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# Stochasticity: A Feature for Analyzing and Understanding Textures

Abdourrahmane M. ATTO<sup>1</sup>, Yannick BERTHOUMIEU<sup>2</sup>, Rémi MÉGRET<sup>3</sup>,

**Abstract**—The paper addresses the breaking of semantic gaps in image feature characterization through the stochasticity or randomness appearance. Measuring stochasticity involves finding suitable representations that can significantly reduce statistical dependencies of any order. Wavelet packet representations provide such a framework for a large class of stochastic processes through an appropriate dictionary of parametric models. From this dictionary and the Kolmogorov stochasticity index, the paper proposes semantic stochasticity templates upon wavelet packet subbands in order to support high level classification and content-based image retrieval. The approach is shown to be relevant for texture images.

**keywords:** Texture Descriptors; Stochasticity Measurements; Semantic gap; Parametric modeling.

## I. INTRODUCTION

The diversity of real world images has led researchers to use various mathematical tools in order to extract relevant image features or retrieve suitable information in images. For instance, probabilistic models, geometry properties and functional analysis have raised much dissertation in the last decades. In practice, the selection of appropriate features is driven by the class of images of interest. In this paper, the class of images we deal with can be conceptually defined through its departure from the class of regular images.

From the literature, a *regular* image is defined as either *smooth* or *geometrically regular* [1]: the image is composed of different smooth regions delimited by singularity curves. In contrast, a *non-regular* image is such that: when splitting the image into smaller and smaller subimages (sub-surfaces), almost every subimage is non-regular in that it is expected to contain many delimitation curves.

From the above consideration, a texture can be identified as either geometrically regular (composed of different or repetitive regions that are smooth except along their delimitation curves) or non-regular. Geometrically regular textures can be well characterized by local or global regularity measurements such as Holder exponents [1], [2], [3], [4], [5], [6], [7] or spectral measurements [8], [9], [10] [11]. In contrast, regularity measurements fail to be efficient for the

characterization of non-regular textures since measuring very low regularity parameters is not straightforward.

The approach proposed below to characterize non-regular textures involves most relevant features that have proven useful in texture analysis [2]. These features are considered jointly in the framework of 1) *stochasticity*, a concept which relies on, but is not limited to: coarseness, roughness and 2) wavelet packet transform, a representation that provides time-frequency, directionality, as well as other suitable statistical properties mentioned below.

The stochasticity degree (or randomness appearance) is hereafter measured by using the Kolmogorov stochasticity parameter [12]. This parameter applies under assumption that data are *independent and identically distributed (iid)* and their cumulative distribution function is completely specified. Recent works related to this parameter concern measuring the randomness degree of discrete sequences from dynamical systems and number theory [13], as well as measuring the contribution of randomness in the cosmic microwave background [14]. In these works, the Kolmogorov parameter has been used for specific datasets that are expected to comply with the underlying *iid* assumption, with a known distribution function.

In a more general framework involving real world textures, this *iid* assumption is very restrictive due to non-stationarity, correlation and other more intricate statistical dependencies that occurs among real world images.

The contributions of the present paper with respect to [13], [14] concern relaxing these restrictive assumptions by:

- 1) Considering the wavelet packet transform, a transform that makes it possible to distribute many random processes as stationary, independent and identically distributed sequences, see for instance [15], [16], [17];
- 2) Considering a dictionary of parametric models that are relevant with respect to the statistical distribution of the wavelet packet coefficients.

Under the above considerations, stochasticity can be measured even for correlated and non-stationary data through their wavelet packet representations. Furthermore, from the order structure that characterizes wavelet packet bases, we derive two different semantic templates for supporting high level texture description: 1) generating a semantic stochasticity template upon a fixed wavelet packet basis and 2) learning a wavelet packet tree structure that support best stochastic bases of training samples, provided that a critical stochasticity value is fixed.

The presentation of this paper is as follows. Section II introduces the Kolmogorov stochasticity parameter and

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assesses its relevance in detecting deterministic regular patterns. Section III addresses texture classification by using stochasticity templates. Section IV presents application of stochasticity analysis to standard content-based image retrieval by providing stochastic structuring of databases. Section V provides semantic based texture retrieval concepts and experimental results. Finally, Section VI provides a conclusion to the paper.

## II. STOCHASTICITY MEASUREMENTS

### A. Kolmogorov stochasticity index - Deterministic pattern

Let  $x = (x_1, x_2, \dots, x_N)$  be a sample set that follows from *iid* random variables with *probability density function*, *pdf*  $f$  and *cumulative distribution function*, *cdf*  $F$ . The Kolmogorov stochasticity parameter [12] is:

$$\kappa(x, F) = \sup_t |F_{x,N}(t) - F(t)|. \quad (1)$$

where  $F_{x,N}$  is the empirical *cdf* of the  $N$ -sample sequence  $x$ .

Standard approaches in testing random generators are based on binary hypothesis testing (stochastic or not) and focus on the asymptotic of  $\sqrt{N}\kappa(x, F)$  with  $N$ . In contrast with these approaches, we assume no binary hypothesis since we will use the heights of  $\kappa(x, F)$  to compare textures in term of their randomness appearances, whatever the values of the stochasticity indices.

Note that  $\kappa(x, F) \ll 1$  for datasets that are stochastic with respect to  $F$  (consequence of the Glivenko-Cantelli theorem) This implies that any  $x$  satisfying  $\kappa(x, F) = 1$  is non-stochastic with respect to  $F$ . For instance, since we are dealing with a dictionary of continuous *cdfs*, we will say that a constant sequence is deterministic with respect to this dictionary: for such a sequence, the reader can check that  $\sup |F_{x,N}(t) - F(t)| = 1$  as far as  $N \geq 2$ . Furthermore, we have that the presence of a value with large occurrence in a dataset can be qualified as a deterministic pattern since it impacts as well  $\sup |F_{x,N}(t) - F(t)|$ .

The following section addresses the relevance of  $\kappa(x, F)$  in pointing out deterministic patterns, in comparison with other stochasticity measures available from the literature.

### B. The relevance of the Kolmogorov stochasticity parameter in detecting deviations from a specified distribution

The results presented in this section concern the sensitivity of different stochasticity measures when data with a given stochasticity degree are corrupted with elementary deterministic patterns with increasing sizes.

There are basically two criteria that distinguish stochasticity measures:

- 1.) the norm used, which can be cumulative or uniform.
- 2.) the distribution, which can be specified as *pdf* or *cdf*.

