

# **Perceptually-Driven Statistical Texture Modeling**

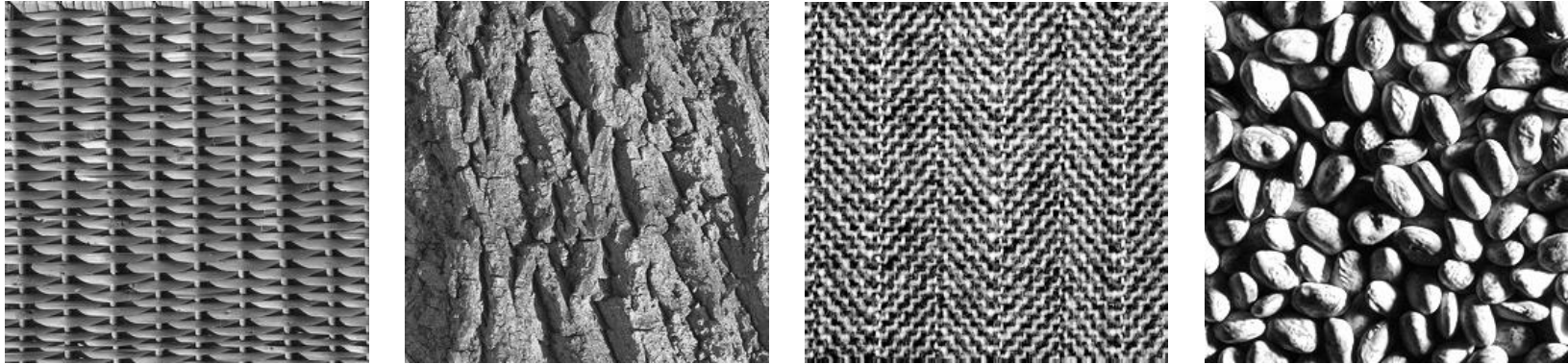
**Eero Simoncelli**

Howard Hughes Medical Institute, and  
New York University

**Javier Portilla**

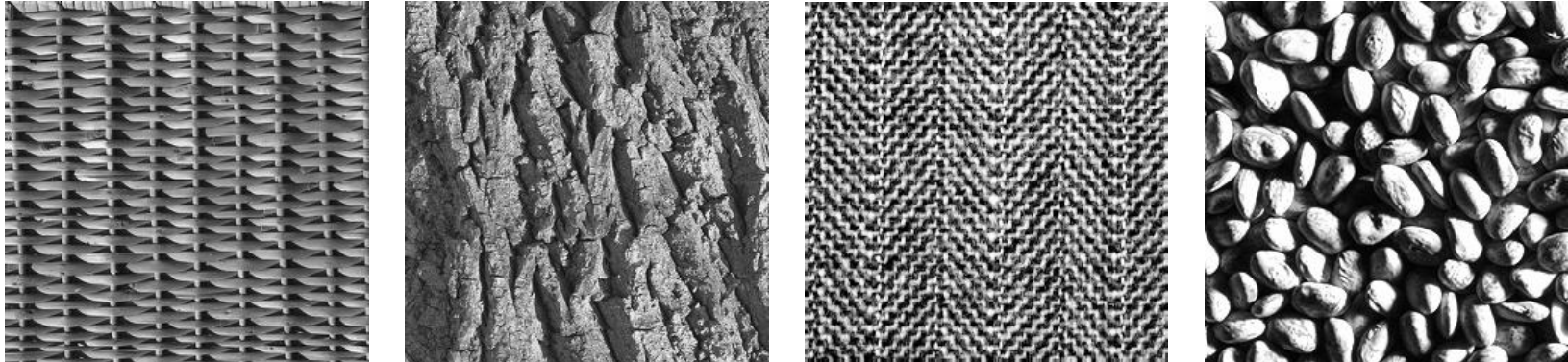
University of Granada, Spain

## What is “Visual Texture”?



Homogeneous, with repeated structures....

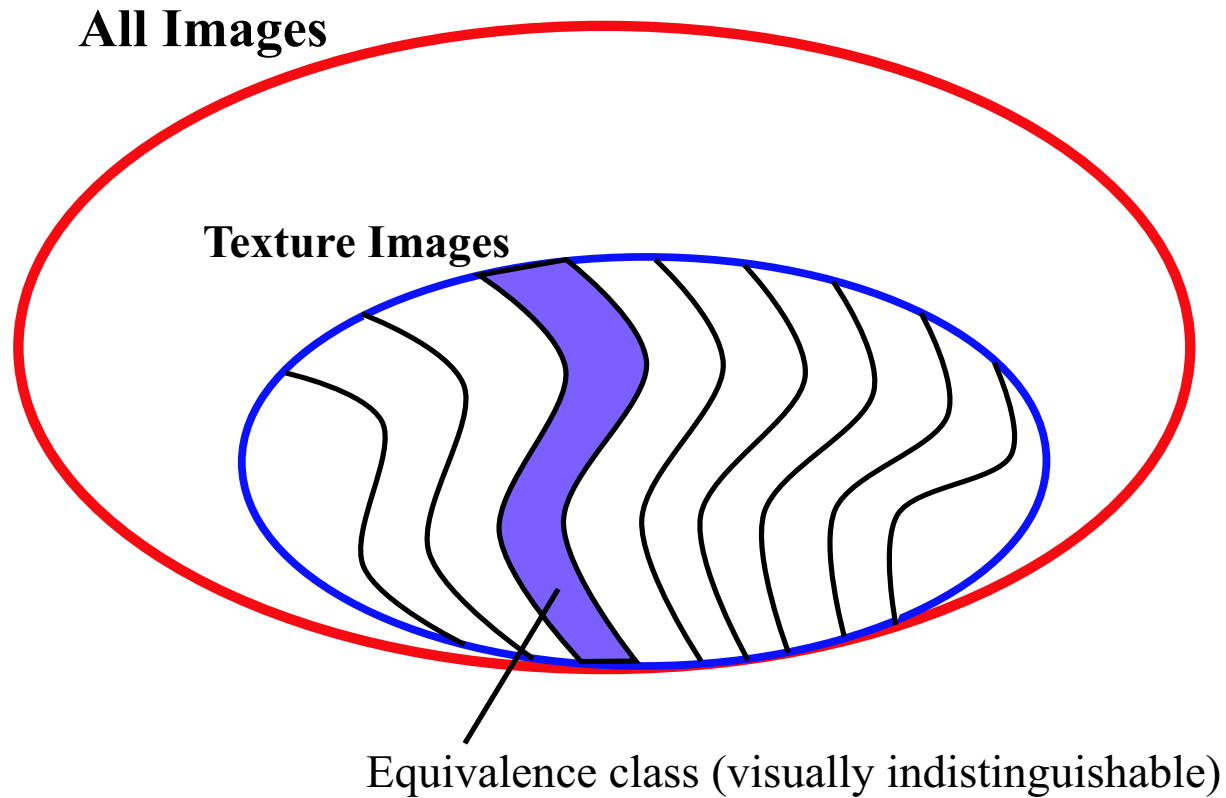
## What is “Visual Texture”?



Homogeneous, with repeated structures....

“You know it when you see it”

# Perceptual Texture Description



Perceptual model:

- Set of texture images divided into equivalence classes (metamers)
- Perceptual “distance” between classes

## Julesz's Conjecture (1962)

Hypothesis: two textures with identical  $N$ th-order pixel statistics look the same (for some  $N$ ).

- Explicit goal of capturing perceptual definition with a statistical model
- Statistical measurements should be:
  - universal (for all textures)
  - stationary (translation-invariant)
  - a minimal set (necessary and sufficient)
- Julesz (and others) constructed counter-examples for  $N=2$  and  $N=3$ , dismissing the hypothesis...

