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Image Segmentation using Improved Imperialist Competitive Algorithm and a Simple Post-processing

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Abstract
Image segmentation is a fundamental step in many image processing applications. In most cases the image pixels are clustered only based upon the pixels' intensity or color information, and neither spatial nor neighborhood information of pixels is used in the clustering process. Considering the importance of including spatial information of pixels which improves the quality of image segmentation, and using the information of neighboring pixels, cause the accuracy of segmentation to be enhanced. In this paper the idea of combining the K-means algorithm and the improved imperialist competitive algorithm is proposed. Also before applying the hybrid algorithm, a new image is created and then the hybrid algorithm is employed. Finally, a simple post-processing is applied to the clustered image. Comparing the results of applying the proposed method to different images with other methods shows that in most cases, the accuracy of non-local imperialistic competitive algorithm (NLICA algorithm) is better than the other methods.

Keywords: *Image Segmentation, Clustering, Improved Imperialist Competitive Algorithm, Post-processing, Berkley Images Dataset*

1. Introduction
Image segmentation is one of the most fundamental steps in digital image processing. In many image processing applications, such as medical image processing, computer vision and face recognition, it is an essential and important requirement to begin processing.
Image segmentation is to separate the pixels of an image into distinct regions such that the pixels belonging to each region are similar in terms of the characteristics such as intensity, texture. Segmentation divides the image into K regions so that the following conditions are met [1]: 1. Each pixel should be part of a region. 2. Each pixel only belongs to one region. 3. Pixels of each region are similar in terms of some features or attributes. 4. The members of various regions are different in the feature or features. After segmenting the image, the pixels of each region are displayed with the same intensity or get equal labels.
Image segmentation is performed using various methods, which could generally be divided into two categories: region-based methods and the methods based on edge detection. Clustering pixels based on pixels' features is one of the most important techniques in the image segmentation [2]. For many clustering methods, the pixels are clustered based on the characteristics such as brightness or color [3] and none of the spatial and neighborhood information of pixels are used in the clustering process, which makes these methods to have no desired performance in noisy image segmentation.
In the proposed algorithm, termed as non-local imperialistic competitive algorithm (NLICA), first, a new image is generated using the information of the pixels located within the large window around each pixel in the input image, and then the improved imperialist competitive algorithm is used to search for the optimal cluster centers of the new image pixels. After clustering the pixels of the new image, a simple post-processing is applied to the

clustered image to enhance the accuracy of segmentation.
The rest of this paper is organized as what follows: In Section 2, the basic concepts used in the proposed algorithm are described and an overview of the previous methods is performed. In Section 3, the proposed method is explained in details and the proposed algorithm is verified by the segmentation experiments applied to synthetic and natural images. Section 4 presents the conclusion and future works.

2. Background
In this section the basic concepts used in the proposed method are explained and an overview of the past approaches and algorithms is given.

2.1. Related works
Y. Yang et al. [6] have imposed the influence of the neighboring pixels on the central pixel of the neighborhood by modifying the objective function of the FCM algorithm and adding a penalty term. According to the new cost function, if pixels i and j are adjacent, pixel i belongs to cluster k with a high degree of membership and the membership degree of pixel j in cluster k is small, then the cost function will be penalized. Ahmed et al. [7] have modified the objective function of the FCM algorithm in order to impose the restriction of the similarity between the adjacent pixels. In the new objective function, if the average of distances between adjacent pixels of the central pixel intensity values and the intensity of cluster center i, is high, then in this case, the membership degree of the center pixel in the *i*th cluster should have a small value. Szylagy et al. [8] have replaced the pixel values by an amount proportional to the total value of the considered pixel intensity value and the average of the pixels adjacent to the central pixel's intensity values, and then the FCM algorithm is employed for clustering the new image pixels. Cai et al. [9] have used the criterion that is similar to the FCM algorithm cost function for clustering the image pixels; they have also used a criterion in which despite using the Euclidean distance between the pixels intensity values, the spatial distance (coordinate) between two pixels has been used,.
Recently, Zhao et al. [10] have proposed a method based on the S-FCM algorithm and using the non-local information of the pixels. In this method, all the pixels are arranged according to their degrees of membership in the clusters and then r number of the pixels that have the greatest membership values among the whole pixels of the image are selected.

