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

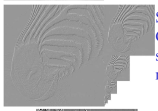
1

Last time: image pyramids

- Gaussian

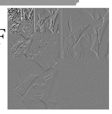
Progressively blurred and subsampled versions of the image. Adds scale invariance to fixed-size algorithms.

- Laplacian



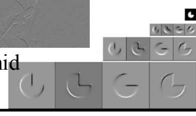
Shows the information added in Gaussian pyramid at each spatial scale. Useful for noise reduction & coding.

- 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.

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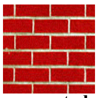
The Challenge

- 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



repeated

stochastic

Both?

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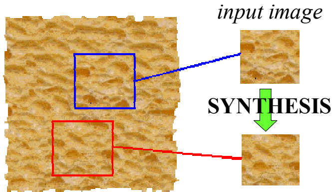
http://www.cs.berkeley.edu/~efros/research/NPS/efros-iccv99.ppt

The Goal of Texture Synthesis

input image



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"

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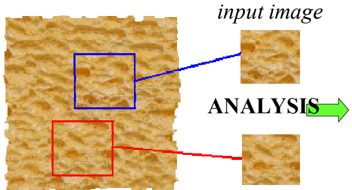
The Goal of Texture Analysis

input image



True (infinite) texture *generated image*

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

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Pre-attentive texture discrimination

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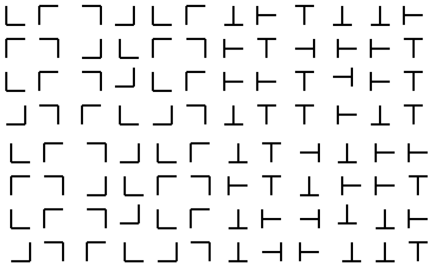
Pre-attentive texture discrimination



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Pre-attentive texture discrimination

Same or different textures?

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Pre-attentive texture discrimination

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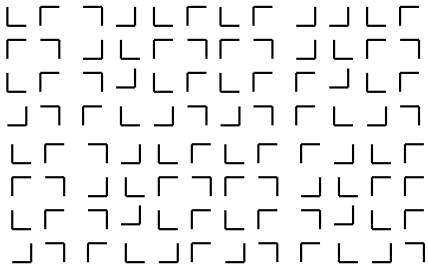
Pre-attentive texture discrimination



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Pre-attentive texture discrimination

Same or different textures?

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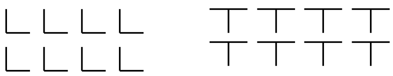
Julesz

- 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

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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

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Bergen and Adelson, Nature 1988

Learn size-tuned filter responses.

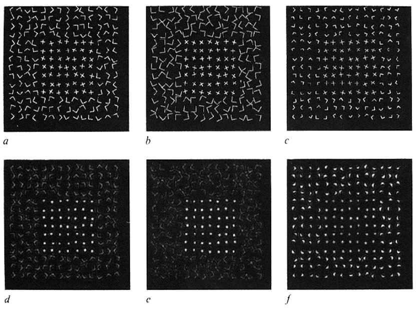
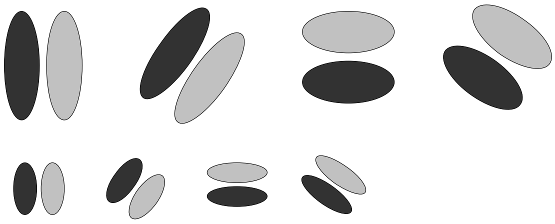


Fig. 1 *Top row*, Textures consisting of Xs within a texture composed of Ls. The micropatterns are placed at random orientations on a randomly perturbed lattice. *a*, The bars of the Xs have the same length as the bars of the Ls. *b*, The bars of the Ls have been lengthened by 25%, and the intensity adjusted for the same mean luminance. Discriminabitity is enhanced. *c*, The bars of the Ls have been shortened by 25%, and the intensity adjusted for the same mean luminance. Discriminabitity 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

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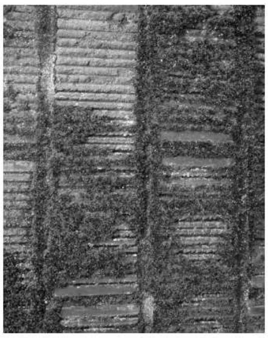

