in

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advance, to replace the neighborhood term of FCM_S. Thus, the execution times of both FCM_S1 and FCM_S2 are considerably reduced.

Szilagyi *et al.* [13] proposed the enhanced FCM (EnFCM) algorithm to accelerate the image segmentation process. The structure of the EnFCM is different from that of FCM_S and its variants. First, a linearly-weighted sum image is formed from both original image and each pixel's local neighborhood average gray level. Then clustering is performed on the basis of the gray level histogram instead of pixels of the summed image. Since, the number of gray levels in an image is generally much smaller than the number of its pixels, the computational time of EnFCM algorithm is reduced, while the quality of the segmented image is comparable to that of FCM_S [13].

More recently, Cai *et al.* [16] proposed the fast generalized FCM algorithm (FGFCM) which incorporates the spatial information, the intensity of the local pixel neighborhood and the number of gray levels in an image. This algorithm forms a nonlinearly-weighted sum image from both original image and its local spatial and gray level neighborhood. The computational time of FGFCM is very small, since clustering is performed on the basis of the gray level histogram. The quality of the segmented image is well enhanced [16].

However, EnFCM as well as FGFCM, share a common crucial parameter $a$ (or $\lambda$). This parameter is used to control the tradeoff between the original image and its corresponding mean- or median-filtered image. It has a crucial impact on the performance of those methods, but its selection is generally difficult because it should keep a balance between robustness to noise and effectiveness of preserving the details. In other words, the value of $a$ has to be chosen large enough to tolerate the noise, and, on the other hand, it has to be chosen small enough to preserve the image sharpness and details [13]. Thus, we can conclude that the determination of $a$ is in fact noise-dependent to some degree. Since the kind of image noise is generally *a priori* unknown, the selection of $a$ (or $\lambda$) is, in practice, experimentally made, usually using trial-and-error experiments [9], [12], [13]. Moreover, the value of $a$ (or $\lambda$) is fixed for all pixel neighborhoods over the image.

This paper deals with the above mentioned problems. It presents FLICM, a novel robust fuzzy local information c-means clustering algorithm, which can handle the defect of the selection of parameter $a$ (or $\lambda$), as well as promoting the image segmentation performance. In FLICM, a novel fuzzy factor is defined to replace the parameter $a$ used in EnFCM and FCM_S and its variants, and the parameter $\lambda$ used in FGFCM and its variants. The new fuzzy local neighborhood factor can automatically determine the spatial and gray level relationship and is fully free of any parameter selection. Thus, FLICM has the following attractive characteristics: 1) it is relatively independent of the types of noise, and as a consequence, it is a better choice for clustering in the absence of prior knowledge of the noise; 2) the fuzzy local constraints incorporate simultaneously both the local spatial and the local gray level relationship in a fuzzy way; 3) the fuzzy local constraints can automatically be determined, so there is no need of any parameter determination; 4) the balance among image details and noise is automatically achieved by the fuzzy local constraints, enhancing concurrently the clustering performance. All these characteristics make FLICM a more general and suitable for image clustering algorithm.

The remainder of the paper is organized as follows. Section II briefly describes fuzzy c-means clustering algorithms with spatial constraints (FCM_S, FCM_S1 and FCM_S2), followed by the EnFCM and the FGFCM algorithms. The FLICM algorithm is introduced in Section III. Experimental results are presented in Section IV and conclusions are drawn in Section V.

## II. Preliminary Theory

### A. Fuzzy C-Means (FCM) Algorithm

The fuzzy c-means (FCM) clustering algorithm was first introduced by Dunn [17] and later extended by Bezdek [10]. The algorithm is an iterative clustering method that produces an optimal $c$ partition by minimizing the weighted within group sum of squared error objective function $J_m$ [10]

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{c} u_{ji}^m d^2(x_i, v_j) \tag{1}$$

where $\mathbf{X} = \{x_1, x_2, \ldots, x_N\} \subseteq \mathbb{R}^m$ is the data set in the $m$-dimensional vector space, $N$ is the number of data items, $c$ is the number of clusters with $2 \leq c < N$, $u_{ji}$ is the degree of membership of $x_i$ in the $j^{th}$ cluster, $m$ is the weighting exponent on each fuzzy membership, $v_j$ is the prototype of the center of cluster $j$, $d^2(x_i, v_j)$ is a distance measure between object $x_i$ and cluster center $v_j$. A solution of the object function $J_m$ can be obtained through an iterative process, which is carried as follows.

