Texture Synthesis

COS 526: Advanced Computer Graphics

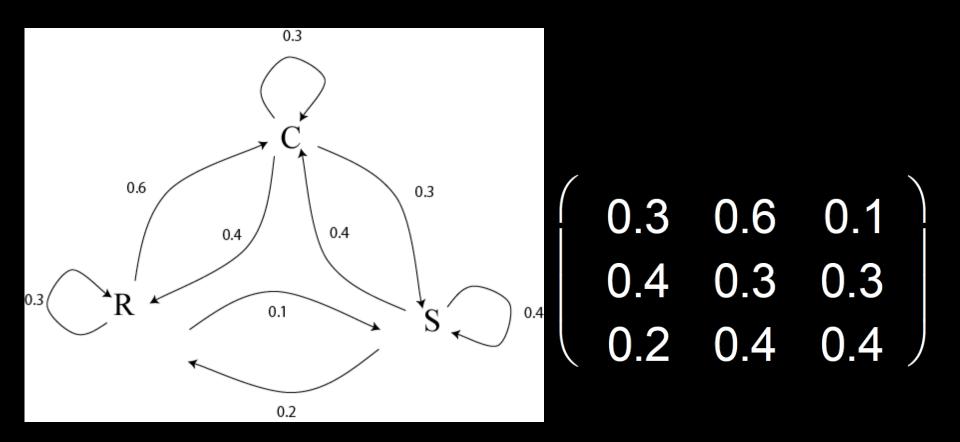


Slide credits: Alyosha Efros, Tom Funkhouser, Ravi Ramamoorthi.

Weather Forecasting for Dummies

- Let's predict the weather:
 - Given today's weather only, we want to know tomorrow's
 - Suppose weather can only be {Sunny, Cloudy, Raining}
- Simpel 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



What if we know today's and yesterday's weather?

Text Synthesis

- [Shannon,' 48] proposed a way to generate English-looking text using N-grams:
 - Assume a generalized Markov model
 - Use a large text to compute prob. distributions of each letter given N-1 previous letters
 - Starting from a seed repeatedly sample this Markov chain to generate new letters
 - Also works for whole words

WE NEED TO EAT CAKE

Mark V. Shaney (Bell Labs)

- Results (using alt.singles corpus):
 - "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"

