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Color Image Segmentation based on 4-D Histogram using JND Color and Spatial Connectivity

Aniket V. Gokhale
Research Scholar
Department of Electronics Engineering
Y.C.C.E., Nagpur

Kishor K. Bhoyar
Professor
Department of Information Technology
Y.C.C.E., Nagpur

Kishor M. Bhurchandi
Professor
Department of Electronics and Communication
V.N.I.T., Nagpur

ABSTRACT
Although there are several color image segmentation algorithms proposed in the literature, the image segmentation task still remains a challenge, due to very high computational complexity involved in finding the segments that are as close as possible to the ground truth. This paper proposes a color image segmentation algorithm based on 4-D Histogram, using JND color and spatial connectivity of pixels. This algorithm is an improved version of the algorithm proposed earlier in [22], which was based on limitations of human vision perception. In this work we have successfully addressed two major drawbacks of earlier work, that is missing connectivity of color segments and higher computational complexity of the segmentation algorithm. The 4D color histogram of the image is determined using JND color similarity threshold and connectivity of the neighboring pixels, by comparing current pixel with the previously encountered immediate 8-neighbor pixels. Initial segments are then merged using a slightly higher JND threshold by applying concept of agglomeration. The proposed algorithm is first tested on synthetic image dataset to validate the proposed algorithm and then applied on images in the Berkeley segmentation datasets, BSD300 and BSD500. The performance of the algorithm is estimated using Probabilistic Rand Index (PRI) and Peak Signal to Noise Ratio (PSNR). The proposed algorithm successfully identifies connected segments and shows improved results over CCH and JND color histogram based segmentation algorithms in terms of PRI, PSNR and computational complexity.

General Terms
Color Image Segmentation

Keywords
JND threshold, 4D Color Histogram, PRI, PSNR

1. INTRODUCTION
Image Segmentation performs partitioning of an image into a set of homogeneous and meaningful regions, such that the pixels in each partitioned region have an identical set of properties. Image segmentation is one of the most challenging tasks in image processing and is a very important pre-processing step for the problems in the area of image analysis, computer vision, and pattern recognition [5,6]. The quality of final object classification and scene interpretation depends largely on the quality of the segmented output [7]. In segmentation, an image is partitioned into different non-overlapping homogeneous regions, where the homogeneity of a region may be composed based on different criteria such as gray level, color or texture.

Image segmentation techniques can be broadly classified into histogram based, edge based, region based, clustering and combination of these techniques [8,9] . There are many segmentation algorithms reported in literature, but there is no single algorithm that can be considered good for all images [7]. Algorithms developed for a one class of images may not always produce good results for other classes of images.

Histogram of an image manifests an important statistics of digital image, which can be used for a number of analysis and processing algorithms in image processing. Color features of images are represented by color histograms. These are easy to compute, and are invariant to rotation and translation of image content. The algorithms and techniques proposed for gray images were initially applied to the color images considering the RGB color images as combination of the three independent gray images in terms of R, G and B intensities. But a number of these strategies failed due to the increased dimensionality of color space, increased redundancy in color coordinates and inability of this scheme in incorporating the correlation between the three color channels. For the RGB images, three separate histograms for the R, G and B shades were plotted and used for further analysis or processing, but this type of color image histogram cannot incorporate the correlation between the color coefficients.

In the conventional color histogram (CCH) two colors will be considered totally different if they fall into two different bins even though they might be very similar to each other for human perception. That is, CCH considers neither the color similarity across different bins nor the color dissimilarity in the same bin. Therefore it is sensitive to noisy interferences such as illumination changes and quantization errors. Also CCH's high dimensionality (i.e. the number of histogram bins) requires large computations on histogram comparison. Conventional color histograms do not include any spatial information and are therefore not suitable to support image indexing and retrieval, based on local image contents. To address such issues various novel approaches were suggested, like spatial color histogram [2], merged color histogram [3], fuzzy color histogram [4] and JND (Just Noticeable Difference) color histogram [11, 22, 23, 24].

In JND (Just Noticeable Difference) color histogram, color corresponding to each bin in such histogram is visually dissimilar from that of any other bin; whereas each bin contains visually similar colors. The color similarity mechanism is based on the threshold of similarity which is based on Euclidean distance between two colors being compared for similarity. The JND color histogram [11, 22] classifies the image into color based segments and has a drawback of classifying two or more distant regions in the image as single segment only based on color similarity.

