Color texture classification across illumination changes

Mozhdeh Seifi, Xiaohu Song, Damien Muselet and Alain Trémeau; Laboratoire Hubert Curien UMR CNRS 5516; Saint Etienne, France

Abstract

Color has been shown to be a very important clue in the context of texture classification. However, since color is not stable across illumination changes, color invariant descriptors are required when the illumination is not controlled. In this paper, we propose to characterize color textures by analyzing the rank correlation between pixels located in the neighborhood from each other. Thus, considering one distance and one direction in the image space, we obtain a correlation measure which i) is related to the colors of the pixels, ii) is not sensitive to illumination changes, iii) represents the spatial interactions between different color components of neighbored pixels. Furthermore, we show how this measure can be very fast extracted from co-occurrence matrices. The discriminative power of this descriptor is assessed on a public color texture database.

Introduction

In this paper, we specifically address the problem of color texture classification across illumination changes. For this purpose, we consider images of color textures acquired with the same viewpoint and the same scale factor but under three different illuminations (see fig. 1). In this context, different approaches for color texture description have been introduced [6, 31]. For example, the structural approach consists in analyzing the relative positions of features extracted from the image [2]. One other approach tries to model the spatial repartition of the colors in the image. In this aim, one can use Markov Random Fields [7, 33] or Local Binary Pattern [28, 23]. The third approach transforms the image into a spatial frequency domain in order to extract discriminative information. Several transforms can be used such as the discrete cosine transform [11], the Gabor filters [30] or wavelet decomposition [9]. The last approach consists in characterizing the content of an image thanks to statistical parameters. These parameters can be extracted from first-order histograms [23], from co-occurrence matrices [29, 20], from sum and difference histograms [35, 24] or from run-length matrices [17, 36].

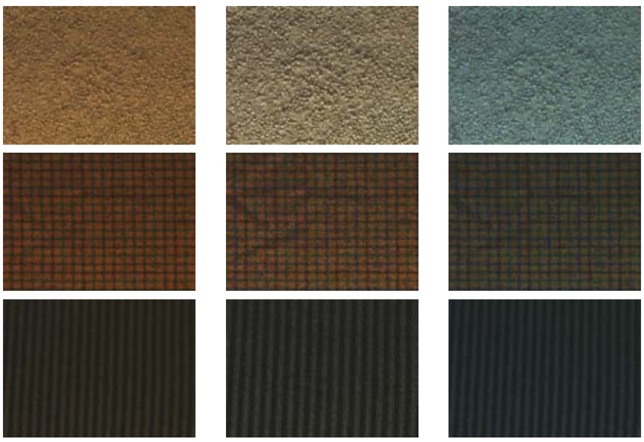

Figure 1. Three textures under three different illuminations. These images are from the Outex14 database [27] (http://www.outex.oulu.fi).

The analysis of the results provided by the most recent works shows that color is a very important clue to charaterize textures and that it is more efficient to use descriptors which account the spatial interactions between different color components than descriptors which are based on the spatial interactions within each color component independently [29, 3, 21, 31]. Thus, since the co-occurrence matrices provide good results, we propose to extract color texture descriptors from the inter-component co-occurrence matrices [29].

However, we know that the color of a pixel is not stable across illumination changes. To cope with this problem, the most classical approach consists in applying a pre-processing step in order to transform the color images into invariant images where the pixels are characterized by invariant components which are less sensitive to illumination changes. The invariant components are based either on a local normalization (e.g. iterative normalization [12], Retinex [8], color ratios [10, 16]) or a normalization based on the whole image (e.g. greyworld [4], color by correlation [13]). Unlike the classical approaches which model the color variations in case of illumination changes by linear transformations, Finlayson proposed a non-linear transformation based on the rank measures of the pixels [14].

