Color Segmentation for a Region-Based Attention Model

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Abstract: Most of the existing models of artificial visual attention suffer from the problems of high computation time, imprecise localization of focus of attention, and inability to accurately signify the shapes of objects under attention. Hence a region based model is being developed to cope with these problems. This paper proposes a color segmentation method that produces suitable input for the novel attention model. The innovations of seed classification and integration of edge detection while region growing allow to meet the requirements of the region-based attention mechanism. The results show that the proposed method has successfully produced suitable output in a reasonable time and has competed well with the existing methods that utilize heavy statistical techniques to produce good segmentation.

1 Introduction

Artificial visual attention has become a topic of interest for many researchers in computer vision around the world. Many methods and models have been proposed to make the artificial systems workable according to the role model of human vision. It has been established by the research in psychology and neurobiology that the human brain does not process all the information coming in from the eyes in detail. A filtering mechanism selects some important areas from the complete scene and directs attention towards them using shifts of gaze. The understanding or recognition of a given scene is completed in a multitude of eye saccades. Some of the known psychological stimuli that cause a shift of attention include color contrast [1], symmetry [2], eccentricity [3], orientation [4], and motion or a sudden change [5]. The problem of abundance of the input data is even more crucial in artificial vision systems because they do not possess a massively parallel computing power as that of the biological systems. More intelligent and precise machine vision can be performed on selected objects if the strategy of the natural eyes is followed. Artificial visual attention tries to apply a filtration process on the input so that detailed processing could be restricted only to the salient and important locations of the visual input.

Existing attention models suffer from improper localization of focus of attention (FOA), the inability to reproduce the shape of FOA so that it could be directly sent to the higher level vision procedures, and high requirement of computation time which does not allow real-time applications. We suggest an attention model using a region based approach to eradicate the said problems.

Good segmentation is the primary prerequisite for a region-based attention system. Segmentation needed for visual attention has to cope with two conflicting objectives: Firstly, the produced regions should not be suffering from over-segmentation in which a single colored object splits into many parts and secondly, minor color fluctuations have to be taken into account in order to be able to discriminate distinct regions possessing similar colors. This paper presents the specialized segmentation technique that optimizes the said two objectives so that it could work as the foundation step for the region-based attention mechanism.

2 Problem Definition

Existing models of artificial visual attention compute feature maps from the given input using a coarse-to-fine scale strategy and then use these maps to find out the salient locations in the scene. Then a process of inhibition of return (IOR) determines the focus of attention among the many available salient locations. Some models such as [6], [7], and [8] apply a system of neural fields for this purpose while others such as [9] and [10] use unsupervised learning for saliency detection and a masking strategy for IOR. A grouping based method for this purpose can be seen in [11] while a fuzzy growing approach is suggested in [12].

There are some common drawbacks in the existing methods due to the use of coarse scales and frequency domain filters. Firstly the shapes of salient clusters turn into fuzzy clouds that do not match with the actual shapes of the objects in the scene. Secondly the positions of the activity clusters are dislocated from their precise positions. Hence the clusters obtained as foci of attention cannot be directly used by the further vision tasks making the processing time spent for the attention procedures into an overhead. Most of the existing methods require a significant amount of computation time making them unusable in time critical applications of machine vision.

A region-based scheme is proposed to cope with the aforementioned issues. The basic idea is to apply the feature processing and computation of IOR to pixel groups or segments rather than redundantly addressing individual pixels. Segments represent a natural collection of pixels that belong together and most of the times they correspond to complete objects in a scene. Hence our approach first addresses to the color segmentation of the visual input and then the resulting segments are used for computing features and finding the focii of attention. An attended region under this scheme will not only precisely localize the FOA but could be sent directly to the higher computer vision algorithms as well. Moreover feature computation for regions can be performed much faster as compared to raw pixel data. Thus the proposed approach for artificial visual attention can significantly improve the quality and efficiency of the process.

