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Comparative Evaluation of Interactive Segmentation Algorithms Using One Unified User Interactive Type

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***Abstract*: In interactive segmentation, user inputs are required to produce cues for the algorithms to extract the object of interest. Different input types were recommended by the researchers in their developed algorithms. The most common input types are points, strokes and bounding box. Different evaluation parameters were used in the researches in this field for comparison. Our previous work shows that, for non-complex image, segmentation result will not be affected by the user input type used. Complex images are defined as images whereby the colors of the objects of interest and the background are similar and vice-versa. In some of the complex images, parts of the color of the objects of interest are present in the background. This paper extends our previous work by using the proposed unified input types, which consists of a bounding box to locate the object of interest range and a stroke for the foreground, on three interactive segmentation algorithms for non-complex and complex image. Three different evaluation measures are computed to compare the segmentation quality: Variation of Information (VI), Global Consistency Error (GCE) and Jaccard index (JI). From the experiment results, it is noticed that, all three algorithms perform well for non-complex images but could not perform as good for complex images.**

***Keywords*:** interactive segmentation, complex, non-complex, user input, bounding box, stroke.

I. Introduction

Image segmentation algorithms help human to extract object of interest from images for further processing. Generally, image segmentation will partition an image into certain number of regions which have certain coherent features like texture and colors. These coherent features would be grouped into meaningful pieces for better perceiving [1]. From the technical perspective, image segmentation can be divided into: fully-automated, semi-automated or interactive, and manual segmentation [2]. Fully automated segmentation, as the name implies, does not require user intervention. Semi-automated or interactive segmentation, where user automation is at medium, requires user to initialize the algorithms to appropriately mark the object of interest. Some of these algorithms will require user to provide feedback to the algorithms in order to improve the segmentation results. In manual segmentation, the object of interest is delineated by hand. In most of the practical applications of image segmentation, large number of images are needed to be handled by human. Therefore, human intervention in the segmentation process should be as minimal as possible. This makes automated image segmentation more appealing [3]. However, automated segmentation still exhibits certain constraints and cannot produce satisfactory results due to the complexity of the images, especially using natural images [4-7]. To overcome this, semi-automated or interactive segmentation use human operator to provide cue to the segmentation algorithms.

This paper is organized as follows: Section II. will present a brief introduction on the general interactive segmentation and the three different algorithms used. The purpose of this paper is also explained in this section. Section III. presents the experiment settings and the results obtained. Conclusion are presented in Section V.

II. Interactive Segmentation

In interactive segmentation, the user intention is incorporated in the user interaction [8]. The user will provide intuitive interaction which serves as high level or prior information to the interactive segmentation algorithms to extract the object of interest [9-14]. A general functional view of an interactive segmentation system is depicted in Figure 1. The system consists of User Input Module (Step 1), Computation Module (Step 2) and Output Display Module (Step 3) [15]. In Step 1, the module will receive user input and the intention of the user will be recognized at this stage. The main part of the whole system is the Computation Module, i.e Step 2, whereby the segmentation algorithms will run according to the user input to generate the segmentation results. The segmentation results will be displayed in Step 3. These steps are iterative whereby the user can input additional input after Step 3 and the system will go back to Step 1 until

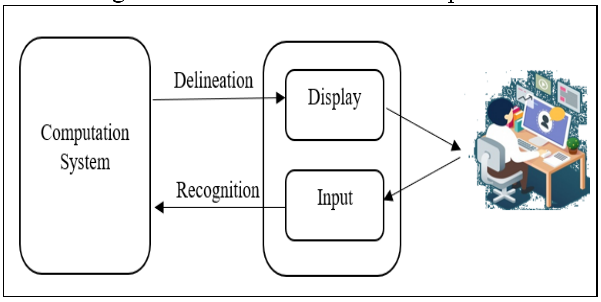

Figure 1. General functional view of an interactive segmentation system whereby a user can produce interaction to the system until a satisfactory result [15].

