ELBA BIOFLUX

Extreme Life, Biospeology & Astrobiology
International Journal of the Bioflux Society

Texture analysis methods for the characterisation of biological and medical images

Ştefan Ţălu

The Technical University of Cluj-Napoca, Faculty of Mechanics, Department of AET, Discipline of Descriptive Geometry and Engineering Graphics, Cluj-Napoca, Romania. Corresponding author: Ş. Ţălu, stefan_ta@yahoo.com

Abstract. Adaptations can be extreme in many cases and they help organisms survive in their habitat or ecological niche. These adaptations can affect their anatomy, ethology or physiology. Anatomical adaptations are physical features such as animal's shape, particularities at the skeleton level, texture of exoskeleton, surface of the skin in animals or cuticula in plants etc. The purpose of this paper is to present a synthesis concerning the texture analysis methods used for the characterisation of biological and medical images. Texture analysis methods of biological and medical images provide noninvasive tools that allow biologists, physicians and researchers the early detection and diagnosis of diseases.
Key Words: Biology, biomedical image processing, medicine, texture analysis.

Rezumat. Adaptarea organismelor la mediu poate fi adesea extremă şi le ajută pe acestea să supravieţuiască în habitatul sau nişa lor ecologică. Aceste adaptări le pot afecta anatomia, etologia sau fiziologia. Adaptările anatomice sunt caractere de natură fizică, precum: forma corpului animalelor, particularităţi ale scheletului, textura exoscheletului, suprafaţa pielii animalelor sau a cuticulei la plante etc. Scopul acestei lucrări este de a prezenta o sinteză privind metodele de analiză a texturii utilizate pentru caracterizarea imaginilor biologice şi medicale. Metodele de analiză a texturii imaginilor biologice şi medicale furnizează instrumente neinvazive care permit biologilor, medicilor şi cercetătorilor detectarea precoce şi diagnosticarea bolilor.
Cuvinte cheie: Biologie, procesarea imaginii biomedicale, medicină, analiza texturii.

Introduction. Texture analysis is an important research field in image processing, pattern recognition and computer vision. The texture is a variable involved in specific adaptations of the living organisms from microorganisms to plants and vertebrates. These adaptations can affect the organism anatomically, ethologically or physiologically. Texture is related first of all to anatomical adaptations.

In the field of image analysis, no specific and universal definition has been given for the concept of texture and in general different researchers use different definitions depending upon the particular area of application (Tuceryan & Jain 1998).

One reason is that natural textures are neither completely structured nor purely stochastic, and often display different yet contradicting properties, which cannot be described easier in a unified manner.

The term "texture" was derived from the Latin "textura", the past participle of the verb texere, to weave (Reyes-Aldasoro & Bhalerao 2011).

In a general sense, image textures are defined as complex visual patterns composed of entities having characteristic brightness, colors, slopes, sizes etc. Thus, texture can be regarded as a similarity grouping in an image (Rosenfeld 1982; Materka & Strzelecki 1998).

The properties of the local subpattern give rise to the perceived lightness, uniformity, density, roughness, regularity, linearity, frequency, phase, directionality, coarseness, randomness, fineness, smoothness, and granulation, of the texture as a whole (Levine 1985; Materka & Strzelecki 1998).

Textures, as patterns of information or arrangements of the structures found in an image, could be broadly classified into two categories, namely, "tactile" and "visual" textures. By spatial homogeneity, textures can be classified into homogeneous, weakly-homogeneous, and inhomogeneous patterns (Zhou 2006).

Different techniques have been developed in the image processing literature for texture feature extraction, segmentation, classification, synthesis and shape from texture (Materka & Strzelecki 1998; Tuceryan & Jain 1998; Zhou 2006; Bankman 2008).

In Fig. 1 is represented a typical process of texture analysis in a computer vision system (Zhou 2006; Pham 2010). The algorithms of image enhancement can be assigned as pre- and postprocessing in all areas (Deserno 2011).

