Colour Contrast Occurrence matrix: a vector and perceptual texture feature

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Abstract

Texture discrimination was the second more important task studied after colour perception and measurement. A lot of works have explored it using a separated channel processing and very few have addressed the vector aspect of this spatio-chromatic information. In this paper we propose a novel vector processing for colour texture characterization: the Colour Contrast Occurrence matrix (C_2O). The C_2O is expressed using a perceptual distance in the CIELab colour space and two angles characterizing the chromaticity, and darker or lighter direction of local differences. The set of local differences, the contrast occurrences, is represented in a 3D representation, offering an understandable representation of the texture variations. In this work, we analyze also the feature invariance to changes in illumination, viewpoint and spectrum of the light source. Performances in classification tasks on several texture databases show the added-value of the C_2O for texture discrimination especially when the texture content becomes complex.

INTRODUCTION

Colour and texture are two visual characteristics highly important in low level image processing applications. However the definition of texture is linked to a human semantic meaning [23]. Researches from the point of view of human perception by Julesz [13], Caelli [8] and Landy [14] have shown that texture modeling can be approached from local, structural approach or a combination of both. So, there is no formal mathematical definition for texture [3]; while the color rendering can be define quantitatively [1].

Foundations of texture assessment for image processing started with Haralick, who translated the purposes of Julesz into the cooccurrence construction [11]. Since these works, a lot of methods was developed to express the texture information into digital features (histograms difference, cooccurrence, run-length matrix, Fourier transformations, local binary patterns ...) in grey-level. But the extension to colour is not straightforward. The first constructions follow the hypothesis of Poirson and Wandell separating the colour information from the texture one [4, 10, 16]. Other ones analyse colour and texture together under the hypothesis that the spatio-chromatic variations are a combination of three grey-level texture affected to colour channel [16], or a combination of grey-level texture affected to cross-channel [4, 20].

Texture feature performances are evaluated on classification tasks, using image databases with controlled lightning and viewing conditions (OUTEX, ALOT, ...) or uncontrolled (VISTEX, STEX ...) conditions. The invariance in acquisition conditions is important in computer vision applications, mainly in images where the appearance varies significantly with changes in lighting as in natural textures [7]. Without these invariance, multiple training images corresponding to the multiple cases are required [23]. In addition, industrial or artificial textures present periodic structures easy to acquire under controlled conditions. By opposition, natural textures may not have any detectable periodic structures, due to random and deep scale variations [5].

Inside this work, we propose a new vector processing for colour texture characterization, the Colour Contrast Occurrence matrix (C_2O). This new texture feature is based on colour difference assessment. To be link to the human perception, colour differences are expressed using a perceptual distance processed in $CIELab$ and two angles characterizing the chromaticity and darker or lighter direction [17]. Our work presents the invariance of this texture feature in front of changes in lighting, orientation and intensity of the light source [23]. In a second time, we compare our approach performances in texture classification in front of the other approaches adapted to colour domain as cooccurrence matrices and Local Binary Patterns (LBP) .

METHOD

Colour Contrast Occurrence Matrix definition

Our feature defines the probability to have a specific *colour difference* between two pixels separated by a spatial vector. This spatial vector is defined classically by a spatial distance in a particular direction. The colour difference is expressed in $CIELab$ through a perceptual distance ΔE and two angles. The first angle is defined on the ab plane characterizing the chromatic orientation of the colour difference. The second angle is defined between the colour difference vector and the ab plane characterizing a darker or lighter difference[17]. So the Colour Contrast Occurrence (C_2O) is defined for each pixel location p_{ci} and considering the second pixel location p_{cj} as

