Color Invariant For Person Images Indexing

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Abstract

Many colored object recognition methods tend to fail when the incident illumination varies. In the context of image indexing, a method is presented, which does not depend on lighting conditions. A new approach for indexing images of persons moving in areas in where the acquisition is monitored by color cameras is developed to cope with the variations of the lighting conditions. We consider that illumination changes can be described using a simple linear transform. For comparing two images, we transform the target one according to the query one by means of an original color histogram specification based on color invariant evaluation. For the purpose of indexing, we evaluate invariant color signatures of the query image and the transformed target image, through the use of the color co-occurrence matrices. Results of tests on real images are very encouraging, with substantially better performance than those of other methods tested.

1. Introduction

Supervision of public sites requires a high number of cameras, so that each of them can observe persons as they enter or leave the site under control. For this purpose, the cameras are fixed above the entrances so as to acquire top view color images of persons (see figure 1). As the aim of such a multi-cameras system is to recognize the persons as they move under the different cameras controlling the access points, we propose in this paper an original approach for indexing and retrieve person images acquired by different color cameras. These cameras observe the different entrances under different lighting conditions. Figure 1 shows a database of color target person images acquired with different color cameras. These images correspond to eight persons, each of them being represented by three different images acquired under three different lighting conditions. Each image is referenced by a letter between A and H associated with the observed person, and a number between 1 and 3, which correspond to one of the three images associated to each person.

For the purpose of indexing, we look for target images of this base which contain the same person as a person represented in a query image.

Since a person is observed under different lighting conditions, its color in the query image is different from its color in the three corresponding target images of the base.

In order to cope with this problem, we consider the query image and each of the target images of the database pair by pair. In order to compare these different pairs of images, we transform the target image using the color histogram specification which is presented in the second section of this paper and which consists in color invariant processing.

For the purpose of indexing, we evaluate invariant color signatures of the query image and the transformed target images, by using the color co-occurrence matrices described in the third section of this paper.

The last section compares the performance of our approach with solutions based on classical color invariants.

2. Color Invariant by Trichromatic Histograms Specification

2.1. Assumptions

The trichromatic components R,G,B of a surface observed by a camera depend on the illuminant $E(\lambda)$, its reflectance factor $b(\lambda)$ and $R(\lambda)$, $G(\lambda)$, $B(\lambda)$ which are the three spectral sensitivity coefficients of the camera[1]:

$$\begin{cases} R = \int_{\lambda=380}^{\lambda=780} R(\lambda)\beta(\lambda)E(\lambda)d\lambda, \\ G = \int_{\lambda=380}^{\lambda=780} G(\lambda)\beta(\lambda)E(\lambda)d\lambda, \\ B = \int_{\lambda=380}^{\lambda=780} B(\lambda)\beta(\lambda)E(\lambda)d\lambda. \end{cases} \quad (1)$$

First, we suppose that the three sensors of the camera are sensitive to specific wavelength intervals without any overlap. The three intervals $[\lambda_0; \lambda_1]$, $[\lambda_1; \lambda_2]$ and $[\lambda_2; \lambda_3]$ are associated with the blue, green and red sensor sensitivities respectively with 380 nm $\leq \lambda_0 \leq \lambda_1 \leq \lambda_2 \leq \lambda_3 \leq$ 780 *nm*.

So the trichromatic components of a pixel are defined as:

$$\begin{cases} R = \int_{\lambda_2}^{\lambda_3} R(\lambda)\beta(\lambda)E(\lambda)d\lambda, \\ G = \int_{\lambda_1}^{\lambda_2} G(\lambda)\beta(\lambda)E(\lambda)d\lambda, \\ B = \int_{\lambda_0}^{\lambda_1} B(\lambda)\beta(\lambda)E(\lambda)d\lambda. \end{cases} \tag{2}$$

Second, we suppose that for each sensor wavelength interval, the illuminant $E(\lambda)$ can be expressed by three constants e_R, e_G and e_B associated with the three wavelength intervals, so that:

$$\begin{cases} R = e_R\int_{\lambda_2}^{\lambda_3} R(\lambda)\beta(\lambda)d\lambda, \\ G = e_G\int_{\lambda_1}^{\lambda_2} G(\lambda)\beta(\lambda)d\lambda, \\ B = e_B\int_{\lambda_0}^{\lambda_1} B(\lambda)\beta(\lambda)d\lambda. \end{cases} \tag{3}$$

2.2. Trichromatic Histograms Specification

The aim of histogram modeling techniques[2] as histogram equalization is to modify the dynamic range and contrast of a grey-level image so that its intensity histogram has a desired shape.

Sometimes it is desirable to control the shape of the output histogram in order to highlight some specific intensity levels in an image. This can be accomplished by an histogram specification.

