Texture Synthesis and Hole-Filling

Computational Photography

Derek Hoiem, University of Illinois

Next section: The digital canvas

Cutting and pasting objects, filling holes, and blending

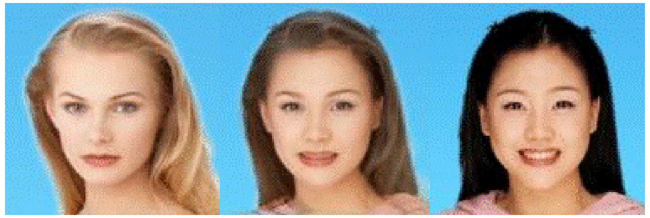


Image warping and object morphing

Today's Class

- Texture synthesis and hole-filling

Texture

- Texture depicts spatially repeating patterns
- Textures appear naturally and frequently

radishes

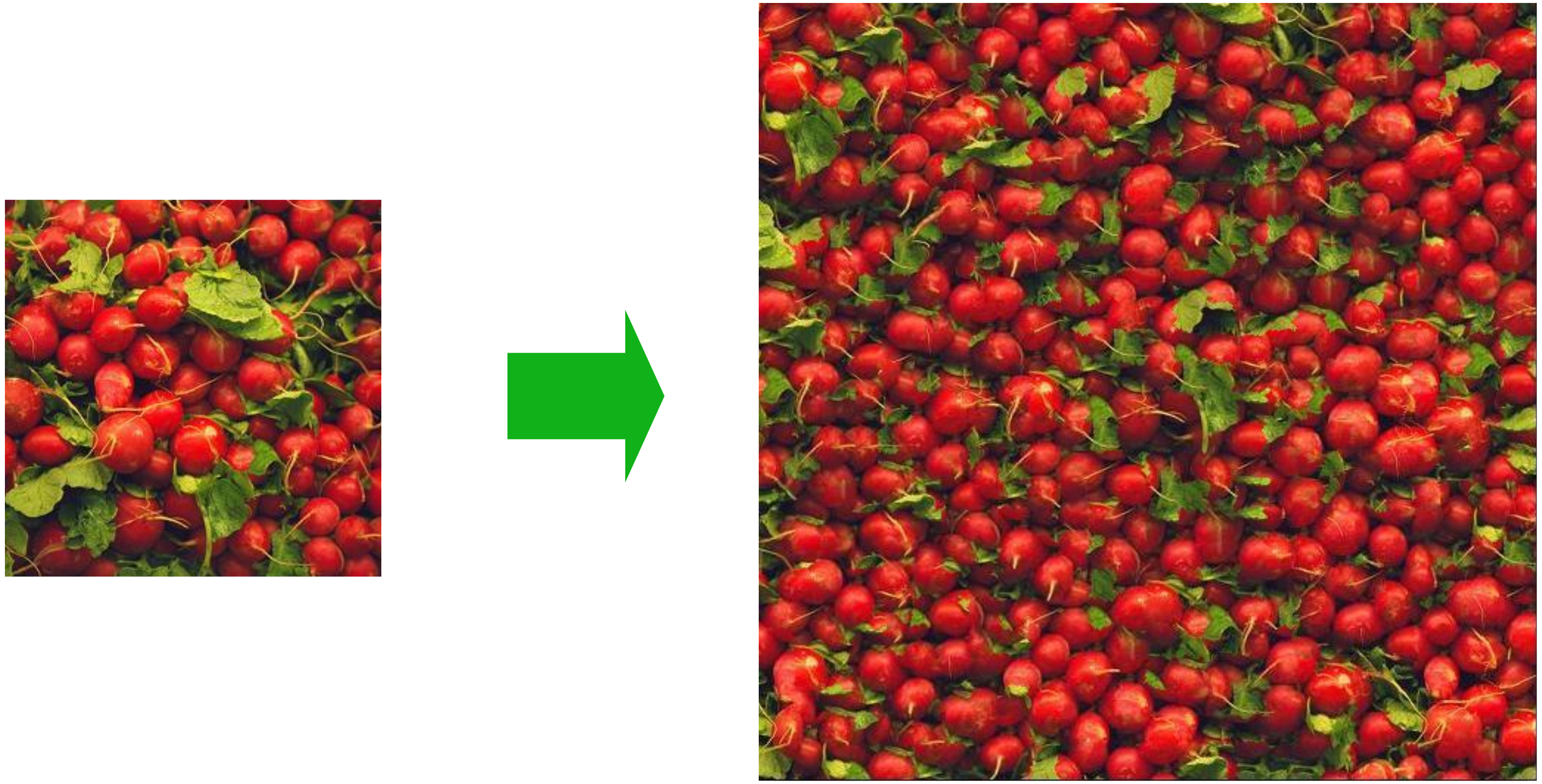
rocks

yogurt

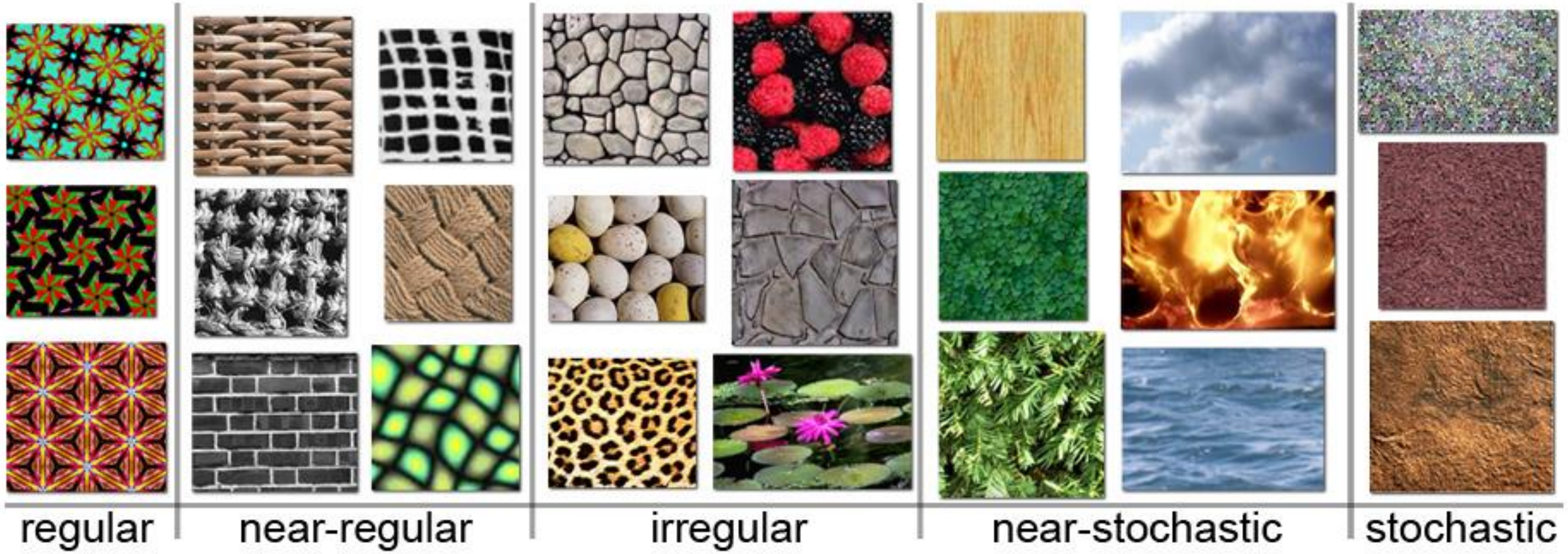
Many slides from James Hays

Texture Synthesis

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



The Challenge

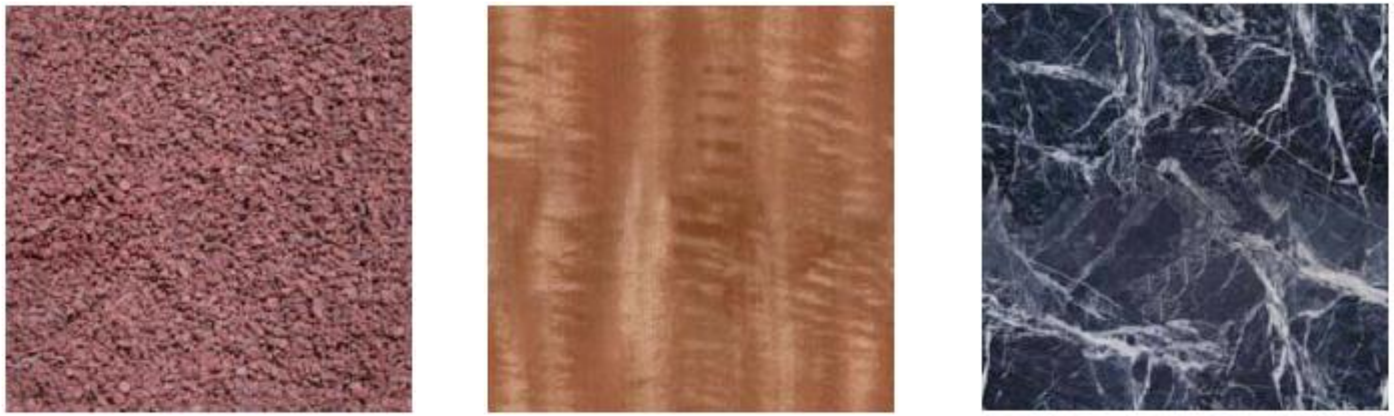


Need to model the whole spectrum: from repeated to stochastic texture

One idea: Build Probability Distributions

Basic idea

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



- D. J. Heeger and J. R. Bergen. Pyramid-based texture analysis/synthesis. In *SIGGRAPH ’95.*
- E. P. Simoncelli and J. Portilla. Texture characterization via joint statistics of wavelet coefficient magnitudes. In *ICIP 1998.*

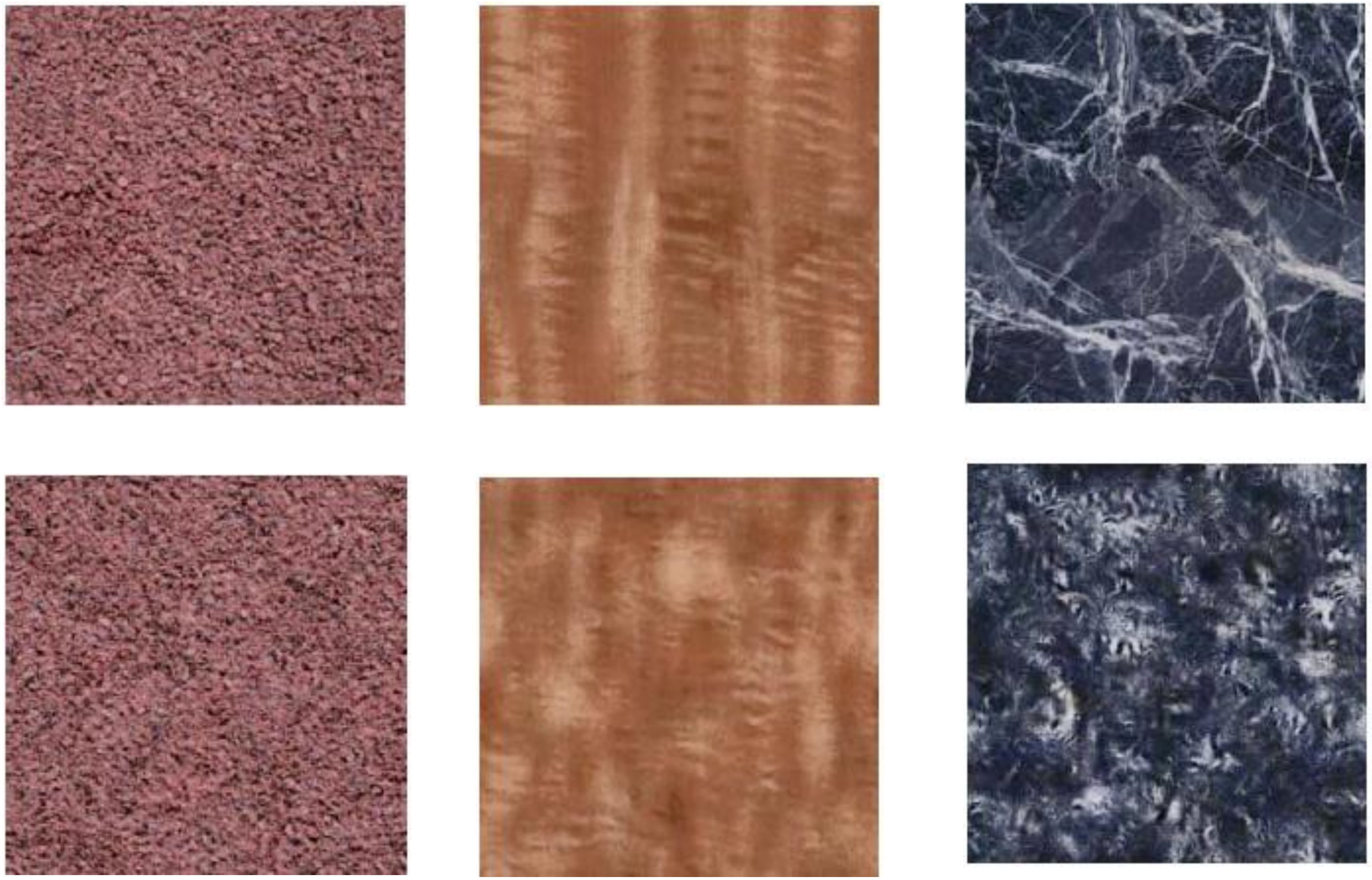
One idea: Build Probability Distributions

But it (usually) doesn’t work

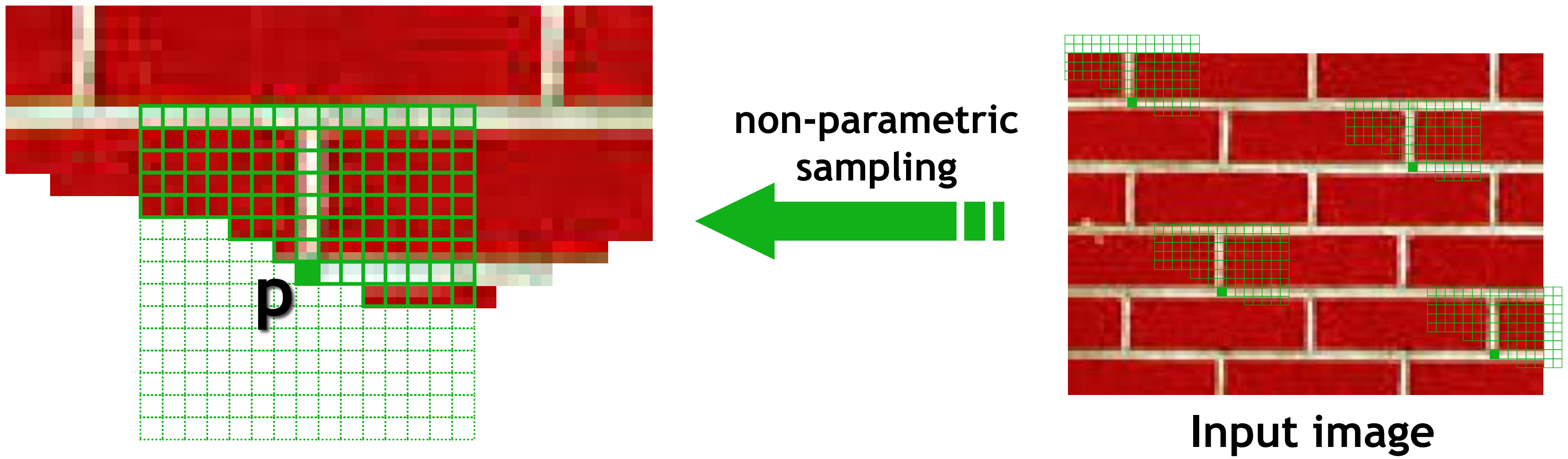
- Probability distributions are hard to model well