1) Set values for $c$, $m$, and $\varepsilon$.
2) Initialize the fuzzy partition matrix $U^{(0)}$.
3) Set the loop counter $b = 0$.
4) Calculate the $c$ cluster centers $v_j^{(b)}$ with $U^{(b)}$

$$v_j^{(b)} = \frac{\sum_{i=1}^{N} \left(u_{ji}^{(b)}\right)^m x_i}{\sum_{i=1}^{N} \left(u_{ji}^{(b)}\right)^m}. \tag{2}$$

5) Calculate the membership matrix $U^{(b+1)}$

$$u_{ji}^{(b+1)} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ji}}{d_{ki}}\right)^{2/m-1}}. \tag{3}$$

6) If $\max\left\{U^{(b)} - U^{(b+1)}\right\} < \varepsilon$ then stop, otherwise, set $b = b + 1$ and go to step 4.

### B. Fuzzy Clustering With Constraints (FCM_S) and Its Variants

Ahmed *et al.* [9] proposed a modification of the standard FCM by introducing a term that allows the labelling of a pixel to be influenced by labels in its immediate neighborhood. The neighborhood effect acts as a regularizer and biases the solution toward piecewise-homogeneous labelling. The modified objective function of FCM_S is defined as follows:

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{c} u_{ji}^m \|x_i - v_j\|^2 + \frac{a}{N_R}\sum_{i=1}^{N}\sum_{j=1}^{c} u_{ji}^m \sum_{r\in N_i} \|x_r - v_j\|^2 \quad (4)$$

where $x_i$ is the gray level value of the $i^{th}$ pixel, $N$ is the total number of pixels, $v_j$ is the prototype value of the $j^{th}$ center, $u_{ji}$ represents the fuzzy membership of the $i^{th}$ pixel with respect to cluster $j$, $N_R$ is its cardinality, $x_r$ represents the neighbor of $x_i$, and $N_i$ stands for the set of neighbors falling into a window around pixel $x_i$. The parameter $a$ is used to control the effect of the neighbors term. By definition, each sample point $x_i$ satisfies the constraint that $\sum_{j=1}^{c} u_{ji} = 1$. The calculation of membership partition matrix and the cluster centers is performed as follows:

$$u_{ji} = \frac{\left(\|x_i - v_j\|^2 + \frac{a}{N_R}\sum\limits_{r\in N_i}\|x_r - v_j\|^2\right)^{1/m-1}}{\sum\limits_{k=1}^{c}\left(\|x_i - v_k\|^2 + \frac{a}{N_R}\sum\limits_{r\in N_i}\|x_r - v_k\|^2\right)^{1/m-1}} \quad (5)$$

$$v_j = \frac{\sum\limits_{i=1}^{N} u_{ji}^m \left(x_i + \frac{a}{N_R}\sum\limits_{r\in N_i} x_r\right)}{(1+a)\sum\limits_{i=1}^{N} u_{ji}^m}. \quad (6)$$

The second term $1/N_R \sum_{r\in N_i} x_r$ in the numerator of (6) is in fact a neighbor average gray level value around $x_i$ within a window. The image composed by all the neighbor average values around the image pixels forms a so-called mean-filtered image.

Chen and Zhang [12] proposed FCM_S1, a variant of FCM_S, where the neighborhood term is presented much more simplified. The objective function is written as follows:

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{c} u_{ji}^m \|x_i - v_j\|^2 + a\sum_{j=1}^{c}\sum_{r\in N_i} u_{jr}^m \|\overline{x_r} - v_j\|^2 \quad (7)$$

where $\overline{x_r}$ is the average of neighboring pixels lying within a window around $x_r$. Unlike (4), $\overline{x_r}$ can be computed in advance, reducing the whole computation time since $1/N_R \sum_{r\in N_i} \|x_r - v_j\|^2$ in (4) is replaced by $\|\overline{x_r} - v_j\|^2$. An iterative algorithm for the minimization of (7) with respect to $u_{ji}$ and $v_j$ can be similarly to FCM_S derived as follows:

$$u_{ji} = \frac{\left(\|x_i - v_j\|^2 + a\|\overline{x_i} - v_j\|^2\right)^{1/m-1}}{\sum\limits_{k=1}^{c}\left(\|x_i - v_k\|^2 + a\|\overline{x_i} - v_k\|^2\right)^{1/m-1}} \quad (8)$$

$$v_j = \frac{\sum\limits_{i=1}^{N} u_{ji}^m \left(x_i + a\overline{x_i}\right)}{(1+a)\sum\limits_{i=1}^{N} u_{ji}^m}. \quad (9)$$

The essence of FCM_S1 is to make both the original and the corresponding mean-filtered image, have the same prototypes or clustering results. Furthermore, FCM_S1 not only considerably reduces the execution time, but also improves the robustness to Gaussian noise [12].

