

Course Calendar

Lecture	Date	Description	Readings	Assignments	Materials
1	2/1	Course Introduction Cameras and Lenses	Req: FP 1.1, 2.1, 2.2, 2.3, 3.1, 3.2	PSo out	
2	2/3	Image Filtering	Req: FP 7.1 - 7.6		
3	2/8	Image Representations: Pyramids	Req: FP 7.7, 9.2		
4	2/10	Image Statistics		PSo due	
5	2/15	Texture	Req: FP 9.1, 9.3, 9.4	PS1 out	
6	2/17	Color	Req: FP 6.1-6.4		
7	2/22	Guest Lecture: Context in vision			
8	2/24	Guest Lecture: Medical Imaging		PS1 due	
9	3/1	Multiview Geometry	Req: Mikolajczyk and Schmid; FP 10	PS2 out	
10	3/3	Local Features	Req: Shi and Tomasi; Lowe		

Course Calendar

Lecture	Date	Description	Readings	Assignments	Materials
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Today

5	2/15	Texture	Req: FP 9.1, 9.3, 9.4	PS1 out	
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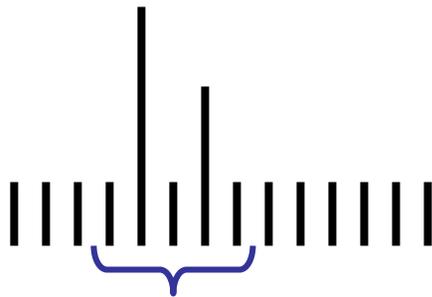
Non-linear filtering example

Median filter

Replace each pixel by the median over N pixels (5 pixels, for these examples).

Generalizes to “rank order” filters.

In:



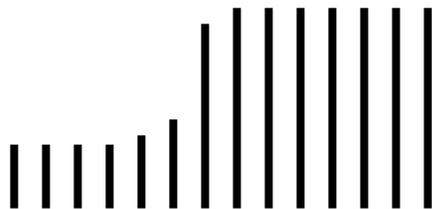
5-pixel
neighborhood

Out:

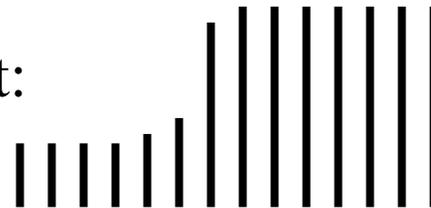


Spike
noise is
removed

In:



Out:



Monotonic
edges
remain
unchanged

Degraded image



Radius 1 median filter



Because the filter is non-linear, it has the opportunity to remove the scratch noise without blurring edges.

Radius 2 median filter



Comparison with linear blur of the amount
needed to remove the scratches



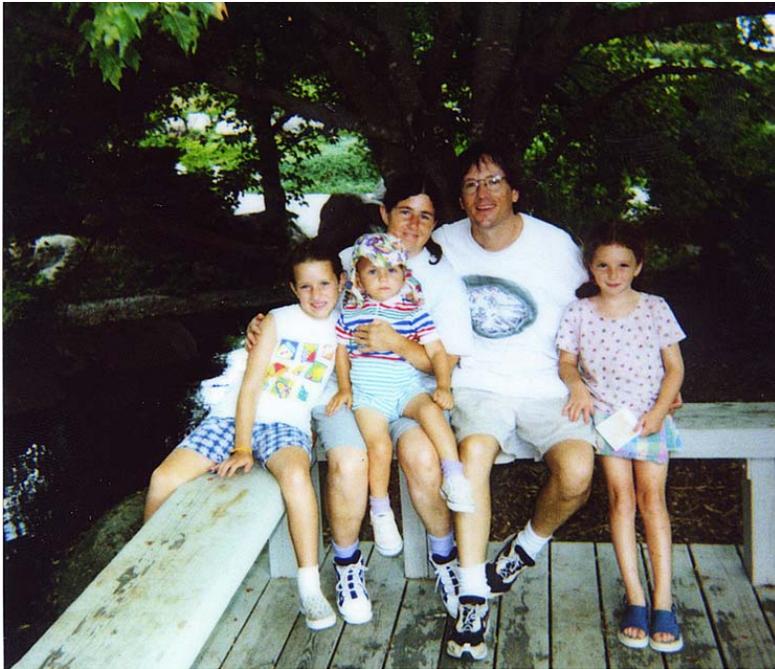
CCD color sampling

Color sensing, 3 approaches

- Scan 3 times (temporal multiplexing)
- Use 3 detectors (3-ccd camera, and color film)
- Use offset color samples (spatial multiplexing)

Typical errors in temporal multiplexing approach

Color offset fringes

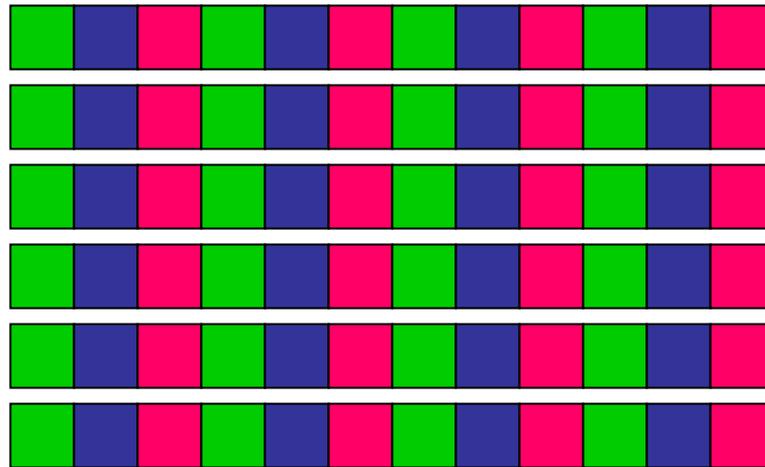


Typical errors in spatial multiplexing approach.

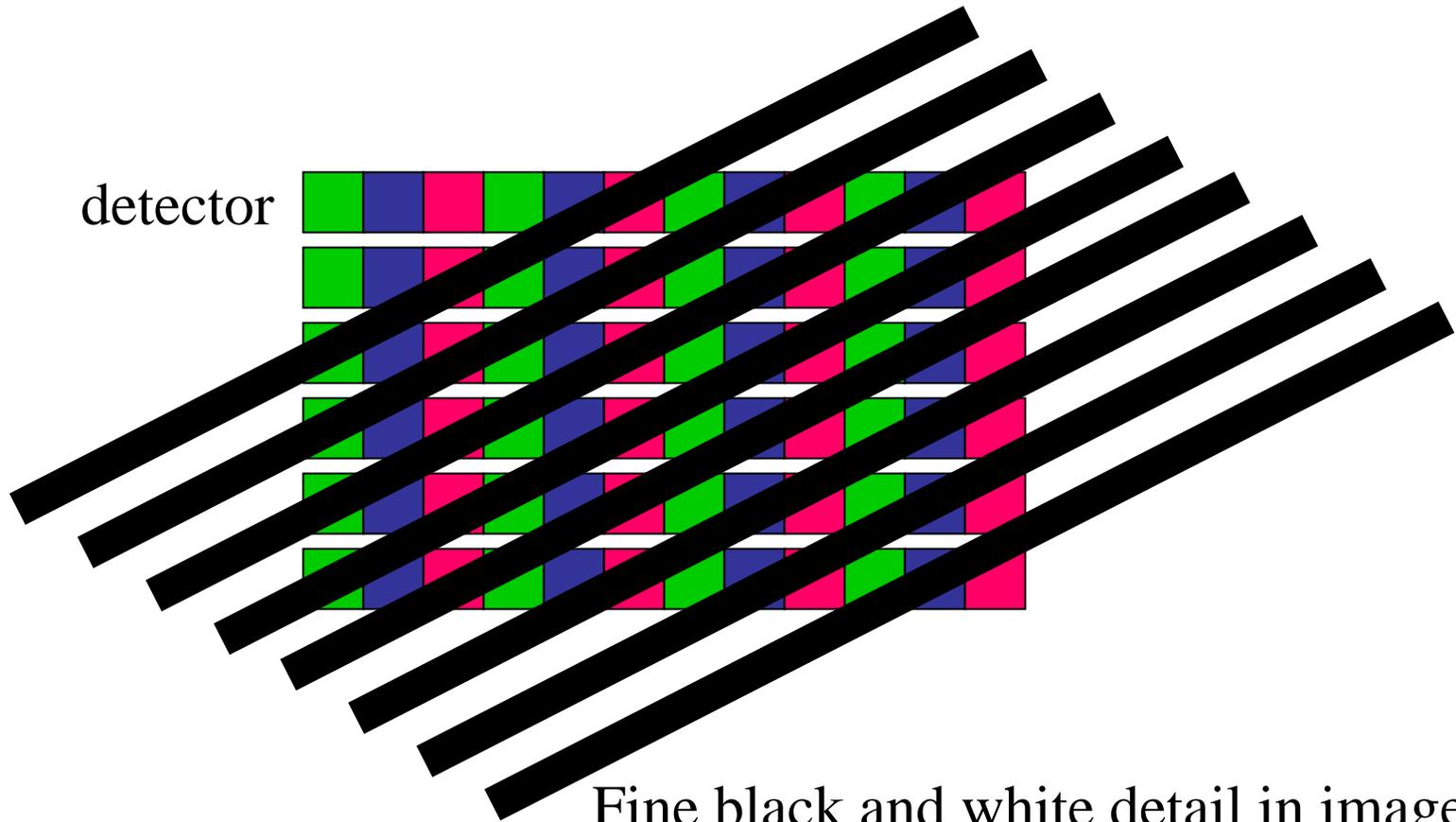
Color fringes.

CCD color filter pattern

detector



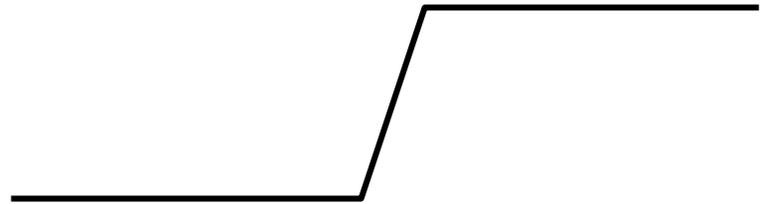
The cause of color moire



Fine black and white detail in image
mis-interpreted as color information.

Black and white edge falling on color CCD detector

Black and white image (edge)



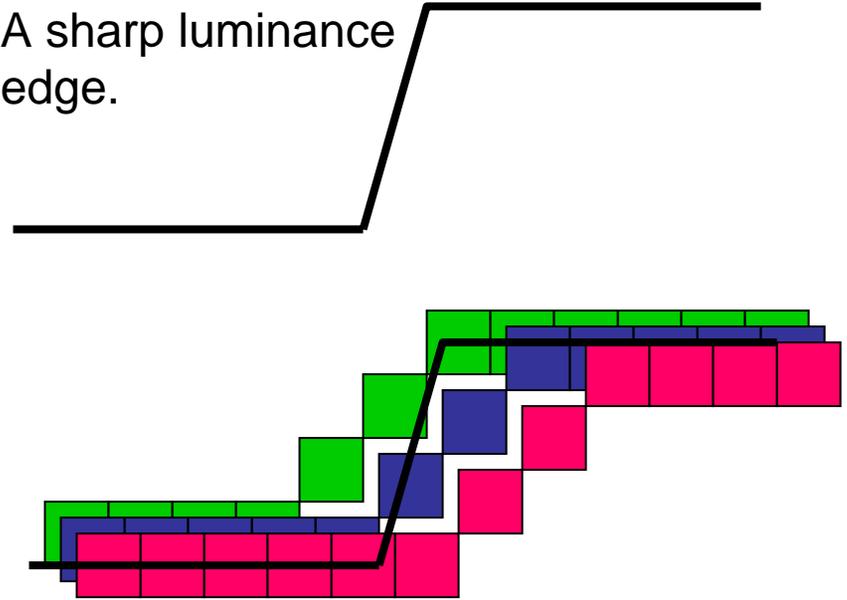
Detector pixel colors



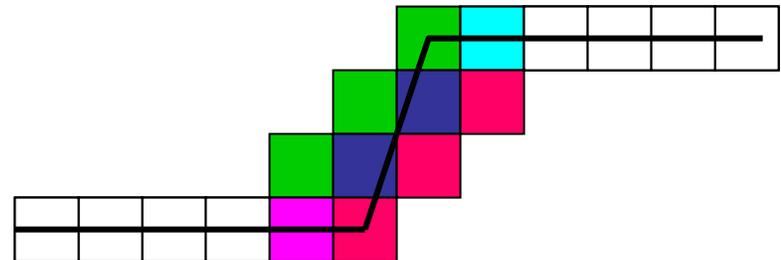
Color sampling artifacts

Interpolated pixel colors, for grey edge falling on colored detectors (linear interpolation). The edge is aliased (undersampled) in the samples of any one color. That aliasing manifests itself in the spatial domain as an incorrect estimate of the precise position of the edge. That disagreement about the position of the edge results in a color fringe artifact.

A sharp luminance edge.



The response of independently interpolated color bands to an edge.



The mis-estimated edge yields color fringe artifacts.

Typical color moire patterns

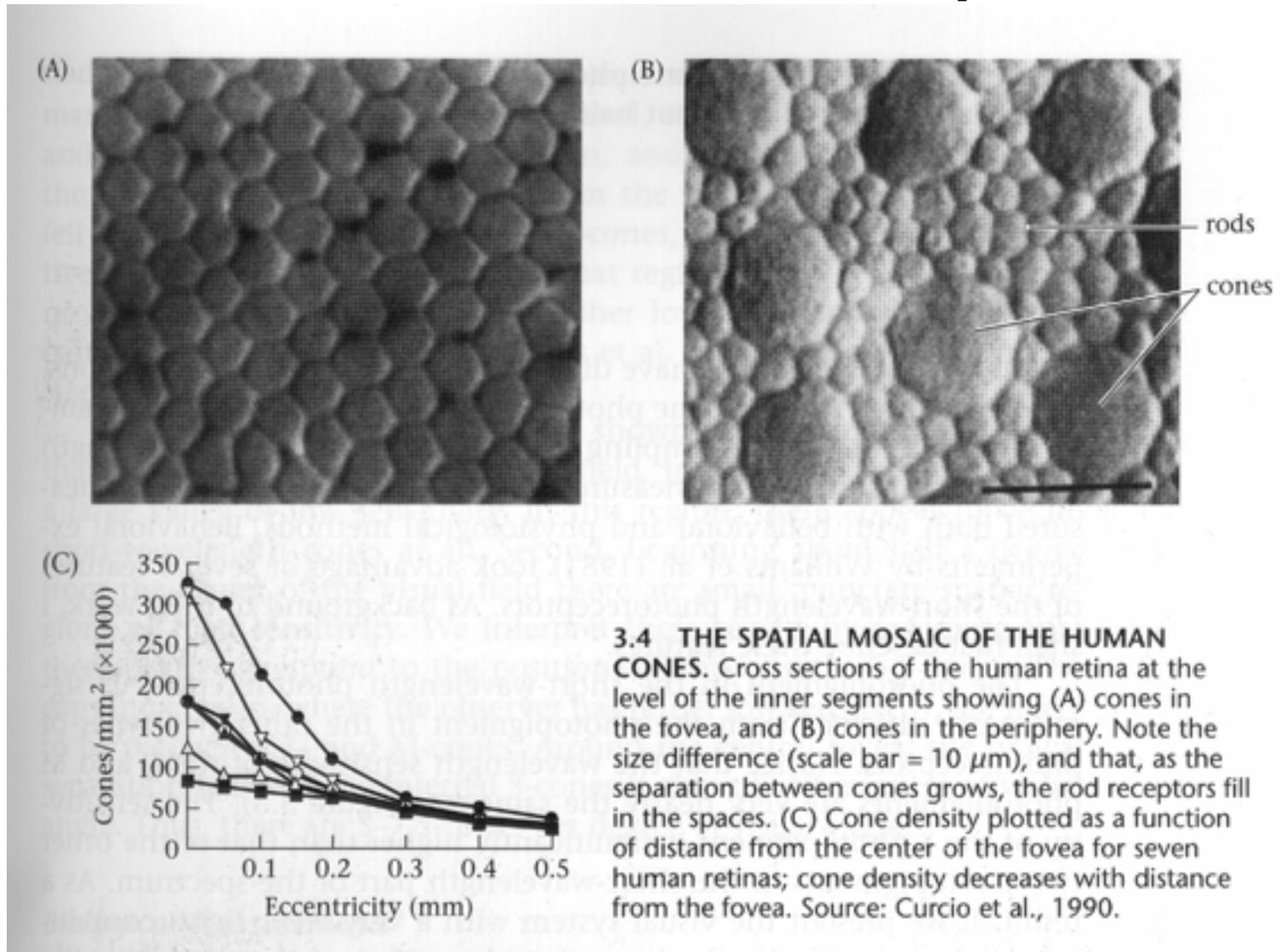


Blow-up of electronic camera image. Notice spurious colors in the regions of fine detail in the plants.

Color sampling artifacts



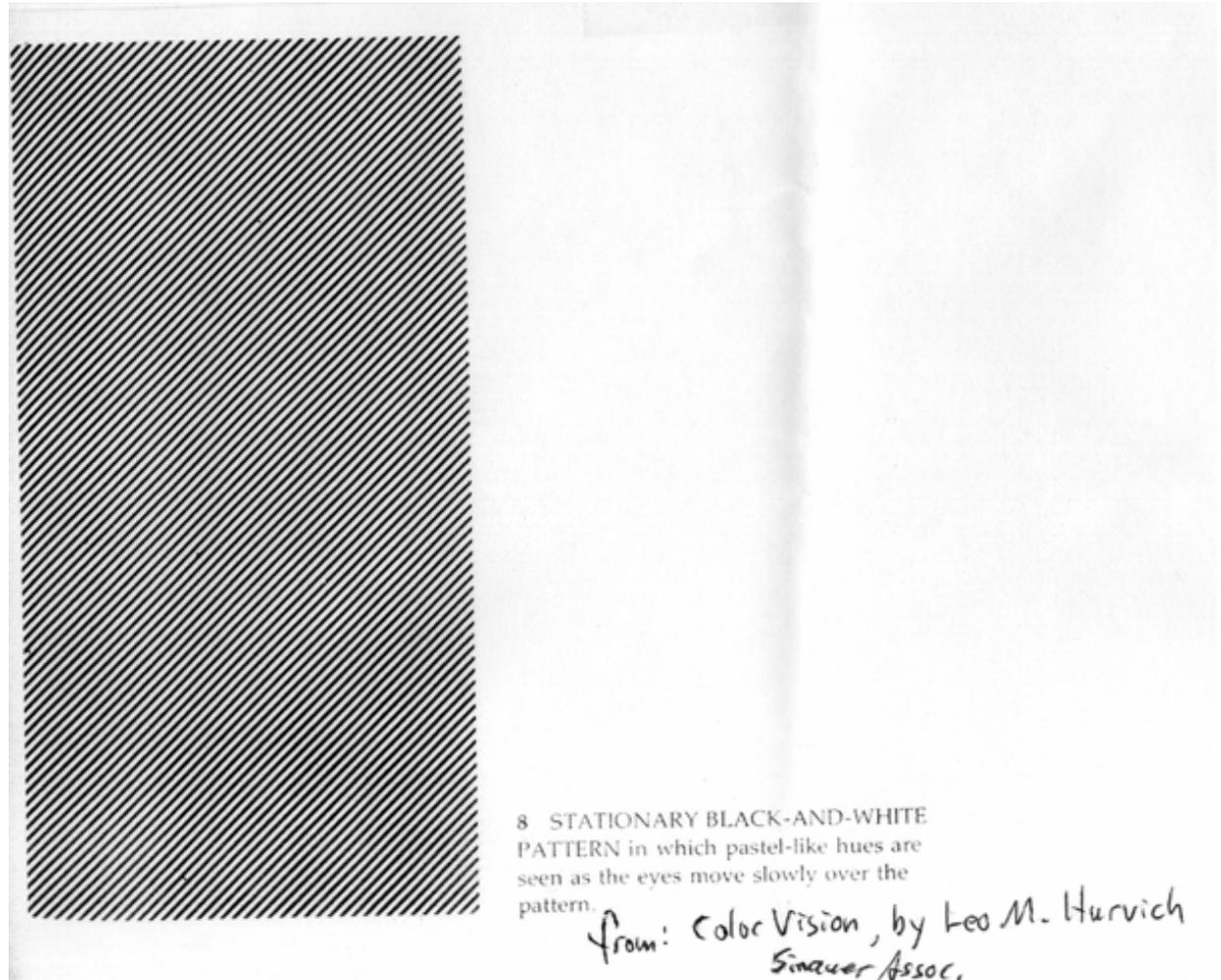
Human Photoreceptors



(From Foundations of Vision, by Brian Wandell, Sinauer Assoc.)

