

Evaluation of Different User Input Types in Interactive Segmentation

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Abstract—Interactive image segmentation is the process of extracting the desired object(s) with the help of the human operator. It is a looping process whereby users are required to provide input until the desired object is segmented. The placement accuracy of the user input will help to reduce the number of loops required. Normally, users are required to place strokes on the foreground and background of the desired objects. However, segmentation algorithms tend to misinterpret the intention of the users although the foreground and background strokes were placed. Therefore, user input constitutes a very important step in the success of interactive segmentation algorithm. Currently, to the knowledge of the authors, there is no research on the use of these different types of input on the accuracy of the segmentation results. Therefore, this paper intends to fill this gap. In this paper, we present a brief review on the different input types that had been used as the initial input and in the refinement process. Next, a series of experiments had been carried out on the use of these different types of user input to study the effect on these common users input types on the segmentation results. The experiments will look into the location, number and length of these different input types using Berkeley image database with the nonparametric higher-order learning. It was noticed that, the location, number and length of the different user input types will affect the segmentation results on complex images while remain consistent for simple images.

Index Terms—Image Segmentation; Interactive Segmentation; User Input; User Intention.

I. INTRODUCTION

Segmentation plays an important role in computer vision and it is one of the crucial steps in pattern recognition. According to Wiki [1], image segmentation refers to the process of partitioning a digital image into multiple segments (sets of pixels, also known as superpixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze.

Image segmentation is used in various domain areas. In medical field, blood cell is extracted from a complicated background and later every cell is segmented into the morphological components such as nucleus, cytoplasm, holes and other organelles [2]. Apart from this, segmentation is also applied in remote sensing data whereby object of interest on the satellite images is segmented based on the input from user [3, 4].

With the advancement of computer technology, image segmentation process can be fully automated. The objective of fully automated segmentation is to reduce the involvement of user and produce more accurate results as comparing with manual segmentation. However, many researchers [5-13]

addressed that fully automatic segmentation still exhibit difficulties and cannot provide satisfactory result due to the complexity of the images, especially using natural images. In order to solve this, human operator plays an important role in the segmentation process.

II. INTERACTIVE SEGMENTATION

The involvement of human operator in the segmentation is called interactive or semi-automatic segmentation. Based on the definitions from various sources [5-7, 9, 14-22], it can be summarized that the purpose of interactive segmentation is to extract the desired object with the involvement of human/user by providing a high level or priori information. The general process of interactive segmentation is shown in Figure 1. In this figure, the user places an initial input to specify the background and foreground of the desired object on the image. The segmentation algorithm will produce a segmentation result to the user. The user will then assess the result and the segmentation process will stop if the user agrees on the result. Otherwise, input refinement process, whereby the user is going to enter additional input, will take place. This refinement process will loop until the desired object had been segmented. The ultimate goal of an interactive segmentation algorithm is to minimize the refinement process and segment the desired object as quickly and accurate as possible. In other words, an interactive segmentation algorithm is considered better, in the matter of maintaining the similar accuracy when comparing with another interactive segmentation algorithm, if the number of additional input required is less. The key for a segmentation algorithm to quickly segment the desired object is to understand the intention of the user. In order to understand the intention of the user, the algorithm needs to understand precisely the meaning of the user input. In this paper, an introduction to the various categories of segmentation, followed by input types that had been used as the initial input and in the input refinement process, are presented. The common practice of the researchers in the domain of interactive segmentation is mainly focusing on the segmentation results without a detailed analysis on the effects of these different user input types on the final results. Therefore, this research intends to fill this gap. In this paper, a series of experiments using the common inputs were carried out and the effects on the segmentation results are presented. The paper ends with a detailed analysis and suggestions pertaining to the analysis.