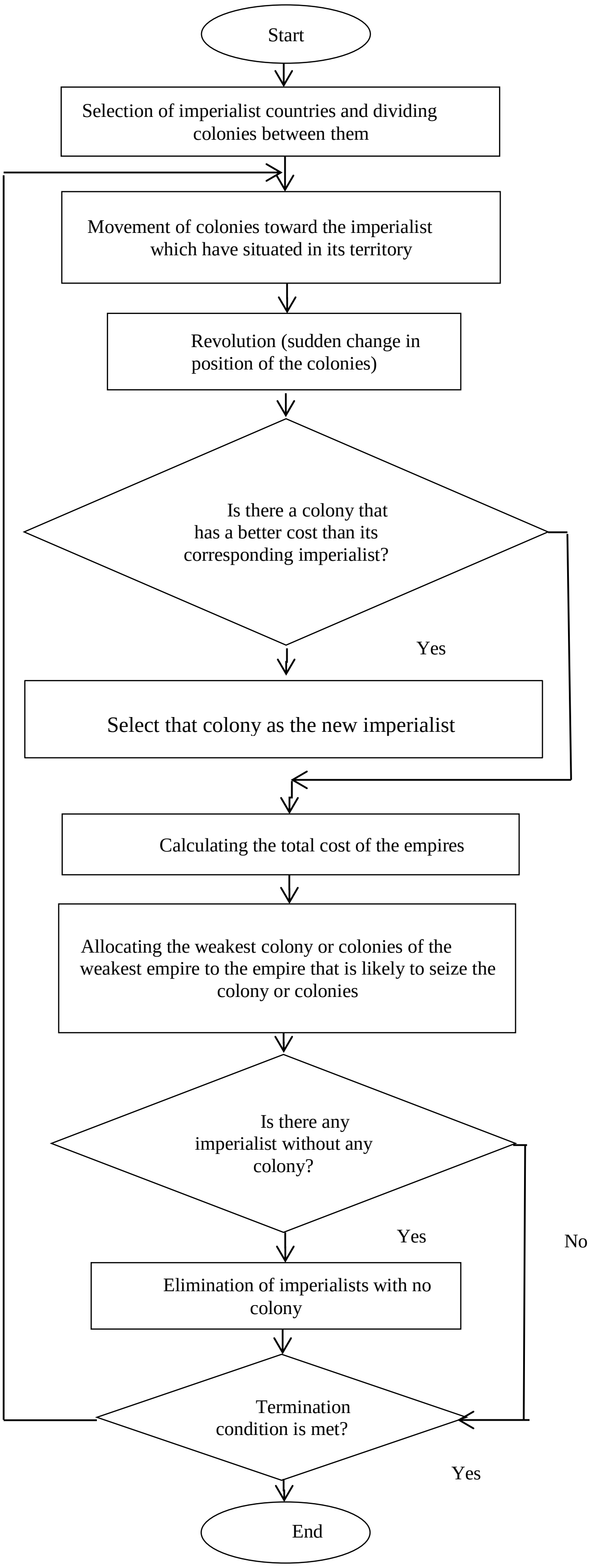


Figure 1. Flowchart of the imperialistic competitive algorithm

Then their membership degrees in the cluster in which they have the highest membership degree are increased. The non-local information for each pixel is calculated using a weighted average of the intensity values of the pixels located within a great neighborhood window centered at the pixel of interest [11]. Then, the weights between the central pixel and its neighboring pixels are calculated in a consistent manner.

2.2. K-means algorithm

In the K-means algorithm, some data points are randomly selected from the data set as the cluster centers. Then the other data points are assigned to the clusters according to their proximity to the cluster centers. By averaging the data attributed to each cluster, the new cluster centers are calculated and again the data points are assigned to clusters based on the proximity and similarity to the new cluster centers. The above-mentioned steps will be repeated until the cluster centers do not change.

2.3. Imperialist competitive algorithm

The imperialist competitive algorithm is an evolutionary algorithm that models the process of socio-political development of countries [5], and it has been used for solving different optimization problems. Figure 1 shows a flowchart of this algorithm.

2.4. Edge detection using sobel method

The purpose of edge detection in image is to mark the places where the intensity changes sharply. The basic theory in many ways of edge detection is to calculate a local derivative operator. We utilized the Sobel edge detector [4] because of its simplicity; the input image is convolved only with two 3×3 masks. In the Sobel method, a derivative of the image is made by filtering the image with Sobel masks. Sobel masks are applied to the image in both the horizontal and vertical conditions, and gradient magnitude for every pixel of the image is computed using the horizontal and vertical gradients. The average gradient magnitude for edge pixels were computed as a threshold. Then, the pixels whose gradient magnitude values were greater than the threshold were selected as the edge pixels. Edge detection in noisy images is a challenging task [12].

