Evaluating The Effectiveness Of Region Growing And Edge Detection Segmentation Algorithms.

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Abstract: One of the important problems that ever exist in performance evaluation of any segmentation algorithm is that, when we ingrain the obtained results in a specific application, these results may not be expandable to any other application. So, it is very difficult to appraise whether one algorithm produces more precise segmentation than the other one. This paper, presents a novel technique through which the evaluation of the effectiveness of Region Growing and Edge Detection segmentation algorithms is carried out. The proposed evaluation metric is based on the EXOR measure approach, which was originally proposed for the evaluation of skin tumor borders [1]. This performance measure is then extended to a condition where the evaluation of these two image segmentation algorithms can be compared in a suitable and appropriate manner. In order to validate the proposed performance measure, we used 300 images from the publicly available Berkley Segmentation Dataset. These images are classified into seven groups of images, according to the dominant image. The evaluation and comparison results shows that the effectiveness of edge detection segmentation algorithm is better than region growing segmentation algorithm in many applications. [Journal of American Science 2010;6(10):580-587]. (ISSN: 1545-1003).

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1. Introduction

Nowadays, Image Segmentation has different application in our real world. The most important ones include: Face recognition, Image-guided surgery, Fingerprint recognition, and automated inspection of industrial parts.

Image segmentation is the process of partitioning the digital image into different regions that can be associated with the properties of one or more criterion. Regions are elementary picture elements in a segmented image, formed as an aggregation of pixels. Their internal properties, like color, texture, intensity, shape, etc. help us to identify regions clearly with their external relations; like adjacency, inclusion, and similarity of properties.

These relations are used to build groups of regions that have a particular meaning in a more abstract context. The combination of regions forming the group is again a region with both internal and external properties and relations. We cannot easily identify an object in a given picture by simply searching for a region with single color or texture; it is the collection of projected surface spaces that allow the recognition of that object in a picture.

The correctness of segmentation is highly dependent on the success or failure of each computerized analysis procedure. After the segmentation process is over, we should know which pixel belongs to which object, the discontinuities where abrupt changes lie, tell us the locations of boundaries of regions.

The connectedness of any two pixels is identified when there exists a connected path wholly within the set, where a connected path is a path that always moves between neighboring pixels. Therefore, region is a set of adjacent connected pixels.

Extensive researches have been made in designing and creating different segmentation algorithms [2, 3], however, still no algorithm is found from the researches results that can be accepted and appropriate for all kinds of images, obviously, all segmentation algorithms cannot be equally applicable to a certain application. For this reason, this paper presents a novel technique, through which we can evaluate and compare the effectiveness of two different segmentation algorithms on many different images, which are drawn from the publicly available Berkley Segmentation Dataset [4], these images are classified into seven groups of images according to the dominant image.

Even though there exist different kinds of segmentation algorithms, only region growing and edge detection segmentation algorithms are considered in this paper, where they are assumed to have strong correlation, their effectiveness are evaluated by different parameters which will be discussed later.

This paper is organized as follows: In Section 2, we provide an overview of the previous related works on objective segmentation evaluation that relate most closely to our proposal evaluation method. In Section 3, we describe in some details, the region growing and edge detection algorithms. The proposed evaluation and comparison technique is presented in Section 4. Results and analysis are presented in Section 5. Finally, Section 6 concludes the paper.

2. Material and Methods

1. Related work

While they do not require ground truth image segmentation as the reference, a number of researches on the evaluation of image segmentation have been developed in the past few decades. In these evaluation methods, the segmentation performance is usually measured by some contextual and perceptual properties. This is done by subdividing an image into its constituent parts and extracting the interesting parts. In [5], the evaluation of segmentation algorithm is a visual-based evaluation method, in which the average value of the gray level of all pixels inside a region can be used to identify that region.

This method has its own problem, i.e. the difficulty of evaluating the goodness of the segmentation arises when two adjacent regions have similar values of average gray level. Besides, the human eye is not able to distinguish between regions which have very close gray levels. In [6], the authors presented a segmentation technique which basically depends on the conventional region growing segmentation algorithm.