- $||\overrightarrow{p_{ci}, p_{cj}}|| = d$ and $\llcorner(\overrightarrow{Ox}, \overrightarrow{p_{ci}p_{cj}}) = \theta$
- c_i and c_j being the corresponding colour coordinates in $CIELab$

$$\begin{aligned} \overrightarrow{\Lambda(c_i, c_j)} \quad &: \quad prob\left(\overrightarrow{\Lambda(c_i, c_j)}\right) \quad \forall p_{ci}, p_{cj} \in I \qquad (1) \\ &\text{with} ||\overrightarrow{\Lambda(c_i, c_j)}|| = \Delta E(c_i, c_j) \\ &\text{and} \llcorner(\overrightarrow{Oa}, \overrightarrow{c_i c_j}) = (\alpha, \beta) \end{aligned}$$

Feature from the C_2O Matrix

Albuz et al. [2] carried out a quantization from $CIELab$ space making a book of codes in order to reduce the information contained in a database. Following this direction, we propose to construct the texture feature directly from the Colour Contrast Occurrence matrix. As the C_2O matrix creates a cloud of occurrences centered around the origin, the proposed feature is the spherical quantization from center to the border (increasing Δ_i), then for each α_j the number of occurrences with β_k is pushed in the signature[17]:

$$
\begin{aligned}
& Sig_{C_2O}(I) = \left\{ h_{\Delta_i \alpha_j \beta_k} \right\} \text{ with} \\
& h_{\Delta_i \alpha_j \beta_k} = \text{prob}\left(\Delta_i \leq \| \overrightarrow{\Lambda(c_i, c_j)} \| < \Delta_j + \Delta E_{step} \right) \\
& \qquad \text{and } \frac{\pi}{n_\alpha} j \leq \alpha < \frac{\pi}{n_\alpha}(j+1) \\
& \qquad \text{and } 0 \leq \beta < \frac{2\pi}{n_\beta}(k)
\end{aligned}
\tag{2}
$$

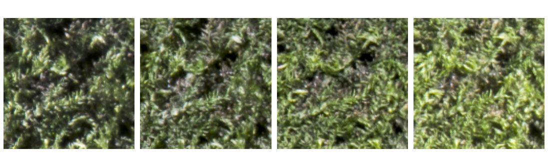
where ΔE_{step},n_α and n_β define the steps of the norm, chromatic and lightning quantization respectively.

RESULTS AND DISCUSSION

C2O stability on illumination, rotation and viewpoint changes for ALOT database

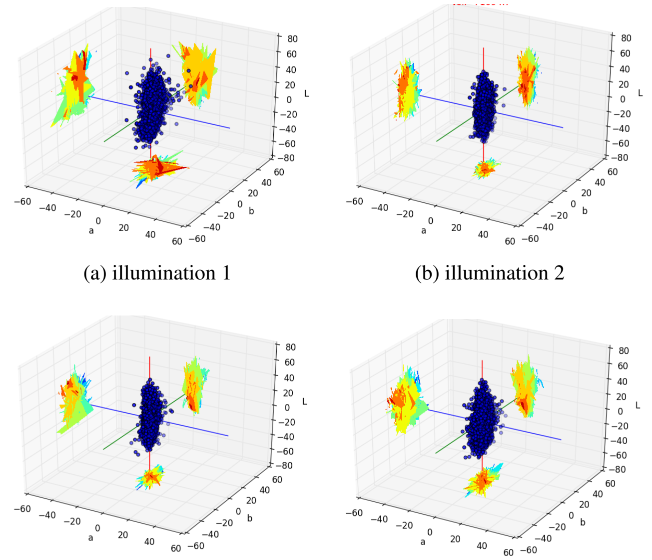
ALOT [12] is an impressive colour image collection of 250 distinct rough textures, acquired by 4 different colour cameras ($c = 1, \ldots, 4$). For each image and camera, six illuminations are considered ($I = (1,2,3,4,5,8)$) and 4 rotations ($r = 0^o, 60^o, 120^o, 180^o$). Three image sizes are proposed: full resolution (1536×1024), half resolution (768×512) and quarter resolution (384×256) pixels. The colour resolution is expressed on 24 bits. These differences make that this database has been used by some researchers to assess changes in illumination and viewpoint using mathematical morphology [3], to verify the invariance to rotation by means of Markov chains [23], and study the impact of the reduction of images in the percentages of classification in large databases [22].

