UNIVERSITY OF AMSTERDAM

Texture Synthesis for Material Classification

Master's Thesis in Artificial Intelligence – Intelligent Systems

Author:
Jasper van Turnhout
jturnhou@science.uva.nl
Student number: 0312649

Supervisors:
Prof. dr. Theo Gevers
Dr. Jan-Mark Geusebroek
Informatics Institute, Faculty of Science, University of Amsterdam

Abstract

Research description comes here

Contents

Chapter 1

Introduction

1.1 Material Recognition

The first part of the project is this... bla bla...

1.2 Reflection Models

The second part of the project is this... bla bla...

Chapter 2

Related work

2.1 Varma & Zisserman

In earlier research on the topic of material recognition, a lot of focus was on the albedo variation on top of a flat surface. More recently, this focus has shifted towards surface normals, which cause the 3D effects we perceive. Photometric stereo based classification algorithms have been developed to capture these features. The need for larger texture databases that captures the variety in viewpoint and illumination resulted in the creation of the CUReT database (Dana et al, 1999). Dana and Nayar developed parametric models based on surface roughness and correlation lenghts which were tested against the CUReT database. However, in their research, no significant results were reported.

Leung and Malik (2001) were the first to introduce the texton modeling method...

- CUReT Database
- Texton Dictionary
- Filter banks (LM, MR8, Schmid)
- Chi-squared distance
- Nearest Neighbour classifier

2.2 Broadhurst

- CUReT Database
- eqi-count histograms
- MR8 filter bank
- Mallow distance
- multivariate Gaussian classifier

In his article, Broadhurst presents a parametric approach to estimate the likelihood of homogeneously textured images. His work extends the framework proposed by Levina (PhD thesis, 2002) by using a Gaussian Bayes classifier instead of a 1-NN classifier. To model each texture class, he uses multivariate Gaussian distributions to model the intra-class variability of each marginal histogram. This is done by mapping the joint marginal histograms into Euclidean space and applying PCA [to obtain the eigenvalues and expected projection error for each class]. Marginal distributions of each filter response are estimated by using non-parametric histograms. There are several advantages to this: 1.This approach eliminates effectively the need to use a texton dictionary as proposed by Varma & Zisserman (2004). The use of such dictionary would limit the generalization of a texture class and also needs clustering in high-dimensional spaces. 2. Marginal distributions can be estimated accurately, while joint distributions often suffer from the curse of dimensionality. Although less descriptive than joint conditional distributions, the dependencies among filter responses are captured by estimating the joint intra-class variation of the marginals. This approach increases the descriptive power of the marginal distributions while still maintaining the computational efficiency. The method is applied to the MR8 filter bank (described in Varma & Zisserman).

In order to perform statistical analysis on the marginal distributions, the distributions are mapped to points in Euclidean space. Responses are represented as marginal histograms [as described in another paper, look this up]. The Mallow Distance is used to measure distribution similarity in the Euclidean space. The Mallow Distance used for comparing two continuous one-dimensional distributions is given by [insert formula]. To compare discrete distributions, consider two equi-count histograms x and y with n bins and the average value of each bin stored. Consider these values sorted in order [n values are sorted]. x and y can be represented as vectors x and y. The Mallows distance between these vectors is given by: [insert formula]. The described representation maps histograms to points in Euclidean space with distances corresponding to M2 histogram distances.

Experiments are run on samples from the CUReT database, which consists of 61 texture classes with each 205 different viewing and illumination conditions. Each class experiences 3D effect such as interreflections, speculars and shadowing, which gives a large intra-class variability, but the database is sparse in its rotation and scaling conditions. In a preprocessing step, the images are converted to gray-scale and are processed to have zero-mean and unit-variance to get intensity invariance. The MR8 filter bank is used to gain rotationally invariant features by using the maximum responses over the orientations. Levinka has developed a framework for classification using filter banks, marginal histograms, the Mallow distance and a 1NN classifier. The 1-NN classifier requires a distance measure between two sets of marginal distributions. Broadhurst defines this to be the product of the M2 marginal distances described in section 2. The variation of marginal distributions can be measured jointly or independently. A joint 1-NN classifier measures the distance between a target image and all the training images as the distance between each set of marginals. The target image is then classified using the closest training image. For an independent 1-NN classifier, the minimum M2 distance between each target marginal and each class is computed. The total distance to a class is defined as the product of each minimum marginal distance.

4. Gaussian Bayes Classification

(skip the Markov Random Field parts as they are not in the scope of the thesis)

2.3 Targhi

- PhoTex database
- ALOT database
- Photometric Stereo
- Lambertian reflection
- Broadhurst experiment

Chapter 3

Approach

3.1 Photometric Stereo

- core formula
- Lambertian assumption

3.2 Classification

- multivariate Gaussian Classifier, Mallow distance
- Texton Dictionary, Chi-distance

Chapter 4

Empirical Models

For the texture synthesis of the materials, various local reflection [1] models can be used. This chapter will outline the empirical models used in the process of texture synthesis. These models capture reflectance behaviour using mathematical models without using any basic laws of physics. Such models are widely used for their simplicity and because they can be controlled by setting only a small set of parameters to obtain desired results.

