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A way to Calibrate a Colour Texture Feature

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Abstract

Several colour descriptors are presented each year. The existing protocols to evaluate and compare these descriptors are restricted to the use of image databases without information about the spatio-chromatic content. In this article, we present a first answer to calibrate a colour texture descriptor. By calibration, we intend evaluate the capacity of the descriptor to discriminate the non-uniform aspect according to different scales of samples. In order to assess all the possibilities in term of spatial frequencies and colour content, we propose to use reference images based on a fractal vector colour model. Three texture features are compared from this protocol allowing to express the interest of the proposed calibration sequence.

Introduction

To compare descriptors discriminative capacity, Mikolajczk *et al.* [1, 2] proposed a comparative method for detectors and descriptors. In these articles, the authors introduced a new database with ground truth to geometric transformation between a series of images. They count the number of correct matching. Other comparative studies exist for dedicated task: Gauglitz *et al.* [3] follow objects, Mandal *et al.* [4] focus on facial recognition and Hietanen *et al.* [5] classify objects. Several evaluation articles focus on colour images and compare colour descriptors performance [6–8]. Nevertheless, it is not possible to extrapolate the obtained performances from these results. Indeed the databases are not defined by the scale of theirs spatio-chromatic content.

Our problematic is not to compare a pair {descriptor, similarity measure} but to propose a database and protocol that objectively evaluate the pair. The comparison is the next step. We focus on texture[1] features. The non-uniform aspect is defined by a specific spatio-chromatic distribution. Therefore, we expect a database capable of exploring the full range of spatial frequencies and colour distributions. A real image database cannot reach such a requirement. Each real image database covers a part, overlapping or not, of the spatio-chromatic content. To create texture, we need to link the colour and spatial distributions. A simple coloured noise, will be perceived as noise and not considered a texture. To answer our problematic, we propose a protocol based on the use of fractal colour vector models. Fractal models were already used to evaluate complexity perception as proposed in [9].

Experimental Protocol

To calibrate a descriptor, we first need a completely scale of samples to verify the feature's ability. With several samples for one reference and different scales, our objective is to find the reference associated to the sample. The calibration will allows to measure the feature ability to assign the sample to the right reference. This is a classification task allowing to assess the resolution in the discrimination between spatio-chromatic contents.

These samples scales cannot be physically obtained for the moment. This can be achieved only with a synthetic database based on a mathematical model. As we are interested in texture features, the model must be related to non-uniform aspect which is defined according to Julesz [10] by the first and second order statistics. That's why we oriented our choice to an isotropic fractal colour model. The fractal model is more important and generic than the database, that can be reproduced by everyone according to the selected scales of study.

In this protocol, we will briefly introduce the fractal model and the scales of references, then we will present the colour spaces used for the experiment. Finally, we present the evaluation criteria.

Synthetic Database

The heart of this proposition is the use of a colour fractional Brownian motion (fBm). The interest of fractal model is first to insure a known energy level at any spatial frequency thanks to a complexity parameter: the Hurst coefficient. The spectral power density of the model follows the law

$$F(f) \propto \frac{1}{f^{2H+1}}, \tag{1}$$

where f is the frequency and H the Hurst coefficient. The colour and vector construction is obtained using a quaternionic Fourier transformation from the *CIELAB* colour space. An alternative solution is to create the colour content directly in the spatial domain using the colour midpoint displacement approach [11].

Secondly, the random generation allows to control the chromatic content of each generated image. Therefore the whole spatio-chromatic space can be explored.

The fractal synthetic database has different parameter for the generation:

- μ: the target mean value of the colour distribution;
- Σ: the covariance matrix responsible for the correlation between channels *i.e.* the shape of the colour distribution;
- H: the Hurst coefficient linked to the relative image complexity and of the Spectral Power Density.

To change μ implies a variation on the colour average, but not on the distribution shape distribution. The smaller H Hurst coefficient is, the more complex the image is (images appear sharper whith a small H, with more small local variations). Σ influences both the first and second order statistics. It is responsible for the shape of the colour distribution and therefore the probability to find a colour next to another. The Table 1 summarize the parameters.