Examples issued from random generator testing are a) Kolmogorov-Smirnov test [18], based on the uniform ( $\ell_\infty$ ) norm and comparing two *cdfs* in a binary hypothesis testing, b) the chi-square test [19], based on the cumulative

$\ell_2$  norm and comparing two *pdfs* in a binary hypothesis testing problem.

Let us consider a dataset having stochasticity degree  $\eta$  with respect to a given distribution model. Assume that these data are affected by a deterministic pattern in the sense that a proportion  $K/N$  of the data is set to a constant value. Since a stochasticity measure can be seen as a dissimilarity measure between distribution functions, then a relevant stochasticity measure is such that its stochasticity parameter should increase as  $K$  increases.

In the following experiments, a deterministic pattern consisting in the insertion of  $K$  occurrences of a fixed value is introduced in datasets and the relevance of different stochasticity measures is tested when the size  $K$  of this pattern increases. These experiments are performed upon the detail wavelet coefficients of texture images. These coefficients are expected to be very small in smooth regions and large in the neighborhood of edges. Increasing the number of null coefficients (if any) by forcing  $K$  large coefficients to zero (deterministic pattern) results in smoothing some edges of the image. This implies reducing the intrinsic stochasticity of the data when  $K$  increases. A relevant stochasticity measure should depart from the initial stochasticity degree<sup>1</sup>, when  $K$  increases.

We consider the experimental setup presented in Table I: different combinations between norms ( $\ell_2, \ell_\infty$ ) and distribution specifications (*cdf*, *pdf*) are used for testing stochasticity measures. In this table,  $\|\cdot\|$  specifically denotes either the  $\ell_\infty$  and  $\ell_2$  norms. The Kullback-Leibler<sup>2</sup> Divergence (KLD) is also used for comparison purpose. In addition, if  $c_{j,n}$  denotes the wavelet packet coefficients obtained at subband  $\mathbf{W}_{j,n}$ , then  $c_{j,n}^K$  corresponds to the dataset obtained by setting the  $K$  largest values of  $c_{j,n}$  to 0. In particular,  $c_{j,n}^0 = c_{j,n}$ .

Departure from the initial stochasticity value of the wavelet coefficients is measured with respect to the *generalized gaussian* distributions. In addition, Gaussian, triangle and Epanechnikov kernels have been used for the estimation of the empirical *pdfs* involved in Table I. The results provided in Figures 1 and 2 are obtained with a Gaussian kernel and the wavelet decomposition has been performed with a Daubechies wavelet function of order 7. These results concern the images ‘‘Fabric.0004’’ and ‘‘Fabric.0018’’ from the VisTeX database (see Figure 1). Results are similar for other textures from the VisTeX database and for other kernels (concerning *pdf* based measures).

As it can be seen in Figures 1 and 2, the uniform norm on the *cdfs* (Kolmogorov strategy) is the sole strategy that guarantee non-decreasing Relative Stochasticity

<sup>1</sup>The initial stochasticity degree is the value of the stochasticity parameter when no coefficients are forced to zero.

<sup>2</sup>The Kullback-Leibler similarity measure between random variables  $X_1$  and  $X_2$  having probability distribution functions  $f_{X_1}$  and  $f_{X_2}$  is defined as

$$\begin{aligned} \mathcal{H}(X_1, X_2) &= \mathcal{H}(X_1 \| X_2) + \mathcal{H}(X_2 \| X_1), \\ \text{with } \mathcal{H}(X_i \| X_j) &= \int_{\mathbb{R}} f_{X_i}(x) \log \frac{f_{X_i}(x)}{f_{X_j}(x)} dx, \quad i, j = 1, 2. \end{aligned}$$

TABLE I  
 EXPERIMENTAL SETUP FOR TESTING THE RELEVANCE OF THE UNIFORM ( $\ell_\infty$ ) NORM VERSUS THE CUMULATIVES  $\ell_2$  NORM AND KULLBACK-LEIBLER DIVERGENCE (KLD) IN STOCHASTICITY MEASUREMENTS. THE QUANTITIES INVOLVED IN THE COMPUTATION OF THE RELATIVE STOCHASTICITY VALUE (RSV) ARE THE EMPIRICAL DISTRIBUTION AND THE MODEL.

<b>For <math>0 \leq K \leq 150</math>, do:</b>	
<b>Compute</b>	the wavelet coefficients $(c_{j,n})_{j,n}$ of the input image.
<b>Introduce</b>	a deterministic pattern among the coefficients of a subband by setting the $K$ largest coefficients to zero (notation $(c_{j,n}^K)_{j,n}$ ).
<b>Compute</b>	the stochasticity parameters: Check the distribution type from variable "specification"
<b>Case</b>	specification is "cdf", <b>then:</b>
Compute RSV( $K$ ) =	$\frac{\left  F_{c_{j,n}^K, N} - F_\theta(c_{j,n}^K) \right }{\left  F_{c_{j,n}^0, N} - F_\theta(c_{j,n}^0) \right }$
<b>Case</b>	specification is "pdf", <b>then:</b>
Compute RSV( $K$ ) =	$\frac{\left  f_{c_{j,n}^K, N} - f_\theta(c_{j,n}^K) \right }{\left  f_{c_{j,n}^0, N} - f_\theta(c_{j,n}^0) \right }$
<b>End</b>	
<b>Compare</b> the measurements obtained: for a relevant stochasticity measure, RSV is a non-decreasing function of $K$ .	

