Determining Distance Measure in Fast Scanning Algorithm for Image Segmentation

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***Abstract*—Segmentation is an essential and important process that separates an image into regions that have similar characteristics or features. Various algorithms have been proposed for image segmentation and this includes the Fast Scanning algorithm which has been employed on food, sport and medical images. The clustering process in Fast Scanning algorithm is performed by merging pixels with similar neighbor based on Euclidean Distance. Such an approach leads to a weak reliability and shape matching of the produced segments. This study investigates the alternatives distance measure to be employed in Fast Scanning algorithm. Distance between pixels is identified for four measures; Euclidean, City Block, Dice and Sorensen. Results show that the Sorensen is a better measure to be used in Fast Scanning algorithm for image segmentation**

***Index Terms*—Fast Scanning Algorithm; Image Segmentation; Euclidean Distance; City Block Distance; Dice Distance; Sorensen Distance.**

I. INTRODUCTION

Image segmentation is one of the steps in image processing. It segments images for accurate boundaries that transform the image's representation for detail [1]. Its key point is that the image is divided into a number of sets that do not have mutual overlapping zones; these zones either have meaning to currently mission or help to explain correspondence between them and the actual object or some parts of object [2].Hence, it is a process in which divide an image into disjoint regions that are meaningful with feature section and removes that relevant objects.

Many image segmentation techniques have been developed by researchers and scientists, and these techniques can be generally classified into three major categories [3]. The segmentation techniques that are based on discontinuity property of pixels are considered as boundary or edges based techniques and the ones that are based on similarity or homogeneity are considered as region based techniques. On the other hand, the hybrid techniques are the ones that merge techniques from the first and second categories [4].

The region based segmentation approach partitions an image into similar/homogenous areas of connected pixels [5]. Each of the pixels in a region is similar with respect to some characteristics or computed property such as colour, intensity and/or texture. Region growing is a simple region-based image segmentation method. It is also classified as a pixel-based image segmentation method since it involves the selection of initial seed points [6]. This approach examines neighboring pixels of initial "seed points" and determines whether the pixel neighbors should be added to the region. The selection of seed points can be adaptively and fully automatic by unseeded region growing (URG). It does not depend on tuning parameters and is additionally free from manual input [7]. Fast Scanning algorithm is an example of URG segmentation algorithms which consider automation in selecting the start seed. It is based on the assumption that the neighboring pixels within one region have identical value [8]. The current process includes the scan on all pixels in the image and clusters each pixel by comparing one pixel with its upper and left neighbor pixels. Hence, clustering is done by merging pixels with similar neighbor [9]. Clustering in image segmentation capture the global characteristics of the image through the selection and calculation of the image features, which are usually based on the color or texture [10]. By using a specific distance measure that ignores the spatial information, the feature samples are handled as vectors. The objective is to group them into compact, but well-separated clusters. Hence, similarity measure plays a critical role in clustering [11].

In standard Fast Scanning algorithm, distance between pixels is identified using a fixed distance measure (i.e. Euclidean distance). This study investigates the employment of various similarity measures in Fast Scanning algorithm such as the City Block [12], Dice [13] and Sorensen [14].

II. FAST SCANNING ALGORITHM

Fast Scanning algorithm is an example for the URG [15]. Its application can be found in nature images, medical images and food images. It does not require a seed point in segmentation process. The selection of Fast Scanning algorithm in muscle image segmentation is due to the fact that it is faster thanother existing segmentation algorithm [16]. Besides that, it offers the ability that each cluster isconnected and has similar pixel value. A good image segmentation algorithm should have the following three advantages: (1) fast speed, (2) good shape connectivity, and (3) good shape matching [7].

Fast Scanning algorithms have been applied on Gray-level and colour images. Also, three candidate popular algorithms have been applied like region growing, K-means and watershed for this kind of role. However, none of the three algorithms have these three characteristics at the same time. Efficient image segmentation based on one-timeFast Scanning and upper-left Merging algorithms were proposed [16]. It based on apply the techniques of Fast Scanning, the adaptive region mean, and the vertical / horizontal difference but, each pixel is processed only once. The proposed Fast Scanning algorithm can also be applied to the colour image. With these techniques, the segmentation results of their method are as well as those of the region growing method, but the computation time is less [17].