However, FCM_S1 is unsuitable for images corrupted by impulse noise [12]. In order to overcome this problem, Chen and Zhang [12] designed the FCM_S2, a variant of FCM_S1 in which the mean-filtered image is replaced by the median-filtered one.

The iterative algorithm that solves the objective functions of FCM_S, FCM_S1 and FCM_S2 is more or less the same used in the classical FCM algorithm. Just the corresponding functions should be replaced and the mean and median-filtered images (only for FCM_S1 and FCM_S2) should be calculated before the first iteration.

### C. Enhanced Fuzzy C-Means Clustering (EnFCM)

Szilagyi *et al.* [13] proposed the EnFCM algorithm to speed up the clustering process for gray level images. In order to accelerate FCM_S, a linearly-weighted sum image $\xi$ is in advance formed from the original image and its local neighbor average image in terms of

$$\xi_i = \frac{1}{1+a}\left(x_i + \frac{a}{N_R}\sum_{j\in N_i} x_j\right) \quad (10)$$

where $\xi_i$ denotes the gray level value of the $i$th pixel of the image $\xi$ and $N_i$ stands for the set of neighbors $(x_j)$ falling into a window around $x_i$. The parameter $a$ plays the same role as before, that is to control the effect of the neighbors term. Then, the clustering method [13] is performed on the gray level histogram of the newly generated image $\xi$. As a consequence, the objective function in this case is defined as

$$J_m = \sum_{i=1}^{M}\sum_{j=1}^{c} \gamma_i u_{ji}^m (\xi_i - v_j)^2 \quad (11)$$

where $v_j$ represents the prototype of the $j$th cluster, $u_{ji}$ represents the fuzzy membership of gray level value $i$ with respect to cluster $j$, $M$ denotes the number of gray levels of image $\xi$, which is generally much smaller than $N$, and $\gamma_i$ is the number of pixels having gray level value equal to $i$. Thus, $\sum_{k=1}^{M}\gamma_k = N$ and under the constraint that $\sum_{j=1}^{c} u_{ji} = 1$ for any $i$, the $J_m$ (11) is minimized, using the following equations for calculation of the membership partition matrix and the cluster centers:

$$u_{ji} = \frac{(\xi_i - v_j)^{2/m-1}}{\sum\limits_{k=1}^{c}(\xi_i - v_k)^{2/m-1}} \quad (12)$$

$$v_j = \frac{\sum\limits_{i=1}^{M}\gamma_i u_{ji}^m \xi_i}{\sum\limits_{i=1}^{M}\gamma_i u_{ji}^m}. \quad (13)$$

The iterative process of the EnFCM algorithm is similar to FCM, but it is applied to the new image $\xi$ (10) by using (12) and (13).

Due to fact that the gray level value of the pixels is generally encoded with 8 bit resolution (256 gray levels), the number $M$ of gray levels is generally much smaller than the size $N$ of the image. Thus, the execution time is significantly reduced.

EnFCM provides comparable segmenting results to FCM_S, but the segmenting quality depends on the chosen window size, the parameter $a$ and the filtering method. If the parameter $a$ is chosen large enough, then the method is resistant to noise, but, on the other hand, when $a$ is chosen small enough the segmented image maintain its sharpness and details. However, when there is no prior knowledge about the image noise, the selection of parameter $a$ is not an easy task and has to be made by experience or by using the trial-and-error method.

### D. Fast Generalized Fuzzy C-Means Clustering (FGFCM)

Cai *et al.* [16] proposed the fast generalized fuzzy c-means (FGFCM) algorithm to improve the clustering results, as well as to facilitate the choice of the neighboring control parameter. In order to improve the clustering results FGFCM exploits a local similarity measure that combine both spatial and gray level image information, in terms of

$$S_{ij} = \begin{cases} e^{-\max(|p_i-p_j|,|q_i-q_j|)/\lambda_s - \|x_i-x_j\|^2/\lambda_g \sigma_i^2}, & i \neq j \\ 0, & i = j, \end{cases} \tag{14}$$

where the $i$th pixel is the center of the local window and the $j$th pixel represents the set of the neighbors falling into the window around the $i$th pixel. $(p_i, q_i)$ are the coordinates of pixel $i$ and $x_i$ is its gray level value. $\lambda_s$ and $\lambda_g$ are two scale factors playing a role similar to factor $a$ in EnFCM, and $\sigma_i$ is defined as

