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Automatic Marker Generation to Similarity Based Region Merging Algorithm using Edge Information



Abstract: - One of the most important tasks in computer vision is image segmentation. Several interactive strategies are utilized for picture segmentation because automated techniques are difficult for this kind of work. The outcome of interactive methods is mostly determined by user input. Obtaining excellent interactions for huge datasets is challenging. However, automated picture segmentation is starting to play a significant role in image analysis and computer vision. Effective and efficient segmentation outcomes are obtained using the interacting region merging method suggested by Maximal Similarity based region merging algorithm. Limitation of MSBRM is it requires some efforts on the part of users and is yet not a fully-automatic approach. Here, we suggest a completely fresh unsupervised image segmentation method that combines edge information with MSBRM. We propose an integrated framework to generate object markers for similarity based region algorithm using edge information. Long edges give rough distribution of objects in image. After retrieving edges using phase congruency, edge processing operations are employed to remove small edges and to group color similar long boundaries. Centroids of long boundaries are used as object markers to the MSBRM algorithm. The generation of object markers is done using edge segment grouping. These object markers guide the region merging process. The proposed method shows its effectiveness in segmenting natural real world color images.

Keywords: Image Segmentation, MSRM, Region Growing, Mean-Shift, Interactive Image Segmentation (IIS), Watershed, Level Set, EDISON-Segmentation system, Phase Congruency, Log Gabor Wavelet

I. INTRODUCTION

Segmenting an image into various parts or areas, depending on the properties of the image's picture elements, texture and shape, is commonly done in the processing of computerized images and study. Segmentation in machine vision relates to dividing the content of a computerized picture into several parts [1]. The process of segmentation more specifically, is the action of allocating identification to every single pixel within a picture so that picture elements having an identical label share specific pictorial attributes [1, 2, 3]. Segmenting picture into parts is a primary process in most of the image understanding and computer visualization applications such as medical images, iris recognition, and food grain grading and data compression algorithms [2]. The color image segmentation is attracting more consideration due to the fact that color image provides more meaningful information than the gray images.

Segmentation of pictures containing natural scenes acquired in varying condition and classification of such imagery data is an exciting task in the image dealing industry because of variability and complication related with it. Images of natural surroundings encompass a rich mixture of spatial and geographical structure containing great details at fine scales [2, 4]. The effort of image segmentation turns out to be unreliable and difficult if it approaches to segmenting color pictures. A solid computational effort is required to process color images containing natural scenes due to variety of textures and real world objects in image.

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In this work, we propose embedded integration strategy for color image segmentation that utilizes edge information to generate marker information to similarity region merging algorithm (MSBRM) [1, 4, 5]. MSBRM algorithm [1] shows its effectiveness in segmenting natural complex images but it requires user interaction. It is tedious and time consuming to get user involvement for dataset having large number of images. To generate marker information automatically edges are first determined. After removing small length edges, color similar edges are grouped and assigned identical label. Centroid of long edges is used as foreground markers to MSBRM algorithm. For better segmentation outcomes, we used the original similarity-based region merger method suggested by Jifeng Ling et al. [1]. In order to split the image into uniform areas for the merger, this technique first requires lower-level segmentation. Two phases make up the entire procedure, which are alternately carried out until no further merging takes place. Each of the regions of background as feasible are combined while object regions are prevented from being joined together. After background areas are combined, the object of interest can be extracted.

II. RELATED WORK

In last few decades, interactive image segmentation algorithms have remained active area of research [6]. The idea is to provide prior information about elements in image using user interactions. One common exercise is operators manually mark some part of image as object and background as prior interactions. To divide image into parts, interactive image segmentation (IIS) procedures requires user interaction. User information can be supplied in different ways such as seeds, strokes, boundary box or lines to mark elements in image [6]. Without considering algorithms, IIS methods can be classified depending on the type of user involvement as (1) Seed Based and (2) ROI Based [6,7]. Seed based methods can be further classified as boundary-based and region-based. Early seed based methods include intelligent scissors [8], Live wire [9], Riverbed [10] whereas examples of region based methods are interactive grab cut [11], random walk [12], active contours [6, 13] and their variations. Some methods use hybrid using combination of boundary seeds and region seeds [6].

Alternate interactive approach to guide segmentation process is to mark ROI and then information about background and object is retrieved from pixels inside and outside the ROI. GrabCut is popular interactive segmentation algorithm that uses ROI to separate objects from background. Different algorithms are devised to improve performance of Grabcut such as OneCut [14], LooseCut [15], PointCut [16], SuperCut [17], DenseCut [18], DeepCut [19], DeepGrab-Cut [6], and NC Cut [20]. The key challenge in IIS algorithm is to minimize user interaction and improve segmentation outcomes. This can be achieved by Deep Learning based algorithm that improves segmentation outcomes with minimum user involvement [6]. IIS algorithms are further classified as active IIS methods and passive IIS methods. Passive user interaction is commonly used whereas active interaction is used in specific applications to collect user responses.

Depending on algorithms used IIS methods can be classified as different variations of Contour-based (CB), GrabCut, Random Walk [12], Region Growing/Region Merging, Deep Learning based and other hybrid approaches [6]. CB based methods focus on retrieving object contours using boundary information. Followed by earlier intelligent scissors, Riverbed, supervised ACM, interactive CAC (convex active contours) [13], multiphase level set, and different variations of ACM have been presented. CB based methods determine boundary information accurately and useful for object segmentation. These methods need manual tuning of initial parameters. GrabCut and its variations are most popular approaches of IIS. Interactive GC employs histograms to model background (BG) and foreground (FG) whereas GC employs Gaussian mixture model (GMM). Random Walk (RW) employs graph constructed from image. Different algorithms are proposed in literatures that extend the original idea of random walk [6].

