

# CSCE 448/748 - Computational Photography

---

## Texture Synthesis

Nima Kalantari

Many slides from Alexei A. Efros

# Texture

- Texture depicts spatially repeating patterns
- Many natural phenomena are textures



radishes



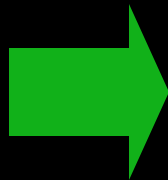
rocks



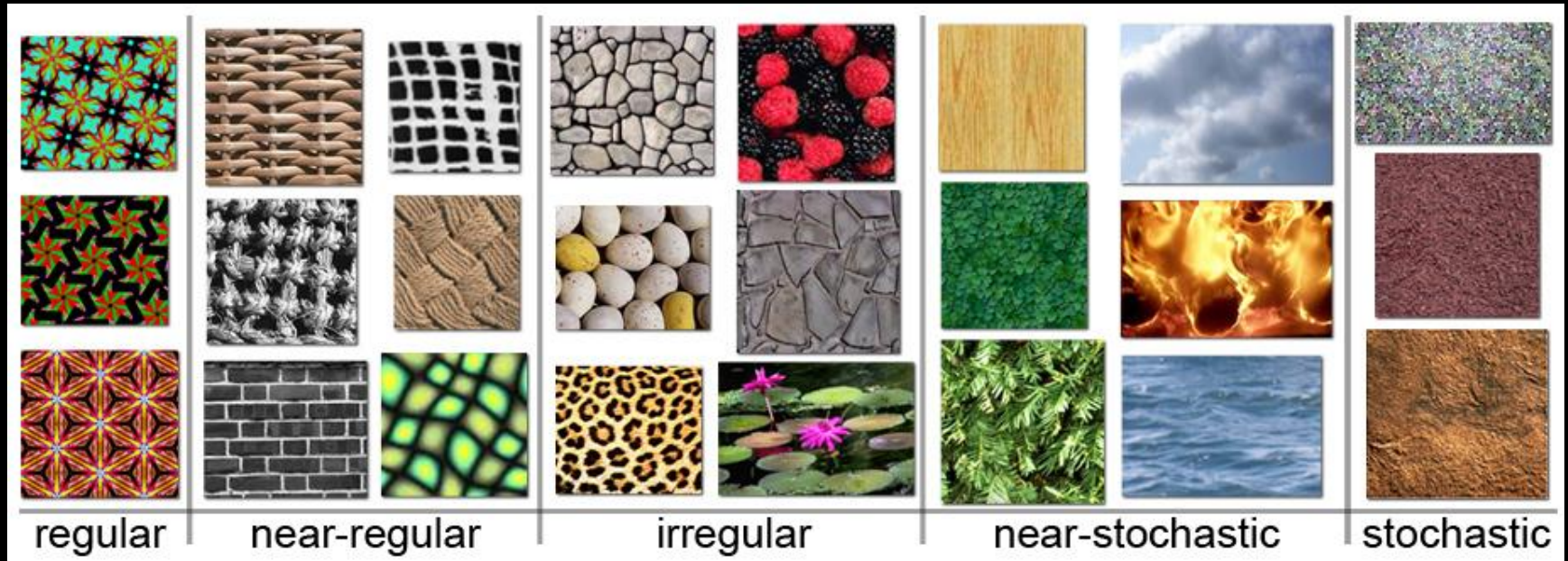
yogurt

# Texture Synthesis

- Goal of Texture Synthesis: create new samples of a given texture
- Many applications: hole-filling, texturing surfaces



# The Challenge



- Need to model the whole spectrum: from repeated to stochastic texture

# Weather Forecasting

---

Let's predict weather:

- Given today's weather only, we want to know tomorrow's
- Suppose weather can only be {**S**unny, **C**loudy, **R**aining}

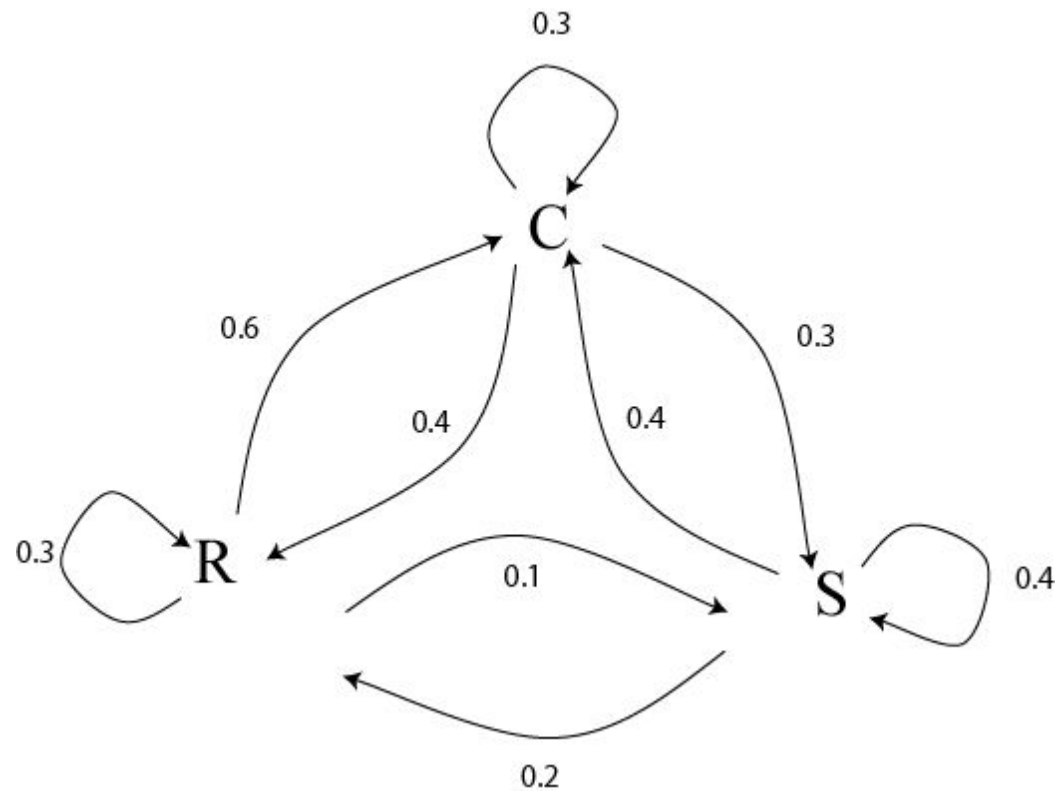
The “Weather Channel” algorithm:

- Over a long period of time, record:
  - How often S followed by R
  - How often S followed by S
  - Etc.
- Compute percentages for each state:
  - $P(R|S)$ ,  $P(S|S)$ , etc.
- Predict the state with highest probability!
- It's a Markov Chain



# Markov Chain

---



		Tomorrow		
		R	C	S
Today	R	0.3	0.6	0.1
	C	0.4	0.3	0.3
	S	0.2	0.4	0.4

What if we know today and yesterday's weather?

