# Gradual Color Clustering Elimination as a Novel and Efficient method for Outdoor Image Segmentation

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## Abstract

One of the color reduction methods is color clustering, which has been applied for segmentation. Nonetheless, it has not been an appropriate method due to the automatically images change by luminance effects and color/texture variety. Hence, it can be done by improving the usual color clustering methods called customizing segmentation methods. This study focuses on customizing the color clustering methods for segmentation and object recognition in the outdoor images by utilizing a multi-phase procedure through a multi-resolution platform, based on self-organizing neural network, called gradual color Cluster Elimination (GCCE). The proposed method has been evaluated on outdoor images dataset namely BSDS and the results have been compared to PRI, NPR, and GCE statistical metrics of the latest segmentation methods which demonstrated that the proposed method has a satisfactory performance for the segmentation of the outdoor scenes.

*Keywords:* segmentation; color clustering; outdoor image

## 1. Introduction

Outdoor scenes processing and analysis have gained a special importance in computer vision systems in recent years. They have the most applications in traffic control [1], security organization [2], automated analysis of the images of cities [3], mobile robots [4], and wearable computers designs [5], assistance of nearly blind or blind people for travel [6]. Color is one of the main low-level features of images, which leads to objects detection of images. Hence, color images give much more information than gray-level ones, but there are more than 16 million colors that lots of them are visually similar and are difficult to analyse. For displaying color images using low devices having a limited number of colors and/or pixels, the input image must be displayed with a limited number of colors and it should be as similar as possible to the original one.

Generally, color quantization methods, which select a small number of code vectors from a large set of available colors to cluster color images, are utilized for reducing the colors of images. Color reduction is essential factor for image segmentation, which reduces storage space of the image by margined the similar colors and creating a new image with a limited number of colors. GNC [7], FOSART [8], Median cut method (MCA), k- means and neural network are some helpful used techniques for image color reduction. Nevertheless, they have been unsuccessful to make appropriate pre-patterns for color reduction of outdoor scenes [9]. Accordingly, we have proposed a new customized method based on self-organizing neural network to reduce and cluster the colors efficiently, which has assured the good quality for outdoor image segmentation.

## 2. Background

The purpose of color clustering is merging sub patterns and representing homo-chromatic objects

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[10]. By applying common clustering methods, based on partitioning the color space or statistical patterns such as k-means and neural networks, while we expect the color clusters developed from the reduction process represent important objects and patterns in outdoor images, some extracted pre-patterns have shown that the related colors contain more pixels [9]. RGB Comparative quantization method assigns a greater number of the final color box entries to the colors comprising more pixels which can improve the visual quality of the images via color reduction process. However it decreases the method efficiency for colors clustering in order to segment and recognize the objects [9-11].

As seen in Figure 1, standard color clustering algorithm can’t extract the primary colors matching the real segments of the image in which:

- Detail textures create discrete sub- regions such as in the grass.
- Color shadows of a single object developing from luminance effects of the outdoor images generate different regions in an object such as sky and grass.
- Some smaller objects with different colors are merged with larger objects due to the few numbers of buildings pixels on the left side of the image.

(a) (b)

**Figure 1:** Effect of Standard Color Clustering on an Outdoor Image. (a)The Original Image and (b) The Clustered Image.

## 3. Method

Hence, we proposed a new customized GCCE method for creating a 9-color image using Kuwahara smoothing filter which consists of the stages below:

1. Using a smoothing filter, three blurred versions of the image that have been respectively called, B1, B2 and B3 emerged. Figure2 represents the three blurred images along with the original one.

