Effects of Different Superpixel Algorithms on Interactive Segmentations

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Abstract— Semi-automated segmentation or more commonly known as interactive image segmentation is an algorithm that extracts a region of interest (ROI) from an image based on the input information from the user. The said algorithm will be repetitively fed with such input information until required region of interest is successfully segmented. To accelerate this segmentation procedure as well as enhancing the result, pre-processing steps can be applied. The application of superpixel is an example of such pre-processing step. Superpixel can be defined as a collection of pixels that share common features such as texture and colours. Though employed as pre-processing step in many interactive segmentation algorithms, to date, no study has been conducted to assess the effects of such incorporations on the segmentation algorithms. Thus, this study aims to address this issue. In this study, five different types of superpixels ranging from watershed, density, graph, clustering and energy optimization categories are evaluated. The superpixels generated by these five algorithms will be used on two interactive image segmentation algorithms: i) Maximal Similarity based Region Merging (MSRM) and ii) Graph-Based Manifold Ranking (GBMR) with single and multiple strokes on various images from the Berkeley image dataset. The result of testing had shown that MSRM achieved better result compared to GBMR in both single and multiple input strokes using SEEDS superpixel algorithm. This study summary concluded that at different superpixel algorithms produced different results and that it is not possible to single out one particular superpixel algorithm that can work well for all the interactive segmentation algorithms. As such, the key to achieving a decent segmentation result lies in choosing the right superpixel algorithms for a given interactive segmentation algorithm.

Keywords— Interactive Image Segmentation, Strokes, Superpixel, User input.

I. INTRODUCTION

IMAGE segmentation is a crucial function in image processing. It helps human to retrieve region of interest (ROI) from an image. There are different types of image segmentation algorithms which could be broadly categorised as manual, semi-automated to fully automated. Fully automated the whole segmentation process will be the ultimate goal of image segmentation. However, the result generated from fully automated segmentation still facing a lot of challenges as a result of the high complexity of the images, which is particularly true for the natural scene images. Therefore, semi-automated segmentation is still the preferred solution.

II. INTERACTIVE SEGMENTATION

Interactive segmentation is also known as semi-automated image segmentation. In interactive segmentation process, the guidance from the user will be inputted to the segmentation system. The guidance normally consists of information of the background and the object of interest. Segmentation process will be performed based on the guidance and the result will be evaluated by the user. The process of guidance input, segmentation process and evaluation will be repeated until satisfaction result is obtained. Minimal input from the user with high segmentation accuracy is the utmost aim of the interactive segmentation system. To achieve this aim, the interactive segmentation should be designed in such a way so that the algorithm could comprehend the message behind the user input.

Various kinds of user input were used in interactive segmentation algorithms to offer guidance to the segmentation system on the background and object of interest information. The most popular input type is stroke [4-6], followed by bounding box [7, 8] and seed point [9, 10]. For stroke and seed point input types, background information and region of interest will be represented by two different colours to differentiate these two categories of information. Conversely, a bounding box is used by placing the bounding box around the object of interest in the image. Three commonly used user input in interactive segmentation is shown in Fig. 1.

(a) (b) (c)

Fig. 1 Different user input types in interactive image segmentation: (a) Strokes. (b) Bounding box. (c) Seed points.

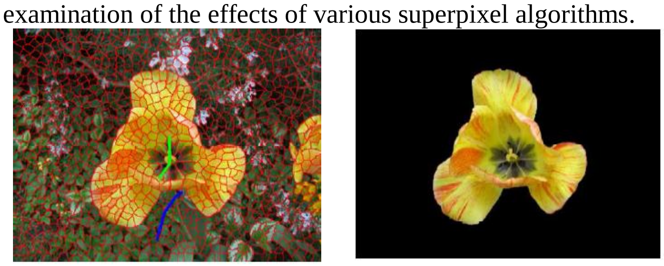
The object of interest will start to be extracted from the background after the user input process during the segmentation process. Conventionally, image segmentation is done based on the information on the individual pixel on the image. However, this process consumes a lot of processing power. Therefore, superpixel has been introduced by Ren and Malik [11] to solve this problem. Superpixel can be defined as a collection of pixels that have the same features such as texture or colour. With the introduction of the superpixel, it had changed the processing steps in the segmentation process.

There are many interaction segmentation algorithms that had incorporated superpixel as one of the pre-processing steps since the introduction of superpixels [6, 12-16]. According to Stutz, Hermans [17], the superpixel algorithms can be categorized into watershed, density, graph, contour, path, clustering, energy optimization and wavelet-based. However, no study has been conducted to date that examines the effects of different types of superpixel on interactive image segmentation algorithms. From the review [9, 14, 18-22], different superpixel algorithms were used as the pre-processing step in the interactive segmentation approaches. As a result, evaluating the effects of various categories of superpixel algorithms in interactive segmentation algorithms will help to close this research gap.