Texture

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



radishes



rocks

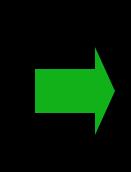


yogurt

Texture Synthesis

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

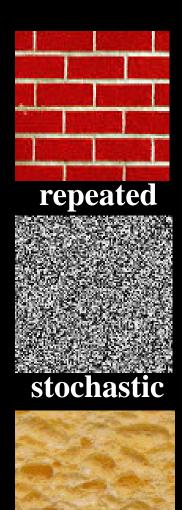






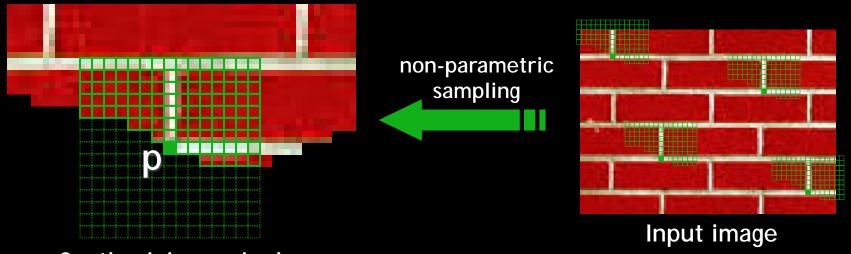
The Challenge

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





Efros & Leung Algorithm



Synthesizing a pixel

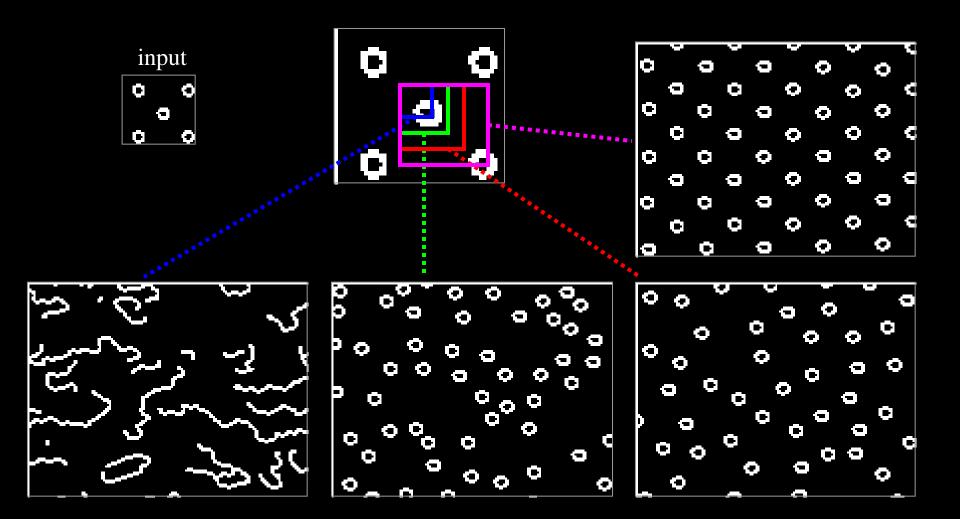
• Assuming Markov property, compute P(p|N(p))

- 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

Some Details

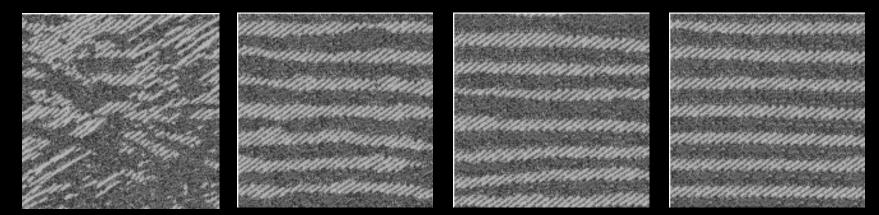
- Growing is in "onion skin" order
 - Within each "layer", pixels with most neighbors are synthesized first
 - If no close match can be found, the pixel is not synthesized until the end
- Using Gaussian-weighted SSD is very important
 - to make sure the new pixel agrees with its closest neighbors
 - Approximates reduction to a smaller neighborhood window if data is too sparse

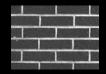
Neighborhood Window

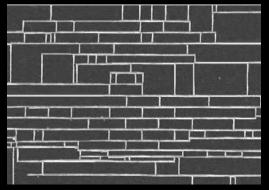


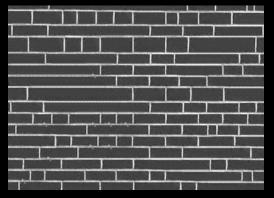
Varying Window Size







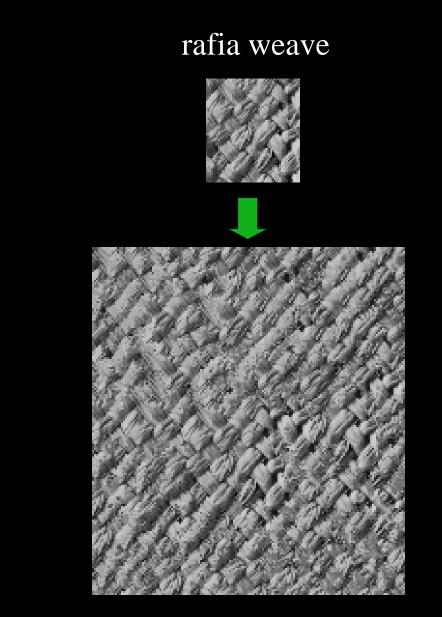




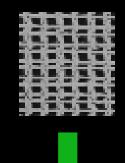
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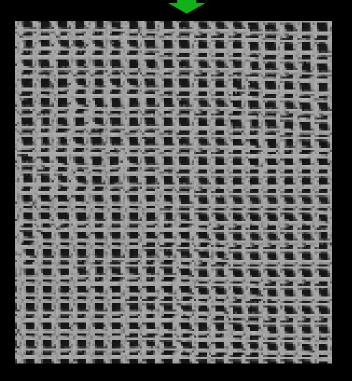
Increasing window size

