Characterization of the anisotropy in color textures

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Abstract

Our approach deals with a modeling of the local spatial distributions of the variations of color. It is an extension to color textures of the Neighbouring Gray Level Dependence Matrices (NGLDM) introduced by Sun et al. [1] and completed by Berry et al. [2]. To our knowledge, this is the first time that this extension has been proposed. We will name these matrices NCDM: Neighbouring Color Dependence Matrices. This approach consists in estimating the dependences of colors between a pixel and its neighbours. These matrices, associated with an isotropic mask, characterize the textures [5]. We have chosen to use an anisotropic neighbourhood corresponding to the eight principal directions to seek the dominant directions in a color texture. NCDM matrices evaluate the homogeneity or the heterogeneity of the color distribution for each direction.
The variations of the color shades are computed in uniform perceptual color spaces such as LAB and HSV. We have chosen the color space "L1 norm" introduced by Angulo, Hanbury and Serra [3, 4].

1. Introduction

We propose to characterize the anisotropy of color textures by evaluating the homogeneity or the heterogeneity of the distribution of colors according to the eight principal directions. We propose an extension to color textures of the Neighbouring Gray Level Dependence Matrices (NGLDM). The matrices NGLDM were defined by Sun and Wee in 1983 [1], and were then completed by Berry and Goutsias in 1991 [2]. To our knowledge, this is the first time that this extension has been proposed. We will call these matrices NCDM: Neighbouring Color Dependence Matrices. These matrices, associated with an isotropic neighbourhood, characterize the textures [5]. We have chosen to use an anisotropic neighbourhood corresponding to the eight principal directions to seek the dominant directions in a color texture. NCDM matrices evaluate the homogeneity or the heterogeneity of the color distribution for each direction.
To build the matrix, we chose a neighbourhood of pixels (5x1 for a distance d=2 pixels, 1x7 for d=3). Then, for each pixel of the image, we count its

neighbours that have a similar color. Each element of the matrix NCDM, noted $Q_{d,a}(c, s)$ represents the number of pixels of color c in the image, which have exactly s neighbours (with a distance d) and the variation of color with c does not exceed a (proximity between two colors).
Initially, we will present existing works on the characterization of the anisotropy of color textures. Then, we will present the matrices NCDM by indicating the notations used, giving a definition, explaining the useful properties, and finally by giving an example of this matrix on a color texture that has a dominant direction. Then, we will show the weaknesses of the color spaces HSV and HLS in order to present a new color space with interesting properties: the color space "L1 norm". We will present two algorithms of characterization of the anisotropy. The first one is based on the research of the maximum coefficients in the matrix NCDM. The second algorithm computes statistical tests (chi-square tests) on the coefficients of the matrix NCDM. We will illustrate our two algorithms of characterization of the anisotropy in color textures using a series of results. Finally, we will present our conclusion and the prospects for future work.

2. Previous works

Firstly, we will discuss the perceptual properties that are noticed when a texture is examined.
Rao and Lohse [7] reported the results of an experiment in which the aim was to find the high level characteristics of the texture for human vision. Twenty people were advised to classify independently 30 textures of the Brodatz album. The authors determined the most significant characteristics which are the regularity (a pattern which is repeated), followed by the orientation and the complexity.
Mojsilovic *et al.* [10] presented the results of a similar experiment with color textures. They asked 28 subjects to specify numerically, on a scale from 0 to 100 the similarities between each possible combination of 20 color textures extracted from a set of fabrics. After a statistical analysis, they identified five significant perceptual characteristics. Two characteristics were specific to the color: the dominant color and the purity of the color. The three other characteristics corresponded to the

characteristics found by Rao and Lohse: directionality and orientation, regularity, complexity and density.

The matrices NCDM, which are presented in the next section, give indications on the dominant color, the orientation and the structure of the textures.

Hanbury and Serra [3, 4] have worked with oriented textures for studies on the automatic classification of wood according to two criteria: the color and the texture. They sought the dominant directions in the neighbours of each point of the image. Serra and Hanbury used the algorithm proposed by Rao to find these directions. The first step of the Rao's algorithm [7] applies a Gaussian filter to texture. It is necessary to calculate an angle for each pixel with the images of horizontal and vertical gradient. The dominant angle is calculated in the neighbourhoods to produce an angle image. Each pixel in the angle image corresponds to the dominant direction in a neighbourhood.

