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

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***Abstract:*** *Automatic processing of outdoor images as one of the most important issues in computer vision system has variety of applications in traffic control, robots navigation, and assisting visually impaired people for safe travel. The low-level features analysis, presents an enormous challenge to the segmentation of the outdoor images since the special characteristics of such images are subject to changes (for example luminance effects and color/texture variety). Moreover, large and small objects often result in either over-segmentation or under-segmentation. This study is an attempt to customize the color clustering methods for segmentation and object recognition in the outdoor images, using a multi-phase procedure through a multi-resolution platform, called Color Cluster Elimination (GCCE). In each phase, the primary color clusters are detected and then gradually eliminated, to allow the smaller clusters to emerge in much clearer versions of the image. The proposed method can not only overcome the segmentation problems but also build up substantial resistance against noise. The major clusters are identified using the adaptive statistical method and color histogram analysis. Moreover, the morphology functions are used to eliminate the sub-regions and the weighted graphs are employed to estimate the number of the primary colors and merge the adjacent homogenous regions. The proposed method has been evaluated on outdoor images dataset namely BSDS and the results have been compared to PRI and GCE statistical metrics of the latest segmentation methods. The comparative tables show the proposed method has got premising performance for the segmentation of outdoor image*.

***Keywords:*** *Image Segmentation, Outdoor Image, Color Cluster, GCCE.*

## I. Introduction

Classifying and reducing the number of colors in the images has many applications; analysis simplification, segmentation, compression and reduction of the storage spaces as well as the required bandwidth for transmitting the images. Each image in its true colors is expressed in RGB cube-shaped space using 8-bit colors. There are more than 16 million colors that lots of them are visually similar and are difficult to analyse. Often machine processing with limited number of colors is much easier. The reason is that analytic functions will deal with a limited range of variables [1]. A simple, efficient and fast way for clustering is using *k*-means algorithm [2] by fuzzy C-means or FCM have many applications in image processing and machine learning. Some algorithms have been proposed in recent studies [3]. Neural networks are also used for color features clustering. For instance, Kohenen self-organizing map [4] is popular for reducing the colors and it has been frequently adopted. Another set of color reduction methods are based on successive partitioning of a color space. The methods not only have an acceptable quality compared to statistical clustering algorithms but also work faster such as RGB Comparative Quantization [5]. These methods interpret the color reduction as a vector quantization. Each pixel in the image is considered as a vector with color feature components for example, the contribution of the primary colors red and blue in its composition. In the process of quantization, the vectors need to be merged to produce new ones which can well represent the primary colors of the image stand for objects and patterns images. In other words, reducing is conversion from a wide vector space to a narrower one. Every color image can be assumed as a set of pixels. Each pixel corresponds to a point in RGB color space.In this regard, many algorithms have been offered for color clustering, but unfortunately none of them work well for all kinds of images while images of real world are very different in colors, shapes and noise [6].

On the other hand, the specific features of outdoor images have made object segmentation and recognition more difficult. Some of the problems are luminance variance and dynamic luminance range [7], color variation and ample detail textures [8], several patterns [9], the lack of homogeneity of local or region statistics and complexity and non-geometric features of the object model [10], the lack of control on luminance conditions of the environment [11], the presence of small and heterogeneous objects in the images [12], and the diversity of objects [10]. Although most of the studies have adopted feature-based and cluster-based algorithms for analysing outdoor images, the results of these studies have proved to be far from satisfactory and they have suffered from high computational load, extra multi-dimensional clustering, and lack of feasibility (for example calculation of the optimal threshold in noisy environments, processing real-time tasks) [13-15]. Moreover, some adjacent objects with similar colors may form a color region while the textures are dissimilar [16-18]. Despite using both color and texture features as the most important low-level features of the images can significantly enhance the segmentation quality, this issue has received scant attention.

Addressing the above gaps, we offer a novel color reduction approach in order to overcome the above-mentioned drawbacks and reduce the complexity of the multi-dimensional clustering while providing acceptable accuracy to facilitate object recognition.

