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Perceptual Based Color Image Segmentation And Object detection Through A BBO Algorithm Modified With Evolutionary Strategy.

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Abstract –Color image segmentation is one of the challenging problems in image analysis and pattern recognition. It can be treated as a process of dividing a color image into regions with some coherent internal properties and each region is homogeneous. This paper addresses a perceptual based color image segmentation approach using a Biogeography based optimization (BBO) algorithm combined with Evolutionary Strategy (ES), which exploits the structurally challenging objects based on color, texture, edge information and saliency map in the CIE L*a*b color space. The color and texture of each segment does not typically exhibit uniform geometric characteristics in the segmentation of natural scenes. The proposed approach combines knowledge of human perception based on Gestalt law with an understanding of signal characteristics in order to segment natural scenes into perceptually uniform regions. The objects are grouped together without depending on a priori knowledge of the structurally challenging objects. The experimental results show that the proposed method outperformed the current state-of-the-art image segmentation approaches and achieved accurate segmentation quality on natural scene in terms of both qualitative and quantitative assessment.

***Keywords* – Water Cycle Optimization (BBO), Evolutionary Strategy (ES), Gestalt law, Image Segmentation, CIE L*a*b**

I INTRODUCTION

Color image segmentation is an area of great importance in the field of image processing as it is a fundamental task for many applications of computer vision such as image analysis and pattern recognition. Color image segmentation is defined as the process of splitting or separating an image into meaningful object that exhibit similar features with respect to criterion such as color, texture, gradient [1],[2]. Color images carry much more information than gray ones; hence extracting object from color images is a difficult and challenging task [3]. Color image segmentation has been studied for decades and recently received much attention in image retrieval, video surveillance and object classification [4]. Image segmentation algorithms are generally based on one of two basic properties of the intensity values of the image pixels: discontinuity and similarity. In discontinuity, the methodology is to partition an

image based on sudden changes in intensity values. Edge detection techniques fall in this category which is similar to boundary extraction. On the other hand, in the similarity, the idea is to partition the image into different regions such that pixels belonging to a given region are similar with respect to a set of predefined criteria's [5].

Human- based segmentation is tedious and time consuming because of the information contained in images and their unpredictable complexity. Hence a color image segmentation algorithm should be able to accurately define the desired regions or object boundaries automatically or semi-automatically with minimal input. Existing color image segmentation algorithms can be broadly classified as: feature based, region based, graph based and segmentation based on evaluation function optimization.

Hybrid techniques utilizing a blend of the techniques above are also popular. Feature-based methods [6]-[7] extract image features by collecting the main characteristics of the color image. The edge information of the color image is usually not preserved and pixels from disconnected segments may be grouped together. Region-based methods [8] detect regions that satisfy some predefined criteria, it preserves the relationship between pixels in a color image. Graph based methods [9] represent a problem in terms of a graph where each vertex corresponds to a pixel or region, node corresponds to a pixel in an image and an edge connecting each pair of vertices. The weight relates to the color and texture feature corresponds to the edge connecting two adjacent regions or pixels depends on the likelihood that they belong to the same region. Color image segmentation based on evaluation function optimization [10]-[12] usually uses an evaluation function incorporating the feature-based and spatial information.

II RELATED WORKS

The heuristic nature of the traditional methods, allow us to formulate the segmentation problem as an optimization problem by formalizing an objective criterion. Optimization is the process of trying to find 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. An optimizer can prompt effective solutions for optimal segmentation. The K-means algorithm doesn't really track down the most ideal design, corresponding to the minimum global objective function. A histogram-based k-means cluster [13] performs segmentation in different color spaces. The algortithm is additionally fundamentally touchy to the underlying arbitrarily selected cluster centers. Automatic fuzzy clustering [14] based on adaptive multi-objective differential evolution for remote sensing imagery.

In the recent years, EAs have been applied to image segmentation with promising results [15]-[19] because of their fast computing ability. In EAs the decision making processes are guided by "fitness" information alone. Parallel exploration over the search space can greatly reduce the possibility of getting stuck in local optima. In [20], different kinds of evolutionary algorithms are employed to perform color image segmentation using clustering algorithms. The GA with a learning operator (GA-L) is proposed in [21] to improve optimal stability by increasing the average fitness value. Particle swarm optimization (PSO), the individuals are evolved by cooperation and competition between the individuals in a generation [22].

