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Creating New Color Space Using Convex Constraint Programming Applied to Skin Color Detection

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Abstract: Each three-component collection such as {Red, Green, Blue} (RGB), and {Luminance Y, Chrominance Cr, Chrominance Cb} (YCbCr) is termed as a color space. Many color spaces are related to each other by linear transformations that are captured by 3×3 matrices. Hence a given color, and thereby any color image, can be represented in terms of another color space by transforming its 3-d vector representation using the 3 × 3 matrix. The Main target of this paper is introduce new color transform from viewpoint of convex constraint programming. Skin detection is used as benchmark problem for the proposed algorithm. In the New color space, the skin and non-skin classes are separated as well. This problem is converted to a convex constraint programming which Lagrange multipliers method is used for solving this problem. Founded converting matrix is tested in skin detection in simple to complex scene. Obtained results over many databases are compared with existing methods which show superiority of the proposed method. Skin and non-skin clusters in the new space color have clustering criteria better than RGB and YCbCr color space.

Keywords: Color space; Convex constraint programming; Skin detection; Clustering criteria; Lagrange multipliers.

1. Introduction

Color is a 3-dimensional psychophysical phenomenon and is represented in color space models whereby individual colors are specified by points in these spaces. R, G, B primaries can produce a gamut of $(2^8)^3$ different colors [1]. RGB is the color space usually used in digital images. Each pixels use 8 bits for each one of its color components (R, G and B), in a total of 24 bits for pixel. The color space converter transforms the color information form the RGB space to the other spaces as YCbCr space and it should maintain the representation of each one of the new space components with the same amount of bits used to represent each component of the input space (R, G and B). The calculations performed in the color space conversion from RGB to YCbCr are presented below. Parcels of each R, G and B input components are considered in the calculation of the output components in the space YCbCr [2].

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 0.299 & 0.578 & 0.114 \\ -0.169 & -0.331 & 0.5 \\ 0.5 & -0.419 & -0.081 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (1)$$

CIE standardized color order systems by specifying the light source, the observer and the methodology used to derive the values for describing a color. The XYZ color system is also accepted then and it has been used ever since. In this system, Y represents the brightness (or luminance) of the color, while X and Z are virtual (or not physically realizable) components of the primary spectra [3].

Many color spaces are presented but other viewpoint is theories of color vision which are derived from the sums and differences of the three cone types. One mechanism (often referred to as the ‘‘luminance’’ mechanism) signals a weighted sum of long-wavelength-selective (L) and medium-wavelength-selective (M) cones, i.e., ‘‘L+M’’ (with some debate regarding the contribution of short wavelength selective (S) cones: [4, 5, and 7]. Two chromatic mechanisms signal weighted sums and differences of the cones. The ‘‘L-M’’ mechanism signals differences between L- and M-cones (and is often referred to as the ‘‘red/green’’ mechanism). The ‘‘S-(L+M)’’ mechanism signals differences between S-cones and the sum of L- and M-cones (and is often referred to as the ‘‘blue/yellow’’ mechanism).

Other viewpoint to color space is selection of best space. In this regard, different transformations of RGB color space (as HSI, HSV and Lab) are compared to find the best method for separating target/clutter or foreground/background and so on in color images taken by a digital photo camera [7]. Some of researchers used a color space in a specific application in the computer vision as skin detection in HSV [8], face recognition in new space based on K-L[1] transform [9], lip tracking into the CIELAB, CIELUV color spaces [10], object recognition into illumination invariant type of RGB color space [11], Image restoration into the CIELAB color space [12], and so on. The performance of an image analysis procedure is known to depend on the choice of the color space. In [13], the properties of six color spaces are discussed for detection of specific surface defects. They show that these defects are well detected when the clustering analysis is performed in the RGB space. Authors of [14] apply two classification methods using different color spaces. By means of a visual appreciation of the results, they also conclude that the RGB space is the best among all the considered color spaces.

