A Color Image Segmentation Scheme for Extracting Foreground from Images with Unconstrained Lighting Conditions

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Abstract Segmentation plays a functional role in most of the image processing operations. In applications like object recognition systems, the efficiency of segmentation must be assured. Most of the existing segmentation techniques have failed to filter shadows and reflections from the image and the computation time required is marginally high to use in real time applications. This paper proposes a novel method for an unsupervised segmentation of foreground objects from a non-uniform image background. With this approach, false detections due to shadows, reflections from light sources and other noise components can be avoided at a fair level. The algorithm works on an adaptive thresholding, followed by a series of morphological operations in low resolution downsampled image and hence, the computational overhead can be minimized to a desired level. The segmentation mask thus obtained is then upsampled and applied to the full resolution image. So the proposed technique is best suited for batch segmentation of high-resolution images.

Keywords Thresholding . Morphological operation . Upsampling . Downsampling.

1 Introduction

Image segmentation is a crucial process in image analysis and computer vision applications. Image segmentation splits images into a number of disjoint sections such that the pixels in each section have high similarity and pixels among different sections are highly divergent. Since the detection of the foreground area of an image is an important task in image analysis, researchers are in search of accurate segmentation algorithms that consumes less time. Image segmentation is frequently used as the pre-processing step in feature extraction, pattern recognition, object recognition, image classification and image compression [1]. While considering

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an object recognition system, the primary task is the accurate extraction of the foreground area of the whole image. Various features can be extracted from this foreground area and further classification is based on the extracted features. If the segmentation is inefficient, relevant features cannot be extracted from the region of interest and may lead to false predictions.

Image Segmentation can be widely classified into supervised and unsupervised segmentation [2-3] methods. Supervised segmentation algorithms use prior knowledge by using a training set of images. However, in unsupervised algorithms, the segmentation process depends on parameters from the test image itself. Adoption of a particular algorithm among various supervised and unsupervised techniques depends on various factors like image type, nature of foreground and background, target application and computation time. Segmentation using Otsu's [4] thresholding is an example for unsupervised segmentation while Markov Random Field [5] based segmentation belongs to the supervised approach.

Unsupervised image segmentation methods can be further classified into thresholding-based, edge-based and region-based segmentation [1]. The thresholding-based segmentation [6] finds a threshold from a gray scale or color histogram of the image and this threshold acts as the barrier to segment the image into foreground and background areas. Edge-based segmentation [7] is suitable for boundary detecting applications such as text recognition. In region-based segmentation, the process starts with a few seed pixels and these seed points merge with the neighboring pixels with similar property around the seed pixel area. This process repeats until every pixel in the image gets scanned.

In the proposed work, the main objective is to develop an efficient segmentation algorithm that can perform well with color images with shadows and reflections from light sources due to non-uniform lighting conditions. The segmented output should be free from background region and noise, and can be used in object recognition applications [8]. Edge-based segmentation approach often fails to detect complex object boundaries, when the image is distorted by shadows or reflection noise. The efficiency of region based segmentation relies on the selection of appropriate seed points, and may end in erroneous results, if the selected seed points are incorrect. Existing threshold based techniques are simple and the computation time required is low compared to other unsupervised segmentation methods. However, the thresholding should be adaptive and should remove image background, shadows and reflection noise from the image

This article proposes an accurate threshold-based image segmentation technique for color images. In this system, the input image gets initially filtered by an adaptive median filter [9]. The filtered image is then downsampled to a lower resolution, and a thresholding is applied to segment the foreground area. The thresholding is based on certain parameters and these parameters help to remove shadows and high intensity light reflections from the image. The mask obtained after thresholding might contains noise elements and these are eliminated by applying a series of morphological operations. The mask thus obtained is then upsampled to the original resolution and is used to segment the foreground area of the image.

