

Texture synthesis and image analogies



15-463, 15-663, 15-862
Computational Photography
Fall 2017, Lecture 9

Course announcements

- Please take Doodle for second make-up lecture, link on Piazza.
- Homework 3 is out.
 - Due October 12th.
 - Shorter, but longer bonus component.

Overview of today's lecture

- Reminder: non-local means.
- Texture synthesis.
- Texture by non-parametric sampling.
- Image quilting.
- Inpainting.
- Texture transfer.
- Image analogies.
- Deep learning teaser.

Slide credits

Most of these slides were adapted from:

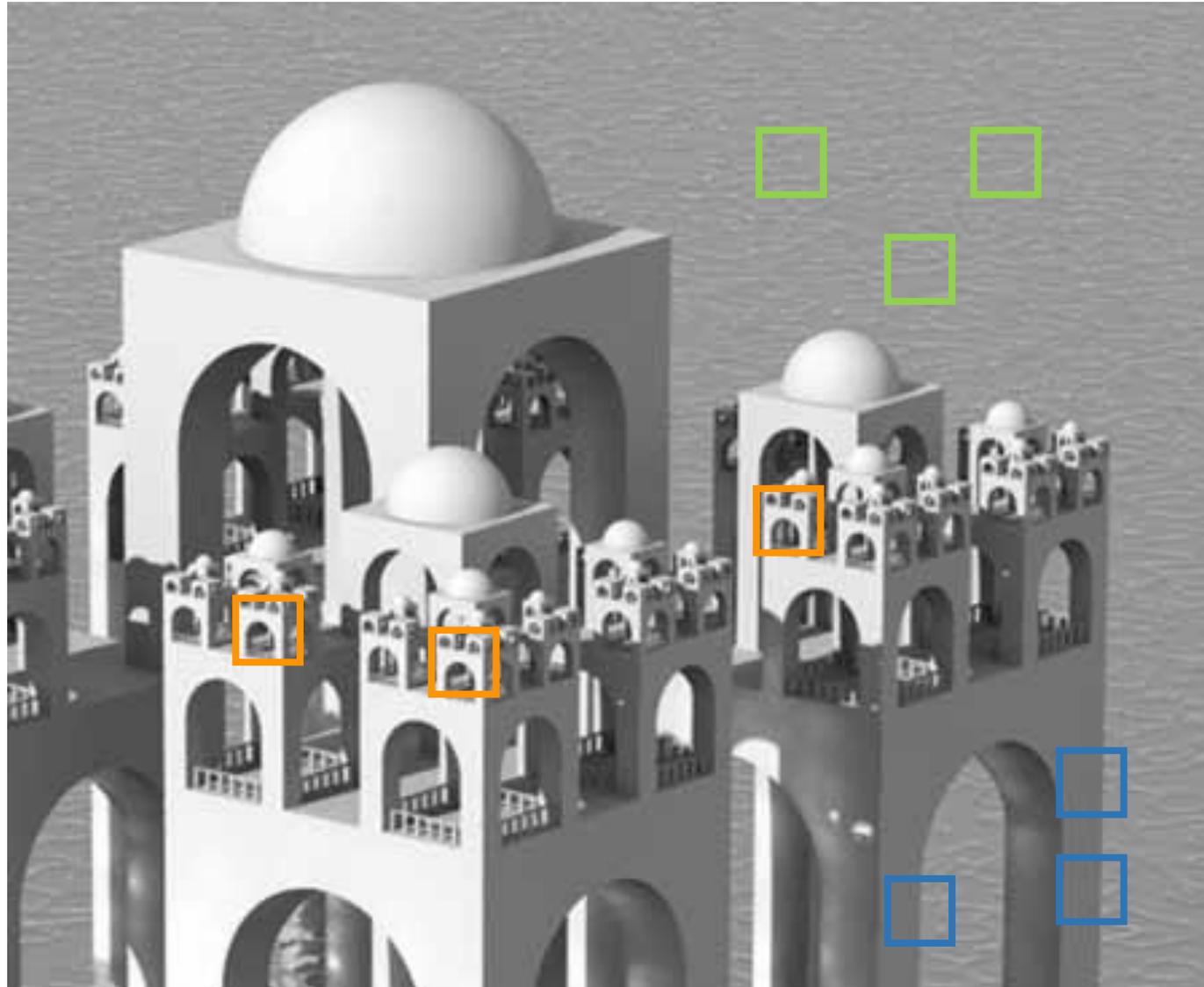
- Kris Kitani (15-463, Fall 2016).

Some slides were inspired or taken from:

- Fredo Durand (MIT).
- James Hays (Georgia Tech).

Reminder: non-local means

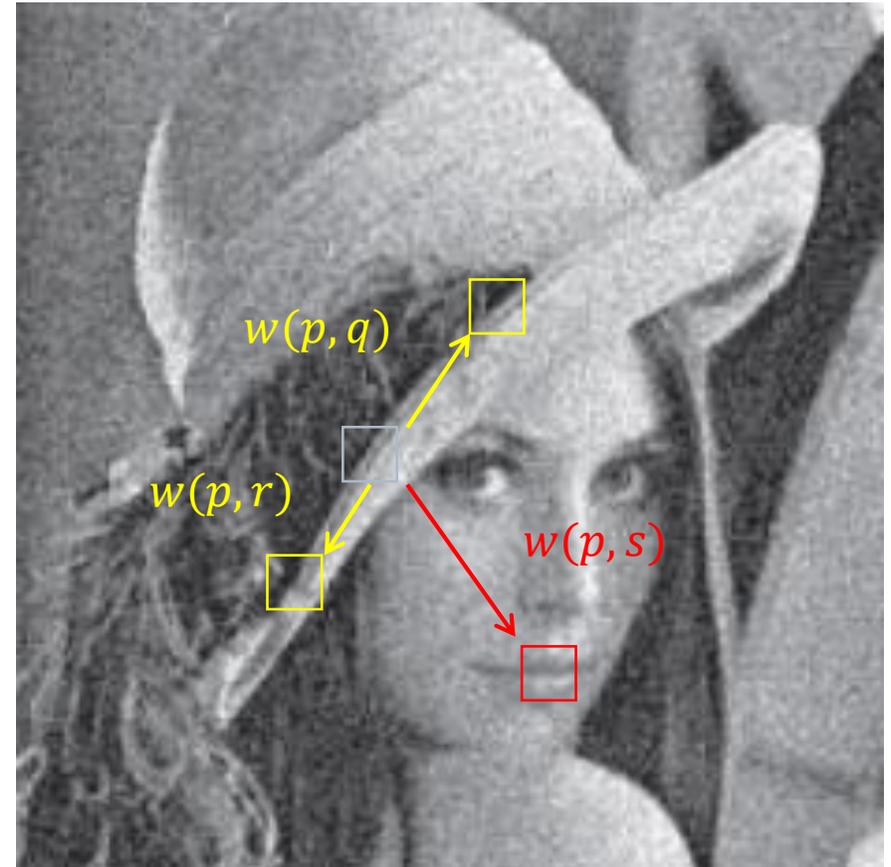
Redundancy in natural images



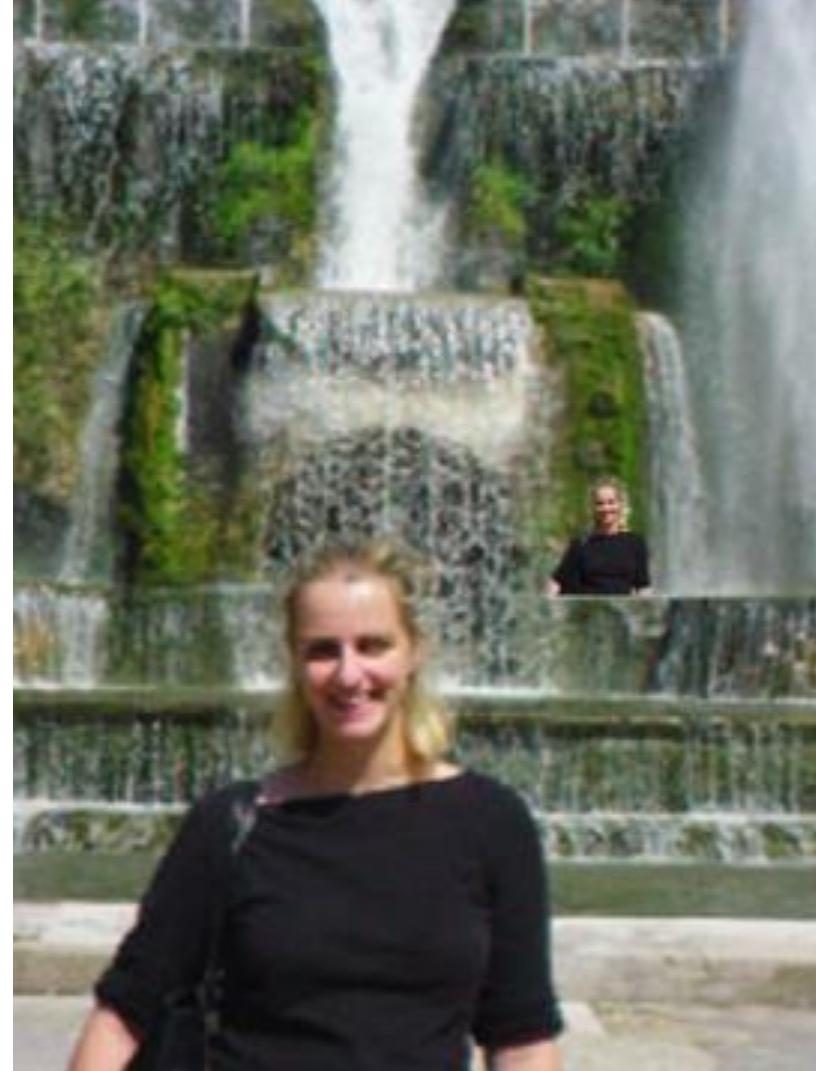
Non-local means

No need to stop at neighborhood. Instead search *everywhere* in the image.

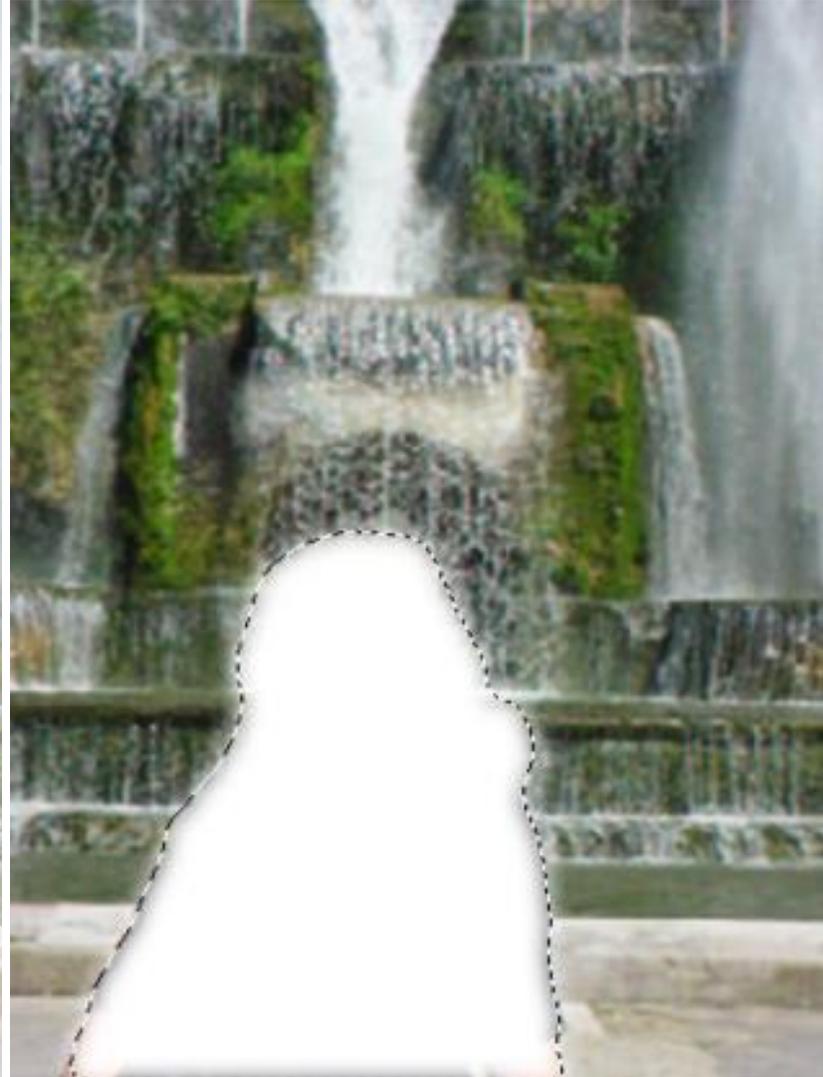
$$\hat{x}(i) = \frac{1}{C_i} \sum_j y(j) \underbrace{e^{-\frac{SSD(y(N_i) - y(N_j))}{2\sigma^2}}}_{w(i,j)}$$



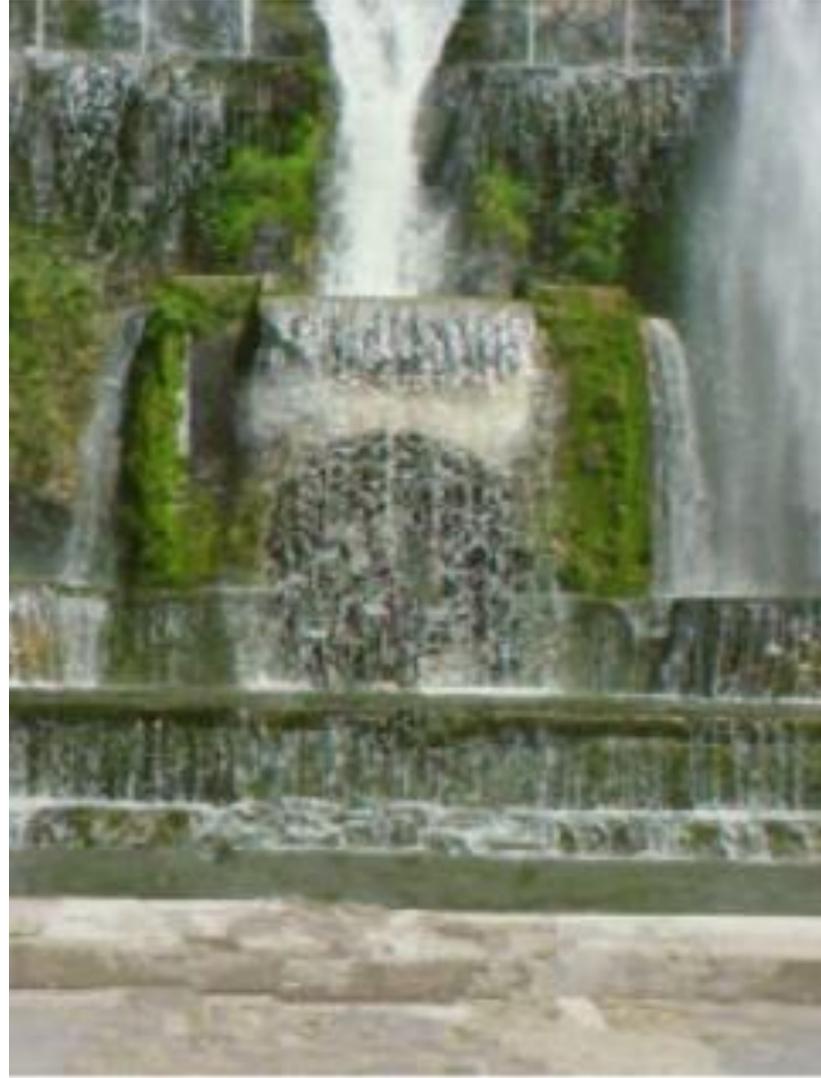
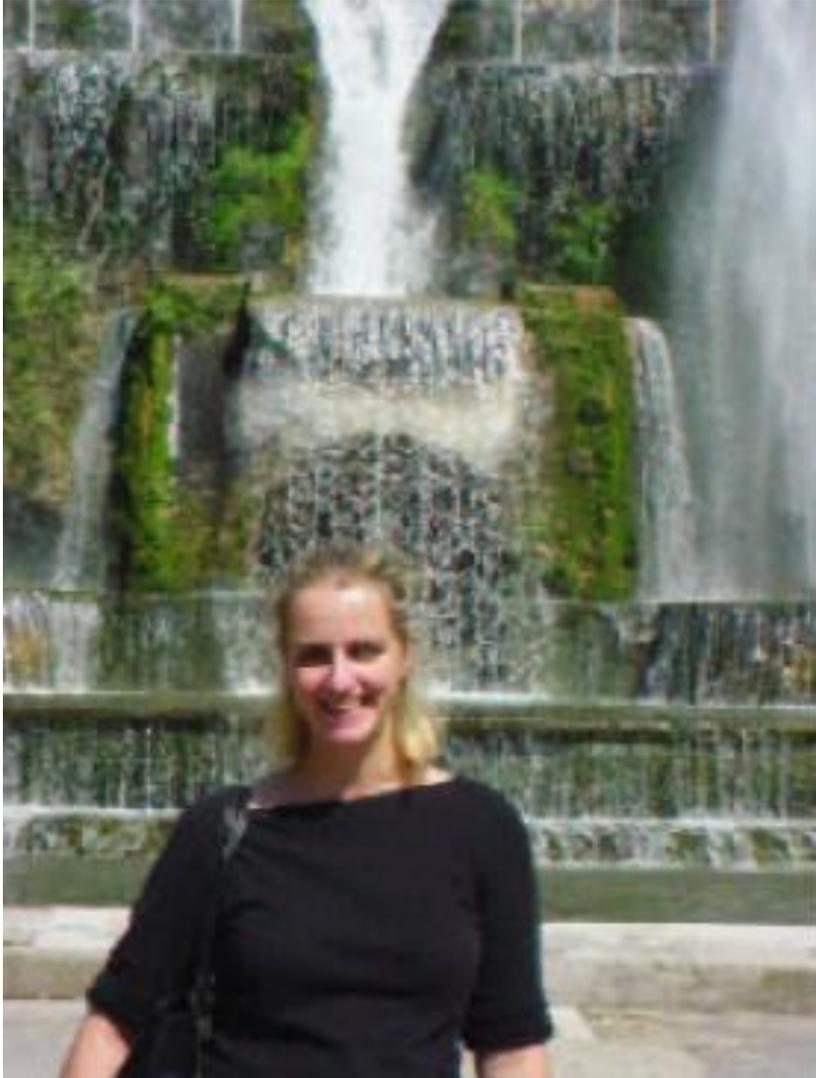
Last couple of classes: adding things to the image