In this paper we present a color spatial segmentation scheme based on spatial color JND (Just Noticeable Difference) histogram based on color similarity and spatial connectivity. The drawback of The JND color histogram [11, 22] has been overcome by using additional spatial information while formation of the histogram based on comparison with previously encountered neighbors in place of all previous neighbors for spatial connectivity of similar pixels.

The rest of the paper is organized as follows. Section 2 gives the brief overview of JND model and computation of color similarity threshold in RGB space, Section 3 computation of spatial color JND histogram by proposed scheme. and the algorithm for agglomeration of JND histogram and the subsequent segmentation based on JND histogram. Section 4 presents the results of the proposed algorithm on BSD, and its comparison based on two measures of segmentation quality namely Probabilistic Rand Index (PRI) and Peak signal to Noise Ratio (PSNR). Section 5 gives the concluding remarks and future work.

2. CONCEPT OF JND COLOR MODEL AND BASIC JND HISTOGRAM

The JND color model in RGB space based on limitations of human vision perception as proposed in [11] is briefed here for ready reference. The human retina contains two types of light sensors namely; rods responsible for monochrome i.e. gray vision and cones for color vision. There are three types of cones viz, Red, Green and Blue which respond to specific ranges of wavelengths corresponding to the three basic colors Red, Green and Blue. The concentration of these color receptors is maximum at the center of the retina and it goes on reducing along radius. According to the three color theory of Thomas Young, all other colors are perceived as linear combinations of these basic colors. According to [12] a normal human eye can perceive at the most 17,000 colors at maximum intensity without saturating the human eye. In other words, if the huge color space is sampled in only 17,000 colors, a performance matching close to human vision at normal illumination may be obtained. A human eye can discriminate between two colors if they are at least one 'just noticeable difference (JND)' away from each other. The term 'JND' has been qualitatively used as a color difference unit [10].

If we decide equal quantization levels for each of the R, G and B axes, then we require approximately 26 quantization levels each to accommodate 17000 colors. But from the physiological knowledge, the red cones in the human retina are least sensitive, blue cones are moderately sensitive and the green cones are most sensitive. Keeping this physiological fact in mind, the red axis has been quantized in 24 levels and the blue and green axes are quantized in 26 and 28 levels [11]. The 24x26x28 quantization in the RGB space results in slight over sampling (17,472 different colors) but it ensures that each of the 17,000 colors is accommodated in the sampled space. Heuristically it may be verified that any other combination of quantization on the R,G and B axes results in either large under sampling or over-sampling as required to accommodate 17000 colors in the space. Although the actual value of the just noticeable difference in terms of color co-ordinates may not be constant over the complete RGB space due to non-linearity of human vision and the non-uniformity of the RGB space, the 24x26x28 quantization provides strong basis for deciding color similarity and subsequent color segmentation as demonstrated in this work.

Using this sampling notion and the concept of 'just noticeable difference' the complete RGB space is mapped on to a new color space Jr Jg Jb where Jr, Jg and Jb are three orthogonal axes which represent the Just Noticeable Differences on the respective R,G and B axes. The values of J on each of the color axes vary in the range (0,23), (0,25) or (0,27) respectively for red, blue and green colors. This new space is a perceptually uniform space and offers the advantages of the uniform spaces in image analysis.

The research in physiology of human eye indicates two types of JND factors involved in the human vision system. The first is the JND of human eye referred to as JNDeye and the second is the JND of human perception referred to as JNDh. It is found that the neural network in human eye is more powerful and can distinguish more colors than those ultimately perceived by the human brain. The approximate relationship between these two [11] is given by equation (1) .

$$JND_h = 3 \times JND_{eye} \text{-------------(1)}$$

As formulated in [22] the JND_{eye}= sqrt (285.27) which means the squared JND threshold Θ of human perception is 2567. The squared distance is used, to avoid square root computation and hence to reduce time complexity. For practical applications the range of Θ for fine to broad vision is

$$JND_{eye}^{\ 2} \le \Theta \le JND_h^{\ 2}.$$

3. PROPOSED ALGORITHMS

For preparing the 4D color histogram, the histogram is defined in two data structures Nx4 and (mxn)x3. The first data structure Table 1 consists of N rows corresponding to the color shades detected and first three columns correspond to R, G and B as color tri-stimulus corresponding to pixel color and 4th column represents the population of that color. Second data structure Table 2 has (m x n) rows corresponding to the total pixels of the image and first two columns corresponding to spatial location of the pixels in terms of row and column and third column represents the color index corresponding to the row number in Table 1.

