

# Two Patch-based Algorithms for By-example Texture Synthesis

**Bruno Galerne**

bruno.galerie@parisdescartes.fr

MAP5, Université Paris Descartes

Master MVA

Cours “Méthodes stochastiques pour l’analyse d’images”

Lundi 27 février 2017

Slide credits:

Alyosha Efros, Bill Freeman (SIGGRAPH presentation)

Rob Fergus (NYU course)

# Textures

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



radishes

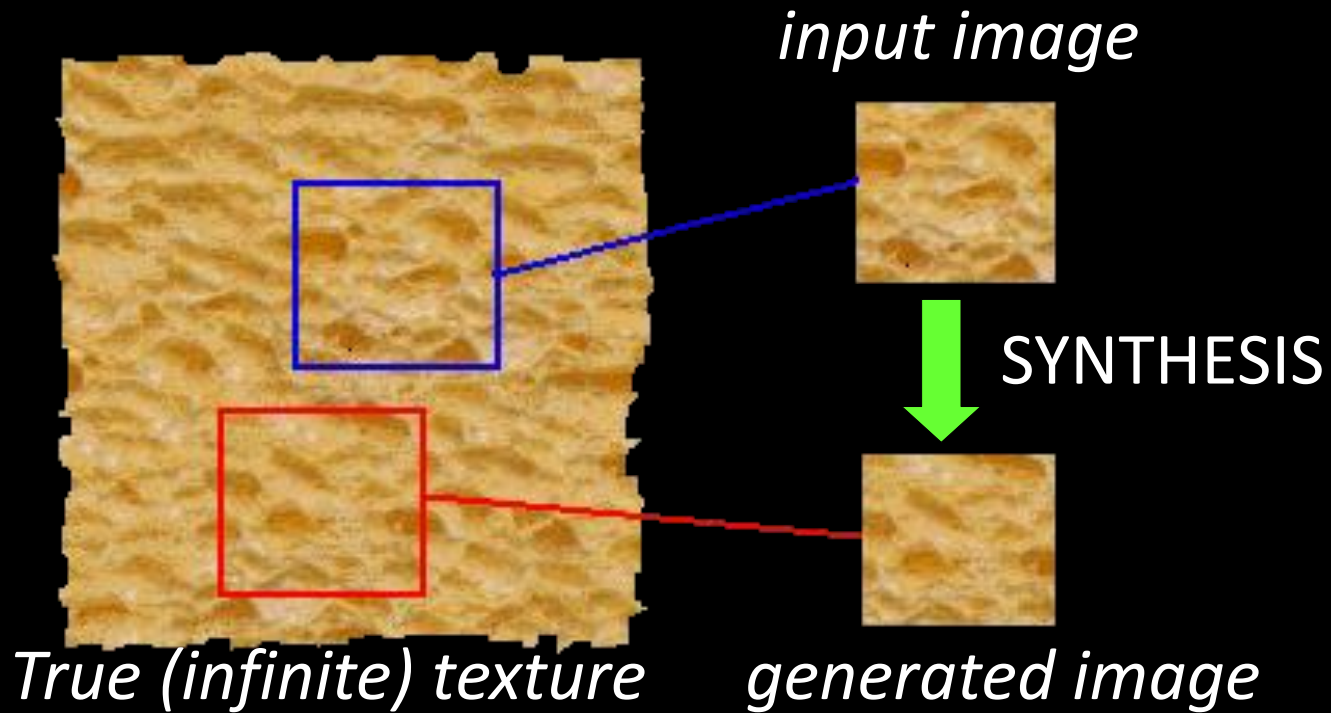


rocks



yogurt

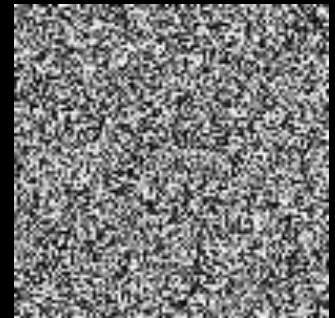
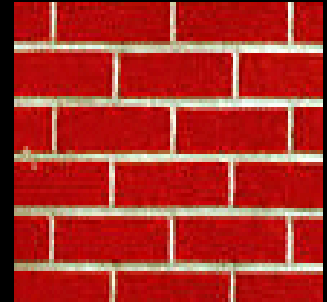
# The Goal of Texture Synthesis



- Given a finite sample of some texture, the goal is to synthesize other samples from that same texture

# Challenge

- Need to model the whole spectrum: from repeated to stochastic texture
- Micro-textures and macro-textures



# Outline

- The “Alexei Efros course”
  - Texture Synthesis by Non-parametric Sampling [Efros & Leung, ICCV’99]
  - Image Quilting for Texture Synthesis & Transfer [Efros & Freeman, SIGGRAPH 2001]
- TP
  - Test Efros-Leung with IPOL demo
  - Implement Image Quilting in Matlab! (with some help)

# Improvements...

- Of course many more contributions and improvements since 1999
  - Multi-scale approach [Wei & Levoy, 2000]
  - ... with global optimization instead of sequential synthesis [Kwatra et al. 2003, Kwatra et al. 2005]
  - ... with parallel evaluation [Lefebvre & Hoppe, 2005]

# Importance of Efros & Leung '99

- First paper with patch-based algorithm
- Concept of redundancy of patches
- Strong influence for many applications
  - Inpainting
  - Image editing (Image analogies, PatchMatch)
  - Denoising (Non-Local Means algorithm)

# Texture Synthesis by Non-parametric Sampling

[Efros & Leung, ICCV'99]

IPOLE demo [Aguerreberre, Gousseau, Tartavel, 2013]



# Shannon

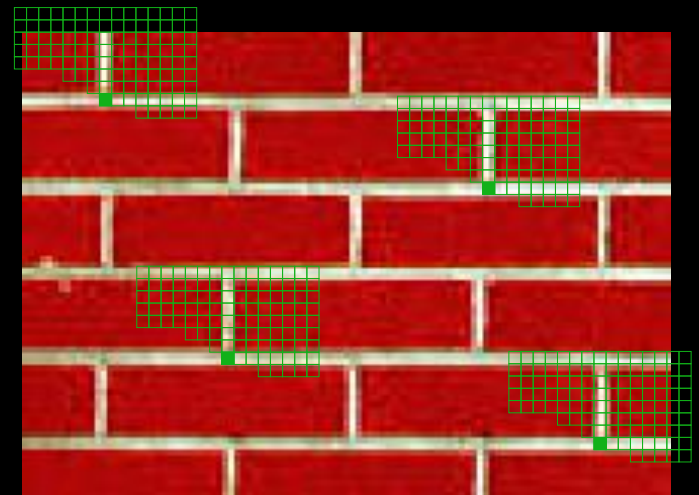
## Shannon's approach for text synthesis

- Markov model
- Draw an N-gram with marginal distribution
- Add characters sequentially using the conditional distribution of N-gram given the first N-1 characters
- Using 4-grams:

THE GENERATED JOB PROVIDUAL BETTER  
TRAND THE DISPLAYED COVE ABOVERY

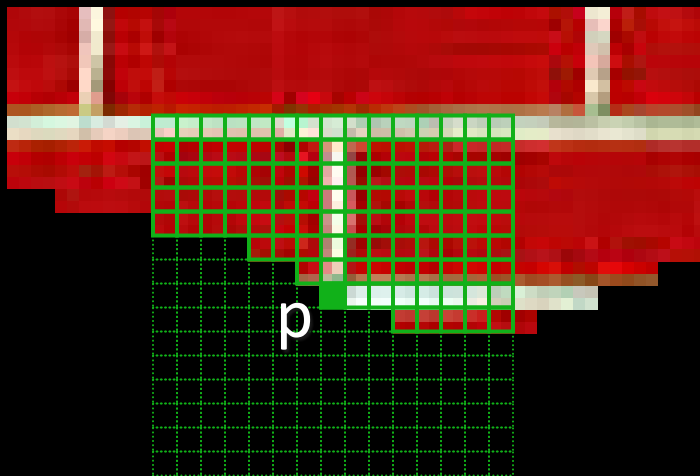
# Shannon for Texture Synthesis?