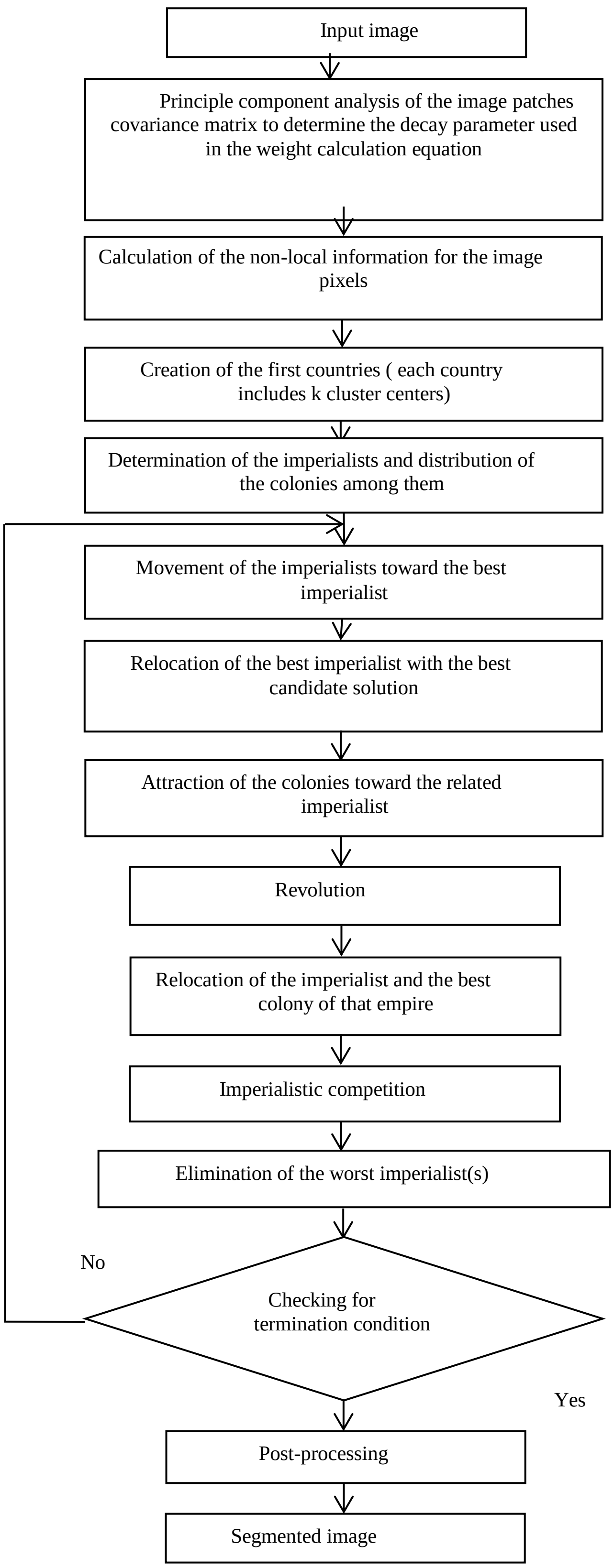


Figure 2. Flowchart of the NLICA algorithm.

3. Proposed method

In the proposed algorithm, termed as NLICA, a way for gathering the neighborhood information of the pixels in a large neighborhood window has been introduced. In the second stage, a combination of the improved imperialist competitive algorithm and the K-means clustering algorithm is presented for clustering the new image pixels. Finally, a simple post-processing that is applied to the clustered image is presented. A flowchart of the proposed algorithm is shown in figure 2.

3.1. Obtaining non-local information

In the proposed algorithm, in order to collect the spatial information for each pixel, the weighted average of the intensity values for the surrounding pixels that are located within a large window around the pixel of interest is calculated as the feature for clustering that pixel. After calculating the non-local information for all the pixels, a combination of the improved imperialist competitive algorithm and K-means algorithm for the purpose of clustering of the image pixels is used. In fact, the cost function of the K-means algorithm is optimized via the improved ICA optimization algorithm. To do so, the improved ICA searches for the cluster centers such that the allocation of the data points (image pixels) to them, minimizes the intra-cluster distances and maximizes the inter-cluster differences. A pixel that is situated within the large neighborhood window and has a similar structure to the neighborhood configuration of the central pixel, gets a big weight in the calculation of the weighted average for the central pixel. In figure 3, the large $r \times r$ neighborhood window and the small $s \times s$ neighborhood window around the central pixel are shown.

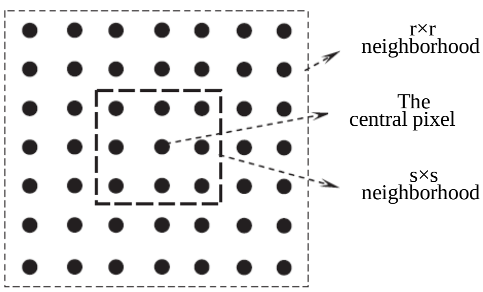


Figure 3. The neighborhood windows (Up: the large r × r neighborhood, Down: the small s × s neighborhood around the central pixel).

In order to calculate the weights between the central pixel and its neighboring pixels, situated within the large neighborhood window, the intensity values for the pixels in the Gaussian filtered and the details images are used. A Gaussian filter is a low-pass filter, and applying it on it to the images reduces the noise with loss of the image details. The variance parameter of the Gaussian filter determines the smoothing amount of the image. Hence, in the proposed method, the variance parameter is considered to be 1 in order to avoid the loss of more image details. The residual image is obtained via calculation of the difference between the input noisy image and the image smoothed by the Gaussian filter. The eliminated details of the original image are obtained by reduction of the residual image noise. In order to reduce the effect of the noise on the residual image, the mean filter with the typical size of 3×3 is used. The resulting image after applying the mean filter on the residual image includes some details such as the weak edges of the original image. If x, y, $\hat{x}$, and $\hat{n}$ are the original noise-free image, noisy image, smoothed image, and residual image respectively, then we can write a formula for the input noisy image according to (1):

$$\hat{n} = y - \hat{x} \rightarrow y = \hat{x} + \hat{n} \tag{1}$$

with the assumption of the Gaussian noise presence in the input image, the original image can be expressed as (2):

$$x = y - n = \hat{x} + \hat{n} - n = \hat{x} + Vx \tag{2}$$

In (2), Δx is indicative of the residual image signal or detailed image and n is the Gaussian noise.

