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Genetic Algorithm -Based Color Space Generation

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Abstract. Many color spaces can be creating by linear transformations that are captured by 3×3 matrices from others. The Main target of this paper is introducing new color transform that Lip detection is used as benchmark problem for this color space. In the New color space, the Lip and non-Lip classes are separated as well. This problem is converted to a convex constraint programming which Genetic Algorithm is used for solving this problem. Founded converting matrix is tested in Lip detection in simple to complex scene. Obtained results over many databases are compared with existing methods which show superiority of the proposed method.

Keywords: Genetic Algorithm, Color space; convex constraint programming; Lip detection; clustering criteria.

1. Introduction

Target color detection is a challenging issue in image processing and machine vision. It is gaining wide portion in recent works in these areas. In this work, generation of a novel multi-objective color space using non-linear convex constraint programming is proposed to deal with target area detection problem in color images. 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].

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

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 [6].face recognition in new space based on K-L[1] transform [8], object recognition into illumination invariant type of RGB color space [10], Image restoration into the CIELAB color space [11], and so on. The performance of an image analysis procedure is known to depend on the choice of the color space. In [12], 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 [13] 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

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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. Then Lip color detection is used as benchmark problem to test of the proposed algorithm. For evaluation, clustering criteria is used. Optimum color space in Lip color detection over selected data base is caused Lip and non-Lip cluster to be separated is created as well. Manifest features of the proposed method involved by 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.

2. Founding new color space based on 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,

$$\begin{bmatrix} X_1 \\ X_2 \\ X_3 \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \\ w_{31} & w_{32} & w_{33} \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (2)$$

With regard to (2), we can write for each pixel:

$$\begin{aligned} X_1 &= w_{11}R + w_{12}G + w_{13}B \\ X_2 &= w_{21}R + w_{22}G + w_{23}B \\ X_3 &= w_{31}R + w_{32}G + w_{33}B \end{aligned} \quad (3)$$

w_{ij} in (3) must be founded to create new color space (X_1, X_2, X_3), in order to optimal clustering vector target and non-target with the following criteria,

$$\Psi(W) = \sum_{j=1}^{N} d_{1j} + \sum_{j=1}^{M} d_{2j} - L \quad (4)$$

Where d_{1j} is the distance of j[th] sample from the center of class 1, and d_{2j} is the distance of j[th] 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.

2.1. Constraints

With respect to above equations some constraints express as bellow,

$$\begin{aligned} 1 &= w_{11} + w_{12} + w_{13} & 256 &= w_{11}255 + w_{12}255 + w_{13}255 \\ 1 &= w_{21} + w_{22} + w_{23} & 256 &= w_{21}255 + w_{22}255 + w_{23}255 \\ 1 &= w_{31} + w_{32} + w_{33} & 256 &= w_{31}255 + w_{32}255 + w_{33}255 \end{aligned} \quad (5)$$

$$\begin{aligned} R_i w_{11} + G_i w_{12} + B_i w_{13} &\le 256 & -(R_i w_{11} + G_i w_{12} + B_i w_{13}) &\le -1 \\ R_i w_{21} + G_i w_{22} + B_i w_{23} &\le 256 & -(R_i w_{21} + G_i w_{22} + B_i w_{23}) &\le -1 \\ R_i w_{31} + G_i w_{32} + B_i w_{33} &\le 256 & -(R_i w_{31} + G_i w_{32} + B_i w_{33}) &\le -1 \end{aligned} \quad (6)$$

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

2.2. 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 (4). If $\Psi(W)$ is minimized subject to mentioned constraints in last section, new color space is generated with the optimum form. In new color space, each pixel is converted using (3) and center of each clusters are obtained using (7,8) as follows,

$$\begin{cases} \mu_{X1}^1 = w_{11}\overline{R}^1 + w_{12}\overline{G}^1 + w_{13}\overline{B}^1 \\ \mu_{X2}^1 = w_{21}\overline{R}^1 + w_{22}\overline{G}^1 + w_{23}\overline{B}^1 \\ \mu_{X3}^1 = w_{31}\overline{R}^1 + w_{32}\overline{G}^1 + w_{33}\overline{B}^1 \end{cases} \quad \begin{cases} \mu_{X1}^2 = w_{11}\overline{R}^2 + w_{12}\overline{G}^2 + w_{13}\overline{B}^2 \\ \mu_{X2}^2 = w_{21}\overline{R}^2 + w_{22}\overline{G}^2 + w_{23}\overline{B}^2 \\ \mu_{X3}^2 = w_{31}\overline{R}^2 + w_{32}\overline{G}^2 + w_{33}\overline{B}^2 \end{cases} \qquad (7), (8)$$