Evolutionary algorithm based multilevel thresholding [23] for a color satellite image has been presented to solve the color image segmentation problem. A saliency-directed color image segmentation approach using ''simple'' modified particle swarm optimization (MPSO) is proposed, in which both low-level features and high-level image semantics extracted from each color image are employed [24]. Color image segmentation based on flower pollination

optimization algorithm (FPOA) aims to improve the objective characteristics of the basic FPOA approach [25]. The ant colony optimization (ACO) method introduced in [26] is an entropy-based object segmentation approach to obtain the optimal parameters. Automatic Clustering Using an Improved Differential Evolution Algorithm is introduced in [27]. Whale Optimization Algorithm (WOA) and Moth-Flame Optimization (MFO) to decides the ideal multilevel thresholding for image segmentation [28]. The MFO algorithm is propelled from the natural behavior of moths which have a special navigation style at night since they fly utilizing the twilight, while, the WOA algorithm emulates the natural cooperative behaviors of whales in many real-world applications.

This paper focuses on image segmentation based on a new color image segmentation algorithm, which exploits the information obtained from the detected edges in the CIE L*a*b color space. It elaborates a global optimization method using a hybrid Biogeography-based optimization for automatically grouping the pixels of a color image into disjoint homogenous regions. The perceptual organization model (POM) for boundary detection quantitatively incorporates a list of Gestalt laws and therefore is able to capture the non-accidental structural relationships among the constituent parts of a structured object [29]. The POM model can distinguish the limits of different striking organized items under various outside conditions.

Biogeography Based Optimization characteristic which makes it distinctive from Genetic Algorithm is its migration mechanism, which affects selection process. It has good optimization performance due to its migration operator. It also provides noise free image and compute fast computational speed as compared to other algorithm in terms of 1.28 seconds. The experimental results show that our proposed method outperformed state-of-the-art approaches on challenging image databases [30] consisting of a wide variety of outdoor scenes and object classes. Therefore, the hybrid Biogeography Based Image Segmentation is more reliable and faster for image segmentation.

The remainder of this paper is organized as follows. Section 2 introduces some related studies, including color space transform, perceptual organization model (POM) and the objective function. Section 3 describes the basic principle and implementation procedure of BBO combined with IR and ES algorithm in detail, followed by Section 4, series of comparison experiments are conducted to verify the effectiveness of our proposed approach. Our concluding remarks are contained in the final section.