Brewster's colors example (subtle).

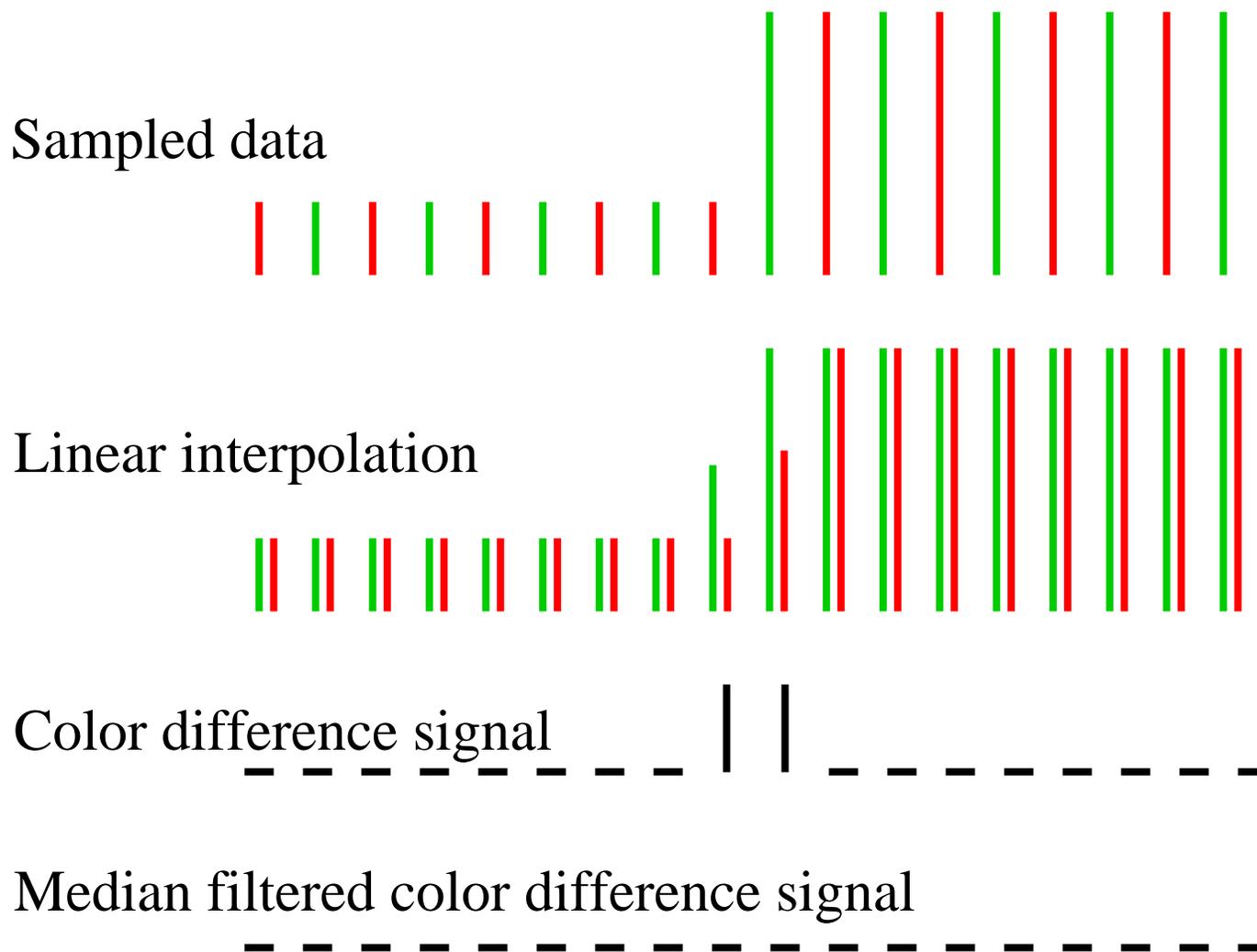
Scale relative
to human
photoreceptor
size: each line
covers about 7
photoreceptors.



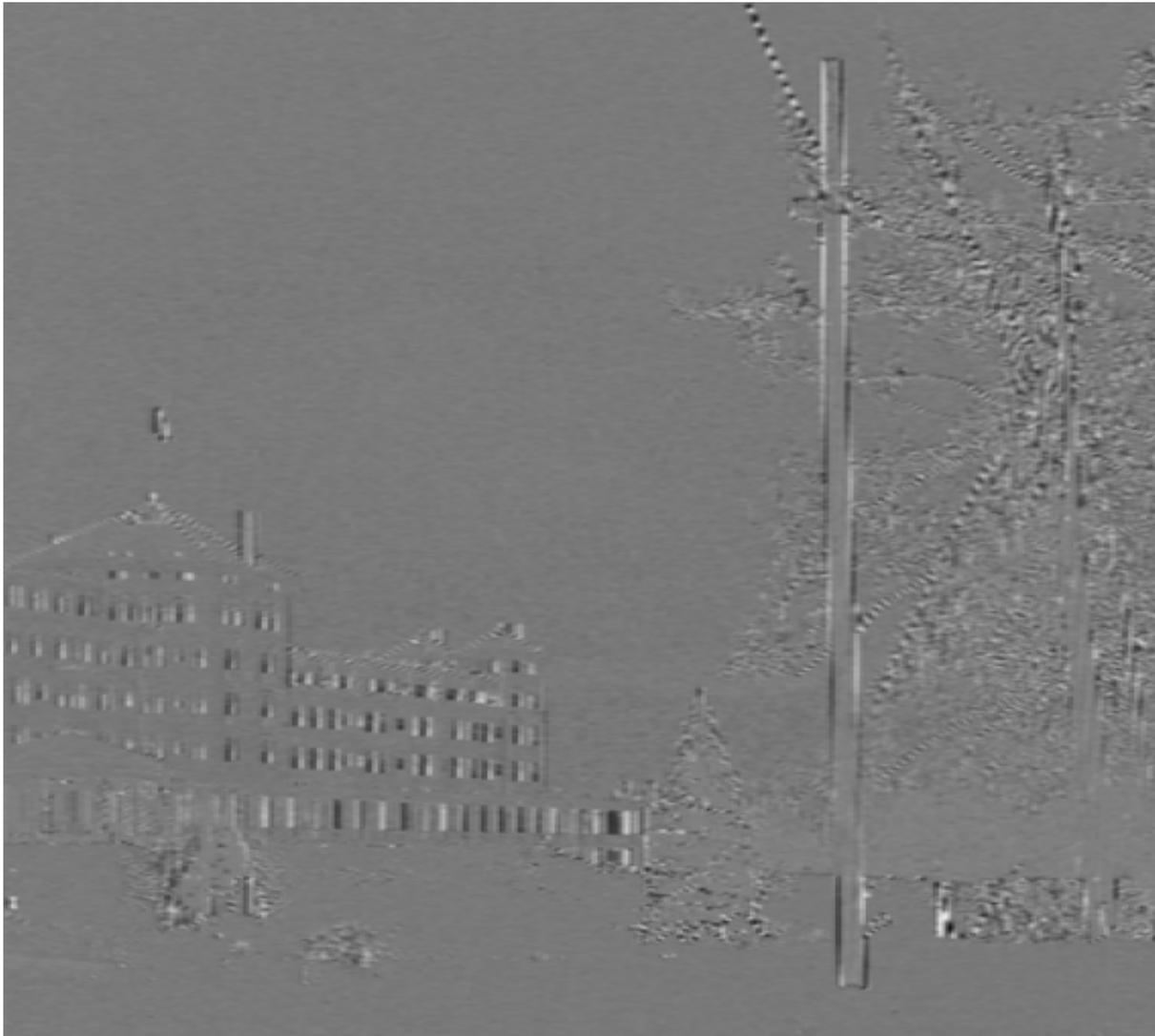
Median Filter Interpolation

- 1) Perform first interpolation on isolated color channels.
- 2) Compute color difference signals.
- 3) Median filter the color difference signal.
- 4) Reconstruct the 3-color image.

Two-color sampling of BW edge



R-G, after linear interpolation



R – G, median filtered (5x5)



Recombining the median filtered colors

Linear interpolation



Median filter interpolation



References on color interpolation

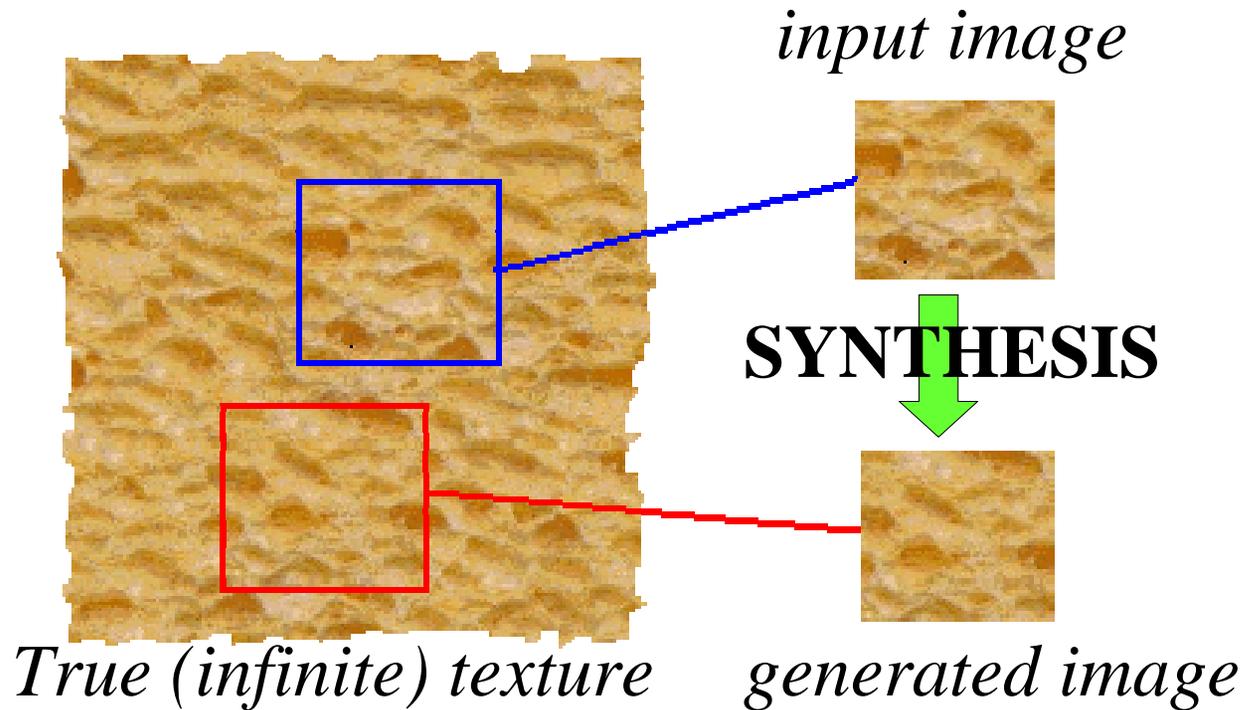
- Brainard
- Shree nayar.

Image texture

Texture

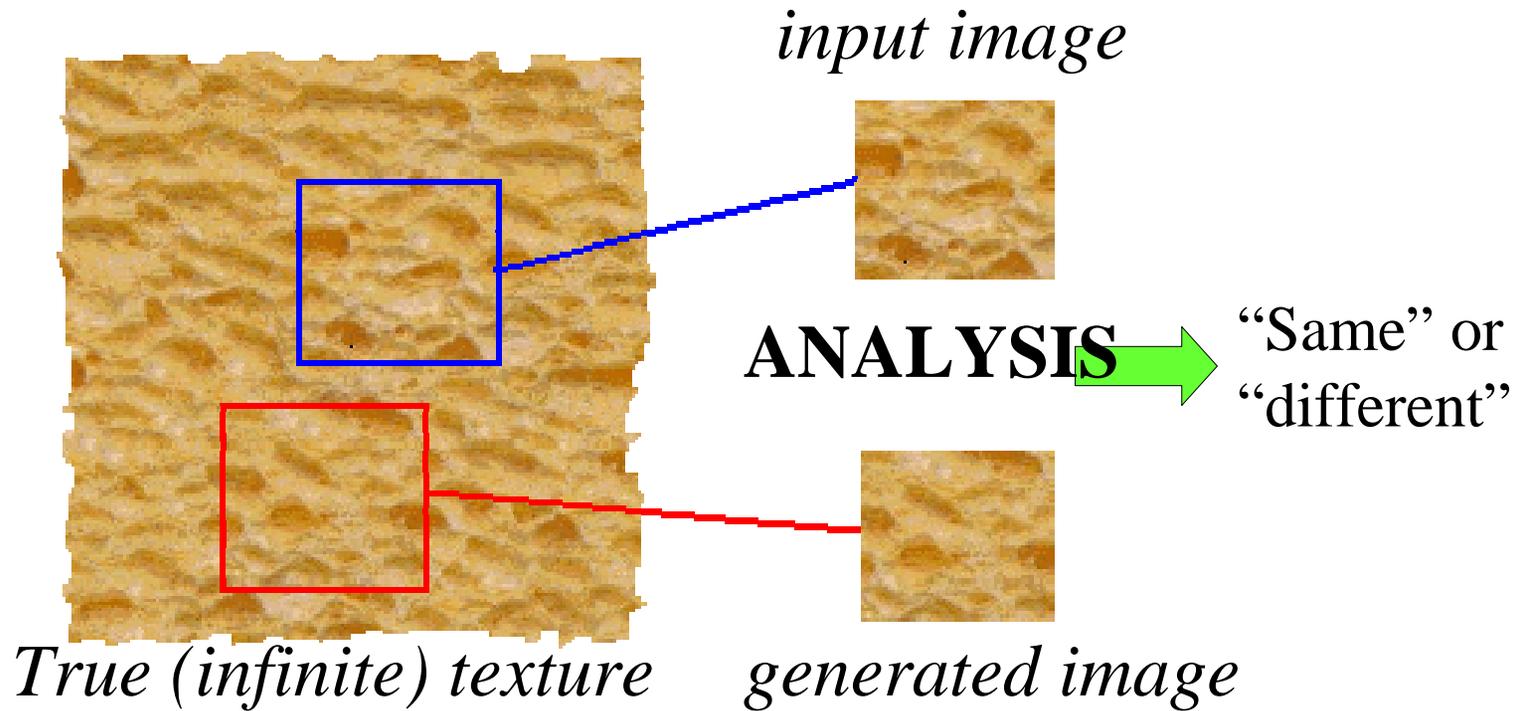
- Key issue: representing texture
 - Texture based matching
 - little is known
 - Texture segmentation
 - key issue: representing texture
 - Texture synthesis
 - useful; also gives some insight into quality of representation
 - Shape from texture
 - cover superficially

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"