Germain *et al.* [9] worked on the characterization of the anisotropy of the textured images. In their works, they reported that the dominant direction or the anisotropy in the textures strongly depends on the observation scale. They introduced a new operator for the estimation of the dominant direction, the Directional Mean Vector (DMV).

Shu and Jain [11] presented a method based on the properties of vector fields, for the estimation of a set of symbolic descriptors from linear orientation fields. The authors presented results of experiments on noise-added synthetic flow patterns and real oriented textures.

Almeida *et al.* [8] presented a Markov random field (MRF) model for digital images capable of representing anisotropic textures with arbitrary orientations. Works relating to the characterization of textures in gray levels with the matrices NGLDM were proposed by Smolarz in 2003 [5].

3. Neighbouring Color Dependence Matrix (NCDM)

We present the notations used and a definition.

- $C(l, c) = [H\ B\ S]$ three random variables (Hue, Brightness, Saturation) associated to the color of the pixel with coordinates *(l, c)*. C is defined on the set $E = \{1, 2, \ldots 256\}^3$

- d is the parameter fixing the size of the neighbourhood around a pixel, V_d is the number of neighbours of a pixel, located at a maximum distance *d* of this pixel. The neighbourhood can be isotropic or anisotropic.

- $\rho\left((l_1,c_1),(l_2,c_2)\right) = \max\left(\left|l_1 - l_2\right|, \left|c_1 - c_2\right|\right)$ is

the distance between two pixels of respective coordinates (l_1, c_1) *and* (l_2, c_2).

- DP (Perceptual Difference) is the parameter fixing the degree of proximity between the colors of close pixels; it is an Euclidean distance [4]. DP = ($(R_1-R_2)^2$ + $(G_1-G_2)^2$ + $(B_1-B_2)^2$)$^{1/2}$ if the colors are written with Cartesian coordinates (for example C=[R G B]). DP = $((B_1-B_2)^2 + S_1 + S_2 - 2*S_1*S_2*\cos(H_1-H_2))^{1/2}$ if the colors are written with Cylindrical coordinates (here C = [H B S]). To simplify, we will write DP = $C_1 - C_2$.

- S is the random variable associated to the number of neighbours of a pixel which have a close color to this pixel (distance DP).

The construction of the matrix NCDM depends on 2 parameters: the parameter *"d"* presented above (size of the neighbourhood) and the parameter *"a"* which is the threshold of difference between 2 colors: if the perceptual difference DP is lower than the threshold *"a"*, then we estimate that these 2 colors have close colors. The value of parameter *"a"* depends on the analyzed texture; it is fixed automatically by computing the mean Euclidean distance that separates the colors the most represented.

To simplify the notations, the matrix NCDM will be named Q in the formulas. The dimensions are [number of colors * number of neighbours]. It appears on equation 1 (# means number).

We present on figure 1 a line of the matrix NCDM computed with the texture named "basket" (figure 2). The selected neighbourhood is anisotropic for the horizontal direction, with *d=4*: it is a vector 1x9. The central pixel of the mask is not used. Each pixel has between 0 and 8 neighbours (4 pixels on both sides of the central pixel) with close colors. The figure must be read in the following way:

The color n°29 (orange) has in 31 cases: 0 neighbours with a close color, in 70 cases: 1 neighbour with a close color, in 173 cases: 2 neighbours, in 225 cases: 3 neighbours... Therefore, the color n°29 appears 31 + 70 + 173 + 225 + 479 + 454 + 423 + 400 + 899 = 3154 times. These pixels with color n°29 are shown in figure 3; they are extracted from the texture "basket" (figure 2).

The color n°29 addresses 31*(0+1) + 70*(1+1) + 173*(2+1) + 225*(3+1) + 479*(4+1) + 454*(5+1) + 423*(6+1) + 400*(7+1) + 899*(8+1) = 20961 pixels which have a close color to the color n°29, and which are in the neighbourhood of a pixel with color n°29.
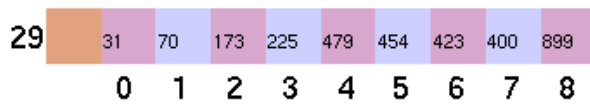
$$Q_{d,a}(c,s) = \#\{(\ell,c) \mid C(\ell,c) = C_1 \text{ and } \#[(i,j) \mid \rho((\ell,c),(i,j)) \leq d \text{ and } C(\ell,c) - C(i,j) = DP \leq a] = s\}$$