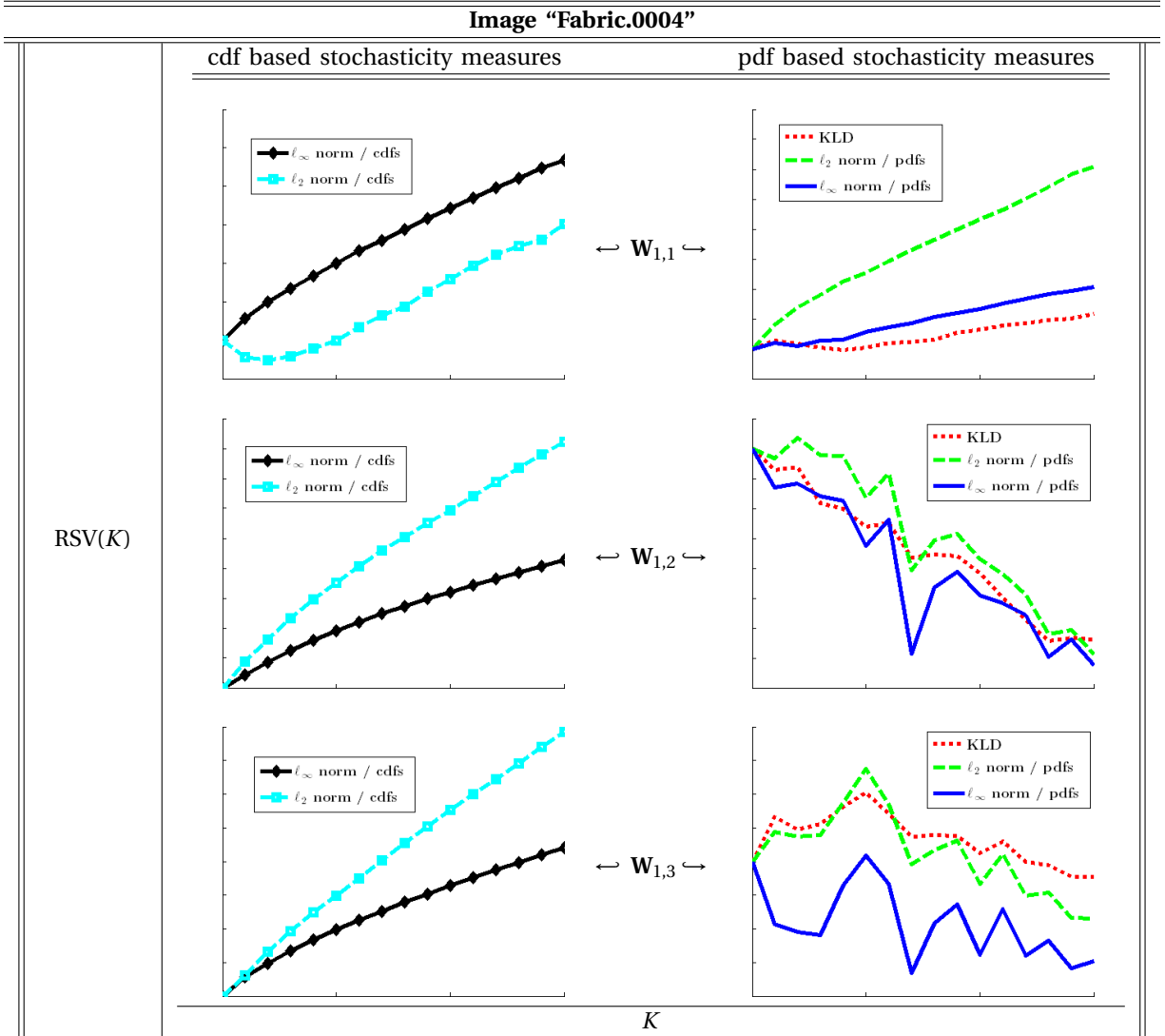


Fig. 1. Relative stochasticity values for the image "Fabric.0004" from the VisTeX database. The RSV of a relevant stochasticity measurement must be an increasing function of the size  $K$  of the deterministic pattern. We have  $K = 0, 10, 20, \dots, 150$  and  $N = 68644$ .

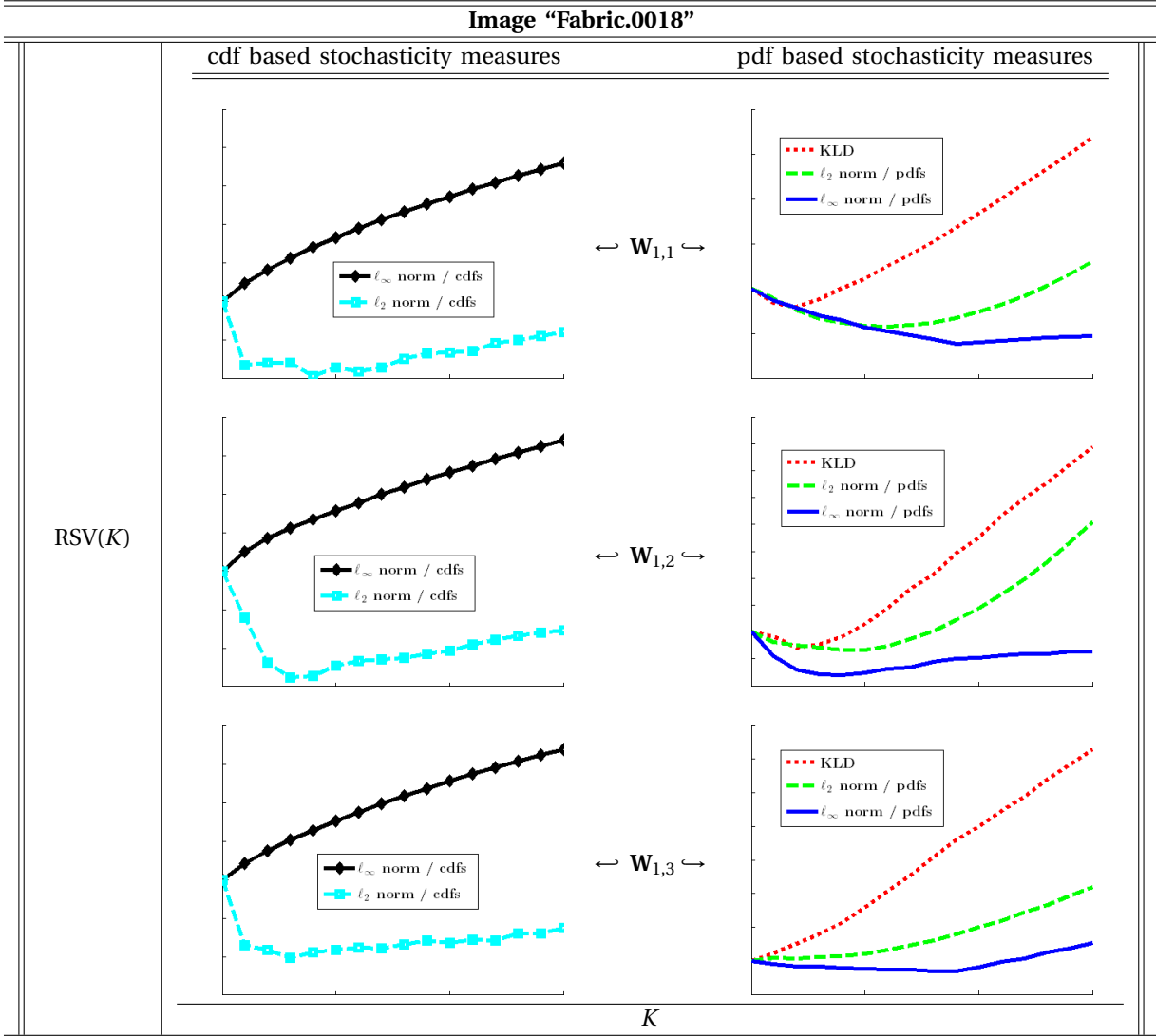


Fig. 2. Relative stochasticity values for the image “Fabric.0018” from the VisTeX database. The RSV of a relevant stochasticity measurement must be an increasing function of the size  $K$  of the deterministic pattern. We have  $K = 0, 10, 20, \dots, 150$ , and  $N = 68644$ .

