



**Universitat  
Autònoma  
de Barcelona**

**Segmentation, classification and  
modelization of textures by means of  
multiresolution decomposition techniques**

A dissertation submitted by **Felipe Lumbreras  
Ruiz** at Universitat Autònoma de Barcelona to  
fulfil the degree of **Doctor en Informàtica**.

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a mi gente

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Felipe Lumbreras Ruiz

# Abstract

An interesting problem in computer vision is the analysis of texture images. In this work, we have developed specific methods to solve important aspects of this problem. The first approach involves segmentation of a specific type of textures, i.e. those of microscopy images of thin marble sections. These images comprise a pattern of grains whose sizes and shapes help specialists to identify the origin and quality of marble samples. To identify and analyze individual grains in these images represents a problem of image segmentation. In essence, this involves identifying boundary lines represented by valleys which separate flat areas corresponding to grains. Of several methods tested, we found those based on mathematical morphology particularly successful for segmentation of petrographical images. This involves a pre-filtering step for which again several approaches have been explored, including multiresolution algorithms based on wavelets.

In the second approach we have also used multiresolution analyses to address the problem of classifying texture images. In contrast to more global approaches found in the literature, we have explored situations where visual differences between textures are rather subtle. Since we have tried to impose relatively few restrictions on these analyses, we have developed strategies that are applicable to a wide range of related texture images, such as images of ceramic tiles, microscopic images of effect pigments, etc.

The approach we have used for the classification of texture images involves several technical steps. We have focused our attention in the initial low-level analyses required to identify the general features of the image, whereas the final classification of samples has been performed using generic classification methods. To address the early steps of image analysis, we have developed a strategy whereby the general features of the image fit one of several pre-defined models with increasing levels of complexity. These models are associated to specific algorithms, parameters and calculations for the analysis of the image, thus avoiding calculations that do not provide useful information.

Finally, in a third approach we want to arrive to a description of textures in such a way that it should be able to classify and synthesize textures. To reach this goal we adopt a probabilistic model of the texture. This description of the texture allows us to compare textures through comparison of probabilistic models, and also use those probabilities to generate new similar images.

In conclusion, we have developed strategies of segmentation and classification of textures that provide solutions to practical problems and are potentially applicable with minor modifications to a wide range of situations. Future research will explore (i) the possibility of adapting segmentation to the analysis of images that do not necessarily involve textures, e.g. localization of subjects in scenes, and (ii) classification of effect pigment images to help identify their components.

# Resumen

El análisis de texturas es un área de estudio interesante con suficiente peso específico dentro de los diferentes campos que componen la visión por ordenador. En este trabajo hemos desarrollado métodos específicos para resolver aspectos importantes de dicha área. El primer acercamiento al tema viene de la mano de un problema de segmentación de un tipo de texturas muy concreto como son las imágenes microscópicas de láminas de mármol. Este primer tipo de imágenes se componen de un conjunto de granos cuyas formas y tamaños sirven a los especialistas para identificar, catalogar y determinar el origen de dichas muestras. Identificar y analizar los granos que componen tales imágenes de manera individual necesita de una etapa de segmentación. En esencia, esto implica la localización de las fronteras representadas en este caso por valles que separan zonas planas asociadas a los granos. De los diferentes métodos estudiados para la detección de dichos valles y para el caso concreto de imágenes petrográficas son los basados en técnicas de morfología matemática los que han dado mejores resultados. Además, la segmentación requiere un filtrado previo para el que se han estudiado nuevamente un conjunto de posibilidades entre las que cabe destacar los algoritmos multirresolución basados en *wavelets*.

El segundo problema que hemos atacado en este trabajo es la clasificación de imágenes de textura. En él también hemos utilizado técnicas multirresolución como base para su resolución. A diferencia de otros enfoques de carácter global que encontramos extensamente en la literatura sobre texturas, nos hemos centrado en problemas donde las diferencias visuales entre las clases de dichas texturas son muy pequeñas. Y puesto que no hemos establecido restricciones fuertes en este análisis, las estrategias desarrolladas son aplicables a un extenso espectro de texturas, como pueden ser las baldosas cerámicas, las imágenes microscópicas de pigmentos de efecto, etc.