Nevertheless, it has been shown that the rank measures of the pixels are not systematically invariant in case of illumination changes [26]. Indeed, since some elementary surfaces may have the same color under one illuminant and different colors under another illuminant (metamerism), some pixels may have the same rank measures in one image and different rank measures in another image. Consequently, in [26], the authors have proposed to characterize the content of the images with a rank correlation measure which copes with this problem. This measure was shown to provide very good results in the context of object recognition across illumination changes [25, 32]. The aim of this paper is to use this measure in order to classify color textures. Indeed, when this measure is extracted from inter-component co-occurrence matrices, it represents the correlation between different color components of neighbored pixels. Thus, it seems to be very well adapted to color texture classification task since : i) it is based on color, ii) it represents the spatial interactions between different color components and iii) it is invariant to illumination changes.

The exploited rank correlation measure was initially proposed by Kendall [22] and is presented in the next section. Then, in the third section we show how we can extract this measure from the inter-component co-occurrence matrices. Finaly, the proposed classification system is assessed on the outex14 database [27] in the fourth section.

Rank measures and rank correlation

The color images $\mathbf{I}$ are decomposed into color component images I^R, I^G and I^B in which the pixels P_i are characterized by their red ($c^R(P_i)$), green ($c^G(P_i)$) and blue ($c^B(P_i)$) levels, respectively. Next, within each color component image I^k, the pixels P_i

are sorted in increasing order of their levels and characterized by their rank measures expressed as:

$$\mathscr{R}^k[\mathbf{I}](P_i) = \frac{Card\{P_j \in \mathbf{I}/c^k(P_j) \leq c^k(P_i)\}}{Card\{P_j \in \mathbf{I}\}}. \qquad (1)$$

Finlayson assumed that these rank measures are invariant to illumination changes and showed that this normalization is equivalent to three 1D-histogram equalizations. Because of the non-linearity of this normalization, this approach provides better results than previous classical ones [14].

The aim of rank correlation coefficients is to provide a measure of the strength of dependency between two variables by checking the correlation between the rank measures of these variables. Applied to color images, the variables are the color component levels of the pixels and the coefficients measure the correlation between the rank measures of the pixels.

As illustration, we propose to evaluate the correlation between the red rank measures and the green rank measures of n_{pix} pixels of a color image. This evaluation can be easily generalized to any pair of color components.

Kendall rank correlation [22] requires to consider each pixel pair $\{P_i, P_j\}$, $i \neq j$, of a color image. If the red and green levels of the two pixels P_i and P_j are ordered in the same manner, i.e. if $c^R(P_i) < c^R(P_j)$ and $c^G(P_i) < c^G(P_j)$ or if $c^R(P_i) > c^R(P_j)$ and $c^G(P_i) > c^G(P_j)$, the pair $\{P_i, P_j\}$ is called concordant. Otherwise, if these pixels are such as $c^R(P_i) < c^R(P_j)$ and $c^G(P_i) > c^G(P_j)$ or such as $c^R(P_i) > c^R(P_j)$ and $c^G(P_i) < c^G(P_j)$, the pair is called discordant. By analyzing all the pairs among the n_{pix} pixels of the considered image, we obtain a measure S which evaluates the difference between the number of concordant pairs and the number of discordant pairs. In order to compute the Kendall's rank correlation coefficient τ, S is normalized by the total number of pixel pairs $\frac{n_{pix}(n_{pix}-1)}{2}$ so that:

$$\tau = \frac{2S}{n_{pix}(n_{pix}-1)}. \qquad (2)$$

Unfortunately, this rank correlation measure does not consider the case where the levels of the pixels are equal. In this case, the pair is neither concordant nor discordant so it is not taken into account during the evaluation of S. Consequently, the Kendall's τ depends on the number of tied pixels (characterized by the same level) in the considered image. Considering two images of the same scene acquired under different illumination conditions, we assume that the pixels which are characterized by the same rank measure in the first image may be characterized by different rank measures in the second image [26]. Therefore, the number of tied pixels in the two images may be different and consequently the Kendall's τ may be different although the images represent the same scene. Thus, because of metamerism, the Kendall's τ is only coarsely invariant to illumination changes.