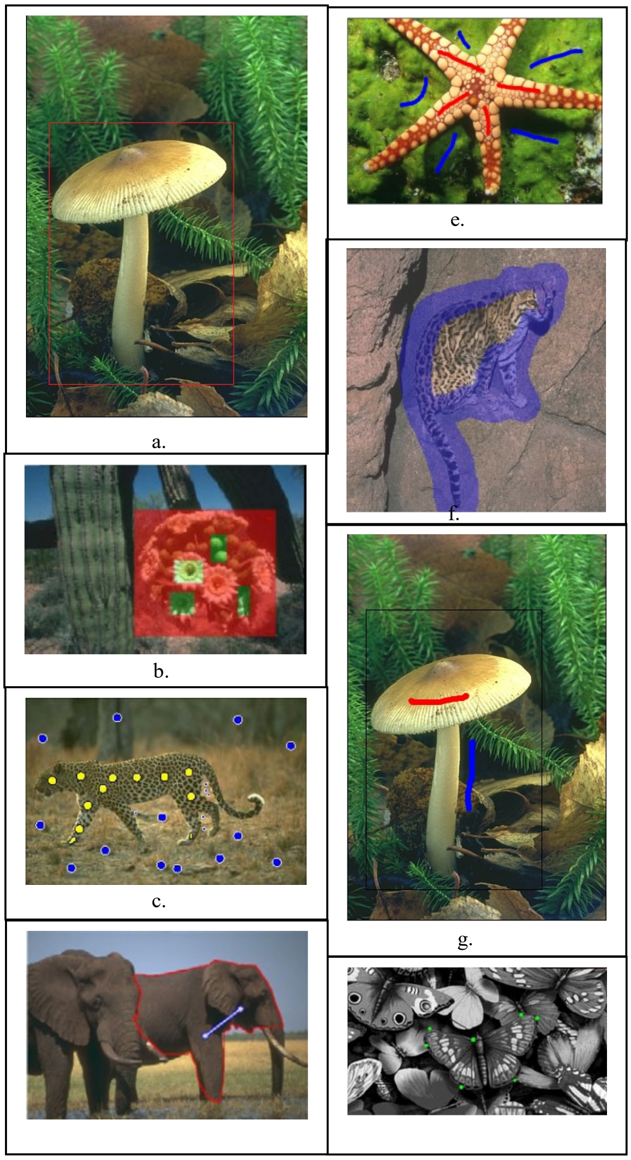

Figure 2. Input types used in interactive segmentation: a: bounding box. b: bounding boxes for foreground object. c: seed points for the background and foreground of the image. d: placing the skeleton on the object of interest. e: background and foreground strokes on the image. f: stroke on the contour of the object. g: bounding box with strokes on the object and background, and h: seed point on the contour of the object.

the user satisfies with the output produced. Thus, this is a human-machine collaborative method whereby, the machine will need to understand the user intention based on the human interaction and the human's input will affect the machine behavior in solving the problem [16].

There are several user interactive or input types used in the current researches to offer the information about the background and foreground regions. The most commonly used input type is placing strokes in the foreground and background in the image [4, 6, 7, 9, 13, 17-23]. Besides strokes, rectangle or bounding box is also used to locate the target object range [11, 24-28]. In addition, seed points are also used to be placed on foreground and background on the image [29-31] or on the contour of the object of interest [32, 33]. Mixed input types were also applied in some of the research. For example, [34] combined seed points with strokes on the background and foreground of the image to extract the object of the interest. Figure 2 shows the use of different input types used in interactive segmentation.

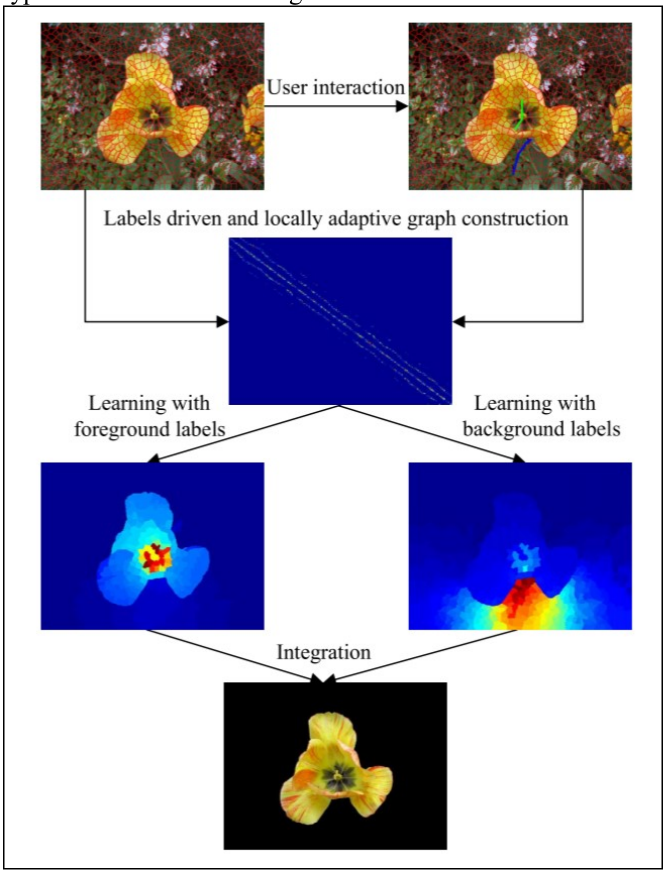

Figure 3. The overall framework of [38].

In our previous work [35], we had compared four commonly used user input types, i.e, seed point, foreground and background strokes, foreground stroke with background bounding box, and bounding box as foreground and background using the nonparametric higher-order learning algorithm by [36] for the simple or non-complex and complex images from the Berkeley image database [37]. Our previous findings show that, the use of bounding box to locate the object of interest range can improve the segmentation results for complex image. In addition, we also found that, the location and length of strokes or seed points used have an impact on the segmentation accuracy. In this work, we will extend the previous work by comparing and evaluating the use of bounding box as input type for three different interactive segmentation algorithms: robust interactive image segmentation via graph-based manifold ranking [38], nonparametric higher-order learning for interactive segmentation [36] and interactive image segmentation by maximal similarity based region merging [39]. Quantitative comparison evaluation on the segmentation results will be done with three evaluation parameters: Variation of Information (VI), Global Consistency Error (GCE) and Jaccard index (JI) [40]. Between two segmentation, the GCE is the error measure, JI measures the similarity and VI measures the distance.