This class: removing things from the image



This class: removing things from the image



Texture synthesis

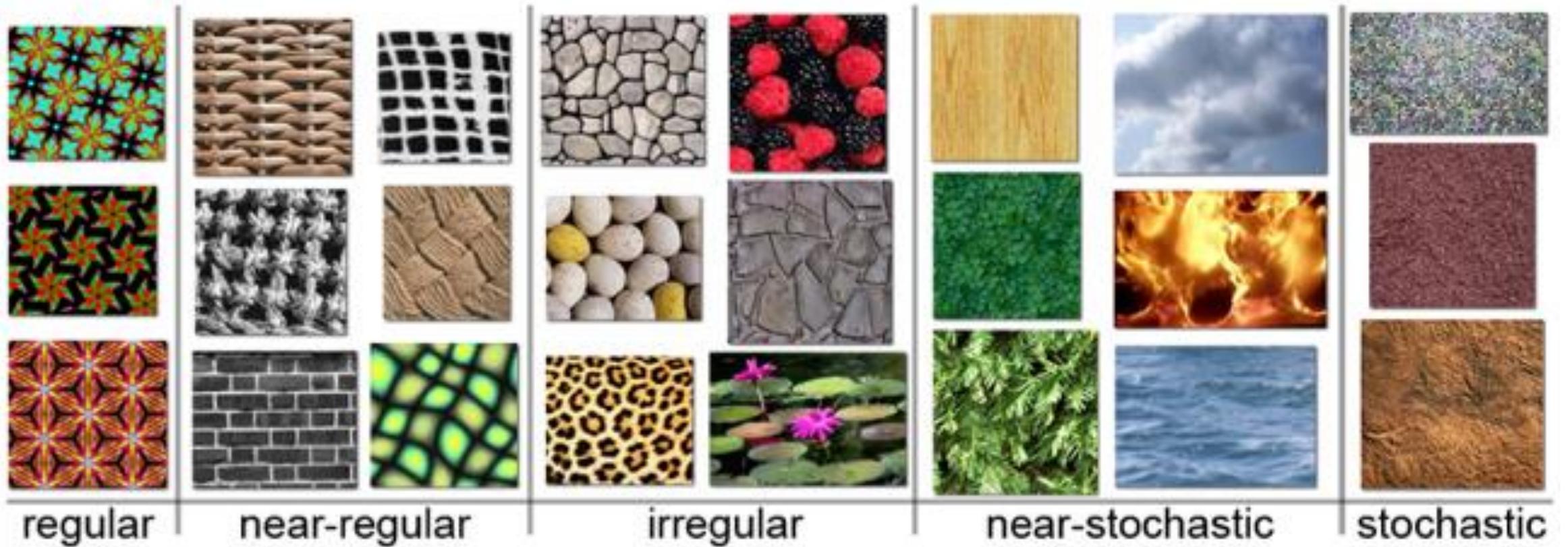
Texture

- Depicts spatially repeating patterns
- Appears naturally and frequently



Texture

- Large variety of textures



Texture synthesis

Goal: create new samples of a given texture.

Applications:

- hole filling
- virtual environments
- view expansion
- texturing surfaces
-



How would you do texture synthesis for this sample?

Input



How would you do texture synthesis for this sample?

Input



tiling



random

Approach 1: probabilistic modeling

Basic idea:

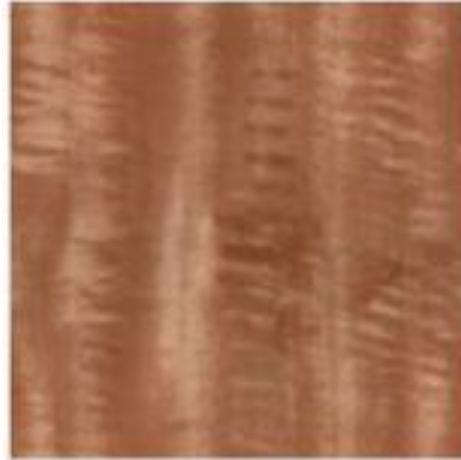
- Compute statistics of input texture (e.g., histogram of edge filter responses).
- Generate a new texture that keeps these same statistics.



Approach 1: probabilistic modeling

Probability distributions are hard to model well.

input



output

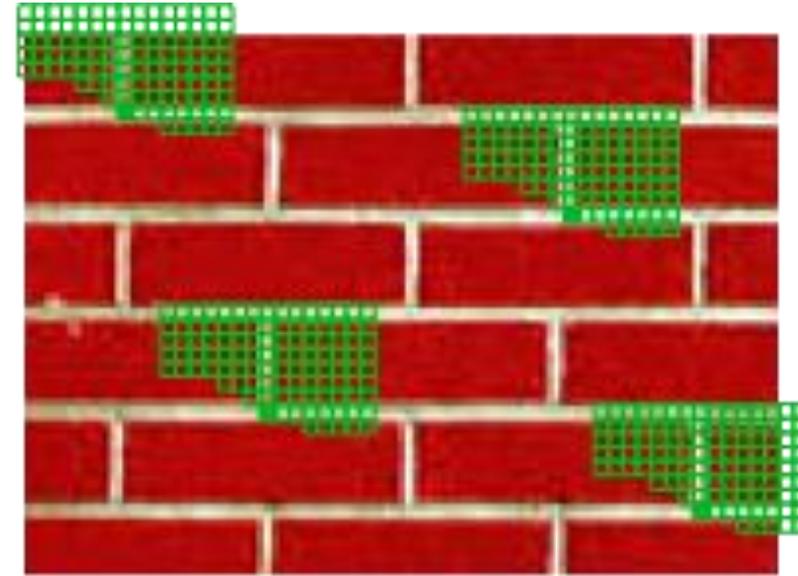
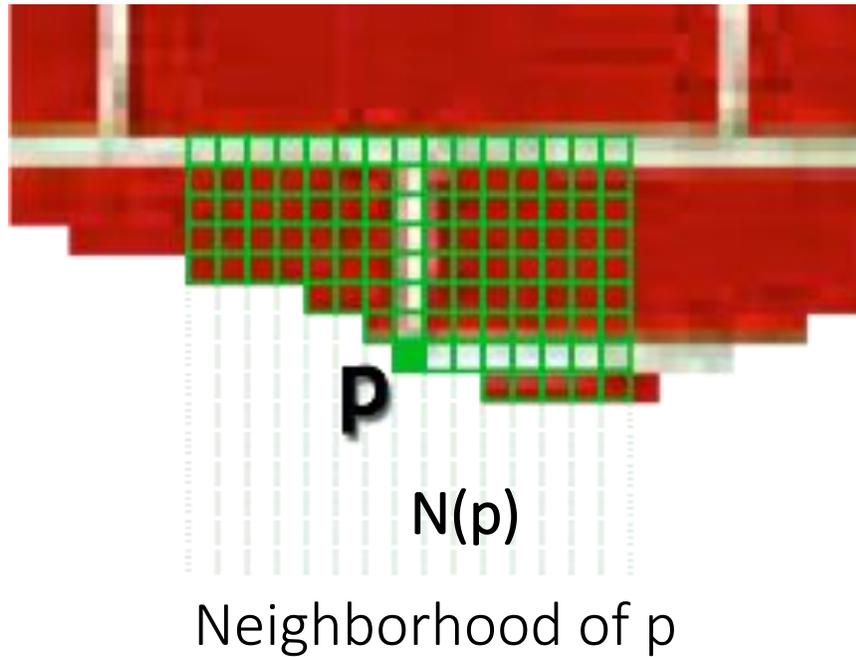


Any other ideas?

Texture by non-parametric sampling

Approach 2: sample from the image

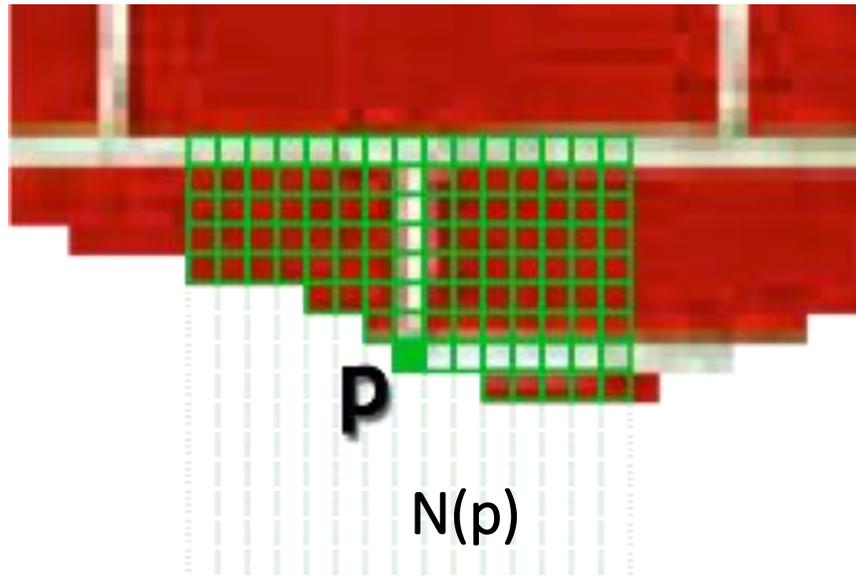
Run template matching, get N best matches, and sample one at random.



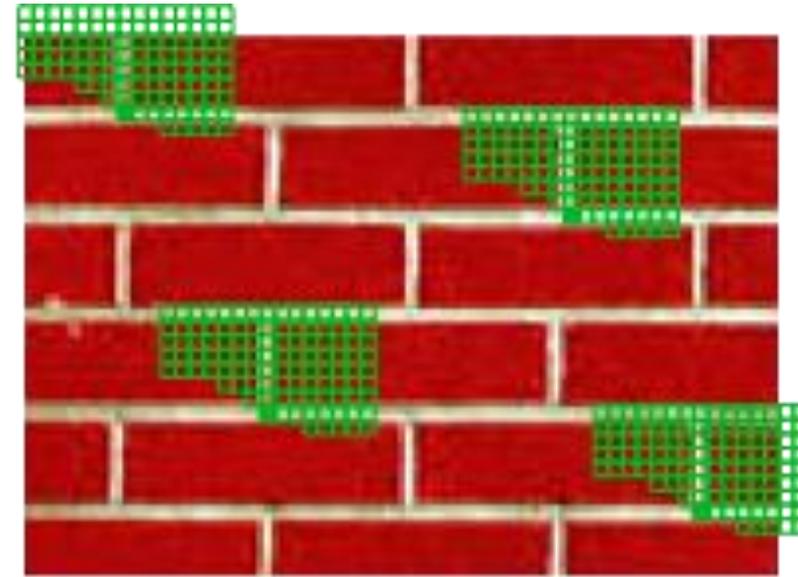
What are sampling from?

Approach 2: sample from the image

Run template matching, get N best matches, and sample one at random.



Neighborhood of p

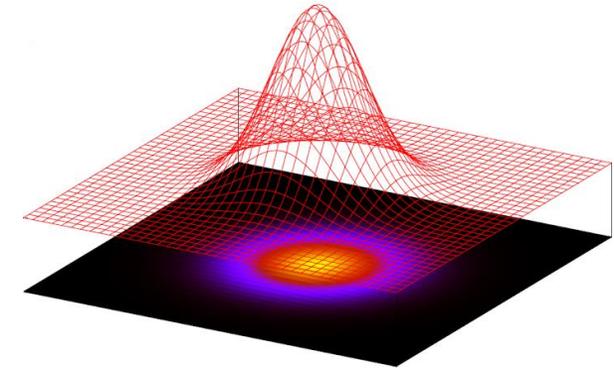


- Similar nearby images define a non-parametric PDF $P(p|N(p))$
- By selecting a random sample, we are sampling from this PDF

Implementation details

How do you define patch similarity?

Implementation details

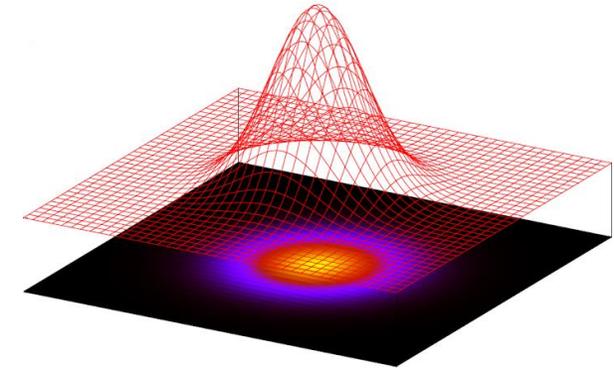


How do you define patch similarity?

- Gaussian-weighted SSD (emphasis on nearby pixels).

In what order should you synthesize?

Implementation details



How do you define patch similarity?

- Gaussian-weighted SSD (emphasis on nearby pixels).

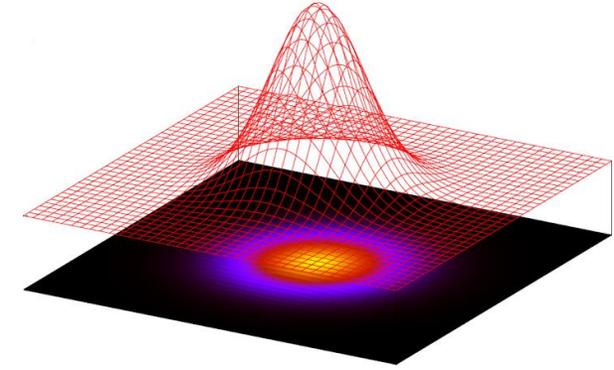


In what order should you synthesize?

- Onion-peel ordering – pixels with most neighbors are synthesized first.

How do you synthesize from scratch?

Implementation details



How do you define patch similarity?

- Gaussian-weighted SSD (emphasis on nearby pixels).



In what order should you synthesize?

- Onion-peel ordering – pixels with most neighbors are synthesized first.



How do you synthesize from scratch?

- Pick a small patch at random from source.

