A Study on Image Segmentation Techniques used in Color Detection

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***Abstract*— to humans, an image is a meaningful arrangement of regions and objects, whereas to computers, an image is merely a random collection of pixels. This work exploits some of the techniques based on the extraction of the color of an image in the real-time environment. Image segmentation is an intense research area in Computer Vision, however, enhancements or results still on to produce accurate segmentation results for images. Relating with other surveys that compare multiple techniques, this paper takes the advantage to select of the most used technique(s). Our study may be helpful for Augmented Reality environment, object detection and tracking as well as other real-time technologies. Interested reader will obtain knowledge on various categories and types of research challenges in the image-based segmentation within the scope of colored images environments.**

Keywords- Segmentation; Intensity; color; photometry; thresholding; Real-time Image Processing; Augmented Reality

I. Introduction

Partitioning of an image into separate regions is considered to be a part of content analysis and image under-standing [1]. The process of Image segmentation is a critical step in many applications. Nowadays, it is fundamentally used in Augmented Reality technology in the cases of object tracking, registration, and when inserting the synthetic object(s) to the scene. Work on methods and techniques for segmentation had been done thoroughly, but still, results are not yet accurate which makes it difficult to find a method to be called the most suitable. However, the technique taken on in this paper is to scientifically and practically prove in an environment-dependent way to compare between each segmentation method so that the performance can be the judge [2].

Although, the field of Augmented Reality has come out to transparence for over one or two decades, work is getting more interesting for researchers; several conferences and seminars have been dedicated to describe the problems of Augmented Reality and to digest its developments. Registration is basically meant to save the geometrical and the distance of the annotated objects in the scene. That means, the accuracy of registration de-pends on object tracking technique which relies on the scene environment. Alas, it is difficult to find a reliable technique to know where the real objects are allocated in the real scene. The first process in most of the tracking techniques is to define the boundaries, edges, and shapes along the image, which is image segmentation [2].

Image segmentation techniques are divided into two categories; human-guided techniques, also called supervised and unsupervised where segmentation generation is based on software computing. In other words, unsupervised segmentation is where the computation analyses are based on learning algorithm to do the grouping of common pixels. On the other hand, when the user can select the groups of common pixels it is then supervised segmentation. That includes the user ability to set the ranges of how close the similarities in each group to be [3].

Many ideas have been presented to develop feasible output for image segmentation. In the next discussion, details of the different supervised and semi-supervised methods are presented.

II. Types of Image Segmentation Techniques

Defining boundaries, edges, and shapes in an image makes it easy to understand its environment that helps applications in Computer Vision, Artificial Intelligence, CAD and many other areas. For example, locating a moving object, motion recognition, detection of suspicious activities, video indexing, human-computer interaction (gesture recognition, eye gaze tracking), vehicle navigation and traffic tracking, also CAD applications like resemble, analyze and modify parts of objects to do reconstructions or new or improve models, and modeling of aesthetic designs use material prototypes (erosion, marbles, rough surfaces, etc.) [4].

Image segmentation techniques are divided into several categories; Edge-based and Region-based Detection techniques, Partial Differential Equation, Artificial Neural Network and Clustering based, and Multiobjective Image Segmentation. In addition to Thresholding Method is also important to be considered. In this paper, study is focused on two types, position estimation methods and color estimation methods, comparing each method performance under an environment-dependent scope.

A. Color Estimation Methods

Classification groups like Grey-level, color, texture, depth, and motion are considered to be essential types for various methods in image based segmentation. Grey-level image based segmentation techniques are the most fundamentally widely used [5], it is generated by controlling thresholds to transform the image data to a binary region map [5]. Simple thresholding technique can be noted as follows:

$$g(x,y) = 0\,,\ \text{if}\, f(x,y) < \text{T and}$$
$$g(x,y) = 1, \text{if}\, f(x,y) \geq \text{T} \qquad (2$$

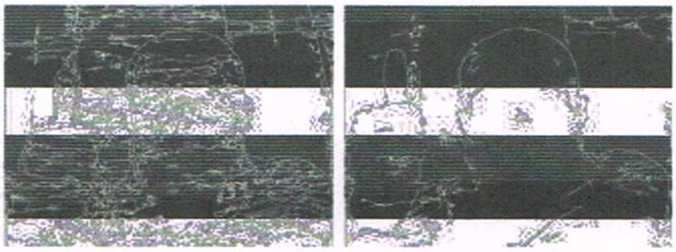

Figure 1: two images for two different thresholding regions in the same environment.