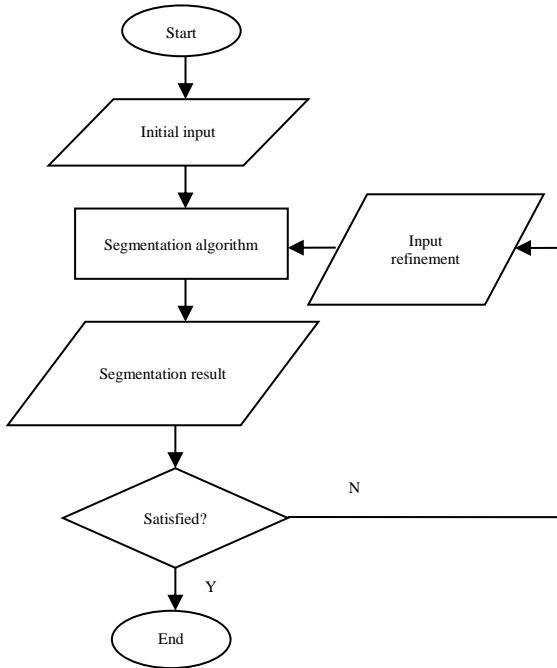


Figure 1: General interactive image segmentation process

A. Categorization of Image Segmentation

Based on the literature in [23], it can be concluded that image segmentation can be divided into unsupervised, semi-supervised and supervised. In the unsupervised case, the algorithm will extract the object of interest by itself without any user’s guidance. Automated segmentation falls in this category. On the other extreme, in supervised segmentation, the features for the object of interest need to be known prior to performing the segmentation algorithm. Interactive segmentation, on the other hand, belongs to semi-supervised category whereby it requires users to label the object by putting a marker or seed in the image. In the semi-supervised segmentation, the algorithm will utilize both the labelled data points obtained from the maker or seed from user input and unlabeled data to extract the object of interest.

From the analysis of [8, 18, 22, 24-26], it can be summarized that interactive segmentation can be further divided into region based, boundary/contour and graph based. In the region based category, the algorithm grouped or partitioned the regions of similar pixels based on the foreground and background markers. Boundary/contour based segmentation detects the object of interest based on the marker along the boundary of the object, while graph based approach represents region and boundary of an image in a graph structure.

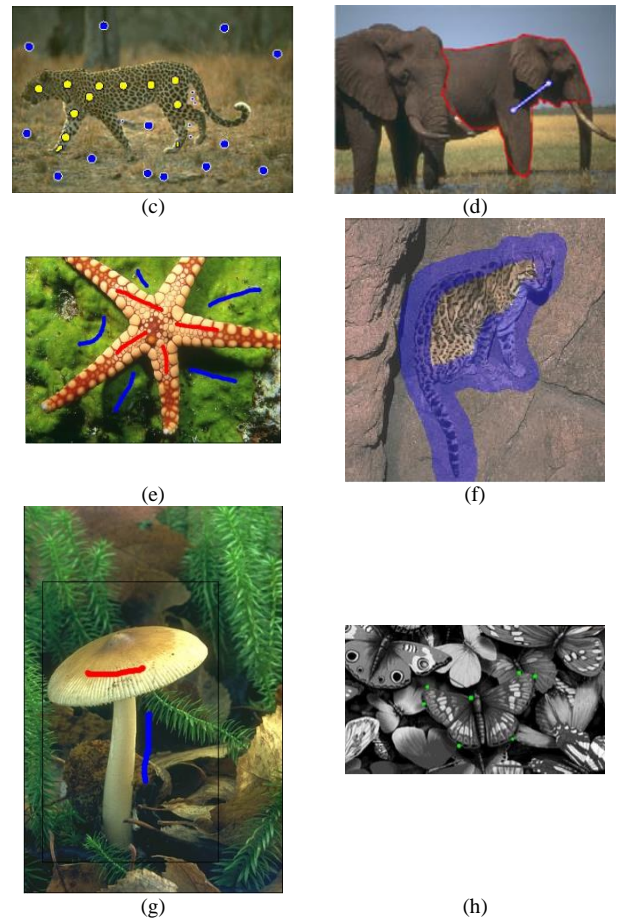
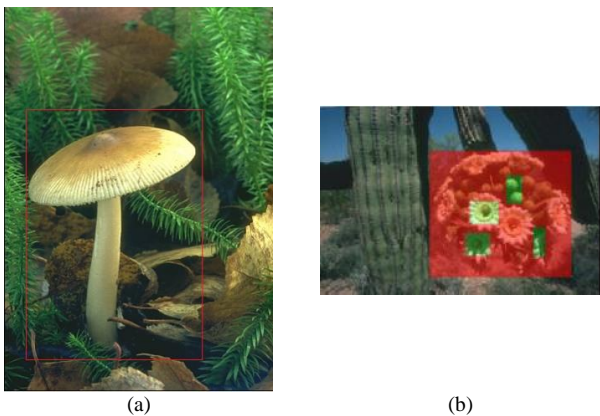