Input

Synthesized



Another idea: Sample from the image



Synthesizing a pixel

Input image

- 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

Efros and Leung 1999 SIGGRAPH

Idea from Shannon (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

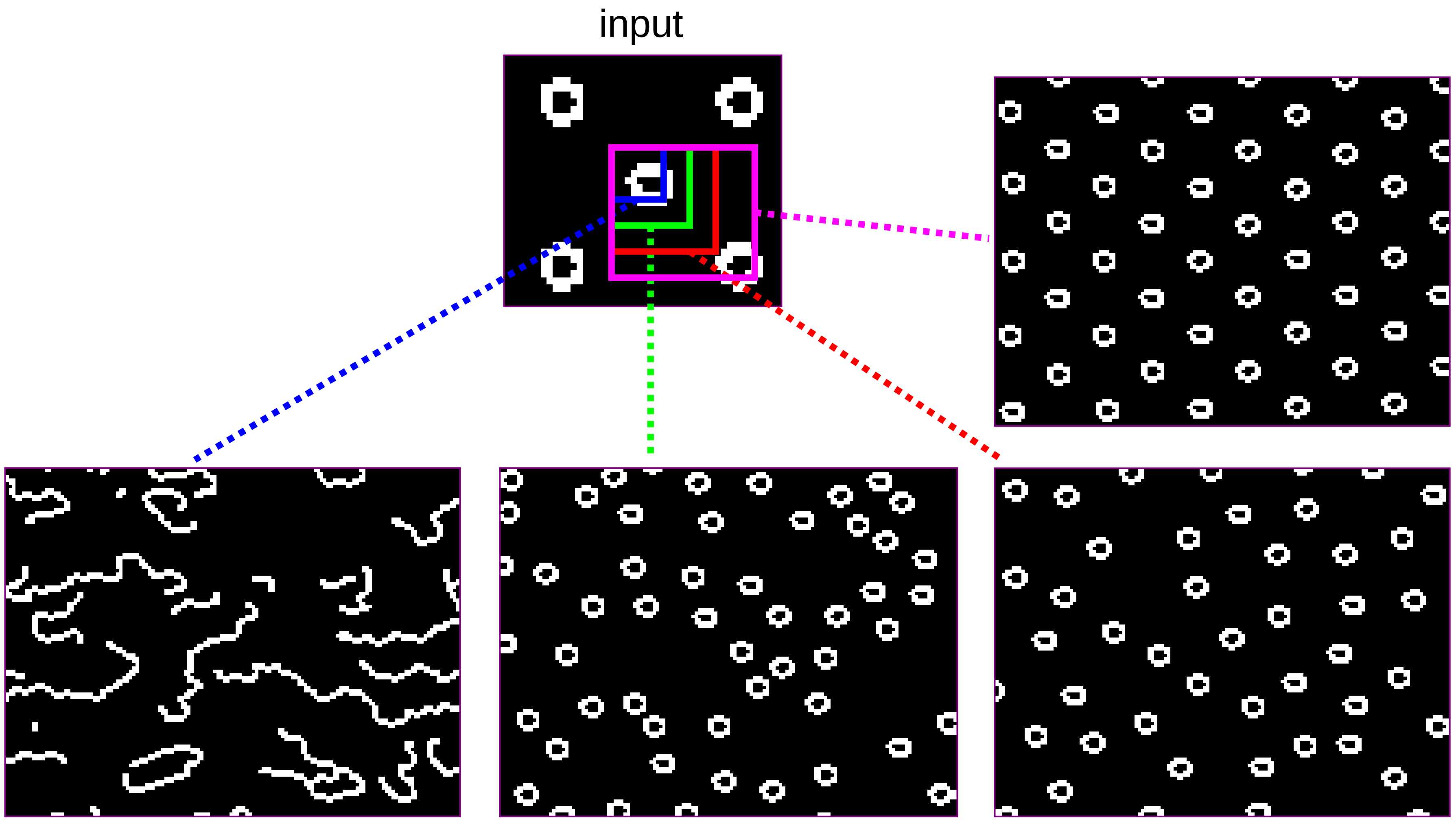
"I spent an interesting evening recently with a grain of salt."

(example from fake single.net user Mark V Shaney)

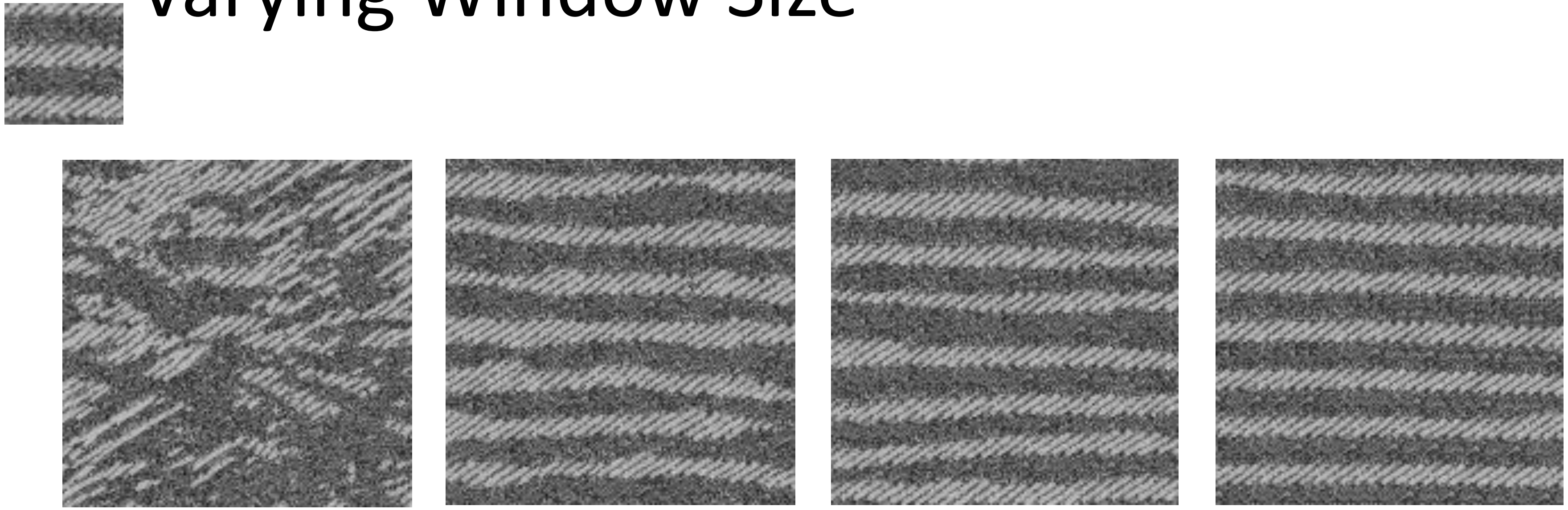
Details

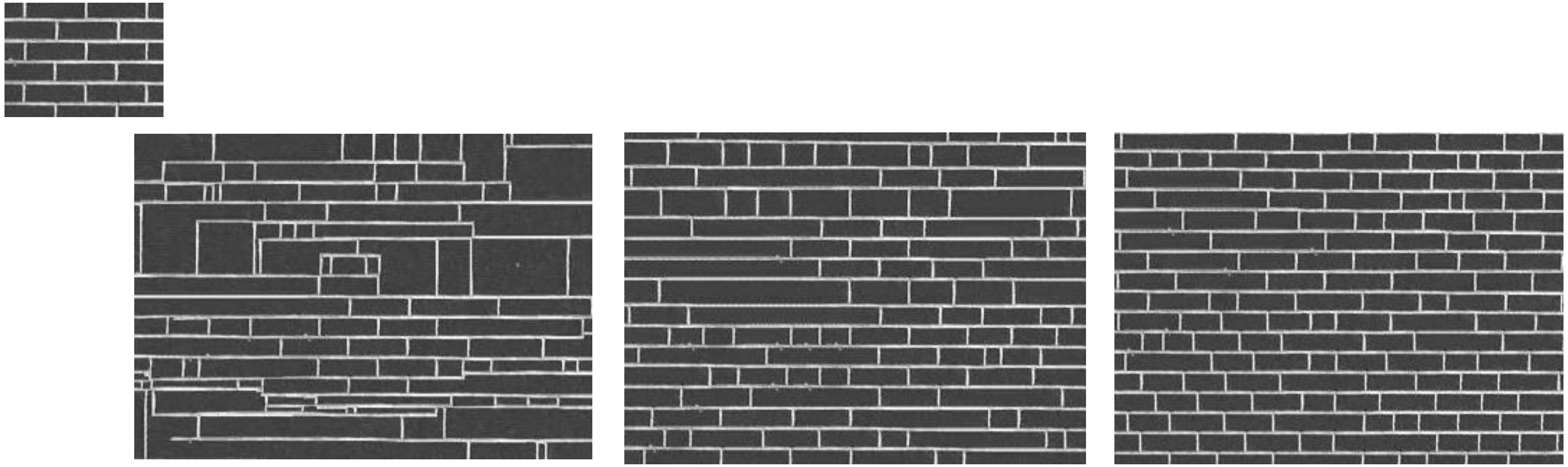
- How to match patches?
  - Gaussian-weighted SSD (more emphasis on nearby pixels)
- What order to fill in new pixels?
  - “Onion skin” order: pixels with most neighbors are synthesized first
  - To synthesize from scratch, start with a randomly selected small patch from the source texture
- How big should the patches be?

Size of Neighborhood Window



Varying Window Size





Increasing window size

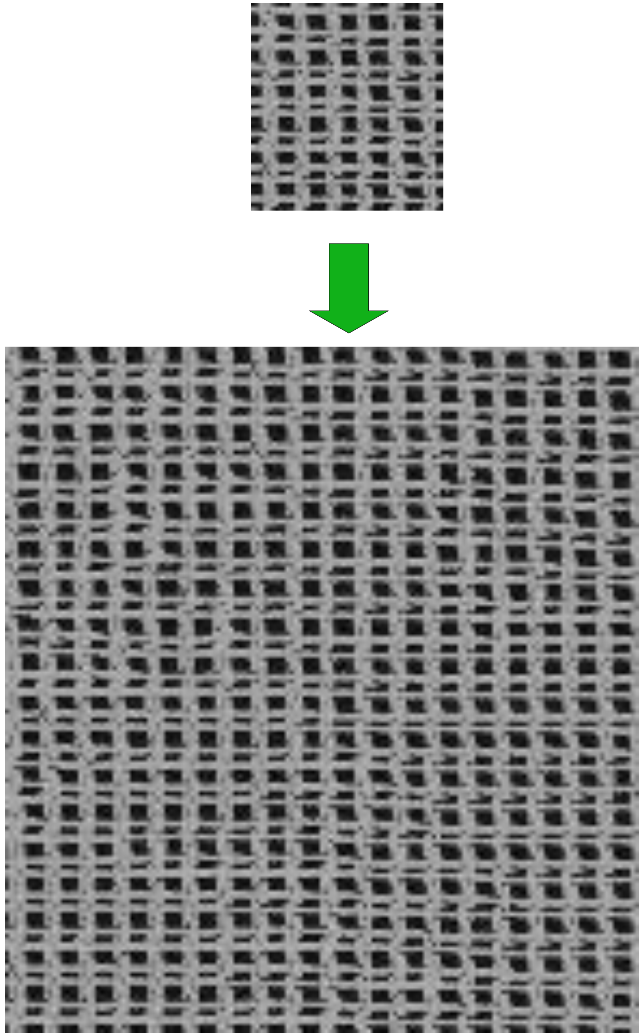
Texture synthesis algorithm

While image not filled

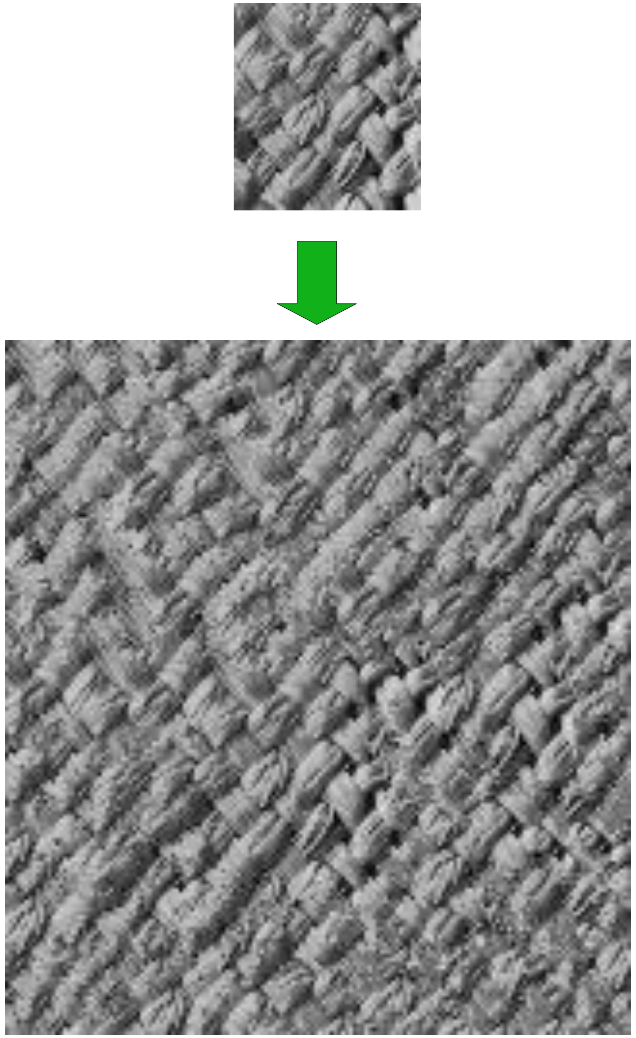
1. Get unfilled pixels with filled neighbors, sorted by number of filled neighbors
2. For each pixel, get top N matches based on visible neighbors
   - Patch Distance: Gaussian-weighted SSD
3. Randomly select one of the matches and copy pixel from it