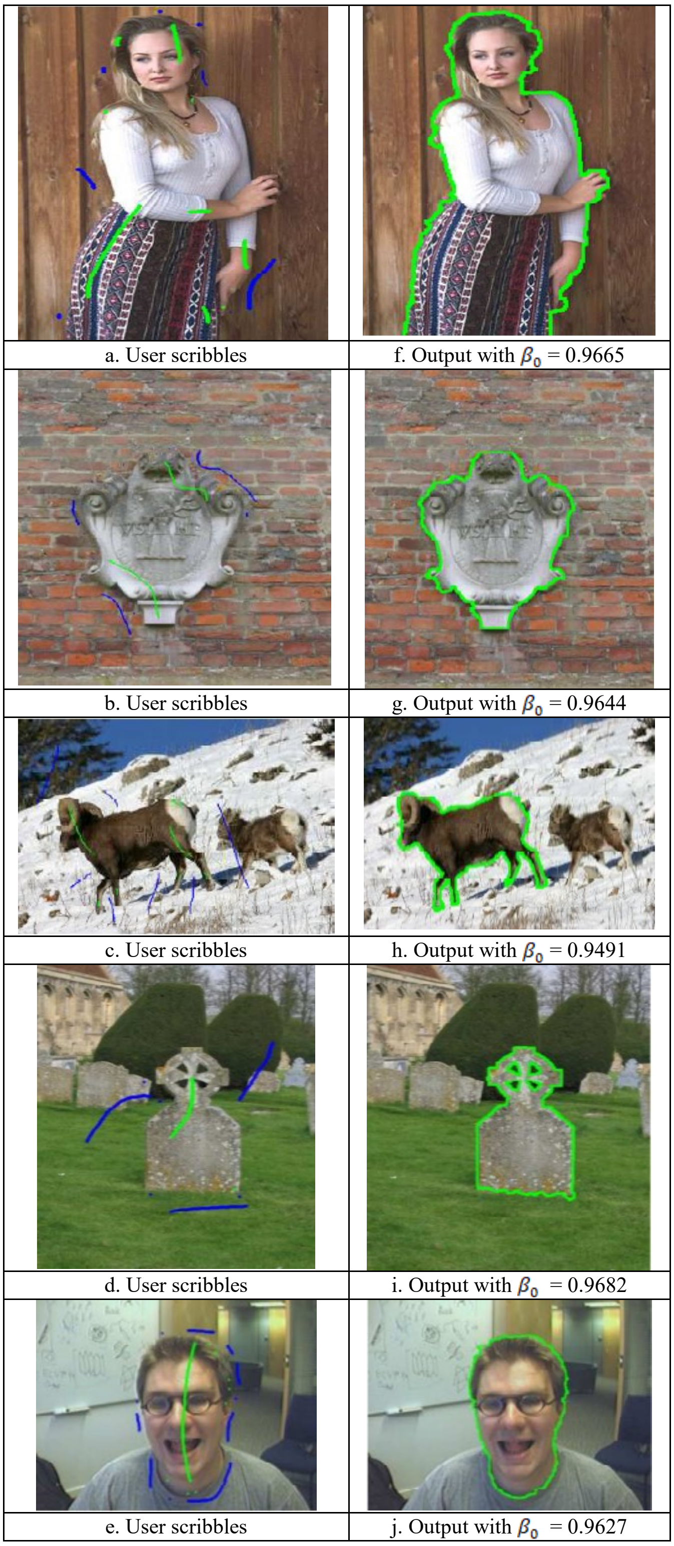

Figure 4. Segmentation results obtained using [38]: a. to e. multiple user scribbles for foreground and background labels, and f. to j. the corresponding result obtain.