## II. Typical Methods Of Segmentation And Segmentation Quality Evaluation

Successful recognition of objects depends upon the segmentation quality of the images and various methods have been proposed and analysis by the researchers for the segmentation of outdoor images. Here, GCCE procedures for image segmentation are discussed in details in the followings as these two methods could contribute significantly in the field of image processing. In addition, various methods are suggested for segmentation quality evaluation and this study evaluates the quality of the proposed algorithm on three indexes: PRI and GCE.

### 2.1 The GCCE procedure

Image segmentation is the process of dividing a given image into homogenous regions with respect to certain features corresponding to real objects in the actual scene. According to Literature, common color clustering algorithms have some limitations for performing outdoor image segmentation such as wrong identification of images and wrong detection of objects. Rasti *et al*. has proposed a color reduction procedure based on k-means algorithm for creating 6-colored and 9-colored images [19]. By this method, in each level of pyramid using clustering, multi resolution images can recognize important objects and then remove them from the lower levels of the pyramid. A drawback of adopting the multi resolution pyramid is that by applying the soothing filter, the color and the shape of the image edges will change. This causes the edges of the image to be considered as a new color class. For this reason new customized color clustering algorithms must be offered, which can eliminate current drawbacks.

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


**Figure 1**: 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 2, using the k-means algorithm, the image B3 (the most blurred version of the image) is divided into three colour clusters. Figure 2 (a) shows the 3-colored version of image B3 and Figure 2(b) illustrates the 3-coloured version of the original image. These three clusters correspond to main colours 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 colours are different from the colour 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 2 (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 2 (f).
7. The obtained clusters in the image which were divided into 9 classes (Figure 2) 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.

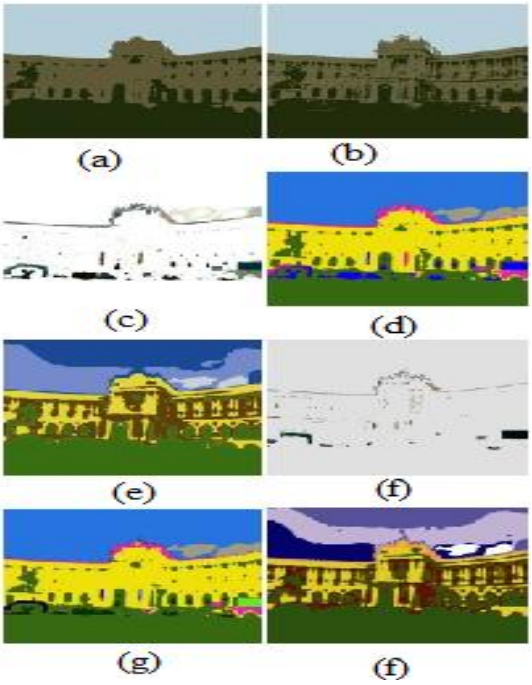


**Figure 2:** The Effects of Standard Clustering on an Outdoor Image: (a) The Original Image, (b) The Three-Colored Version of B3, (C) the Original Colored Image, (d) The six-Colored Version of B2, (e) The Six-Colored Image created by the Multi Resolution Pyramid, (f) The pixels that are not included in 6 main color clusters, (g) The 9-Colored Version of GCCE method, (h) the 9-Colored Image Created by Standard Clustering.

### 2.2 Estimating the number of color cluster

Our purpose of clustering is to establish an appropriate model for segmenting and recognizing outdoor objects. One of the major issues of color clustering is detecting the accurate numbers of the image colors [20, 21]. creating a lot of pre-patterns taking into account the large number of the final colors in the color reduction process, can make the segmentation process difficult and lead to over segmentation [22]. To estimate the color clusters in each clustering phase, we will follow this procedure:

1. Using the RGB comparative quantization algorithm, the dense pixels are found in the color space. The number of the colors needs to be more than that of commonly seen in the outdoor images.
2. We will create a fully connected weighted graph that each node has the average color features in a cluster in the CIE–lab color space and the weight of each edge is the Euclidean distance between the two ends of the nodes which corresponds to the visual difference between them.
3. The edge with the lowest weight shows the minimum Euclidean distance equal to the minimum of the visual difference in the two colors. If the weight of the edge is less than a given threshold, the nodes (colors) of the two ends of this edge are prone to merge with each other since they are similar. Therefore, we will merge the two colors and create one color. In addition, we will merge the two nodes in the graph structure equivalent to the two colors and document the average color as the color feature of the new node. Then we will update the weight of edges that have been linked to one of the previous two nodes. By pruning the graph [23] , we will ensure that the lowest weight of the edge in the graph (the minimum of the visual difference between the two clusters) is more than the given threshold (we cannot find two similar colors). The remaining number of nodes represents the number of image color clusters.

The threshold level is a percentage of the maximum Euclidean distance in the CIE-lab color space. The higher this percentage is, the probability of the colors to be merged is more. This means that lower number of color clusters will be at any stage and more general pre-patterns will be created. To have a more detailed segmentation, the percentage should be lessened. In this study, the best result was seen in 5%. The number of clusters is given to CCE algorithm to create more suitable clusters for the segmentation patterns.

**2.3 Identifying Orphan Pixels Using Color Histograms Analysis**

Clustering the colors of an image by thresholding the color histogram has been the focus of numerous studies [24, 25]. In present study, the color histograms analysis can be used to identify orphan pixels. The steps of identifying each cluster orphan pixels on the hue histogram analysis are as follows:

1) We will 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. Aggregation or color density index in this issue is the frequency of the same color pixels or it is the mode of the statistical distribution of color in a cluster. In other words, the colors that are far from their frequent colors are orphan and need to be re-clustered. Although in the normal or quasi-normal distributions both mean and mode are equal, but henceforth the mode index stands for density.
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. This color is called U. If while we are searching for U color, we will reach the end of the histogram and fail to find the color, we can start the search from scratch as the hue histogram has a circular shape.
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.

**2.4 Eliminating Sub-Regions Using Morphology Functions**

A color cluster might include a large number of regions all over the image. Each of the regions can be a main segment; however some regions are too small to be a segment. In this method, first we need to identify the pores of each region which is less than the given threshold, and then we will label the pores as we did for the regions by the steps below:

1. We will document the features of the sub-regions (the regions that are less than the given threshold).
2. Considering each cluster, we will add the registered sub-regions from the step 1 to the cluster in order to fill the pores.
3. Using the opening function [26], we will eliminate the sub-regions that are out of the continuity place of the cluster. We have used 5 cm Disk structuring element.
4. We will label or mark the obtained points according to the related cluster.
5. For processing other clusters we will return to step 2.

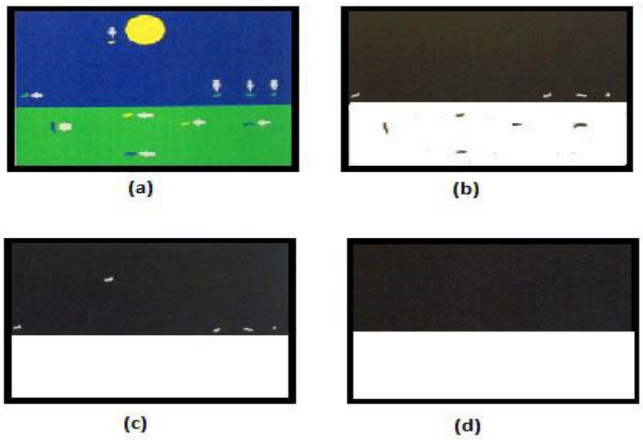


**Figure 3:** Refining a sample image using the proposed method: (a) The original image in which the sub-regions are indicated by the arrows, (b) the gray tone figure of the green cluster, (c) the outcome of adding the sub-regions to a cluster, (d) the outcome of opening function and final figure of the green cluster