Figure 2: Input types used as the initial input in the interactive segmentation: (a) bounding box. (b) bounding boxes for foreground object. (c) seed points for the background and foreground of the image. (d) placing the skeleton on the object of interest. (e) background and foreground strokes on the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

B. User input types

There are various input types that had been used in interactive segmentation algorithms. A general categorization of these input types is based on whether the input is placed initially or later (refinement input) in the interactive segmentation process.

a. Inital input

The most widely used input type in interactive segmentation algorithm is placing strokes on the background and foreground of the image [5, 6, 9, 10, 12, 18, 23-37]. On top of this, [19] had introduced a method using a single stroke on each background and foreground of the image together with additional edge information to improve the segmentation result. Oppositely, [38] and [39] applied only one stroke on the object of interest and [40] required the user to place a stroke on the contour of the object.

Besides strokes, [15, 41, 42] used bounding box on the object of interest. [43] and [44], on the other hand, included additional background and foreground strokes inside the bounding box as an additional information to the segmentation algorithm. In another research by [45], users are required to specify additional bounding boxes for foreground object in the initial bounding box.

Apart from strokes and bounding box, seed points are also applied. [46] and [47] applied seed points on the background and foreground on the image. [48] and [49] required the user to place a single seed point on the object of interest. [11] and

[16], required the user to place seed points on the contour of the object of interest. On the other hand, [7] used a different approach than others, whereby it required the user to place the skeleton on the object of interest.

Furthermore, [50] used the combination of different input types, i.e. combining seed points with strokes on the background and foreground of the image. Figure 2 shows the use of the above mentioned different input types as the initial input in the interactive segmentation algorithm.

b. Refining input

There are several input types introduced by the researchers to help the users to refine their segmentation results after they were shown with the segmentation results from their initial input. The most popular type was requiring the user to place additional strokes on the initial segmentation result obtained from their initial input [5, 6, 18, 19, 24, 32, 33, 42, 50]. [31] and [37] on the other hand, allowed users to remove strokes placed previously. Apart from strokes, users could place new seed points to control the final segmentation or connect tiny objects to the object of interest. Besides this, [29] refined the segmentation result by clicking and dragging polygon vertices on the contour of the segmented result. Lastly, [7] refined the segmentation results through adding new vertices. All of these input types are considered as passive refinement of segmentation result.

In the passive refinement, users will constantly provide input based on the result produced by the system. This process will be very time consuming if applied to complex images. In order to minimize this problem, active refinement is introduced, whereby the algorithm will assess the output of the segmentation and identify the ambiguous parts. The ambiguous parts are next shown to the users. Users are then required to provide input on those ambiguous parts. With this, the number of inputs in the refinement process will be reduced. [30] and [23] fall into this category whereby their work provided suggestions on places to add an extra stroke or to refine the strokes.

III. ANALYSIS OF USER INPUT

Despite the strengths and weaknesses of active and passive refinement, it is believed that the coverage of the user input in the initial process of the interactive segmentation and also in the refinement process in covering the foreground and background information will affect the final segmentation result. This is supported by [24], whereby according to this research, user input should cover as many different regions of foreground and background as possible for getting satisfied segmentation results. From the review in Section II, it could be seen that, a user input could be as small as a point as in the seed input or a stroke which could cover more pixels as comparing to the seed point. The use of bounding box could further limit the attention of the algorithm by focusing on the object of interest. The main characteristic of these different input types is the extended coverage of the foreground and background on the image. However, the question on the effect of the input coverage of foreground and background placed in the images on the segmentation result using a common interactive segmentation algorithm is not presented. Therefore, in the next section, a series of experiments had been carried out in order to answer this question.

