COLOR SYSTEM CODING FOR COLOR IMAGE PROCESSING

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ABSTRACT

Many authors use different color systems for color image processing. In many cases, these color systems must be coded, so that their components range between the same unsigned integer values. In this paper, we propose a color system coding scheme which preserves the properties of the color systems. We apply this coding scheme to color image segmentation.

Keywords: *Color systems, Coding scheme, Image segmentation.*

1. INTRODUCTION

The pixels of a color image are digitized according to three components, red (R), green (G) and blue (B). In general, each one of these three components is coded on 8 bits and can take 256 different unsigned integer values in the interval $[0, 255]$. Several color transformations can be used for color image segmentation. The color is then represented by three transformed components whose signed real values do not always range in the interval $[0, 255]$. In order to compare histograms or euclidean distances defined in different color systems as well as for image storage or display in different color systems, a specific coding scheme is required [1, 2].

In the second section of this paper, it is shown how color systems can be classified according to well defined families which share similar properties. In the third section, we propose a color system coding scheme which preserves these properties of the color systems so that they are not modified by this coding scheme. We apply this coding scheme to the determination of the most discriminating color texture feature space for a specific problem of color image segmentation in the fourth section.

2. COLOR SYSTEM FAMILIES

When considering the multitude of available color systems, it is necessary to classify them into a few categories according to their definitions. We propose to group the most classical color systems into 4 principal families which are divided into sub-families. In the figure 1, we distinguish 4 main families: the ***primary systems***, the ***luminance-chrominance systems***, the ***perceptual systems*** and the ***statistical independent component systems***. The dotted rect-

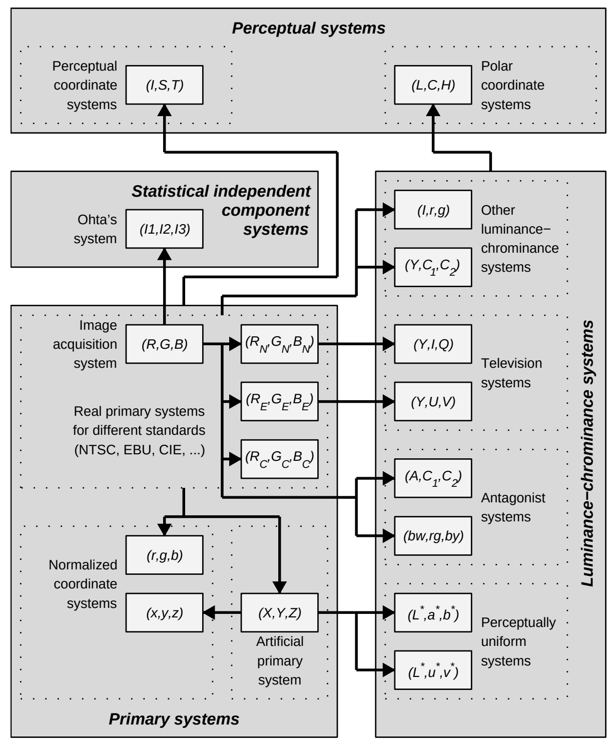


Figure 1: Color system families

angles within the principle rectangles correspond to sub-families of color systems. In general, color images are acquired through a (R, G, B) system that we call the image acquisition system. So, all color systems are defined by an equation whose inputs are R, G and B. In the figure 1, we can see how is determined any color system by following the arrows starting from the (R, G, B) system. Let us describe these 4 families.

2.1. Primary systems

The primary systems are based on the trichromatic theory which assumes that we are able to match any color by mixing appropriate amounts of three primary colors. So, a primary system depends on the choice of a set of primary colors and a reference white or illuminant. We distinguish two type of primary systems.

2.1.1. The (R, G, B) real primary systems

By analogy to the human eye physiology, the primary colors are close to the red (R), the green (G) and the blue (B). According to the application field, different (R, G, B) systems are proposed such as the CIE (R_C, G_C, B_C) system for colorimetry or the NTSC (National Television System Committee) (R_N, G_N, B_N) system and the EBU (European Broadcasting Union) (R_E, G_E, B_E) system for television.