Our previously proposed region-based model, presented in [13], demonstrates a primitive version of the region-based attention. It constructs convex hulls of regions obtained after illumination tolerant segmentation and computes the features for each region through these convex polygons. This method proved that the visual attention mechanism can be made significantly faster if regions instead of individual pixels are used for feature computation and inhibition of return. As this earlier model suffered from uncertainty of results in some situations because of its dependency on many approximations, hence a newer model is being built based upon experiences from this work. This paper presents the newly developed segmentation algorithm that has the capability to produce a suitable segmentation result for the attention system in a reasonable computation time.

If we want to compare the results of the artificial attention systems with the human behavior then the region construction has to be done in accordance with the human perception. Segments that represent regions as perceived by human vision will be useful for a biologically plausible artificial attention system. The first objective for such segmentation is to construct regions that largely correspond to the shapes of actual objects in the image. This can be achieved with optimal tolerance to illumination effects so that neither too many regions are produced for an object having variations of a uniform color, nor distinct regions get merged into one. In many situations objects with similar colors overlap each other and create a difficult situation for segmentation. This is a challenging objective for our color segmentation scheme to discriminate such objects without going into over-segmentation. The third objective is to complete the segmentation step in a minimum possible time so that enough time is left over for the other procedures of visual attention and recognition etc. For this reason we avoid using the existing model-based statistical techniques that produce quite good results, especially on textures, but require significantly long time to complete their processing. Another requirement is to be able to process a variety of input images without needing to tune the parameters.

3 Related Work

Work on color segmentation has a history of about at least three decades. Early publications such as [14] discussed color features that could be used for pixel comparison in segmentation. Histogram based techniques such as [15], divide the image into regions by applying thresholds on peaks of color histograms. The method of applying a quantization first and then segmenting spatially, as in [16], has been a common practice. In [17], a similar approach has been proposed involving color clustering and then merging clusters based on color similarity and spatial adjacency. The technique given in [18] constructs coarse regions first using a threshold on color distance in RGB space and then detailed segmentation using an irregular pyramid structure. Edge based techniques such as [19] have a common problem that they fail to take into account the correlation among the color channels and miss certain crucial information revealed by color [20].

Graph based techniques, such as [21], can also produce good results. These techniques arrange regions as vertices of a graph where an edge between two vertices reflects the difference of color attributes between them. The idea of integrating the checks for boundary crossing and region expandability can be found in [22] and [23]. In [22] a nonlinear transform is used for finding the attraction force on pixels that is exerted on them by the neighboring regions. This extracts structures from the given image at multiple scales and detects regions and edges in the transformed domain. This technique is able to handle only grey scale images and make use of computationally heavy processes. In [23] color edges in YUV space are obtained to get the major geometric structures in an image and the centroids between these adjacent edge regions are taken as the initial seeds for seeded region growing. This technique is specialized only for segmenting humans in video streams.

The concept of categorizing the whole color spectrum into a few classes was used in [24] for developing a query-by-color method that takes into account the human cognition capabilities. Their concept is based upon the psychological findings that humans can perceive colors in so called focal color categories labeled after the colors that humans consider while thinking and speaking, namely, red, green, blue, yellow, orange, brown, pink, purple, black, white, and gray. They also segment the hue-intensity plane into the eight regions representing the chromatic colors from the said list, as shown in figure 1 (a). Color categorization in normalized RGB space was done in [25] for segmenting objects in a RoboCup soccer field. They propose to put the possible variations of the colors into a lookup table and decide the class of input pixels by comparison to these values. The scope of this approach is limited to distinguishing regions with one of the three colors: blue, yellow, and orange. In [26] and [27] categorization of colors has been done into chromatic and achromatic colors, further classification within the chromatic colors is not practiced. Each category is treated with a different set of conditions during region construction.

