

Advances in Computer Vision

Michal Haindl  
Jiří Filip

Visual

Accurate Material A

# **Advances in Computer Vision and Pattern Recognition**

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Michal Haindl • Jiří Filip

# Visual Texture

Accurate Material Appearance  
Measurement, Representation  
and Modeling

 Springer

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*To our families, for their continuous support*

# Preface

The main purpose of this book is to provide a comprehensive state-of-the-art survey of the newly emerging area of physically correct visual texture modeling. Multi-dimensional visual texture is the appropriate paradigm for physically correct representation of material visual properties. The book presents recent advance in the texture modeling methodology used in computer vision, pattern recognition, computer graphics, and virtual and augmented reality applications.

While texture analysis is a well-established research field, it is still predominantly restricted to the simplest and most approximate texture representation—either gray-scale or color textures. Several books devoted to such simple static texture analysis have been published, but there is no book dedicated to either the area of more general texture modeling or recent state-of-the-art textural representations.

Several features set our book apart from the few other visual texture books published.

- The only book with comprehensive treatment of texture synthesis.
- The only book covering all known aspects of the most advanced visual surface representation which can be recently applied—the Bidirectional Texture Function (BTF).
- The right timing. This book arrives at a time of advanced computing and graphics hardware which can process and store enormous amounts of data needed for physically correct material modeling and recognition; likewise, recent GPU programming progress allows users to utilize relatively intuitive and economical programming. This allows for fast implementation, thereby enabling real industrial applications of the presented methods.
- A complete reference. This self-contained book covers the entire pipeline from material appearance representation, measurement, analysis, and compression, to modeling, editing, visualization, and perceptual evaluation.

Recent progress in computing and acquisition technology of advanced visual data, together with advances in theories of mathematical modeling, provide us with timely opportunity to achieve new breakthroughs beyond the current state of computer vision art. Finally, it is possible to measure not only the ordinary static color

textures, but also the far more complicated and accurate high-dimensional visual texture representations.

Natural visual textures provide ample information about local lighting field structure as well as the surface relief, accounting for such effects as self-occlusions, self-shadowing, inter-reflection or subsurface scattering. Moreover, the appearance of real materials dramatically changes with, for example, illumination and viewing variations. The prevailing computer vision methodology uses only a small fraction of this readily available and potentially rich information source, but we believe that this emerging research area will soon have significant impacts on further progress in artificial visual cognition and related applications. Our aim is thus to offer the first book with this focus, in order to foster this development.

The book builds on the authors' work in this field over two decades and was inspired by positive feedback to several of our tutorials: *Bidirectional Texture Function Modelling* at CVPR 2010, San Francisco, *Accurate Material Appearance Modelling* at SCIA 2011, Ystad, *Advanced Textural Representation of Materials Appearance* at SIGGRAPH 2011, Hong Kong, and *Advanced Nature Exteriors Modelling* at ICPR 2012, Tsukuba.

The book starts from the basic principles and builds on the fundamentals and basic visual texture taxonomy introduced as a foundation for using the latest techniques in texture modeling. The reader is expected to possess graduate level knowledge in statistics and probability theory as well as competence in basic computer graphics principles. However, it is also suitable for newcomers to the field of computer graphics and computer vision, as well as for practitioners who wish to be brought up to date on the state-of-the-art methodology of texture modeling. This survey book will provide a useful reference and textbook for researchers, lecturers, industry practitioners, and students interested in this new and progressive research area.

We tried to keep the book as concise as possible to maintain its scope at an acceptable level. Rather than explaining mathematical and implementation details of all methods, we refer to the original publications. Our ambition was to provide the reader with general knowledge about state-of-the-art visual texture modeling. Attempting to rigorously explain, for example, the Markovian or mixture models used in this book would require at least twice as many pages.

