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Multi Color Image Segmentation using L*A*B* Color Space

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Abstract— *Image segmentation is always a fundamental but challenging problem in computer vision. The simplest approach to image segmentation may be clustering of pixels. my works in this paper address the problem of image segmentation under the paradigm of clustering. A robust clustering algorithm is proposed and utilized to do clustering on the L*a*b* color feature space of pixels. Image segmentation is straight forwardly obtained by setting each pixel with its corresponding cluster. We test our segmentation method on fruits images, medical and Mat lab standard images. The experimental results clearly show region of interest object segmentation.*

Keywords— color space, L*a*b* color space, color image segmentation, color clustering technique.

I. INTRODUCTION

A Lab color space is a color-opponent space with dimension L for lightness and a and b for the color opponent dimensions, based on nonlinearly compressed CIE XYZ color space coordinates. The coordinates of the Hunter 1948 L, a, b color space are L, a, and b [1][2]. However, Lab is now more often used as an informal abbreviation for the CIE 1976 (L*, a*, b*) color space (also called CIELAB, whose coordinates are actually L*, a*, and b*). Thus, the initials Lab by themselves are somewhat ambiguous. The color spaces are related in purpose, but differ in implementation. Color spaces usually either model the human vision system or describe device dependent color appearances. Although there exist many different color spaces for human vision, those standardized by the CIE (i.e. XYZ, CIE Lab and CIE Luv, see for example Wyszecki & Stiles 2000) have gained the greatest popularity. These color spaces are device independent and should produce color constancy, at least in principle. Among device dependent color spaces are HSI, NCC rgbI and YIQ (see Appendix 1 for formulae). The different versions of HS-spaces (HSI, HSV, Fleck HS and HSB) are related to the human vision system; they describe the color's in a way that is intuitive to humans.

The three coordinates of CIELAB represent the lightness of the color (***L**** = 0 yields black and ***L**** = 100 indicates diffuse white; specular white may be higher), its position between red/magenta and green (***a****, negative values indicate green while positive values indicate magenta) and its position between yellow and blue (***b****, negative values indicate blue and positive values indicate yellow). The asterisk (*) after *L*, *a* and *b* are part of the full name, since they represent *L**, *a** and *b**, to distinguish them from Hunter's *L*, *a*, and *b*, described below. Since the *L*a*b** model is a three-dimensional model, it can only be represented properly in a three dimensional space. Two-dimensional depictions are chromaticity diagrams: sections of the color solid with a fixed lightness. It is crucial to realize that the visual representations of the full gamut of colors in this model are never accurate; they are there just to help in understanding the concept. Because the red/green and yellow/blue opponent channels are computed as differences of lightness transformations of (putative) cone responses, CIELAB is a chromatic value color space. A related color space, the CIE 1976 (*L**, *u**, *v**) color space (a.k.a. CIELUV), preserves the same *L** as *L*a*b** but has a different representation of the chromaticity components. CIELUV can also be expressed in cylindrical form (CIELCH), with the chromaticity components replaced by

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correlates of chroma and hue. Since CIELAB and CIELUV, the CIE has been incorporating an increasing number of colors appearance phenomena into their models, to better model color vision. These color appearance models, of which CIELAB, although not designed as [3] can be seen as a simple example [4], culminated with CIECAM02.

II. COLOR SPACE

The nonlinear relations for L*, a*, and b* are intended to mimic the nonlinear response of the eye. Furthermore, uniform changes of components in the L*a*b* color space aim to correspond to uniform changes in perceived color, so the relative perceptual differences between any two colors in L*a*b* can be approximated by treating each color as a point in a three dimensional space (with three components: L*, a*, b*) and taking the Euclidean distance between them [5].