Images in the figure 1 show natural texture of grass in which only the illumination has changed (same camera ($c = 1$), the same viewpoint ($r = 0^o$)). In the figure 2 firstly, C_2O shape could be approximate as an ellipsoid, few shape differences appear. The main ellipsoid orientation is organized around the L axis. Among the illuminant nature, the lightning difference varies from important (Illumination 1, due to a large range of contrast) to less important (Illumination 4). This fact is in adequation with our perception. In a more accurate observation, the illuminant variations induce change in the assessment of the chromatic difference observed on the *ab* plane, that is also in adequation with the physical construction of the observed scene as a multiplication of the illuminant spectrum by the reflectance spectrum. Inside this first study, we can take interest also to the bounding-box volume of the ellipsoid as a measure of the lightning impact on the scene.



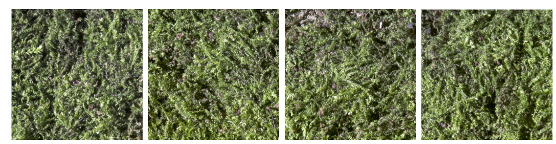
(a) Illumin. 1 (b) Illumin. 2 (c) Illumin. 3 (d) Illumin. 4

Figure 1. *Illumination changes for image* moss *from ALOT database.*



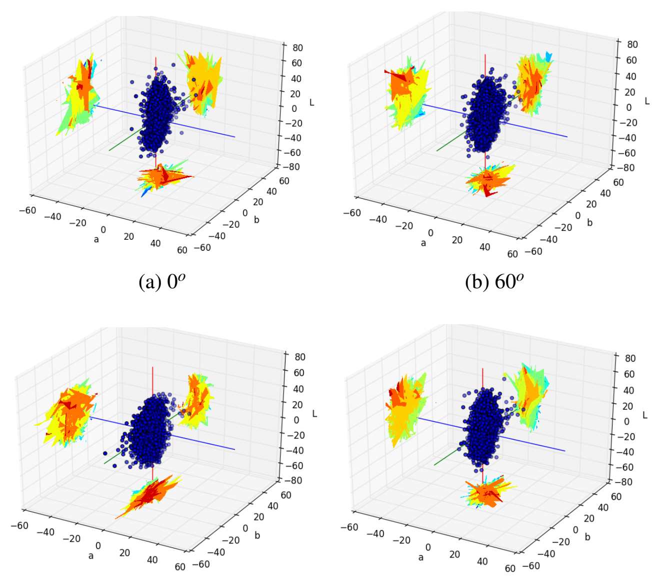
(a) illumination 1 (b) illumination 2 (c) illumination 3 (d) illumination 4

Figure 2. *Colour Contrast Occurrence (C_2O) for illumination changes in image* moss *from ALOT database.*



(a) 0^o (b) 60^o (c) 120^o (d) 180^o

Figure 3. *Viewpoint changes for image* moss *from ALOT database.*



(a) 0^o (b) 60^o (c) 120^o (d) 180^o

Figure 4. *Colour Contrast Occurrence (C_2O) for viewpoint changes in image* moss *from ALOT database.*

The second experiment assesses the impact of the orientation changes on the C_2O feature. To show the impact, we select one of the previous images with the illumination $I = 1$ (to see figure 3). The selected orientations to compare results were $r = 0^o, 60^o, 120^o, 180^o$. We show, in figure 4, that the C_2O shape is slightly modified, even if the volume measure is well preserved. The main ellipsoid axis keep the orientation among the L axis. A more accurate observation indicate that some problems appear in the ALOT process for the rotation change. The transform is not limited to a simple rotation but include also a translation. This problem is visible for the rotation $r = 120^o$, where the background appear and is not present on the others images. Consequently the C_2O shape is impacted by this texture part, that is not present in the other images.