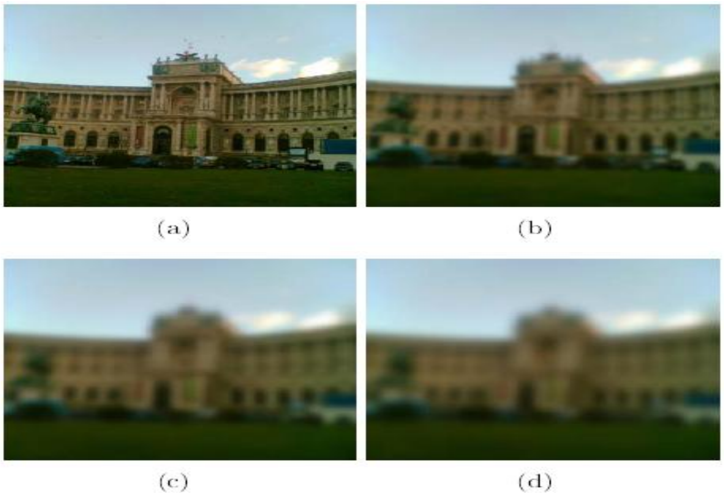



**Figure 2**: The Blurred Versions of an Outdoor Image (a) The Original Image, (b) The Image B1, (c) The Image B2 and (d) The image B3

2. As shown in Figure 3, using the k-means algorithm, the image B3 (the most blurred version of the image) is divided into three color clusters. Figure 3(a) shows the 3-colored version of image B3 and Figure 3(b) illustrates the 3-coloured version of the original image. These three clusters correspond to main colors of the images, which have high pixel density. An important point is that there are the numbers of pixels, which are not really similar to these three clusters, or they belong to other objects and their colors are different from the color of the three clusters but they are forced to be in the clusters. The next phase will be clustering these points separately.
3. We will calculate the Euclidean distance of the points of the image B2 to the three centroids obtained from the previous step. The points, which their Euclidean distance of three centroids is greater than the *th-1* threshold, don't fall into the color clusters and need to be re-clustered again. These points, which are called orphan pixels, are shown in Figure 3(c). The white parts of the image are non-orphan pixels, which they have found their appropriate centroids in the first phase of clustering.
4. We will divide the orphan points into three new clusters to have of 6 color clusters totally (Similar to the method adopted in phase 2).
5. We will compare the image pixels with the obtained centroids of the clusters. Each pixel that shares more similarity to the cluster centroids will be attributed to that cluster.
6. The Euclidean distance of the points of the image B1 to the three centroids obtained from the previous step will be calculated according to the adapted method in phase 4. Those points that their Euclidean distance of three centroids is greater than the *th-2* threshold, don't fall into the color clusters and need to be re-clustered again. The newer orphan pixels are shown in Figure 3(f).
7. The obtained clusters in the image which were divided into 9 classes as shown in Figure 3(h) are more suitable for segmentation than those classes which came out of the initial division of the image. For a better comparison, in the figure, we have used a different color palette and flashy colors for pseudo-coloring.