Synthesis Results

french canvas

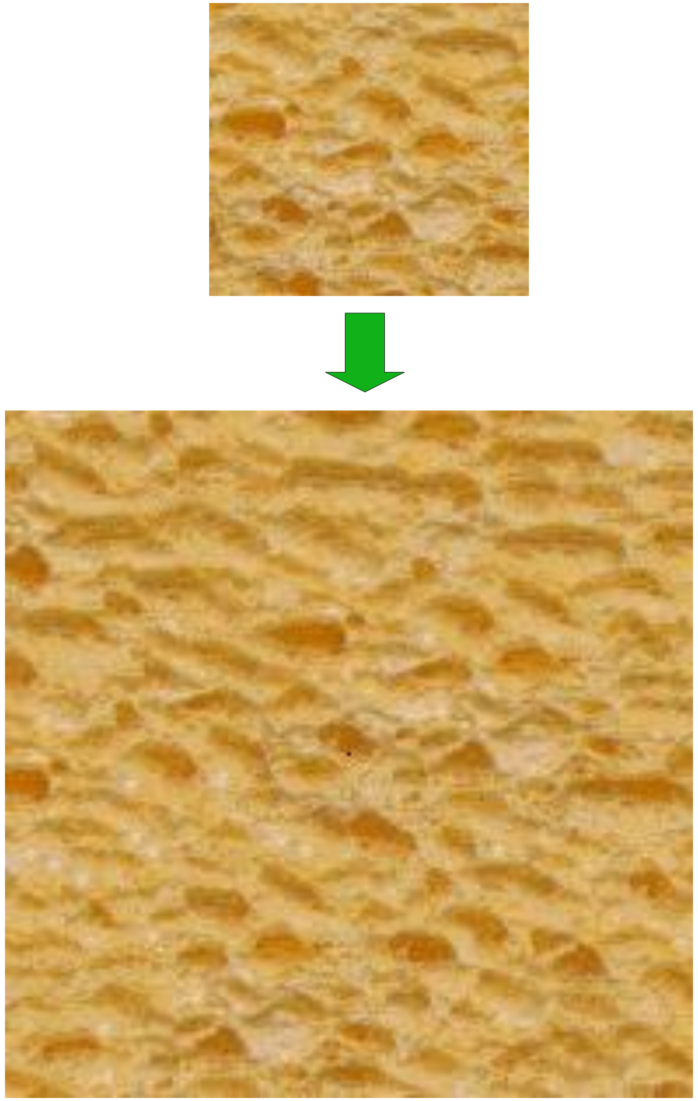


rafia weave

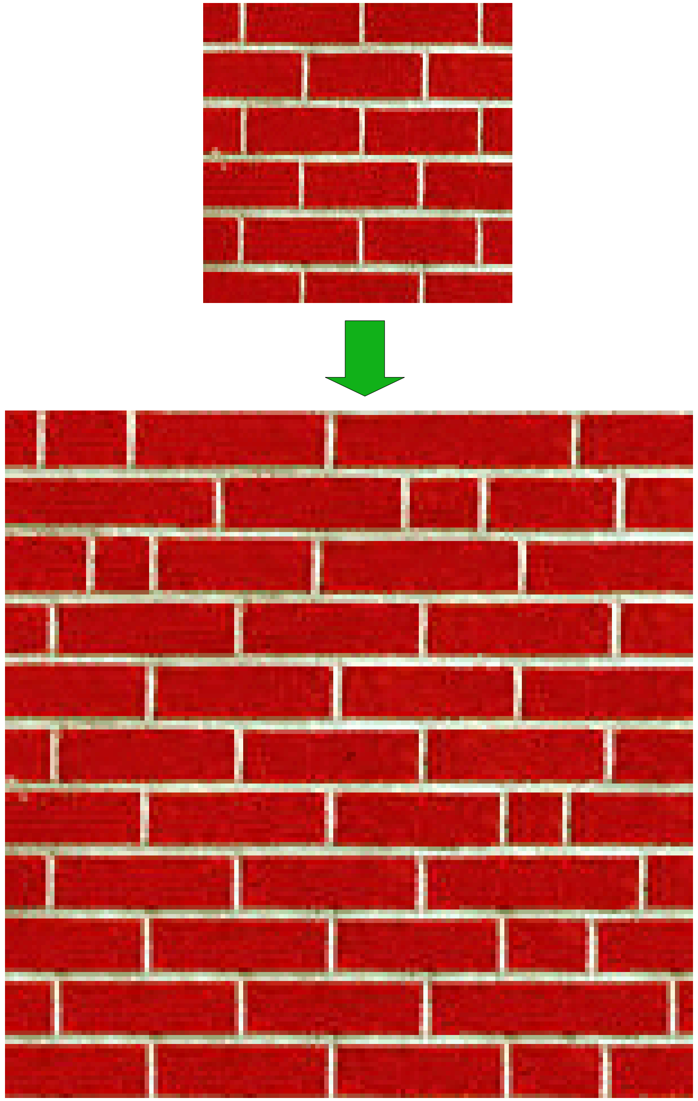


More Results

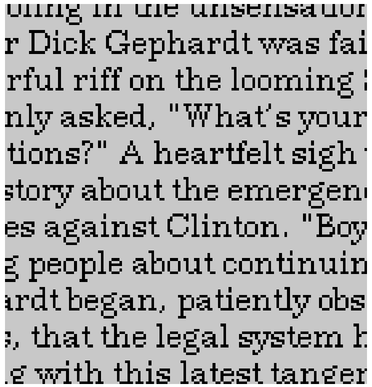
white bread

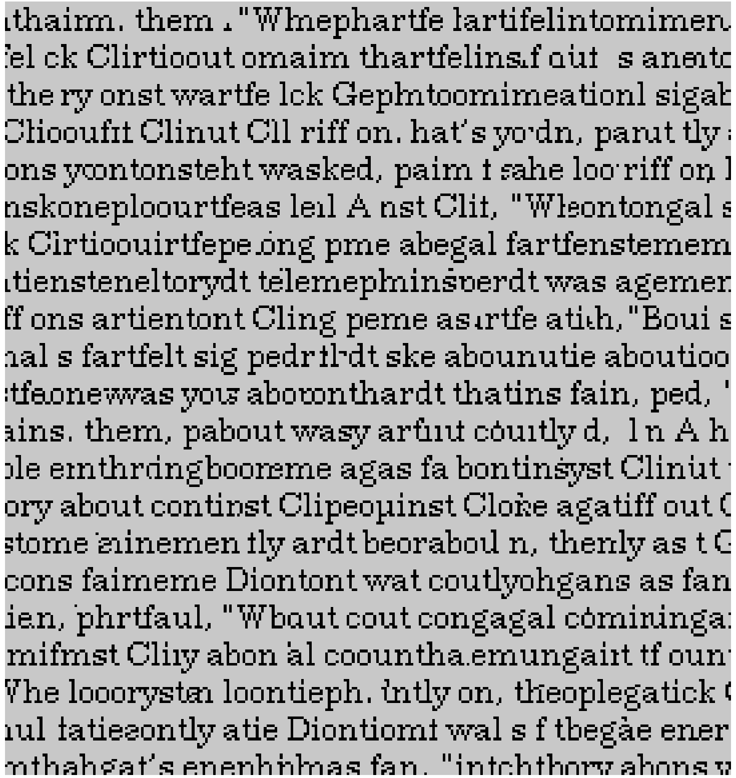


brick wall

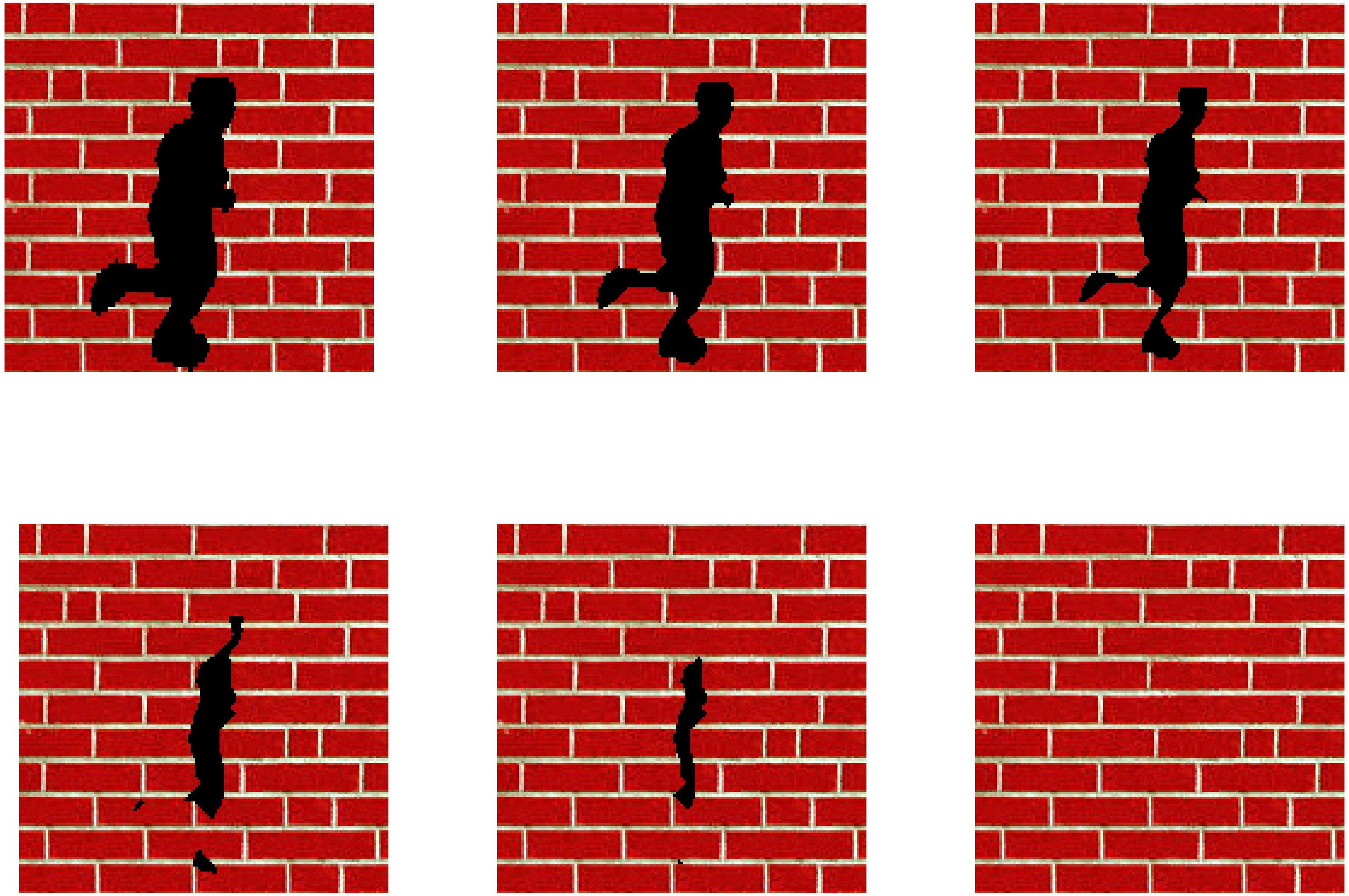


Homage to Shannon

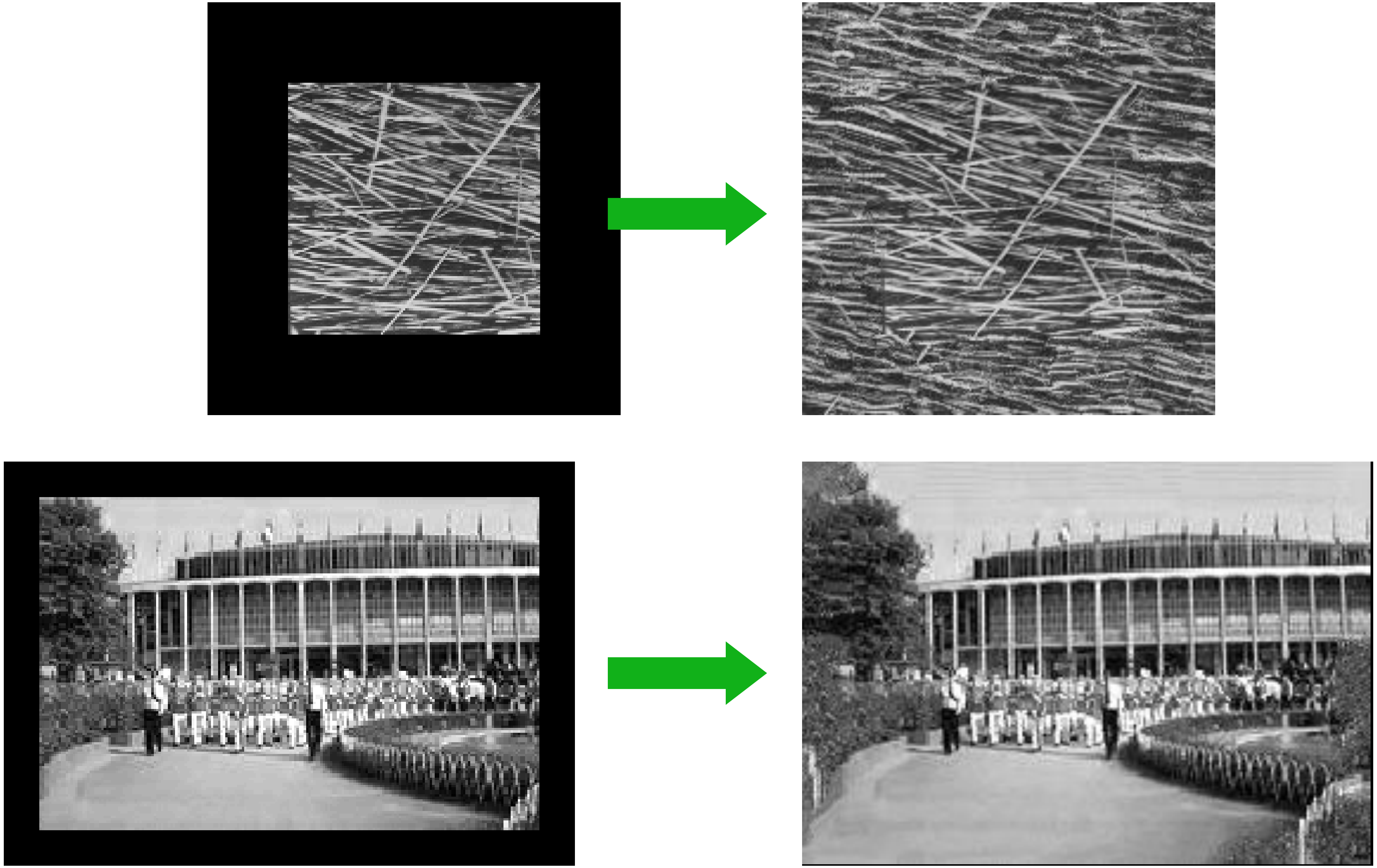




Hole Filling



Extrapolation



In-painting natural scenes

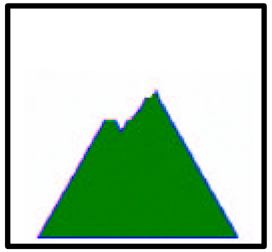
Criminisi, Perez, and Toyama. "Object Removal by Exemplar-based Inpainting," Proc. CVPR, 2003.

Key idea: Filling order matters

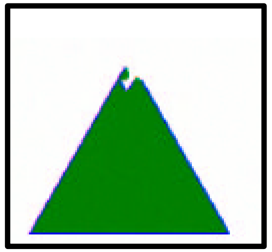
In-painting Result

Image with Hole

Raster-Scan Order



Onion-Peel
(Concentric Layers)



Gradient-Sensitive
Order

Criminisi, Perez, and Toyama. "Object Removal by Exemplar-based Inpainting," Proc. CVPR, 2003.

Filling order

Fill a pixel that:

1. Is surrounded by other known pixels
2. Is a continuation of a strong gradient or edge

Criminisi, Perez, and Toyama. “Object Removal by Exemplar-based Inpainting,” Proc. CVPR, 2003.

Comparison

Original With Hole Onion-Ring Fill Criminisi

Criminisi, Perez, and Toyama. "Object Removal by Exemplar-based Inpainting," Proc. CVPR, 2003.

Comparison

a

b

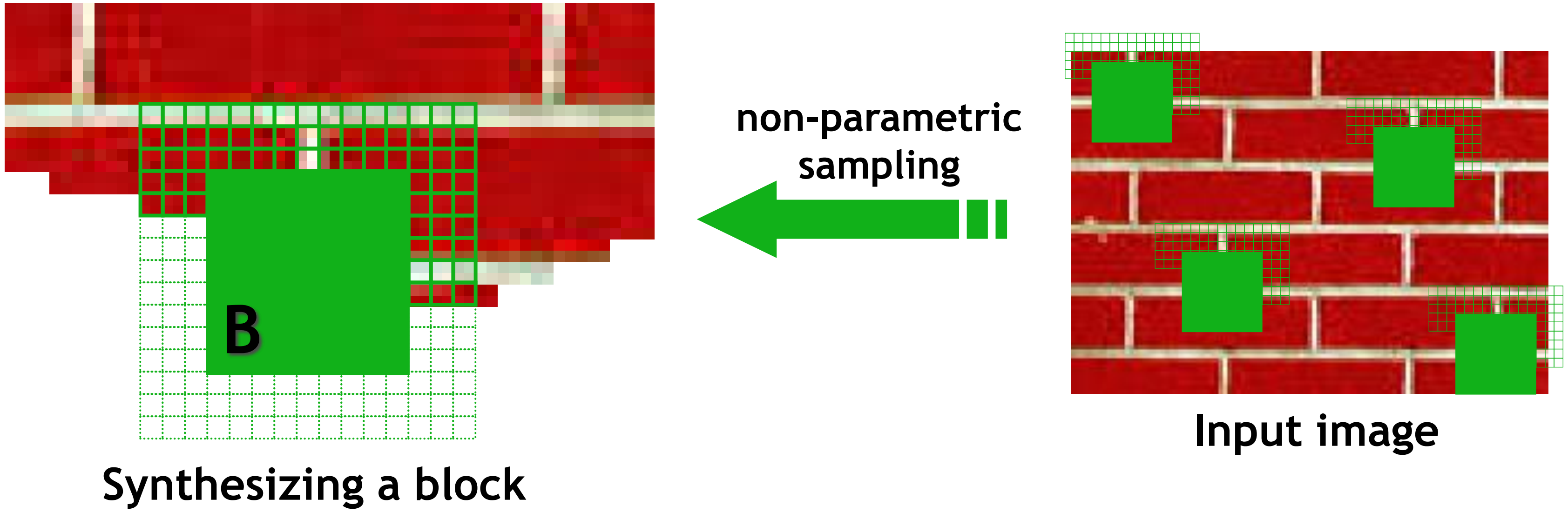
Concentric Layers

Gradient Sensitive

Summary (so far)

- The Efros & Leung texture synthesis algorithm
  - Very simple
  - Surprisingly good results
  - Synthesis is easier than analysis!
  - …but very slow

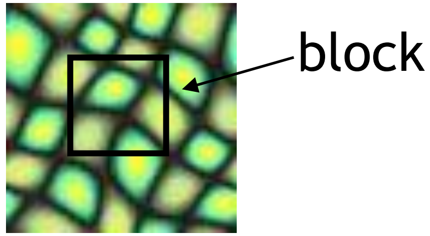
Image Quilting [Efros & Freeman 2001]