4.1 Lambertian reflectance

One of the most used empirical models is Lambertian reflectance. In computer graphics, this model is mainly used to model diffuse reflectance. Surfaces with such properties appear equally bright from all viewing angles because the light is reflected with equal intensity in all directions. The brightness of the surface is only dependent of the angle θ between the surface normal $\vec{\mathbf{n}}$ and the light source direction $\vec{\mathbf{l}}$ as shown in figure X. We can look at a diffuse surface on microscopic level to understand how this works.

If we look at 4.1, we can see how an incoming light beam projects a differential area dA on the surface. If the surface normal and the light direction are parallel and in the same direction as shown in figure 4.1, the energy the area receives and reflects is proportional to dA. If the beam is projected on the surface such that it covers a larger area as shown in 4.1, the amount of energy reflected from area dA is proportional to $\cos\theta$. The amount of energy reflected per unit area is less on surface 2 compared to surface 1 since the beam covers a larger area. This observation of radiance behaviour is also known as Lambert's Cosine Law. In general, for Lambertian reflectance, the amount of light observed by the viewer is indepenendent of the viewing angle, and is only dependent on the angle of the incidence of the light source. The full equation is given by:

$$I = I_p k_d \cos\theta$$

Here, I is the reflected amount of light, I_p is the intensity of the light source, k_d is the diffuse reflection coefficient which varies between 0 and 1 and is material dependent. The cosine term is defined between 0^0 and 90^0. This means that the surface is treated as self-occluding; angles outside this range will result in negative values for the cosine term and are treated as a $max(0, \cos\theta)$, resulting in zero intensity falling on the surface. If both $\vec{\mathbf{n}}$ and $\vec{\mathbf{l}}$ are normalized, we can write the equation as:

$$I = I_p k_d(\vec{\mathbf{n}} \cdot \vec{\mathbf{l}})$$

[1] Another set of reflection models are global illumination models. These are beyond the scope of this thesis.

This model is used effectively for the synthesis of diffuse surfaces and in interactive software since the reflection term doesn't need to be recomputed whenever the view changes. However, most materials are deviating from Lambertian for angles of view or incidence greater than 60^0 [2]. Another shortcoming of Lambertian reflectance is that it does not include the observation of speculars on materials. For these reasons the model is insufficient to synthesize materials with a more glossy nature since they will need the speculars to be present.

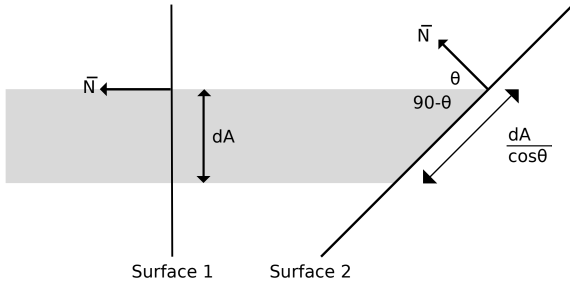

Figure 4.1: Beam shown in gray, projecting an area on surfaces. The projected area on surface 1 equals dA, and on surface 2 equals $\frac{dA}{\cos\theta}$. *Image adapted from Computer Graphics, Principles and Practice [3]*

4.2 Phong Reflectance

With the Lambertian assumption of light reflecting equally into all direction, we can expect poor quality synthesis when we're dealing with more glossy/specular surfaces such as metallic, stone and plastic materials. As Bui-Tuong Phong wrote in his article, if the goal in shading a computer-synthesized image is to simulate a real physical object, then the shading model should in some way imitate real physical shading situations [5]. Phong reflectance is a popular model, based on the empirical observation of how shiny surfaces can have small specular highlights, and how these observed speculars are related to the view direction of the observer. The general idea of Phong reflection is shown in figure 4.2. Here we have an incident angle θ_i and an equal reflection angle θ_r. The incident light is reflected into the direction of $\vec{\mathbf{R}}$

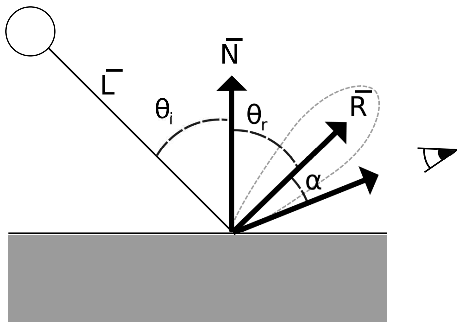

Figure 4.2: Specular reflection. θ_i is the angle of the incoming light, and is equal to the reflected angle θ_r. α is the angle between the view direction and the reflected light.

4.3 Blinn-Phong Reflectance

Chapter 5

Physical Models

In the previous section, the reflection models were based on emperical observations, which result in non-perfect synthesis when applied. In this section, more complex reflection models for diffuse (and specular) reflection are outlined. These models are based on a roughness model, micro-facets, and were introduced by Torrance and Sparrow [7].

5.1 Oren-Nayar Reflectance

A big deficiency in approximating the body reflectance under the Lambertian assumption is that its view independent. This results in inaccurate approximations for several real-world objects, as experiments have demonstrated on several rough diffuse surfaces such as plaster, sand and cloth [4]. To overcome this deficiency, M. Oren and S.K. Nayar propose a more general reflection model for diffuse surfaces [4].

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