### 2.5 Merging Regions Using Region Adjacency Graph

The stages of this method are similar to merging based graph. However each graph node includes the mean color of one image region, only the nodes corresponding to the adjacent regions will be connected to one another. The edge weight between two nodes is equal to the Euclidean distance of two adjacent regions in CIE-lab color space. After creating the adjacency graph, we will examine the weight of the edges. The edges with the lowest weight represent the adjacent regions in the image that their colors are very similar to each other than other regions. If the weight of the edge is less than the given threshold, we will merge two regions and create a new region. Similarly, we will merge the two nodes matching the two regions in the graph structure and we will document the color of the region mean as the color feature of the new node and update the weight of the edges relating to one of the two nodes. We will continue the process to the point where the lowest weight of the edge in the graph (equivalent to the lowest visual difference between the two adjacent color regions) is more than the given threshold (meaning that there are no two regions sharing a lot of similarities). In addition we will set the threshold percentage of the maximum Euclidean in CIE-lab color space. The more the percentage is, the more regions are prone to merge and create bigger regions.

## III. Block Illustration Of The Proposed Method For Color Clustering

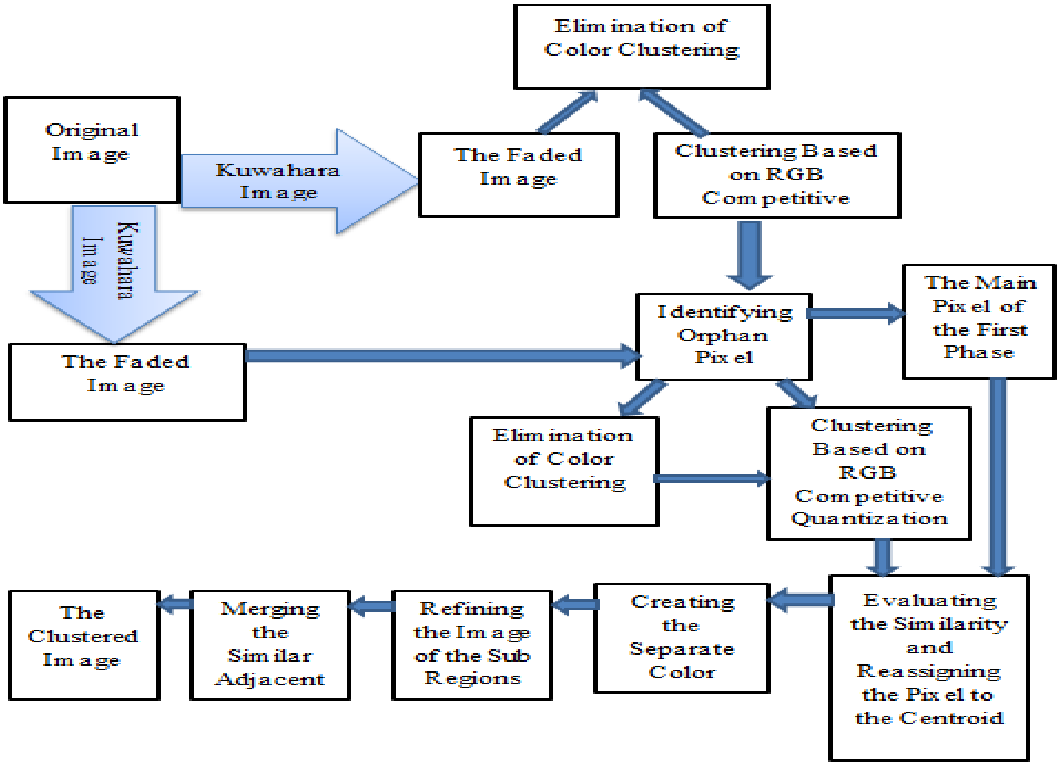


**Figure 4:** Block diagram of the proposed method (GCCE) for color clustering

## IV. Empirical Evaluation

For evaluating a segmentation method quality, a quantitative method must be applied beside visual evaluation. These quantitative methods fall in to three major categories which are analytical methods, supervised empirical methods and unsupervised empirical methods. 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. Segmentation quality will be analyzed by using two well-known quantitative metrics by the following procedure:

1. The Probabilistic Rand Index (PRI) is between [0-1]. If two segments are quite different, the RI is “0”. This happens when the whole image is considered as a segment and each pixel of the image as another segment. If two segments are quite similar, the PRI is “1”. Thus much closer RI (between the segmented image and the reference image) to 1 leads to the more quality and precision of the algorithm.
2. Global Consistency Error (GCE) metric specifies the extent to which segmentation is the modified version of the other segmentation. Comparing the two segmentations, the metric shows the error is trivial and both segmentation are compatible and have classified the image to different detailed levels.