The unseeded region growing segmentation algorithm does not depend on tuning of parameters, nor does it requires seeds from which the region growing process starts. In [7], the author's quantitavily compare three segmentation algorithms namely; mean shift, efficient graph based, and hybrid segmentation, where the comparison is based on the normalized probabilistic rand index as performance metric, accompanied with experimental results.

The segmentation algorithms that we are going to compare in this paper are Region Growing and Edge Detection, which are absolutely different from the algorithms that the above authors worked on. Besides, we will be using the performance metric, i.e., the more elaborate measure, EXOR along with other different kinds of evaluation techniques.

2. Region Growing and Edge Detection Algorithms.

This paper focuses on evaluating the Region growing and Edge detection segmentation techniques as they both are well-developed fields on their own within image processing and Region boundaries. Edges are closely related, since there is often a sharp adjustment in intensity at the region boundaries.

A region in an image can be defined by its border (edge) or it's interior. If we know the interior part of the image, then we can always define the border and vice versa. Because of this, image segmentation approaches can typically be divided into two categories, edge and region based.

2.1 Region Growing Algorithm

Region growing is one of the image segmentation algorithms and as its name indicates, it is the process of merging neighboring areas into larger regions to segment an image, based on the similarity of pixels and works by selecting seed pixels as starting point.

The aim of region-based segmentation techniques is to extract the homogeneous sectors from the given input image, i.e. to partition an image into regions. Regions as aggregations of primitive pixels play an extremely important role in nearly every image analysis task. In mathematical sense, the segmentation of image *I* which is a set of pixels, is the partition of *I* into *n* disjoint sets $R_1, R_2, \ldots, R_n$, called segments or regions, such that the union of all regions equals I [8].

$$I = R_1 \cup R_2 \cup \ldots \cup R_n$$

This segmentation approach examines the neighboring pixels of the initial seed point, then decides whether the pixel to be added to the seed point or not. The regions are iteratively grown by comparing the pixels that are not allocated to the regions until all pixels are allocated. The basic formulation for Region-Based Segmentation can be given as follows [9, 10]:

A. $\bigcup_{i=1}^{n} R_i = R$
B. R_i is a connected region , i = 1,2,3…..,n.
C. $R_i \cap R_j = \emptyset$ for all, i and j and $i \neq j$
D. $P(R_i)$ = TRUE for i =1,2,3…..,n.

E. $P(R_i \cup R_j)$=false for any adjacent Region Ri $i \neq j$.

Where: P (R_i) is a logical predicate defined over the points in set P (R_k) and $\varnothing$ is the null set**.**
(A) Indicates that the segmentation must be complete; that is, every pixel must belong to a region.
(B) Indicates that pixels in a region must be connected (i.e. all pixels have the same homogeneity values)
(C) Indicates that the regions must be disjoint (i.e. Pixels in each Region must have different values).
(D) States that pixels in a region must all share the same property – The logic predicate
P (Ri) over a Region must return TRUE for each point in that region.
(E) Indicates that region R_i and R_j are different in the sense of predicate P.

2.2. Edge Detection Algorithm.

Edge detection is currently becoming a problem of fundamental importance in image analysis, even if it is one of the different image segmentation techniques. In typical images, edges characterize object boundaries, and are therefore useful for segmentation and detection of objects in a scene.

Edge detection is a term in image processing and computer vision, it refers to algorithms which aim at identifying points in a digital image at which there is an abrupt change in image brightness or more formally, has discontinuities or simply where there is a jump in intensity from one pixel to the next [11].

There are many ways to perform edge detection; however, the majority of different methods may be grouped into two categories: [12]

- Gradient: The gradient method detects the edges by looking for the maximum and minimum in the first derivative of the image.
- Laplacian: The Laplacian method searches for zero crossings in the second derivative of the image to find edges. An edge has the one-dimensional shape of a ramp/slope/rise, calculating the derivative of the image can highlight its location.

