# An Analytical Approach for Sampling the RGB Color Space Considering Physiological Limitations of Human Vision and its Application for Color Image Analysis

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***Abstract***

Most of the *color image processing algorithms do not consider the non-linearity of human vision, and the limitations of the human vision like- capability to discriminate between two similar colors and maximum number of colors human vision can respond to. In this paper, the nonlinearity and physiological limitations of human vision have been used for sampling the RGB color space. The large redundancy, non-linearity and huge color space dimensionality in the real life color image data reduces the efficiency of color image processing, coding and analysis algorithms. This approach, along with sampling the color space, automatically reduces the redundancy in the data. This reduction in redundancy in color image data has been carried out, while maintaining the visual similarity with the original image. Further a new form of the RGB space named* $J_R$, $J_G$ *and* $J_B$ *which is linear and perceptually uniform has been proposed. Finally some applications of this approach have been presented.*

## 1. Introduction

Most of the work in the field of image processing has been dedicated to the processing, analysis and interpretation of gray images. The computer vision applications require color image analysis, processing and interpretation. The color images are expressed as spatially varying spectral radiance or reflectance distribution [6]. To analyze color image data, we need to map the colors in an image into a color space i.e. a color representation system. Real life color images include large number of colors. Large amount of information is embedded in these images as compared to gray images. The large number of colors available in the images cause problems in most of the image processing applications. In advanced applications using fuzzy reasoning, it is still more computationally complex to handle such large color space, as the fuzzification may further increase the space dimensionality in multiples [1, 14, 15].

The reduction in the number of colors leads to reduction of the search space and hence improves the convergence time considerably. After removing the redundancy and reducing the number of colors in a digital color image, the efficiency of the algorithms may considerably increase. The process of representing the complete color space using a comparatively few representative colors without compromising much on the image quality is widely known as quantization or sampling on the color axes.

The modern computer graphics systems may be able to generate millions of colors, yet a sound vision observer (as defined by CIE) can respond to only 17000 colors at the maximum intensity [2] and thus the huge space containing millions of colors may be mapped on to a new space containing approximately 17000 colors by maintaining the same perceptual quality of the image. Use of sampling theorem in this direction has yet remained unexplored [8,18]. The methods of sampling the color images like oct-tree, population, Heckbert's median–cut and others [9, 10] are mostly statistical in nature, application specific. But none of them consider the human vision capabilities and limitations.

The proposed approach rather modifies the color space itself considering the physiological limitations of human color vision resulting in reduction in number of over all colors in the space and at the same time reducing the redundancy in any color image data. And thus the RGB space transforms into a new color space having much less dimensionality (approximately 900 times less), yet more immunity to redundancy.

The human retina contains a spatial array of three types of color sensors namely red cones, green cones and blue cones which are responsible for color vision [2, 3, 8] and a different type of sensors called rods which are responsible for gray vision. This RGB color sensors in the human retina are excited by different color wavelengths to different extents. Though their responses to this range of wavelengths are not completely orthogonal but still the behavior can be modeled up to a large extent using the orthogonal R,G,B axes[2,17].

The most commonly used color representation is based on the classical three-color theory of Thomas Young, who stated that any color can be reproduced by mixing an appropriate set of three primary colors (R-red, G-green, and B-blue. Also other recent studies have established that there are three different types of cones in the human retina and their spectral responses can be represented as $S_1(\lambda)$, $S_2(\lambda)$ and $S_3(\lambda)$ where, $\lambda_{min}$ = 380 nm and $\lambda_{max}$ = 780 nm. Based on three - color theory the spectral energy distribution of a 'colored' light, $C(\lambda)$ produces a color sensation by integrating the spectral responses of the cones.

Visual discrimination performance as a function of light intensity, have been attributed to the non-linearity in the visual system. Poisson processes were used to overcome this problem [8]. Using the $H_1H_2H_3$ color space, quantization heuristics was improved [10]. Various other color representation systems are described in [6]. The work done in this field involves moment preserving thresholding [4] for reducing the color space dimensionality. Further various works have been proposed on edge detection, segmentation and analysis of color images based on crisp and fuzzy processing. Though the traditional algorithms as proposed in [1,12,13,14,16] were modified in due course of time and yielded good results, but if they use the proposed approach further improvement or at least the same results are possible in less computational complexity.

