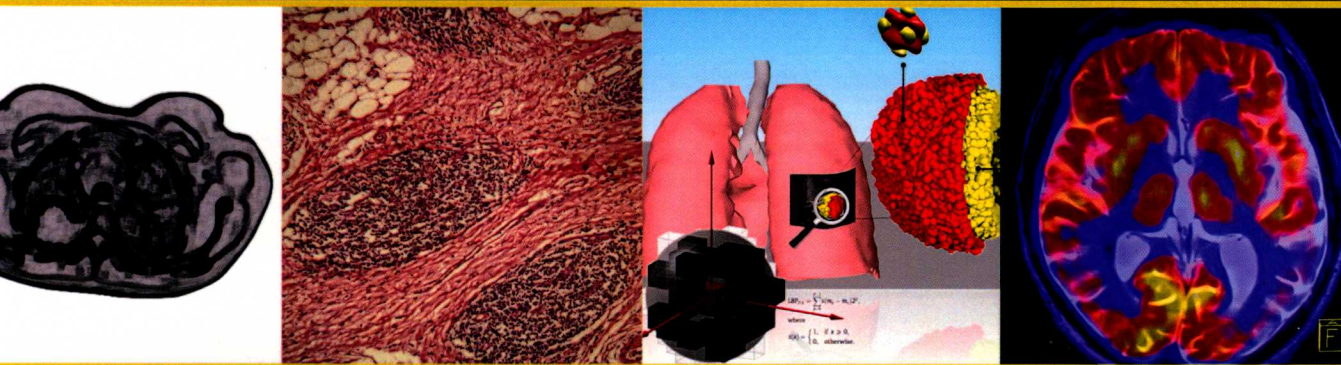


BIOMEDICAL TEXTURE ANALYSIS

FUNDAMENTALS, TOOLS
AND CHALLENGES



Edited by
Adrien Depeursinge,
Omar S Al-Kadi, and J. Ross Mitchell



BIOMEDICAL TEXTURE ANALYSIS

Fundamentals, Tools and Challenges

Edited by

ADRIEN DEPEURSINGE

University of Applied Sciences Western Switzerland
(HES-SO)

OMAR S. AL-KADI

King Abdullah II School for Information Technology,
University of Jordan

J. ROSS MITCHELL

Mayo Clinic College of Medicine,
and Department of Biomedical Informatics
at Arizona State University, USA



ACADEMIC PRESS

An imprint of Elsevier

Academic Press is an imprint of Elsevier
125 London Wall, London EC2Y 5AS, United Kingdom
525 B Street, Suite 1800, San Diego, CA 92101-4495, United States
50 Hampshire Street, 5th Floor, Cambridge, MA 02139, United States
The Boulevard, Langford Lane, Kidlington, Oxford OX5 1GB, United Kingdom

Copyright © 2017 Elsevier Ltd. All rights reserved.

No part of this publication may be reproduced or transmitted in any form or by any means, electronic or mechanical, including photocopying, recording, or any information storage and retrieval system, without permission in writing from the publisher. Details on how to seek permission, further information about the Publisher's permissions policies and our arrangements with organizations such as the Copyright Clearance Center and the Copyright Licensing Agency, can be found at our website: www.elsevier.com/permissions.

This book and the individual contributions contained in it are protected under copyright by the Publisher (other than as may be noted herein).

Notices

Knowledge and best practice in this field are constantly changing. As new research and experience broaden our understanding, changes in research methods, professional practices, or medical treatment may become necessary.

Practitioners and researchers must always rely on their own experience and knowledge in evaluating and using any information, methods, compounds, or experiments described herein. In using such information or methods they should be mindful of their own safety and the safety of others, including parties for whom they have a professional responsibility.

To the fullest extent of the law, neither the Publisher nor the authors, contributors, or editors, assume any liability for any injury and/or damage to persons or property as a matter of products liability, negligence or otherwise, or from any use or operation of any methods, products, instructions, or ideas contained in the material herein.