The proposed technique is intended for application in object recognition systems, where images need to be segmented prior to classification stage. Here the segmentation mask is generated in the lower resolution image, and the processing time can be reduced to a greater extend and thousands of images can be segmented within a short duration of time. Also the segmentation efficiency is much better since the algorithm removes shadows and reflections from the system. The article is organized into following sections: Section 2 briefly describes some related works on unsupervised image segmentation. In Section 3, the methodology of the proposed work is explained. Discussion about the experimental results is conducted in section 4. Finally, concluding remarks are drawn in Section 5.

2 Literature Review

Segmentation results become vulnerable in real world cases due to the impact of reflections from the light sources, non-uniform background. Image segmentation using edge detection methods fails to get the exact border in blurred images and images with complex edges especially in unconstrained illumination conditions. Region based segmentation techniques consume more time and segmentation accuracy cannot be guaranteed in segmenting multi-colored objects. Image thresholding [10] is considered as one of the simple methods to segment an image. Although, the operation is simple, choosing the optimal threshold value is a critical task. This is most commonly used in images where the contrast between foreground and background pixels is high. Most of the threshold-based image segmentation methods are not suitable for images with illumination variations.

Reviews of various segmentation techniques like edge based, threshold, region based, clustering and neural network are explained in the articles [11,12]. Different segmentation methods have been proposed based on active contour models [13-18]. This strategy is particularly suitable for modeling and extracting complex shape contours. The active contour based segmentation is especially suited for the segmentation of inhomogeneous images. In region growing method [19-20] pixels with comparable properties are aggregated to form a region. Several modified region-based segmentation techniques [21-24] have been evolved to improve the segmentation efficiency.

Otsu is an old, but effective method used for segmenting gray level images. Here the image is segmented via histogram-based thresholding. The optimal threshold is evaluated on the basis of maximum between-class variance and minimum within-class variance. Even though the method shows satisfactory results in various images, it becomes unusable, when the difference of gray-level distribution between objects and background is modest. Several popular modifications of Otsu's methods are used in various applications. Methods based on Log-Normal and Gamma distribution models are explained in an article by A. ElZaart et al. [25]. In Otsu methods based on Log-Normal distribution and Gamma distribution, different models for determining maximum between-cluster variance are used.

Another method [26] proposed by Q. Chen et al., discusses an improved Otsu image segmentation along with a fast recursive realization method by determining probabilities of diagonal quadrants in 2D histogram. Article [27] proposes a modified Otsu's thresholding along with firefly algorithm for segmenting images with lower contrast levels. But the algorithm efficiency is not satisfactory in removing shadows from the image.

Watershed transform is a kind of image thresholding based on mathematical morphological operations, which decomposes an image into several similar and non-overlapping regions [28-31]. The approach uses region based thresholding by analyzing peaks and valleys in the image intensity. Standard watershed transform and its various modifications are widely used in both grayscale and color image segmentations [32-34]. The papers [35-37] analyze the drawbacks of the classical watershed segmentation and a new watershed algorithm proposed, based on a reconstruction of the morphological gradient. Here morphological opening and closing operations are used to reconstruct the gradient image, removes noise and avoids over-segmentation. Even though the segmentation results are outstanding in images with proper white balance, this algorithm is not advisable for classifying real-time images with shadows and reflections.

In digital image applications, clustering technique [38] is another widely used method to segment regions of interest. K-means [39] is a broadly utilized model-based, basic partitioned clustering technique which attempts to find a user-specified 'K' number of clusters. While using K-means algorithm in image segmentation [40-45], it searches for the final clusters values based on predetermined initial centers of pixel intensities. Improper initialization leads to generation of poor final centers that induce errors in segmented results.

The main objective of the proposed method is to segment the exact foreground area in the image even if shadows and reflection noises are present. Existing thresholding methods like Otsu's segmentation are inadequate in removing shadows from the image. Since Watershed approaches use regional peaks for segmentation, the accuracy will be much dependent on the lighting conditions and hence such methods cannot be used in images with unconstrained lighting conditions. Clustering techniques can work well with high contrast images. However, the computation overhead of such methods is too high to be used in the batch segmentation of high resolution images. The proposed method uses an advanced thresholding approach along with appropriate mathematical morphological operations to extract the exact foreground area from the image.