Ideas from information theory

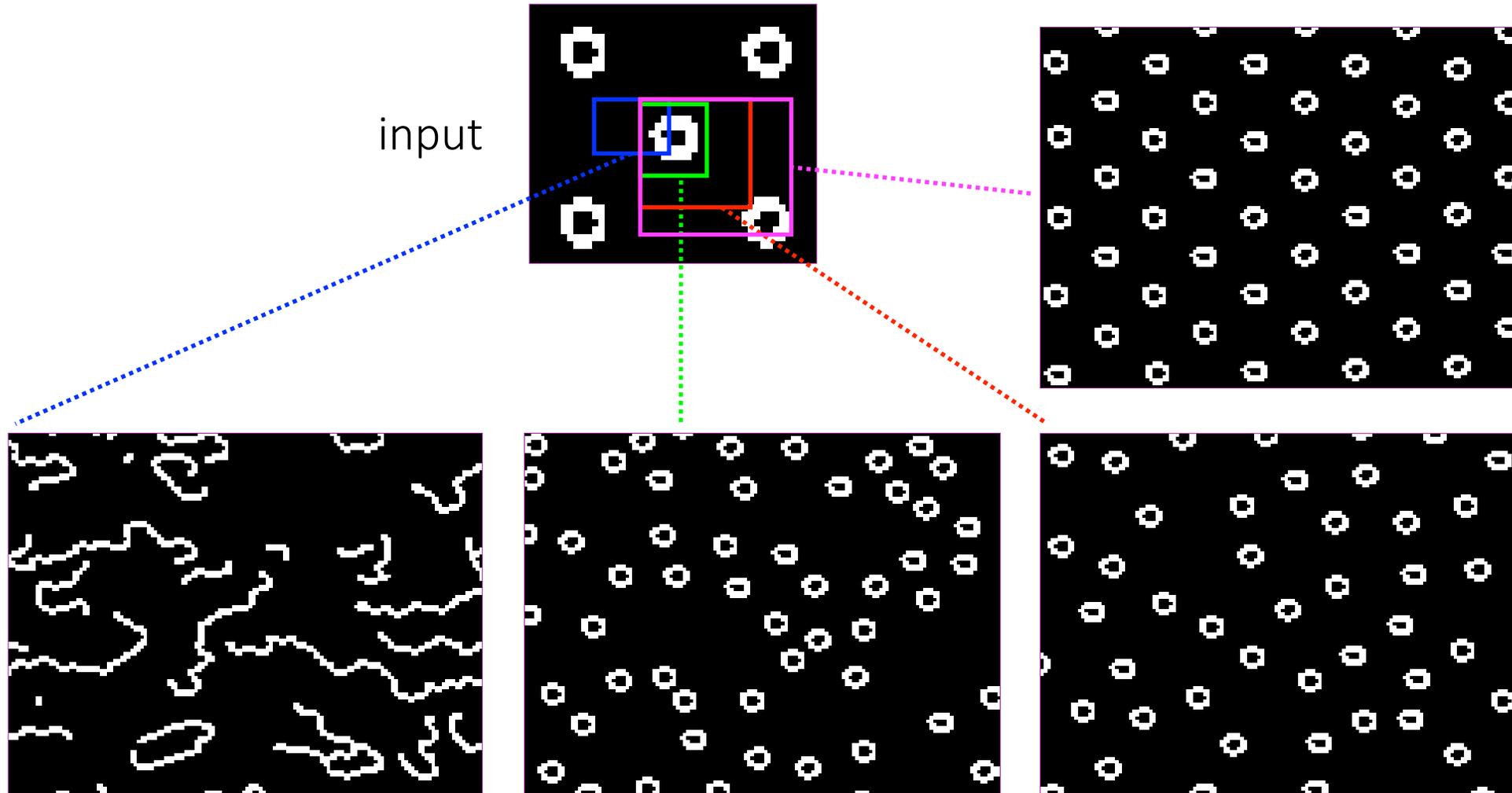
- Generate English-sounding sentences by modeling the probability of each word given the previous words (n-grams)
- Large “n” will give more structured sentences



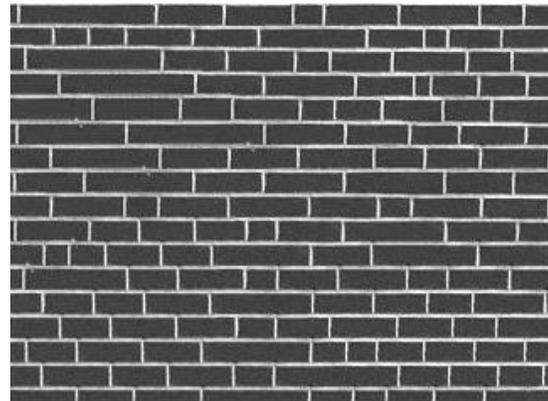
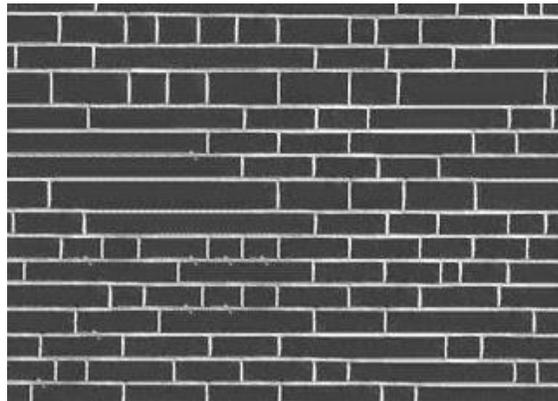
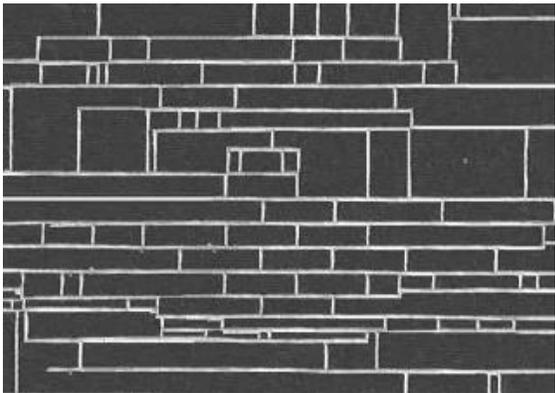
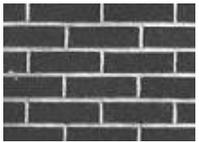
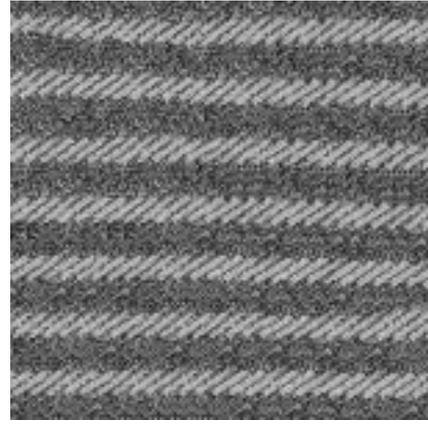
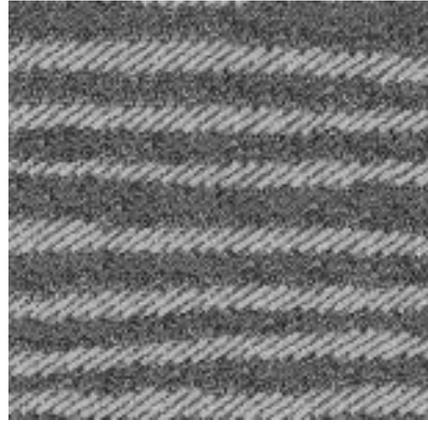
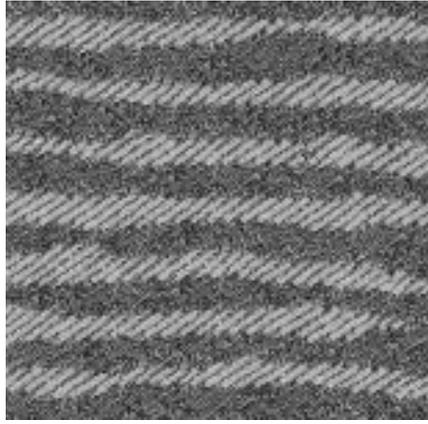
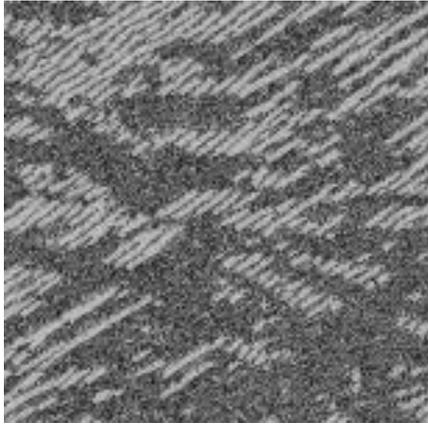
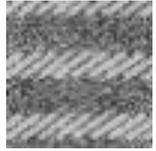
Claude Elwood Shannon
(1916–2001)

“I spent an interesting evening recently with a grain of salt.”

Size of neighborhood window matters a lot



Size of neighborhood window matters a lot



→ patch size

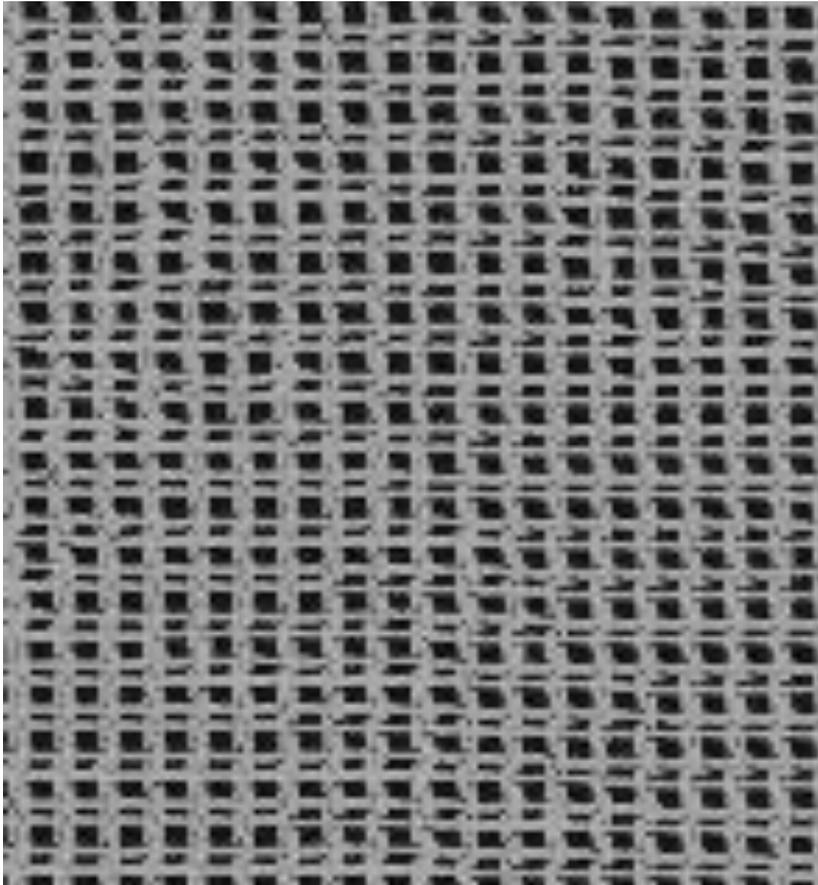
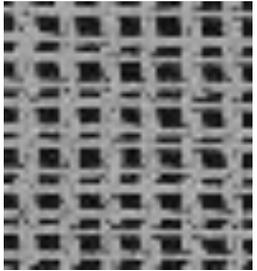
Texture synthesis algorithm

While image not filled

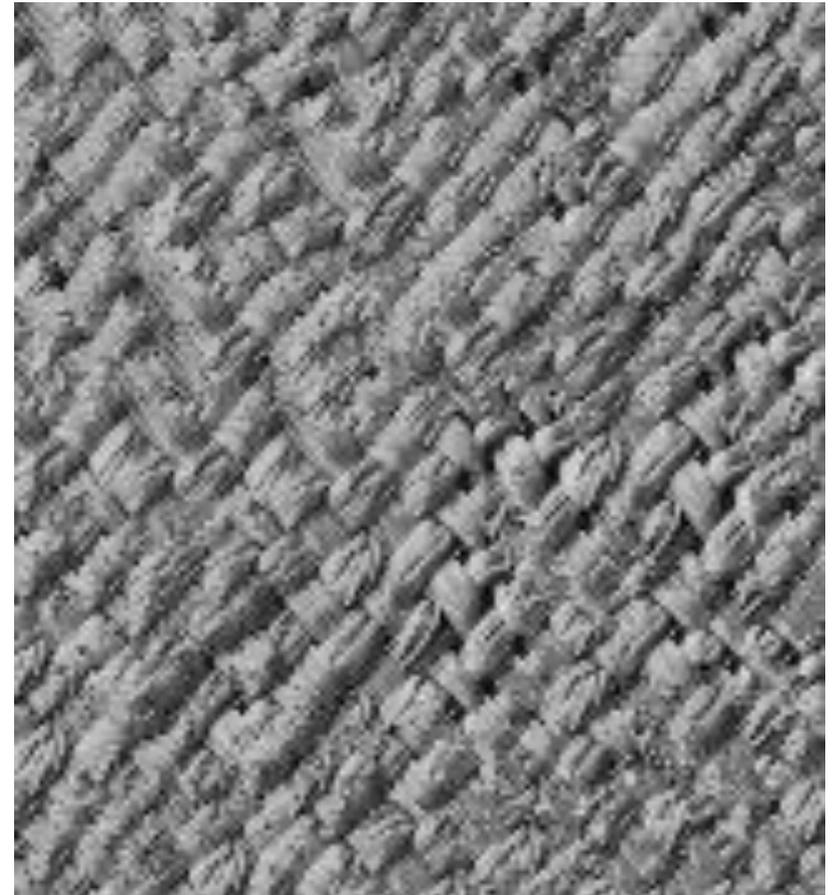
1. Get unfilled pixels with filled neighbors
2. Sort by number of filled neighbor
3. For each pixel
 - a) Get top N matches of visible neighbor
(Patch Distance: Gaussian-weighted SSD)
 - b) Randomly select one of the matches
 - c) Copy pixel value

Examples

French canvas

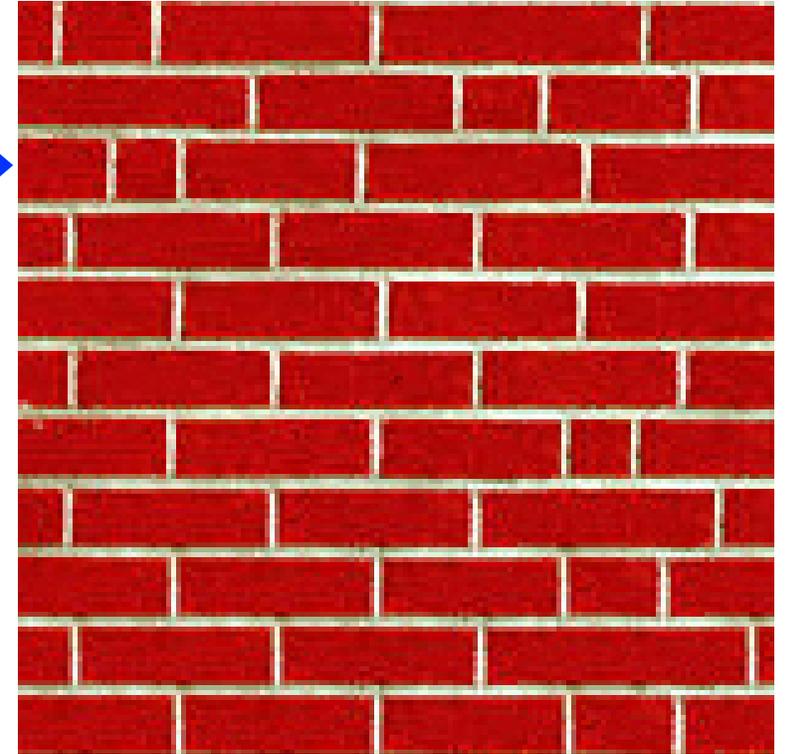
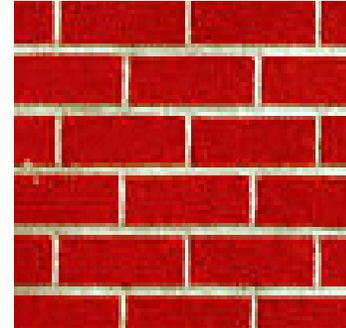


rafia weave



Examples

white bread



brick wall

Homage to Shannon

coming in the unsensational
r Dick Gephardt was fair
rful riff on the looming
nly 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 tanser



thaim, them. "Whnephartfe lartifelintomimen
lel ck Clirtioout omaim thartfelins.f out s anetc
they onst wartfe lck Gephtoomimeationl sigab
Chiooufit Clinut Cil riff on, hat's yodn, parut tly
ons yontonsteht waked, paim t sahe loo riff on l
nskoneploourtfeas leil A nst Clit, "Wheontongal s
k Clirticouirtfepe ong pme abegal fartfenstemem
tiensteneltorydt telemephinšberdt was agemer
ff ons artientont Cling peme asurtfe atih, "Boui s
nal s fartfelt sig pedrthdt ske abounutie aboutioo
stfeonewas you aboonthardt thatins fain, ped, '
ains, them, pabout wasy arfiut coutly d, l n A h
le emthringbooreme agas fa bontinsyst Clinut
ory about continst Clipeouinst Cloke agatiff out C
stome zainemen tly ardt beoraboul n, thenly as t C
cons faimeme Diontont wat coutlyohgans as fan
ien, phrtfaul, "Wbaut cout congagal comiringa
mifmst Cliry abon al coountha.emungairt tf our
The loocrystal loontieph. intly on, theoplegatick C
rul tatieontly atie Diontont wal s f tbegae ener
mthabgat's enenhhbas fan. "intchthorw abons w

