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An Overview: Image Segmentation Techniques for Geometry and Color Detection in Augmented Reality Environments

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ABSTRACT

This work is an accumulative study on some techniques which could help to extract the geometry and color of an image in the real-time environment. Image segmentation is a hot-zone in Computer Vision approach, however, works still on to produce accurate segmentation results for images. In corporation with other surveys which compares multiple techniques, this paper takes the advantage of choosing the most appropriate technique(s) to be adopted for Augmented Reality environment.Interested reader will obtain knowledge on various categories and types of research challenges in the image-based segmentation within the scope of AR environments.

Key words :Segmentation, Intensity, color, photometry, and thresholding, Augmented Reality (AR).

INTRODUCTION

Artitioning of an image into separate regions is considered to be a part of content analysis and image understanding[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 depends 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.

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.

Position Estimation Methods

Position and orientation on an object is defined as pose of an object; To identify specific objects in an image, it is a typical task to determine its pose in both fields of Computer Vision and Robotics relative to its environment. For example, information on real objects or scene dimensions of an AR environment is crucial for markerless AR systems, also it could provide information to a robot to control an object or to avoid it.The geometrical issue is divided to two approaches in image segmentation: edge-based and area-based.

In Edge-based segmentation, Edge refers to the border that separates two different regions, each has different properties. Edge/boundary detection has many approaches since it was explored thoroughly since few decades so far. Approaches like Canny edge detection, first order methods, thresholding and linking, Edge thinning, second-order approaches to edge detection, Differential edge detection, and Phase congruency-based edge detection have shown effective results so far. Research surveys and reviews have been conducted on edge-based segmentation methods [1,4,7]. Follows are up-to-date edge detection methods improved and contributed to the work of the field stated in two categories, statistical and Informative Clustering.

Statistical approaches manipulate information of an image in sort of labels. That means, two regions are separated by edges if the range of statistical information clearly varies. As for examples on statistical approaches, Level-Set segmentation[1], Active Contours (Snakes)[7-9], Novelty Selection[10], and Histogram based[11] algorithms fundamentally depends on statistical analysis of the image. Informative Clustering is usually divided into two steps: First step is classifying information on each connected segment into local/non-local or augmented/non-augmented etc. Second step is then to augment them to each cluster/segment relying on the knowledge extracted from its classification. Several Informative Clustering algorithms were introduced recently like MRF-Based Region Merging[12], Hierarchical Clustering [13], Improved Hyperrectangles-based[14], and Non-local Continuous Min-cut[15].

It is also important to note that Edge segmentation operates better in the images with sharp and low noise environment. Due to that, preceding edge segmentation, a process can be done on the image like filtering operation e.g. sharpening although comparatively, the computational cost. Area based segmentation is commonly based on edge segmentation. Area based segmentation methods aim to cluster and group regions that have common properties. Properties are Intensity values, Textures or Patterns, and if exists Depth. Work on this area is divided into categories, Statistical approaches and Informative Clustering. Statistical approaches, similar to edge-based, an area is significantly segmented if the statistical ranges of two area segments clearly varies. For example, active

Fig. 1: An example to Edge based segmentation

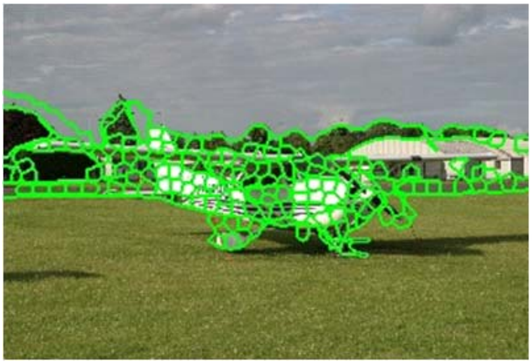

Fig .2: Example on Area based Informative Clustering segmentation[12]

contours[7-9], level sets[1], augmented tree partitioning[16], region growing[17], Hierarchical Clustering[13], novelty selection[10] and Histogram based[11] algorithms also depend on statistical analysis of the image.

Informative clustering,also similar to edge based, it's usually divided into two steps: First step is classifying information on each connected segment into local/non-local or augmented/non-augmented etc. Second step is then to augment them to each cluster/segment relying on the knowledge extracted from its classification. MRF-Based Region Mergin[12], Improved Hyperrectangles-based[14], and Non-local Continuous Min-cut[15] are considered to be recent methods in informative clustering.

