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A Visual Based Color Image Segmentation and Object Detection Algorithm Using an Enhanced Biotic Cross Pollination Algorithm

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Abstract: This study proposes an enhanced Biotic Cross Pollination algorithm for visual based color image segmentation and object detection visual based color image segmentation and object detection. Here, the Global Biotic Cross Pollination Algorithm's (GBCPA) performance is improvised with Evolutionary Strategy (ES) which exploits the structurally challenging objects based on color, texture, entropy and edge information in the Commission Internationale de l'Eclairage (CIE) L*a*b color space. The target objects are correlated by taking into consideration the knowledge of human perception based on Gestalt law with cognizance of signal characteristics in order to split natural scenes into visually unvarying regions. Hence, the object detection is performed with low computational complexity and without depending on a priori knowledge of the physically inspiring objects. The proposed color image segmentation algorithm is simulated using several test images and the results are compared with other proven image segmentation approaches reported in the literature. The test results demonstrate the superiority of the proposed segmentation algorithm in terms of segmentation and detection accuracy.

Key words: Biotic Cross Pollination algorithm, color image segmentation, object detection, evolutionary strategy, pollination refusal

INTRODUCTION

Color image segmentation is considered as one of the crucial problems and received much attention in image analysis, image retrieval, video surveillance and pattern recognition. Image segmentation is the process that splits or separates an image into meaningful object that display similar features with regard to criterion such as color, edges, texture, gradient (Gonzales and Woods, 2001; Shapiro and Stockman, 2001). Color images carry much more information than gray ones; hence extracting object from color images is a difficult and challenging task (Cheng *et al*., 2001). Prevailing color image segmentation algorithms can be categorized as: feature based, region based, graph based and segmentation based on evaluation function optimization. Feature-based methods (Comaniciu and Meer, 2002) mine image features by gathering the principle characteristics of the image. The edge information of the image is usually not preserved and pixels from isolated divisions may be assembled together. Region-based methods (Tao *et al*., 2007a) recognize regions that satisfy some predefined criteria, it preserves the relationship between pixels in an image. Graph based methods (Felzenszwalb and Huttenlocher, 2004) represent a problem in terms of a graph where all vertexes relates to a pixel or region, node narrates to a pixel in an image and an edge connecting each pair of vertices. Image segmentation based on evaluation function optimization (Hammouche *et al*., 2008; Han and Shi, 2006; Das and Konar, 2009) usually uses an assessment capacity function incorporating the feature-based and spatial information.

The empirical nature of the conventional strategy methods, agree us to formulate the segmentation problem as an optimization problem by formalizing an objective criterion. Optimization is the procedure of attempting to discover the best possible solution to a problem within a realistic time limit. The aspiration of an optimization problem is to find an estimation for the variables that maximizes, or minimizes the fitness function and satisfies the constraints. Framing total entropy as an objective function and solving it by using global optimization algorithms attracted significant attention recently. EAs have been applied to image segmentation with promising results because of their fast computing ability. In EAs the decision making processes are guided by "fitness" evidence alone. Metaheuristic techniques like Genetic Algorithms (GAs) (Abbasgholipour *et al*., 2011), Particle

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Swarm Optimization (PSO) (Yin, 2007) and Artifcial Bee Colony (ABC) (Ma *et al*., 2011) can also be found in literature on segmentation.

The K-Means algorithm (KM) (Hartigan and Wong, 1979) is the modest and unobtrusive generally held one which partitions an image into k clusters by an iterative technique and does not essentially find the most optimal configuration, consistent to the minimum overall objective function. Fuzzy C-Means (FCM) clustering is one of the most standard techniques for image segmentation (Cannon *et al*., 1986). This method acquaints the fuzzy idea so that an object can belong to more than one class instantaneously. As an unsupervised technique, FCM clustering does not require prior knowledge about the tested data. On the other hand, this procedure has dif?culties obtaining proper initial cluster centers and a sufficient number of clusters for initialization (Kim *et al*., 2004). The initialization for the FCM clustering technique plays an energetic role in accomplishing optimum final cluster centers. Without proper initialization, this technique could generate sets of poor final cluster that could erroneously represent the clusters.

Agglomerated Just Noticeable Difference Histogram (AJNDH) (Yu *et al*., 2010) is another versatile cluster initialization scheme that counters one of the drawbacks of the random initialization scheme. Recently, several feature-based segmentation techniques have utilized the theory of Ant Colony Algorithm (ACA) to carry out image segmentation. Due to the quick searching capability of the ACA, these methods could accomplish further optimization of segmentation results. To enhance the performance of the ACA, the Ant colony-Fuzzy C means Hybrid Algorithm (AFHA) is introduced (Tao *et al*., 2007b). Essentially, the AFHA integrates the FCM algorithm to the ACA in order to improve the compactness of the clustering results in the feature space. In order to improve the efficiency of the AFHA, the Improved Ant colony-Fuzzy C-means Hybrid Algorithm (IAFHA) is presented (Tan and Isa, 2011). The IAFHA includes an ant sub-sampling based strategies to fine-tune the AFHA in order to reduce its computational complexity thus has higher eficiency. In spite of the fact that the IAFHA's effciency has been increased regardless, it endeavors from high computational complexity.