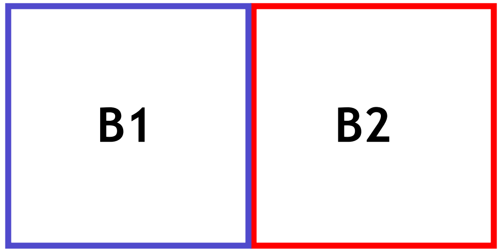
- <u>Observation:</u> neighbor pixels are highly correlated

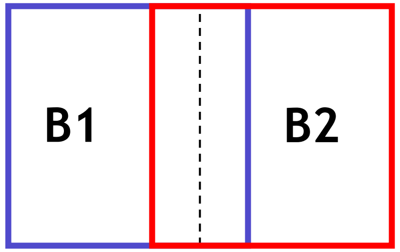
<u>Idea:</u> unit of synthesis = block

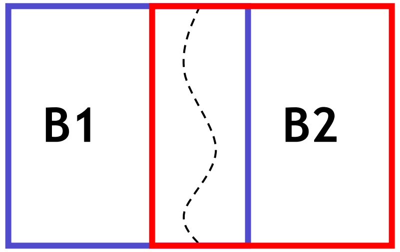
- Exactly the same but now we want P(**B**|N(**B**))
- Much faster: synthesize all pixels in a block at once



