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An enhanced artificial bee colony algorithm using radial bases function neural networks for color image segmentation

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***Abstract*---**The aim of segmentation process is to partition the image into homogeneous regions or objects. The proposed segmentation algorithms using adaptive feature weighting to distinguish the significance of various features. To extract effective feature extraction could be used for establishing regions in region based image segmentation. The main goal of this exploration work is to segment objects that separating the foreground and background of the color images. The segmentation for color images is focused on the Enhanced Artificial Bee Colony segmentation algorithm that utilizes the Radial Basis Function (EABCRBF) neural network algorithm. This work arranges RBF neural networks to predict the end limits of the segmentation, which are formed from the artificial bee colony province made in the image histogram topography. The radial basis function initial parameters, for instance, centers and widths are automatically set upon the histogram peaks and minima. The proposed EABCRBF strategy is compared with two existing techniques of Artificial Bee Colony (ABC) and Fuzzy C-Means (FCM). The EABCRBF method gives great outcomes for color image segmentation as it extracts additional information from color images. The experimentation results are shown through Mat Lab R2013a. The experiments utilize an assortment of three sample color images from the Berkley Dataset and the Oxford Flower 17 Dataset. The input color images have various sizes of

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dimensions. The performance measurement metrics RI, VoI, GCE, and BDE values are compared with existing methods of ABC, FCM and proposed strategy of EABCRBF. The proposed EABCRBF method accomplishes better segmentation results while comparing existing methods. From the Table FCM method gives values for 0.9227 for RI, 0.0934 for GCE, 0.5069 for VOI and 0.1449 for BDE respectively. The ABC segmentation yields the values are 0.9447, 0.0713, 0.4301 and 0.1219. The EABCRBF gives values 0.9907, 0.0137, 0.0966 and 0.0171for the parameters which are superior to FCM and ABC techniques.

Keywords--- Image Segmentation, Classification, Enhanced Artificial Bee Colony, RBF Neural Networks, EABCRBF.

Introduction

Image segmentation is the process of segregating an image into various different regions agreeing with the attributes of color, intensity or texture. The histogram is viewed as an approach to addressing the features of an image depending on the number of characters of each pixels brightness value[1]. An image features are addressed as regions with tops in the image histogram. The neural networks Radial Bases Function (RBF) will be prepared online to find the two nearby minima markers for each segment in the image[2]. The complicated elements of a process can be established using RBF neural networks. Image segmentation is a significant process in image recognition and computer vision[3]. Picture quantization has been smeared to color images and is made out of hybridization, the work of K-means algorithm that works for clustering yet now and takes a long time to merge to an acceptable error, and the ABC algorithm that works to diminish the way to the center of the cluster[4]. The artificial bee colony algorithm is utilized to develop the center of each cluster which is joined with the k-means algorithm as a feature of its optimization[5-6].

The segmentation accuracy will be impacted with be affected with the increase of threshold number[7]. It is utilized to demonstrate the optimal parameters of the fitting capability and practice levy flight to improve the Salp Swarm Algorithm (SSA)[8-9]. Synthetic Aperture Radar (SAR) picture segmentation is the most significant stage in distinguishing the land and ocean regions in a few applications like military in specifically[10]. The automatic detection of WBC cell count is useful for the pathologist in identifying the cells[11]. It will attempt to diminish the mistakes that can emerge during the detection of cells physically. The element vectors of the testing picture feature data set and the trained picture feature vector dataset can be compared to investigations the connection between the vectors. The framework finds the relationship between the two vectors and based on the comparability esteem, classifies the cell[12-13]. The variety and quality of the solution change the strategy of honey source[14]. The initialization utilizes the cluster center made by the K-Means strategy as the underlying honey source rather than the initialization in the standard method. The local optimization ability and the union speed without decreasing the global search, and a unique area search component based on the quantity of cycles in terms of ABC search system and neighborhood determination stage[15]. To find a threshold to isolate the gray scale picture into blood vessels and background parts, then the qualities of the KD-ABC algorithm to the binary processing stage of the fundus retinal vein image[16].

An image segmentation approach takes full advantage of the global optimization search capability of the ABC algorithm and the parallelism of the extended encoding strategy to speed up the convergence speed and improve the exactness of the initial clustering centers of FCM[17]. The salp swarm algorithm to improve multi-threshold GLCM picture segmentation[18]. The levy flight to further develop the SSA algorithm, the technique can adjust investigation and exploitation. The LSSA algorithm is utilized to enhance the GLCM multi-threshold image segmentation technique. In order to raise the optimization ability of the conventional salp swarm algorithm, Levy Flight (LF) approach ought to be moved along. Nevertheless, the segmentation impact becomes less fortunate as the quantity of threshold increments.