Value (RSV, see Table I) when the size  $K$  of the pattern increases. Cumulative measures ( $\ell_2$ , KLD), as well as *pdf* based specifications are not very relevant for stochasticity assessment because of non-increasing deviations from the initial stochasticity degree: the local information is blurred through the averaging effect induced by cumulative measures or through neighborhood consideration when computing *pdfs*. Moreover, the same conclusion as above holds true when the experiments are performed on synthetic random numbers and without the use of wavelet transform.

From now on, we assume that the stochasticity parameter is of Kolmogorov type: uniform norm that applies to compare the empirical *cdf* with the distribution model. Section III-A addresses the choice of different bounds on this parameter for generating a semantic stochasticity template. This makes it possible to classify textures by mapping their sequences of stochasticity values on the stochasticity templates under consideration.

### III. CLASSIFICATION FROM WAVELET PACKET BASED STOCHASTICITY TEMPLATES

#### A. Kolmogorov stochasticity measure versus error-bounds from image estimation

As shown in Section II-B, the Kolmogorov parameter is relevant for detecting deterministic patterns in stochastic datasets and *vice versa*. For the main purpose of this paper, it is convenient to specify stochasticity bounds that make it possible to classify textures depending on their stochasticity degrees.

In the following, we derive different semantic classes consisting in stochasticity categories, by fixing bounds on  $\sup |F_{x,N}(t) - F(t)|$ . This is performed by dealing with  $\sup |F_{x,N}(t) - F(t)| < \eta_i$  as a problem of estimating an unknown function from observed samples, and by fixing  $\eta_i$  so as to guarantee a PSNR greater than  $\Omega_i$  dBs, where  $(\Omega_i)_i$  are bounds taken from standards on PSNR quality from image denoising and compression problems.

The PSNR (Peak Signal-to-Noise Ratio, in deciBel unit,

dB) is given by

$$\text{PSNR} = 10 \log_{10} (d^2 / \text{MSE}), \quad (2)$$

where  $d$  is the dynamic of the image and MSE denotes the Mean Squared Error.

### Proposition 1

Consider the problem of fitting  $F_{x,N}(t_i)$  by  $F(t_i)$  for  $i = 1, 2, \dots, N$ . Then in order to have a PSNR greater than  $\Omega$  dBs, it suffices that  $\eta^2 \leq d \times 10^{-\Omega/10}$ .

The dynamic of  $F_{x,N}$  is 1. Now, we set  $\Omega_0 = 30$  dBs,  $\Omega_1 = 35$  dBs and  $\Omega_2 = 40$  dBs (a minimum of 30 dBs is required for an image denoising or compression algorithm to be relevant). These values are associated with the constants:

$$\eta_i = \sqrt{10^{-\Omega_i/10}}, \quad i = 0, 1, 2,$$

hereafter referred as lower bounds for high, good and fair quality set indicators. Then, we will use below, 4 stochasticity classes:

### Definition 1 (Semantic stochasticity classes)

A sample set  $x$  is said to be strongly stochastic (resp. stochastic, quasi-stochastic, non-stochastic) with respect to a continuous *cdf*  $F$  if  $\kappa(x, F) \in [0, \eta_2]$  (resp.  $\kappa(x, F) \in ]\eta_2, \eta_1]$ ,  $\kappa(x, F) \in ]\eta_1, \eta_0]$ ,  $\kappa(x, F) \in ]\eta_0, +\infty[$ ).

### B. Texture classification by using stochasticity templates upon wavelet packet bases

Wavelet packet bases constitute a general framework for studying dictionaries of functional bases. Indeed, they offer a large family of functional bases with several properties, depending on whether we decide to split a given subband or not [20], [21], [22], [23], among others. *Best basis* algorithms for the representation of signals involves seeking for functional atoms satisfying a given benchmark. In the wavelet framework, this benchmark is usually expressed in terms of *energy* of the coefficients, *sparsity* or number above a threshold and entropy measurements [20], [24], [25]. Recent works on *best basis* algorithms concern compressive sensing and are related to the sparsity benchmark for piecewise regular images [26].

Hereafter the best basis is computed upon the wavelet packet transform and under the stochasticity criterion: starting from the root node  $\mathbf{W}_{0,0}$ , this consist in splitting every wavelet packet node  $\mathbf{W}_{j,n}$  recursively, unless the stochasticity of a node have reached the fixed stochasticity bound. Indeed, the statistical properties of the wavelet packet coefficients (in particular the higher order cumulant decay, see [15], [17], among others) ensure that the Kolmogorov parameter decrease for a large class of stationary and non-stationary random processes. The corresponding algorithm is hereafter called BSB-WP: Best Stochastic Basis upon Wavelet Packets.

We run the BSB-WP algorithm in order to classify the “Fabric” textures of the VisTeX database (see Figure 3). Stochasticity is measured with respect to *cdfs* pertaining

TABLE II  
VIS-TEX “FABRIC” TEXTURE CLASSIFICATION FROM BSB-WP STOCHASTICITY MEASUREMENTS. THE “FABRIC” TEXTURES ARE GIVEN IN FIGURE 3. IN THIS TABLE, “DET” DESIGNATE WAVELET PACKET DETAILS AND “APPROX” DESIGNATE WAVELET APPROXIMATIONS.