A. Device independent color space

Some color spaces can express color in a device-independent way. Whereas RGB colors vary with display and scanner characteristics, and CMYK colors vary with printer, ink, and paper characteristics, device independent colors are not dependent on any particular device and are meant to be true representations of colors as perceived by the human eye. These color representations, called device-independent color spaces, result from work carried out by the Commission International d'Eclairage (CIE) and for that reason are also called CIE-based color spaces. The most common method of identifying color within a color space is a three-dimensional geometry. The three color attributes, hue, saturation, and brightness, are measured, assigned numeric values, and plotted within the color space.

*B. CIE XYZ to CIE L*a*b* (CIELAB) and CIELAB to CIE XYZ conversion*

The forward transformation

$$L^* = 116 f\left(Y/Y_n\right) - 16$$

$$a^* = 500\left[f\left(X/X_n\right) - f\left(Y/Y_n\right)\right]$$

$$b^* = 200\left[f\left(Y/Y_n\right) - f\left(Z/Z_n\right)\right]$$

where,

$$f(t) = \begin{cases} t^{1/3} & \text{if } t > \left(\frac{6}{29}\right)^3 \\ \frac{1}{3}\left(\frac{29}{6}\right)^2 t + \frac{4}{29} & \text{otherwise} \end{cases}$$

Here *Xn*, *Yn* and *Zn* are the CIE XYZ tristimulus values of the reference white point (the subscript n suggests "normalized").

The division of the *f*(*t*) function into two domains was done to prevent an infinite slope at $t = 0$. *f*(*t*) was assumed to be linear below some $t = t0$, and was assumed to match the *t*1/3 part of the function at *t*0 in both value and slope. In other words:

$$t_0^{1/3} = at_0 + b \quad (\text{match in value})$$

$$\frac{1}{3} t_0^{-2/3} = a \quad (\text{match in slope})$$

The slope was chosen to be $b = 16/116 = 4/29$. The above two equations can be solved for a and t_0:

$$a = \frac{1}{3}\delta^{-2} = 7.787037...$$

$$t_0 = \delta^3 = 0.008856...$$

Where $\delta = 6/29$ [8].Note that the slope at the join is $b = 4/29 = 2\delta/3$.

Reverse transformation

$$Y = Y_n f^{-1}\left(\frac{1}{116}\left(L^* + 16\right)\right)$$

$$X = X_n f^{-1}\left(\frac{1}{116}\left(L^* + 16\right) + \frac{1}{500} a^*\right)$$

$$Z = Z_n f^{-1}\left(\frac{1}{116}\left(L^* + 16\right) - \frac{1}{200} b^*\right)$$

Where,

$$f^{-1}(t) = \begin{cases} t^3 & \text{if } t > \frac{6}{29} \\ 3\left(\frac{6}{29}\right)^2\left(t - \frac{4}{29}\right) & \text{otherwise} \end{cases}$$

C. Lab color space

The overall concept starting from conversion of original image to L*a*b* color space and then object segmentation is represented through block diagram.

Figure 1.Color Image Segmentation for Medical Images using L*a*b* Color Space

D. Color difference

The difference or distance between two colors is a metric of interest in color science. It allows people to quantify a notion that would otherwise be described with adjectives, to the detriment of anyone whose work is color critical. Common definitions make use of the Euclidean distance in a device independent color space.