The normalized components, which are named chromaticity coordinates, only take into account the chrominance. The chromaticity coordinates of the (R, G, B) system are denoted r, g, b. Since the (r, g, b) system, $b = 1 - r - g$, color can be represented in the chromaticity diagram (r, g).

2.1.2. The (X, Y, Z) artificial primary system

Because the real primary systems present some drawbacks, the CIE recommends an artificial primary system whose primary colors, denoted X, Y and Z, are virtual [3]. In this system, any color is expressed by strictly positive component values and Y represents the luminance. The (X, Y, Z) system can be determined from any (R, G, B) system (CIE, NTSC, EBU, ...) by linear transformations which also depend to the reference white.

The chromaticity coordinates are denoted x, y and z and define the chromaticity diagram (x, y).

2.2. Luminance-chrominance systems

The luminance-chrominance systems have one luminance component and two chrominance components. There are several kinds of luminance-chrominance systems.

2.2.1. Perceptually uniform systems

Because the euclidian distances evaluated in the (R, G, B) or (X, Y, Z) systems do not correspond to the color differences which are actually perceived by an human observer, the CIE recommends two perceptually uniform systems, the (L^*, u^*, v^*) and (L^*, a^*, b^*) systems, where L^* represents the lightness (luminance component) and where u^*, v^* and a^*, b^* are chromaticity coordinates [3].

2.2.2. Television systems

The transmission of the television signals requires the separation between the luminance and chrominance components. The television standard NTSC makes use of the (Y, I, Q) system where Y is the luminance component and the both I and Q are the chrominance components.

The EBU broadcasting standard is based on the (Y, U, V) system where the chrominance components are U and V.

2.2.3. Antagonist systems

Different color systems are based on the opposed color theory which assumes that the color information is transmitted to the brain according to an achromatic component and two chromatic components which correspond to color opposition. Such antagonist systems are proposed for color image analysis, like the (A, C_1, C_2) system [4] or the (wb, rg, by) system [5].

2.2.4. Other systems

A last kind of luminance-chrominance systems includes other systems, such as the (Y, Ch_1, Ch_2) system proposed by Carron [6], the (I, r, g) system [1] or the (Y, x, y) system [3].

2.3. Perceptual systems

The perceptual systems try to quantify the subjective entities of the color human perception which are related to the luminosity, the hue and the saturation. We distinguish two kinds of perceptual systems.

2.3.1. Polar coordinate systems

The polar coordinate systems correspond to expressions in polar coordinates of the chrominance components which belong to luminance-chrominance systems. Their components are luminance (L), chroma (C) and hue (H).

The (L, C, H) system can be evaluated from the perceptually uniform systems of the CIE [3], from the television systems, from the antagonist systems [4] or from other luminance-chrominance systems [6].

2.3.2. Perceptual coordinate systems

The perceptual coordinate systems correspond to expressions of the subjective entities of the color human perception in terms of intensity (I), saturation (S) and hue (T) components. They are directly evaluated from a primary system. We can distinguish different (I, S, T) systems, like the triangle system, the hexcone system or the double hexcone system [2].

2.4. Independent component systems

The statistical independent component systems can be determined by different methods in order to obtain non-correlated components. For instance, Ohta uses the Karhunen-Loeve Transformation (KLT) in order to propose a color system, denoted $(I1, I2, I3)$ [1].

3. COLOR SYSTEM CODING

The coding of the color systems consists to round, scale and normalize the values of their components in order to process values which range between the unsigned integer values 0 and 255. We propose a color system coding scheme which preserves the properties of each of the color systems presented in the second section.

3.1. Independent and dependent coding

The components of all color systems are defined by one or several successive color transformations of the R, G and B components. Let us denote T_1, T_2 and T_3, the transformed components of any color systems obtained from the R, G and B components by a set of color transformations $\mathbf{T}$ and C_1, C_2 and C_3 the corresponding coded components by our coding scheme $\mathbf{C}$ (see figure 2).