The pixels in the color image are scanned from top pixel to bottom last pixel row and column wise. The color of pixels are compared on the basis of the Euclidian distance between two pixel colors within the threshold of 3-JND (JNDeye) for similarity for merging while formation of the histogram tables.

Table 1 Cumulative color population

Color Index(k)	*Color*			*Population*
	R	*G*	*B*	*H*
1	5	15	20	335
2	10	100	20	450
3	20	50	10	470
.	.	.	.	.
K	25	72	90	200
.	.	.	.	.

Table 2 Color index-pixel location

Color index For(x_i,y_i)	*Spatial Coordinates*	
	X	*Y*
1	x_1	y_1
1	x_1	y_2
.	.	.
K	x_i	y_i
.	.	.
.	.	.

Thus the histogram of an RGB image I=$f(1),f(2),f(3),\ldots\ldots,f(\text{m x n})$ is given by H(r,g,b) as in equation(2), where m and n are rows and columns of the image respectively and I represents the color intensity values[13]. N is a counter variable and r, g, b represents the color coefficients.

$$H(r,g,b)=\sum_{i=1}^{m\times n} N\,|_{f=f(r,g,b)} \text{ ---------------(2)}$$

A traditional histogram does not contain any positional information. With the positional information stored in the proposed histogram, it just becomes transform of an image. In other words, the image can be obtained back from the new histogram with the positional information. The spatial color distribution information also plays an important role in the image analysis. Both of these histogram tables have been shown in Table 1 and Table 2. These new histogram data structures will be collectively called as JND histogram.

For practical purposes already discussed, the color image histograms have to be sampled on R,G and B axis suitably to reduce the number of colors. Most of the literature till now either uses uniform sampling of the R, G, B axis or uses images represented in uniform color spaces. Such a uniformly sampled histogram can be represented by equation (3) with the same symbols. δ represents sampling interval on each axis and p is an integer variable.

$$H(p\partial r, p\partial g, p\partial b)=\sum_{i=1}^{m\times n} N\,|_{f=f(p\partial r, p\partial g, p\partial b)} \text{ ------(3)}$$

Thus Table 1 contains the R, G, B coordinates and the respective frequency information or population (H) of the tri-color stimulus, while Table 2 contains the respective color index (row index) in Table 1 and the x and y positional co-ordinates in the image. The number of rows in Table 1 is equal to the number of different color shades available in the image. In Table 1 there will be one entry for each color shade while in Table 2 there will be one entry for each pixel. The color shades which are not present in the image are not allotted any row in Table 1 and hence in Table 2. The color vectors are entered in the Table 1 in the order of their appearance in the image or in other words, as they are encountered during the scan of the image which starts from the top left corner of the image. The population (H) in Table 1 must satisfy equation (4).

$$\sum H = m\times n \text{ ----------------(4)}$$

The color histogram proposed by K M Bhurchandi, K K Bhoyar [11,22] uses the method of comparing all previously encountered pixels and groups the pixels based on only color similarity and not wrt their spatial location .

- In this method the color histogram computation becomes slow as we move for scanning the latter pixels in the image. While scanning these latter pixels the comparison done is with all previously encountered color bins and in extreme case where the color does not match and new entry has to done the maximum comparisons have to be done and number of operations performed is maximum leading to slow time performance.
- The color bins formed are only based on color similarity and has a drawback that two clusters which are spatially disjoint but with similar color will be treated as single color bin. The spatial connectivity of the pixels is not taken into consideration and hence we can say that the algorithm gives only number of color bins based on only color similarity and hence cannot be directly treated as spatial color segments.