$C2O$ ***stability on illumination and viewpoint changes for OUTEX database***

To assess the impact of lightning change in the OUTEX case [19], we use the TC0014 suite including 68 colour texture images of size 746×538 pixels of 24 bits acquired under three types of illumination: 2300K *horizon sunlight* denoted as "Horizon", 2856K incandescent CIE A denoted as "Inca" and 4000K fluorescent TL84 denoted as "TL84". Figure 5 show the used illuminant.

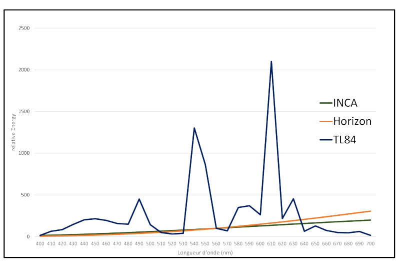
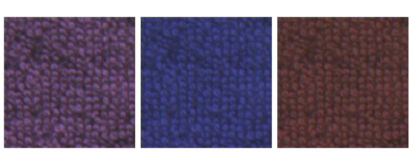


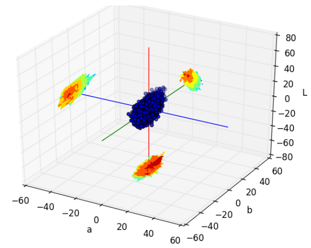
Figure 5. *Spectra of the illuminati for OUTEX database (from OUTEX website).*

In figure 6 we observe the important variations on the content perception induced by the lightning changes. Among the illuminant, image *canvas* appears violet, blue or close to a brown in function of the spectral multiplication between the light spectrum and the reflectance spectrum of the canvas. These differences are explained by the variations in the red part of the spectra. In a first approximation, we expect that the C_2O matrix rotates around the L axis. This fact is obtained between the INCA and TL84 cases. As the Horizon illuminant presents a relative spectral power close to 550nm, as the INCA illuminant, the two ellipsoids have the same orientation. The difference are due to the differences in the spectrum shapes.

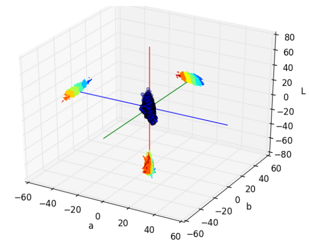


(a) Horizon (b) Inca (c) TL84

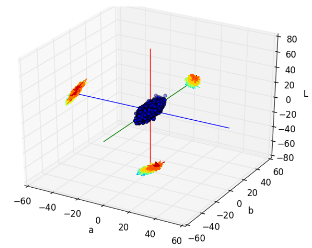
Figure 6. *Variations in the illumination spectrum in the image* canvas *2 OUTEX database.*



(a) Horizon

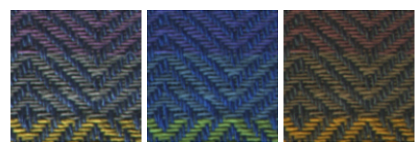


(b) Inca



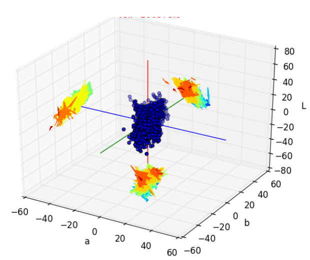
(c) TL84

Figure 7. *Colour Contrast Occurrence (C_2O) graphics for variations in the illumination spectrum in the image canvas 2 OUTEX database.*

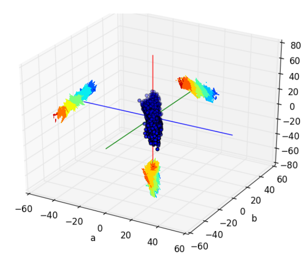


(a) Horizon (b) Inca (c) TL84

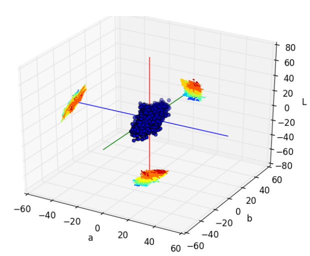
Figure 8. *Variations in the illumination spectrum in the image canvas 20 OUTEX database.*