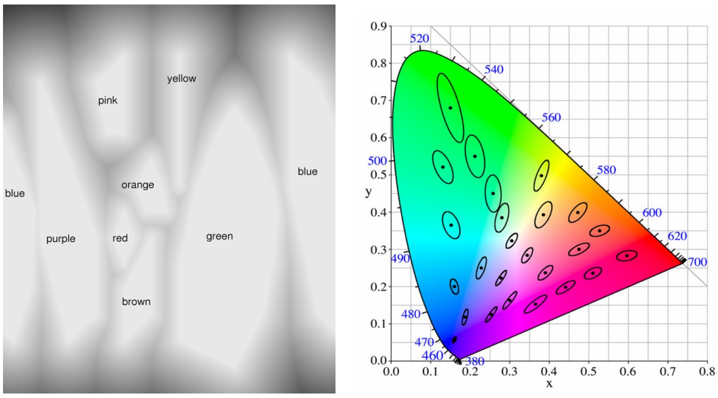
4 Proposed Segmentation Technique

It is evident from recent surveys on the color segmentation techniques, for example [29] and [30] that the area based paradigm is able to yield good quality results in an inexpensive processing time compared to the other categories of segmentation methods. Under the area-based category, the region growing procedure has an advantage of computational simplicity over its split-and-merge counterpart. It is also evident from the same surveys that the hue has a superior immunity to illumination effects like shading, shadowing, and highlights according to human perception over the color components meant for the same purpose in other color spaces. In our application domain, due to the restrictions on allowed computation time and its relation to human perception, the obvious choice of methodology converges to region growing under HIS (hue, intensity, saturation) color space. However we suggest some innovative enhancements in the selected technique in order to improve the quality of output without introducing much escalation in computation time.

4.1 Propositions and Rationale

The first proposed modification to improve the typical region growing mechanism is the integration of region boundary test the within the procedure for region growing. The usual region growing procedure compares the color of the region seed with the expected members of the region. This homogeneity criterion allows a high degree of tolerance to color variations when a large threshold is applied on the allowed color difference. Although this is effective for obtaining fine segmentation quality, especially in real-life images, but this way under-segmentation is likely to occur. Objects separated by a small fluctuation of color, for example an object overlapping another similarly colored object, cannot be distinguished. Reducing the threshold, in order to deal with such situations, leads to over-segmentation of smooth sections of the given input. We propose to test a smoothness criterion between adjacently neighboring members of the region along with the homogeneity condition between the seed and the candidate.

The second proposition is to have different sets of thresholds to deal with different chromatic colors. During the digitization process of the camera input, the converted color values of pixels on a surface, which looks uniformly colored to the human eye, have a significant amount of fluctuations in all of its color components. Magnitudes of these fluctuations differ according to the nature of the involved color. Study of these fluctuations can help in obtaining suitable values for the thresholds that would work well on a vast variety of images. In [31], it has been established that in some colors, like red, yellow, orange, and purple, variation in intensity causes a significant change of stimulus to the retina while in others, like green and blue, intensity variation plays a little role in causing the eye to distinguish the respective color as another one. Another analysis was done in [24], as shown in figure 1(a), where the short vertical span of pink, orange, red, and brown show high sensitivity to intensity changes in these colors. On the other hand, yellow has medium sized span along the intensity axis while blue, purple, and green have quite a large span representing their low sensitivity to intensity variations. Similarly, difference in nature of colors with respect to saturation can be estimated from the MacAdam's ellipses [32], shown in figure 1(b), where greater ellipses in the green, yellow, red, magenta, and cyan areas show the low sensitivity of these colors to saturation changes. The high sensitivity to saturation variation in blue, purple, and pink is visible by the small sized ellipses in areas of these colors.



(a) (b)