	Quasi-stochastic		Stochastic		Strongly-stochastic	
	Det.	Approx.	Det.	Approx.	Det.	Approx.
Fabric.18	✓	✓	✓	✓	✓	–
Fabric.07	✓	✓	✓	✓	–	–
Fabric.17	✓	✓	✓	–	–	–
Fabric.04	✓	✓	✓	–	–	–
Fabric.09	✓	✓	✓	–	–	–
Fabric.11	✓	–	✓	–	–	–
Fabric.15	✓	–	✓	–	–	–
Fabric.00	–	–	–	–	–	–
Fabric.14	–	–	–	–	–	–

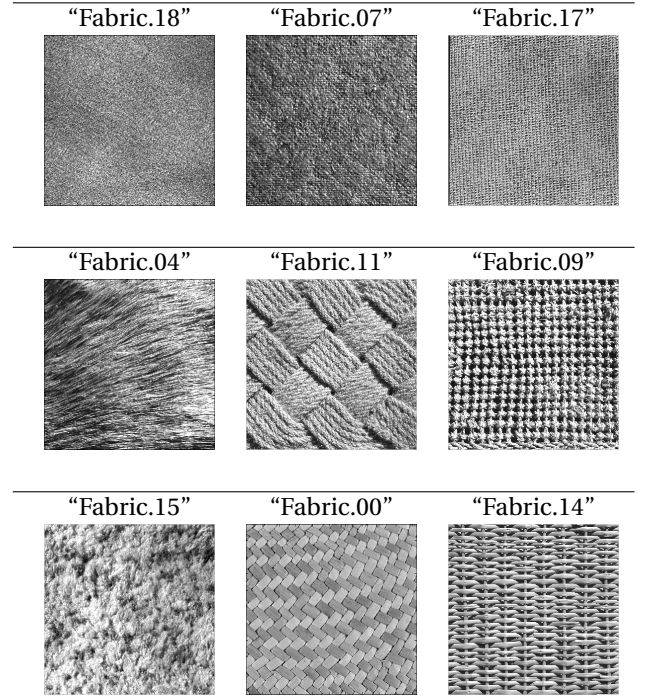


Fig. 3. Textures “Fabrics” from the VisTeX database.

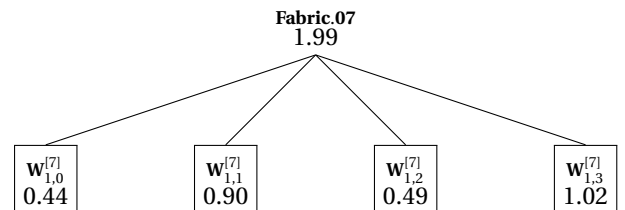


Fig. 4.  $100 \times \kappa$  for texture “Fabric.07” from the VisTeX database. The BSB-WP is composed of framed subbands.

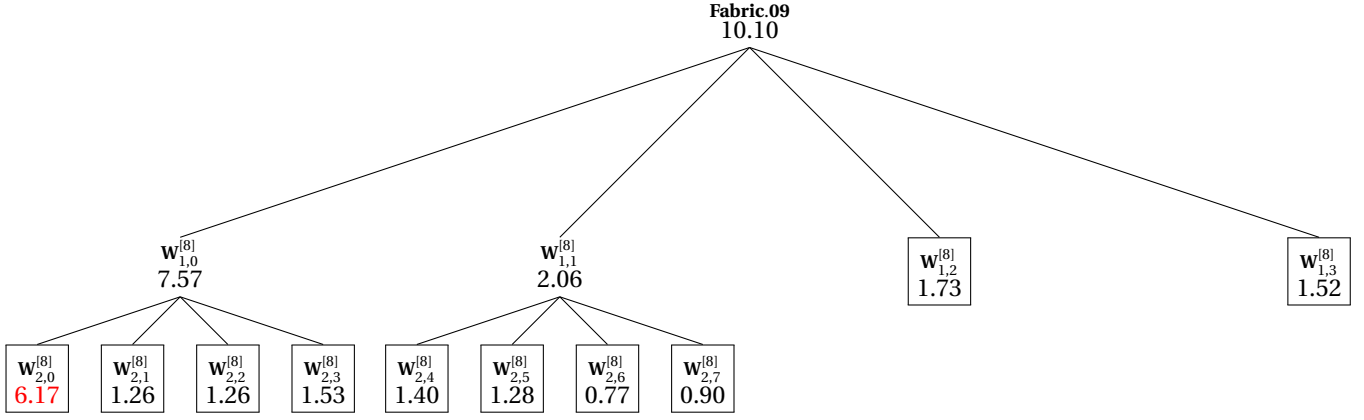


Fig. 5.  $100 \times \kappa$  for texture “Fabric.09” from the VisTeX database. The BSB-WP is composed of framed subbands. The texture is represented as the sum of a smooth approximation and stochastic details.

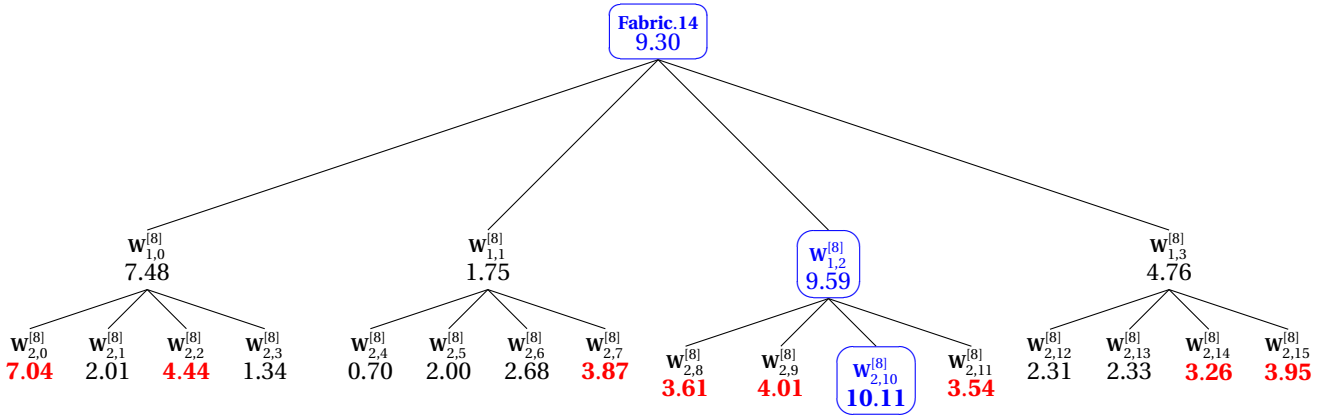


Fig. 6.  $100 \times \kappa$  for texture “Fabric.14” from the VisTeX database at decomposition level 2. Many subbands remain non-stochastic. In addition, the stochasticity parameter  $\kappa$  does not systematically decrease as the decomposition level increases in some detail paths (see the path with oval boxes).

to the exponential class and the 4 semantic classes given in Definition 1 (non-stochastic, quasi-stochastic, stochastic and strongly-stochastic semantic classes). We used a maximum depth  $J^*$  fixed to 4 for the wavelet packet decomposition and the Daubechies wavelet of order 7. Table II summarizes the results obtained.