Fortunately, when there is a high number of tied pixels, a corrected version of the Kendall's τ can be used to account these pixels [22]:

$$\tau' = \frac{S}{\sqrt{(\frac{1}{2}n_{pix}(n_{pix}-1) - Tk_r)}\sqrt{(\frac{1}{2}n_{pix}(n_{pix}-1) - Tk_g)}}, \qquad (3)$$

where $Tk_r = \frac{1}{2}\sum_{r=0}^{L} t_r(t_r-1)$ and $Tk_g = \frac{1}{2}\sum_{g=0}^{L} t_g(t_g-1)$ where t_r (t_g, resp.) is the number of tied pixels characterized by the same red (green, resp.) levels r (g, resp.) in the considered image. L is the number of levels used to quantize the color component in the image, generally set to 256.

Rank correlation from co-occurrence matrices

A 2D co-occurrences matrix $M_{d,o}^{k,k'}[\mathbf{I}]$ of an image $\mathbf{I}$ can be considered as an array of cells indexed by color component levels [29]. The cell $M_{d,o}^{k,k'}[\mathbf{I}](u,u')$ indicates the number of times that, in the image $\mathbf{I}$, a pixel P' whose level $c^{k'}(P')$ is equal to u', is located at the distance d with orientation o from a pixel P whose level $c^k(P)$ is equal to u. Given a distance d and an orientation o, a color image $\mathbf{I}$ is characterized by 6 co-occurrences matrices: $M_{d,o}^{R,R}[\mathbf{I}]$, $M_{d,o}^{G,G}[\mathbf{I}]$, $M_{d,o}^{B,B}[\mathbf{I}]$, $M_{d,o}^{R,G}[\mathbf{I}]$, $M_{d,o}^{R,B}[\mathbf{I}]$ and $M_{d,o}^{G,B}[\mathbf{I}]$. Thus, considering n_d different distances d_i, $i = 1,...,n_d$ and n_o different orientations o_i, $i = 1,...,n_o$, each texture is characterized by $6 \mathrm{x} n_d \mathrm{x} n_o$ co-occurrences matrices.

Considering the red and the green components, the Kendall's τ' represents the mean rank correlation between the red and the green levels of all pixels without taking into account the spatial interaction between the pixels in the image. In order to compensate this drawback, we propose to measure the mean rank correlation between the red level of a pixel and the green levels of the pixels which are located at a distance d from this pixel according to the orientation o. From the definition of the Kendall's τ', we can evaluate this measure by considering pairs of occurrences rather than pairs of pixels. As illustration, we consider in an image, one occurrence of pixels for a particular distance d and a particular orientation o. This occurrence $Occ1_{d,o}$ is constituted by a pair of pixels $\{P1, P1'\}$ which are located at a distance d from each other in the orientation o. Then, we consider a second occurrence in the same image $Occ2_{d,o}$ which is constituted by a pair of pixels $\{P2, P2'\}$. By extending the definition of concordant pairs of pixels to pairs of occurrences, we can say that the pair of occurrences $\{Occ1_{d,o}, Occ2_{d,o}\}$ is a concordant pair according to the red and green components, if the red and green levels of the pixels in the two occurrences are ordered in the same manner, i.e. if $c^R(P1) < c^R(P2)$ and $c^G(P1') < c^G(P2')$ or if $c^R(P1) > c^R(P2)$ and $c^G(P1') > c^G(P2')$. Otherwise, if these occurrences are such as $c^R(P1) < c^R(P2)$ and $c^G(P1') > c^G(P2')$ or such as $c^R(P1) > c^R(P1)$ and $c^G(P2') < c^G(P2')$, the pair of occurrences is called discordant. The advantage of this correlation measure is that it can be very fast extracted from a 2D co-occurrence matrix. Indeed, we show below that the numbers of concordant and discordant pairs of occurrences can be obtained from the corresponding co-occurrence matrix.

