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Kernel Possibilistic Fuzzy *c*-Means Clustering with Local Information for Image Segmentation

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Abstract The kernel weighted fuzzy *c*-means clustering with local information (KWFLICM) algorithm performs robustly to noise in research related to image segmentation using fuzzy *c*-means (FCM) clustering algorithms, which incorporate image local neighborhood information. However, KWFLICM performs poorly on images contaminated with a high degree of noise. This work presents a kernel possibilistic fuzzy *c*-means with a local information (KWPFLICM) algorithm to overcome the noise-related deficiencies of KWFLICM. The proposed approach leverages the robustness to noise of the kernel possibilistic fuzzy *c*-means (KPFCM) algorithm, which is a hybridization of the kernel possibilistic *c*-means (KPCM) and kernel FCM (KFCM), rather than relying on the kernel FCM algorithm. Experiments performed on the various types of images degraded by different degrees of noises prove that proposed algorithm is effectual and efficient, and more robust to noise.

Keywords Fuzzy clustering · Noise robustness · Image segmentation · Local neighborhood information

1 Introduction

Image segmentation has long played a vital role in computer vision and image processing. The image segmentation process produces a set of segments or regions. The accuracy of segmentation, though tough, is highly important in diverse fields like medical fields, remote sensing, and image retrieval, and it may contribute to saving, sustaining, and protecting human life. Image segmentation is generally performed with one of four different methods: thresholding, clustering, edge detection, and region extraction. Our work focuses on image segmentation by using the fuzzy clustering method. Many algorithms have been introduced for segmenting images using fuzzy clustering algorithms [1, 2]. Although the conventional fuzzy *c*-means (FCM) algorithm gives a good result for the images free from any type of noise, outliers, and imaging artifacts, because it does not use the local spatial information and it does not use a Euclidean distance metric that is non-robust. To overcome this drawback, a lot of enhanced FCM algorithms have been introduced that incorporate different components of local spatial information into the FCM objective function [3, 4].

Ahmed et al. [3] proposed FCM_S by adding a spatial neighborhood term into an objective function of original FCM algorithm. However, the main flaw of this algorithm is high running time because the added term is computed iteratively at every step.

Chen and Zhang [4] introduced FCM S1 and FCM S2 which are two versions of FCM_S method. The two versions FCM S1 and FCM S2 are proposed by replacing the neighborhood term FCM_S with priory calculated mean and median-filtered image in order time taken to calculate penalty term after every iteration.

Szilagyi et al. [5] contributed to fasten the process of segmentation by introducing an enhanced FCM (EnFCM) algorithm. First, a weighted image is obtained from the summation of the original image and the image formed from the mean of the pixels lying in a local window surrounding each pixel, and then, the resulting histograms are

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used to perform clustering. Therefore, the time complexity of EnFCM algorithm is very low.

Cai et al. [6] introduced the fast generalized FCM (FGFCM) algorithm where a similarity measure is used, which is a nonlinear weighted summed image that is obtained from the spatial and local intensity information. The histograms of the nonlinear weighted summed image are then used to perform clustering. Thus, the FGFCM algorithm is faster than EnFCM.

The above algorithms cannot directly be applied to the original image because their robustness to noise and their efficiency of segmentation are controlled by user-defined parameters and it is very difficult to automatically optimize these parameters. To overcome these drawbacks, [7] proposed an effective and robustly noise-invariant fuzzy local information c-means clustering algorithm (FLICM). FLICM is independent of any parameter-free algorithm and autonomously performs image segmentation to restrain the noise. An enhanced variant of the FLICM algorithm (RFLICM) [8] exploits local neighborhood information in depth by computing the relationship of pixels with neighbors to make FLICM more robust by replacing the Euclidean distance with the local coefficient of variation as a local similarity measure. These steps are taken to improve the segmentation results by restraining the noise of the image processed by the FLICM algorithm.

Currently, kernel methods are widely used in the field of machine learning. Now kernel methods have made it easy to solve complex nonlinear problems by representing them into low-dimensional feature space. The popular methods are support vector machines (SVM) [9–11]. In particular, kernel methods based on clustering algorithms [12] are found robust to noise. As a result, many modern image segmentation processes now use kernel-based clustering algorithms [13].

Chen and Zhang [4] presented two versions of KFCM which reduce the computational cost associated with the parent algorithm. In order to increase the robustness to noise capability of FLICM, Gong et al. [14] presented a kernel weighted fuzzy clustering with local information (KWFLICM) for image segmentation. KWFLICM uses the Gaussian radial basis function (GRBF) kernel [4] as a kernel function which adaptively calculates the parameter bandwidth σ within GRBF.

Generalized fuzzy c-means clustering algorithm incorporating local information for higher dimensional data has been proposed in order to overcome the disadvantages of FCM as well as to improve the clustering performance [15, 16].

The possibilistic fuzzy c-means (PFCM) algorithm [17] is formed by combining the possibilistic c-means (PCM) and FCM algorithms. The PFCM possess the properties of both PCM and FCM algorithms, and this overcomes many disadvantages of PCM, FCM, and FPCM, i.e., the noise sensitivity defects of FCM, the coincident clusters problem of PCM, eliminates the row sum constraints of PFCM. The kernel versions of PFCM (KPFCM) [11] are very robust to noise.

Therefore, by motivating from KPFCM, this work presents the kernel weighted possibilistic fuzzy c-means clustering with local information (KWPFLICM) algorithm to improve the performance of KWFLICM by removing noise more robustly.

The rest of the paper is organized into four sections. Section 2, describes our motivation of using the local spatial neighborhood information for PFCM. Section 3 explains our proposed algorithm in detail. In Sect. 4, describes and compares our experimental and numerical results. Finally, Sect. 5, draws conclusions.