Table 1
The location and number of seed points input and results obtained.

User Input	Segmentation Result	Overlaid on Ground truth	Results
			GCE=0.17 VI=0.78 JI=0.54
			GCE=0.16 VI=0.77 JI=0.55
			GCE=0.13 VI=0.84 JI=0.65
			GCE=0.04 VI=0.96 JI=0.88
			GCE=0.06 VI=0.93 JI=0.74
			GCE=0.08 VI=0.89 JI=0.58
			GCE=0.03 VI=0.96 JI=0.86
			GCE=0.03 VI=0.96 JI=0.86

IV. EXPERIMENTAL SETTINGS AND RESULTS

Images from the Berkeley image database [51] and interactive segmentation system which is based on nonparametric higher-order learning [52] had been used in the experiment. Four commonly used user input types :1) seed point, 2) foreground and background strokes, 3) foreground stroke with background bounding box and 4) bounding box as foreground and background, are used. Three segmentation evaluation parameters: Variation of Information (VI), Global Consistency Error (GCE) and Jaccard index (JI) [53] had been selected to evaluate the result of segmentation. The GCE is defined as an error measure between two segmentations, JI measures the similarity between two segmentation and VI measures the distance between two segmentations. Note that, the evaluation parameters are comparing the segmentation results obtained when the different user input types were entered with the ground truth segmentation results.

A. Seed Points

In this part of experiment, seed point, which is one point, is input by the user to the algorithm. The locations of the seed point, as well as the number of seed points are tested. Table 1 shows the segmentation results obtained using seed points for two different images. For the image of airplane, the first two images shows that, the location of the seed points do affect the segmentation result. For these two images, the numbers of foreground and background seed points are the same, however, the location of the seed points were different. In the 3rd and 4th image of airplane, more seed points were entered. The GCE results are minimizing (from GCE=0.17 in the first image to GCE=0.04 in the fourth airplane image) showing that the segmentation results are nearer to the ground truth results. This is the same for the mushroom image in Table 1. More segmentation results using seed points could be seen in Appendix A. A special note is on the images: a man with a hat, a bush and two flowers in the Appendix whereby in these images, the color variation in the images are not much. We term these images as simple images or non-complex images. In this type of image, it could be seen that, when more seed points are entered, the accuracy is not affected.

B. Foreground and Background Strokes

In this section, users are required to enter strokes to represent the foreground and background. The location, length and number of strokes input by the users on the segmentation results could be seen in Table 2 and Appendix B.

For each set of different images, the first two images represent the difference in strokes locations. It can be seen that, the location of strokes affect the segmentation accuracy.

Table 2
Foreground and background strokes. The length and number of strokes entered by users and the effects on the segmentation results

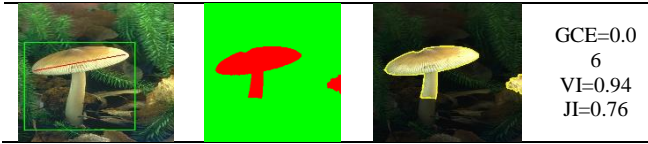
User Input	Segmentation Result	Overlaid on Ground truth	Results
			GCE=0.16 VI=0.78 JI=0.56
			GCE=0.16 VI=0.78 JI=0.56
			GCE=0.15 VI=0.78 JI=0.57
			GCE=0.04 VI=0.96 JI=0.88
			GCE=0.06 VI=0.93 JI=0.82
			GCE=0.06 VI=0.93 JI=0.71

			GCE=0.07 VI=0.92 JI=0.70
			GCE=0.04 VI=0.95 JI=0.84
			GCE=0.06 VI=0.93 JI=0.78
			GCE=0.04 VI=0.96 JI=0.84

There is a positive relationship between number of strokes and segmentation accuracy. The length of the strokes (forth image for each set of image), also affect the segmentation result. The accuracy will remain consistent (3rd and 4th images for each set of image) for simple image with more strokes entered.