As an example on position estimation methods, Simultaneous localization and mapping (SLAM) was incorporated in AR applications to provide pose information[18], [19]. In SLAM, 3D projection map and camera motion map are computed for tracking the camera pose and updating new map of the scene

$$dst(x,y)=src(f_x(x,y)f_x(x,y)) \quad ...(1)$$

The above formula describes the corresponding input-to output projection map in case when specifying the forward mapping $<g_x,g_y>$src-dst. Input is a real-image or a segment of a real image. Assume feature map that consists of a 2D grid with a fixed resolution (e.g. of 100 x 100mm per cell), let's say GridFm(x,y). Speeded-Up Robust Features (SURF) method[20] for feature extraction is applied to extract the geometrical facets of an image. Features are supposed to be invariant with respect to scale and rotation. Each feature describes an abstraction of an interesting part of an image. A feature is a center point of sub-pixel coordinates (xf , yf) and a descriptor vector (contains color, etc). Each feature is mapped to the corresponding cell of the feature map. A feature center point is to be transformed into a 2D world coordinates (xw , yw). Only features with highest response (best feature descriptors) are added in the corresponding grid cells while other features are dropped. SURF, SIFT, FAST, STAR, BRIEF, BRISK and lately FREAK feature extraction algorithms are also useful in terms of extracting

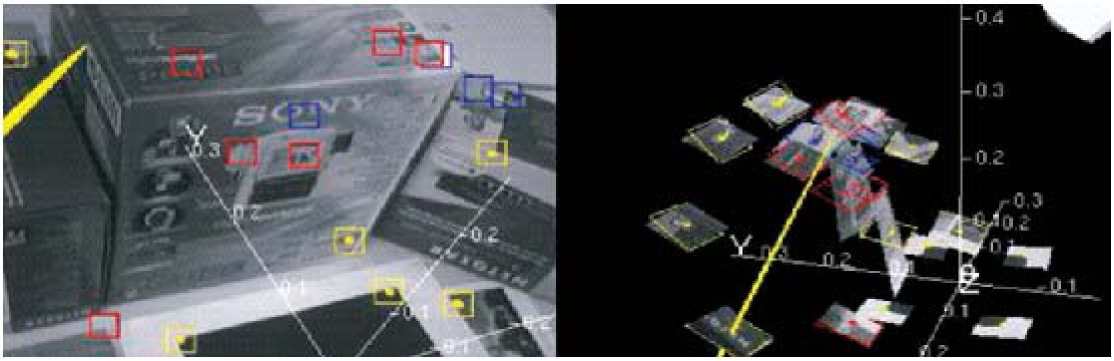

Fig. 3: Example on results of MonoSLAM[75]

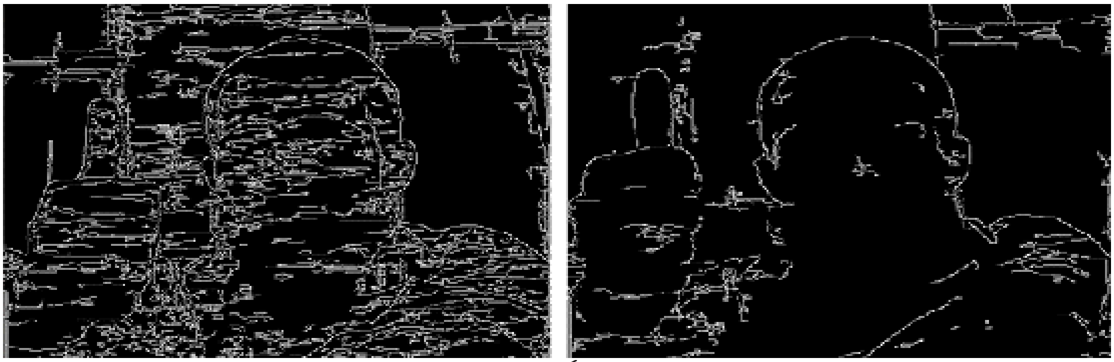

Fig. 6: two images for two different thresholding regions in the same environment

the facets of an image. Details and deep study on both Edge-based and Area-based Segmentation issues, results, and comparisons are stated in the Discussion Section.

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:

$g(x,y)=0$, if $(x,y) < T$ and

$g(x,y)=1$, if $f(x,y) \geq T$ ...(2)

where T is the threshold. For region based thresolding, consider using two thresholds, $T1 < T2$, where a region 1 can have a specific range of grey levels:

$g(x,y)=0$ if $f(x,y)<T1$ OR

$f(x,y) > T2$ and $g(x,y) = 1$ if $T1 \quad f(x,y) \quad T2$. ..(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(n)=[fRed(n) fGreen(n) fBlue(n)]R3,nN ..(4)

Or it can be noted as indexed palette:

f(n) {p(n),c}

$$p(.)\ \{1,2,...P\}, C=[C_1^T - C_P^T - C_P^T]^T$$

$$= [rgb]\quad R^{P\quad 3}$$

Where,

fRed(n): N $\longrightarrow$ R = {r1,r2,...,rR} [0,1]

fGreen(n):N $\longrightarrow$ R = {g1,g2,...,gG} [0,1]

fBlue(n): N $\longrightarrow$ R = {b1,b2,...,bB} [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 $\frac{N^1 * N^2}{M^2}$, where, N1 and N2 are the image size parameters, M is the sampling factor. The resulted image is a sublattice noted as $S_{M\times M}$, for every pixel in every M in both directions (horizontal and vertical):

$y(s)= f(n)_{n=s}=$ [fRed(s) fGreen(s) fBlue(s),
$s \quad s_{m\times m}$=Sublattice (N) ...(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.