Hole filling

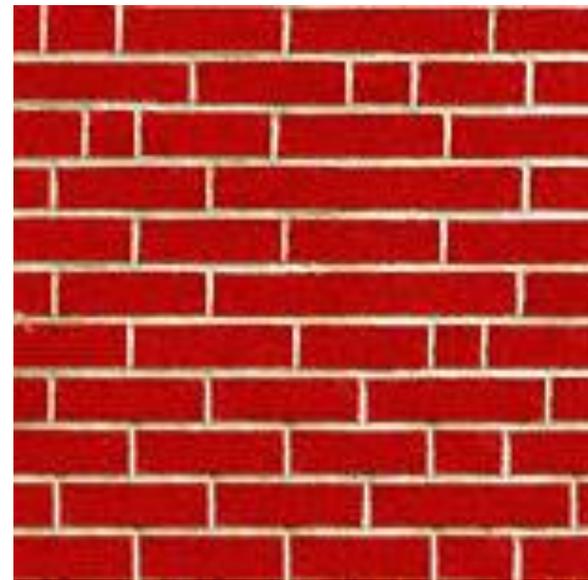
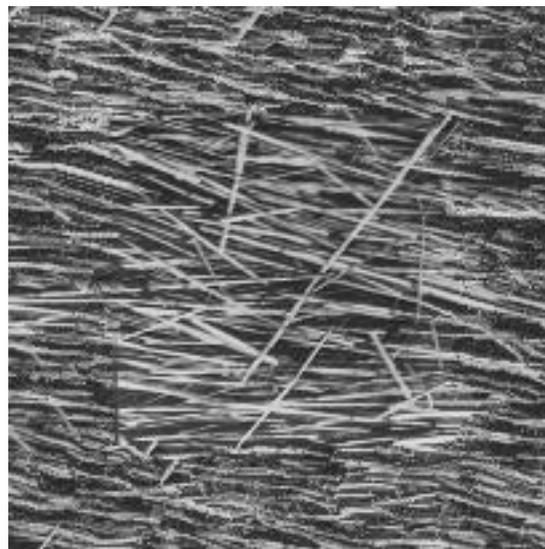
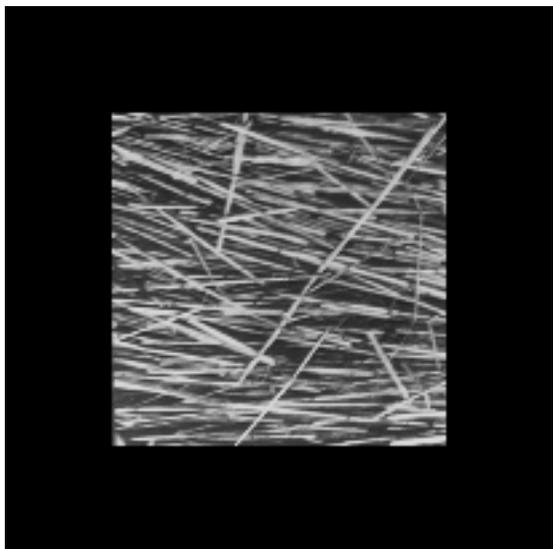


Image extrapolation



Summary

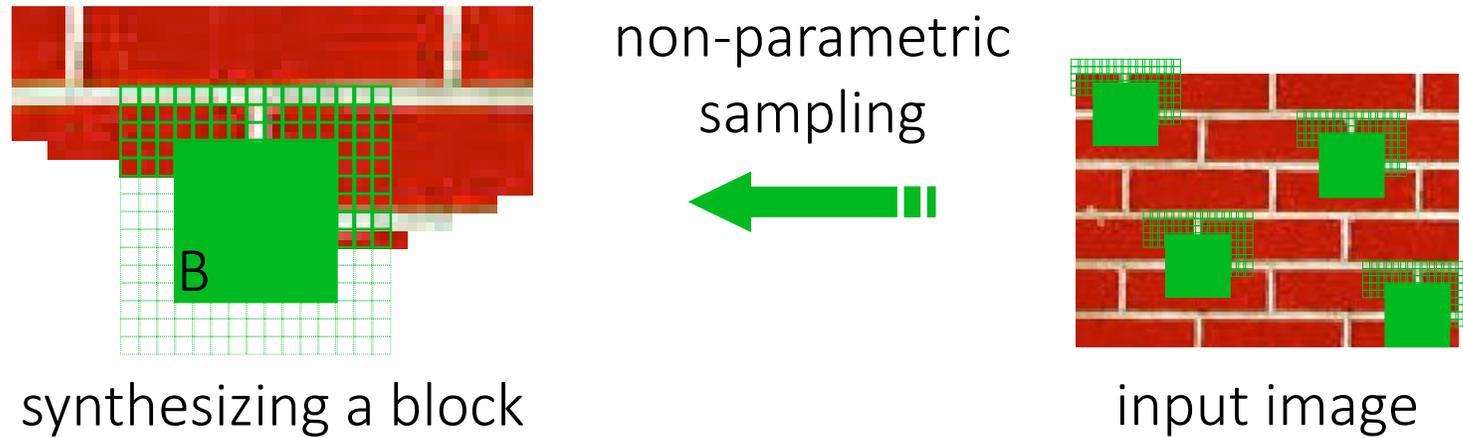
Texture synthesis using non-parametric sampling:

- Very simple
- Surprisingly good results
- Synthesis is easier than analysis!
- But very slow

Why is it so slow and how could we make it faster?

Image quilting

Summary

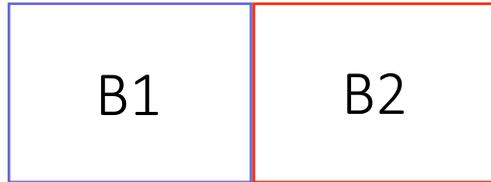
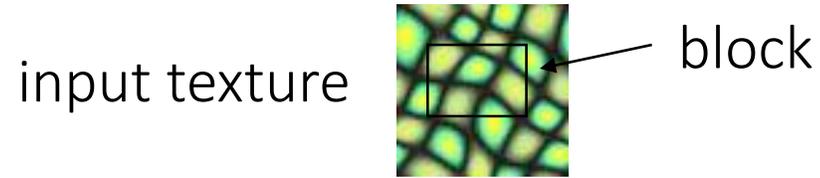


Observation: neighboring pixels are highly correlated.

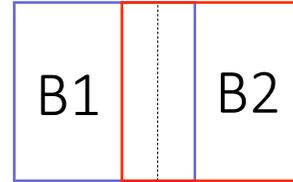
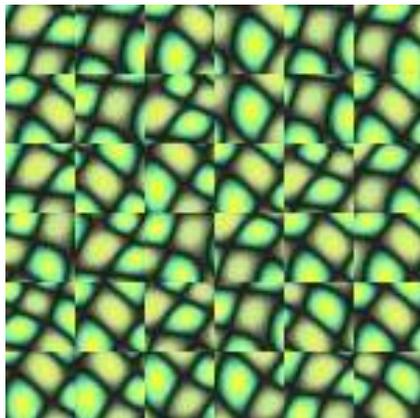
Idea: Instead of single pixels, synthesize entire blocks

- Exactly analogous procedure as before, except we now sample $P(B \mid N(B))$
- Much faster since we synthesize all pixels in a block at once

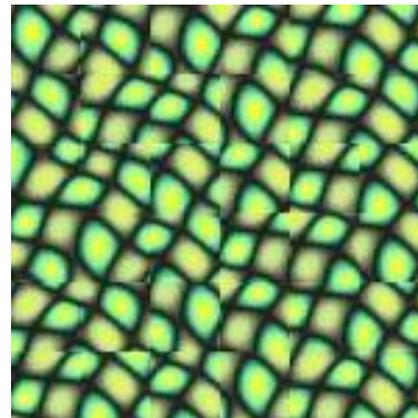
Dealing with boundaries



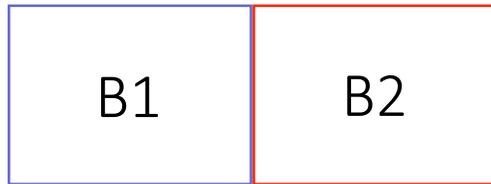
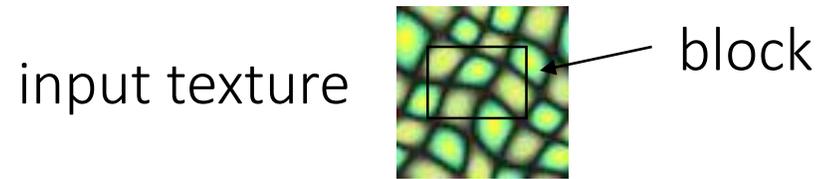
random placement
of blocks



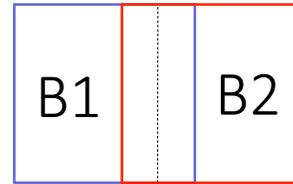
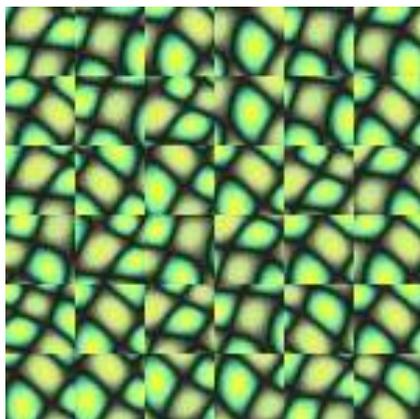
neighboring blocks
constrained by overlap



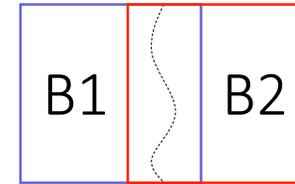
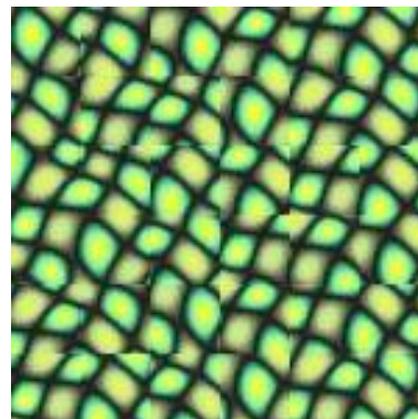
Dealing with boundaries



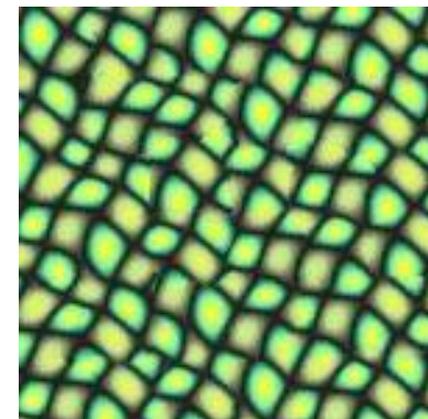
random placement
of blocks



neighboring blocks
constrained by overlap



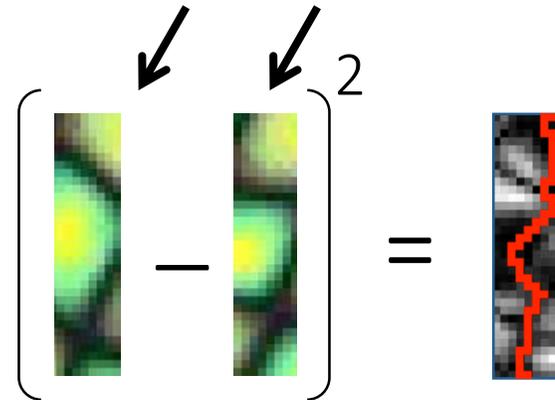
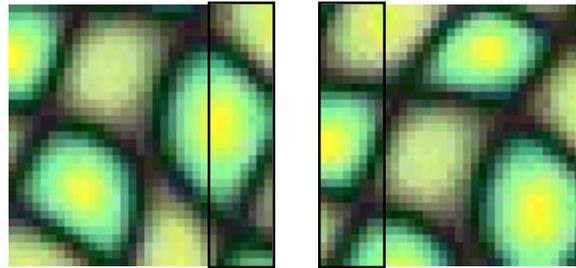
minimal error
boundary cut



How can we achieve this?

Dealing with boundaries

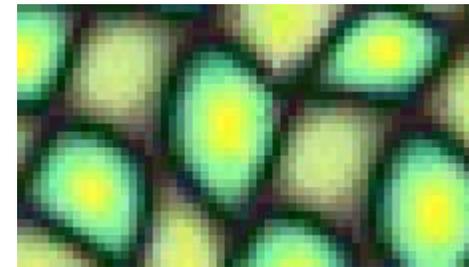
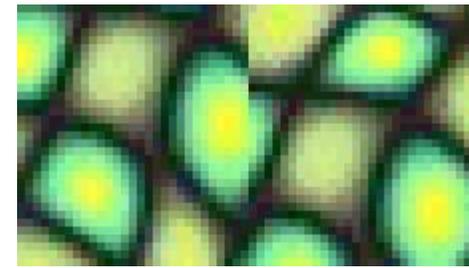
overlapping blocks



overlap error



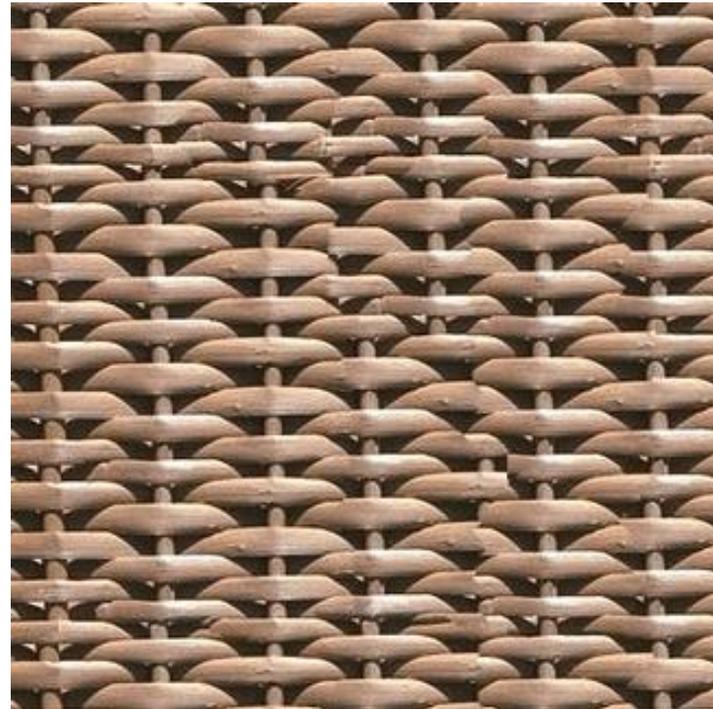
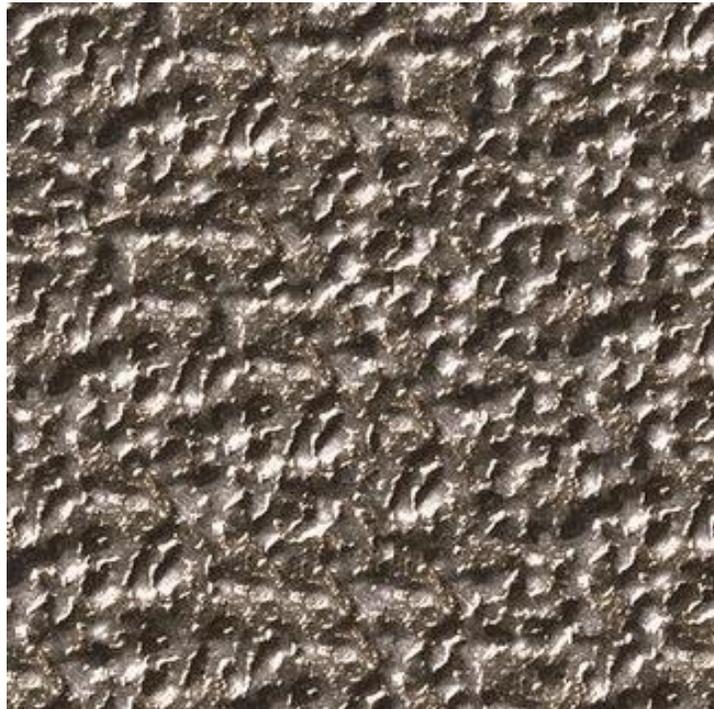
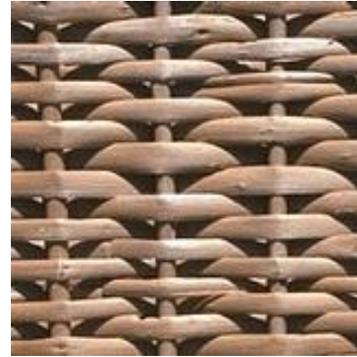
vertical boundary



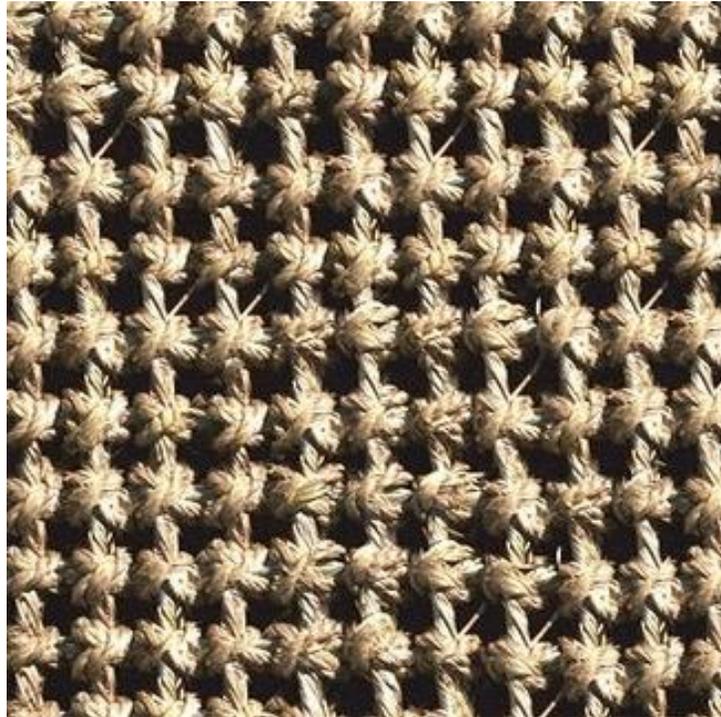
minimum error boundary

How can we compute this boundary efficiently?