3. The proposed evaluation and comparison technique.

In our image segmentation evaluation methods, ground-truth of the Berkley Data set [4] which contains a total of 300 images, is used as a reference against segmented input images, the performance is measured by calculating the discrepancy between the considered segmentation and the ground-truth segmentation. Besides, data that contains the output of the users feelings are collected and analyzed as users are expected to be the end users from the segmented outputs. The proposed evaluation and comparison method, is based on EXOR measure, this technique involves the following points:

- We create a procedure for algorithm evaluation through an example of evaluating the two most known image segmentation algorithms: Region Growing and Edge Detection algorithm.
- We used the 300 images from the publicly available Berkeley Segmentation Data Set and divide it into seven groups of images according to the dominant image, in order to validate the proposed performance measure.
- The proposed technique is different from other former techniques, where it considers not only evaluation techniques but also comparisons that involve the end users.
- As evaluation must be from all walks of life, treating source images that have more unwanted signals than the wanted ones, as well as more wanted signals than the unwanted ones are considered, the cons and pros of each of the obtained outputs are presented.
- The performance measure we used is based on the EXOR measure approach, which was originally proposed for the evaluation of skin tumor borders. This performance measure (EXOR) is then extended to a condition where the evaluation of the two image segmentation algorithms can be compared in a suitable and appropriate manner.

3. Results and analysis

In this section, the outputs obtained from Region Growing and Edge Detection segmentation algorithms are presented, as shown in figures 1 and 2, respectively. Then, the evaluation and comparison for these two algorithms follow next.