Table 3
Segmentation results obtained using bounding box as background and stroke as foreground

User Input	Segmentation Result	Overlaid on Ground truth	Results
			GCE=0.0 5 VI=0.94 JI=0.81
			GCE=0.0 8 VI=0.87 JI=0.60
			GCE=0.0 9 VI=0.89 JI=0.75
			GCE=0.0 5 VI=0.94 JI=0.83
			GCE=0.0 6 VI=0.93 JI=0.72
			GCE=0.0 8 VI=0.90 JI=0.59
			GCE=0.0 3 VI=0.97 JI=0.88



C. Foreground Strokes with Background Bounding Box

The users are required to draw bounding box as the background and enter strokes as the foreground of the images. In this experiment, the location and length of the strokes are examined. Table 3 shows the results obtained. More results can be seen in Appendix C. Comparing the first two and last two images of each set of different image show that, location and length affect the final result. Taking the complex image of the cars, it could be seen that, when one seed/stroke is used as foreground and background, the use of bounding box as background with 1 stroke as foreground produces better result. For simple images, location and length does not have an important effect.

D. Foreground and Background Bounding Boxes

Besides from background bounding box, the use of bounding box as the foreground of the image is also tested. For this, the location, size (length) and number of bounding box used as foreground are tested. The results could be seen in Table 4 and Appendix D. It can be concluded that, the location, length and number of bounding box affected the segmentation results for complex image. However, these effects are not clear in simple images.

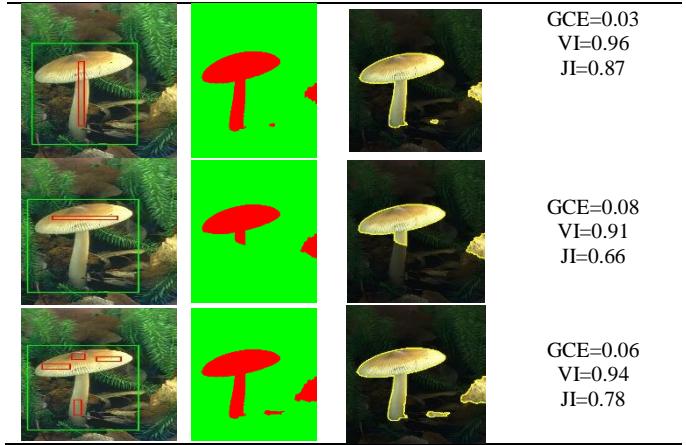
From the experiments and results shown in Table 1 to 6 and Appendix A to D, the finding can be summarized as below:

- The location of the seed points or strokes and bounding box for foreground will affect the final segmentation results.
- The number of seed points or strokes or bounding box for foreground will also affect the final segmentation result. However, when the seed points/strokes/bounding box entered had covered the statistics of the object and background, the final segmentation results would not be further improved with more inputs entered. This could be clearly seen in the picture of mushroom and also the man with a hat. For these two images, the accuracies obtained were static even more input were entered by the users.

Table 4

The effects of the use of bounding box for the foreground and background in the images

User Input	Segmentation Result	Overlaid on Ground truth	Results
			GCE=0.06 VI=0.94 JI=0.84
			GCE=0.08 VI=0.91 JI=0.77
			GCE=0.07 VI=0.92 JI=0.79



- The length of the strokes will affect the final segmentation results. This is true for both the use of strokes in foreground and background and in the bounding box and foreground strokes.
- The use of bounding box as background improves the segmentation results.
- For less complex image, the type of the user input method does not affect much on the segmentation results.
- The use of bounding box as the foreground of the image does not seem to improve the accuracy of the segmentation results as comparing to using strokes as foreground input.