$$\sigma_i = \sqrt{\frac{\sum_{j \in N_i} \|x_i - x_j\|^2}{N_R}}. \tag{15}$$

FGFCM incorporates local and gray level information (14) into its objective function generating in advance a new image $\xi$ as follows:

$$\xi_i = \frac{\sum_{j \in N_i} S_{ij} x_j}{\sum_{j \in N_i} S_{ij}} \tag{16}$$

where $\xi_i$ denotes the gray level value of the $i$th pixel of the image $\xi$, $x_j$ represents the gray level value of the neighbors of $x_i$ (window center), $N_i$ is the set of neighbors falling in the local window and $S_{ij}$ is the local similarity measure between the $i$th and the $j$th pixel.

Furthermore, Cai *et al.* [16] proposed two variants of the FGFCM algorithm, the FGFCM_S1 and the FGFCM_S2, which incorporate modified similarity measures in their objective functions. FGFCM_S1 uses $S_{ij} = 1$ for all $i$ and $j$, and naturally $\xi_i$ is equal to the mean of the neighbors within a specified window, including the $i$th pixel. On the other hand, FGFCM_S2, uses as similarity measure the $S_{ij} = \mathrm{median}\{x_j\}$, that is, $\xi_i$ is the median of the neighbors within a specified window, including the $i$th pixel.

The FGFCM algorithm can be summarized as follows.

1) Set values for $c$, $m$, and $\varepsilon$.
2) Compute the new image $\xi$ in terms of (16).
3) Initialize the fuzzy partition matrix $U^{(0)}$, and set the loop counter $b = 0$.
4) Update the cluster centers $v_j^{(b)}$ using (13).
5) Update the membership matrix $U^{(b+1)}$ using (12).
6) If $\max\left\{U^{(b)} - U^{(b+1)}\right\} < \varepsilon$ then stop, otherwise, set $b = b + 1$ and go to step 4.

The significant reduction of execution time attributes to taking into account a range of distribution of gray levels of the given image, as in EnFCM algorithm.

FGFCM and its variants, provide good enough segmenting results, but the segmenting quality depends on the chosen window size and the parameters $\lambda_s$ and $\lambda_g$. Parameter $\lambda_s$ could be fixed to 3 [16]. Thus, parameter $\lambda_g$ controls the algorithm. If $\lambda_g$ is chosen large enough, then the method is resistant to noise, but on the other hand, when $\lambda_g$ is chosen small enough the segmented image maintain its sharpness and details. However, because there is no prior knowledge about the image noise, the selection of parameter $\lambda_g$ is not an easy task, and has to be made by experience or by using the trial-and-error method.

## III. 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 G

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 $\lambda$) 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

$$G_{ki} = \sum_{\substack{j \in N_i \\ i \neq j}} \frac{1}{d_{ij} + 1} (1 - u_{kj})^m \|x_j - v_k\|^2 \tag{17}$$

where the $i$th pixel is the center of the local window (for example, $3 \times 3$), $k$ is the reference cluster and the $j$th pixel belongs in the set of the neighbors falling into a window around the $i$th pixel $(N_i)$. $d_{i,j}$ is the spatial Euclidean distance between pixels $i$ and $j$, $u_{kj}$ is the degree of membership of the $j$th pixel in the $k$th cluster, $m$ is the weighting exponent on each fuzzy membership, and $v_k$ is the prototype of the center of cluster $k$.

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 adopted 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 $\lambda$) 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 and gray level information into its objective function, defined in terms of

$$J_m = \sum_{i=1}^{N} \sum_{k=1}^{c} \left[ u_{ki}^m \left\| x_i - v_k \right\|^2 + G_{ki} \right]. \tag{18}$$

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

$$u_{ki} = \frac{1}{\sum\limits_{j=1}^{c} \left( \frac{\|x_i - v_k\|^2 + G_{ki}}{\|x_i - v_j\|^2 + G_{ji}} \right)^{1/m-1}} \tag{19}$$

$$v_k = \frac{\sum\limits_{i=1}^{N} u_{ki}^m x_i}{\sum\limits_{i=1}^{N} u_{ki}^m}. \tag{20}$$

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 $\varepsilon$.
Step 2. Initialize randomly the fuzzy partition matrix.
Step 3. Set the loop counter $b = 0$.
Step 4. Calculate the cluster prototypes using (20).
Step 5. Compute membership values using (19).
Step 6. $\max\left\{U^{(b)} - U^{(b+1)}\right\} < \varepsilon$ 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 $U$. This procedure assigns the pixel $i$ to the class $C$ with the highest membership