Input texture



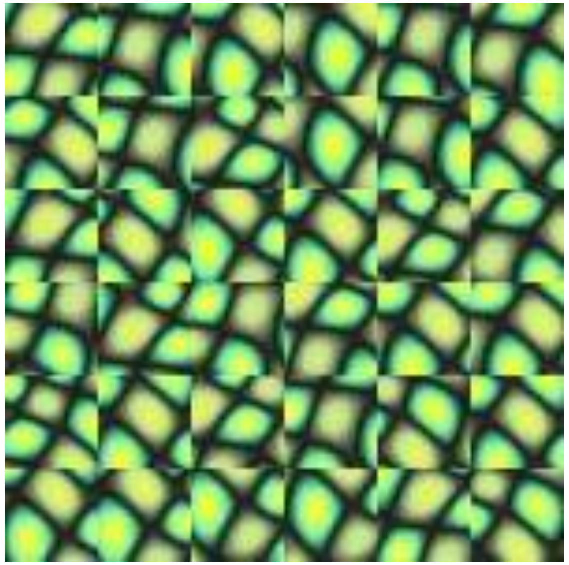


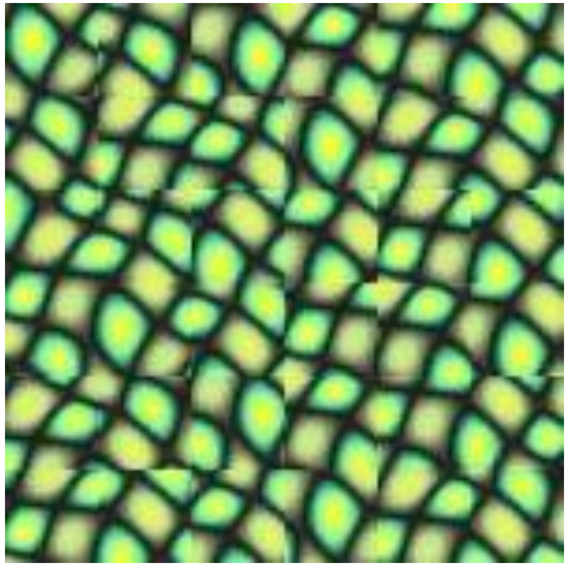


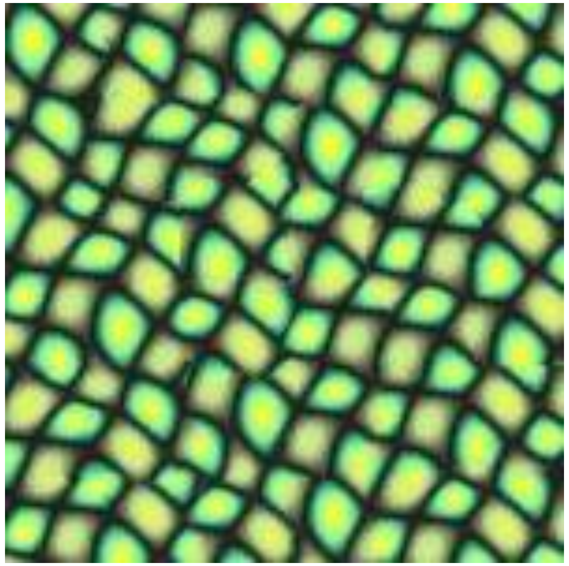
Random placement of blocks

Neighboring blocks constrained by overlap

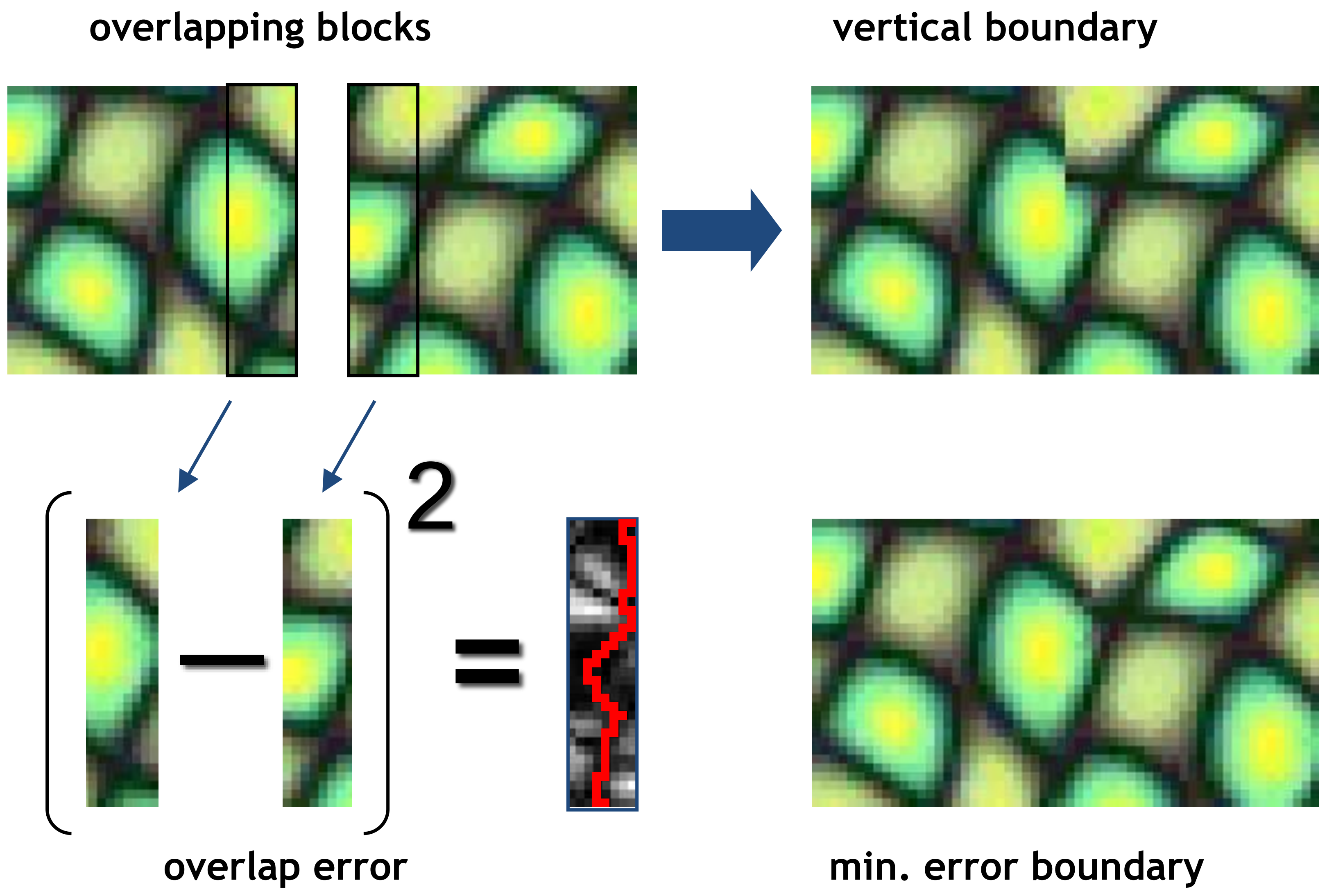
Minimal error boundary cut



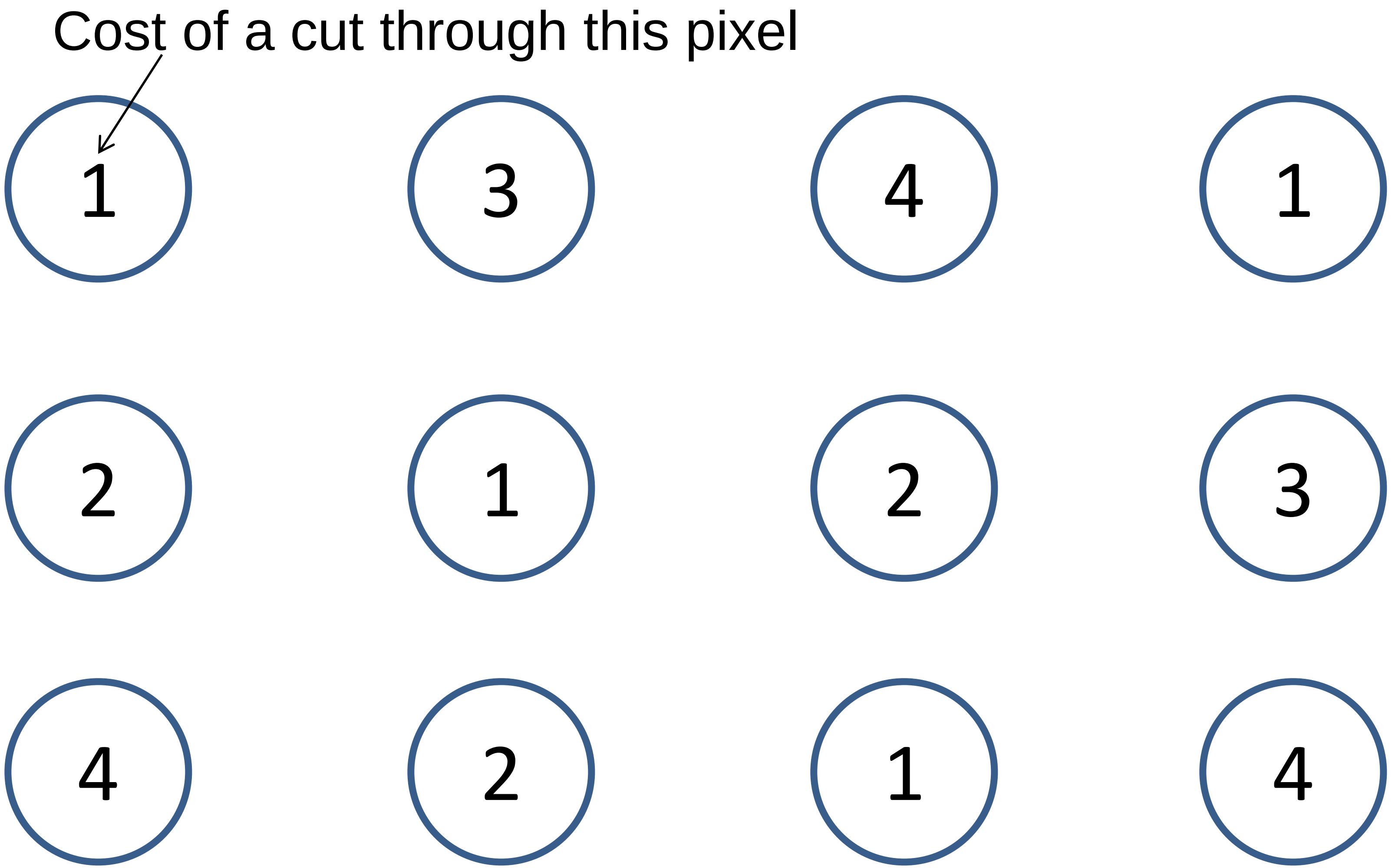




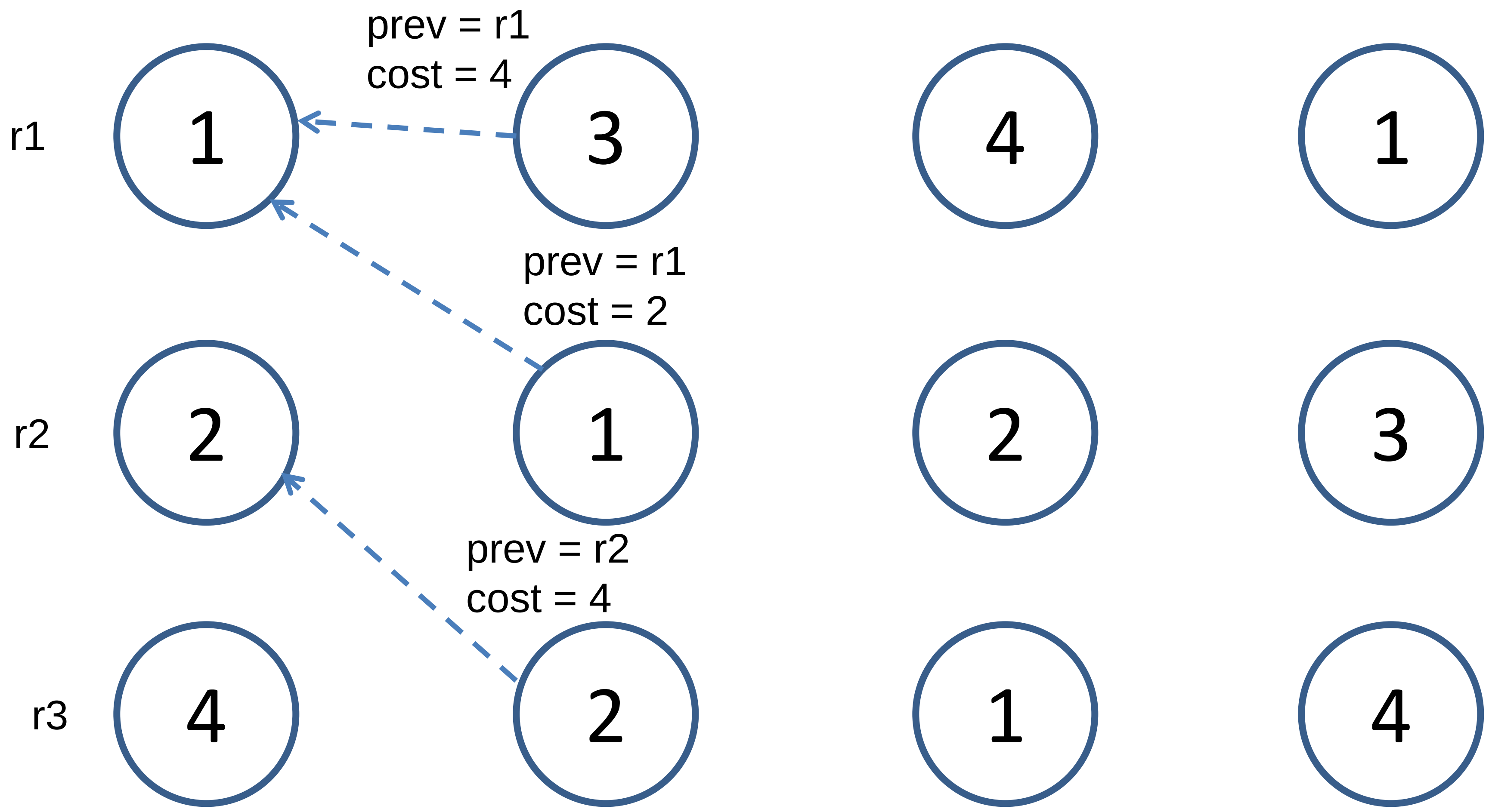
Minimal error boundary



Solving for Minimum Cut Path



Solving for Minimum Cut Path



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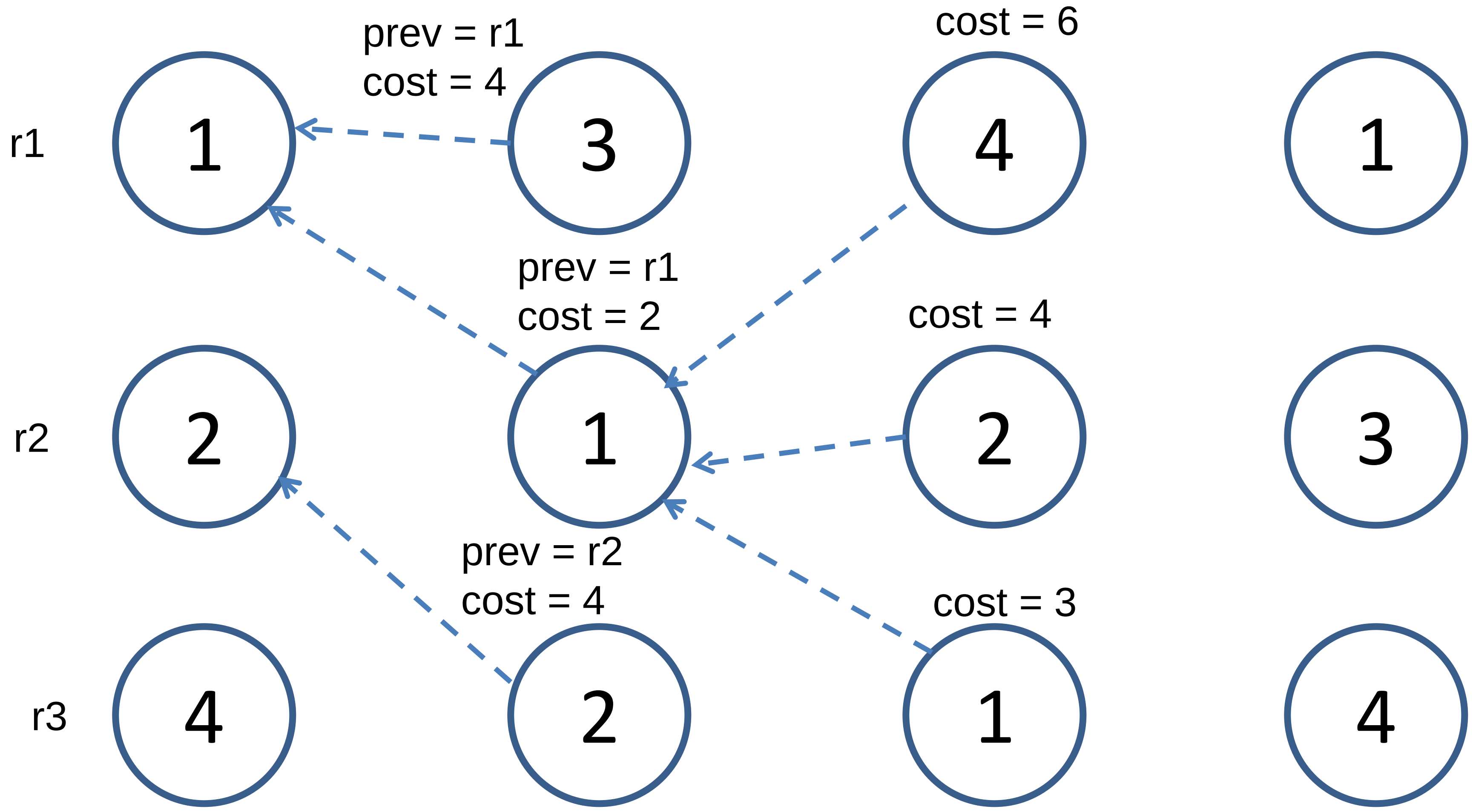

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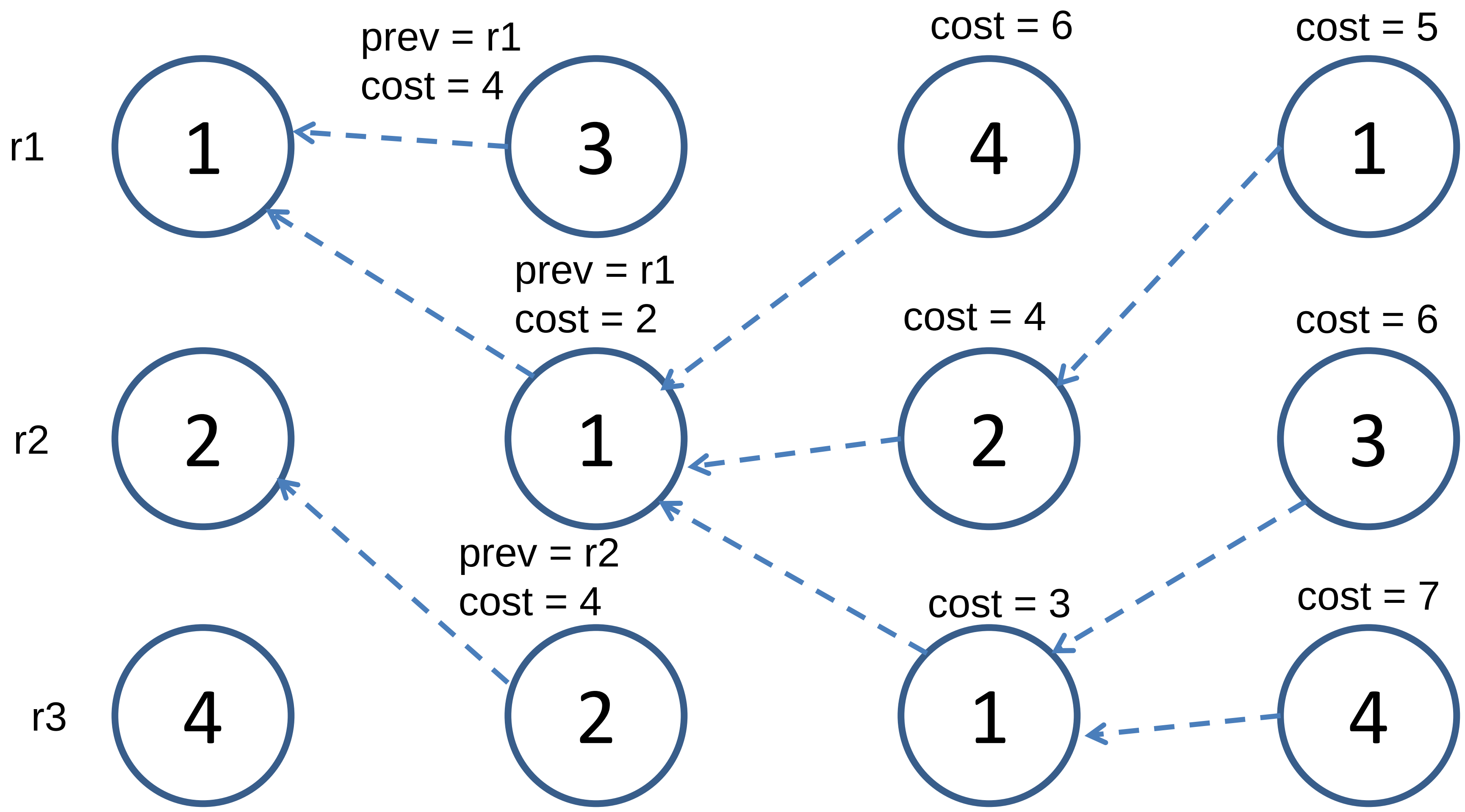

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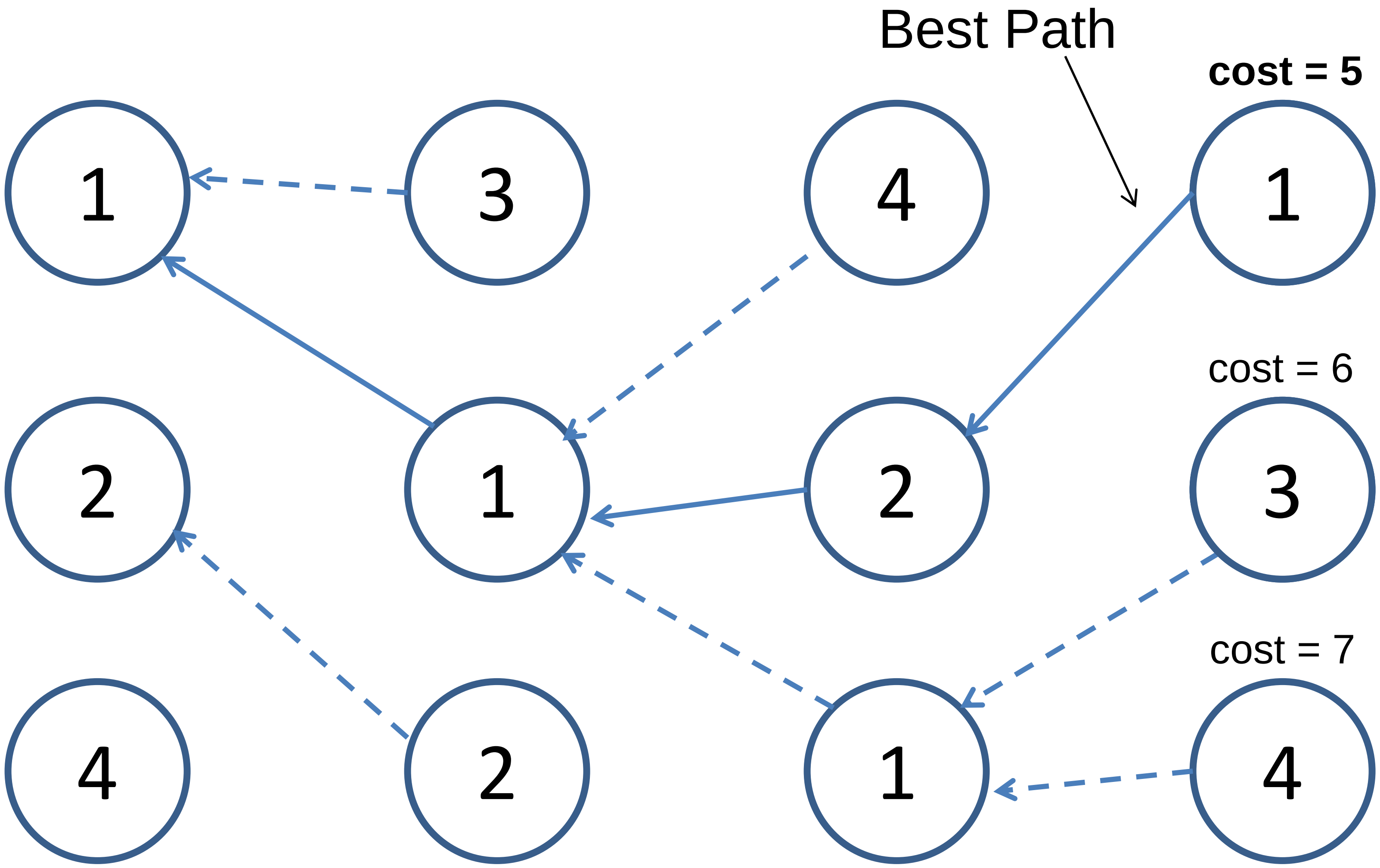
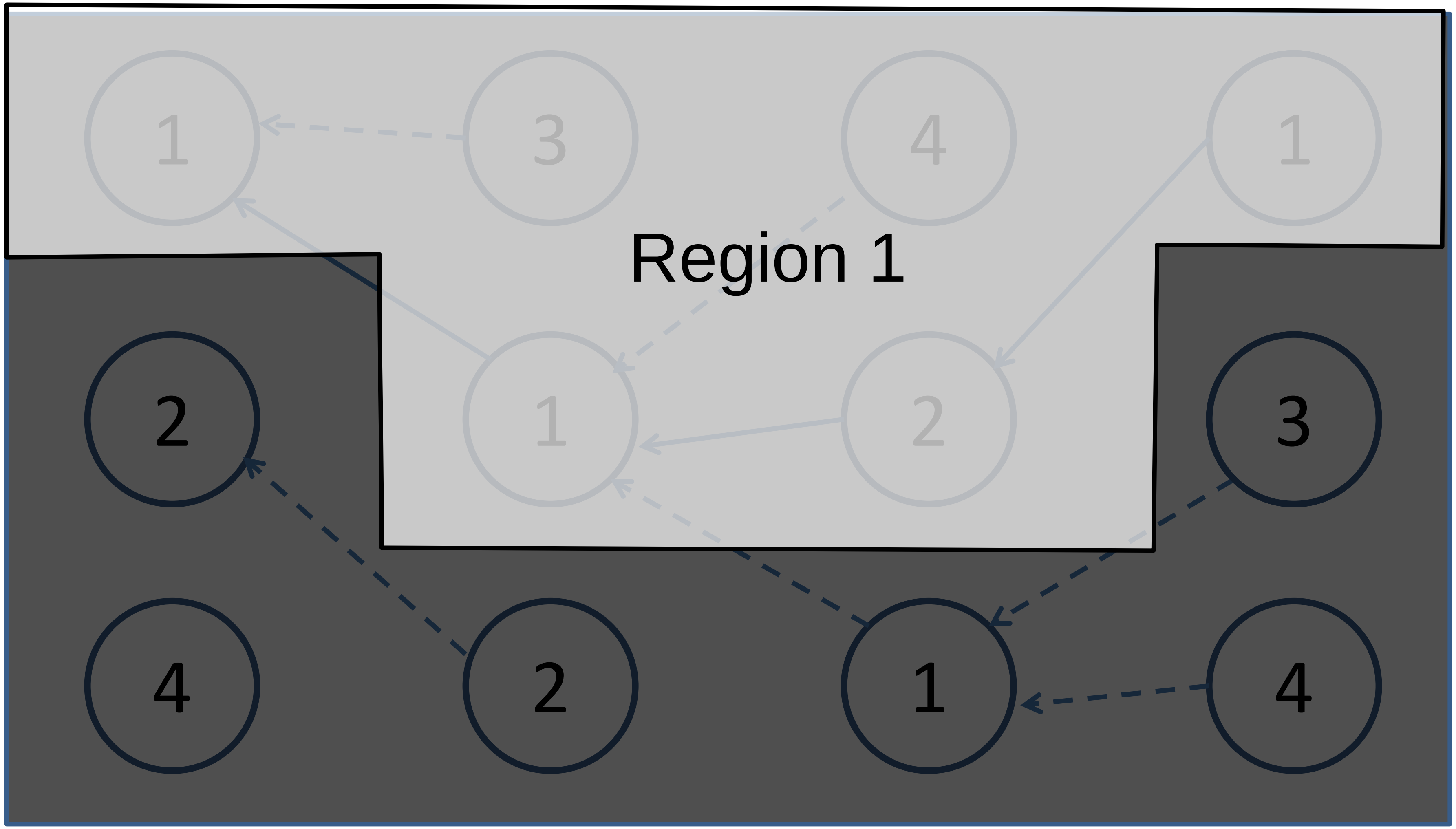
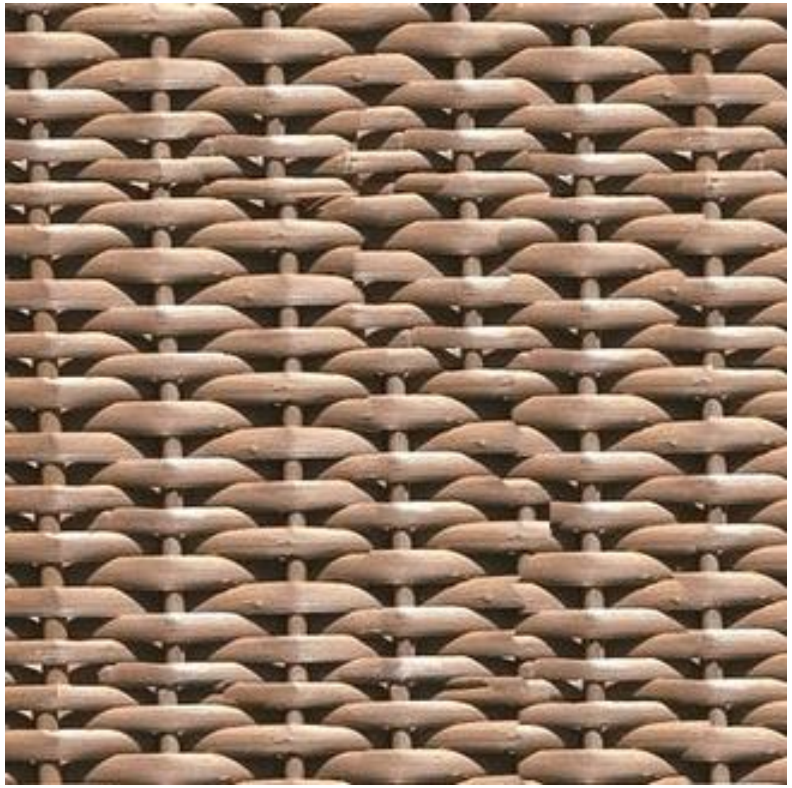