- Differences between textures and texts for applying Shannon's approach
  - No natural order in a 2D pixel grid
  - Pixel similarity: two close pixel values can be exchanged without altering the texture while it is not possible for udys ( $= \text{text} \pm 1$ )
  - Compute the conditional probability is not feasible
- Still Markov model is OK!



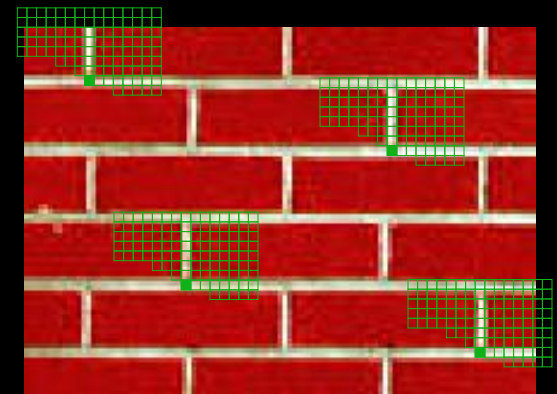

# General Idea

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



Synthesizing a pixel

non-parametric  
sampling



Input image

# Algorithmic Details

- Start from a 3x3 seed from the input
- The new pixel  $p$  to fill is randomly picked among all the ones that have the larger number of neighborhood  
-> synthesis by layer

# Neighborhood Comparison

- Given a partial patch  $\mathcal{N}(p)$  in the output **B** at pixel  $p$ , we compute the distance to all partial patches  $p'$  in input image **A**

$$d(\mathcal{N}(p), \mathcal{N}(p')) = \frac{1}{\sum_{i \in \mathcal{N}(p)} G_{\sigma}(i)} \sum_{i \in \mathcal{N}(p)} (\mathbf{A}(p' + i) - \mathbf{B}(p + i))^2 G_{\sigma}(i)$$

- Squared difference with Gaussian weights since the center of the patch has more importance

# Similar Neighborhood

- The set of “similar neighborhoods” are defined as all patches  $N(p')$  *such that*

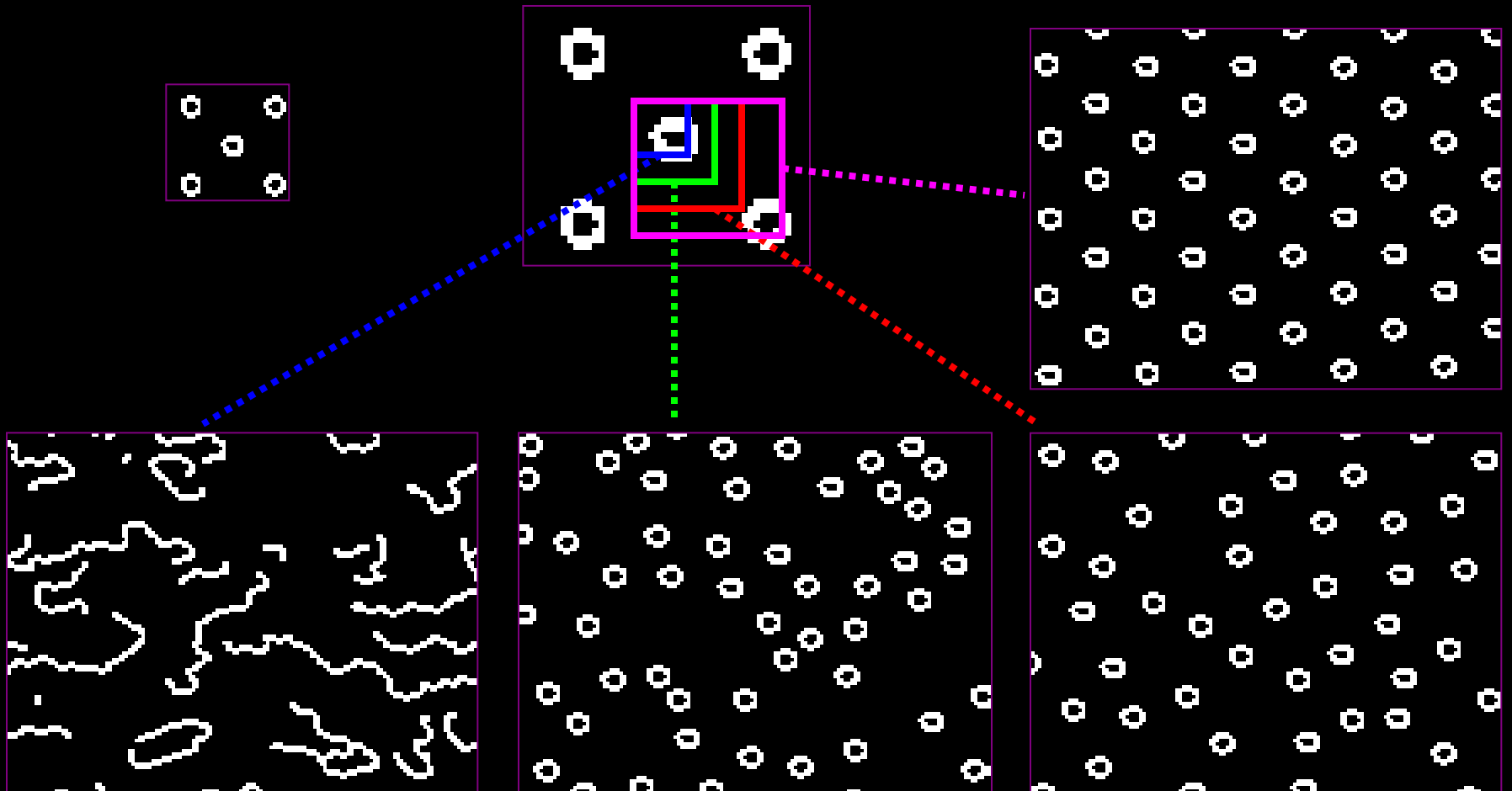
$$d(\mathcal{N}(p), \mathcal{N}(p')) \leq (1 + \varepsilon) \min_{p'} d(\mathcal{N}(p), \mathcal{N}(p'))$$