Equation 1: definition of the matrix NCDM

Fig. 1: one line of the matrix NCDM
computed with the texture « basket »

Fig. 2: the texture
"basket" 128x128

Fig. 3: the pixels
with color n°29

3.1 Matrix NCDM: properties and example

We present here two very useful properties of the matrix NCDM:

Property n°1: For a given color c, if large coefficients appear, especially in the right hand part of the matrix (for example, s varies from 4 to 8 for an anisotropic neighbourhood 1x9), then this color is distributed in a mainly homogeneous way, for the selected direction. In other words, each pixel of color c has frequently between 4 and 8 neighbours that have identical or close colors in the selected direction. The dependence between the pixels according to this direction is high. This direction characterizes the analyzed texture, but is not inevitably dominant. Conversely, if the large coefficients appear, especially in the left hand part of the matrix (for example, s varies from 0 to 3), then the dependences between the pixels are low for the selected direction.

We can notice on figure 1 that the coefficients in the columns for values of s between 4 and 8 are greater than for those between 0 and 3. Consequently, there is a strong dependence between the pixels with color n°29 in the horizontal direction. By studying the 7 other directions, we can conclude that the horizontal direction is dominant in the texture "basket", as is evident in figure 2. We will give more details in the part 5.

Property n°2: To calculate a matrix NCDM on an image coded with 24 bits and a parameter "a" that is too important, is equivalent to ca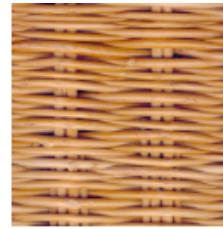lculate a matrix NCDM on this image with a reduced numb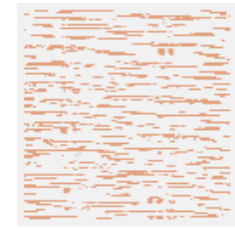er of colors. Indeed, if the parameter "a" is too high, information is redundant on several lines. The interest is to handle a smaller matrix and, therefore, to save computing time.

Figure 4 illustrates several lines of the matrix NCDM corresponding to the texture "basket" (presented in figure 2). Texture "basket" has a size of 128x128 pixels, that is to say 16 384 pixels. The sum of the sizes of the areas (the red numbers on the left) is 15 360, i.e. almost the total number of pixels in the texture (we do not have a perfect equality because of the edge: when the anisotropic mask 1x9 touches the edges of the image).

We are interested in the numbers of pixels of each color area. The detail of calculation is given previously (for color n°29, this number is 20 961). These numbers characterize the degree of homogeneity of the distribution of each color according to the selected direction: the greater this number is, the more the color is distributed in a homogeneous way according to the selected direction. To characterize the anisotropy of the color textures, we use the numbers of the columns that have the maximum of each line in the matrix NCDM. They are framed with the orange color on figure 4; the method is described in the first algorithm, part 5.

The lines of the matrix NCDM are sorted according to the decreasing frequency of appearance of the colors. The expression "the colors the most represented" corresponds to the colors which have a frequency of appearance higher than (average + standard deviation) of the frequencies of appearance.
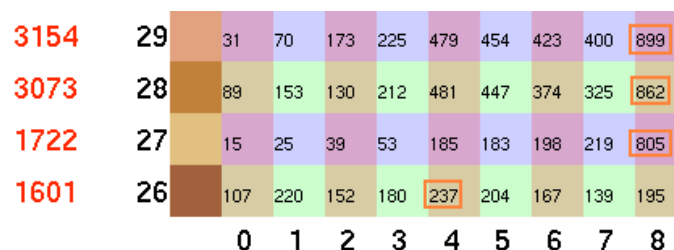

Fig. 4: extract of the matrix NCDM of the texture "basket" (horizontal direction)