Solving for Minimum Cut Path

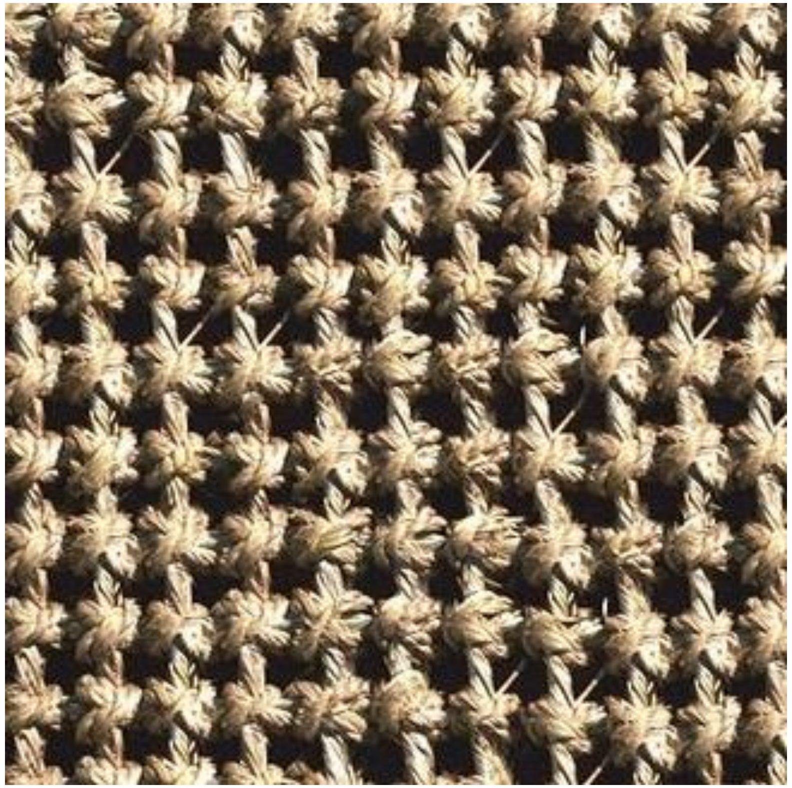


Mask Based on Best Path







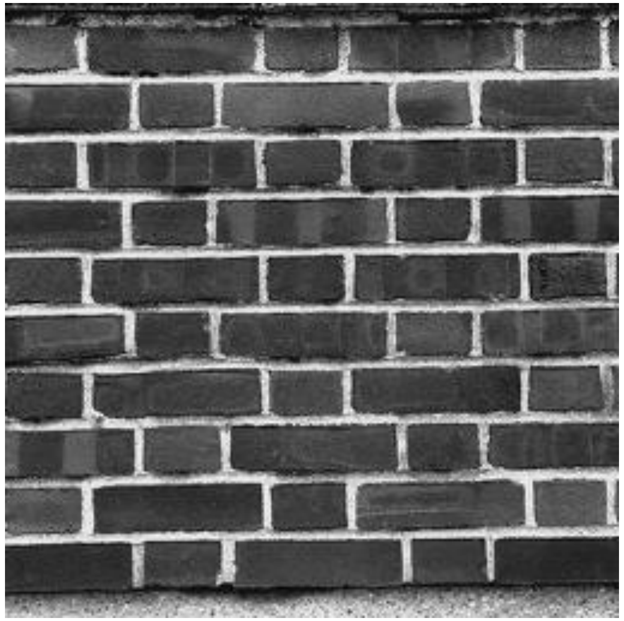




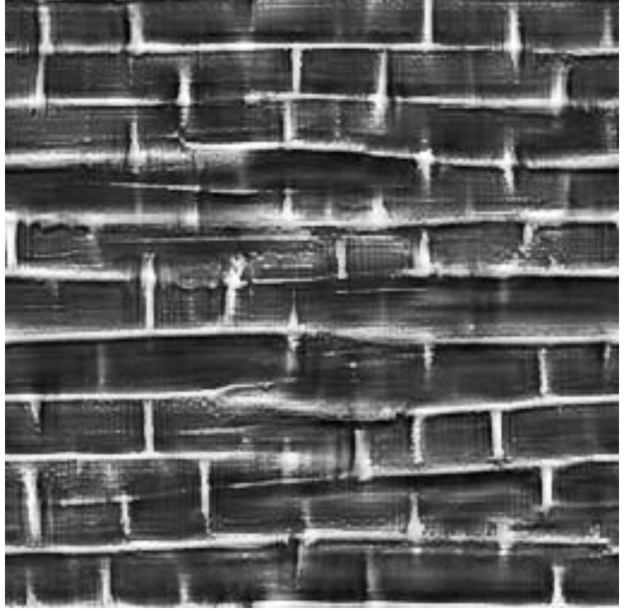

College Inn


College Inn

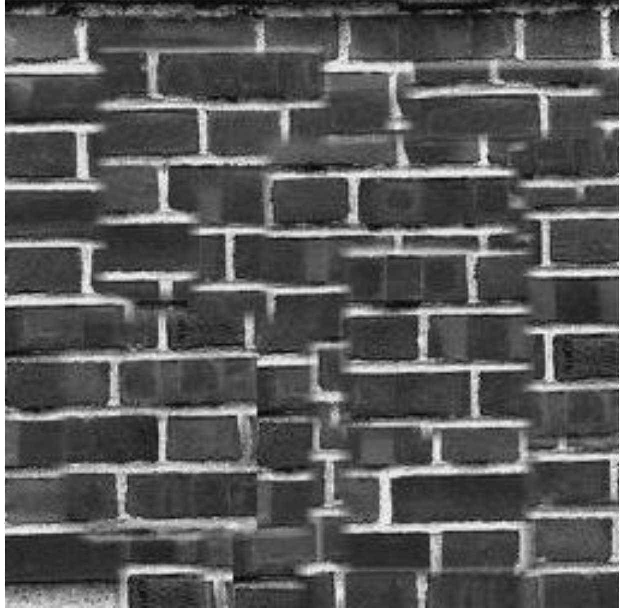


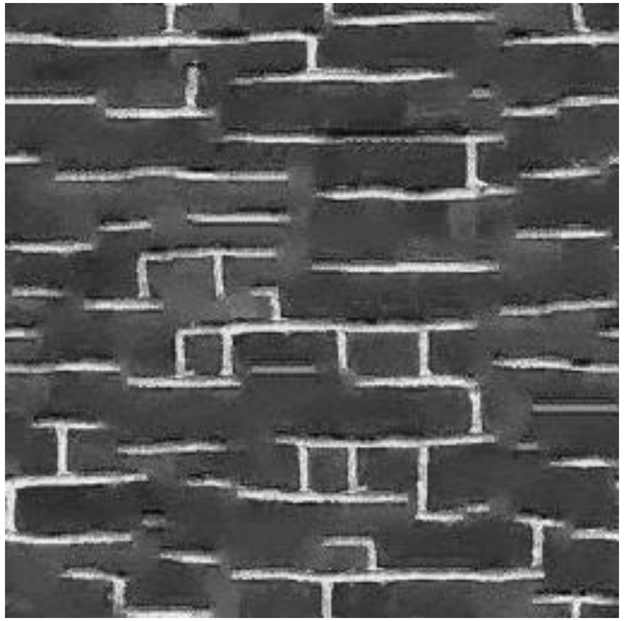
input image



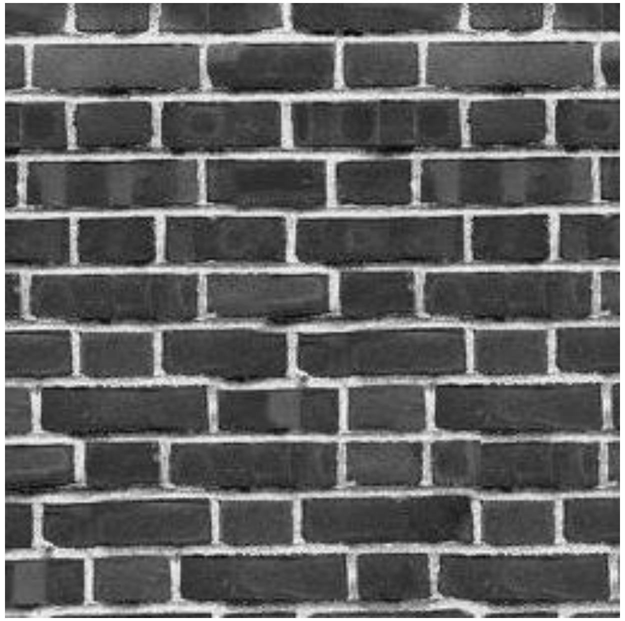
Portilla & Simoncelli



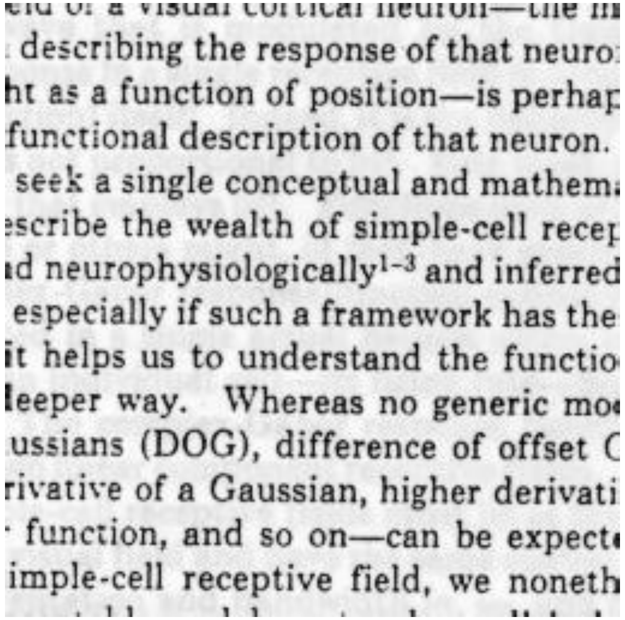
Xu, Guo & Shum



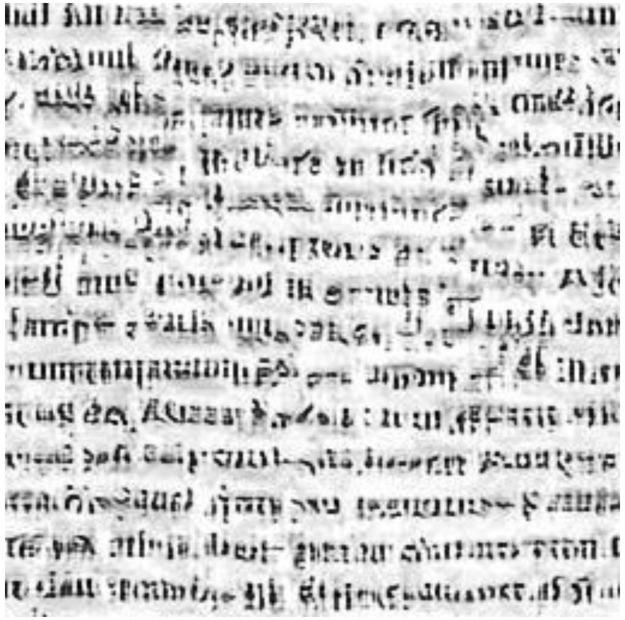
Wei & Levoy



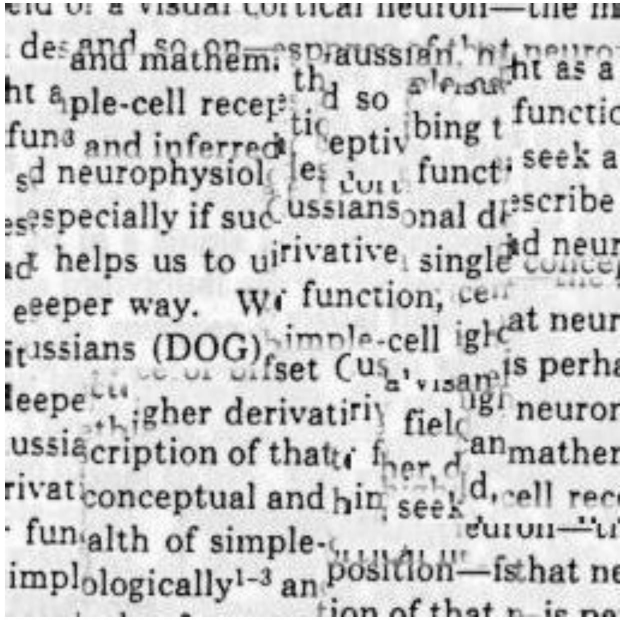
Quilting



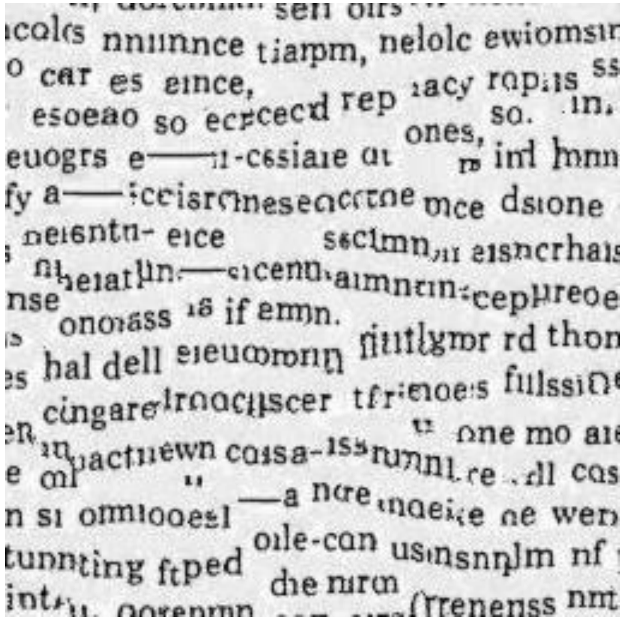
input image



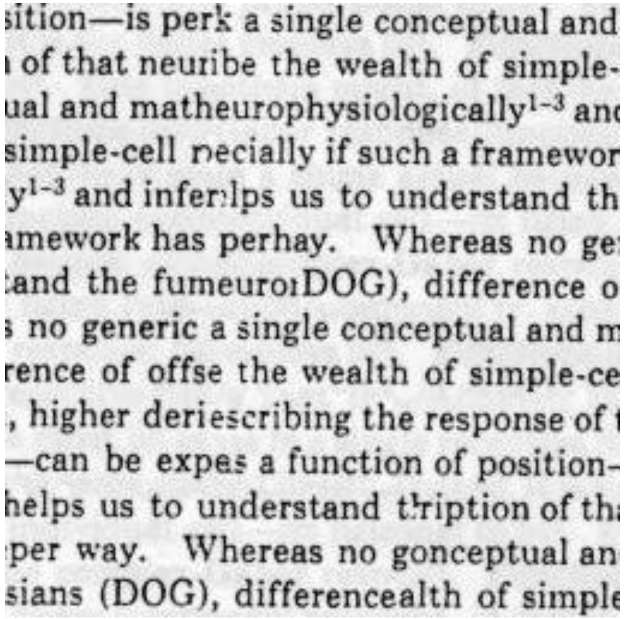
Portilla & Simoncelli



Xu, Guo & Shum

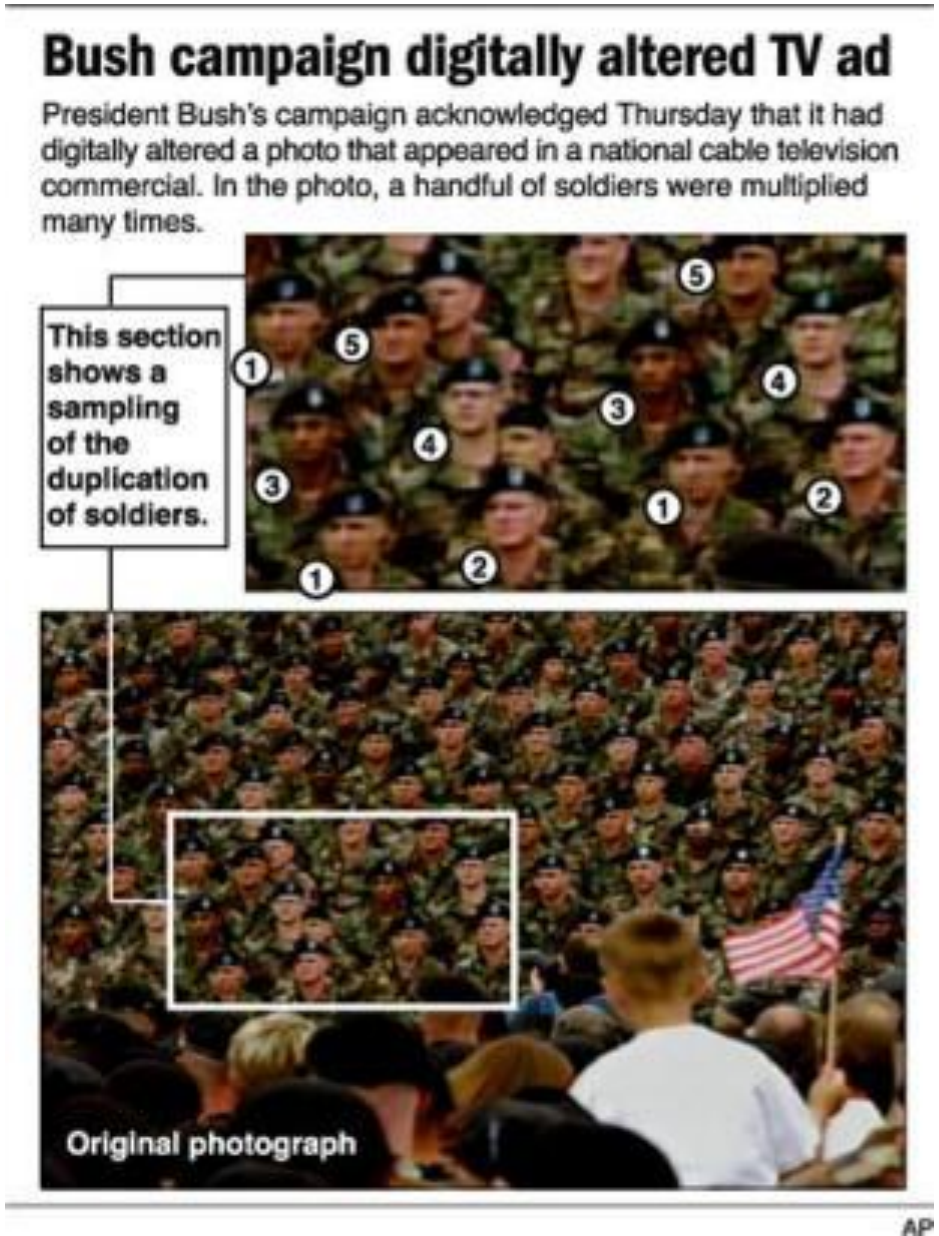


Wei & Levoy



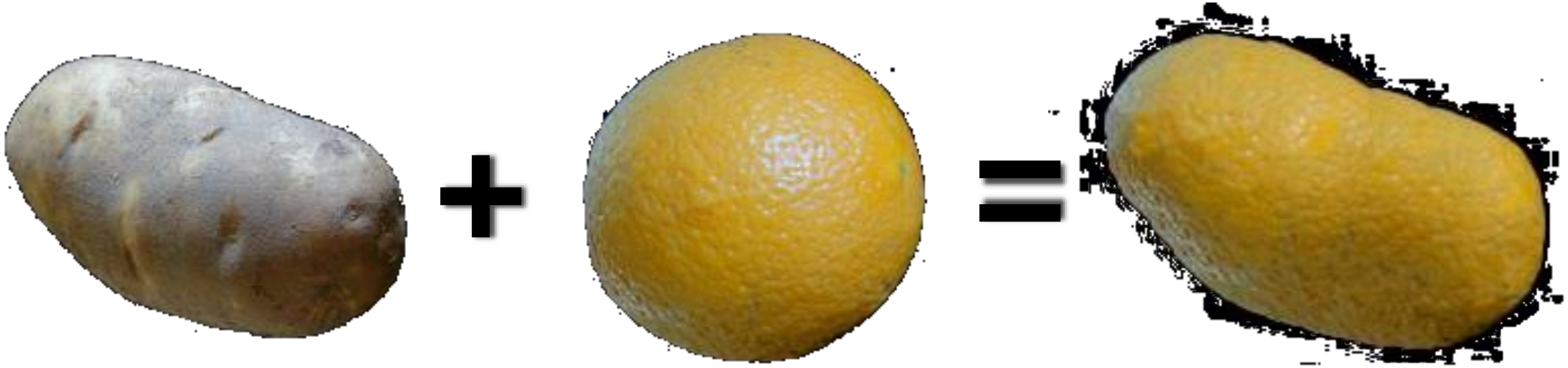
Quilting

Political Texture Synthesis



Texture Transfer

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



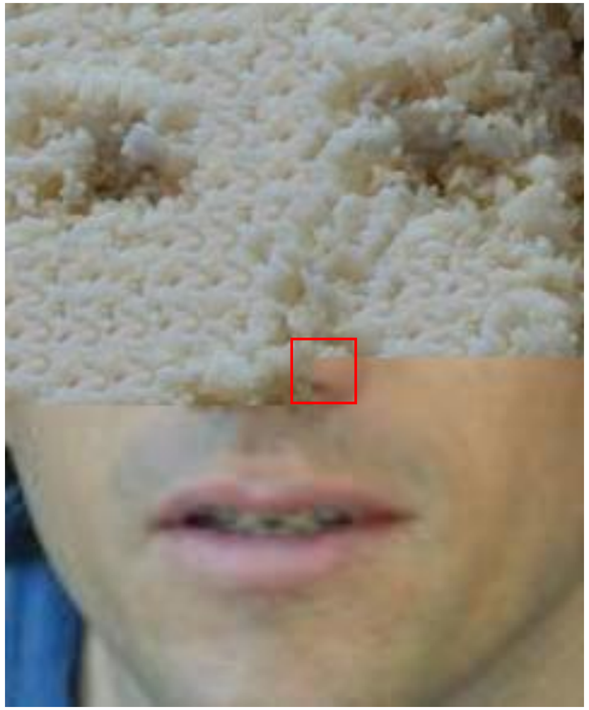
Texture Transfer

Constraint

Texture sample

Texture Transfer

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



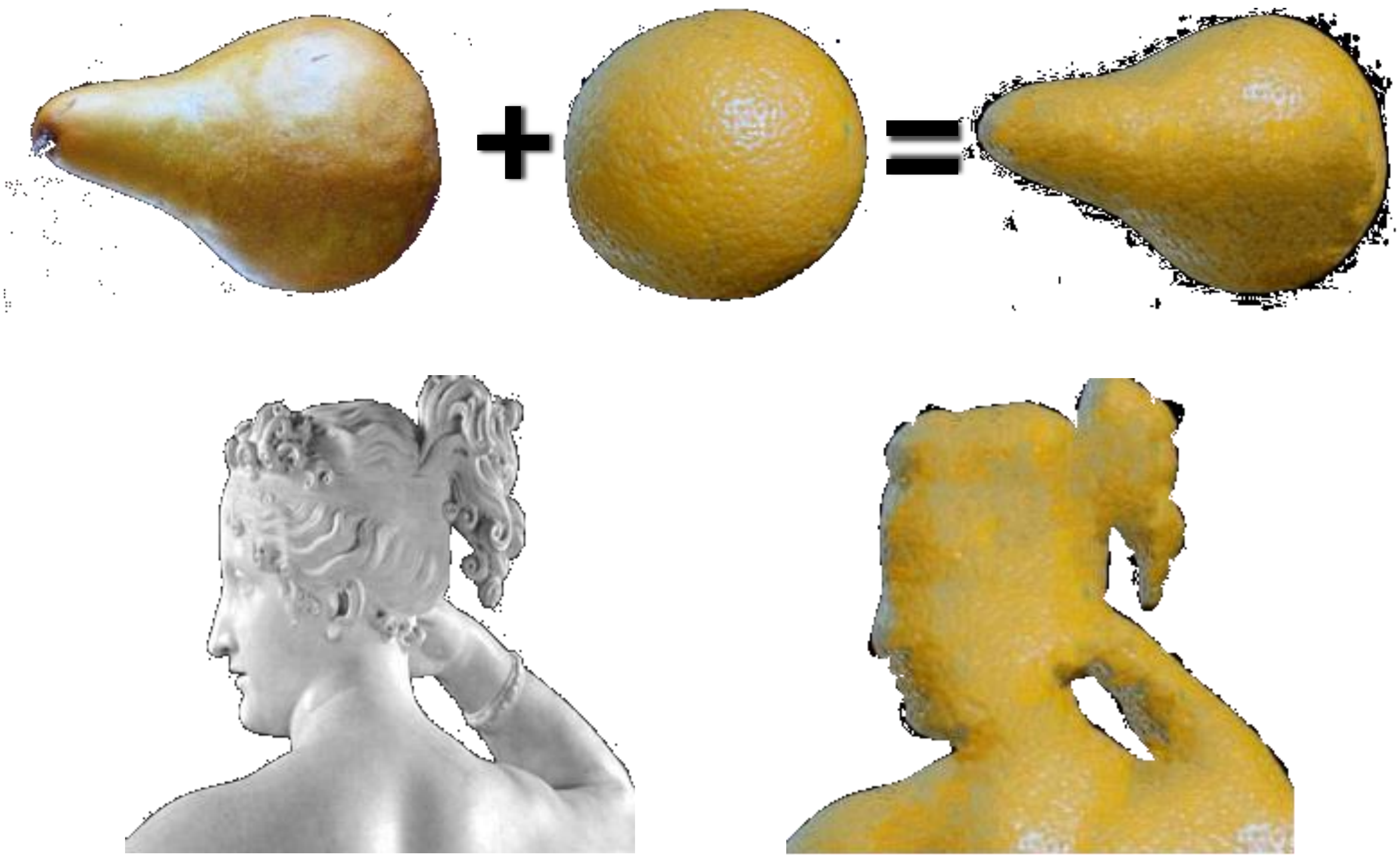
Same as texture synthesis, except an additional constraint:

1. Consistency of texture
2. Patches from texture should correspond to patches from constraint in some way. Typical example: blur luminance, use SSD for distance

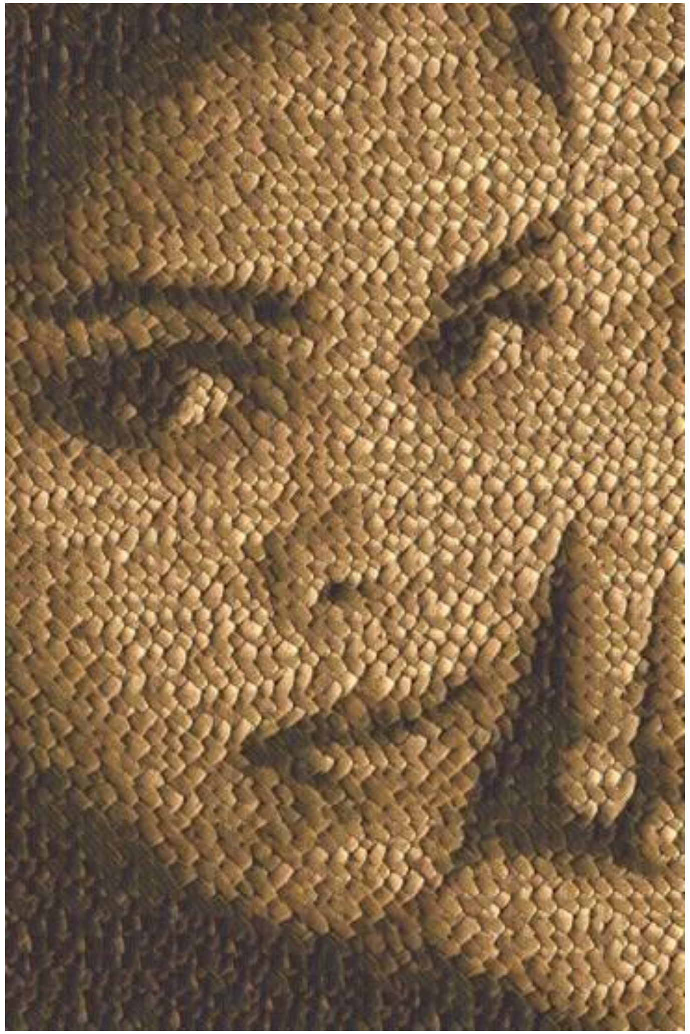
Correspondence maps

- Correspondence maps guide which patches from source are copied into texture
  - Cost to copy a patch is
  $\alpha * SSD_{overlap} + (1 - \alpha) * SSD_{transfer}$
  - $SSD_{overlap}$: sum sq dist of overlapping portion of patch with filled target image
  - $SSD_{transfer}$: sum sq dist of correspondence map in target and source

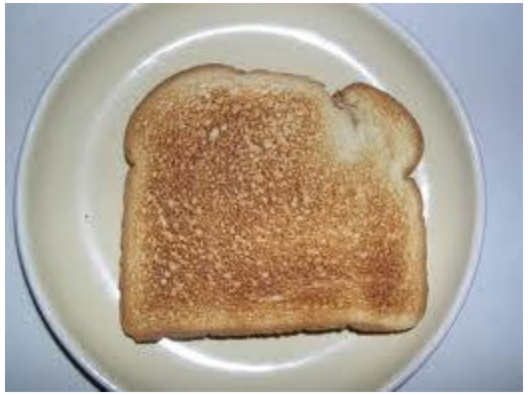
- Correspondence map typically is blurred grayscale version of original source and target
  - Want low frequency intensities to match but not details or color







Making sacred toast



+

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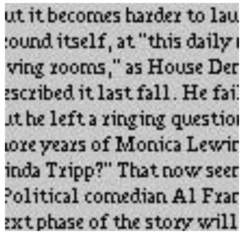