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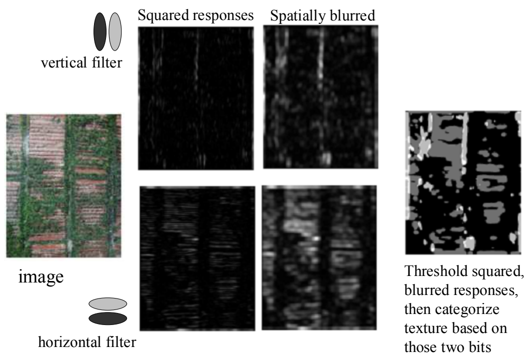

Threshold squared, blurred responses, then categorize texture based on those two bits

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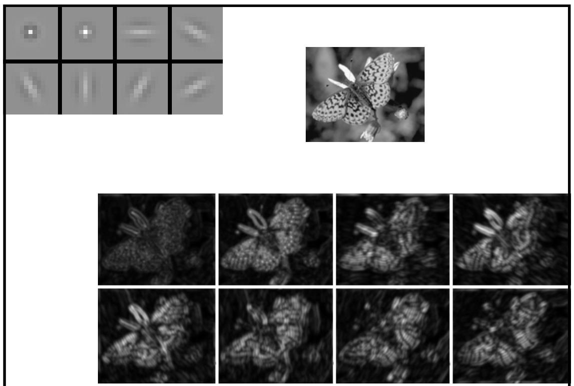

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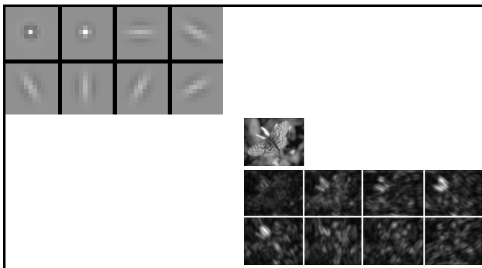

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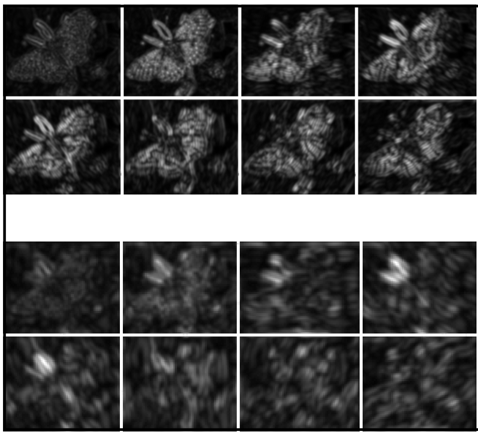

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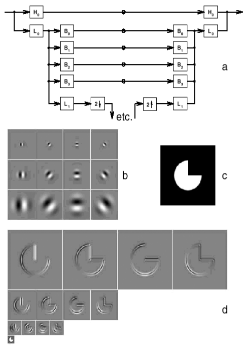
Pyramid-Based Texture Analysis/Synthesis

David J. Heeger*
Stanford University

James R. Bergen†
SRI David Sarnoff Research Center



SIGGRAPH 1994

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Bergen and Heeger

Idea: Learn filter marginal statistics.

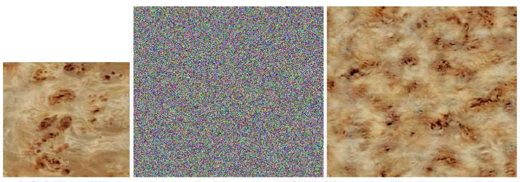

Figure 2: (Left) Input digitized sample texture: burled mappa wood. (Middle) Input noise. (Right) Output synthetic texture that matches the appearance of the digitized sample. Note that the synthesized texture is larger than the digitized sample; our approach allows generation of as much texture as desired.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

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Bergen and Heeger results

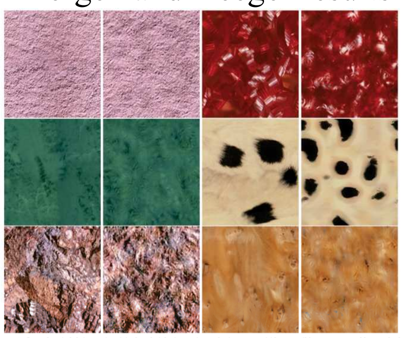

Figure 3: In each pair left image is original and right image is synthetic: stucco, iridescent ribbon, green marble, panda fur, slag stone, figured yew wood.