This short and non-exhaustive bibliography shows that different authors provide contradictory conclusions about the pertinence of the available color spaces in the context of image analysis. Instead of searching the best classical color space for object detection/classification/segmentation, we propose an original approach based on convex constraint optimization technique for converting of color space which can be used in very application. Linear transformation by 3×3 matrix is performed and all pixels of target and non-target are transformed to new space but this matrix must be calculated as in the new space target and non-target are separated as well. So, this problem is converted to the form of a quadratic optimization with a set of constraints. Then skin color detection is used as benchmark problem to test of the proposed algorithm. Color space is mapped to a new space over skin color data base with skin and non-skin color are clustered to best form. For evaluation, clustering criteria is used. Optimum color space in skin color detection over selected data base is caused skin and non-skin cluster to be separated is created as well. Manifest features of the proposed method are,

- Creating of color space from viewpoint of constraint programming
- Finding optimum color space based on type of application
- Effect of the proposed method in a real application

[1] Karhunen-Lo`eve

The paper is organized as follows. First, we mention the color space in Section 2. Section 3 is appropriated to the proposed method in finding optimum color space, which is followed by experimental result over skin/non-skin color detection in Section 4, and finally we conclude with a number of comments in Section 5.

2. Concise acquaintance with color space

Color perception is related to human sense from energy distribution of light spectrum. Difference in color spaces is result of human feeling. The most frequently used color spaces are [15, and 16]:

RGB color space: The red, green and blue colors represent the three components and define the basic color space. However, in RGB color space, there are correlations between the different channels' values. For example, the G and R values will be large if the B value is large. This implies that close relationships exist among three mapping functions. If the functions add the G values and reduce the B values, out-of-gamut may be produced.

Linear and non-linear transform of RGB color space: The RGB primaries can be used to derive a new coordinate system via a linear or a non-linear transform. Examples of linear transformations are the YIQ and the XYZ color spaces [16]. Color coordinate systems obtained from RGB through non-linear transforms are: the IHS, CIELAB, CIELUV color spaces. Most of the transformed systems are more uniform and orthogonal than the original RGB space and their components are substantially decorrelated [15].

$R_NG_NB_N$ color space: One group of commercial televisions use cathode ray tube with three type of phosphor which creat spectrum from each of phosphor is not monochrome and is related to tube manufacturer. Practically, these tubes are compared by standard phosphor introduced by N.T.S.C[2]. YUV color space is used in SECAM and PAL TV system. YUV is a linear transform of $R_NG_NB_N$ as follow,

$$\begin{aligned} Y &= 0.299R_N + 0.587G_N + 0.114B_N \\ U &= \frac{(B_N - Y)}{2.03} = 0.493(B_N - Y) \\ V &= \frac{(R_N - Y)}{1.14} = 0.877(R_N - Y) \end{aligned} \quad (2)$$

YC_bC_r color space is very close to YUV space. This space is scaled and shifted YUV color space so as Cb and Cr is between range of (0,1) and are obtained as follows,

[1] National Television System Committe [2]

$$C_b = (B_N - Y)/1.772 + 0.5$$
$$C_r = (R_N - Y)/1.402 + 0.5 \qquad (3)$$

In this paper, new color space is introduced and compared to YC_bC_r and RGB color spaces.

3. Creating new color space using constraint programming technique

Many color spaces are related to each other by linear transformations through 3×3 matrices. Hence a given color, and thereby any color image, can be represented in terms of another color space by transforming its 3-d vector representation using the 3 × 3 matrix as follows,

$$\begin{bmatrix} X_1 \\ X_2 \\ X_3 \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \\ w_{31} & w_{32} & w_{33} \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \qquad (4)$$

This converting is performed so as to new color space target and non-target are separated optimally. This subject is shown in Fig 1 from viewpoint of clustering.

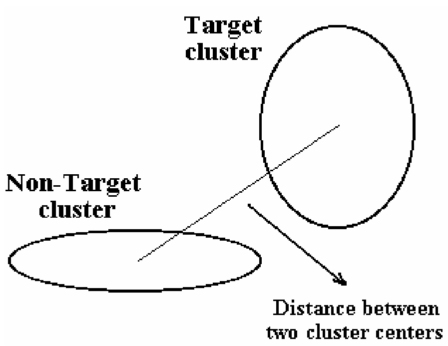

Fig.1: Target and non-target clusters

With regard to (4), we can write for each pixel:

$$X_1 = w_{11}R + w_{12}G + w_{13}B$$
$$X_2 = w_{21}R + w_{22}G + w_{23}B \qquad (5)$$
$$X_3 = w_{31}R + w_{32}G + w_{33}B$$

w_{ij} in (5) must be founded to creat new color space (X_1, X_2, X_3), in order to optimal clustering vector target and non-target with the following criteria,

$$\Psi(W) = \sum_{j=1}^{N} d_{1j} + \sum_{j=1}^{M} d_{2j} - L \qquad (6)$$

where d_{1j} is the distance of jth sample from the center of class 1,and d_{2j} is the distance of jth sample from the center of class 2, and L is the distance between two center class. And N, M are number of sample in class 1, 2 respectively and W is a matrix including w_{ij} for i, j=1,2,3. Now, creating color space problem is converted to an optimization problem which includes some constraints. We follow for minimization of cost function $\Psi(W)$ with following constraints.

3-1-Constraints

Group 1: In (5) for R, G, B equal to one, (X_1, X_2, X_3) are forced to one for each pixel of target and non-target using following constraints:

$$1 = w_{11} + w_{12} + w_{13}$$
$$1 = w_{21} + w_{22} + w_{23} \qquad (7)$$
$$1 = w_{31} + w_{32} + w_{33}$$

*Group 2:*In (5) for R, G, B equal to 255, (X_1, X_2, X_3) are forced to 256 for each pixels of target and non-target using following constraints:

$$256 = w_{11}255 + w_{12}255 + w_{13}255$$
$$256 = w_{21}255 + w_{22}255 + w_{23}255 \qquad (8)$$
$$256 = w_{31}255 + w_{32}255 + w_{33}255$$

Group 3: In (5) for each RGB pixel in the input space, (X_1, X_2, X_3) must be smaller than 256 which is ascertainable using following constraints:

$$R_i w_{11} + G_i w_{12} + B_i w_{13} \le 256$$
$$R_i w_{21} + G_i w_{22} + B_i w_{23} \le 256 \qquad (9)$$
$$R_i w_{31} + G_i w_{32} + B_i w_{33} \le 256$$

Group 4: In (5) for each RGB pixel in the input space, (X_1, X_2, X_3) must be bigger than one which is converted to small inequality to following form:

$$-(R_i w_{11} + G_i w_{12} + B_i w_{13}) \le -1$$
$$-(R_i w_{21} + G_i w_{22} + B_i w_{23}) \le -1 \qquad (10)$$
$$-(R_i w_{31} + G_i w_{32} + B_i w_{33}) \le -1$$

Group 5: Also, all weights must be limited into defined range as $a \le w_{ij} \le b$.

3-2-Cost function $\Psi(W)$

Clustering criteria is used to construct cost function of $\Psi(W)$ which includes these notes, density of each cluster and distance of clusters centers and is shown in (6). If $\Psi(W)$ is minimized subject to mentiond constraints in (7, 8, 9, 10), new color space is generated with the optimum form. In new color space, each pixel is converted using (5) and center of each clusters are obtained using (11, 12) as follows,

$$\begin{cases} \mu^{1}_{X1} = w_{11}\overline{R}^{1} + w_{12}\overline{G}^{1} + w_{13}\overline{B}^{1} \\ \mu^{1}_{X2} = w_{21}\overline{R}^{1} + w_{22}\overline{G}^{1} + w_{23}\overline{B}^{1} \\ \mu^{1}_{X3} = w_{31}\overline{R}^{1} + w_{32}\overline{G}^{1} + w_{33}\overline{B}^{1} \end{cases} \quad (11)$$

$$\begin{cases} \mu^{2}_{X1} = w_{11}\overline{R}^{2} + w_{12}\overline{G}^{2} + w_{13}\overline{B}^{2} \\ \mu^{2}_{X2} = w_{21}\overline{R}^{2} + w_{22}\overline{G}^{2} + w_{23}\overline{B}^{2} \\ \mu^{2}_{X3} = w_{31}\overline{R}^{2} + w_{32}\overline{G}^{2} + w_{33}\overline{B}^{2} \end{cases} \quad (12)$$