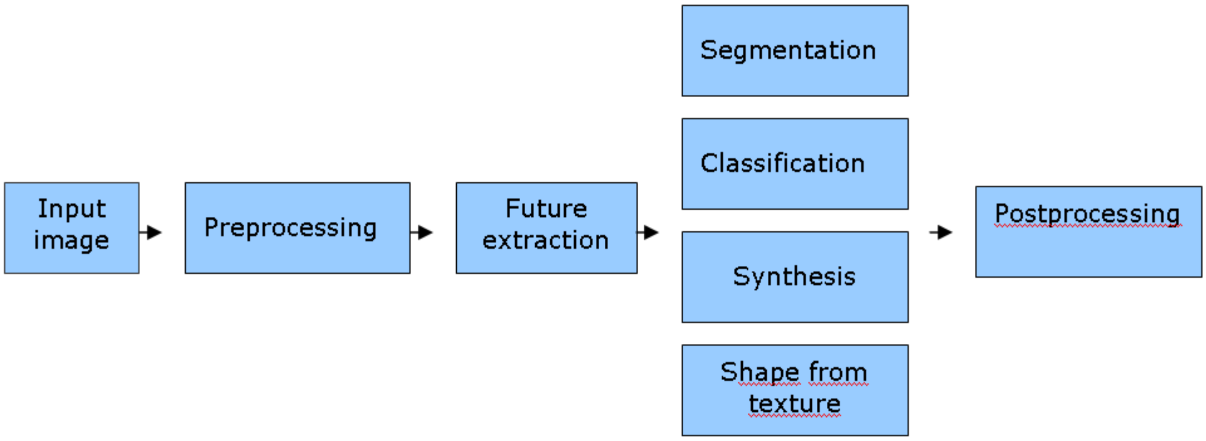

Figure 1. The components of a typical computer vision system.

The feature extraction is the first stage in all four types of texture analysis.

The first stage of image texture analysis is feature extraction (high level), which yields a characterisation of each texture class in terms of feature measures. It is necessary to identify and select distinguishing features that are invariant to irrelevant transformation of the image, such as translation, rotation, and scaling (geometric transformations) (Zhou 2006; Deserno 2011).

The main aim in feature extraction is to compute a characteristic of a digital image able to numerically describe its texture properties (Materka & Strzelecki 1998). Features, that contain the relevant information of an image, are divided into different classes based on the kind of properties they describe.

In image segmentation the purpose is to establish boundaries (lines, curves etc.) between different image regions, that is more meaningful and easier to analyze (Mirmehdi et al 2008; Nailon 2010). The texture boundaries, so that each region is homogeneous with respect to certain texture characteristics, can be established even it is not possible to classify the textured surfaces.

Segmentation methods can be categorized using various criteria. Texture segmentation could also be supervised or unsupervised depending on if prior knowledge about the image or texture class is available or not (Zhou 2006). However, segmentation is intrinsically more difficult than classification.

Supervised texture segmentation identifies and separates one or more regions that match texture properties previously learnt in training samples. Unsupervised texture segmentation has to discriminate the texture classes from an image before separating them into regions. Compared to supervised segmentation, the unsupervised case is more flexible for real world applications (Zhou 2006; Melendez et al 2010).

In texture classification the main aim is to produce a map which enables classification of the input image(s) to the desired classes (Tuceryan & Jain 1998). A classifier is a function which takes the selected features as inputs and texture classes as outputs (Zhou 2006). In this way a texture could be assigned to a specific category, based on the classifier. Texture classification can sort image data and make an image more interpretable for specific applications.

In three-dimensional computer graphics applications, the synthesis of image texture is the process of algorithmically constructing of complex and realistic looking surfaces from a set of compressed data.

Shape from texture is the problem of estimating a 3D surface shape by analysing texture property of a 2D image (Zhou 2006).

The texture analysis methods applied to an image allow the identification with precision of the boundaries between regions with different textures, where texture feature values change significantly.

In our paper, we consider the image texture as a function of the spatial variation in pixel intensities (gray values) (Tuceryan & Jain 1998). The spatial variation is a main characteristic of texture (Reyes-Aldasoro & Bhalerao 2011).

The texture, as a fundamental characteristic in many natural images, is a scale-dependent property, and each particular texture class usually has an optimum scale or resolution level for representation and feature extraction (Ruiz et al 2002). Different types of texture are visible at different scales.

In digital imaging, a two-dimensional digital image is made up of little rectangular blocks called pixels (picture elements), and a three-dimensional digital image is made up of little volume blocks called voxels (volumetric picture elements - considered as a 3D generalization of pixels); each is represented by a set of coordinates in space, and each has a value, representing the grey-level intensity of that picture or volume element in space (Castellano et al 2004).

In such a space, an implicit relationship exists between each element (pixel or voxel) with each of its neighbors, to create the texture. The texture of a single element cannot be described (Reyes-Aldasoro & Bhalerao 2011).

Since an image is made up of pixels, a group of related pixels can be considered as a texture minimal unit, called as texture primitives or texture elements (texels) (Srinivasan & Shobha 2008). Texture patterning in an image can be characterized as associations between texels.