We consider the red-green matrix $M_{d,o}^{R,G}[\mathbf{I}]$. The cell c_i in the figure 2 represents the number of time that, in the image $\mathbf{I}$, a pixel P' whose level $c^R(P')$ is equal to r, is located at the distance d for the orientation o from a pixel P whose level $c^G(P)$ is equal to g. From the definition, we know that these occurrences constitute discordant pairs with the occurrences characterized by red levels lower than r and green levels higher than g. The cells associated with these occurrences constitute the surface denoted $DISC_i$ in the figure 2. Note that we consider only the occurrences characterized by a green level higher than g so that each occurrence pair is accounted only once in the evaluation of S. Consequently, the number of discordant pairs associated with the cell c_i in the figure 2 is:

$$\begin{aligned} discordant(c_i) = M_{d,o}^{R,G}[\mathbf{I}](r,g) \times \\ \sum_{n_r=0}^{r-1} \sum_{n_g=g+1}^{L-1} M_{d,o}^{R,G}[\mathbf{I}](n_r,n_g) \end{aligned} \qquad (4)$$

We propose to use a similar approach as Bay [1] in order to speed-up this evaluation. Indeed, we propose to evaluate the

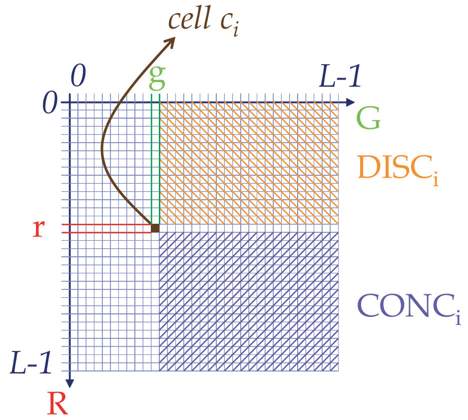

Figure 2. *A red-green co-occurrence matrix* $M^{R,G}_{d,o}[\mathbf{I}]$.

top-right integral co-occurrence matrix $Mtr^{R,G}_{d,o}[\mathbf{I}]$ from the matrix $M^{R,G}_{d,o}[\mathbf{I}]$. This integral matrix is evaluated as:

$$Mtr^{R,G}_{d,o}[\mathbf{I}](r,g) = \sum_{n_r=0}^{r-1} \sum_{n_g=g+1}^{L-1} M^{R,G}_{d,o}[\mathbf{I}](n_r,n_g), \quad (5)$$

for all $\{r,g\} \in [0;L-1]$.

This top-right integer matrix is used for the calculation of the numbers of discordant pairs associated with all the cells c_i so that equation becomes:

$$discordant(c_i) = M^{R,G}_{d,o}[\mathbf{I}](r,g) \times Mtr^{R,G}_{d,o}[\mathbf{I}](r,g). \quad (6)$$

Thus, by this way, the evaluation of the number of discordant pairs is very fast.

In the same way, we can evaluate the number of concordant pairs associated with the cells c_i:

$$concordant(c_i) = M^{R,G}_{d,o}[\mathbf{I}](r,g) \times Mbr^{R,G}_{d,o}[\mathbf{I}](r,g), \quad (7)$$

where $Mbr^{R,G}_{d,o}[\mathbf{I}]$ is the bottom-right integer matrix deduced from the matrix $M^{R,G}_{d,o}[\mathbf{I}]$ thanks to the following equation:

$$Mbr^{R,G}_{d,o}[\mathbf{I}](r,g) = \sum_{n_r=r+1}^{L-1} \sum_{n_g=g+1}^{L-1} M^{R,G}_{d,o}[\mathbf{I}](n_r,n_g). \quad (8)$$

The number in the cell c_i of this bottom-right matrix is the sum of the numbers in the cells which constitute the surface denoted $CONC_i$ in figure 2.

Thus, for each cell c_i in the matrix $M^{R,G}_{d,o}[\mathbf{I}]$, we obtain very fast the numbers of concordant and discordant pairs by this way. The value of S is just deduced from the sum of the differences between the number of concordant pairs and the number of discordant pairs for all the cells:

$$S = \sum_i concordant(c_i) - discordant(c_i). \quad (9)$$

By this way, from each matrix $M^{k,k'}_{d,o}$, we extract the mean rank correlation between the color components k and k' of pixels located at a distance d from each other for an orientation o. Thus, a color texture is characterized by $6 \text{x} n_d \text{x} n_o$ rank correlation measures, i.e. $6 \text{x} n_d \text{x} n_o$ real values. In order to compare the contents of two different textures, we propose to use the Euclidean distance between the vectors constituted by the $6 \text{x} n_d \text{x} n_o$ rank correlation coefficients.

