Relocated Colour Contrast Occurrence Matrix and adapted similarity measure for colour texture retrieval

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Abstract. For metrological purposes, distance between texture images is crucial. This work study as a pair the couple texture feature/similarity measure. Starting from the Colour Contrast Occurrence Matrix (C_2O) definition, we propose an adapted similarity measure improving texture retrieval. In a second step, we propose a modified version of the C_2O definition including the texture's colour average inside a modified similarity measure. Performance in texture retrieval is assessed for four challenging datasets: Vistex, Stex, Outex-TC13 and KTH-TIPS2b databases facing to the recent results from the state-of-the-art. Results show the high efficiency of the proposed approach based on a simple pair feature/similarity measure facing to more complex approaches including Convolutional Neural Networks.

1 Introduction

Texture provides a semantic description to characterize the similarity between images. Although, different efficient texture descriptors have been developed in the literature. *Cooccurrence* matrix and *Run-Length Matrix* (RLM) [28] are good descriptors of texture content, but are not suitable for direct use with a distance or similarity measure. The *Local Binary Pattern* [21] attribute retains only a very reduced part of texture information about spatial-frequency composition. Yet, it is suitable for a distribution operation with matching metrics of similarities. Nevertheless the pair attribute and similarity measure is very efficient for texture classification or discrimination.

The transition to colour images is not straightforward with the vector aspect of the pair descriptor/measure of similarity. Marginal and/or crossed marginal (channel by channel) approaches can produce simplest descriptors but sliced the difficulty of the vector data management to the similarity measure function. It exists few vector expressions of texture features, among them the *Colour Contrast Occurrence* (C_2O) matrix [22] proposes a vector descriptor producing a distribution of colour differences present in an image or region of interest. In previous work, we shown the metrological potential of the C_2O [22], but in the

same time the performances in texture classification were not as expected. In this work, we study the impact of the similarity metric on classification performance, and we propose an improved version of the C_2O definition more adapt to texture image retrieval in databases.

In the following, we first describe the Colour Contrast Occurrence (C_2O) construction (sec. 2). Then, we develop the question of similarity measurement between trichromatic distributions (sec. 3). Considering the invariance of the C_2O to the average lightning change, we propose the Relocated Colour Contrast Occurrence matrix (RC_2O) and an adapted expression of the similarity (sec. 3.4). In a first experiment, similarity measure performances are studied from some images of classic image databases (KTH, Stex). Then we compare performances of the RC_2O using the proposed similarity metrics with a recent of state of the art approaches for Vistex, Stex, Outex-TC13 and KTH-TIPS2b databases (sec. 4.2).

2 Color contrast occurrence matrix

The C_2O texture feature is inspired from the first Julesz conjecture³ [12]. The initial idea was to define a compact probability density function adapted to direct distance/similarity measurements between features.

The colour contrast occurrence matrix proposed in [17] expresses the probability $\Lambda(\overrightarrow{c_i c_j})$ to find a specific local colour difference $\overrightarrow{c_i c_j} = \overrightarrow{\chi}$. This probability is assessed between two pixels separated by a vector defined by a spatial distance d and an orientation θ . The colour difference is defined in spherical coordinates by a perceptual color difference measurement $\Delta E_{\overrightarrow{\chi}}$ established in CIELAB by two angles (α, β) .

³ The first Julesz conjecture states that preattentive discrimination of textures is possible only for textures that differ on second-order correlation statistics.

Fig. 1. Some color textures from Outex with their C_2O distributions ($d = 1, \theta = 0$)

$$\begin{aligned}
\overrightarrow{\Lambda(c_i, c_j)} : \text{prob}(\overrightarrow{\Lambda(c_i, c_j)} = \overrightarrow{\Lambda_\chi}) \\
\text{With } \|\overrightarrow{\Lambda(c_i, c_j)}\| = \Delta E_\chi \\
\text{and } \perp(\overrightarrow{Oa}, \overrightarrow{c_i c_j}) = (\alpha, \beta)
\end{aligned} \tag{1}$$

Concretely, the C_2O matrix is a probability density function expressed in a $(\Delta_L, \Delta_a, \Delta_b)$ space. When texture is stationary, the C_2O matrix is centred at the origin in a dense distribution (examples in Figure 1).