III. DISTANCE MEASURE

Distance-based approaches calculate the distance from each point to a particular point in the data set [18]. In image analysis, the distance is the measure of each object point to the nearest boundary and it is an important tool in computer vision and image processing. There have been considerable efforts in finding the appropriate measures for various applications such as in pattern classification, clustering, and information retrieval problem [19]. Distance to the mean, averaged distance between the query point and all points in the data set, and maximum distance between the query point and data set points, are examples of the many available options [20]. Since the performance of clustering relies on the choice of an appropriate measure, many researchers have taken elaborate efforts to find the most meaningful distance measures. Numerous binary distance measures and similarity measures have been proposed in various fields. There are several distance measures used in color image processing. As well as, each color image has three colors representing by blue, green and blue colors then by merging the three matrices will produced the real colors [21]. In this study, we focus on City Block, Dice and Sorensen.

A. City Block Distance

The City Block distance is introduced by Hermann Minkowski in late 19th century [22]. It is also known as rectilinear distance, taxicab norm, or Manhattan distance. The name is given based on the distance of a car driven in a city laid out in square blocks, like Manhattan. According to [18] City Block distance assumes a triangular distribution and it is particularly useful for discrete descriptors. In addition, the City Block Distance (DCB) relies on the choice on the rotation of the coordinate system, but does not depend on the translation of the coordinate system or its reflection with respect to a coordinate axis [23]. It is defined as:

$$DCB = \sum_{i=1}^{d} |Pi - Qi| \tag{1}$$

where the P and Q are two points. In a three-color space P with the coordinates ($p1$, $p2$, $p3$), Q with the coordinates ($q1$, $q2$, $q3$). The d refers to dimensions and i is point counter.

B. Dice Distance

This index was first proposed by Dice in 1945 as a measure of distance or similarity derived from Dice's coincidence index [13]. It has separately developed by the botanists Thorvald Sørensen and Lee Raymond Dice, whom then published in 1948 and 1945 respectively. It is more regarding to the Jaccard coefficient, with further weight being given to cases of mutual agreement. The dice distance ($DDICE$) measure is defined as:

$$D\,DICE = \frac{2\sum_{i=1}^{d} \mathrm{PiQi}}{\sum_{i=1}^{d} Pi2 + \sum_{i=1}^{d} Qi2} \tag{2}$$

where the P and Q are two points. In a three- color space P with the coordinates ($p1$, $p2$, $p3$), Q with the coordinates ($q1$, $q2$, $q3$). The d refers to dimensions and i is point counter.

C. Sorensen Distance

It is similar to Jaccard's index and its applications are familiar in several fields especially in ecology [24] Sorensen distance is a settlement method that views the space as grid similar to the City Block distance. It has a good property that if all coordinates is positive, its value is between zero and one. The Sorensen distance ($Dsor$) measure is defined as using absolute difference divided by the combination [20] as in the below equation:

$$\frac{\sum_{i=1}^{d} /Pi - Qi/}{\sum_{i=1}^{d}(Pi + Qi)} \tag{3}$$

where the P and Q are two points. In a three- color space P with the coordinates ($p1$, $p2$, $p3$), Q with the coordinates ($q1$, $q2$, $q3$). The d refers to dimensions and i is point counter.

IV. METHODS

This section presents the methodology implemented in this study. The phase incorporates two major tasks; Data Collection and Identification of Suitable Distance Measure.

A. Data Collection

The Data Collection phase includes the process of building the image repository. A collection of Iraqi and Saudi car images (images that contains car plates segments) is utilized as the dataset. The dataset includes images of private and public transportation (i.e. taxis) in both countries. The collection is built upon images captured in public parking and garages using digital camera and stored as JPEG format with RGB color space and dimensions 600*600 pixels. In total, there are 13 Iraqi car images and 12 Saudi car images included in the collection. Samples of the images are shown in Figure 1.

Figure 1: Sample of Images

B. Identification of Distance Measure

The aim of this study is to determine the suitable distance measure to be used in Fast Scanning algorithm for grouping pixels. The RGB space color have been used as input dataset and four distance measures are compared; Euclidean, City Block, Dice and Sorensen Distance. In detail, this study investigated the distance for 25 adjusted pairs of pixels in each image of the dataset.

Once the measure with the smallest distance is identified, we evaluate the segments produced by Fast Scanning algorithm. This evaluation is based on the Peak Signal to Noise Ratio (PSNR) that represents region homogeneity of the final partitioning. The higher the value of PSNR, the better the segmentation is. PSNR is calculated in decibels (dB) and is obtained using:

$$PSNR = 20log_{10}\left(\frac{255}{MAE}\right) \quad (4)$$

$$MAE = \frac{1}{MN}\sum\sum|F(i,j) - f(i,j)| \quad (5)$$

where, 255 is max of pixels' number and *MAE* is abbreviation of *t* mean- absolute error, is *F (i, j)* - segmented image, *f (i, j)* - source image that contains *M* by *N* pixels.