This study focuses on image segmentation based on a new color image segmentation algorithm which exploits the evidence obtained from the detected edges in the CIE L*a*b color space. It elaborates a global optimization method using an enhanced Pollination based optimization for automatically grouping the pixels of a color image into disjoint homogenous regions. The Perceptual Organization Model (POM) for boundary detection quantitatively consolidates a list of Gestalt laws and subsequently is able to capture the non-accidental structural relationships among the constituent parts of a structured object (Cheng *et al*., 2012). It produces distinctive clusters from a desired input image that share certain visual characteristics such as color, intensity or texture pattern. Pollination based optimization characteristic which makes it distinctive from genetic algorithm is its proximity probability which switch between local pollination to global pollination. It has worthy optimization performance due to its flower consistency. The experimental results demonstrates that the proposed method out performed state-of-the-art approaches on challenging image databases (Martin *et al*., 2001) comprising of a wide variety of outdoor scenes and object classes. Therefore, the enhanced Pollination Based Image Segmentation is more reliable and faster for image segmentation.

Preliminaries: Before performing the splitting process by the proposed algorithm, some preprocessing should be done on original images, including color space transform, feature extraction and over segmenting object images into small regions. The CIE $L^*a^*b^*$ color space**,** POM and Flower Pollination Optimization Algorithm (FPOA) will also be introduced in this section.

CIE $L^*a^*b^*$ color space: In this approach, a vector quantization process is used to reduce the number of colors in a color image and the RGB color space is transformed into a perceptually uniform color space, namely, the $L^*a^*b^*$ color space for better modeling of human perception. Color conversion to $L^*a^*b^*$ color space enables differentiation between luminance and chrominance information. The $L^*a^*b^*$ color space is a color-opponent space designed to approximate human vision. L^* denotes the luminosity or brightness layer, chromaticity layer a* indicates color falls along red-green axis and chromaticity layer b* indicates the blue-yellow axis (Wyszecki and Stiles, 1982). They are computed as:

$$L^* = 116 \times h\left(Y/Y_W\right) - 16 \quad (1)$$

$$a^* = 500 \times \left[h\left(X/X_w\right) - h\left(Y/Y_w\right)\right] \quad (2)$$

$$b^* = 200 \times \left[h\left(Y/Y_w\right) - h\left(Z/Z_w\right)\right] \quad (3)$$

Where:

$$h(q) = \begin{cases} \sqrt[3]{q} & q > 0.008856 \\ 7.78/1167 + 16 & q \le 0.008856 \end{cases} \quad (4)$$

Where:

X, Y, Z = The can be computed by linear transformation from RGB coordinates

X_w, Y_w, Z_w = The tristimulus values of X, Y, Z of the reference white, respectively

Perceptual Organization model: Color image comprises of background and foreground objects. Foreground objects are frequently self-possessed of multiple parts, with dissimilar surface characteristics (e.g., color, texture, etc.). Generally, structured objects should be over segmented while segmenting an image into multiple patches. After identifying the background patches the remaining image spots relate to the essential parts of structured objects. The contest here is how to slice the set of organized fragments of a structured object together to form a region without any particular knowledge of the object. To challenge this problem, a POM was developed.

The POM groups the patches to larger regions that correspond to semantically meaningful fragments of structured objects. The Gestalt laws cluster these categories of regions and find a region that relates to a structured object (Shirakawa and Nagao, 2009). The principle of non-accidentalness between the constituent fragments of a structured object may be able to split the set of fragments together by seizing these distinct structural relationships. The process works as follows initially an image part is picked and then tries to group its neighbors with the region. The process standstills when none of the region's neighbors can be clustered with the region. The region measurement measure how accurately a region is grouped and can find the best region that contains the initial part. The best region corresponds to a single structured object or the semantically meaningful fragment of the structured object (Lowe, 2012; Chen *et al.*, 2009; Cheng *et al.*, 2012).

Objective function: The two objectives, edge value and overall deviation, are optimized simultaneously. These objectives are important factors of image segmentation. The edge value is expressed in Eq. 5. This objective function evaluates the overall summed distances on boundaries between the regions. This assessment is the measure of the change in the boundary limit between the regions:

$$\mathrm{edge}(R) = -\sum_{i=1}^{N} \sum_{j \in F_i} x_{i,j}$$

Where:

$$x_{r,s} = \begin{cases} \delta(r,s) & \text{if } \exists R_k : r,s \in R_k \\ 0 & \text{otherwise} \end{cases} \qquad (5)$$

Where:

N = The number of pixels

R = The set of all regions

F = Indicates the four neighboring pixels of pixel

i δ = The Euclidean distance function

This edge value is also minimized which generally diminishes the number of regions (clusters). The second objective, overall deviation is defined in Eq. 6. This equation gives the overall summed distances between the pixels and the center value of the corresponding region (cluster) they belongs (Shirakawa and Nagao, 2009). Overall deviation is a measure of the similarity of pixels in the same region:

$$\mathrm{dev}(R) = \sum_{R_k \in R} \sum_{i \in R_k} \delta(i, \mu_k) \qquad (6)$$

Where:

μ_k = The centroid of the pixels in the region R_k

δ = The distance function

Overall deviation should be minimized. Minimizing overall deviation roughly increases the number of regions (clusters). The distance function using the CIE L*a*b* color space (Wyszecki and Stiles, 1982) is defined in Eq. 7. The CIE L*a*b* color space has a uniform chromaticity scale:

$$\delta_{L^*a^*b^*} = \sqrt{\left(L_2^* - L_1^*\right)^2 + \left(a_2^* - a_1^*\right)^2 + \left(b_2^* - b_1^*\right)^{*2}} \qquad (7)$$

where, (L_1^*, a_1^*, b_1^*) and (L_2^*, a_2^*, b_2^*) are the two colors in L*a*b*. By minimizing these two objectives, a variety of different image segmentations are generated. In other words, the proposed method returns a range of solutions that have different numbers of regions.