The strategy behind region growing (RG) and region merging (RM) is to start with user supplied seeds or labels and to merge identical regions based on likeness criteria [1, 5, 6]. MSRM has shown its effectiveness in segmenting natural color images using over segmented outcomes from low level segmentation algorithms and user interactions [1]. As MSBRM performed well on complex natural images, several variations of MSBRM are proposed in literature. MSRM is adaptive to the contents in image and does not need to set threshold in advance. MSRM can intelligently join regions and designate the non-marker regions as background or foreground with the use of operator inputs. However, MSBRM is not a completely automated solution and still needs some user effort. In the literature, there aren't many attempts to create marker information automatically for the MSBRM algorithm. In the next section, we provide a brief explanation of the interactive version of MSBRM because our study is an expansion of interactive MSBRM [1].

III. MSBRM ALGORITHM

The system offered by Jifeng Ling et. al. [1] employs the mean shift technique for starting process as it has lower over-segmentation. Also it maintains the object's boundaries effectively. Other lower-level image segmentation strategies include Superpixels [28], mean-shift hill climbing algorithm [26, 27], watershed method [31], and levelset [32]. To acquire the starting segmentation maps, it specifically employs the mean-shift segmentation program of the edge-detection image Segmentation EDISON-Segmentation system [29]. Those who are running segmentation software will designate certain areas as objects and background sections in the collaborative image segmentation. The user-generated data is presented as markings, which the users enter to loosely denote the location and key characteristics of the objects and surroundings. Simple marks may be used as points. The main challenge in region merging is figuring out how to compare labeled and unlabeled regions similarly so that the equivalent areas can be combined with some sort of control. This is accomplished using the SBRM method [1]. With the aid of these markers, MSBRM algorithm determines the relationship of various regions after user-inputted marker data, and combines them according to the maximum similarity formula.

Mean-shift [26, 27], a common segmentation algorithm, and may have fewer over-segmentation than watershed algorithm while still effectively retaining the object's boundary details [1]. A smaller over-segmentation enables the MSBRM merging technique to more reliably compute the statistical characteristics of each region that will be utilized for directing the region joining process. The novel MSBRM process, which is adjustable to picture information and doesn't require a predetermined threshold, is the key component of participatory region merging [1]. The non-marker object regions are determined and kept from being combined to the background using the region-merging technique, whereas the non-marker background parts are autonomously combined and labeled. The object outline can then easily retrieve from the background soon after all the non-marker areas have been labeled. Although the method is very straightforward, it effectively extracts object from complex images.

A. Initial Segmentation Map

To segment the picture into uniform regions, a primary segmentation map is needed. This stage can be accomplished using any fundamental segmentation technique currently in use, including Superpixels, mean-shift, watershed, and levelset. Since it has lower over-segmentation and is capable of preserving object borders, the mean-shift method is utilized. To get the initially generated segmentation layout, it specifically uses EDISON-segmentation program [1, 29].

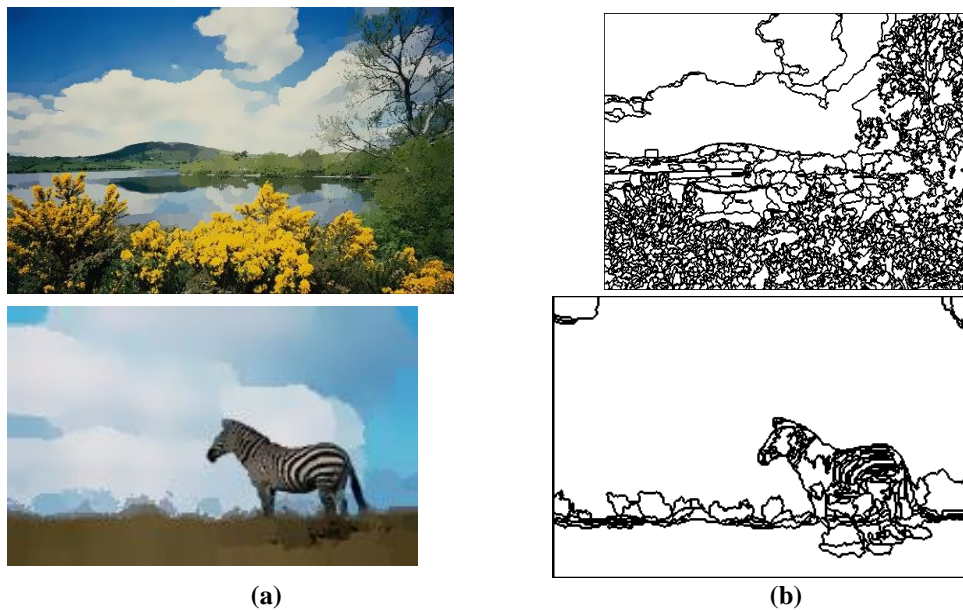


Figure 1. Low Level Segmentation (a) Original Image (b) EDISON Segmentation Software Output

B. Region representation and Merging Criteria

We have a large number of tiny regions possible following mean-shift initial segmentation. To effectively describe the objects color characteristic information, the color histogram is calculated using the RGB color system. Each

color band is equally divided into sixteen levels, and each region's histogram is computed in the feature space of 4096 bins. The area R's standardized histogram is denoted by the symbol HR.

Users will annotate certain areas in MSBRM method [1] of image segmentation as objects and background regions. How to find marked and unmarked regions equality so that the comparable regions can be combined is the main challenge in region-merging. To allow for comparisons of different regions, we must establish a measure of similarity $BC(A, B)$ between two regions A and B. The Bhattacharyya coefficient is used in this instance to gauge how close A and B are –

$$BC(A, B) = \sum_{n=1}^{4096} \sqrt{H_A H_B} \quad (1)$$

Where, the n denotes the nth element of the standardized histograms of A and B, respectively. H_A and H_B are their respective normalized histograms. The level of similarity between A and B is measured by the Bhattacharyya coefficient, which increases with an increasing likeness.