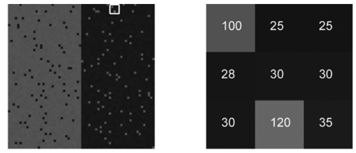
$$C_i = \arg_k \left\{ \max\{u_{ki}\} \right\}, \quad k = 1, 2, \ldots, c. \tag{21}$$

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 (18) 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 in (18). $G_{ki}$ 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 $3 \times 3$ 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 corresponding 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 $3 \times 3$ 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




| | | |
|---|---|---|
| 0.51 | 0.97 | 0.02 |
| 0.01 | 0.85 | 0.66 |
| 0.58 | 0.38 | 0.44 |

$v_L = 65.60$
$v_R = 63.94$

(a)

| | | |
|---|---|---|
| 0.58 | 0.48 | 0.62 |
| 0.58 | 0.46 | 0.52 |
| 0.47 | 0.49 | 0.44 |

$v_L = 68.06$
$v_R = 61.91$

(b)

| | | |
|---|---|---|
| 0.56 | 0.79 | 0.83 |
| 0.72 | 0.73 | 0.79 |
| 0.73 | 0.43 | 0.76 |

$v_L = 95.88$
$v_R = 33.87$

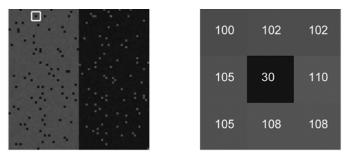
(c)

| | | |
|---|---|---|
| 0.77 | 0.99 | 0.99 |
| 0.95 | 0.94 | 0.97 |
| 0.96 | 0.65 | 0.96 |

$v_L = 98.05$
$v_R = 31.77$

(d)

Fig. 1. $3 \times 3$ 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, and (d) after five iterations.




| | | |
|---|---|---|
| 0.61 | 0.93 | 0.20 |
| 0.78 | 0.95 | 0.69 |
| 0.64 | 0.86 | 0.35 |

$v_L = 65.60$
$v_R = 63.94$

(a)

| | | |
|---|---|---|
| 0.55 | 0.57 | 0.53 |
| 0.57 | 0.64 | 0.52 |
| 0.56 | 0.56 | 0.58 |

$v_L = 68.06$
$v_R = 61.91$

(b)

| | | |
|---|---|---|
| 0.19 | 0.21 | 0.19 |
| 0.22 | 0.44 | 0.23 |
| 0.21 | 0.23 | 0.21 |

$v_L = 95.88$
$v_R = 33.87$

(c)

| | | |
|---|---|---|
| 0.01 | 0.01 | 0.01 |
| 0.01 | 0.20 | 0.01 |
| 0.01 | 0.01 | 0.01 |

$v_L = 98.05$
$v_R = 31.77$

(d)

Fig. 2. $3 \times 3$ 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, and (d) after five iterations.

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 $a$. Thus, it is generally hard to choose the proper method (FCM_S1 or FCM_S2) and the optimal parameter $a$ for good clustering results. On the other hand, FGFCM is independent of the noise type, but its clustering results depend also on parameter $\lambda$. Parameter $\lambda$ 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;
- it is applied on the original image.

## 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 nonfuzzy 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]

$$SA = \sum_{i=1}^{c} \frac{A_i \cap C_i}{\sum_{j=1}^{c} C_j} \tag{22}$$

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.

In our numerical experiments, we generally choose the parameters to be $\lambda_s = 3$, $\varepsilon = 0.00001$ and $N_R = 8$ (a $3 \times 3$ window centered around each pixel, except the central pixel itself) [16].

First, we apply these algorithms to a synthetic test image (Fig. 3(a): $128 \times 128$ 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 $\lambda_g$ is set equal to $\lambda_g = 6.0$ 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. It is clearly illustrated that the proposed FLICM algorithm gives rise to better denoising performance than FCM_S type, EnFCM, FGFCMs, and nonfuzzy algorithms, presenting robustness to all considered kind of noises against to the other eight algorithms.

Furthermore, we apply the nine clustering algorithms to the real image *eight* [23] [Fig. 4(a)], contaminated with salt & pepper $(30\%)$ [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 $\lambda_g = 6.0$. It is clearly illustrated in Fig. 4(c)–4(j) that FCM_S1, FCM_S2, EnFCM, FGFCM, and its variants and the two nonfuzzy 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 $\lambda$ has been performed by trial-and-error method selecting those with the smallest optimal segmentation accuracy (SA) error.