3.1 Algorithm for Computing the Spatial Color JND Histogram By comparing only previously encountered immediate neighbors

i) Initialize two data structures Table 1 and Table 2. Initialize the first entry in Table 1 by the first color vector in the image i.e. top left pixel color vector [R,G,B] and the frequency(population) by one. Initialize the first entry in Table 2 by the current row index value of Table 1 i.e. 1 , and the top left pixel position row and column i.e. y(column)=1 and x(row)=1. Also initialize a (row, column) pointer to top left corner of the image. Select a similarity threshold JND_{eye} approximated to 300 (285.27) depending on the precision of vision from fine to broad as required by the application.

ii) Read the next pixel color vector in scan line order.

iii) Compare the next pixel in scan line with previously encountered pixel using a neighborhood tile of 3 x 3 as shown in figure 1 below i.e. pixel C is compared with only pixel P.

P	**P**	**P**
P	**C**	**F**
F	**F**	**F**

Figure. 1. The 3x3 tile for color comparison of current & immediate previous neighbors

The center Pixel ‘C’ is the current pixel in the scan line, pixels ‘P’ are the previously encountered pixels in the scan line and pixel ‘F’ are future non encountered pixels in the scan line. The current pixel C is compared with the pixels P for similarity based on JND threshold using Euclidian distance between the tri-stimulus color vectors of the pixels. If color found similar include the pixel in respective bin. Update the entry in Table 1 by increasing population of respective color bin and update entry in Table 2 by entering row number of the Table 1 updated bin as color index and row and column numbers of C for spatial location of the pixel and go to step v.

iv) If the new color vector is not equal to any of the previously recorded color vectors in Table 1, increment the row index of Table 1, enter the new color vector in it, set the population to 1 , make the index , row and column entry in Table 2 and go to step ii.

v) Repeat step ii) to iv) for all the pixels in the image in scan line order.

vi) Sort Table 2 in the increasing order of the color index.

vii) Save the Table 1 and Table 2 for latter analysis of the histogram.

3.2 Algorithm for agglomerative merging of the bin clusters to form segments based on spatial connectivity and JND color similarity

i) Find the similar colors in the table 1 using similarity threshold Θ more than JND_{eye} threshold, we have choose it to be of human perception i.e. JND_h and mark them with additional entry in column 5 of table 1 as similarity color index (S). The similarity threshold Θ used here is in squared form to eliminate the square root calculations in Euclidian distance for color similarity calculations i.e. $\Theta = JND_h^2$=2400 (2567).

ii) This will give us the maximum dissimilar colors available in the image as perceived by humans.

iii) Perform merging of the color bins with same similarity color index (S) in Table 1.

iv) Starting from the first color bin in Table 1, compare the color with the next color in Table 1 whose similarity color index (S) is same as that of first color bin on the basis of the same logic of neighborhood connectivity of previous algorithm.

v) If the two segments are similar using threshold-2, merge the ith color with the previous one (the first in Table 1), their populations will be added and the color of larger population will represent the merger.

vi) The merged entry will be removed from Table 1. This reduces number of rows in Table 1. In Table 2, the color index to be merged is changed by the index to which it is merged.

vii) Thus the first color in the Table 1 will be compared with every remaining color in Table 1 whose similarity color index (S) is same as that of first color bin.

viii) Step iv to vii are repeated for every color in the Table 1.

ix) Steps iii to vii are repeated till the Table 1 does not reduce further i.e. equilibrium has reached.

x) Table 2 is sorted in ascending order of the color index.

3.3 Major contributions of proposed algorithm

The major enhancements of the proposed algorithm over previous are

- As we are using here the 3 x 3 tile for comparison, the number of comparisons for all the pixels independent of their location is maximum equal to four whereas in previous algorithm as stated above the comparison complexity increased as the pixel scan line proceeds.
- Also the comparison is between previously encountered immediate neighbors which assures the spatial connectivity of the pixels while formation of the bins.
- The number of bins formed here will be more than previous algorithm as similar color regions which are not connected spatially are included as separate color bins.
- This ensures formation of the spatial 4D color histogram which has color bins on color similarity as well as the spatial connectivity.
- The scan line pixel comparison has a drawback of accommodating shapes with acute angle on boundary as more than one bin. This can be overcome by simply checking whether the previous neighbors P are in similar region and are part of different similar color bins then these bins can be merged and the same is reflected in the Table 1 and Table 2 entries by modifying them.