2 Motivation

This work is inspired from FLICM [7], where a constraint factor G_{ab} is added that serves as a fuzzy local similarity measure, in order to remove noise and preserve the image details. Consider an image A with M pixels, where each pixel has a gray level p_a. The grouping of image pixels $\{p_i\}_{a=1}^{M}$ into k clusters is made as follows:

$$J_m = \sum_{a=1}^{M} \sum_{b=1}^{k} u_{ab}^{m} \|p_a - c_b\|^2 + G_a b \tag{1}$$

where m represents the degree of fuzziness (usually $m = 2$) and the partition array $U = \{u_{ab}\}$ denotes the belongingness of image intensity values to each cluster. The members of the U array must satisfy the following condition

$$U \in \left\{ \sum_{b=1}^{k} u_{ab} \in [0,1] \middle| \sum_{b=1}^{k} u_{ab} = 1, \quad \forall b \text{ and } 0 < \sum_{a=1}^{M} u_{ab} < M, \forall b' \right\} \tag{2}$$

The fuzzy factor G_{ab} is defined as

$$G_{ab} = \sum_{j \in M_i, a \neq j} \frac{1}{d_{aj} + 1} \left(1 - u_{bj}\right)^m \|p_j - c_b\|^2 \tag{3}$$

where the rectangular local window is used around the central pixel p_a, M_a is the set of neighbors of ath central pixel obtained by applying a rectangular window around the central pixel, the jth pixel belongs to M_a, and d_{aj} is the spatial Euclidean distance between the pixels a and j. The variable u_{ab} denotes the degree of belongingness of pixel p_a to cluster b, and c_b is the prototype of bth cluster. The fuzzy clustering is performed through an objective function, J_m, optimization by updating the membership u_{ab} and the cluster center c_b, calculated as follows:

$$u_{ab} = \frac{1}{\sum_{l=1}^{k} \left(\frac{\|p_a - c_b\|^2 + G_{ab}}{\|p_a - c_l\|^2 + G_{al}} \right)} \quad (4)$$

$$c_b = \frac{\sum_{a=1}^{M} u_{ab}^m p_a}{\sum_{a=1}^{M} u_{ab}^m} \quad (5)$$

where G_{ab} is automatically calculated even in the absence of any prior knowledge of noise. Due to this intentionally weighted approach, the FLICM algorithm is more robust to outliers.

Gong et al. [14] proposed KWFLICM to make FLICM algorithm more robustness to noise and outliers by opting a trade-off between a weighted fuzzy factor and the kernel method. The KWFLICM minimizes the following objective function:

$$J_m = \sum_{a=1}^{M} \sum_{b=1}^{k} u_{ab}^m (1 - K(p_a, c_b)) + G'_{ab} \quad (6)$$

where enhanced fuzzy local similarity measuring factor, G'_{ab} is calculated as follows:

$$G'_{ab} = \sum_{a=1}^{M} \sum_{b=1}^{k} u_{ab}^m \sum_{\substack{a \neq j \\ j \in M_b}} w_{aj} \left(1 - u_{bj}\right)^m \left(1 - K(p_j, c_b)\right) \quad (7)$$

where w_{aj} represents the trade-off of the weighted fuzzy factor of the jth pixel. The non-Euclidean distance between pixels is calculated by $(1 - K(p_j, c_b))$, based on the kernel method. The updated memberships u_{ab} and cluster centers c_b are calculated to minimize the objective function J_m:

$$u_{ab} = \frac{1}{\sum_{l=1}^{k} \left(\frac{(1 - K(p_a, c_b)) + \sum_{a \neq j_{j \in M_b}} w_{aj} \left(1 - u_{bj}\right)^m \left(1 - K(p_j, c_b)\right)}{(1 - K(p_a, c_l)) + \sum_{a \neq j_{j \in M_b}} w_{aj} \left(1 - u_{lj}\right)^m \left(1 - K(p_j, c_l)\right)} \right)^{\frac{1}{m-1}}} \quad (8)$$

$$c_b = \frac{\sum_{a=1}^{M} u_{ab}^m K(p_a, c_b) p_a}{\sum_{a=1}^{M} u_{ab}^m K(p_a, c_b)} \quad (9)$$

Local coefficient of variation V_j for each jth neighbor pixel is calculated as follows:

$$V_j = \frac{\mathrm{var}(p)}{(\overline{p})^2} \quad (10)$$

where $var(p)$ and $\overline{p}$ represent the pixel intensity value variance and mean value of the local window, respectively. The mean of the V_j for all neighbors belonging to M_a is obtained by

$$\overline{V} = \frac{\sum_{j \in M_a} V_j}{n_a} \quad (11)$$

where n_a represents the local cardinality of the local window.

$$\chi_{aj} = \exp\left[-\left(V_j - \overline{V}\right)\right], j \in M_a \quad (12)$$

$$\psi_{aj} = \frac{\chi_{aj}}{\sum_{i \in M_a} \chi_{ai}} \quad \text{and} \quad \mathrm{w_{gc}} = \begin{cases} 2 + \psi_{\mathrm{aj}} & \mathrm{V_j} < \overline{\mathrm{V}} \\ 2 - \psi_{\mathrm{aj}} & \mathrm{V_j} \geq \overline{\mathrm{V}} \end{cases} \quad (13)$$

Here, a constant value 2 is added to ensure that w_{gc} is always nonnegative. The w_{aj} used in the enhanced G'_{ab} formula is obtained by

$$w_{aj} = \left(\frac{1}{d_{aj} + 1} \right) w_{gc} \quad (14)$$

KWFLICM uses the GRBF kernel function and computes as follows:

$$K(p_a, c_b) = e^{\left(-\frac{\|p_a - c_b\|^2}{\sigma} \right)} \quad (15)$$

$$\overline{p} = \frac{\sum_{a=1}^{M} P_a}{M} \quad (16)$$

$$d_a = \|P_a - \overline{p}\| \quad (17)$$

$$\overline{d} = \frac{\sum_{a=1}^{M} d_a}{M} \quad (18)$$

The bandwidth parameter σ, is found by

$$\sigma = \frac{1}{\sqrt{\frac{1}{M-1} \sum_{a=1}^{M} (d_a - \overline{d})^2}} \quad (19)$$

As such, the distance for multi-dimensional dimensional feature space can then be computed as:

$$D_{ab}^2 = 1 - K(p_a, c_b) = 1 - e^{\left(-\frac{\|p_a - c_b\|^2}{\sigma} \right)} \quad (20)$$

Though both FLICM and KWFLICM algorithms are found robust to noise still there is a need of method to deal higher degrees noise.