To achieve this objective, the effect of five different superpixels algorithms on two interactive segmentation were used and evaluated in this paper. Strokes, which is the most popular user input type, is used as the input guidance to both interactive segmentation algorithms. The two interactive segmentation algorithms chosen were: 1. Robust Interactive Image Segmentation via Graph-Based Manifold Ranking (GBMR) [22] and, 2. Maximal Similarity-based Region Merging (MSRM)[21]. The five different superpixel algorithms were chosen from the five different superpixel categories: 1. Compact Watershed (superpixel category: Watershed), 2. Quick Shift (QS) (superpixel category: Density), 3. Algorithm proposed by Felzenswalb and Huttenlocher (FH) (superpixel category: Graph), 4. Simple Linear Iterative Clustering (SLIC) (superpixel category: Clustering), and 5. Superpixels Extracted via Energy Driven Sampling (SEEDS) (superpixel category: Energy Optimization). A short summary on the two interactive segmentations used and the five superpixel algorithms are given below:

A. Robust interactive image segmentation via Graph-based Manifold Ranking (GBMR) [22]

This algorithm uses a locally adaptive kernel parameter and driven labels to form an affinity graph matrix by approximating the k-regular sparse graph. To generate the segmentation result, the stroke information from the background and object of interest is incorporated into the superpixel images. Fig. 2(a) depicts the superpixel on the image with the strokes on the background and the object of interest, and Figure 2(b) depicts the segmentation result. This algorithm, according to Li, Wu [22], used superpixels as the primary processing unit. Superpixel's incorrect over-segmentation will have an effect on the final segmentation result. However, the selection of superpixel was not the focus of this algorithm, which resulted in a more thorough examination of the effects of various superpixel algorithms.



(a) (b)

Fig. 2 Segmentation process achieved from algorithm (H. Li et al., 2015): (a) Superpixel with strokes on background and object of interest. (b) Segmentation result.

B. Maximal Similarity-based Region Merging (MSRM) [21]

This algorithm is based on region merging which is adaptive to image content and does not require a preset threshold. Initially, the image is converted into superpixels by using mean shift segmentation. The algorithm automatically merges the regions that are initially segmented by mean shift segmentation, and then effectively extracts the object contour by labelling the regions which are non-marked as either regions of interest or background. Fig. 3(a) presents the superpixel of the image with strokes on the background and object of interest and (b) shows the result of the segmentation. According to Ning, Zhang [21], the user input markers must cover the main features of the object and background in order to successfully extract the object contour from different backgrounds. Aside from that, the proposed method is founded on some form of initial segmentation, such as mean shift or super-pixel. As a result, if the initial segmentation fails to provide a solid foundation for region merging, the algorithm may fail. The evaluation of different superpixel algorithms, on the other hand, was not the main focus of this algorithm.

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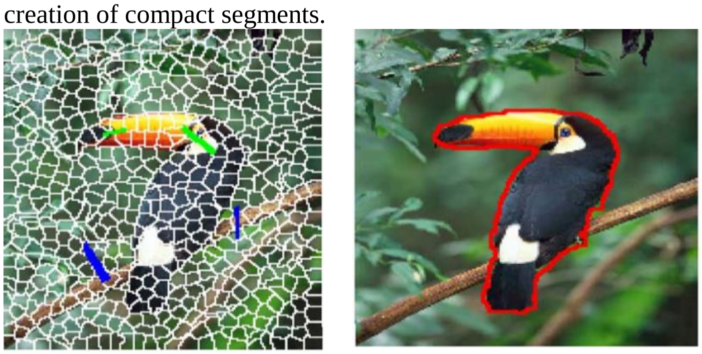
C. Compact Watershed (CW)[23], Category: Watershed

Compact watershed (CW) is an extremely fast algorithm that is based on the Watershed algorithm. The watershed algorithm's problem, on the other hand, is the irregular size and varying boundaries of the superpixel produced. As a result, the compact watershed included a compactness constraint, which is the distance to the seed point. The resulting distance metric is a weighted combination of the conventional appearance-based distance and the pixel's Euclidean distance to the segment seed. As a result, the size and elongation of the segments are constrained, favoring the creation of compact segments.



(a) (b)

Fig. 3 Segmentation process of the algorithm (Ning et al., 2010): (a) strokes input by users on the superpixel. (b): the segmentation result.

D. Simple Linear Iterative Clustering (SLIC)[24] , Category: Clustering

Simple Linear Iterative Clustering (SLIC) is a clustering approach based on k-means that employs CIELAB colour space and spatial proximity information. This information is used by this algorithm to control the size and compactness of superpixels.