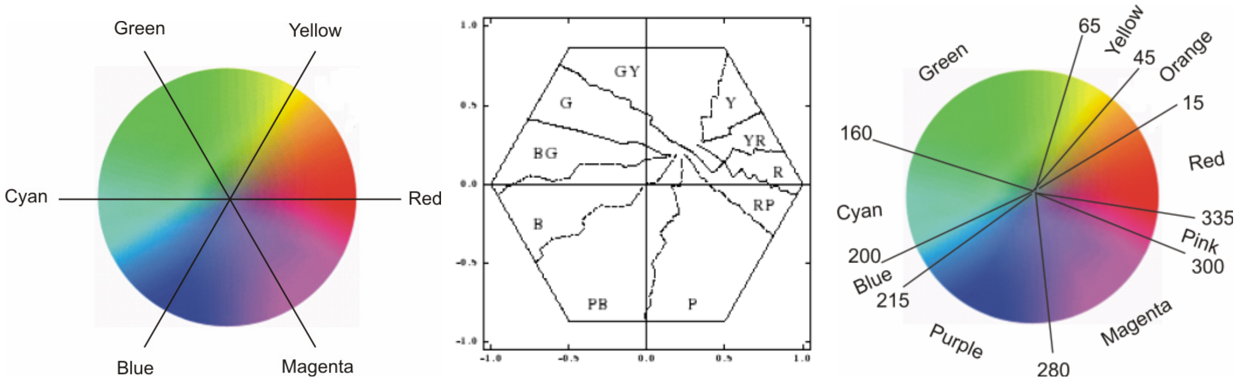
Figure 1: (a) Hue (horizontal axis) and intensity (vertical axis) dimensions of HIS-color space as a probability space. Segments are labeled with the color names of respective categories [24]. (b) Chromaticity diagram with MacAdam's ellipses [32]. Hue and saturation are plotted along horizontal and vertical axis respectively. Wavelengths, in nanometers, of the saturated colors are specified on the boundary of the horseshoe.

The third innovation is to process each achromatic color (white, black, and grey) with a different procedure and also deal with the chromatic colors separately. Unwanted results can occur if images containing a mixture of these color categories are treated with a single procedure. Achromatic colors have to be dealt by using only saturation and intensity values of pixels while chromatic colors need all of their components to be considered. The seed is evaluated before starting the region growing process and a suitable growing procedure is adopted according to the nature of the seed.

4.2 Seed Classification and Dynamic Thresholds

The color of a seed pixel is classified at two different steps each for a specific purpose. In the first classification step it performs categorization on the hue component of the given seed for selecting a different set of thresholds depending upon the size of hue range to which this value belongs. A division of the hue circle into ten named color categories has been done in [33], as shown in figure 2(b), where the groups of hue angles are made under the names red, red-yellow, yellow, green-yellow, green, blue-green, blue, purple-blue, purple, and red-purple after experiments with human subjects. Their division shows bigger pie slices for green (and its derivatives) and purple while smaller slices of different sizes for other colors. Another usual division of the hue cycle is done by making six chunks of 60 degrees each and naming them according to the primary colors: red, yellow, green, cyan, blue, and magenta respectively, starting the red at the zero degree, as shown in figure 2 (a). Combining these division and naming conventions with the focal color categories of [24] we decide to categorize the hue angles of the chromatic colors into nine groups under the names red, orange, yellow, green, cyan, blue, purple, magenta, and pink, each having a different size of span in the hue circle. Figure 2 (c) shows the ranges of hue angles, as used in our segmentation method, during which the color remains under the same name for a human observer. It may be noted that we do not intend to segment objects possessing only these colors; rather we want to pick a set of thresholds that suits the nature of the related color group.

There are seven main thresholds used during the region making process that are adjusted dynamically during the first step of classification. The set of thresholds includes Γ_n^h for the allowed hue difference between a seed pixel and its neighborhood, Γ_n^s for the permitted saturation difference between seed and its neighborhood, Γ_n^i for tolerance of intensity difference around the seed, Γ_e^h for allowed hue difference between a current region pixel and its immediate neighbor (to determine region edge), Γ_e^s for permissible saturation difference between two immediate neighbors, Γ_e^i for allowed intensity difference between two adjacent pixels of the region, and the minimum size Δ that a constructed region should have. These thresholds are set to smaller values for the colors that cover a short range in the hue circle such as orange, yellow, blue, and pink. Bigger values are set for the large ranges of green, purple, and magenta. Medium values are given to the thresholds for seeds with other colors.



(a) (b) (c)

Figure 2: (a) The hue circle with angles of basic colors. (b) Hue cycle divided as done in [33]. (c) Division of hue circle in the proposed segmentation method.