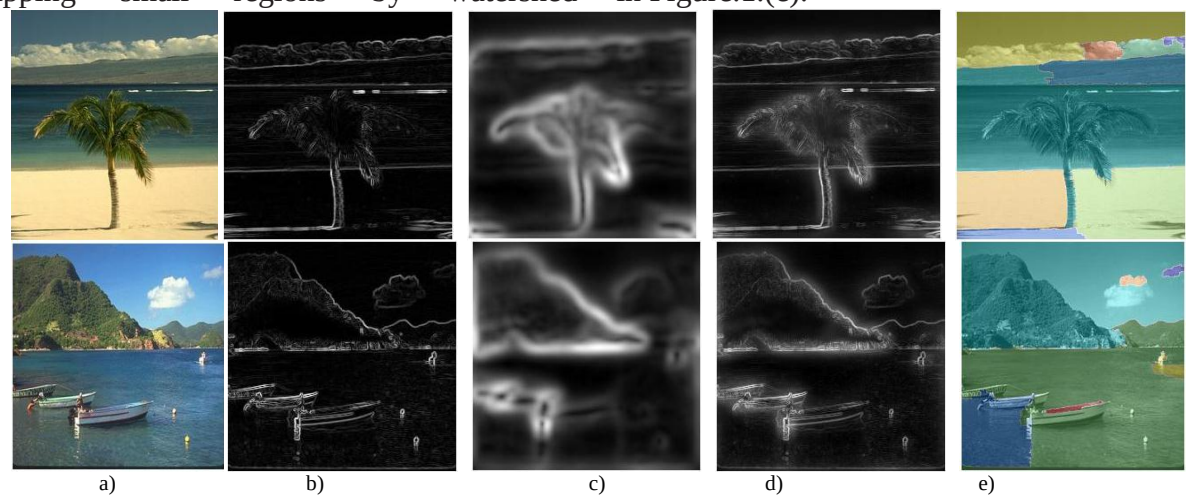
III IMPLEMENTATION OF BBO COMBINED WITH IR AND ES FOR IMAGE SEGMENTATION

A new biogeography based technique [32] for image segmentation. BBO is a populace based streamlining calculation it doesn't include proliferation or the age of "youngsters". As we began we select a seed utilizing some arrangement of predefined measures. In the wake of choosing inspects neighbor pixels of seed focuses and we compute CMC shading distance between adjoining pixels. According to BBO approach make three islands HIS, MSI and LSI. HSI (highly Suitability index) that contain pixels which have more comparable properties. Medium suitability index (MSI) fundamentally contains pixels which have medically appropriate. Low suitability index (LSI) that contain pixels which contain pixels that not all that recognizable. HIS will in general have countless species, while those LSI have a Small number of animal categories. HIS have numerous species that emigrate to close environments, basically by temperance of the enormous number of species that they have. HIS have a low animal types migration rate since they are as of now almost soaked with species. Subsequently, HSI habitats are more static in their species distribution than LSI habitats. LSI has a high species immigration rate because of their sparse populations. At that point we select edge esteem.

On the off chance that our determined distance is not as much as limit, it migrates to other region, otherwise it makes its own region.. The Image Segmentation using BBO combined with IR and ES [33],[34] algorithm can be informally described with the following algorithm.

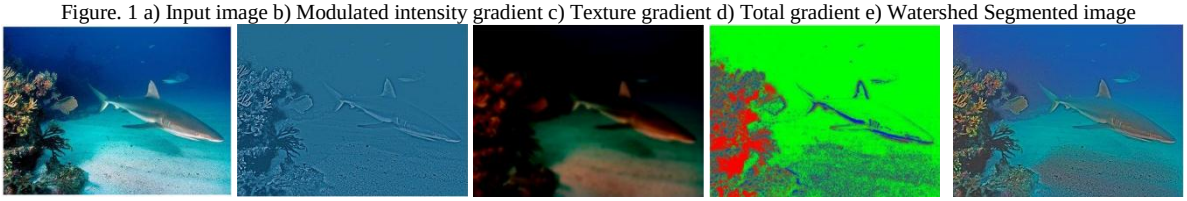
Stage 1 Preprocessing

Extract the features, intensity gradient, texture gradient and over segment object image into non-overlapping small regions by watershed segmentation. The preprocessing results of the segmentation algorithm at different stages are presented in Figure.1.(a)-(e). The input RGB image is shown in Figure.1(a). The outcome of modulated intensity gradient is shown in Figure.1.(b). The texture gradient generated using local entropy calculation and total gradient is displayed in Figure.1.(c) and 1(d). The segmented image using the watershed algorithm is displayed in Figure.1.(e).



a) b) c) d) e)

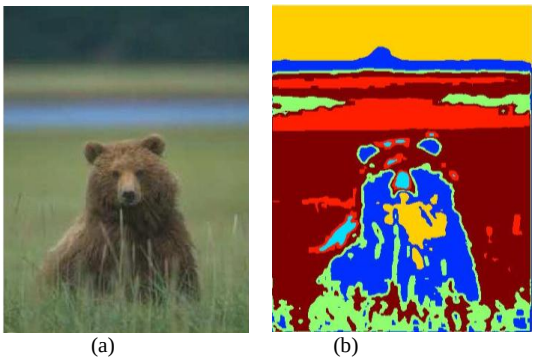
Figure. 1 a) Input image b) Modulated intensity gradient c) Texture gradient d) Total gradient e) Watershed Segmented image



a) b) c) d) e)

Figure.2. a) Input image b)Color Corrected image c) Estimated bias field d) Partition matrix e) Illumination

The results of the algorithm at different stages are presented in Figure.2 (a)-(e). The input RGB image and its color corrected image are shown in Figure.2. (a),(b). The outcome of the estimated bias field on the color image is shown in Figure.2.(c). The partition matrix classifies the pixels of the color image is shown in Figure.2. (d). Figure.2.(e) represents the illumination image. Poor illumination causes difficulty in extracting the image features. The input image and its segmentation map are represented by Figure.3.(a) and 3(b).