Synthesis Results



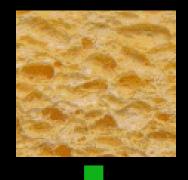
french canvas

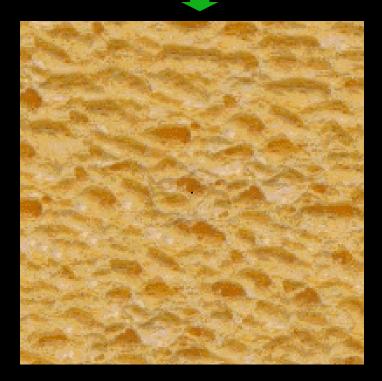




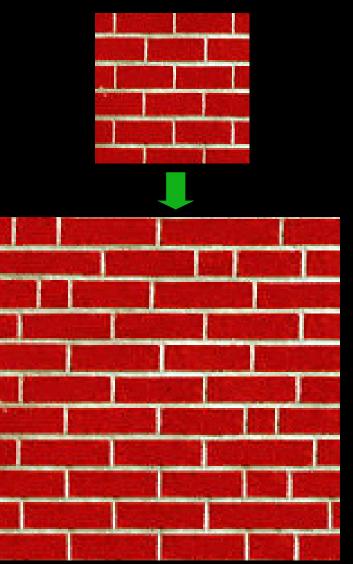
More Results

white bread





brick wall



Homage to Shannon

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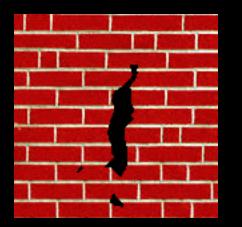
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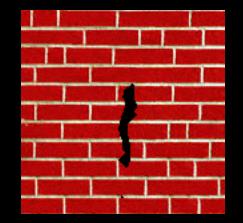
Hole Filling

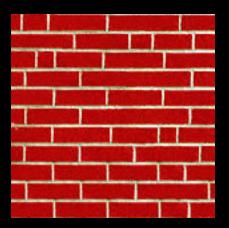




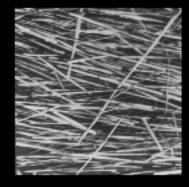


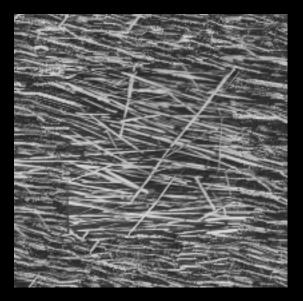






Extrapolation







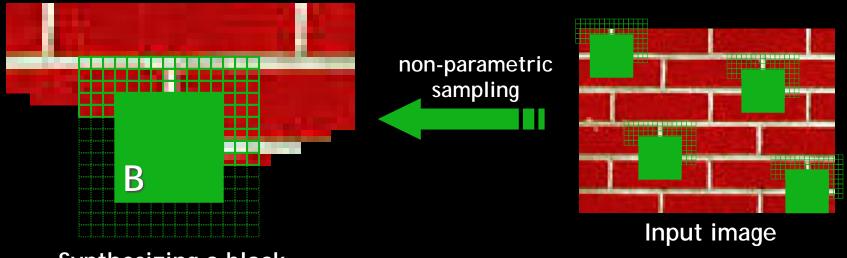




Summary

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

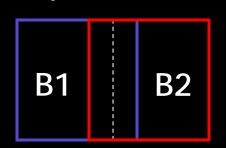
Image Quilting [Efros & Freeman]



Synthesizing a block

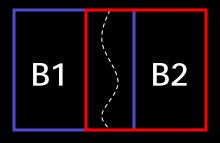
- <u>Observation</u>: neighbor pixels are highly correlated
 <u>Idea</u>: unit of synthesis = block
 - Exactly the same but now we want P(B|N(B))
 - Much faster: synthesize all pixels in a block at once
 - Not the same as multi-scale!