E. Superpixel algorithm by Felzenszwalb and Huttenlocher [25], Category: Graph

This algorithm is based on graph theory. This method represents an image pixel using an undirected graph and partitions the graph based on the edge weight. The edge weight is usually determined by pixel information such as intensity, colour, and location. The pairwise region comparison predicate with segmentation algorithm was introduced to measure the evidence for a boundary between two regions and produce segmentation with a simple greedy decision.

F. Quick Shift (QS)[26], Category: Density

Quick Shift (QS) is based on a density approach, and an improved mode seeking clustering algorithm is applied to the density image. It operates in non-Euclidean spaces in a straightforward manner, seeking energy modes by connecting nearest neighbours at higher energy levels and trading-off mode over- and under-fragmentation. Furthermore, this algorithm disregards the compactness and number of superpixels.

G. Superpixels Extracted via Energy Driven Sampling (SEEDS)[27], Category: Energy Optimization

Superpixels Extracted via Energy Driven Sampling (SEEDS), it is based on a hill-climbing optimization with efficient pixel exchanges between superpixels. The optimised energy function is based on enforcing colour distribution homogeneity within superpixels. Using the intersection distance between histograms, the hill-climbing algorithm produces a very efficient evaluation of this energy function.

III. Experiment Settings

In this study, the stroke user input was further divided into single and multiple strokes input. In single user input, one stroke was placed either on the background or the object of interest to differentiate the background from the object of interest. For multiple strokes, a user could input multiple number of strokes of different colours for background and object of interest. The effects of the number of strokes in interactive segmentation algorithms is not the focus of this paper as this had been reported in the authors' previous study [28]. Therefore, in this research work, the images used were categorized into simple and complex images. Complex images can be defined as images where the object of interest and the background has similar colour and/or the object of interest is overlapped with another object. The simple image, on the other hand, has a clear contrast colour between background and object of interest. In Fig. 4, images 6 and 7 are the simple images, while images 1 to 5 are the complex image. The ground truth of these images, together with the single and multiple strokes used on these images are also shown in this figure. In addition, the superpixel images generated using the five different superpixel algorithms are included in Fig. 5.

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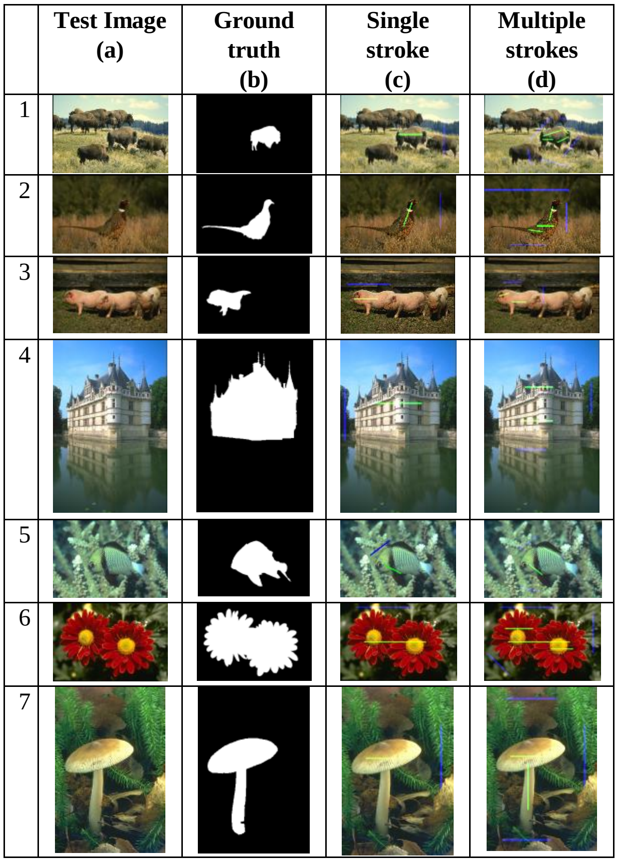
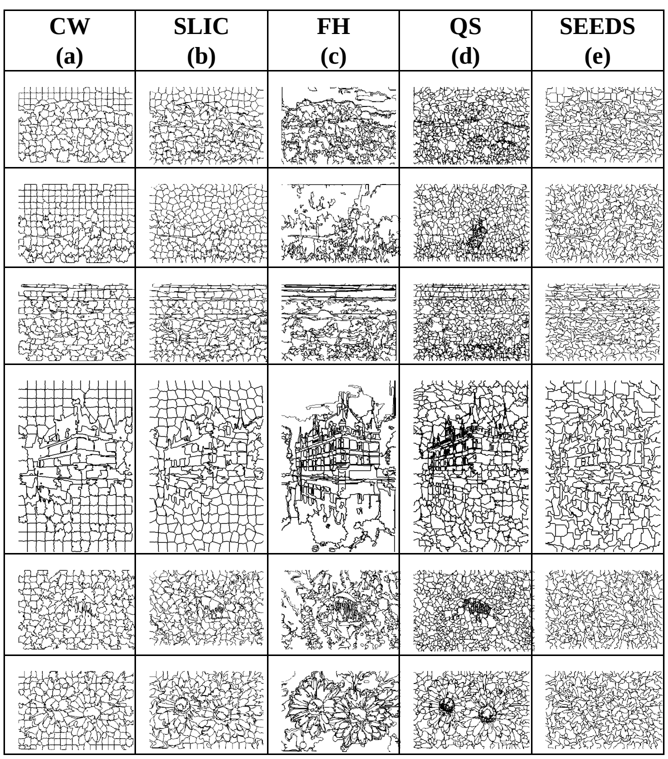