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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.

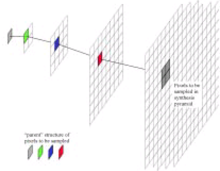


Figure 8: The distribution from which pixels in the synthesis pyramid are sampled is conditioned on the "parent" structure of those pixels. Each element of the parent structure contains a vector of the feature measurements at that location and scale.

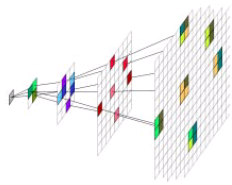
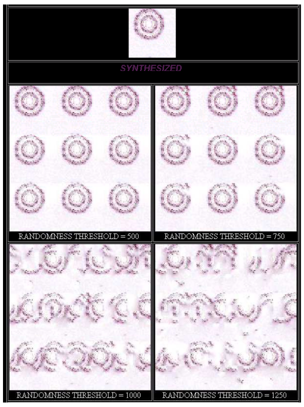
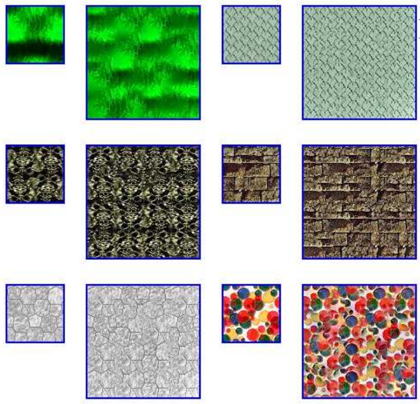


Figure 9: An input texture is decomposed to form an analysis pyramid, from which a new synthesis pyramid is sampled, conditioned on local features within the pyramids. A filter bank of local texture measures, based on psychophysical models, are used as features.



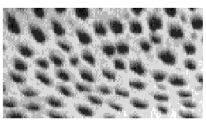
DeBonet



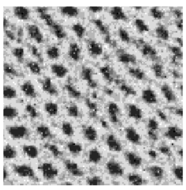
DeBonet

Zhu, Wu, & Mumford, 1998

Gibbs sampling of Markov Random Field model:



a



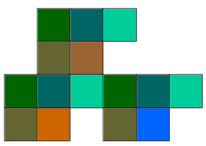
b

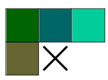
Cheetah Synthetic

IEEE International Conference on Computer Vision, Corfu, Greece, September 1999

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.
{efros,leungt}@cs.berkeley.edu





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

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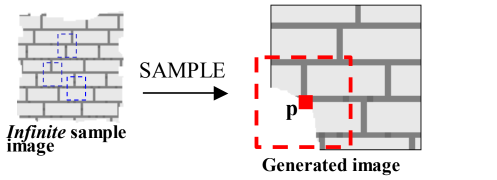
http://www.cs.berkeley.edu/~efros/research/NPS/efros-iccv99.ppt

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

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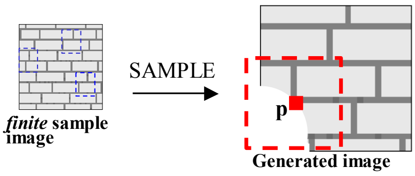
http://www.cs.berkeley.edu/~efros/research/NPS/efros-iccv99.ppt

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

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http://www.cs.berkeley.edu/~efros/research/NPS/efros-iccv99.ppt

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

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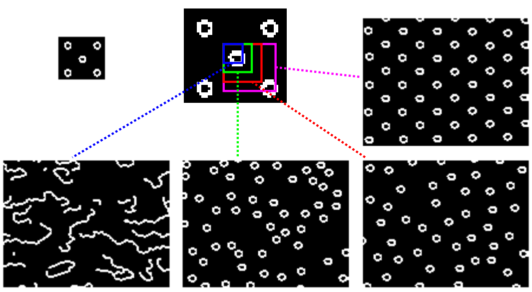
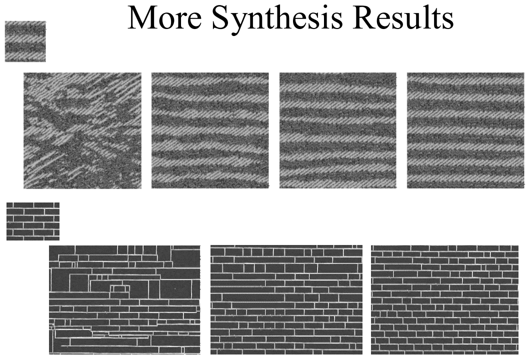
http://www.cs.berkeley.edu/~efros/research/NPS/efros-iccv99.ppt

