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**EVALUATION OF INTERACTIVE AND NON-INTERACTIVE SEGMENTATION  
ALGORITHMS**

**Sameena Banu\*, Apparao Giduturi, Syed Abdul Sattar**

Dept. of CSE, Khaja Banda Nawaz College of Engg., Gulbarga, Karnataka, India

Dept. of CSE, Gitam University, Vishakhapatnam, Andhrapradesh, India

Dept. of E & CE, Royal Institute of Technology, Hyderabad, Andhrapradesh, India

**ABSTRACT**

This paper presents the evaluation framework for both Interactive and Non-interactive segmentation. For the evaluation of interactive segmentation, four algorithms, SRG, BPT, IGC and SIOX are considered.

These algorithms evaluated by considering the accuracy and efficiency measures. Boundary accuracy is measured by fuzzify Jaccard index and object accuracy is measured by binary Jaccard index. It is found that the performance of BPT and IGC is almost same and better than SRG and SIOX. For the evaluation of non-interactive segmentation a new framework is proposed, which is based on composite ground truth. A composite ground truth is constructed by using input segmentation and multiple ground truths. Distance measure is used to measure the quality of segmentation. The proposed measure is compared with F-measure and Probabilistic (PR) index. the proposed method produces the closest results to the human perception.

**KEYWORDS:** Image segmentation, interactive segmentation, non-interactive segmentation, image segmentation evaluation, ground truth..

**INTRODUCTION**

Image segmentation is a fundamental problem in computer vision. Effective and efficient segmentation is an important task in object recognition. In automatic segmentation, the objects are detected automatically. In the interactive segmentation, the user is allowed to intervene in the segmentation process. The user can choose the objects to be segmented by giving object marker and background marker. The Interactive Image Segmentation (IIS) is becoming more and more popular.

This paper presents evaluation method for both automatic and interactive segmentation. Human beings play an important role in evaluating the quality of image segmentation. There are two types of evaluations: the subjective evaluation is most reliable assessment of the segmentation quality. However, it is expensive,

*Table 1: Selected interactive algorithms*

Method	Example Algorithm
1. Region growing	Seeded Region Growing
2. Classifiers	Simple Interactive Object Extraction
3. Graph and MRF model	Interactive Graph Cut
4. Hierarchical/split and merge	Interactive Segmentation using Binary Tree Partition

**A. SEEDED REGION GROWING**

The seeded region growing algorithms proposed by [1], is a simple and computationally inexpensive technique for interactive segmentation of images in which the relevant regions are characterized by connected pixels with similar color values. Although it does not have any statistical, optimizational and probabilistic mathematical foundation, and suffers from certain limitations, it has gained popularity due to its speed and simplicity of implementation.

**B. INTERACTIVE GRAPH CUTS**

The interactive graph cut algorithm, proposed by [2], formulates the interactive segmentation problem within a MRP-MRF framework, subsequently determining a globally optimal solution using a fast min-cut/max-flow algorithm. Due to the algorithm's speed, stability and strong mathematical foundation, it has become popular and several variants and extensions have been proposed. The "GrabCut" algorithm and "Lazy Snapping" algorithms are two such variants developed by Microsoft. We used the original algorithm in our experiments.

**C. SIMPLE INTERACTIVE OBJECT EXTRACTION**

The simple interactive object extraction algorithm, described in [3], uses the pixels marked by the user to build a color model of the object and background regions. It then classifies the pixels in the image as either object or background based on their distance from this model.

The algorithm assumes a feature space that correlates well with human perception of color distances with respect to the Euclidean metric. As such, the first step in the method is to transform the image color into the CIE-lab space.

**(ii) Object accuracy**

For measuring the object accuracy, binary Jaccard index can be applied. The object accuracy measure is given by

$$A_o = \frac{|G_o \cap M_o|}{|G_o \cup M_o|} \quad (4)$$

**EXPERIMENTAL ANALYSIS**

Experiment is performed on different input images.

The below tables show the object accuracy and boundary accuracy and average time required by 4 algorithms to complete a task.

**Table2: Average boundary accuracy and object accuracy obtained.**

Algorithm	Boundary Accuracy		Object Accuracy	
	Best	Final	Best	Final
BPT	0.78	0.78	0.93	0.92
IGC	0.78	0.77	0.93	0.92
SRG	0.70	0.88	0.88	0.88
SIOX	0.64	0.64	0.85	0.85

The Table shows the resulting accuracy values for four algorithms. From the table it is clear that BPT and IGC performance is best. The SOIX algorithm is poorest.