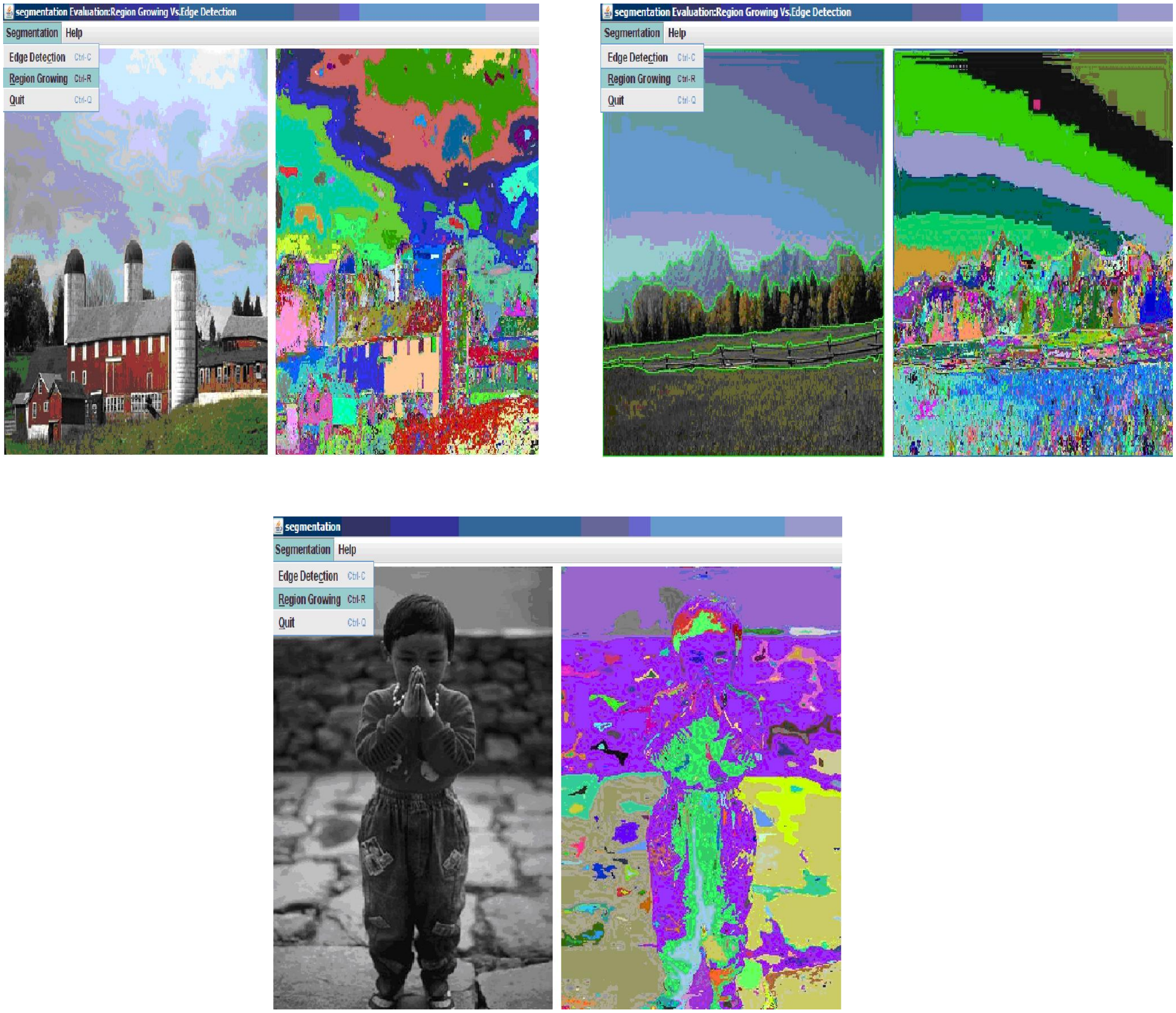

Figure 1: Results obtained using Region Growing Algorithm, the input Images (Left) and The Segmented Image results (Right).