When PSNR value approaches infinity the mean absolute error (MAE) approaches zero; this shows that a higher PSNR value provides a higher image quality. On the other end, a small value of the PSNR implies high numerical differences between images [25].

V. RESULTS

Results presented in this section includes the ones obtained using the four distance measures; Euclidean (D $_{EUC}$), City Block Distance (D $_{CB}$), Dice Distance (D $_{DIC}$) and Sorensen Distance (D $_{SOR}$), and the PSNR for the obtained image segmentation. Illustration in Figure 2 shows samples of image produced by Fast Scanning algorithm using the four distance measures. It can be noted that images produced by Sorensen distance is more clear and better compared to images produced by other three measures.

Euclidean | City Block | Dice | Sorenson

Figure 2: Sample of Images of Fast Scanning with Four Distance Measures

Data in Table 1 depicts the results on distance value between pixels of the images under analysis. The value represents distance between pixels (25 pairs) for all images with respect to the different types of employed measures. All distance measure produced different values of distance for the pair of pixels. Depending on numerical examples which shown Table 1, the Sorensen distance measure produced the smallest distance (average) of pixels pairs for all images in the dataset. The smallest distance was 0.001 while the farthest was 0.08. In Table 2, results on PSNR for the 25 images are presented and it includes the ones obtained using Fast Scanning with Euclidean and Fast Scanning using Sorensen. The data shows that when using Sorensen distance measure, the Fast Scanning algorithm produced better segmentation; the highest PSNR is 51.5 dB and the lowest is 33.6 dB. On the other hand, Fast Scanning that employs the Euclidean Distance only obtained as high as 27 dB.

Table 1
Distance: Euclidean vs. City Block vs. Dice vs. Sorensen

Image	D $_{EUC}$	D $_{CB}$	D $_{DIC}$	D $_{SOR}$
1	52.81 %	86.16 %	0.962 %	0.088 %
2	25.90 %	42.68 %	0.991 %	0.062 %
3	2.04 %	3.24 %	0.999 %	0.005 %
4	15.05 %	23.08 %	0.994 %	0.018 %
5	3.18%	14.6 %	0.998 %	0.004 %
6	10.70 %	18.44 %	0.998 %	0.017 %
7	20.07 %	34.64 %	0.989 %	0.050 %
8	2.05 %	3.12 %	0.999 %	0.002 %
9	7.94 %	12.68 %	0.983 %	0.029 %
10	7.46 %	12.24 %	0.998 %	0.015 %
11	5.93 %	9.08 %	0.998 %	0.009 %
12	2.04 %	3.32 %	0.999 %	0.001 %
13	2.74 %	4.84 %	0.999 %	0.003 %
14	24.44 %	41.52 %	0.992 %	0.039 %
15	16.62 %	28.4 %	0.983 %	0.066 %
16	2.76 %	4.8 %	0.998 %	0.003 %
17	21.32 %	34.4 %	0.995 %	0.032 %
18	6.05 %	9.8 %	0.998 %	0.009 %
19	2.84%	4.46 %	0.998 %	0.016 %
20	3.29 %	5.28 %	0.996 %	0.024 %
21	7.01 %	10.8 %	0.999 %	0.011 %
22	10.15 %	16.08 %	0.995 %	0.043 %
23	13.43 %	30.72 %	0.998 %	0.061%
24	1.83 %	2.92 %	0.998 %	0.001 %
25	24.30 %	40.44 %	0.980 %	0.050 %

Table 2
PSNR: Fast Scanning with Euclidean and Sorensen

Image	Fast Scanning with Euclidean	Fast Scanning with Sorensen
1	22.3267 dB	40.8659 dB
2	20.9571 dB	42.0770 dB
3	22.6875 dB	43.5071 dB
4	24.4341 dB	44.4744 dB
5	20.7392 dB	46.2370 dB
6	22.2288 dB	46.6260 dB
7	23.4403 dB	38.9482 dB
8	21.5217 dB	48.2959 dB
9	21.3919 dB	47.7655 dB
10	23.4721 dB	33.6031 dB
11	24.0230 dB	45.8519 dB
12	23.9077 dB	42.7739 dB
13	24.9842 dB	43.1586 dB
14	23.1338 dB	51.4769 dB
15	20.5870 dB	47.3067 dB
16	23.6166 dB	41.9966 dB
17	20.4396 dB	50.2132 dB
18	21.5516 dB	43.1609 dB
19	26.5983 dB	43.9811 dB
20	26.9025 dB	42.1207 dB
21	21.2291 dB	43.4534 dB
22	22.9223 dB	43.7182 dB
23	20.9021 dB	44.0606 dB
24	22.2408 dB	40.8380 dB
25	21.6995 dB	39.3502 dB

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