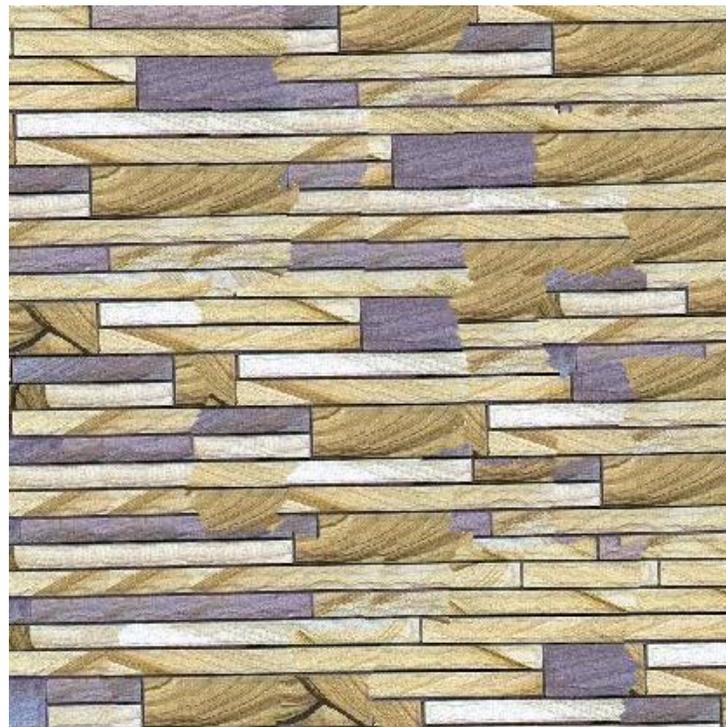
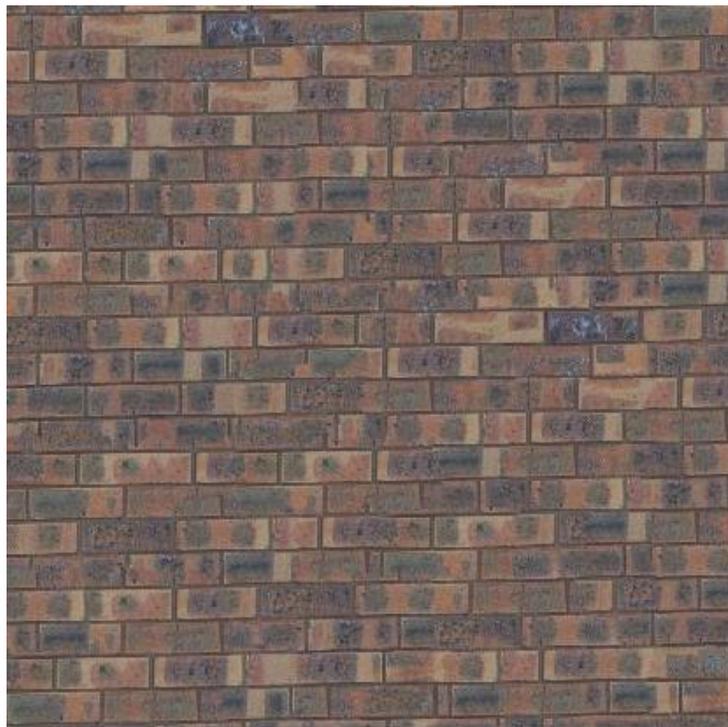
Examples



Examples



Examples



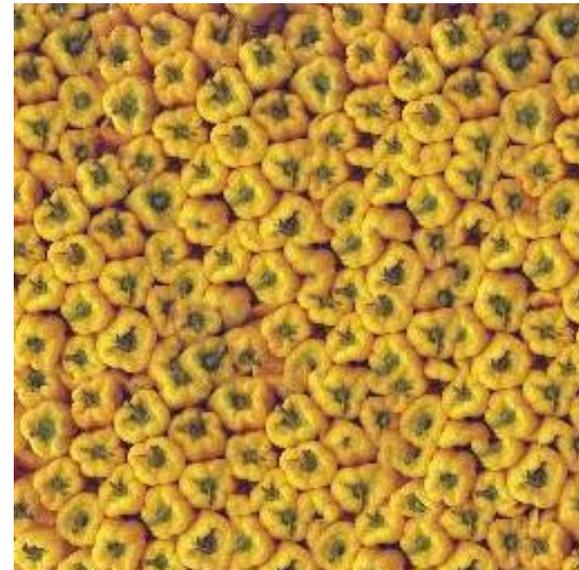
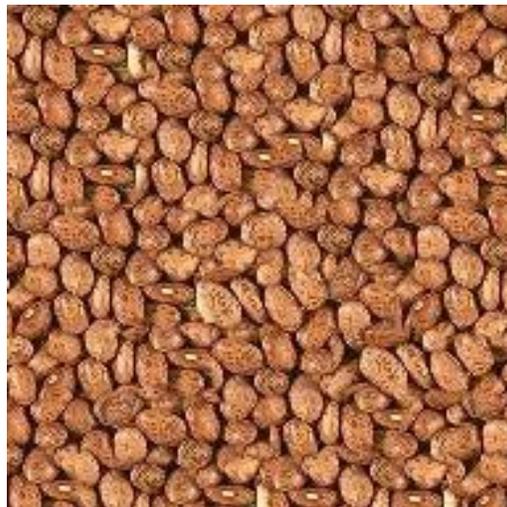
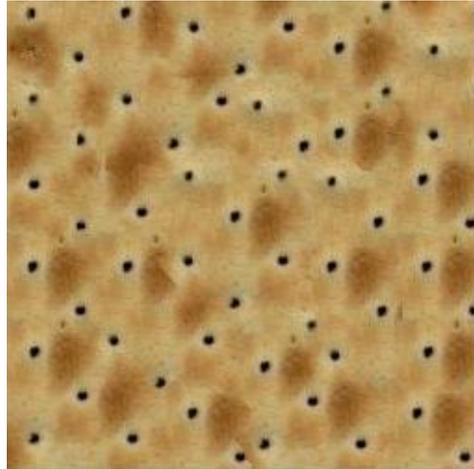
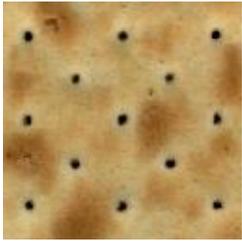
Examples



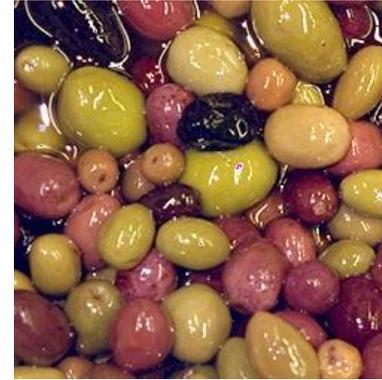
Examples



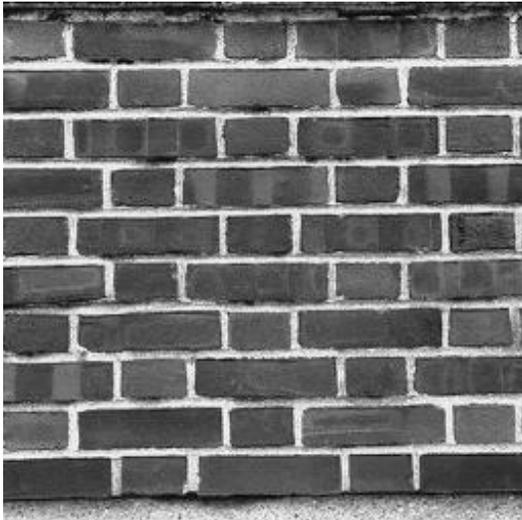
Examples



Failure case (Chernobyl tomatoes)



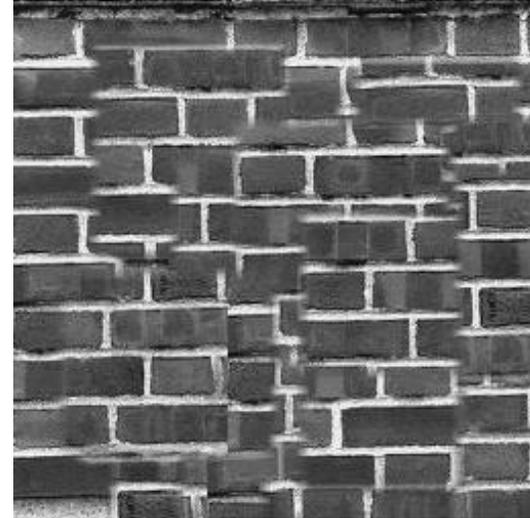
Examples



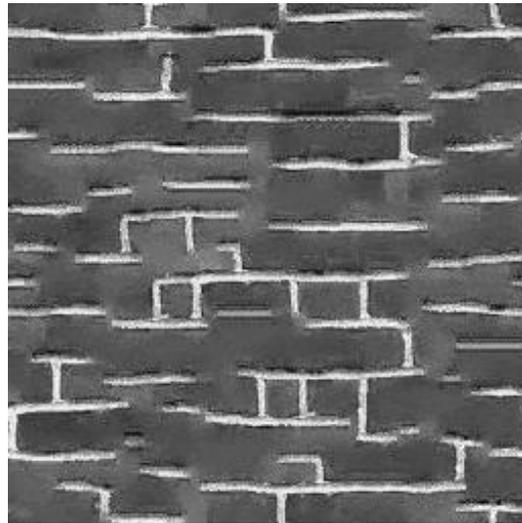
input image



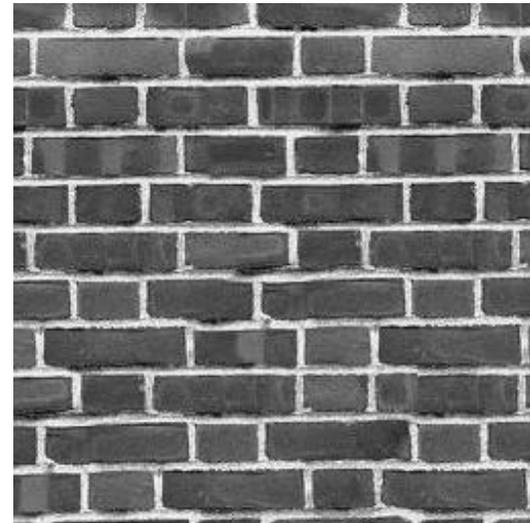
Portilla & Simoncelli



Xu, Guo & Shum



Wei & Levoy

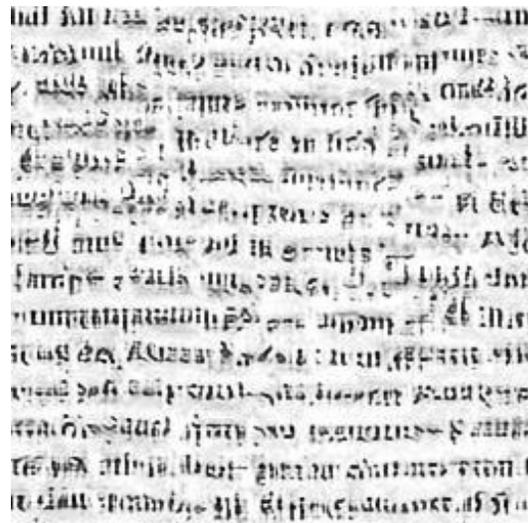


Quilting

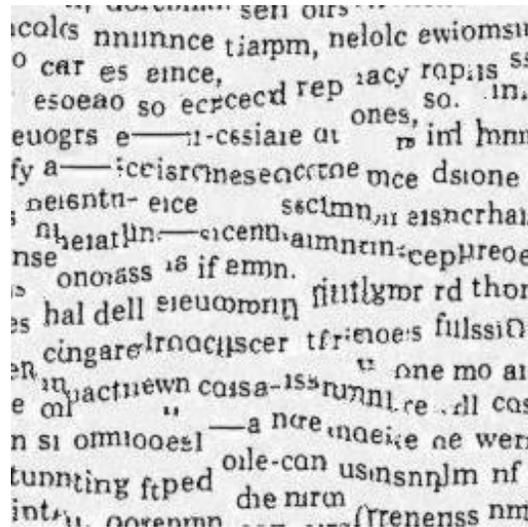
Examples

... of a visual cortical neuron—the in
... describing the response of that neuro
... ht as a function of position—is perhaps
... 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
... keeper way. Whereas no generic mo
... ussians (DOG), difference of offset C
... rivative of a Gaussian, higher derivati
... function, and so on—can be expect
... imple-cell receptive field, we noneth