When both regions have equivalent content, their histograms will also be identical, resulting in an increased Bhattacharyya index and a very tiny angle among the two histogram matrices. It is undoubtedly possible for two visually distinct areas to have histograms that are extremely similar. Since the region's histograms are native histograms and represent regional characteristics of images, such instances are thankfully uncommon. Even when two histograms from visually distinct areas are similar, their similarity is not often the highest in the nearby. It should be emphasized that the suggested region-merging method can also be used with other color models, like the HSI color space, as well as additional distance metrics, such as the distance measured by Euclid between histogram vectors [1].

C. *Foreground and Background Marking*

The users of MSBRM segmentation must define both the object and background. Users can enter interactive data by annotating a picture with markings, such as lines, contours, and marks. Thus, regions with pixels within object identifiers are referred to as object marker areas, and regions with pixels inside backgrounds markers are referred to as background marker areas. The Green color is used for object marker whereas blue color is used for background marker. It is essential for user to mark small part of the object regions and surrounding regions. In actuality, the few inputs from users that are needed, the more powerful and practical the MSBRM algorithm is. The marked object location, the marked background location, and the non-marker region are the three types of regions that are formed. Each non-marker region must be immediately given the appropriate label as object region or background region in order to fully extract the object outline. For ease of use, we designate the groups of marked object regions and surrounding regions as M_O and M_B , accordingly, and the collection of non-marker regions as N.

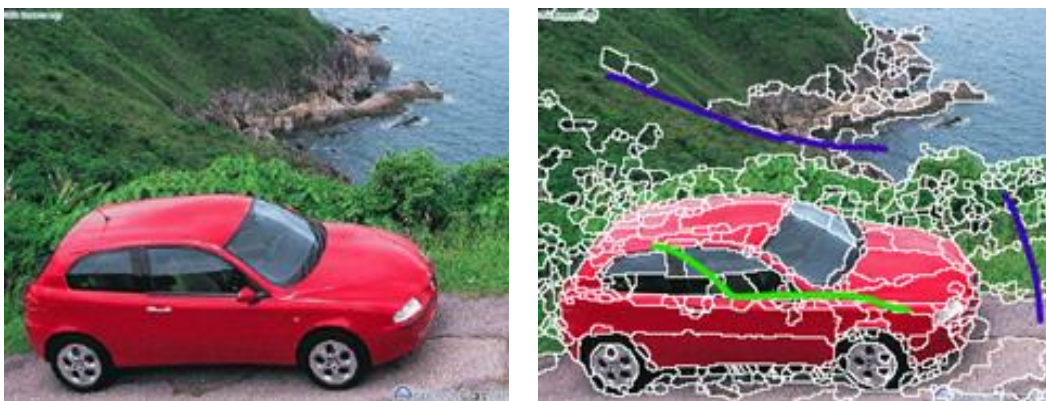




Figure 2: Object and Background marking [1]

D. Foreground and Background Marking

Major characteristics of the object and surrounding are given by the corresponding object and background markings. The region-merging technique also begins with the starting markers regions and progressively labels all non-marker areas either as object portions or background much like how graph-cut and watershed use the markers as the algorithm's initial region development seed [1].

Steps of MSBRM are illustrated in following section [1]-

Let Q is neighboring region of R and indicated by S_Q , the collection of Q 's neighboring regions. Equality between Q and all its neighboring regions $BC(Q, S_i^Q)$ are calculated. It is clear that R is a part of S_Q . MSBRM will combine R and Q , if equivalence of R and Q is maximum.

Although the merging-formula is very straightforward, it serves as the framework for the region-merging procedure. Only a tiny portion of the object and surroundings are covered by the marker regions. Non-marker object regions, or those that are not marked by the user, need to be recognized and kept separate from the backgrounds. The non-marker object regions typically share more similarities with the marked object regions than the surrounding regions because they are from the same object.

E. Foreground and Background Marking

Steps of process are iteratively carried out until no additional merging takes place make up the entire MSBRM process. The goal is to fuse as many surrounding regions as feasible while preventing the merging of object regions. It first tries to combine marked background regions with neighbors. For each region B member of \mathbf{M}_B , we create the set of its neighboring regions S_B . After that for every A_i and A_i is not included in the collection of \mathbf{M}_B , it creates list of its neighboring regions S_{A_i} . It is clear that B is a member of S_{A_i} . The equivalence between A_i and every member in S_{A_i} is calculated. If B and A_i meet the requirements for joining as per merging criteria (2), i.e.

$$BC(A_i, B) = \max_{i=1,2,\dots,k} BC(A_i, S_j^{A_i}) \tag{2}$$

Then, B and A_i is combined to a single region and the resulting region shares region B 's name:

$$B = B \text{ union } A_i \tag{3}$$

If not, B and A_i won't combine.

The aforementioned process is carried out repeatedly.

Still, it has some non-marker background regions, though, that cannot be combined as their equality values to one another are greater than their closeness scores to the marked background regions. In the final phase, it concentrates on the non-marker regions that were left over from the initial stage in order to finish the job of target object retrieval. N is divided into two parts: the background and the target object.

During this phase, the non-marked background areas and non-marked foreground regions will combine together under the supervision of the maximum similarity rule [1].