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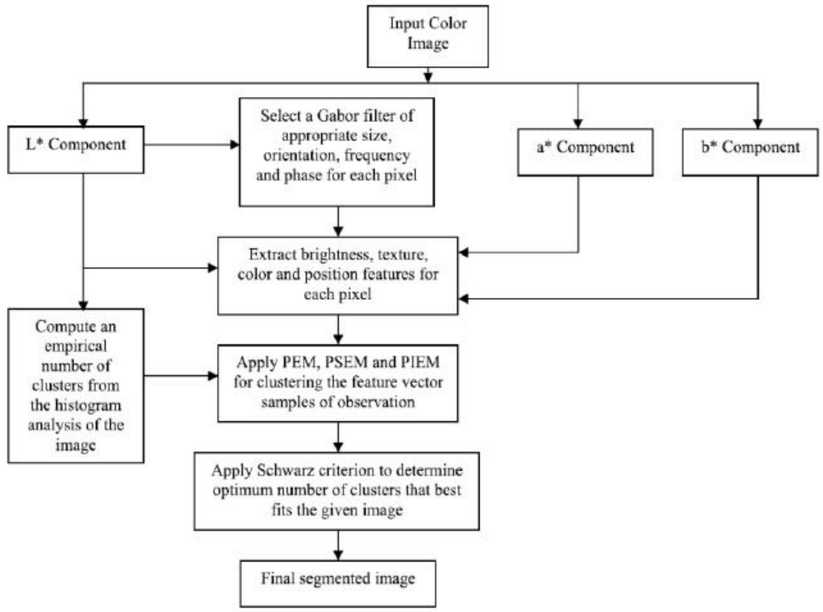

a. Delta E

The International Commission on Illumination (CIE) calls their distance metric Δ*E***ab* (also called Δ*E**, dE*, dE, or ―Delta E‖) where delta is a Greek letter often used to denote difference, and **E** stands for *Empfindung*; German for "sensation". Use of this term can be traced back to the influential Hermann von Helmholtz and Ewald Hering. In theory, a Δ*E* of less than 1.0 is supposed to be indistinguishable unless the samples are adjacent to one another. However, perceptual non-uniformities in the underlying CIELAB color space prevent this and have led to the CIE's refining their definition over the years. These non-uniformities are important because the human eye is more sensitive to certain colors than others. A good metric should take this into account in order for the notion of a "just noticeable difference" to have meaning. Otherwise, a certain Δ*E* that may be insignificant between two colors that the eye is insensitive to may be conspicuous in another part of the spectrum [6].Unit of measure that calculates and quantifies the difference between two colors -- one a reference color, the other a sample color that attempts to match it -- based on L*a*b* coordinates. The "E" in "Delta E" comes from the German word "Empfindung," meaning "feeling, sensation Delta" comes from the Greek language, and is used in mathematics (as the symbol Δ) to signify an incremental change in a variable, i.e., a difference. So, "Delta E" comes to mean "a difference in sensation." A Delta E of 1 or less between two colors that are not touching one another is barely perceptible by the average human observer; a Delta E between 3 and 6 is typically considered an acceptable match in commercial reproduction on printing presses. (Note: Human vision is more sensitive to color differences if two colors actually touch each other.) The higher the Delta E, the greater the difference between the two samples being compared. There are several methods by which to calculate Delta E values, the most common of which are Delta E 1976, Delta E 1994, Delta E CMC, and Delta E 2000. Delta E 2000 is considered to be the most accurate formulation to use for small delta E calculations (<5). Daylight human vision (a.k.a., photopic vision) is most sensitive to the green region of the color spectrum around 550nm, and least sensitive to colors near the extremes of the visible spectrum (deep blue purples at one end and deep reds at the other). For that reason, color differences in the latter regions are harder for the average human observer to detect and quantify, making Delta E measurements for those colors possibly less accurate.

b. Tolerance

Tolerancing concerns the question "What is a set of colors that are imperceptibly/acceptably close to a given reference?" If the distance measure is perceptually uniform, then the answer is simply "the set of points whose distance to the reference is less than the just-noticeable-difference (JND) threshold." This requires a perceptually uniform metric in order for the threshold to be constant throughout the gamut (range of colors). Otherwise, the threshold will be a function of the reference color—useless as an objective, practical guide. In the CIE 1931 color space, for example, the tolerance contours are defined by the MacAdam ellipse, which holds L* (lightness) fixed. As can be observed on the diagram on the right, the ellipses denoting the tolerance contours vary in size. It is partly due to this non-uniformity that lead to the creation of CIELUV and CIELAB. More generally, if the lightness is allowed to vary, then we find the tolerance set to be ellipsoidal. Increasing the weighting factor in the aforementioned distance expressions has the effect of increasing the size of the ellipsoid along the respective axis [7].Turgay Celik and Tardi Tjahjadi [7] presented an effective unsupervised color image segmentation algorithm which uses multi scale edge information and spatial color content. The segmentation of homogeneous regions is obtained using region growing followed by region merging in the CIEL*a*b* color space.