(a) (b)

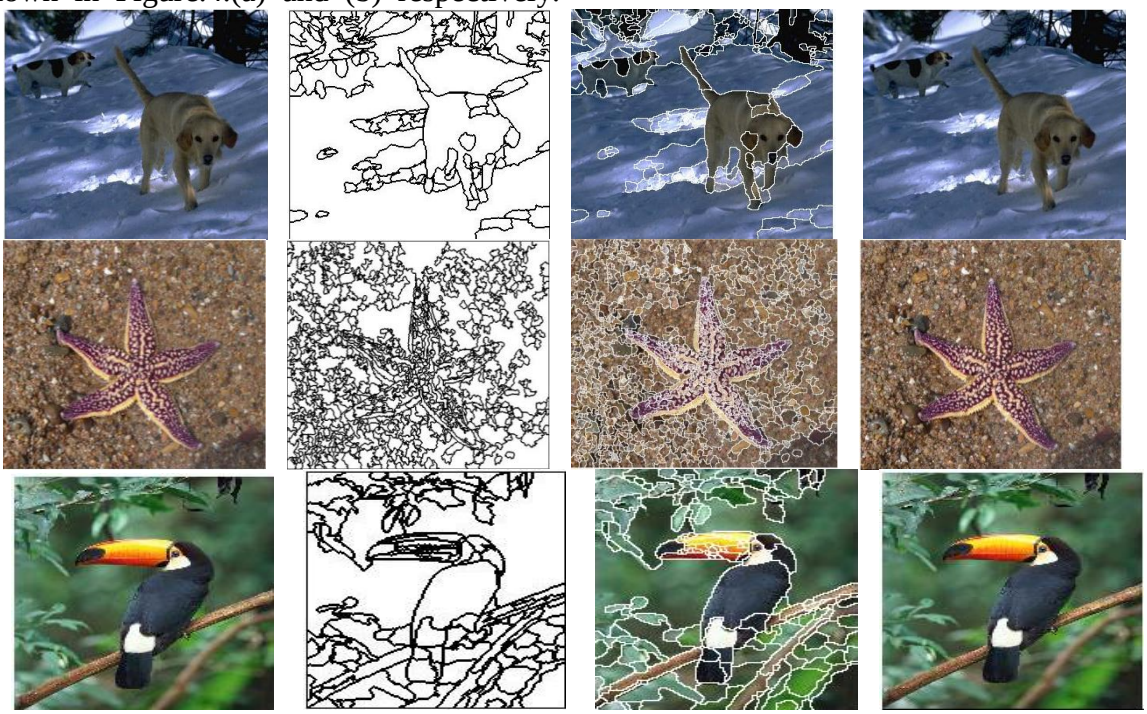
Figure.3. (a)Input Image (b)Segmentation Maps

Stage 2 Transformation

Step 2.1:. Convert a RGB image into CIE LAB image using the color space transform.

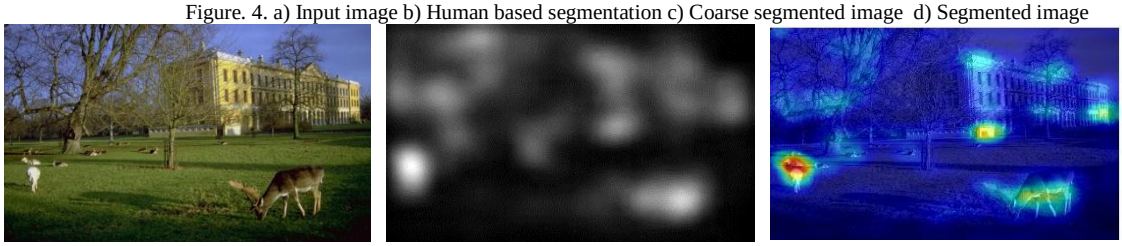
Step 2.2: Using Region Growing based Image Segmentation criteria select a seed point. Based on some predefined criteria, examine their neighboring pixels of seed points.

Step 2.3: Using the Nearest Neighbor Rule classify each Pixel and calculate CMC distance between neighboring pixels that have similar characteristics. The results of the image classification at different levels are presented in Figure.5.(a)-(d). The input image and its manual segmentation are shown in Figure.4.(a) and (b) respectively. The outcome of the coarse segmented image by the nearest neighbor rule is shown in Figure.4.(c). The coarse segmented image eliminates small region from quantized image by region elimination process. The segmented image is shown in Figure.4.(d). The input image its saliency map and saliency image are presented in Figure.5.(a)-(c). The saliency based visual attention model generates the saliency map. The salient regions of the uniformly quantized image are shown in the salient image.



a) b) c) d)

Figure. 4. a) Input image b) Human based segmentation c) Coarse segmented image d) Segmented image



a) b) c)