# Second Order Markov Chain

---

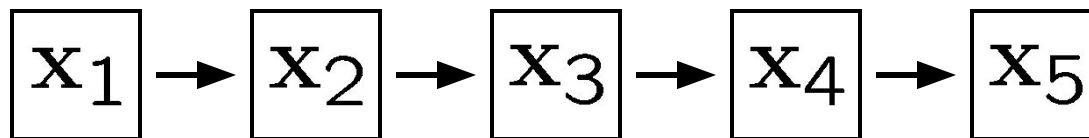
		Tomorrow			
		R	C	S	
Observation	Today	R,R	0.3	0.6	0.1
		R,C	0.4	0.3	0.3
		R,S	0.2	0.4	0.4
		G,R	0.3	0.4	0.4
		C,C	0.4	0.3	0.3
		C,S	0.2	0.4	0.4
		S,R	0.3	0.6	0.1
		S,C	0.4	0.3	0.3
		S,S	0.2	0.4	0.4

# Markov Chains

---

## Markov Chain

- a *sequence* of random variables  $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n$
- $\mathbf{x}_t$  is the **state** of the model at time  $t$



- **Markov assumption:** each state is dependent only on the previous one
  - dependency given by a **conditional probability**:

$$p(\mathbf{x}_t | \mathbf{x}_{t-1})$$

- The above is actually a *first-order* Markov chain
- An  $N$ 'th-order Markov chain:

$$p(\mathbf{x}_t | \mathbf{x}_{t-1}, \dots, \mathbf{x}_{t-N})$$



# Text synthesis

---

Create plausible looking poetry, love letters, term papers, etc.

## Most basic algorithm

1. Build probability histogram
  - find all blocks of  $N$  consecutive words/letters in training documents
  - compute probability of occurrence  $p(\mathbf{x}_t | \mathbf{x}_{t-1}, \dots, \mathbf{x}_{t-(n-1)})$
2. Given words  $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_{k-1}$ 
  - compute  $\mathbf{x}_k$  by sampling from  $p(\mathbf{x}_t | \mathbf{x}_{t-1}, \dots, \mathbf{x}_{t-(n-1)})$

# Markov Chain Example: Text

“A dog is a man’s best friend. It’s a dog eat dog world out there.”

$\mathbf{x}_{t-1}$

a		2/3		1/3							
dog			1/3				1/3	1/3			
is	1										
man’s				1							
best					1						
friend											1
it’s	1										
eat		1									
world									1		
out										1	
there											1
.						1					

$\mathbf{x}_t$

$p(\mathbf{x}_t | \mathbf{x}_{t-1})$

# Mark V. Shaney (Bell Labs)

---

## Results:

- *“As I've commented before, really relating to someone involves standing next to impossible.”*
- *“One morning I shot an elephant in my arms and kissed him.”*
- *“I spent an interesting evening recently with a grain of salt”*

# Markov Random Field

---

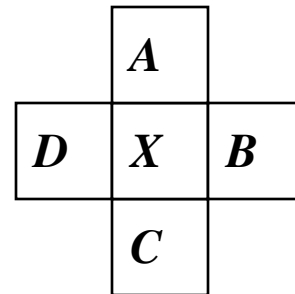
## A Markov random field (MRF)

- generalization of Markov chains to two or more dimensions.

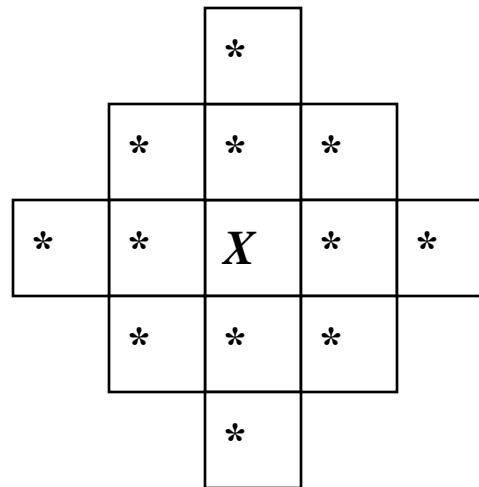
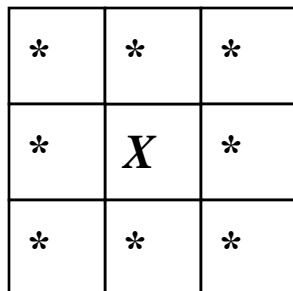
### First-order MRF:

- probability that pixel  $X$  takes a certain value given the values of neighbors  $A$ ,  $B$ ,  $C$ , and  $D$ :