# Julesz's Conjecture, Revisited

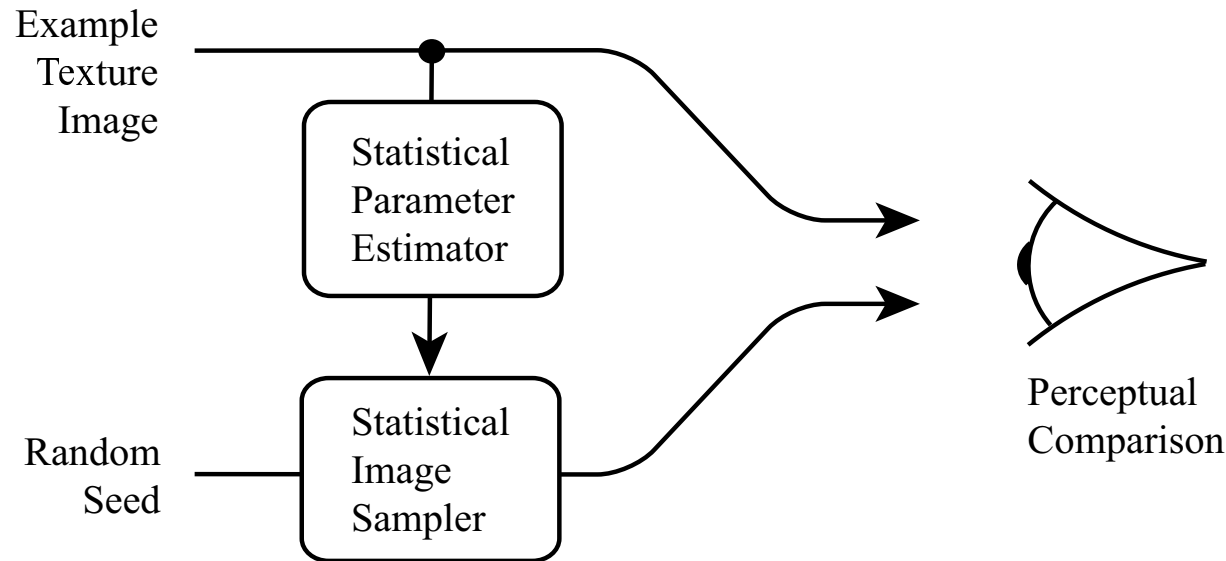
Why did the early attempts fail?

- Right hypothesis, wrong model: A set of measurements equivalent to the visual processes used for texture perception should satisfy the hypothesis.
- Lacked a powerful methodology for testing whether a model satisfies the hypothesis
- We can benefit from advances of the past few decades:
  - scientific: better understanding of early vision
  - engineering/mathematical: “wavelets”, statistical estimation, statistical sampling
  - technological: availability of powerful computers, digital images

## Testing a Texture Model

- As with most scientific test, we seek counter-examples
- Fundamental problem: we usually work with a small number of examples (tens or hundreds).
- Classification is an important application, but a weak test
- Synthesis can provide a much stronger test...

# Testing a Model via Synthesis



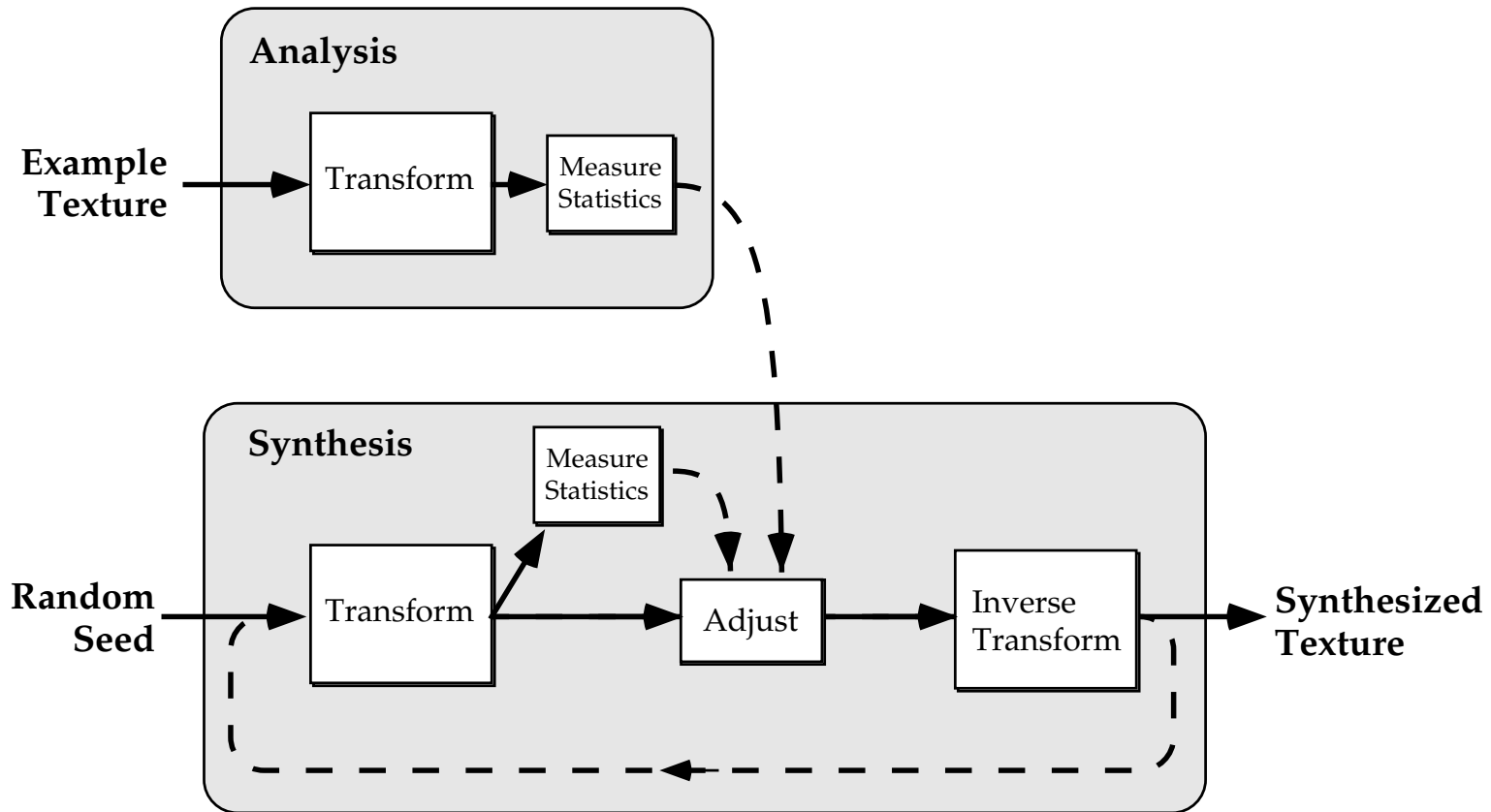
- Positive results are compelling, assuming:
  - reference texture set contains a sufficient variety
  - statistical sampler generates “typical” examples
- Negative results are definitive: A single failure indicates insufficiency of constraints!
- Partial necessity test: remove a constraint and find a failure example
- Studying failures allows us to refine the model



## Methodological Ingredients

1. Representative set of example texture images: Brodatz, VisTex, our own
2. Method of estimating parameters: sample mean
3. Method of generating sample images from model: primary topic of this work
4. Perceptual test: informal viewing