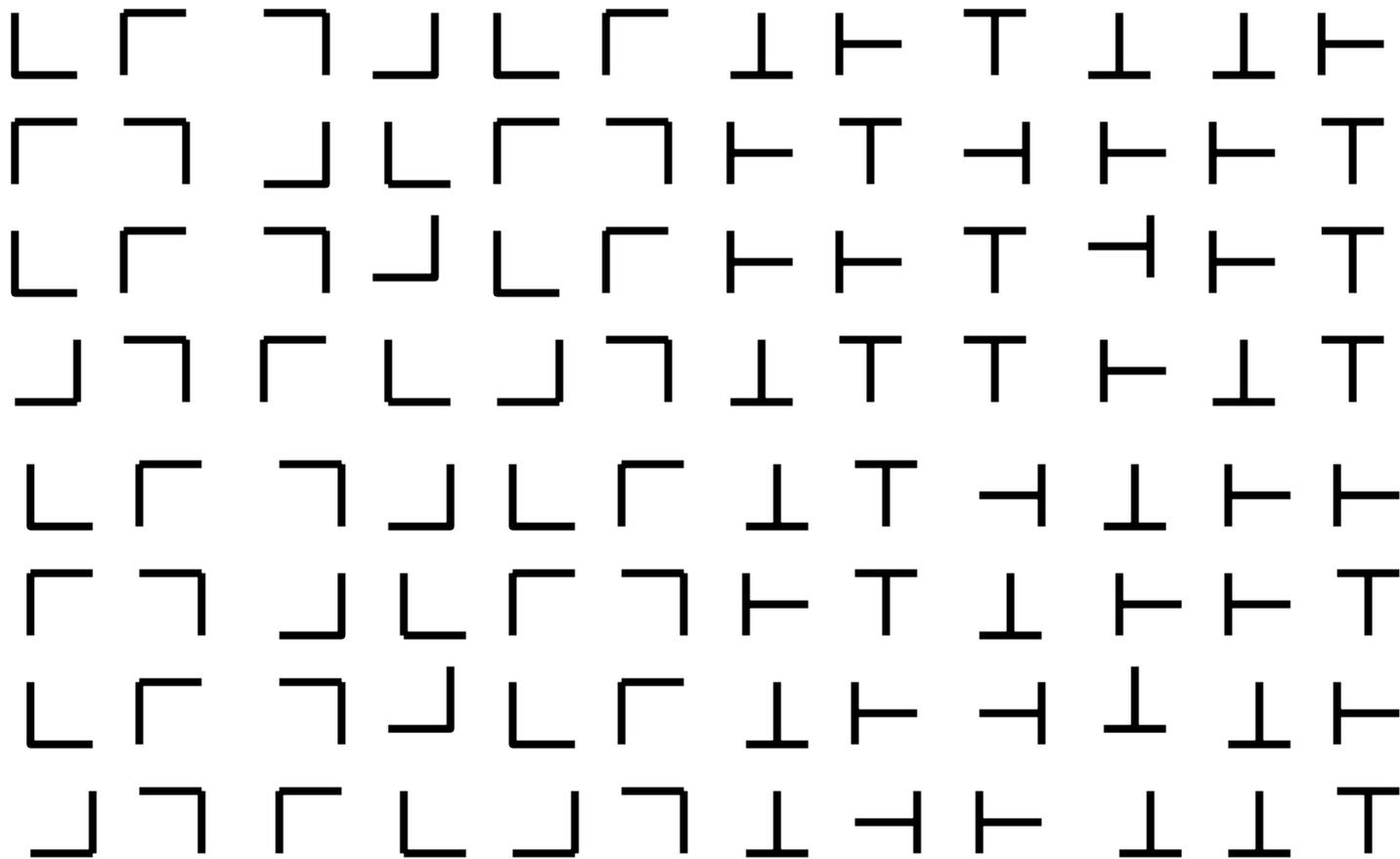
The Goal of Texture Analysis



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

Pre-attentive texture discrimination

Pre-attentive texture discrimination

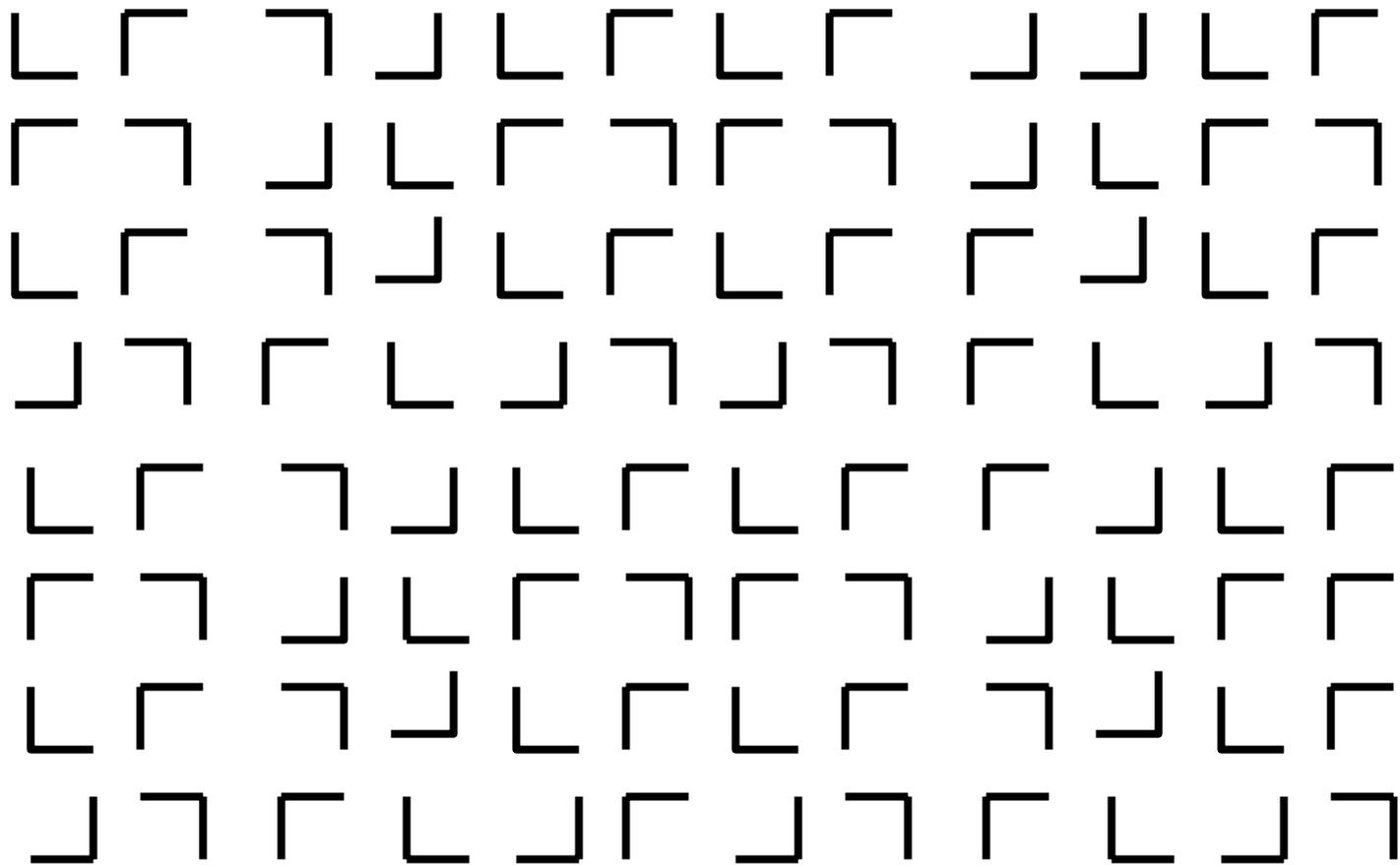


Pre-attentive texture discrimination

Same or different textures?

Pre-attentive texture discrimination

Pre-attentive texture discrimination

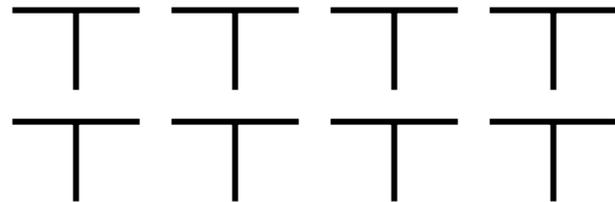
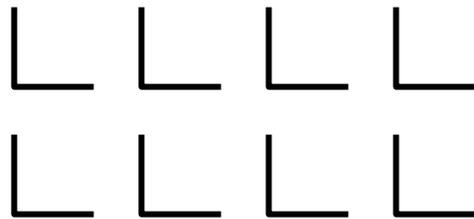


Pre-attentive texture discrimination

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...



Influential 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

Bergen and Adelson, Nature 1988

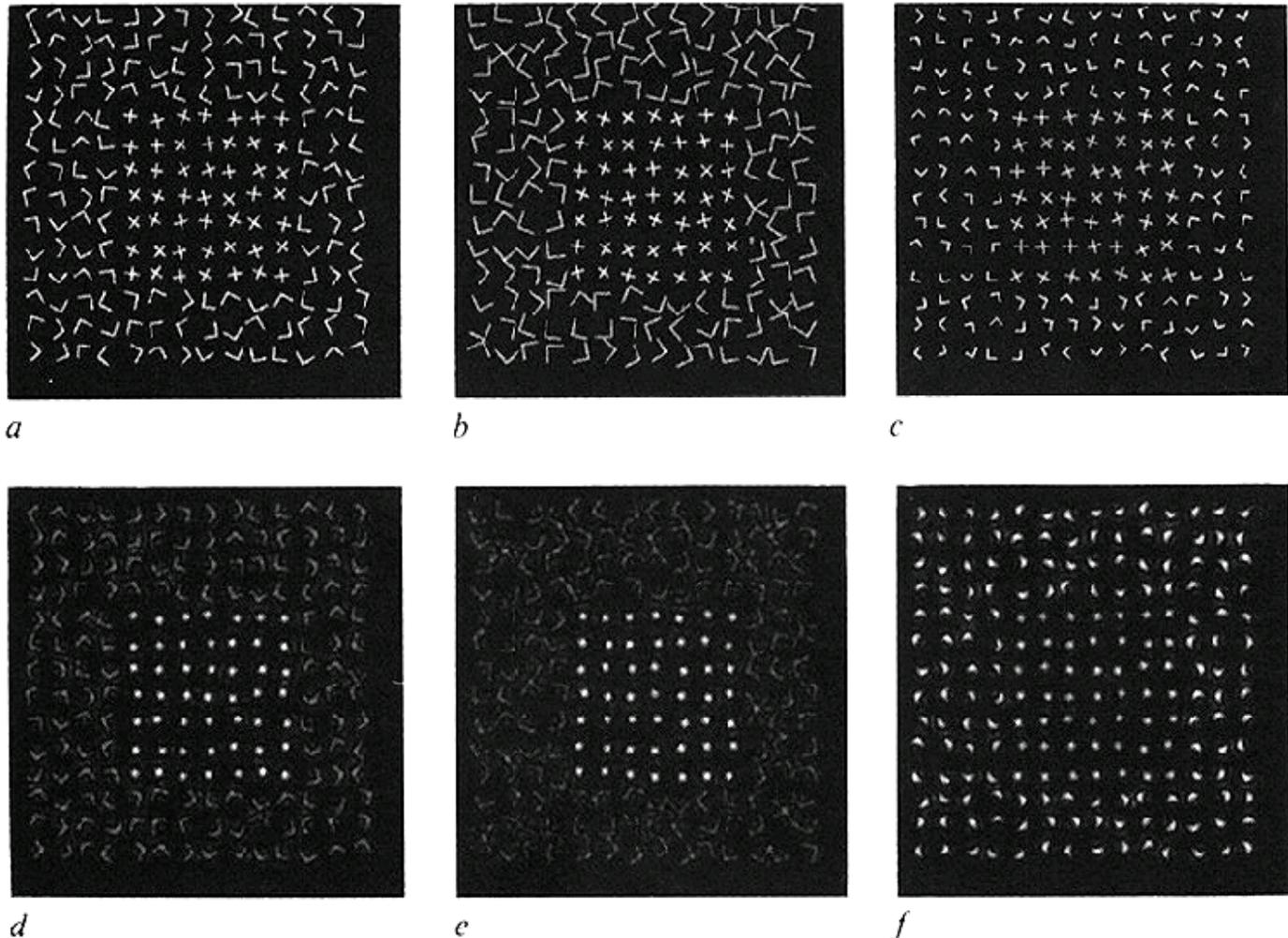
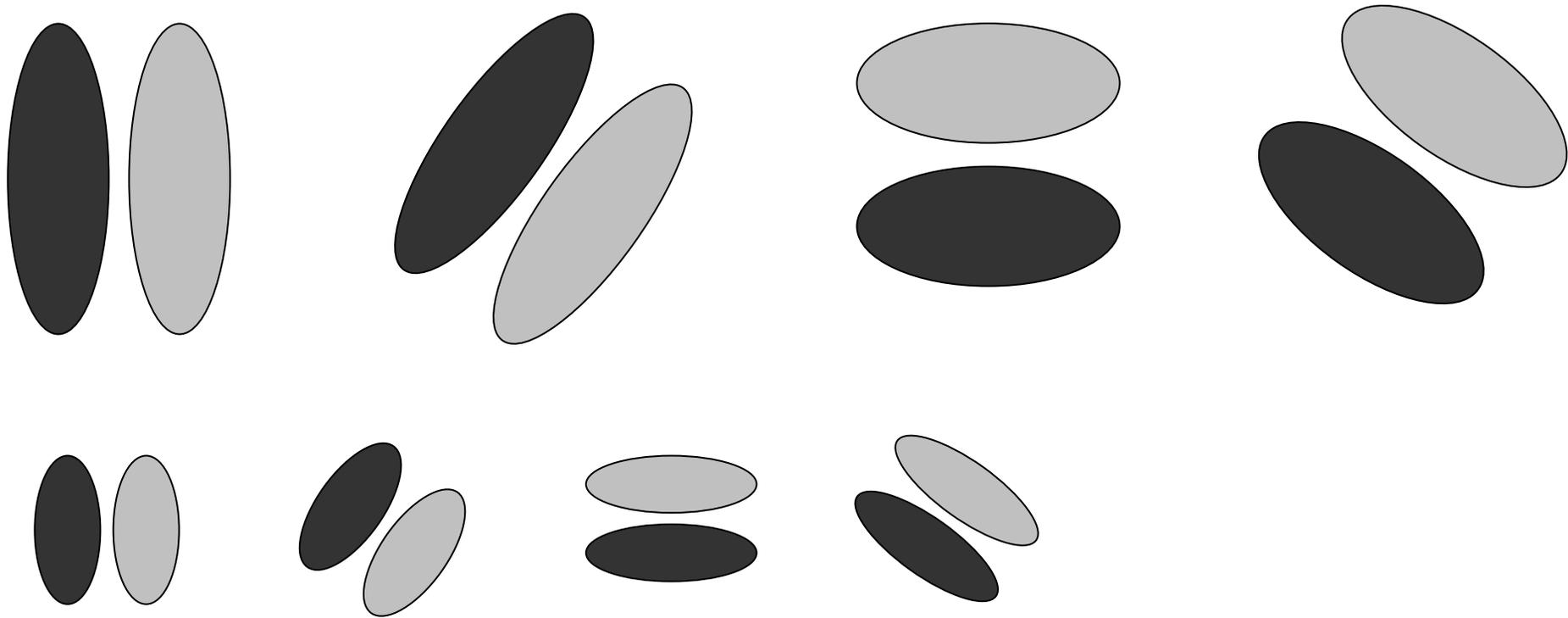


Fig. 1 *Top row*, Textures consisting of Xs within a texture composed of Ls. The micropatterns are placed at random orientations on a randomly perturbed lattice. *a*, The bars of the Xs have the same length as the bars of the Ls. *b*, The bars of the Ls have been lengthened by 25%, and the intensity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

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

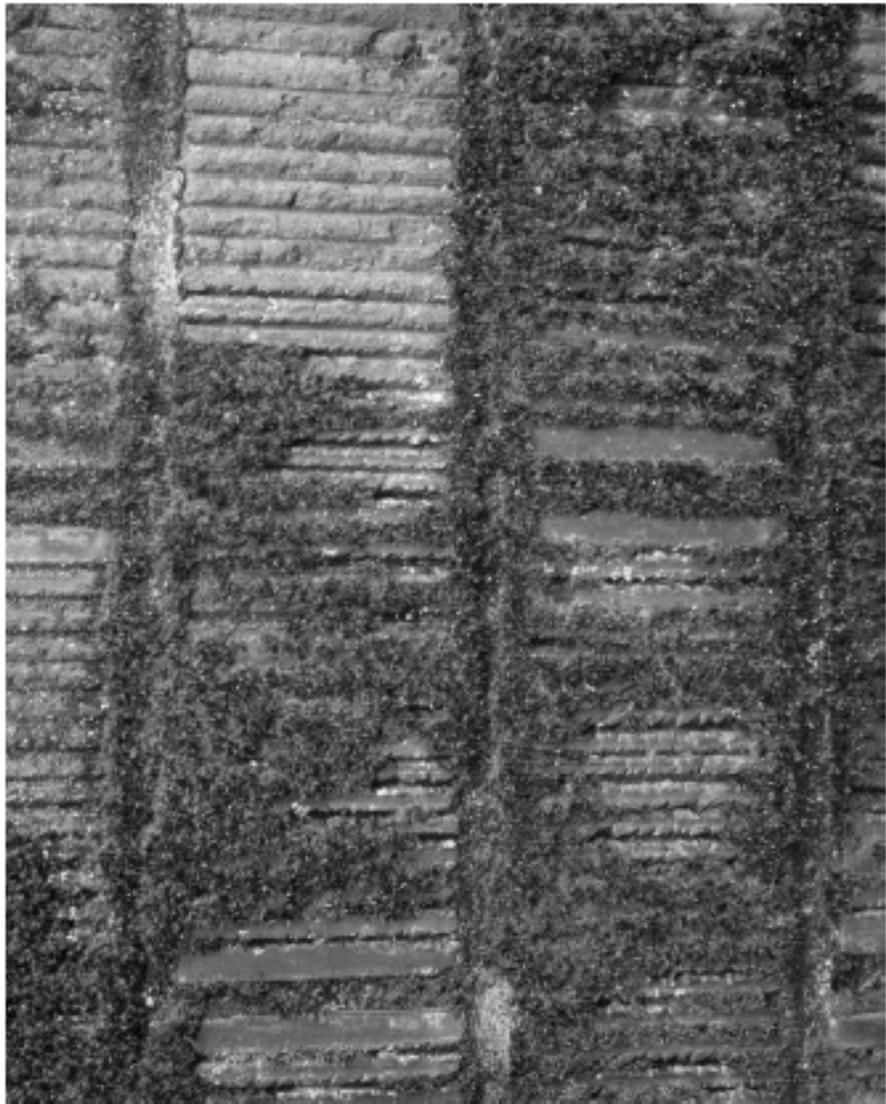
Malik and Perona

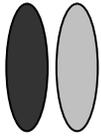


Malik J, Perona P. Preattentive texture
discrimination with early vision
mechanisms. J OPT SOC AM A 7: (5) 923-
932 MAY 1990

Representing textures

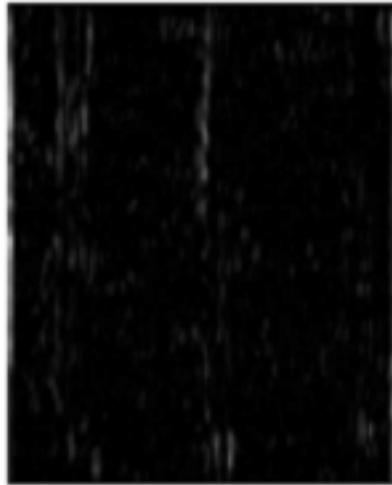
- Textures are made up of quite stylised subelements, repeated in meaningful ways
- Representation:
 - find the subelements, and represent their statistics
- But what are the subelements, and how do we find them?
 - recall normalized correlation
 - find subelements by applying filters, looking at the magnitude of the
- What filters?
 - experience suggests spots and oriented bars at a variety of different scales
 - details probably don't matter
- What statistics?
 - within reason, the more the merrier.
 - At least, mean and standard deviation
 - better, various conditional histograms.



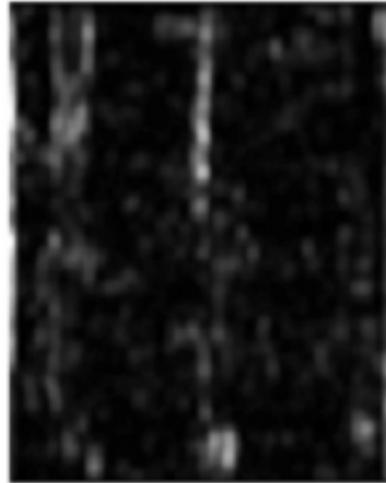


vertical filter

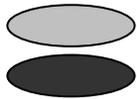
Squared responses



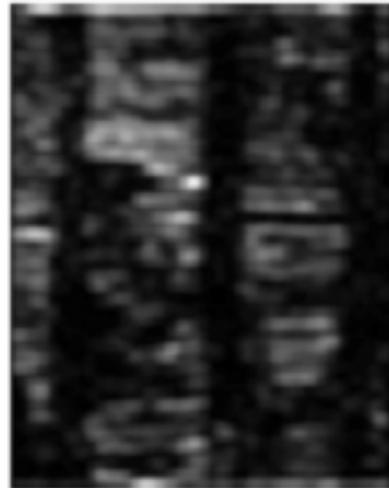
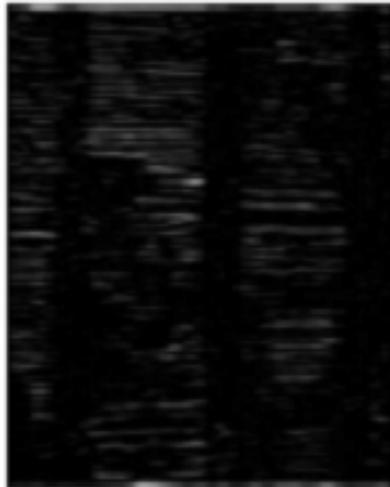
Spatially blurred