For the purpose of color histograms specification, we consider the three 1*D* trichromatic histograms.

The trichromatic histogram specification consists in transforming one color component of each pixel P^{tar_0} of a target image I^{tar_0}, so that it becomes similar to the same color component of the pixel P^{que} of the query image I^{que} which represents the same observed surface.

We consider the image I^{que} acquired under the illuminant $E^{que}(\lambda)$ characterized by the three constants e_R^{que}, e_G^{que} and e_B^{que}. Using equation 3, the components (R^{que}, G^{que}, B^{que}) of the pixel P^{que} can be expressed as:

$$\begin{cases} R^{que} = e_R^{que}\int_{\lambda_2}^{\lambda_3} R(\lambda)\beta(\lambda)d\lambda, \\ G^{que} = e_G^{que}\int_{\lambda_1}^{\lambda_2} G(\lambda)\beta(\lambda)d\lambda, \\ B^{que} = e_B^{que}\int_{\lambda_0}^{\lambda_1} B(\lambda)\beta(\lambda)d\lambda. \end{cases} \tag{4}$$

Similarly, the three components $(R^{tar_0}, G^{tar_0}, B^{tar_0})$ of the pixel P^{tar_0} of image I^{tar_0} which is acquired with the illuminant $E^{tar_0}(\lambda)$ characterized by the three constants $e_R^{tar_0}$, $e_G^{tar_0}$ and $e_B^{tar_0}$, are expressed as:

$$\begin{cases} R^{tar_0} = e_R^{tar_0}\int_{\lambda_2}^{\lambda_3} R(\lambda)\beta(\lambda)d\lambda, \\ G^{tar_0} = e_G^{tar_0}\int_{\lambda_1}^{\lambda_2} G(\lambda)\beta(\lambda)d\lambda, \\ B^{tar_0} = e_B^{tar_0}\int_{\lambda_0}^{\lambda_1} B(\lambda)\beta(\lambda)d\lambda. \end{cases} \tag{5}$$

As we consider the same observed surface, the reflectance factor $\beta(\lambda)$ is the same in equations 4 and 5.

Furthermore, we assume that the three spectral sensitivity coefficients $R(\lambda)$, $G(\lambda)$ and $B(\lambda)$are the same for all the cameras.

From equations 4 and 5, we can express the components $(R^{tar_0}, G^{tar_0}, B^{tar_0})$ of the pixel P^{tar_0} under the illuminant $E^{tar_0}(\lambda)$, with the components (R^{que},G^{que},B^{que}) of the pixel P^{que} under the illuminant $E^{que}(\lambda)$ with the following linear equations:

$$\begin{cases} R^{tar_0} = \dfrac{e_R^{tar_0}}{e_R^{que}} \times R^{que}, \\ G^{tar_0} = \dfrac{e_G^{tar_0}}{e_G^{que}} \times G^{que}, \\ B^{tar_0} = \dfrac{e_B^{tar_0}}{e_B^{que}} \times B^{que}, \end{cases} \tag{6}$$

To compare the two images, we propose to specify the trichromatic histograms of I^{tar_0} with the trichromatic histograms of I^{que}, in order to construct the transformed image I^{tar_1}.

The first step consists in determining the three histogram specification coefficients K_R, K_G and K_B used to transform the target image I^{tar_0} into an image I^{tar_1}. which will be suitable for comparison with the query image I^{que}. We assume that if the target and query images represent the same person, we can extend equation 6 to all the pixels of these two images. We determine these coefficients by using the ratio of mean values of the two images:

$$\begin{cases} K_R = \dfrac{\dfrac{\sum_{P\in I^{que}}(R^{que})}{card(I^{que})}}{\dfrac{\sum_{P\in I^{tar_0}}(R^{tar_0})}{card(I^{tar_0})}} \\ K_G = \dfrac{\dfrac{\sum_{P\in I^{que}}(G^{que})}{card(I^{que})}}{\dfrac{\sum_{P\in I^{tar_0}}(G^{tar_0})}{card(I^{tar_0})}} \\ K_B = \dfrac{\dfrac{\sum_{P\in I^{que}}(B^{que})}{card(I^{que})}}{\dfrac{\sum_{P\in I^{tar_0}}(B^{tar_0})}{card(I^{tar_0})}} \end{cases} \tag{7}$$

where *card*(*I*) indicates the number of pixels of image *I*.

These equations lead to a linear transformation of the trichromatic components of the pixels of I^{tar_0} for evaluating the trichromatic color components (R^{tar_1}, G^{tar_1}, B^{tar_1}) of the pixels of the transformed image I^{tar_1} as:

$$\begin{cases} R^{tar_1} = K_R \times R^{tar_0} \\ G^{tar_1} = K_G \times G^{tar} \\ B^{tar_1} = K_B \times B^{tar_0} \end{cases} \tag{8}$$

Now we have to compare the query image I^{que} with the target image I^{tar_1} which is transformed using the trichromatic histograms specification. The retrieval method is presented in the next section of this paper.