- $\varepsilon > 0$  is a global parameter

# Pseudo-code of the Efros-Leung Algorithm

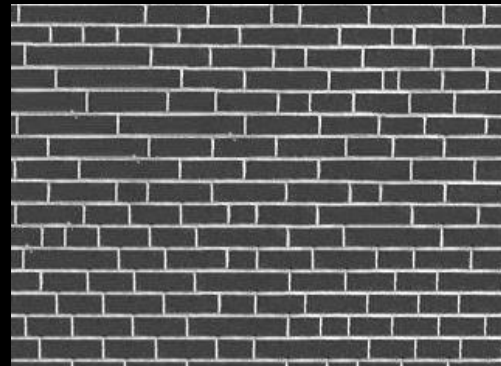
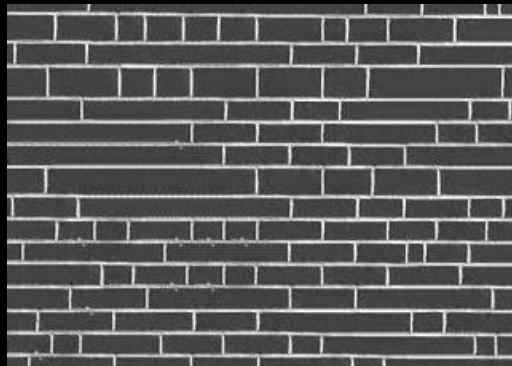
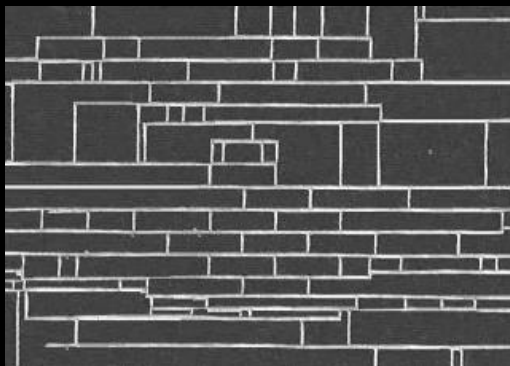
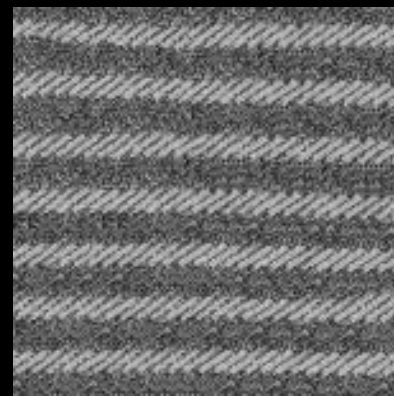
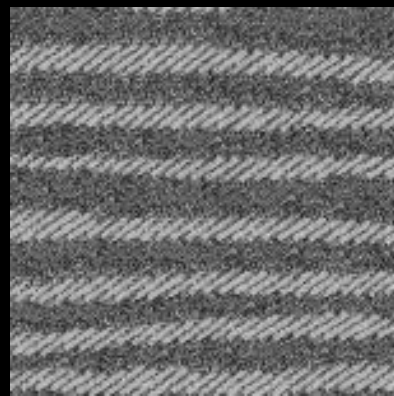
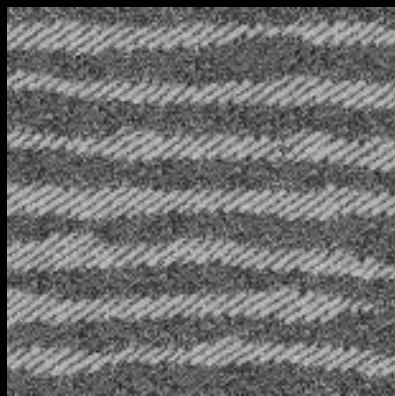
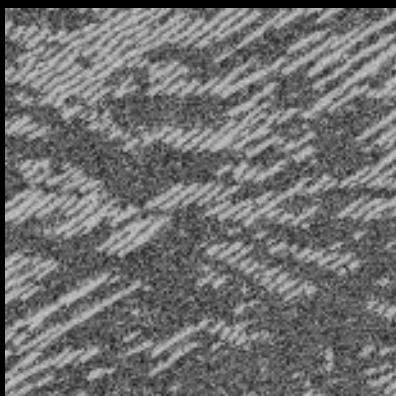
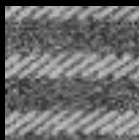
- **Input arguments:** Input image **A**, output size
  - **Parameters :** neighborhood size,  $\epsilon$
1. Initialize with 3x3 random seed of **A**
  2. While output **B** not filled
    1. Pick a pixel  $p$  in **B** with maximal neighbor pixels
    2. Compute the distance of  $N(p)$  to all patches of input **A**
    3. Pick randomly one the similar neighborhood  $p'$
    4. Set  $B(p) = A(p')$  (= Fill  $p$  with central value)

# Neighborhood Size

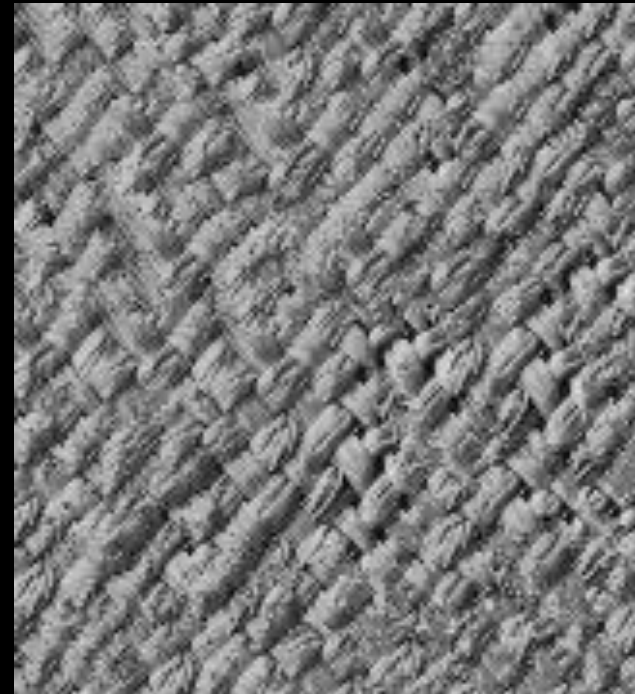
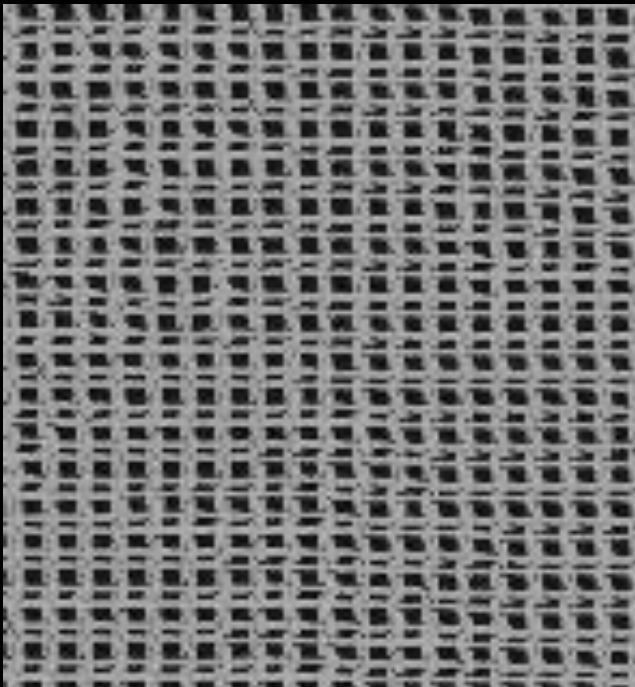
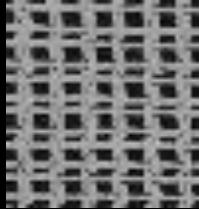




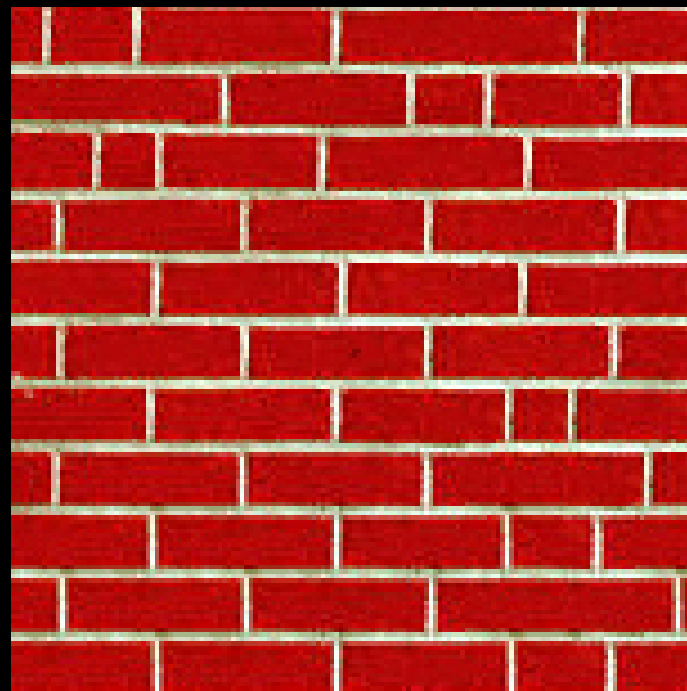
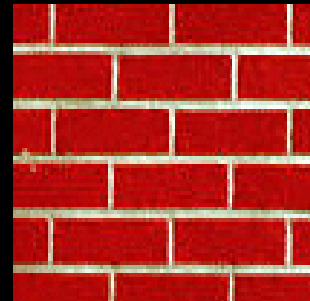
# Varying Neighborhood Size



# Synthesis Results



# Synthesis Results



# Homage to Shannon

...oming in the unsensational  
...r Dick Gephardt was fail  
...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 tanger

...ing in the unsensational  
...r Dick Gephardt was fail  
...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 tanger