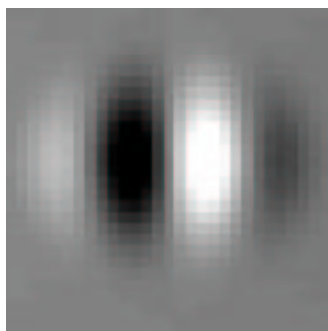
# Iterative Synthesis Algorithm



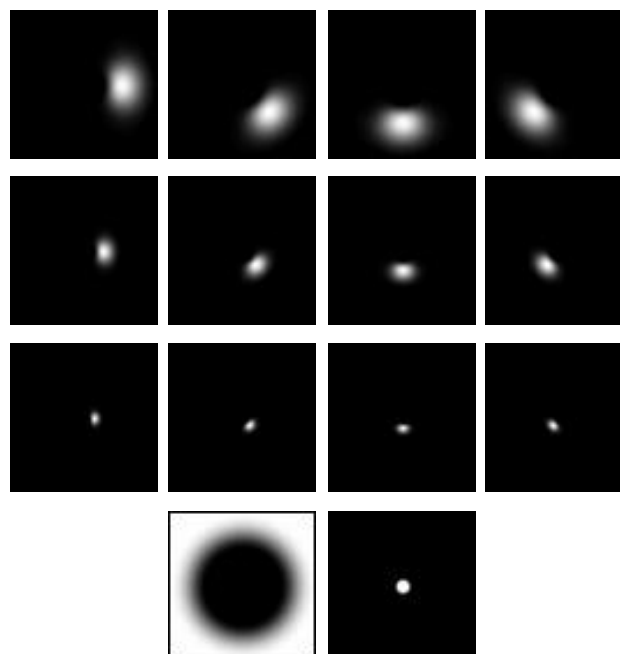
Heeger & Bergen, '95

# Transform: Steerable Pyramid

Example basis function



Spectra



Linear basis: multi-scale, oriented, complex.

Basis functions are oriented bandpass filters, related by translation, dilation, **rotation** (directional derivatives, order  $K-1$ ).

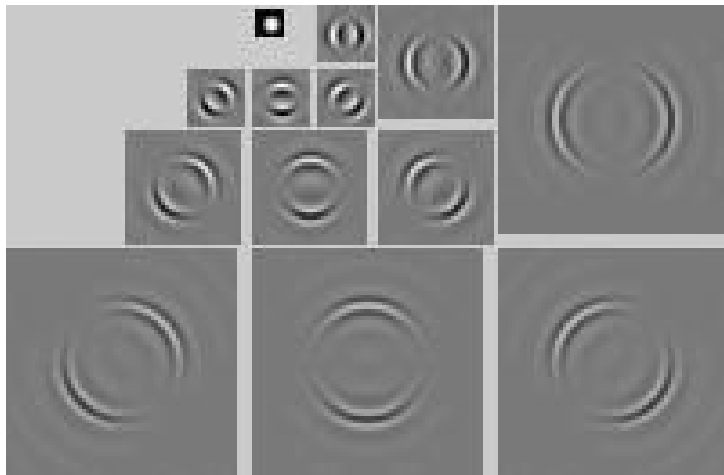
Tight frame,  $4K/3$  overcompleteness for  $K$  orientations.

Translation-invariant, rotation-invariant.

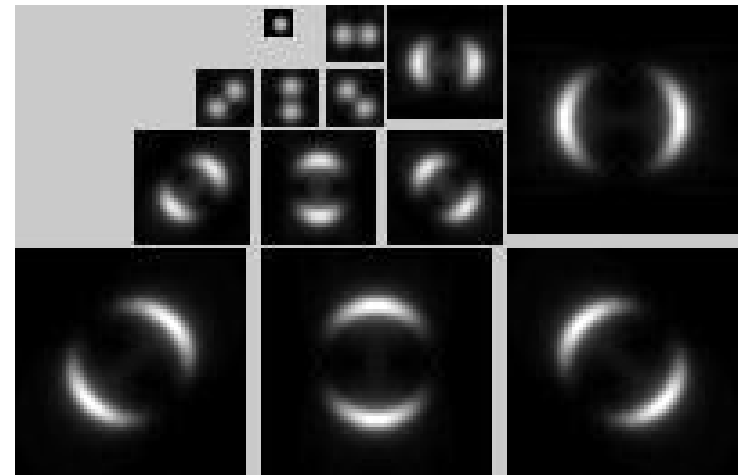
Motivation: image processing, computer vision, biological vision.

# Steerable Pyramid: Example Decomposition

Real part of coefficients



complex magnitude of coefficients



Decomposition of a “disk” image

## Parameters: Marginal Statistics

Distribution of intensity values is captured with the first through fourth moments of both the pixels and the lowpass coefficients at each pyramid scale.

Note: A number of authors have used marginal histograms:

Faugeras '80 (pixels), Heeger & Bergen '95 (wavelet), Zhu et al. '96 (Gabor).

15 parameters

## Parameters: Spectral

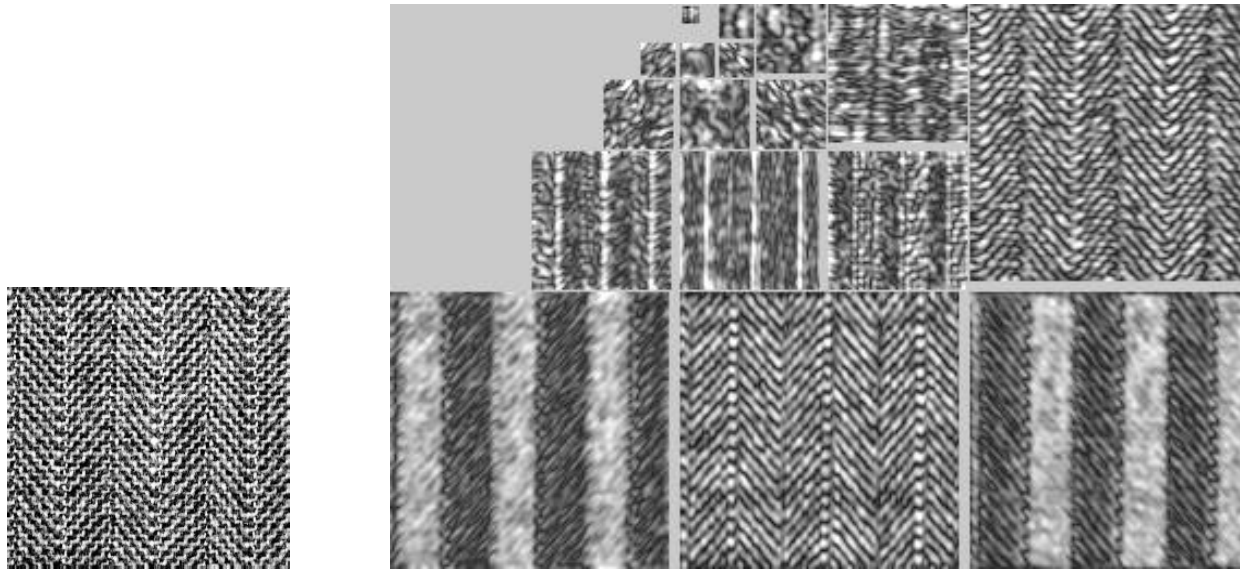
Periodicity and globally oriented structure is best captured by frequency-domain measures (Francos, '93).

Can be captured by autocorrelation measurements (included in most texture models).

In our model: central  $7 \times 7$  region of the autocorrelation of each subband provides a crude measure of spectral content *within* each subband.

125 parameters

## Parameters: Magnitude Correlation



Coefficient magnitudes are correlated both spatially and across bands. We capture this with local autocorrelation and cross-correlation measurements.

472 parameters

## Parameters: Phase Correlation

Phases of complex responses at adjacent scales are aligned near image “features”.

We capture this using a novel measure of relative phase:

$$\phi(f, c) = \frac{c^2 \cdot f^*}{|c|},$$

where  $f$  is a fine-scale coefficient,  $c$  is a coarse-scale coefficient at the same location.