4.3 Region Construction

The segmentation algorithm works in two passes. This two pass operation optimizes the output according to the requirements of visual attention. In the first pass the thresholds are kept strict and only those seeds are allowed to grow that have high value of saturation and intensity. This results in construction of those regions first that have higher probability of getting attention of the machine vision system. It is done keeping in view the psychological aspect of human vision that our attention first goes towards those objects that have more bright and pure colors. Dull and dim objects get our attention either after such items or get totally ignored. Hence even small regions representing fine details in the scene are preserved in this stage. In the second pass, the thresholds are relaxed in order to allow the regions to grow with more freedom using high tolerance to variations in shades and illuminations.

A specialized region-growing methodology is utilized as the basic building block in the proposed technique. Let $\mathcal{S}$ be the set of categorized seed pixels S_i^c (the superscript *c* represents the category and the subscript i is the index of seed) from the input image $\boldsymbol{\mathcal{I}}$, then the output of segmentation procedure will be a set $\mathcal{R}$ consisting of regions R_i each constructed around a related seed S_i^c. Each R_i will be a set of pixels $P(x, y)$ from the image defined as follows:

$$R_i = \{ \, P(x, y) \mid (x, y) \in \mathcal{N}^{t}(R_i) \; and \; \mathcal{A}^{c}(P) = \mathcal{C}^{c} \; \forall \; (x, y) \in \boldsymbol{\mathcal{I}} \, \}$$

where $\mathcal{N}^{t}(R_i)$ is the neighborhood pixels of R_i at time t ($R_i = S_i^c$ at $t = 0$). $\mathcal{A}^{c}(P)$ is the set of attributes related to the point P collected in accordance with the category c of the seed S_i^c. This set should match to the set of clauses $\mathcal{C}^{c}$ that is created dynamically for each seed again depending upon its type (black, white, grey, or chromatic), which is determined in the second step of classification applied before region growing. For a black seed, the growing condition is only that the neighbor should have intensity lower than I_b, i.e., the intensity level for black color. Hence the set of clauses for a black seed may be defined as

$$\mathcal{C}^{\mathrm{c}} = \{\ \mathrm{I}(P) \le I_b\ \}\ \forall\ black\ S_i^{\mathrm{c}}$$

Where $\mathrm{I}(P)$ is a function that extracts the intensity component from the color of given pixel P. For a white seed the criterion for region growing is also simply that the neighborhood should have intensity above a high threshold I_w. Hence

$$\mathcal{C}^{\mathrm{c}} = \{\ \mathrm{I}(P) \ge I_w\ \}\ \forall\ white\ S_i^{\mathrm{c}}$$

For a grey seed the set of clauses contains three members. Firstly, the saturation of the given neighbor pixel P should be below the saturation for grey S_g. Second member of the set is the clause to test the intensity difference between the seed pixel and the neighboring pixel P. The third clause examines if the given pixel P lies on edge of the region R_i. So

$$\mathcal{C}^{\mathrm{c}} = \{\ \mathrm{S}(P) \le S_g,\ |\ \mathrm{I}(P) - \mathrm{I}(S_i^{\mathrm{c}})\ | \le\ \Gamma_n^i\ ,\ |\ \mathrm{I}(P) - \mathrm{I}\ [N^{\,t\text{-}1}(P)]\ | \le\ \Gamma_e^i\ \}\ \forall\ grey\ S_i^{\mathrm{c}}$$

where $N^{\,t\text{-}1}(P)$ is the neighbor of P that was made part of R_i before reaching P. For a seed having a chromatic color the set $\mathcal{C}^{\mathrm{c}}$ consists of eight clauses. The first two stop growth of the region if the neighbor pixel P is grey or white respectively. These clauses are necessary to secure survival of grey and white regions otherwise they will get swallowed by other colors due to convergence of all hues at low saturation and extremes of intensity. The next three clauses are checks to allow small differences between hue, saturation, and intensity components of the seed pixel S_i and those of the given neighbor P. The last three clauses inspect if a region edge is being crossed in terms of hue, saturation, or intensity. So this version of $\mathcal{C}^{\mathrm{c}}$ can be defined as:

$$\begin{aligned}\mathcal{C}^{\mathrm{c}} = \{\ & \mathrm{S}(P) > S_g,\ \mathrm{I}(P) < I_w,\ |\ \mathrm{H}(P) - \mathrm{H}(S_i^{\mathrm{c}})\ | \le\ \Gamma_n^h\ ,\ |\ \mathrm{S}(P) - \mathrm{S}(S_i^{\mathrm{c}})\ | \le\ \Gamma_n^s\ , \\ & |\ \mathrm{I}(P) - \mathrm{I}(S_i^{\mathrm{c}})\ | \le\ \Gamma_n^i\ ,\ |\ \mathrm{H}(P) - \mathrm{H}\ [N^{\,t\text{-}1}(P)]\ | \le\ \Gamma_e^h\ , \\ & |\ \mathrm{S}(P) - \mathrm{S}\ [N^{\,t\text{-}1}(P)]\ | \le\ \Gamma_e^s\ ,\ |\ \mathrm{I}(P) - \mathrm{I}\ [N^{\,t\text{-}1}(P)]\ | \le\ \Gamma_e^i\ \}\ \forall\ chromatic\ S_i^{\mathrm{c}}\end{aligned}$$

Here $\mathrm{H}(P)$ is a function that extracts the hue component and $\mathrm{S}(P)$ returns the saturation of the color of given pixel. Other symbols are already described previously. The final output is a list of regions containing basic information about the region such as average values of their color components, size, rectangular boundary, and a list of indices of all directly connected regions.

5 Results and Discussion

The proposed approach of color segmentation was tested using many artificial and real life images. The results are very encouraging and the segmentation output was found suitable according to the requirements of the region-based attention model. We have also compared our results with some existing methods that use computationally heavy statistical methods and produce fairly good results for general-purpose segmentation. Figure 3 presents results of the proposed and two existing methods. A qualitative comparison can be done by observing these results. The graph-based method has performed very well with the chromatic colors but has flaws in the achromatic areas. For example, it splits the uniform black background of the image in the second column into many regions while it merges the white border line of the road into the grey road in the traffic scene. On the other hand the scale space method [34] handles these situations in a better way but it is over segmenting in chromatic regions. Both of the competitive methods are unable to separate the yellow colored melon overlapping the similarly colored banana in the fruit image. The proposed method has shown a good balance in separating distinct regions while tolerating illumination effects on uniformly colored objects.

Figure 4 demonstrates a quantitative comparison of the results from the proposed method and some of the existing ones after experiments with a large number of images having different resolutions. Figure 4(a) shows a comparison of computation time taken by these methods after being executed on the same machine. The proposed method has the lowest curve showing its advantage over the other methods. Two methods having the closest processing time are included in the figure while methods taking very long time were excluded.

Figure 4(b) demonstrates the performance of the proposed method and two other selected techniques in context of number of regions constructed in contrast to the manually estimated (actual) count of regions in the test images. Although the curve of the proposed method is higher than the best competitor but the qualitative analysis has shown that this minor over-segmentation was indispensable in order to obtain an optimization between the two conflicting objectives of illumination tolerance and separation of distinct objects even with similar colors.