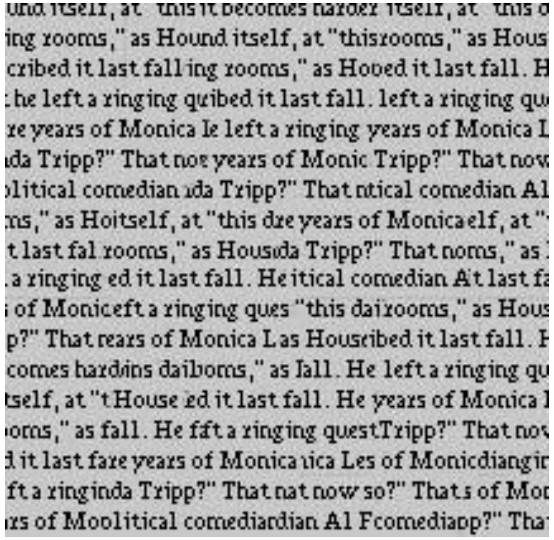
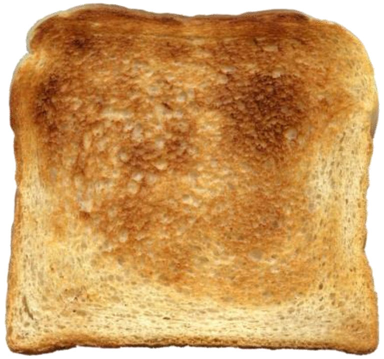
http://www.nbcnews.com/id/6511148/ns/us_news-weird_news/t/virgin-mary-grilled-cheese-sells/

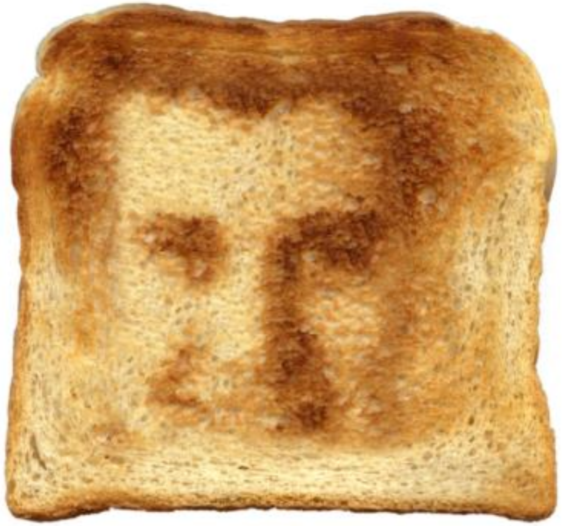
Project 2: texture synthesis and transfer

- https://courses.engr.illinois.edu/cs445/fa2022/projects/quilting/ComputationalPhotography_ProjectQuilting.html
- Note: this is significantly more challenging than the first project









Texture Synthesis and Transfer Recap

For each overlapping patch in the output image

1. Compute the cost to each patch in the sample
   - Texture synthesis: this cost is the SSD (sum of square difference) of pixel values in the overlapping portion of the existing output and sample
   - Texture transfer: cost is $\alpha * SSD_{overlap} + (1 - \alpha) * SSD_{transfer}$ The latter term enforces that the source and target correspondence patches should match.
2. Select one sample patch that has a small cost (e.g. randomly pick one of K candidates)
3. Find a cut through the left/top borders of the patch based on overlapping region with existing output
   - Use this cut to create a mask that specifies which pixels to copy from sample patch
4. Copy masked pixels from sample image to corresponding pixel locations in output image

PatchMatch

- Efros & Leung synthesis is very slow: for every pixel to be filled, match surrounding patch across the source image
- "Image Quilting" is faster by copying a patch at a time and blending it into the output
  - Typically neighboring pixels in source should stay together, so copy them patch by patch
- PatchMatch solves this in a more efficient and general way

Barnes et al. Siggraph 2009
http://gfx.cs.princeton.edu/pubs/Barnes_2009_PAR/index.php

PatchMatch

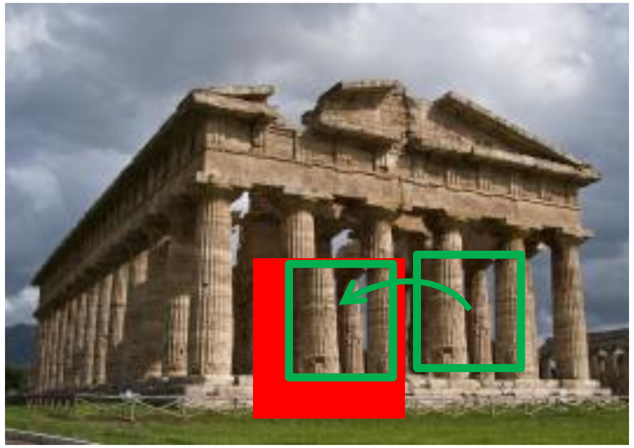
- Goal: Solve for labels that minimize some cost function

Hole Fill-in:
For each pixel (i,j) in the hole, solve for pixel coordinate (n,m) from source to minimize sum of SSD of patches between target and source

How to solve for this efficiently?