Library of Congress Cataloging-in-Publication Data

A catalog record for this book is available from the Library of Congress

British Library Cataloguing-in-Publication Data

A catalogue record for this book is available from the British Library

ISBN: 978-0-12-812133-7

For information on all Academic Press publications
visit our website at <https://www.elsevier.com/books-and-journals>



Working together
to grow libraries in
developing countries

www.elsevier.com • www.bookaid.org

Publisher: Mara Conner
Acquisition Editor: Tim Pitts
Editorial Project Manager: Andrae Akeh
Production Project Manager: Paul Prasad Chandramohan
Designer: Victoria Pearson Esser

Typeset by VTeX

The Elsevier and MICCAI Society Book Series

Advisory board

Stephen Aylward (*Kitware, USA*)

David Hawkes (*University College London, United Kingdom*)

Kensaku Mori (*University of Nagoya, Japan*)

Alison Noble (*University of Oxford, United Kingdom*)

Sonia Pujol (*Harvard University, USA*)

Daniel Rueckert (*Imperial College, United Kingdom*)

Xavier Pennec (*INRIA Sophia-Antipolis, France*)

Pierre Jannin (*University of Rennes, France*)

Also available:

Balocco, Computing and Visualization for Intravascular Imaging and
Computer Assisted Stenting, 9780128110188

Wu, Machine Learning and Medical Imaging, 9780128040768

Zhou, Medical Image Recognition, Segmentation and Parsing,
9780128025819

PREFACE

Computerized recognition and quantification of texture information has been an active research domain for the past 50 years, with some of the pioneering work still widely used today. Recently, the increasing ubiquity of imaging data has driven the need for powerful image analysis approaches to convert this data into knowledge. One of the most promising application domains is biomedical imaging, which is a key enabling technology for precision medicine (e.g., radiomics and digital histopathology) and biomedical discovery (e.g., microscopy). The colossal research efforts and progress made in the general domain of computer vision have led to extremely powerful data analysis systems. Biomedical imaging relies upon well-defined acquisition protocols to produce images. This is quite different from general photography. Consequently, the analysis of biomedical images requires a paradigm change to account for the quantitative nature of the imaging process. Texture analysis is a broadly applicable, powerful technology for quantitative analysis of biomedical images.

The aims of this book are:

- Define biomedical texture precisely and describe how it is different from general texture information considered in computer vision;
- Define the general problem to translate 2D and 3D texture patterns from biomedical images to visually and biologically relevant measurements;
- Describe with intuitive concepts how the most popular biomedical texture analysis approaches (e.g., gray-level matrices, fractals, wavelets, deep convolutional neural networks) work, what they have in common, and how they are different;
- Identify the strengths, weaknesses, and current challenges of existing methods including both handcrafted and learned representations, as well as deep learning. The goal is to establish foundations for building the next generation of biomedical texture operators;
- Showcase applications where biomedical texture analysis has succeeded and failed;
- Provide details on existing, freely available texture analysis software. This will help experts in medicine or biology develop and test precise research hypothesis.

This book provides a thorough background on texture analysis for graduate students, and biomedical engineers from both industry and academia who have basic image processing knowledge. Medical doctors and biologists with no background in image processing will also find available methods and software tools for analyzing textures in medical images.

By bringing together experts in data science, medicine, and biology, we hope that this book will actively promote the translation of incredibly powerful data analysis

methods into several breakthroughs in biomedical discovery and noninvasive precision medicine.