3 Similarity measure between C_2O matrix

3.1 Indirect measurement

The main objective of the C_2O construction was to obtain a compact 3-dimensional probability distribution functions associated to an adapted distance or similarity measure. The initial construction in [17] was associated to a quantification using a spiral path in order to obtain a texture signature $Sig_{C_2O}(I)$ (Equation 2 and Figure 2). Then the distance between two textures is obtained using a L_2 norm between texture signatures.

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

where ΔE_{step} , n_α and n_β represent respectively the contrast norm, chromatic and lightning steps.

Fig. 2. C_2O signature proposed in [17] for some Outex textures. The signature is not compact and present periodic patterns due to the distribution's quantification using a spiral path from the distribution center (Equation 2).

3.2 Measurement using Kullback Leibler divergence

Considering C_2O matrix as a probability density function, *f-divergence* are well adapted to assess the similarity between them. Inside this group, the Kullback-Leibler divergence is the most used. In [8], the authors analysed and compared several similarity functions between colour distributions. In this work, they shown the Kullback-Leibler divergence takes into account all colour changes between the two considered distributions, whatever their magnitude. This divergence is also used for texture discrimination as in [18] using features based on energy from multi-scale Gabor-filters.

The Kullback-Leibler measure of information $KL(P/Q)$ assess the quantity of information lost when Q is used to estimate P (Equation 3) [14].

$$KL(P/Q) = \int_{-\infty}^{\infty} p(x) \ln\left(\frac{p(x)}{q(x)}\right) dx \quad (3)$$

where p and q are the respective densities of P and Q . In order to define a similarity measure, the Kullback-Leibler divergence is defined as the sum of the measure of information of P relative to Q and the measure of information of Q relative to P .

$$div_{KL}(P, Q) = KL(P/Q) + KL(Q/P) \quad (4)$$

The direct application of the Kullback-Leibler divergence is costly. In order to solve this problem, Wang and Goldberger proposed methods accelerating this process but loosing in precision [10, 27].

3.3 Estimation of the KL-divergence

Due to the difficulty and cost of a direct processing, adaptations of the Kullback-Leibler measure of information were proposed for different types of distributions. For example, Mathiasan [18] proposed a dedicated estimation for Gamma distribution. Obviously, the most used case assumes that the probability density function can be assessed as a multivariate normal distribution. In this case, the KL measure of information is defined according to the average location μ and variance-covariance matrix Σ of each distribution (Equation 5).

$$KL(P/Q) = \frac{1}{2} \left(\log\left(\frac{|\Sigma_Q|}{|\Sigma_P|}\right) + tr(\Sigma_Q^{-1} \Sigma_P) + (\mu_Q - \mu_P)^t \Sigma_Q^{-1} (\mu_Q - \mu_P) - 3 \right) \quad (5)$$

The observations of different textures' C_2O distributions allow us to approximate them as multivariate normal distributions. Technically, the distribution can be approximated by a 3-dimensional ellipsoid in the C_2O feature space $(\Delta L, \Delta a, \Delta b)$. The quality of this approximation can be observed in Figures 1, 4 and 5 thanks to the drawn ellipsoids in green. The ellipsoid surface is plotted as being at a Mahalanobis distance of 3 units from the distribution average, hence 99.7% of the samples must be considered as being inside this ellipsoid.

3.4 Relocated Colour Contrast Occurrence

The C_2O matrix describes the internal colour variations of texture. When the texture is stationary, the C_2O is a distribution centred at the origin of the representation space. For application in Quality Control, all textures belonging to the same category have a similar colour average. But in order to assess the performance of the pair feature/similarity measure, we search to adapt the purpose to texture classification from image database. In this case, the colour average of each image is different. As shown in a lot of studies on texture discrimination, the colour average can be important for the texture retrieval or classification [25].

We define the *Relocated Colour Contrast Occurrence Matrix* (RC_2O) as being the distribution of the C_2O relocated at the image colour distribution's average in the *CIELAB* colour space. Then the similarity measurement between two textures is assessed with the similarity between the two C_2O distributions taking into account their colour average difference.