...thaim, them. "Whnephartfe lartifelintomimen  
...fel ck Clirtioout omaim thartfelins.f out s aneto  
...the ry onst wartfe lck Gephtoomimeationl sigab  
...Clieoufit Clinut Cil riff on, hat's yodn, parut tly  
...ons ycontonsteht wasked, paim t sahe loo' riff on  
...nskoneploourtfeas leil A nst Clit, "Wleontongal s  
...k Clirtioouirtfepe.ong pme abegal fartfenstemem  
...tiensteneltorydt telemephinsverdt was agemer  
...ff ons artientont Cling perme asrtfe atikh, "Boui s  
...al s fartfelt sig pedrtf'dt ske abounutie aboutioo  
...tfeoneewas you abowonthardt thatins fain, ped, '  
...ains, them, pabout wasy arfuit coultly d, l n A h  
...ple emthringbooreme agas fa bontinsyst Clinut  
...ory about continst Clieopinist Cloke agatiff out  
...stome zinemen tly ardt beorabou n, thenly as t C  
...cons faimeme Diontont wat coutlyohgans as fan  
...dien, phrtfaul, "Wbaut cout congagal comininga  
...mifmst Clily abon al coountha.emungairt tfoun  
...Whe loocrystan loontieph, intly on, theoplegatick  
...aul fatieozontly atie Diontiomt wal s f tbegea ener  
...nthahgat's enephbbas fan, "intchthorv abons v

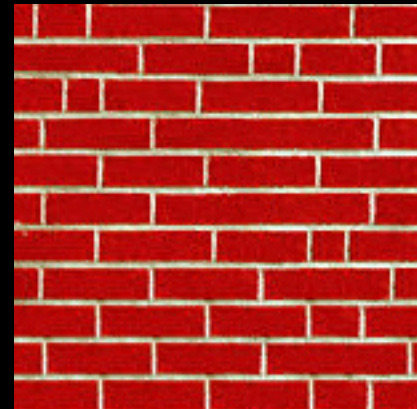
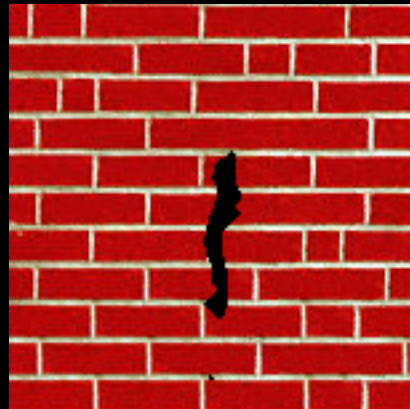
# Not only for texture synthesis

## Other applications

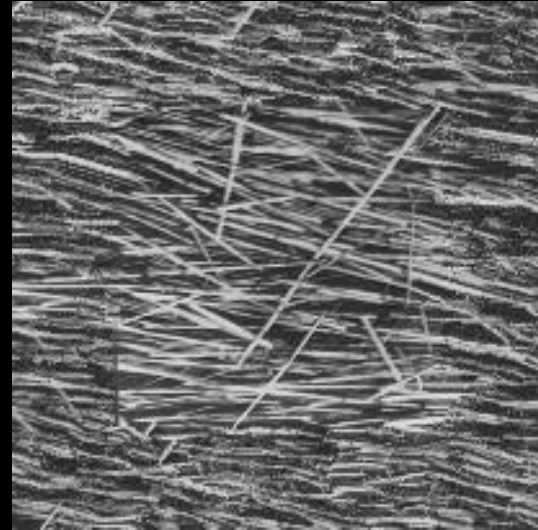
- Texture inpainting (or hole filling)
- Texture/Image extrapolation



# Application: Texture Inpainting



# Application: Image Extrapolation

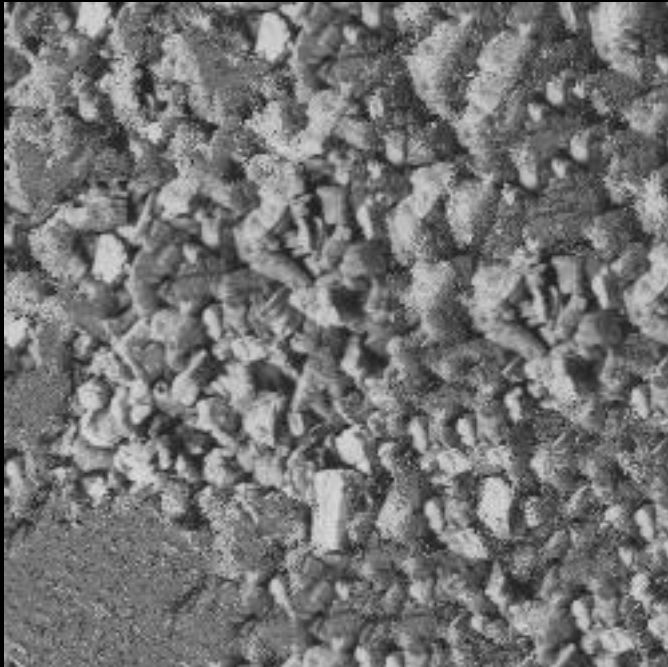
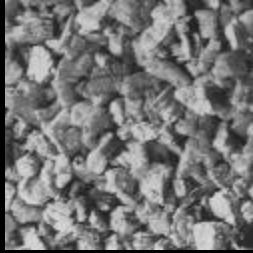


# Back to Texture Synthesis

- Surprisingly good results for structured textures!
- **Failure cases**
  1. *Verbatim copy*
  2. *Growing garbage*



# Failure Cases



**Growing garbage**



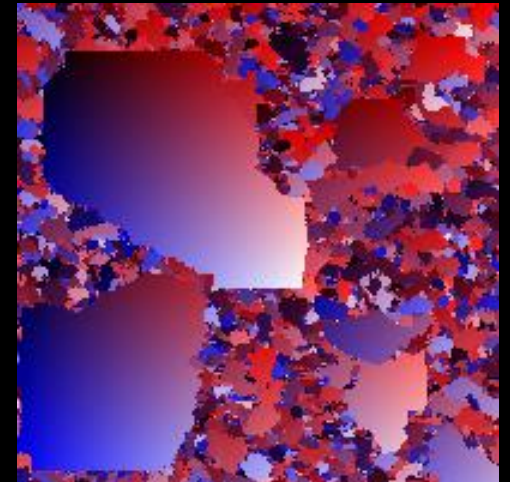
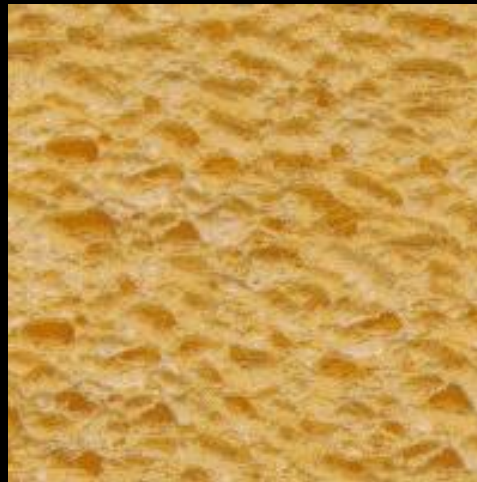
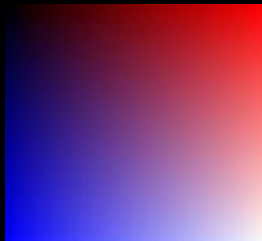
**Verbatim copying**

# Pros & Cons

- Advantages
  - Conceptually simple
  - Satisfying for a wide range of real-world textures
  - Naturally does hole-filling
- Disadvantages
  - Slow
  - Parameters are hard to set: thin space (if any) between **verbatim copy** and **growing garbage**
  - No ensured quality: trial and error