3 Methodology

Motivated by the above-mentioned descriptions, we propose a kernel weighted possibilistic fuzzy c-means using local information for image segmentation (KWPFLICM) algorithm for robust noise removal. The KWPFLICM minimizes the following objective function:

$$J_m = \sum_{a=1}^{M} \sum_{b=1}^{k} \left\{ \begin{array}{c} \sum_{k=1}^{c} u_{ab}^m t_{ab}^m (1 - K(p_a, c_b)) \\ + \sum_{b=1}^{k} \gamma_b \sum_{a=1}^{M} u_{ab}^m (1 - t_{ab})^n + G''_{ab} \end{array} \right\} \quad (21)$$

Our enhanced G''_{ab} fuzzy factor is calculated as:

$$G''_{ab} = \sum_{a=1}^{M}\sum_{b=1}^{k}\left\{\begin{array}{c} u_{ab}^{m}\sum\limits_{\substack{a\neq j\\ j\in M_i}} w_{aj}\left(1-u_{bj}\right)^{m} \\ \times\left(1-t_{bj}\right)^{n}\left(1-K(p_j,c_b)\right)\end{array}\right\} \tag{22}$$

where p_a represents the central pixel p_j belongs to the jth neighboring pixel from the set of neighbors of p_a, i.e., $p_a(M_i)$. The variable d_{aj} denotes the spatial Euclidean distance of pixel a with j. The coefficients u_{ab} and t_{ab} represent the degree of fuzzy membership and possibilistic typicality of pixel p_j for the cluster b, respectively, and c_b is the prototype of the bth cluster. The exponent m represents the degree of fuzzy, n is the weighted index of typicality, and the parameter γ_b of cluster b is a right positive value, which is defined from objective function as

$$\gamma_b = 2K\frac{\sum_{a=1}^{M}u_{ab}^{m}t_{ab}^{m}\left(1-K(p_a,c_b)\right)}{\sum_{a=1}^{M}u_{ab}^{m}t_{ab}^{m}} \tag{23}$$

Normally, the value of K is set to 1.

The fuzzy membership u_{ab}, possibilistic typicality t_{ab}, and center c_b, which are collectively used to minimize the objective function, are defined as follows:

$$u_{ab} = \frac{1}{\sum_{l=1}^{k}\left(\frac{t_{ab}\left(1-K(p_j,c_b)\right)+\sum_{a\neq j_{j\in M_i}} w_{aj}\left(1-u_{bj}\right)^{m}\left(1-t_{bj}\right)^{n}\left(1-K(p_j,c_b)\right)}{t_{al}\left(1-K(p_j,c_b)\right)+\sum_{a\neq j_{j\in M_i}} w_{aj}\left(1-u_{bj}\right)^{m}\left(1-t_{bj}\right)^{n}\left(1-K(p_j,c_b)\right)}\right)^{\frac{1}{m-1}}} \tag{24}$$

$$t_{ab} = \frac{1}{\left\{1+2\left(\frac{\left(\begin{array}{c}\left(1-K(p_i,c_b)\right)+\sum_{a\neq j_{j\in M_i}} w_{aj}\left(1-u_{bj}\right)^{m}\\ \times\left(1-t_{bj}\right)^{n}\left(1-K(p_j,c_b)\right)\end{array}\right)}{\gamma_b}\right)^{\frac{1}{n-1}}\right\}} \tag{25}$$

$$c_b = \frac{\sum_{a=1}^{M}u_{ab}^{m}t_{ab}^{n}\left(1-K(p_i,c_b)\right)p_a}{\sum_{a=1}^{M}u_{ab}^{m}t_{ab}^{n}K(p_i,c_b)} \tag{26}$$

In order to overcome convergence to the trivial solution, the middle term is added in the objective function of the proposed method. Steps of our proposed KWPFLICM are mentioned below.

Step 1 Set the values for typicality n, local window size M_a, fuzzifier m, the maximum iteration number $itr_{\max}$, and set the threshold for stopping the algorithm, ϵ.

Step 2 Initialize cluster centers, fuzzy membership, and kernel function with the resultant cluster center, respectively, obtained by running the KWFLICM algorithm.

Step 3 Compute w_{aj} and D_{ab}^{2} by using Eqs. (14) and (20), respectively.

Step 4 Compute the γ_b parameter by using Eq. (23)

Step 5 Update by Eq. (25)

Step 6 Update by Eq. (24)

Step 7 Update by Eq. (26)

Step 8 Stop if $\max\left\|C^{(itr)}-C^{(itr+1)}\right\|<\epsilon$ or $itr>itr_{\max}$, otherwise $itr=itr+1$, and go to Step 4.

The flowchart as shown Fig. 1 describes detailed elaboration of the steps of the proposed KWPFLICM algorithm.