Fig. 4 (a) Test image (1-5 complex images, 6-7 simple images). (b) Ground truth of test images. (c) Single stroke on the test images. (d) Multiple strokes on the test images.



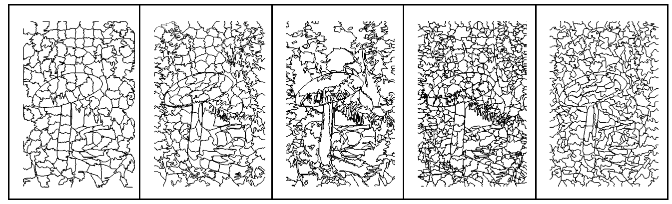


Fig. 5 (a) Superpixel generated from CW algorithm (b) Superpixel generated from SLIC algorithm (c) Superpixel generated from FH algorithm (d) Superpixel generated from QS algorithm (e) Superpixel generated from SEEDS algorithm.

In order to evaluate the effectiveness of the superpixel algorithms in the interactive segmentation, pixel accuracy, F-score and Jaccard index which had been adopted by Tang, Gorelick [29], [Taha and Hanbury [30]] and [Ranjbar, Mori [31]] are chosen to be used in this study. Pixel accuracy, A, is the percentage of the pixel in the segmented result that are classified correctly after comparing with ground truth (Eq.1). However, pixel accuracy has included the percentage of pixel correctly map to the background information. Therefore, the Jaccard Index, J, and F-score, F. are introduced. Jaccard index (Eq. 2) which is also known as intersection over union, is used to measure the overlapping ratio between the ground truth and result. F-score, F, (Eq. 5) on the other hand, measures the total accuracy by taking consideration of both precision, P, (Eq. 3) and recall, R (Eq. 4).

$$A = \frac{True\ Positive + True\ Negative}{True\ Postive + True\ Negative + False\ Positive + False\ Negative} \quad (1)$$

$$J = \frac{True\ Positive}{True\ Postive + False\ Positive + False\ Negative} \quad (2)$$

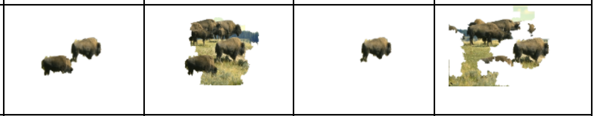
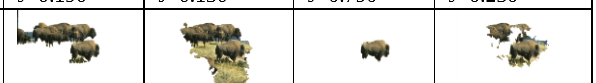
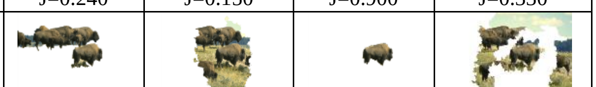
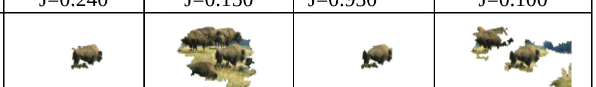
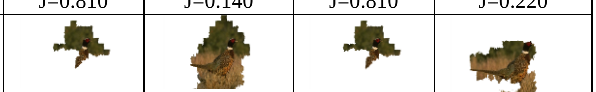
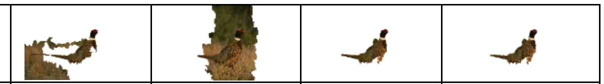
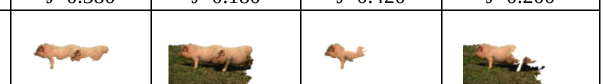
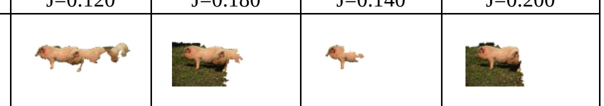
$$P = \frac{True\ Positive}{True\ Postive + False\ Positive} \quad (3)$$

$$R = \frac{True\ Positive}{True\ Postive + False\ Negative} \quad (4)$$

$$F = 2 * \left(\frac{P * R}{P + R}\right) \quad (5)$$

IV. Results and Discussion

To better visualize the results, the output obtained using the five different superpixel algorithms tested on the two interactive segmentations with single and multiple strokes were grouped for each input image (Fig. 6).