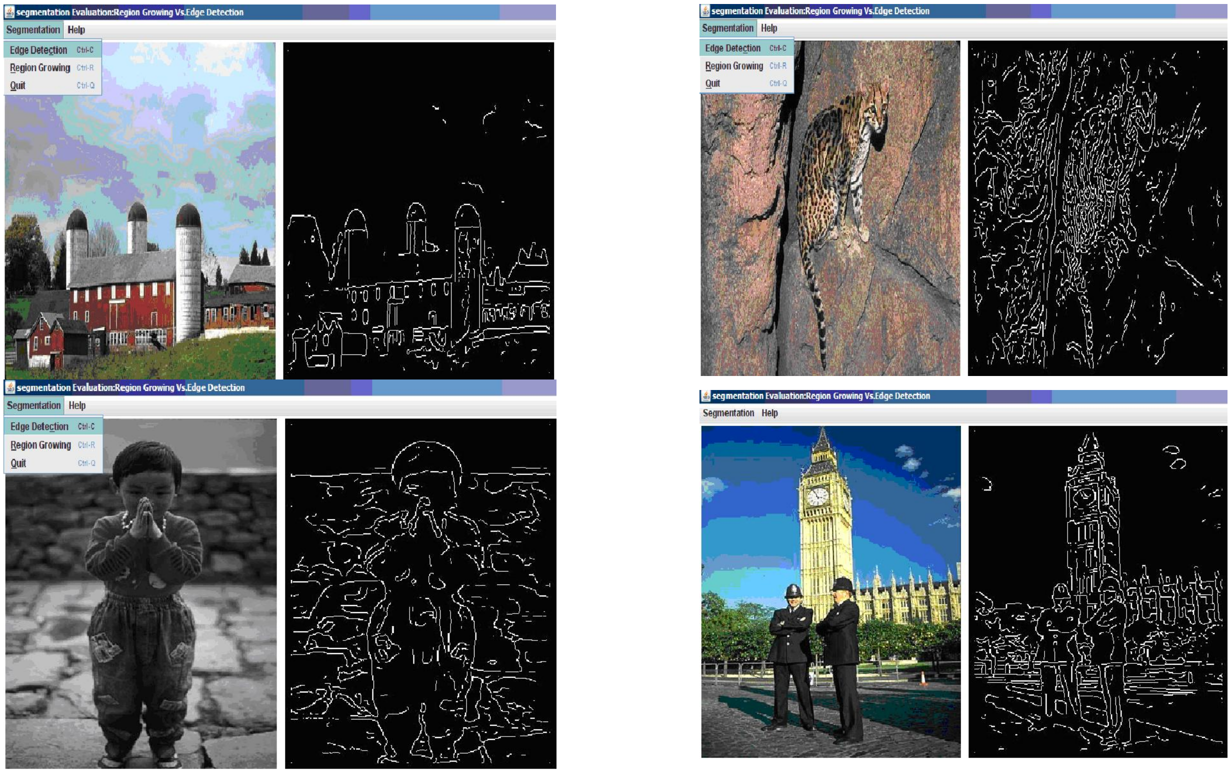

Figure 2: Results obtained using Edge Detection Algorithm, the input Images (Left) and The Segmented Image results (Right).

4.1 Comparison by Empirical Goodness Method.

Empirical Goodness method evaluates the effectiveness of Region Growing and Edge Detection segmentation algorithms based on "How well it is equivalent to the desired characteristics of a good segmentation". This is based on human judgements, therefore, a total number of 150 people's judgment about the segmented results is obtained. The People's judgments are classified into 5 categories, where each one assigned to a certain rank as follows:

Excellent=5, Very Good=4, Good=3, Poor=2, and Unacceptable=1.

The Empirical Goodness Method is carried out on 300 images of Berkley dataset [4]. The images are grouped into seven groups. The ranks values to an image are averaged, and the segmentation evaluation is based on the calculated attained value X as follows: X< 2.5 à Unacceptable segmentation, and X>=2.5 à Acceptable Segmentation. The obtained results are shown in Figures 3 and 4.

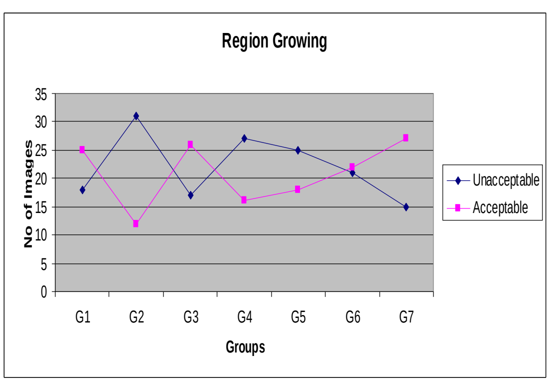

Figure 3: Results for Region Growing algorithm for the seven groups obtained from users' comparison.

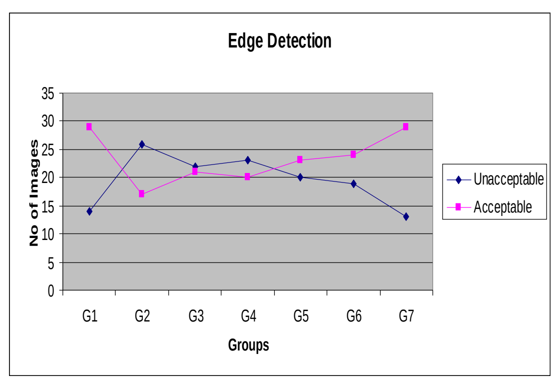

Figure 4: Results for Edge detection algorithm for the seven groups obtained from users' comparison.

Looking at Figures 3 and 4, we feel that the Edge detection segmentation method is more successful than the Region Growing on the same input images like G1, G5, G6 and G7. In our opinion, the achievement of the edge detection method over region growing can be due to the fact that; the objects of our interest shown in the image contains more number of pixels and therefore, it is easy to recognize the signal from the noise since it has a visible resolution. But this case might fail in areas where objects of our interest absorb very little number of pixels.