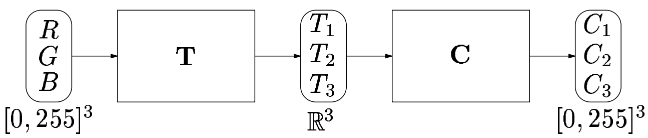


Figure 2: Color system coding

In order to achieve the coding of each transformed component T_1, T_2 and T_3, we must determine the extreme values of their ranges. Let us denote m_k and M_k, the minimum and maximum values of the transformed component T_k respectively, so that $\Delta_k = M_k - m_k$ represents the range of the transformed component T_k. In order to adjust the width of this range to 255, the transformed component T_k can be coded independently of the two other components by means of equation 1. This kind of coding scheme is an *independent coding* scheme.

$$C_k = \frac{255}{\Delta_k} \times (T_k - m_k) \tag{1}$$

According to the properties of a color system, we must sometimes make use of a *dependent coding* scheme. Let Δ_{max} denote the larger range of the three components of a color system, defined as:

$$\Delta_{max} = \max_{T_k} (\Delta_k) \tag{2}$$

The dependent coding of the components of a color system is achieved by means of equation 3 so that the range of at least one component is equal to 255.

$$C_k = \frac{255}{\Delta_{max}} \times (T_k - m_k) \tag{3}$$

The dependent coding scheme achieves an equal scale process to each component of a color system. So, the relative position of colors in the space defined by this system is not modified. Furthermore, the euclidean distances between colors are preserved thanks to such a coding scheme.

In order to preserve their properties, we apply one of the two above defined coding scheme to the color systems of the 4 families.

3.2. Application to color systems

3.2.1. Primary systems

The transformation of a (R, G, B) system to an other primary system is a linear transformation which depends on the choice of the primaries and the reference white. For instance, the transformation from the NTSC (R_N, G_N, B_N) system to the CIE (X, Y, Z) system with the C illuminant is defined by a matricial transformation $[X\ Y\ Z]^T = \mathbf{T}\ [R_N\ G_N\ B_N]^T$ where:

$$\mathbf{T} = \begin{bmatrix} 0.607 & 0.174 & 0.200 \\ 0.299 & 0.587 & 0.114 \\ 0.000 & 0.066 & 1.116 \end{bmatrix} \tag{4}$$

The chromaticity coordinates of the C illuminant are $x_n = 0.310$ and $y_n = 0.316$, and those of the primaries R_N, G_N, B_N are $x_r = 0.670$, $y_r = 0.330$, $x_g = 0.210$, $y_g = 0.710$, $x_b = 0.140$ and $y_b = 0.080$ respectively. Table 1 contains the coding parameters of the (X, Y, Z) system.

	X	Y	Z
m_k	0	0	0
M_k	250.16	255.00	301.41

Table 1: X, Y and Z components extremes values

Ohta proposes to code this system by means of an independent coding scheme which is associated to a matrix $\mathbf{C}_{ind}$ so that $[C_1\ C_2\ C_3]^T = \mathbf{C}_{ind}\ \mathbf{T}\ [R_N\ G_N\ B_N]^T$ with [1]:

$$\mathbf{C}_{ind}\ \mathbf{T} = \begin{bmatrix} 0.618 & 0.177 & 0.205 \\ 0.299 & 0.587 & 0.114 \\ 0.000 & 0.056 & 0.944 \end{bmatrix} \tag{5}$$

With such a coding scheme, the evaluated chromaticity coordinates are $x_n = 0.333$, $y_n = 0.333$, $x_r = 0.674$, $y_r = 0.326$, $x_g = 0.224$, $y_g = 0.743$, $x_b = 0.162$ and $y_b = 0.090$. They do not correspond to the coordinates which are computed thanks to the matrix $\mathbf{T}$. So, because the position of the illuminant C in the chromaticity diagram has changed with the independent coding scheme, we can conclude that the definition of the system (X, Y, Z) from the primary system NTSC is modify by such a coding scheme. By extending the case of the illuminant to all colors, we conclude that the *spectrum locus* contained in the chromaticity diagram is distorted by the independent coding scheme.

