6.891

Computer Vision and Applications

Prof. Trevor. Darrell

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

Readings: F & P 9.1, 9.3, 9.4
Last time: image pyramids

- **Gaussian**
  Progressively blurred and subsampled versions of the image. Adds scale invariance to fixed-size algorithms.

- **Laplacian**
  Shows the information added in Gaussian pyramid at each spatial scale. Useful for noise reduction & coding.

- **Wavelet/QMF**
  Bandpassed representation, complete, but with aliasing and some non-oriented subbands.

- **Steerable pyramid**
  Shows components at each scale and orientation separately. Non-aliased subbands. Good for texture and feature analysis.
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

- 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

Compare textures and decide if they’re made of the same “stuff”.
Pre-attentive texture discrimination
Pre-attentive texture discrimination
Pre-attentive texture discrimination

Same or different textures?
Pre-attentive texture discrimination
Pre-attentive texture discrimination
Pre-attentive texture discrimination

Same or different textures?
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...
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**

* SRI 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
Learn size-tuned filter responses.

Fig. 1 Top row, Textures consisting of Xs within a texture composed of Ls. The micropatterns are placed at random orientations on a randomly perturbed lattice. a, The bars of the Xs have the same length as the bars of the Ls. b, The bars of the Ls have been lengthened by 25%, and the intensity adjusted for the same mean luminance. Discriminability is enhanced. c, The bars of the Ls have been shortened by 25%, and the intensity adjusted for the same mean luminance. Discriminability is impaired. Bottom row: the responses of a size-tuned mechanism d, response to image a; e, response to image b; f, response to image c.
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 those two bits.
Pyramid-Based Texture Analysis/Synthesis

David J. Heeger
Stanford University

James R. Bergen†
SRI David Sarnoff Research Center

SIGGRAPH 1994
Bergen and Heeger

Idea: Learn filter marginal statistics.

Figure 2: (Left) Input digitized sample texture: burled mappa wood. (Middle) Input noise. (Right) Output synthetic texture that matches the appearance of the digitized sample. Note that the synthesized texture is larger than the digitized sample; our approach allows generation of as much texture as desired. In addition, the synthetic textures tile seamlessly.
Bergen and Heeger results

Figure 3: In each pair left image is original and right image is synthetic: stacco, iridescent ribbon, green marble, panda fur, slag stone, figured yew wood.
Bergen and Heeger failures

Figure 8: Examples of failures: wood grain and red coral.

Figure 9: More failures: hay and marble.
DeBonet

Learn filter conditional statistics across scale.

Figure 8: The distribution from which pixels in the synthesis pyramid are sampled is conditioned on the “parent” structure of those pixels. Each element of the parent structure contains a vector of the feature measurements at that location and scale.

Figure 9: An input texture is decomposed to form an analysis pyramid, from which a new synthesis pyramid is sampled, conditioned on local features within the pyramids. A filter bank of local texture measures, based on psychophysical models, are used as features.
DeBonet
DeBonet
Zhu, Wu, & Mumford, 1998

Gibbs sampling of Markov Random Field model:

Cheetah

Synthetic
Texture Synthesis by Non-parametric Sampling

Alexei A. Efros and Thomas K. Leung
Computer Science Division
University of California, Berkeley
Berkeley, CA 94720-1776, U.S.A.
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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

Increasing window size
Brodatz Results

reptile skin

aluminum wire

More Brodatz Results

french canvas

raffa weave

More Results

wood

granite

More Results

white bread

brick wall
Constrained Synthesis
Visual Comparison

Synthetic tilable texture

[DeBonet, ‘97]  Simple tiling  Our approach

Failure Cases

Growing garbage

Verbatim copying

Texturing a sphere

Sample image

Image Extrapolation
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.
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 $P(B|N(B))$
- Much faster: synthesize all pixels in a block at once
- Not the same as multi-scale!
Random placement of blocks

Neighboring blocks constrained by overlap

Minimal error boundary cut
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
Failures
(Chernobyl
Harvest)
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
input image

Portilla & Simoncelli

Xu, Guo & Shum

Wei & Levoy

Image Quilting
Homage to Shannon!

input image

Portilla & Simoncelli

Xu, Guo & Shum

Wei & Levoy

Image Quilting
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

Input image

Nebojsa Jojic, Brendan Frey and Anitha Kannan, ICCV 2003
www.research.microsoft.com/~jojic/epitome.htm
Compressed example-based model

A set of image patches

Input image

Epitome

Nebojsa Jojic, Brendan Frey and Anitha Kannan, ICCV 2003
www.research.microsoft.com/~jojic/epitome.htm
Compact representation

Nebojsa Jojic, Brendan Frey and Anitha Kannan, ICCV 2003
www.research.microsoft.com/~jojic/epitome.htm
Learning the epitome

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

Nebojsa Jojic, Brendan Frey and Anitha Kannan, ICCV 2003
www.research.microsoft.com/~jojic/epitome.htm
More examples

mean

variance

Nebojsa Jojic, Brendan Frey and Anitha Kannan, ICCV 2003
www.research.microsoft.com/~jojic/epitome.htm
More examples

Nebojsa Jojic, Brendan Frey and Anitha Kannan, *IEEECV 2003*
www.research.microsoft.com/~jojic/epitome.htm
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

Original image

Noisy image

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

Reconstruction using an 80x80 epitome

(in both cases, the patch size was 8x8)

Nebojsa Jojic, Brendan Frey and Anitha Kannan, ICCV 2003

www.research.microsoft.com/~jojic/epitome.htm