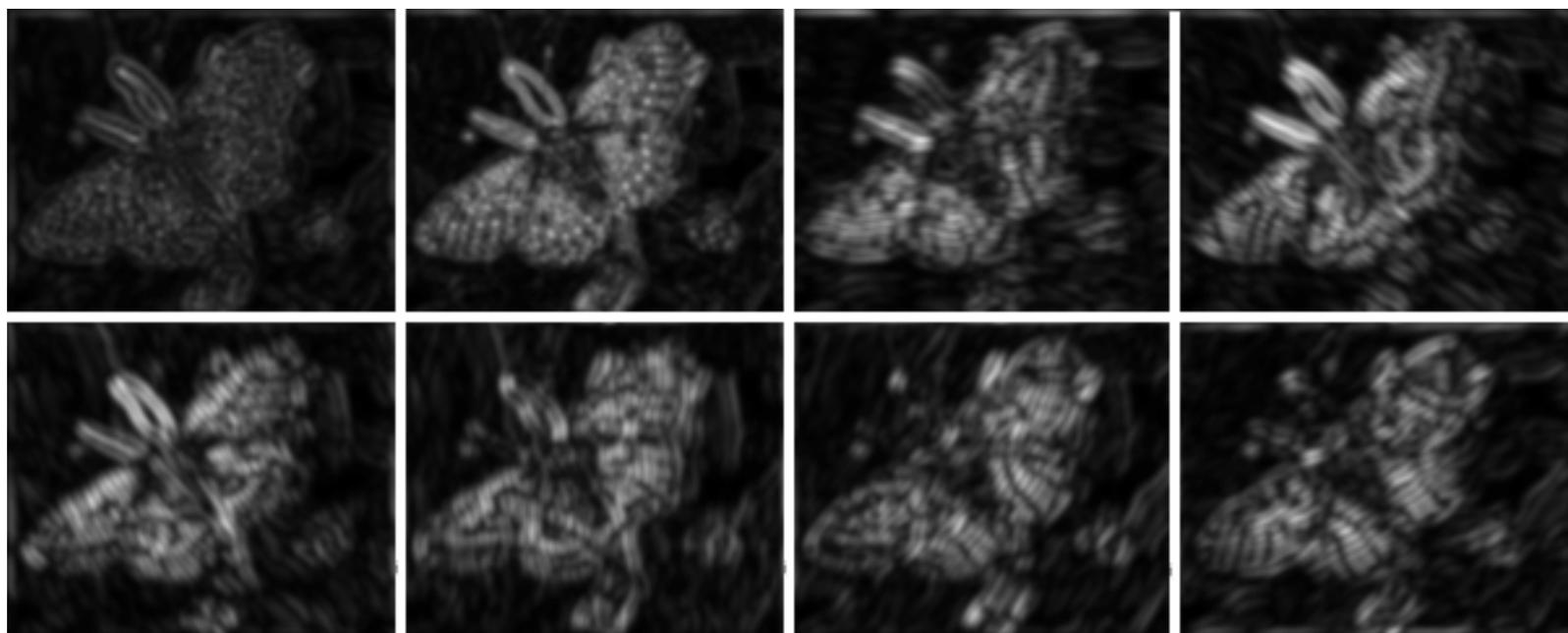
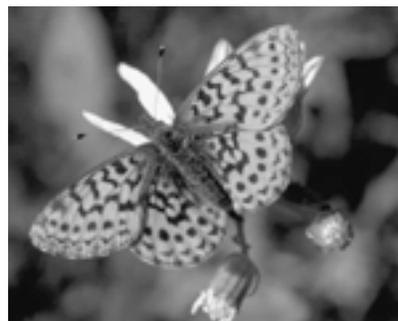
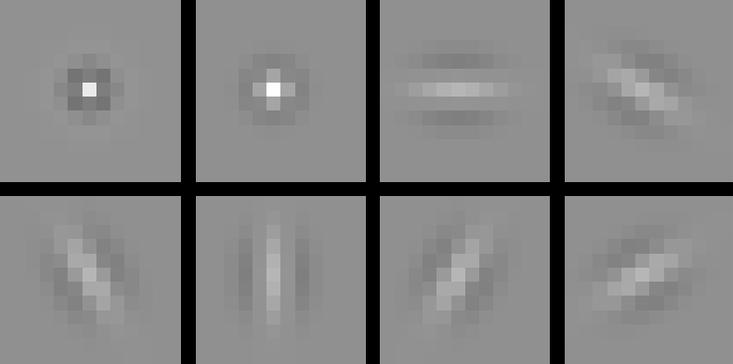
image

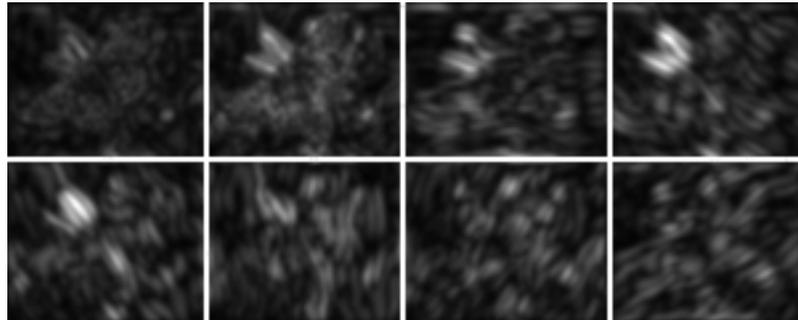
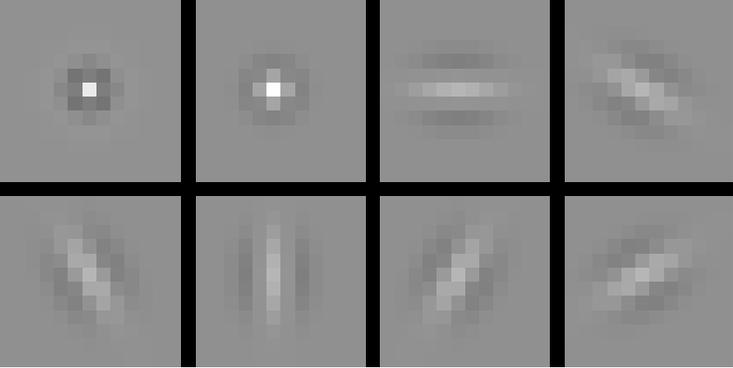


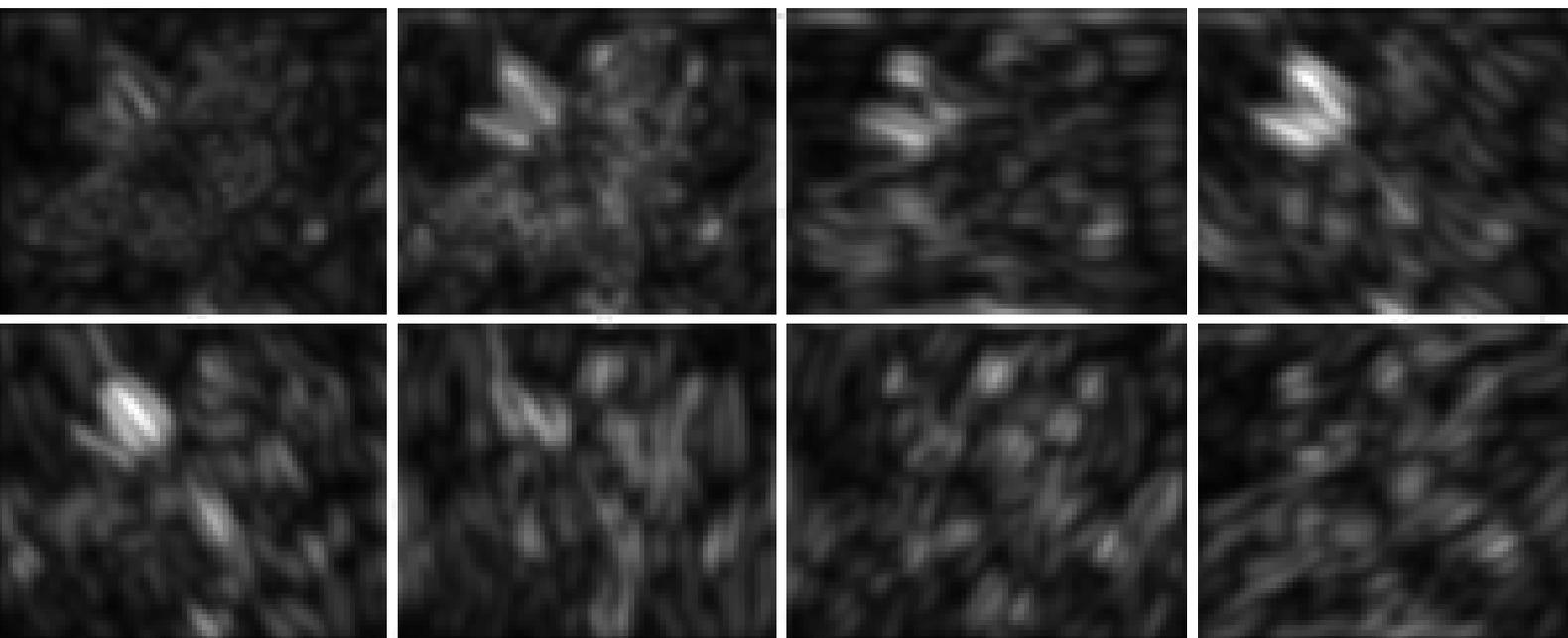
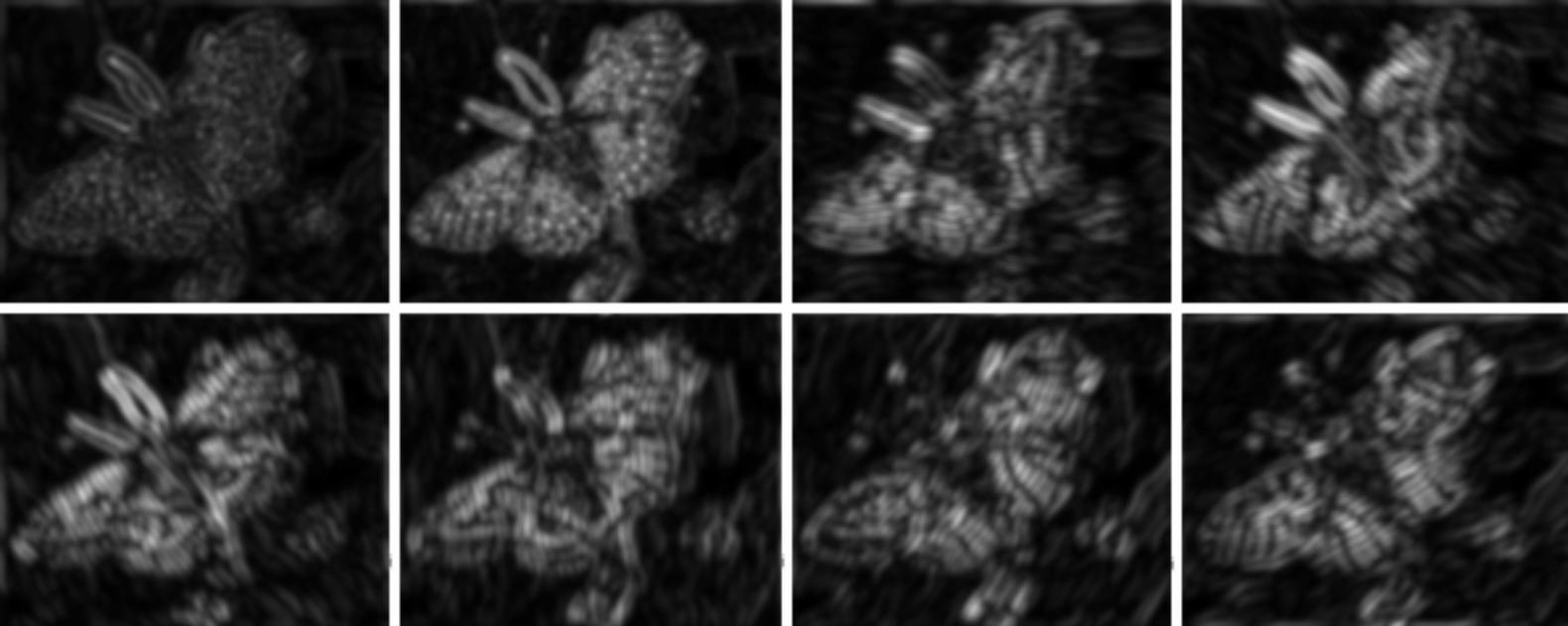
horizontal filter



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





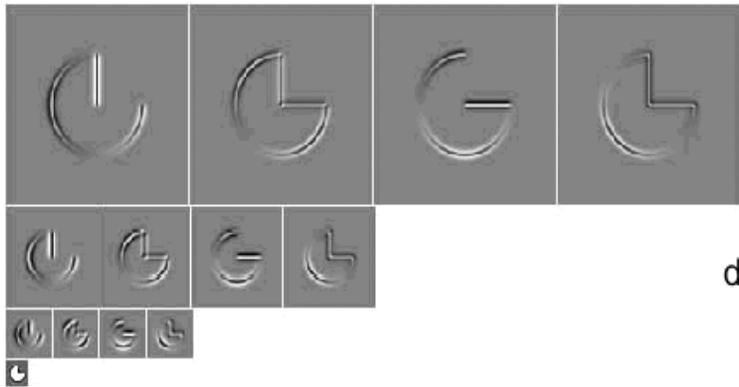
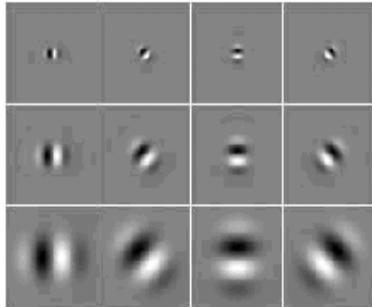
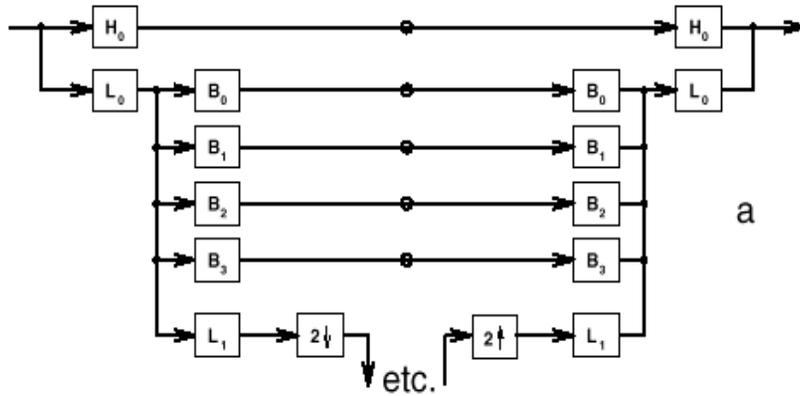


Pyramid-Based Texture Analysis/Synthesis

David J. Heeger[‡]
Stanford University

James R. Bergen[†]
SRI David Sarnoff Research Center

SIGGRAPH 1994



c

Show block diagram of heeger bergen

- And demonstrate it working with matlab code. Ask ted for example.

Learn: use filter marginal statistics.

Bergen and Heeger

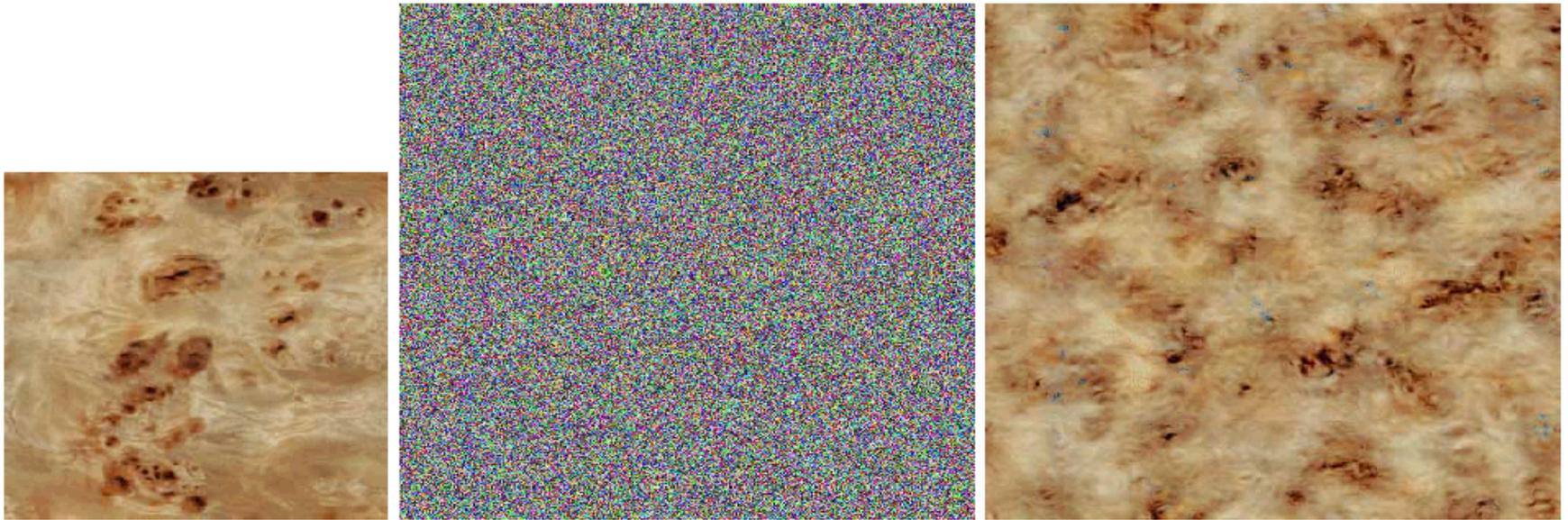


Figure 2: (Left) Input digitized sample texture: burl wood. (Middle) Input noise. (Right) Output synthetic texture that matches the appearance of the digitized sample. Note that the synthesized texture is larger than the digitized sample; our approach allows generation of as much texture as desired.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

Matlab examples

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.

Bergen and Heeger failures

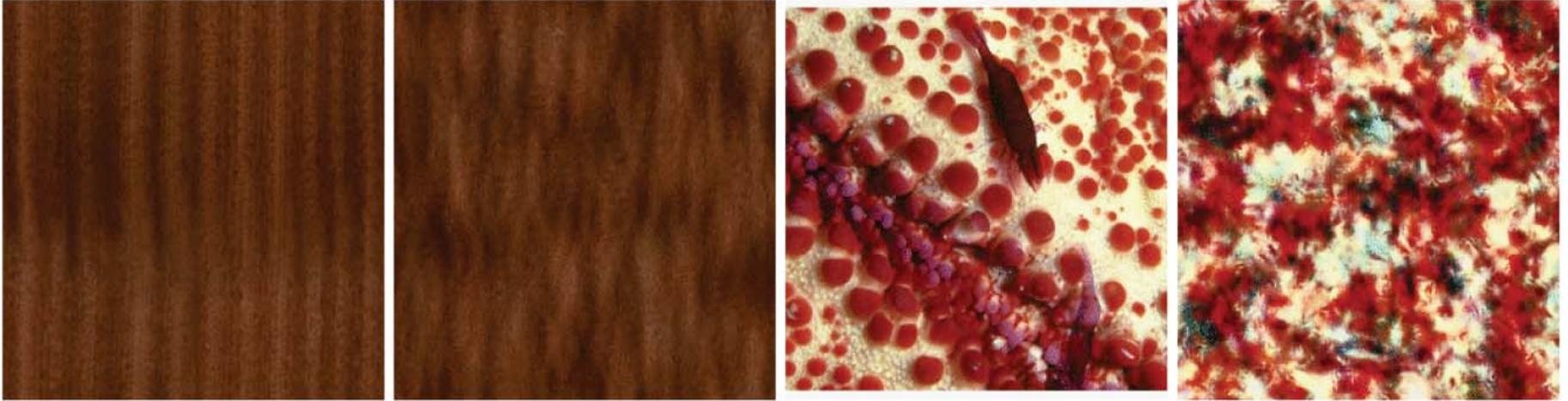


Figure 8: Examples of failures: wood grain and red coral.

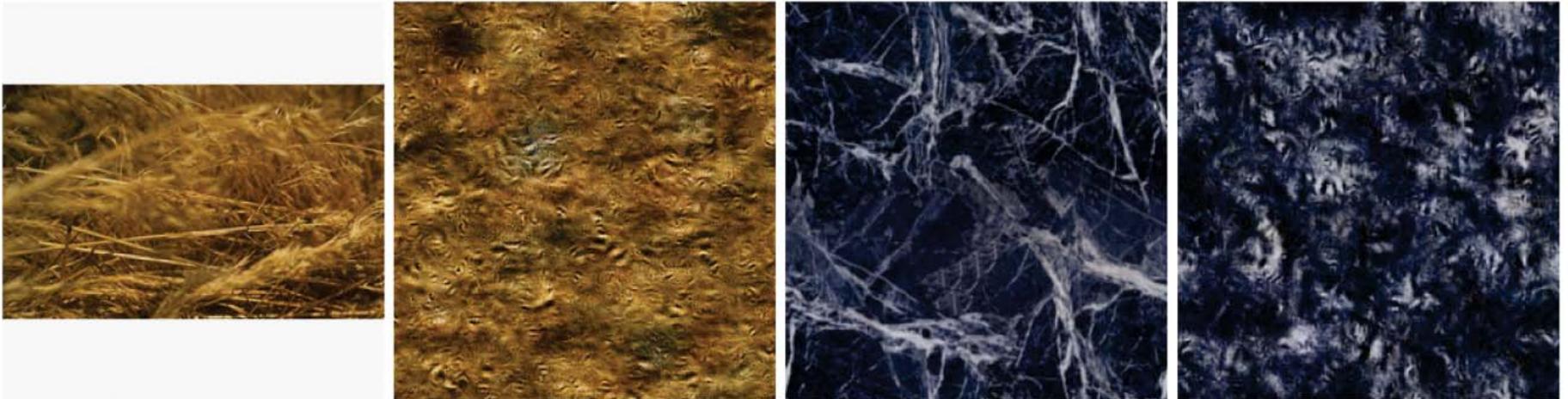


Figure 9: More failures: hay and marble.