Flower Pollination Optimization Algorithm (FPOA): Flower Pollination Optimization Algorithm (FPOA) is an optimization algorithm developed by Yang (2012) and Xing and Gao (2014). Pollination is inherited from the natural stimulation of flowering plants flow pollination process. It mimics the progression of flowering plants reproduction via pollination. As pollinators are primarily responsible for spreading pollens among flowers, pollination may happen in either local or global flow.

Pollination process can be categorized into biotic and abiotic centered on the pollens transferring mechanism. In biotic pollinations, flowers constantly depend on insects or animals as pollinators to transferal the flowering pollens. However for abiotic, flowers do not prerequisite any pollinators for the pollens relocating process. Obviously most of flowers deliberated to follow the biotic pollination form. This stipulates that pollination or cross pollination process can take place by pollinators' activities or travelling extensive distances initiating a global pollination. Travelling pollinators generally follows the L'evy's flight behavior (Yang, 2012). For every kind of pollinators, there is a precise type of flowers that it is accountable for, this called flower consistency. Flower consistency abolishes the learning, investigation and switching. In order to supremely formalize the flower pollination algorithm, characteristics of pollination process, flower constancy and pollinator behavior should be approximated based on the following essential rules:

- Global pollination attained by L'evy's flights` travelling pollinators for both biotic and cross-pollination
- Local pollination accomplished abiotic and self-pollination
- The new generation reproduction probability depends on the flower consistency and proportional to flowers similarities/differences
- The proximity probability pϵ(0, 1) controls the alteration between local and global pollination

FPOA modification: A hybrid evolutionary algorithm is an attempt to pool two or more evolutionary algorithms. This can get the finest from the algorithms that are combined together. Hybrid algorithms can combine the advantages of each algorithm so as to produce better performance.

Evolutionary Strategies (ES): Evolutionary Strategies (ES) mimic the process of natural evolution; make use of the recombination, mutation and selection operators to produce the individuals of the new generation. During the selection process, the users can assess the whole population individuals which help in selecting the best participants for the next generation (Beyer and Schwefel, 2002).

Pollination Refusal (PR): In the original GBCPA, whether to perform local or global pollination and from where to receive pollens are based on the proximity probability. That is, if the probability of the pollen is less than some threshold it sends the solution feature to perform global pollination and its fitness is also less than that of the proximity probability, the flow pollination process will refuse the pollinating solution features to perform local pollination. This idea is called pollination refusal.

MATERIALS AND METHODS

Implementation of the proposed algorithm: A new Enhanced Global Biotic Cross Pollination algorithm using evolutionary strategy for image segmentation is proposed. GBCPA is a biology based computational intelligence optimization algorithm it doesn't involve reproduction or the generation of "children". Select a seed utilizing some set of predefined criteria. After selecting examines neighbor pixels of seed points and calculate CMC color distance between neighboring pixels and then select threshold value. If the calculated distance is less than threshold then it pollinate to other region, otherwise it makes its own region. The Image segmentation using GBPCA algorithm can be informally described with the following algorithm.

Stage 1; preprocessing: Preprocessing is the initial step of the method to extract the features of an image. Intensity gradient of an image can be utilized to extract data from images. Every pixel of a gradient image measures the variation in intensity of that similar point in the original image in a given direction. Texture gradient contributes information about the spatial arrangement of color or intensities in an image or selected region of an image. Edge detection focus the number of edge pixels in a predetermined region also regulate a characteristic of texture complexity. Watershed segmentation over segment object image into non-overlapping small regions. The preprocessing results of the segmentation algorithm at different stages are presented in Fig. 1. The input RGB beach image is shown in Fig. 1a. The outcome of intensity gradient is shown in Fig. 1b. The texture gradient

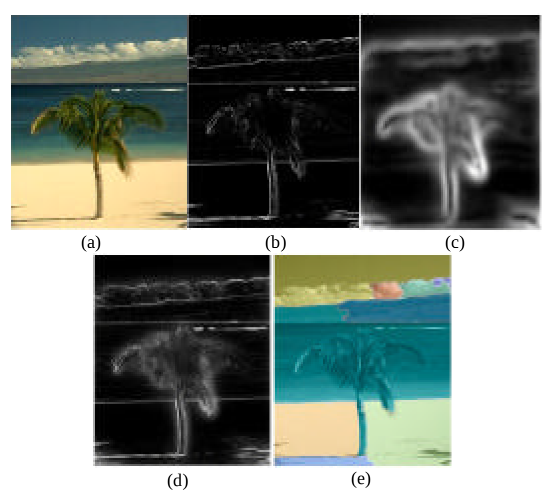


Fig. 1: a) Input image beach; b) Intensity gradient; c) Texture gradient; d) Edge detection and e) Watershed segmented image

(a) (b)

Fig. 2: a) Input image mountain and b) CIE $L^*a^*b^*$ image

generated using local entropy calculation and edge detected image is displayed in Fig. 1c and d. The segmented image using the watershed algorithm is displayed in Fig. 1e.

Stage 2; transformation: Convert a RGB image into CIE L*a*b* image using the color space transform. The input RGB Mountain image and its color conversion CIE L*a*b* image is shown in Fig. 2a and b.