	Single stroke		Multiple strokes	
	MSRM	GBMR	MSRM	GBMR
CW				
	P=0.202 R=0.985 A=0.801 F=0.336 J=0.200	P=0.133 R=1.000 A=0.668 F=0.235 J=0.130	P=0.913 R=0.981 A=0.994 F=0.946 J=0.900	P=0.152 R=0.992 A=0.718 F=0.264 J=0.150
SLIC				
	P=0.189 R=0.966 A=0.786 F=0.316 J=0.190	P=0.131 R=1.000 A=0.662 F=0.232 J=0.130	P=0.801 R=0.977 A=0.986 F=0.881 J=0.790	P=0.235 R=0.987 A=0.836 F=0.380 J=0.230
FH				
	P=0.240 R=0.978 A=0.841 F=0.385 J=0.240	P=0.154 R=1.000 A=0.720 F=0.267 J=0.150	P=0.946 R=0.950 A=0.995 F=0.948 J=0.900	P=0.334 R=0.997 A=0.898 F=0.500 J=0.330
QS				
	P=0.244 R=0.984 A=0.844 F=0.392 J=0.240	P=0.151 R=1.000 A=0.713 F=0.262 J=0.150	P=0.966 R=0.960 A=0.996 F=0.963 J=0.930	P=0.101 R=0.995 A=0.547 F=0.183 J=0.100
SEEDS				
	P=0.853 R=0.943 A=0.989 F=0.896 J=0.810	P=0.138 R=1.000 A=0.680 F=0.242 J=0.140	P=0.865 R=0.924 A=0.989 F=0.893 J=0.810	P=0.217 R=0.954 A=0.822 F=0.354 J=0.220
CW				
	P=0.195 R=0.362 A=0.838 F=0.254 J=0.150	P=0.205 R=0.953 A=0.716 F=0.338 J=0.200	P=0.873 R=0.861 A=0.980 F=0.867 J=0.770	P=0.311 R=0.947 A=0.836 F=0.468 J=0.310
SLIC				
	P=0.148 R=0.999 A=0.564 F=0.258 J=0.150	P=0.190 R=0.940 A=0.691 F=0.316 J=0.190	P=0.926 R=0.893 A=0.986 F=0.909 J=0.830	P=0.239 R=0.989 A=0.760 F=0.385 J=0.240
FH				
	P=0.996 R=0.375 A=0.952 F=0.545 J=0.370	P=0.131 R=0.987 A=0.500 F=0.231 J=0.130	P=0.852 R=0.880 A=0.979 F=0.866 J=0.760	P=0.265 R=0.985 A=0.791 F=0.417 J=0.260
QS				
	P=0.276 R=0.742 A=0.832 F=0.402 J=0.250	P=0.184 R=0.949 A=0.675 F=0.308 J=0.180	P=0.955 R=0.801 A=0.982 F=0.871 J=0.770	P=0.287 R=0.961 A=0.815 F=0.441 J=0.280
SEEDS				
	P=0.954 R=0.353 A=0.950 F=0.515 J=0.350	P=0.188 R=0.964 A=0.681 F=0.315 J=0.190	P=0.946 R=0.924 A=0.990 F=0.935 J=0.880	P=0.255 R=0.984 A=0.781 F= 0.405 J=0.250
CW				
	P=0.412 R=0.849 A=0.908 F=0.555 J=0.380	P=0.178 R=0.987 A=0.691 F=0.302 J=0.180	P=0.998 R=0.424 A=0.961 F=0.595 J=0.420	P=0.201 R=0.988 A=0.734 F=0.334 J=0.200
SLIC				
	P=0.531 R=0.828 A=0.939 F=0.647 J=0.480	P=0.174 R=0.988 A=0.683 F=0.296 J=0.170	P=0.927 R=0.688 A=0.975 F=0.790 J=0.650	P=0.212 R=0.986 A=0.752 F=0.349 J=0.210
FH				
	P=0.120 R=0.991 A=0.509 F=0.215 J=0.120	P=0.182 R=0.991 A=0.699 F=0.308 J=0.180	P=0.141 R=0.923 A=0.613 F=0.244 J=0.140	P=0.205 R=0.980 A=0.742 F=0.339 J=0.200
QS				
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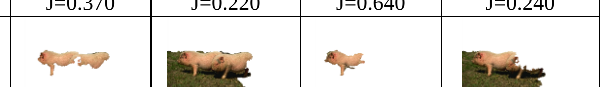
SEEDS				
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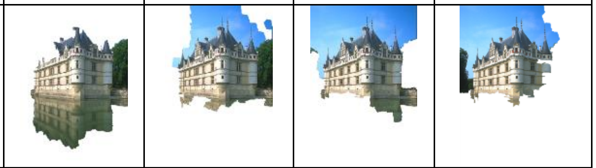
CW				
	P=0.801 R=0.959 A=0.930 F=0.873	P=0.451 R=0.960 A=0.697 F=0.613	P=0.491 R=0.979 A=0.740 F=0.654	P=0.450 R=0.906 A=0.700 F=0.602