Thus, we have shown that the Kendall rank correlation between pixels located at a particular distance in a particular orientation can be very fast extracted from the corresponding co-occurrence matrix. Futhermore, we have also demonstrated that the Kendall rank correlation is invariant across illumination changes whereas the co-occurrence matrices in the *RGB* space are very sensitive to illumination changes. Thus, the propose features do not require any color invariant transformation before being extracted. The next section assesses the performance of this feature in the case of color texture classification across illumination changes.

Experiments and results

The outex database is used for testing [27] (http://www.outex.oulu.fi). This database contains color images from textures acquired under different conditions. Particularly, the subset called Outex_TC_00014 contains images of 68 different textures, each one being acquired under one of three available illuminants : 2300K horizon sunlight, 2856K incandescent CIE A light source or 4000K fluorescent TL84 (see fig. 1).

In order to compare our color texture descriptor with other ones, we propose to use the classification process as those used by recent papers [18, 19, 23]. Thus, we have used the k-NN classifier with k=3. The training set was constituted by sample images of each texture illuminated by incandescent light. For this, each image was divided into 20 non-overlapping sub-images, each of size 128×128 pixels, producing 1360 training images since the size of the original image is 746×538 pixels. The test set was constituted by the images acquired under the two other illuminants (horizon sunlight and fluorescent TL84), once again with 20 sub-images per texture. For each illumination source, 1360 images are available, making a total of 2720 test images. The only difference between the paper from Hafiane [18] and the papers from Handbury [19] and Mäenpää [23] is that Hafiane reduce the number of textures from 68 to 24. So, we have first tested our method on the 24 textures chosen by Hafiane and then we have used the complete outex_TC_00014 database in order to compare our results with those provided by Handbury and Mäenpää.

Table 1 presents the classification rates obtained by our descriptors on the reduced database (24 classes). Our descriptor is called *SC* τ' (Saptio-Colorimetric Kendall's τ') in this table. Furthermore, Hafiane [18] provides the performance of the following texture descriptors on this reduced database:

- Median Binary Pattern [18], called MBP in table 1,
- Local Binary Pattern [28], called LBP in table 1,
- Haralick parameters extracted from gray-level co-occurrence matrices [20], called GLCM in table 1,
- Gabor filter [34], called Gabor in table 1,
- Gaussian Markov Random Field [5], called GMRF in table 1.

In Hafiane's paper, all these descriptors were computed from gay-level images.

In table 1, for each tested descriptor, we add the dimension of the feature vector. This information can be interesting for time processing considerations. Indeed, in the context of color texture classification (or recognition), the time required for classifying a query texture is directly related to the dimension of the used feature vector. Considering our descriptor, we have selected 4 directions from 0^o to 135^o and 5 distances from 5 to 20. Thus, for one sample image, we extract $6 \times 4 \times 5 = 120$ Kendall rank correlations.

Descriptors	Classification rates			Dimension of the feature vector
	Tl84	Horizon	Average	
MBP	97.3	96.1	96.7	1536
LBP	94.1	90.0	92.1	256
GLCM	11.3	11.1	11.2	112
Gabor	46.2	44.7	45.5	4
GMRF	39.7	55.6	47.7	12
SCτ'	**99.0**	**98.9**	**99.0**	**120**

Color texture classification rates obtained by several descriptors on the reduced outex_TC_00014 database (24 classes). The classifier is k-NN with k=3. The training set is under incandescent light.