The agglomerative merging used here has following advantages

- The number of rows in the Table 1 gives us the total color segments in the image which are based on color similarity and spatial connectivity.
- The similarity color index gives us how many similar color segments are available in the image.
- As we are using here the threshold for comparison more than the JND_{eye} threshold the similar connected bins of smaller size merge to form larger similar color regions which are spatially connected.
- The number of bins reduces but the merging is still performed on the basis of spatial connectivity and JND color similarity.

The human retina performs a low pass filtering operation following Poisson's distribution around every point on the retinal image and the neural activity initially notes and interprets the predominant or above average outputs of the retinal sensors passed to the brain via visual cortex [12]. Though we have not implemented the classical Poisson's distribution based spatial integration, the agglomeration in this work has carried out the task of low pass filtering in the color space. This reduces the number of colors in an image from several thousands to a few tens. Based on this human physiological background, the prominent segments of the image can be estimated from the agglomerated histogram.

Segmentation procedure is straightforward with the data structures given in Table 1 and Table 2. In Table 2, the pixel entries are sorted spatially from left to right and from top to bottom. Segmented image can simply be formed by assigning to each pixel position a JND color from Table 1 as pointed to by the respective index in Table 2. Thus the 4D histogram structure can be easily used to reconstruct the image back and can be used as a transform and inverse transform.

3.4 Validating the algorithm with synthetic image data set

The proposed algorithm was initially validated by using segmentation results of the synthetic image data set [25]. This data set consists of 100 synthetic color images of size 100x100. The results of the dataset showed that the segments are formed on the basis of color similarity as well as the spatial connectivity. The similar color segments located at different locations in image were identified as different segments. The sample results are given in figure 2. In Image S1 the number of segments and number of colors is same, but in Image S29_1 and S89 there are segments of similar color which are identified as different segments due to spatial separation between the segments.

4. EXPERIMENTAL RESULTS

In this section, we demonstrate the segmentation results of the proposed algorithm on natural images from Berkeley Segmentation Database (BSD)[19]. It Contains 300 real life RGB images of different categories and same size 481x321 pixels. It also contains benchmark segmentation results (ground truth database) of 1633 segmented images manually obtained from 30 human subjects. i.e. multiple ground truth segmentations of each image. For each image, the quality of segmentation obtained by any algorithm can be evaluated by comparing it with ground truth hand segmentations.

The results of proposed segmentation algorithm are presented here and its effectiveness is compared with the conventional histogram based segmentation & the simple JND color histogram [22], using two quantitative measures, namely, the Probabilistic Rand Index (PRI)[20] and Peak signal to Noise Ratio (PSNR)[20].

PRI Counts the fraction of pairs of pixels whose labeling are consistent between the computed segmentation and the ground truth, averaging across multiple ground truth segmentations to account for variation in human perception. This measure takes the values in the interval [0,1]; more is better. We will consider the segmentation 'good' if for any pair of pixels xi, xj we would like the labels of those pixels li Stest, lj Stest to be the same in the test segmentation if the labels li Sk,lj Sk were the same in the ground truth segmentations, and vice versa.

PSNR represents region homogeneity of the final partitioning. The higher the value of PSNR the better is segmentation. The PSNR measure [21] between the image I and the first order approximation based on the segmentation result S is calculated by equation (5).

$$PSNR(I,S) = 10 \times \log_{10}\left(\frac{255^2 \times rows \times columns \times channels}{\sum_i^{rows}\sum_j^{columns}\sum_k^{channels}(I(i,j,k) - S(i,j,k))^2}\right) \quad \text{------------(5)}$$

The algorithm is applied to BSD database of 500 images. The average PRI and PSNR values of all the images for two algorithms is given in Table 3. The comparison between the PRI and PSNR values of all the images in BSD 300 database is given in Table 4 for the conventional histogram based segmentation, the JND color histogram [22] and the proposed color histogram based segmentation using spatial connectivity.