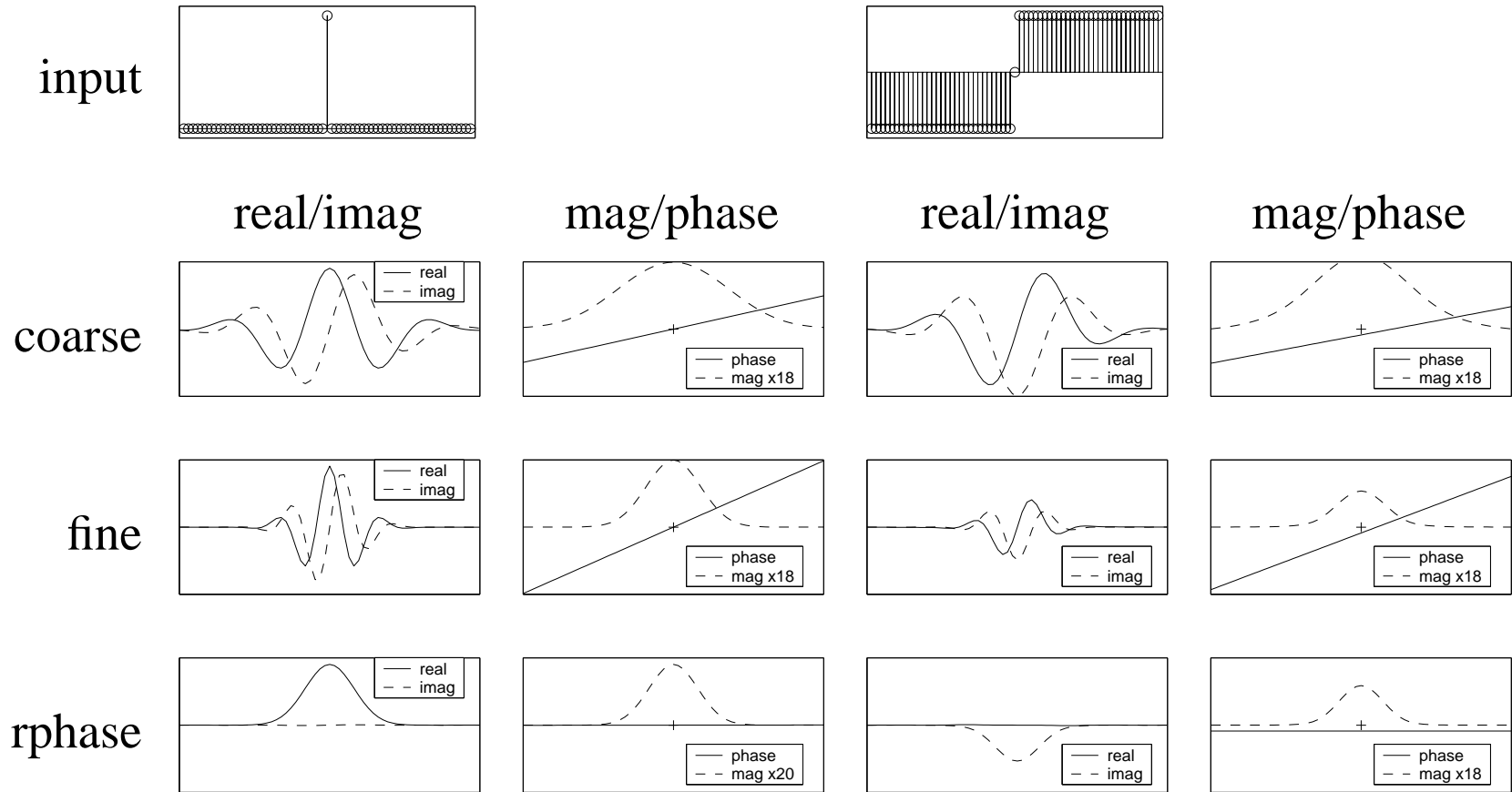
96 parameters

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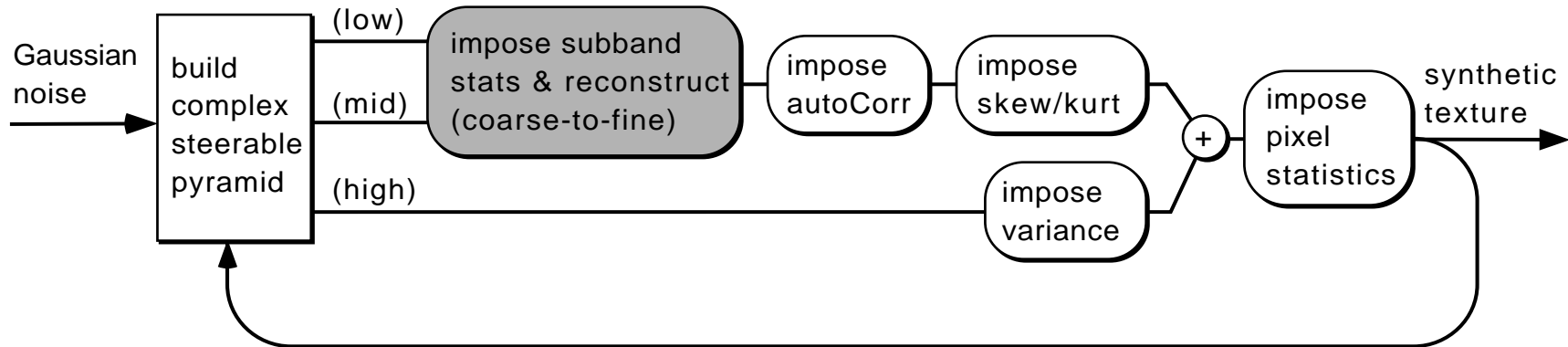
Total parameters: 708



# Phase Correlation Example



# Implementation



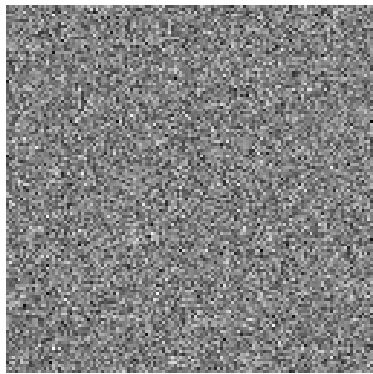
Each statistic,  $\phi_k(\vec{I})$ , is imposed by gradient projection:

$$\vec{I}' = \vec{I} + \lambda_k \vec{\nabla} \phi_k(I), \quad \text{s.t. } \phi_k(\vec{I}') = m_k,$$

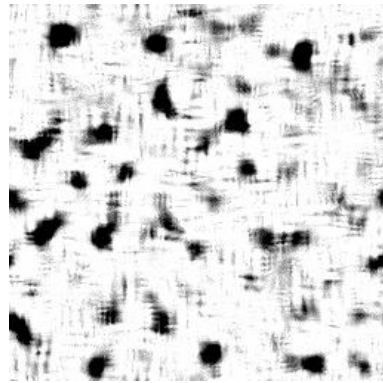
where  $m_k$  are the parameter values estimated from the example texture.