Randomness Parameter



http://www.cs.berkeley.edu/~efros/research/NPS/efros-iccv99.ppt

More Synthesis Results



Increasing window size →

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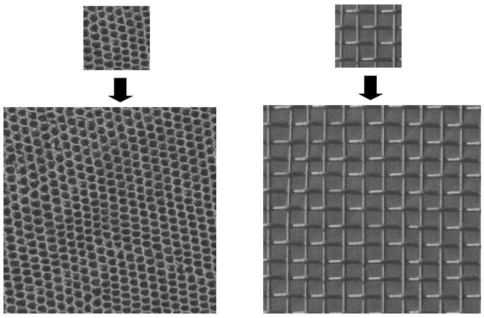
http://www.cs.berkeley.edu/~efros/research/NPS/efros-iccv99.ppt

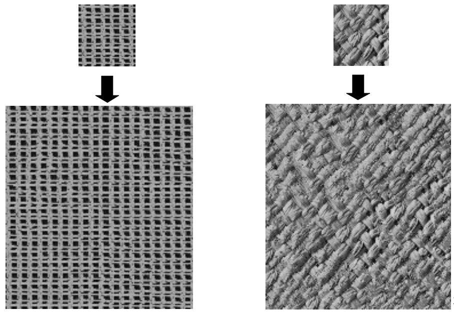
Brodatz Results

reptile skin aluminum wire



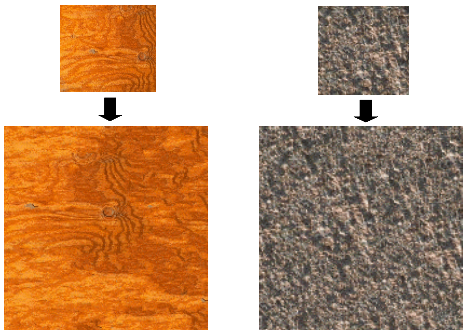
More Brodatz Results

french canvas rafia weave



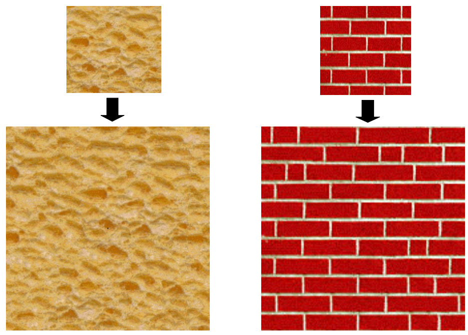
More Results

wood granite

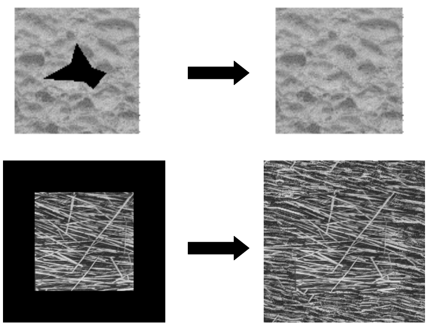


More Results

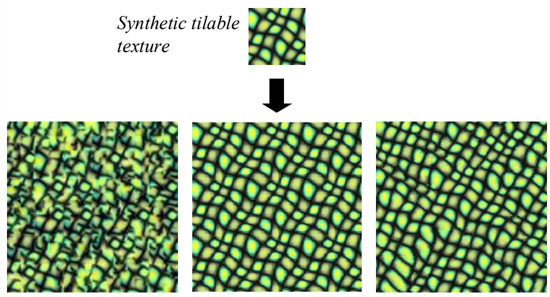
white bread brick wall



Constrained Synthesis

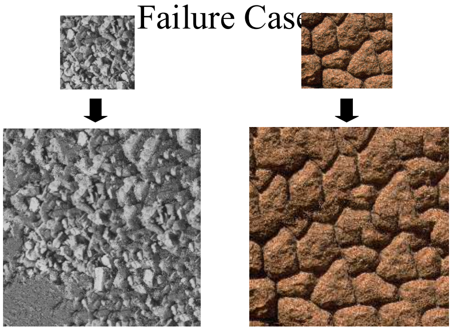


Visual Comparison



[DeBonet, '97] **Simple tiling** **Our approach**

Failure Case



Growing garbage **Verbatim copying**

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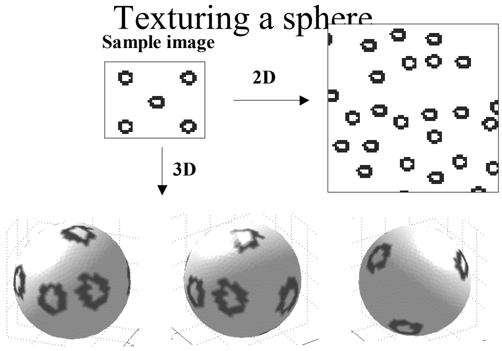
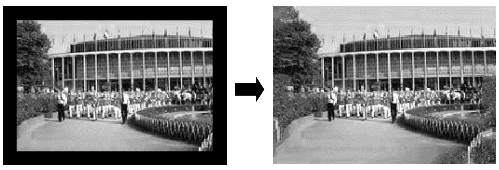
http://www.cs.berkeley.edu/~efros/research/NPS/efros-iccv99.ppt