Stage; 3 GBPCA segmentation algorithm

Step 1; initialization: Initialize the GBCPA parameter considering every color as different pollen gametes and each pixel as species. A population of the pollen with random solution, i.e., each color value in an image is represented as:

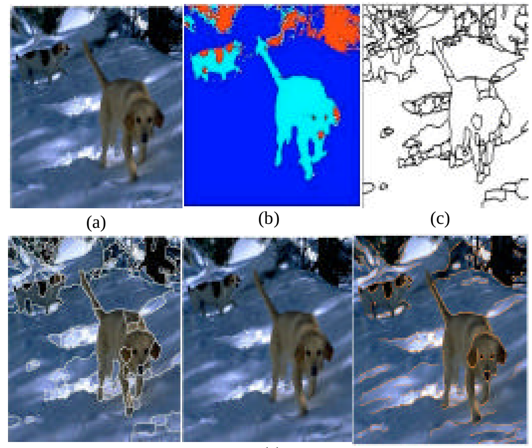
$$n = \left[n^1, n^2, \ldots n^i, \ldots n^N\right] \tag{8}$$

Where i = 1, 2… N. Each pollen is one of the possible solutions for the problem. In pollen n^i the component refers to the pixel value of the i^{th} pollen.

Step 2; identification of best pollen: In GBCPA, the best pollen in each iteration are preserved from modifications caused by pollination. Thus, an elitism parameter is used to provide a memory for the algorithm. Based on the best values of each pollen, which refers to the edge value of the image a set of 'g_*' elite pollens, are preserved. Pollens with best (i.e., maximum) pixel value is chosen as elite pollens in each iteration.

Step 3; defining a proximity probability: The proximity probability lies between [0,1]. Set probability for every single region. Probability is similar to a threshold values. The probability P the region contains exactly S pixels. Ps changes from time to time as follows:

$$P_s(t+\Delta t) = P_S(t)(1-\lambda_s\Delta t - \mu_s\Delta t) + P_{s-1}\lambda_{s+1} + P_{s+1\mu s+1}\Delta t \tag{9}$$



(a) (b) (c)

(d) (e) (f)

Fig. 3: a) Input image; b) Super pixel; c) Human based segmentation; d) Coarse segmented image; e) Segmented image and f) Background identification

Step 4; global pollination: In global pollination, pollinators such as insects are intend to travel long distances to achieve the global optimization of reproduction based on flower consistency, this can mathematically achieve by:

$$x_i^{t+1} - x_i^t + L\left(x_i^t - g\right) \tag{10}$$

Where:

x_i^t = The pollen i or solution vector x_i at iteration t

g = The current best solution found among all solutions at the current generation/iteration

L = The strength of the pollination which essentially is a step size

Using region growing based image segmentation criteria select a seed point. Taking into account on some predefined criteria, scrutinize their neighboring pixels of seed points. Using the nearest neighbor rule characterize every pixel and evaluate euclidean distance between neighboring pixels that have similar characteristics.

The outcomes of the image classification at different levels are presented in Fig. 3a-f. The input image and its super pixel image generated by the Felzenszwalb's algorithm (Felzenszwalb and Huttenlocher, 2004) are displayed in Fig. 3a and b, respectively. The manual segmentation and the result of coarse segmented image by the nearest neighbor rule are demonstrated in Fig. 3c and d. The coarse segmented image eliminates small region from quantized image by region eradication process. The segmented color image is indicated in Fig. 3e. The background classifier for background structured objects identification was determined implementing the POM technique. The outcome of the background identification image by the visual perceptual model is indicated in Fig. 3f.

Insects can play the role of pollinators for developing flower consistency. In FPA, the estimation of flower consistency is set equivalent to a probability called reproduction which is proportional to the resemblance of two flowers involved. Controlling the interaction or switching between the local and global pollination through a probability parameter p which falls within the range of [0; 1]. When receiving pollination from other pollen, apply the pollination refusal idea to decide whether or not to accept the local pollination.

Step 5; mutation: Update the species count probability for each child pollens using Eq. 9. Elitism is carry out by setting species count probability to zero for p elite pollens.

Step 6; evaluation of fitness of the population: Calculate the fitness for each individual pollen including parent and child pollens in GBCPA. The fitness is designed using a function f given in Eq. 11. Pollens with maximum f value is said to have high proximity and vice versa. The segmentation fitness is defined as:

$$\text{Fitness} = \frac{1}{\sum_{x=1}^{C}\sum_{y=1}^{Rx}\sum_{z=1}^{p} d(p_{xyz}, m_x)} \tag{11}$$

Where:

- Rx = The aggregate number of regions in the xth cluster
- P = The aggregate number of pixels in the yth region
- p = Denotes the zth pixel in the y-th region of the xth cluster and
- m_x = The centroid of all pixels of the xth cluster
- C = In feature space

In Eq. 11, a more precise segmentation evaluation can be obtained by working on watershed region classification:

$$d(p_{xyz}, m_x) = \sqrt{\sum_{g=1}^{F}\left(p_{xyz_g} - m_{x_g}\right)^2} \tag{12}$$

where, F is the number of features and $p_{xyz\ g}$ and m_{xg} signify the gth feature of the recent pixel and cluster centroid, respectively.

Step 7: Based on the features hired from ES, select the best n pollens from the n parents and n children as the population for the next generation.

Step 8; termination criterion: Check for the termination criteria. If maximum generation is grasped stop execution otherwise go to step 4. For each pollen modernize the proximity probability of its species count using step 4. Increase the euclidean distance for every iteration. Iterate till the essential number of pollens are left.

RESULTS AND DISCUSSION

In this study, the whole test image dataset from the Berkeley Segmentation Data Set (BSDS) (Martin *et al*., 2001) is utilized. BSDS conveys a gathering of hand-labeled segmentations from different human subjects as ground truth. The images comprise a widespread variety of natural and man-made objects such as people, animals, flowers, buildings and cars. This information set affords ground truth object class segmentations that associate each region with one of the semantic classes (sky, grass, road, water, building, tree, mountain or foreground). BSDS has been widely used as a benchmark for many boundary detection and segmentation algorithms in technical literature.