On the other hand, the dependent coding scheme provides a matrix $\mathbf{C}_{dep}$ so that:

$$\mathbf{C}_{dep}\ \mathbf{T} = \begin{bmatrix} 0.514 & 0.147 & 0.169 \\ 0.253 & 0.497 & 0.096 \\ 0.000 & 0.056 & 0.944 \end{bmatrix} \tag{6}$$

The dependent coding scheme does not modified the true chromaticity coordinates. This example can be generalized to the other primary systems. So, in order to preserve the colorimetric properties of a primary system, we propose to achieve a dependent coding for each of its components.

3.2.2. Luminance-chrominance systems

The systems of this family are defined by two kinds of transformations: linear or non linear ones.

The color systems obtained through a linear transformation can be considered as primary systems and must be coded with a dependent coding scheme for the same reasons as the primary systems.

For the non linear transformations, we take the (L^*, a^*, b^*) system as an example. By applying an independent coding to the components of this system, the ellipses of MacAdam are distorted so that the color distances which are evaluated in this system do not correspond to the color differences which are perceived by an human observer. In order to preserve the MacAdam ellipses shape and so, to preserve an adequation between the euclidean distance and the visual perception, we propose to apply a dependent coding to the perceptually uniform systems. We extend this dependent coding scheme to all luminance-chrominance systems obtained through a non linear transformation.

3.2.3. *Perceptual systems*

Because the components of the perceptual systems represent three subjective entities to qualify a color, we consider independently these three components. Furthermore, in order to compare two colors, the euclidean distance is meaningless since the hue component is periodical. So, we propose to apply an independent coding to the perceptual system components.

3.2.4. *Statistical independent component systems*

Because the components of the statistical independent component systems are determined by linear transformations, they can be considered as primary systems so that they have to be coded with a dependent coding scheme.

4. APPLICATION TO COLOR IMAGE SEGMENTATION

In order to track players during a soccer game, we have proposed a color image segmentation method based on pixel classification [7, 8]. We suppose that the team of each player is identified by the color and the texture of its soccer suit. Consequently, the pixels which represent the players with the same soccer suit constitute one class of *player pixels*. The pixel classification algorithm analyses the *color texture features*, which are computed by tacking into account the color components of the neighbor pixels. We determine the most discriminating color texture features among a multidimensional set of color texture features by means of an iterative feature selection procedure associated to an information criterion.

Certain color texture features are based on an histogram evaluation or an euclidean distance which are processed by tacking into account color components. So, in order to compare the color texture features we need that the evaluation of histograms or euclidean distances is not modified by a coding scheme. That leads us to apply our coding scheme to our color image segmentation algorithm.

In a first time, we built a color texture feature space. Then, we describe the classification algorithm used to cluster the pixels represented in this space. Finally, we apply our approach to soccer image segmentation.

4.1. Color texture feature space

4.1.1. *Color texture features*

A player pixel neighborhood can be characterized by color texture feature values which are computed by tacking into account the color components of its neighbor player pixels.

We use a non exhaustive list of texture features. The *mean* of the pixel values in a neighborhood, the *median* and the *mode* are used to evaluate the central value of this neighborhood. The variability of the pixel values around a central value is estimated by means of the *variance* or its square root, the *standard deviation*. The *skewness* estimates the degree of asymmetry of the pixel values around a central value. The variance and the skewness can be evaluated around the mean, the median or the mode. Let N_t denote the number of available texture features which are computed using one color component.

There is a total of N_c available coded color components which constitute the different above mentioned color systems.

By taking into account the $N_f = N_c \times N_t$ available color texture features, we define an N_f-dimensional color texture feature space. The large dimension of this space inevitably generates burden and redundancy. Furthermore, a classification algorithm is very time consuming in a large dimensional space. So, our goal is to look for the best subset of color texture features for discriminating the different classes of pixels.