The most usual approaches for texture description and analysis are traditionally classified into four categories: structural methods, statistical methods, model based-methods and transform-based methods (Materka & Strzelecki 1998; Castellano et al 2004). These different approaches require various computational algorithms with different efficiency to texture analysis.

In essence, the texture analysis allows the evaluation of the position and intensity of signal features, i.e. pixels or voxels, and their grey-level intensity in digital images. Mathematical parameters determined from the distribution of pixels characterize the texture type and implicit reflect the texture features (Castellano et al 2004).

While texture can be assessed by a set of features, these features are distorted due to the imaging process and the perspective projection (Tuceryan & Jain 1998)

In high-level processing of biomedical images, the term "semantic gap" refers to the discrepancy between the cognitive interpretation of a diagnostic image by the physician (high level) and the simple structure of discrete pixels, which is used in computer softwares to represent an image (low level) (Deserno 2011).

The structural methods. Structural approaches represent texture by well-defined primitives (called microtexture) and a hierarchy of spatial arrangements (called macrotexture) of those primitives.

In order to describe the texture, one needs to define the primitives and the placement rules. The choice of a primitive (from a set of primitives) and the probability of the chosen primitive to be placed at a particular location can be a function of location or the primitives near the location.

The structural approach allows a good symbolic description of the image (Levine 1985; Materka & Strzelecki 1998).

The statistical methods. Statistical approaches represent the texture indirectly by the non-deterministic properties that govern the distributions and relationships between the grey levels of an image (Materka & Strzelecki 1998).

Statistical methods can be used to analyze the spatial distribution of gray values, by computing local features at each point in the image and deriving a set of statistics from the distributions of the local features (Pham 2010).

Statistical methods describe the texture by a collection of statistics of selected features and provides the most efficient description on a variety of textured images (especially for biological and medical ones).

Based on the number of pixels defining the local feature, statistical methods are broadly classified into first-order (one pixel), second-order (pair of pixels) and higher-order (three or more pixels) statistics (Materka & Strzelecki 1998; Zhang & Tan 2002; Pham 2010; Nailon 2010).

The first-order statistics estimate properties (e.g. average, variance, coarseness, skewness, kurtosis, energy and entropy) of individual pixel values by waiving the spatial interaction between image pixels. In this case, the histogram of image intensity characterizes information on texture and because is measured the frequency of a particular grey-level at a random image position, no account correlations, or co-occurrences, between pixels are considered (Pham 2010; Nailon 2010). The benefit of this approach is its simplicity due to the use of standard descriptors.

The second-order and higher-order statistics estimate properties of two or more pixel values occurring at specific locations relative to each other (Zhang & Tan 2002; Pham 2010). Information on texture in second-order statistics is based on the probability of finding a pair of grey-levels at random distances and orientations over an entire image, whereas to higher-order statistics the number of variables studied increases (Nailon 2010).

The model based-methods. Model based approaches represent the texture in an image using complicated mathematical models (such as fractal or stochastic) (Materka & Strzelecki 1998; Castellano et al 2004; Zhou 2006; Ţălu 2012).

These methods describe an image as a probability model or as a linear combination of a set of basic functions (Zhang & Tan 2002). A disadvantage of these solutions is choosing the correct model suitable for the selected texture and the computational complexity involved in utilizing them.

Biofractals are the fractal textures/contours in biology whose properties aid in the classification of biological and medical data and images (Sztojánov et al 2009).

Fractal theory provides an extremely compact coding and computationally efficient methods that offers a new language for accurately examining of the complex textures found in biological and medical images (Losa et al 2005; Ţălu 2012).

The transform-based methods. Transform based approaches represent an image in a space whose co-ordinate system has an interpretation that is closely related to the characteristics of a texture (such as frequency or size).

These methods are based on the Fourier, Gabor or Wavelet transform. The Wavelet transform is the most widely and favoured tool by researchers (Materka & Strzelecki 1998; Zhang & Tan 2002; Castellano et al 2004; Pham 2010).

Conclusions. Adaptations can be extreme in many cases and they help organisms survive in their habitat or ecological niche. These adaptations can affect their anatomy, ethology or physiology. Anatomical adaptations are various physical features such as animal's shape, particularities at the skeleton level, texture of exoskeleton, shape of organs or parasitized tissues etc. The multitude of genetic variants corroborated with a lot of environmental combinations possible results in a great variability of the living organisms. Texture is such a variable of animals, plants and microbes and, therefore, biological and medical images possess a vast amount of texture information. The texture analysis methods are essential in automatic and semi-automatic systems for investigation of the biological structures and medical diagnosis support.