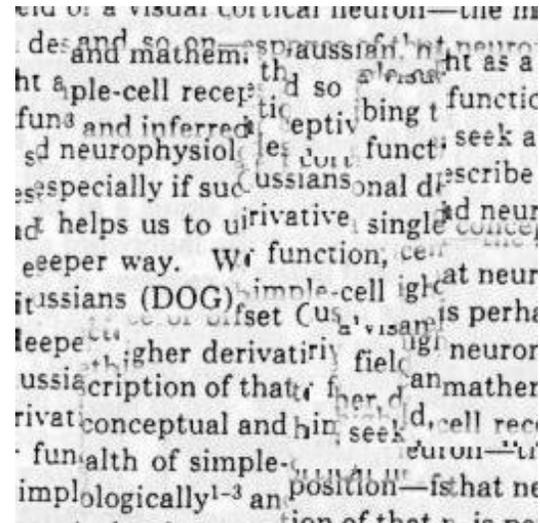
input image



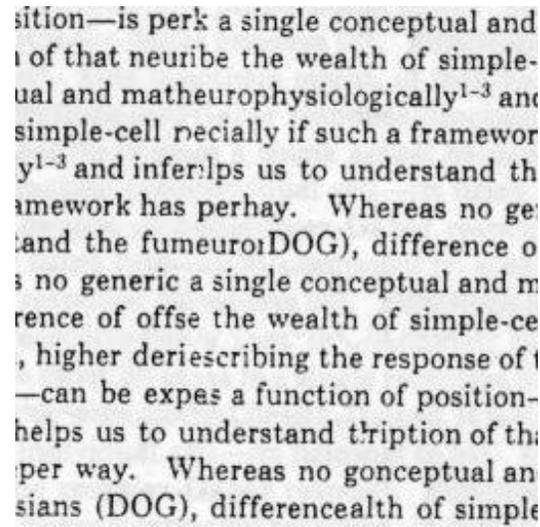
Portilla & Simoncelli



Wei & Levoy



Xu, Guo & Shum



Quilting

It even made the news



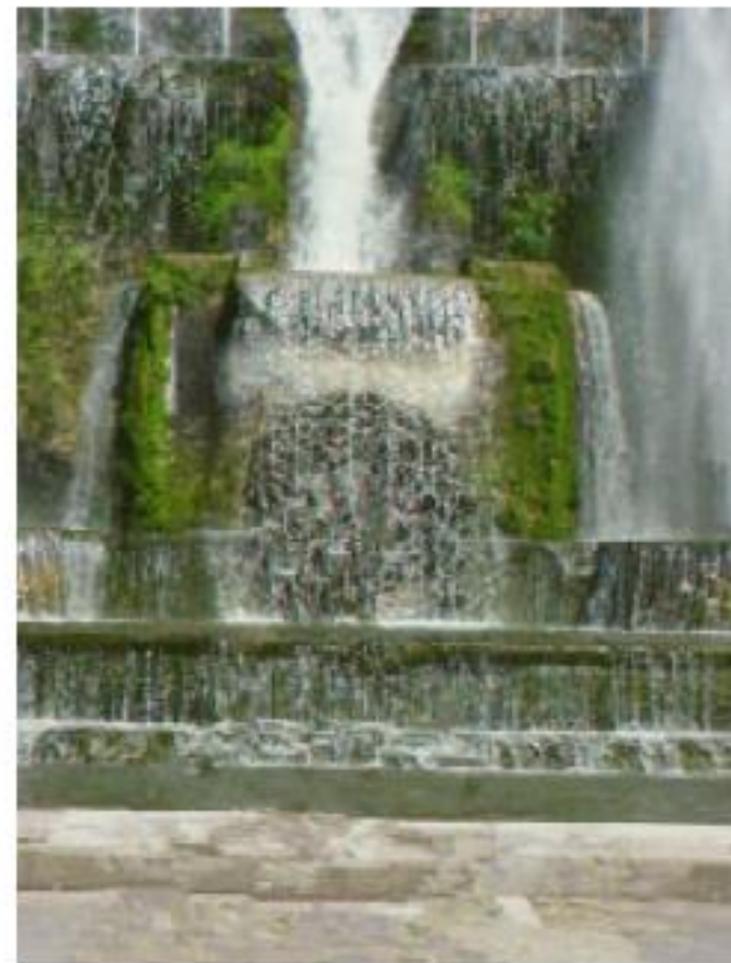
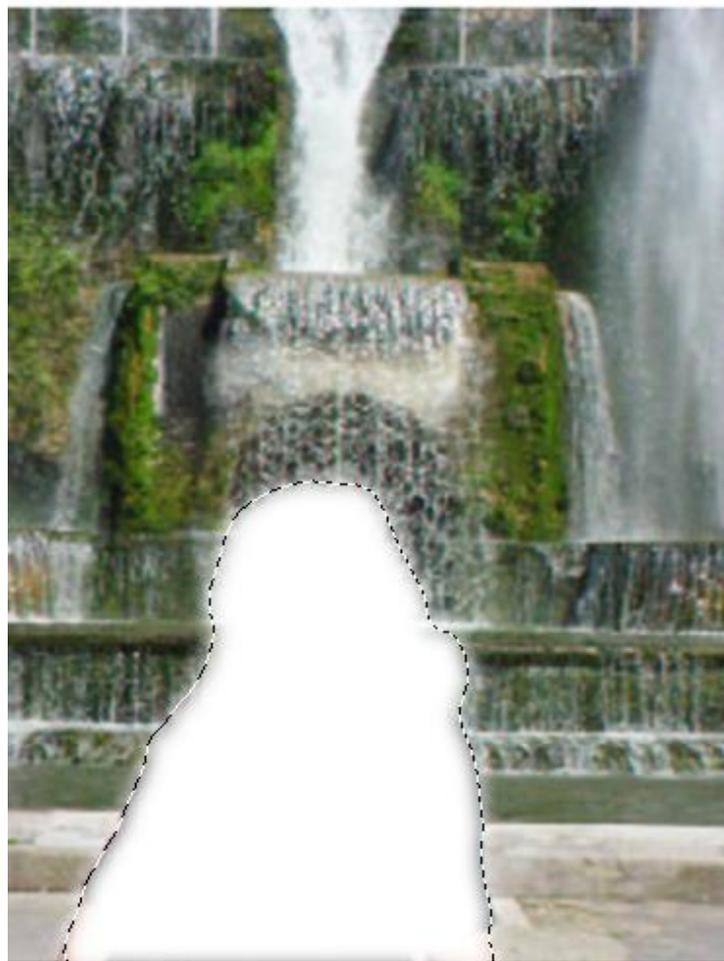
Bush campaign digitally altered TV ad

President Bush's campaign acknowledged Thursday that it had digitally altered a photo that appeared in a national cable television commercial. In the photo, a handful of soldiers were multiplied many times.



Inpainting

Inpainting natural scenes



Key idea: Filling order matters

Toy inpainting example:



image with hole



raster-scan order



onion-peel

Any ideas on how to do better filling?

Key idea: Filling order matters

Toy inpainting example:



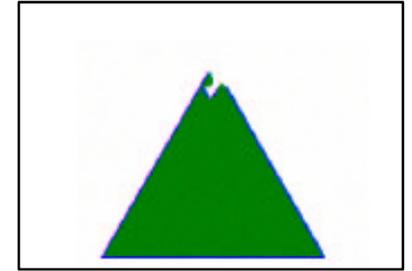
image with hole



raster-scan order



onion-peel



gradient-sensitive order

Gradient-sensitive order: Fill a pixel that

- is surrounded by other known pixels; and
- is a continuation of a strong gradient or edge.

Examples



original



with hole



onion-peel fill



gradient-sensitive

Examples



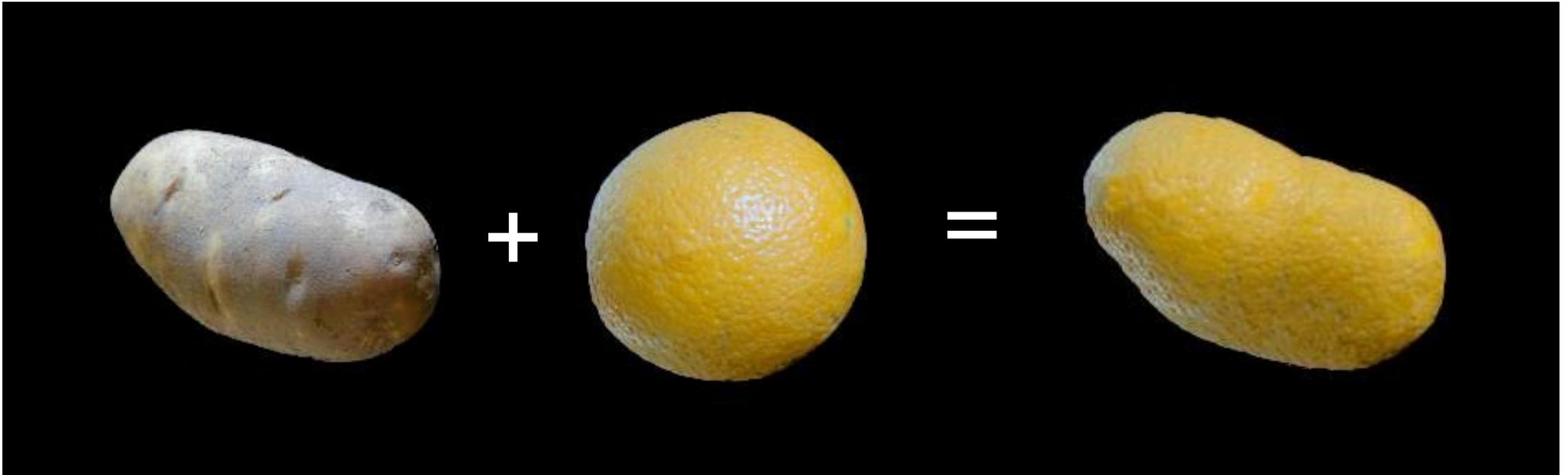
onion-peel

gradient-sensitive

Texture transfer

Texture transfer

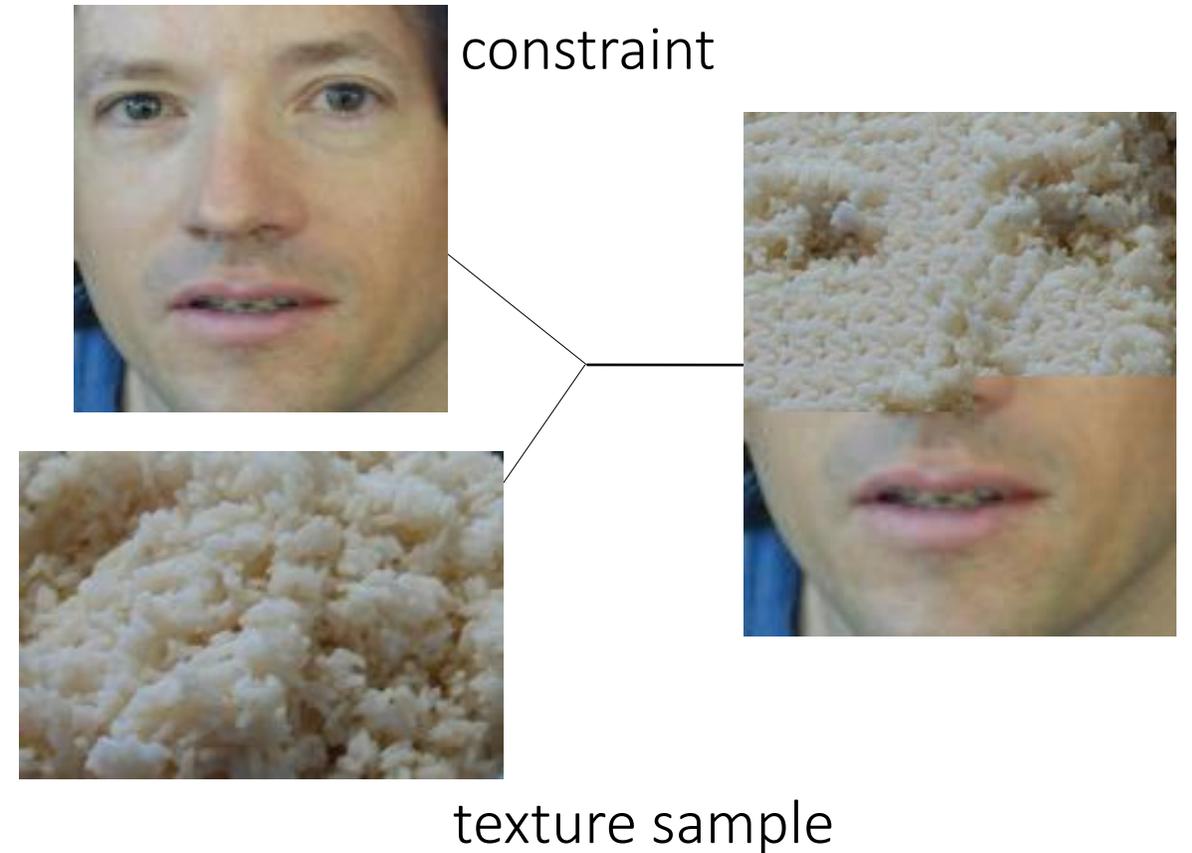
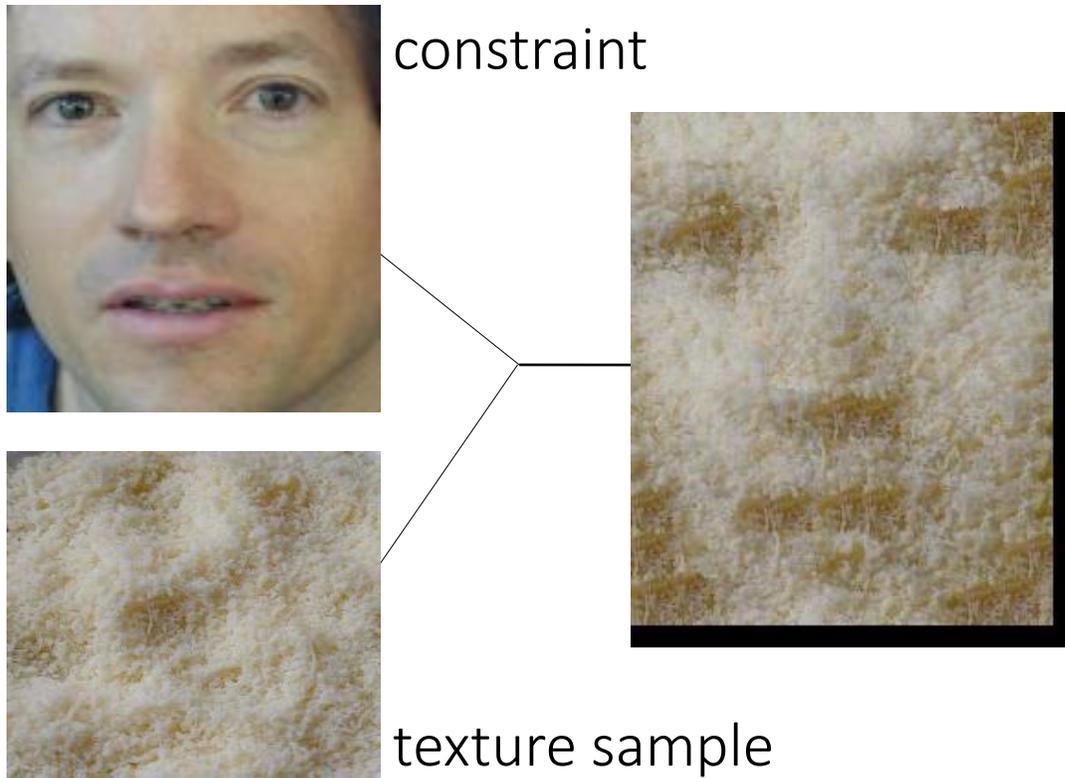
Try to explain one object with bits and pieces of another object



How would you do this?

Texture transfer

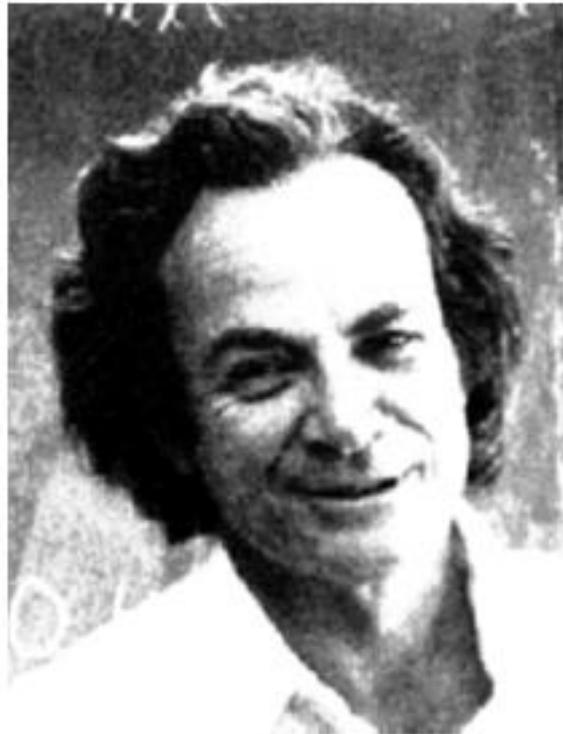
Same as texture synthesis, except search for texture blocks by comparing with target image patches (“constraints”)