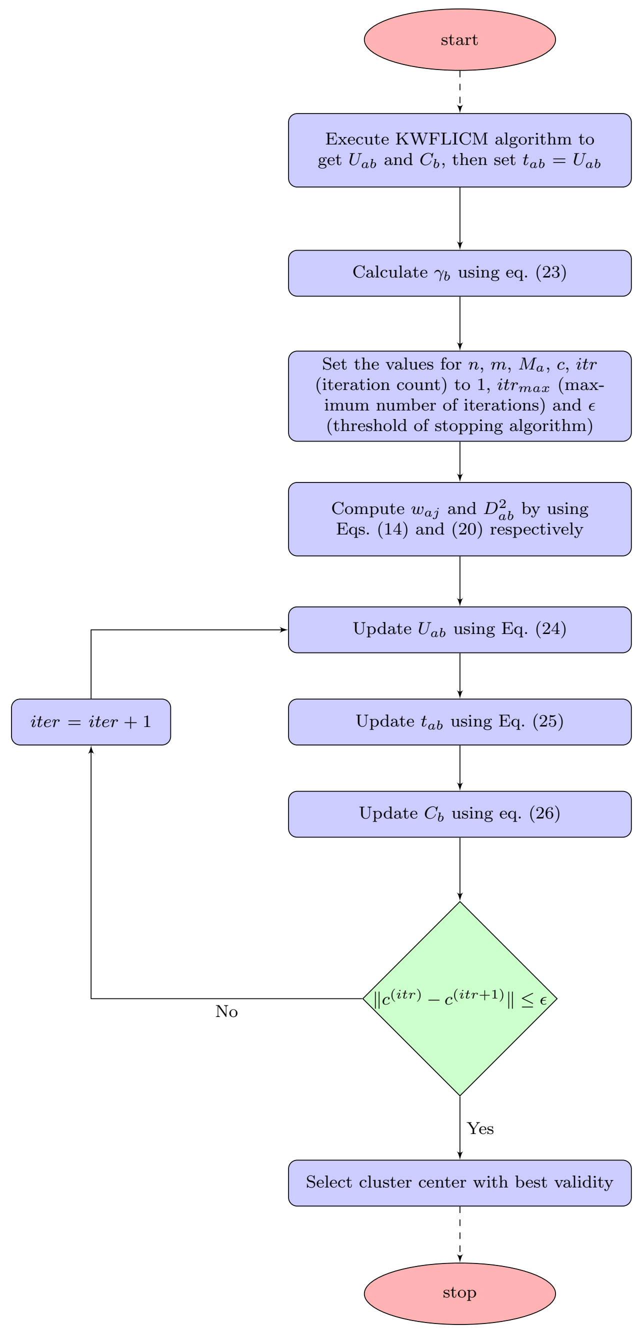

Fig. 1 The flowchart of the proposed KWPFLICM algorithm

The defuzzification of the fuzzy segmented image into a crisp, segmented image takes place after algorithm converges by using the maximum membership method of defuzzification. In this method, the ath pixel with the highest membership is assigned to class c_b:

$$c_b = \arg\{\max\{u_{ab}\}\}, \ (b = 1, 2, \ldots, c) \tag{27}$$

4 Experimental Results and Analysis

This section evaluates the segmentation performance of KWPFLICM by segmenting the synthetic, natural, and real images that have different types of noise added. We generally use throughout all the experiments a fixed value for $\epsilon = 0.001$, $M_a = 8$ (a 3×3 local window centered on each pixel, except for the central pixel itself), fuzzifier $m = 2$ and for KWPLFICM, $a = 2$ and $b = 2$. Furthermore, the segmentation results of KWPFLICM are compared with four other algorithms that use pixels' local neighborhood information, i.e., FLICM [1], RFLICM [12], WFLICM, and KWFLICM, in order to measure the robustness and efficiency of KWPFLICM.

4.1 Results on the Synthetic Images

In this section, we use two synthetic test images composed of 120×120 pixels each and are shown in Figs. 2a and 3a. The number of cluster sets is 4 and 2 for synthetic image-1 and synthetic image-2 as shown in Figs. 2a and 3a, respectively. We added different degrees of Gaussian and salt-and-pepper noise to these images then we applied the above-mentioned algorithms on the obtained corrupted image. The denoising performance of all of the algorithms is measured by the optimal segmentation accuracy (SA), and the SA is computed by the following equation [3]:

$$SA = \sum_{b=1}^{k} \frac{\alpha_b \cap \beta_b}{\sum_{j=1}^{k} \beta_j} \tag{28}$$

where σ_b denotes the all the pixels belonging to the bth class after segmentation process finished, k is the number of clusters, and σ_b denotes the all pixels belonging to the bth class in the reference segmented image.