Figure.5. a) Input image b) Saliency map c) Salient image

Stage 3 BBO combined with IR and ES Segmentation Algorithm

Step 3.1) Initialization

Initialize the BBO parameter considering every color as different habitat and each pixel as species. Allocate the parameters such as number of habitats N, habitat modification probability P_{mod}, mutation probability P_{mut}, maximum mutation rate m_{max}, maximum immigration rate I,

maximum emigration rate E, lower limit for immigration probability per gene λ_{lower}, upper limit for immigration probability per gene λ_{upper}, step size for numerical integration *dt*, elitism parameter p, maximum number of iteration. Also initialize the edge intensity i.e., number of SIV *m*, maximum and minimum pixel value of an image. Since the real comparison of pixel values is the decision variables, they are represented as SIV in a habitat. A population of habitat ie) each color value in an image is represented as,

$$H = \left[H^1, H^2, ...H^i, ...H^N\right] \quad (1)$$

Each habitat consists of m number of SIVs. An individual habitat H_i with SIVs is represented as,

$$H^i = SIV^{ij} = \left[SIV^{i1}, SIV^{i2}, ..., SIV^{im}\right] = \left[P^{i1}, P^{i2}, ..., P^{im}\right] \quad (2)$$

where $i=1,2,....,N$ and $j=1,2,3,....,m$. Each habitat is one of the possible solutions for the problem. In a habitat H^i the component SIV^{ij} refers to the pixel value of the *m*th pixel of the *i*th habitat.

Step 3.2) Initialization of SIV Each SIV in the framework H is arbitrarily instated inside the base and greatest pixel esteem separately

Step 3.3) Identification of Elite habitats

In BBO the best habitats in each iteration are conserved from alterations caused by migration and mutation. Accordingly an elitism boundary is utilized to give a memory for the algorithm. Based on the HSI values of each habitat, which refers to the edge value of the image a set of 'p' elite habitats, are preserved. Habitats with best (i.e., maximum) pixel value chosen as elite habitats in each iteration.

Step 3.4) Migration

3.4.1 Calculate the immigration rate λ_i and emigration rate μ_i for each habitat using the Equations.(3 and 4).

$$\lambda_i = I\left(1 - \frac{k(i)}{n}\right) \quad (3)$$

$$\mu_i = E * \left(\frac{k(i)}{n}\right) \quad (4)$$

Where *I* and *E* are maximum immigration and emigration rate respectively. *k(i)* is the fitness rank of the *i*th individual and *n* is number of candidate solutions in a population.

3.4.2 Probabilistically immigration rate and emigration rate are used to modify each non-elite habitat using migration operation. The likelihood that a territory is altered is corresponding to its movement rate and the likelihood that the wellspring of the adjustment comes from a habitat is proportional to the emigration rate

3.4.3 Set probability for each region. Probability is like threshold values. The probability *P* the region contains exactly *S* pixels. *Ps* changes from time to time as follows:

$$P_s(t+\Delta t) = P_S(t)(1 - \lambda_s \Delta t - \mu_s \Delta t) + P_{s-1}\lambda_{s+1} + P_{s+1\mu\alpha+1}\Delta t \quad (5)$$

3.4.4 The migration operation for each non elite habitat is performed as below:

Select a habitat H_i with probability proportional to i
If H_i is selected
For j=1 to N
Select another habitat H_j with probability proportional to μ_j
If H_j is selected
Randomly select an *SIV* from habitat H_j
Replace a random *SIV* in H_i with that selected *SIV* of H_j
end
end
end

3.4.5 When receiving immigration from other islands, use the immigration refusal idea to decide whether or not to accept the immigration.

Step 3.5) Mutation

3.5.1 Update the species count probability for each child habitat using the Equation (5).
3.5.2 Elitism is implemented by setting species count probability to zero for *p* elite habitats
3.5.3 Mutation process for each non elite habitat is carried out as below:
for i=1:N
for j=1:m
Select a SIV Hij with a probability proportional to species count.
if Hi(j) is selected
Replace Hi(j) with a randomly generated SIV within its feasible region
end
end
end

Step 3.6) Evaluation of fitness of the population

Calculate the fitness of each individual habitat including parent and child habitat which is known as HSI in BBO. The fitness is calculated using a function *f* given in Equation.(6

Euclidean distances in Feature space between every pixel and the centroids of the cluster it belongs to are calculated to obtain the optimal segmentation. Then, we sum up all these distances and use the reciprocal of this summation as the fitness of BBO combined with IR and ES. The segmentation fitness is defined in Equation(11).

$$fitness = \frac{1}{\sum_{i=1}^{C}\sum_{j=1}^{Ri}\sum_{k=1}^{p} d\left(p_{ijk}, m_i\right)} \qquad (6)$$