4.1.2. *Supervised learning scheme*

In order to determine a low dimensional color texture feature space, we require samples which are representative of the classes of pixels. At the beginning of a supervised learning scheme, we interactively select several *player windows* which have the same size from a set of *presegmented learning images*. In these images, the ground is withdrawn thanks to an adaptation of the Ohlander's algorithm in order to extract the player pixels [9]. The player windows contain player pixels which represent players in different situations (running, pushing the ball, dribbling...) and in different positions (facing the camera, backing the camera...). Figure 3 represent a few player windows. These player windows are selected from presegmented learning images where there are four kinds of players wearing different soccer suits.

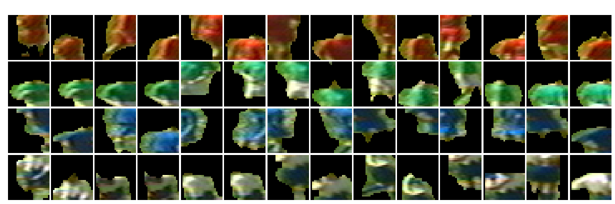


Figure 3: Selected player windows

Let C_j, $j = 1, ..., N$, denote a class of player pixels where N is the number of classes. For each class C_j, we interactively select the same number N_ω of player windows $\omega_{i,j}$, where i indicates the serial number of the player window ($i = 1, ..., N_\omega$). The player windows are used to determine the color texture feature space which yields the best separation between the classes.

4.1.3. *Color texture feature space selection*

In order to reduce the dimension of the color texture feature space, we use an iterative feature selection procedure. At each step k of this procedure, we consider $(N_f - k + 1)$ k-dimensional candidate color texture feature spaces for which we compute their discriminating power thanks to an information criterion J. The candidate space which maximizes J is the best one for discriminating the N classes. The procedure is iterated until stabilization of the value of J. Let k_0, be the rank of the iteration process which corresponds to the beginning of the stabilization of J. k_0 is the dimension D of the color texture feature space.

This classical multiple discriminant analysis method does not yield the optimal solution but a satisfying one which is less computation time consuming.

The evaluation of the discriminating power supposes that the more the classes are well separated and compact in the candidate color texture feature space, the higher the discriminating power of the selected features is. That leads us to choose measures of classes separability and compactness as measures of the discriminating power.

At each step k of the procedure and for each of the $(N_f - k + 1)$ k-dimensional candidate color texture feature spaces, we define, for each player window $\omega_{i,j}$ associated to the class C_j, a *feature vector* $X_{i,j} = [x^1_{i,j}, ..., x^k_{i,j}]^{\mathrm{T}}$ where $x^k_{i,j}$ is the k^{th} color texture feature.

The measure of compactness of each class C_j is defined by the intra-class dispersion matrix Σ_C:

$$\Sigma_C = \frac{1}{N_\omega \times N} \times \sum_{j=1}^{N} \sum_{i=1}^{N_\omega} (X_{i,j} - M_j)(X_{i,j} - M_j)^{\mathrm{T}} \quad (7)$$

where $M_j = [m^1_j, ..., m^k_j]^{\mathrm{T}}$ is the *mean vector* of the k color texture features of the pixels assigned to the class C_j.

The measure of class separability is defined by the inter-class dispersion matrix Σ_S:

$$\Sigma_S = \frac{1}{N} \times \sum_{j=1}^{N} (M_j - M)(M_j - M)^{\mathrm{T}} \quad (8)$$

where $M = [m^1, ..., m^k]^{\mathrm{T}}$ is the mean vector of the k color texture features for all the pixels of all the classes.

The most discriminating candidate color texture feature space is that one that maximizes the information criterion:

$$J = \mathrm{trace}\Big((\Sigma_C + \Sigma_S)^{-1}\Sigma_S\Big). \quad (9)$$

In order to only select features which are not correlated, we measure, at each step $k \geq 2$ of the procedure, the correlation between the candidate color texture feature and each of the $k-1$ other color texture features constituting the considered space. The correlation value ranges between 0 and 1. The closer is the correlation to 1, the more correlated the two features are. If one of the computed correlation is higher than a correlation threshold equal to 0.75, the candidate color texture feature is rejected.