For region-based thresolding, consider using two thresholds, T1 < T2, where a region 1 can have a specific range of grey levels:

$$g(x,y) = 0 \text{ if } f(x,y) < \text{T1} \qquad \text{OR}$$
$$\text{f(x,y)} > \text{T2 and g(x,y)} = 1 \text{ if T1} \leq \text{f(x,y)} \leq \text{T2}. \qquad (3$$

Thresholding types and techniques are Simple greyscale thresholding, Adaptive thresholding, and Colour thresholding [5].

Attention has been extensive on algorithms for segmentation of color images, although the often use of gray level image segmentation techniques knowing that they supplanted many techniques in gray-level image segmentation. Color Segmentation is crucial for indexing and managing image content. In order to understand color based image segmentation, it's fundamental to recognize color representation in terms of its features; clustering and thresholding. Clustering techniques use the special properties of colors, color quantization is inseparable as a problem of clustering points in three-dimensional space, while in thresholding, similarly to gray-level segmentation reduces the color level of an image to color spaces [21].

Although, image texture segmentation techniques are not accurate enough to measure or help clustering an image, but still attempts to use texture properties to cluster texels in an image are growing and showing an interest for researchers [1], [21–23].

Segmentation based on depth is an inspiration from the depth maps. In respect to the definition of depth map as an image that provides information on how objects in an image are located, combining color image segmentation technique with the depth information can greatly improve the accuracy of the segmentation.

Motion based segmentation is the process of recognizing an object in a sequence of images that moves dynamically from frame to frame. Motion based segmentation methods aim to partitioning an image into regions based on motion fields of continuity and the probability of any parametric motion model. Few techniques are proposed like Top-down techniques, Joint estimation, and Grouping of elementary regions.

As an example on color based segmentation [24], let a color image be denoted as a vector function f. Color image f is usually represented in terms of RGB format (Red, Green, and Blue), where:

$$f(\text{n}) = [f\text{Red(n)} * f\text{Green(n)} * f\text{Blue(n)}] \in R^3 \quad , n \in \text{N}$$

Or it can be noted as indexed palette:

$$p(.) \in \{1,\ldots,\text{P}\}, \text{C} = \left[c_1^T \ldots c_p^T \ldots c_P^T\right]^T = [r\ g\ b] \in \text{R}^{P*3}$$

Where,

$$f\text{Red(n)} : \text{N} -> \text{R} = \{\text{r1, r2}, \ldots, \text{rR}\} \in [0,1]$$
$$f\text{Green(n)} : \text{N} -> \text{R} = \{\text{g1, g2}, \ldots, \text{gG}\} \in [0,1]$$
$$f\text{Blue(n)} : \text{N} -> \text{R} = \{\text{b1, b2}, \ldots, \text{bB}\} \in [0,1]$$

In this example, four stages of computations are presumed: down sampling, low-pass filtering, color quantization, and color matching in the $L * u * v$ color space.

Down-sampling is the process to reduce the number of pixels based on spatial information of RGB components to about $\frac{\text{N1*N2}}{\text{M}^2}$, where, N1 and N2 are the image size parameters, M is the sampling factor. The resulted image is a sublattice noted as $S_{M\times M} = sublattice(N)$, for every pixel in every M in both directions (horizontal and vertical):

$$y(s) = f(n)_{|n=s} = [f\text{Red}(s) f\text{Green}(s) f\text{Blue}(s)]^T,$$
$$s \in S_{M\times M} = sublattice(N) \qquad (5$$

Then for each of the three color components of $y(s)$ is to be low-pass filtered by means of Gaussian FIR so that it adds smoothness to the image and populates the RGB space with new colors which helps in determining the main colored regions. Next is to apply color quantization method like Heckbert's minimum variance quantization method [25] for featuring homogeneous colors into regions. Basically, color quantization is used to reduce the color palette of an image into a smaller one. The parameter Q represents segmentation resolution for every color space.

Lastly and as a final point is to implement a color matching algorithm in the L*u*v color space; every color space is identified by measuring Euclidean distances corresponding to apprehended color differences.