## Example Synthesis Sequence

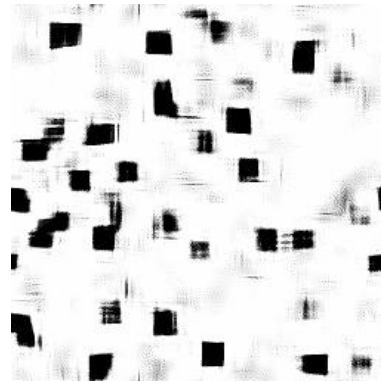
Initial



1



4



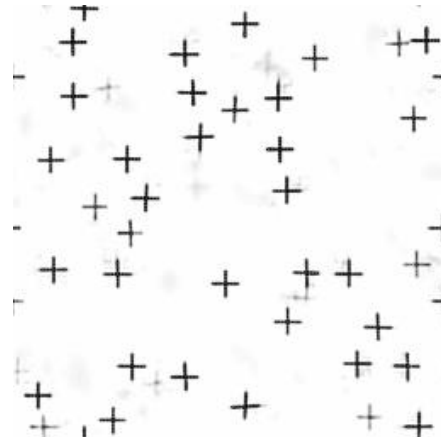
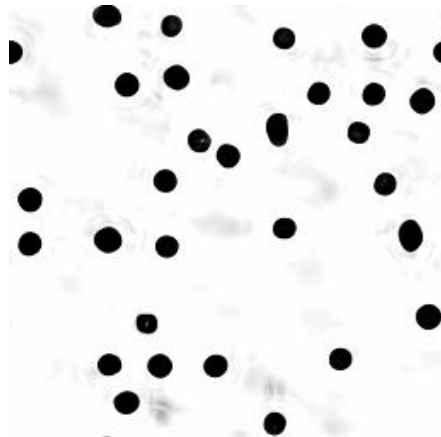
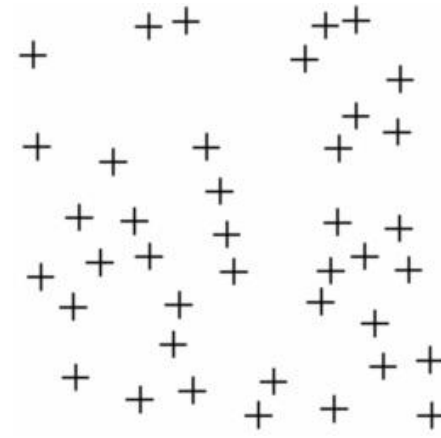
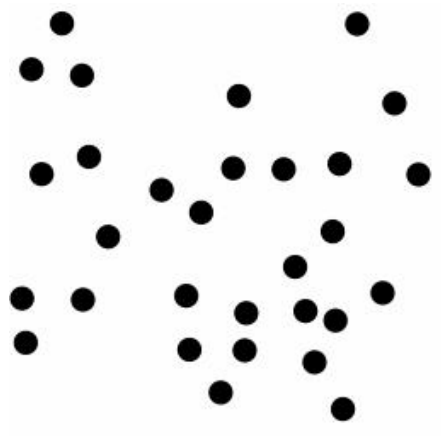
64



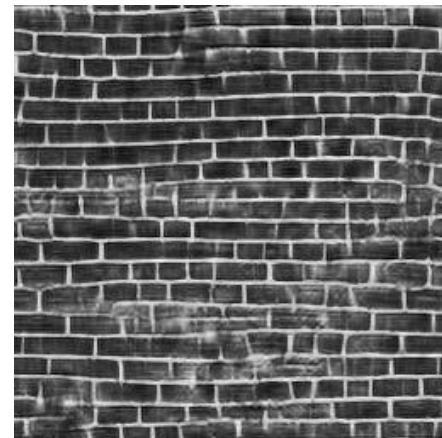
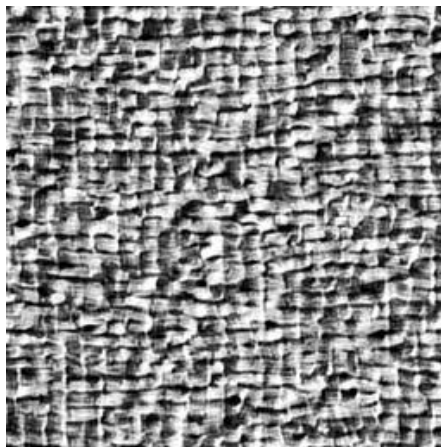
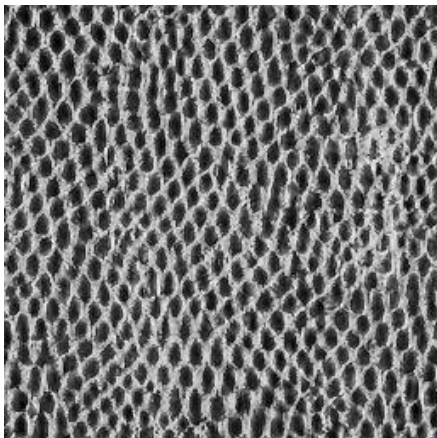
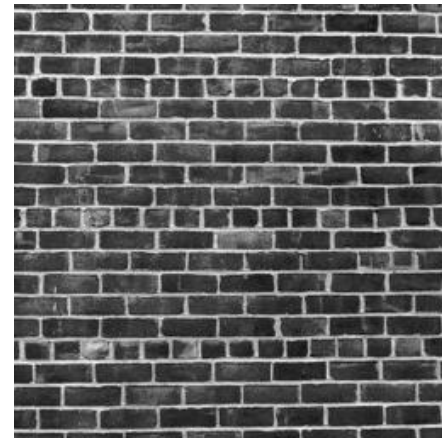
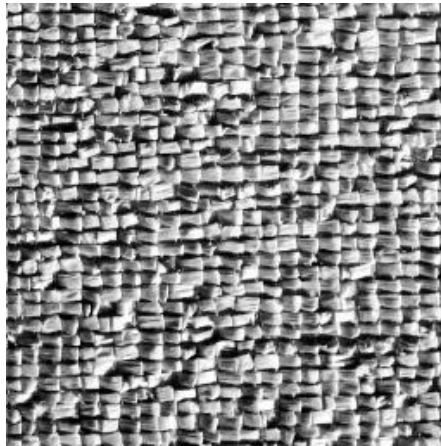
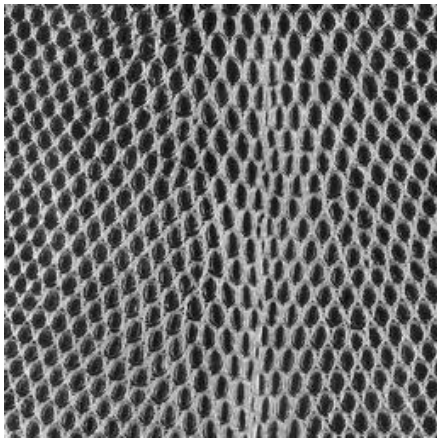
We cannot prove convergence. But in practice, algorithm converges rapidly (typical: 50 iterations).

Run time:  $256 \times 256$  image takes roughly 20 minutes (500 Mhz Pentium workstation, matlab code)

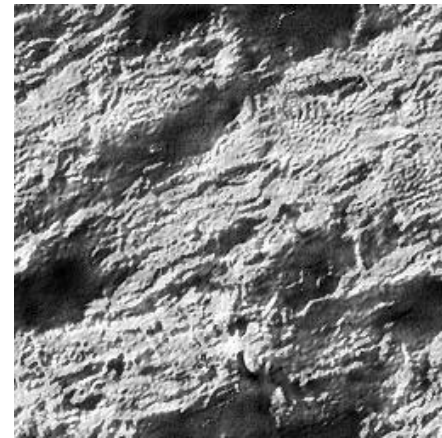
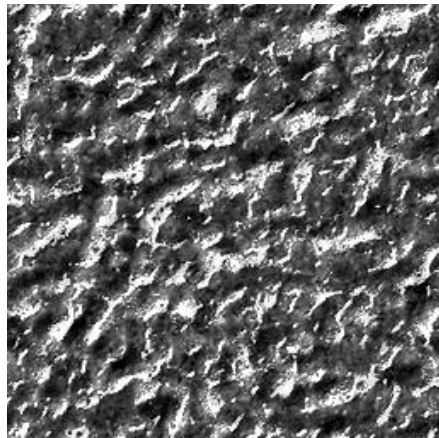
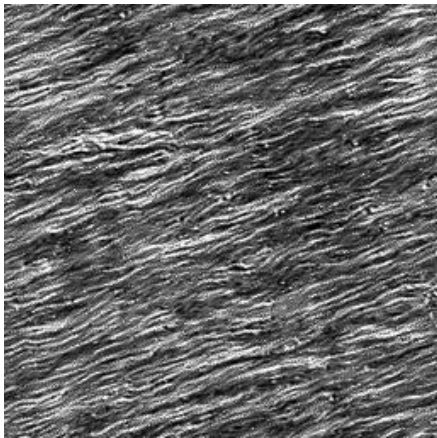
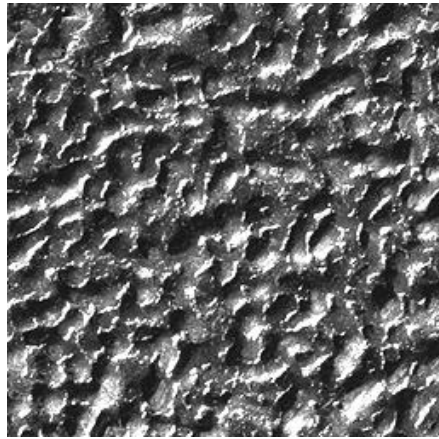
# Examples: Artificial