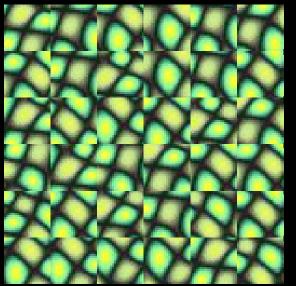
Input texture

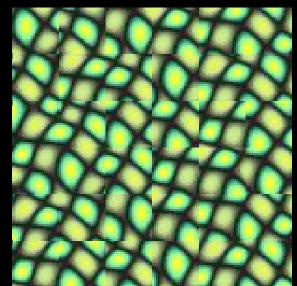
block

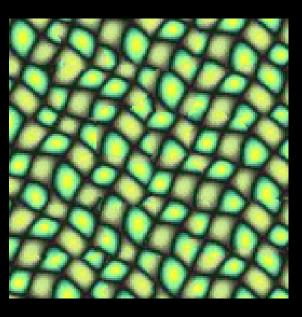


Random placement of blocks Neighboring blocks constrained by overlap

Minimal error boundary cut

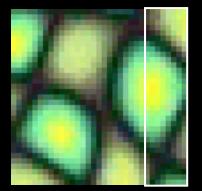


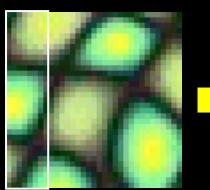




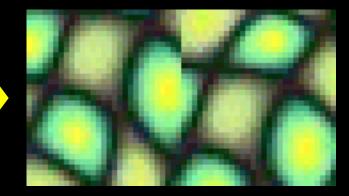
Minimal error boundary

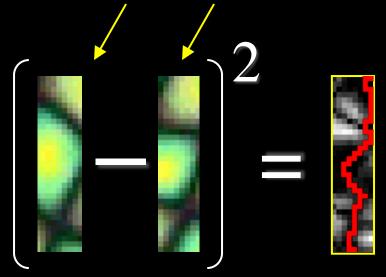
overlapping blocks





vertical boundary







overlap error

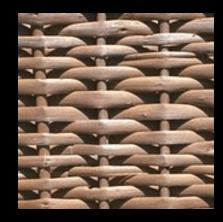
min. error boundary

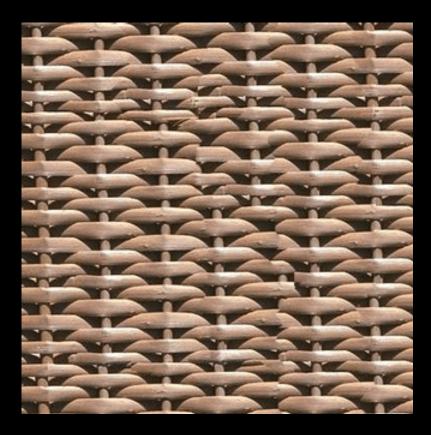
Our Philosophy

- 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

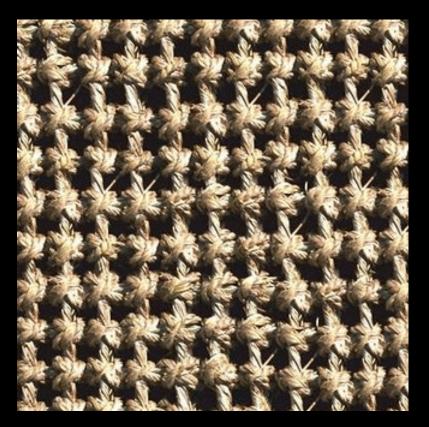






































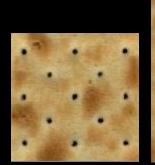


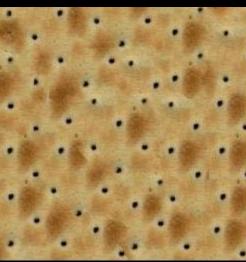
