# Verbatim Copy

- To get a better understanding, one can plot the pixel coordinate map



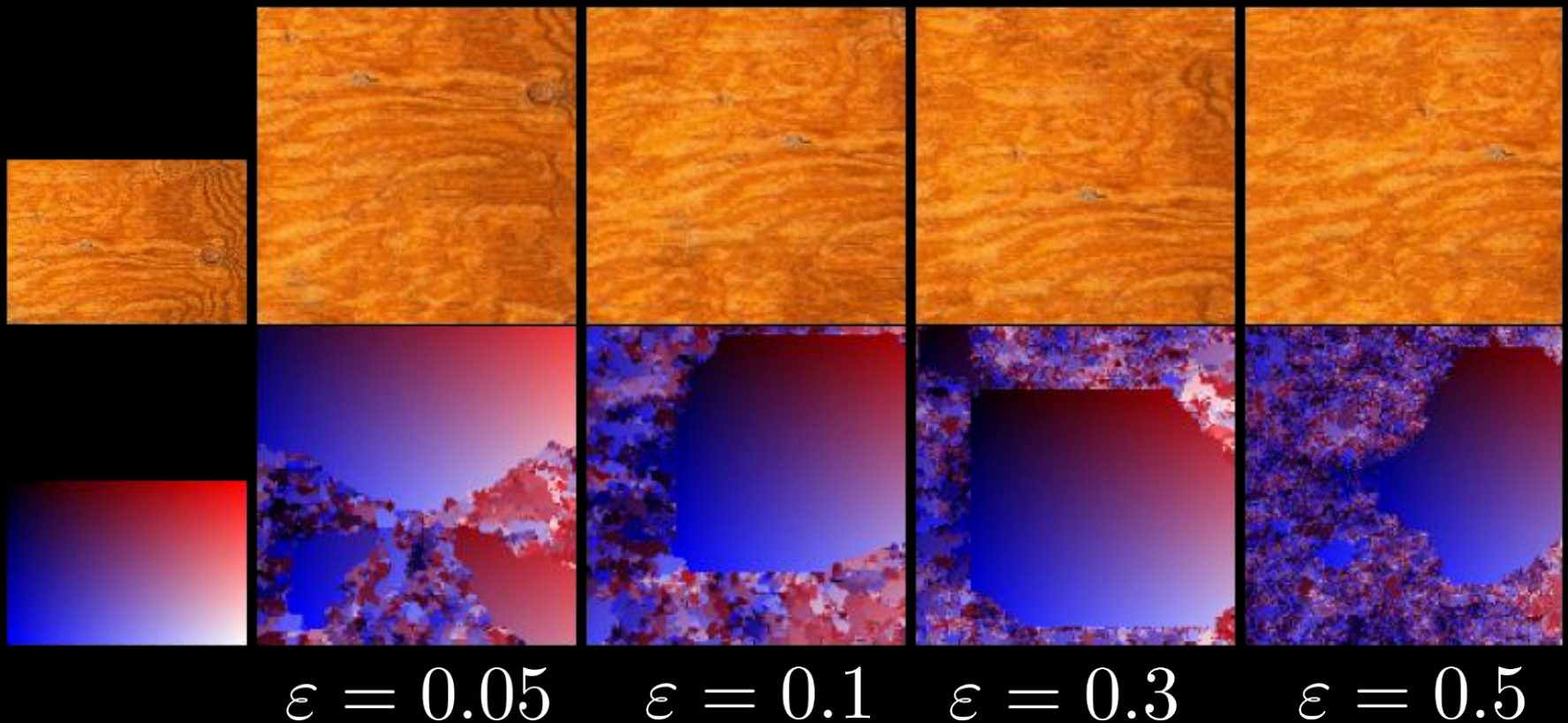
- Although pixels are generated one pixel at a time, whole pieces of input are reproduced

# Verbatim Copy

- The problem comes from the fact that when  $d_{\min} = 0$  reproducing the input is generally the only possibility

# Innovation Capacity

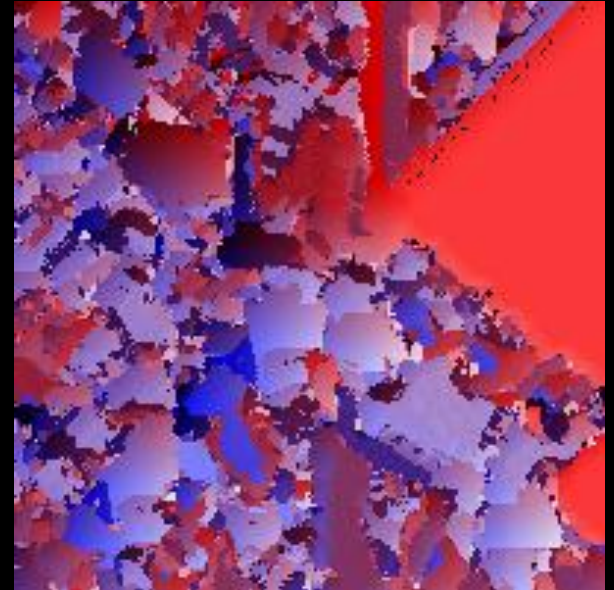
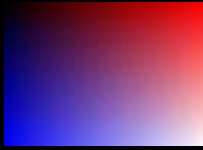
- Innovation capacity increases with  $\varepsilon$





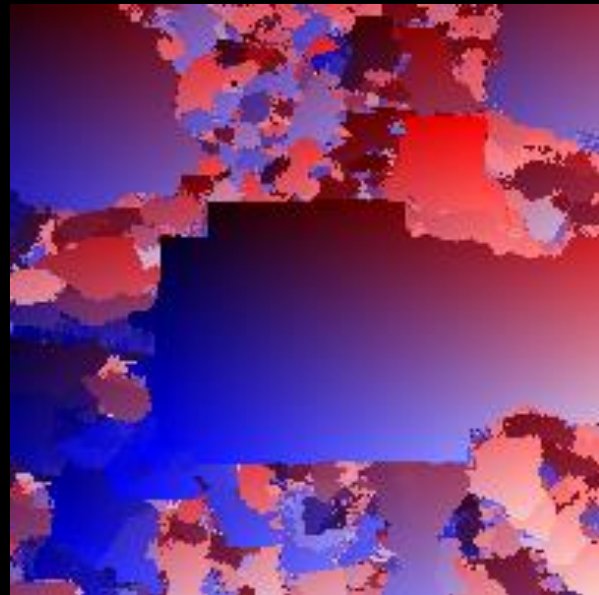
# Growing Garbage

- Happens when the algorithm is stuck in some local loop



# Avoid Failure

- For some textures it is hard to find a balance between verbatim copy and growing garbage



# Acceleration

- The computational cost comes from the comparison to all patches of the input textures at each step
- The neighborhoods have different shapes so it is hard to use some data structure to accelerate the computation of the distance
- Squared sum computation
  - Partial sum of distance: discard as soon as larger than threshold
  - Works even better with PCA coordinates (more variance for first coordinates) (of half-patches)



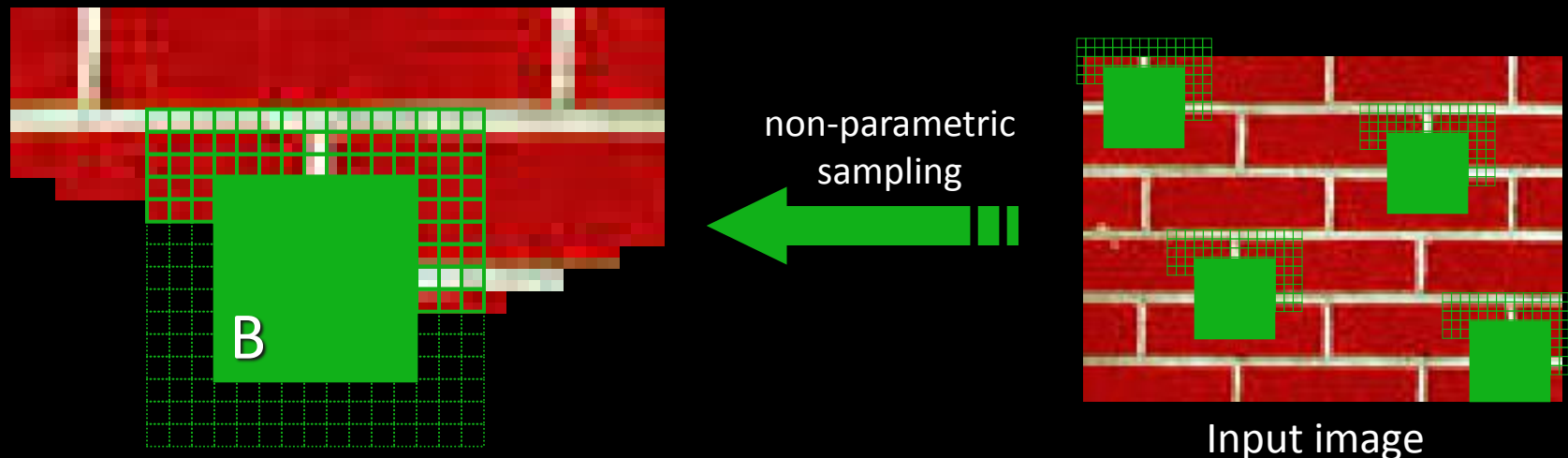
Questions?