3. Indexing Using Color Co-Occurrence Matrices

We propose to use a color image signature based on color co-occurrence matrices denoted Mat_{c_1,c_2} which represent spatial and colorimetric interactions between neighboring pixels.[3] To compare the query image I^{que} and the transformed target image I^{tar_1}, we consider the intersections between the corresponding co-occurrence matrices evaluated as:

$$Inter(Mat^{que}_{c_1,c_2}, Mat^{tar}_{c_1,c_2}) = \sum_{u=0}^{n-1}\sum_{v=0}^{n-1} \min(m(I^{que}), m(I^{tar_i})) \quad (9)$$

with

$$m(I) = \frac{Mat^{I}_{c_1,c_2}(u,v)}{\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} Mat^{I}_{c_1,c_2}(i,j)}$$

where c_i (i = 1, 2, 3) represents the trichromatic components R,G,B and n is the number of values used to quantify the color components. The denominators are simple normalization terms.

As the maximal value of the intersection between two matrices is equal to one, the total distance between the query and the transformed target images is:

$$Inter = \sum_{C_1=R,G,B}\sum_{C2=R,G,B} (1 - Inter(Mat^{que}_{C1,C2}, Mat^{tar_i}_{C1,C2}))^2 \quad (10)$$

The lower the value of *Inter* is, the more similar are the two compared images.

4. Experiments Results

The proposed method has been tested on the 24 person-images database presented in section 1 (see figure 1). For this purpose, we evaluated the intersections between the cooccurrence matrices of the query image and the transformed target images and sorted them according to decreasing values of their intersections.

For example, if the query image is $A1$ (see figure 1), the best best sorting should regroup $A1$, $A2$ and $A3$ as the three first graded images.

In order to evaluate our method and to compare it with classical ones, a pertinence criterion P is evaluated. For each query image i, we evaluate the sum S_i of the position numbers in the sorting of the three target images which represent the same person as the query image. The pertinence criterion of a method is evaluated as:

$$P = \frac{\sum_{i=A}^{H}\left(\frac{S_i}{6} - 1\right)}{8} \quad (11)$$

where i indicates one of the eight persons of the database. S_i is normalized by its lowest value which correspond to the ideal retrieval case, so that the target images which represent the same person as the query image, are sorted as the three first ones.

Tables 1, 2 and 3 show the indexing results achieved thanks to two well known color invariants methods-the Gevers and Smeulders[4] and the Funt and Finlayson[5]-and our approach, respectively.

These tables show that our method provides the lowest pertinence criterion value and in that way, provides the best indexation results with these images acquired under different lighting conditions.

5. Conclusion

In this paper, we have proposed an original approach for color invariant evaluation. Instead of defining an invariant equation for all images as Smeulders or Funt, we propose to consider each couple formed by the query image and one of the target images. If these two images contain the same person, the color co-occurrence matrices of the query image and the transformed target image should be similar thanks to the color histogram specification. If these two images do not contain the same person, these matrices should be different. This approach is applied to the indexation of persons observed under different lighting conditions. Our approach proves to be an improvement when compared to two well known methods based on color invariants.

6. References

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Biography

D. Muselet receives his engineer degree from Ecole des Mines de Douai in 2001 and is preparing his thesis in image analysis. He works in the Laboratory I^3D of the University of Lille1, with L. Macaire who is assistant-professor and Professor J-G. Postaire. His doctoral work involves developing an indexation system of color video images.

Table 1. Target images sorting-indexation with the Gevers and Smeulders method[4]