**Table3: Average time needed for users to achieve best accuracies and average total time used to compute a task (seconds)**

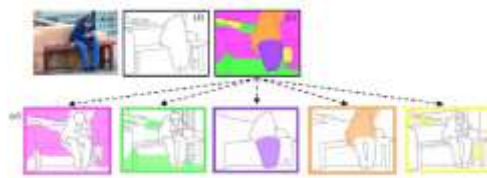
Algorithm	Best Boundary Accuracy	Best Object Accuracy	Final/Total time
BPT	59.76	59.09	64.25
IGC	62.93	62.53	66.43
SRG	69.88	68.90	73.08
SIOX	80.77	80.73	85.32

The Table 3 shows the time required by each algorithm for different accuracies. The below figure shows the time-accuracy characteristics for each of the algorithm.

**EVALUATION OF NON-INTERACTIVE SEGMENTATION ALGORITHMS**

Here an evaluation framework is proposed to evaluate automatic (non-interactive) segmentation algorithms. It is based on multiple ground truths, whereas the existing methods matches the segmentation results with single ground truth. The available dataset of ground truths might not contain the desired ground truth which is suitable to match the input segmentation. Hence such kind of comparison often leads to a certain bias on the result or is far from the goal of objective evaluation.

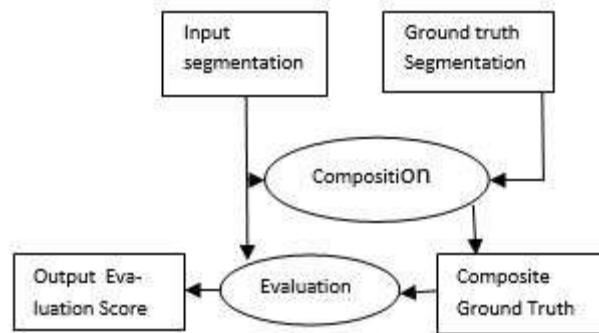
The proposed framework solved this problem. The basic idea is illustrated in Fig. 2.



**Fig. 2. The basic idea which shows composite interpretation between the segmentation and ground truths. (a)Input image and (b) is a segmentation of it. Different parts (shown in different colors (c) of the segmentation can be found to be very similar parts of different human-labeled ground truths, as illustrated in(d).**

Fig.2(b) shows a possible segmentation of the image in Fig. 2(a), and it is not directly identical to any of the ground truths listed in Fig. 2(d). However, one would agree that Fig. 2(b) is a good segmentation, and it is similar to these ground truths in the sense that it is composed of similar local structures to them.

Fig.3 illustrate the flowchart of the proposed framework. Firstly a new composite ground truth is adaptively constructed from the ground truths in the database, and then the quantitative evaluation score is produced by comparing the input segmentation and the ground truth..



**Fig.3 Flowchart of the proposed segmentation evaluation framework.**

$$E(l) = \sum_j D(l_{gj}) + \lambda \cdot \sum_{\{g_j, g_{j'}\} \in M} u_{\{g_j, g_{j'}\}} \cdot T(l_{gj} \neq l_{g_{j'}}) \tag{a}$$

There are two terms in the energy function. The first term  $D(l_{gj})$  is called the data term. It penalizes the decision of assigning  $l_{gj}$  to the elements  $g_j$ , and thus can be taken as measure of difference. Suppose that the normalized distance between the ground truths and the segmentation S is  $\Delta d(s_j, g_j)$ , we can define:

$$D(l_{gj}) = \Delta d(s_j, g_j) \tag{b}$$

The second term  $u_{\{g_j, g_{j'}\}} \cdot T(l_{gj} \neq l_{g_{j'}})$  indicates the cost of assigning different labels to the pair of elements  $\{g_j, g_{j'}\}$  in  $G^*$ . M is neighborhood system and T is an indicator function:

$$T(l_{gj} \neq l_{gj'}) = \begin{cases} 1 & \text{if } l_{gj} \neq l_{gj'} \\ 0 & \text{otherwise} \end{cases} \quad (c)$$

We call  $u_{\{g_j, g_{j'}\}} \cdot T(l_{gj} \neq l_{gj'})$  the smoothness term, which assigns same labels for the same region and it can be defined as:

$$u_{\{g_j, g_{j'}\}} = \min\{\overline{\Delta d_j}, \overline{\Delta d_{j'}}\} \quad (d)$$

Where  $\Delta d_j$  is the average distance between  $g_j^*$  and  $\{g_j^1, g_j^2, \dots, g_j^k\}$ .

In Eq. (a), the parameter  $\lambda$  is used to control the relative importance of the data term versus the smoothness term.