# Image Quilting for Texture Synthesis & Transfer

[Efros & Freeman, SIGGRAPH 2001]

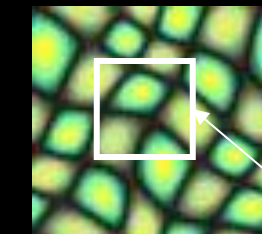
IPOL demo: [Raad, Galerne, 2017]

# Efros & Leung '99 extended



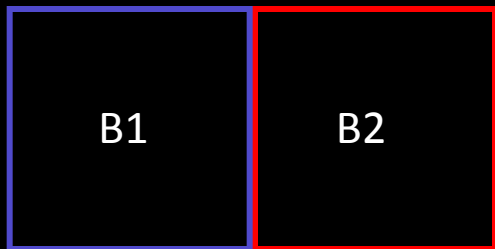
- Observation: neighbor pixels are highly correlated and copied one pixel at a time
- Idea: unit of synthesis = block
  - Exactly the same but now we want  $P(B|N(B))$
  - Much faster: synthesize all pixels in a block at once

# Quilting: Main Idea

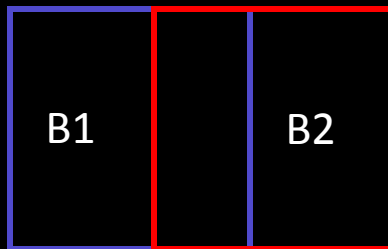


block

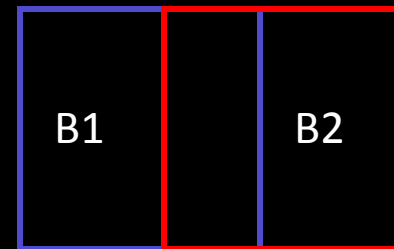
Input texture



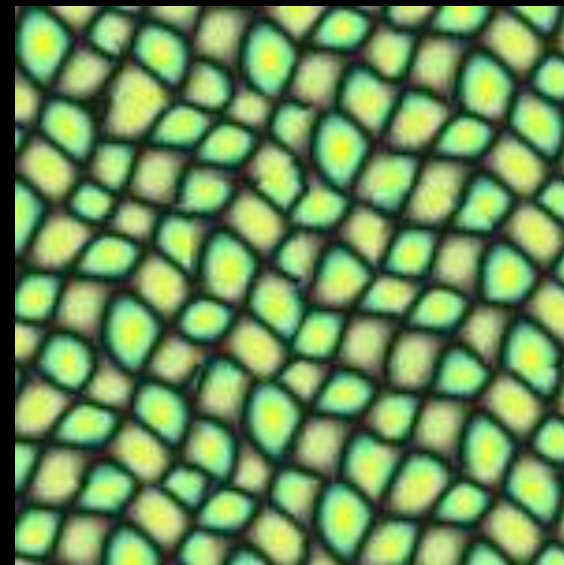
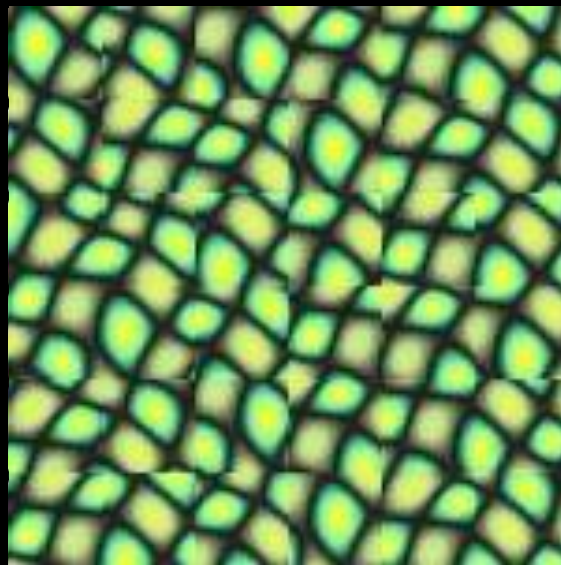
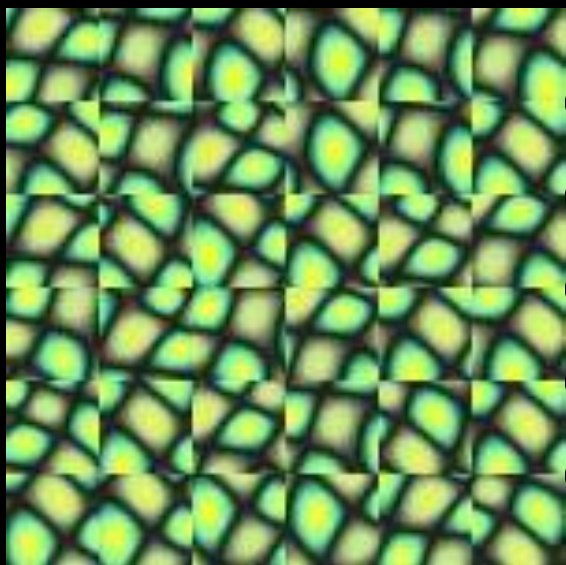
Random placement  
of blocks



Neighboring blocks  
constrained by overlap

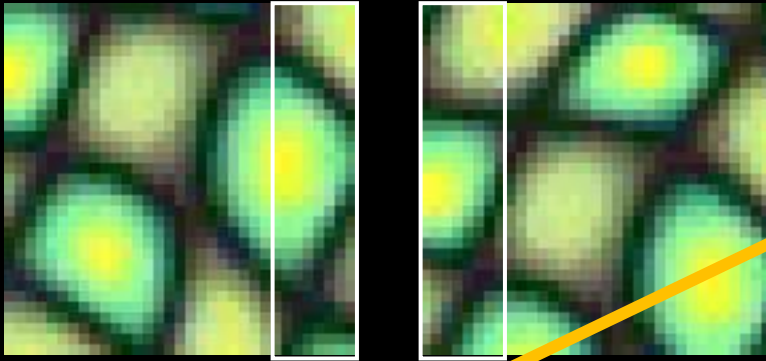


Minimal error  
boundary cut



# Minimal Error Boundary

overlapping blocks



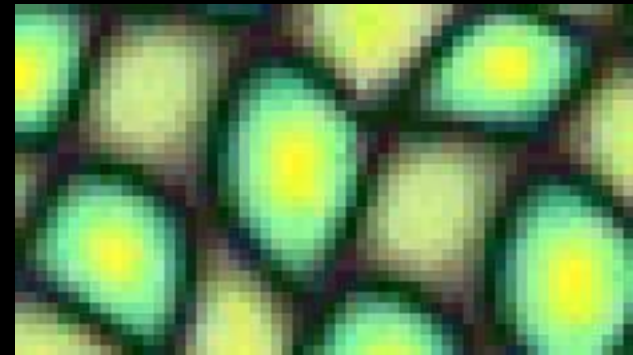
vertical boundary



**DETAILS LATER**



overlap error



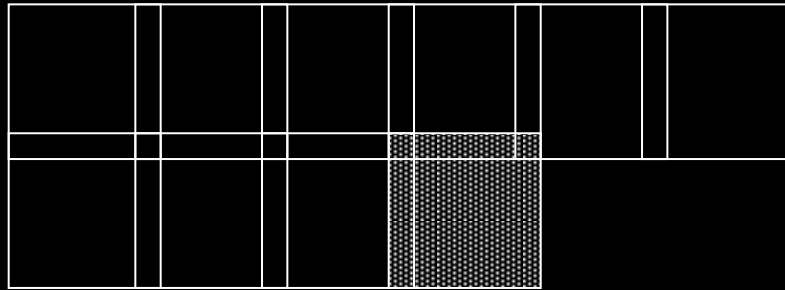
min. error boundary

# Philosophy

- Texture blocks are by definition correct samples of texture
- The problem is connecting them together