El enfoque que hemos seguido para la clasificación de texturas implica la consecución de una serie de pasos. Hemos centrado nuestra atención en aquellos pasos asociados con las primeras etapas del proceso requeridas para identificar las características importantes que definen la textura, mientras que la clasificación final de las muestras ha sido realizada mediante métodos de clasificación generales. Para abordar estos primeros pasos dentro del análisis hemos desarrollado una estrategia mediante la cual las características de una imagen se ajustan a un modelo que previamente hemos definido, uno de entre varios modelos que están ordenados por complejidad. Estos modelos están asociados a algoritmos específicos y sus parámetros así como a

los cálculos que de ellos se derivan. Eligiendo el modelo adecuado, por tanto, evitamos realizar cálculos que no nos aportan información útil para la clasificación.

En un tercer enfoque hemos querido llegar a una descripción de textura que nos permita de forma sencilla su clasificación y su síntesis. Para conseguir este objetivo hemos adoptado por un modelo probabilístico. Dicha descripción de la textura nos permitirá la clasificación a través de la comparación directa de modelos, y también podremos, a partir del modelo probabilístico, sintetizar nuevas imágenes.

Para finalizar, comentar que en las dos líneas de trabajo que hemos expuesto, la segmentación y la clasificación de texturas, hemos llegado a soluciones prácticas que han sido evaluadas sobre problemas reales con éxito y además las metodologías propuestas permiten una fácil extensión o adaptación a nuevos casos. Como líneas futuras asociadas a estos temas trataremos por un lado de adaptar la segmentación a imágenes que poco o nada tienen que ver con las texturas, en las que se perseguirá la detección de sujetos y objetos dentro de escenas, como apuntamos más adelante en esta misma memoria. Por otro lado, y relacionado con la clasificación, abordaremos un problema todavía sin solución como es el de la ingeniería inversa en pigmentos de efecto, en otras palabras la determinación de los constituyentes en pinturas metalizadas, y en el que utilizaremos los estudios aquí presentados como base para llegar a una posible solución.



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# Chapter 1

## Introduction

The purpose of this thesis is to explore the usefulness of the multiresolution decomposition schemes in problems related to texture analysis. On the one hand, wavelet theory is a synthesis of ideas from many different research fields. It merges aspects such as multiresolution analysis and filter banks. On the other hand, texture recognition systems are often present in many computer vision systems because most natural surfaces and their images exhibit texture. We can find texture in fields as different as industrial inspection and medical image analysis.

In this work we have addressed several applications, one of them more academic and related to the segmentation of marble samples in order to obtain a classification by experts, and others related to some industrial problems as porcelanic tiles classification and paint pigments recognition. The textures appearing in each one of these problems are very different: the first ones are acquired with microscope from marble semitransparent samples with transmitted and polarized light at low magnification; the second ones are acquired with a line scan camera from tile samples on a conveyor belt in motion, the last ones are also acquired with a microscope but with reflected light and high magnification. Though each set of images comes from different problems, they all share a common goal, namely, the recognition and classification into representative classes. One way or another, multiresolution wavelet decompositions bring us to the final solution. The stages where multiresolution decompositions have been applied and also the goals are very different depending on the application. In the first application of marble recognition, a wavelet decomposition has been used as a preprocessing filtering stage in order to reduce annoying noise, amplifying the outstanding elements in the images useful for our purposes. In the other two applications, tile and paint recognition, several decomposition schemes have been studied in-depth in order to represent the information in a useful way so as to extract compact and meaningful features.

The main goals in this work have been to provide useful models and algorithms to recognize texture images providing a better understanding of the factors that influence their performance. Arriving to a global solution for any kind of texture is nowadays a



challenging and out of reach task. Our approach has been to analyze this problem from different points of view, that is, focusing efforts on specific problems of this domain but representative enough to easily extend the results to other application domains. Also, classification of textures has been analyzed using a number of decomposition schemes, base families, specific bases, and number of levels. This methodology has made feasible to select the best set of elements for the analysis as well as to see globally this problem assessing the importance of each factor in the solution.

All the works presented here, though apparently diverse, have links to the texture field and the techniques used are related to wavelet decompositions. Therefore, these two topics are the thread of the entire dissertation. The novel contributions of this work can be separate in two fields: (i) image segmentation, and (ii) classification of textures. Both related with textures and wavelets but not directly connected. Due to the fact that we do our research in a center devoted to machine vision (research and development), most of the work we have done starts as an application. In our case, applications are the excuse to study in-depth a specific topic and then expand their results to new related problems.