De Bonet (and Viola)

SIGGRAPH 1997

Multiresolution Sampling Procedure for Analysis and Synthesis of Texture Images

Jeremy S. De Bonet -
Learning & Vision Group
Artificial Intelligence Laboratory
Massachusetts Institute of Technology

EMAIL: jsd@ai.mit.edu
HOMEPAGE: <http://www.ai.mit.edu/~jsd>

Learn: use filter conditional statistics across scale.

DeBonet

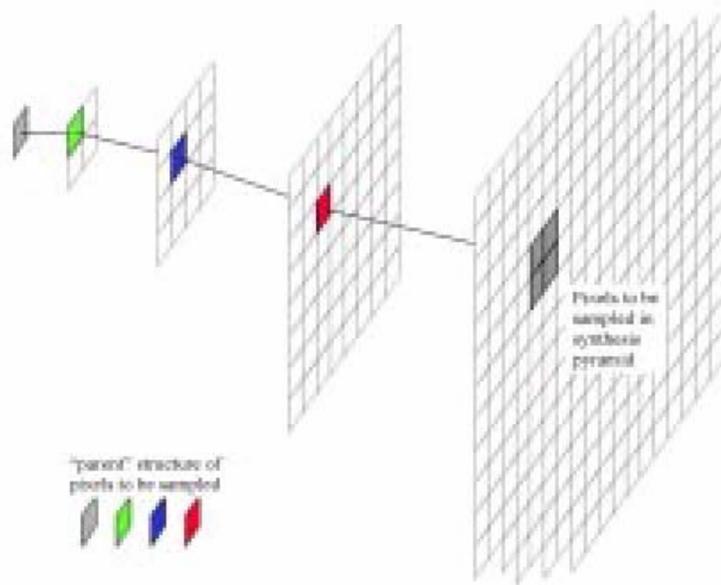


Figure 8: The distribution from which pixels in the synthesis pyramid are sampled is conditioned on the “parent” structure of those pixels. Each element of the parent structure contains a vector of the feature measurements at that location and scale.

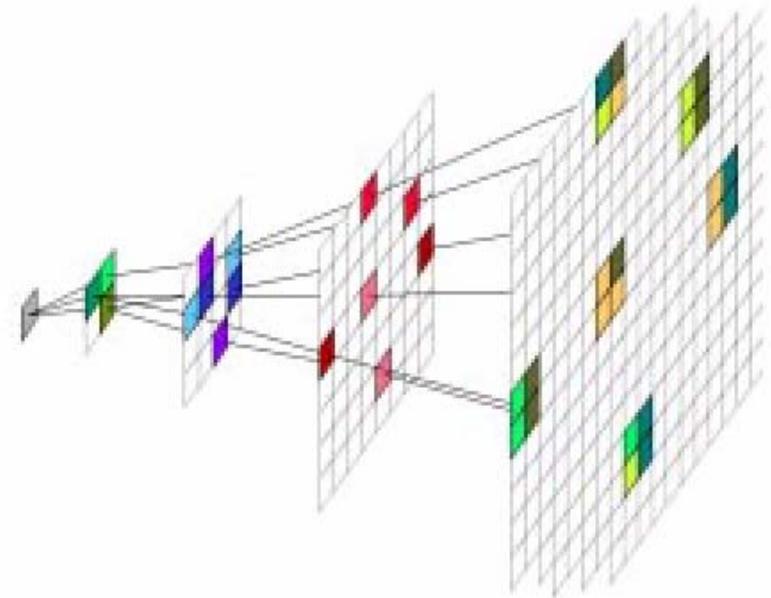
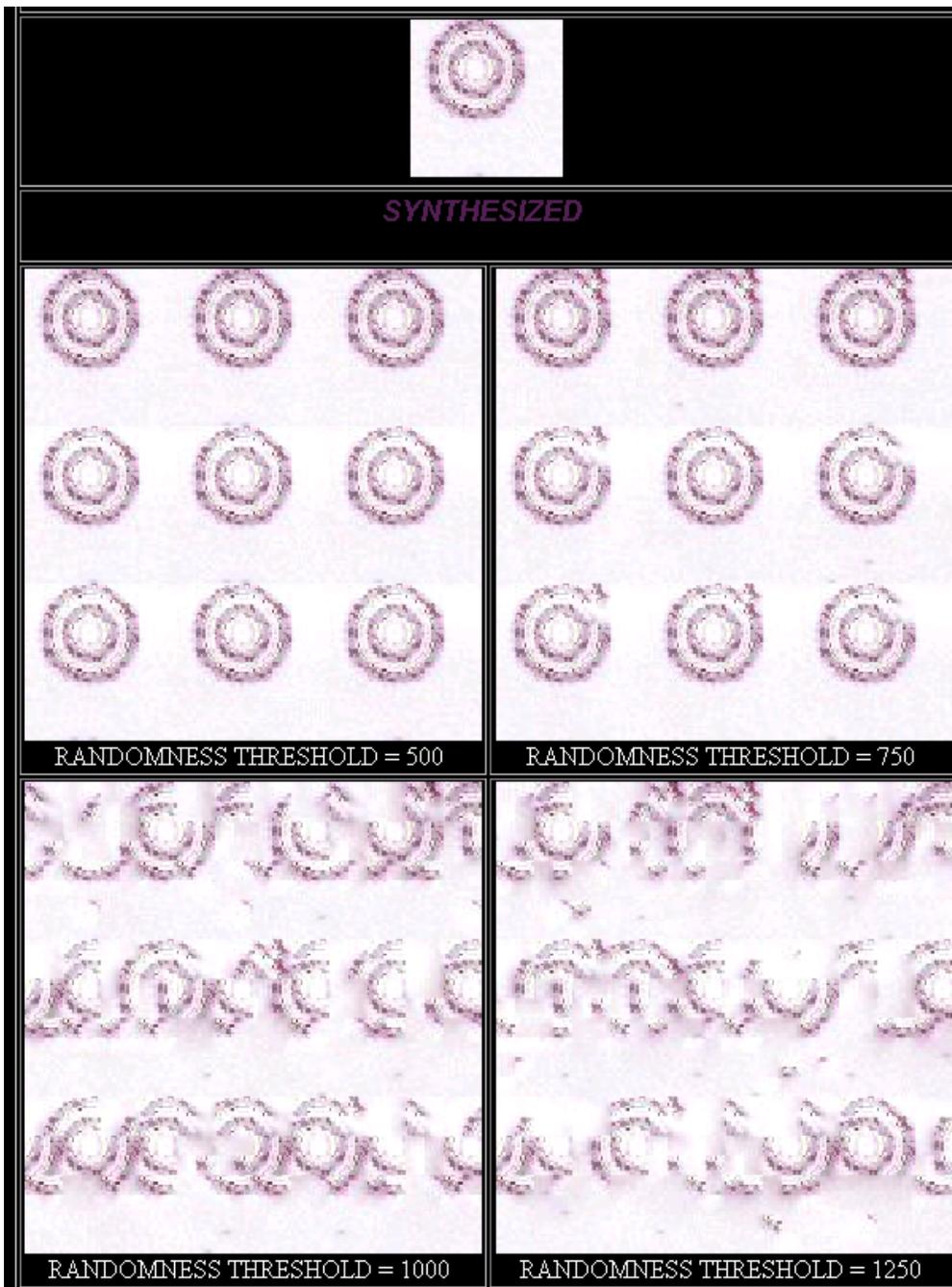
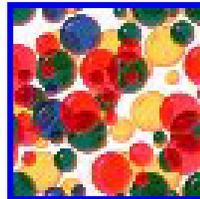
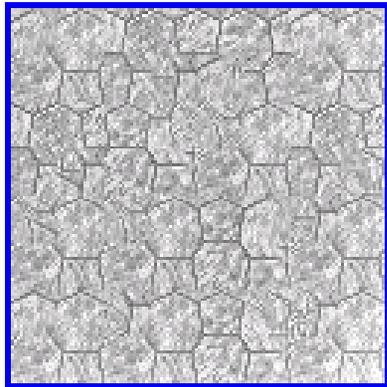
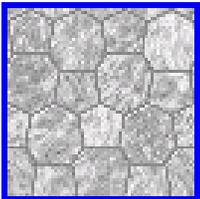
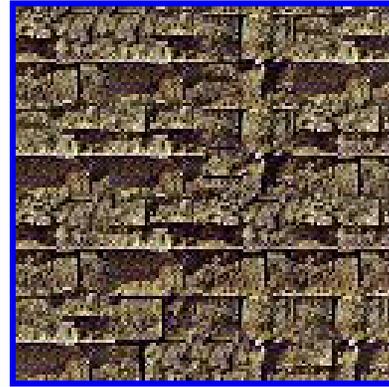
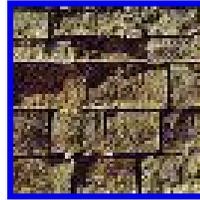
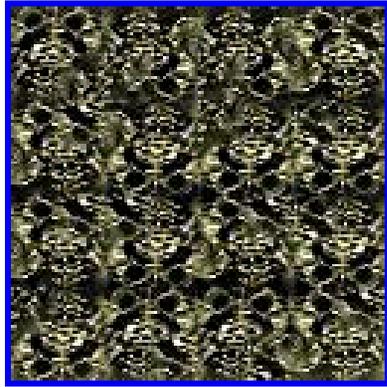
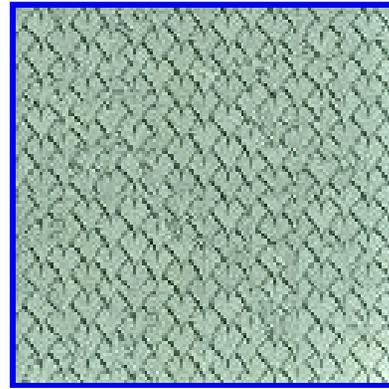
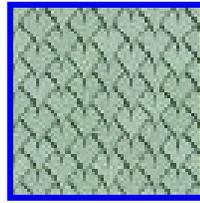
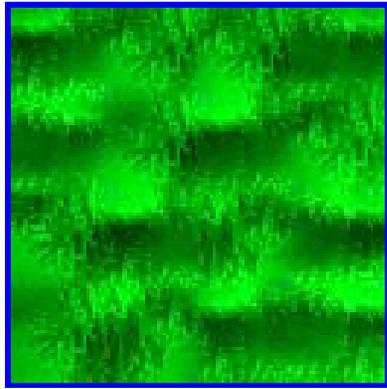
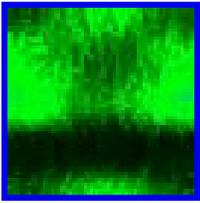


Figure 9: An input texture is decomposed to form an analysis pyramid, from which a new synthesis pyramid is sampled, conditioned on local features within the pyramids. A filter bank of local texture measures, based on psychophysical models, are used as features.

DeBonet



DeBonet



Portilla and Simoncelli

- Parametric representation.
- About 1000 numbers to describe a texture.
- Ok results; maybe as good as DeBonet.

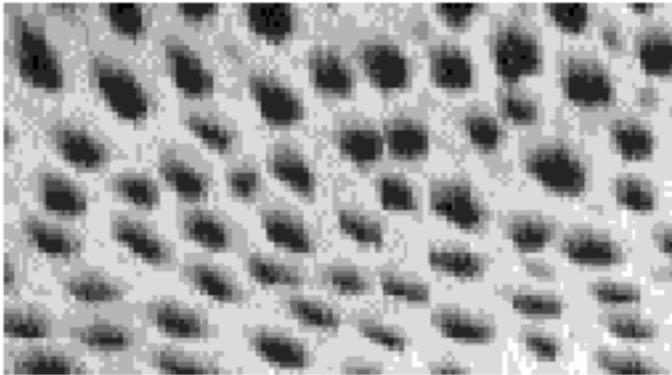
Portilla and Simoncelli



Zhu, Wu, & Mumford, 1998

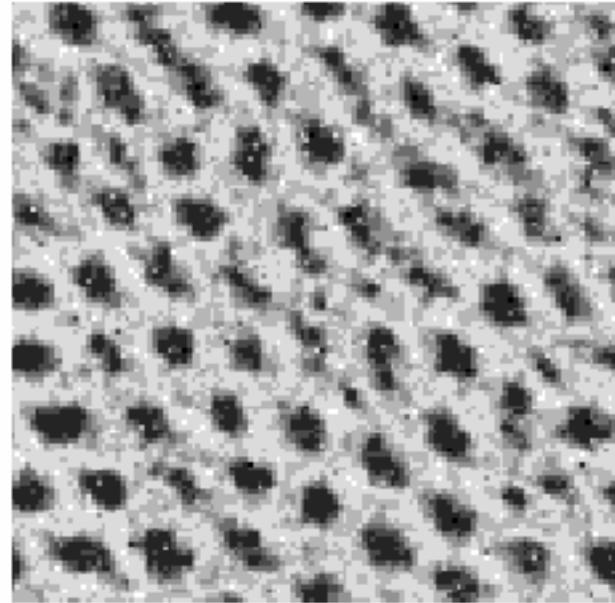
- Principled approach.
- Synthesis quality not great, but ok.

Zhu, Wu, & Mumford



a

- Cheetah

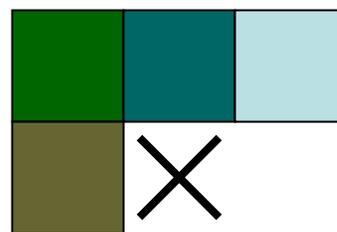
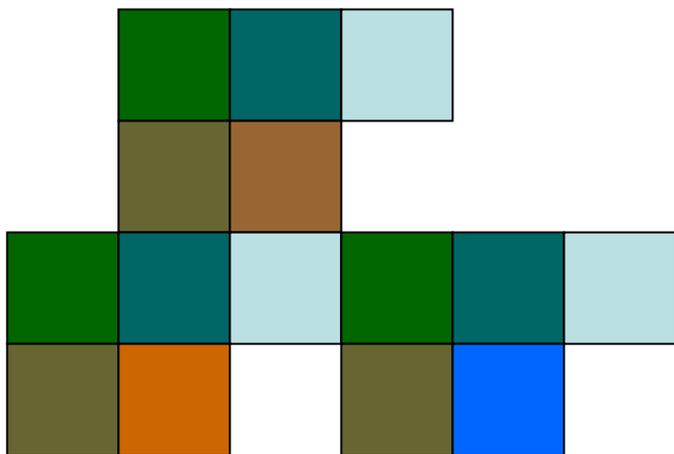


b

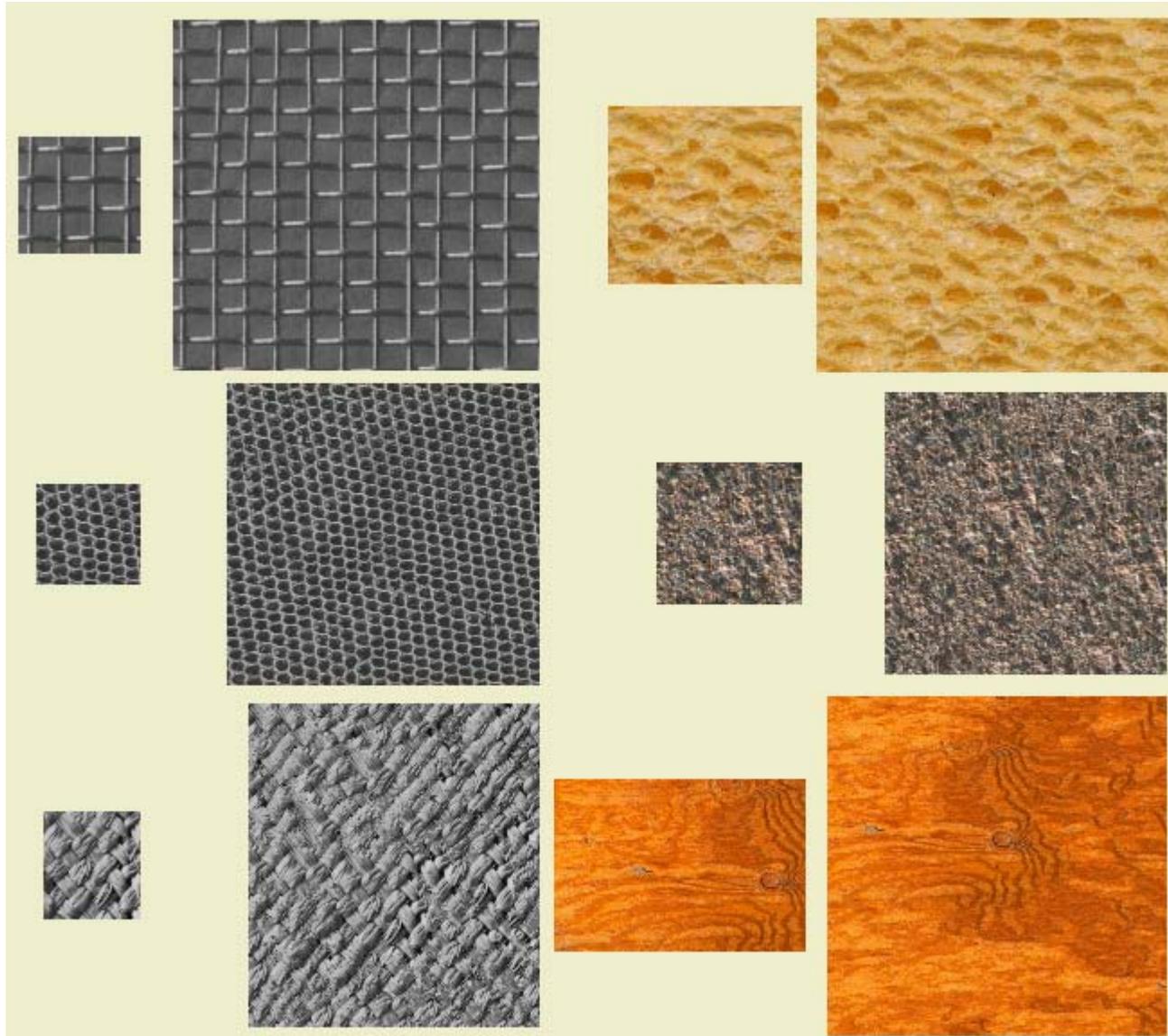
Synthetic

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



Efros and Leung



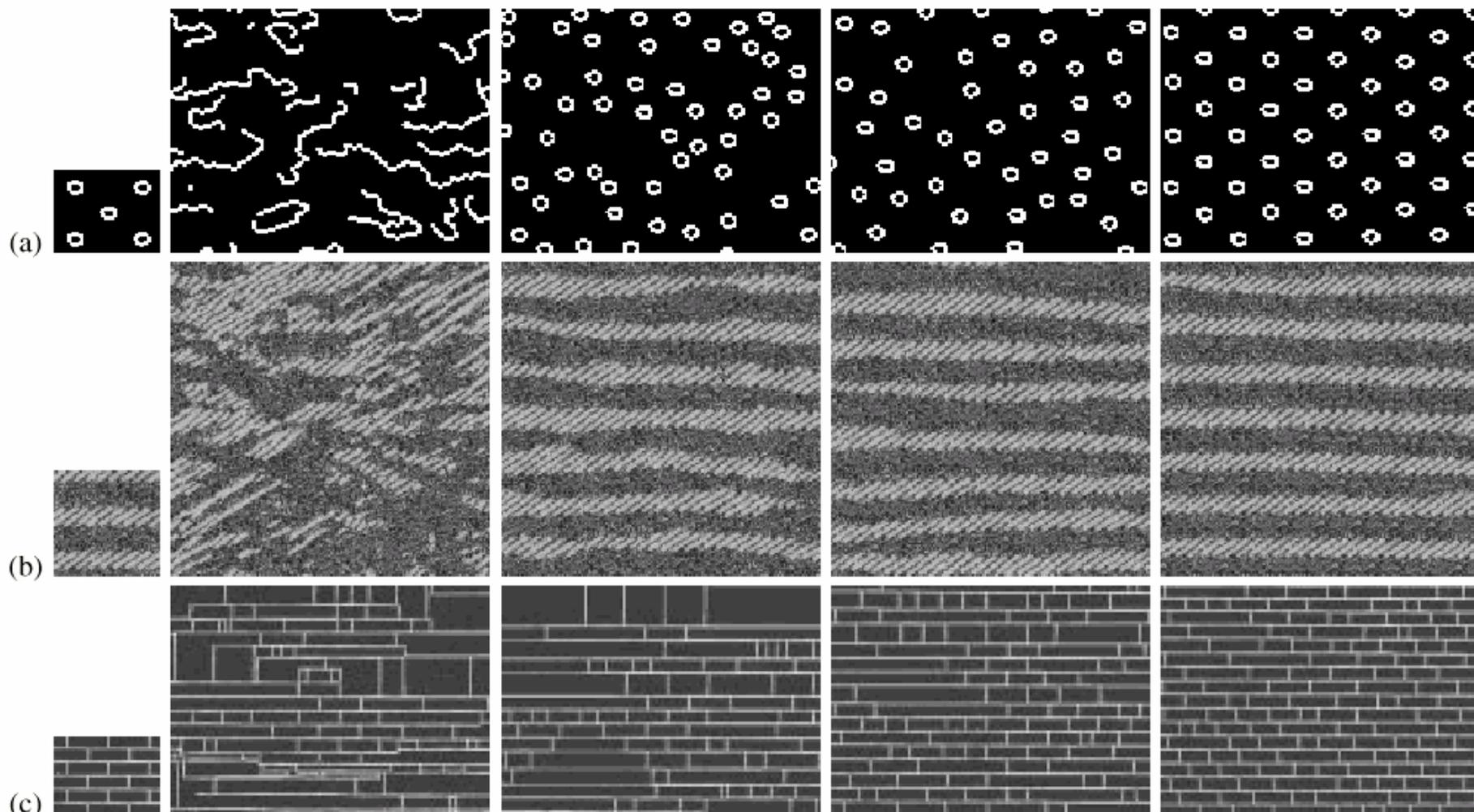


Figure 2. Results: given a sample image (left), the algorithm synthesized four new images with neighborhood windows of width 5, 11, 15, and 23 pixels respectively. Notice how perceptually intuitively the window size corresponds to the degree of randomness in the resulting textures. Input images are: (a) synthetic rings, (b) Brodatz texture D11, (c) brick wall.