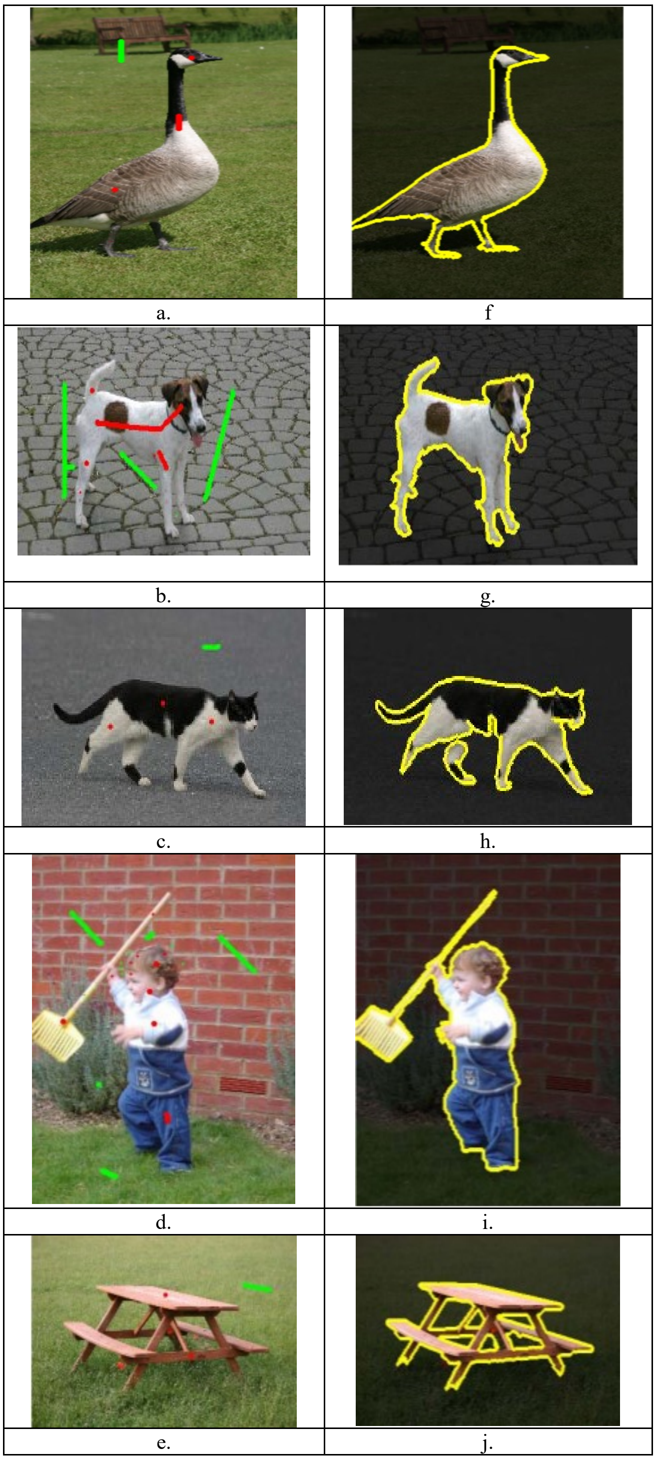

Figure 5. Segmentation results obtained using algorithm [36]: a. to e. user scribbles used, f. to j. the corresponding results.

A. Robust Interactive Segmentation via Graph-based Manifold Ranking [38]

In this work, using graph-based semi-supervised learning theory and superpixel, an interactive segmentation system was developed. At the beginning of the process, the image is over-segmented into small homogeneous regions using superpixels. To cater the user intention, scribbles are entered as the foreground and background labels. There is no limit on the amount of foreground and background scribbles that may be input by the user. These foreground and background labels information will be integrated into the superpixels. Next, using the proposed labels driven and locally adaptive kernel parameter, the *k*-regular sparse graph is approximated to form the affinity graph matrix. By calculating and integrating the ranking scores, the final segmentation result is generated to form the foreground and background indicator vectors from the user scribbles. The overall framework is shown in Figure 3. Figure 4 shows some of the segmentation results the authors obtained. In their work, the normalized overlap, β_0, is used to measure the similarity between the segmentation results and the preset ground truth. However, the average β_0 obtained from all the tested images was not reported. In addition, the authors reported that, the proposed algorithm managed to segment the input images in less than 2 seconds.

The key contributions of this work are:

- A novel framework that combines the graph-based semi-supervised learning theory with region-based models to efficiently segment out the desired object,
- A novel graph construction strategy which models the graph as an approximate *k*-regular sparse graph that integrate spatial relationships and user provided scribbles, and
- A new graph edge weights computing strategy that forms the weights using a locally adaptive kernel width parameter.

B. Nonparametric higher-order learning for interactive segmentation [36]

This generative interactive model was based on multi labels. An algorithm was proposed to estimate the pixels likelihood for each label. Using the mean shift unsupervised learning algorithm [41], a new higher-order cost function of pixel likelihoods to partly enforce the label consistency inside the regions generated was designed. The algorithm considers the relationships between the pixels and the corresponding regions in a multi-layer graph. To estimate the pixels likelihoods, the higher-order cues of the representative region likelihoods are used. The non-parametric learning technique is introduced to recursively estimate the higher-order cues from the resulting likelihoods of pixels included in each region. This will consider the connections between the regions that aid in the propagation of the local grouping cues across the image areas. Figure 5 shows the scribbles used and the corresponding segmentation results for some of the images tested by the authors. The authors reported that the algorithm resulted in 4.34% of error rate.

The key contributions of this algorithm are:

- The pixel likelihood for each label is estimated,
- The representative region likelihoods are defined as higher-order cues to estimate the pixel likelihoods, and
- Using the resulting likelihoods of pixels included in each region, a nonparametric learning technique was addressed to recursively estimate the higher order cues.

For the pixel and region properties, only color values were used.

C. Interactive image segmentation by maximal similarity-based region merging [39]

For this method, strokes are used not only as the markers to indicate the location, but also to label the object and background. For the different regions, the similarity between these regions are calculated. Utilizing the assistance of the markers input by the user, the similar regions are merged based on the proposed maximal similarity rule. This proposed maximal similarity-based region merging does not require a preset threshold value and is adaptive to image content. The method manages to merge and label the non-marker background automatically.