Adrien Depeursinge, Omar S. Al-Kadi, J. Ross Mitchell

CONTENTS

Preface

xiii

1. Fundamentals of Texture Processing for Biomedical Image Analysis	1
Adrien Depeursinge, Julien Fageot, Omar S. Al-Kadi	
1.1. Introduction	1
1.2. Biomedical texture processes	3
1.2.1. Image intensity versus image texture	3
1.2.2. Notation and sampling	5
1.2.3. Texture functions as realizations of texture processes	7
1.2.4. Primitives and textons	9
1.2.5. Biomedical image modalities	12
1.3. Biomedical Texture Analysis (BTA)	12
1.3.1. Texture operators and aggregation functions	12
1.3.2. Normalization	18
1.3.3. Invariances	19
1.4. Conclusions	23
Acknowledgements	24
References	24
2. Multiscale and Multidirectional Biomedical Texture Analysis	29
Adrien Depeursinge	
2.1. Introduction	29
2.2. Notation	31
2.3. Multiscale image analysis	31
2.3.1. Spatial versus spectral coverage of linear operators: the uncertainty principle	32
2.3.2. Region of interest and response map aggregation	34
2.4. Multidirectional image analysis	38
2.4.1. The Local Organization of Image Directions (LOID)	40
2.4.2. Directional sensitivity of texture operators	41
2.4.3. Locally rotation-invariant operators and moving frames representations	44
2.4.4. Directionally insensitive, sensitive, and moving frames representations for texture classification: a quantitative performance comparison	46
2.5. Discussions and conclusions	48
Acknowledgements	50
References	50
3. Biomedical Texture Operators and Aggregation Functions	55
Adrien Depeursinge, Julien Fageot	
3.1. Introduction	55

3.2. Convolutional approaches	57
3.2.1. Circularly/spherically symmetric filters	59
3.2.2. Directional filters	59
3.2.3. Learned filters	71
3.3. Gray-level matrices	79
3.3.1. Gray-Level Cooccurrence Matrices (GLCM)	80
3.3.2. Gray-Level Run-Length Matrices (GLRLM)	81
3.3.3. Gray-Level Size Zone Matrices (GLSZM)	82
3.4. Local Binary Patterns (LBP)	84
3.5. Fractals	87
3.6. Discussions and conclusions	89
Acknowledgements	91
References	91
4. Deep Learning in Texture Analysis and Its Application to Tissue Image Classification	95
Vincent Andrearczyk, Paul F. Whelan	
4.1. Introduction	95
4.2. Introduction to convolutional neural networks	96
4.2.1. Neurons and nonlinearity	96
4.2.2. Neural network	97
4.2.3. Training	98
4.2.4. CNN	101
4.3. Deep learning for texture analysis: literature review	105
4.3.1. Early work	105
4.3.2. Texture specific CNNs	106
4.3.3. CNNs for biomedical texture classification	107
4.4. End-to-end texture CNN: proposed solution	108
4.4.1. Method	109
4.4.2. Experiments	111
4.4.3. Results and discussions	113
4.4.4. Combining texture and shape analysis	118
4.5. Application to tissue images classification	119
4.5.1. State-of-the-art	120
4.5.2. Method	120
4.5.3. Datasets	121
4.5.4. Results and discussions	124
4.6. Conclusion	126
References	126
5. Fractals for Biomedical Texture Analysis	131
Omar S. Al-Kadi	
5.1. Introduction	131
5.2. Tissue texture	133

5.3. Basic concepts of fractal geometry	136
5.3.1. Self-similarity	136
5.3.2. Ordered hierarchy	137
5.3.3. Degree of irregularity	137
5.4. Methods for computing fractal dimensions	140
5.4.1. Differential Box-Counting (DBC) method	141
5.4.2. Fractional Brownian motion methods	142
5.4.3. Area-based methods	143
5.5. Types of fractals	146
5.6. FD parameter estimation optimization	147
5.7. Lacunarity analysis	148
5.7.1. Assessing image texture sparsity	148
5.7.2. Rotation-invariance	150
5.7.3. Clinical significance	150
5.8. Tumor tissue characterization	152
5.8.1. Surface roughness	153
5.8.2. Tumor fractal analysis	154
5.9. Considerations for fractal analysis	157
5.9.1. Choosing a suitable method for estimating the FD	157
5.9.2. Multivariate fractal analysis	157
5.9.3. Performing fractal or multifractal analysis	157
5.10. Conclusion	157
References	158
6. Handling of Feature Space Complexity for Texture Analysis in Medical Images	163
Yang Song, Weidong Cai	
6.1. Introduction	163
6.2. Applications of texture analysis	164
6.2.1. Lesion detection	164
6.2.2. Disease categorization	166
6.2.3. Image retrieval	167
6.3. Review of classification methods	168
6.3.1. Ensemble classification	169
6.3.2. Subcategorization	170
6.3.3. Sparse representation	170
6.4. Subcategory-based ensemble classification	171
6.4.1. Large Margin Local Estimate (LMLE)	172
6.4.2. Locally-constrained subcluster representation ensemble	176
6.5. Experiments	179
6.5.1. Dataset and implementation	179
6.5.2. Results of patch classification	181
6.6. Conclusions	186
References	186