What we've learned from the previous texture synthesis methods

From Adelson and Bergen:

examine filter outputs

From Perona and Malik:

use multi-scale, multi-orientation filters.

From Heeger and Bergen:

use marginal statistics (histograms) of filter responses.

From DeBonet:

use conditional filter responses across scale.

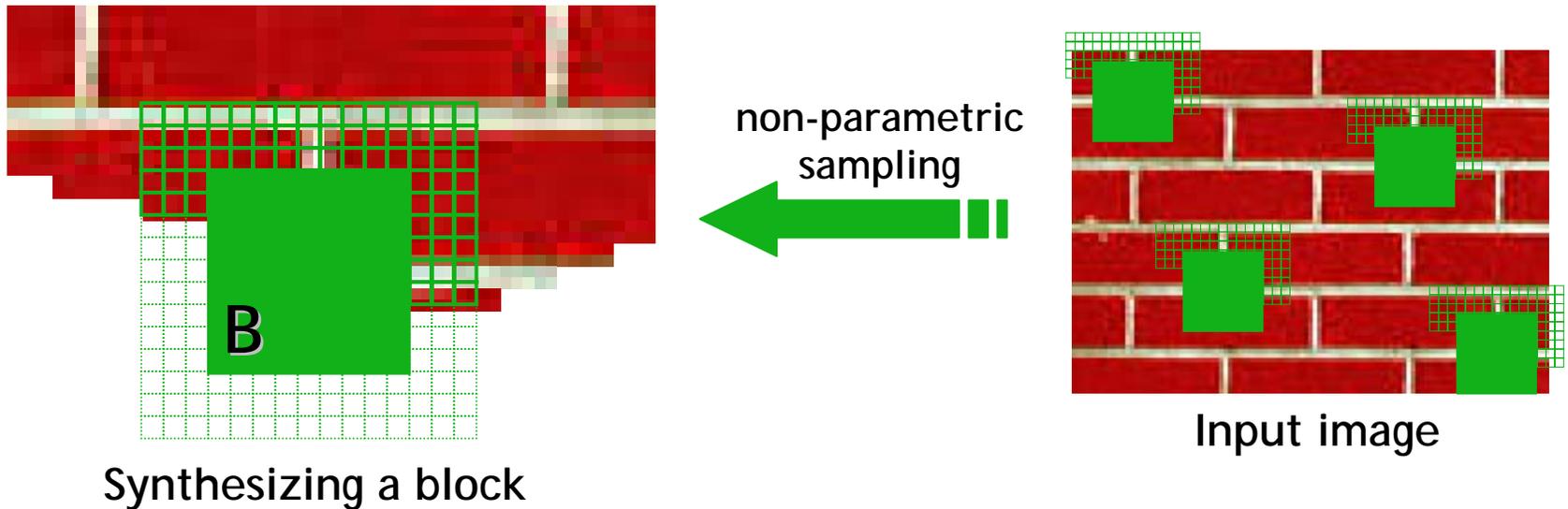
What we learned from Efros and Leung regarding texture synthesis

- 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 '99

- 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]

Efros & Leung '99 extended



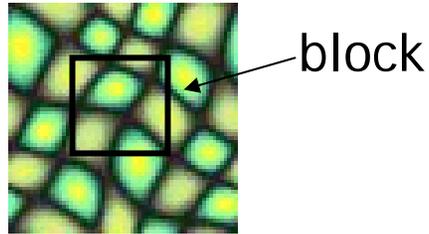
- Observation: neighbor pixels are highly correlated

Idea: unit of synthesis = block

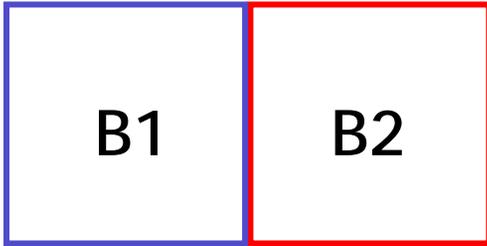
- Exactly the same but now we want $P(B | N(B))$
- Much faster: synthesize all pixels in a block at once
- Not the same as multi-scale!

Image Quilting

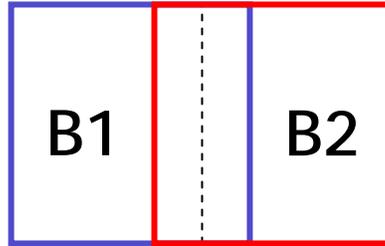
- Idea:
 - let's combine random block placement of Chaos Mosaic with spatial constraints of Efros & Leung
- Related Work (concurrent):
 - Real-time patch-based sampling [Liang et.al. '01]
 - Image Analogies [Hertzmann et.al. '01]



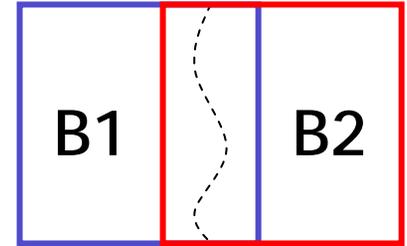
Input texture



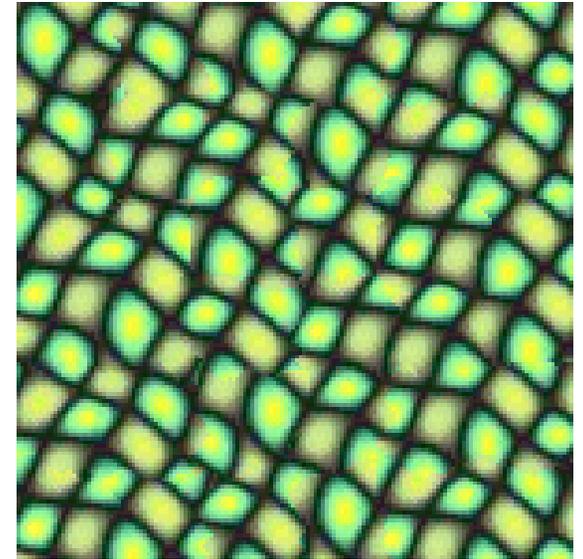
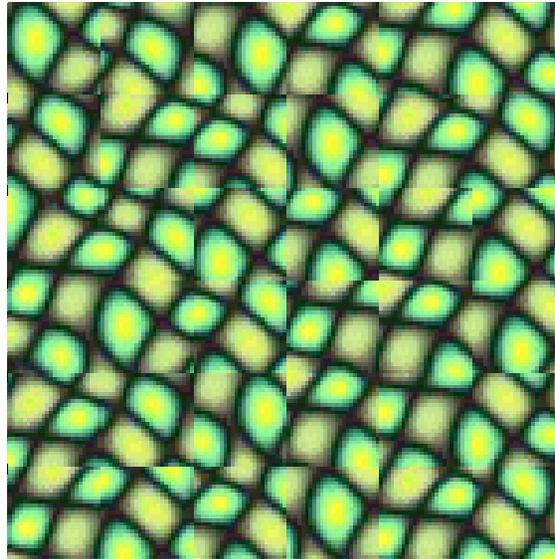
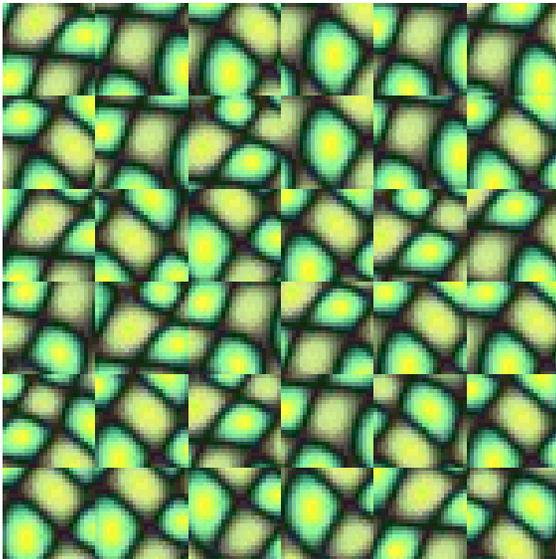
Random placement
of blocks



Neighboring blocks
constrained by overlap

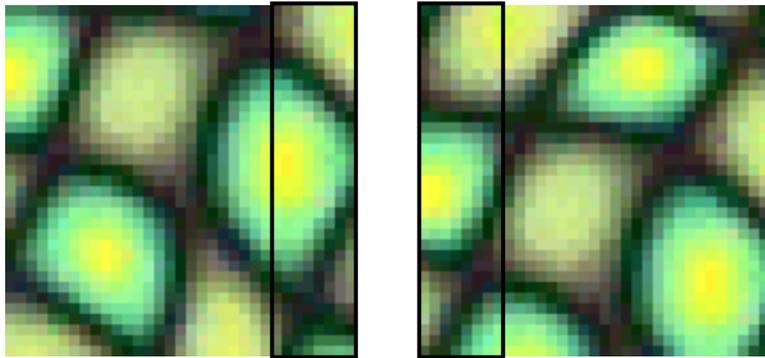


Minimal error
boundary cut

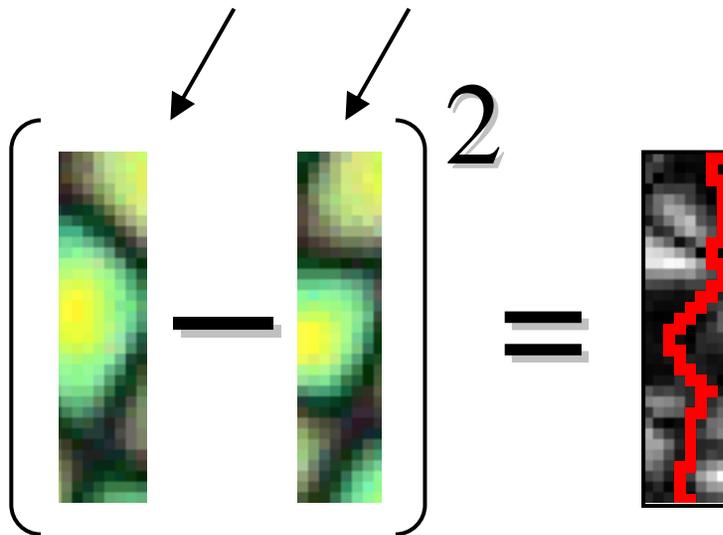
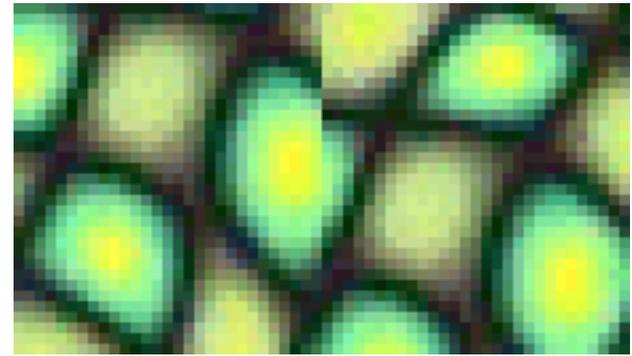


Minimal error boundary

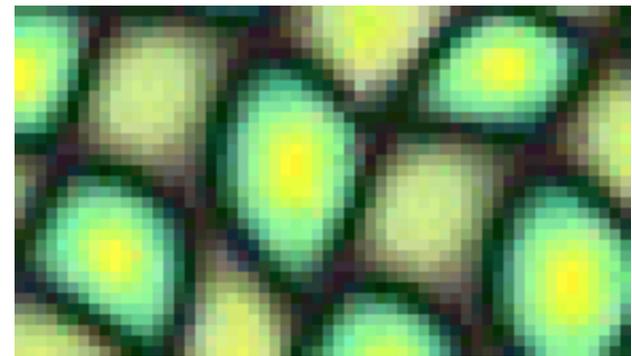
overlapping blocks



vertical boundary



overlap error



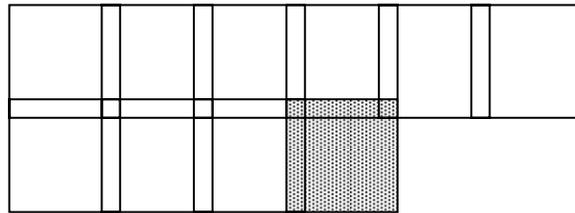
min. error boundary

Our Philosophy

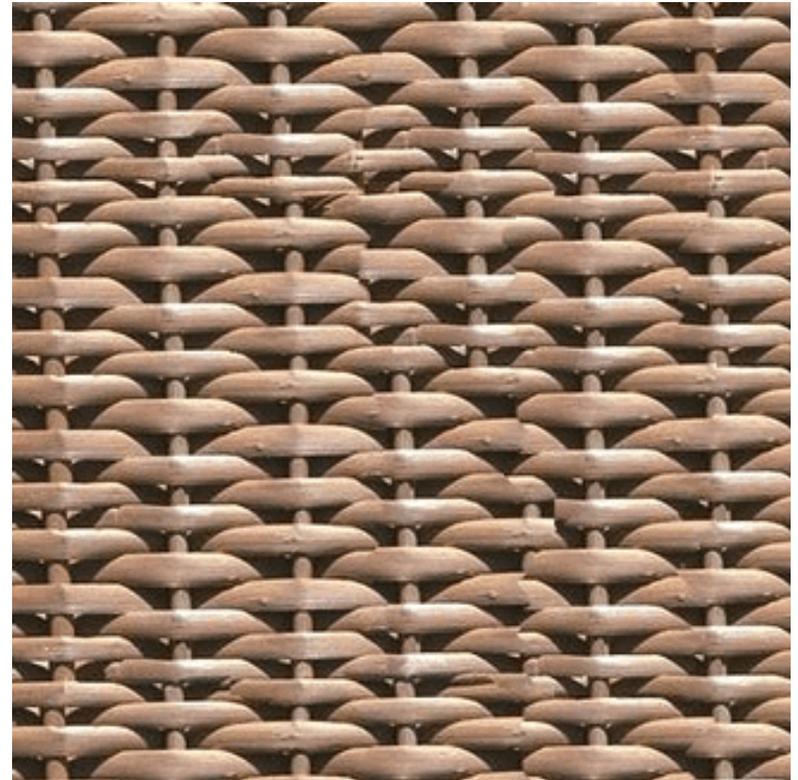
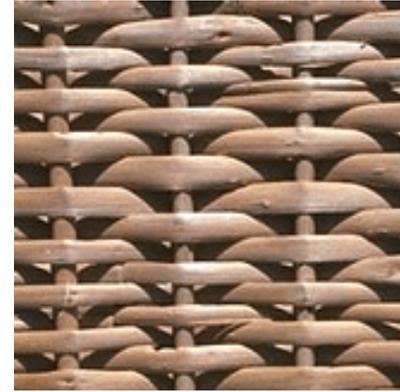
- The “Corrupt Professor’s Algorithm”:
 - Plagiarize as much of the source image as you can
 - Then try to cover up the evidence
- Rationale:
 - Texture blocks are by definition correct samples of texture so problem only connecting them together