One can note that these results are consistent with the visual perception of randomness appearance. Furthermore, we derive from these results that textures “Fabric.18” and “Fabric.07” can be well characterized by using probabilistic distribution modeling applied on the nodes involved in their best bases. In contrast, probabilistic distribution modeling is not relevant for describing non stochastic textures such as “Fabric.00” and “Fabric.14” because their wavelet packet coefficient distribution deviate significantly from the continuous *cdfs* used. Note that the latter textures are regular and thus, the appropriate criterion for their characterization needs to be based on regularity: regular images are sparse in the wavelet packet domain and the sparsity criterion is thus expected to be more relevant.

The following provides some examples for illustrating BSB-WP texture characterization.

#### Example 1

Texture “Fabric.07” is intrinsically quasi-stochastic:  $\kappa_{\text{Fabric.07}} < \eta_0$ . BSB-WP provides a basis (see the basis

composed of framed subbands in Figure 4) where all subbands involved in the representation are stochastic:  $\kappa_{c_{1,n}[\text{Fabric.07}]} < \eta_1$  for every  $n = 0, 1, 2, 3$ . BSB-WP basis with higher stochasticity property ( $\kappa < \eta_2$ ) has not been found up to decomposition level  $J^*$ .

#### Example 2

Texture “Fabric.09” is not intrinsically stochastic:  $\kappa_{\text{Fabric.09}} > \eta_0$ . BSB-WP provides a basis where the texture can be represented as a deterministic (smooth) approximation and stochastic details:  $\kappa_{c_{j,n}[\text{Fabric.09}]} < \eta_1$  for every nodes  $(j, n)$  involved in the tree of Figure 5, with  $n \neq 0$ .

#### Example 3

Texture “Fabric.14” is not stochastic.  $\kappa$ -measurements are out of stochasticity bounds for the input texture as well as for many of its wavelet packet subbands up to decomposition level  $J^*$ . In addition, this texture presents a “singular” path in the sense given in [15]. Indeed, depending on the input process, some paths are such that no *cdf* regularization can be expected. In this case, stochasticity measures can increase as the decomposition level increases. This occurs for the path with subbands marked in oval frames in Figure 6.

Table II and Figure 3 highlight that stochasticity measurements in the wavelet domain are sensitive to the roughness/coarseness/coherence of textures and reflect the “randomness-appearance” of textures.

#### IV. CONTENT-BASED IMAGE RETRIEVAL WITH STOCHASTIC STRUCTURING

In what follows,  $\mathcal{T}$  denotes a texture database assumed to be heterogeneous in the sense that it contains both stochastic and regular textures. We consider the problem of structuring the elements of  $\mathcal{T}$  by using the stochasticity degree. The structuring proposed is a splitting of database  $\mathcal{T}$  in two metaclasses: stochastic versus regular textures. This structuring will be used as a pre-classification for level 1 Content-Based Image Retrieval (CBIR) based on parametric modeling of the statistical distributions of the wavelet coefficients. In this standard 1 CBIR [27], the query is completely specified through the statistical distributions of texture pixel values.

##### A. Stochastic structuring

The structuring is performed with respect to the stochasticity measurements in the wavelet domain. The wavelet transform used is the Stationary Wavelet Transform (SWT). Indeed the SWT is appreciated for its shift-invariance property and is known to be relevant for the level 1 CBIR under consideration [28].

We consider the Edgeworth expansions of order 4 for modeling the SWT approximation subbands and the Generalized Gaussian, Pareto and Weibull distributions for modeling the detail SWT coefficients. Model validation regarding the above issues can be found in [28]. The symmetric Kullback-Leibler divergence is used as similarity measure between the statistical distributions given above.

Experimental tests concern 40 texture classes of the VisTeX database. The database structuring for these classes is given, in terms of stochastic versus regular textures, in Table III: this structuring yields a stochastic metaclass composed with 22 texture classes and a regular metaclass composed with 18 texture classes.

##### B. Content-based image retrieval on structured databases

This section provides CBIR experimental results on structured databases, in comparison with the results obtained without stochastic structuring. The experimental setup is the one used in [28]: any texture class (among the 40 texture classes considered) is composed with 16 images obtained by splitting every large texture image in 16 non-overlapping subimages. Thus, we have a test database  $\mathcal{T}$  composed with 640 images, among which, 352 images forming a database structure  $\mathcal{T}_1$  are issued from a stochastic class; whereas the 288 remaining textures constitute a database structure  $\mathcal{T}_2$  associated with regular texture classes, with  $\mathcal{T} = \mathcal{T}_1 \cup \mathcal{T}_2$ .

We then run CBIR from parametric modeling and similarity measurements, as described in [28], with the Symlet wavelet of order 8. Experimental tests are performed independently on the tree database structures  $\mathcal{T}_1, \mathcal{T}_2, \mathcal{T}$ .

For a given structure, performance measurements concern the retrieval rates, when a query is any subimage of the structure under consideration. Retrieval rates per class are given in Table III concerning  $\mathcal{T}_1$  and  $\mathcal{T}_2$ . Average retrieval rates per structures structures  $\mathcal{T}_1, \mathcal{T}_2, \mathcal{T}$  are given in Table IV for comparison purpose.

TABLE IV  
AVERAGE VALUES OF TEXTURE-SPECIFIC RETRIEVAL FOR THE WHOLE DATABASE  $\mathcal{T}$ , THE DATABASE COMPOSED OF *stochastic textures*  $\mathcal{T}_1$  AND THE DATABASE COMPOSED OF *regular textures*  $\mathcal{T}_2$ , WITH  $\mathcal{T}_1 \cup \mathcal{T}_2 = \mathcal{T}$ . EXPERIMENTAL RESULTS PERFORMED WITHOUT STOCHASTIC STRUCTURING (BLIND APPROACH) ARE GIVEN FOR COMPARISON PURPOSE.