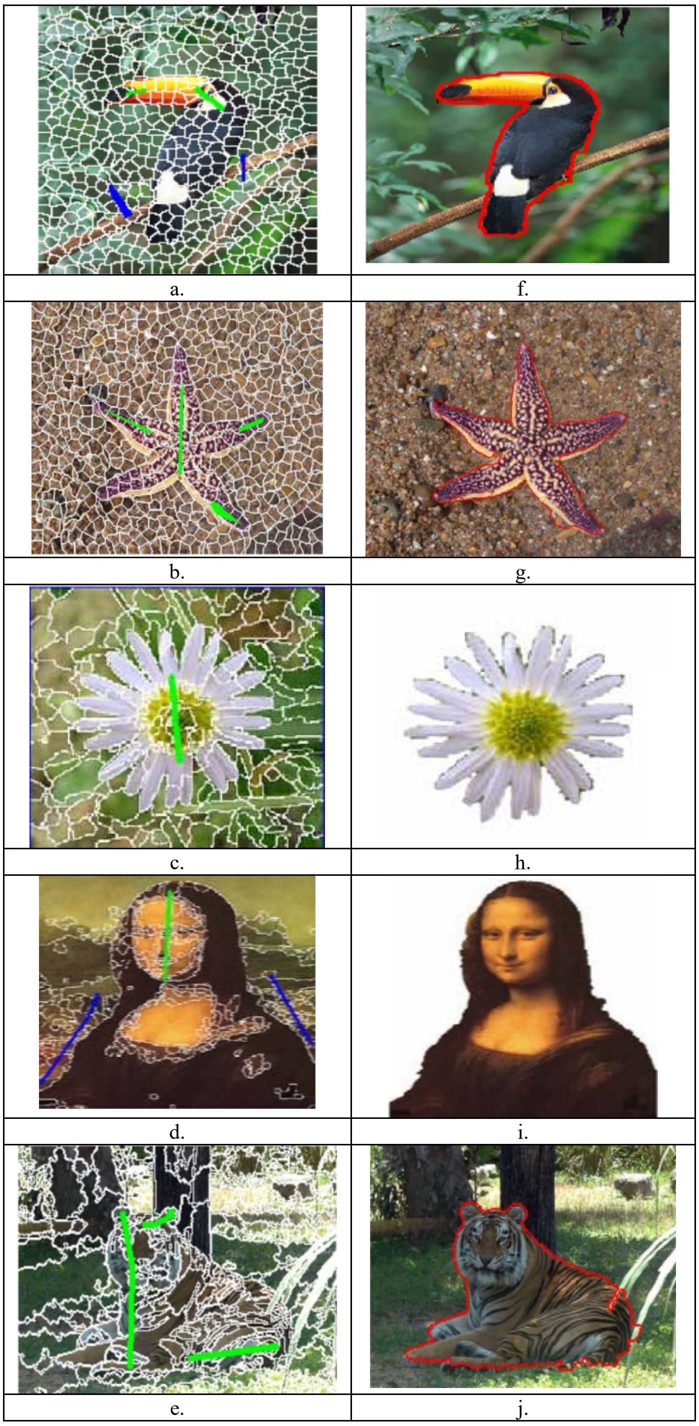

Figure 6. Segmentation results obtained using algorithm [39]: a. to e. show the user input, f.to j. show the segmentation outputs obtain.

In addition, the method also successfully determined the non-marker object regions, and these are avoided from being merged with the background. The object contours are next extracted from the background after all the non-marker regions are labeled. The authors claimed that this method is the first to use the markers entered by the user to guide the region merging for object contour extraction. Some of the results obtained using this method are shown in Figure 6.

The authors manually labelled the desired object in the images and used this as the ground truth. The evaluation parameters used are: true positive rate and false positive rate. True positive rate is defined as the number of correctly classified object pixels over the total number of object pixels in the ground truth. The ratio of the number of background pixels which are wrongly classified as object pixels over the total number of background pixels in the ground truth is the false positive rate.

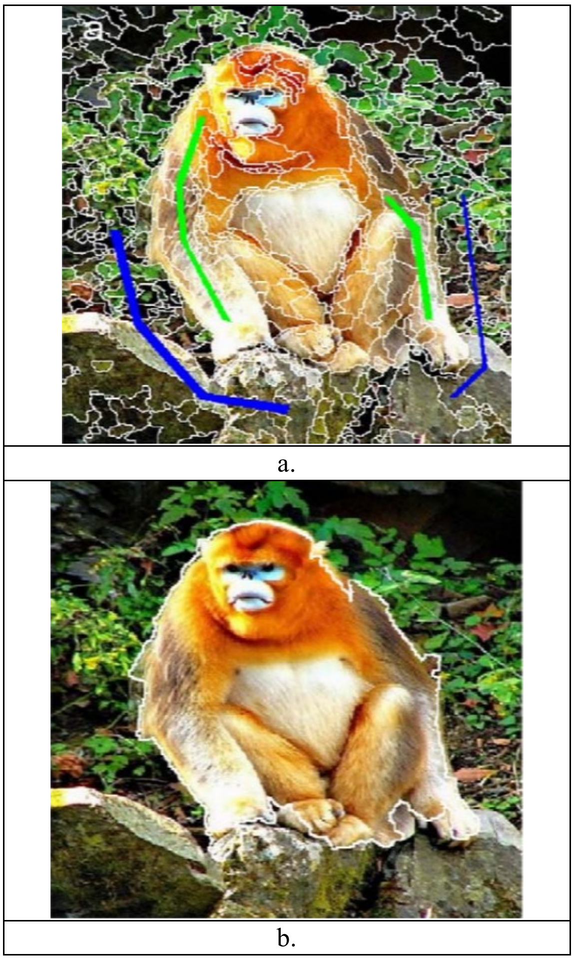

Figure 7. Failure example of algorithm [39]: a. Part of the object and background have very similar features and many scribbles were use, b. segmentation result obtained.