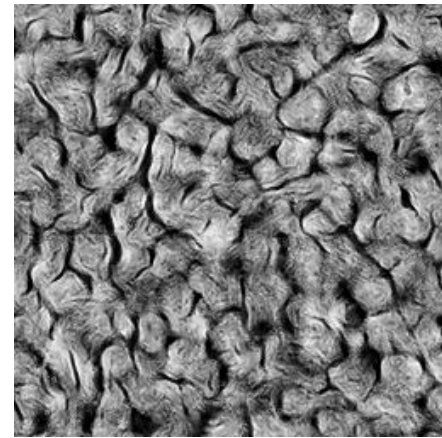
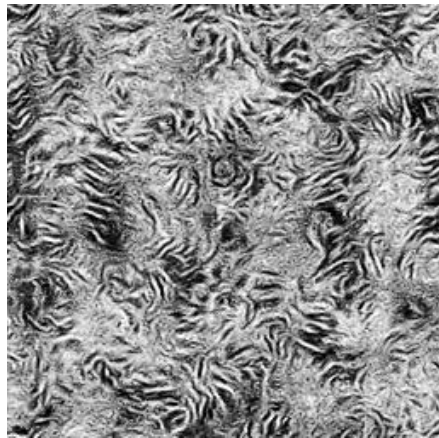
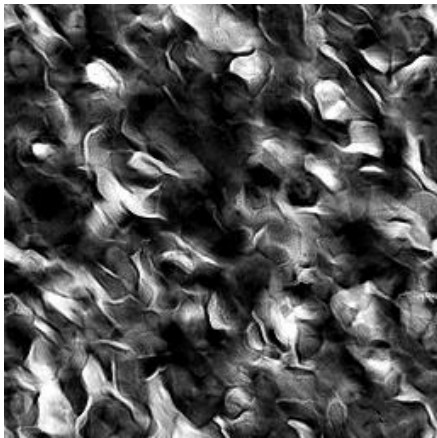
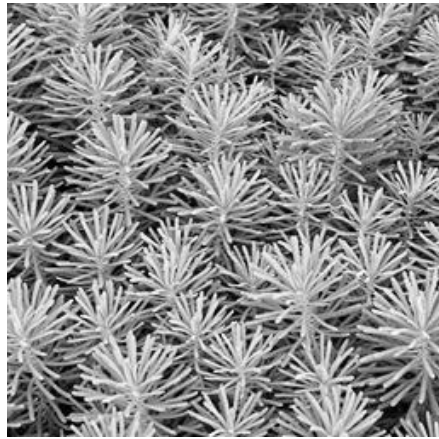
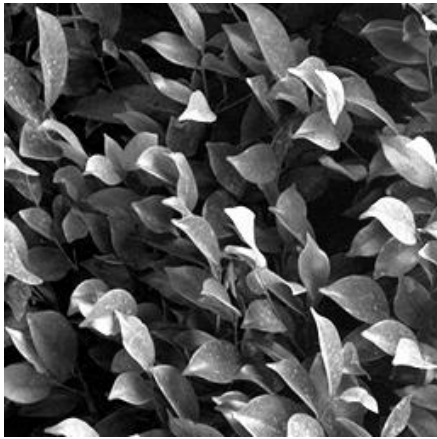
# Examples: Photographic, Quasi-periodic



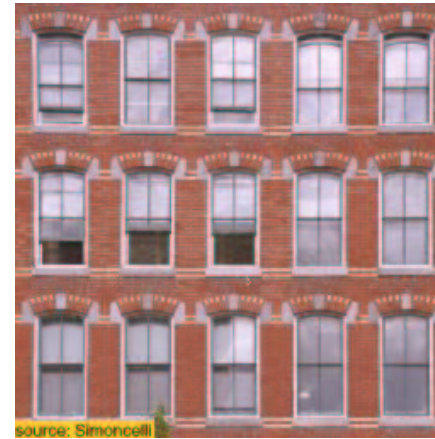
# Examples: Photographic, Aperiodic



# Examples: Photographic, Structured



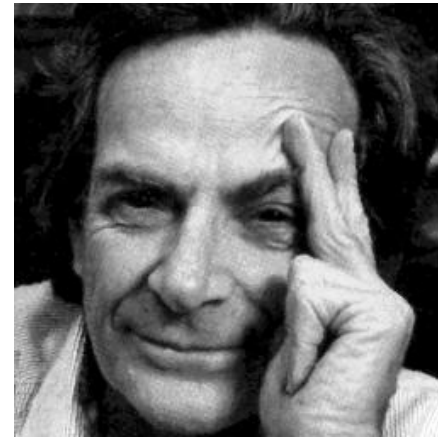
## Examples: Color



Color is incorporated by transforming to YIQ space, and including cross-band magnitude correlations in the parameterization.



# Examples: Non-textures?



# Necessity: Marginal Statistics

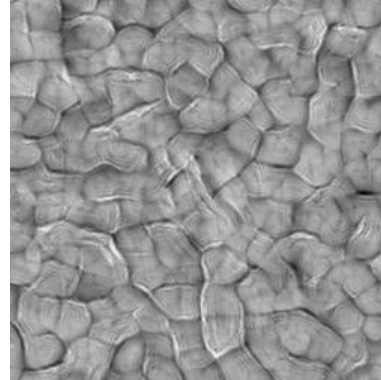
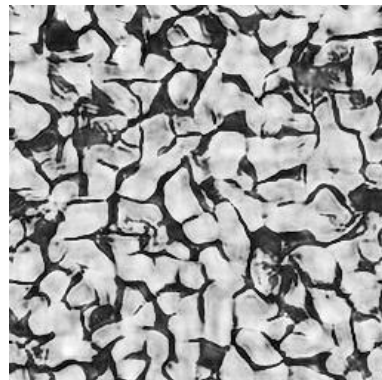
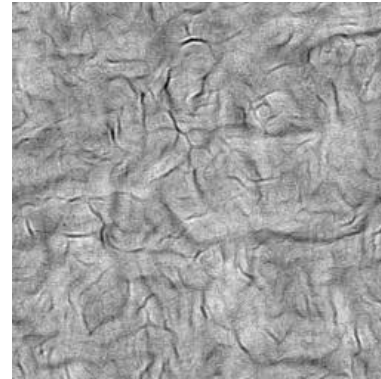
original



with



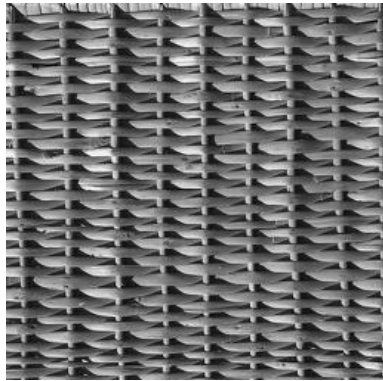
without



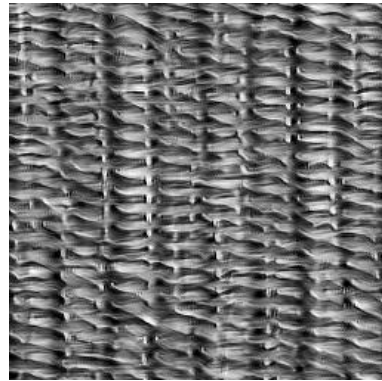
Needed for proper distribution of intensity values (at each scale).