4.2 Comparison using Empirical Discrepancy Method: The EXOR Measure

The XOR measure, first used by Hance et al. [1] quantifies the percentage border detection error by:

$$Error = \frac{Area(M \oplus A)}{Area\ (M)}$$

Where $M \oplus A$ is the difference between the region in the manual, and the region in the automatic Segmentation. Area (M) or Area (A) calculates the number of pixels in the image.

In the following section, quantitative evaluation technique is used, the methodology and techniques used to quantitatively evaluate the two segmentation algorithms, is described below.

Assume that we have a manually segmented image which is known to be a Ground Truth, as shown in figure 5.

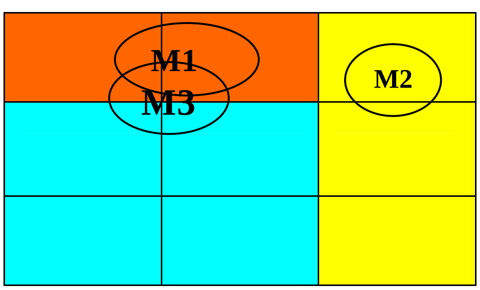

Figure 5: Manually segmented Image.

The original input Image is segmented using the two segmentation algorithms, figure 6 shows the output obtained.

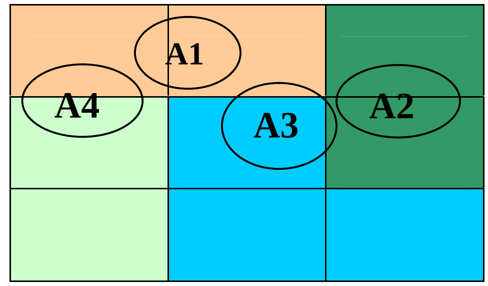

Figure 6: Result from the Automatic segmentation.

For each region, we can identify target and background. Target is all pixels that make up the region. Background is equal to all pixels in the picture minus target pixels of the region. For example, for the manual segmentation of region 1 (A1):

Target = {(1, 1), (1, 2)}

Background ={(1,3),(2,1),(2,2),(2,3),(3,1),(3,2),(3,3)}

Similarly, for the automatic segmentation of region 3 (A3), we can define Target and Background as:

Target = {(2, 2), (3, 2), (3, 3)}

Background = {(1,1) ,(1,2),(1,3),(2,1) ,(2,3),(3,1)}

To compare the similarity of regions in the automatic and manual segmentations we can define the error as follows using XOR:

$$Error = \frac{Area(M \oplus A)}{Area\ (M)} = (FT + FB)/\ (TT+TB)$$

Note that, FT = False Target, FB = False Background, TT = True Target, and TB = True Background.

The meaning of these values is shown in Table 1.

Table 1: Meaning of detected values.

		Detected as	
		Target	**Background**
Actual Pixel	**Target**	TT	FB
	Background	FT	TB

For example, if a background pixel is detected as target, it is considered as FT. Then, we can compare each region of the manual segmentation, with all regions of the automatic segmentation, and take the minimum value.

For example, when region 1 (A1) of the manual segmentation is compared with all four regions of the automatic segmentation, the error is calculated as follows:

$$Error = \frac{Area(M \oplus A)}{Area\ (M)} = (FT + FB)/\ (TT+FB)$$

With region A1: Error = (0+0)/ (2+0) = 0
With region A2: Error= (2+2)/ (0+2) = 4/2
With region A3: Error= (3+2)/ (0+2) = 5/2
With region A4: Error= (2+2)/ (0+2) = 4/2

Table 2 shows all comparisons:

Table 2: Comparisons between Manual and Automatic Segmentation.

		Manual Regions		
		1	2	3
Automatic Regions	1	0	5/3	6/4
	2	4/2	1/3	6/4
	3	5/2	4/3	3/4
	4	4/2	5/3	2/4
Minimum		0	1/3	2/4
Average		= (0 + 1/3 + 2/4)/ (3) = 10/36		

From Table 2, we can see that the minimum is taken, then the average is taken as the error of the automatic segmentation when compared to the ground truth. The same process is followed for each of the remaining regions. Finally, the mean is computed for the two segmentation algorithms considered (Region growing and Edge detection). Then, the minimum error value is taken as the best segmentation algorithm.