Prague, Czech Republic

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# List of Abbreviations

## *Acronyms*

2D BM	2D Bernoulli Distribution Mixture Model
2D CAR	2D Causal Auto-Regressive Model
2D DM	2D Probabilistic Discrete Mixture Model
2D GM	2D Gaussian Mixture Model
2D GMRF	2D Gaussian Markov Random Field
3D CAR	3D Causal Auto-Regressive Model
3D CMRF	3D Compound Markov Model
3D GMRF	3D Gaussian Markov Random Field
3D NCMRF	3D Partially Non-parametric Compound Markov Model
3D PCMRF	3D Potts Compound Markov Model
3D PMRF	3D Gaussian Pseudo-Markov Random Field
3D SAR	3D Simultaneous Auto-Regressive Model
ABRDF	Apparent Bidirectional Reflectance Distribution Function
BDTF	Bidirectional Dynamic Texture Function
BRDF	Bidirectional Reflectance Distribution Function
BRTTF	Bidirectional Reflectance Transmittance Texture Function
BSDF	Bidirectional Scattering Distribution Function
BSSRDF	Bidirectional Surface Scattering Reflectance Distribution Function
BTDF	Bidirectional Transmittance Distribution Function
BTF	Bidirectional Texture Function
CAR	Causal Auto-Regressive
CN	Contextual Neighborhood
CPU	Central Processing Unit
DPI	Dot Per Inch
DMT	Dynamic Multispectral Texture
DT	Dynamic Texture

EM	Expectation Maximization algorithm
FFT	Fast Fourier Transformation
FIR	Finite Impulse Response
GL	Gaussian–Laplacian pyramid
GPU	Graphics Processing Unit
GRF	General Reflectance Function
HDR	High Dynamic Range
IBRDF	Isotropic Bidirectional Reflectance Distribution Function
K-L	Karhunen–Loeve expansion
LDR	Low Dynamic Range
LDS	Linear Dynamical System
LED	Light Emitting Diode
LOD	Level Of Details
LTS	Local Texture Space
MAE	Mean Average Error
MCMC	Markov Chain Monte Carlo methods
MDS	Multi-Dimensional Scaling
MRF	Markov Random Field
MSE	Mean Squared Error
NR	Near-Regular texture
PCA	Principal Component Analysis
PSNR	Peak Signal-to-Noise Ratio
RBF	Radial Basis Functions
RGB	Red, Green, and Blue color space
SLF	Surface Light Field
SNR	Signal-to-Noise Ratio
SRF	Surface Reflectance Field
SSIM	Structure Similarity Index Metric
ST	Static Multispectral Texture
STAR	Spatio-Temporal Autoregressive model
SVBRDF	Spatially Varying Bidirectional Reflectance Distribution Function
VDP	Visual Difference Predictor
VR	Virtual Reality

*Basic Notation and Convention*

$A \setminus B$	set of $A$ elements which are not in $B$
$\mathbf{b}_i, \mathbf{b}_v$	barycentric weights
$\mathbf{B}$	local surface bitangent (orthogonal to normal and tangent)
$D()$	facets distribution function
$E$	expectation
$f_d$	diffuse reflectance
$f_s$	specular reflectance at normal incidence
$F()$	Fresnel function
$G$	graph
$G()$	shadowing/masking function
$H()$	transfer function
$I$	discrete $d$ -dimensional rectangular lattice of $N_1 \times \dots \times N_d$ size ( $N \times M$ for $d = 2$ )
$I_r$	neighborhood system associated with $I$
$I_{(r)}$	discrete rectangular lattice $I$ except the site $r$
$I_r^*$	non-symmetric half-plane of $I_r$
$I_r^u$	unilateral neighborhood
$I_r^c$	causal neighborhood
$I_r^2$	the second-order hierarchical neighborhood
$k_d$	diffuse coefficient
$k_s$	specular coefficient
$L$	radiance/random field, line field
$M$	number of rows
$\mathbf{M}$	matrix of eigen-vectors weighting coefficients
$N$	number of columns
$\mathbf{N}$	local surface normal (equivalent to $\omega_n$ )
$n$	refraction index
$n_i$	number of spatial illumination angles
$n_l$	number of lobes of a reflectance model
$n_p$	rank of polynomial
$n_v$	number of spatial viewing angles
$R_e$	autocovariance function
$S_Y$	spectral density function
$(s, t)$	texture mapping coordinates
$\mathbf{T}$	local surface tangent
$\mathbf{v}$	vertex coordinate
$\hat{\mathbf{U}}$	a subset of applied eigen-vectors
$\tilde{X}$	corrupted observable image
$\check{X}$	a CMRF control random field
$Y$	random field, true unobservable image
$Y^{(0)}$	random field at fine resolution ( $Y^{(1)}$ coarser resolution)
$Y_r$	random variable at the site $r$
$Y_{(r)}$	random field except the random variable $Y_r$
$\tilde{Y}_r$	centered random variable