Where μ_{Xi}^k 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 (9) :

$$\begin{aligned} d_i = {} & \left(w_{11}(R_i^1 - \overline{R}^1) + w_{12}(G_i^1 - \overline{G}^1) + w_{13}(B_i^1 - \overline{B}^1)\right)^2 + \\ & \left(w_{21}(R_i^1 - \overline{R}^1) + w_{22}(G_i^1 - \overline{G}^1) + w_{23}(B_i^1 - \overline{B}^1)\right)^2 + \\ & \left(w_{31}(R_i^1 - \overline{R}^1) + w_{32}(G_i^1 - \overline{G}^1) + w_{33}(B_i^1 - \overline{B}^1)\right)^2. \end{aligned} \quad \begin{aligned} r_i = {} & \left(w_{11}(R_i^2 - \overline{R}^2) + w_{12}(G_i^2 - \overline{G}^2) + w_{13}(B_i^2 - \overline{B}^2)\right)^2 + \\ & \left(w_{21}(R_i^2 - \overline{R}^2) + w_{22}(G_i^2 - \overline{G}^2) + w_{23}(B_i^2 - \overline{B}^2)\right)^2 + \\ & \left(w_{31}(R_i^2 - \overline{R}^2) + w_{32}(G_i^2 - \overline{G}^2) + w_{33}(B_i^2 - \overline{B}^2)\right)^2. \end{aligned} \qquad (9)$$

Where d_i and r_i are distances of each pixel of Lip and non-Lip 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 Lip and non-Lip clusters are obtained by calculating eq.9 for any class's member. The distance between classes can be obtained to form of (10). Then $\Psi(w)$ is obtained from (9,10). 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 Genetic Algorithm 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. According eq.4 and 9 sum of d ,r and L calculated,

$$\begin{aligned} L = {} & \left(w_{11}(\overline{R}^1 - \overline{R}^2) + w_{12}(\overline{G}^1 - \overline{G}^2) + w_{13}(\overline{B}^1 - \overline{B}^2)\right)^2 + \\ & \left(w_{21}(\overline{R}^1 - \overline{R}^2) + w_{22}(\overline{G}^1 - \overline{G}^2) + w_{23}(\overline{B}^1 - \overline{B}^2)\right)^2 + \\ & \left(w_{31}(\overline{R}^1 - \overline{R}^2) + w_{32}(\overline{G}^1 - \overline{G}^2) + w_{33}(\overline{B}^1 - \overline{B}^2)\right)^2 \end{aligned} \qquad (10)$$

In order to minimize clustering error and obtain optimum transformation weights the Genetic Algorithm is utilized. In fact, Genetic Algorithm searches a 9-dimensional space for optimum weights. The key point that validates this method is the generalization capability of the obtained weights. Indeed, because of approximately fixed position of skin pixels in 3-D space over any color image, weights optimized on some sample image, can lead to acceptable results over any test image**.**

3. Genetic Algorithm

Genetic Algorithms are adaptive heuristic search algorithm premised on the evolutionary ideas of natural selection and genetic. In general genetic algorithm is an iterative procedure that consists of a constant-size population of individuals, each one being represented by a limited string of symbols, known as the genome, encoding a possible solution in a given problem space. This space is known as the search space, consisting of all possible solutions to the problem one is trying to solve. In general, the genetic algorithm is applied to spaces which are too large to be exhaustively searched [16].

3.1. General Algorithm for Genetic Algorithm

In general in genetic algorithm there is an initial population which is created from a random selection of solutions. Then fitness value is assigned according to a criteria decided by the person solving the problem. This fitness is assigned to each solution (chromosome) depending on how close it actually is to solving the problem. Those chromosomes with a higher fitness value are more likely to reproduce offspring (which can mutate after reproduction). The offspring is a product of the father and mother, whose composition consists of a combination of genes from them (this process is known as "crossing over". If the new generation contains a solution that produces an output that is close enough or equal to the desired answer then the problem has been solved. If this is not the case, then the new generation will go through the same process as their parents did. One continues this process until a possible solution is reached.