After the initial phase, for each non-marked regions either object or backgrounds, named as P, which is member of set N, set of neighboring regions is formed denoted by S_p . For each region (H_i) which is not member of set of object regions or background regions, list of neighboring regions is created, named as S_H . The equality between H_i and each element in S_H is determined. If P and H_i meet the merging rule, i.e.

$$BC(P, H_i) = \max_{i=1,2,\dots,k} BC(H_i, S_j^{H_i}) \tag{4}$$

P and H_i are then combined into a single area.

$$P = P \text{ union } H_i \tag{5}$$

If not, P and H_i won't combine. The aforementioned process is carried out repeatedly, and looping ends when the complete set of non-marker regions N fails to discover additional merging regions. Up until there is no more merging, the algorithm's first and second phases are iteratively carried out. In the end, each area is assigned to either the objects or backgrounds class. The object outline can be retrieved by simply separating the object regions. The entire procedure can be reduced into the following [1]:

The MSBRM algorithm [1]

Input: low-level segmentation algorithm output.

Output: Segmentation output.

Phase 1: Combining non-marked regions in N with marked background-regions

- a) Create the collection of its neighboring regions for every region B that is an element of M_B .
- b) Make the set of neighboring regions (S_{A_i}) for every region A_i that is not a part of set M_B .
- c) Compute $BC(A_i, S_j^{A_i})$. If $BC(A_i, B) = \max_{i=1,2,\dots,k} BC(A_i, S_j^{A_i})$, then merge B and A_i . If not, B and A_i won't combine.
- d) Change set MB and set N according to results of merging
- e) The first step concludes if the regions in MB are unable to discover new merging regions. Alternatively, return to (a).

Phase 2: Combining dynamically N non-marker areas

Input: Segmentation outcome of first phase.

- a) Create the collection of neighboring regions S_B for each region P which is element of.
- b) Make the set of neighboring regions (S_{H_i}) for every region H_i that is not a part of set M_B and M_o
- c) Compute $BC(H_i, S_j^{H_i})$. If $BC(P, H_i) = \max_{i=1,2,\dots,k} BC(H_i, S_j^{H_i})$, then P and H_i will merge. If P and H_i are not similar, would not merge
- d) Update N.

The 2nd step ends if the regions in N are unable to discover new merging regions. Alternatively, return to (a).

End

IV. AUTONOMOUS MSBRM

The MSBRM algorithm presented in the previous section is an interactive scheme. In this scheme user input is needed. In this paper, we propose a new autonomous region growing algorithm which uses edge information to generate object markers. The interactive region merging technique proposed by Jifeng Ling et al [1] produces good segmentation results. The main disadvantage of MSBRM is that user needs to identify object and background markers. To make segmentation process autonomous edge segment grouping has been used to generate markers automatically.

A. *Generating Object Markers using Edge Information*

Interactive MSBRM produces good segmentation outcomes for natural complex images but this method requires user interaction. It is difficult to get markings for object and backgrounds for every image in large dataset. In order to make MSBRM algorithm autonomous this work proposes a method based on edge information to generate marker information for similarity based region merging algorithm. There are numerous edge operators based on first order and second order derivative such as canny, prewitt but this work used phase congruency because it is insensitive to different lightning conditions and contrast variation [22, 24, 33, 34]. Details of this phase congruency can be found in the work by Peter Kovese [22, 23, 24,]. Matlab code for determining phase congruency is made available by Peter Kovese. Edges are determined using Log Gabor Wavelet based feature detector Phase Congruency. Long Edges provide an approximate estimate of the object distribution in images [24, 25]. While shorter boundaries have been removed, edge segment grouping is employed to group edges with comparable colors. The centroid, which is computed, is the algebraically calculated means of the pixels (x, y coordinates) along each long edge. For region-merging, these centroids serve as object identifiers. The method to generate object markers using edge information has following steps –

Input: Image to be segmented

Output: Object Markers

1. Read the image and convert it to gray scale.
2. Calculate Phase congruency feature map.
3. Apply Non Maximal Suppression and hysteresis thresholding to obtain edge maps.
4. Remove pixels on the boundary of object without allowing edge to break using morphological operations.
5. To find eight connected components in binary image. Do 2D convolution of binary image with convolution mask as follows –