PatchMatch

- Goal: Solve for labels that minimize some cost function

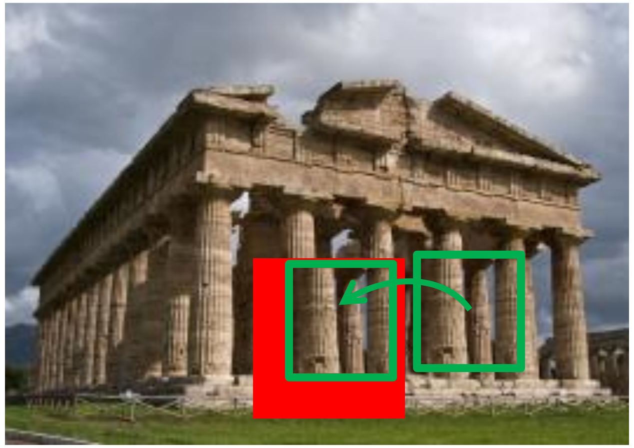


Hole Fill-in:
For each pixel (i,j) in the hole, solve for ~~**pixel coordinate (n,m)**~~ **offset (a,b)=(n,m)-(i,j)** from source to minimize sum of SSD of patches between target and source

When copying a patch, offset is piecewise constant

PatchMatch

- Goal: Solve for labels that minimize some cost function
- Key assumption: a pixel and its neighbor very likely have the same or similar labels



Hole Fill-in:
For each pixel (i,j) in the hole, solve for **offset (a,b)=(n,m)-(i,j)** from source to minimize sum of SSD of patches between target and source

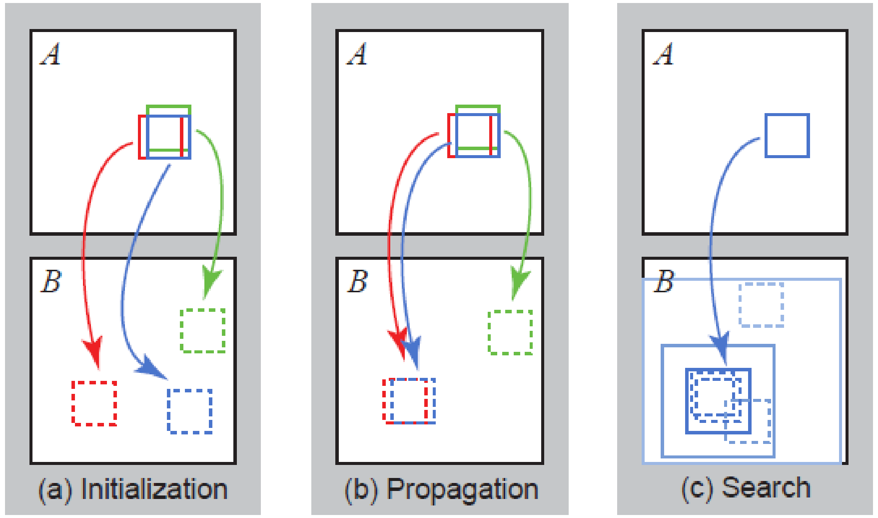
When copying a patch, offset is piecewise constant

PatchMatch: Optimization

- Goal: Solve for labels that minimize some cost function
- Key assumption: a pixel and its neighbor very likely have the same or similar labels

PatchMatch Algorithm basics

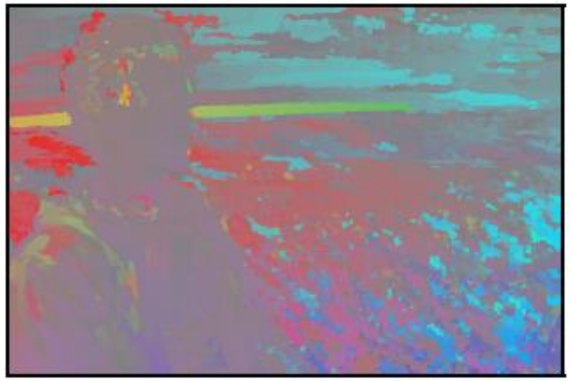
1. Randomly initialize matches
2. Scan across image (forward and backward)
   a. Check if neighbor's offsets or random perturbations around current offset produce better scores
   b. Keep best found so far
3. Repeat (2) several times



PatchMatch: Convergence

(a) originals (b) random (c) $\frac{1}{4}$ iteration (d) $\frac{3}{4}$ iteration (e) 1 iteration (f) 2 iterations (g) 5 iterations

Example of convergence with retargeting (find offsets to map bottom image onto top)



Why so fast?

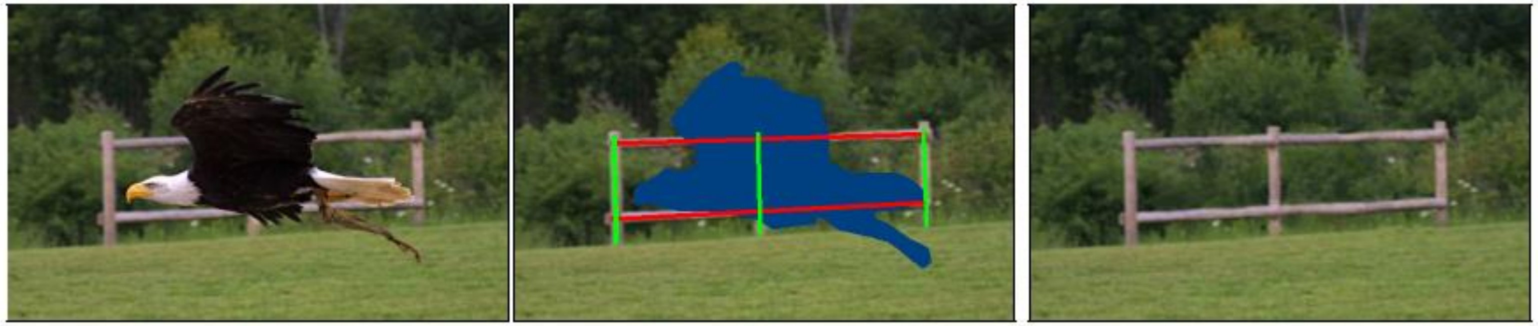
- Offset has constant or similar values in large regions
- Very good chance that at least one pixel gets lucky in random assignment
- Good assignments propagate quickly

PatchMatch: Image Completion

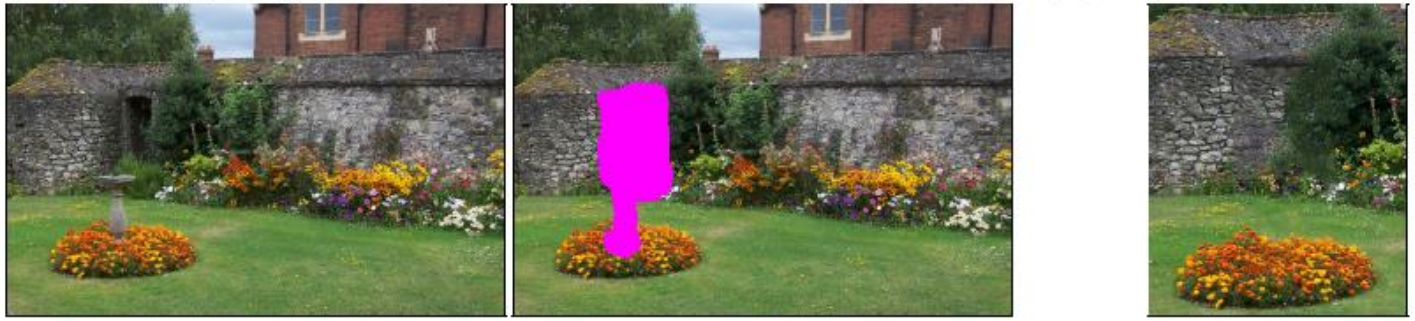
Guides constrain search

(a) original (b) hole+constraints

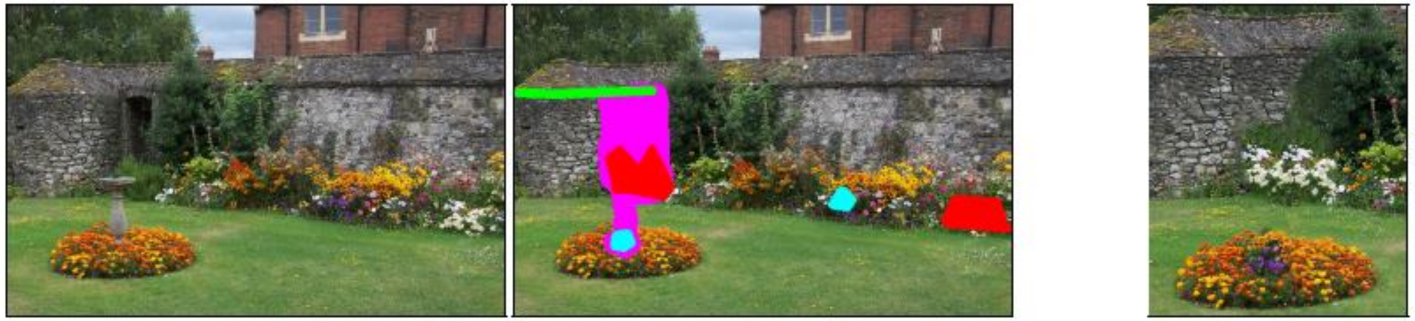
(c) hole filled



(a) input (b) hole and guides (c) completion result



(d) input (e) hole (f) completion (close up)



(g) same input (h) hole and guides (i) guided (close up)

PatchMatch: retargeting

- Produce output image of target size with optional constraints
- Bi-directional matching: each patch in source should match something in target and vice-versa

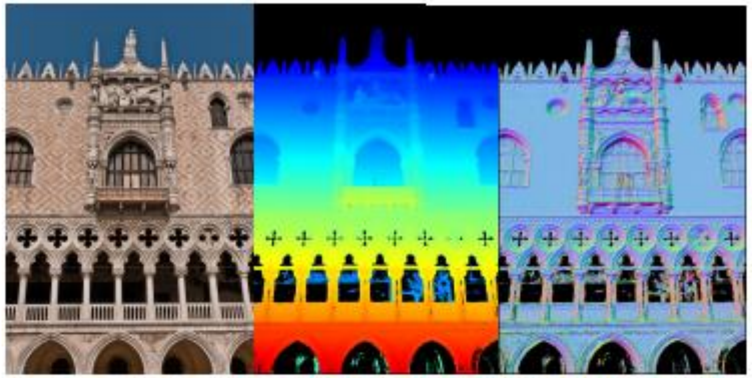
PatchMatch: other applications and extensions

Applications

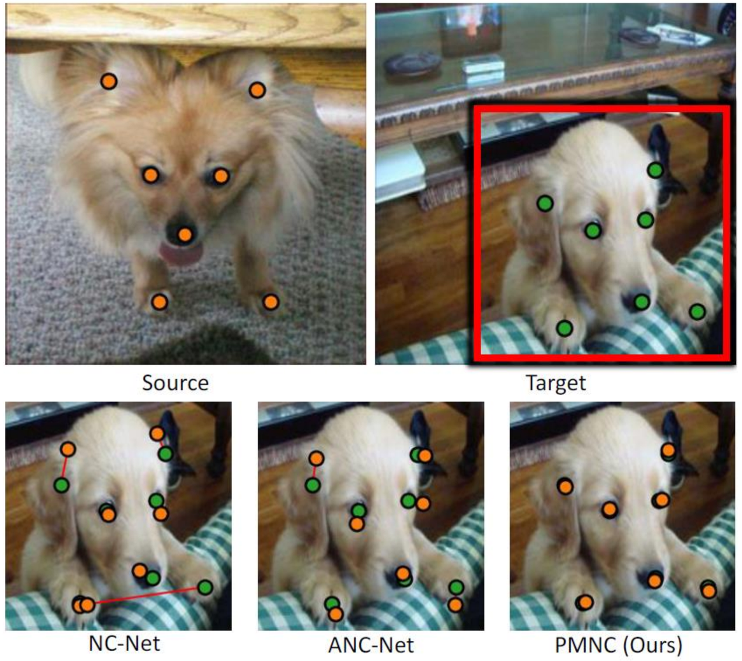
- Two-view stereo: labels are displacements
- Multiview stereo: labels are plane parameters
- Semantic correspondence: labels are offsets
- Denoising, symmetry detection, …

Extensions

- Red/black propagation for efficient GPU implementation
- Varying propagation/scoring schemes



Schoenberger et al. ECCV 2016



Lee et al. CVPR 2021

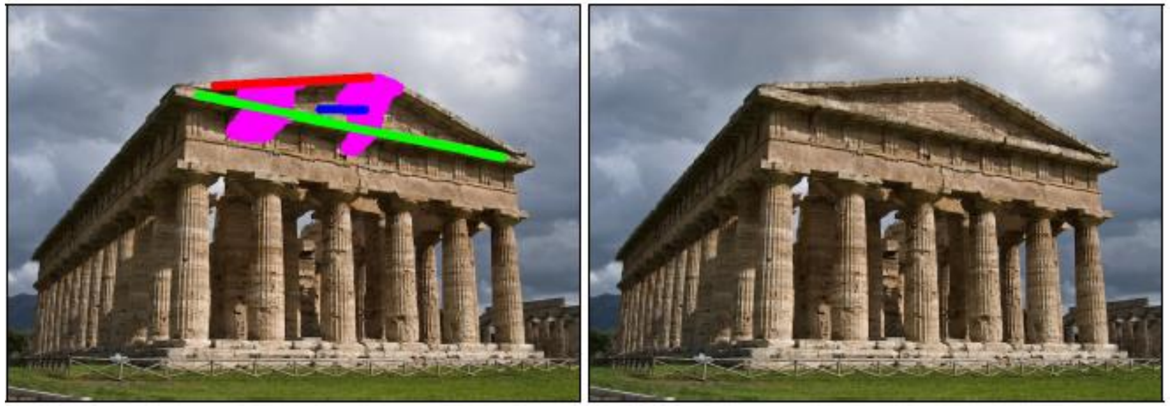
Things to remember

- Texture synthesis and hole-filling can be thought of as a form of probabilistic hallucination

- Simple, similarity-based matching is a powerful tool
  - Synthesis
  - Hole-filling
  - Retargeting
  - And much more…

- Key is how to define similarity and efficiently find neighbors

- PatchMatch provides flexible and highly efficient optimization



Next class

- Cutting and seam finding