Where Ri is the number of regions in the i-th cluster, P is the number of pixels in the j-th region, p denotes the k-th pixel in the j-th region of the i-th cluster, and m_i is the centroid of all pixels of the i-th cluster in feature space. In Equation.(6), a more precise segmentation evaluation can be obtained by operating on watershed region classification..

$$d\left(p_{ijk}, m_i\right) = \sqrt{\sum_{g=1}^{F}\left(p_{ijk_g} - m_{i_g}\right)^2} \qquad (7)$$

F is the number of features and $p_{ijk\ g}$ and m_{ig} denote the g-th feature of the current pixel and cluster centroid respectively. Therefore, the aim of BBO combined with IR and ES is to find an individual with maximum fitness.

Store the fitness for the use in the next generation.

Step 3.7) Based on the features borrowed from ES, select the best n islands from the n parents and n children as the population for the next generation.

Step 3.8) Termination criterion

Check for the termination criteria. If maximum generation is reached stop execution otherwise go to step 3.4.1. For each habitat update the immigration and emigration rate of its species count using step 3.4.1. Increase the CMC distance for every iteration. Iterate till the required number of habitats are left.

IV EXPERIMENTAL RESULTS

In this paper, the whole test image dataset from the Berkeley segmentation data set (BSDS) [35] containing training set of 200 images and a test set of 100 images is employed. The images contain a wide variety of natural and man-made objects such as people, animals, flowers, buildings and cars. This data set provides ground truth object class segmentations that partner every locale with one of the semantic classes (sky, tree, road, grass, water, building, mountain, or foreground). BSDS has been generally utilized as a benchmark for many boundary detection and segmentation algorithms in technical literature.

The proposed BBO combined with ES and IR algorithm was implemented with a Core 2 Duo 1.86GHZ personal computer using MATLAB. Since the compared

algorithms, except the KM method, are stochastic and random population-based optimization methods, each of them is repeated 200 times. The population size is 30. In all experiments, to ensure that the initial values of each random algorithm are equal, we use the MATLAB command rand ('state',sum(i * 30)).The value of i used at the beginning of each run in all algorithms is equal.

The optimization problem considered in this paper is to solve the color image segmentation problem using BBO combined with IR and ES approach. Our 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 performance of IS using our algorithm is validated by applying it to various natural images. The original images taken for the quantitative evaluation of our method is shown in Figure.6. Image1 to image 8 are taken from BSDS of size 481 X 321.

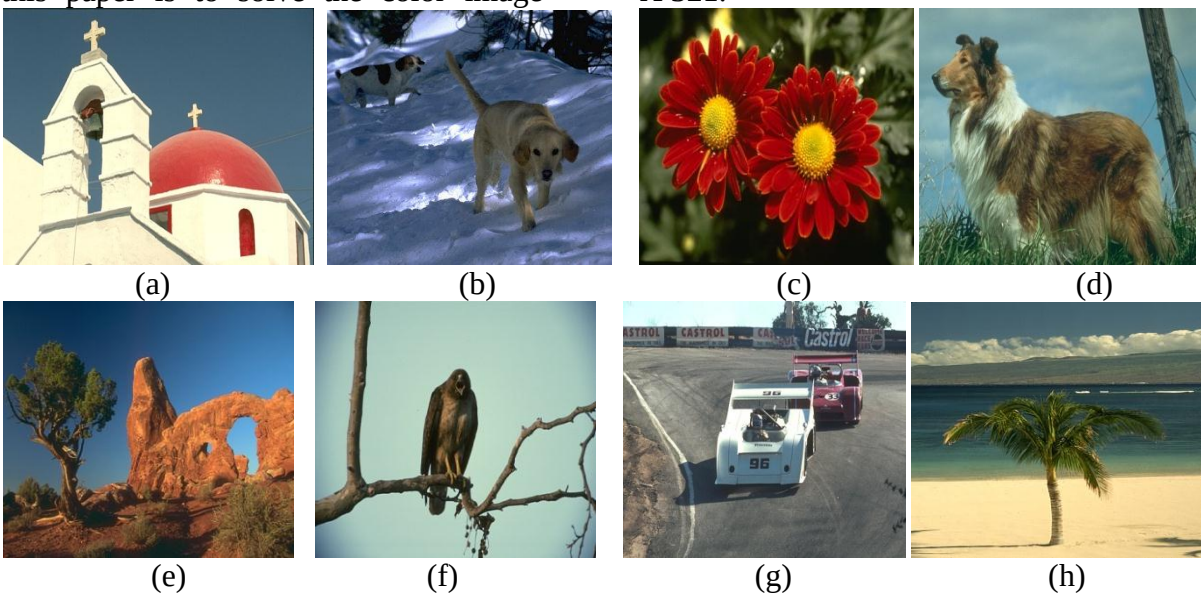
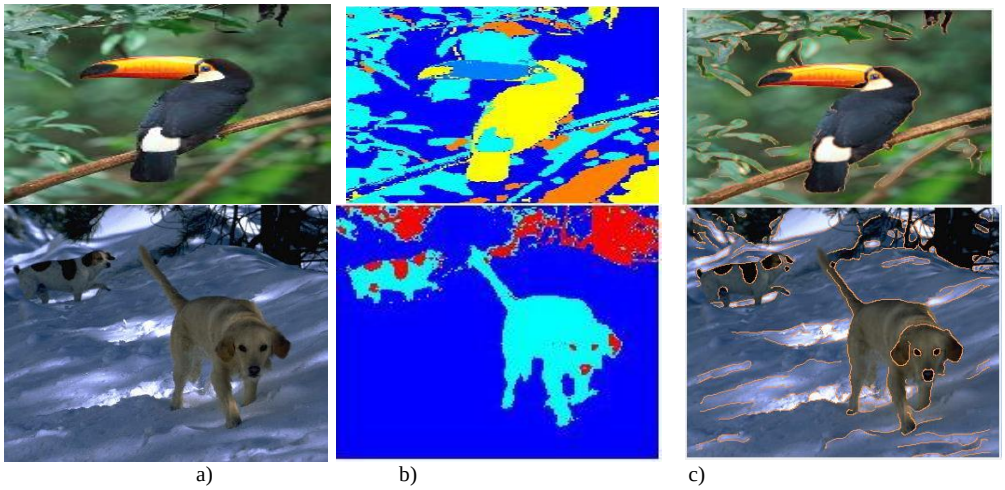