In this paper, based on the non-linearity of human vision, the RGB color space has been non-linearly sampled. This has been done for reducing the redundancy in colors and for reducing the color space dimensionality. Based on this physiological knowledge of human vision, the non-uniform RGB space has been mapped into a new perceptually uniform space $J_R$, $J_G$, and $J_B$. Further an edge detection and segmentation algorithm have been proposed based on the optimally sampled color space. These algorithms are found to be computationally more efficient and effective as compared to the traditional algorithms.

## 2. Color Space Selection

Typical color images, particularly those, generated by a digital imaging system are represented as red, green, blue and are normally called RGB images. In HSI system, RGB color information is transformed into a mathematical space that de-couples the brightness information from the color information. Then the image information consist of a one – dimensional brightness, or luminance, space and a two dimensional color space RGB. Brightness (w*) or lightness (L) or intensity (I) varies along the vertical axis, hue (H) varies along the circumference and saturation (S) varies along the radial distance. HSL or HIS [6,10,15] is one such color space, which describes colors as perceived by human beings. HSL or HSI stands for hue saturation lightness or intensity. 'Hue' is what the human beings perceive as color (example- Orange, red etc.), 'Saturation' is the measure of whiteness in the color and 'Lightness' is the brightness of colors. Another perceptually non-uniform color space is - SCT (Spherical Coordinate Transform). In nonuniform spaces, two different colors in one part of the color space will not exhibit the same degree of perceptual difference as two colors in another part of the color space, even though they are the same 'distance' apart. In digital computer imaging applications, perceptually uniform color spaces are of great importance. To overcome this problem, CIE (Commission International de l' Eclairage) has developed CIE color spaces. They include standard CIE xyz color space and other perceptually uniform color spaces like L*u*v*, L*a*b* etc.

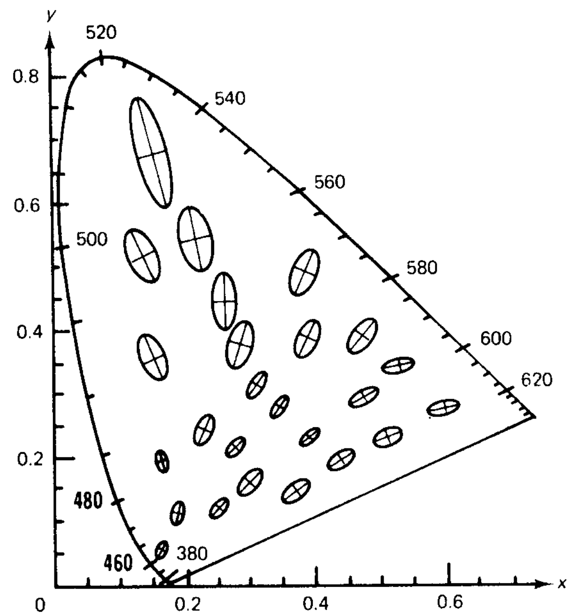


Figure 1 Just noticeable difference ellipses in xyz system

Figure1 shows the ellipses enclosing the color points. These ellipses indicate that the colors lying inside them are perceptually same. Another method of expressing the colors in an image is - Principal Component Transform (PCT), which examines all the RGB vectors of an image and finds the linear transformation that aligns the coordinate axes, so that most of the information is along one axis called principal axis. PCT color spaces help in image compression as we can get about 90% or more information into one band. Every color representation system has its advantages and disadvantages [ 6]. In this work we have used RGB images and the work can be easily ported to other color representation systems using appropriate mathematical transformations.