c. Delta difference and tolerance

The difference between two color samples is often expressed as Delta E, also called DE, or ΔE. 'Δ' is the Greek letter for 'D'. This can be used in quality control to show whether a printed sample, such as a color swatch or proof, is in tolerance with a reference sample or industry standard. The difference between the L*, a* and b* values between the reference and print will be shown as Delta E (ΔE). The resulting Delta E number will show how far apart visually the two samples are in the color 'sphere'.

Customers may specify that their contract proofs must have tolerances within ΔE 2.0 for example. Different tolerances may be specified for greys and primary colors. A value of less than 2 is common for greys and less than 5 for primary CMYK and overprints. This is somewhat contentious however. Proofing RIPs sometimes have verification software to check a proof against a standard scale, such as an Ugra/ Fogra Media Wedge, using a spectrophotometer. Various software applications are available to check color swatches and spot colors, proofs, and printed sheets. Delta E displays the difference as a single value for color and lightness. ΔE values of 4 and over will normally be visible to the average person, while those of 2 and over may be visible to an experienced observer. Note that there are several subtly different variations of Delta E: CIE 1976, 1994, 2000, cmc delta e [8].

III. METHODOLOGY

User draws region and this finds pixels in the image with a similar color, using Delta E. As well as the RGB image is converted to LAB color space and then the user draws some freehand-drawn irregularly shaped region to identify a color. The Delta E (the color difference in LAB color space) is then calculated for every pixel in the image between that pixel's color and the average LAB color of the drawn region. The user can then specify a number that says how close to that color would they like to be. The software will then find all pixels within that specified Delta E of the color of the drawn region.

IV. COLOR-BASED SEGMENTATION USING PROPOSED CLUSTERING TECHNIQUE

The proposed approach performs clustering of color space. A particle consists of K cluster centroids representing L*a*b* color triplets. The basic aim is to segment colors in an automated fashion using the L*a*b* color space and K-means clustering. The entire process can be summarized in following steps

Step 1: Read the image. Read the image from mother source which is in .JPEG format, which is a fused image.

Step 2: For color separation of an image apply the De-correlation stretching.

Step 3: Convert Image from RGB Color Space to L*a*b* Color Space. How many colors do we see in the image if we ignore variations in brightness? There are three colors: white, blue, and pink. We can easily visually distinguish these colors from one another. The L*a*b* color space (also known as CIELAB or CIE L*a*b*) enables us to quantify these visual differences. The L*a*b* color space is derived from the CIE XYZ tristimulus values. The L*a*b* space consists of a luminosity layer 'L*', chromaticity-layer 'a*' indicating where color falls along the red-green axis, and chromaticity-layer 'b*' indicating where the color falls along the blue-yellow axis. All of the color information is in the 'a*' and 'b*' layers. We can measure the difference between two colors using the Euclidean distance metric. Convert the image to L*a*b*color space.

Step 4: Classify the Colors in 'a*b*' Space Using K-Means Clustering. Clustering is a way to separate groups of objects. K-means clustering treats each object as having a location in space. It finds partitions such that objects within each cluster are as close to each other as possible, and as far from objects in other clusters as possible. K-means clustering requires that you specify the number of clusters to be partitioned and a distance metric to quantify how close two objects are to each other. Since the color information exists in the 'a*b*' space, your objects are pixels with 'a*' and 'b*' values. Use K-means to cluster the objects into three clusters using the Euclidean distance metric.

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Step 5: Label Every Pixel in the Image using the results from K-MEANS.

For every object in our input, K-means returns an index corresponding to a cluster. Label every pixel in the image with its cluster index.