The ultimate aim is to achieve lower false positive rate and at the same time, higher true positive rate. The true positive rate and false positive rate obtained for the images in Figure 6 are: bird (94.64% and 0.29%), starfish (90.25% and 0.26%), flower (97.59% and 1.08%), Mona Lisa (98.85%, 0.71%) and tiger (91.70%, 0.75%).

The author had noted that, since the proposed algorithm is based on some initial segmentations, such as mean-shift or superpixel, therefore, if the initial segmentation does not provide a good basis of region merging, the proposed method will fail.

In terms of user input, the experiments conducted by the authors showed that, the user input had to cover the main feature regions in odder for the object of interest to be correctly extracted. In addition, the authors had also conducted experiments on the different number of user input. It was concluded that, the images with more user inputs will produce better segmentation results. The algorithm was noticed to produce not so encouraging results when shadow, low-contrast edges and ambiguous areas occur. In an experiment using an image where parts of the object regions are very similar to the background, as shown in Figure 7, the segmentation result obtained was poor although many markers were used.

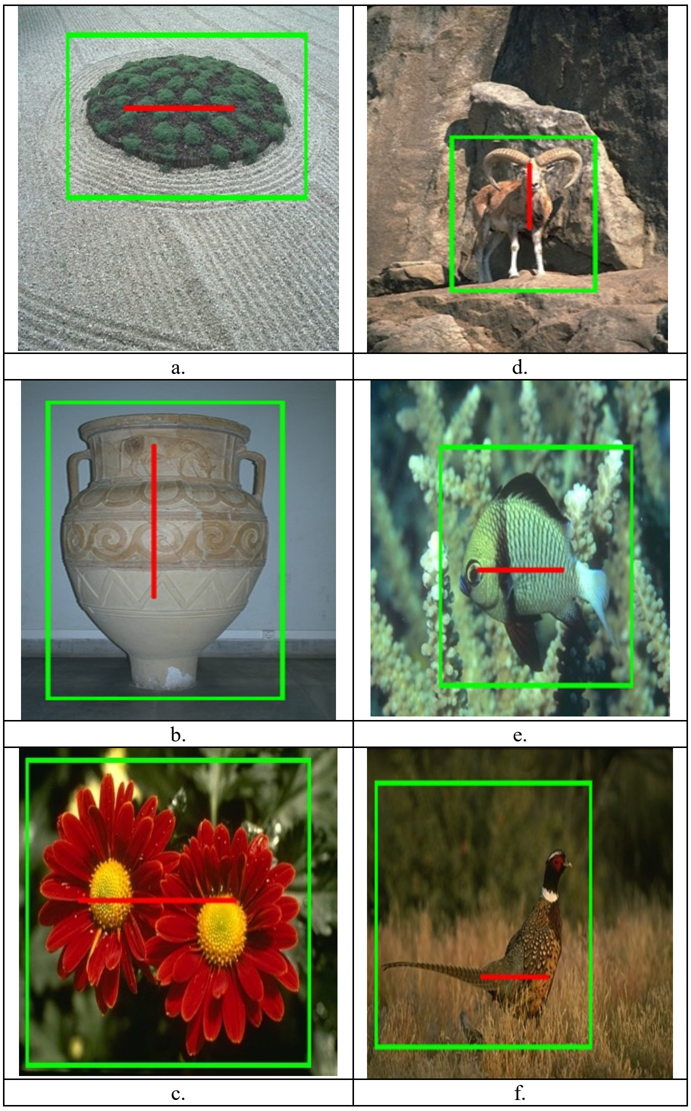

Figure 8. The bounding box and foreground stroke used as the input image for the three different interactive segmentation algorithms. Image a, b and c are non-complex images used while, d, e and f images are in the category of complex images.

III. Experiment Settings and Results

A. Observations

From the previous section, it can be seen that, the three algorithms use strokes to indicate the foreground and background in the image. Multiple inputs are required from the user to accurately provide the cue for the algorithms for segmentation purpose. In addition, there is no common evaluation features used. Therefore, in this study, the experiments settings will: 1) compare the three algorithms based on the unified single bounding box and one stroke for the foreground in a set of images that are divided into complex and non-complex categories, and 2) use the same evaluation parameters to compare and evaluate the segmentation results.