As the colour average and the C_2O distribution are not calculated in parallel, we propose an easy way to process the similarity between the RC_2O of two textures (Equation 6). The new measure of information, for the RC_2O , $KLc(S_1, S_2)$ is estimated from the estimation of the KL measure of information (Equation 5).

$$KLc(S_1, S_2) = \frac{1}{2} \left(\log \left(\frac{|\Sigma_2|}{|\Sigma_1|} \right) + tr(\Sigma_2^{-1} \Sigma_1) + (\mu_{S_1} + \mu_1 - \mu_{S_2} - \mu_2)^t \Sigma_2^{-1} (\mu_{S_1} + \mu_1 - \mu_{S_2} - \mu_2) - 3 \right) \quad (6)$$

Where μ_i and Σ_i represent respectively the mean and the variance-covariance matrix of the C_2O descriptor of the image i , and μ_{S_i} represents the average

Fig. 3. Ellipsoid modelling of C_2O and the proposed RC_2O distributions ($d = 1, \theta = 0$) from two Vistex textures (*Fabric* and *Flowers* presented in Figure 4). As observed the RC_2O distribution will induces a bigger difference between the two textures.

coordinate of the image i in the $CIELAB$ space. The similarity measure between two image thanks to the Relocated Colour Contrast Occurrence Matrix is defined by the sum of the two KL measures of informations:

$$d_{KLc} = KLc(S_1, S_2) + KLc(S_2, S_1) \quad (7)$$

Figure 3 presents the similarity assessed by the initial writing form using the C_2O distribution (Figures 3(a) and 4(a)) or using the Relocated Colour Contrast Occurrence Matrix (Figures 3(b) and 4(b)). As observed, the second solution induces the biggest measure of difference than the first one, only based on the differences of the local colour variations.

4 Experiments and Discussion

4.1 Dataset and Results

For experimentation, we use four challenging databases: Vistex, Stex, Outex-TC13 and KTH-TIPS2b.

The classification is based on a nearest neighbour approach. The image is affected to the same class as its closest image from the learning set. So, each image category is defined by the union of the images from the learning set. This construction allows to take into account the lack of stationarity of some images coming from the natural world (vegetation typically).

The Outex [2] database is a large collection of 68 classes. Following Arvis's process [5] for the classification, each colour image was divided into 20 sub-images of 128×128 pixels so the total of 1360 images. we take 50% of them for the training and the remaining 50% for validation.

The Figure 1 shows some Outex textures with their C_2O distribution. Visually, we can notice the great similarity between the two classes *Barleyrice 1* and *Barleyrice 11*. This similarity is validated firstly by their C_2O distribution and then by the estimated distance $D_{KL} = 2.052$ (see Table 1). On the other hand the *Barleyrice 11* classe is far from the *Canvas 2* texture in the feature space, that is expressed by the difference value $D_{KL} = 90.435$.

Vistex test [3] is built of 54 colour images, whose initial size are 512×512 pixels, these images are acquired using uncontrolled conditions. As the Outex case,

Table 1. Inter and intra-class D_{KLc} distance for images of Outex database.

Outex	Barleyrice 1	Barleyrice 11	Canvas 2	Canvas 23
Barleyrice 1	0	2.052	50.634	39.782
Barleyrice 11	2.052	0	90.435	72.330
Canvas 2	50.634	90.435	0	17.233
Canvas 23	39.782	72.330	17.233	0

each colour image was divided into 16 sub-images of 128×128 pixels, resulting 432 images. The Figure 4 presents some classes from Vistex with their C_2O distributions while Table 2 shows the inter and intra-class D_{KL_c} distance between them. The inter class distance is still zero while the intra-class distance varies according to the similarity between classes. The smallest distance is between the *Fabric* and the *Food* (5.025) which shows their big resemblance.

Fig. 4. Some color textures from Vistex with their: (a) C_2O distributions ($d = 1, \theta = 0$) and (b) Relocated C_2O distributions.

Table 2. Inter and intra-class D_{KL_c} distance for images of Vistex database.

Vistex	Fabric	Flowers	Food	Leaves
Fabric	0	184.052	5.025	81.305
Flowers	184.052	0	99.175	24.311
Food	5.025	99.175	0	34.327
Leaves	81.305	24.311	34.327	0

The Stex database (Salzburg texture images) [1] is composed by 476 color texture images, whose acquisition conditions are not defined. Each colour image is split up into 16 non-overlapping 128×128 sub-images.