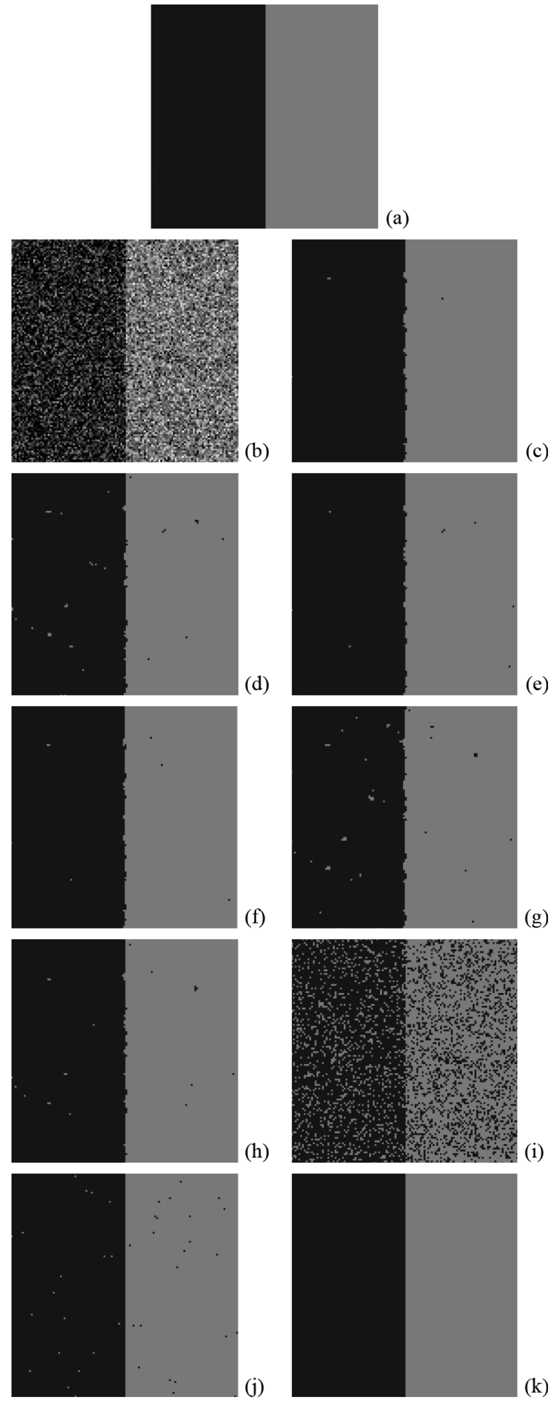



Fig. 3. Clustering of a synthetic image. (a) Original image, (b) the same image with gaussian noise (20%), (c) FCM_S1 result, (d) FCM_S2 result, (e) EnFCM result, (f) FGFCM_S1 result, (g) FGFCM_S2 result, (h) FGFCM result, (i) k-means result, (j) SLINK result, and (k) FLICM result.

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 $a$ for FCM_S1, FCM_S2 and EnFCM, as well as parameter $\lambda_g$ for FGFCM

TABLE I
SEGMENTATION ACCURACY (SA%) OF NINE ALGORITHMS ON SYNTHETIC IMAGES

| | FCM_S1 | FCM_S2 | EnFCM | FGFCM_S1 | FGFCM_S2 | FGFCM | k-means | SLINK | FLICM |
|---|---|---|---|---|---|---|---|---|---|
| Gaussian 8% | 99.28 | 99.71 | 99.30 | 97.58 | 99.81 | 98.62 | 92.08 | 99.77 | **99.89** |
| Gaussian 10% | 98.34 | 99.34 | 98.36 | 97.51 | 99.43 | 98.48 | 88.96 | 99.22 | **99.64** |
| Gaussian 15% | 97.21 | 98.04 | 97.25 | 97.04 | 97.72 | 97.60 | 79.93 | 98.49 | **98.95** |
| Uniform 8% | 99.98 | 99.98 | **99.99** | 97.65 | 99.92 | 98.68 | 82.88 | 81.92 | 99.98 |
| Uniform 10% | 99.49 | 99.76 | 99.52 | 97.61 | 99.78 | 98.56 | 81.55 | 68.05 | **99.89** |
| Uniform 15% | 96.54 | 95.67 | 96.26 | 96.41 | 94.25 | 95.92 | 80.01 | 57.92 | **98.74** |
| Salt & Pepper 8% | 99.60 | 99.62 | 99.60 | 97.66 | 74.90 | 88.12 | 92.82 | 99.29 | **99.93** |
| Salt & Pepper 10% | 99.45 | 99.53 | 99.45 | 97.51 | 74.89 | 86.69 | 92.78 | 99.17 | **99.91** |
| Salt & Pepper 15% | 99.10 | 99.46 | 99.10 | 97.34 | 74.88 | 83.33 | 91.31 | 98.68 | **99.90** |