3 Proposed Algorithm

The Proposed system aims at developing an efficient segmentation system for real world color images with minimal computational overhead.. The subsequent steps of the algorithm are shown in Fig.1.

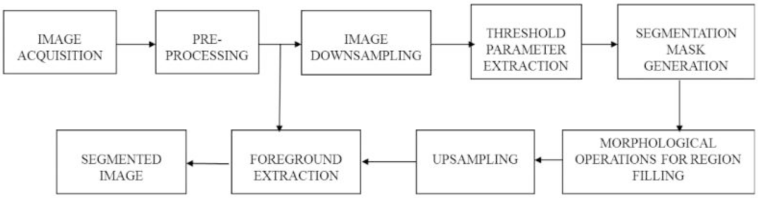


Fig 1: Proposed System Workflow

3.1 Image Acquisition and Pre-processing

The images were captured by a 5 MP webcam with 1024x1024 pixel resolution and 24-bit color depth. For creating the database of images, different objects were placed either on a nearly black background area or on a white surface. Image background can be a table top or anything with a nearly uniform texture. The images were captured in unconstrained lighting conditions and many images seemed to be affected by impulse noise [46], shadows and reflections of light sources.

A filtering process is used to remove impulse noise textures and tiny unwanted objects from the image. Adaptive Median Filtering (AMF) [47-49] is applied to remove impulse noise from the image. Since the input is a color image, AMF need to be applied to the individual color planes and then combined together, so as to result in the noise free color image. Before segmenting the foreground, a background color detection process is used to check whether the object is placed on a white surface or dark surface. This is calculated by finding the average pixel intensity among the border pixels of the image using equation (1),

$$B = \begin{cases} Black & ; \quad if\ P_{avg} < 50 \\ White & ; \quad if\ P_{avg} > 150 \\ Bad\ quality & ; \quad otherwise \end{cases} \tag{1}$$

where P_{avg} is the average pixel intensity of the border pixels of the grayscale image. If the value of P_{avg} is on the lower side of gray level, the image can be treated as the one with black background and if it is on the higher side of the grayscale, it is considered as a white background image. The segmentation result may not be good if P_{avg} lies in the middle range of gray intensity scale. Segmentation efficiency appears to be good when the object is placed in nearly white or black backgrounds.

3.2 Image Downsampling

The segmentation algorithm works on the downsampled low resolution version of the image. The actual resolution of the input images is high and will take much time while finding the full resolution segmentation mask. Here the images are first converted to 180x320 pixel resolutions and the computational overhead can be reduced to nearly $1/16^{th}$ of the full resolution image. Further steps of the algorithm will be processed on this low resolution image.

3.3 Extraction of Threshold Parameters

The primary objective of the algorithm is to filter shadows and reflections (from light sources) from the background area. Complex modeling of reflection and shadows are avoided here and a simple way to detect most of the noisy pixels with minimum time, is proposed. Firstly, individual color planes: Red, Green and Blue, get separated and two parameters are calculated at every pixel position of the image. The parameter *Dxy*, represents the average of the difference of pixels in different color planes at the location (x,y) and is obtained as

$$D_{xy} = \frac{|(i_r - i_g)| + |(i_r - i_b)| + |(i_g - i_b)|}{3} \quad (2)$$

where i_r, i_g, and i_b are the intensity values of red, green and blue color plane at position (x,y). Another parameter *Sxy* , the average of the sum of individual color pixels at the location (x,y) is obtained by

$$S_{xy} = \frac{(i_r + i_g + i_b)}{3} \quad (3)$$

From the earlier background color detection phase, the image can be classified either into white background or black background. Let us first consider a white background image. The effect of shadows in this image might be higher than that of a black background image. Normally the pixels in the shadow region are closer to the gray-level axis of the RGB color space in Fig.2.