Thanks to this iterative procedure, we select the space constituted by the most discriminating color texture features among the N_f available ones.

4.2. Soccer image segmentation

4.2.1. *Player pixel classification*

In order to classify a player pixel P, we compute its color texture feature vector $X_P = [x^1_P, ..., x^D_P]^{\mathrm{T}}$ in the above determined D-dimensional color texture feature space. For that, we consider the set of the neighbor player pixels falling into a neighborhood of P. This neighborhood is defined by a *neighborhood window* which is centered on the player pixel P of size equal to the player window size.

For each class C_j, we evaluate the euclidean distance D^P_j between X_P and the mean vector $M_j = [m^1_j, ..., m^D_j]^{\mathrm{T}}$ of the class C_j in the D-dimensional color texture feature space. A minimum distance decision rule is used to assign P to the class C_j for which D^P_j is minimum.

4.2.2. *Results*

In order to illustrate our method, we present four color images extracted from a sequence (see figure 4). In these images, there are four classes of player pixels.

The analysis of player windows of figure 3 yields the most discriminating color texture feature space which is constituted of the mean value of the x color component, the mean value of the Ch_2 color component of the Carron's system and the skewness around the median associated to the hue color component of the system (Y, I, Q).

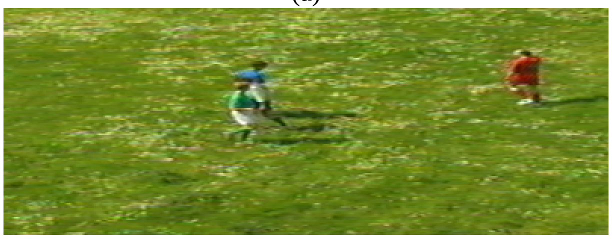
The images of figure 5 shows the player pixels which have been classified in this space. In these images, we distinguish the four classes of player pixels by different grey levels. The player pixels have been very well extracted despite the bad quality of the ground. We notice that the players are always well separated. That is particularly noticeable in the image 5.(c) where the three players are actually identified whereas in the image 4.(c), it is visually difficult to separate them. We observe that there are three players thanks to their shadows.

5. CONCLUSION

In this paper, we have proposed an original overview of the most classical color systems and a color system coding scheme which preserves the properties of each of them. We apply this scheme to color image processing and more precisely, to soccer image segmentation. Our coding scheme can be used to code color in any color systems. It is well suited to define a color texture feature space. This space is determined thanks to an iterative feature selection procedure associated to an information criterion and a correlation threshold.

(a)

(b)



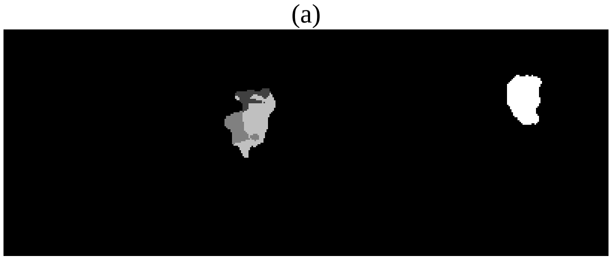
(c)

(d)

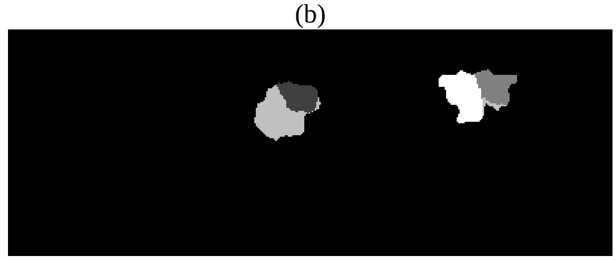
Figure 4: Color images of a sequence

(a)

(b)



(c)



(d)

Figure 5: Classified player pixels

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