4 A new color space: "L1 norm" space

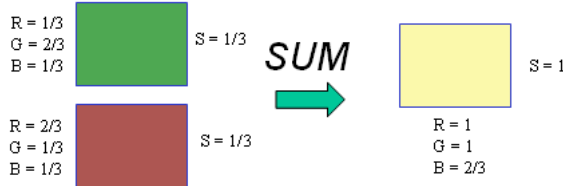We show here the weaknesses of the color spaces HSV and HLS. Then, we present a new color space, introduced by Serra and Angulo in [3, 4]: "L1 norm" space, which has interesting properties. Newton's disk set has seven colors: purple, indigo, blue, green, yellow, orange and red. The principal

property of this disk is that the sum of two colors with opposite hues and same saturation is a grey, i.e. a color with a null saturation. Thus, we have:
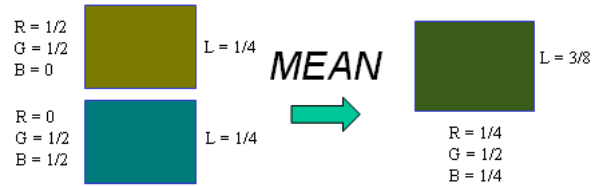
Saturation (r + g) ≤ Saturation (r) + Saturation (g). Perceptual uniform spaces such as HSV and HLS are appropriate for qualitative applications, but not for quantitative applications. These spaces are not compatible with the experiments of Newton's disk

[3, 4]. Let us take in space HLS, for example, the green color (R=1/3, G=2/3, B=1/3) and the brick color (R=2/3, G=1/3, B=1/3). For these two colors, saturation is equal to 1/3. If we take the sum of these two colors, we obtain yellow color (R=1, G=1, B=2/3). The saturation of the resulting color should be lower or equal to 2/3. However, it is equal to 1, which is theoretically false. Same thing with the brightness. (See figure 5).

Problem with HLS Saturation

R = 1/3
G = 2/3
B = 1/3
S = 1/3

SUM

R = 2/3
G = 1/3
B = 1/3
S = 1/3

S = 1
R = 1
G = 1
B = 2/3

Problem with HLS Luminance

R = 1/2
G = 1/2
B = 0
L = 1/4

MEAN

R = 0
G = 1/2
B = 1/2
L = 1/4

L = 3/8
R = 1/4
G = 1/2
B = 1/4

$$L = \frac{max+min}{2} \qquad S_c = \begin{cases} \frac{max-min}{max+min} & \text{if} \quad L \leq \frac{1}{2} \\ \frac{max-min}{2-max-min} & \text{if} \quad L > \frac{1}{2} \end{cases}$$

Figure 5: the experiments of Newton's disk

The "L1 norm" space is a perceptual uniform space. There are several perceptual uniform spaces. The most famous are LAB, HSV and their derivatives. We tested several perceptual uniform spaces and retained "L1 norm" space introduced by Serra in 2001 in [3, 4]. This space is better than HSV (and its derivatives) on several points: "L1 norm" space is compatible with the experiments of Newton's disk. The parameters of intensity (brightness and saturation) are norms. The parameters of intensity are independent: we can change one parameter without modifying the other parameter. Brightness is linear with respect to R, G, B values.

"L1 norm" space is a space of the type (brightness M for Mean, hue H, saturation S). The formulas of transformation from color space RGB are:

$m = (\max + mid + \min)/3$

$s = 3(\max - m)/2$ if $\max + \min \geq 2mid$

$s = 3(m - \min)/2$ if $\max + \min \leq 2mid$

$$h = 42\left[\lambda + \frac{1}{2} - (-1)^\lambda \frac{\max + \min - 2mid}{2s}\right]$$

with $\lambda = 0$ if $r > g \geq b$, 1 if $g \geq r > b$, 2 if $g > b \geq r$, 3 if $b \geq g > r$, 4 if $b > r \geq g$, 5 if $r \geq b \geq g$ and max = maximum of (R, G, B), min = minimum of (R, G, B), mid = median of (R, G, B).

The hue describes a circle. The equation for the hue is H = (λ + φ) * k. We pass from a sector of the circle to another sector by adding to φ the quantity which varies from 0 to 5. The constant k allows to the hue to vary on 256 levels.

Serra's aim was to represent the RGB cube with polar coordinates. The principal diagonal of the cube is called the achromatic axis and contains the

brightness information. All chromatic information is carried by the chromatic plan which is perpendicular to the achromatic axis at the origin (top of RGB cube of black color). This chromatic plan contains the hue and saturation axes.

The presence of characteristic lines on the histograms luminance/saturation (first order method) hints at the relevance of "L1 norm" space for segmentation tasks. Serra uses these characteristic lines via inverse transforms to characterize spectral homogeneous zones (reflections, shadows).