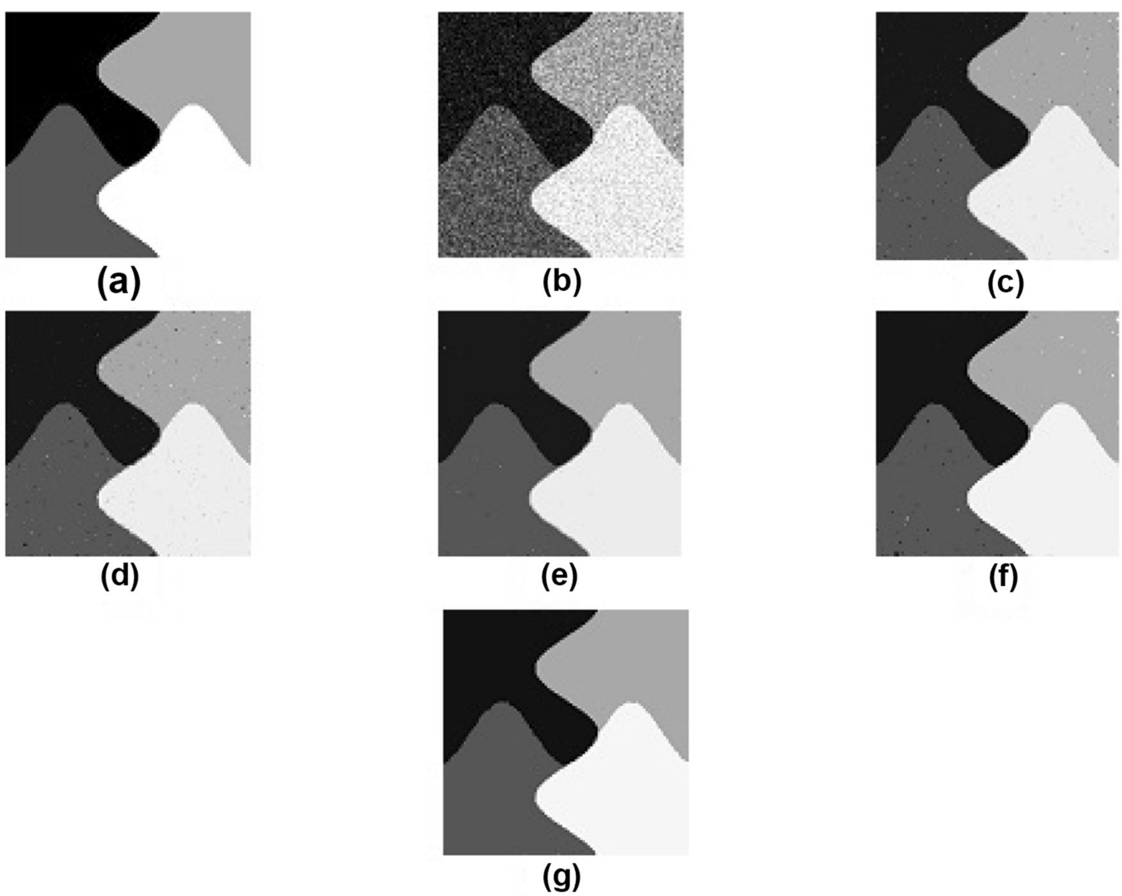

Fig. 2 Segmented results for the Synthetic image-1: **a** Original image, **b** corrupted by (40%) Gaussian noise, **c** FLICM, **d** RFLICM, **e** WFLICM, **f** KWFLICM, **g** KWPFLICM

Figure 2c–f shows the clustering results of all the algorithms operating on synthetic image-1 corrupted with 40% of Gaussian noise. Figure 3c–f shows the clustering results of all the algorithms operating on synthetic image-2 corrupted with 60% of Gaussian noise. Figures 2 and 3 reveal that the FLICM, RFLICM, and WFLICM algorithms are not robust to noise and in fact are heavily affected by noise. While KWFLICM, shown in Figs. 2f and 3f, demonstrates good noise removal, the presence of artifacts indicates that it is not a thoroughly robust noise removal algorithm. However, our proposed algorithm, shown in Figs. 2g and 3g, is very robust to noise because KWPFLICM removes the entire added noise which is a highly satisfactory result. Table 1 describes the segmentation accuracy (SA) obtained from the experiments performed by using synthetic image-1 corrupted with various degrees of Gaussian noise (G) and salt-and-pepper noise (SP). Hence, KWPFLICM is found more robust to noise than all other algorithms for synthetic images.

4.2 Results for Natural and Real Images

The natural and real images are used to perform this experiment. We cannot calculate the segmentation accuracy because this type of image does not have an unambiguous ground truth available. Therefore, an entropy-based information evaluation function [18] is used to assess the performance of all of the above-mentioned algorithms. The entropy of the cluster or region k is defined as

$$H(R_b) = -\sum_{m \in V_b} \frac{L_b(m)}{S_b} \log \frac{L_b(m)}{S_b} \tag{29}$$

The segmented image expected entropy is described as

$$H_r(I) = \sum_{b=1}^{k} \left(\frac{S_b}{S_I}\right) H(R_b) \tag{30}$$

The entropy of the layout is described as

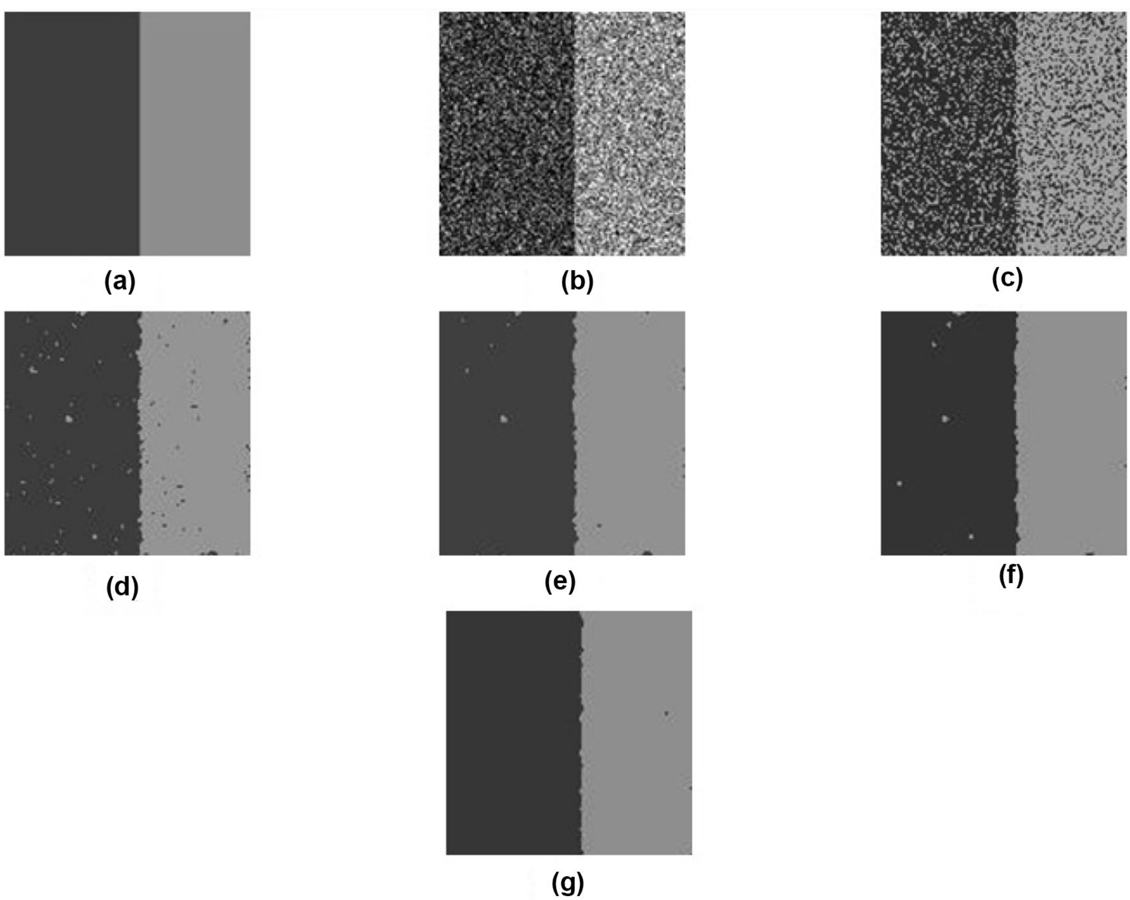

Fig. 3 Segmented results for the Synthetic image-2: **a** Original image, **b** corrupted by (60%) Gaussian noise, **c** FLICM, **d** RFLICM, **e** WFLICM, **f** KWFLICM, **g** KWPFLICM