Colour Spaces

The second question is which colour space for this synthetic database? The ideal would the physical space associated with the scene, but this solution is not available yet. The images are generated in *CIELAB*. The idea is to anticipate psycho-physical

[1]The CIE prefers the term *non-uniform aspect*. In this article, both are used as synonyms.

experiments where the colour difference would need to be related to perception, the fBm being defined by the relationship between the standard deviation of colour differences for a given spatial distances.

The features are estimated in 3 colour spaces, the RGB_{FV} colour space of the sensor (considering the sensor spectral sensitivity functions), the *CIERGB* space which is a reference *RGB* colour spaces and the *CIELAB* space. We are expecting the *CIELAB* results to be superior to the other.

The database is constituted of 400 images per targeted mean μ_i. Half of it is generated with a covariance matrix Σ_k, the other half with Σ_l. Five images par mean μ and covariance Σ have been generated with 10 different Hurst coefficient from 0.01 to 0.9. The Table 1 summarize the parameters and their occurrences.

Evaluation Criteria

We classify images with a k nearest neighbour approach. The precision is estimated for a given k:

$$P@k = \frac{\#TP}{k}, \tag{2}$$

where TP is the set of the k-first images well-classified and # is the cardinal of the set. As each class is composed of 5 images, we use the $P@5$. The average precision (AveP) considers all images from a class. The average precision is given by:

$$AveP = \sum_{k=T_k} P@k, \tag{3}$$

where T_k is a set containing k if the item at rank k is a well-classed image.

These two measure quantify the quality of a classification for one image of the database. The usually studied measure are their respective means ($MP@5$ and MAP) on all images from the database.

Compared descriptors

We present in this section the 3 descriptors studied: Colour Local Binary Pattern (LBP), Colour Contrast Occurrences (C_2O), Relocated Colour Contrast Occurrences(RC_2O). These 3 features are probability based, therefore the Kullback-Leibler divergence is used to measure similarity. The Table 2 summarize the different parameters of the descriptors describe below.

Colour Local Binary Pattern

The LBP, introduced by Ojala *et al.* [12], presents a coherent pair descriptors/similarity measure. It is based on the pixel value comparison with its neighbours. It was adapted to colour in [13] with a colour quantification to created a non sparse histogram.

Table 1 **- Summary of the variables and their occurrences.**

	Database
H	10 values of Hurst's coefficient
μ	4 means
Σ	2 covariance matrices

Table 2 **- Summary of the descriptors parameters.**

	Features		
	C_2O	LBP	RC_2O
Colour spaces	3	3	3
Distances (d)	4	1	4
Angles (θ)	4	$\varnothing$	4

To increase the discrimination power of this feature, Porebski *et al.* [14] use a cross correlation channel approach. the central pixel and its neighbour are compared by channel and between channels.

The LBP are calculated with the 8 connected neighbours of the pixel with en distance $d = 1$ as presented in its first version by [12].

We use the *CCMA* (*Cross Channel Marginal Approach*) for the *CIERGB* space and a simply marginal approach (*Colour Marginal Approach CMA*)for the other two colour spaces RGB_{FV} and *CIELAB* which are supposed to be orthogonal.

Colour Contrast Occurrences

Martinez *et al.* [15] proposed the *Colour Contrast Occurrences* (C_2O) inspired by the Haralick [16] co-occurrences features. Haralick descriptor does not fit with an adapted similarity measure, that's why it is not developed in this article.

The C_2O idea is to measure colour differences between two pixels distant from a given vector v. It is considered as a probability:

$$C_2O(d,\theta) : \begin{cases} P\Big(\Delta\big(I(x), I(x+v)\big)\big) = \delta\Big), \\ \quad \text{with } v \in \mathbb{R}^2, \|v\| = d \text{ and } \widehat{v} = \theta, \\ \quad \text{and } \delta \in \mathbb{R}^3, \end{cases} \tag{4}$$

where P is the probability to find a colour pair with a spatial difference of v and a colour difference of δ.