The optimization problem deliberated in this paper is to solve the color image segmentation problem using enhanced GBPCA. The aspiration is to optimize the objective function in order to distinguish the objects by minimizing the number of pixels in the edges value and overall deviation. The execution of IS by means of the algorithm is validated by applying it to various natural images. The original images engaged for the quantitative assessement of the strategy is shown in Fig. 4. Three standard analyses are used to evaluate the segmentation outcomes of the randomly initialized FCM, AS, IAFHA, AJNDH, RFHA and GBPCA techniques. These standard analyses are used to assessment the realistic goodness of the segmentation results with some human characterizations of ideal segmentation and which require no prior knowledge of correct segmentation. These analyzes are defined as follows; F(I) proposed by Liu and Yang (1994):

$$f_{F(I)} = \frac{\sqrt{M}\sum_{j=1}^{M} e_j^2}{N_j} \tag{13}$$

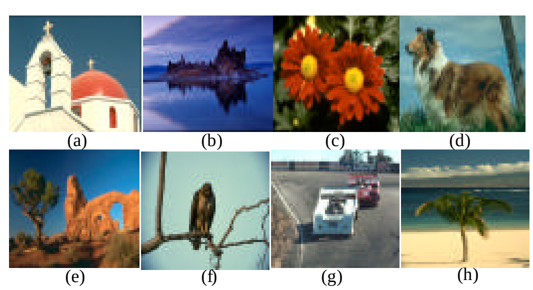


Fig. 4: The original image used in this study are shown: a) Church (118035); b) Mountain (143090); c) Sunflower (124084); d) Dog (247085); e) Mountain (295087); f) Eagle (42049); g) Cars (21077) and h) Beach (46076)

F'(I) proposed by Borsotti *et al*. (1998):

$$F'(I) = \frac{\sum_{j=1}^{M} e_j^2 \sqrt{\sum_{a=1}^{Macarea} \left[S(a)\right]^{1+(1/a)}}}{(1000\times N)\sqrt{N_j}} \tag{14}$$

and Q(I) further refined from Borsotti *et al*. (1998):

$$Q(I) = \frac{1}{1000\times N}\sqrt{M}\sum_{j=1}^{M}\left[\frac{e_j^2}{1+\log N_j}+\left(\frac{S(N_j)}{N_j}\right)^2\right] \tag{15}$$

Where:

- I = An image
- N = The pixels in I. The segmentation can be defined as the transfer of pixels in the image I into M regions
- C_j = Denotes the set of pixels in region j, whereas
- N_j = $|C_j|$ symbolizes the number of pixels in C_j
- e_j = Uniformity within a region, is defined as the Euclidean distance among the color of the pixels of region j and the color vector qualified in the segmented image
- S = Symbolizes the number of regions in image I that has an region of exactly a and maxarea to denotes largest region in the segmented image

Qualitative assessment on segmentation results: In this study, the segmentation results for the FCM, the IAFHA, the AJNDH, the RFHA and the GBPCA are evaluated visually by using 4 out of 200 tested images. Generally as shown in Fig. 5-8, the GBPCA method produces better segmentation results compared to the FCM, the IAFHA, the AJNDH and the RFHA techniques.

For the image Beach the proposed GBPCA method gives better segmentation results than to the FCM, the IAFHA, the AJNDH and the RFHA techniques by producing more homogeneous beach and sea as depicted in Fig. 5. As in Fig. 6, the image eagle demonstrates the segmented images produced by the proposed method experiments a superior result than the FCM, the IAFHA, the AJNDH and the RFHA techniques by producing more homogenous background and foreground objects.

As for as for image church the GBPCA gives better segmentation results by outperforming other approaches by giving more homogenous roof and wall as demonstrates in Fig. 7. In the image mountain, in spite of the fact the FCM, the IAFHA, the AJNDH and the RFHA techniques produces homogenous sky region but an obvious classification error could be seen where these approaches mistakenly assign the shadow of the

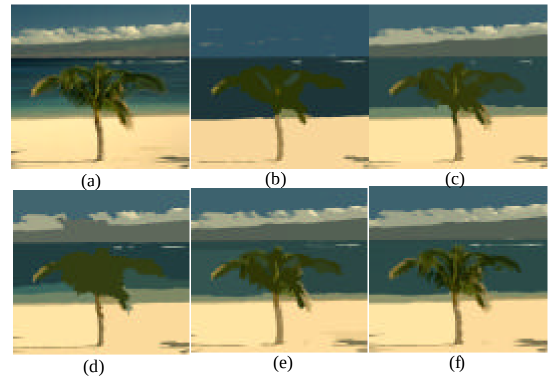


Fig. 5: Typical segmentation results of beach obtained from the compared algorithms on the image: a) Original image; b) FCM; c) IAFHA; d) AJNDH; e) RFHA; f) GBPCA

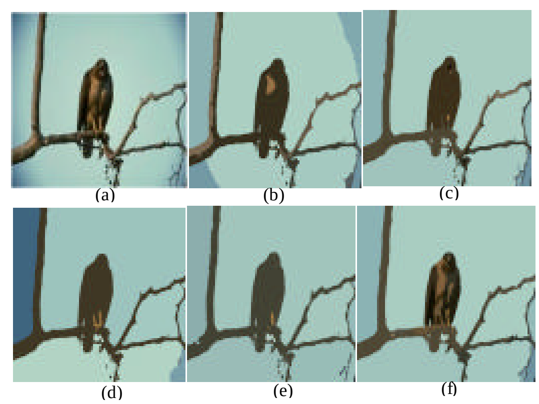


Fig. 6: Typical segmentation results of eagle obtained from the compared algorithms on the image: a) Original image; b) FCM; c) IAFHA; d) AJNDH; e) RFHA; f) GBPCA