7. Rigid Motion Invariant Classification of 3D Textures and Its Application to Hepatic Tumor Detection	193
Sanat Upadhyay, Saurabh Jain, Manos Papadakis	
7.1. Introduction	193
7.2. Isotropic multiresolution analysis	198
7.3. Implementing rotations with compactly supported refinable functions	204
7.4. Connecting IMRA with stochastic texture models using Gaussian Markov Random Fields (GMRF)	206
7.5. Feature space for rotationally invariant texture discrimination	211
7.5.1. Self-distance for 3D textures	212
7.6. 3D texture-based features	212
7.7. Conclusion	215
References	218
8. An Introduction to Radiomics: An Evolving Cornerstone of Precision Medicine	223
Sara Ranjbar, J. Ross Mitchell	
8.1. Introduction	223
8.2. Background on cancer care	224
8.2.1. Biomarkers and cancer care	226
8.2.2. Limitations of response assessment process	227
8.2.3. Limitations of characterization process	228
8.2.4. Limitations of current biomarkers	229
8.3. The potential areas of radiomics utility	229
8.4. Workflow of radiomics	231
8.4.1. Image acquisition	232
8.4.2. Segmentation	233
8.4.3. Feature extraction	234
8.4.4. Analysis and validation	235
8.5. Examples of radiomics literature	236
8.6. Challenges of radiomics	238
8.7. Conclusions	239
References	239
9. Deep Learning Techniques on Texture Analysis of Chest and Breast Images	247
Jie-Zhi Cheng, Chung-Ming Chen, Dinggang Shen	
9.1. Introduction	247
9.2. Computer-aided detection	248
9.2.1. Lung nodule detection in CT scans	249
9.2.2. Other detection problems for CT scans	252
9.3. Computer-aided diagnosis	253
9.3.1. Computer-aided diagnosis on breast lesions in ultrasound images	255
9.3.2. Computer-aided diagnosis on pulmonary nodules in CT scans	259
9.3.3. Other computer-aided diagnosis problems in pulmonary CT scans	264

9.4. Automatic mapping from image content to the semantic terms	265
9.4.1. Semantic mapping with the conventional pattern recognition paradigm	266
9.4.2. Deep learning for semantic mapping	268
9.5. Conclusion	273
Acknowledgements	273
References	273
10. Analysis of Histopathology Images	281
Oscar Jimenez-del-Toro, Sebastian Otálora, Mats Andersson, Kristian Eurén, Martin Hedlund, Mikael Rousson, Henning Müller, Manfredo Atzori	
10.1. Histopathology imaging: a challenge for texture analysis	281
10.2. Traditional machine learning approaches	284
10.2.1. Preprocessing	284
10.2.2. Detection and segmentation of structures	285
10.2.3. Feature extraction	286
10.2.4. Feature selection and dimensionality reduction	287
10.2.5. Classification	288
10.3. Deep learning approaches	289
10.3.1. Supervised and unsupervised feature learning architectures	290
10.3.2. Deep convolutional neural networks	292
10.3.3. Deep learning approaches to histopathology image analysis	292
10.4. Histopathology challenges	295
10.4.1. Datasets	295
10.4.2. Tasks	296
10.4.3. Evaluation metrics	297
10.5. Detecting mitoses	299
10.6. Frame and whole slide image classification	302
10.7. Structure segmentation	303
10.8. Discussion and conclusions	306
Acknowledgements	308
References	308
11. MaZda – A Framework for Biomedical Image Texture Analysis and Data Exploration	315
Piotr M. Szczypiński, Artur Klepaczko	
11.1. Introduction	315
11.1.1. Related work	317
11.2. Texture analysis with MaZda	318
11.2.1. Overview of the image analysis workflows	318
11.2.2. Regions of interest	321
11.2.3. Feature extraction	322
11.2.4. Image preprocessing	326
11.2.5. Feature naming convention	327
11.2.6. Feature maps and image segmentation	328