# Algorithm

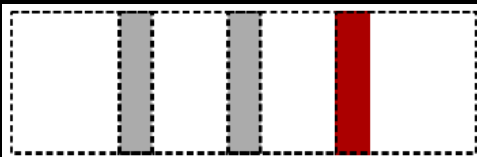
- Parameters: size of block, size of overlap (25%)
- Synthesize blocks in raster order



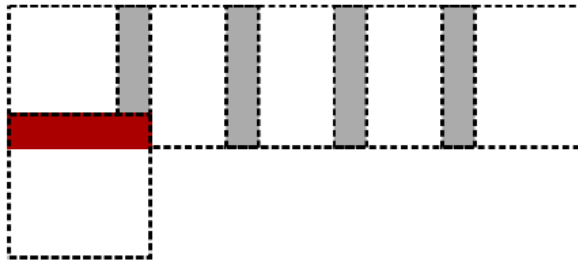
- Search input texture for block that satisfies overlap constraints (above and left)
- Paste new block into resulting texture
  - use *dynamic programming* to compute minimal error boundary cut

# Three overlap cases

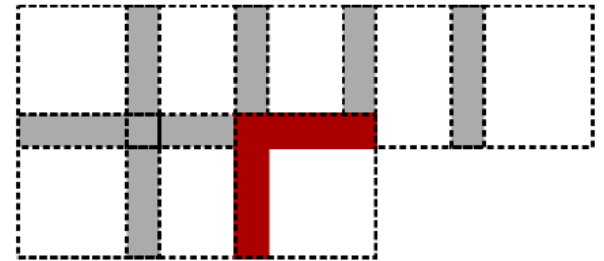
- There are 3 overlap cases
  - Vertical overlap (first row)
  - Horizontal overlap (first column)
  - L-shaped overlap (everywhere else)



(a) Vertical overlap



(b) Horizontal overlap



(c) L-shaped overlap



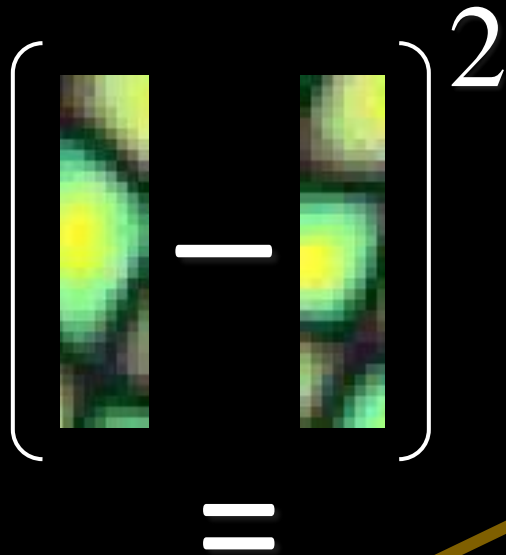
# Overlap Constraint

- We need to search to all blocks that have a similar L-shape

$$d(P, P_A((x, y))) = \sum_{i,j=0}^{w-1} Q(i, j)(P(i, j) - A(x + i, x + j))^2$$

- Can be computed using Fast Fourier transform
- Then cost is only proportional to input size in  $O(MN \log(MN))$ , independent of block size
- Again, pick block at random with error tolerance  $\varepsilon$

# Boundary Error Computation


$$\left[ \begin{array}{c} \text{Image 1} \\ \text{Image 2} \end{array} \right]^2 =$$

- For vertical boundary

- Search the pixel path that minimizes  $e = (A-B)^2$

- **Dynamic programming**

- Starting from bottom compute minimal cumulative error  $E$

$$E_{i,j} = e_{i,j} + \min(E_{i+1,j-1}, E_{i+1,j}, E_{i+1,j+1})$$

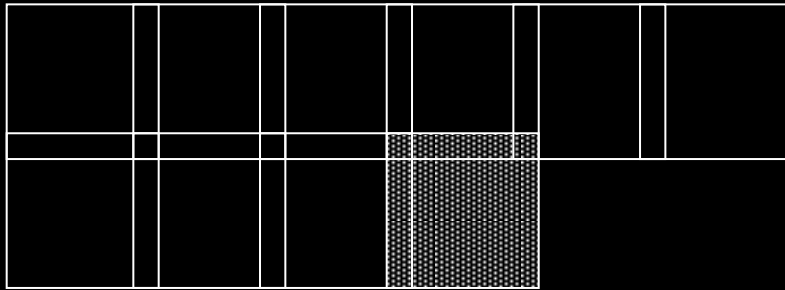
- Starting point is minimal value on top

- Retrace back the minimal path

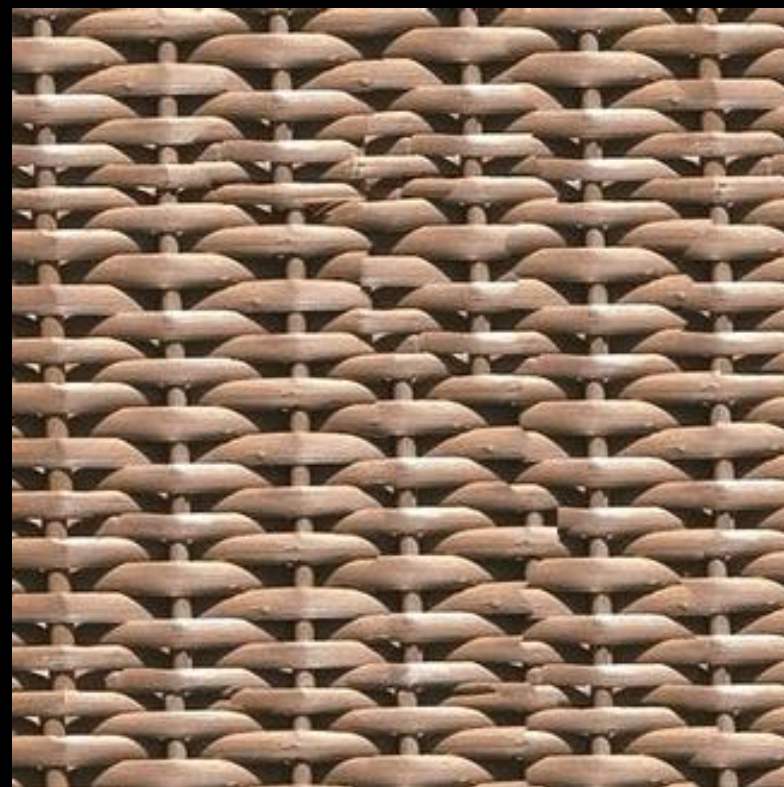
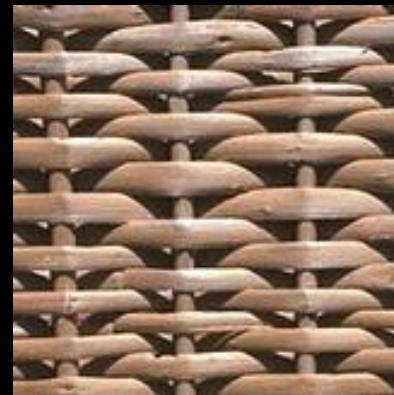


# Boundary Error Computation

- What about L-shape overlap?