The negative point of this features is that it does not keep any information form the initial colour distribution, therefore the first order statistics are completely lost.

Relocated Colour Contrast Occurrences

Introduced by Jebali *et al.* [17], this descriptor completes the C_2O by adding the mean value of the initial colour distribution. The probability can be written as:

$$RC_2O(d,\theta) : \begin{cases} P\Big(\Delta\big(I(x), I(x+v)\big) + \mathbb{E}(I(x)) = \delta\Big), \\ \quad \text{with } v \in \mathbb{R}^2, \|v\| = d \text{ and } \widehat{v} = \theta, \\ \quad \text{and } \delta \in \mathbb{R}^3, \end{cases} \tag{5}$$

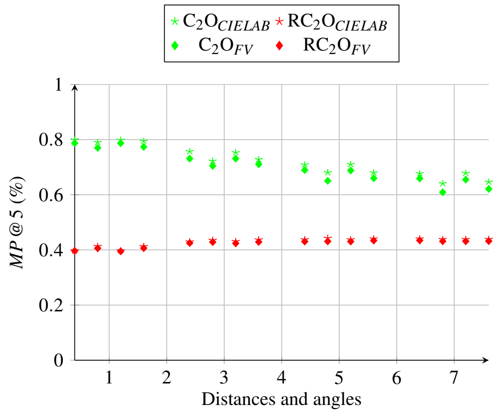
where P is the probability to find a colour pair with a spatial difference of v and a colour difference of δ. The average value of the colour distribution is given by the expected value $\mathbb{E}(I(x))$.

This descriptors contains the first and second order statistics proposed in the first Julesz conjecture [10].

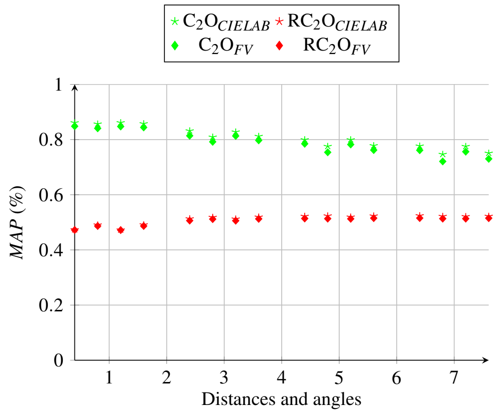
We have estimated the C_2O and RC_2O with four angles: 0°, 45°, 90° and 135°; and four distances: 1, 3, 5 and 7 pixels. The generated fractal images are supposed to be isotropic, therefore we should have similar results with each angles and distances. The Figure 1 presents the C_2O and RC_2O results for each distance and angle. The response seems very similar. For the next results we will only consider the mean of these angles and distances.

Comparing Signature's Length

Each studied descriptors has a particular signature length. The LBP extracts a 256 bin histogram for each comparison (3 channels and 6 cross channels). The signature length is 3 or 9 joined histograms. Those histograms are 1D. They cannot be modelled to diminish their size. The features for C_2O and RC_2O are histograms of colour differences (b bins per channel). Their size is $3 \times b$. Nevertheless, these histograms are dense and can be modelled by a Gaussian law as we do it. The signature's size



(a) Mean $P@5$ for each distances and angles



(b) MAP for each distances and angles

Figure 1. *C_2O and RC_2O variation depending on distances and angles. The four angles are centred around the distance $(1, 3, 3, 7)$ with ascending order $(0°, 45°, 90°, 135°)$.*

becomes $9+3$ for the C_2O and $9+3+3$ for the RC_2O. Nine parameters are needed for the covariance matrix and 3 for the mean of the difference distribution (null if the texture is stationary). For the RC_2O we add the mean value of the colour distribution. The C_2O and RC_2O signature size are significantly smaller than the LBP.

Results and Discussion

The database is to be considered as a set of scales with several samples for a reference. We focus on classifying image from one scale at a time to evaluate the discriminative properties of the descriptors. In this study, no images are identical. At best they are similar with the same parameters for the random generation.