References

Bankman I. N. (ed.) 2008 Handbook of Medical Image Processing and Analysis, 2nd Edition, Academic Press, USA, ISBN: 978-0-12-373904-9.

Castellano G., Bonilha L., Li L. M., Cendes F. 2004 Texture analysis of medical images. Clinical Radiology **59**(12):1061-1069.
Deserno T. M. (ed.) 2011 Biomedical Image Processing (Biological and Medical Physics, Biomedical Engineering), Springer-Verlag Berlin, ISBN 978-3-642-15815-5.
Falconer K., 2003 Fractal Geometry: Mathematical Foundations and Applications, 2nd Edition, John Wiley & Sons Ltd.
Haidekker M. A., 2011 Advanced Biomedical Image Analysis, John Wiley & Sons Ltd.
Levine M., 1985 Vision in man and machine, McGraw-Hill, New York, USA.
Losa G. A., Merlini D., Nonnenmacher T. F., Weibel E. (eds.), 2005 Fractals in Biology and Medicine, Vol. IV. Mathematics and Biosciences in Interaction. Birkhäuser Verlag, Basel, Switzerland.
Materka A., Strzelecki M., 1998 Texture analysis methods - a review. Technical University of Lodz, Institute of Electronics, Poland: COST B11 Report.
Melendez J., Puig D., Garcia M. A., 2010 On Adapting Pixel-Based Classification to Unsupervised Texture Segmentation, 20th Int. Conference on Pattern Recognition, Proceedings, IEEE Computer Society, Istanbul, Turkey, August 2010, pp. 854-857.
Mirmehdi M., Xie X., Suri J. (eds), 2008 Handbook of texture analysis, Imperial College Press, 1-84816-115-8, UK.
Nailon W. H. 2010, Texture Analysis Methods for Medical Image Characterisation. In "Biomedical Imaging", pp. 75-100. Edited by: Youxin Mao, InTech, Croatia, ISBN 978-953-307-071-1.
Pham T. A., 2010 Optimization of Texture Feature Extraction Algorithm, MSc. Thesis, Delft University of Technology, The Netherlands.
Reyes-Aldasoro C. C., Bhalerao, A. H., 2011 Volumetric Texture Analysis in Biomedical Imaging. In "Biomedical Diagnostics and Clinical Technologies: Applying High-Performance Cluster and Grid Computing", by Pereira M., Freire M. (eds.), pp. 200-248, IGI Global, ISBN 978-1-60566-280-0.
Rosenfeld A., Kak A., 1982 Digital Picture Processing, vol. 1, Academic Press, New York.
Ruiz L. A., Fdez.-Sarría A., Recio J. 2002, Evaluation of texture analysis techniques to characterize vegetation. In "Recent Advances in Quantitative Remote Sensing", by Sabrino S.A. (ed.), pp. 514-522, University of Valencia, Spain, ISBN 84-370-5515-6.
Srinivasan G. N., Shobha G., Statistical Texture Analysis, PWASET, vol. 36, December 2008, pp. 1264-1269, ISSN 2070-3740.
Sztojánov I., Crişan D. A., Mina C. P., Voinea V., 2009 Image Processing in Biology Based on the Fractal Analysis. In "Image Processing", pp. 323-344. Edited by: Yung-Sheng Chen, InTech, Croatia, ISBN 978-953-307-026-1.
Tuceryan M., Jain A. K., 1998 Texture Analysis. In "The Handbook of Pattern Recognition and Computer Vision", 2nd Edition, by Chen C. H., Pau L. F., Wang P. S. P. (eds.), pp. 207-248. World Scientific Publishing Co., Singapore, ISBN 9-810-23071-0.
Ţălu Ş., 2012 Mathematical methods used in monofractal and multifractal analysis for the processing of biological and medical data and images. ABAH Bioflux **4**(1):1-4.
Zhang J., Tan T., 2002 Brief review of invariant texture analysis methods. Pattern Recognition **35**(3):735-747.
Zhou D., 2006 Texture analysis and synthesis using a generic Markov-Gibbs image model, Ph.D. Thesis, The University of Auckland, New Zealand.

Received: 10 February 2012. Accepted: 10 May 2012. Published online: 10 June 2012.
Author:
Ştefan Ţălu, The Technical University of Cluj-Napoca, Faculty of Mechanics, Department of AET, Discipline of Descriptive Geometry and Engineering Graphics, B-dul Muncii 103-105, Cluj-Napoca 400641, Romania, e-mail: stefan_ta@yahoo.com
How to cite this article:
Ţălu Ş., 2012 Texture analysis methods for the characterisation of biological and medical images. ELBA Bioflux 4(1):8-12.