The candidate solution is made among the triangle region planned by the current solution, global best solution and a few randomly choosen elite solutions to avoid the premature convergence difficult[19]. Fuzzy c-means (FCM) clustering technique has been developed for the segmentation in variety of color images. The FCM needs an undrlying number of cluster centers and as the quantity of cluster center are assigned higher, it gives segmentation, yet in addition raises the execution time, number of emphases and data complexity with extra segmentation of neighborhood clusters. In any case, when the quantity of cluster centers is selected, the resulting clusters are overlapping. The remainder of this paper is examined as follows: Section 2 discusses the methodology. Section 3 discusses the result and discussion and section 4 concludes the paper.

2. Methodology

The proposed image segmentation method of an Enhanced Artificial Bee Colony utiliziing Radial Basis Function (EABCRBF) incorporates the equal probability of choosing noise and edge points. To stifle the clamor, a Median filter is embraced in preprocessing, which successfully take out the random noise. Then, at that point, the image histogram, which will be developed in stages isolated into intervals depending on the image height. A RBF neural network will be prepared at each interval in order to set the Gaussian base centers, widths, and weights. Then Gaussian widths will help as positions for picture region markers. An ABC based approach is utilized to accomplish the output segmented image that characterizes regions of interest. In color images, a morphology reconstruction process is utilized to upgrade the objective image regions.

2.1 Preprocessing

An image preprocessing procedure is used to improve the quality of an image prior to handling and sending it into an application. The advancement choose to eliminate noise, unfortunate image contrast, weak boundaries and unrelated parts are normal qualities of color images. The image preprocessing strategy involves a minor neighborhood of a pixel in an input image to get a brightness value in the output image.

2.2 Median Filter

Median filter is an execution of a non-linear filter for the persistence of noise removal. The designated noisy pixels are exchanged by the median value of their neighbours. The filtering window size directs the number of neighbours. The median value is just assigned as the mid value in an arranged succession.

Median (P) = Med {Pi}

Median (P) = Med {Pi}

= Pi(k +1)/2, k is odd

= ½[Pi(k/2)+ Pi(k/2)+1], k is even

P1, P2, P3 ....Pk is the sequence of neighbouring pixels. All pixels in the picture must be arranged in either ascending or descending order, prior to applying filtering. In the wake of performing aranging, the resulting picture pixel sequence will be Pi1≤Pi2≤Pi3≤......Pik, .k is normally odd.

2.3 Classification using Radial Basis Function

The Radial Basis Function (RBF) neural network is one of the neural network models with a three-layer, specifically an input layer, hidden layer, and an output layer. The performance of the RBF neural network relies upon the decision of precisely three significant parameters such as cluster center, distance and weight. Every input variable is dispensed to the neuron in the input layer and arrives directly to the hidden layer without weight. In the hidden layer, the RBF neural network plays out a nonlinear change of the information from the input layer utilizing the fundamental radial function before it is linearly handled at the output layer.

In Fig. 1, (x_i, i = 1, 2, . . . p) are input neurons, (φ_j, j = 1, 2, . . . , q) are hidden neurons, and $f(x)$ is output neuron. The weights between the hidden layer and the output layer are denoted as w_j and the bias w_0 is added to the hidden layer. The activation function (x) is determined by the mean cluster and width of the cluster. The RBF neural network is portrayed by the activation function, which is remembered for the class of radial basis functions. The activation function of the RBF neural network for Gaussian activation function is,

$$\varphi(x) = \exp\left(-\frac{(x-c)^2}{r^2}\right) \qquad \ldots(1)$$

where c is the mean of cluster, r is maximum distance of every object to the mean of cluster. The output y of the RBF neural network model is the linear combination of the weights w_j including ω_0 and the activation function $\varphi_j\ (x)$

$$f(x) = \sum_{j=1}^{q} w_j \varphi_j(x) + w_0 = \sum_{j=1}^{q} w_j \exp\left(-\sum_{i=1}^{p} \frac{(x_i - c_{ji})^2}{r_{ji}^2}\right) + w_0 \quad ...(2)$$