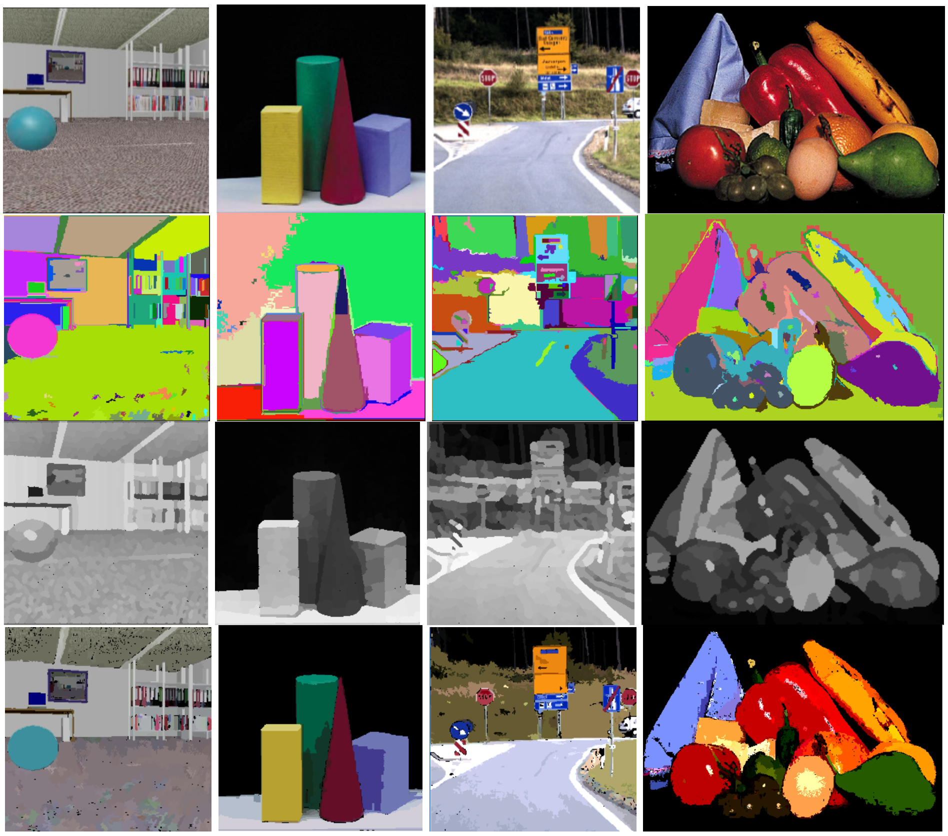
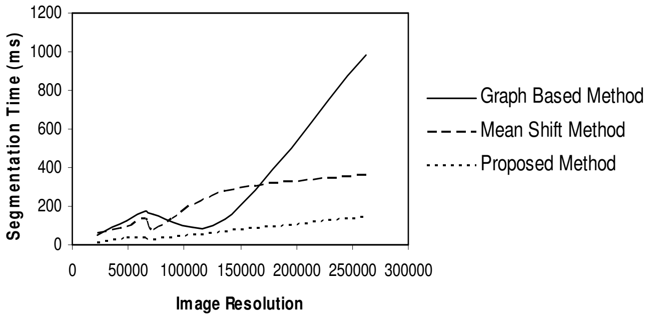
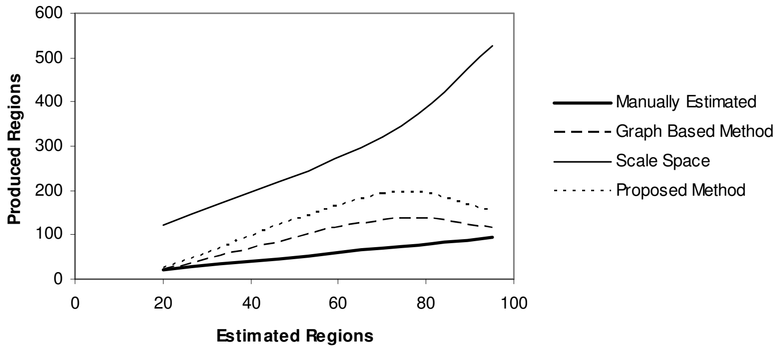


Figure 3: Top row: input images. Second row: results of graph-based method [21]. Third row: results of scale space method [34]. Bottom row: results of the proposed method.

It can be concluded that the proposed segmentation method has succeeded in fulfilling the requirements of the concerned area of application. The output is generated in a significantly low computation time making it applicable for attention systems preserving enough time per frame for other procedures. Another salient advantage is its ability to perform well on a vast variety of input data without needing to tune any parameters. The robustness of the method itself can also be seen through the fact that it performed well on raw images without pre-processing them with smoothing filters or quantization that ultimately result in distortion of the original shape of objects in the scene. Such distortions due to pre-processing can be seen in some of the output images by other methods. Ability to handle textures is not included in the current method in order to save processing time but texture processing can be added to the proposed technique by analyzing the neighborhood of the obtained regions and then merging together the texture regions.



(a)



(b)

Figure 4: (a) Comparison of computation time with the efficient statistical methods [21] and [35] (time of method in [34] is too high for this comparison). (b) Comparison of number of regions produced by proposed and existing methods with respect to estimated actual number of regions.

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