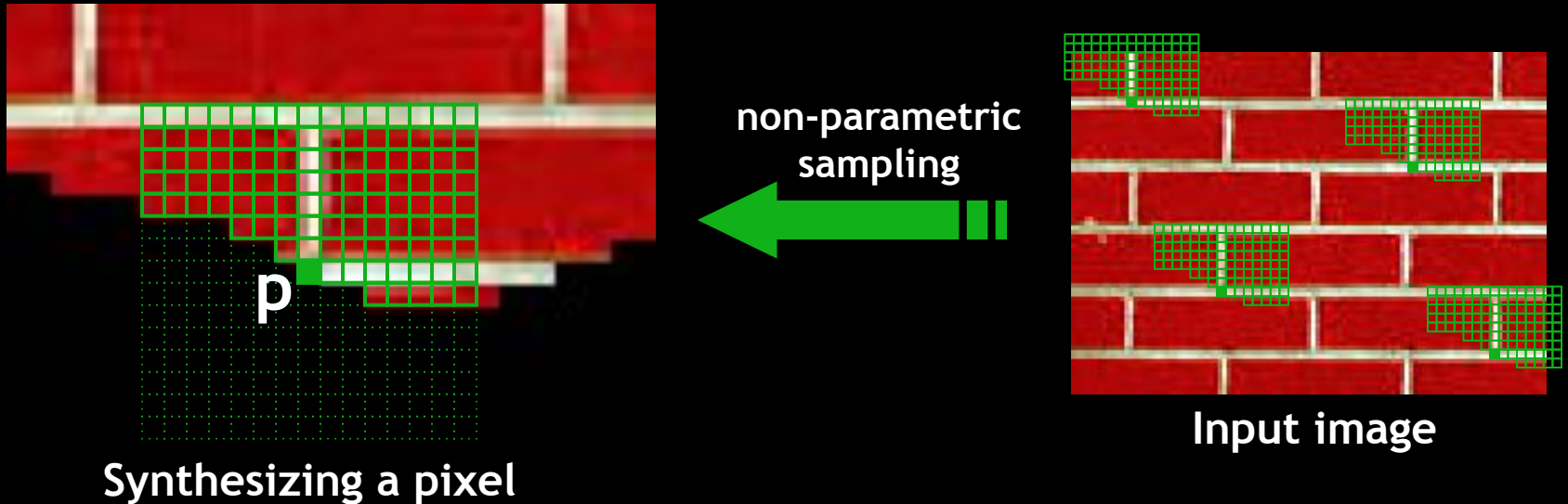
$$P(X|A, B, C, D)$$



- Higher order MRF's have larger neighborhoods

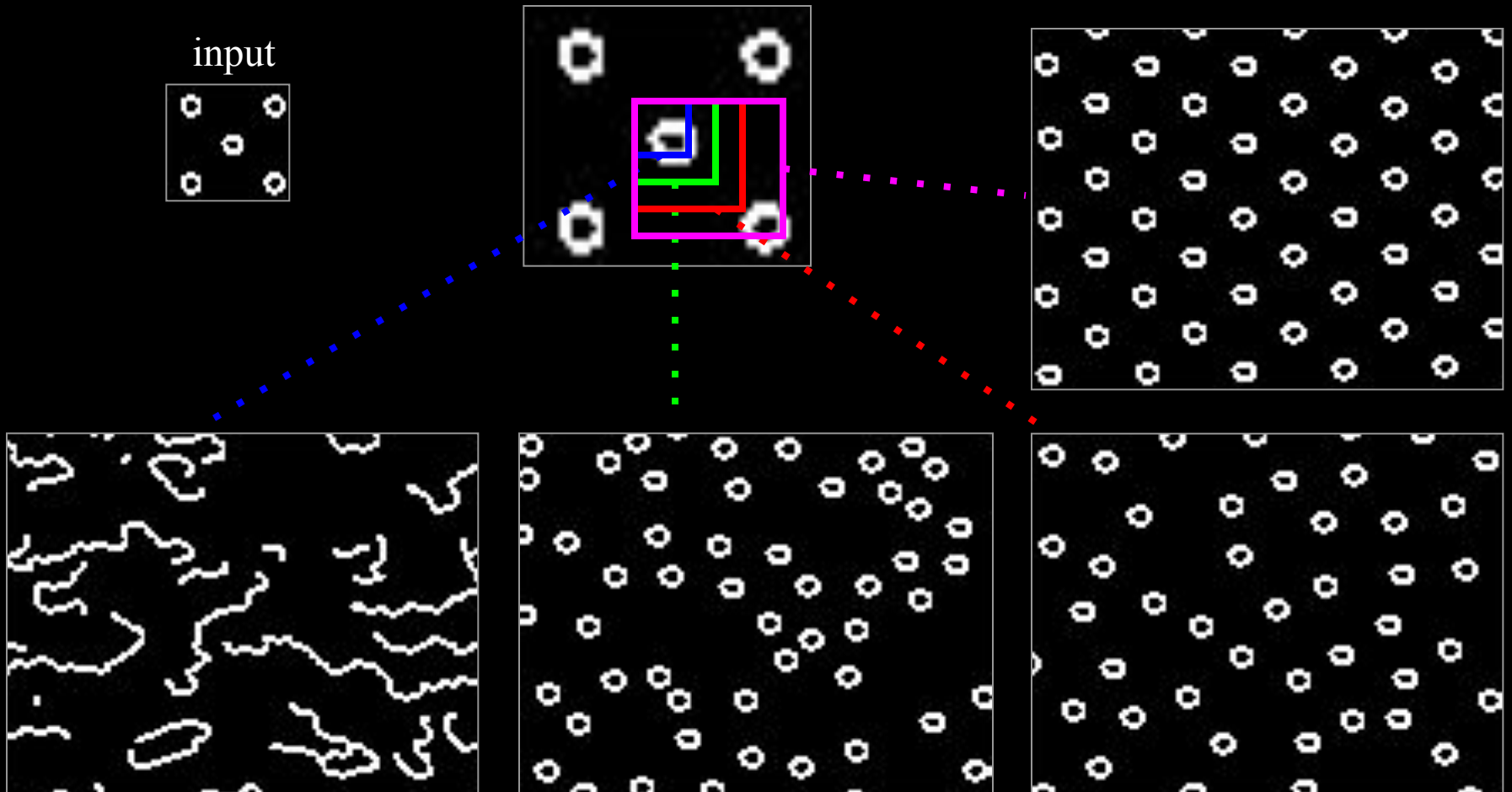


# Efros & Leung Algorithm

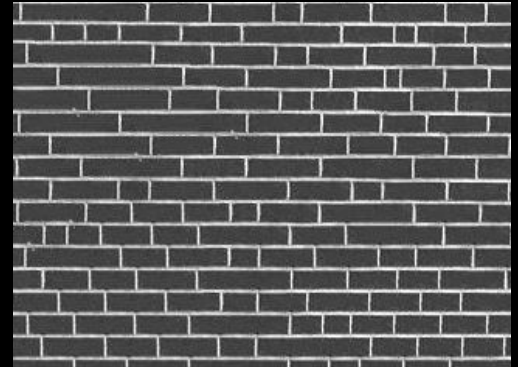
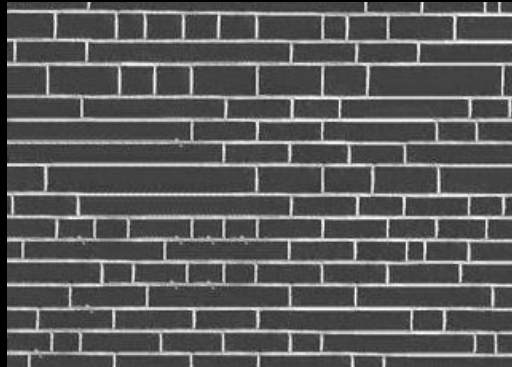
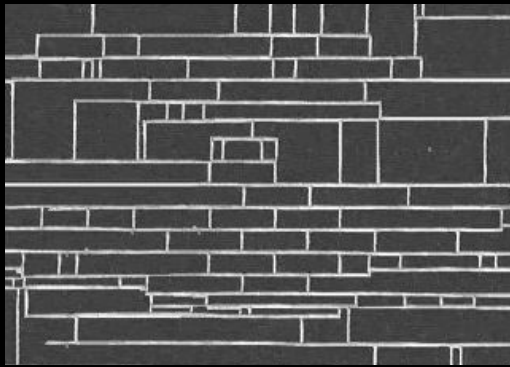
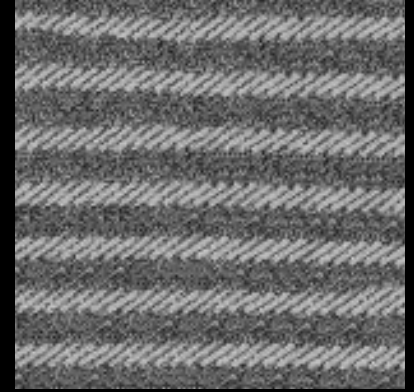
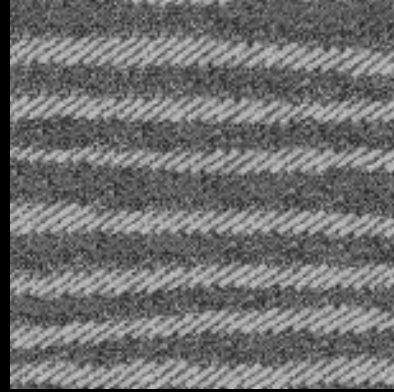
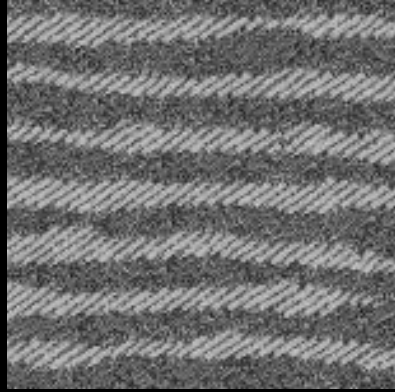
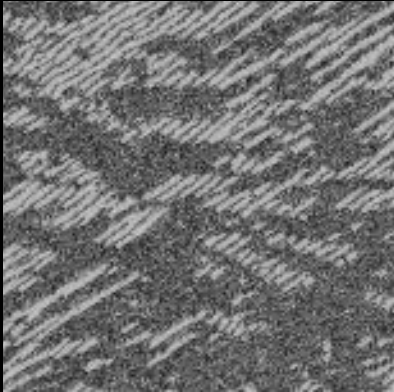
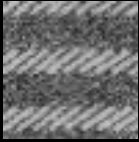