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0 0 0 0 0
0 1 1 1 0
0 1 1 1 0
0 1 1 1 0
0 0 0 0 0

```

6. Label each connected component in binary image (bwalabel of MATLAB).
7. For each connected component find set of properties such as

Line Descriptor = [Centroid, Average HSV Color Values, Percentage]

Where Percentage = No of pixels on line/ Total No of pixels in Image

8. Remove small edges if percentage of pixels in edge is below threshold.
9. Calculate HSV color difference between edges using Euclid as

ED= EuclideanDistance(Edge_i, Edge_j)

10. Assign same label to HSV color similar edges.
11. Repeat the process 9 and 10 until the color difference between edges becomes above threshold
12. Update Centroids of edge after combining color Similar edges

The whole process of generating object markers to MSBRM algorithm is summarized in figure 3

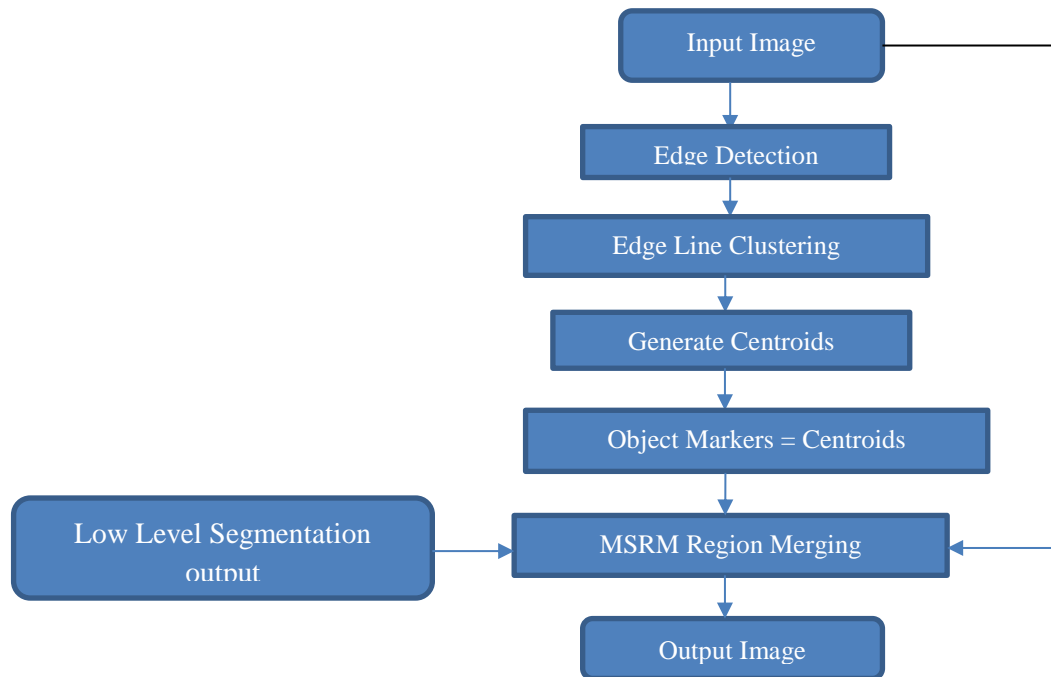


Figure 3. Autonomous MSBRM

The autonomous MSBRM procedure can be broken down into two phases, which are executed recurrently as long as there is no more merging. Neighboring object marker and non-marker regions are combined if they meet merging criteria i.e their Bhattacharyya distance value will be very high. First, we attempt to combine neighboring regions of marker object regions. After this stage, some background regions that don't have markers will be combined with the corresponding object markers if they meet merging criteria. As a result of their greater level of similarity with one another than with the marker object regions, some non-marker regions still exist that cannot be combined

In the second stage in order to finish the image segmentation job, we will concentrate on the non-marker regions that were left over from the first stage. Under the direction of the MBSRM merging rule, the non-marker object regions will be combined to one another at this point.

V. EXPERIMENTAL RESULTS