Different classification are processed. First, we evaluate classification regarding the mean value of a class image leaving other parameters fixed (changing the position of the distribution). Then, we aim te recognize the images thanks to their covariance matrix (the distribution shape varies). The following experiment is focused on the fractal dimension classification (changing the relation to the neighbours). The last classification allows all parameters to vary and measure the classification properties of the colour textures features proposed.

Discrimination over the Colour Average

In this experiment, the Hurst coefficient and the covariance matrix is fixed. The objective is to evaluate the classification properties with a variation of only the mean value.

The Table 3 presents the classification results. The descriptors RC_2O and CCMA-LBP gives a 100% good classification. The pair C_2O/Kullback-Leibler divergence does not consider the mean in its feature. It explains the weak classification results of this descriptor. For the next two test, the mean will be fixed and the C_2O weakness will disappear.

If the question seems easy, it brings back to the method to measure similarity between two coloured surfaces. Should the texture and colour be considered jointly or separately? If it is considered separately, how can we combined both similarity measure to keep the metrological validity? The RC_2O is built to naturally integrate both texture and colour jointly leaving only one similarity measure. Both C_2O and LBP does not consider the mean value of the texture. Nonetheless, the LBP, estimated with the cross channel information, has a small access the mean by comparing values between channels. A larger number of means and images should be used to show the limits of this approach.

Table 3 **- Classification with only μ varying.**

		$MP@5$	MAP
C_2O	*CIELAB*	97.3 %	98.7 %
	RGB_{FV}	97.2 %	98.6 %
	CIERGB	97.2 %	98.6 %
LBP	*CMA-CIELAB*	79.9 %	88.9 %
	CMA-RGB_{FV}	69.2 %	81.7 %
	CCMA-RGB	100 %	100 %
RC_2O	*CIELAB*	100 %	100 %
	RGB_{FV}	100 %	100 %
	CIERGB	100 %	100 %

Table 4 **- Classification with only Σ varying.**

		$MP@5$	MAP
C_2O	*CIELAB*	86.9 %	94.9 %
	RGB_{FV}	90.2 %	95.1 %
	CIERGB	90.2 %	95.1 %
LBP	*CMA-CIELAB*	65.9 %	79.8 %
	CMA-RGB_{FV}	63.5 %	77.9 %
	CCMA-RGB	76.2 %	86.4 %
RC_2O	*CIELAB*	68.7 %	81.5 %
	RGB_{FV}	70.4 %	82.9 %
	CIERGB	70.4 %	82.9 %

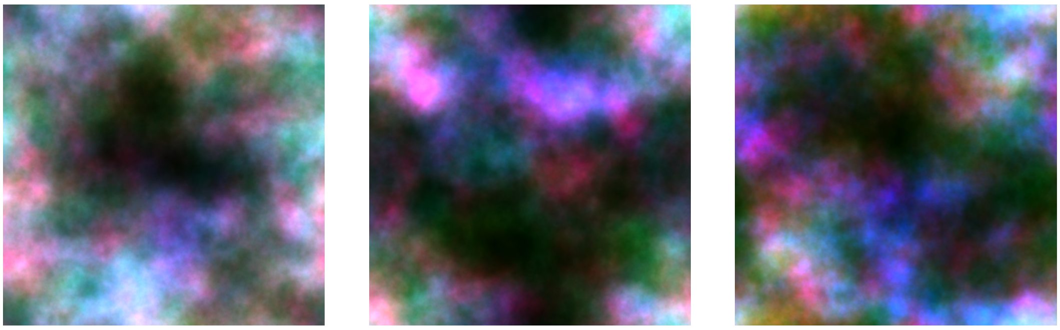
Discrimination over the Colour Distribution Shape

This test compares images with the same colour average and Hurst coefficient. The objective is to measure the discriminative properties of the textures features over the colour distribution shape, so the images covariance.

The Table 4 presents the classification results. The best classification rate ($MP@5 = 90.6\%$ and $MAP = 95.3\%$) are obtained with the C_2O feature proving so its discriminative power when the colour mean value is not an issue. In another manner, the RC_2O, that consider the colour average in addition to the C_2O, obtains weaker results.