## 3. Color Space Quantization and the Just Noticeable Difference

A sound human eye can perceive, at the most 17,000 colors at maximum illumination intensity that a human eye can respond normally. So these 17,000 colors are be mapped into the RGB space to simulate the human color vision performance.The red color cones have minimum spectral sensitivity, green color cones have the maximum sensitivity while blue color cones have moderate but near to green sensitivity. Using 24 samples in each basic color shade for color rendition experiments ( McCammy[13] ) and color calibration work ( Chang[20]). This quantization of the RGB space gives 13,824 shades of different colors. For accommodating approximately 17,000 colors in the RGB space, keeping the same number of samples (24) on red axis as the red color sensors are least sensitive, we have selected more number of samples on Green and blue axes. Thus 24 quantization levels on R axis, 26 quantization levels on B axis due to moderate sensitivity of blue receptors and 28 quantization levels on G axis due to the maximum sensitivity of green receptors were selected. Though this heuristic quantization results in slight over-sampling (24x28x26=17,472 as against the required 17,000), it ensures that every perceivable shade by a human being is accommodated in the color space. The issue of non-linearity of the vision is addressed further. Buchsbaum [9] modelled the non-linearity of human vision considering saturation effect as in equation (1).

$$Y(I) = \frac{K}{(4q + p^2) * \left[ \tan^{-1} \frac{(2qI + p)}{\sqrt{4q - p^2}} \right]^2} + C \qquad \text{...........(1)}$$

where, y(I) represents spectral response of the human vision system. I is the intensity input to the system. K is a multiplicative constant. C is an additive constant. The p and q are also constants. K,C ,p and q collectively model the adoption of the eye and the illumination conditions. The vision non-linearity in equation (1) for a typical receptor is

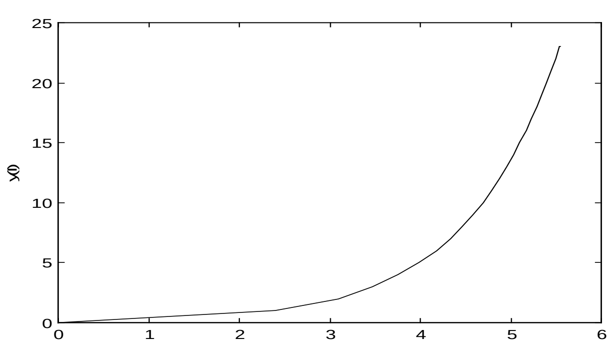


Figure 2 Response of a typical receptor

tansigmoidal in nature and is plotted in figure2, in arbitrary units of y and I, for p=0.0667,q=0.003, K=3.33 and C= -435 after experimentation. The rods and cones have similar nature and thus equation (1) can be used to represent cones i.e. color vision. An experimentation was carried out on twenty sound vision observers for finding out these parameters and modeling the non-linearity of the human vision in normal cases of adoption under broad day-light conditions as defined by CIE (D65 illuminant lamp).

The method of getting responses in the incremental steps of just noticeable differences on intensity axis as suggested in [6] was followed for obtaining the human vision response. The 8-bit colors were used for preparing the pallets in three basic colors R,G and B. In each basic color 64 pallets of size 5cmx5cm [3]were prepared and the observers were asked to discriminate between two successive color shade pallets on a gray background, from a distance of 30cms. The number pallets in each color (64 ) and their size was selected based on the physiological knowledge of human vision[2] and color rendition charts proposed by McCammy [3,11]. The just noticeable differences in each basic color were noted for each of the observers. Then out of these twenty data sets one optimal data set was computed for each color shade.using averaging. Further it is required to fit equation (1) in the data set. It is difficult to fit the above equation in the data set due to its non-standard form. So the following three approaches can be adopted for finding the best fit.

1. The arctan function can be reduced to its equivalent series and fit.
2. Directly an arbitrary polynomial function can be fit using least squares procedure.
3. A neural network with tan-sigmoidal transfer function can be trained and the parameter values in equation (1) can be calculated. The allowed error threshold value can be selected equal to 1/64. A layer of tan-sigmoidal neurons followed by a single linear neuron in the output layer is sufficient to fit equation (1).

Further it was also observed that the neural processor has a linear response. Thus there is a scope to believe that the non-linearity in the human vision is due to the color receptors embedded in the retina and the cortex , i.e., the non-linearity is due to the color receptors. Further the variations in the human observers' performance is due to the variation in the characteristics of the optical components of the system and the fluid in the eye-ball. In other words, the behavior of color receptors in color normal observers is more or less similar and can be roughly modeled using a set of mathematical equations. Thus a specific type of cone in the human retina can be roughly modeled using the above method to decide the parameters. Likewise three different sets of values of K, C, p and q can be calculated for three types of cones in the human retina. An interesting point to be noted here is that changing conditions of adoption of the eye and illumination may be automatically taken care of by changing the conditions at the time of observations by the observers on the pallets.