Table 3 BSDS500 Image Metrics for segmentation using color spatial histogram based segmentation

	BSDS500-ALL	BSDS500-TEST 200	BSDS500-TRAIN 200	BSDS500-VAL 100
PRI	0.7347	0.7435	0.7309	0.7247
MSE	71.4752	74.0469	71.4716	66.3392
PSNR	30.0727	29.8735	30.1183	30.3799

Table 4 BSDS300 Image Metrics for segmentation comparison

Segmentation Method	PRI	PSNR
CCH [22]	0.7181	21.37
JND based Color Histogram [22]	0.7193	25.60
JND based Color Histogram using spatial color segmentation (3x3 tile) BSD300	0.7288	30.20
JND based Color Histogram using spatial color segmentation (3x3 tile) BSD500	0.7347	30.07

The total number of colors and segments in all 500 images of BSDS500 dataset and average number of colors and segments in each image is given in Table 5. It is clear from the this table that the number of segments are more than the number of colors as segmentation is based on color as well as spatial connectivity.

Table 5. BSDS500 Image Metrics for segmentation: number of colors and number of segments

BSD Images	500
Total number of Colors in all Images	7747
Total number of Segments in all Images	918719
Average number of Colors in each Image	15.494
Average number of Segments in Each Image	1837.44

The quantitative comparison as given in Table 3,4,5 and the qualitative (visual) comparison presented in figure 3 clearly demonstrate the superiority of proposed algorithm.

For example in Figure3a) Image-29030, the car is identified as multiple segments and the background due to large variation in shade and shadow of car multiple segments are available. In Figure3c) Image-108004, the stripes on the tiger are identified as different segments though they are of similar color due to spatially at different location. In Figure3e) Image-35010, the white flowers in background are identified as different segments due to spatial separation. In Figure3f) Image-65019, every yellow block is identified as different segment, also the text in black color is also identified as different segment.

5. CONCLUSION AND FUTURE WORK

Comparison of results of proposed segmentation algorithm with the conventional histogram based segmentation algorithms, on BSD segmentation datasets are summarized in Table 3. It can be observed that the proposed segmentation approach is better than the conventional histogram based segmentation algorithms (CCH & the simple JND color histogram), in terms of PRI as well as PSNR. Also due to only maximum 4 comparisons for color matching of pixels which was comparison with all previously encountered neighbors in previous algorithm there is reduction in time required to perform the segmentation of all the images in the dataset, with the proposed approach. The number of colors identified is less than number of segments due to consideration of spatial positions of the color segments. The connectivity check added to the algorithm makes it suitable for applications in the areas where disconnected components are counted as different segments.

Synthetic Image | Segmented Grayscale Image | Segmented Color Image

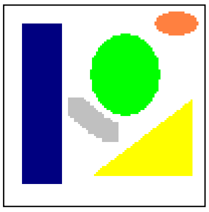
Image S1


Segments: 06 colors: 06

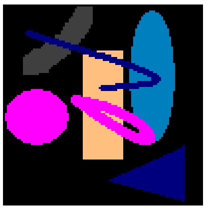
Image S29_1


Segments: 16 colors: 06

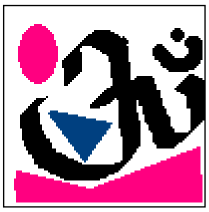
Image S89


Segments: 07 colors: 04

Figure 2 Segmentation results on Synthetic Dataset Images [25].

Original BSD Image

Segmented Output

a)
Image 29030

PRI 0.6187

PSNR 29.5230

Colors 15

Segments 1000

Time for segmentation 2.574 Sec

Figure 3 a) Segmentation results on BSD Images

Original BSD Image

Segmented Output

b)
Image 35049

PRI 0.6517

PSNR 28.2244

Colors 17
Segments 933

Time for segmentation 2.625 Sec

c)
Image 108004

PRI 0.3557

PSNR 31.5761

Colors 14

Segments 2549

Time for segmentation 1.98 Sec

d)
Image 12003

PRI 0.7124

PSNR 30.9697

Colors 26

Segments 2764

Time for segmentation 3.787 Sec

e)
Image 35010

PRI 0.8666

PSNR 28.8136

Colors 17

Segments 2091

Time for segmentation 3.327 Sec

Figure 3 b)-e) Segmentation results on BSD Images

Original BSD Image | **Segmented Output**

f)
Image 65019

PRI 0.9482

PSNR 31.6904

Colors 33

Segments 5270

Time for segmentation 3.916 Sec

Figure 3 f) Segmentation results on BSD Images

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