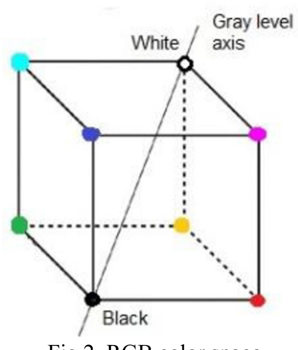


Fig.2. RGB color space

The exact gray levels in RGB color space are shown in the following Table 1.

Table 1. Intensity of color components in RGB color space

Gray level Intensity	Intensity of color components in RGB Space		
	R	G	B
1	1	1	1
2	2	2	2
3	3	3	3
. . .	. . .	. . .	. . .
255	255	255	255

The color component values of ideal gray pixels in a color image are shown in Table 1. Since the pixels in the shadow region belong to the gray level, they can be easily detected by checking the difference of individual color components.

3.4 Segmentation-Mask Generation

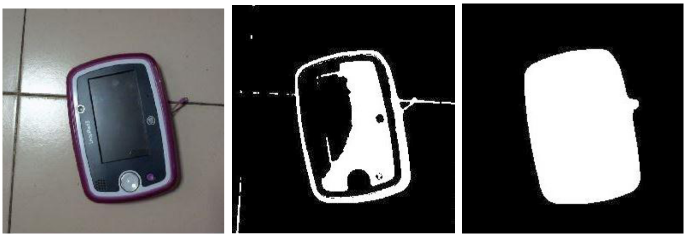
By finding the pixels nearer to the gray level axis, most of the pixels in the shadow region can be identified and removed. For a white background image, the mask, required to segment object is obtained as

$$M = \begin{cases} 0 \;\; ; \; if\ D_{xy} < T1 \;\; and \;\; S_{xy} > T2 \\ \\ 1 \;\; ; \qquad otherwise \end{cases} \tag{4}$$

Where *M* is the mask and *T1* & *T2* are the thresholds used. The threshold values can be adjusted to the optimum values by evaluating some sample images in the dataset. These values are selected in such a way that the pixels nearer to the pure black region are preserved while white background, shadows and reflections are removed. Based on our calculation we set *T1* = 30 and *T2* = 70. Since the reflection region and background lies in the high intensity range, it will also be removed by the above thresholding process. After this step the pixels of the Mask, *M* in the object region is '1' and the background region has '0' value. While considering the images with black background, the distortion due to shadows is comparatively low. So, Otsu's thresholding is applied to create the mask *M*, with binary '1' in the object region and '0' in the background portion.

3.5 Morphological operations for region filling

The ultimate aim of the proposed algorithm is to segment ROI from raw images and this segmented image shall be used for recognition and classification purposes. Even after the preceding thresholding operation, the resultant binary mask *M*, may suffer from holes in the object region and may have small noise pixels in the background and are as shown in Fig.3(b).



a) (b) (c)

Fig. 3 (a) Input image (b) Mask obtained after initial thresholding, (c) Mask obtained after morphological operations

The issue can be solved by using proper mathematical morphological operations [1]. Morphological operations depend only on the relative arrangement of pixel values and are particularly, suited for processing binary images. Due to the filtering operations used in the section 3.3, pixels in the range of gray axis will be removed and may result in holes in the object region. For getting the complete object region, a region filling operation is applied and the small white noisy pixels are removed by morphological opening of the mask 'M' with a disc shaped structural element 'S', having a radius of 3 pixels. Morphological opening is the erosion followed by a dilation, using the same structuring element for both operations. It can be represented as

$$M \circ S = (M \ominus S) \oplus S \tag{5}$$

where $\ominus$ and $\oplus$ denote erosion and dilation respectively. The Mask after this operation is as shown in the Fig.3(c)

3.6 Mask Upsampling

All the above segmentation steps were processed on the downsampled image and the mask thus obtained has only the low resolution. The Mask should be upsampled to the original resolution in order to operate on the actual resolution image.