For the purpose of assigning a weight between the central pixel *i* and the *j'th* neighboring pixel located within a large $r \times r$ window centered at the pixel *i*, the weighted Euclidean distance between the vector of intensity values of the pixels within a small $s \times s$ window centered at the pixel *i* in the original image and the vector of the intensity values of the pixels within a small $s \times s$ window centered at the *j'th* neighboring pixel in the original image is calculated [10,11]. Here the original image (noiseless image) is approximated by adding the Gaussian-filtered image to the detailed image. The Euclidean distance between the neighborhoods of the pixels *i* and *j* in the approximated original image is calculated using (3):

$$\begin{aligned}&\|X(N_i)-X(N_j)\|^2 = \\ &\sum_k (x_i^k - x_j^k)^2 = \sum_k \left[\hat{x}_i^k + \Delta x_i^k - \hat{x}_j^k - \Delta x_j^k\right]^2 \\ &= \sum_k \left(\hat{x}_i^k - \hat{x}_j^k\right)^2 + \sum_k \left(\Delta x_i^k - \Delta x_j^k\right)^2 + \\ &2\sum_k \left(\hat{x}_i^k - \hat{x}_j^k\right)\left(\Delta x_i^k - \Delta x_j^k\right)\end{aligned} \quad (3)$$

In this equation, $\hat{x}^k$ and Δx^k are the intensity values for the *k'th* neighbor of the pixels i and j situated within the $s \times s$ window centered at the pixels i and j in the Gaussian-filtered image and the detailed image respectively. N_i and N_j specify $s \times s$ neighborhood windows centered at the pixels *i* and *j*. The weight between the central pixel *i* and the *j'th* neighboring pixel located within a large $r \times r$ window centered at the pixel *i* is calculated [10] according to (4):

$$w_{ij} = \frac{1}{Z_i}\exp\left(-\frac{\|x(N_i) - x(N_j)\|_{2,\sigma}^2}{h^2}\right) \quad (4)$$

In this equation , z_i is the sum of the weights between the central pixel *i* and all the pixels situated within the r×r window centered at the pixel *i* [10]. This normalization term is calculated using the Equation 5:

$$Z_i = \sum_j \exp\left(-\frac{\|x(N_i) - x(N_j)\|_{2,\sigma}^2}{h^2}\right) \quad (5)$$

Dividing the weights by z_i causes them to lie in the (0,1) interval. In the proposed algorithm, the values for the parameters r and s have been chosen to be 9 and 5 respectively and the variance of the Gaussian function that is used in calculation of the weights for the vectors of Euclidean distances between the intensity values of the pixel neighborhoods is considered 1. In Equations 4 and 5, the parameter h is the same. The value for the parameter h that determines the decay of the exponential term in the equation of weight calculation has an important role in how to calculate the non-local information for the pixels [10]. If the value for this parameter is selected to be a large number, then this will cause the deterioration of weak edges and details in the segmented image. In the case of selecting a small amount for the parameter h, the effect of noise in the segmented image would be evident. For the purpose of specifying an appropriate value for this parameter, first the input image is divided into small patches with sizes 7×7 such that these patches have overlap. After conversion of the patches into the feature vectors with dimensions of 49 × 1 and subtracting the mean of these vectors from each of them, the covariance matrix of the distribution of image patches is obtained and finally, the value for the parameter h^2 is chosen to be equal to $2 \times \sqrt{\lambda_m}$ in which λ_m is the smallest eigenvalue of the covariance matrix [13,14]. The weighted non-local mean feature value for the pixel i is obtained according to (6):

$$\text{Accuracy} = \frac{\text{number of pixels that are classified correctly}}{\text{total number of pixels}} \quad (6)$$

In this equation, w_{ij} is the weight between the central pixel *i* and the *j'th* neighboring pixel of *i* situated within the $r \times r$ neighborhood window centered at the pixel *i*, y_j is the intensity value of the *j'th* neighboring pixel in the noisy input image and W_i^r is an $r \times r$ neighborhood window centered at the pixel *i*.

3.2. Hybridization of K-means and improved imperialist competitive algorithm

The K-means algorithm with two stages of assigning the data points to the clusters and updating the cluster centers, tries to minimize the sum of distances from the data points to the cluster centers. The possibility of converging to a local minimum of the objective function is high, because the objective function has many local minima. Therefore, the improved imperialist competitive algorithm is used for searching the optimal cluster centers [15] of the new image pixels. After calculating the weighted non-local mean feature for all the pixels in the image, the improved imperialist competitive algorithm using the objective function of the K-means algorithm, clusters the pixels based on the weighted non-local mean features of them. In other words, the improved imperialist competitive algorithm segments the image via searching for the optimal cluster centers in the pixels' weighted non-local mean feature space.

3.2.1. Coding

The structure of countries or coding in the proposed method is an array of cluster centers in such a way that each entry of the array includes a float number in the interval 0 to 1([0-1]), and this value specifies the weighted non-local mean feature of the corresponding cluster center of that entry. An example of the structure of a country in the proposed algorithm is shown in figure 4.

3.2.2. Attraction operator

Attraction policy in the NLICA algorithm is implemented in such a way that the values for the variables in the colony's vector get closer to the values for the variables in the imperialist's vector in the problem space. First, the differences between all entries of imperialist's vector and the corresponding entries in the colony's vector are calculated and any discrepancy obtained is multiplied by different random numbers in the [0,1] interval. Then each element of the resulting vector is multiplied by the weight $\beta = 2$ and the final resulting vector is added to the colony's vector so that the new position of the colony is obtained. We have selected the value 2 for β, based on our experiments.

3.2.3. Revolution operator

In order to implement the revolution operator, first one of the entries of the considered colony's vector will be randomly selected and a random number in the interval [0,1] is generated and the previous content of the selected entry in the colony is replaced by the generated random number.

0.6	0.21	… 0.83	

Figure 4. Structure of the countries in the NLICA algorithm.