### 2.2 Quantities Metrics:

We have used BSDS500 consists of 500 outdoor images which are divided into 7 to 9 segments based on their objects of outdoor and natural scenes. (Figure5)

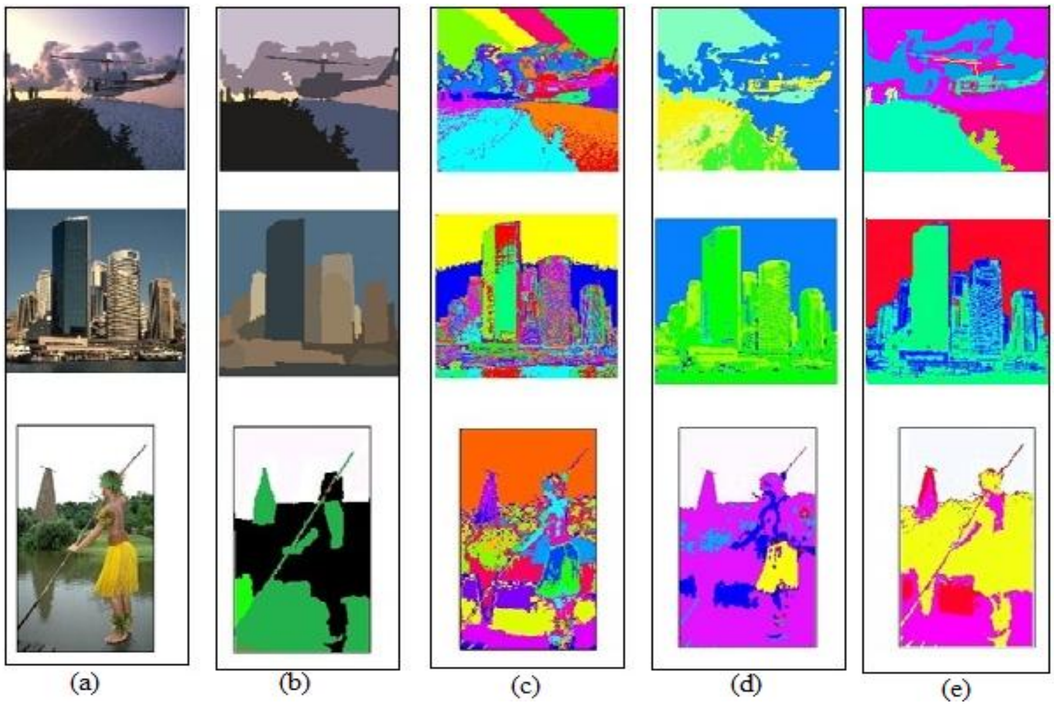


**Figure 5:** Comparisons between Trimmed Mean, Hue Histogram and *K*-means method in BSDS500 dataset. (a) The original image, (b) The ground truth image, (c) The color clustered image by k-means,(d) The 9-color clustered by Trimmed Mean,(e) The 9-color clustered image by Hue method.

## V. Experimental Result, Analysis And Discussion

To assess the quality of color clustering algorithm based on the gradual elimination and to compare it with the standard clustering algorithms for a better segmentation patterns, both algorithms are evaluated against three bases (BSDS500) and the created images are compared with the reference images. The results of the comparison are presented in the PRI and GCE metrics. Table1and table2 show the results. It is clear that the color elimination-based clustering produces a better quality of pre-patterns for segmentation compared to the standard clustering. In addition, the histogram method shows a better performance than the trimmed mean. For example, by selecting 100 images of BSDS dataset 500 which have large clusters and are kinds of landscape, PRI metric will increase to 81%.