Stochastic textures ( $\mathcal{T}_1$ )					
Blind approach			Stochastic structuring		
GG	WBL	PRT	GG	WBL	PRT
<b>88.12</b>	<b>87.82</b>	<b>66.05</b>	<b>90.45</b>	<b>90.02</b>	<b>66.67</b>
Regular textures ( $\mathcal{T}_2$ )					
Blind approach			Stochastic structuring		
GG	WBL	PRT	GG	WBL	PRT
<b>78.95</b>	<b>79.60</b>	<b>83.18</b>	<b>81.10</b>	<b>81.81</b>	<b>83.51</b>
Whole texture database ( $\mathcal{T}$ )					
Blind approach			Stochastic structuring		
GG	WBL	PRT	GG	WBL	PRT
<b>83.99</b>	<b>84.12</b>	<b>73.76</b>	<b>86.24</b>	<b>86.33</b>	<b>74.25</b>

From Table IV, it follows that the retrieval is more concise when the search focuses either on  $\mathcal{T}_1$  or on  $\mathcal{T}_2$  than on the whole structure  $\mathcal{T}$ . Since  $\mathcal{T}_1$  and  $\mathcal{T}_2$  have low cardinality, the structuring also eases the search. In addition, from Table IV and when comparing the role played by the distribution type on the metaclass, it follows that the more relevant family is:

- the GG family for modeling the stochastic textures,
- the PRT family for modeling the regular textures,
- the WBL family for modeling the whole database containing both regular and stochastic textures.

The above remarks confirm the suitability of separating a heterogeneous database into structures with approximately the same stochasticity degrees.

#### V. CONTENT-BASED STOCHASTICITY RETRIEVAL

This section addresses stochasticity consideration for CBIR feature selection in texture databases. This CBIR takes into account the inference made in Section III for deriving different stochasticity templates. It is worth noting that the stochasticity degree can be seen as an index aggregating many low-level texture features (statistical distributions) in order to derive a high-level feature: the randomness-like appearance of a dataset. In this respect, we are concerned by the level 2 CBIR [27]. The motivation in using a stochasticity criterion for level 2 CBIR is the following.

Consider a geometrically regular image (a human face, textures “Fabric.00” and “Fabric.14” given in Figure 3, etc). For such an image, the form (through primitives) and the regularity are known to be relevant features for content description [10], [29]. Consider now a stochastic texture (see for instance “Fabric.18” and “Fabric.07”). Such a texture is not regular and has no structured components that can be





- Query “Fabric.0007”, associated with the lowest randomness degree among the two classes, reduces the search database from 16 to 8 including 7 good retrieval/8.
- Query “Fabric.0018”, associated with the highest randomness degree among the two classes, reduces the search database from 16 to 7 including 7 good retrieval/8.

From these experiments, stochasticity, as a feature measuring the intrinsic coherence of a texture, can be used to generate a stochasticity tree structure representing the BSB-WPs a texture observed through some training samples.

### B. Content-based stochasticity retrieval by learning the stochasticity bounds

Depending on constraints such as computational load or dealing with a large number of semantic classes, it may sometimes be desirable to fix the decomposition basis. In this section, we consider a fixed wavelet packet basis  $\mathbf{B} = \bigcup_{p=1,2,\dots,L} \mathbf{W}_{J_p, n_p}$  and propose high-level CBSR by computing, from training samples, the subspace where the stochasticity parameters are expected to lie within.

Assume the availability of  $K$  samples (subimages) for every texture class  $m$  considered, with  $1 \leq m \leq M$  (training set for this texture). Let us denote by  $\kappa_{m_\ell}(J_p, n_p)$ , the value of the stochasticity parameter (see Eq. (1)) associated with the subband  $\mathbf{W}_{J_p, n_p}$  coefficients of subimage  $m_\ell$ . The sequence  $(\kappa_{m_\ell}(J_p, n_p))_{\ell=1,2,\dots,K}$  represents the behaviour of the stochasticity parameters of the projection of texture  $m$  samples on subband  $\mathbf{W}_{J_p, n_p}$ . Let us denote  $\kappa_{\min}^m(J_p, n_p) = \min\{\kappa_{m_\ell}(J_p, n_p), \ell = 1, 2, \dots, K\}$  and  $\kappa_{\max}^m(J_p, n_p) = \max\{\kappa_{m_\ell}(J_p, n_p), \ell = 1, 2, \dots, K\}$ . Define the stochasticity hypercube associated with the samples of texture  $m$  on basis  $\mathbf{B}$  by

$$\mathcal{H}_L^m = \prod_{p=1}^L [\kappa_{\min}^m(J_p, n_p), \kappa_{\max}^m(J_p, n_p)].$$

The CBSR principle considered in this section is the following: a query sample admitting stochasticity parameters  $\kappa(J_1, n_1), \kappa(J_2, n_2), \dots, \kappa(J_L, n_L)$  on basis  $\mathbf{B}$  is decided to belong to class  $m$  if the vector  $(\kappa(J_1, n_1), \kappa(J_2, n_2), \dots, \kappa(J_L, n_L)) \in \mathcal{H}_L^m$ .

In this respect, a texture can be characterized by the hypercube defined from the lower and upper bounds of the stochasticity parameters of its sample coefficients on the basis  $\mathbf{B}$ . This hypercube defines the semantic class of the texture.

Assume that a new sample of the texture is available. Then we can re-evaluate the stochasticity bounds when some of the additional stochasticity parameters of this sample are out of the texture stochasticity hypercube. In addition, depending on the distribution of the stochasticity parameters, the user can discard those behaving as outliers in order to tighten the stochasticity hypercube and avoid overlapping with stochasticity hypercubes associated to other semantic classes. This re-evaluation is known to be useful in integrated CBIR systems [30].

The following provides CBSR experimental results obtained for  $M = 40$  textures from the VisTeX database. The experimental setup used is described below:

- First, we construct the learning database by using the top-half of the images: each top-half image is splitted into  $K = 8$  non-overlapping subimages ( $128 \times 128$  pixels per subimage). These  $K$  subimages are used to compute the stochasticity hypercube  $\mathcal{H}_L^m$  for  $m = 1, 2, \dots, 40$ .
- Then, we constitute the test database by using the down-half of the images: each down-half image is splitted into 8 non-overlapping subimages. Thus, the test database is composed of  $8 \times M$  subimages.
- In order to increase the number of experiments, we have also permuted the roles played by the learning and the test database (top-half becomes down-half and *vice-versa*).