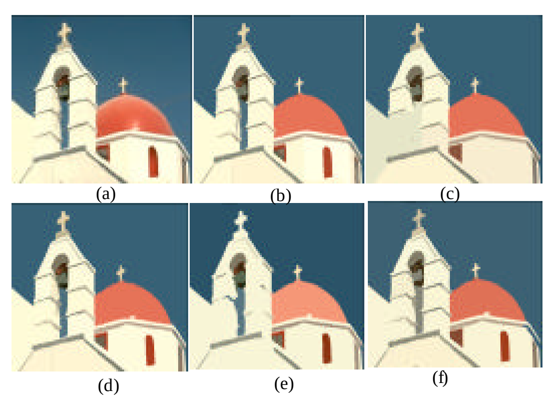
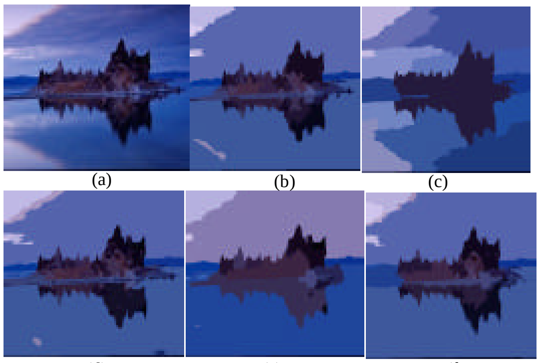


Fig. 7: Typical segmentation results of church obtained from the compared algorithms on the image: a) Original image; b) FCM; c) IAFHA; d) AJNDH; e) RFHA; f) GBPCA



(a) (b) (c) (d) (e) (f)

Fig. 8: Typical segmentation results of mountain obtained from the compared algorithms: a) Original image; b) FCM; c) IAFHA; d) AJNDH; e) RFHA; f) GBPCA

Table 1: Overall deviation and the edge value of the proposed method

Image	Overall deviation	Edge value
118035	0.860	0.289
143090	0.845	0.316
124084	0.698	0.362
247085	0.832	0.334
295087	0.627	0.381
42049	0.438	0.509
21077	0.547	0.432
46076	0.773	0.395

Table 2 : Objective values of the proposed method

Image name	GBPCA
118035	0.9578
143090	1.3526
124084	1.3548
247085	1.2467
295087	1.4972
42049	1.4751
21077	1.2665
46076	1.4573

Table 3: Computational time for the compared algorithms

Image name	FCM	IAFHA	AJNDH	RFHA	GBPCA
118035	18.7	22.0	14.6	10.6	9.50
143090	15.4	29.7	15.3	8.2	7.90
124084	35.8	53.3	37.1	15.6	13.40
247085	18.7	28.8	20.5	13.8	12.90
295087	10.5	11.6	8.2	7.4	7.20
42049	18.4	20.8	17.2	14.9	14.50
21077	16.2	16.6	19.7	14.7	14.20
46076	57.8	61.2	45.6	24.3	21.16

mountain as part of the mountain. The proposed approach effectively keeps away this classification error and produces more homogeneous hill and water region as indicated in Fig. 8.

Evaluation of the objective function: The performance of Image segmentation technique can be measured by overall deviation and the edge value. The overall deviation and the edge value for segmenting the image

Table 4: Clusters produced by different techniques

	Algorithm				
Image	FCM	IAFHA	AJNDH	RFHA	GBPCA
247085	11	14	13	11	11
143090	7	3	3	7	7
124084	14	17	12	14	14
118035	10	10	11	10	10
295087	20	5	26	20	20
42049	12	16	15	12	12
21077	8	4	3	8	8
46076	9	9	10	9	9

Table 5: Assessment of segmentation results of the F (I) evaluation function

	Algorithm				
Image	FCM (1.0e+3)	IAFHA (1.0e+3)	AJNDH (1.0e+3)	RFHA (1.0e+3)	GBPCA (1.0e+3)
247085	1.1347	0.8508	0.6723	0.6705	0.6792
143090	0.2195	0.4752	0.4752	0.1526	0.2634
124084	0.5878	0.4045	0.4298	0.3653	0.3437
118035	0.4588	0.4609	0.3659	0.4038	0.4612
295087	0.2162	1.5562	0.2899	0.2193	0.2039
42049	1.3999	1.7343	0.9772	1.2481	1.1418
21077	0.3109	0.2909	0.2909	0.1564	0.1453
46076	1.2136	1.4679	1.0654	1.1972	1.1194

using the proposed method is indicated in Table 1. Table 2 shows the objective values of the proposed method for different images.

The computational time of the FCM, the IAFHA, the AJNDH and the RFHA are generally more than the GBPCA when segmenting all the images. Table 3 depicts the computational time of compared algorithms. Therefore, the GBPCA approach has more prominent effectiveness because of contrasting its straightforwardness. While comparing with the other population based algorithm the proposed method takes less time.

Evaluation of cluster number: Based on the qualitative results shown in the previous study, the proposed GBPCA algorithm can adaptively initialize cluster center and the centroid values. The GBPCA algorithm offers a superior cluster center initialization mechanism that guarantees effective classifcation capability and less misrepresentation during the segmentation process. Except randomly initialized FCM technique, all of the other algorithms have their own distinctive mechanism for cluster center initialization. Table 4 shows the number of clusters produced by the randomly initialized the FCM, the IAFHA, the AJNDH, the RFHA and GBPCA techniques.