The marginal LBP feature on orthogonal spaces fails at distinguishing the different colour distribution shapes. It's the same for the CCMA-LBP, comparing between similar and different channels. But the cross-channel approach gives better results than the marginal one.

These results can be explained thanks to the Table 5. The colour mean and the standard deviation of each sample have been calculated per μ-class from the generated images. The mean ΔE is also calculated. This value is considered in the RC_2O induc-



(a) μ_1 et Σ_1,
$\mu = (45.7, 3.7, -8.8)$,
$\Delta E(2b, 2a) = 18.0$.

(b) Reference image: $H = 0.9$,
μ_1 et Σ_1,
$\mu = (29.3, 10.2, -12.0)$.

(c) μ_1 et Σ_2,
$\mu = (31.3, 9.0, -10.3)$,
$\Delta E(2b, 2c) = 2.9$.

Figure 2. *CIELAB generated means inconsistent with each other.*

ing the uncertainty in the colour distribution shape recognition, by opposition to the basic C_2O feature. From the previous experiment, we shown that the cross-channel marginal approach (CCMA) was able to well consider the colour average. This experiment shows that in fact the relative combination of the different channels allows to assess a part of the first-order statistics, that cannot be considered in a marginal processing.

The Figure 2 presents two images from the same class (Fig. 2b and 2a) and one where only the covariance matrix is different (Fig. 2c). The central image (Fig. 2b) is used as a reference in this comparison. Under the other two images (Fig. 2a and 2c), we give the ΔE between the colour distribution's means of the image and the reference image. Even if the covariance matrices used to generate the two right images are different, the visual difference is smaller than between the two left images belonging to the same class. It shows the importance of integrating the mean value in the similarity measure. But it also shows an uncertainty between the defined colour average for the reference generation and the obtained one.

Discrimination over the Spectral Power Density

The two first experiments were defined to assess the ability of texture features to discriminate textures according to the first-order statistics (colour average, colour distribution shape). This third test will consider the discrimination over the spectral power density. By changing the Hurst coefficient of the fBm, we are changing the distribution of energy according to the spatial frequencies. The more complex are the images, the more energy is present in the high spatial frequencies, inducing fine details/variations. So this experiment is dedicated to the performances according to the high-order statistics. The experiment is designed to discriminate the samples according to the scale defined by the H complexity.

The Figure 3 presents two images from the same class (Fig. 3b and 3a) and one with a different Hurst coefficient (Fig. 3c). The central image (Fig. 3b) is used as reference for this comparison. Under the other two images (Fig. 3a et 3c), we give the ΔE with the reference image mean. Even if the ΔE between the image from the same class is higher than the ΔE with the other class, the visual pairing done comparing complexity would associate the two left images belonging to the same class. The approaches sensitive to the first statistics (RC_2O, CCMA-LBP) will be biased due to the uncertainty between the defined and generated average.

Table 5 **- Mean and standard deviation verification per generated μ.**

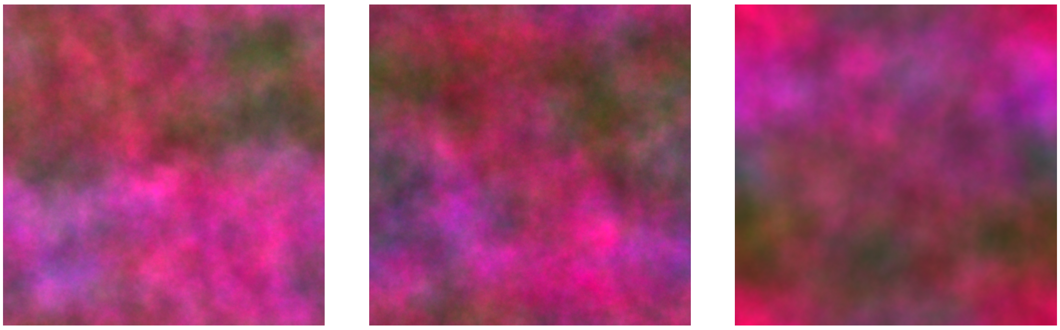
	Measured mean			Standard Deviation			ΔE
	L	a	b	L	a	b	
μ_1	52.2	5.6	-8.6	1.8	2.1	0.7	2.8
μ_2	35.1	63.4	-9.4	2.7	2.2	0.8	3.6
μ_3	48.3	0.2	40.5	6.4	1.3	3.0	7.2
μ_4	31.4	11.3	-13.0	3.3	3.7	4.4	6.6