- Assuming Markov property, compute  $P(p|N(p))$ 
  - Building explicit probability tables infeasible
  - Instead, we *search the input image* for all similar neighborhoods — that's our pdf for  $p$
  - To sample from this pdf, just pick one match at random

# Neighborhood Window



# Varying Window Size



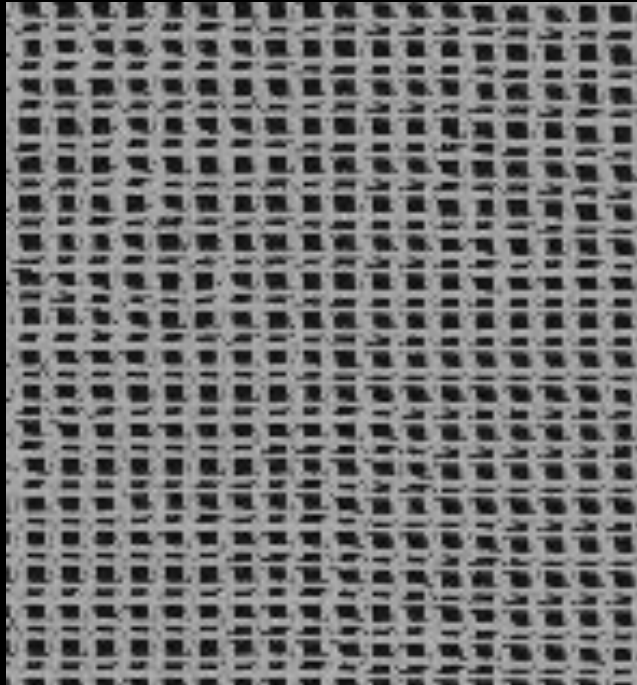
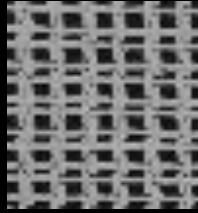
Increasing window size



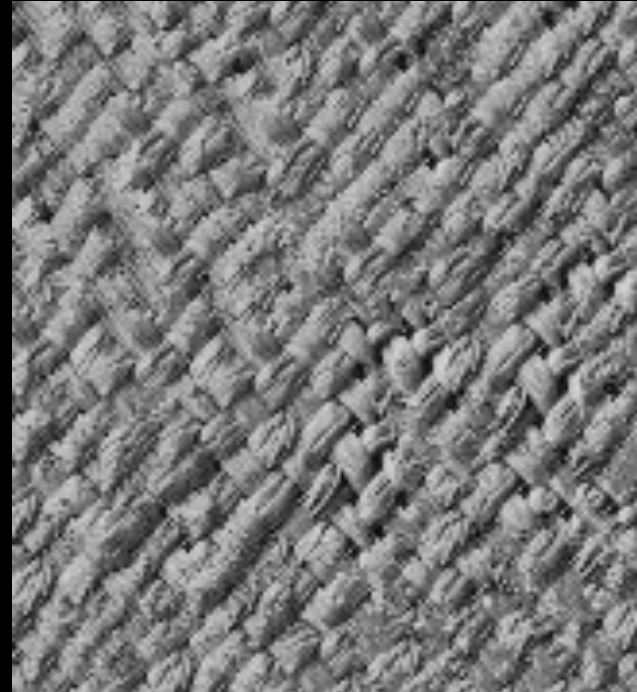
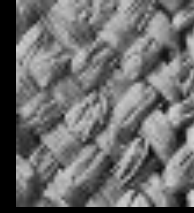