Texturing a sphere



http://www.cs.berkeley.edu/~efros/research/NPS/efros-iccv99.ppt

Image Extrapolation



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http://www.cs.berkeley.edu/~efros/research/NPS/efros-iccv99.ppt

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.

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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]

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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

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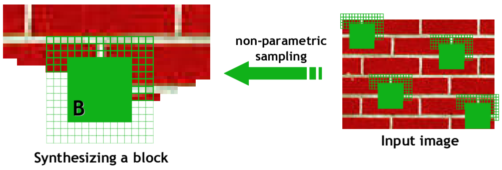
Quilting: Efros & Freeman



- 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!

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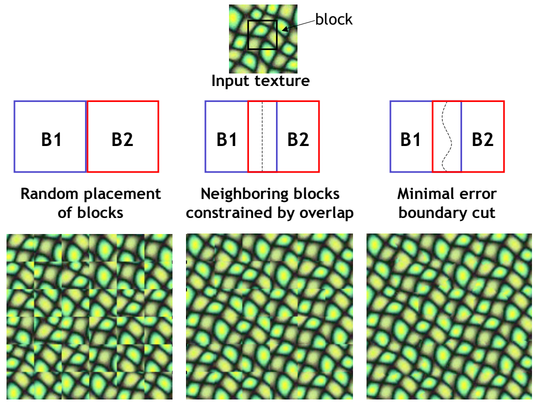
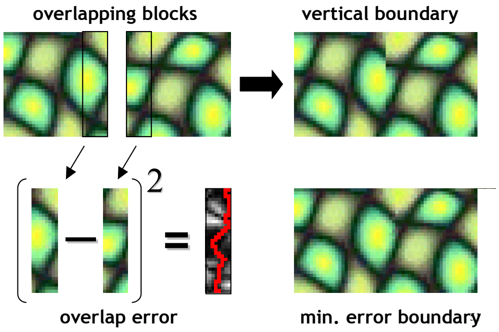
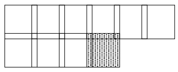


Minimal error boundary



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

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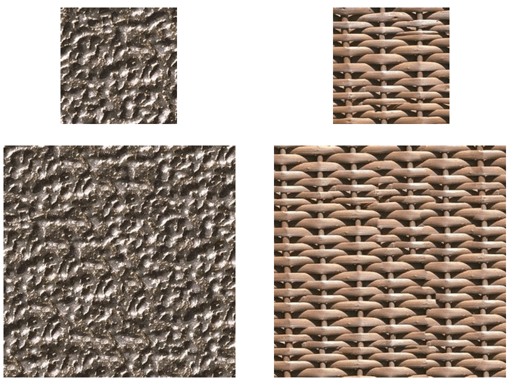

