6.891
Computer Vision and Applications

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Lecture 4: Texture
- Filter-based models
- Example-based / Non-parametric approaches
- Quilting and Eptomes

Readings: F & P 9.1, 9.3, 9.4

The Challenge
- How to capture the essence of texture?
- Need to model the whole spectrum: from repeated to stochastic texture
- This problem is at intersection of vision, graphics, statistics, and image compression

The Goal of Texture Synthesis

input image
SYNTHESIS
True (infinite) texture generated image
- Given a finite sample of some texture, the goal is to synthesize other samples from that same texture
  - The sample needs to be "large enough"

The Goal of Texture Analysis

input image
ANALYSIS
True (infinite) texture generated image
- "Same" or "different"

Compare textures and decide if they're made of the same "stuff".

Pre-attentive texture discrimination
Pre-attentive texture discrimination

Same or different textures?

Pre-attentive texture discrimination

Pre-attentive texture discrimination

Julesz

- Textons: analyze the texture in terms of statistical relationships between fundamental texture elements, called "textons".
- It generally required a human to look at the texture in order to decide what those fundamental units were...

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Representing textures

- Textures are made up of quite stylized subelements, repeated in meaningful ways
- Representation:
  - find the subelements, and represent their statistics
  - But what are the subelements, and how do we find them?
    - recall normalized correlation
    - find subelements by applying filters, looking at the magnitude of the response

Influential early paper:

**Early vision and texture perception**

James R. Bergen* & Edward H. Adelson**

* SHI David Sarnoff Research Center, Princeton, New Jersey 08540, USA
** Media Lab and Department of Brain and Cognitive Science, Massachusetts Institute of Technology, Cambridge, Massachusetts 02139, USA

Bergen and Adelson, Nature 1988

Learn size-tuned filter responses.

Malik and Perona

Learn: use lots of filters, multi-ori&scale.

Malik J, Perona P. Preattentive texture discrimination with early vision mechanisms. J OPT SOC AM A 7: (5) 923-932 MAY 1990

Threshold squared, blurred responses, then categorize texture based on these two bits
Pyramid-Based Texture Analysis/Synthesis

David L. Heeger
Stanford University

James R. Bergen
SRI David Sarnoff Research Center

SIGGRAPH 1994

Bergen and Heeger

Idea: Learn filter marginal statistics.

Bergen and Heeger results
Bergen and Heeger failures

DeBonet
Learn filter conditional statistics across scale.

Zhu, Wu, & Mumford, 1998
Gibbs sampling of Markov Random Field model:

Cheetah
Synthetic
Efros and Leung ‘99

- preserve local structure
- model wide range of real textures
- ability to do constrained synthesis
- method:
  - Texture is “grown” one pixel at a time
  - conditional pdf of pixel given its neighbors synthesized thus far is computed directly from the sample image

Synthesizing One Pixel

- Assuming Markov property, what is conditional probability distribution of p, given the neighbourhood window?
- Instead of constructing a model, let’s directly search the input image for all such neighbourhoods to produce a histogram for p
- To synthesize p, just pick one match at random

Really Synthesizing One Pixel

- However, since our sample image is finite, an exact neighbourhood match might not be present
- So we find the best match using SSD error (weighted by a Gaussian to emphasize local structure), and take all samples within some distance from that match

Growing Texture

- Starting from the initial configuration, we “grow” the texture one pixel at a time
- The size of the neighbourhood window is a parameter that specifies how stochastic the user believes this texture to be
- To grow from scratch, we use a random 3x3 patch from input image as seed

Randomness Parameter

More Synthesis Results
Failure Case

Growing garbage
Verbatim copying

Texturing a sphere

Sample image
2D

3D

What we learned from Efros and Leung regarding texture synthesis

• Don’t need conditional filter responses across scale
• Don’t need marginal statistics of filter responses.
• Don’t need multi-scale, multi-orientation filters.
• Don’t need filters.

Image Extrapolation

Efros & Leung

• The algorithm
  – Very simple
  – Surprisingly good results
  – Synthesis is easier than analysis!
  – … but very slow
• Optimizations and Improvements
  – [Wei & Levoy, ’00] (based on [Popat & Picard, ’93])
  – [Harrison, ’01]
  – [Ashikhmin, ’01]

Quilting

• The “Corrupt Professor’s Algorithm” - Freeman:
  – Plagiarize as much of the source image as you can
  – Then try to cover up the evidence
• Rationale:
  – Texture blocks are by definition correct samples of texture so problem only connecting them together
Quilting: Efros & Freeman

- Observation: neighbor pixels are highly correlated

**Idea: unit of synthesis = block**
- Exactly the same but now we want \( P(B|Ni(B)) \)
- Much faster: synthesize all pixels in a block at once
- Not the same as multi-scale!

**Minimal error boundary**

- Overlapping blocks
- Vertical boundary
- Overlap error
- Min. error boundary

**Algorithm**
- Pick size of block and size of overlap
- Synthesize blocks in raster order
- Search input texture for block that satisfies overlap constraints (above and left)
  - Easy to optimize using NN search [Liang et al., '01]
- Paste new block into resulting texture
  - Use dynamic programming to compute minimal error boundary cut
Texture Transfer

- Take the texture from one object and “paint” it onto another object
  - This requires separating texture and shape
  - That’s HARD, but we can cheat
  - Assume we can capture shape by boundary and rough shading

- Then, just add another constraint when sampling: similarity to underlying image at that spot

![Examples of texture transfer with images of a person's face and different textures like parmesan and rice.](image-url)
Homage to Shannon!

The essence of life is not just the sum of all its parts, but the way they interact. In a similar vein, the essence of Shannon's information theory lies in the interaction of symbols and their probabilities. Portilla & Simoncelli have extended this idea to the field of image processing, where they use statistical models to analyze and synthesize images. The model is based on the concept of a Markov random field, which allows for the representation of dependencies between different parts of the image. This approach can be used for tasks such as image denoising, segmentation, and compression. Theoretical and empirical results show that this method can produce high-quality images with low bit rates, making it a powerful tool in the field of image processing.

Summary of image quilting

- Quilt together patches of input image
  - randomly (texture synthesis)
  - constrained (texture transfer)
- Image Quilting
  - No filters, no multi-scale, no one-pixel-at-a-time!
  - fast and very simple
- Results are not bad

Example-based model

A set of image patches

Compressed example-based model

Input image

A set of image patches

Epitome

Nabaneige Asa, Brotodito R. and Arthur Konik, ICIP 2003
www.research.technion.ac.il/~arthur/Konik
Compact representation

Learning the epitome
- For each patch, infer the posterior over the mappings
- Average all patches using the posterior as a weight
- Estimate the variance

More examples

More examples

Mean

More examples

What is epitome good for?
- A better way to learn a library of patches (for SR, texture synthesis and analysis, …)
- A tool for easy editing
- Organizing visual memory for recognition
- An alternative both to templates and low-order statistics (e.g., histograms) in vision systems
Denoising

SNR=13dB

SNR=18.4dB

SNR=19.2dB

Original image

Noisy image

Reconstruction using a mixture of 1000 patches learned from the noisy image

(1000 cases, the patch size was 8x8)

Nobuyuki Sato, Brendan Fick and Annette Keramani, ICIP 2011

www.research.microsoft.com/group/graphic