3.7 Foreground area Extraction using Mask

After getting the full resolution mask, the object area from the input image is extracted by using the following expression.

$$O_{xy} = \begin{cases} 0 & ; \quad if\ M_{xy} = 0 \\ I_{xy} & ; \quad if\ M_{xy} = 1 \end{cases} \tag{6}$$

where 'I' is the Median filtered input image, 'O' is the Output image and M is the mask obtained by the proposed method. 'x' and 'y' are the pixel coordinates in the images. The result after segmentation is shown in the Fig.4.

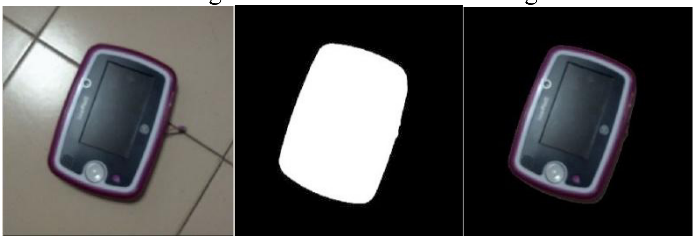
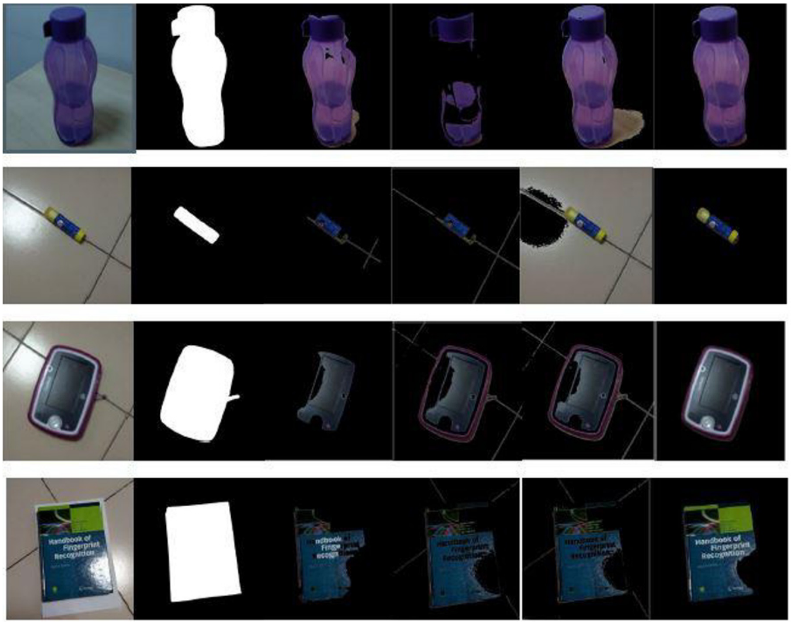


Fig.4 (a) Input image (b) Final Mask (c) Segmented Output

4 Experimental results

The proposed segmentation method aims for extracting object areas from images taken in unconstrained light conditions. Here we used a set of images taken by a digital webcam of 5MP resolution. The test images have a resolution of 1024x1024-pixel resolution and 24-bit color depth. Here MATLAB R2013b is used as the software tool to implement the proposed algorithm. All testing processes were executed on a system with Intel i5 processor and 4GB RAM. The results of proposed segmentation algorithms are compared with some traditional unsupervised methods like Active Contour based, Otsu's thresholding and K-means segmentation. The segmentation results of some sample images are shown in Fig.5.



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

Fig.5. Segmentation results (a)Input image (b)Ground Truth (c)Active contour (d)K-means (e)Otsu's segmentation (f)Proposed method

Segmentation efficiency is analyzed on the basis of object-based measures [50]. Measures were focused on two aspects: The first one is a pixel to pixel similarity measurement of segmented image and ground truth image. The second one evaluates how effectively the object boundary is detected. The proposed segmentation approach has been tested with 50 images in various working conditions and the result shows considerable improvement in comparison with the performance of existing segmentation methods. The computation time required is slightly higher than the Otsu's method. However, the exact foreground or background extraction is possible with this approach which would be further helpful in the recognition processes.

4.1 Pixel based Object Measures

In this analysis the ground truth image and the segmented output are compared and the following parameters were evaluated. Let P_g and N_g refers to the positive and negative pixel classes in the ground truth image respectively. Similarly, P_s and N_s are the positive and negative pixels in Segmented result.