3.2.4. Imperialists' movement

In the standard imperialist competitive algorithm, imperialist countries do not have any movement and only the colonies move toward their relative imperialists in the space of variables. To enhance the power of the NLICA algorithm, in this algorithm the imperialists approach the most powerful imperialist with a random angle and distance. The imperialist that has the best cost, is selected as the most powerful imperialist and the other imperialists move toward the powerful imperialist. The movement of imperialists toward the powerful imperialist is similar to the attraction of the colonies toward the relative imperialist. The difference is that here the value for the weight parameter is selected to be equal to 0.95. In figure 5, an example of the imperialists' movement is shown.

3.2.5. New operator of searching around best imperialist

In order to explore the space around the most powerful imperialist (the imperialist with the best cost), some candidate countries within a certain radius around them are produced, and if one of these countries (solutions), has a cost better than the cost of the strong imperialist, then the position of the strong imperialist changes to the position of the new generated country in the space of variables. If r is the radius of the new answers generation, then a vector of uniform random numbers whose values are in the interval $[-r, r]$ is generated. The length of this vector (quantity of generated random numbers) is equal to the number of clusters. The generated vector is then added to the most powerful imperialist's vector. The radius of the solution production is variable and in each decade it decreases. Its value at the beginning of the algorithm is equal to 0.5 and then becomes half of the radius of the previous decade. Figure 6 shows an example of the generated solutions around the best imperialist.

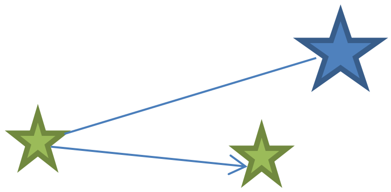


Figure 5. The imperialists' movement.

3.2.6. Cost function

In evolutionary algorithms, the quality of the solutions is determined via computing the cost function for them. The cost selected for the NLICA algorithm is similar to that for the K-means algorithm, and is equal to the total distance of the weighted non-local mean feature values of the pixels from the non-local feature value of the associated cluster centers.

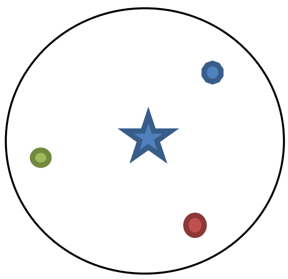


Figure 6. The produced candidate solutions around the most powerful imperialist.

3.2.7. Proposed post-processing

After clustering the pixels, each pixel is labeled with the associated cluster's number or the number of the region that belongs to. Then a simple post-processing, inspired by the fact that the adjacent pixels in the image are similar [10], is performed on the clustered image. In order to extract the image edges, the Sobel method is used. If the pixel's gradient magnitude is greater than the threshold, that pixel would be selected as part of the image's edges and the value for the corresponding pixel in the edge map image is determined to be equal to 1. The values for the other pixels that are not part of an edge are selected to be equal to zero in the edge map image. If Gmax is the greatest value for the gradient magnitude among the pre-processed image pixels and Gmin is the smallest value for the gradient magnitude between the pre-processed image pixels, in this case, the value for the threshold is determined according to (7):

$$\text{Threshold} = 0.15 \times \left(\text{Gmax} - \text{Gmin}\right) + \text{G} \qquad (7)$$

We have chosen 0.15 as the multiplier for the difference between the greatest and the lowest gradient magnitudes in order to keep the threshold magnitude small and this value has been selected based on our experiments. The standard deviation of the pre-processed image pixels (image in which the value of each pixel is replaced with the weighted non-local mean of the surrounding pixels) is calculated. If the standard deviation value is larger than 0.1, the erosion operator is applied in order to remove the edges caused by noise in the edge map image. In the post-processing step, labels of the edge pixels are not altered in order to preserve the details, and the other pixels are labeled with the maximum repeated label of the pixels situated within the specified neighborhood around the pixel of interest. This idea of allocation of the neighborhood pixels' labels to the label of the pixel of interest is derived from the fact that the neighboring pixels and adjacent image blocks are correlated. A flowchart of post-processing is shown in figure 7.

4.1. Experiments

In order to evaluate the NLICA algorithm, several images have been selected as benchmark for image segmentation using the algorithm. These images are divided into two categories: synthetic images and natural images. Natural images are selected from the Berkeley database [16] images and Gaussian noise is added to all of these images. The NLICA algorithm is implemented in MATLAB, and the program runs on PC P8400 with 2.26GHz processor speed. The synthetic test images are shown in figure 8. Image number 1 comprised of two regions with 60 and 100 brightness values and Gaussian noise with zero mean and a normalized variance equal to 0.005 is added to it. Image number 2 contains three regions with the brightness values 0, 128 and 255 and this image is corrupted with Gaussian noise that has normalized variance equal to 0.01. Image number 3 contains four regions with the brightness values of 0, 100, 145 and 200, respectively and Gaussian noise with normalized variance equal to 0.01 is added to it. In order to evaluate the segmentation results of the benchmark images, the accuracy criterion is used. The class labels for synthetic images are known, since we have generated them. Therefore, we have ground truth images for the synthetic images. For the images picked from the Berkley dataset, the pixels of each region or cluster are labeled manually by experts with the number of that region and these images are called the reference segmented images. The ground truth images were provided along with the raw images. To calculate the amount of accuracy, the labels of the pixels in the segmented image are compared with the corresponding pixel labels in the reference image and by counting the number of pixels of the segmented image that have the same label as the label of the corresponding pixel in the reference image, we can calculate the accuracy of the method of interest. As the number of pixels that are clustered correctly based on the reference image, increases, the accuracy becomes higher and vice versa. The accuracy is calculated using (8):

$$\text{Accuracy} = \frac{\text{number of pixels that are classified correctly}}{\text{total number of pixels}} \qquad (8)$$

The parameters of the proposed algorithm are specified as follows: the number of imperialists is 5, and the number of colonies is 25. Since the number of colonies is more than the number of imperialists [5], we have distributed 25 colonies among 5 imperialists. Parameter β is equal to 2 based on our experiments and the suggestions of the ICA algorithm authors [5]. Again, the probability of revolution is 0.1 according to multiple runs of the algorithm with different values of this parameter. Parameter α is selected to be equal to 0.1 after trying multiple values in our experiments and the number of decades of the algorithm is selected to be equal to 30; this is because the algorithm usually converges after 30 iterations.