Figure.6. The Original image1 to image 8 used in this study are shown in (a)-(h)

The results of the image background identification at different stages are presented in Figure.7.(a)-(c). The input image and its superpixel image generated by the Felzenszwalb's algorithm [36] are shown in Figure.7. (a) and (b) respectively. The background classifier for background identification is determined using the POM method The outcome of the background identification image by the visual perceptual model is shown in Figure.7.(c). The background classifier identifies the background structured objects.

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

IMAGE NAME	OVERALL DEVIATION	EDGE VALUE
IMAGE1	0.860	0.289
IMAGE2	0.845	0.316
IMAGE3	0.698	0.362
IMAGE4	0.832	0.334
IMAGE5	0.627	0.381
IMAGE6	0.438	0.509
IMAGE7	0.547	0.432
IMAGE8	0.773	0.395



a) b) c)

Figure. 7. a) Input image b) Superpixel c) Background identification

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 using the proposed algorithm is shown in Table.1. Figure.8.(a)-(f) shows the results of BBO with IR and ES algorithm in comparison with the IS algorithms with varying texture descriptors. The input image consists of foreground and background objects with varying illumination are shown in Figure.8. (a). Figure.8. (b)-(e) shows significant lose in image details due to the varying illumination conditions. The outcome of the proposed method shows better segmented image in Figure. 8.(f).

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

Figure 8. Typical segmentation results obtained from the compared algorithms on the image (a) Original image, (b) KM (c) FCM(d) GA (e) PSO METHOD(f) Proposed Method

Table.2 shows the objective values compared with traditional IE techniques and the proposed method for different images.

Table 2 Objective values compared with traditional IS techniques.

IMAGE NAME	GA	DE	PSO	DPSO	BBO IR & ES
IMAGE1	0.8775	0.6775	0.7775	0.7975	0.9578
IMAGE2	0.9934	1.2334	1.3934	0.9345	1.3526
IMAGE3	1.3753	1.1553	1.1753	1.2453	1.3548
IMAGE4	1.3547	1.1247	1.1347	1.3427	1.2467
IMAGE5	1.2896	1.2396	1.2222	1.3696	1.4972
IMAGE6	1.3776	1.1776	1.2656	1.2976	1.4751
IMAGE7	1.3443	1.1145	1.1447	1.3427	1.2665
IMAGE8	1.2896	1.2596	1.2352	1.34236	1.4573

Figure.9. represents the objective function of the proposed method with various iterations. Table.3 depicts the computational time of compared algorithms. While comparing with the other population based algorithm the proposed method takes less time.