11.2.7. Machine learning	330
11.3. Applications	334
11.3.1. Lesion detection with MaZda and Weka	337
11.4. Summary	342
Appendix 11.A	343
11.A.1. List of feature name symbols	343
11.A.2. List of implemented methods	344
References	345
12. QuantImage: An Online Tool for High-Throughput 3D Radiomics Feature Extraction in PET-CT	349
Yashin Dicente Cid, Joël Castelli, Roger Schaer, Nathaniel Scher, Anastasia Pomoni, John O. Prior, Adrien Depeursinge	
12.1. Introduction	349
12.2. Methods	352
12.2.1. PET-CT alignment	352
12.2.2. Intensity-based features	353
12.2.3. Distance features: measures of cancer invasiveness	356
12.2.4. Texture features	357
12.3. The QuantImage online image analysis platform	363
12.3.1. Parameter setting	364
12.3.2. File upload	367
12.3.3. Output CSV data structure	368
12.4. Discussions and conclusions	369
Acknowledgements	374
Appendix 12.A	374
References	374
13. Web-Based Tools for Exploring the Potential of Quantitative Imaging Biomarkers in Radiology	379
Roger Schaer, Yashin Dicente Cid, Emel Alkim, Sheryl John, Daniel L. Rubin, Adrien Depeursinge	
13.1. Introduction	379
13.2. Methods	383
13.2.1. Overview of ePAD	383
13.2.2. Quantitative imaging features	385
13.2.3. Feature aggregation	388
13.2.4. Classification	388
13.2.5. Web technologies	390
13.2.6. System architecture	391
13.3. Use-cases	394
13.3.1. Analysis of whole ROIs	395
13.3.2. Patch-based ROI analysis	399
13.3.3. Training a statistical model and classifying ROIs	402

13.3.4. Helper tools for segmentation	405
13.4. Discussion	407
13.5. Conclusions	408
Acknowledgements	408
References	409
<i>Index</i>	<i>411</i>

CHAPTER 1

Fundamentals of Texture Processing for Biomedical Image Analysis

A General Definition and Problem Formulation

Adrien Depeursinge^{*}, Julien Fageot[†], Omar S. Al-Kadi[‡]

^{*}École Polytechnique Fédérale de Lausanne (EPFL), Biomedical Imaging Group, Lausanne, Switzerland

[†]University of Applied Sciences Western Switzerland (HES-SO), Institute of Information Systems, Sierre, Switzerland

[‡]University of Jordan, King Abdullah II School for Information Technology, Amman, Jordan

Abstract

This chapter aims to provide an overview of the foundations of texture processing for biomedical image analysis. Its purpose is to define precisely what biomedical texture is, how is it different from general texture information considered in computer vision, and what is the general problem formulation to translate 2D and 3D textured patterns from biomedical images to visually and biologically relevant measurements. First, a formal definition of biomedical texture information is proposed from both perceptual and mathematical point of views. Second, a general problem formulation for biomedical texture analysis is introduced, considering that any approach can be characterized as a set of local texture operators and regional aggregation functions. The operators allow locally isolating desired texture information in terms of spatial scales and directions of a texture image. The type of desirable operator invariances are discussed, and are found to be different from photographic image analysis. Scalar-valued texture measurements are obtained by aggregating operator's response maps over regions of interest.

Keywords

Quantitative image analysis, Spatial stochastic process, Texton, Heterogeneity, Texture analysis

1.1 INTRODUCTION

Everybody agrees that nobody agrees on the definition of *texture* information. According to the Oxford Dictionaries¹ texture is defined as “the feel, appearance, or consistency of a surface or a substance.” The context in which the word *texture* is used is fundamental to attach unambiguous semantics to its meaning. It has been widely used in extremely diverse domains to qualify the properties of images, food, materials, and even music. In the context of food and sometimes material sciences, characterizing texture information often involves measuring the response of the matter subject to forces such as shearing, cutting, compressing, and chewing [1,2]. Starting from the early