A coherent and robust real-time video segmentation can be achieved under conditions that will be described in Discussion Section.

III. DISCUSSION

In the previous sections, right the way through the study of image segmentation and its methods, it clearly becomes noticeable, the importance of image segmentation in the field of Augmented Reality [77]; One important question is: what is the best way to achieve geometry and color for object detection? Or in other words, is there an optimal way for geometry and color segmentation that suites AR scene? This study provides a comparison between the varieties of image segmentation techniques aiming to select the most appropriate in the scope of AR scene. Several papers have been devoted to comparative analysis of either geometry or color segmentation [26–32].

For color segmentation, this work depends on Bahadir Ozdemir et. al. [32] parameters to evaluate each method. Next is to compare the results between them. Bahadir divided the parameters as precision, recalls performance, and detection accuracy.

$$\text{precision} = \frac{\#\ of\ correctly\ detected\ objects}{\#\ \text{of all detected objects}} = \frac{No - FA}{No} \quad (7$$

$$\text{recalls} = \frac{\#\ of\ correctly\ detected\ objects}{\#\ \text{of all objects in the image}} = \frac{Nr - MD}{Nr} \quad (8$$

$$detection\ accuracy = \frac{\#\ of\ completely\ detected\ objects}{\#\ \text{of all objects in the image}} = \frac{Nc - MCD}{Nc} \quad (9$$

where FA, MD and MCD are respectively, number of unmatched objects in the algorithm output (False Alarms), and unmatched objects in the image (Missed Detections). Table 1 shows the results from each algorithm.

Color estimation methods and as it has been discussed above in its section, color based methods observations are along these lines: Histogram-based patterns methods [11], [42-46], [52], these methods are already used in AR and have shown good results in terms of accuracy. In [11], image calibration using four-point mapping and Harris corner detection are proposed to identify different pictures in an image. Pixel-based method [24] uses palletized formats for representing color images. Steps taken for the process are Down sampling, Color Quantization accounting spatial color interactions through low-pass filtering and then Clustering colors in the RGB space. This method aims to develop unsupervised automatic setting of the parameters towards color image segmentation. The method has proved feasibility in terms of accuracy and precision. Methods based on integration of color and texture descriptors [21] are partially supervised multi-class image segmentations algorithms focused on the multi-class, single-label setup, where each image is assigned one of multiple classes. Such methods are used to give one focused/single detail of an image. The accuracy of these methods are considered to be low comparing to others. Methods based on variations caused by shadows, shading, and highlights [53] aims that the dominant colors trace connected ridges in the chromatic histogram using Ridge based Distribution Analysis (RAD). It is a real-time unsupervised approach with high accuracy results.

As for Grey-Level and Color based segmentation, Multinomial logistic regression with Active Learning meth-od [54] is a semi-supervised segmentation algorithm for high-dimensional data, class distributions are modeled using multinomial logistic regression for active learning. However, this method is suitable for high dimensional data. Several Active Contours based segmentation methods [6-9], [55-58] have been used in color segmentation for AR. Ohlyger et. al. [9] method uses two new initialization methods; the DTA and EMA which are based on Hrtigan's dip test and excess mass information. This method has been used for both position and shape adaptive initialization of region-based active contours. Active Contour based segmentation methods have proved high quality of accuracy although the less percentage of recalls. Scale-Invariance based segmentation [59] is a supervised approach trained classifier used to classify structures of different classes at all scales. The posterior probabilities, outputted by the classifier, is then used to select appropriate scales at all locations. The scope of this algorithm is limited to primitive shapes and abstract images although its high accuracy results.

Moreover, Texture-based segmentation methods, Modal Energy of Deformable Surfaces approach [22] based on energy function which expresses the local smoothness of an image area that is derived by utilizing deformations of a 3D deformable surface model. The limitation of this method is threshold or number of iterations required to improve the accuracy of the segmentation and being in real-time. Segmentation based on major features in curvelet domain approach [60] is a SVM semi-supervised segmentation method used for medical images to classify features like angular second moment, contrast, correlation, and entropy. Its results are no in real-time that it takes from 5-12seconds in processing. Among the Color and Texture based segmentation put to use methods, Particle Swarm Optimization based method [3] benefited from the use of Multi-Elitist Particle Swarm Optimization (MEPSO) implementation for color image. Although it uses color and texture based segmentation, still worst results of this method are un-reliable for low threshold real-time systems.