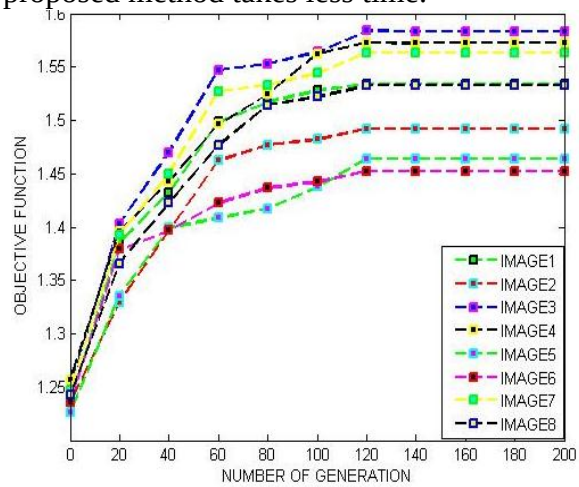


Figure.9. Objective function verses Number of generation

Table 3. Computational time for the compared algorithms.

IMAGE NAME	KM	GA	DE	PSO	BBO IR & ES
IMAGE1	6.238	14.391	12.042	13.546	5.821
IMAGE2	7.463	15.241	12.541	10.342	6.631
IMAGE3	4.523	13.622	8.627	9.345	4.723
IMAGE4	5.789	14.976	11.675	9.254	7.342
IMAGE5	5.142	11.345	9.542	8.657	6.256
IMAGE6	5.543	12.453	11.763	9.237	5.971
IMAGE7	4.777	12.625	10.623	10.359	4.923
IMAGE8	5.382	13.972	9.652	9.758	5.372

The segmentation and recognition should not be separated it should be treated as an interleaving procedure and requires some background object as starting point. The main portions of the objects can be splited without recognizing individual object parts. Perceptual based color IS seems to be adaptable to the variation of number of semantic classes. The outcomes of the object detection process are presented in Figure.10. (a)-(f). The input image and its foreground object extraction are shown in Figure.10. (a)-(c) respectively. The outcome of the object identification image by the visual perceptual model is shown in Figure. 10.(d) and (e). The detection of structured objects is shown in Figure.10.(f). POM does not gain any prior knowledge from training images for the structured objects. Our POM achieves very stable performance on segmenting the difficultly structured objects on the full data set which have different appearance and shape

characteristics. This shows that our POM can successfully handle various structured objects appearing in outdoor scenes. The performance of Image Segmentation technique can be measured by comparing NPR value [37]. The NPR value for segmenting the image using the proposed algorithm is compared with other traditional techniques are shown in Table.4 . The NPR value compared with traditional IS techniques shows the proposed method has the highest value illustrating performs consistently better than other algorithms qualitatively and quantitatively.

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

Figure 10. a) Input image b) object extraction c) coarse object extraction d) image classification e) object identification f) structured object detection

Table 4 NPR values compared with traditional IS techniques.

IMAGE NAME	KM	GA	DE	PSO	DPSO	BBO with IR & ES
IMAGE1	0.467	0.532	0.597	0.655	0.687	0.734
IMAGE2	0.354	0.376	0.432	0.495	0.534	0.586

IMAGE3	0.386	0.502	0.576	0.622	0.657	0.697
IMAGE4	0.316	0.333	0.382	0.451	0.499	0.576
IMAGE5	0.333	0.398	0.411	0.444	0.523	0.561
IMAGE6	0.442	0.551	0.653	0.681	0.713	0.843
IMAGE7	0.323	0.378	0.391	0.437	0.519	0.551
IMAGE8	0.296	0.392	0.443	0.517	0.572	0.667

V. CONCLUSION

The objective of the proposed work is to segment the image and detail in an image by minimizing the fitness criteria based on color, edge value and texture. The proposed algorithm was successfully applied to segment the image and detail in the test image by minimizing the fitness criterion and adopting the parameters. The proposed method is applicable to wide variety of image and video sequences. From numerous many years, image segmentation is carried out utilizing numerous strategies like PSO, GA and so on. BBO combined with IR and ES is uniquely a biogeography strategy utilized for carried out color image segmentation which gives more exact segmented image as compared to other evolutionary algorithm. The simulation results show the effectiveness of the algorithm in terms of quality assessment and computation efficiency with the other image segmentation algorithms. Comparative experimental results on real-world natural images have demonstrated the efficiency and effectiveness of the proposed method.

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