Begin GA
  g:=0 { generation counter }
  Initialize population P(g)
  Evaluate population P(g) { i.e., compute fitness values }
  While not done do
    g:=g+1
    Select P(g) from P(g-1)
    Crossover P(g)
    Mutate P(g)
    Evaluate P(g)
  end while
end GA

Fig 1: Genetic Algorithm

4. Simulation results

The proposed method is implemented in MATLAB 7 framework. Space conversion weights are obtained using the Lip image that composed by collecting several Lip pixels and these weights are as follows:

$$W = \begin{bmatrix} 0.3022 & -.0654 & -0.1933 \\ 1 & -0.6303 & -0.2830 \\ -1 & 0.6595 & 0.2378 \end{bmatrix} \qquad (11)$$

Figure 2 shows Genetic Algorithm clustering result. Excellence and incredible efficiency of proposed method can be investigated in the generalization capability of the method.

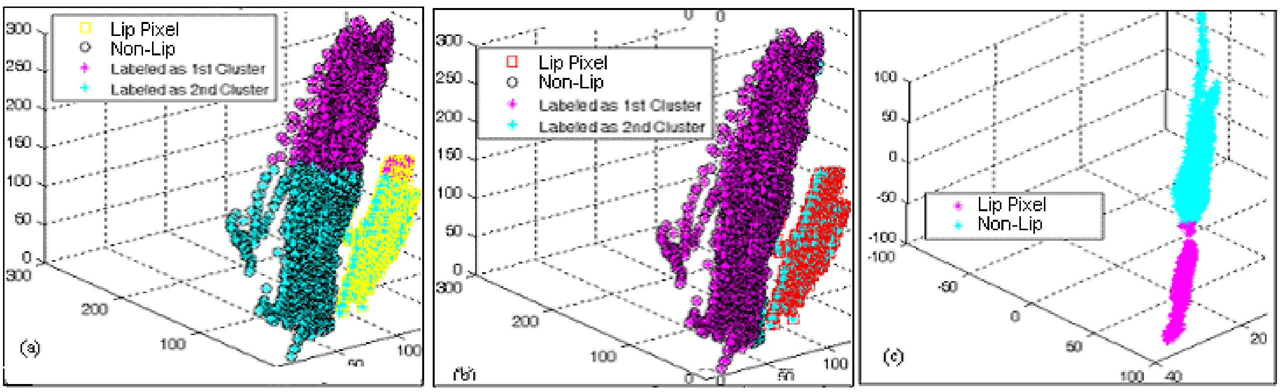

Fig 2: a) Clustering by proposed method b) Lip and non-Lip pixels in original color space c) Clustering in more sensible space.

As seen in figure 3 Genetic algorithm yields to cost function minimization and obtain optimum transformation weights by repetition and by evolutionary search.

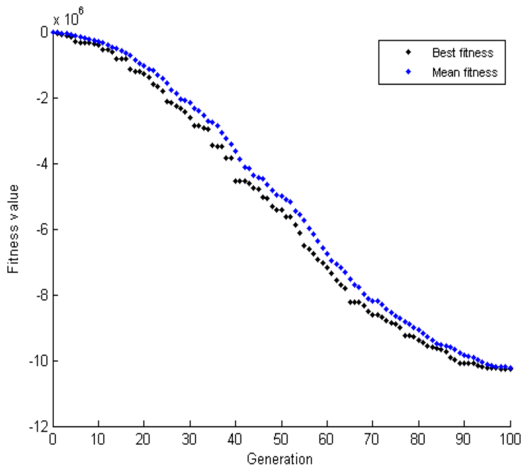

Fig 3: Genetic Algorithm generation evolution

Fig 4: result of proposed algorithm

5. Conclusion

In this paper, a new idea is presented to solve the frequently applied problem of target color detection. It is based on finding a linear transformation in a way that satisfies a predefined clustering criterion. Thus target detection problem converted into a convex constraint programming problem, which is a famous mathematical problem with definite solution. We presented the method results and compared it with newly published works. A comparative study of color spaces shows the superiority of newly generated space for Lip detection. As far as we know, this method is the most simple and powerful one that has ever been presented. It works under various lighting conditions and for different target color detection problems. Efficiency of this method in other color spaces may be investigated as our future work. Also it is expected that optimization of constraints lead us to better achievements. In other words there is still argument on constraints setup and making them more reliable. We aim to follow these matters in our future works.

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