V. SUGGESTIONS AND CONCLUSIONS

This paper presents a review of various user inputs in the interactive segmentation. A series of experiments using the commonly used user input types had been carried out. The performances of these different user input types focusing on the coverage of the input had been tested on the classical image segmentation database. The segmentation results had shown that, the location, number of input and the length of the user input will affect the segmentation results. However, these effects will not affect the segmentation results on non-complex image. For the simple image, the segmentation result will remain similar, invariant to location, number and length of the different user input types. From the experiments, it could be concluded that, user input with a bounding box as background outperformed the seed points and strokes used as the input method. Moreover, it can be noticed that, the placement of foreground and background strokes maybe different from each individual and this would affect the final segmentation results. The placement of bounding box as background, on the other hand, is similar for different users as users will draw the bounding box as closely as possible to cover the object of interest only.

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APPENDIX

A. Seed Points Entered

User Input	Segmentation Result	Overlaid on Ground truth	Results
			GCE=0.14 VI=0.85 JI=0.87
			GCE=0.10 VI=0.90 JI=0.91
			GCE=0.03 VI=0.97 JI=0.97
			GCE=0.03 VI=0.97 JI=0.97
			GCE=0.20 VI=0.58 JI=0.14
			GCE=0.18 VI=0.56 JI=0.25
			GCE=0.06 VI=0.93 JI=0.76
			GCE=0.15 VI=0.74 JI=0.39
			GCE=0.01 VI=0.99 JI=0.98
			GCE=0.01 VI=0.99 JI=0.98
			GCE=0.01 VI=0.99 JI=0.98
			GCE=0.01 VI=0.99 JI=0.98
			GCE=0.07 VI=0.52 JI=0.09
			GCE=0.02 VI=0.98 JI=0.98

			GCE=0.02 VI=0.98 JI=0.97
			GCE=0.02 VI=0.97 JI=0.97
			GCE=0.26 VI=0.52 JI=0.18
			GCE=0.21 VI=0.60 JI=0.18
			GCE=0.19 VI=0.67 JI=0.41
			GCE=0.18 VI=0.70 JI=0.43

B. Foreground and Background Strokes

User Input	Segmentation Result	Overlaid on Ground truth	Results
			GCE=0.15 VI=0.52 JI=0.57
			GCE=0.14 VI=0.85 JI=0.87
			GCE=0.03 VI=0.97 JI=0.97
			GCE=0.03 VI=0.97 JI=0.97
			GCE=0.10 VI=0.89 JI=0.91
			GCE=0.20 VI=0.58 JI=0.14
			GCE=0.17 VI=0.77 JI=0.35
			GCE=0.14 VI=0.80 JI=0.45

C. Foreground Strokes with Background Bounding Box

				User Input	Segmentation Result	Overlaid on Ground truth	Results
							GCE=0.05 VI=0.95 JI=0.80
							GCE=0.17 VI=0.77 JI=0.34
							GCE=0.01 VI=0.99 JI=0.98
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							GCE=0.01 VI=0.99 JI=0.98

			GCE=0.03 VI=0.97 JI=0.97				GCE=0.01 VI=0.99 JI=0.98
			GCE=0.02 VI=0.98 JI=0.97				GCE=0.01 VI=0.99 JI=0.98
			GCE=0.02 VI=0.98 JI=0.97				GCE=0.02 VI=0.98 JI=0.97
			GCE=0.05 VI=0.77 JI=0.17				GCE=0.02 VI=0.98 JI=0.97
			GCE=0.02 VI=0.75 JI=0.07				GCE=0.02 VI=0.98 JI=0.97
			GCE=0.18 VI=0.77 JI=0.47				GCE=0.18 VI=0.73 JI=0.45
			GCE=0.18 VI=0.74 JI=0.45				GCE=0.19 VI=0.75 JI=0.44
							GCE=0.16 VI=0.75 JI=0.51

D. Foreground and Background Bounding Boxes

User Input	Segmentation Result	Overlaid on Ground truth	Results
			GCE=0.03 VI=0.97 JI=0.97
			GCE=0.06 VI=0.94 JI=0.94
			GCE=0.04 VI=0.96 JI=0.96
			GCE=0.14 VI=0.78 JI=0.45
			GCE=0.15 VI=0.79 JI=0.42
			GCE=0.16 VI=0.66 JI=0.34
			GCE=0.01 VI=0.99 JI=0.98

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