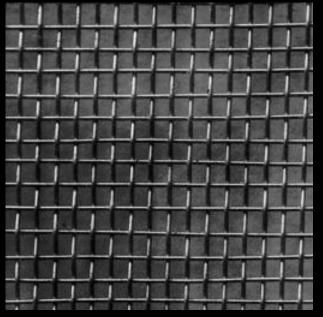


Failures (Chernobyl Harvest)

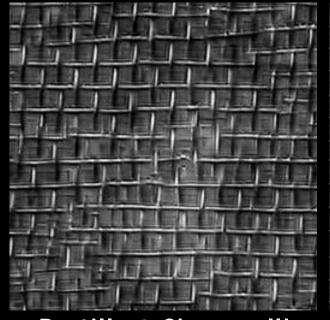




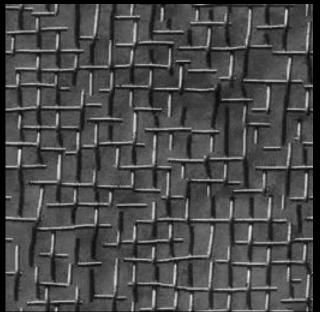


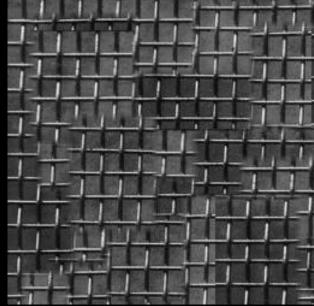


input image

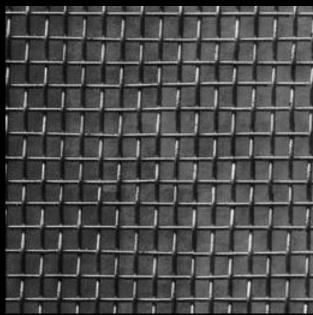


Portilla & Simoncelli



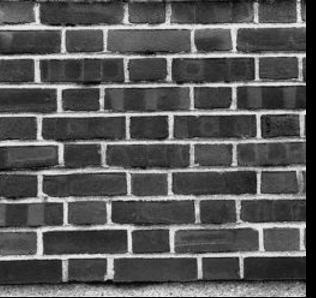


Xu, Guo & Shum



Wei & Levoy

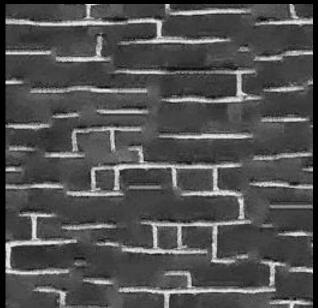
Our algorithm



input image

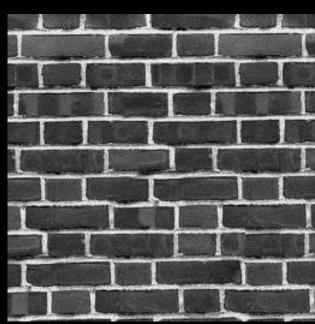


Portilla & Simoncelli





Xu, Guo & Shum



Wei & Levoy

Our algorithm

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Portilla & Simoncelli

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Wei & Levoy

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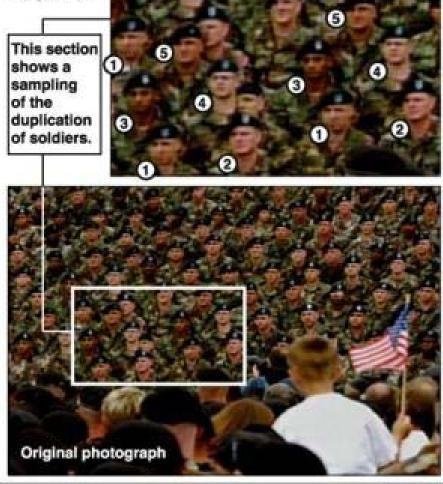
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Our algorithm

Political Texture Synthesis!