where μ^{k}_{Xi} is the center of k^th cluster in the new color space in the i^th dimension. $\overline{R}^{i}, \overline{G}^{i}, \overline{B}^{i}$ are mean values of R, G, B components in the i^th cluster (skin and non-skin). w_{ij} are conversion weights. The Distance of each pixels in each cluster to its center can be obtained from (13, 14) :

$$\begin{aligned} d_i = & \left(w_{11}(R_i^{1} - \overline{R}^{1}) + w_{12}(G_i^{1} - \overline{G}^{1}) + w_{13}(B_i^{1} - \overline{B}^{1}) \right)^2 + \\ & \left(w_{21}(R_i^{1} - \overline{R}^{1}) + w_{22}(G_i^{1} - \overline{G}^{1}) + w_{23}(B_i^{1} - \overline{B}^{1}) \right)^2 + \\ & \left(w_{31}(R_i^{1} - \overline{R}^{1}) + w_{32}(G_i^{1} - \overline{G}^{1}) + w_{33}(B_i^{1} - \overline{B}^{1}) \right)^2 . \end{aligned} \quad (13)$$

$$\begin{aligned} r_i = & \left(w_{11}(R_i^{2} - \overline{R}^{2}) + w_{12}(G_i^{2} - \overline{G}^{2}) + w_{13}(B_i^{2} - \overline{B}^{2}) \right)^2 + \\ & \left(w_{21}(R_i^{2} - \overline{R}^{2}) + w_{22}(G_i^{2} - \overline{G}^{2}) + w_{23}(B_i^{2} - \overline{B}^{2}) \right)^2 + \\ & \left(w_{31}(R_i^{2} - \overline{R}^{2}) + w_{32}(G_i^{2} - \overline{G}^{2}) + w_{33}(B_i^{2} - \overline{B}^{2}) \right)^2 . \end{aligned} \quad (14)$$

where d_i and r_i are distances of each pixel of skin and non-skin from their centers in the new color space respectively. R_i, G_i, B_i are pixel values in RGB space. So, sum of distances for total pixels in each cluster from centers of skin and non-skin clusters are obtained from (15, 16). From (11, 12) the distance between classes can be obtained to form of (17). Then $\Psi(w)$ is obtained from (15, 16, 17).

Now, this problem converted to one of the most common problems in calculus is that of finding minima (in general, "extrema") of a function subject to constraints. The method of Lagrange multipliers is a powerful tool for solving this class of problems without the need to explicitly solve the conditions and use them to eliminate extra variables.

$$\begin{aligned} \sum_{i=0}^{n} d_i = & \sum_{i=0}^{n} \left(w_{11}(R_i^{1} - \overline{R}^{1}) + w_{12}(G_i^{1} - \overline{G}^{1}) + w_{13}(B_i^{1} - \overline{B}^{1}) \right)^2 + \\ & \sum_{i=0}^{n} \left(w_{21}(R_i^{1} - \overline{R}^{1}) + w_{22}(G_i^{1} - \overline{G}^{1}) + w_{23}(B_i^{1} - \overline{B}^{1}) \right)^2 + \\ & \sum_{i=0}^{n} \left(w_{31}(R_i^{1} - \overline{R}^{1}) + w_{32}(G_i^{1} - \overline{G}^{1}) + w_{33}(B_i^{1} - \overline{B}^{1}) \right)^2 . \end{aligned} \quad (15)$$

$$\begin{aligned} \sum_{i=0}^{n} r_i = & \sum_{i=0}^{n} \left(w_{11}(R_i^{2} - \overline{R}^{2}) + w_{12}(G_i^{2} - \overline{G}^{2}) + w_{13}(B_i^{2} - \overline{B}^{2}) \right)^2 + \\ & \sum_{i=0}^{n} \left(w_{21}(R_i^{2} - \overline{R}^{2}) + w_{22}(G_i^{2} - \overline{G}^{2}) + w_{23}(B_i^{2} - \overline{B}^{2}) \right)^2 + \\ & \sum_{i=0}^{n} \left(w_{31}(R_i^{2} - \overline{R}^{2}) + w_{32}(G_i^{2} - \overline{G}^{2}) + w_{33}(B_i^{2} - \overline{B}^{2}) \right)^2 \end{aligned} \quad (16)$$