# Synthesis Results

french canvas



rafia weave

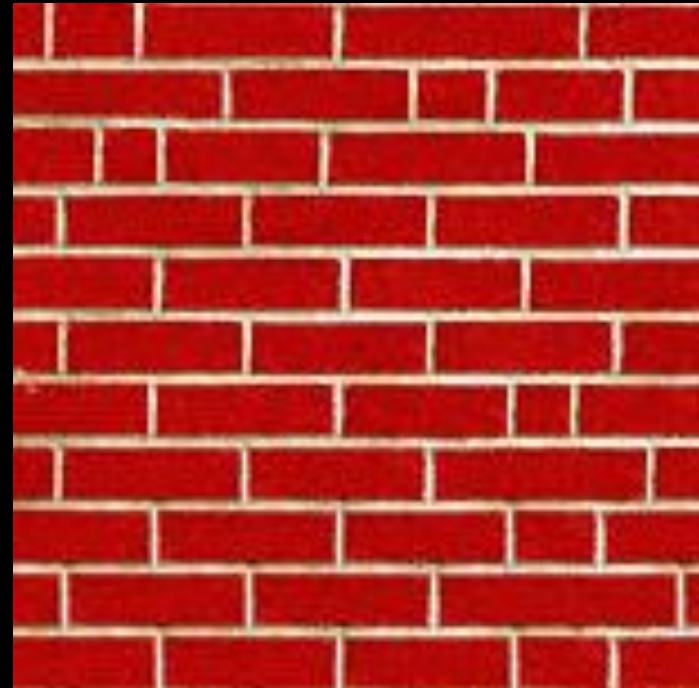
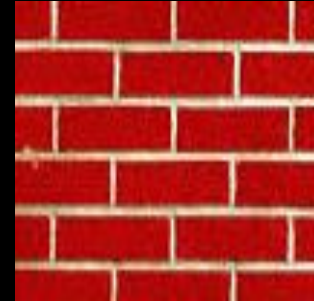


# More Results

white bread



brick wall



# Homage to Shannon

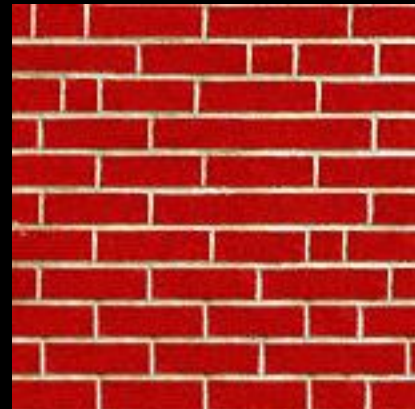
coming in the unsensational  
r Dick Gephardt was fai  
rful riff on the looming  
only asked, "What's your  
tions?" A heartfelt sigh  
story about the emergen  
es against Clinton. "Boy  
g people about continuin  
ardt began, patiently obs  
s, that the legal system h  
g with this latest tanger

st... al...  
... h... l... th...  
... la... f...  
... er... A...  
... as "he...  
... te... fit...  
... dtab... h...  
... t... h...  
... t... s...  
... bnt u...  
... id...  
... utonuc...  
... thenly...  
... dthf...  
... s...  
... e...  
... tin...  
... s...  
... h...  
... d...  
... t...  
... n...  
... m...  
... B...  
... t...

athaim, them. "Whnephartfe lartifelintomimen  
fel ck Clirtioout omaim thartfelins.f out s anento  
the ry onst wartfe lck Gephtoomimeationl sigab  
Chioouft Clinut Clil riff on, hat's yo'dn, parut tly  
ons yontonsteht wasked, paim t sahe loo riff on  
nskoneplocourtfeas leil A nst Clit, "Wleontongal s  
k Clirtioouirtfepe ong pme abegal fartfenstemem  
tiensteneltorydt telemephminsverdt was agemer  
ff ons artientont Cling peme as artfe atich, "Boui s  
hal s fartfelt sig pedritdt ske abounutie aboutioo  
tfaonewwas you abounthardt thatins fain, ped, '  
ains, them, pabout wasy arfint coultly d, l n A h  
ple emthringbooreme agas fa bontinsyst Clinut  
ory about continst Clipseopinst Cloke agatiff out C  
stome zinemen tly ardt beorabou n, thenly as t C  
cons faimeme Diontont wat coutlyohgans as fan  
ien, phrtfaul, "Wbaut cout congagal comininga  
mifmst Clily abon al coountha.emungairt tf oun  
The loocrysta loontieph, intly on, tieoplegatick C  
aul tatiezontly atie Diontiomt wal s f tbegae ener  
nthahgat's enenhhmas fan, "intchthory abons w



# Hole Filling



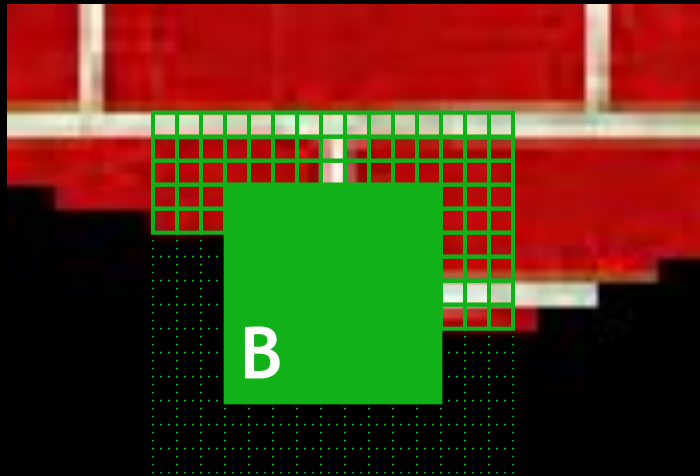
# Extrapolation



# Summary

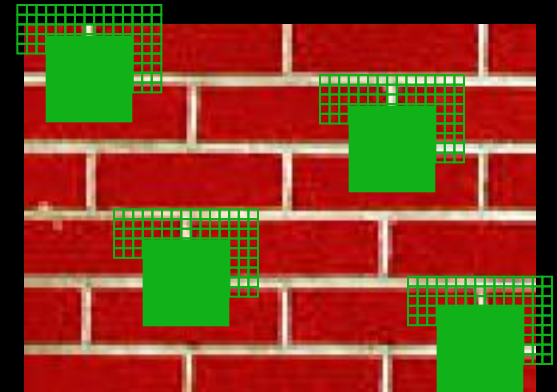
- The Efros & Leung algorithm
  - Very simple
  - Surprisingly good results
  - ...but very slow