Quantitative evaluation of segmentation results: The quantitative results obtained for the F (I), F' (I) and Q (I) evaluation functions are organized in Tables 5-7, seperately. The proposed GBPCA technique delivers the best (smallest) F(I), F'(I) and Q(I) values for the images

Table 6: Assessment of segmentation results of the F' (I) evaluation function

	Algorithm				
Image	FCM (1.0e+2)	IAFHA (1.0e+2)	AJNDH (1.0e+2)	RFHA (1.0e+2)	GBPCA (1.0e+2)
247085	1.1283	0.8432	0.6680	0.6662	0.6324
143090	0.2229	0.4912	0.4912	0.1552	0.1465
124084	0.3365	0.5104	0.3537	0.2582	0.2182
118035	0.4644	0.4673	0.3713	0.4098	1.5794
295087	0.2190	1.6031	0.2947	0.2226	0.2047
42049	1.4144	1.7555	0.9868	1.2627	1.2753
21077	0.3148	0.3057	0.3057	0.1587	0.1400
46076	1.2279	1.4889	1.0775	1.2121	1.2116

Table 7: Comparison of segmentation results of the Q (I) evaluation function

	Algorithm				
Image	FCM (1.0e+3)	IAFHA (1.0e+3)	AJNDH (1.0e+3)	RFHA (1.0e+3)	GBPCA (1.0e+3)
247085	101.2350	15.2742	56.7537	55.7933	17.2149
143090	0.7623	2.0572	2.0572	0.4605	0.4290
124084	0.6727	0.5449	0.5813	0.5039	0.4896
118035	6.1626	4.3036	8.5993	5.9558	5.7091
295087	1.2547	3.8594	0.8117	0.9247	0.8931
42049	4.8139	4.3146	5.0855	3.4418	3.1043
21077	1.7599	1.3058	1.3058	0.7073	0.6432
46076	0.9854	1.0013	0.9044	0.9709	0.9765

Table 8: Performance assessment of segmentation results based on average values of F (I), F' (I) and Q (I) for 200 standard BSDS images

	Benchmark quantitative evaluation function		
Algorithm	F(I) (1.0e+2)	F'(I) (1.0e+1)	Q(I) (1.0e+5)
FCM	8.3500	8.4600	0.5660
AFHA	8.4900	8.6200	0.5910
AJNDH	7.8200	7.9300	1.3300
RFHA	7.5600	7.6600	0.4900
GBPCA	7.1200	7.2400	0.3620

Mountain, sunflower and cars and the second best values for the images, red church, mountain and eagle. By producing smaller values the F(I), F'(I) and Q(I) evaluation functions, the segmented regions created by the proposed GBPCA technique are more homogeneous and demonstrate less distortion compared with the other techniques.

The GBPCA algorithm yields promising F(I), F'(I), and Q(I) assessment capacities for all images. The GBPCA algorithm delivers the smallest values of F (I), F' (I) and Q (I). By refinement, the normal AFHA technique yields the largest normal estimations of F (I) and F' (I), as an extensive estimation of Q (I). The proposed GBPCA algorithm is superior to the other techniques because it can produce more compact and unchanging segments during segmentation process. The small values of F (I), F' (I) and Q (I) at a constant space during the segmentation process demonstrate that the proposed algorithm will be outstanding color image as segmentation technique (Table 8).

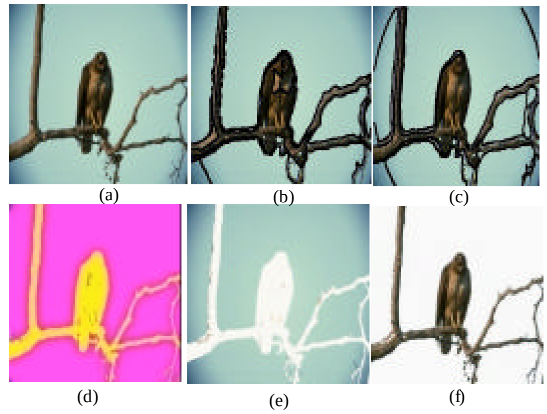


Fig. 9: Eagle image: a) Orginal image; b) Object extraction; c) Coarse object extraction; d) Image classification; e) Object identification and f) Structured object detection

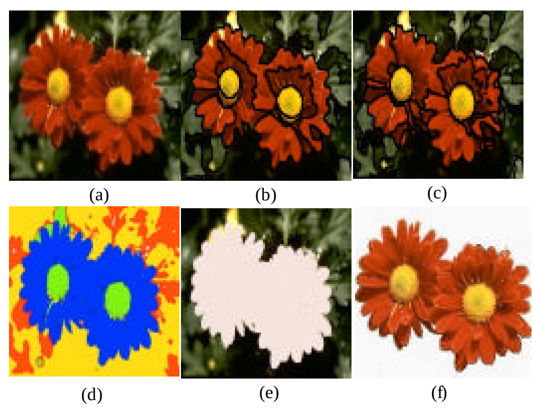


Fig. 10: The image sunflower: a) Orginal image; b) Object extraction; c) Coarse object extraction; d) Image classification; e) Object identification and f) Structured object detection

The results of the object detection process are exhibited in Fig. 9-13. As in image eagle, the foreground object extraction and the coarse object extraction are indicated in Fig. 9a-c, separately. The outcome of the object classification and object identification image by the visual perceptual model is presented in Fig. 9d and e. In classification the eagle is classified along with the wood based on the similarity of pixels. The detection of structured objects in Fig. 9f demonstrates the detection of object separated from its background.