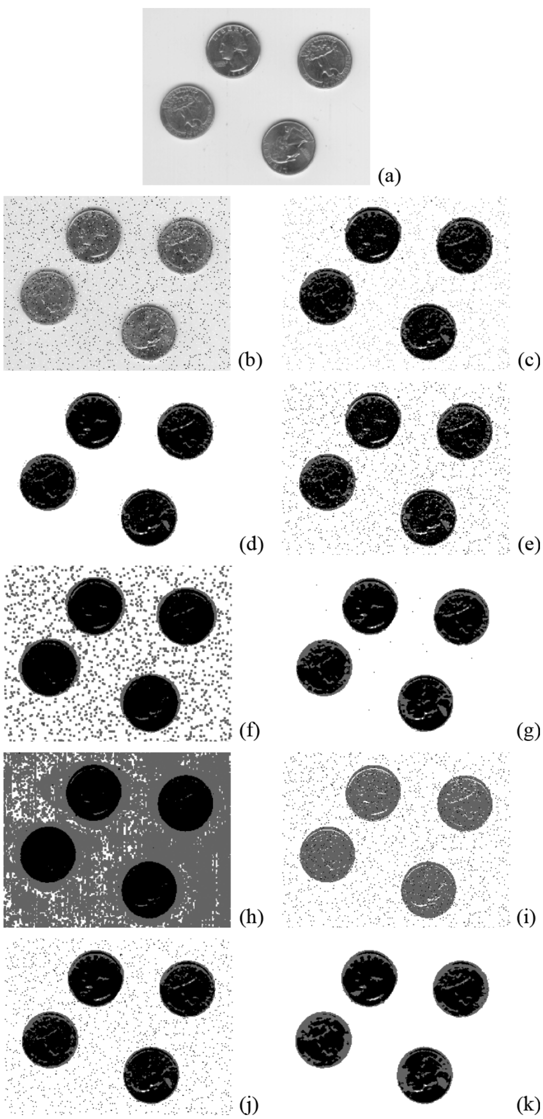


Fig. 4. Clustering results on eight image. (a) Original image, (b) the same image with salt & pepper noise (30%), (c) FCM_S1 result, (d) FCM_S2 result, (e) EnFCM result, (f) FGFCM_S1 result, (g) FGFCM_S2 result, (h) FGFCM result, (i) k-means result, (j) SLINK result, and (k) FLICM result.

and its variants were selected by performing the trial-and-error method and choosing those that maximizing the $r$ 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
COMPARISON SCORES (R%) OS 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** |

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

$$r = \sum_{i=1}^{c} \frac{A_i \cap C_i}{A_i \cup C_i} \tag{23}$$

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. 7 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