$Z$	Gibbs normalization constant
$\mathcal{D}$	intrinsic dimensionality (BTF dimensionality)/ non-negative diagonal matrix containing eigen-values
$\mathcal{E}_V$	class of extreme elements of $\mathfrak{N}_V$
$\mathcal{F}$	Fourier (discrete, continuous) or Z transformation
$\mathcal{L}$	(log-)likelihood function
$\mathcal{N}()$	Gaussian distribution
$\mathcal{R}$	space of real numbers
$\mathcal{Z}$	space of integers
$\alpha$	specular parameter
$\gamma$	parameter vector/guess rate (response to zero stimulus)
$\theta$	elevation angle (measured from surface normal)/parameter vector
$\lambda$	eigenvalue/parameter/miss rate (response to large stimulus)
$\rho()$	autocorrelation, sample correlation function
$\rho$	material albedo coefficient
$\varphi$	azimuthal angle
$\sigma$	width of isotropic specular lobe
$\sigma^2$	variance
$\sigma_x, \sigma_y$	width of anisotropic specular lobe
$\psi$	psychometric function
$\omega = \{\omega_1, \dots, \omega_{N \times M}\}$	the interpretation random vector for the lattice $I$ , $\omega_i \in \hat{\Omega}$
$\omega_i$	illumination (incoming) direction
$\omega_v$	viewing (outgoing) direction
$\omega_h$	half-way direction (between illumination and viewing direction)
$\omega_n$	direction of surface normal
$\omega_t$	transmittance direction (measured from inverted surface normal)
$\omega_r$	direction of an ideal mirror reflection
$\Omega$	a set of all possible configurations of $Y$ on $I$
$\hat{\Omega} = \{\hat{\omega}_1, \dots, \hat{\omega}_K\}$	set of all possible interpretation labels
•	all possible values of the corresponding index
$\otimes$	Kronecker product/convolution operator
$\ \cdot\ $	norm of a matrix

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# Chapter 1

## Motivation

**Abstract** Visual information is the most important information on which the majority of all living organisms base their cognition and survival strategy. A visual scene has two important cognitive categories, which are crucial for image understanding: shapes and materials. This book focuses on the latter category—visual aspects of surface materials which manifest themselves as visual textures. Visual texture is of key importance for recognition of objects as well as for estimation of their properties. Pixels, as the basic elements of any digitized visual texture, are known to be highly spatially, and spectrally correlated, but they are also correlated in the time or viewing and illumination angular spaces. Representations of visual textures which respect these multi-dimensional visual space correlations thus form an advantageous foundation for any advanced visual information processing applied to both cognitive (analysis) and modeling (synthesis) purposes.

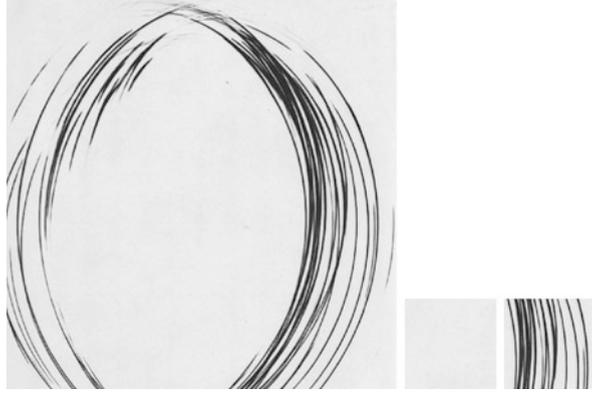
### 1.1 Visual Texture Definition

The notion of texture comes from Latin word *texere* which means to weave; and *textura* is a weaving, web, structure. Its meaning may, according to *Oxford* or *Webster's dictionaries*, be any of these:

- The process or art of weaving; the fabricating or composing of schemes, writings, etc. A woven fabric, or any natural structure having an appearance or consistence as if woven.
- The character of a textile fabric (fine, coarse, close, loose, etc.) resulting from a way in which it is woven.
- The constitution, structure, or substance of anything with regard to its constituents or formative elements.
- Something composed of closely interwoven or intertwined threads, strands, or the like elements.
- The essential part of something, an identifying quality.
- The size and organization of small constituent part of a body or substance; the visual or tactile surface characteristics and appearance of something.

The exact meaning of texture depends on the application area. While in geology it is a physical appearance or rock character, in material science it is a distribution

**Fig. 1.1** Brodatz “texture” D44 [1] and two of its cutouts



of crystallographic orientations, in soil research it describes the proportion of grain sizes, in cosmology it is a type of a topological defect, for artists it is the look and feel of the canvas, for graphic designers it is often any image mapped onto a surface, etc.