	J=0.780	J=0.440	J=0.490	J=0.430
SL IC				
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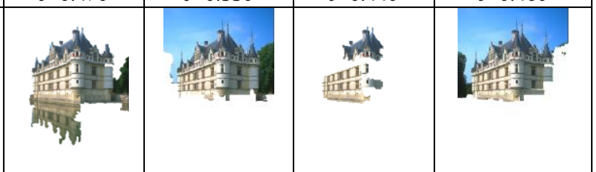
FH				
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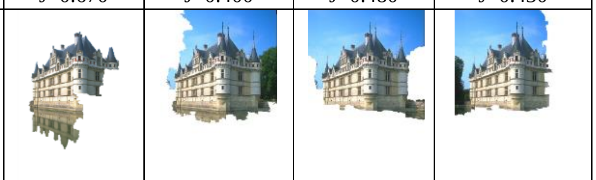
QS				
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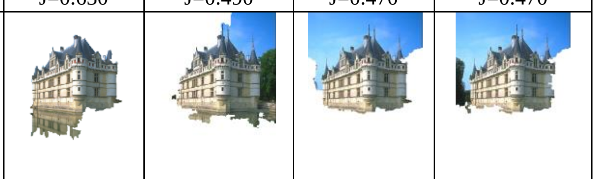
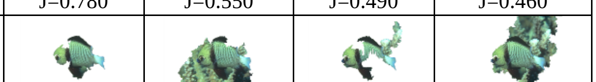
SE E DS				
	P=0.806 R=0.965 A=0.933 F=0.878 J=0.780	P=0.568 R=0.960 A=0.807 F=0.714 J=0.550	P=0.498 R=0.977 A=0.748 F=0.660 J=0.490	P=0.470 R=0.955 A=0.719 F=0.630 J=0.460
C W				
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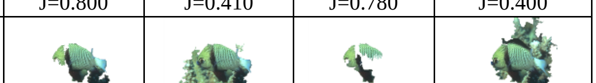
SL IC				
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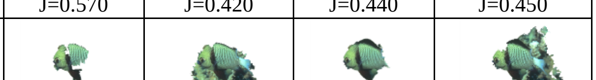
FH				
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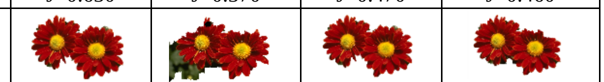
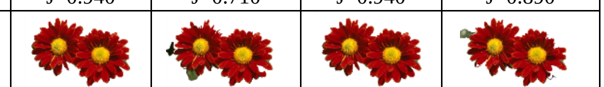
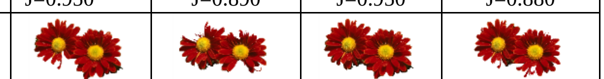
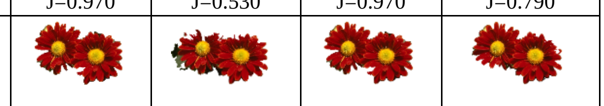
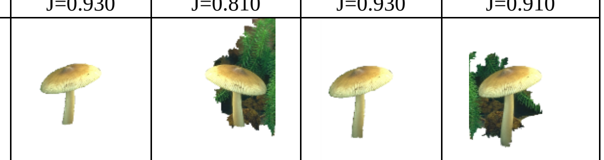
	A=0.930 F=0.731 J=0.580	A=0.821 F=0.623 J=0.450	A=0.967 F=0.895 J=0.810	A=0.789 F=0.592 J=0.420
QS				
	P=0.987 R=0.535 A=0.924 F=0.694 J=0.530	P=0.445 R=0.994 A=0.799 F=0.615 J=0.440	P=0.985 R=0.464 A=0.912 F=0.631 J=0.460	P=0.428 R=0.998 A=0.785 F=0.599 J=0.430
SE E DS				
	P=0.926 R=0.659 A=0.936 F=0.770 J=0.630	P=0.387 R=0.898 A=0.754 F=0.541 J=0.370	P=0.946 R=0.487 A=0.913 F=0.643 J=0.470	P=0.462 R=0.993 A=0.812 F=0.630 J=0.460
C W				
	P=0.981 R=0.959 A=0.974 F=0.970 J=0.940	P=0.807 R=0.852 A=0.843 F=0.829 J=0.710	P=0.981 R=0.959 A=0.974 F=0.970 J=0.940	P=0.971 R=0.919 A=0.952 F=0.944 J=0.890
SL IC				
	P=0.988 R=0.966 A=0.980 F=0.977 J=0.950	P=0.949 R=0.931 A=0.947 F=0.940 J=0.890	P=0.988 R=0.966 A=0.980 F=0.977 J=0.950	P=0.966 R=0.912 A=0.947 F=0.938 J=0.880
FH				
	P=0.978 R=0.926 A=0.957 F=0.951 J=0.910	P=0.983 R=0.771 A=0.892 F=0.864 J=0.760	P=0.967 R=0.981 A=0.977 F=0.974 J=0.950	P=0.991 R=0.907 A=0.955 F=0.947 J=0.900
QS				
	P=0.987 R=0.979 A=0.985 F=0.983 J=0.970	P=0.650 R=0.749 A=0.709 F=0.696 J=0.530	P=0.988 R=0.979 A=0.985 F=0.983 J=0.970	P=0.899 R=0.870 A=0.899 F=0.884 J=0.790
SE E DS				
	P=0.974 R=0.959 A=0.970 F=0.966 J=0.930	P=0.924 R=0.869 A=0.910 F=0.896 J=0.810	P=0.974 R=0.959 A=0.970 F=0.966 J=0.930	P=0.979 R=0.928 A=0.959 F=0.952 J=0.910
C W				
	P=0.991 R=0.850 A=0.980	P=0.304 R=0.866 A=0.728	P=0.992 R=0.894 A=0.985	P=0.421 R=0.949 A=0.826