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

| Segmentation Algorithm | PRI |
|---|---|
| PRIF(2010)-CTEX(2008)-MIS(2009) | 0.80 |
| FCR(2008)-MD25 mean-shift (2011) | 0.79 |
| CONSENSUS(2009)-HMC(2009)-MD25 *K*-means(2011)-FELZ-HUTT(2004)-GCE(2013) | 0.78 |
| A-IFS-HRI(2009)-JSEG(2001) | 0.77 |
| CTM(2007)-ST-SVGMM(2008)-Means Shift(2003)-FASTMAP *K*-means | 0.76 |
| NTP(2008)-IHMRF(2010) | 0.75 |
| CBMS(2006)-PCA *K*-means(2011) | 0.73 |
| PROPOSE METHOD | 0.81 |

**Table2:** Comparison of the standard clustering and the gradual elimination based clustering performance on the BSDS500 dataset

| Segmentation Algorithm | GCE |
|---|---|
| CTM(2007) | 0.18 |
| Felz-Hutt(2004) | 0.19 |
| N-Cuts(2000) | 0.22 |
| FCR(2008) | 0.24 |
| Mean-Shift(2003) | 0.26 |
| Proposed Method | 0.18 |

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:

1. 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% [27] . 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.
2. Appropriate for the Conditions of Outdoor Images: Compared to the standard clustering, the gradual elimination based clustering method is more resistant to inappropriate conditions of the outdoor images (e.g. similar color shades and luminosity effects) and does not show a single object in the form of similar colors. In the proposed method, not only the shades of a color ,which are treated as a single object but also those segments which are eliminated in the standard method will be shown.
3. 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.
4. High Quality for the Images with the Big Clusters: since color clustering use the low level features of images, this algorithm for the images with the big clusters (e.g. landscape) shows a better quality than the images with similar colors.

## VI. 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 and GCE) demonstrated that the gradual based elimination clustering produced a better segmentation quality than the standard clustering.

## References

[1]. O. Sakarya, "Applying fuzzy clustering method to color image segmentation," in *Computer Science and Information Systems (FedCSIS), 2015 Federated Conference on*, 2015, pp. 1049-1054.

[2]. R. O. Duda, P. E. Hart, and D. G. Stork, *Pattern classification*: John Wiley & Sons, 2012.

[3]. P. Ng and C.-M. Pun, "Skin color segmentation by Texture Feature Extraction and K-mean Clustering," in *Computational Intelligence, Communication Systems and Networks (CICSyN), 2011 Third International Conference on*, 2011, pp. 213-218.

[4]. Y. Li, F. Sohel, M. Bennamoun, and H. Lei, "Outdoor scene labelling with learned features and region consistency activation," in *Image Processing (ICIP), 2015 IEEE International Conference on*, 2015, pp. 1374-1378.

[5]. W. Farhat, H. Faiedh, C. Souani, and K. Besbes, "Effect of color spaces on video segmentation performances," in *Computer Networks and Information Security (WSCNIS), 2015 World Symposium on*, 2015, pp. 1-5.

[6]. J. Li, J. Wang, and J. Mao, "Color moving object detection method based on automatic color clustering," in *Control Conference (CCC), 2014 33rd Chinese*, 2014, pp. 7232-7235.

[7]. S. Pavya, "Segmentation of visual images under complex outdoor conditions," in *Communications and Signal Processing (ICCSP), 2014 International Conference on*, 2014, pp. 100-104.

[8]. C. Doukim, J. Dargham, and A. Chekima, "State of the art of content-based image classification," in *Computational Science and Technology (ICCST), 2014 International Conference on*, 2014, pp. 1-6.

[9]. A. Ramya and P. Raviraj, "Performance evaluation of detecting moving objects using graph cut segmentation," in *Green Computing Communication and Electrical Engineering (ICGCCEE), 2014 International Conference on*, 2014, pp. 1-6.

[10]. P. K. Jain and S. Susan, "An adaptive single seed based region growing algorithm for color image segmentation," in *2013 Annual IEEE India Conference (INDICON)*, 2013, pp. 1-6.