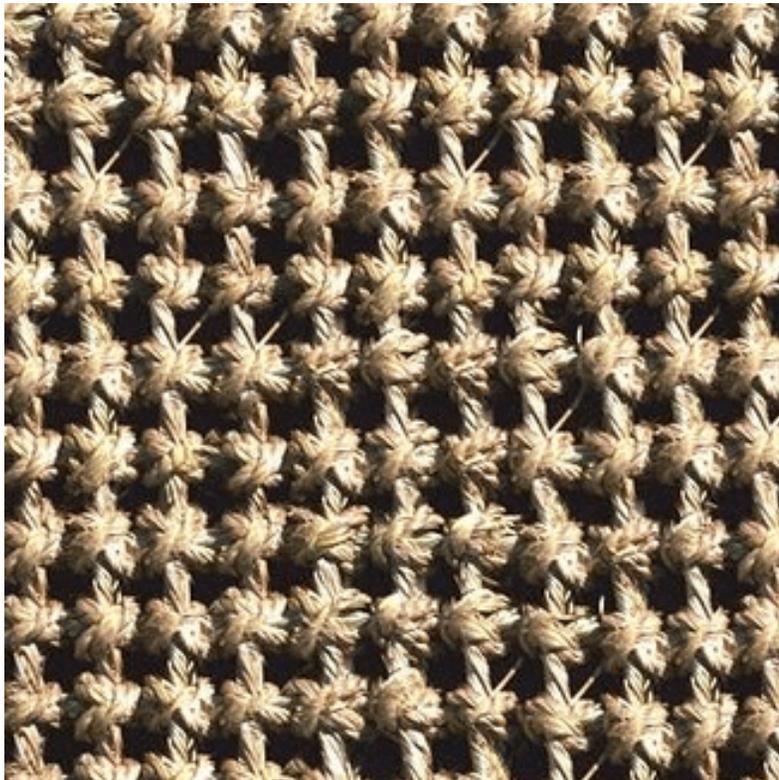
Algorithm

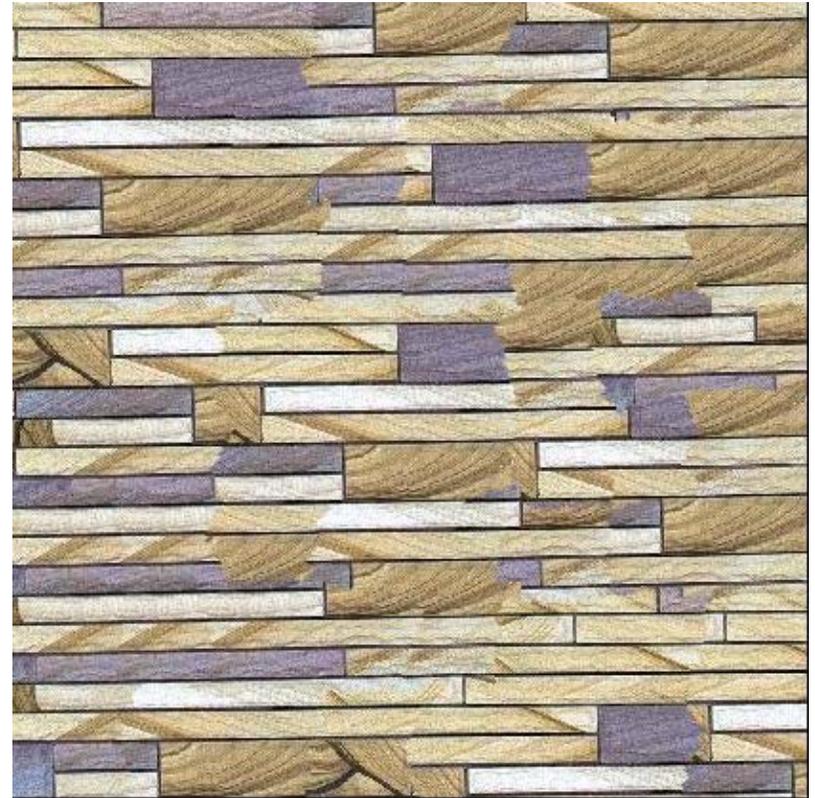
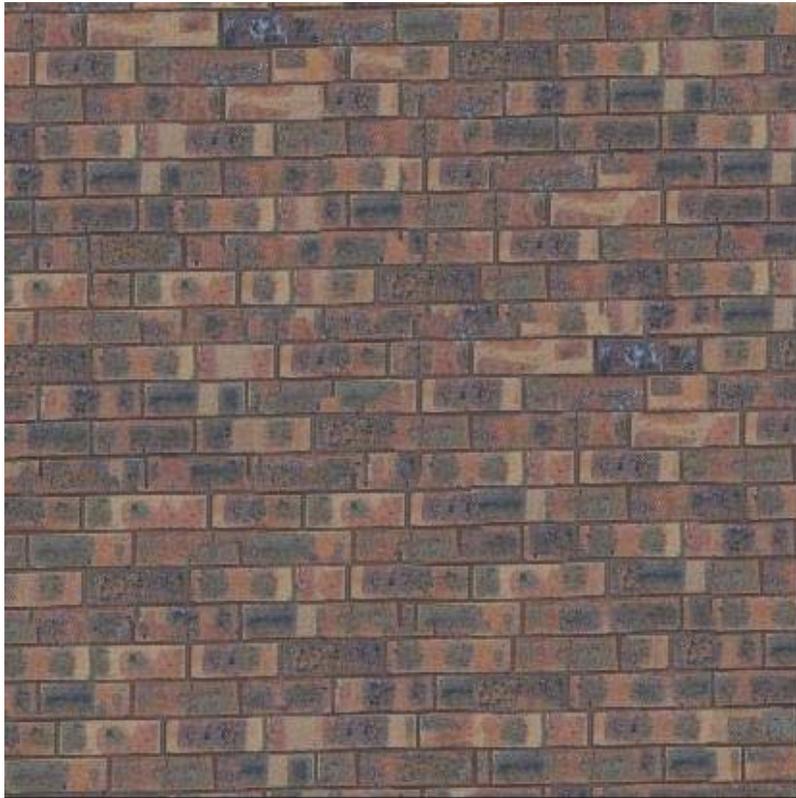
- Pick size of block and size of overlap
- Synthesize blocks in raster order



- 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

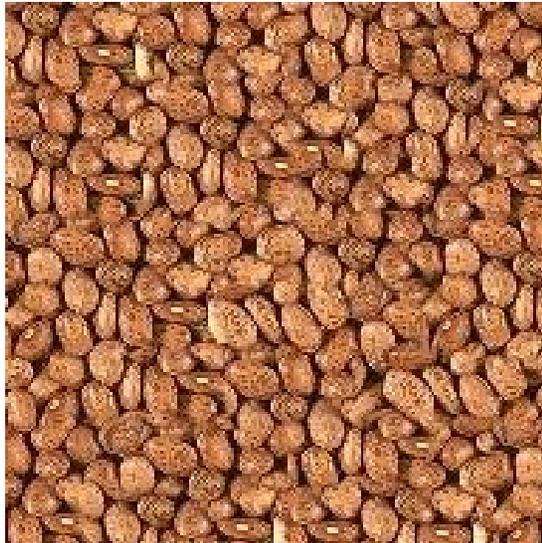
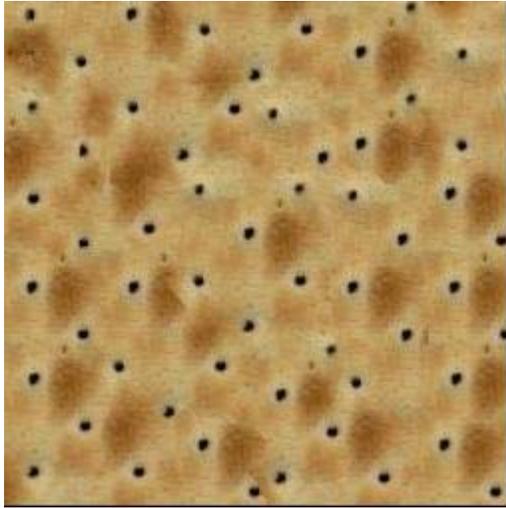
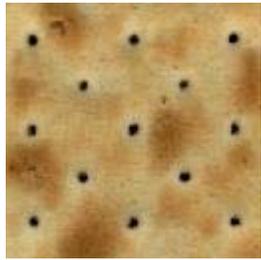


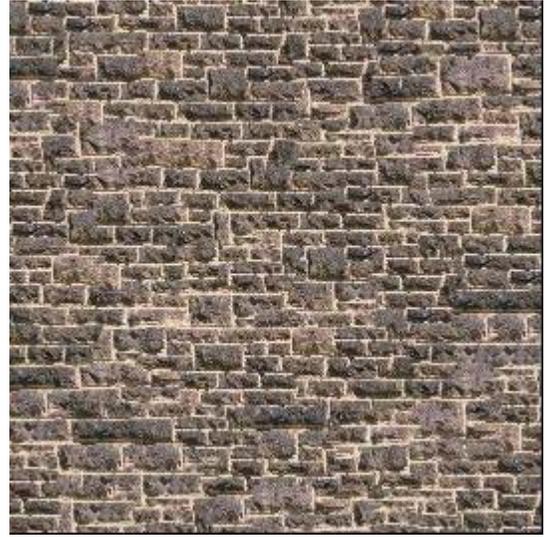
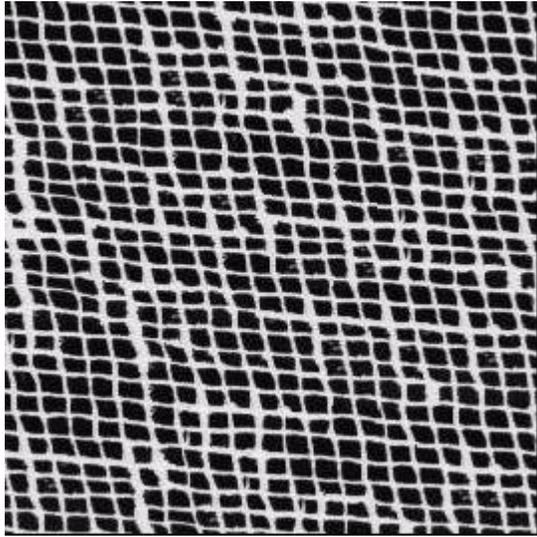
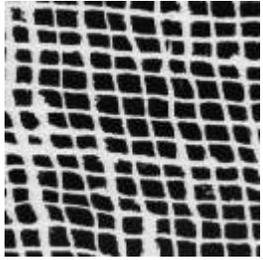






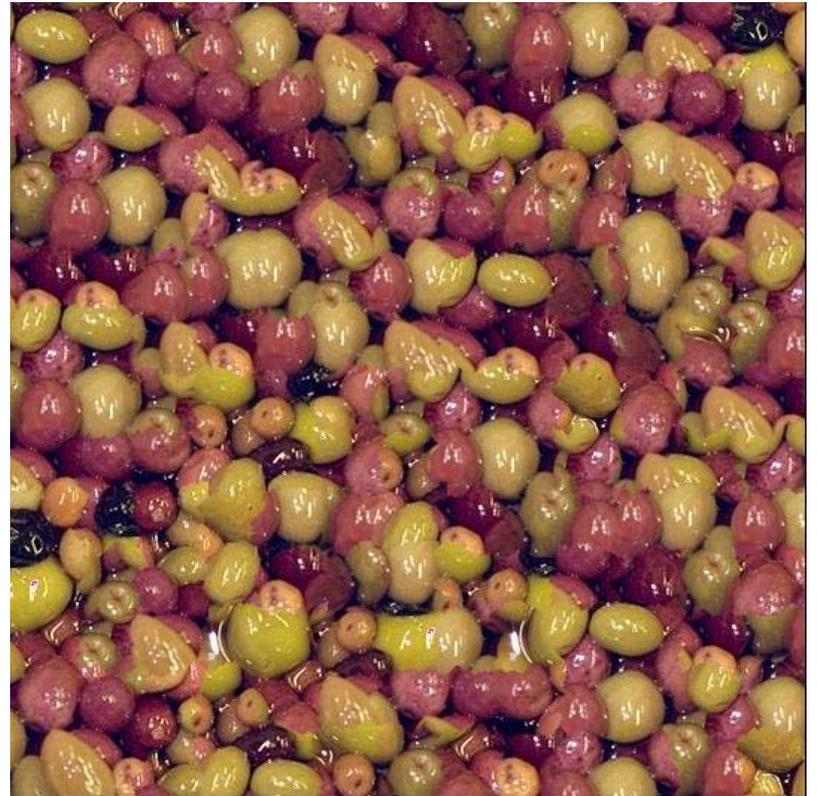
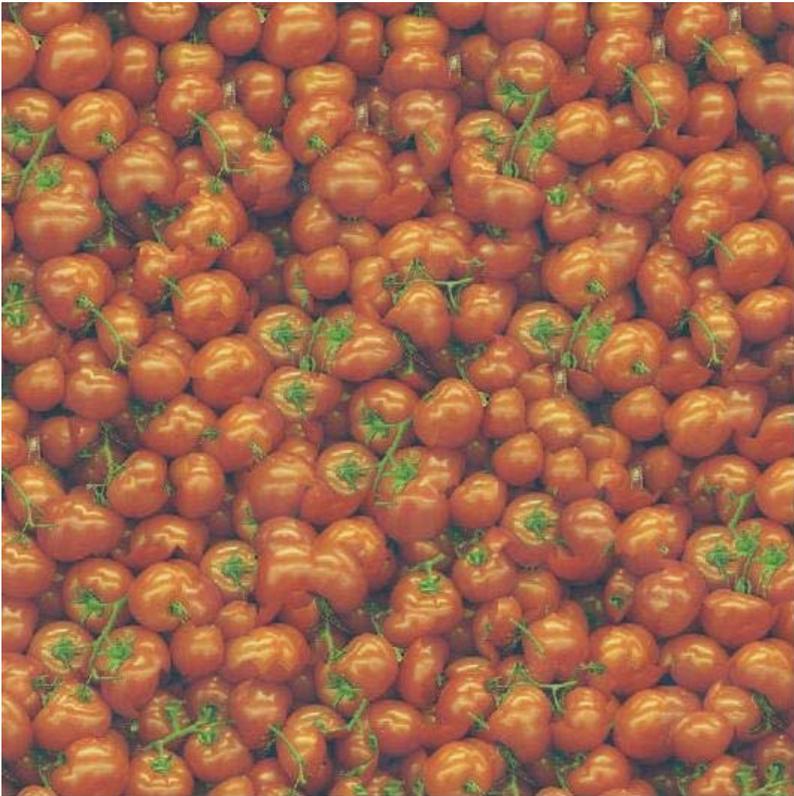
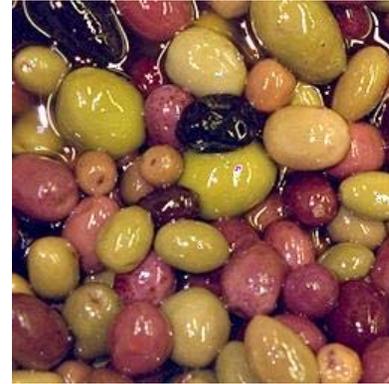






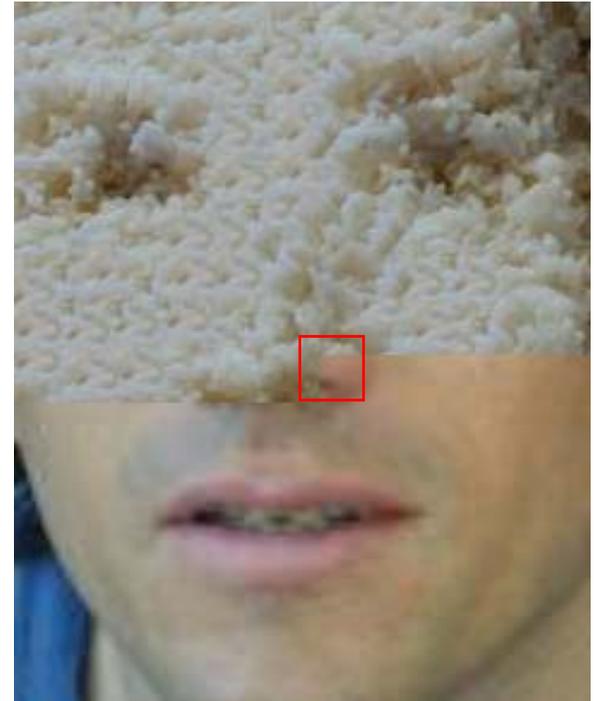


Failures (Chernobyl Harvest)



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

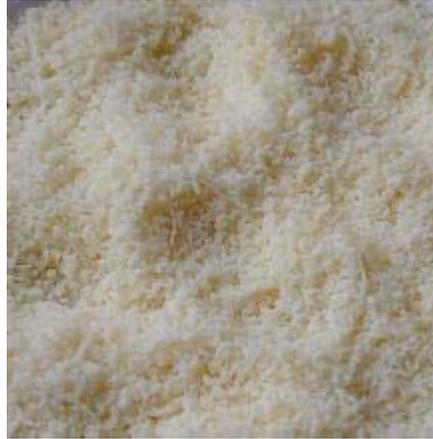


Then, **just** add another constraint when sampling:
• **Similarity to underlying image at that spot**

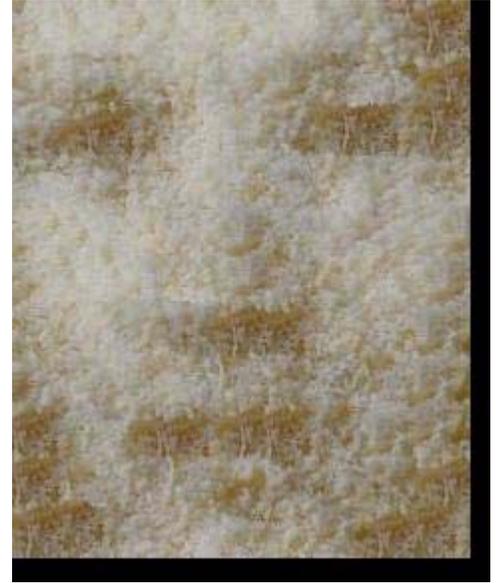
parmesan



+



=



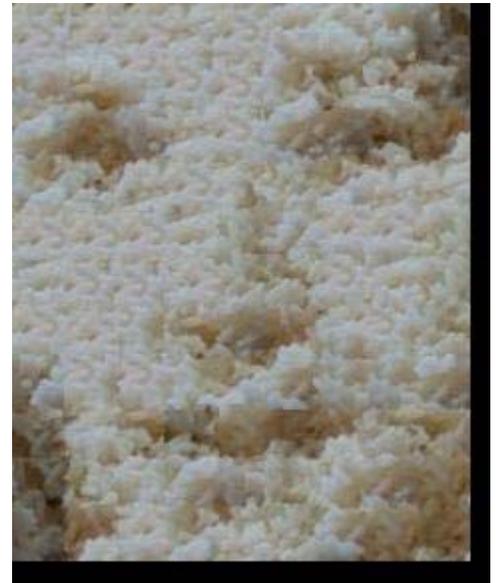
rice

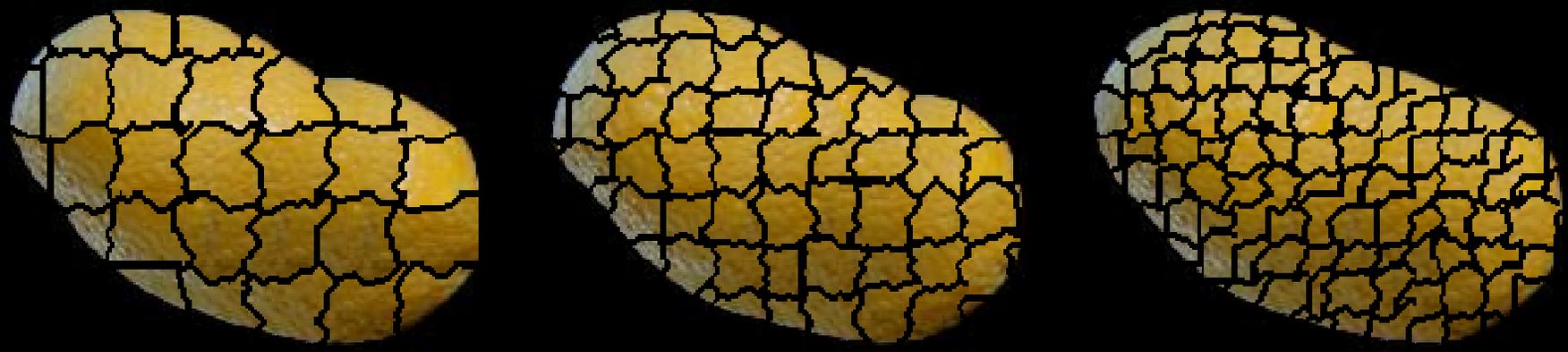
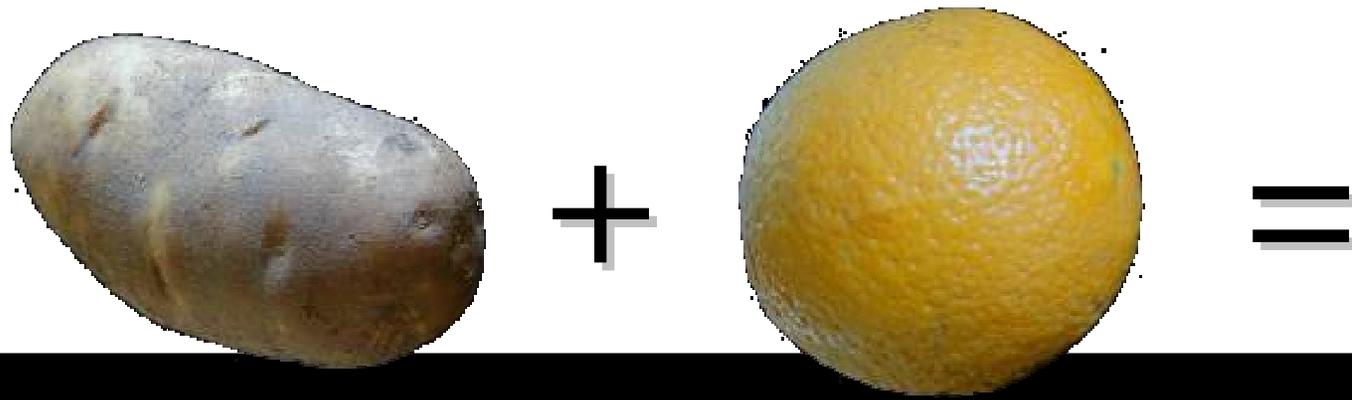