Table 1 SA (%) on synthetic image-1 with various levels

Noise	FLICM	RFLICM	WFLICM	KWFLICM	KWPFLICM
G15%	99.969	99.972	99.981	99.988	99.997
G20%	99.945	99.951	99.945	99.982	99.991
G30%	99.786	99.863	99.872	99.878	99.893
G40%	98.430	98.450	98.780	99.360	99.790
SP30%	99.145	99.182	99.188	99.988	99.997
SP50%	98.430	98.630	98.780	99.360	99.760

$$H_l(I) = -\sum_{b=1}^{k} \left(\frac{S_b}{S_I}\right) \log \frac{S_b}{S_I} \tag{31}$$

Entropy-based information evaluation function can be calculated as

$$E = H_l(I) + H_r(I) \tag{32}$$

where R_b denotes the sub-segments of the original image, $L_b(m)$ represents the number of pixels in the bth region (cluster) having a intensity value m, v_b is the set of possible gray-level values in the bth cluster (R_b), and $S_b = |R_b|$ is the cardinality. The minimal value of E shows the best segmentation performance.

The first natural image chosen is "cameraman" of size 512×512 pixels, as shown in Fig. 4a. The second natural image "scene" is obtained from the University of Massachusetts at Amherst [19], where the image is mainly composed of three different regions, namely, sky, forest, and road, with the dimension of 200×200 pixels as mentioned in the literature shown in Fig. 5a.

Furthermore, the cameraman image is contaminated with 50% of Gaussian noise, as shown in Fig. 4b. The

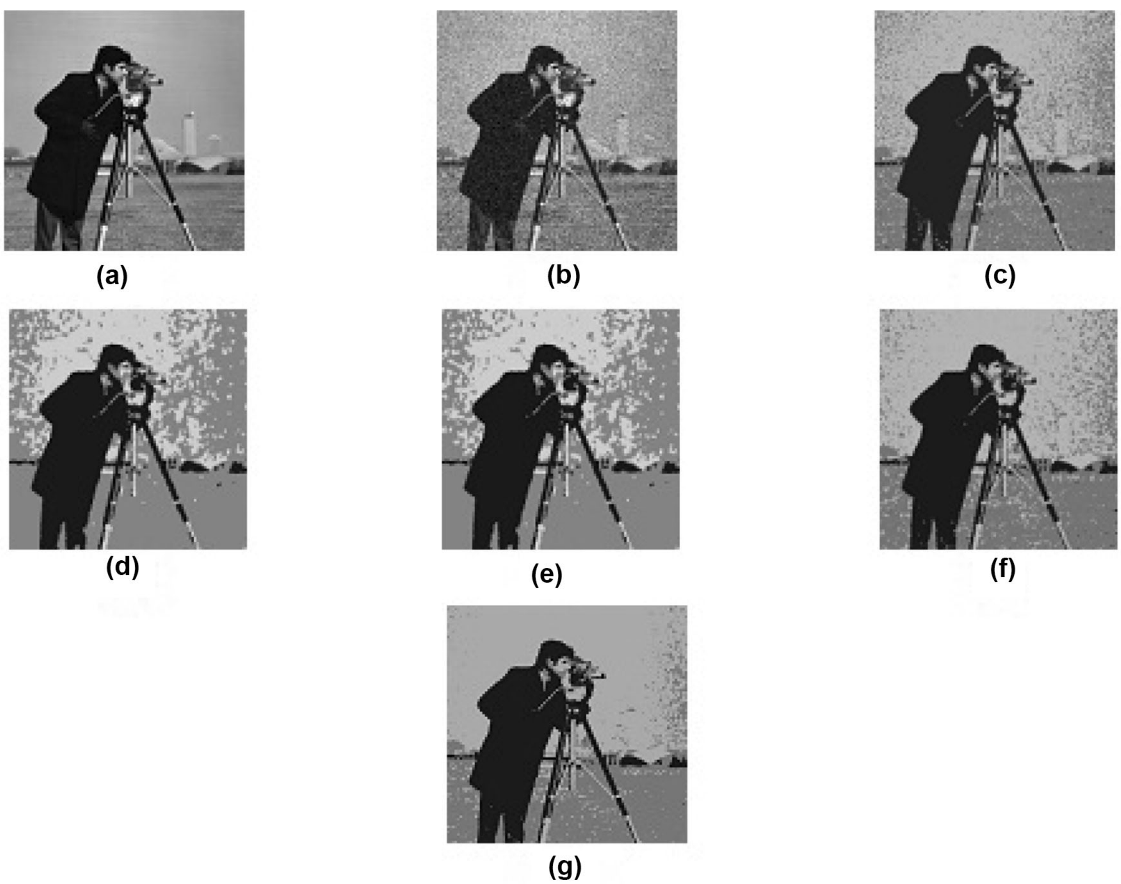

Fig. 4 Segmented results for the Cameraman natural image: **a** Original image, **b** corrupted by (50%) Gaussian noise, **c** FLICM, **d** RFLICM, **e** WFLICM, **f** KWFLICM, **g** KWPFLICM

number of clusters for the cameraman image is set to 3. The scene image is contaminated with 15% of Gaussian noise, as shown in Fig. 5b.

Figure 4c–g shows the clustering results of all algorithms on the noisy cameraman image, and Fig. 5c–g shows the clustering results of all algorithms on the noisy scene image. Table 2 describes the entropy obtained from the experiments performed by using cameraman image corrupted with various degrees of Gaussian noise and salt-and-pepper noise. It is clear from the results that the FLICM, RFLICM, WFLICM, and KWFLICM algorithms are influenced by noise. Hence, it is demonstrated that these four algorithms are sensitive to salt-and-pepper or Gaussian noises. In contrast, the results of our proposed algorithm show that it eliminates the noise effectively and preserves the clear edges and details of the image.

In the final experiment, in order to show the effect of noise on real images, real images namely "wolf and "stag" are taken from Berkeley Segmentation Dataset and Benchmarks 500 (BSDS500) [20] used for segmentation.