4.1.1. Experiments on synthetic images

The NLICA algorithm is used for segmenting the synthetic test images and the accuracy of segmentation and the number of misclassified pixels considering the reference image, is compared with the results obtained using other segmentation algorithms, such as FCM, PFCM, SKFC and SFCM. We obtained the accuracies on the test images without any error in accuracy. In other words, since we had the reference ground truth images, we were able to count the exact number of misclassified pixels in different test images segmented using various methods including our algorithm. According to Tables 1 to 3, the accuracy of the segmenting image number 1 using the NLICA algorithm is greater than the accuracy of the other methods, except for the PFCM algorithm. Also NLICA performs better than the other mentioned algorithms in segmenting image numbers 2 and 3. Figure 8 shows the synthetic test images we used in our experiments, and all of these images have size of 256×256 pixels.

4.1.2. Experiments on natural images

The selected images from the Berkley images database are shown in figure 9. These images are segmented using the NLICA algorithm, and the results are compared with the results obtained from segmenting the same images using the FCM, S-FCM, EnFCM, FGFCM and OSFCM-SNLS algorithms. The Gaussian noise with mean zero and normalized variance 0.005 is added to the image #238011 and the image #167062 is demolished using the same noise with normalized variance equal to 0.01. Also the normalized variance of the Gaussian noise added to the test image #42049 is chosen to be equal to 0.03. Table 4 shows the results of segmenting the noisy test images using the NLICA algorithm and other methods. In order to compare the above-mentioned algorithms with the proposed algorithm fairly, the size of the neighborhood window in S-FCM, EnFCM and FGFCM is selected to be 3×3, and the parameter β used in the EnFCM algorithm is considered to be equal to 6. According to the results of investigating the FGFCM algorithm, the parameters λ_S and λ_G are selected as 3 and 6 respectively. The fuzzy index parameter, number of maximum iterations, and quantity of the threshold are considered to be equal to 2, 500 and 10^{-5}, respectively for all the mentioned algorithms and finally the parameters r and s for the OSFCM-SNLS algorithm are set equal to 21 and 7, respectively. The NLICA algorithm segments the noisy test images with a higher accuracy than the other algorithms in most cases. The superiority of the proposed algorithm by comparing its segmentation results with the results of the FCM algorithm becomes obvious. OSFCM-SNLS algorithm is an algorithm that segments the noisy images using the pixels' non-local information excellently and its segmentation results are competitive with the results of the NLICA algorithm. OSFCM-SNLS has segmented the image #167062 slightly better than the proposed method but the results obtained by segmenting the test images using NLICA especially in segmenting image #42049, are significant in comparison with all methods in most cases. The segmented images of one of the natural images using different algorithms are shown in figure 10.

For each pixel in the case that it is not an edge pixel

Consider a neighborhood window of size 40 × 40 centered at the pixel of interest

While at least one of the pixels within the specified window is an edge pixel

Decrease the radius of the neighborhood window by one unit

Check belongingness of the pixels situated within the new neighborhood window in the edge pixels set

Set the label of the central pixel of the neighborhood the same as the most repeated label of the pixels within the specified neighborhood window

Figure 7. Flowchart of the post-processing step.

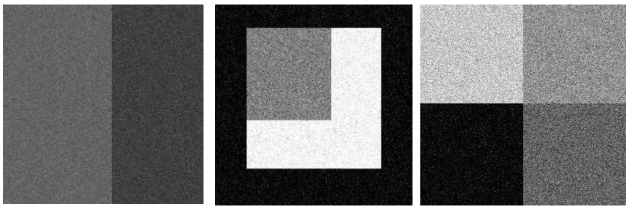


Figure 8. The synthetic test images.

4.1.3. Stability of NLICA algorithm

Stability of the evolutionary algorithms becomes clear by comparing the solutions obtained in various runs of the algorithm. To demonstrate the stability of the algorithm, therefore, the stability diagram at ten runs of the NLICA algorithm for segmenting each one of the test images, are drawn. Figure 11 shows the stability diagrams for the results obtained in segmentation of some of the test images. Given the stability diagrams, the NLICA algorithm for three of the test images in all of the ten runs gives the same results and for the other three test images, the generated solutions in ten runs of the algorithm are very close to each other.

4.1.4. Convergence of NLICA algorithm

To demonstrate the speed and accuracy of the proposed algorithm convergence, the convergence diagram of the NLICA algorithm that is used for various image segmentations is plotted with respect to cost function. The NLICA algorithm converges the optimum solution in less than 20 iterations in segmentation of all the test images. The convergence diagrams for some of the test images are plotted in figure 12.