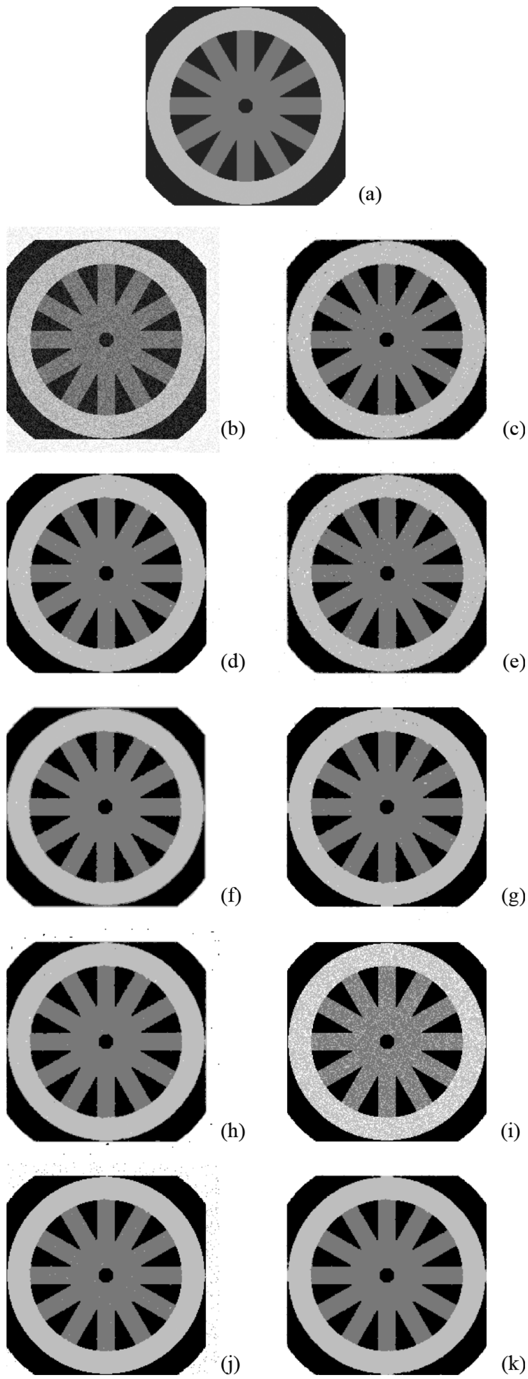



Fig. 5. Clustering results on wheel image. (a) Original image, (b) the same image with Gaussian noise $(30\%)$, (c) FCM_S1 result, (d) FCM_S2 result, (e) EnFCM result, (f) FGFCM_S1 result, (g) FGFCM_S2 result, (h) FGFCM result, (i) k-means result, (j) SLINK result, and (k) FLICM result.

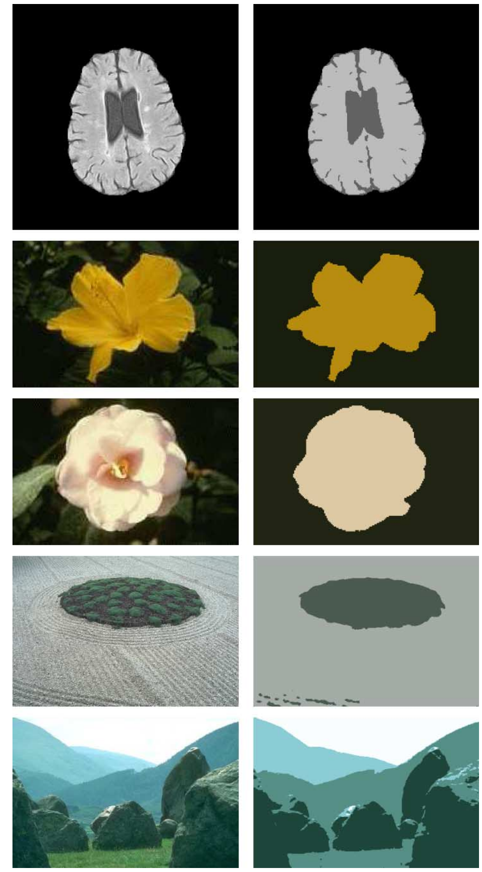


Fig. 6. Clustering results on real application image data by the proposed algorithm.

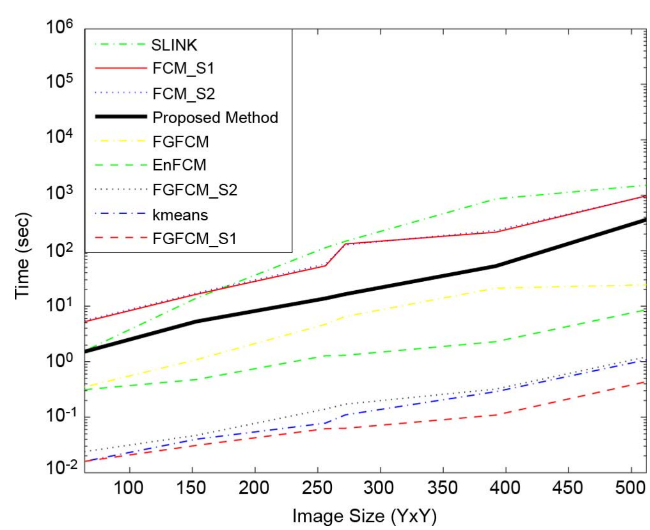



Fig. 7. Computational cost (in seconds) of the nine clustering algorithms.

complicated programming part. All experiments were performed on a Pentium IV (3 GHz) workstation under Windows XP Professional without any particular code optimization.

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 $O(nc)$ ($n$ is the histogram's length and $c$ 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 paper, 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 enforced by the way that spatial and gray level image information are combined in the algorithm; the factor $G_{ki}$ 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 $\lambda$), 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. This is also enhanced, by the fact, that almost all the other methods perform the clustering on a precomputed image, while FLICM is applied on the original image.

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