The KTH-TIPS2b [7] database includes 11 different texture classes with four samples of each. This database contains in total number of 4752 images, which captured at nine different scales, four illumination conditions and three poses. The Figure 5 presents a Lettuce-leaf texture from the KTH-TIPS2b with different scale variations (scale 1, scale 6 and scale 9). We can show the highest similarity measurement between all C_2O distributions whose is almost stable for the two scales 6 and 9. The inter-class estimated distances are presented in Table 3, all values are very weak which confirms the similarity between these textures. Therefore we can validate the C_2O robustness to scale variation.

Fig. 5. Lettuce-leaf texture from KTH-TIPS2b database with their C_2O distributions ($d = 1, \theta = 0$) with different scale variation

Table 3. Inter-class D_{KLc} distance for Lettuce-leaf texture from KTH-TIPS2b database with different scale variation.

	Lettuce-leaf	Scale 1	Scale 6	Scale 9
Scale 1		0	5.201	4.323
Scale 6		5.201	0	0.696
Scale 9		4.323	0.696	0

4.2 Performance in Classification

In this section, we present the obtained classification rates for our proposition based on the *Relocated Colour Contrast Occurrence* matrix RC_2O_{DKL} in comparison to results recently published (Table 4).

Firstly, it can be observed that for three of the four datasets, the RC_2O_{DKL} have the better classification rate : Vistex (100%), Stex (87.24%) and KTH-TIPS2b (96.21%). For the Outex database, the greatest classification rate is obtained by the *3D-ASDH* method (95.8%) [24] and the third highest classification rate of (92.4%) is achieved by our proposed approach after the LSTM network [6].

Secondly, we compare the gain of the proposed contribution to the initial C_2O construction. For the Outex database, the content is essentially manufactured with reduced local colour intra-variations, but important colour variations between the textures. In this case, the good-classification score gain is around 12%, in accordance with the information captured by the proposed RC_2O_{DKL} . The other image databases have more images from the natural world, local variations (so the textured aspect) are more important than in the Outex case therefore the gain is reduced but always positive.

It is interesting to note that when the image database content becomes more complex with a bigger number of images from the natural world, the different approaches present smallest good-classification scores (case of Stex image database). In this case, an important part of images is not stationary.

Table 4. Comparison of the classification rates (%) achieved on Vistex, Stex and Outex-TC13 and multi-scale KTH-TIPS2b databases. The proposed approach RC_2O_{DKL} obtains good performances facing the initial C_2O and more complex approaches using Convolutional Neural Networks.

Methods	Vistex	Stex	Outex TC13	KTH TIPS2b
LED+ED [20]	94.70	80.08	76.67	-
CLP [23]	97.70	83.90	82.10	-
LSTM network [6]	99.09	-	94.7	-
3D-ASDH [24]	-	-	95.8	91.3
SMGD [16]	97.5	77.6	89.7	-
GLACI [15]	88.42	41.91	87.67	-
CCMA [11]	91.89	57.58	83.67	-
BF+CLBP+S/M+ScatNet [19]	-	-	-	78.09
FC-CNN+FV-CNN [26]	-	-	-	83.3
STD [4]	98.89	-	90.3	-
Compact DITC [13]	-	-	-	69
3D connectivity [9]	-	-	84.26	83.54
C_2O [17]	99.3	76.65	82.64	-
RC_2O_{DKL}	100	87.24	92.4	96.21

To finish result analysis, we also note that the good performances of the pair RC_2O feature/similarity measure are obtained compared to some approaches based on Deep-Learning solutions. These results show the interest of an accurate texture feature associated to an efficient similarity measurement function that obtain a good classification score on a basic classification scheme (1-NN).

5 Conclusion

In this paper, we proposed a new texture feature associated with an adapted similarity measure: the Relocated Colour Contrast Occurrence matrix associated to a Kullback-Leibler divergence. This texture feature characterizes the local colour difference processed in a perceptual colour space and take into account the colour average of the texture. The proposed construction is fully in accordance with the first Julesz conjecture. In order to consider the non-stationarity of some categories, each texture is considered as a collection of Relocated Colour Contrast Occurrence matrix.

The presented results show that the proposed texture feature is robust to different image changes and very efficient for texture image classification. The Relocated Colour Contrast Occurrence matrix presents the best classification score in three cases out of four, and is the third for the last one. These results will be extended to more image databases in order improve the ranking of this pair texture feature/similarity measure.

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