4.2. Statistical tests

The proposed algorithm is used for segmentation of the six test images and for both of the test images, the algorithm produces the same optimal solutions in 30 runs. For the other test images, the solutions obtained are very close to each other with a small standard deviation. Thus the statistical methods are applied to four images that have distorted solutions in 30 runs. One of the primary methods for the detection of whether the data follows a normal distribution is plotting the Q-Q diagram of the data. In this diagram, a line is fitted based on the normal distribution and whatever the points of the diagram are closer to the line, distribution of the data is closer to a normal distribution. The Q-Q diagrams of the solutions obtained in 30 runs of the NLICA algorithm that used for the segmentation of the four test images, that had deviated solutions in different runs are conducted, and the conclusion is that the data does not follow a normal distribution. The Kolmogorov-Smirnov test is used to check whether the data is normally distributed or not. Null hypothesis for this test is defined to be: we want to determine if the sample is obtained from a normally distributed population. If the p-value obtained is less than 0.05, the assumption of normality of the data is rejected and vice versa. By performing experiments on images that have deviated solutions, the p-value for each image was less than 0.05 which indicates that the population is not normal. Thus for the inference of data we chose non-parametric methods such as the Wilcoxon test. This test is a non-parametric statistical test used to assess the similarity of two associated samples with the rating scale. For the purpose of testing the equality of a population mean with a given value, the Wilcoxon test is used. This test has been conducted for the images for which the answers of the NLICA segmentation algorithm in thirty runs had deviation. The result of the Wilcoxon test is shown in Table 6. For performing this test, the solutions obtained in 30 runs of the NLICA algorithm on each one of the test images is divided into two groups of fifteen elements each and the mean equality test (Wilcoxon) is done for them. The results of the Wilcoxon test are positive in all cases.

(b) Image #167062

(a) Image #238011

(c) Image #42049

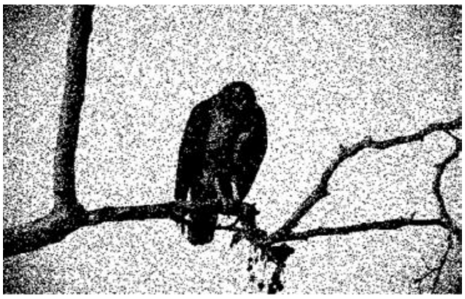
Figure 9. The selected test images from Berkeley database.

Table 1. Segmentation results of image number 1.

Metric	**Algorithms**				
	FCM	**SFCM**	**SKFC**	**PFCM**	**NLICA**
Number of misclassified pixels	4520	386	17	10	12
Accuracy (percent)	93.103	99.411	99.974	99.985	99.981

Table 2. Segmentation results of image number 2.

Metric	**Algorithms**				
	FCM	**SFCM**	**SKFC**	**PFCM**	**NLICA**
Number of misclassified pixels	564	27	8	9	3
Accuracy (percent)	99.1394	99.9588	99.9878	99.9862	99.9954



(b) FCM

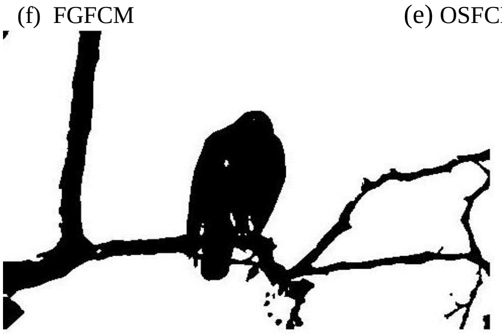
(a) The noisy image

(d) SFCM

(c) EnFCM

(f) FGFCM

(e) OSFCM-SNLS



(g) NLICA

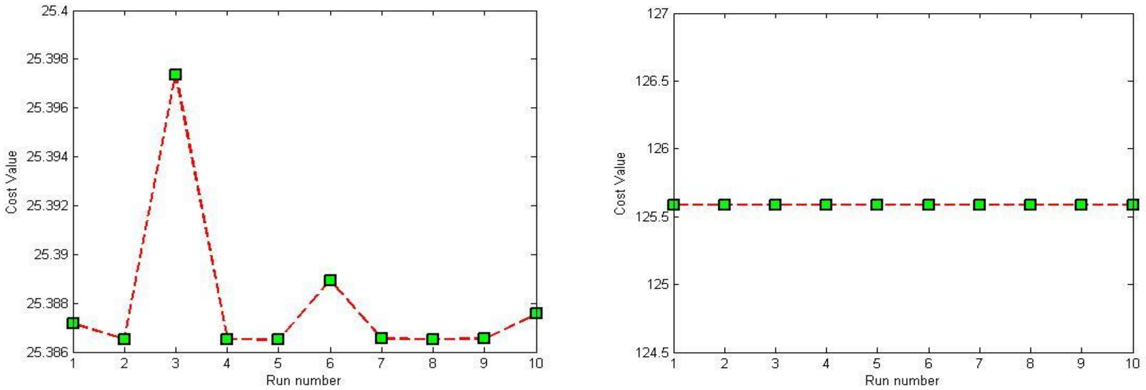
Figure 10. Segmentation results of image #42049 using different algorithms.

Table 3. Segmentation results of image number 3.