$$\begin{aligned} L = & \left(w_{11}(\overline{R}^{1} - \overline{R}^{2}) + w_{12}(\overline{G}^{1} - \overline{G}^{2}) + w_{13}(\overline{B}^{1} - \overline{B}^{2}) \right)^2 + \\ & \left(w_{21}(\overline{R}^{1} - \overline{R}^{2}) + w_{22}(\overline{G}^{1} - \overline{G}^{2}) + w_{23}(\overline{B}^{1} - \overline{B}^{2}) \right)^2 + \\ & \left(w_{31}(\overline{R}^{1} - \overline{R}^{2}) + w_{32}(\overline{G}^{1} - \overline{G}^{2}) + w_{33}(\overline{B}^{1} - \overline{B}^{2}) \right)^2 \end{aligned} \quad (17)$$

In the Lagrange multipliers technique , a new variable λ is added to the problem, and to minimize a defined function:

$$F(w, \lambda) = \Psi(w) + \lambda C(w) \quad (18)$$

where $C(w)$ include total of constraints of equality and non-equality. For optimization, it is sufficient to solve following equations :

$$\begin{cases} \dfrac{\partial F(w,\lambda)}{\partial w} = 0 \\ \dfrac{\partial F(w,\lambda)}{\partial \lambda} = 0 \end{cases} \tag{19}$$

4. Simulation results

To calculate new color space conversion weights, equation (18) and (19) must be solved. Solving these equations results in the following matrix :

$$w_{ij} = \begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \\ w_{31} & w_{32} & w_{33} \end{bmatrix} = \begin{bmatrix} 0.314 & -0.2867 & 0.1393 \\ 1 & 0.1666 & -1 \\ -1 & 0.1666 & 1 \end{bmatrix} \tag{20}$$

Meanwhile to examine this algorithm,we used some face image database and image samples , as tenesses and some article samples from [17] , [16]. Moreover we constructed a special a special database and used to test on algorithm.

Skin in the new color space separated from non skin and modeled by :

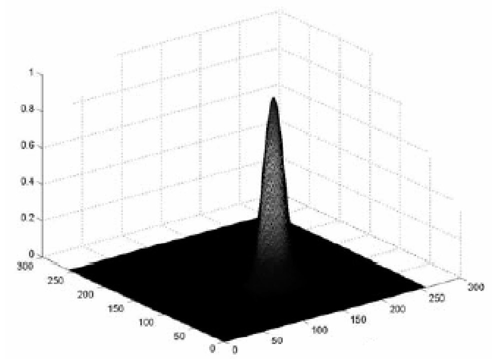

Fig2:Skin color model in the new color space

Although, skin and non skin clustered in the new color space, but existence of similar skin region, in the environment cause clustered this type as skin , and algorithm separate it's in the result from non skin.Selection each pixel in initial stage for making Skin and non skin clusters, valuable .Each clusters must be involved by full skin or non skin spectrum colors. This subject shown in the figure(3).

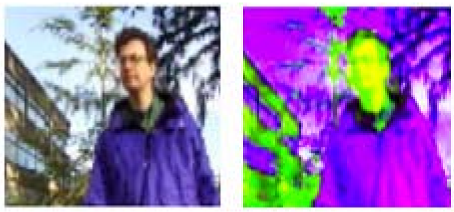

Fig 3 :Similar Skin region effect

Moreover , fig(4) illustrated from viewpoint of skin clustering respect to non skin. In this figure big distance that created between skin and non skin completely obvious.

Fig 4:Skin and non skin separation

In the new color space cost function calculated , and compared with other color space ,and obtained by fig (5). According to the fig (5) ,the cost that calculated for new color space to be smaller than other color space .

Color space	Cost
HSV	223
YCbCr	127
New color space	-4.23e-14

Fig 5: Cost calculation for some of color space

Using new color space conversion in various experiments shows desirable quality in increasing distance between skin and nonskin clusters, in figure(6) the separation of skin and non skin tissues is obvious.

5-Conclusion

In this article for first time ,skin region segmented from non skin region. innovation of this article allocated to new color space creation by using convex constraint ,that able to segment skin region from non skin region . the result of algorithm that earned by testing algorithm in image, that involve skin and non skin regions confirm this subject.

Fig 6: result of proposed algorithm

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