'Just noticeable difference' between two colors is the minimum difference between two colors, which can be perceived by a normal human eye as different colors. Thus with quantization, the levels on each of the RGB axis should represent the just noticeable differences on the three axes. Any given image which was previously represented as a random function of the RGB variables can now be reduced to this new crisp-quantized but still visually exactly similar image. This new form of the original image can now be used for various image processing, analysis and interpretation applications. Moreover the just noticeable difference space which was heuristically proposed by CIE as shown in Fig.2 now reduces to a systematically modeled and computationally simple RGB color space. This space is sampled non-uniformly in terms of small color cubes, each of them representing visually identical , yet co-ordinate wise many different colors. Here the original color image is mapped in to a new perceptually uniform space $J_R$ $J_G$ $J_B$ ,which express the basic colors in terms of their just noticeable differences on the R,G and B axes. The ellipses in figure 1 now reduce to non-uniform size cuboids in RGB space or uniform size cuboids in $J_R$ $J_G$ $J_B$ space. The respective dimension of each cuboid in RGB space depends on the non-linearity of the vision on the respective axis i.e. R, G and B.

With the above discussion on color space quantization and just noticeable differences, it is obvious that we can find out noticeably different color intensities by differentiating the equation (1) with respect to I as in equation (2) and then substituting the required sample number (i.e. from 1 to 24 for red, 1 to 26 for blue and 1 to 28 for green) for dy(I) to calculate I. One point to be noted here is that these just noticeably different intensities may drastically change

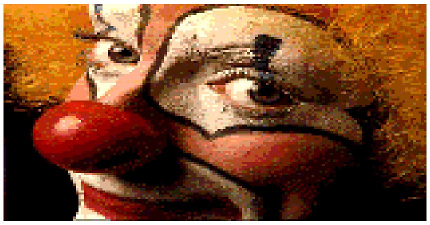

Figure 3(a) Clown

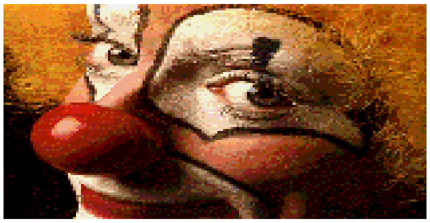

Figure 3(b) Colors Reduced by 5%

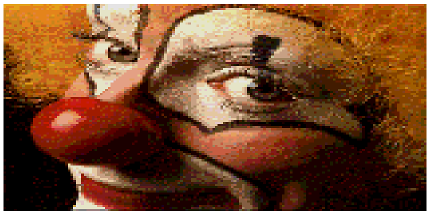

Figure 3(c ) Colors Reduced by 10%

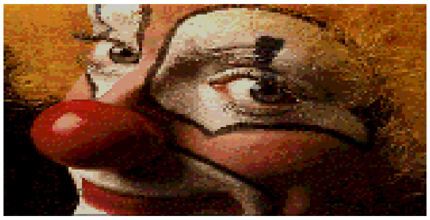

Figure 3(d) Colors Reduced by 20%

depending upon the adoption of the eye and the illumination.

The equation (1) can be more easily used to compute the numerical differentiation of the non-linearity.

Thus the sampling approach has been formulated in Algorithm1 presented below.

**Algorithm1**

1. **Compute the quantization levels on each axis using equation (1).**
2. **Read image pixel color coordinates and truncate them to the lower just noticeable difference on each axis.**
3. **Repeat step2 for all the image pixels.**

## 4.Redundancy in Colors

As discussed above the redundancy in the real life color image data is minimized and the original data is reduced to its respective nearest just noticeable lower color co-ordinates. Figure 3(a) shows an example original image while figure 3(b), (c) and (d) show the reduced color images by 5%,10% and 20%. One may note here that the 5% reduction in colors of the original image is hardly noticeable. While 10% and 15% color differences are noticeable. This means the original image definitely has some redundancy in it. Thus a definition for redundancy in color image data, for color vision applications may be proposed as follows.