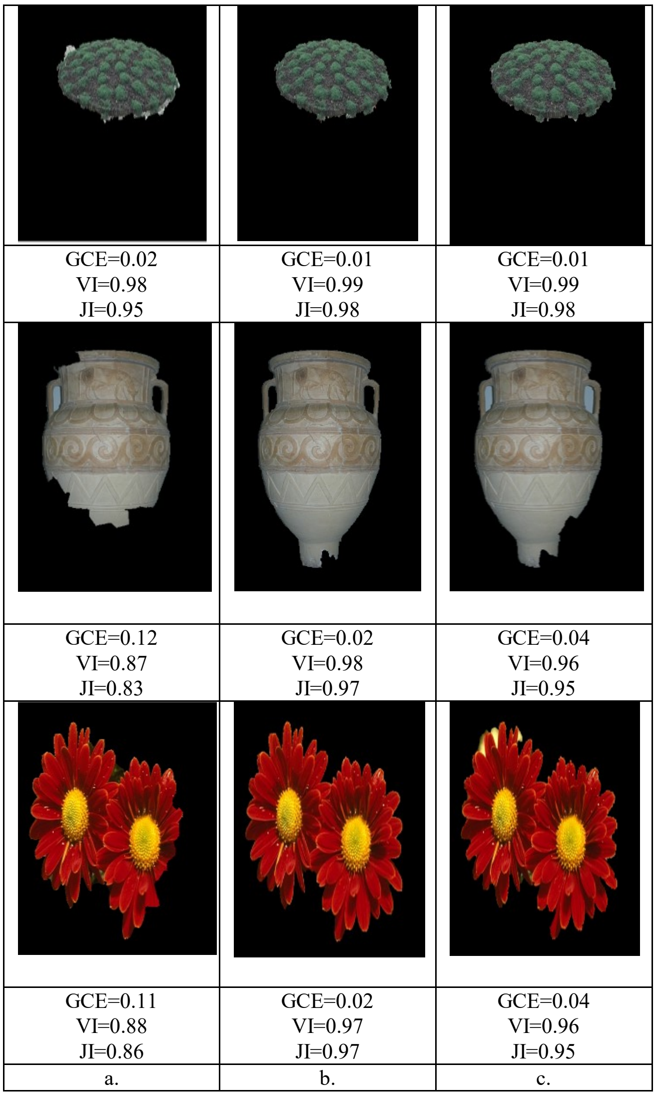

Figure 9. Qualitative and quantitative segmentation results obtain using non-complex images for: a. Robust Interactive Segmentation via Graph-based Manifold Ranking [38], b. Nonparametric higher-order learning for interactive segmentation [36], and c. Interactive image segmentation by maximal similarity-based region merging [39].

B. Dataset

The Berkeley image database [37] consists of around 12,000 hand-labeled segmentations of 1,000 Corel dataset from 30 human subjects. This database was available publicly for research on image segmentation and boundary. Using the images from the Berkeley image database [37], the images are divided into non-complex and complex images. Non-complex images are images whereby the color of the objects of interest and background are not similar while for complex images, the objects of interest and the background are having akin color. In some of the complex images, parts of the color of the object of interest are present in the background.

In the first stage, the user input which includes the bounding box to locate the range of the object of interest and a stroke for the foreground will be drawn on the selected images. Next, these user scribbled images are input into the three different interactive segmentation algorithms. The three evaluation parameters: Variation of Information (VI), Global Consistency Error (GCE) and Jaccard index (JI) are calculated for the segmentation results.