(a) Horizon



(b) Inca

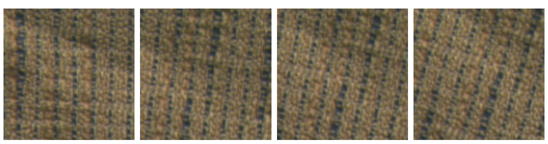


(c) TL84

Figure 9. *Colour Contast Occurrence (C_2O) for variations in the illumination spectrum in the image canvas 20 OUTEX database.*

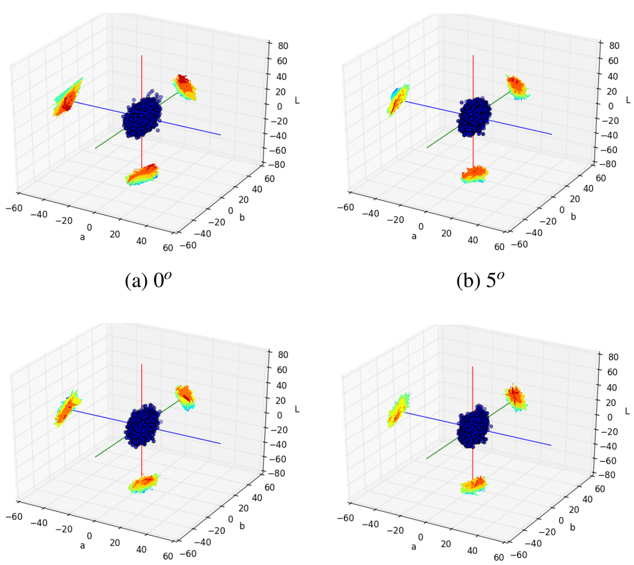
For a more complex texture, as in the case of *canvas* 20 (fig. 8), the same interactions between the lightning changes and the texture generate the same C_2O modifications, even if the colour content is more complex. Such result induces the ability to identify the light modifications between two textures. In a second level of observation, the C_2O matrix are sufficiently different to allow the discrimination between the two *canvas* textures.

The set "outex TC 00030", derived of colour version of above "Outex TC 00020", provides 68 images of colour texture of 128×128 pixels with different rotation angles ($0^o, 5^o, 10^o, 15^o, 30^o, 45^o, 60^o, 75^o$ and 90^o). The illumination conditions are the same for the 12240 ($68 \times 180 = 12240$) images [15]. The graphic 10 shows the texture *canvas* 0 with rotations of $0^o, 5^o, 10^o$, 15^o. As in the ALOT case, the transformation applied to the image is not a pure rotation, and a translation appears also. Unfortunately the texton size is close from the image size so the translation induces some texture feature modifications. Nevertheless the C_2O shapes are similar (to see figure 11) and the obtained volumes are in the same range(outside the second case (5^o)).



(a) 0^o (b) 5^o (c) 10^o (d) 15^o

Figure 10. *Viewpoint changes for image canvas 0 OUTEX database.*



(a) 0^o (b) 5^o

(c) 10^o (d) 15^o

Figure 11. *Colour Contrast Occurrence (C_2O) for viewpoint changes for image canvas 0 OUTEX database.*

Illumination and viewpoint direction performance

After this subjective comparison, we develop an objective test to assess the feature stability among different variations. To do it, we use the classification schema suggested by Aptoula [3] for testing the ALOT database. The suite is cropped in two parts; the train set are the first 200 samples defined as $c(1,4)$,$l(1,4,8)$ and $r(0,120)$; and the test set is composed for the same samples with $c(2,3)$,$l(3,5)$, $r(0,120)$, $c3l2(0,120)$ $c2l2r0$ and $c1ir0$) [23], [3]. The table 1 shows the correct classification percentage between C_2O and approaches invariants to lighting changes as cooccurrence in their extension to colour (Cross-Channel Marginal Approach CCMA) [17] and Local Binary Pattern (LBP) extended to colour (LBP-CCMA) by Porebsky [21]. C_2O obtain the better score with a gain of 8.85% on the LBP colour approach.