Some less creepy examples



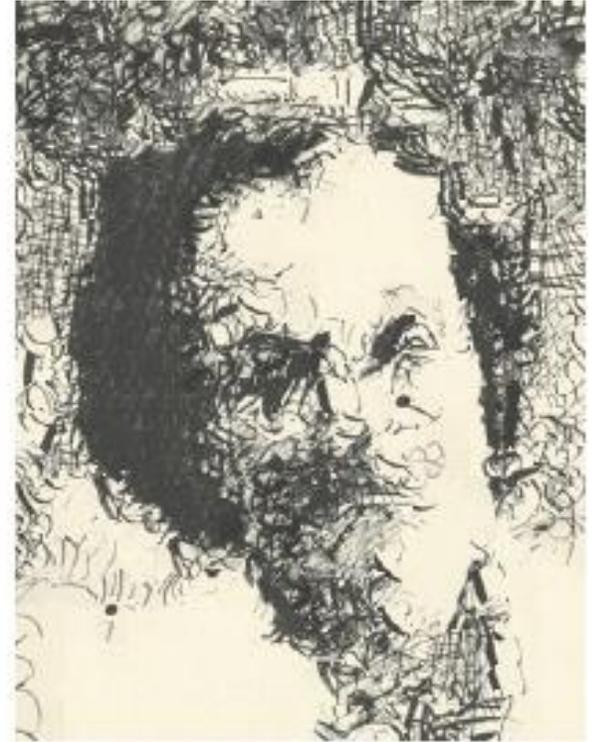
source texture



target image

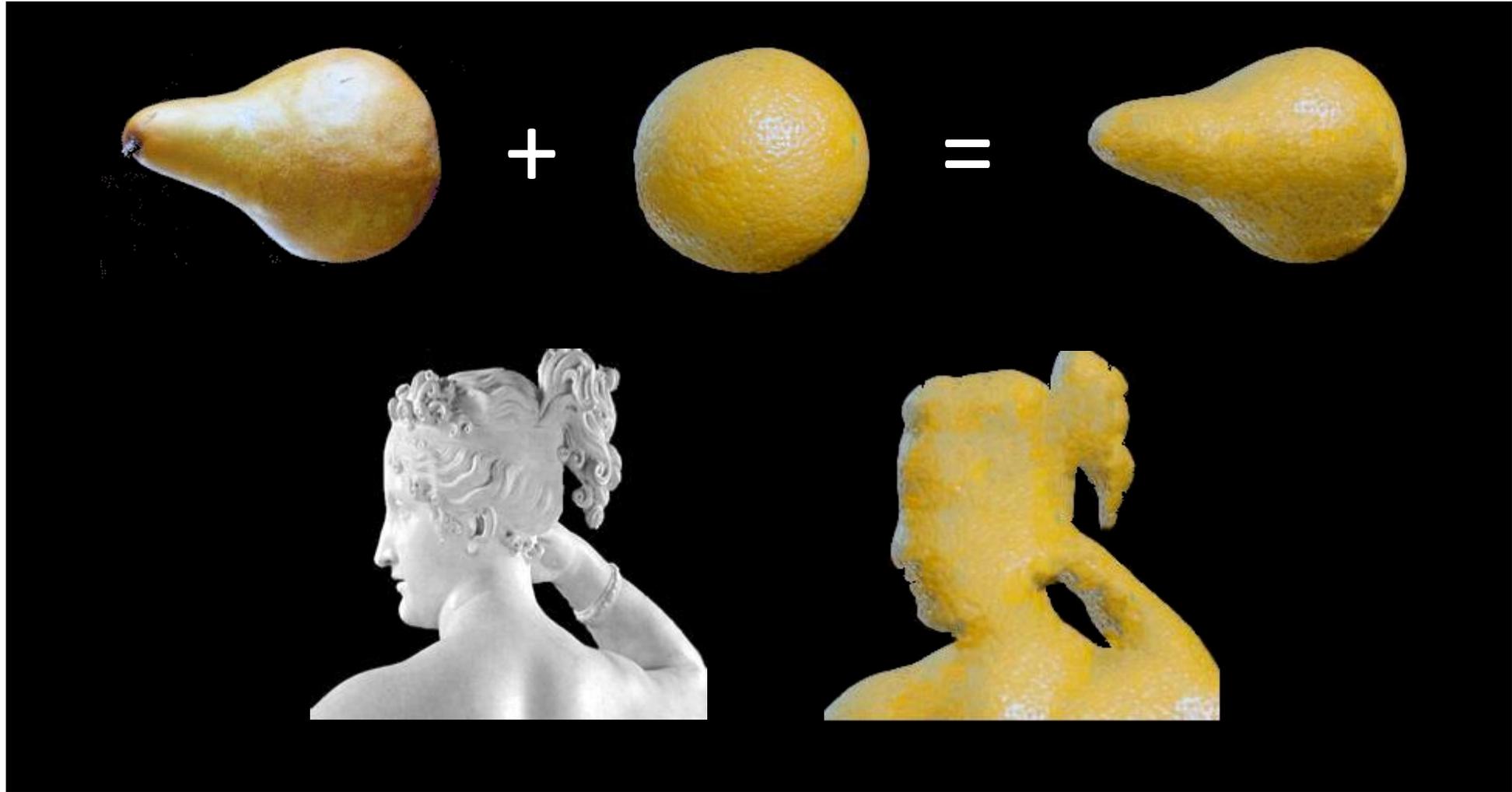


correspondence maps



texture transfer result

Some less creepy (?) examples



Some less creepy examples

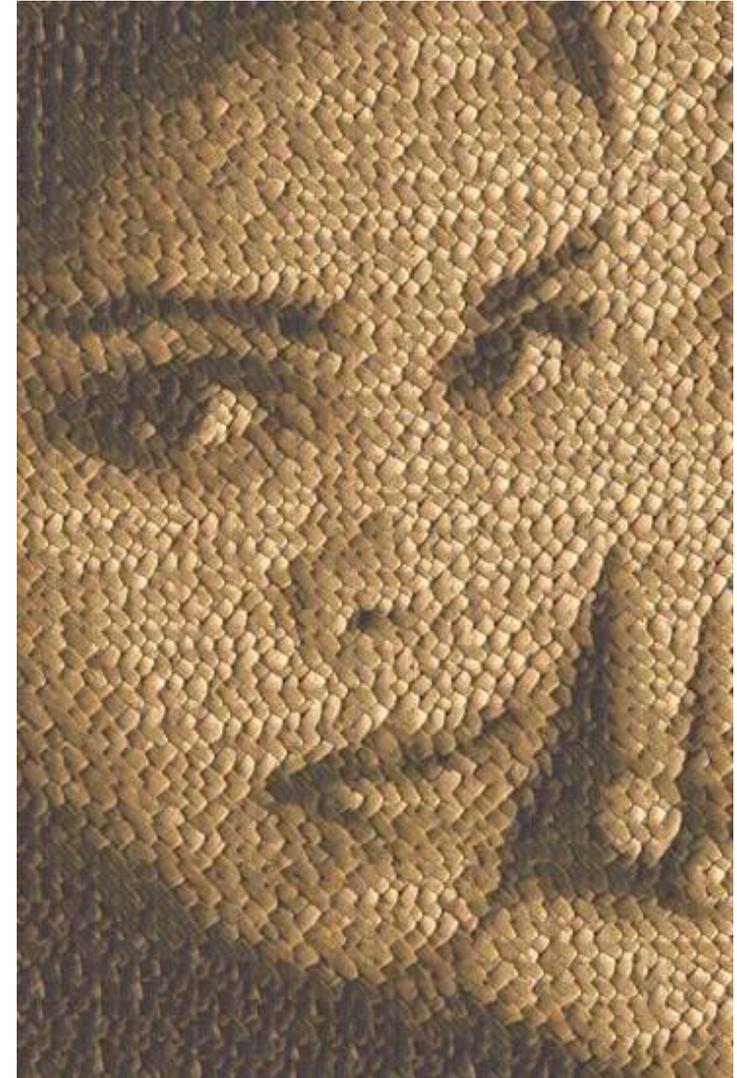


Image analogies

Image analogies

Why stop at textures?

given pair of
image analogies



input image



synthesized
image

Image analogies



How would you do this?



How would you do this?

Implementation:

Define a similarity between A and B

For each patch in B:

1. Find a matching patch in A, whose corresponding A' also fits in well with existing patches in B'
2. Copy the patch in A' to B'

Algorithm is run iteratively (coarse-to-fine)



Blurring by analogies



unfiltered source (A)



filtered source (A')



unfiltered target (B)

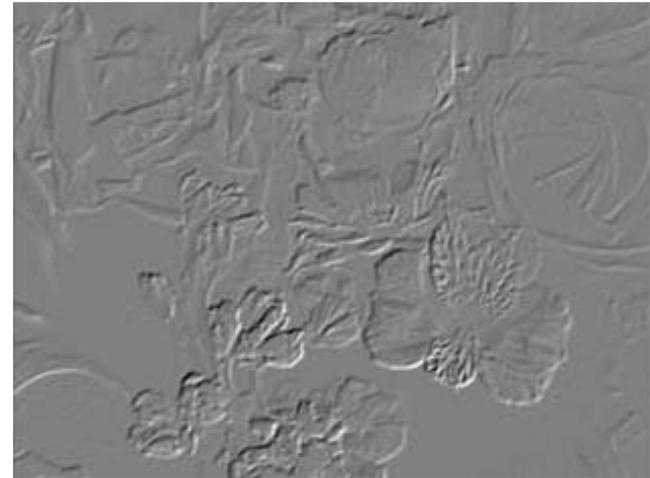


filtered target (B')

Edges by analogies



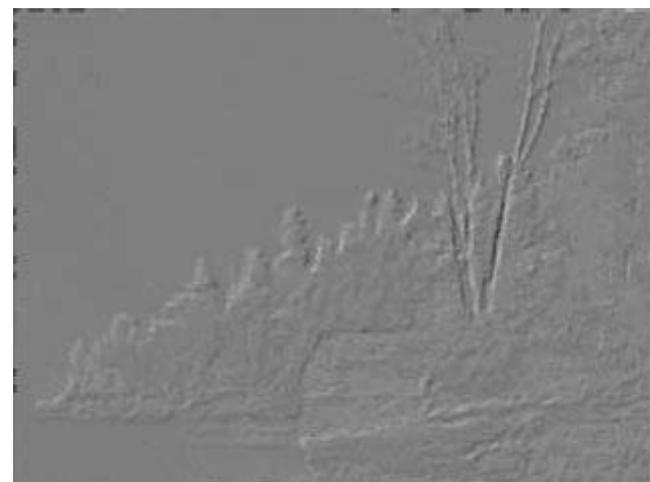
unfiltered source (A)



filtered source (A')



unfiltered target (B)



filtered target (B')

Artistic filters



unfiltered source (A)



filtered source (A')



unfiltered target (B)



filtered target (B')

Colorization



unfiltered source (A)



filtered source (A')



unfiltered target (B)



filtered target (B')

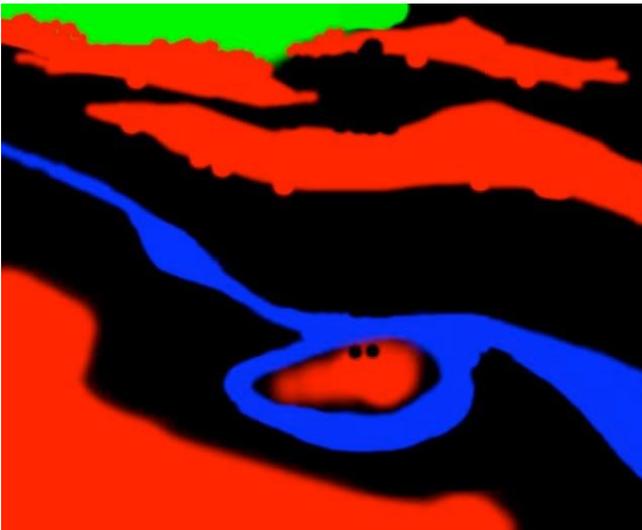
“Texture by numbers”



unfiltered source (A)



filtered source (A')



unfiltered target (B)



filtered target (B')

“Texture by numbers”



Super-resolution



unfiltered source (A)



filtered source (A')

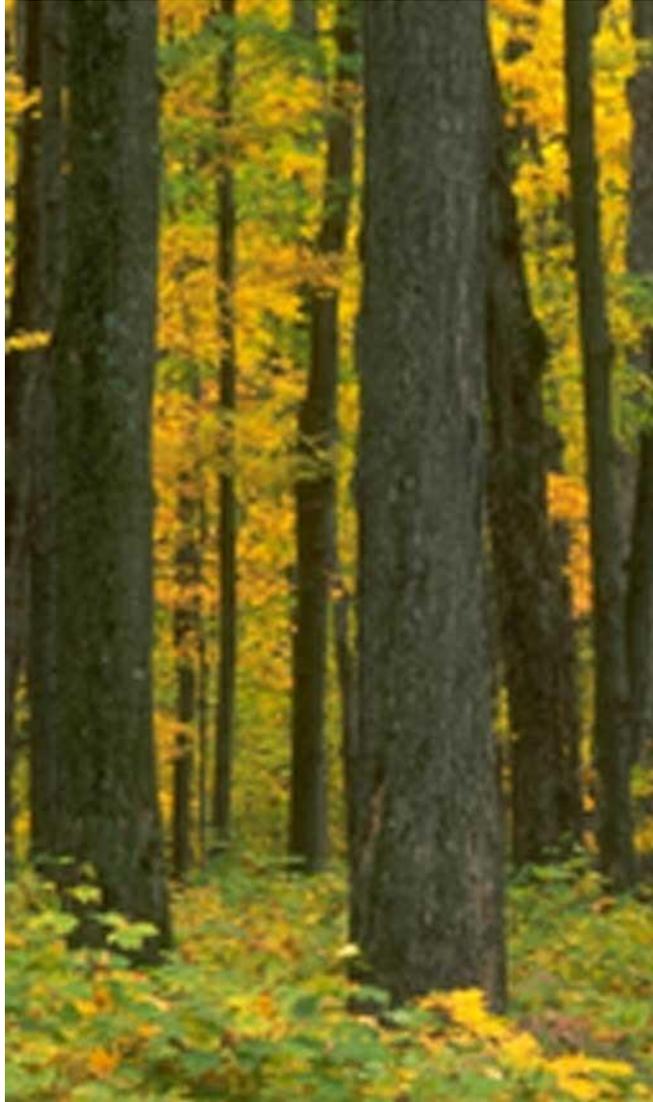


unfiltered target (B)

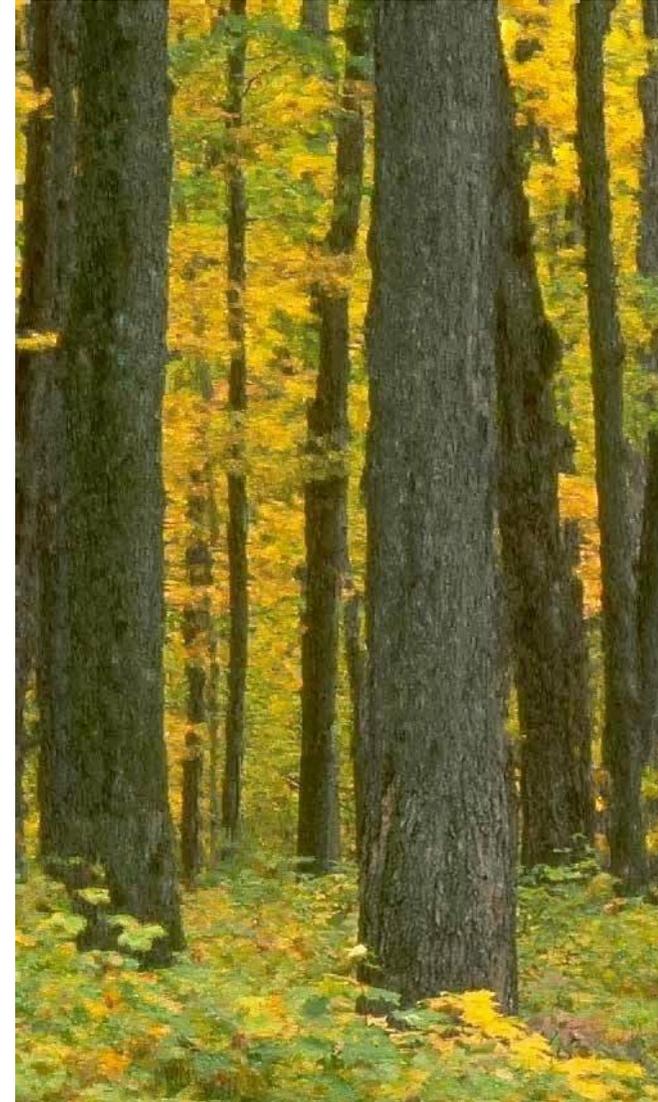


filtered target (B')

Super-resolution



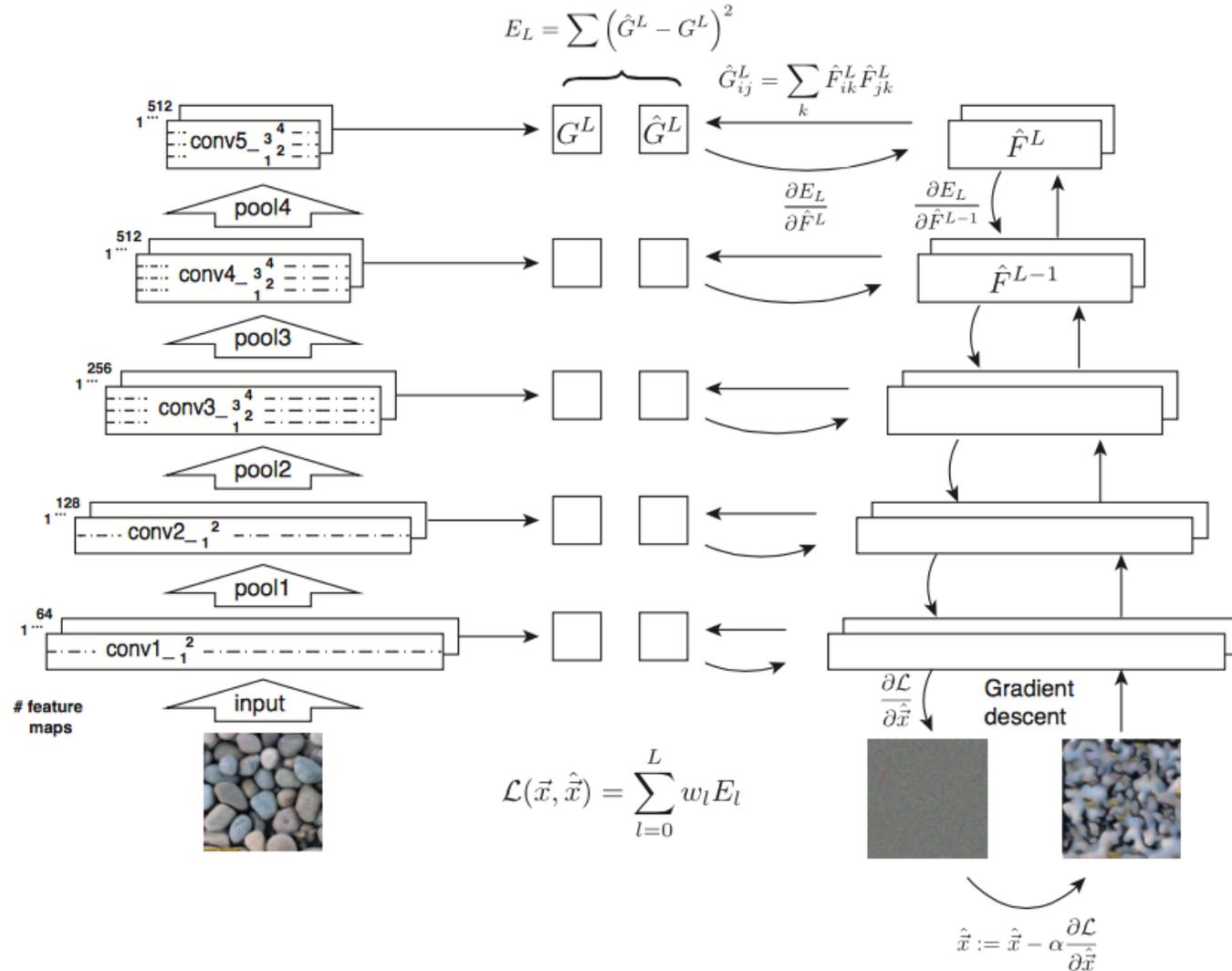
unfiltered target (B)



filtered target (B')