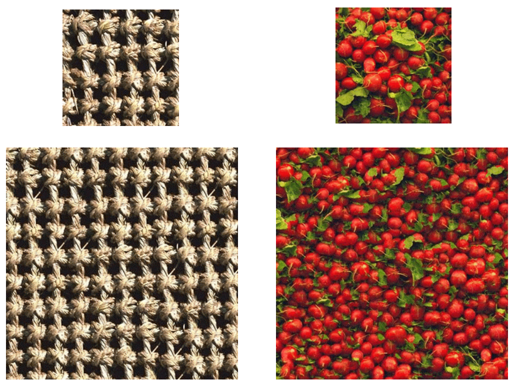

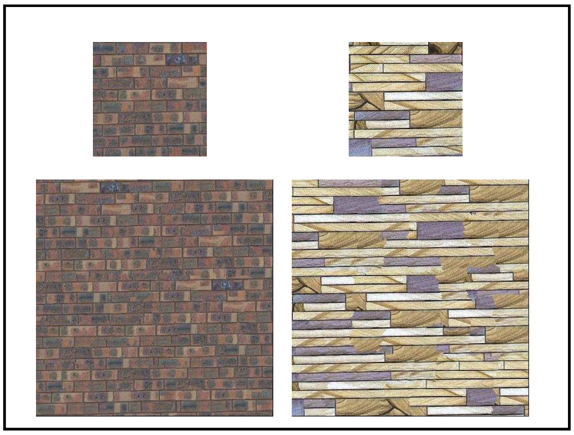

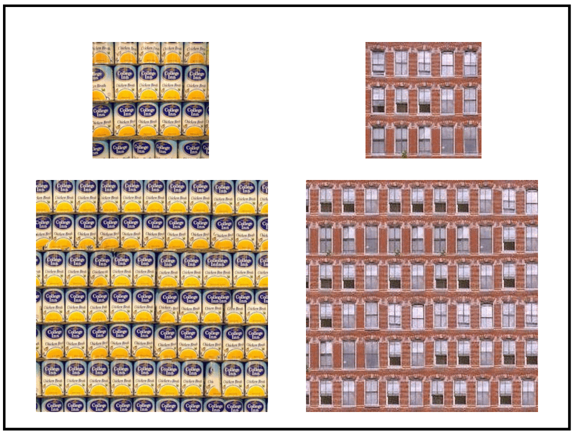

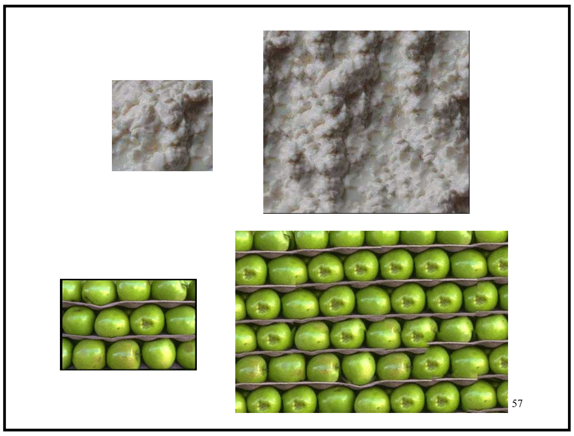
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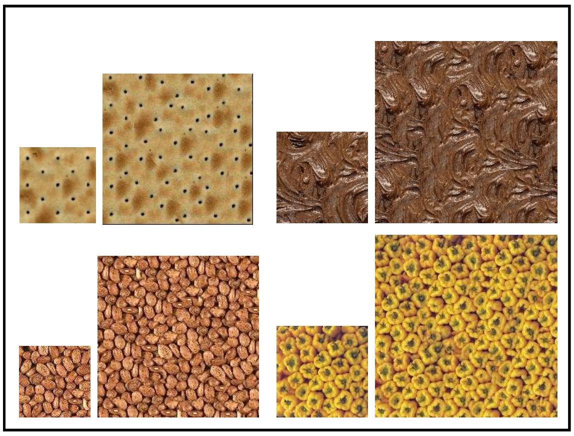
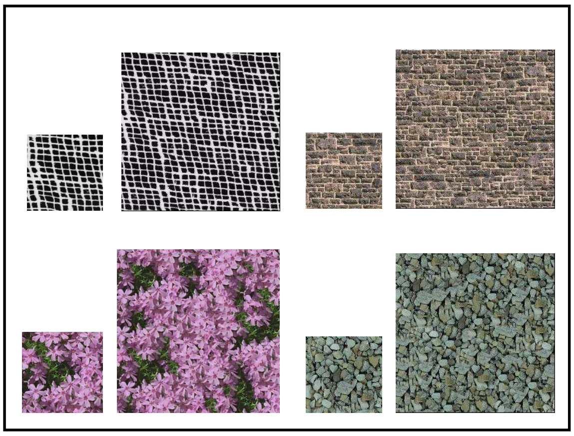
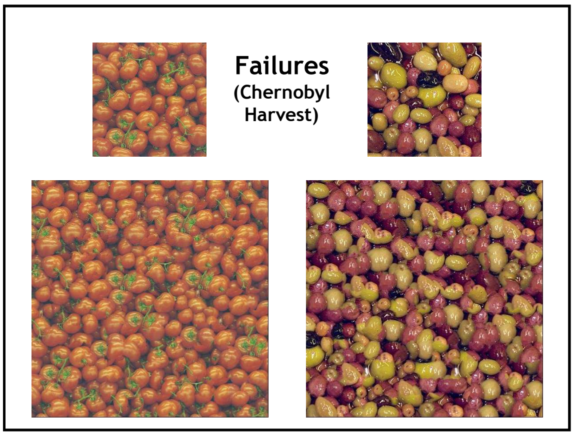
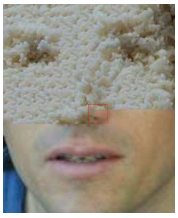