Metric	Algorithms					
	FCM	SFCM	EnFCM	FGFCM	OSFM-SNLS	NLICA
Number of misclassified pixels	14522	4443	707	662	249	30
Accuracy (percent)	78.84	93.22	98.92	98.99	99.62	99.95

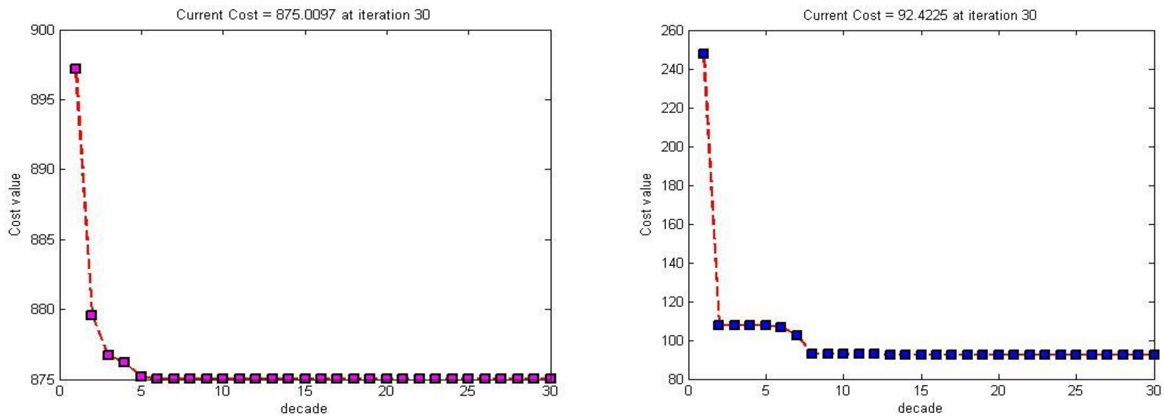
Table 4. Results of the natural test images' segmentation using different algorithms (in terms of accuracy (percent)).

Images	Algorithms					
	FCM	S-FCM	EnFCM	FGFCM	OSFM-SNLS	NLICA
#238011	56.79	94.25	64.14	63.91	96.09	96.74
#167062	92.2	81.74	98.48	98.41	99.11	99
#42049	84.4	93.72	95.50	95.46	96.14	96.53



(b) (a)

Figure 11. Stability diagram plotted using the results obtained in ten runs of the NLICA algorithm in segmentation process of the Berkley test images: (a) #238011 and (b) #42049.



(b) (a)

Figure 12. The convergence diagrams of the NLICA algorithm in segmentation process of the Berkley test images: (a) #238011 and (b) #42049.

Table 6. Results of the Wilcoxon test.

Test image	µ	Z	p-value	Result
Number 2	8.3742	-1.342	0.18	Positive
Number 3	25.2104	-2.814	0.05	Positive
#167062	125.8554	-1.362	0.173	Positive
#238011	92.4226	-1.604	0.109	Positive

5. Conclusion and future work

In this paper, an algorithm for clustering the image pixels using non-local information is proposed such that in the first step of the algorithm, the non-local information for each pixel is computed and then in the second step, the hybrid of improved imperialist competitive algorithm and K-means algorithm for the purpose of searching the optimal cluster centers of the new image pixels is exploited. Finally, a simple post-processing for increasing the accuracy of segmentation is applied on the clustered image. The accuracy of the segmented images using the NLICA algorithm is more than the other algorithms' results in most cases, and the accuracy has an increase of 0.35% to 1% compared to the other methods. The proposed algorithm is capable of competing with the other algorithms in this area. It is proposed to modify the coding and cost function of the proposed algorithm in a way that it would be able to specify the number of image regions or clusters automatically. It is also recommended to use the texture features beside the intensity and spatial information of pixels for the purpose of clustering them.

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نشریه هوش مصنوعی و داده کاوی

بخش‌بندی تصویر با استفاده از الگوریتم رقابت استعماری بهبودیافته و یک پس‌پردازش ساده

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چکیده:

بخش‌بندی تصویر گام اساسی در بسیاری از کاربردهای پردازش تصویر است. در اغلب موارد، پیکسل‌های تصویر فقط براساس اطلاعات شدت روشنایی و رنگ پیکسل‌ها خوشه‌بندی شده و اطلاعات مکانی و محلی از پیکسل‌ها در فرایند خوشه‌بندی استفاده نمی‌شود. با توجه به اهمیت اطلاعات مکانی پیکسل‌ها که کیفیت بخش‌بندی تصویر را بهبود می‌بخشد، استفاده از اطلاعات پیکسل‌های همسایه، باعث افزایش دقت بخش‌بندی می‌شود. در این مقاله ایده ترکیب الگوریتم K-means و الگوریتم رقابت استعماری بهبود یافته پیشنهاد شده است. همچنین قبل از اعمال الگوریتم ترکیبی، یک تصویر جدید بر اساس تصویر ورودی ایجاد شده و سپس الگوریتم پشنهاد شده استفاده می‌شود. درنهایت یک پس‌پردازش ساده بر روی تصویز خوشه‌بندی اعمال می‌گردد. مقایسه نتایج استفاده از روش پیشنهادی برای بخش‌بندی تصاویر مختلف با روش‌های دیگر نشان می‌دهد که در اغلب موارد، دقت الگوریتم رقابت استعماری غیرمحلی (الگوریتم NLICA) بهتر از سایر روش‌ها است.

کلمات کلیدی: بخش‌بندی تصویر، خوشه‌بندی، الگوریتم رقابت استعماری بهبودیافته، پس‌پردازش، مجموعه داده‌های برکلی.