Our previous works [6] proved the effectiveness of "L1 norm" space for second order methods of characterization of textures, such as the co-occurrence matrices. Therefore, this color space seems well indicated for the matrices NCDM.

For more information, the reader can consult [3, 4]. The most important thing is to understand that HSV space and its derivatives are appropriate for qualitative applications and "L1 norm" space is appropriate for quantitative applications.

This criterion interests us because the construction of the matrix NCDM is based on calculations of distance from colors. Thus, we detect, in a best way, the difference of colors with a perceptual uniform space.

5 Characterization of the anisotropy in color textures

We present two algorithms of characterization of the anisotropy. The first one is based on the research of the maximum coefficients in the matrix NCDM. The second algorithm computes statistical tests (chi-square tests) on the coefficients of the matrix NCDM.

In the first algorithm: we seek the maximum coefficients in the matrix NCDM.

Step 1: We reduce the texture to 64 colors, which allows a good simplification of the heterogeneous zones without degrading them too much. This number of colors is a compromise between speed of calculation and performance of classification. The algorithm used to reduce the colors is named "minimum variance quantization".

Step 2: We transfer the texture in the "L1 norm" space.

Step 3: We calculate the matrices NCDM with an anisotropic neighbourhood according to eight principal directions: 0°, 22.5°, 45°, 67.5°, 90°, 112.5°, 135° and 157.5°. Previously, the parameter "a" is automatically computed (part 3). The value of "d" (size of the neighbourhood) is equal to 4. Thus, our neighbourhood are vectors of size 1*8 pixels.

We have eight matrices NCDM, one matrix for each direction. Each matrix has 64 rows and nine columns: from 0-8 neighbours. The central pixel of the mask is not used. The computing time of these eight matrices NCDM is lower than 1 second.

Step 4: For each matrix (that is to say for each direction) and for the most represented colors, we seek the column where the maximum is (the numbers framed with orange color on figure 4). We note the number of column. For each direction, we calculate the average number of column. If this average varies between five and eight, it means that the colors vary in a homogeneous way according to this direction. For all the directions, if the averages are high, then the texture is mainly isotropic and the dependences between the pixels are high. For all the directions, if the averages are weak, then the texture is mainly isotropic and is almost homogeneous. The concept of texture depends on the observation scale: a texture "on a large scale" can be comparable at a homogeneous zone. We precise that the size of the neighbourhood (the value of d) allows us to vary the observation scale.

We present the results of research of the dominant direction for three textures: T1 is a mainly isotropic texture, T2 has a vertical dominant direction and T3 has a horizontal dominant direction (table 1).

In table 1, the averages of the numbers of columns according to the eight directions (columns T_1c, T_2c, T_3c) are shown. These averages can vary from 0 to 8.

For texture T_1, the averages are weak and vary between 0.04 and 1. Therefore, the texture is mainly isotropic and the dependences between the pixels are rather weak (random texture). For texture T_2, the direction 90° (vertical) is largely dominant and the close directions (67.5° and 112.5°) are logically rather high. That means that, in this direction, each pixel of texture T_2 has, mainly, 8 neighbours with close colors: 4 pixels on the top and 4 pixels below.

Same analysis for texture T_3. But, this time, the horizontal direction dominates.

In the second algorithm, we measure the independence of the pixels with a chi-2 test. This method, proposed by Smolarz in [5], was extended to color textures. With the hypothesis of independence of the pixels in a neighbourhood, we can establish a probabilistic model of the estimated distribution in the matrix NCDM. Thus, this model allows us to evaluate the independence of the pixels with the chi-2 distance.

Let us clarify this model:

$Q_{d,a}(c, s)$ (see equation 1) allows us to estimate the probability $P_{d,a}(S = s / C = c)$ that a pixel with color c has exactly s neighbours with a close color to c (DP < a). With the hypothesis that the pixels belonging in the neighbourhood are independent, the probability $P_{d,a}(S = s / C = c)$ is modelled by the binomial distribution function with parameters V_d and $p_1 = P(DP \leq a)$. The test is done by calculating the chi-2 distance for each color (p_1 depends on the color c). Then, we calculate the difference $D(c)$ between the chi-2 distance and the decision threshold χ_α^2, obtained for a first type error α equal to 5%. Then, we calculate the mean $D_{m,\theta i}$ on the set of the most represented colors in the matrix Q and for each direction θ_i (i=1,..,8). Finally, in order to have a standardized criterion, we calculate $\dfrac{D_{m,\theta i}}{\sum_i |D_{m,\theta i}|}$ for each direction θ_i.