Failures
(Chernobyl
Harvest)

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



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

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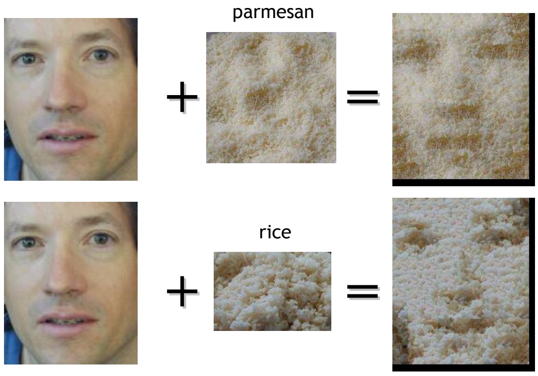
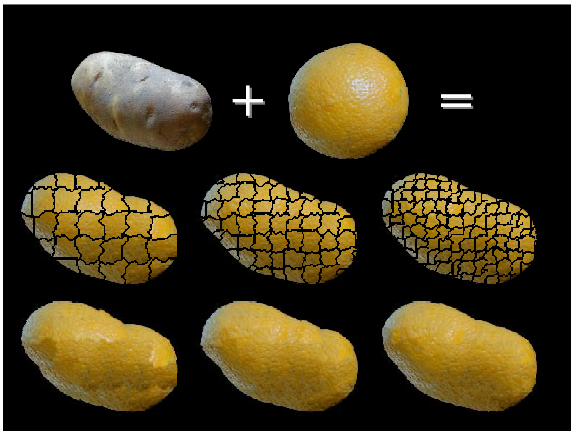
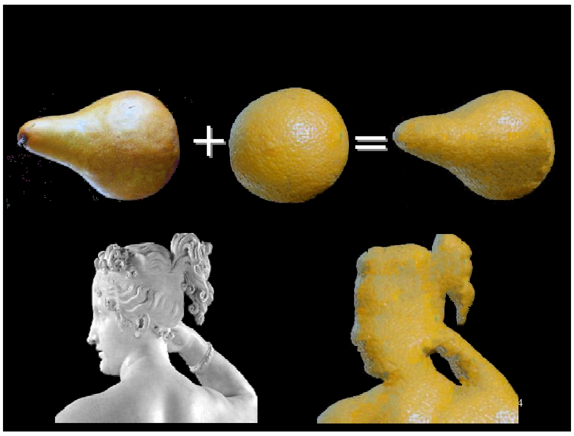