	F=0.915 J=0.840	F=0.450 J=0.290	F=0.940 J=0.890	F=0.583 J=0.410
SL IC				
	P=0.994 R=0.795 A=0.973 F=0.883 J=0.790	P=0.367 R=0.915 A=0.786 F=0.524 J=0.350	P=0.995 R=0.930 A=0.990 F=0.962 J=0.930	P=0.407 R=0.947 A=0.816 F=0.570 J=0.400
FH				
	P=0.998 R=0.724 A=0.964 F=0.839 J=0.720	P=0.303 R=0.970 A=0.710 F=0.462 J=0.300	P=0.996 R=0.954 A=0.994 F=0.975 J=0.950	P=0.424 R=0.975 A=0.827 F=0.591 J=0.420
QS				
	P=0.884 R=0.930 A=0.975 F=0.906 J=0.830	P=0.281 R=0.817 A=0.708 F=0.418 J=0.260	P=0.997 R=0.735 A=0.966 F=0.846 J=0.730	P=0.347 R=0.915 A=0.768 F=0.503 J=0.340
SE E DS				
	P=0.983 R=0.811 A=0.974 F=0.889 J=0.800	P=0.327 R=0.850 A=0.757 F=0.473 J=0.310	P=0.985 R=0.808 A=0.974 F=0.888 J=0.800	P=0.404 R=0.953 A=0.814 F=0.568 J=0.400

Fig. 6 Individual image segmentation result performed by MSRM and GBMR on CW, SLIC, FH, QS and SEEDS with single and multiple strokes.

The average values for Precision, P, Recall, R, pixel accuracy, A, Jaccard Index, J, and F-score, F, for the five superpixel algorithms on the two interactive segmentations for single stroke are shown in Table 1 while Table 2 shows these values using multiple strokes. The average values of the evaluation matrices obtained combining the single and multiple strokes for the five superpixel algorithms on the two interactive segmentations are shown in Table 3.

Table 1. Overall image segmentation result performed by MSRM and GBMR on CW, SLIC, FH, QS and SEEDS with a single stroke

Single stroke						
		CW	SLIC	FH	QS	SEEDS
P	GBMR	0.357	0.399	0.379	0.345	0.387
	MSRM	0.646	0.575	0.711	0.646	0.861
R	GBMR	0.937	0.949	0.93	0.93	0.933
	MSRM	0.830	0.893	0.794	0.835	0.776
A	GBMR	0.732	0.765	0.717	0.728	0.755
	MSRM	0.914	0.841	0.862	0.906	0.956
F	GBMR	0.478	0.514	0.476	0.473	0.498
	MSRM	0.685	0.636	0.639	0.669	0.791
J	GBMR	0.337	0.383	0.339	0.324	0.364
	MSRM	0.584	0.514	0.516	0.546	0.679