Table 6 **- Classification with only H varying.**

		$MP@5$	MAP
C_2O	*CIELAB*	73.9 %	83.5 %
	RGB_{FV}	71.4 %	81.3 %
	CIERGB	71.4 %	81.3 %
LBP	*CMA-CIELAB*	93.0 %	95.9 %
	CMA-RGB_{FV}	96.0 %	97.8 %
	CCMA-RGB	68.7 %	79.0 %
RC_2O	*CIELAB*	47.0 %	57.0 %
	RGB_{FV}	45.8 %	55.7 %
	CIERGB	45.8 %	55.7 %

As expected, the obtained results for RC_2O are weaker than those from C_2O and in the same manner between CCMA-LBP and CMA-LBP. The second remark is about the difference of performance between the C_2O and the *LBP* approaches. The *LBP* approaches are processed for a single distance ($d = 1$), when the C_2O-based approaches are averaging the response for 4 different distances ($d = 1, 3, 5, 7$) before obtaining the final feature signature. Such a combination of spatial scales is usual in texture discrimination, but the results are expressing the induced uncertainties in texture discrimination. By averaging several spatial analysis scales, the feature looses in discrimination for the high spatial frequencies responses.

The Figure 4 presents the $P@5$ and the MAP for the 3 descriptors depending on the Hurst coefficient. We note an overall decay when H increases, which corresponds to a complexity reduction. The less complex is the image, the higher the scale is to estimate a representative variation of the non-uniform aspect you need. Yet, the LBP are only looking at the 8 closest neighbor, the C_2O and RC_2O at a maximum distance of 7 pixels. In other words, these distances are too small to evaluate weak complexity. Choosing too big distances will forbid to discriminate high complexity images. This shows the importance of integrating a spatial multi-scale analysis for descriptors which could easily be evaluated with a fractal database.

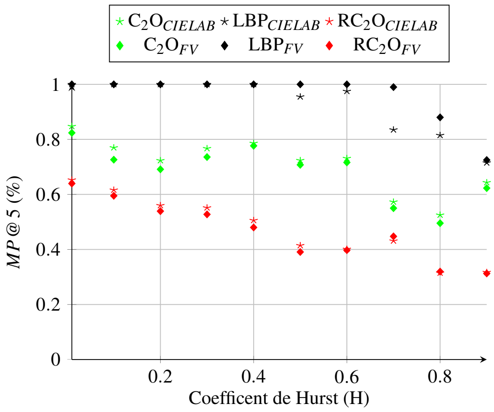


(a) μ_1, Σ_1 et $H = 0.6$, $\mu = (39.5, 67.0, -9.1)$, $\Delta E(3b, 3a) = 7.1$.

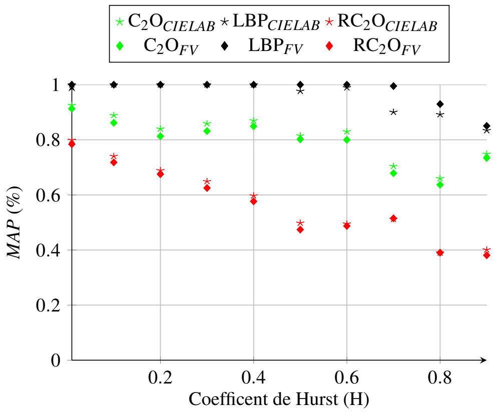
(b) μ_1, Σ_1 et $H = 0.6$, $\mu = (34.2, 62.5, -9.1)$.