The second test is processed on the OUTEX extended database already mentioned as "OUTEX TC 00030". In this case we follow the Arvis classification way. The 12240, images were divided in 50% for train set and 50% for test in a random split data. We mixed all angles variations. The same table 1 shows that the C_2O obtains the better correct classification percentage in front of LBP-CCMA and the cooccurrence-CCMA[17].

Comparison of correct classification score between cooccurrence-CCMA, Local binary Pattern (LBP)-CCMA and Colour Contrast Occurrence matrix C_2O in front of viewpoint modification.

	Coocurrence	LBP	C_2O	difference
outex	70.4	85.3	94.15	8.85%
alot	48.22	63.72	70.4	6.72%

Illumination spectrum performance

Using the TC00014 from the OUTEX database, we obtained 1380 sub-images of 128×128 with 3 different lighting therefore 4080 sub-images forming 68 class of 60 samples each. The classification scheme was processed using 50% of the sample for the training and 50% for the classification in a random split data. [18]. The C_2O feature obtains the better performance in front of the LBP and Cooccurrence (table 2).

In the ALOT case, we used four illuminations with 250 images for each one, that means 1000 images, then we applied the last classification schema, we cropped each image in 20 sub-images of 128×128, that means a base of 20000 sub-images. There is a different of 12.6% more high of C_2O (to see table 2).

Comparison of correct classification score between cooccurrence-CCMA, Local binary Pattern(LBP)-CCMA and Colour Contrast Occurrence matrix C_2O in front of illuminations spectrum changes.

	Coocurrence	LBP	C_2O	difference
outex	54.01	74.07	75.04	0.97%
alot	65	72.13	84.7	12.6%

As shown in figure 5, the illuminati spectrum of "Horizon" and "Inca" in OUTEX database are very close, therefore results in table 2 could theoretically be the same using the "TL84" spectrum and any of the other two illuminations such as "Horizon" and "Inca". The figure 12, display the comparison of the rate of good classification using the three individual spectrum of lighting, as well as the possible combinations between them. Graphic "Horizon" and "Inca" spectrum have the same rate of good classification results (71.17%). By contrast the TL84 spectrum lighting has 3% more such a high rate (74.26%). Combining several lightning increase the good classification rate, the better combination being obtained using "TL84". With samples of the three lightning, a gain of 4% is reached (75.07%).

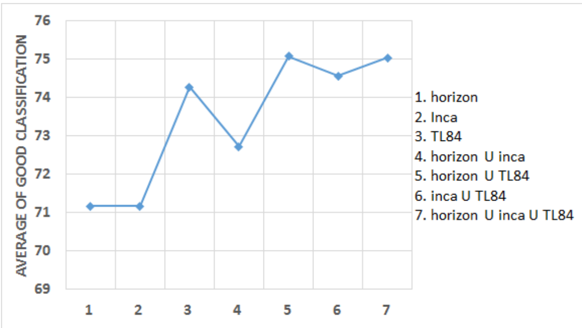


Figure 12. *Comparison of correct classification score for three illuminations spectrum: Horizon, Inca and TL84 in OUTEX database.*

In the case of the ALOT database, we have 4 different illuminations, with the same light spectrum, (3075 K) by varying the angle ($45^o, 30^o, 0^o$ and 60^o) of the light source to the image. The results carry out classification using a single lighting, the combination of two of them, three and four. Results are shown in figure 13, where it can be seen that greater precision can be achieved with illumination 3 (85.08%) corresponding to the point where the image is located perpendicular with the light source (0^o). When combining two or three illuminations, the higher result is that involves the illumination 3 and the illumination 4 (86.65%). When the four lightning angle combinations are associated, a good classification rate is obtained (84.78%), nevertheless the better rate are obtained when the angle 1 is not combined with the others (86.65%).