True Positive (TP): Pixels that are detected as an object and also labeled as so on the ground truth image.

$$\mathrm{TP} = P_s \cap P_g \tag{7}$$

True Negative (TN): Pixels that are detected as a background and also labeled as so on the ground truth image.

$$\mathrm{TN} = N_s \cap N_g \tag{8}$$

False Positive (FP): Pixels that are detected as an object and labeled as background on the ground truth image.

$$\mathrm{FP} = P_s \cap N_g \tag{9}$$

False Negative (FN): Pixels that are detected as background and labeled as an object region in the ground truth image.

$$\mathrm{FN} = N_s \cap P_g \tag{10}$$

From the above parameters, the following performance measures were calculated.

$$Precision = \frac{TP}{TP+FN} \tag{11}$$

$$Recall = \frac{TP}{TP+FP} \tag{12}$$

Even though Precision and Recall [51] are robust measures to represent the accuracy, harmonic mean of these parameters gives a general tradeoff between them. This parameter is termed as F- measure and is given as

$$F = 2 * \frac{(Precision * Recall)}{(Precision + Recall)} \tag{13}$$

4.2 Boundary based Object Measures

Boundary based measures help to check how well the system identifies the boundary of the foreground object. For finding these measures, Canny edge detection [52] is applied on both the ground truth and segmented image and all the parameters: Precision, Recall and F-measure are again calculated by comparing the boundaries of ground truth and segmented result.

The following table shows the performance comparison of the proposed method with the existing segmentation techniques.

Table 2: Performance Analysis of various Segmentation Approaches

Measure Representation		Active Contour	K-means	Otsu's Method	Proposed Method
Pixel-based Measures	Precision	0.93	0.68	0.85	0.98
	Recall	0.65	0.85	0.60	0.96
	F-Score	0.76	0.84	0.68	0.97
Boundary-based Measures	Precision	0.12	0.05	0.07	0.79
	Recall	0.19	0.18	0.29	0.81
	F-Score	0.16	0.09	0.11	0.80
Average computation time (in Seconds)		9.28	93.56	1.74	2.31

From Table 2, It can be concluded that the proposed method performs with better segmentation accuracy both in pixel-wise and boundary based approach. Since the work aims at a fast and accurate segmentation, the time complexity should also be considered. The computation time taken for various segmentation methods along with the proposed approach is given below: -

Table 3: Analysis of computation time for various segmentation techniques on sample images

Input Image	The computation time (in Seconds) for segmentation methods			
	Active contour based Segmentation	K- means segmentation	Otsu's thresholding	Proposed method
Bottle	9.21	100.78	1.32	2.08
Glue	7.9	85.07	1.37	1.73
Tab	9.53	111.62	1.54	2.68
Text	9.58	69.79	2.18	2.79

From Table 2 and 3 it can be seen that computation time required for the proposed method is much less than that of Active contour and K-means segmentation. In comparison with a modified Otsu's method [27], the computation time is slightly high for the proposed algorithm. Otsu's segmentation techniques are faster since they operate directly on gray level histogram while the proposed method use pixel by pixel information for thresholding and hence requires a little more execution time. However, the segmentation accuracy (refer table 2) of the proposed method is much better than that of Otsu's method.

5 Conclusion and Future work

The proposed method is suitable for the segmentation of large number of images within a short duration of time. The approach is an unsupervised one and is devoid of training time. From the experimental results, it can be seen that the segmentation accuracy is considerably good and the object boundaries are much clear and accurate, when compared to some of existing techniques in the related area. The segmented results are also free from the effects of shadows and reflections from various light sources. Hence the segmentation approach can be efficiently used for various image processing applications. Also, the result analysis shows that computational overhead is reasonably low when compared to other similar algorithms. By incorporating modifications in selecting optimal threshold values, the proposed system can be further improved. Also the proposed segmentation can be extended as a part of an efficient object recognition system.

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