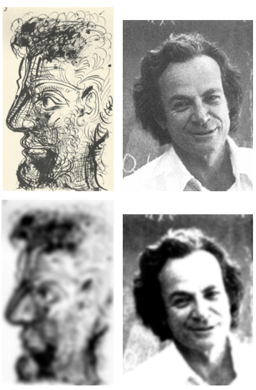


Source texture

Target image

Source correspondence image

Target correspondence image



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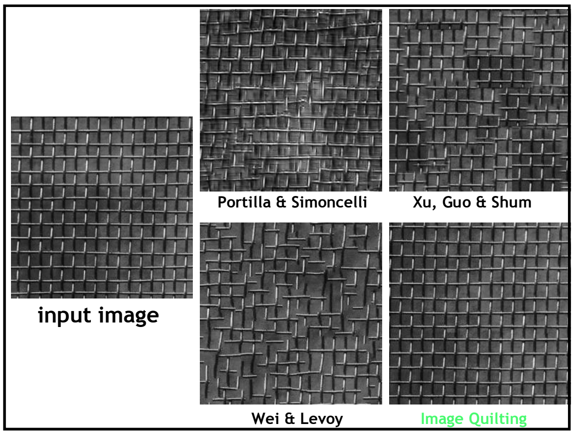
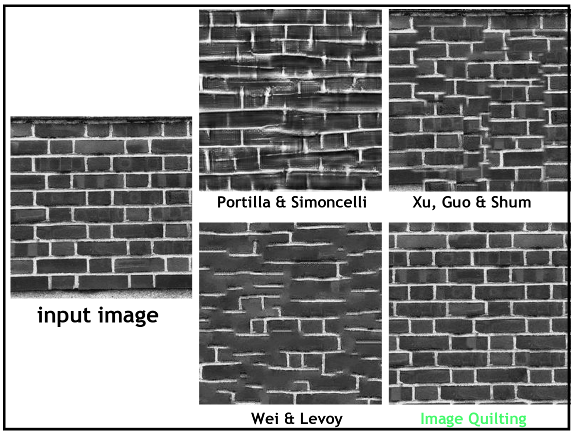
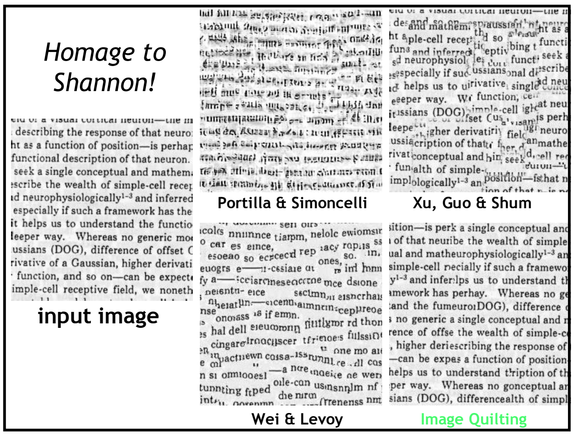
66







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

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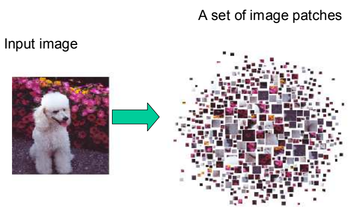
Example-based model

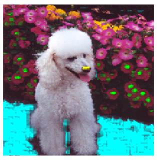


Nebojsa Jojic, Brendan Frey and Anitha Kannan, ICCV 2003 71
www.research.microsoft.com/~jojic/epitome.htm

Compressed example-based model

Nebojsa Jojic, Brendan Frey and Anitha Kannan, ICCV 2003 72
www.research.microsoft.com/~jojic/epitome.htm

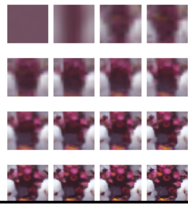
Compact representation



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

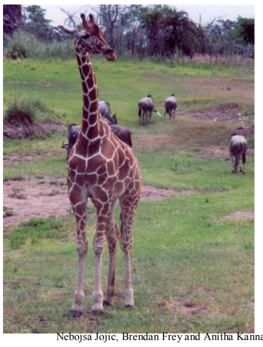


Nebojsa Jojic, Brendan Frey and Anitha Kannan, ICCV 2003
www.research.microsoft.com/~jojic/epitome.htm

More examples

mean

variance



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

More examples

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More examples

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

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

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

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

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

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