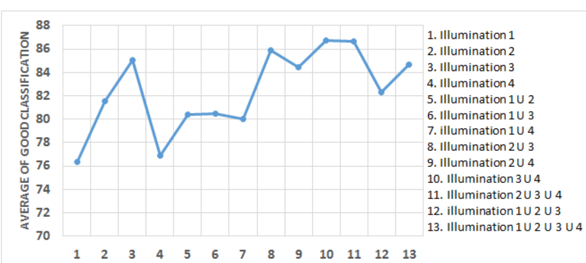


Figure 13. *Comparison of correct classification score for four illuminations spectrum in ALOT database.*

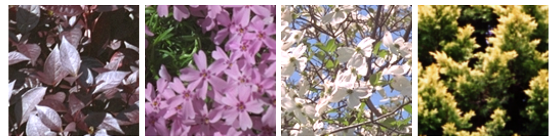
With these two previous experiments we tested the perceptual sense of vector C_2O to be sensitive to changes in the light spectrum and the changes caused by the illumination.

Stability in front of natural textures

In this experiment, we assess the behavior of the C_2O performance in texture discrimination for image databases acquired without controlled lightning conditions.

VISTEX database is constructed from images of natural textures acquired using uncontrolled conditions. The image set is composed by 54 colour images of 512×512 pixels with some natural textures (to see figure 14). This set is the "Contrib TC 00006" in the same website of OUTEX.

Figure 15 shows some images of STEX database [9]. This is based on the image set labelled "Salzburg texture image database". STEX includes 476 colour texture images, whose initial size are 512×512 pixels [6]. Some textures can be defined as stationary, but others appear as a collection of natural scenes as flowers and trees.



(a) leaves 11 (b) flowers 2 (c) flowers 4 (d) flowers 5

Figure 14. *Image set of VISTEX database.*

(a) bark 06 (b) bush 01 (c) flower 07 (d) tree 01

Figure 15. *Image set of STEX database.*

Table 3 shows the good classification rate obtained by all the approaches in the VISTEX case, close to 99%. The C_2O obtain the better performance with a gain of 0.7%. In STEX case, the gain is biggest, due to the highest complexity of the images. The difference of 14.86% with respect to LBP-CCMA of C_2O, denotes a better stability to changes in lighting.

Comparison of correct classification score between cooccurrence-CCMA, Local binary Pattern (LBP)-CCMA and Colour Contrast Occurrence matrix (C_2O) in unknown illumination conditions.

	Cooc	LBP	C_2O	difference
vistex	98.6	97.45	99.3	0.7%
stex	67.58	71.24	86.1	14.86%

CONCLUSIONS

In this paper we present a new way to include the colour informations inside the texture feature, using the Julesz's and Haralick's contributions in the computational sense and the results of Drimbarean and Palm in colour and texture analysis. The Colour Contrast Occurrence matrix is processed in $CIELab$ to obtain a correct behavior in front of the human vision and to keep the idea of the occurrence but translated into a normalized colour difference.

The results shown that, with the limits induced by the two selected databases with variations in illumination and viewpoints (ALOT and OUTEX), the C_2O features obtain good stability performances in texture discrimination, under various viewing point or illumination changes. Local Binary Patterns obtain close scores due to a similar construction based on the local difference assessment. To precise this stability, we assessed the performance on two databases acquired with unknown lighting conditions (VISTEX and STEX) and including more natural textures. In this second case, the C_2O obtain the better score, with a gain highest of 14.86% for STEX that includes images with highest complexity.

An important aspect of this feature lies in the fact that the C_2O construction produces a dense structure, by opposition to the cooccurrence. As we shown, the relationship between the color and the texture is directly understandable. At this step, the used feature is a spherical quantization of the three-dimensional clouds. In current works, a modelization is developed to reduce the feature size and improve the classification rate.

To conclude, the C_2O matrix offers an important alternative to improve the texture discrimination in computer vision system and other application fields where the environment conditions as viewpoint or illuminations aren't controlled.

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