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; 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 comparing between position estimation methods, this work has been inspired from Jaulmes et.al.[33]. They obtained Performance results achieved by mapping each algorithm into an image map then compared them to the real position image map. This position map contains the number of distance surfaces in the image. Suppose S(x) is the surface of x, RealMap is the real position map, and AlgoMap is the algorithm result of position map, then

$$Q = \frac{S(\text{realmap} \cap \text{algomap})^2}{S(\text{realmap})\, S(\text{algomap})} \quad ..(6)$$

where, Q is the quality of the algorithm. Table 1 describes the quality of each algorithm

In the analysis of Table 1; Area based statistical approaches have been observed as follows; Level-set segmentation techniques have shown the ability for run in real-time environment and mostly used for motion detection and tracking, it is efficient in its implementation as the quality of it is proven to work under inconsistent environment[1],[34,35]. Active Contours (Snakes) use data fitting energy to control the segmentation process. I draws upon intensity information in local regions at a convenient scale[6,8]. It is feasible to be adopted but in less quality comparing to level-set segmentation technique. Augmented Tree partitioning[16] is useful as a structure for partitioning a set of surfaces into one surface. It is supervised, fast, robust and structured. Quality of this approach is high due to its structure. AR application can benefit not only in achieving geometry and object tracking but also as a color based segmentation. Some Region growing techniques are limited to specific image structures and are based on linear scanning of the image[36-39]. A paper was introduced earlier on segmenting capsule images[17]. Such algorithms are fast and useful for abstract structured images. Hierarchical Clustering [13, 40,41] is an adaptive unsupervised and human-guided algorithms to target a recursive merging of best selected clusters. In other words, choose specific region to be segmented then to divide it into clusters then to merge the best available exiting clusters. Hierarchical clustering shows good results in terms of quality, however, it is costly in terms of time consumption due to its recursive formula. Novelty Selection[10] is a pre-processing supervised algorithm that is used to reduce the number of labeled data points keeping the its fundamental structure. It is a real-time and not tied to any specific semi-supervised learning method. And it can be adapted with other graph-based semisupervised methods. The quality results of this approach are promising and feasible for enhancement by integration with other graph-based algorithms for better results.

Although Histogram based approaches[11],[42-46] are applicable and real-time, the quality of its segmentation is not yet accurate due to the one pass through the pixel. Area-based Informative clustering algorithms have been also observed as follows; Markov Random Field (MRF) based Region Merging[12] focused partitioning on specific area with many partitions while MRF is used to decide merge-or-not-merge among segment pairs using graph nodes. Results of this algorithm are promising in terms of quality and are similar to the results of Statistical Hierarchical Clustering approach. Improved Hyperrectangles-based approach[14] which uses supervised classification SVM decisions to reject the ambiguities in the learning set partitions of an image. This method works also in unsupervised environment, has a low cost performance, and its results are similar to SVM classification results. It is novel implementation of SVM classification to be employed in image clustering due to information on an image[47-51]. Non-local Continuous MinCut[15] semi-supervised segmentation algorithm is based on energy minimization. Energy minimization can be achieved by adding constraints and labels to translate the min-cut algorithm into a non-local min-cut algorithm. The algorithm shows results with noise at the edges in the natural image and is not adaptive with the inconsistent environment. For color egmentation, 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.

$$precision = \frac{\#of\_correctly\_detected\_object}{\#of\_all\_detected\_object} = \frac{No - FA}{No} \quad ..(7)$$

$$recall = \frac{\#of\_correctly\_detected\_object}{\#of\_all\_detected\_object} = \frac{Nr - MD}{Nr} \quad ..(8)$$

$$detection\_accuracy = \frac{\#of\_completely\_detected\_object}{\#of\_all\_object\_in\_image} = \frac{Nc - MCD}{Nc} \quad ...(9)$$

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 2 shows the results from each algorithm. In the analysis of Table 2 of 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 method [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. Ohliger 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 althoughits 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 unreliable 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 disparity 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.

CONCLUSION

Even though geometry and 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, 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. This survey had achieved that although general methods that solve multiple variables in an image can provide a framework to achieve information from different image features, the need for more efficient solutions for informative image segmentation are more practically crucial. This paper has surveyed the recent and well-known methods to solve the image processing challenges of Augmented Reality environments. The work included a detailed explanations and experimental results on both geometry and color segmentation methods of a real images in real time. It was intended to survey each method taking into account the limitations as supervised, semi-supervised, or unsupervised and if either statistical or informative and where if it was area-based, grey-color, color, texture, depth, or motion based. Results on each method performance help the reviewer to find and select the most suitable method for his implementation.

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