Although the notion of visual texture is tied to the human semantic meaning and texture analysis is an important area of image processing, there is no mathematically rigorous definition of texture that would be accepted throughout the computer vision community. Sometimes even its interpretation is subjective. E.g., is the Brodatz [1] texture D44 (Fig. 1.1) really a texture? This image obviously violates the homogeneity condition (see below), if not others as well. Rather than enlarging the list of rather philosophical definitions of texture, we understand a textured image or the *visual texture* to be a realization of a random field, and our effort is simply to find its parameterizations in such a way that the real texture representing certain material appearance measurements will be visually indiscernible from the corresponding random field’s realization, whatever the observation conditions might be. Some work distinguishes between texture and color. We regard such separation between spatial structure and spectral information to be artificial and principally wrong because there is no bijective mapping between grayscale and multi-spectral textures. Thus our random field model is always multispectral.

The notion of a visual texture is based on several ingredients:

*Homogeneity:* A texture is homogeneous if its spatial covariance function is translation invariant.

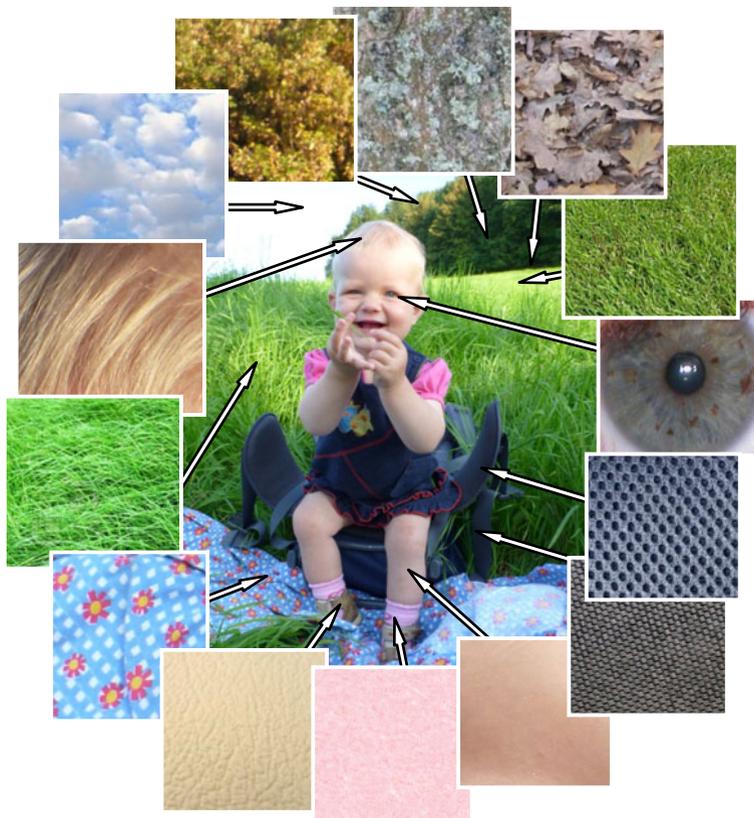
*Uniform structure:* Texture consists of some uniformly arranged elements (texels or textons). This arrangement is approximately the same everywhere within the textured region.

*Variable reflectance:* Texture is manifested by locally variable reflectance even if it is globally uniformly illuminated.

*Scale dependency:* Based on the resolution scale any surface material can appear as smooth (low resolution) or textured (high resolution).

*Regionality:* Texture is a property of an image region.

*Materiality:* Texture represents a surface material appearance.



**Fig. 1.2** Visual textures represent an omnipresent natural part of the real world

Visual textures form a natural part of our environment as we are learning to understand, estimate and predict their properties solely based on their visual appearance (Fig. 1.2); however, they are also an integral part of any plausible virtual world (Fig. 1.3).

As appearance of the visual textures depends heavily on the lighting and viewing conditions (Fig. 1.4), this dependency should be taken into account in various application scenarios.

This large range of the real-scene variable illumination and viewing condition is illustrated in the fish-eye image from the Prague Metro (Fig. 1.5). The subway station contains several materials (stone tiles, ceramic tiles, aluminum panels, stainless steel, lacquered iron, glass) and identical illumination lights placed at regular distances. Reflectance variations are clearly visible on floor stone tiles and stainless steel columns as well as on the aluminum wall panels. Even the textile overcoat and leather handbag of the lady standing in the foreground show clear material illumination dependency.