The learning process in RBF neural network incorporates unsupervised learning to determine the number of hidden neurons alongside acquiring the parameter values of the radial basis function, and supervised learning to attain the weights amongst the hidden layer and output layer. The quantity of neurons in the hidden layer matches the quantity of basis functions. Unsupervised learning is performed using the artificial bee colony technique. It is ordinarily utilized in RBF neural network modeling, whose situation of the objects in the Euclidian distance is generally utilized. The Euclidian distance between two points $P(x_1, x_2, \ldots, x_p)$ and $Q(y_1, y_2, \ldots, y_p)$ is expressed as

$$d(P,Q) = \sqrt{(x_1 - y_1)^2 + \cdots + (x_p - y_p)^2} \quad ...(3)$$

2.4 Artificial bee colony optimization (ABC)

Artificial

Bee Colony optimization (ABC) is major areas of strength and efficient algorithm based on the intelligence behavior of honeybee swarm. The ABC computation, swarm tends to an excepted solution and the nectar amount of a food source matches the idea of the associated solution described as fitness. The solution has high fitness, the more prominent possibility being picked of this solution by onlooker bees. The amount of scout bees is facilitated by limit. If a solution showing a food source doesn't improve during different primers, beforehand it is abandoned by its used bee and the employed bee becomes a scout bee. The number of food sources equivalents to employed bees additionally number of employed bees ascends to the number of onlooker bees. All employed bees primarily behave as scout bees and starting swarm collected by employed bees is made by Equation.

$$x_{ij} = x_{min}^{j} + rand\,(0,1)(x_{max}^{j} - x_{min}^{j}) \quad ...(4)$$

where x_i demonstrates a solution in the population, i = {1, 2, . . ., SN} and SN is the size of population j = {1, 2, . . ., D} and D is the quantity of parameters (decision variables) in a solution. As indicated by this, the choose subrange x_{min}^{j} is the lower bound of j^{th} parameter and x_{max}^{j} is the upper bound of j^{th} parameter.

Subsequent to producing the solutions, fitness values for each of them are determined by equation.

$$fit_i = \begin{Bmatrix} 1/(1+f_i) & f_i \geq 0 \\ 1+abs(f_i) & f_i \geq 0 \end{Bmatrix} \quad ...(5)$$

where fit_i is the fitness value of i^{th} solution in the population. The employed bee defines a food source in the neighborhood of the food source and estimates the greatness of another one. The new source in the neighborhood of the current source is determined by Equation.

$delta = \phi_{ij}(x_{ij} - x_{kj})$ and $v_{ij} = x_{ij} + delta$ ...(6)
where delta is the variance value. ϕ_{ij} is a random number between $[-1,1]$. v_i represents new solution, x_k is the neighbor solution choose randomly, k ∈ {1, 2, . . ., SN}. x_{ij} is j^{th} parameter of i^{th} solution meant by the current employed bee. j is a irregular number in the range of [1,D].

After the employed bees have found the new food sources, they share their information with onlooker bees. Onlooker bees pick a utilized an employed bee for leadership. For this reason, a roulette wheel is utilized by relying upon the probabilities determined by equation.

$$p_i = \frac{fit_i}{\sum_{SN}^{n=1} fit_i} \quad ...(7)$$

After the onlooker bees select a food source as an aide, the candidate food source is determined by Eq. (7). In this way, the avaricious choice process is spread for the onlooker bees. ABC practices just a single control parameter that is called limit. A food source won't be misused any longer and it is thought to be uncontrolled when breaking point is beaten for the source.

2.5 Morphological Reconstruction Processing

Morphological Reconstruction is a transformation process that envelops dilating and eroding the original picture and includes a Structuring Element (SE). Dilation and erosion processes are used that thicken and thin the objects in the picture. This smoothen the inside objects as well as preserves the boundary of the objects. The dilation and erosion of the picture f by structuring element B indicated by $f \oplus B$ and $f \ominus B$, individually, are defined as follows:

$$(f \oplus B)(x,y) = \max\{(x - x1, y - y1) + (x1, y1) | (x - x1, y - y1) \in Z, (x1, y1) \in Z) \quad ...(8)$$

$$(f \ominus B)(x,y) = \min\{(x + x1, y + y1) - (x1, y1) | (x + x1, y + y1) \in Z, (x1, y1) \in Z) \quad ...(9)$$

Where Z is the structuring frame size. $\vartheta(f)$ denotes the opening of f by using it's the element B, where $\vartheta(f)$ is given by

$$\vartheta(f) = f.B = (f \ominus B) \oplus B.$$

The finishing of image f by structuring element B is distinct as

$$\theta(f) = f.B = (f \oplus B) \ominus B.$$

To smooth the image f by reconstruction operator, use the equation

$$R(f) = \left(\theta l, (f \oplus B)\right), \qquad 0 \le l \le n$$

where β is reconstruction operator, θl is reference picture which is acquired by closing the image f, l times, and n is the size of the structure element B.