+



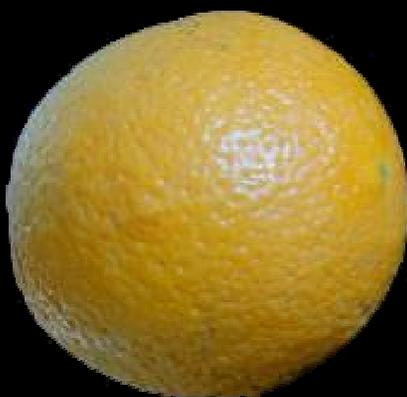
=







+



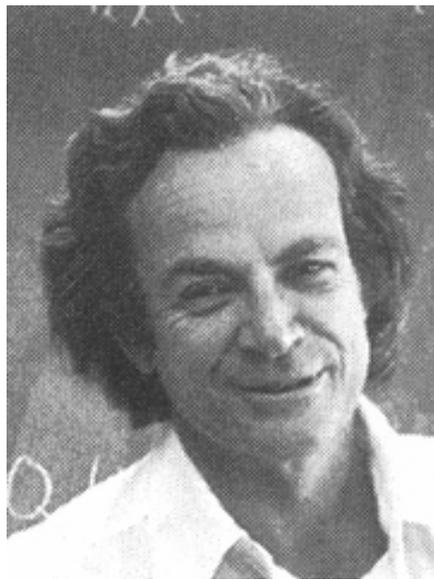
=



Source
texture



Target
image

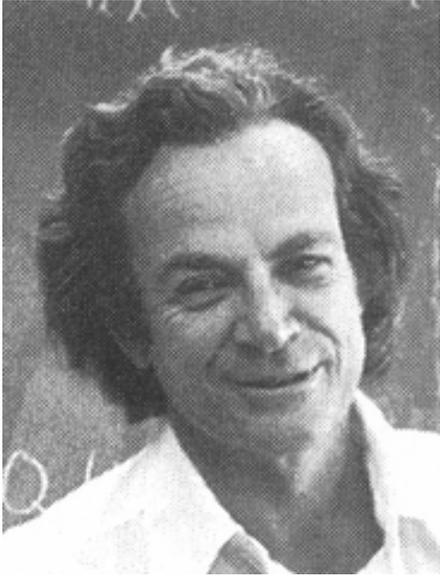


Source
correspondence
image



Target
correspondence
image



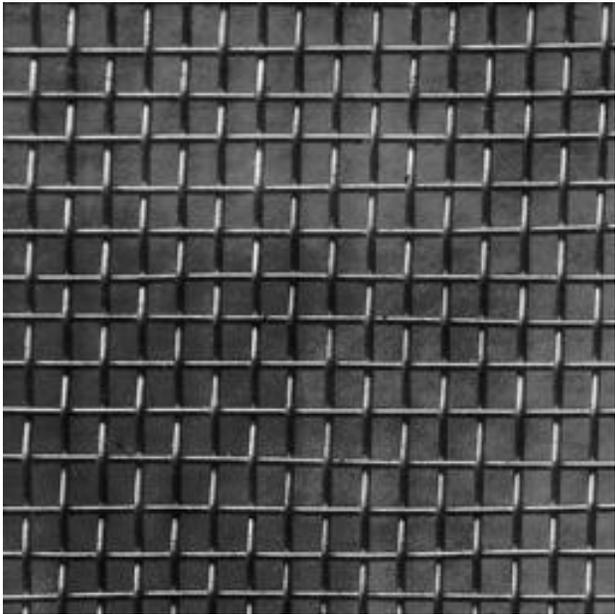


+

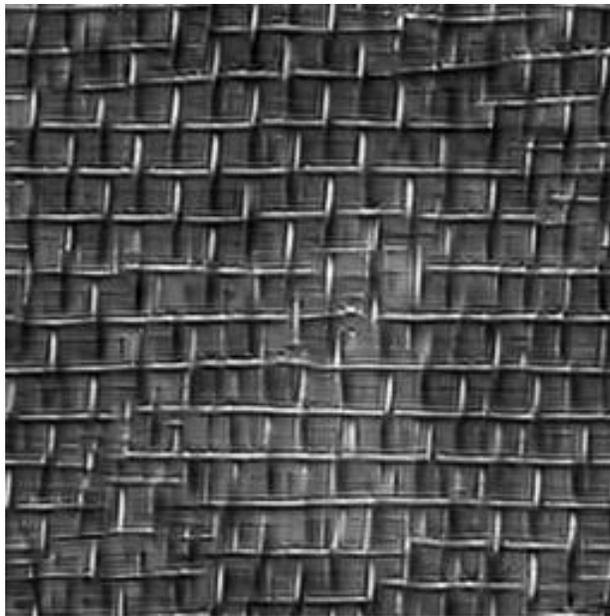


=

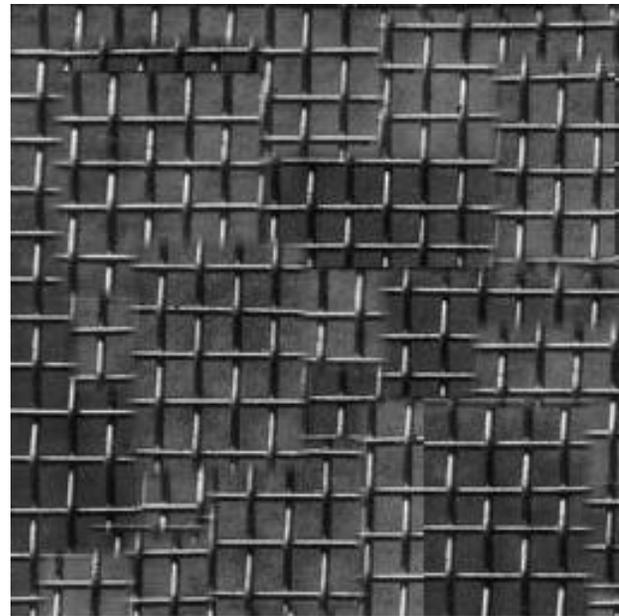




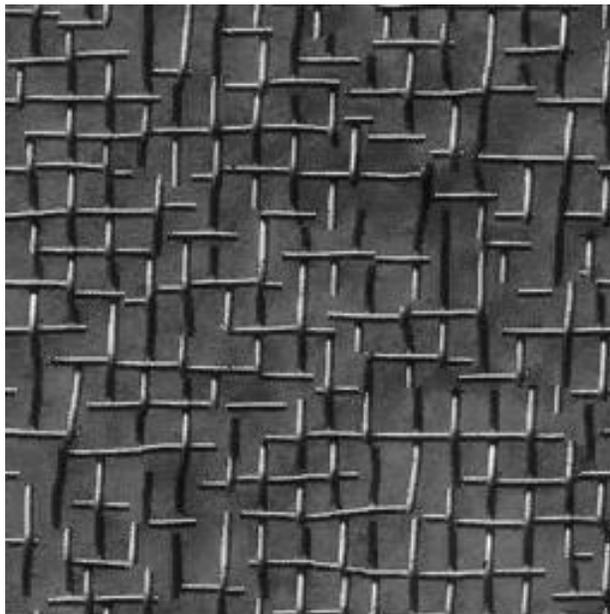
input image



Portilla & Simoncelli



Xu, Guo & Shum



Wei & Levoy

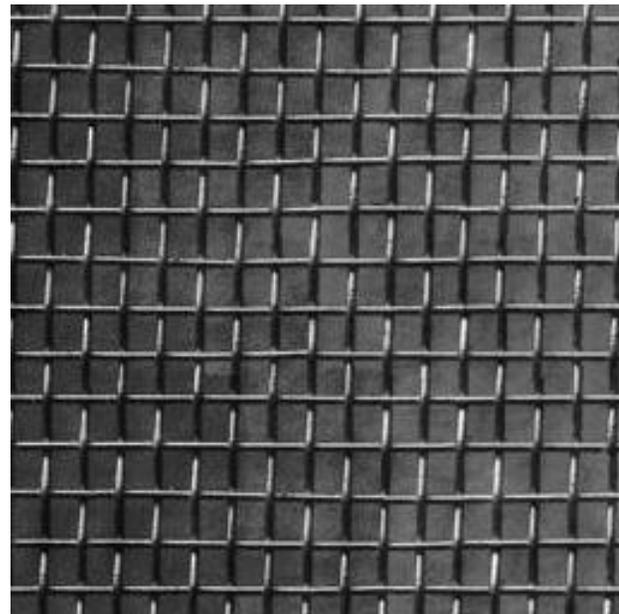
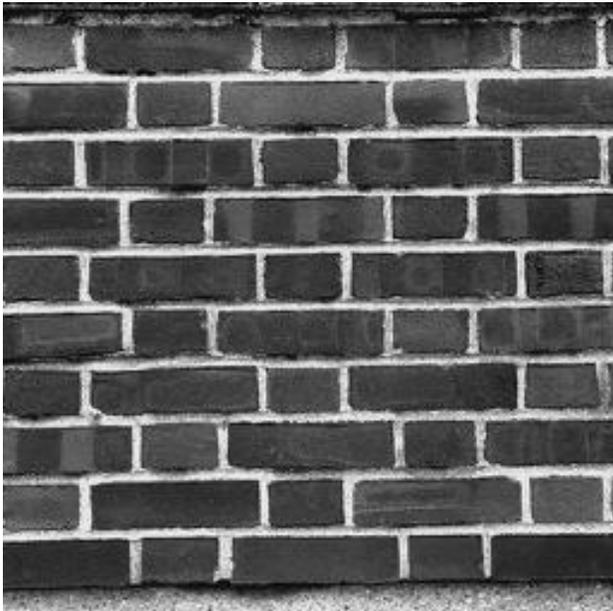


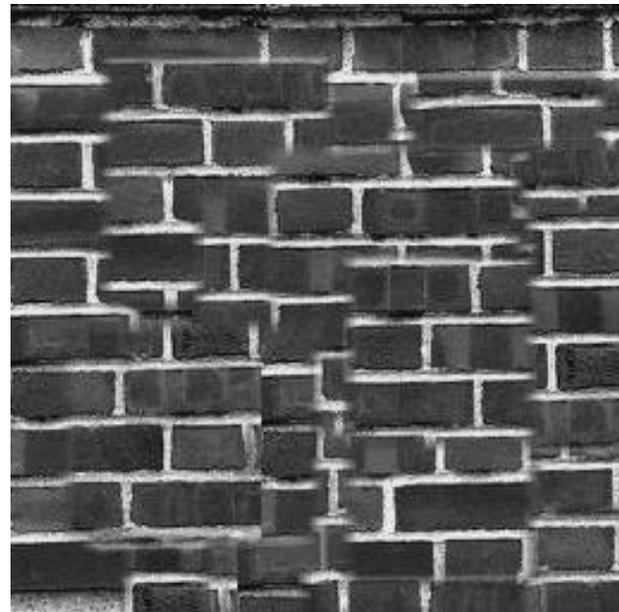
Image Quilting



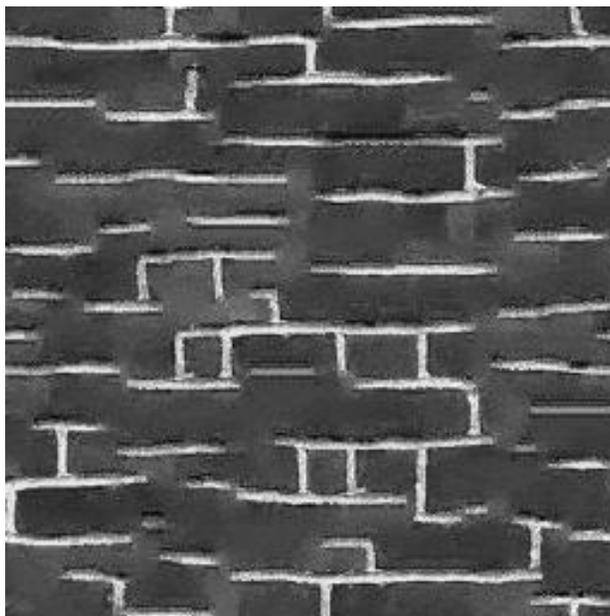
input image



Portilla & Simoncelli



Xu, Guo & Shum



Wei & Levoy

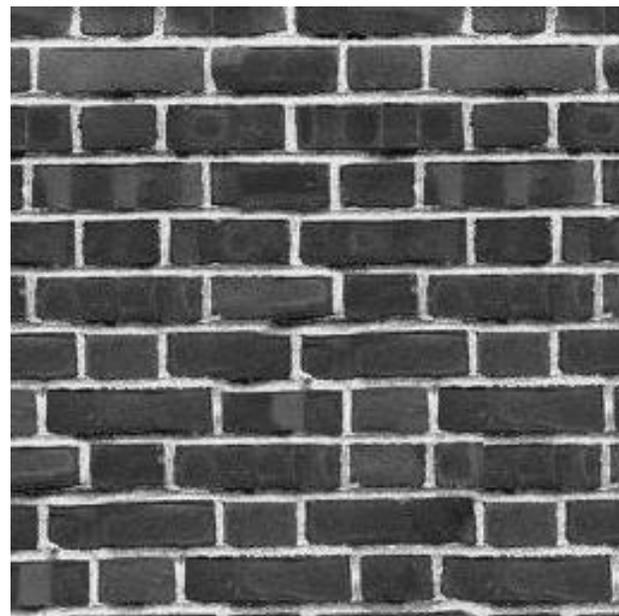
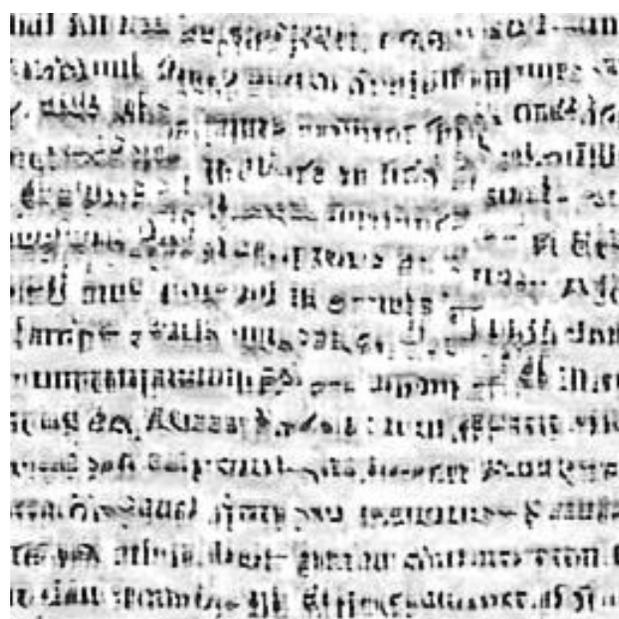


Image Quilting

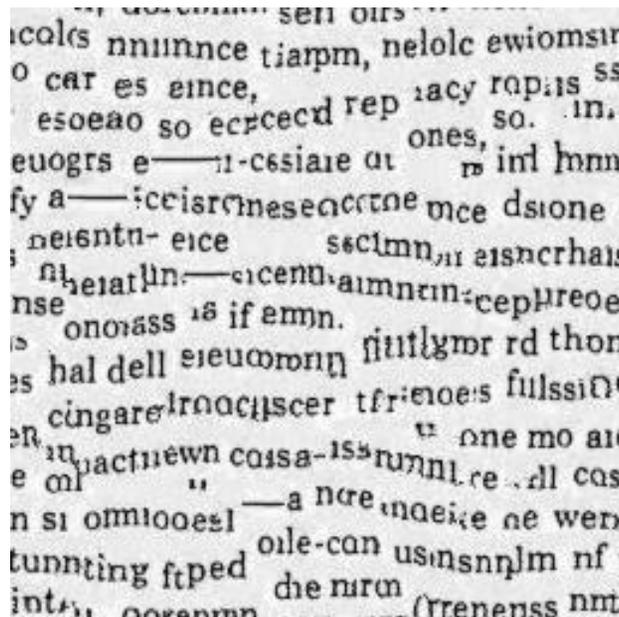
Homage to Shannon!

... of a visual cortical neuron—the in
... describing the response of that neuro
... ht as a function of position—is perhap
... functional description of that neuron.
... seek a single conceptual and mathem
... describe the wealth of simple-cell recep
... and neurophysiologically¹⁻³ and inferred
... especially if such a framework has the
... it helps us to understand the functio
... deeper way. Whereas no generic mod
... ussians (DOG), difference of offset C
... rivative of a Gaussian, higher derivati
... function, and so on—can be expect
... simple-cell receptive field, we noneth

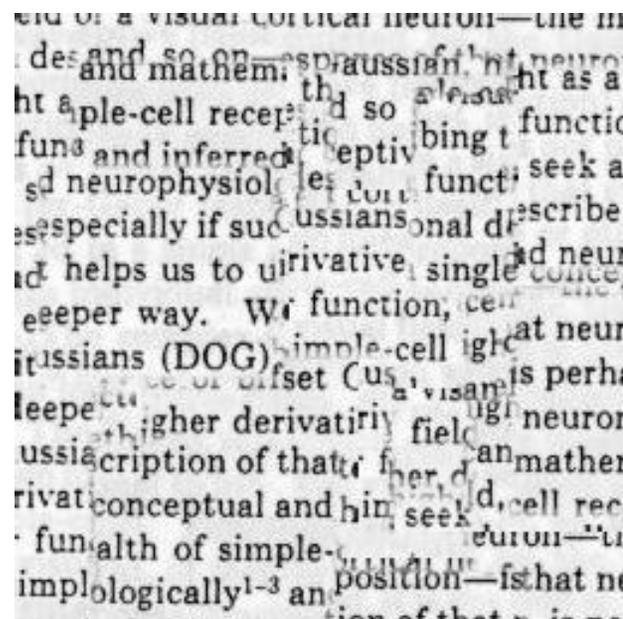
input image



Portilla & Simoncelli



Wei & Levoy



Xu, Guo & Shum

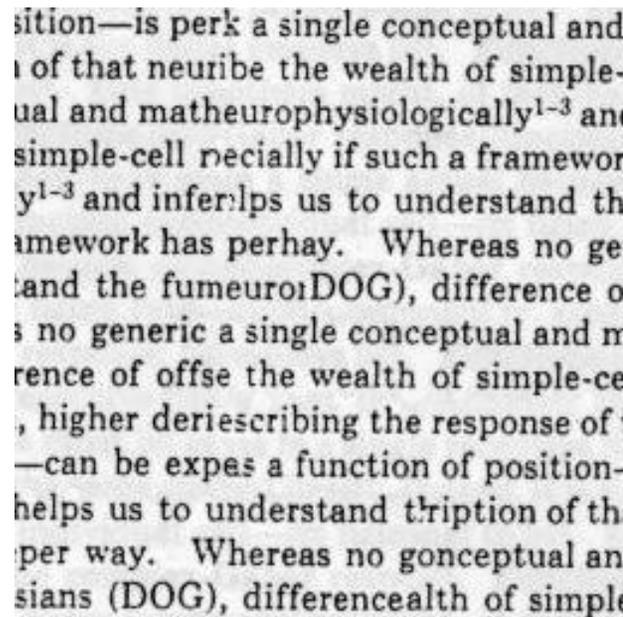


Image Quilting

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



end