To obtain segmentation results, interactive MSBRM and proposed autonomous MSBRM segmentation algorithms were applied on diverse kinds of images that represent real world scenes. To prove usefulness of edge information guided autonomous MSBRM technique complex images containing scenes of nature, building, lakes, flowers, birds are used as input to segmentation process. Interactive and autonomous MSBRM are capable of segmenting more complex images. For these algorithms, sample images from BSD dataset (Berkeley) are employed..

A. Interactive MSBRM Results

Experimental results were obtained first for interactive MSBRM technique. We have used the mean-shift segmentation scheme, the EDISONS method to obtain the preliminary subdivision map. If low level segmentation map for corresponding image from EDISON system is not available then our segmentation system gets low level segmentation output using watershed algorithm automatically. A user friendly GUI is used to mark object and background regions. In interactive image segmentation user marks some region as object and background region. Blue lines were used for object marker while green lines were used for background marker. After marking background and object region, MSRM algorithm was used to merge regions.

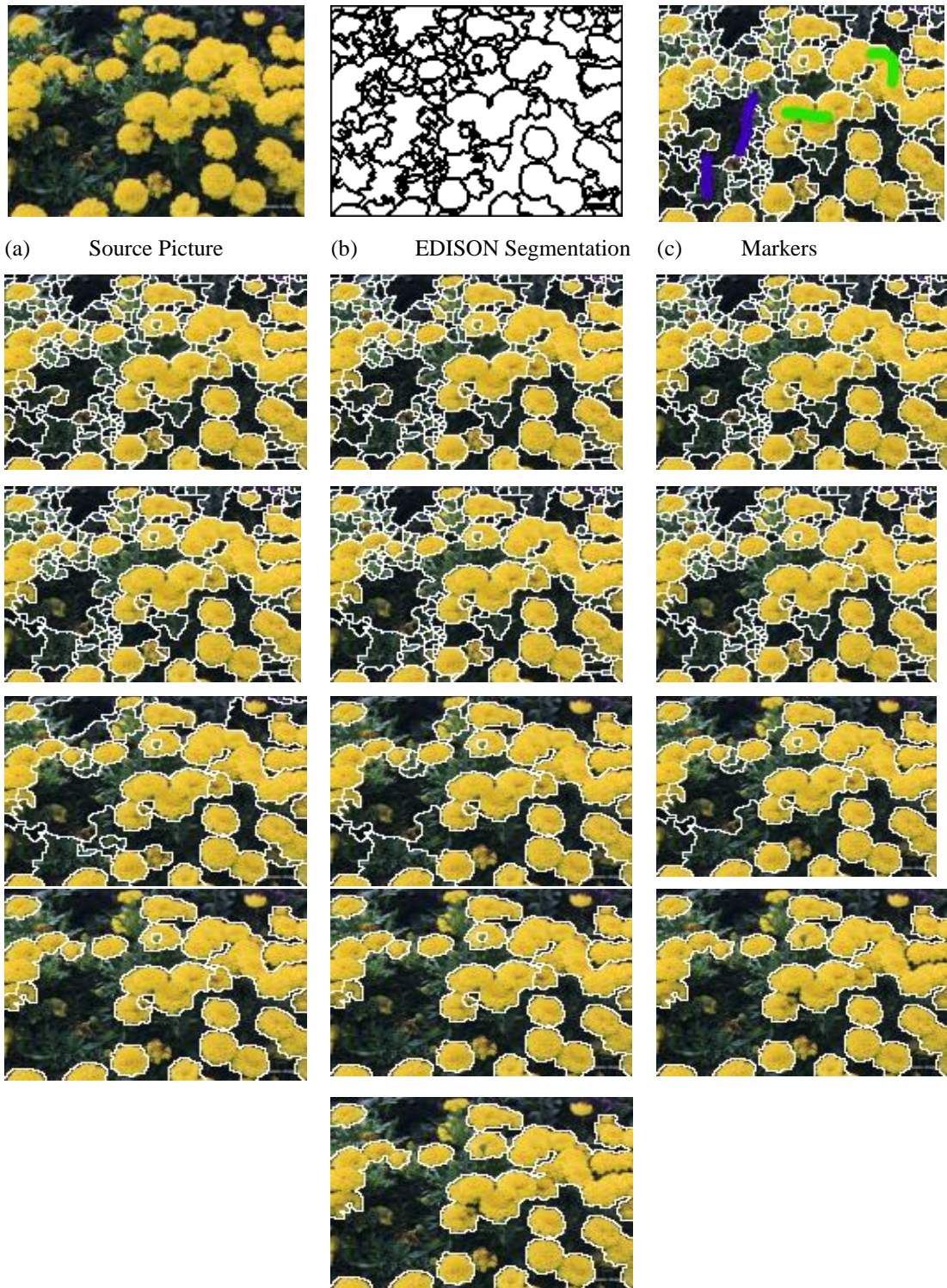
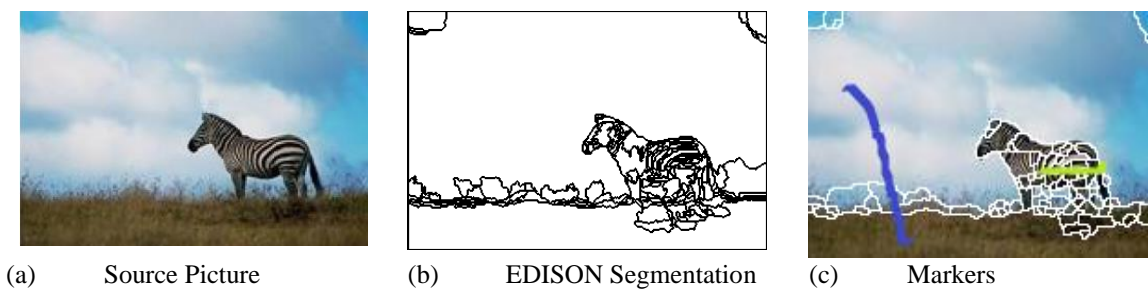


Figure 4: MSBRM Segmentation Results: Flowers



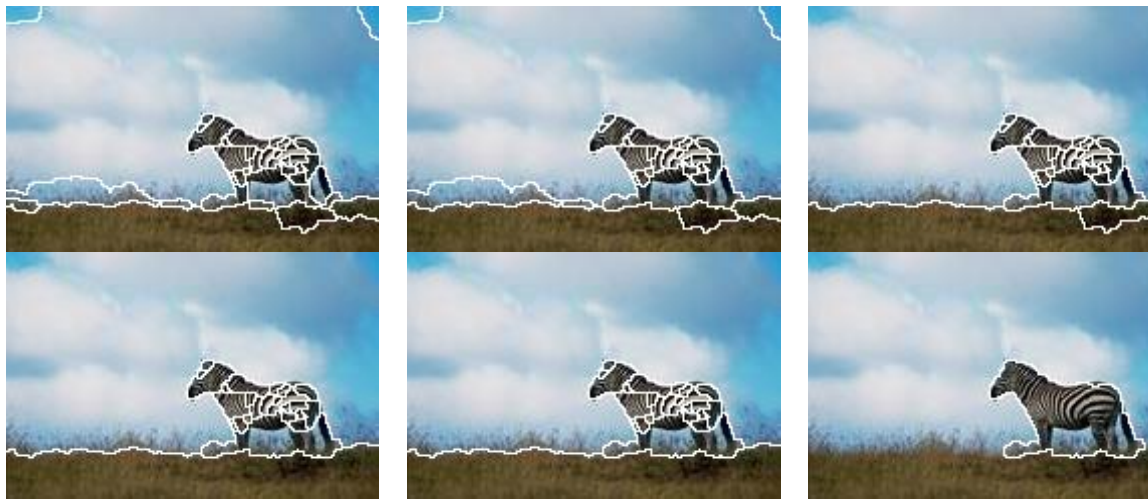


Figure 5: MSBRM Segmentation Output: Horse

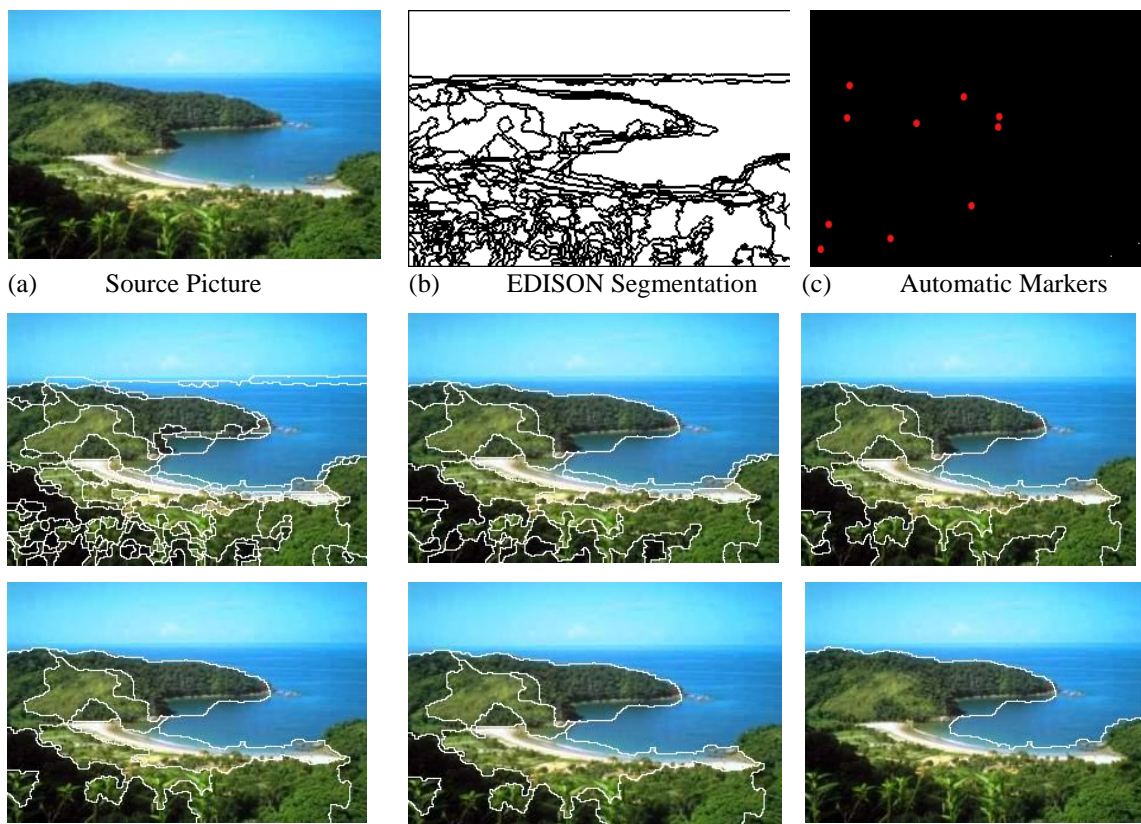


Figure 6: Autonomous MSBRM Segmentation Output: Sea

B. Autonomous MSBRM Results

Experimental result shows that interactive MSRM algorithm produces good segmentation results. But it requires input from user. We have implemented autonomous region algorithm which uses centroids generated from edge line clustering as object markers. This algorithm also requires output from low level segmentation method. EDISON segmentation system was used to generate low level segmentation for experimentation. If output from EDISON segmentation is not available then our segmentation system automatically obtains it by using watershed segmentation algorithm.