# Necessity: Autocorrelation

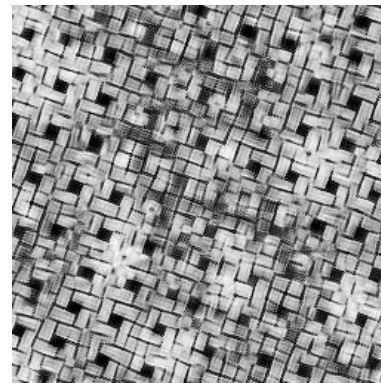
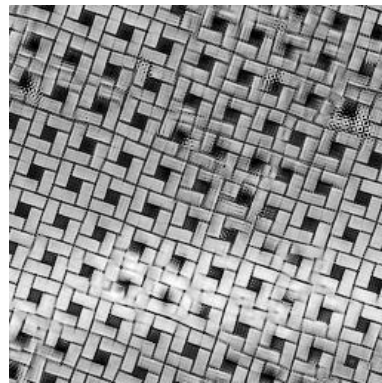
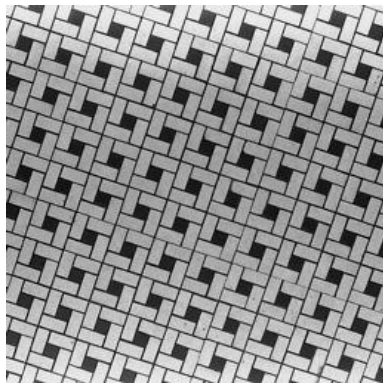
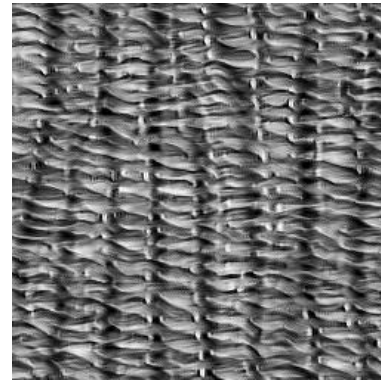
original



with



without



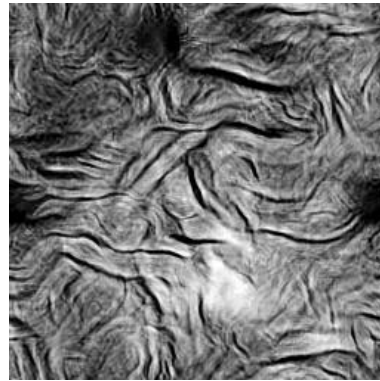
Needed for capturing periodicity and global orientation.

# Necessity: Magnitude Correlation

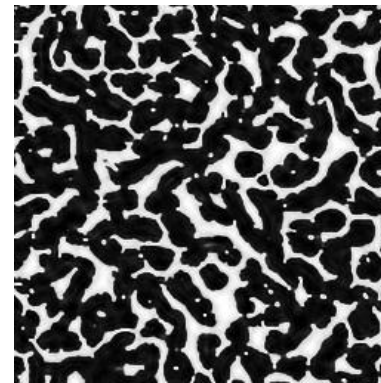
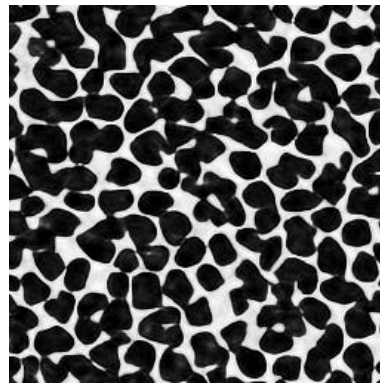
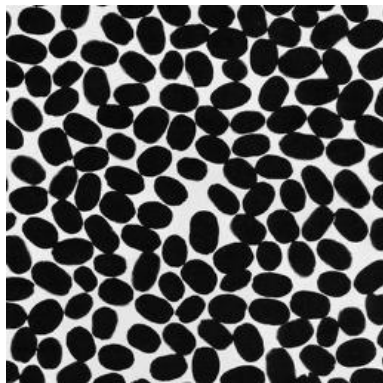
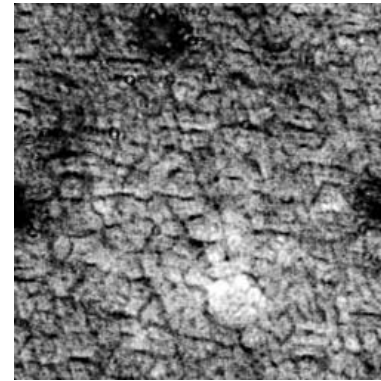
original



with



without



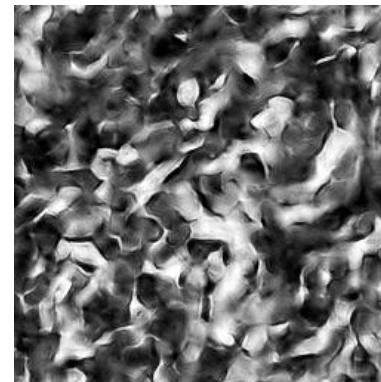
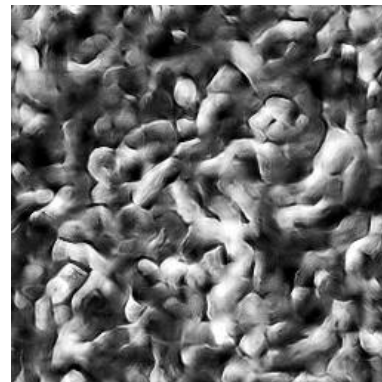
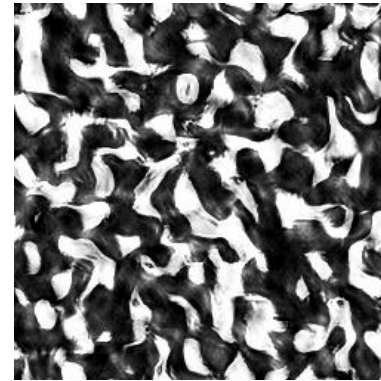
Needed for capturing periodicity local structure.