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.

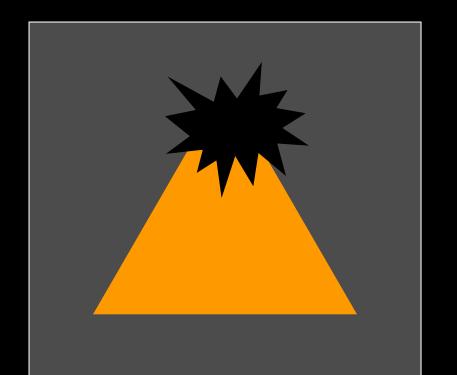


Fill Order



• In what order should we fill the pixels?

Fill Order

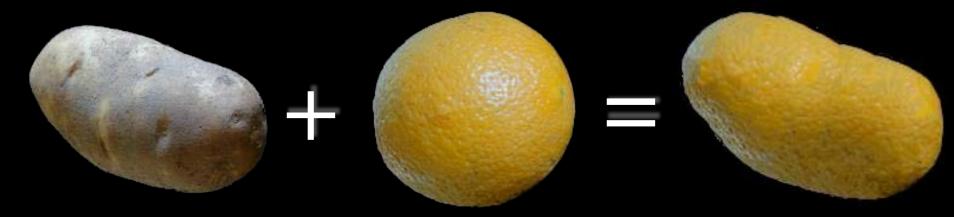


- In what order should we fill the pixels?
 choose pixels that have more neighbors filled
 - choose pixels that are continuations of lines/curves/edges

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

Application: Texture Transfer

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



Texture Transfer



Constraint



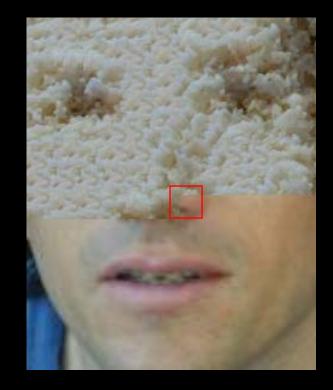


Texture sample

Texture Transfer

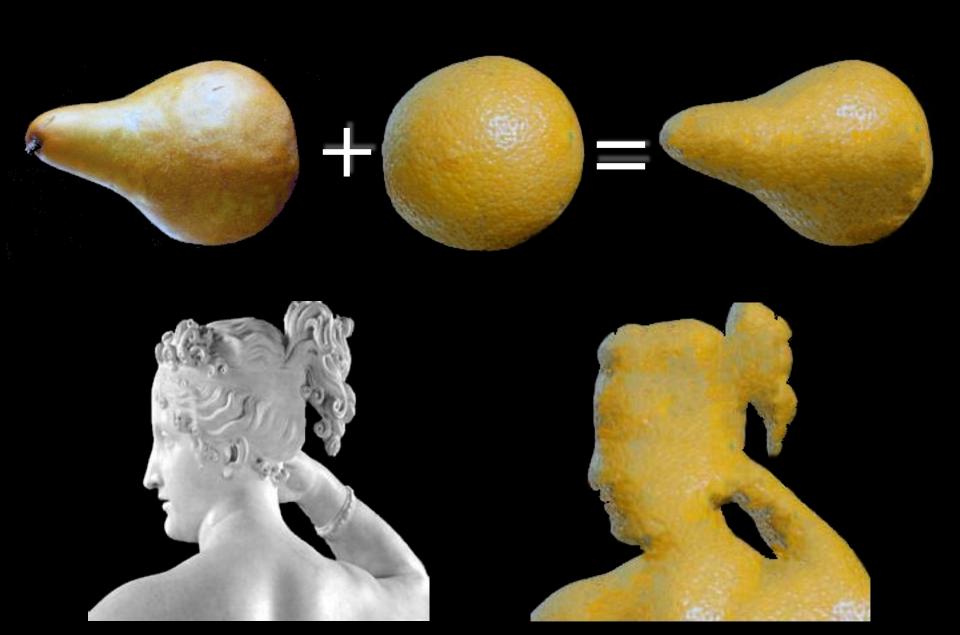
• Take the texture from one image and "paint" it onto another object