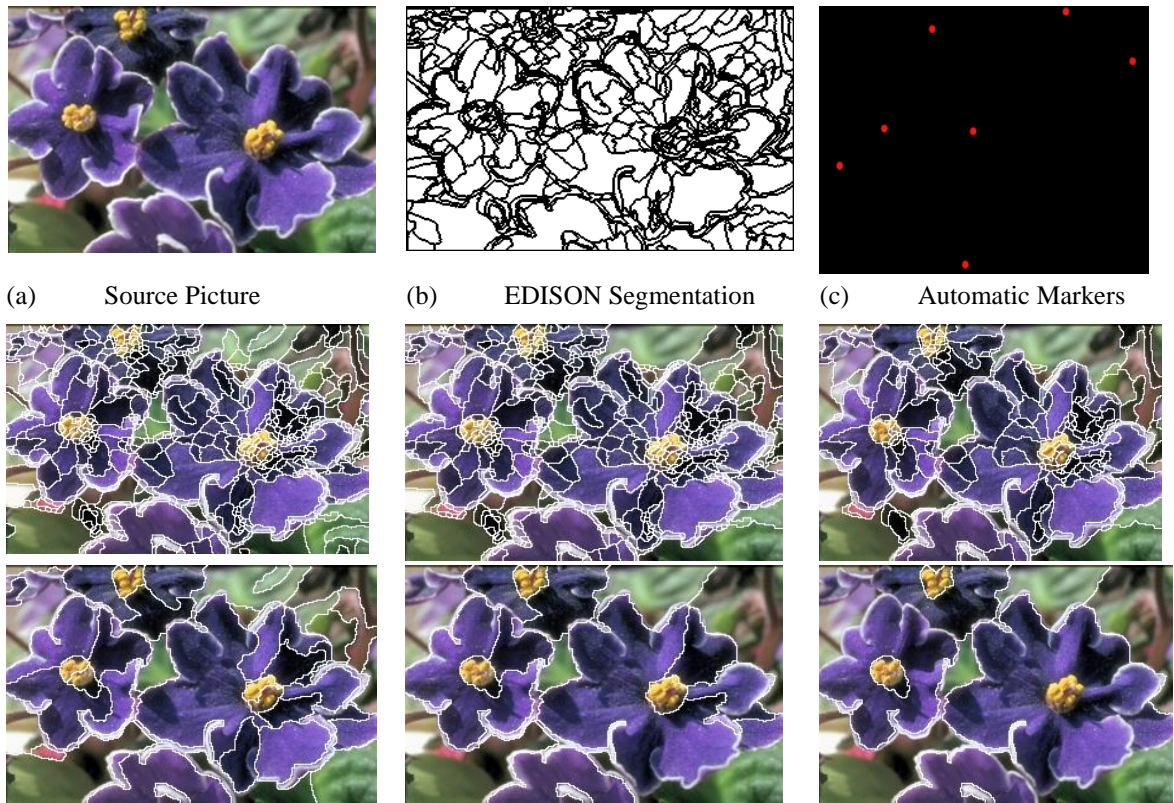


Figure 7: Autonomous MSBRM Segmentation Output: Image (flower3.jpg)

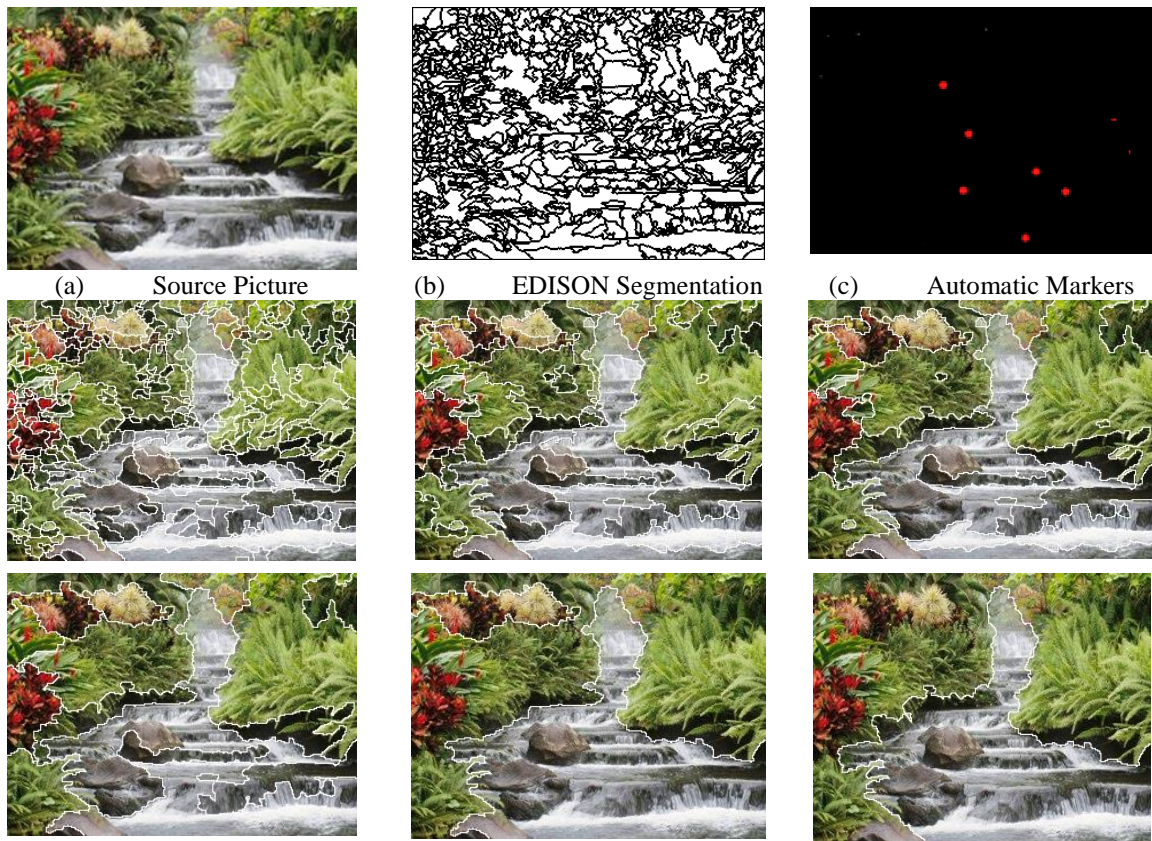


Figure 8: Autonomous MSBRM Segmentation Output: Image (creek)

C. Comparison of Segmentation Results

To assess outcomes of segmentation systems, elements in the image are carefully labeled and used for comparison as ground truth image. For images from BSD dataset, available labeled images are used. FPR (False Positive Rate) and TPR (True Positive Rate) values are calculated for segmentation outcomes.

$$TPR = \frac{\text{The number of Correctly Classified foreground Pixels}}{\text{The number of total foreground pixels in the Ground Truth}} \quad (6)$$

$$FPR = \frac{\text{The number of background pixels but classified as foreground}}{\text{The total number of background pixels in image}} \quad (7)$$

Clearly, higher value of TPR and the lower value of FPR indicate that method is accurate in segmenting image. Table 1 shows number of pixels in image along with object pixels and background pixels. Table 2 lists the TPR and FPR results by the segmentation methods on test images.

Table 1 Ground Truth Information for test Images

Image	Size	Count of Pixels in Image	Total Count of Object Pixels	Total Number Of Background Pixels
22.jpg	168×168	28224	9305	18919
Flower (1.BMP)	285×217	61845	40124	21721
Flower (2.BMP)	163×122	19886	7792	12094
Creek.bmp	307×230	70610	13059	57551

Table 2 TPR and FPR values of different segmentation approaches on the test images

Image	Method	TPR(%)	FPR(%)
22.jpg	Interactive Region Merging	99%	0%
	Autonomous Region Merging	99%	2%
Flower(1.BMP)	Interactive Region Merging	100%	5%
	Autonomous Region Merging	86%	15%
flowers(2.BMP)	Interactive Region Merging	95%	1%
	Autonomous Region Merging	69%	1%
Creek.jpg	Interactive Region Merging	91%	0%
	Autonomous Region Merging	99.3%	0.3%