### THE DEFINITION OF DISTANCE

The distance  $\Delta d$ , which is used in Eq. (b) and Eq. (d) needs to be defined to optimize the labeling energy function Eq. (a). There are many distance measures in the existing literature. We have consider Structural similarity index *CW-SSIM* proposed by Sampat et al. (2009). It is a general purpose image similarity index, which uses complex wavelet coefficient. The *CW-SSIM* is slightly modify into a new one called *G-SSIM*, which uses the complex Gabor filter coefficients of an image instead of complex wavelet transform coefficients. The Gabor filtering coefficients are obtained by convolving segmentation with 24 Gabor kernels, which are on 3 different scales and along 8 different directions, respectively. As a result, the *G-SSIM* on each Gabor kernel is defined as:

Where  $\overline{\Delta d_j}$  is the average distance between  $g_j^*$  and  $\{g_j^1, g_j^2, \dots, g_j^k\}$ .  $R_{sj}$  achieves highest value 1 when the distance between  $g_j^*$  and  $\{g_j^1, g_j^2, \dots, g_j^k\}$  is zero and achieves the lowest value zero when the situation is reversed.

### EXPERIMENTAL RESULTS

This section presents the experiments conducted on different images and here the proposed measure is compared with F-measure and the Probabilistic Rand (PR) Index.

The F-measure is mainly used in the boundary based evaluation. Specifically, a precision-recall framework is introduced for this measure. Precision is the fraction of detections that are true positive rather than false positive, while recall is the fraction of true positive that are detected rather than missed. The below Eq. gives the expression for F-measure.

$$F = \frac{PR}{\tau R + (1 - \tau)P}$$

Where  $\tau$  is a relative cost between precision ( $P$ ) and recall ( $R$ ). In the experiments it is set to be 0.5.

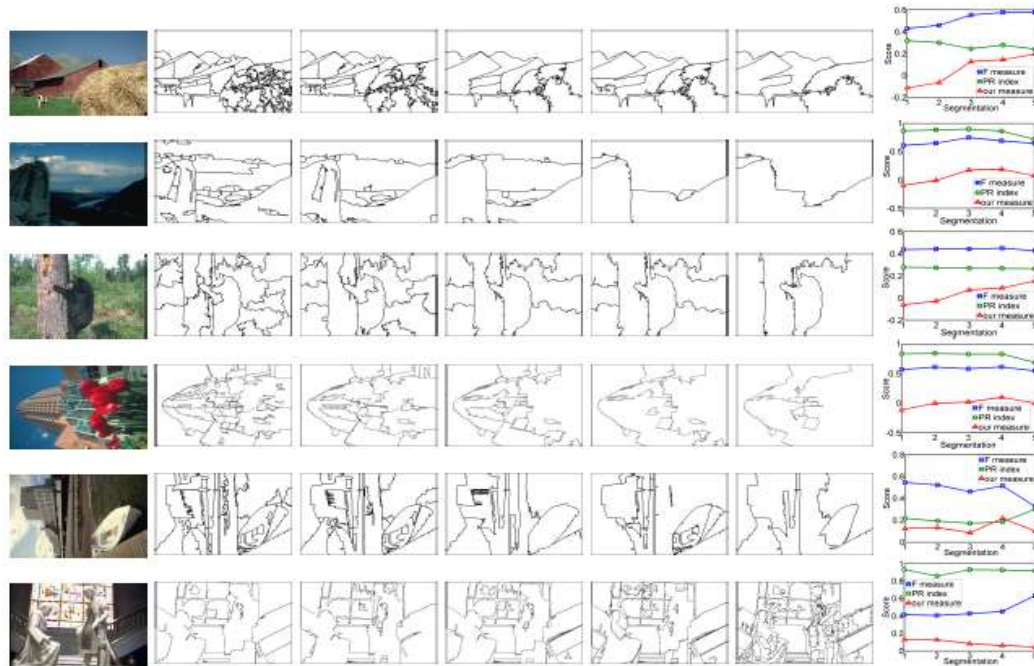
The PR index examine the pair-wise relationship in the segmentation. If the label of pixels  $x_j$  and  $x_{j'}$  are the same in the segmentation image, it is expected that their labels to be the same in the ground truth image for a “good” segmentation and vice-versa.

Fig. 6. shows the different segmentations of the given images produced by the mean-shift method. The right most column shows the plots of scores achieved by F-measure(in blue), PR index (in green) and the proposed method (in red). From graph it is clear that the proposed method produces the closest results to the human perception.

### CONCLUSION

This paper presents the evaluation methods for both interactive and non interactive segmentation algorithms. In case of interactive algorithms, the four basic algorithms i.e., BPT, IGC, SRG and SIOX are considered. The accuracies(boundary and object) and efficiencies are measured different input images. It is found that BPT and IGC performs in almost same manner. The performance of SIOX is poor.

This paper also present an evaluation framework for non-interactive segmentation. The framework is designed by considering the multiple ground truths, whereas the existing methods are based on single ground truth. The method is tested for different input images. The results found are closest to human perception.



**Fig. 6. Example of measure scores for different segmentations. For each original image, 5 segmentations are obtained by the mean shift algorithm. The rightmost column shows the plots of scores achieved by F-measure (in blue), PR index (in green) and proposed method (in red).**

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