We run this procedure when the decomposition is performed by using a wavelet basis with  $J^* = 2$ . The stochasticity is measured with respect to dictionary  $\mathcal{D}$  (Table V) and with respect to a single distribution family: the GG distributions (Table VI). Specifically, in these tables, we have that 2 stochasticity coordinates out of  $\mathcal{H}_L^m$  are tolerated, that is, 2 stochasticity parameters out-of-bounds are tolerated among a set of  $3 * J^* + 1 = 7$  stochasticity parameters  $\kappa(J_1, n_1), \kappa(J_2, n_2), \dots, \kappa(J_L, n_L)$  with  $L = 7$ . In Tables V and VI, TPR denotes the True Positive Rate defined as the ratio (fraction relevant queries per class):

$$\text{TPR}[m] = \frac{\text{Number of admissible subimages that are issued from texture } m}{\text{Total number of relevant subimages,}}$$

and FAR denotes the False Alarm Rate per class:

$$\text{FAR}[m] = \frac{\text{Number of admissible subimages that are not issued from texture } m}{\text{Total number of subimages that are not issued from texture } m}$$

TABLE V  
TRUE POSITIVE RATE (TPR) AND FALSE ALARM RATE (FAR) FOR CBSR BY LEARNING THE STOCHASTICITY BOUNDS. DICTIONARY  $\mathcal{D}$  IS USED FOR STOCHASTICITY MEASUREMENTS.

Texture	TPR	FAR	Texture	TPR	FAR
Bark.00	62.50	08.97	Food.08	56.25	0
Bark.06	37.50	07.69	Grass.01	37.50	04.81
Bark.08	62.50	00.80	Leav.08	68.75	12.66
Bark.09	75.00	10.58	Leav.10	43.75	09.13
Bric.01	31.25	01.44	Leav.11	56.25	04.65
Bric.04	37.50	02.56	Leav.12	43.75	04.65
Bric.05	50.00	06.89	Leav.16	62.50	01.92
Buil.09	37.50	00.96	Meta.00	50.00	01.92
Fabr.00	43.75	01.92	Meta.02	68.75	00.32
Fabr.04	50.00	07.05	Misc.02	62.50	00.64
Fabr.07	62.50	01.12	Sand.00	31.25	02.24
Fabr.09	37.50	00.48	Ston.01	56.25	08.01
Fabr.11	56.25	01.44	Ston.04	62.50	01.92
Fabr.14	50.00	0	Terr.10	50.00	08.01
Fabr.15	68.75	00.80	Tile.01	31.25	02.40
Fabr.17	56.25	01.12	Tile.04	37.50	00.96
Fabr.18	68.75	00.48	Tile.07	25.00	0
Flow.05	31.25	07.21	Wate.05	62.50	02.40
Food.00	62.50	01.92	Wood.01	56.25	12.18
Food.05	31.25	03.21	Wood.02	56.25	09.29

TABLE VI  
TRUE POSITIVE RATE (TPR) AND FALSE ALARM RATE (FAR) FOR CBRS BY  
LEARNING THE STOCHASTICITY BOUNDS. THE GG FAMILY IS USED FOR  
STOCHASTICITY MEASUREMENTS.

Texture	TPR	FAR	Texture	TPR	FAR
Bark.00	100	18.27	Food.08	75.00	00.48
Bark.06	75.00	13.78	Grass.01	50.00	07.85
Bark.08	68.75	03.37	Leav.08	75.00	16.03
Bark.09	75.00	20.83	Leav.10	56.25	14.58
Bric.01	62.50	03.85	Leav.11	62.50	06.89
Bric.04	68.75	04.01	Leav.12	43.75	04.81
Bric.05	75.00	08.97	Leav.16	75.00	02.56
Buil.09	56.25	02.56	Meta.00	68.75	02.72
Fabr.00	62.50	02.88	Meta.02	87.50	00.64
Fabr.04	50.00	13.62	Misc.02	68.75	00.96
Fabr.07	81.25	01.44	Sand.00	62.50	03.37
Fabr.09	75.00	00.64	Ston.01	62.50	13.94
Fabr.11	81.25	02.40	Ston.04	68.75	03.53
Fabr.14	87.50	00.16	Terr.10	68.75	16.35
Fabr.15	87.50	02.08	Tile.01	37.50	04.17
Fabr.17	87.50	03.05	Tile.04	68.75	02.08
Fabr.18	81.25	01.12	Tile.07	31.25	0
Flow.05	56.25	11.06	Wate.05	81.25	07.69
Food.00	93.75	02.56	Wood.01	93.75	24.20
Food.05	50.00	04.17	Wood.02	75.00	15.22

As it can be seen in these tables, stochasticity based retrieval is relevant for most textures given in this database. Low TPRs occur when texture is very regular (Example: “Tile.0001”, “Tile.0007”), see Figure 7. High FARs occur when texture have non-homogeneous subimages (Example: “Wood.0001”): the bounds define a large interval which is expected to contain stochasticity values related to many other textures, see Figure 7.

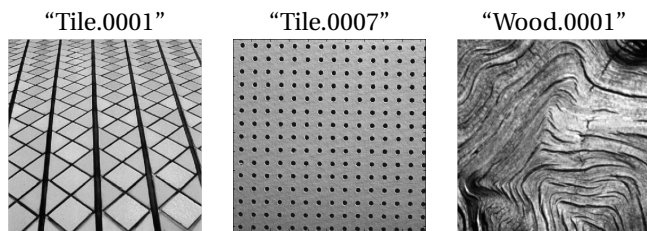


Fig. 7. Textures “Tile.0001”, “Tile.0007”, “Wood.0001” from the VisTeX album.

Experiments on the Brodatz album yield approximately the same results. The global TPR is 69% for the Brodatz album (resp. 70% for the VisTeX album) and the global FAR is 10% for the Brodatz album (resp. 7% for the VisTeX album), when GG modeling is used for stochasticity measurements. Tables concerning Brodatz album are omitted because 111 textures are concerned by the tests.

## VI. CONCLUSION

The paper has addressed semantic texture description and understanding through stochasticity or randomness appearance. The framework used for measuring stochasticity is that of the wavelet bases because of their suitable statistical properties. The Kolmogorov stochasticity parameter is shown to be relevant for pointing out deterministic smooth patterns from wavelet coefficients of textures. The relevance of the stochasticity consideration is proven to be efficient

for classification, database structuring and content-based image retrieval involving textured images.

Open issues related to this work may concern the analysis and the interpretation of the sequence of wavelet subband stochasticity parameters. In this work, we have considered the whole stochasticity hypercube obtained from the minimum and the maximum values of the stochasticity parameters of texture training samples. However, more investigations need to be performed in order to derive, among these sequences of parameters, some clusters or the manifold that describes well the observed stochasticity sequences.

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