From TPR and FPR values, it can be seen that interactive region merging segmentation has the highest TPR and the lowest FPR simultaneously, which implies that it achieves the best segmentation performance. But for interactive MSBRM algorithm user interaction is essential. To overcome this problem we have implemented autonomous region merging algorithm that uses edge detection to generate marker information automatically. Result analysis shows that autonomous region growing produced good segmentation results. It only fails if color difference between background and object region is less. Such cases are rare.

VI. CONCLUSION

Autonomous segmentation of real world natural images is tough task. Any single technique is not likely to produce satisfactory results. When segmenting complex photographs, such outdoor and nature images, it might be challenging to get satisfying results with only one of these approaches. This is because complex picture segmentation involves extra challenges because of factors like shade, uneven lighting, and textures. By providing strategies for utilizing information from edge data, integrated approaches enable us to better utilize the rich information that is offered by edge processing. Interactive MSBRM shows its effectiveness in segmenting natural real world images. But it requires user involvement. To accurate and reliable segmentation this work uses integrated technique that incorporates edge information into MSBRM to make it autonomous. Both interactive and

autonomous algorithms are tested on variety of complex natural images representing different classes. To evaluate performance of segmentation algorithms, evaluation metrics such as TPR and FPR are used. Experimentation shows that interactive MSBRM and autonomous MSBRM produce good segmentation outcomes for natural complex images resulting in TPR from 69% to 99% and FPR from 14% to 0%. From our experimentation this work comes to conclusion that proposed autonomous MSBRM is most suitable for segmenting natural complex images.

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