(c) μ_1, Σ_1 et $H = 0.9$, $\mu = (32.7, 61.0, -8.6)$, $\Delta E(3b, 3c) = 2.1$.

Figure 3. *$CIELAB$ generated means inconsistent with the theoretic mean.*



(a) Mean $P@5$ per Hurst coefficient



(b) MAP per Hurst coefficient

Figure 4. *Precision variations with the Hurst coefficient.*

Classification according to all dimensions

In this last experiment, we are considering all the possible scales of change in the texture aspect: colour average, colour distribution shape and spectral power density. Concretely, we are merging all the generated images for the classification task and assess the performance in texture retrieval from this reference scales. We cannot hope for better results than the weakest obtained on the last three experiments. The Table 7 presents the classification result. The LBP features present the strongest decay (around 8%) compared to the results from the Table 6. The RC_2O decrease of 3.5% for the $MP@5$ and of 5.1% for the MAP. The C_2O show the smallest decay (maximum 2%).

We must note the two colour space RGB used does not show any difference for the C_2O and RC_2O approaches. These two colour spaces $CIERGB$ et RGB_{FV} differ only by a linear transformation which explains that a divergence measures based on mean and covariance does not induce differences. The results in the $CIELAB$ colour space are better except when the goal is to separate images with different means. This colour space varies between -100 and 100 while RGB spaces vary between 0 and 1. the means differences are higher and therefore the divergence measures increases strongly.

Table 7 **- Whole database classification.**

		$MP@5$	MAP
C_2O	$CIELAB$	72.3 %	80.8 %
	RGB_{FV}	70.2 %	79.1 %
	$CIERGB$	70.2 %	79.1 %
LBP	$CMA\text{-}CIELAB$	55.0 %	67.1 %
	$CMA\text{-}RGB_{FV}$	43.3 %	54.2 %
	$CCMA\text{-}RGB$	60.5 %	70.2 %
RC_2O	$CIELAB$	42.9 %	51.1 %
	RGB_{FV}	42.3 %	50.4 %
	$CIERGB$	42.3 %	50.4 %

Discussion

Under the point of view of the better texture feature's selection, the results seems divergent. Nevertheless, the selection of the better feature was not the goal of this work. It was not either to assess the fractal dimension of colour images using texture features. Our purpose was to develop an objective protocol to calibrate the discrimination ability of texture features. In order to consider the first-order statistic (the colour distribution) and the high-order statistics (the spectral power density), we used a fractional Brownian motion to define our reference scales: mean-colour variations, colour distribution shapes, spectral power densities.

These first results are showing that the reference scales must be rearranged according to their calculated colour averages, some bias appearing during the generation process. We can imagine that some bias exist also in the colour distribution shape generation. In [11], the relationship between the generated complexity and the assessed one was demonstrated, with some limits for the weaker complexity. So according to these limits, that can be solved easily, the propose protocol solve the expectations in calibrating texture features.

Concerning the required elements in the texture features, the different experiments are showing that averaging mono-scale responses reduces the discrimination performances. Even if it was not developed in the literature, the cross-channel marginal approaches are embedding a part of the first-order statistics.

Conclusion

In this work, we proposed a protocol to calibrate texture features for the control quality by vision of non-uniform surfaces. The protocol is based on several tests and reference scales defined by a fractional Brownian motion. The proposed reference scales allow to assess the features sensitivity to three dimensions: colour average, colour distribution, and spectral power density change.

Our objective was to present a calibration protocol and not to present the best features with this database. Yet, the protocol shed light on a limit of proposed texture features: there is no multi-scale analysis to evaluate correctly the spectral power density variation. As a future work, we wish to develop this multi-scale approach.

The proposed tests are based on the retrieval of the closest reference in the generated reference scales. The test is considered as a classification task, and the performances defined by usual classification scores. The obtained results are showing the validity of this calibration protocol, and the elements to improve in order to reduce the bias and uncertainties. This calibration protocol extends the images database limited spatio-chromatic content.

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