Step 6: Create Images that Segment the Image by Color.

Using pixel labels, we have to separate objects in image by Color.

Step 7: Segment the Nuclei into a Separate Image.

A. Proposed clustering algorithm

Propose clustering algorithm is under the category of Squared Error-Based Clustering (Vector Quantization) and it is also under the category of crisp clustering or hard clustering. Proposed algorithm is very simple and can be easily implemented in solving many practical problems. Proposed algorithm is ideally suitable for biomedical image segmentation since the number of clusters (k) is usually known for images of particular regions of human anatomy. Steps of the proposed clustering algorithm are given below:

1) Choose k cluster centers to coincide with k randomly chosen patterns inside the hyper volume containing the pattern set (C).

2) Assign each pattern to the closest cluster center. i.e. (C_i , i=1,2,...C)

3) Recomputed the cluster centers using the current cluster memberships. (U):

4)
$$u_{ij} = \begin{cases} 1, if \left\| x_j - c_i \right\|^2 \le \left\| x_j - c_k \right\|^2, foreach k \ne i \\ 0, otherwise \end{cases}$$

5) If convergence criterion is not met, go to step 2 with new cluster centers by the following equation, i.e. minimal decrease in squared error:

$$c_i = \frac{i}{G_i} \sum_{k, X_k \in G_i} X_k$$

Where, $|G_i|$ is the size of G_i or $|G_i| = \sum_{j=1}^{n} u_{ij}$

V. RESULTS AND EVALUATION

After the conversion of image into L*a*b* color space, segmentation algorithm is applied.

Figure 5 shows the results of Matlab standard peppers image for two different Region of interest (ROI) (a) first ROI having Delta E <= 30.9 or >30.9 (b) second ROI having Delta E <= 54.3 or > 54.3. And also represents the complete steps to obtain segmentation with selection of object of interest (Region of Interest (ROI)), L*a*b* representation, their histograms and segmented results with matching colors or not matching colors. Figure 8 shows the results of Human Heart image with (a) Original image (b),(c) and (d) Heart image segmented objects with proposed COLOR CLUSTERING Technique (e) color classification scatter plot representation of the segmented pixels in L*a*b* color space. Scatter plot represents clusters of color pixels in the segmented image. Here various heart vessels and heart chambers are segmented from heart image.

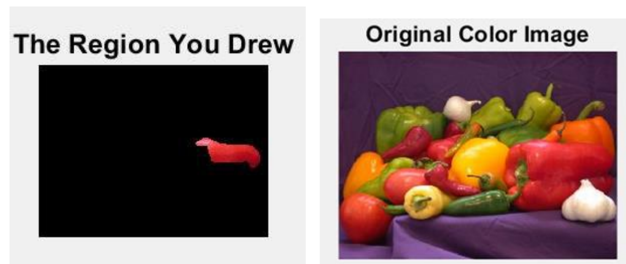

Fig.2. a. Original Image b.Region Drew Image

Fig.3. Delta E between images within masked region

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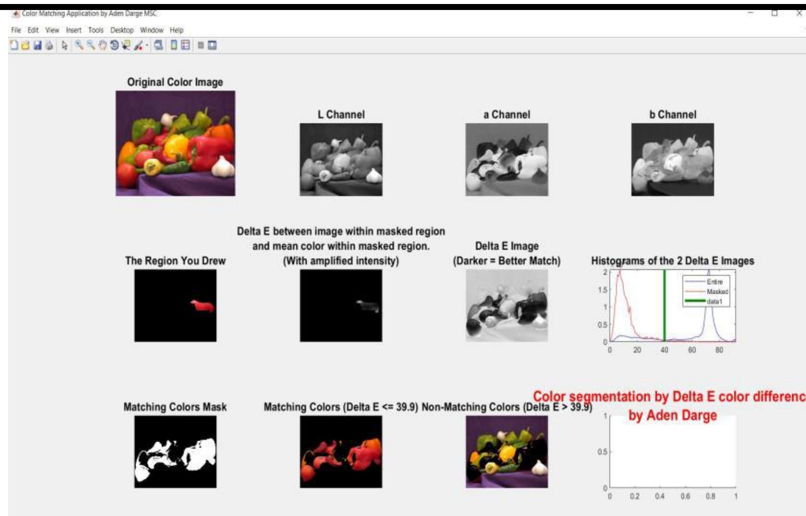