Redundancy in the color image data set can be defined as an allowable percentage change in the overall image data without causing any human perceivable change in the color image.

Here we have chosen a measure of redundancy for a color image data with special reference to the proposed approach as presented in equation (2).

$$R_c = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} \left( I_{(i,j,c)} - \Gamma_{(i,j,c)} \right)}{\sum_{i=1}^{m} \sum_{j=1}^{n} I_{(i,j,c)}} ------(2)$$

Here, Rc is the redundancy for color c (c=1 for rows and columns of the image. The overall redundancy is represented by the average of the three color redundancies.

If the redundancy in color image data is taken care of at the pre-fuzzification level an optimally fuzzified data set may result [1]. This approach may even be used while printing the images to use the costly ink of computer printers economically without causing any change in the visual quality of the printed images. Equation (2) can be used as a membership function for allotting the memberships to different RGB vectors as against the normal distribution and piecewise linearity used in [1,18]. An interesting point here is that the membership function proposed by us may be made adaptive to the adoption condition of the eye and also to the changes in illumination by changing its parameters.

## 5.Edge Detection and Segmentation

Most of the real objects in the worlds and possibly the segments are enclosed by edges. Thus edge detection and segmentation are the prime tasks before object detection, feature recognition and subsequent image analysis.

For finding stronger edges and more robust segments the thresholds may even be incremented in the multiples of the just noticeable differences on the respective axes. Moreover in most of the practical edge detection and segmentation algorithms the concept of global thresholding does not work well. Here we present a local thresholding approach with the computed just noticeable differences as thresholds at that spatial coordinates for edge detection and segmentation. The algorithm is presented below.

Algorithm 2

i) Set pointers to the width and height of the image.
ii) Select a (2 x 2) elemental matrix of the image.
iii) Set the elemental matrix at the top left corner of the image.
iv) Compare the central element of the elemental matrix with its four neighbors , wherever of these positions the difference is greater than the threshold, decided by the color space, the edge is present and the respective point is marked as an edge point in the resulting image matrix..
v) Shift the elemental matrix row wise and column wise successively and repeat the step (iii) to step (iv) by scanning the complete image for all the positions of the elemental matrix.

Another important operation in machine vision applications is the segmentation. Segmentation involves assigning pixels with similar characteristics to the same class in an image. Choosing the just noticeable difference between two colors as a dissimilarity threshold and based on this threshold a region growing approach has been implemented, which yields good segmentation results. Threshold in this case may also be selected in multiples of the just noticeable differences to achieve robust segmentation.

ALGORITHM –3

1) Set pointers to the width and height of the image.
2) Select a (2×2) elemental matrix of the image.
3) Set the elemental matrix at the top left corner of the image.
4) Compare the central element of the matrix with its four neighbours and assign the pixel a class depending on the threshold

The results of this algorithm are presented in the next section.

## 6. Results and Discussion

In this section, some of the results of the above presented algorithms have been presented for a threshold of three just noticeable differences. Figure 4(a) shows the original image. Figure 4(b) shows the color-reduced image using the above approach. Figure 4 (c) shows the edge detection algorithm results. Figure 4(d) presents the segmentation results overlapped with edge detection results.

In real life pictures, it is not at all necessary that if the two colors are separated by just more than a just noticeable difference they will be treated as different colors. Actually the difference perceived in the noticeably different colors in an image, by a human observer, depends on the global color distribution of the image, contextual relation between the different colored objects in the image, knowledge of the observer about colors of the different objects, etc. Number of times even intuition is also one of the factors in the process of color matching and recognition. The proposed sampling approach is suitable for fuzzy processing for its tremendous reduction in the space dimensionality and the color data redundancy. As the newly introduced color space $J_RJ_GJ_B$ is uniform, the membership functions in it can be linear. The reduction in the color space dimensionality and redundancy also benefits the neural network based and genetic algorithm based analysis algorithms.

Figure 4(a) Original Flowers

Figure 4(b) Sampled Flowers

Figure 4(c) Edge Detected Flowers

Figure 4(d) Segmentation with Edge Detection

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