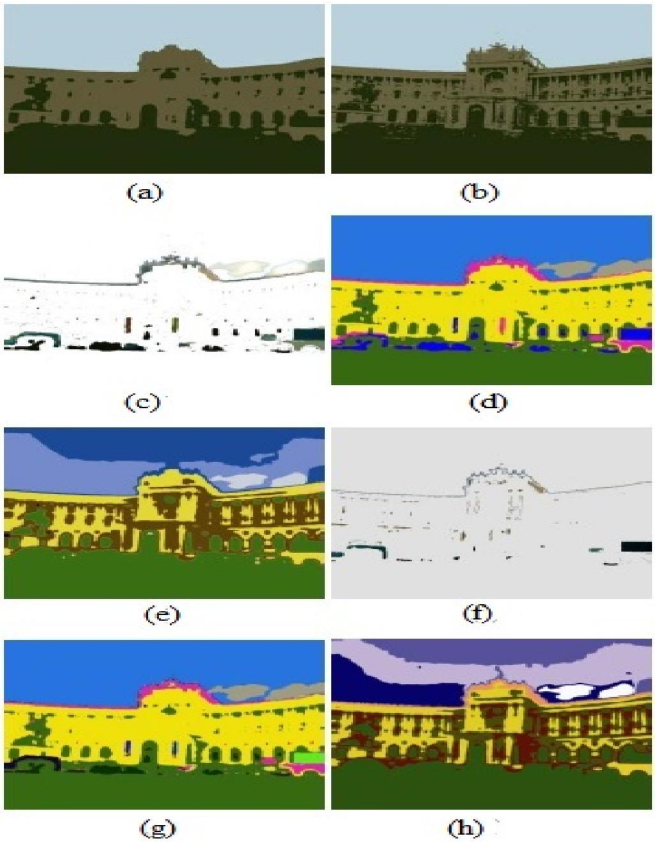



**Figure 3:** The Effects of Standard Clustering on an Outdoor Image: (a) The Original Image, (b) The Three-Colored Version of B3, (C) the Original Colored Image, (d) The six-Colored Version of B2, (e) The Six-Colored Image created by the Multi Resolution Pyramid, (f) The pixels that are not included in 6 main color clusters, (g) The 9-Colored Version of GCCE method, (h) The 9-Colored Image Created by Standard Clustering.

### 3.1 Identifying Orphan Pixels Using Trimmed Mean (Truncated Mean)

According to the proposed method for identifying the orphan pixels of the color clusters based on the statistical concept of the trimmed mean [17], we will determine the threshold $th_1$ as follows :

1. Calculate the Euclidean distance of the pixels to the centroid in a cluster.

2. Start counting the farthest pixel from the centroid of the cluster and continue counting to the point where p% of the cluster outliners is covered. These pixels are orphan and must then be re-clustered in the next phase. The distance between the last counted pixels to the centroid is similar to the threshold, (which is shown by the following equation1)

$$th_i = P_{100-p}^{\{d_i} \qquad (1)$$

### 3.2 Identifying Orphan Pixels Using Color Histograms Analysis

The steps of identifying each cluster orphan pixels on the hue histogram analysis are as follows:

1. Choose the highest peak of the color histogram (μ), which represents the most frequent colors of the cluster and it is the mode of the statistical distribution in a cluster. Notice that in this method the mean of the color clusters doesn't stand for the dense of colors since

they can be negatively impacted by the colors which are away from the centroid

2. From the right side of μ, we are moving to the end of the histogram. We need to spot a color which has no pixels in the image or to reach a point in the histogram where the peak of the edges (belongs to another color) start rising and the number of pixels is less than 50% of the pixels with μ color.
3. From the left side of μ, we are heading off to the end of the histogram to find a color with no pixels in the image or to reach a point in the histogram where the peak of the edges (belongs to another color) start rising and the number of pixels is less than 50% of the pixels with μ color. This color is called L. If during the search for L color, we will come to the end of the histogram and cannot find the color, we will start searching again from the end point since the hue histogram is circular.
4. The colors that some pixels are orphan to them will be identified by the equation bellow:

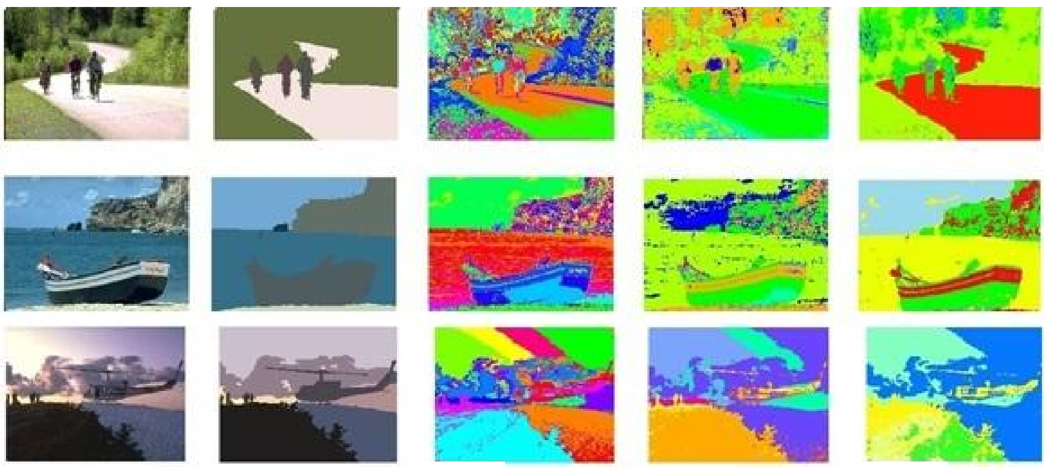
$$\text{Orphan colors} = \begin{cases} (\text{colores below L}) \cup (\text{colors above U}) & if\ L<U \\ (\text{colores below L}) \cap (\text{colors above U}) & if\ L>U \end{cases} \quad (2)$$

## 4. Result and Discussion

We have selected the supervised empirical method since it is the best, the most common and the most precise segmentation algorithms quantitative appraisal method. We need a dataset of outdoor images that is segmented by a human observer. Comparing the results of the segmentation by supervisor (that is called reference images or golden standard) with the automated computer algorithms, we can evaluate the quality of the algorithm.