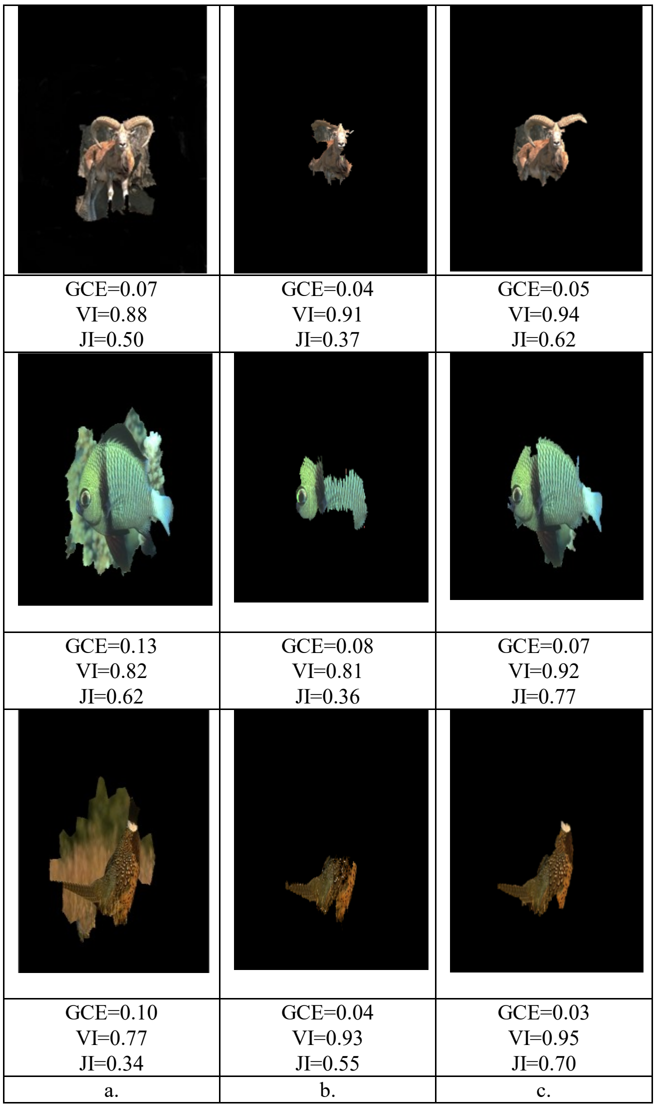

Figure 10. Qualitative and quantitative segmentation results obtain using complex images for: a. Robust Interactive Segmentation via Graph-based Manifold Ranking [38], b. Nonparametric higher-order learning for interactive segmentation [36], and c. Interactive image segmentation by maximal similarity based region merging [39].

C. Results and Discussions

For comparison purpose, three non-complex images and three complex images were used. Figure 8 shows the images in these two categories. In this figure, image a. to c. are non-complex images whereby the background and object of interest could be differentiated easily. Images d. to f. in this figure are complex images. In these complex images, it could be seen that, parts of the objects and the background have very similar color features. The unified bounding box and foreground stroke from the user input is also shown in this figure. Fair comparison is done in the experiments as the length and location of the strokes as well as the size of the bounding box use for the three algorithms are the same. It is worth mentioning that, the over-segmentation technique used in each of the algorithm is remained the same, i.e. there is no change on the original algorithm in terms of over-segmentation technique used.

1) Non-complex Images

For the non-complex images, the segmentation results obtained using the three interactive segmentation algorithms are shown in Figure 9. Using the three evaluation parameters, it can be concluded that, the three interactive segmentation algorithms can extract the object of interest with satisfactory results, with minimum JI=0.83 and GCE=0.12. The best segmentation results obtained was JI=0.98 and GCE=0.01. The Nonparametric higher-order learning for interactive segmentation (NHL) [36], and Interactive image segmentation by maximal similarity based region merging (MSRM) [39] perform better as comparing to the Robust Interactive Segmentation via Graph-based Manifold Ranking (RGMR) [38] with NHL and MSRM achieve more than or equal to 0.95 for JI and GCE less than 0.05. RGMR on the other hand, only managed to achieve the best result using the bush image with JI=0.95 and GCE=0.02. For the other two non-complex images, RGMR only manages to achieve average JI of around 0.85 and GCE of around 0.12. With visual inspection, it could be seen that, the objects extracted mostly do not include the background of the image for the three algorithms. However, the detail of the object, for example, the image of the vase, is partly missed.

2) Complex Images

Using the complex images, as shown in Figure 10, all three algorithms could not perform as good as using the non-complex images. The best interactive segmentation algorithm among these three algorithms is the MSRM which could still produce segmentation result of JI more than 0.60 and GCE of less than 0.10 for all the three complex images used. RGMR produces the highest GCE for all three complex images as comparing to the other two algorithms. In terms of GCE, the ranking of the algorithms from low to high values is: MSRM, NHL and RGMR. However, if using JI, the ranking is: NHL, RGMR and MSRM. With visual inspection, it could be seen that, the segmentation includes the background of the object, which means that, the three algorithms fail to differentiate between the object of interest and the background for complex images.

IV. Conclusion

This paper uses the unified bounding box to locate the ranhe of the object of interest and a stroke in the foreground as user input for the three interactive segmentations: RGMR, NHL and MSRM. The images used are divided into non-complex and complex images. For the images used, the unified input type suggested in this paper, which is a bounding box to locate the object of interest and a stroke placed on the foreground of the images, were drawn. In another words, the location and size/length of the bounding box and stroke are the same for all the test images. In addition, to better compare and evaluate the results, three evaluation parameters are used for all the three interactive algorithms, i.e. GCE, VI and JI. It was found that, all three interactive segmentation algorithms perform well for non-complex images with JI values of more than 0.80. MSRM and NHL outperform RGMR for all the three non-complex images. However, for complex images, only MSRM can achieve JI values of more than 0.60 and GCE values of less than 0.10. RGMR performs the worst among these three algorithms for complex images with highest GCE value obtained only at 0.13 and lowest JI value at 0.34. It can be concluded that, the MSRM algorithm can produce more consistent segmentation results as comparing to the NHL and RGMR algorithms, although for complex images, the results obtained using MSRM deteriorates as comparing to extracting objects of interest in non-complex images. In addition, for MSRM, it can also be generalized that, the influences of the user input type on the segmentation results is not as huge as the NHL and RGMR algorithms for complex images. Visual inspection of the segmentation results reveal that, for complex images, the three interactive segmentation algorithms fail to differentiate between the object of interest with the background and this result in background being included in the final segmentation results.

The proposed unified bounding box and single stroke used in this research suggest a method to extract objects of interest with less required input. However, from the experiments in this study, it can be concluded that, all the three interactive segmentations could not perform well in extracting object of interest for complex images, but the extraction of object of interest is good when using non-complex images. In the future, we would experiment with more complex images and more interactive segmentation algorithms to verify the results obtained.

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