We present the results on the same textures (table 1: columns T_1m, T_2m and T_3m). The results are standardized and vary from -1 to 1. Negative coefficients indicate that there is no dependence between the pixels in the selected direction. We checked it with a "texture" which contains only white noise. The higher the coefficients are, the more the dependence between the pixels is important.

For texture T_1, we find almost the same coefficients for all the directions (except 45° and 135°). Therefore, this texture is mainly isotropic. For texture T_2, the coefficients are almost null except for the vertical direction (90°) and the close directions (67.5° and 112.5°). We have the same analysis with the texture T_3. But, this time, the horizontal direction dominates. We can note that the results agree with the two algorithms.

We present also results on three other textures (table 1). Because a lack of space, we will not comment on these results. For the same reason, we do not present comparative results between color textures and gray levels textures. We specify that we checked with experiments that our algorithms improve the results with color textures.

6. Conclusion and prospects

We presented, in this article, the Neighbouring Color Dependence Matrix (NCDM) which allows us to characterize the anisotropy in color textures.
We saw that the matrix NCDM allows, for a given neighbourhood, to evaluate the homogeneity or the heterogeneity of the color distribution. If this neighbourhood is isotropic, the matrix NCDM allows us to extract the homogeneous areas in the color images. It classes the areas of the color images with levels of homogeneity.
Matrix NCDM is perfectly compatible with an algorithm of color reduction of the analyzed image. Thus, it becomes rather compact and rapid in computing times. Recall that there are not many works on the characterization of color textures. The majority of the existing methods are only an extension to color textures of the methods of characterization of gray levels textures. These methods compute, very often, for each color channel, and are followed by a fusion of the results. On the contrary, the matrix NCDM exploits really the properties of the color spaces. That is why it is very important to transfer the image in another color space according to the considered application. Our future work will consist in exploiting the matrix NCDM in order to characterize, in a quantitative way, the color textures. Our aim is to extract several attributes and to define a space of texture representation for the color images.

7. References

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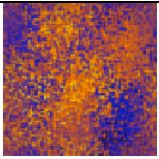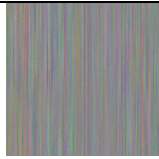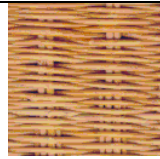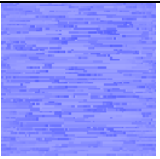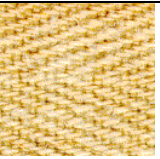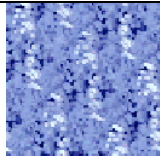
T_1	T_2	T_3	T_4	T_5	T_6

d=4	$T_1 c$	$T_1 m$	$T_2 c$	$T_2 m$	$T_3 c$	$T_3 m$	$T_4 c$	$T_4 m$	$T_5 c$	$T_5 m$	$T_6 c$	$T_6 m$
0°	1.00	0.15	2.32	0.01	**7.00**	**0.54**	**8.00**	**0.11**	2.33	**0.64**	1.42	0.18
90°	1.00	0.15	**8.00**	**0.16**	0.50	0.00	1.36	0.04	1.67	0.01	1.50	0.15
45°	0.04	0.03	2.39	0.01	0.75	0.00	1.21	0.02	1.33	0.00	0.92	0.04
135°	0.04	0.03	2.55	0.01	0.75	0.00	1.43	0.02	1.33	0.00	0.92	0.04
67.5°	1.00	0.16	**3.52**	**0.40**	1.00	0.00	1.14	0.03	1.33	0.01	1.50	0.13
112.5°	1.00	0.16	**3.39**	**0.39**	0.50	0.00	1.43	0.03	1.33	0.01	1.25	0.15
22.5°	1.00	0.16	2.32	0.01	**2.00**	**0.18**	**4.00**	**0.38**	2.33	**0.26**	1.42	0.15
157.5°	1.00	0.16	2.48	0.01	**2.50**	**0.26**	**4.00**	**0.36**	2.00	**0.08**	1.25	0.16

Table1: dominant directions of textures T_1, T_2 et T_3