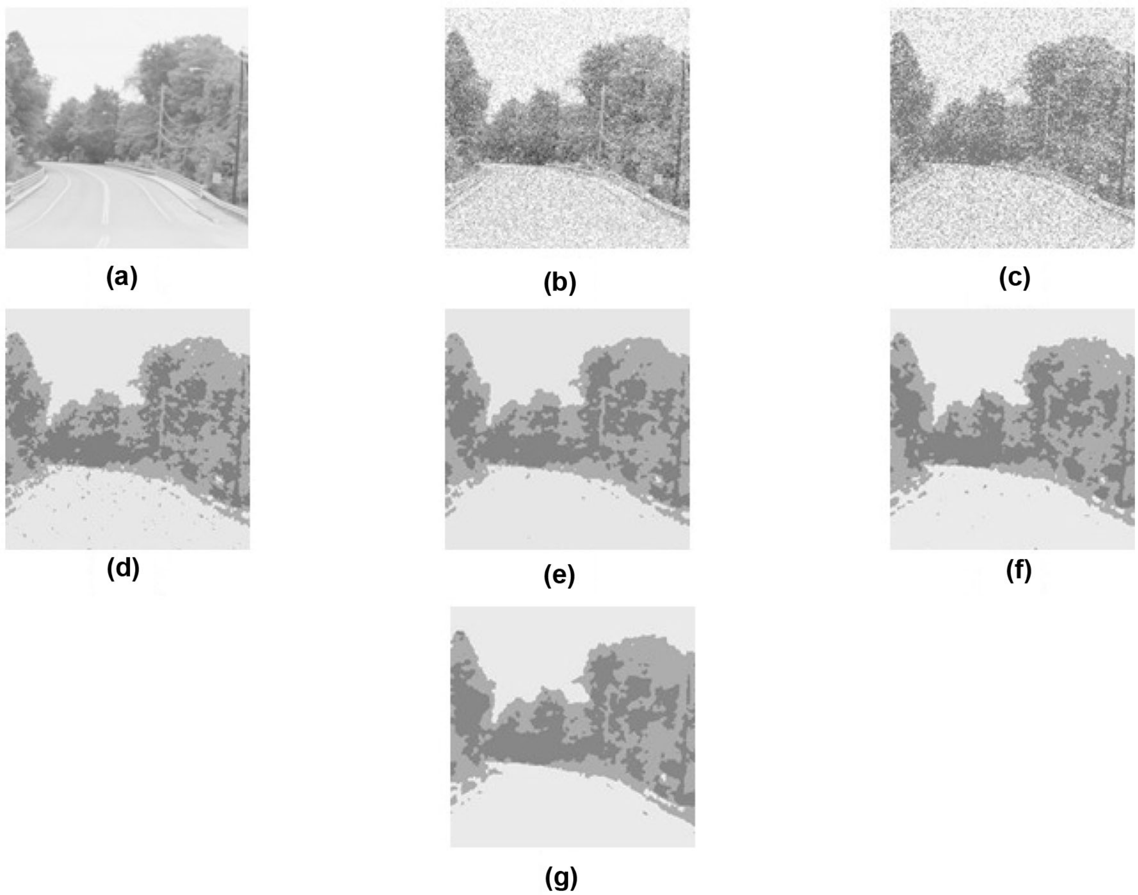

Fig. 5 Segmented results for the scene natural image: **a** Original image, **b** corrupted by (50%) Gaussian noise, **c** FLICM, **d** RFLICM, **e** WFLICM, **f** KWFLICM, **g** KWPFLICM

Table 2 Entropy-based evaluation of cameraman image corrupted by Gaussian noise (50%)

Metric	FLICM	RFLICM	WFLICM	KWFLICM	KWPFLICM
H_r (I)	1.5218	1.5119	1.4686	1.4592	1.4448
H_l (I)	1.0801	1.0800	1.0718	1.0736	1.0618
E	2.6019	2.5919	2.5404	2.5328	2.5098