# Image Quilting [Efros & Freeman]



Synthesizing a block

non-parametric  
sampling



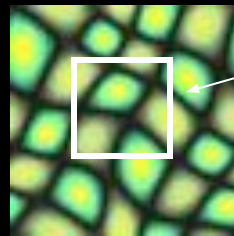
Input image

- Observation: neighbor pixels are highly correlated

Idea: unit of synthesis = block

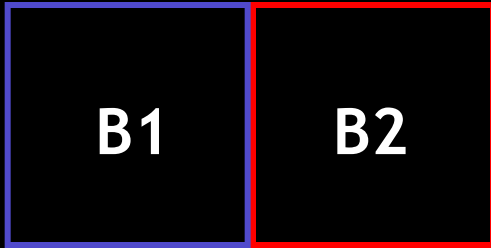
- Exactly the same but now we want  $P(B|N(B))$
- Much faster: synthesize all pixels in a block at once



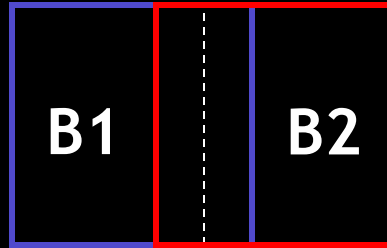


block

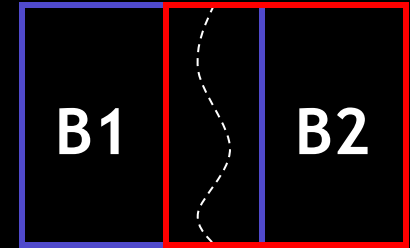
Input texture



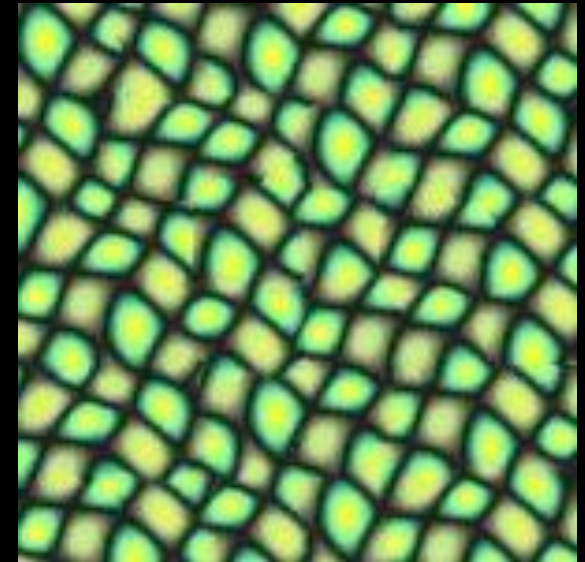
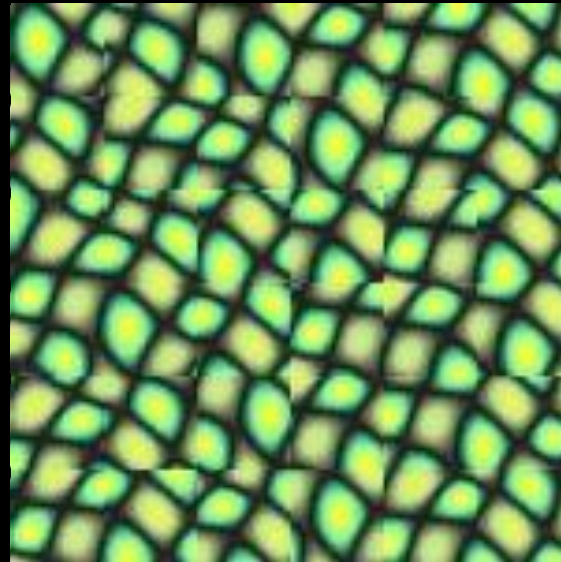
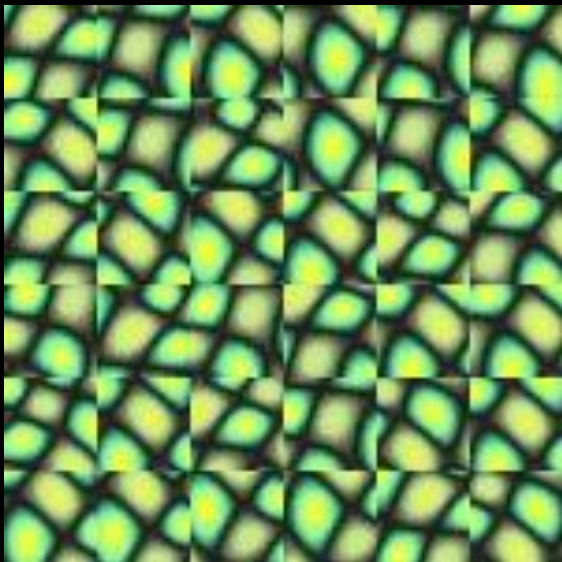
Random placement  
of blocks



Neighboring blocks  
constrained by overlap

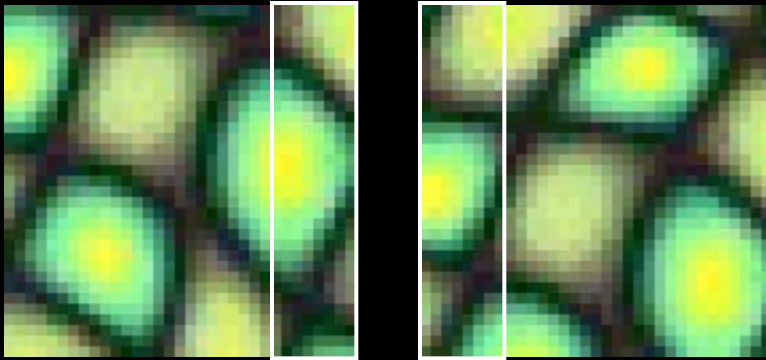


Minimal error  
boundary cut

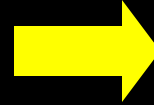
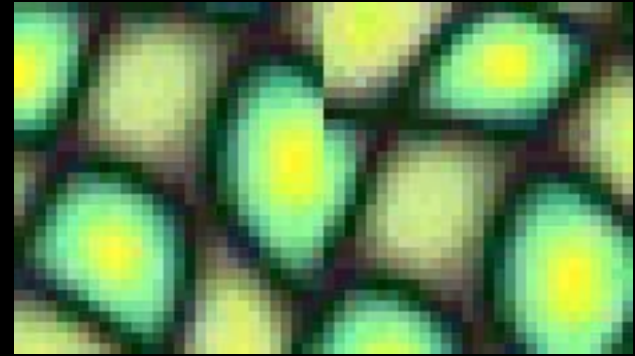