# Necessity: Relative Phase

original

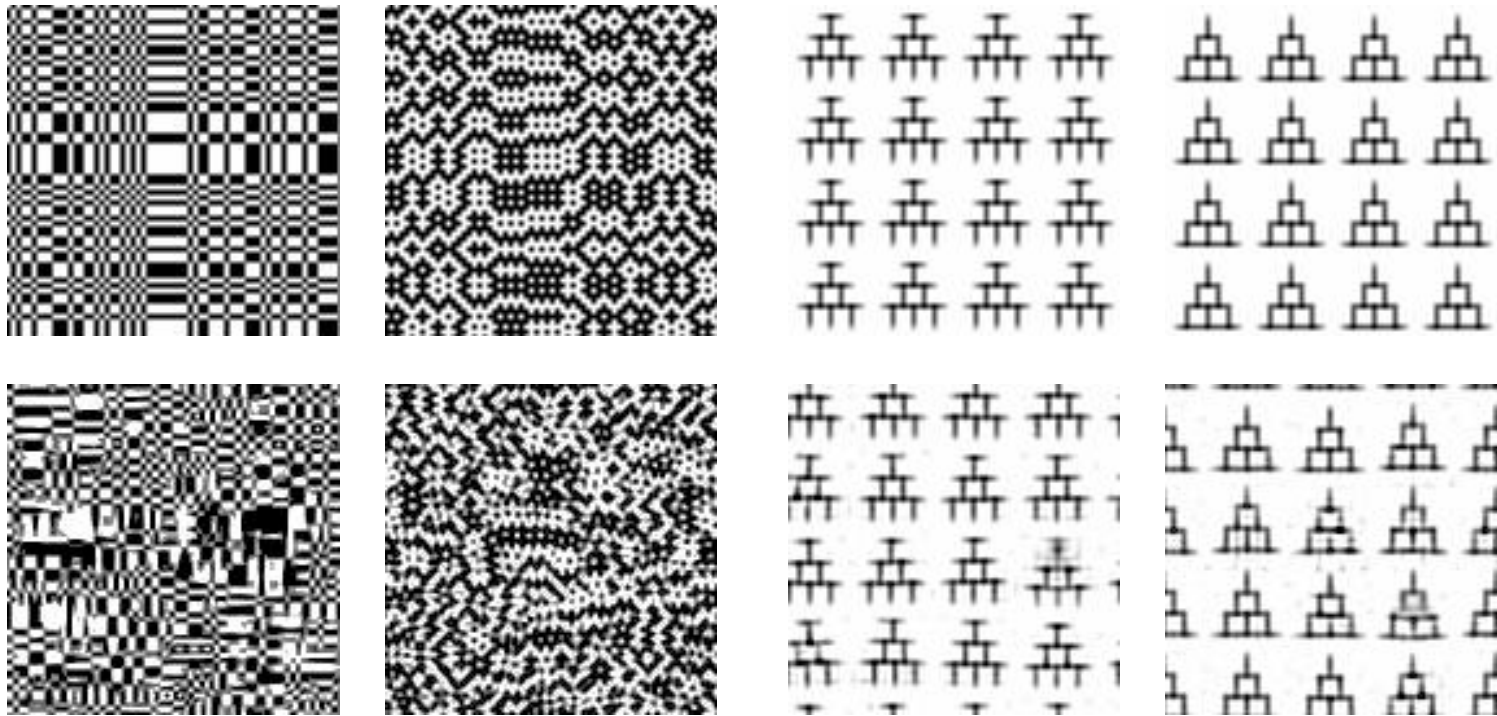
with

without



Needed for capturing details of local structure (edges vs. lines), and shading.

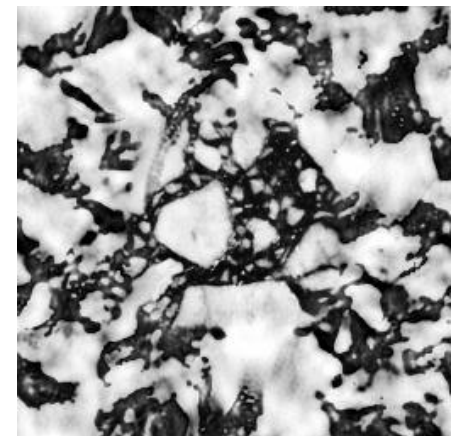
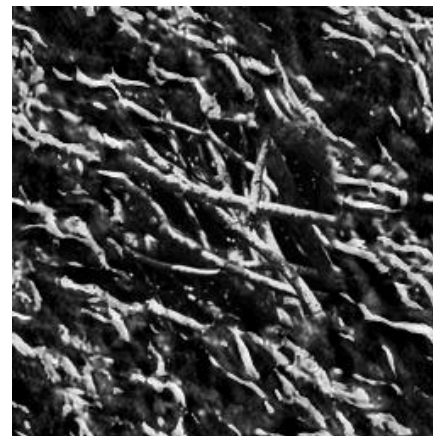
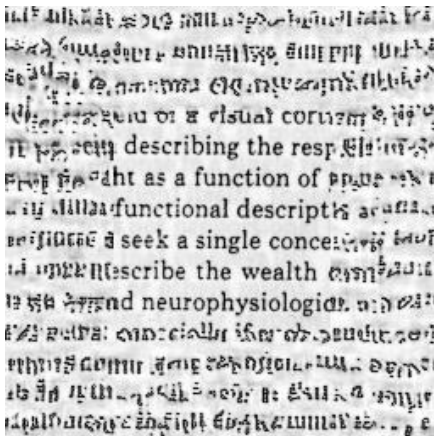
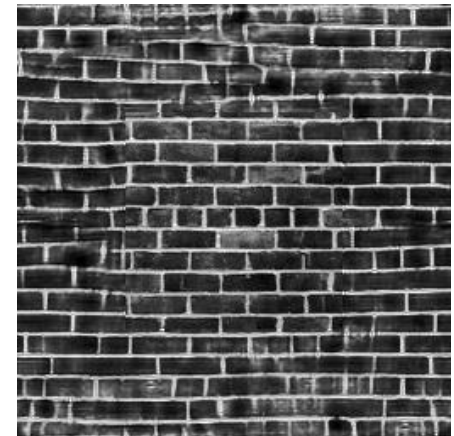
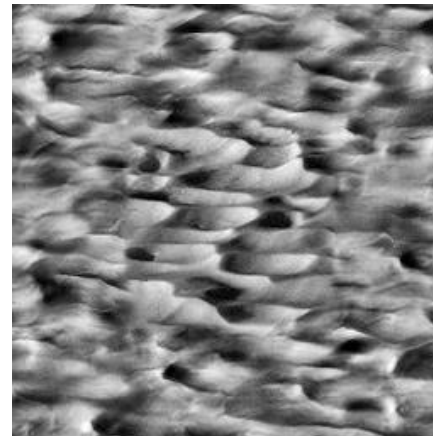
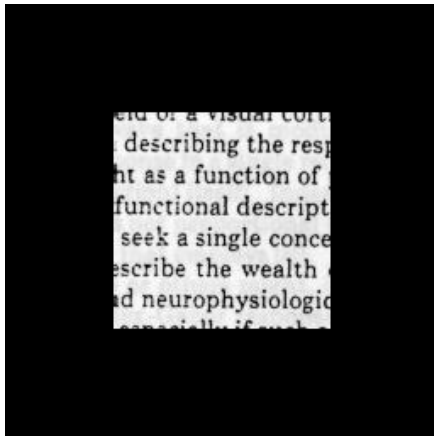
# Julesz Counter-Examples



Examples with identical 3rd-order pixel statistics

Left: Julesz '78; Right: Yellott '93

# Spatial Extrapolation



Modification: incorporate an additional projection operation in the synthesis loop, replacing central pixels by those of the original.

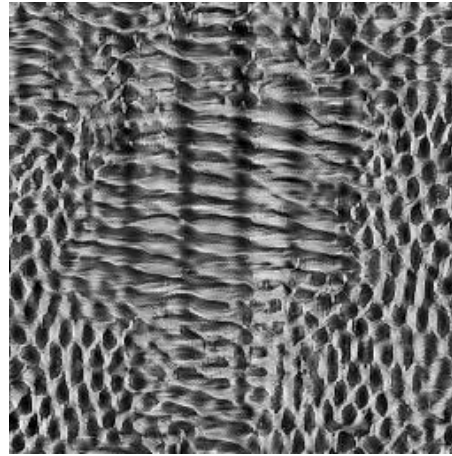
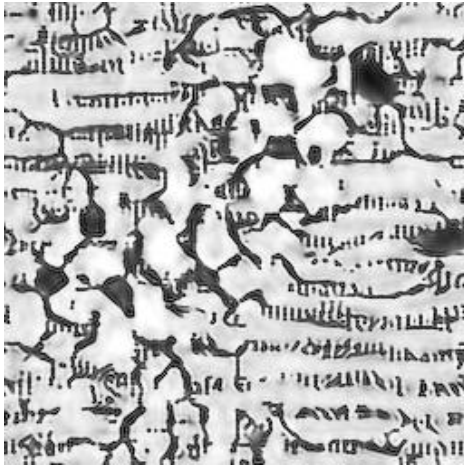
# Scale Extrapolation



Modification: incorporate an additional projection operation in the synthesis loop, replacing coarse-resolution coefficients by those of the original.



## Texture Mixtures



Modification: choose parameter vector that that is the average of those associated with two example textures.

# Conclusions

- A framework for texture modeling, based on that originally proposed by Julesz
- New texture model:
  - based on biologically-inspired statistical measurements
  - includes methodology for testing
  - provides heuristic methodology for refinement
  - can be applied to a wide range of problems

Further information: <http://www.cns.nyu.edu/~lcv/texture>

## To Do

- Adaptive front-end transformation (e.g., Zhu et al '96, Manduchi & Portilla '99)
- Eliminate redundancy of parameterization
- Applications: compression, super-resolution, texture interpolation, texture painting...