Deep learning teaser

A return to parametric models



Step 1: forward pass
input image

Step 2: define loss wrt
forward pass responses

Step 3: update white noise image
according to gradient descent

Texture synthesis examples

Synthesised



Source



Synthesised



Source



Texture synthesis examples

Synthesised



Source



Synthesised

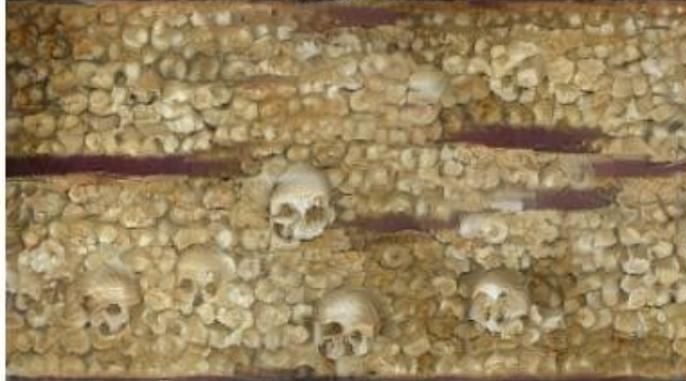


Source



Texture synthesis examples

Synthesised



Source



Synthesised



Source



Texture synthesis examples

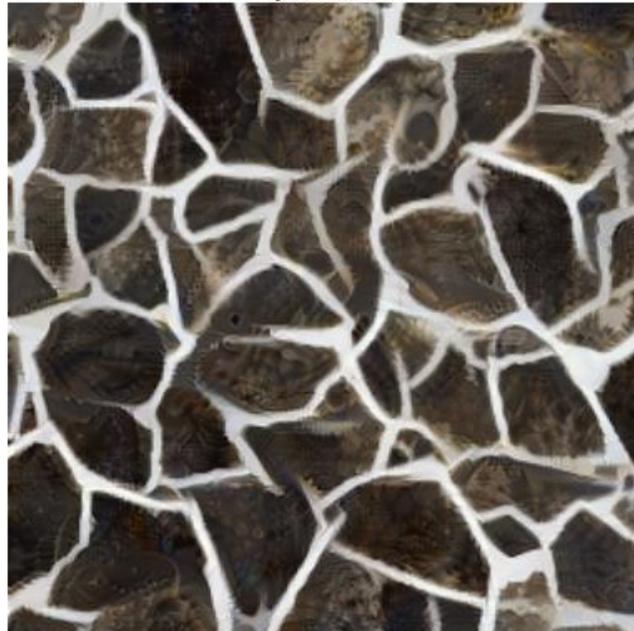
Synthesised



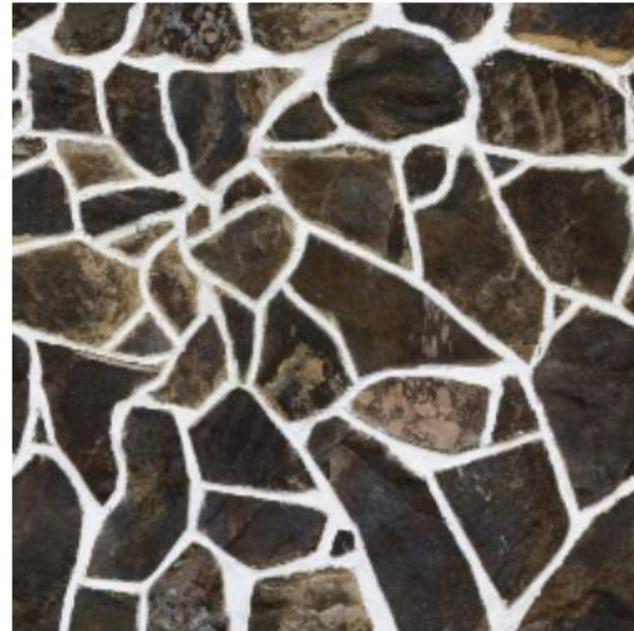
Source



Synthesised

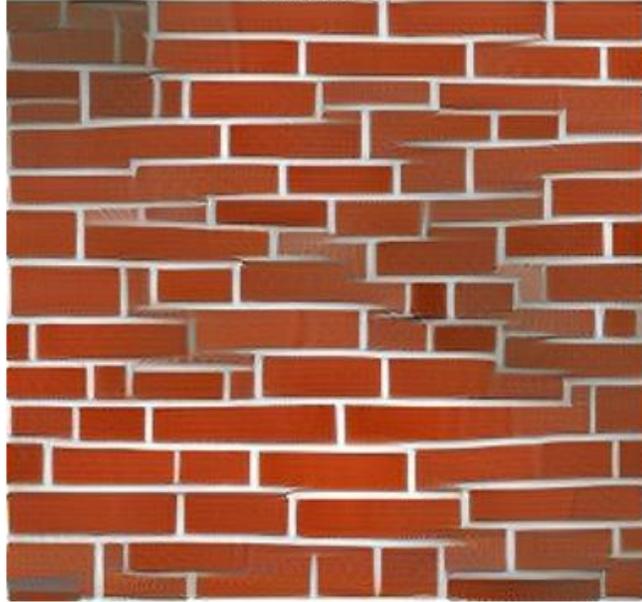


Source

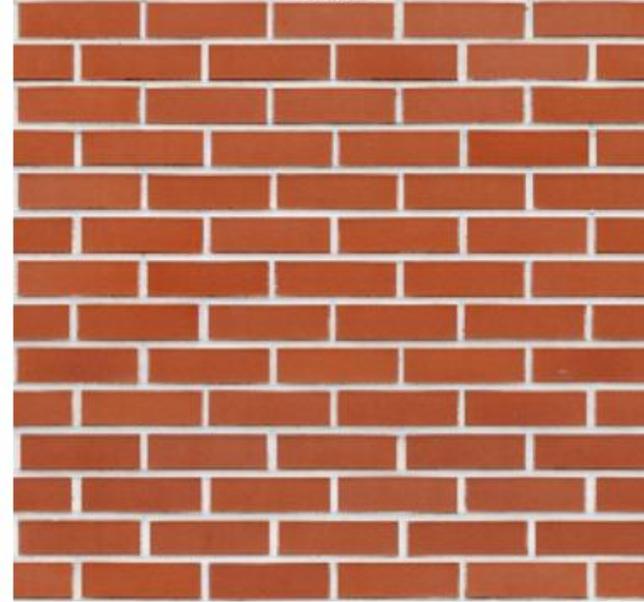


Texture synthesis examples

Synthesised



Source



Synthesised

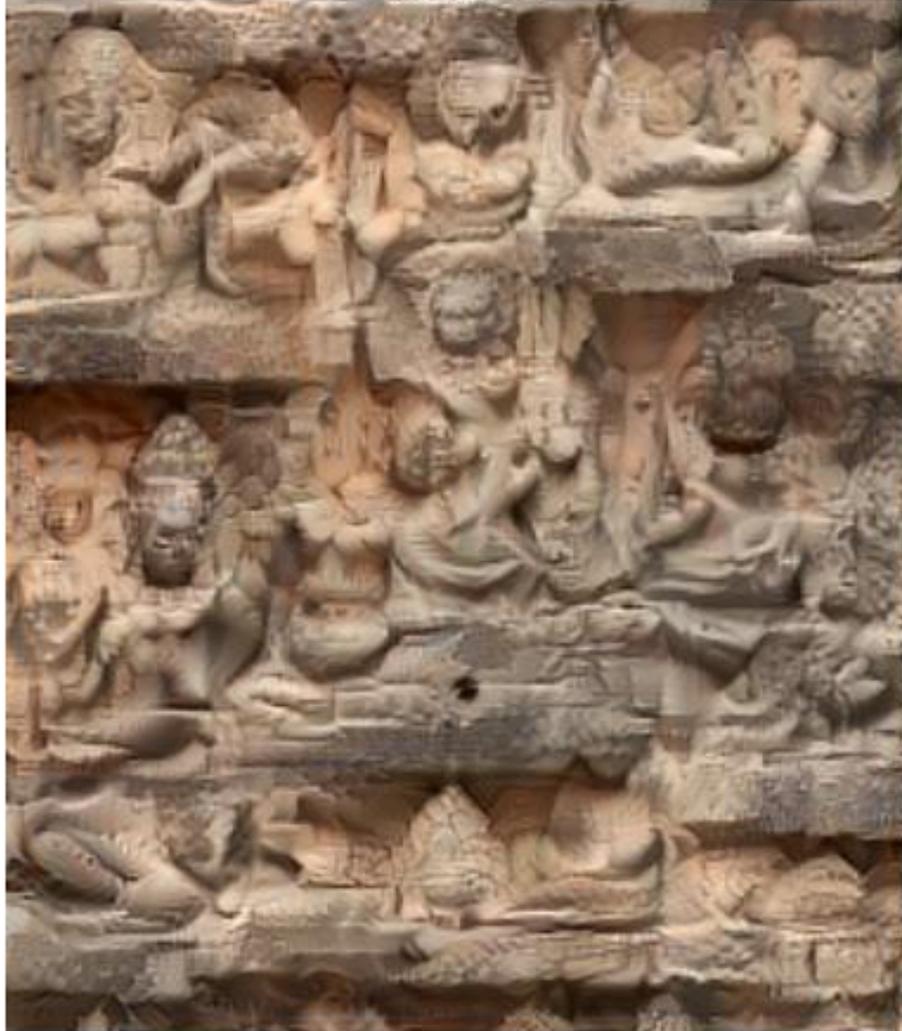


Source



Texture synthesis examples

Synthesised

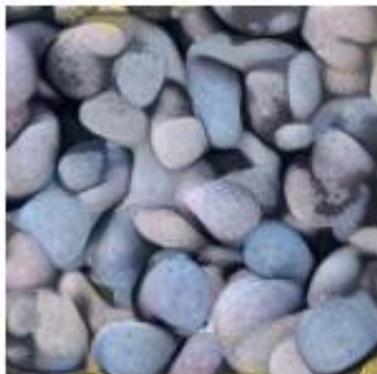


Source

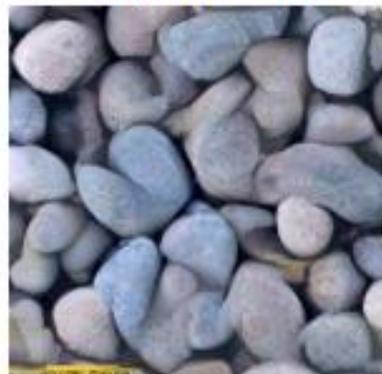


Parameter number matters

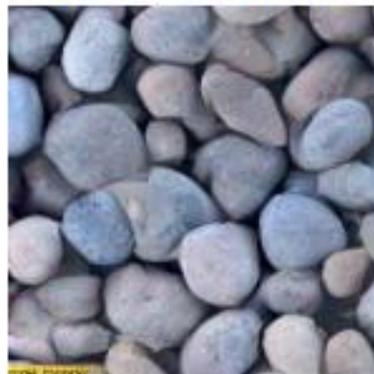
A ~1k parameters



~10k parameters



~177k parameters



~852k parameters



original



Style transfer examples

A



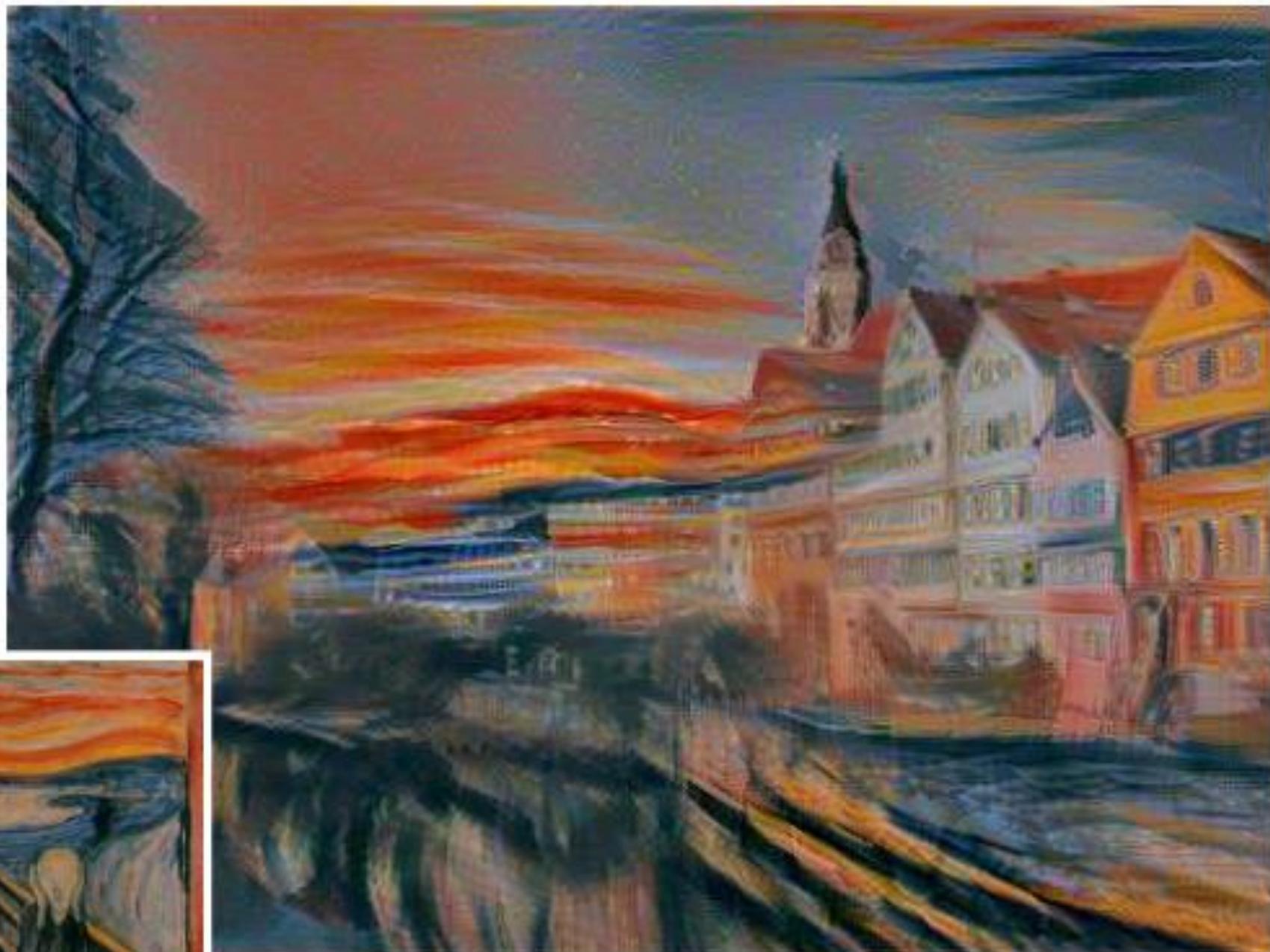
B



C



D



E



F



References

Basic reading:

- Szeliski textbook, Section 10.5.
- Efros and Leung, “Texture Synthesis by Non-parametric Sampling,” ICCV 1999.
- Efros and Freeman, “Image Quilting for Texture Synthesis and Transfer,” SIGGRAPH 2001.
- Hertzmann et al., “Image analogies,” SIGGRAPH 2001.
- Criminisi et al., “Object removal by exemplar-based inpainting,” CVPR 2003.
the titles of the above four papers should be self-explanatory.

Additional reading:

- Gatys et al., “Texture Synthesis Using Convolutional Neural Networks,” NIPS 2015.
texture synthesis using deep learning.
- Gatys et al., “Image Style Transfer Using Convolutional Neural Networks,” CVPR 2016.
implementing image analogies using deep learning.
- Luan et al., “Deep Photo Style Transfer,” arXiv 2017.
implementing photo-realistic style transfer using deep learning.