2.6 RBF Neural Networks for Image Histogram Marking

The artificial bee colony algorithm usually causes over-segmentation due to the fact that the conventional markers of the target picture features are computed. Then an artificial bee colony algorithm is applied to the gradient image. In any case, this reduces the over segmentation issue with the target image objects are marked on their target image. In like manner, the histogram will be gathered step by step, where at each stage a RBF neural network will be ready to perceive the last markers of the image region.

Every model is smoothed to recognize its peaks, and to recognize left and right minima for each peak. The position of the peak will be the point of convergence of the neuron, though the left and right minima will portray its start and end, in this manner its width. The parameters setting and tuning of the RBF network is achieved web containing tuning neurons centers and widths, and tuning the network weights. The back-propagation method is used to change the adaptive centers, as in equations (10, 11):

$$\Delta c_j^i = 2\frac{\alpha}{\sigma_j^i}\left(x_i - c_j^i\right)z_j[(T - f_0)w_j \quad \text{...(10)}$$

$$z_j = exp\left(-\sum_l \frac{(c_j^l - x_l)^2}{(\sigma_j^l)^2}\right) \quad \text{...(11)}$$

where α > 0 which is set to .002 , T is the desired output and f_0 is the network output. The width of the RBF units (σ_j^i) strongly affects the performance of the RBF NNs. Computing roughly the width of the RBFs is not an informal task. The Delta rule is extensively used to change the width of the RBF hidden layer units. The relation $\sigma_i = \beta d_i$ where σ_i is the width of i^{th} neuron, β is a positive scalar and d_i is the minimum of distances from the i^{th} center to its neighbors. The simple procedure for changing the neurons width (σ_j^i) of the RBF network as in (12).

$$\sigma_j^i = \beta c_j^i \quad \text{...(12)}$$

Where σ_j^i is the width of the j^{th} neuron in the RBF hidden layer, c_j^i is the position of the center of j^{th} neuron and β is a positive scalar. The proposed technique gives promising outcomes in further developing the RBF nonlinearities. The output layer weights were updated web based utilizing the Delta rule.

The construction cycle through that the picture histogram is being built until the last histogram is shaped. At each interval, the RBF neural network is prepared to histogram top positions and left and right minima. On behalf of any new peaks are identified, new neurons are added to the network. The completing distribution of Gaussian bases functions establishes the trained RBF neural network.

2.7 Color Image Regions Segmentation

In the final created neural network, every neurons left and right minima characterize the positions of two histogram markers, expecting that similar image regions are addressed in a single histogram, and will be segmented as needs be. The proposed method characterizes markers that are viewed as inputs to the artificial bee colony algorithm, and will be utilized to distinguish the target picture region segments.

2.8 Enhanced Artificial Bee Colony using Radial Basis Function (EABCRBF) Method for Color Image Segmentation

The Enhanced Artificial Bee Colony optimization using Radial Basis Function (EABCRBF) is a powerful and efficient algorithm for color image segmentation. The procedure of the EABCRBF method is given in the accompanying flow diagram:

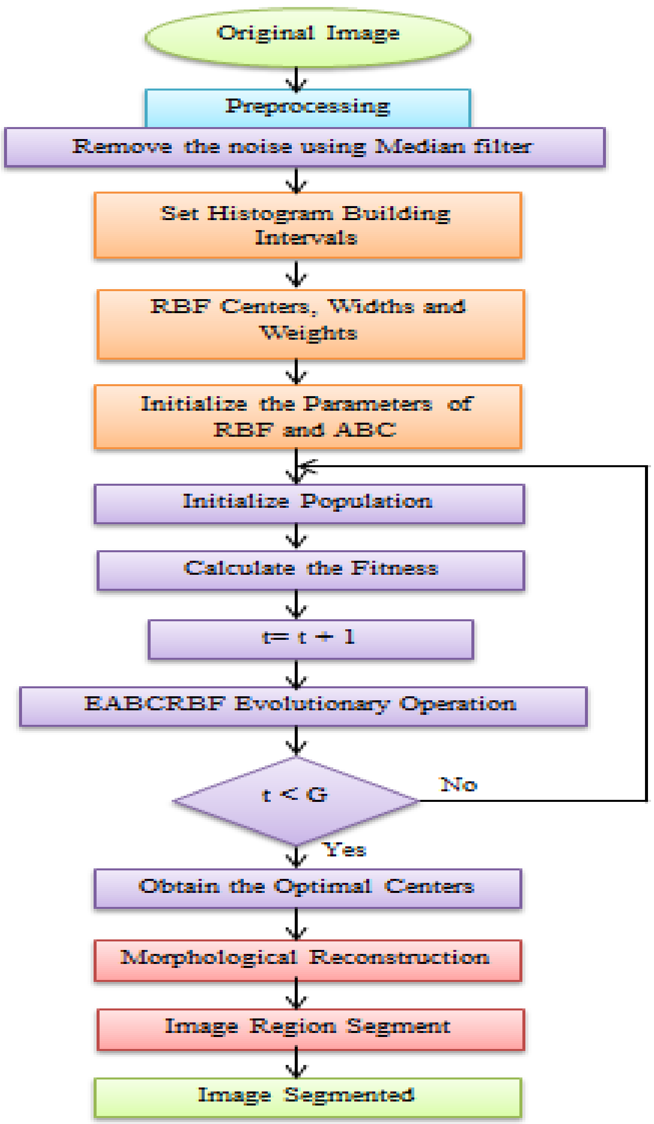


***Figure 1.** Block Diagram of Proposed Methodology*

Algorithm

Step 1: Read the Color Image
Step 2: Perform Preprocessing on Image using Median Filter
Step 3: Set Histogram Building Intervals
Step 4: Find Centers, Widths and Weights using Radial Basis Function
Step 5: Initialize the population of N individuals, each solution X is D dimensional
Step 6: Calculate the fitness of each individual solution
Step 7: Each employed bee generated new position
Step 8: Calculate the fitness of both employed bee position and the original position then apply a greedy selection scheme to choose the better one
Step 9: Calculate the probability value for onlooker bees to choose the food source
Step 10: Generate new food position for each onlooker bee
Step 11: Calculate the fitness of each onlooker bee and new solution, apply greedy selection to choose the better of them.
Step 12: If the solution is not replaced by improved solution after a limit times, the scout bees will replaced the employed bees and search new food source
Step 13: Check the number of the iteration. If the process's cycle time reached the maximum number of iteration, stop and return the best solution, other repeat step 2 to step 10 until the cycle number meet the maximum number of iteration.
Step 14: If the stopping criterion is meet then output the result image with WBC detected out.
Step 15: Recomputed the region having the shortest path
Step 16: Perform morphological operation and Extract object from background
Step 17: Finally get the segmented image

3. Result and Discussion

The experiments used a variety of three sample color images. The input color images have different types of dimensions. The proposed EABCRBF method is tested for different parameters. The experiment is implemented through Matlab R2013a. The performance metrics like Rand Index (RI), Variation of Information (VoI), Global Consistency Error (GCE), and Boundary Displacement Error (BDE).

(i) The Rand index (R) is,

$$R = \frac{a+b}{a+b+c+d} = \frac{a+b}{\frac{n}{2}} \qquad \ldots (13)$$

(ii) The variation of information is,

VI(X; Y) = H(X) + H(Y) – 2I(X, Y) ... (14)

(iii) The Global Consistency Error is as follows,

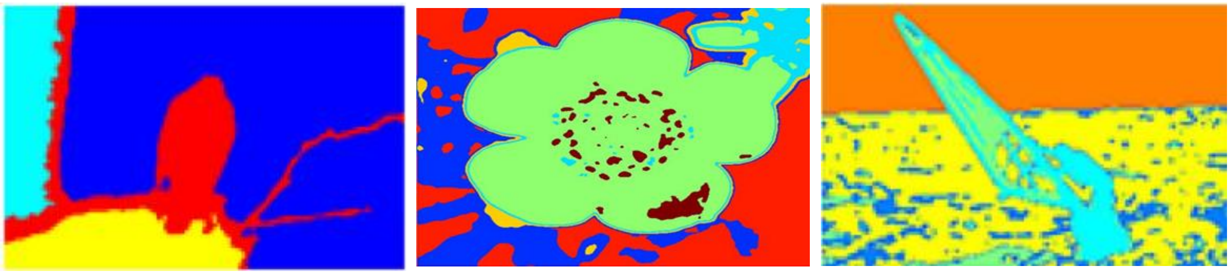
$$GCE = \frac{1}{n} min\{\sum_i E(s1, s2, pi), \sum_i E(s2, s1, pi)\} \qquad \ldots (15)$$