Fig.4: Matching color Mask

Fig.5. Results of Matlab standard peppers image for two different region of interest (ROI) (a) first ROI having Delta E<=39.9 or >39.9

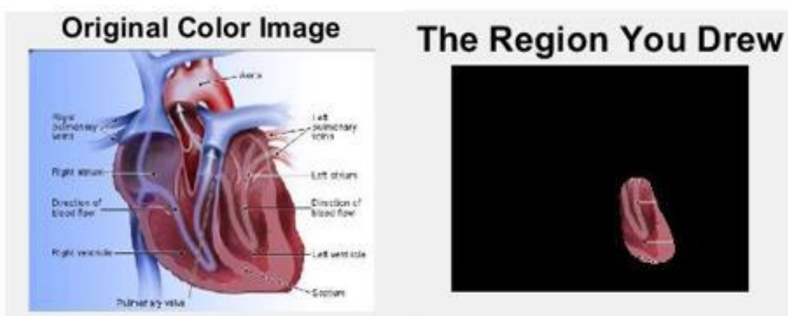

Fig.6. a. Original Image b.Region Drew Image

Fig.7. Delta E between images within masked region

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Fig.8. Matching color Mask

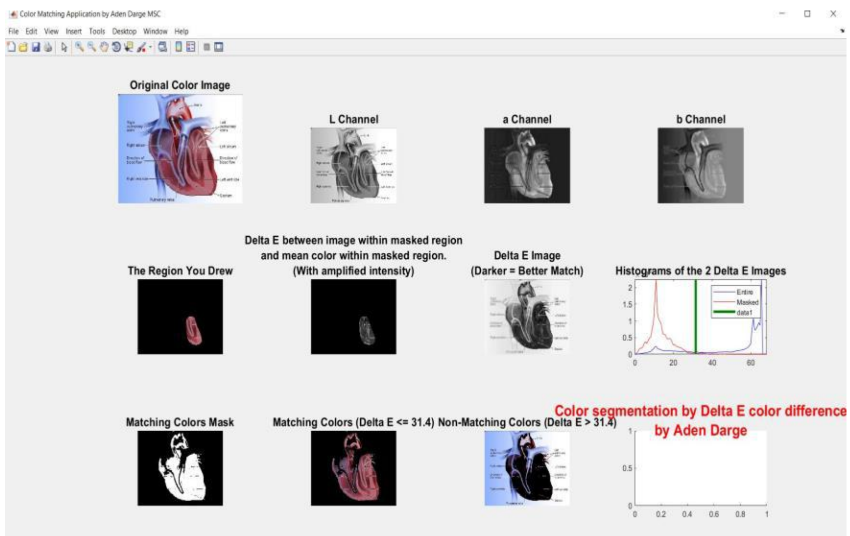

*Fig.9. Results of Human Heart image (a) Original image (b)(c)(d) heart image segemnted objects with proposed COLOR CLUSTERING technique (e) color classification scatter plot representation of the segmented pixels in L*a*b color space having Delta E<=31.4 or >31.4.*

VI. CONCLUSION

The approach of employing color clustering image segmentation using L*a*b* color space for any standard images is proposed. Color clustering image segmentation algorithm, segments the important object information from images. The effectiveness of the proposed method is tested by conducting two sets of experiments out of which one is meant for medical images segmentation and one for standard images from Mat Lab software. This L* a* b* is also providing better segmentation result for all color images.

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