¹ <https://en.oxforddictionaries.com/definition/texture>, as of October 10, 2016.

developmental months of newborn babies, tactile perception of textured surfaces is an important stage of the human brain development [3]. It is an essential step to be successfully acquainted with the physical properties of the surrounding environment [4]. To some extent, estimating the properties and diversity of the latter without having to touch every surface can be efficiently carried out through vision. Human vision learns to recognize texture patterns through extensive experimentation confronting visual and tactile perception of textured surfaces [5]. This provides hints on why human visual texture recognition performs much beyond the use of low level descriptive terms such as *coarse*, *edgy*, *directional*, *repetitive*, and *random*.

In the context of biomedical imaging, texture information relates to the micro- and macro-structural properties of biomedical tissue. Radiologists, pathologists, and biologists are trained to establish links between visual image patterns and underlying cellular and molecular content of tissue samples [6]. Unfortunately, very large variations of this complex mapping occur, resulting in image interpretation errors with potentially undesirable consequences [7–9]. These variations are partly due to the diversity of human biology and anatomy as well as image acquisition protocols and reconstruction, compounded by observer training. Important efforts were initiated by medical imaging associations to construct unified terminologies and grading scores in the context of radiology and histopathology, aiming to limit variations in image interpretation and reporting [10–13]. However, in the particular context of biomedical texture information, the terms used (*e.g.*, *heterogeneous enhancement*, *hypervascular* [12]) are often as inadequate as low level descriptive terms of general textures (*e.g.*, *coarse*, *edgy*) while the perception of human observers is much richer (see Sections 9.4.1 and 9.4.2 of Chapter 9). When considering three-dimensional architectures of biomedical tissue, human observers have limited intuition of these 3D solid textures, because they cannot be fully visualized [14]. Only virtual navigation in Multi-Planar Rendering (MPR) and semitransparent visualizations are made available by computer graphics and allow observing 2D projections.

Computer-based quantitative image texture analysis has a tremendous potential to reduce image interpretation errors and can make better use of the image content by yielding exhaustive, comprehensive, and reproducible analysis of imaging features in two and three dimensions [15–17]. Nevertheless, besides the lack of a clear definition of biomedical texture information, several challenges remain, such as: the lack of an appropriate framework for multiscale, multispectral analysis in 2D and 3D; validation; and, translation to routine clinical applications. The goal of this book is to illustrate the importance of these aspects and to propose concrete solutions for optimal biomedical texture analysis. This chapter will first propose a definition of texture in the particular context of biomedical imaging (Section 1.2). Second, a general theoretic framework for Biomedical Texture Analysis (BTA) will be proposed in Section 1.3. The latter is designed to best leverage the specific properties of biomedical textures. Differences with the classical texture analysis paradigm in computer vision will be highlighted.

Important aspects of texture operator and aggregation function design will be further discussed and illustrated through several concrete examples in Chapter 2. It will also recapitulate key aspects of biomedical texture processes and analysis, with an aim of raising awareness of limitations of popular texture operators used in the biomedical literature while providing directions to design the next generation of BTA approaches. Chapter 3 will use the comparison axes established in Chapters 1 and 2 to compare most popular modern biomedical texture analysis approaches. With the purpose of guiding neophyte or experienced users, a simple checklist is proposed to assess the relevance of the BTA approach in a particular medical or biological applicative context.

1.2 BIOMEDICAL TEXTURE PROCESSES

This section proposes an extensive definition of biomedical texture information under biological, medical, physical, statistical, and mathematical viewpoints.