[11]. A. Bitam and S. Ameur, "Multispectral image segmentation using Gabor filtering and local homogeneity analysis with application to MSG," in *3rd International Conference on Systems and Control*, 2013, pp. 838-843.

[12]. T. Kuestner, C. Wurslin, S. Gatidis, P. Martirosian, K. Nikolaou, N. Schwenzer, *et al.*, "MR image reconstruction using a combination of Compressed Sensing and partial Fourier acquisition: ESPReSSo," 2016.

[13]. C.-H. Hsia and J.-M. Guo, "Improved directional lifting-based discrete wavelet transform for low resolution moving object detection," in *2012 19th IEEE International Conference on Image Processing*, 2012, pp. 2457-2460.

[14]. P. Merveilleux, O. Labbani-Igbida, and E. M. Mouaddib, "Robust free space segmentation using active contours and monocular omnidirectional vision," in *2011 18th IEEE International Conference on Image Processing*, 2011, pp. 2877-2880.

[15]. Z. Zhu and J. Liu, "Graph-based ground segmentation of 3D LIDAR in rough area," in *2014 IEEE International Conference on Technologies for Practical Robot Applications (TePRA)*, 2014, pp. 1-5.
[16]. R. McFeely, M. Glavin, and E. Jones, "Shadow identification for digital imagery using colour and texture cues," *IET image processing,* vol. 6, pp. 148-159, 2012.
[17]. Y. Xiyu, Z. Fugen, B. Xiangzhi, G. Bin, W. Hui, and T. Dongjie, "Supervised image segmentation using learning and merging," in *2013 8th International Symposium on Image and Signal Processing and Analysis (ISPA)*, 2013, pp. 54-59.
[18]. A. Giusti, J. Guzzi, D. C. Cireşan, F.-L. He, J. P. Rodríguez, F. Fontana*, et al.*, "A machine learning approach to visual perception of forest trails for mobile robots," *IEEE Robotics and Automation Letters,* vol. 1, pp. 661-667, 2016.
[19]. J. Rasti, S. A. Monadjemi, and A. Vafaei, "A GRAPH-BASED VISION SYSTEM FOR AUTOMATIC OBJECT DETECTION IN OUTDOOR SCENES," *Annals of DAAAM & Proceedings,* 2011.
[20]. A. Atsalakis and N. Papamarkos, "Color reduction and estimation of the number of dominant colors by using a self-growing and self-organized neural gas," *Engineering Applications of Artificial Intelligence,* vol. 19, pp. 769-786, 2006.
[21]. A. Atsalakis, N. Papamarkos, and I. Andreadis, "On estimation of the number of image principal colors and color reduction through self-organized neural networks," *International journal of imaging systems and technology,* vol. 12, pp. 117-127, 2002.
[22]. J. Batlle, A. Casals, J. Freixenet, and J. Martı, "A review on strategies for recognizing natural objects in colour images of outdoor scenes," *Image and Vision Computing,* vol. 18, pp. 515-530, 2000.
[23]. J. Rasti, S. A. Monadjemi, and A. Vafaei, "A graph-based vision system for automatic object detection in outdoor scenes," *Annals of DAAAM & Proceedings,* pp. 167-169, 2011.
[24]. L. Shafarenko, M. Petrou, and J. Kittler, "Histogram-based segmentation in a perceptually uniform color space," *Image Processing, IEEE Transactions on,* vol. 7, pp. 1354-1358, 1998.
[25]. D.-C. Tseng, Y.-F. Li, and C.-T. Tung, "Circular histogram thresholding for color image segmentation," in *Document Analysis and Recognition, 1995., Proceedings of the Third International Conference on*, 1995, pp. 673-676.
[26]. R. Gonzalez and R. Woods, "Digital image processing: Pearson prentice hall," *Upper Saddle River, NJ,* 2008.
[27]. A. M. Javad Rasti, Abbas Vafaei, "GRADUAL CLUSTER ELIMINATION FOR COLOR CLUSTERING IN OUTDOOR SCENES," *International Journal of Innovative Computing, Information and Control,* vol. 9, pp. 2441-2464, 2013.