### 4.1 Quantities metrics

We have used a version of Berkeley Segmentation Dataset with 500 images of outdoor and natural scenes, BSDS 5oo. (Figure 4)



(a) (b) (c) (d) (e)

Figure 4: Comparisons between Trimmed Mean, Hue Histogram and K-means method in BSDS500 dataset. (a) The original image, (b) The ground truth image, (c) The color clustered image by k-means,(d) The 9-color clustered by Trimmed Mean,(e) The 9-color clustered image by Hue method.

## 4.2 Evaluating the Quality of Color Clustering and Analysing the Results

Table1. Comparison of the standard clustering and the gradual elimination based clustering performance on the BSDS500 dataset

| Clustering algorithm | Standard clustering | Trimmed mean | Histogram analysis |
|---|---|---|---|
| PRI | 0.73 | 0.75 | 0.78 |
| NPR | 0.32 | 0.41 | 0.49 |
| GCE | 0.31 | 0.26 | 0.24 |

## 4.3 Analysis and discussion

In order to offer appropriate patterns of segmentation, we face the challenges of over- and under-segmentation in color clustering of the outdoor images. Such challenges can be eliminated using color cluster elimination based algorithm, which solves the over-segmentation issue by limiting the number of clusters in the first phase and prevents under segmentation issue by focusing on the smaller cluster in the second phase. Features of the proposed algorithm are as follows:

- **Effective Management of the details**: Small objects and texture details will be removed in the initial phase through the soothing process and will emerge as time passes so they do not disturb the clustering process. using the multi resolution pyramid, the similar color are merged and as a result the *homo-chromatic*-pixels in the cluster are evenly distributed which in turn reduces the errors of the segmentation algorithm in dealing with the shades of the same color and texture of the outdoor images and improves the result noticeably. Without the pyramid, the segmentation error will increase for 6% . Using the faded and high resolution images at the same time help us pay attention to the small objects and texture details and take better advantages of them in appropriate circumstances
- **Resistant to Noise:** the multi-resolution platform which is used for the algorithm decreases the effect of noise on the segmentation quality. If the image has some noise, using the soothing filter (especially in the first phase that big clusters are created), the effect of noise will be declined. In the second phase, in the process of estimating the number of the color clusters, only primary colors will be considered. This will lessen the noise effect on the final color clusters.

## 5. Conclusion

We proposed a method to prevent over segmentation in the big clusters and allow the small clusters to find a way to emerge. For recognizing the important clusters in each phase, we needed to know which colors were forced to be in those clusters and identify the orphan pixels in each cluster using a trimmed mean and analysing the histogram. The other details of this method, such as determining the number of the clusters, eliminating the sub regions, merging the adjacent regions were investigated. The proposed method has been evaluated on some outdoor images datasets (BSDS500). Comparing the results with those of the standard clustering using quantitative statistical metrics (PRI, NPR and GCE) demonstrated that the gradual based elimination clustering produced a better segmentation quality than the standard clustering.

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From the questionnaire result and analysis, it can be concluded that majority of respondent have knowledge and aware of the cost management process especially in cost estimation. Also, the result revealed that most frequent used cost estimation method is Price to win method. This is due to nature of business for Company X which is contract based jobs that depends on winning the contract to develop and make profit.

Also, majority of respondent do aware of the importance of proper guidelines in order to lead the cost estimation process in a matured and standardize basis. The instructed guidelines really bother the respondent in manually think of the solution rather than referring to guidelines for any cost estimation related issue. A proper general and structured guideline should be developed and proposed as a cost estimation process manual in the future for better process and implementation.

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