Table 2 presents the classification rates provided by our descriptors on the complete database outex_TC_00014 (68 classes). For comparison, we use the results provided by Handbury [19] and by Mäenpää [23] on this database. Handbury proposed to use standard morphological texture characterisation tools such as variogram and granulometry. Applying to color images, the variogram represents the evolution of the differences between the color of a pixel and the colors of the pixels located at a particular distance in a particular direction while the granulometry is the ratio between the color components of a pixel in the original image and the color components of this pixel after applying a color opening or closing with a structuring element of increasing size. These morphological transformations are applied in the RGB and CIELAB color spaces and on the single L* component of the CIELAB color space. The results provided by these descriptors are reported in table 2: V_{RGB}, V_{Lab} and V_{L*} for variogram and G_{RGB}, G_{Lab}, G_{L*} for granulometry. Furthermore, Handbury proposed to use an illumination-invariant normalization similar to the histogram equalization proposed by Finlayson [14]. Thus, in table 2, we report the classification results provided by the variograms and granulometries after applying this illumination invariant normalization on the outex_TC_00014 database: $V_{inv_{RGB}}$, $V_{inv_{Lab}}$, $V_{inv_{L*}}$, $G_{inv_{RGB}}$, $G_{inv_{Lab}}$ and $G_{inv_{L*}}$.

In his paper, Mäenpää [23] also presents classification rates on the outex_TC_00014 database provided by some descriptors such as:

- Color histogram evaluated after applying the illumination-invariant normalization proposed by Finlayson [15] ($Histo_{inv}$),
- Color ratio histograms obtained from the illumination-invariant normalization proposed by Funt [16] ($CR-histo$),
- Multiresolution Opponent Color Gabor ($Opp-Gabor$),
- Multiresolution grays-sale and color (L*a*b*) LBP ($Multi-gray-LBP$ and $Multi-Lab-LBP$).

Descriptors	Classification rates			Dim. of the feat. vect.
	Tl84	Horizon	Average	
V_{RGB}	73.46	65.66	69.56	200
V_{Lab}	65.76	73.75	69.76	200
V_{L*}	70.07	73.01	71.54	200
G_{RGB}	41.54	47.13	44.34	312
G_{Lab}	37.43	56.10	46.77	312
G_{L*}	16.40	22.72	19.56	104
$V_{inv_{RGB}}$	65.59	60.44	63.02	200
$V_{inv_{Lab}}$	74.12	55.22	64.67	200
$V_{inv_{L*}}$	77.35	78.82	78.09	200
$G_{inv_{RGB}}$	60.44	65.59	63.02	312
$G_{inv_{Lab}}$	69.04	72.13	70.56	312
$G_{inv_{L*}}$	24.41	19.41	21.91	104
$Histo_{inv}$	-	-	34.3	4096
$CR-histo$	-	-	42.7	4096
$Opp-Gabor$	-	-	53.3	84
$Multi-gray-LBP$	-	-	69.5	1053
$Multi-Lab-LBP$	-	-	67.8	3159
SCτ'	**87.8**	**86.3**	**87.05**	**120**

Color texture classification rates obtained by several descriptors on the complete outex_TC_00014 database (68 classes). The classifier is k-NN with k=3. The training set is under incandescent light. The results not available in [23] are displayed as '-'.

From tables 1 and 2, we notice that the proposed spatio-colorimetric rank correlation measure provides promising results in the context of color texture classification. Indeed, the classification rate obtained on the reduced database is almost perfect and the rate obtained on the complete outex_TC_00014 database is significantly higher than the rates obtained by well-known approaches. Furthermore, the proposed descriptor is compact comparing with descriptors which provide similar results. Indeed, only 120 values are required to classify most of the 68 color textures acquired under different illuminations.

Conclusion

In this paper, we have proposed a color descriptor designed for the classification of textures across illumination changes. This descriptor analyzes the rank correlation measures between different color components of pixels located at a particular distance from each other in a particular direction. Thus, it accounts both the colors of the pixels and their spatial interactions. We have shown that this measure can be very fast extracted from the color co-occurrence matrices of the considered image. This extraction does not require any color normalization as pre-processing step since it has been shown that the rank measure of the pixels are coarsely preserved in case of illumination changes. Furthermore, the proposed descriptor is very compact comparing with descriptors which provide similar classification rates. This compactness is very interesting for time processing considerations. We have assessed the performance of this descriptor on a public database showing promising results in the context of color texture classification across illumination changes.

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