Table 2. Overall image segmentation result performed by MSRM and GBMR on CW, SLIC, FH, QS and SEEDS with multiple strokes

Multiple strokes						
		CW	SLIC	FH	QS	SEEDS
P	GBMR	0.415	0.429	0.494	0.4	0.427
	MSRM	0.852	0.864	0.832	0.902	0.88
R	GBMR	0.952	0.957	0.947	0.948	0.963
	MSRM	0.824	0.838	0.863	0.797	0.832
A	GBMR	0.79	0.808	0.844	0.764	0.806
	MSRM	0.934	0.932	0.914	0.935	0.938
F	GBMR	0.537	0.553	0.601	0.52	0.553
	MSRM	0.809	0.821	0.794	0.817	0.831
J	GBMR	0.399	0.41	0.461	0.379	0.414
	MSRM	0.706	0.719	0.713	0.71	0.729

Table 3. Overall image segmentation result performed by MSRM and GBMR on CW, SLIC, FH, QS and SEEDS with both single and multiple strokes

Overall						
		CW	SLIC	FH	QS	SEEDS
P	GBMR	0.438	0.489	0.484	0.421	0.46
	MSRM	0.82	0.797	0.822	0.837	0.903
R	GBMR	0.939	0.945	0.939	0.936	0.944
	MSRM	0.818	0.839	0.818	0.787	0.811
A	GBMR	0.788	0.828	0.816	0.768	0.81
	MSRM	0.94	0.914	0.914	0.935	0.956
F	GBMR	0.547	0.596	0.588	0.53	0.566
	MSRM	0.788	0.77	0.761	0.766	0.834
J	GBMR	0.414	0.466	0.45	0.394	0.438
	MSRM	0.689	0.663	0.66	0.656	0.735

The findings of this research study are summed up as below:

- In the single stroke setting, application of SEEDS superpixel algorithm improves the segmentation results in terms of F-score and Jaccard index as comparing to other superpixel algorithms for the MSRM interactive segmentation algorithm. However, GBMR, on the other hand, had achieved better results by using SLIC superpixel algorithm.

- In terms of multiple strokes setting, once again, using SEEDS superpixel algorithm improves the segmentation result for the MSRM interactive segmentation algorithm. Contradictory, GBMR segmentation algorithm achieves better segmentation results using FH superpixel algorithm in multiple strokes setting. This could be due to the additional strokes information that had helped the GBMR to have a better understanding on the superpixel generated from FH.
- In terms of both single and multiple strokes, the application of SEEDS superpixel algorithm is regarded as the best choice for MSRM. However, inconsistent results can be seen for GBMR as both the SLIC and FH superpixel algorithms achieved good results with single and multiple strokes.
- Overall, MSRM has higher accuracy, F-score and Jaccard index as comparing to GBMR. On the other hand, the SEEDS superpixel algorithm had helped MSRM to achieve higher accuracy, F-score and Jaccard index following by CW. GBMR was able to achieve a good result if this algorithm used the SLIC superpixel algorithm in the pre-processing process.

The preceding summary demonstrated that the selection of superpixel algorithm in interactive segmentation is critical because it can affect the accuracy of segmentation results. When compared to other algorithms, the application of the SEEDS and SLICS superpixel algorithms produced better segmentation results. As a result, if superpixel is to be used in the pre-processing stage, the interactive segmentation algorithm's design must take the choice of superpixel algorithms into account.

V. CONCLUSION

This paper had used five different types of superpixel algorithms and applied these superpixel images on two interactive segmentation algorithms with single and multiple strokes as the user input. Testing was done on simple and complex images. Evaluation matrices such as Accuracy, F-score and Jaccard index, Precision and Recall were chosen to evaluate the results generated. Overall, MSRM obtained better result compared to GBMR in both single and multiple input strokes using SEEDS superpixel algorithm. The application of SEEDS and SLIC superpixel had improved the segmentation results in MSRM and GBMR. From this study, it can be concluded that, selection of the right superpixel algorithm as a pre-processing step is crucial in the design of interactive segmentation. On the other hand, some shortcomings of the study include a narrow focus on a small number of interactive segmentation and superpixel algorithms. As a result, several recommendations for future research could be made, such as increasing the number of test images from other image datasets. Aside from that, the research could be expanded to include other types of superpixels, sizes of superpixels and interactive segmentation algorithms. In addition, in the preprocessing step, the study can incorporate different types of user input, such as bounding boxes. Finally, with the findings from the previous [28] and current studies, it will be possible to determine whether the segmentation result could be improved with the right user input as well as superpixels.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

All authors contributed equally to the writing of this paper.