1.2.1 Image intensity versus image texture

Low-level quantitative image analysis (*i.e.*, pixel-level²) can be separated into two main categories: intensity and texture. Image intensity relates to the statistical distribution of the pixel values inside a defined Region Of Interest (ROI). The pixel values can be either normalized across images (*e.g.*, Hounsfield Units (HU) in X-ray Computed Tomography (CT), Standardized Uptake Values (SUV) in Positron Emission Tomography (PET)), or unnormalized (*e.g.*, Hematoxylin and Eosin (H&E) stains in histopathology, Magnetic Resonance Imaging (MRI)). Classic quantitative measures of image intensity are the four statistical moments of the pixel values' distribution (mean, variance, skewness, and kurtosis). Other measures are specific to the considered imaging modality (*e.g.*, SUV max or Total Lesion Glycolysis (TLG) in PET) [18]. The latter are extremely useful to characterize the image content, but cannot measure the spatial relationships between pixel values (see Fig. 1.1). A qualitative keyword such as *tumor heterogeneity* is ambiguous because it is unclear if the heterogeneity concerns pixel values (intensity) or their spatial organization (texture). It is though commonly used to describe the visual aspect of tumors in radiological images with ambivalent meaning [19–21].

The spatial relationships (*i.e.*, the transitions) between pixel values are precisely what texture information is encoding. Haidekker defined texture as “a systematic local variation of image values” [22]. Petrou stated that “the most important characteristic of texture is that it is scale dependent” and that “different types of texture are visible at different scales” [23]. This highlights the importance of the variation *speed* or *slope* or *oscillation* between pixel values, which will be different in *smooth* versus *rough* textures (see Fig. 1.1 left and right). This first notion of the texture scale relates to the spatial

² The word *pixel* is used to design both 2D and 3D (*voxels*) image samples.

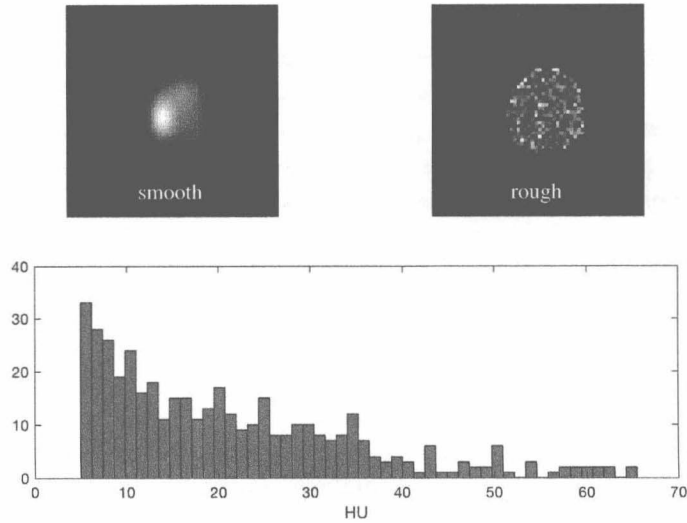


Figure 1.1 The two simulated tumors have identical distribution of the pixel's values and cannot be differentiated using intensity image measures only. They differ in the spatial relationships between the pixels, which is specifically captured by image texture analysis.

frequencies in the image. The higher the spatial frequency, the finer the scale of the transition between proximate pixel values. A second important notion is the direction of the transition. These two notions of spatial scale and direction are fundamental for visual texture discrimination (see Fig. 1.2) [24].

Blakemore et al. provided initial evidence that the human visual system possesses neurons that are selectively sensitive to directional spatial frequencies [25], which has been widely confirmed later on [26]. Most approaches proposed for computerized texture analysis are leveraging these two properties either explicitly (*e.g.*, Gray-Level Cooccurrence Matrices (GLCM) [27], Gray-Level Run Length Matrices (GLRLM) [28], Gray-Level Size Zone Matrices (GLSZM) [29], directional filterbanks and wavelets [30], Histogram of Oriented Gradients (HOG) [31], Local Binary Patterns (LBP) [32], Scattering Transforms (ST) [33,34]) or implicitly (*e.g.*, Convolutional Neural Networks (CNN) [35,36], Dictionary Learning (DL) [37–39]).

A natural mathematical tool to study directional spatial frequency components in D -dimensional signals and images is the Fourier transform and is defined in Eq. (1.1). It is straightforward to see that the Fourier transform for $\omega = 0$ computes the mean of the function, which is not considered as texture information since it relates the mean intensity of the pixels in the image. For $\|\omega\| > 0$ the modulus of the Fourier transform quantifies the magnitude of the transitions, where $\|\omega\|$ is inversely proportional to the scale and the orientation of the vector ω defines the direction of the spatial frequencies.