In addition to Grey-Color, Color, and Texture based segmentation, several methods have used Depth [61-68] and Motion [1], [69-73]as a base for segmenting images. Segmentation by following a planar disparity distribution method [68] is the process of partitioning an image into separate planar regions prior to disparity calculation using a graph cut approach within each segment, producing smooth, accurate disparity maps in ordinarily areas. This method aims to find stereo dis-parity in large and weakly textured regions based on depth information of the image. It is reliable to use this sort of methods in the outdoor AR systems knowing the accuracy of this method is high and reliable for real-time. Graph-based Semi-supervised Learning method [74] using both Motion and Depth based segmentation aims to solve the general image matching problem using graph theoretic semi-supervised learning. It is a useful supervised technique for real-time tracking using optical flow computations. This means it is feasible for AR tracking systems accounting its high accuracy of results.

IV. FUTURE EXPECTATIONS AND CONCLUSION

Even though color segmentation estimation algorithms are becoming practical, real-time, and not requiring high computations, the reader must be aware that the nature of most of these algorithms makes them fragile. None of the algorithms proved the ability to recover the error if the segmentation process fails for any reason. Practically, even the best methods suffer that too, for example targeted segments are dependent on complex and irregular environments (i.e illumination inconstancy-cy, image quality, images with points of interests, and so). One challenge is to develop algorithms for noisy, compressed, unstructured, and inconstantly illuminated images in order to solve the problem of stable segmentation. One more challenge, which has been neglected, can be the integration of algorithms' information. By integrating the image information of geometry, area color/texture based depth, and motion algorithms into dynamic data. The dynamic data is a map that contains camera's position, details on features of each pixel, area segments color description and geometry, and in case of multiple images motion that can be achieved by optical flow techniques. Such combination of image features is crucial for Augmented Reality environment for calibration and tracking of camera and objects. To sum up all-together, the aim is to devise fast image-based area segmentation methods that can detect the targeted areas and compute its pose from a single image taking into consideration of the dynamic motion in case of sequence of images as in AR. Results on each method performance help the reviewer to find and select the most suitable method for his implementation.

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APPENDIX II

TABLE 1: A SUMMARY TABLE FOR COLOR ESTIMATION BASED ON IMAGE SEGMENTATION METHODS.

No.	Method\Technique\Algorithm	Category	Parameter1	Parameter2	Parameter3	Comment
		Color Estimation Methods	Precision	Recall	Accuracy	
1	Histogram based patterns [11], [42–46], [33]	Color based	1	1	70%	used already in the AR environment
2	Pixel-based [24]	Color based	1	1	92%	aims to develop automatic setting of the parameters towards unsupervised color image segmentation.
3	based on integration of color-texture descriptors [21]	Color based	0.5	0.4	40%	to give one focused/single detail of an image
4	based on variations caused by shadows, shadings, and highlights [53]	Color based	1	1	96%	real-time, unsupervised, using histogram information
5	Modal Energy of Deformable Surfaces [33]	Texture based	0.66	0.66	63%	requires to specify the number of iterations to improve the accuracy of segmentation
6	Using multinomial logistic regression with Active Learning [54]	Gray-level and Color based	0.66	0.4	80%	suitable for high dimensional data
7	Active Contours based [6–9], [55–58]	Gray-level and Color based	0.73	0.66	83%	for both position and shape adaptive initialization of region-based active contours.
8	Scale-Invariance based [59]	Gray-level and Texture based	1	1	90%	The scope of this algorithm is limited to primitive shapes images
9	based on major features in curvelet domain [60]	Gray-level and Texture based	0.5	0.4	73%	used for medical purpose, results are not in real-time (take from 5-12 seconds)
10	Particle Swarm Optimization based [3]	Color and Texture based	1	1	93%	worst results are unreliable for low threshold in real-time systems
11	by following a planar disparity distribution [68]	Depth and Texture based	1	1	80%	aim is to find stereo disparity in large and weakly textured regions based on depth information of the image
12	graph based semi-supervised learning [74]	Motion and Depth based	1	1	90%	supervised technique for real-time tracking using optical flow computations