# Minimal error boundary

overlapping blocks



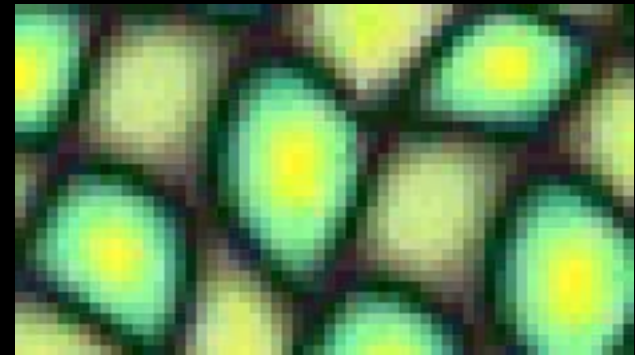
vertical boundary



$$\left( \text{block}_1 - \text{block}_2 \right)^2 = \text{error\_map}$$

The diagram illustrates the calculation of overlap error. It shows two overlapping blocks of the cell image. A yellow arrow points from the overlapping region of the first block to the first block in the subtraction. Another yellow arrow points from the overlapping region of the second block to the second block in the subtraction. The result of the subtraction is a red line on a black background, representing the error map.

overlap error

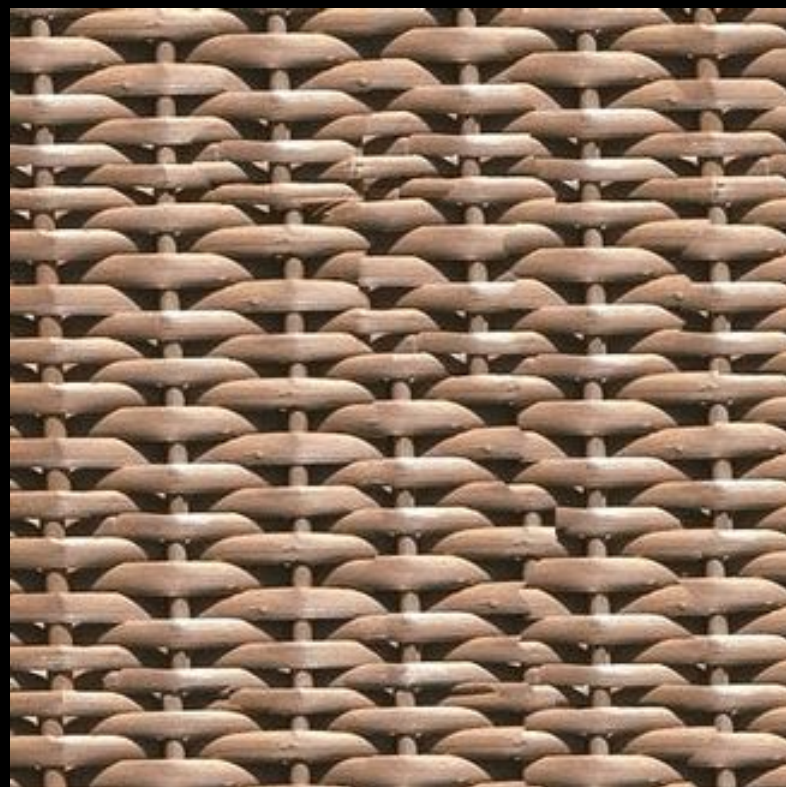


min. error boundary

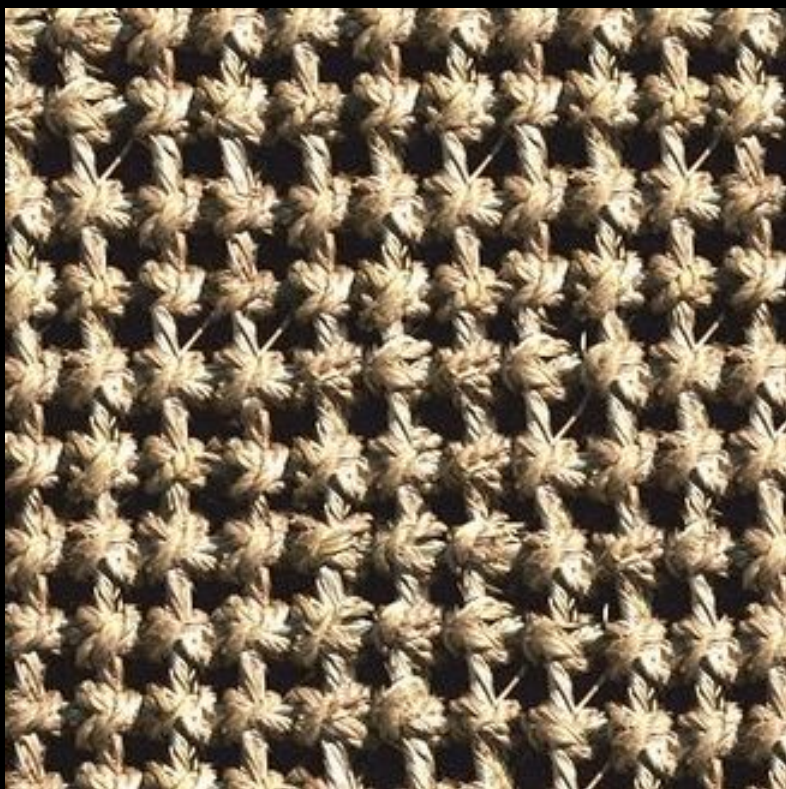
# Our Philosophy

- 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











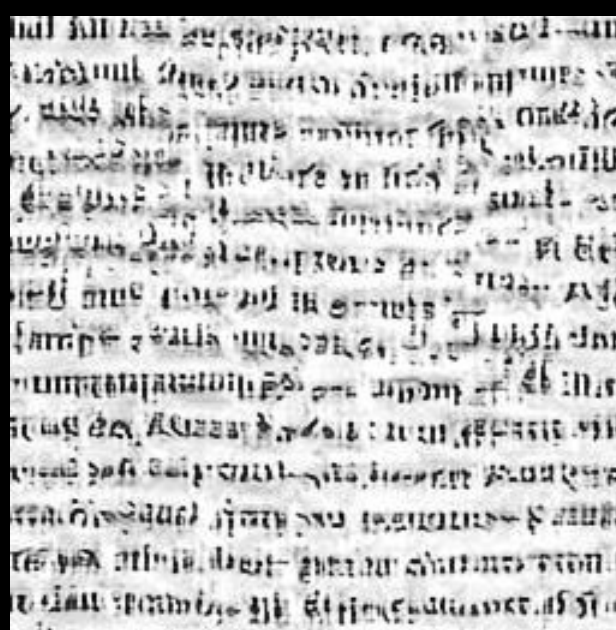




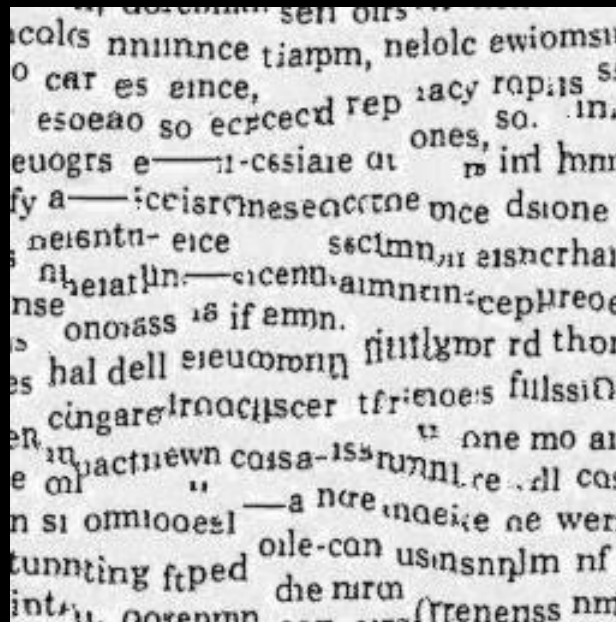


...id of a visual cortical neuron—the in  
describing the response of that neuro  
ht as a function of position—is perhap  