(iv) The Boundary Displacement Error is,

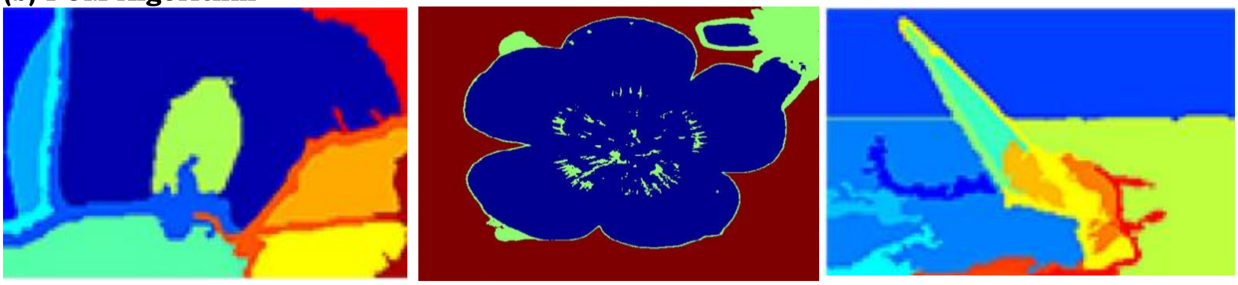
$$\mu_{LA}(u, v) = \begin{cases} \frac{u-v}{L-1} 0 < u - v £ L_1 \\ 0 u - v < 0 \end{cases} \qquad \ldots (16)$$

The proposed EABCRBF method is compared with two existing strategies of Artificial Bee Colony (ABC) and FCM. In Figure 3, row 1 shows the original image, row 2 shows the FCM method, row 3 shows the ABC method and row 4 shows the segmented image of the proposed method of EABCRBF. Table 1 shows RI, VoI, GCE, and BDE values are contrasted and existing methods of ABC, FCM and the proposed method of EABCRBF. The proposed EABCRBF method gives better expected results when compared to the existing methods.

(a) Original Image



(b) FCM Algorithm



(c) ABC Algorithm

(d) EABCRBF Algorithm

***Figure 2.** Segmented Images using EABCRBF Algorithm*

***Table 1.** Performance Evaluation of EABCRBF*

Images	Methods	RI	GCE	VOI	BDE
Image 1	FCM	0.9227	0.0934	0.5069	0.1449
	ABC	0.9447	0.0713	0.4301	0.1219
	EABCRBF	0.9907	0.0137	0.0966	0.0171
Image 2	FCM	0.8781	0.1788	0.8597	0.2875
	ABC	0.8608	0.1658	0.8666	0.1199
	EABCRBF	0.9852	0.0227	0.1560	0.0154
Image 3	FCM	0.8580	0.1598	0.8289	0.1470
	ABC	0.9508	0.1378	0.8756	0.0832
	EABCRBF	0.9867	0.0227	0.1600	0.0182

Conclusion

This study proposes an enhanced artificial bee colony and a radial basis function algorithm to optimize the color image segmentation technique. The proposed EABCRBF predicts the end boundaries of the segmentation which are shaped from the artificial bee colony created in the image. To confirm that the proposed algorithm is a great performance in color image segmentation RI, VoI, GCE and BDE parameters are utilized. The EABCRBF technique gives values of 0.9867 for RI, 0.0227 for GCE, 0.1600 for VOI and 0.0182 for BDE individually and the EABCRBF method gives better values for color image segmentation. The experiment and analysis of color image, the experiment proves that EABCRBF algorithm has a better image segmentation effect compared with existing techniques of FCM and ABC. Accordingly, the EABCRBF algorithm has great image segmentation capacity and can better handle complex image segmentation tasks. As an extend of further research, will proceed to study and further develop the optimization capacity of the ABC algorithm to solve more complex optimization problems. Meanwhile, apply the EABCRBF algorithm to solve more complex image segmentation issues, such as medical image segmentation.

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