The image sunflower and its foreground object extraction are indicated in Fig. 10a-c individually. In coarse object extraction the sunflower is extracted accurately. The extracted image is further classified then, the object is identified. The outcome of the object classification and identification image is demonstrated in

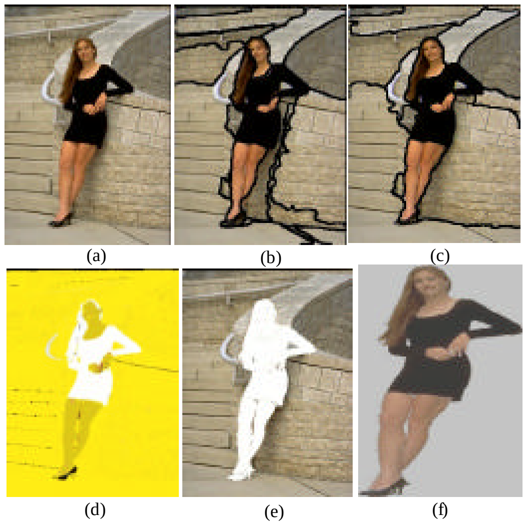


Fig. 11: The image of lady: a) Orginal image; b) Object extraction; c) Coarse object extraction; d) Image classification; e) Object identification; f) Structured object detection

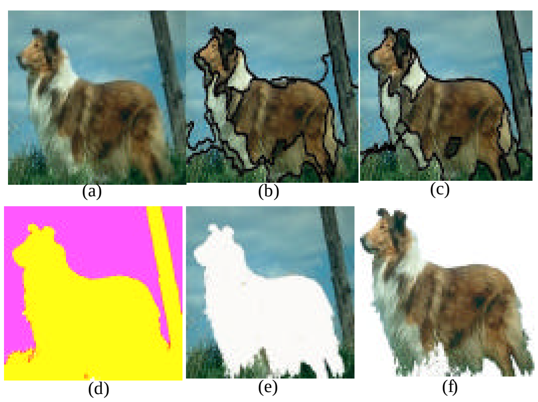


Fig. 12: The wolf image: a) Orginal image; b) Object extraction ; c) Coarse object extraction d) Image classification; e) Object identification and f) Structured object detection

Fig. 10d and e. The detection of structured objects is shown in Fig. 10f. The input image lady and its foreground object extraction are indicated in Fig. 11a-c, respectively. The lady object is classified and identified based on the perceptual model. The outcome of the object classification and object identification image by the visual perceptual model is demonstrated in Fig. 11d and e. The detection of structured objects is shown in Fig. 11f.

As in image wolf its foreground object extraction and the coarse object extraction are shown in Fig. 12a-c individually. In classification the wolf is classified along with the wood as in Fig. 12d but in object identification

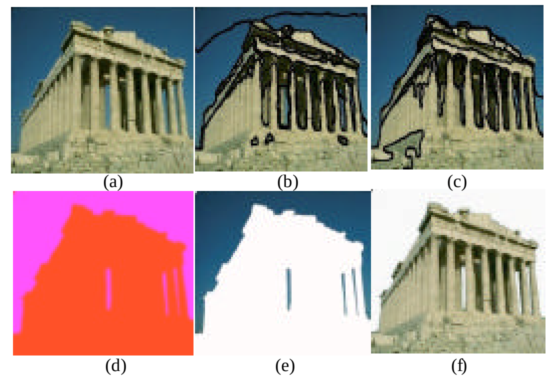


Fig. 13: The building image: a) Orginal image; b) Object extraction; c) Coarse object extraction; d) Image classification; e) Object identification and f) Structured object detection

image by the visual perceptual model the wolf alone is identified as indicated in Fig. 12e. The object is extracted and detected with some loss of image details. The detection of structured objects is shown in Fig. 12f. The input image building its foreground and coarse object extraction are shown in Fig. 13a-c, separately. The results of the object classification and object identification image by the visual perceptual model are indicated in Fig. 13d and e. The detection of structured objects is given in Fig. 13f. The object building is extracted and detected accurately without any loss of image details.

The segmentation and recognition should not be separated, it should be treated as an interlacing method and needs some background object as starting point. The main portions of the objects can be fragmented without recognizing individual object parts. Perceptual based color IS seems to be adaptable to the dissimilarity of number of semantic classes. POM does not gain any prior knowledge from training images for the structured objects. The methodology accomplishes extremely stable performance on segmenting the difficultly structured objects on the full data set which have different appearance and shape characteristics. This shows that the proposed approach can effectievely handle various structured objects appearing in outdoor scenes.

CONCLUSION

This study proposed a robust method for visual based color image segmentation and object detection approach using an enhanced Charged System Search algorithm. This algorithm is modeled using a Global Biotic Cross Pollination Algorithm (GBCPA) integrated with pollination refusal scheme and Evolutionary Strategy (ES) for robust segmenting of various kinds of images. The GBPCA algorithm segments the object based on the color, texture, entropy and edge information and minimizes the fitness criterion. The Gestalt law combined with the algorithm detects the objects by splitting the whole object or the main portions of the objects together without requiring a priori knowledge of the of the individual object parts. Comparative experimental results on real-world BSDS dataset have demonstrated the efficiency and effectiveness of the GBPCA algorithm. The proposed algorithm proves itself as reliable and robust in segmenting various kinds of images. Another advantage is its low computational complexity and is thus, can be simply scaled and adapted for real-time image segmentation processing.

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