functional description of that neuron.  
seek a single conceptual and mathem  
escribe the wealth of simple-cell recep  
ad neurophysiologically<sup>1-3</sup> and inferred  
especially if such a framework has the  
it helps us to understand the functio  
eeper way. Whereas no generic mo  
ussians (DOG), difference of offset C  
rivative of a Gaussian, higher derivati  
function, and so on—can be expecte  
imple-cell receptive field, we noneth

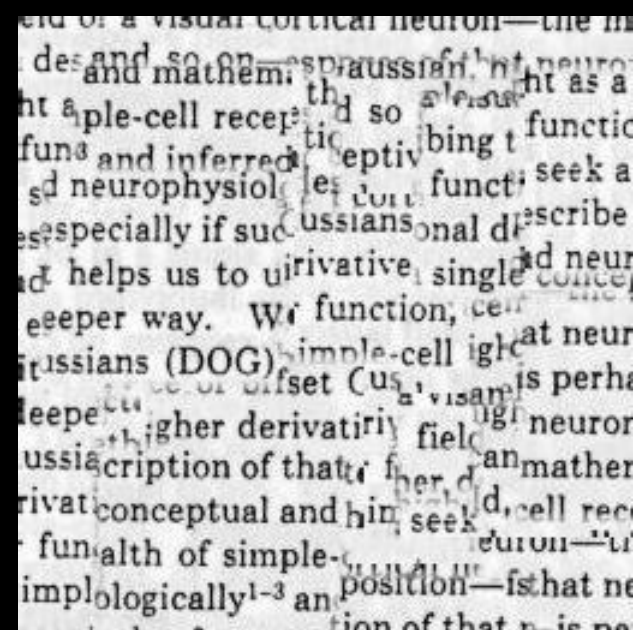
input image



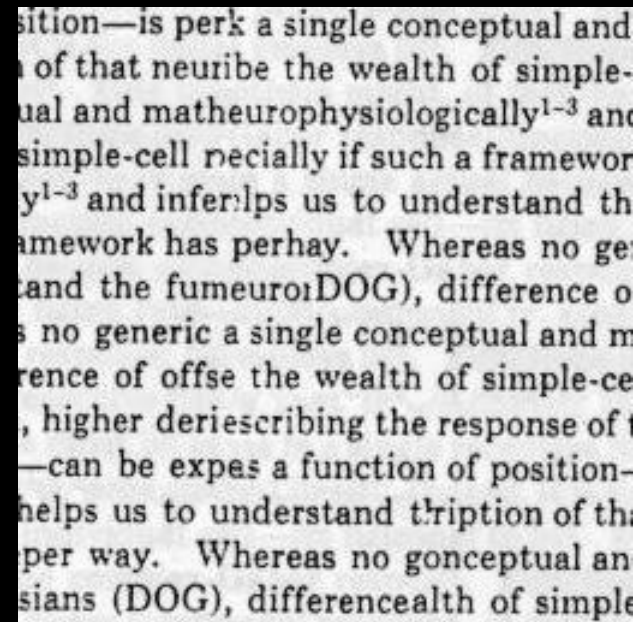
Portilla & Simoncelli



Wei & Levoy



Xu, Guo & Shum



Our algorithm

# Application: Texture Transfer

- Try to explain one object with bits and pieces of another object:



# Texture Transfer



Constraint



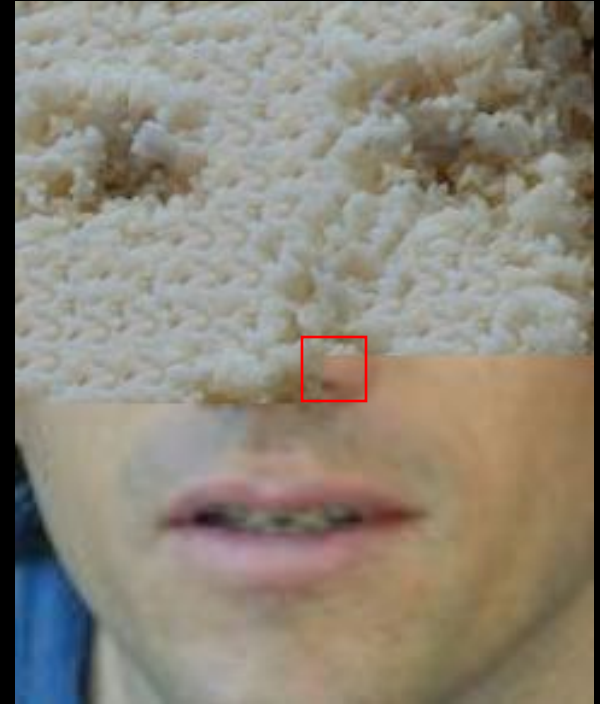
Texture sample





# Texture Transfer

- Take the texture from one image and “paint” it onto another object



Same as texture synthesis, except an additional constraint:

1. Consistency of texture
2. Similarity to the image being “explained”