## 1.1 Thesis outline

The structure of this thesis is strongly correlated in time with our work in these fields. We started by studying the framework defined by multiresolution representations in several fields of computer vision. This is reflected in the introduction to wavelet topics in the next chapter. Once we knew some fundamentals of this discipline we extended a previous work on image segmentation in the light of multiresolution schemes and this constitutes a new chapter. Next, we studied a different problem related to the classification of tile images where we also chose an approach based on wavelets. Then, this classification was extended to other kind of images like microscopic paint images. So, the order of previous developments is a natural way to present them in this work. Next, we summarize the contents of each chapter.

Chapter 2 is a description of the subjects related to this work. We begin with an introduction to texture analysis in Sec. 2.1 where we examine different approaches that found in the literature, and providing the framework followed in this work, namely, filterbanks for feature extraction. Also, we present some of the fields in which texture has a great importance. Next in Sec. 2.2, we present the wavelet transform as the scheme used in most of the solutions presented in this dissertation. This part is a brief introduction to the multiresolution decomposition, giving the fundamentals of the theory and pinpointing some applications that show the versatility of this tool. Finally, we explore the relation between texture analysis and wavelets.

Chapter 3 originates from an application devoted to the study of petrographical marble images that constituted my Master Thesis [56]. Later, this work was extended providing our first solution in this area of wavelet. Therefore, it served as an introduction to the multiresolution decomposition schemes. This chapter contains a fusion of our journal papers [60, 61] and some results of [55]. The basic idea is to achieve a

good segmentation for this kind of images in order to make easier the classification by experts. We focus on the segmentation step and leave to specialists the classification using morphological features. Firstly, we study the formation model of marble images. Next, we perform the segmentation that is carried out with valley/crest detectors with the help of a filtering stage. Due to this last process we have developed a new wavelet filtering approach explained in Sec. 3.6.2. Then, we refine results and arrive to an acceptable solution that can be used by skilled geologists for classification purposes. Finally, we explain how this new technique can be easily extended to other kinds of images.

Chapter 4 deals with nonstructural textures classification. We propose a method to extract useful features in order to classify texture based on a multiresolution decomposition. These features are calculated from cross correlations of color channels and levels of the decomposition depending on the complexity of the images in regard to several proposed models. Results obtained in this stage have been reported in papers [57, 58, 59]. After a brief review of some techniques related to classification of color textures we propose a methodology to obtain texture representation useful for classification purposes. This involves some preprocessing steps such as color space representation, multiresolution decomposition, and extraction of features. This scheme has a lot of possibilities in its realization that have all of them been widely studied in this work. An extension of the results reported in this chapter are reflected in the tables of Appendix A. Next in Sec. 4.3.4, we present several models of texture images. These models are associated to how must be done the study of these images. Next in Sec. 4.3.5, the features that we have calculated feed a classifier based on a linear discriminant analysis. Finally, the methodology we propose is evaluated in real applications, such as images of ceramic tiles (Sec. 4.4) and microscopic images of effect pigments (Sec. 4.5). Later, we analyze other applications and set of images in order to explore the potential of the method and possible drawbacks. These new set images are marble images used in previous chapter (Sec. 4.6) and Brodatz texture database (Sec. 4.7).

Chapter 5 is a first attempt to arrive to a description of textures in such a way that it should be useful in classification and synthesize. The idea is to derive a texture representation that can be directly used to recognize or classify textures by defining a suitable distance or similarity measure between two such descriptions, and, at the same time, be able to apprehend what's the texture(s) ideally recognized or belonging to each class in a supervised framework. On way to do that is being able to synthesize any number of texture samples from a given built class. To implement these ideas, we estimate some probability density functions (pdfs) that describe the analyzed textures. Then, with these pdfs we can classify and synthesize them. Multiresolution decompositions have been included as a preliminary trial in the synthesis scheme. These studies are in a start-up stage and results are not as good as we want. Hence, it should be further analyzed, but the expectatives are good.

Finally, Chapter 6 summarize the principal ideas of this work emphasizing the novel contributions. We also show some directions of future work.