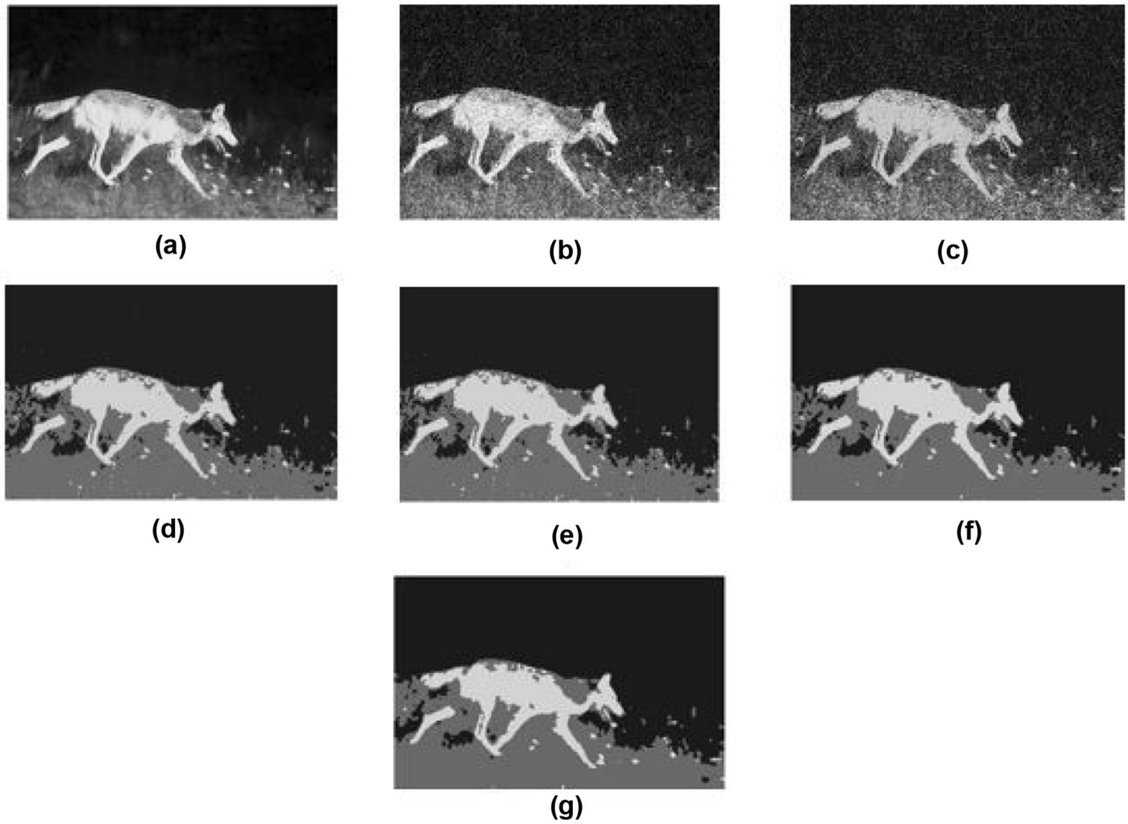

Fig. 6 Segmented results for the “wolf image: **a** Original image, **b** corrupted by (25%) Gaussian Noise, **c** FLICM, **d** RFLICM, **e** WFLICM, **f** KWFLICM, **g** KWPFLICM

Both real images are constituted by 480 × 320 pixels. The distinct number of regions/classes for wolf image is considered three namely: background, grass, and wolf as shown in Fig. 6a. The distinct number of regions/classes for stag image is considered three as shown in Fig. 7a. We have added 25% and 50% Gaussian noise to the original wolf image and stag as corrupted images are shown in Figs. 6b and 7b, respectively, then we have applied clustering methods on these corrupted images. Segmentation result of all the algorithms under consideration is shown in Figs. 6c–g and 7c–g. Table 3 describes the entropy obtained from the experiments performed by using wolf image corrupted with various degrees of Gaussian noise and salt-and-pepper noise. Segmentation results depicted in Figs. 6 and 7, and Table 3 prove that KWPFLICM is found more robust to noise than all other algorithms.

5 Conclusion

In this paper, a new kernel possibilistic fuzzy clustering algorithm is proposed for the robust segmentation of noisy images. Simulation results have demonstrated that kernel-based possibilistic fuzzy clustering is an effective technique for robust image clustering. Our proposed algorithm is a parameter-free approach that improves image segmentation performance. Furthermore, relative to preexisting algorithms, this method shows enhanced robustness to various types of noise and outliers. This algorithm does have the drawback of a high time complexity due to the computation of the fuzzy factor G''_{ab} in each iteration, but its exceptional performance in experiments compensates for this weak point.

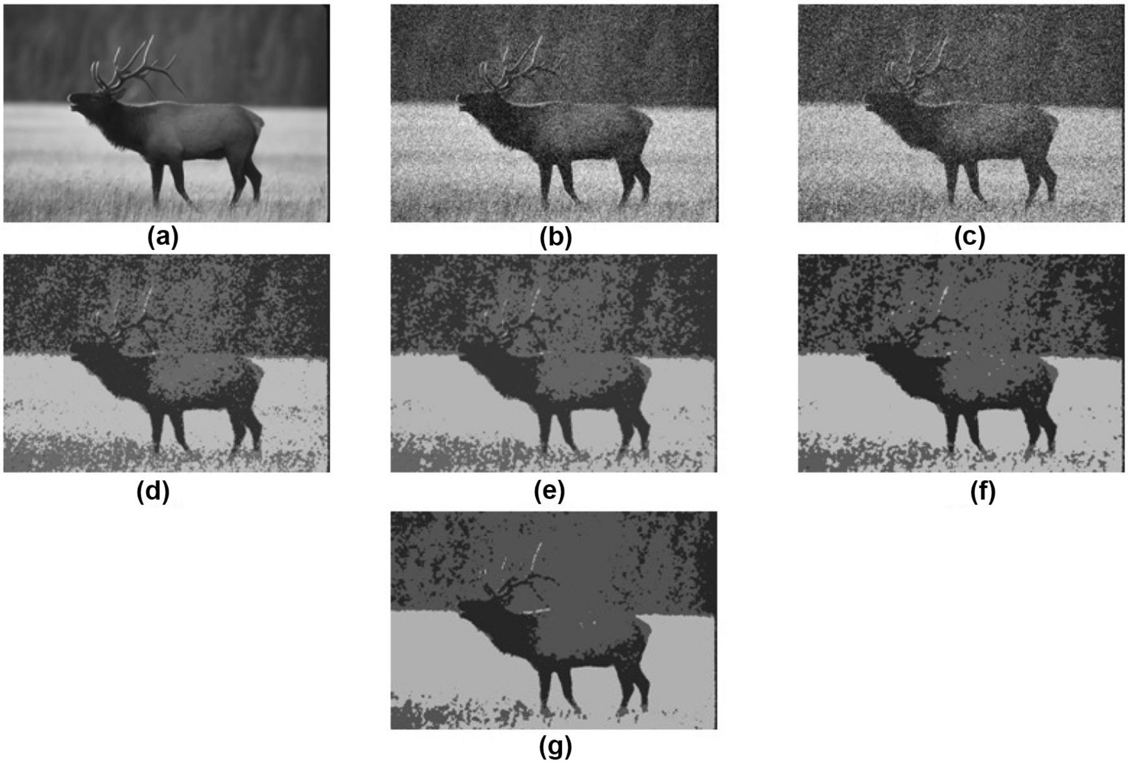

Fig. 7 Segmented results for the "stag image: **a** Original image, **b** corrupted by (50%) Gaussian Noise, **c** FLICM, **d** RFLICM, **e** WFLICM, **f** KWFLICM, **g** KWPFLICM

Table 3 Entropy (E) on real wolf noisy image corrupted by various levels

Noise	FLICM	RFLICM	WFLICM	KWFLICM	KWPFLICM
25% G	5.362	4.9397	4.9338	4.9263	4.9123
20% G	5.3123	4.892	4.865	4.836	4.798
40% SP	5.2371	4.996	4.987	4.9024	4.7065
50% SP	6.391	5.990	5.8341	5.687	5.0814

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