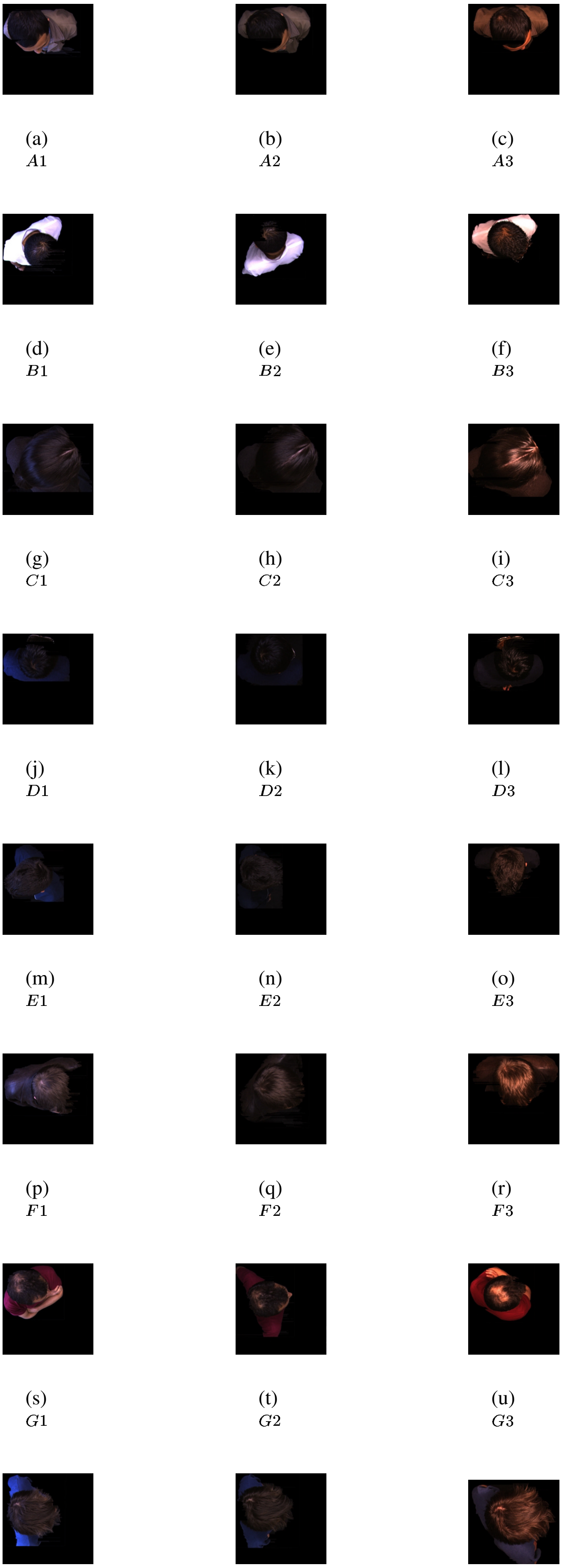
Query	1	2	3	4	5	S_i
$A1$	**A1**	$F1$	$C1$	$H1$	$G1$	32
$B2$	**B2**	**B1**	$F1$	$A1$	$C1$	23
$C3$	**C3**	$F3$	$A3$	$E3$	$H3$	43
$D1$	**D1**	$E1$	**D2**	$B1$	$E2$	17
$E2$	**E2**	$D2$	$C2$	$D3$	**E1**	22
$F3$	**F3**	$A3$	$C3$	$H3$	$E3$	25
$G1$	**G1**	$A1$	$F1$	**G2**	$H1$	25
$H2$	**H2**	$F2$	$B3$	$A2$	$E3$	23
		P	3,38			

Table 2. Target images sorting-indexation with the Funt and Finlayson method[5]

Query	1	2	3	4	5	S_i
*A*1	**A1**	*G*1	**A2**	*G*2	*H*1	10
*B*2	**B2**	**B1**	*G*1	*A*2	*A*1	9
*C*3	**C3**	*G*2	*F*3	*G*3	*H*3	40
*D*1	**D1**	*G*2	*E*2	*H*2	*H*3	24
*E*2	**E2**	*G*2	*D*1	*H*2	*F*2	36
*F*3	**F3**	*G*2	*G*3	*H*3	*E*2	29
*G*1	**G1**	**G2**	*A*2	*A*1	*F*1	10
*H*2	**H2**	**H1**	*G*2	*D*1	*F*2	10
		P	2.50			

Table 3. Target images sorting-indexation with trichromatic histograms specification

Query	1	2	3	4	5	S_i
*A*1	**A1**	**A2**	**A3**	*G*1	*F*3	6
*B*2	**B2**	**B1**	**B3**	*A*2	*A*3	6
*C*3	**C3**	*F*3	*C*2	*E*3	*D*3	15
*D*1	**D1**	*C*1	*E*1	*C*2	**D2**	13
*E*2	**E2**	*C*1	**E1**	*F*1	**E3**	9
*F*3	**F3**	*C*3	**F2**	*E*3	*C*2	11
*G*1	**G1**	**G3**	**G2**	*F*3	*A*1	6
*H*2	**H2**	*E*1	**H3**	**H1**	*D*1	8
		P	0,54			



(a) $A1$ (b) $A2$ (c) $A3$

(d) $B1$ (e) $B2$ (f) $B3$

(g) $C1$ (h) $C2$ (i) $C3$

(j) $D1$ (k) $D2$ (l) $D3$

(m) $E1$ (n) $E2$ (o) $E3$

(p) $F1$ (q) $F2$ (r) $F3$

(s) $G1$ (t) $G2$ (u) $G3$

(v) $H1$ (w) $H2$ (x) $H3$

Fig. 1. Top views of 24 images of 8 persons