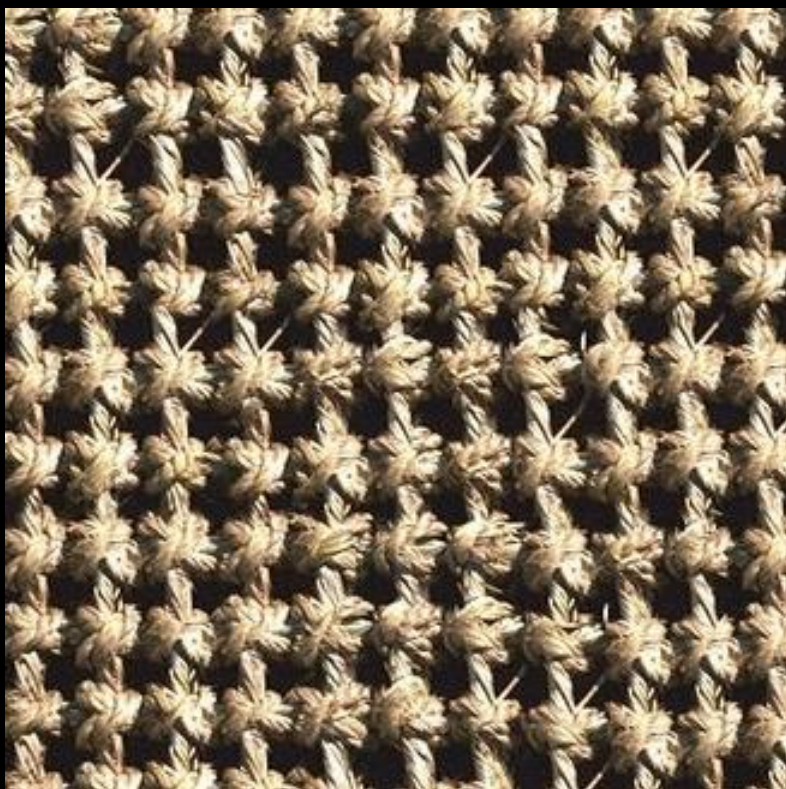


# Results



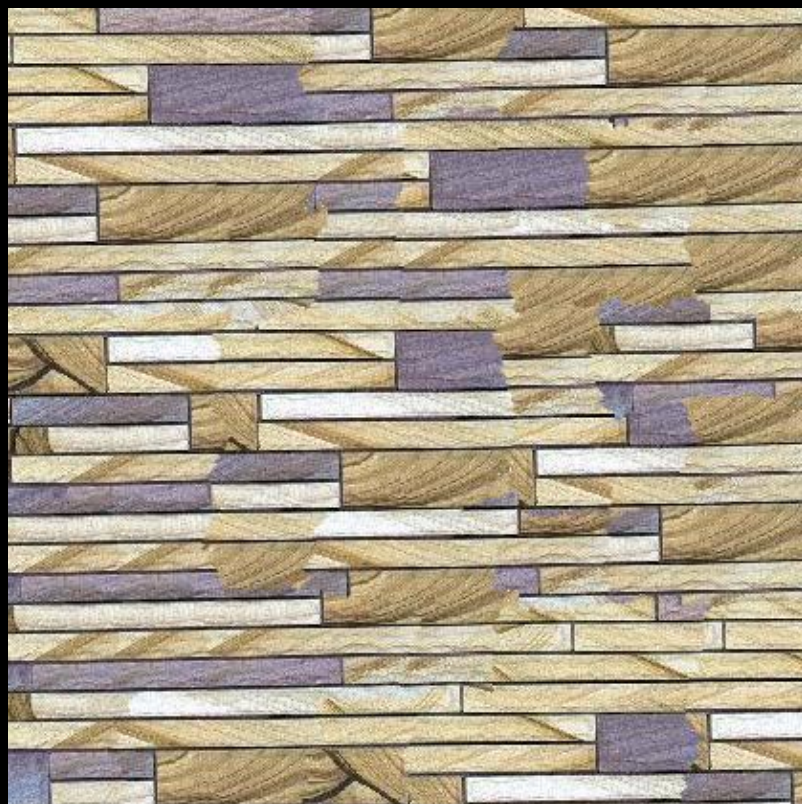


# Results





# Results





# Results

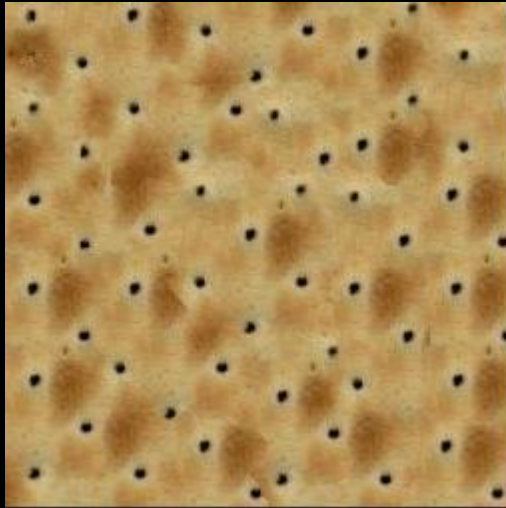
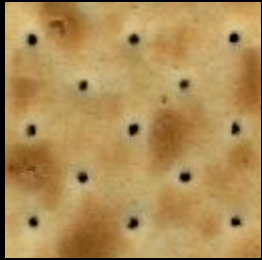


# Results



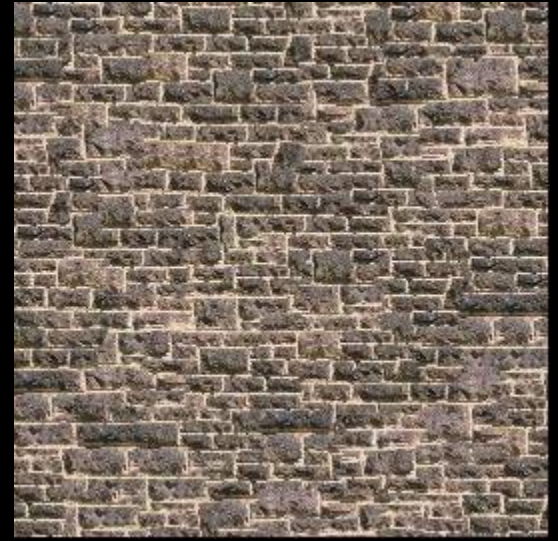
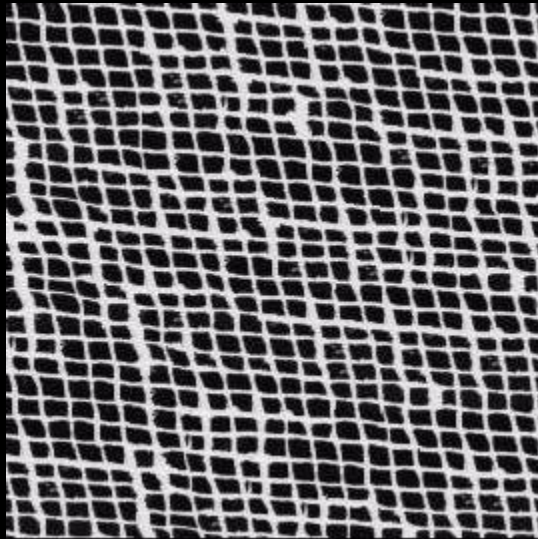
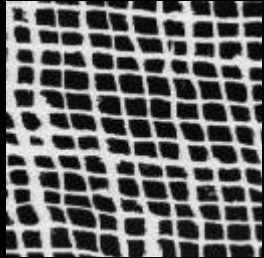


# Results





# Results





# Failures



# Texture Transfer

- Take the texture from one object and “paint” it onto another object
  - This requires separating texture and shape
  - Assume we can capture shape by boundary and rough shading
- Then, just add another constraint when sampling: similarity to underlying image at that spot

# Texture Transfer



+



=



parmesan



+



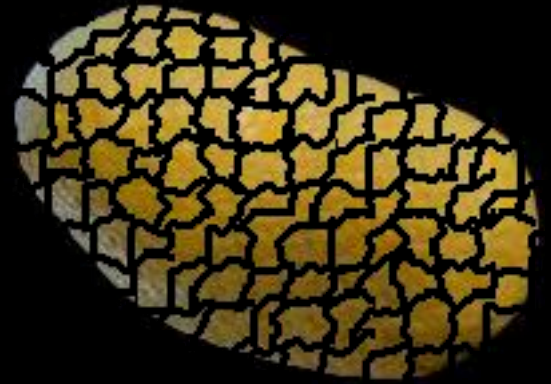
=



rice



# Several Paths with Different Sizes



# Pros & Cons

- Advantages
  - Fast and very simple
  - Good results
- Disadvantages
  - Size parameter hard to set
  - Scanning order: Quality tends to be better in top left corner for large images (TP)

# Questions?