After calculating the error for all regions in both segmentation algorithms, the mean is obtained, analyzed and depicted in Figures 7 and 8.

The following result is obtained by applying the above parameter on each of the segmentation algorithms, for each group G1, G2,…, and G7.

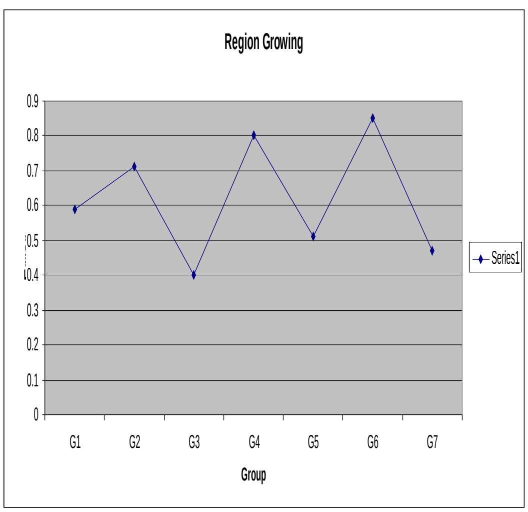

Figure 7: Result of Region Growing Algorithm for the seven groups obtained by EXOR measure.

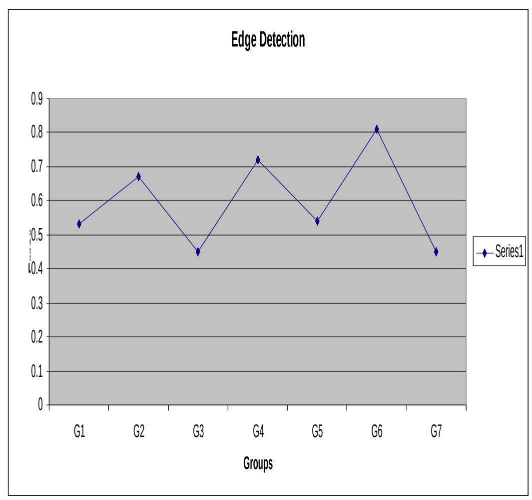

Figure 8: Result of Edge Detection Algorithm for the seven groups obtained by EXOR measure.

From the above results shown in Figures 7 and 8 for the two image segmentation algorithms, Region Growing segmentation algorithms offers a satisfying performance results. In general, we summarize the results obtained with the following two points:

- The implemented Region Growing Algorithm is expected to face source images with regions with almost constant pixel characteristics.
- The edge detection algorithm is implemented with input images that have more unwanted signals, which are hard to be distinguished from the desired signals. In contrast regions, unlike edge detection algorithm, cover more number of pixels and thus we can have more information available in order to attain our regions of interest.

5. Conclusions

This paper specifically evaluates the effectiveness of the Region Growing and Edge Detection segmentation algorithms. Achieving results with all the desired segmentation result is actually difficult, since there is no theory of image segmentation, nor the ad hoc nature of image segmentation techniques.

From the above results, we can conclude that the excellence of the segmented results, highly depends on the sharpness of the source image for both image segmentation algorithms, i.e., if the original image is very sharp edged and does not have noise, the result reaches perfection so that the segmented image results will have simple regions having significantly different values, and boundaries that are simple and easy to visualize.

The evaluation and comparison results shows that the effectiveness of edge detection segmentation algorithm is better than region growing segmentation algorithm in many applications.

With the data obtained, we showed significant differences in the image segmentation algorithm performances, also we illustrated clear dissimilarities that arise from the input or source images provided. In general, our results enable high effectiveness performance comparison between Region Growing and Edge Detection algorithms; also provide possible guidelines in selecting suitable algorithms for the desired applications.

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