Same as texture synthesis, except an additional constraint:

- 1. Consistency of texture
- 2. Similarity to the image being "explained"







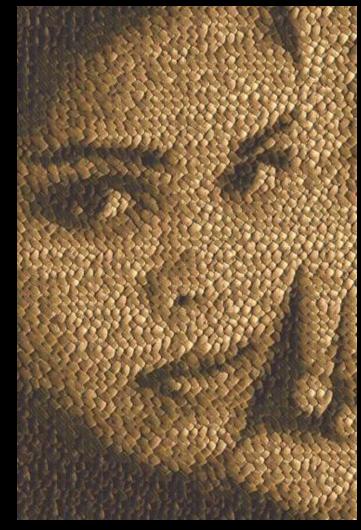


Image Analogies

Aaron Hertzmann^{1,2}

Chuck Jacobs²

Nuria Oliver²

Brian Curless³

David Salesin^{2,3}

¹New York University
²Microsoft Research
³University of Washington

Image Analogies





A'







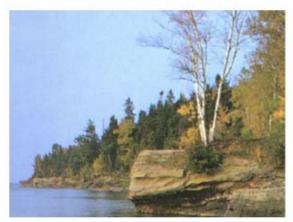
Blur Filter



Unfiltered source (A)



Filtered source (A')



Unfiltered target (B)

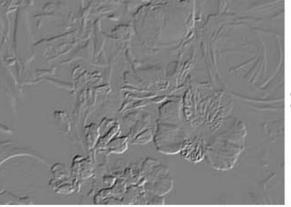


Filtered target (B')

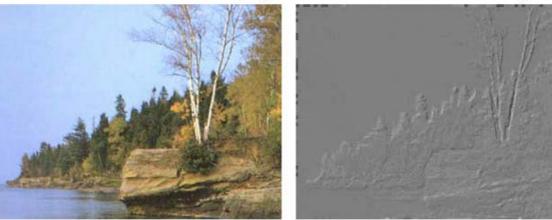
Edge Filter



Unfiltered source (A)



Filtered source (A')



Unfiltered target (B)

Filtered target (B')

Artistic Filters



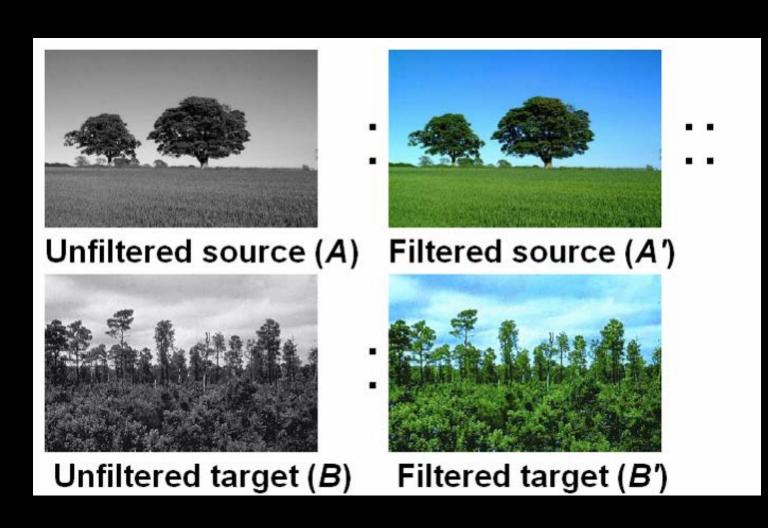


B

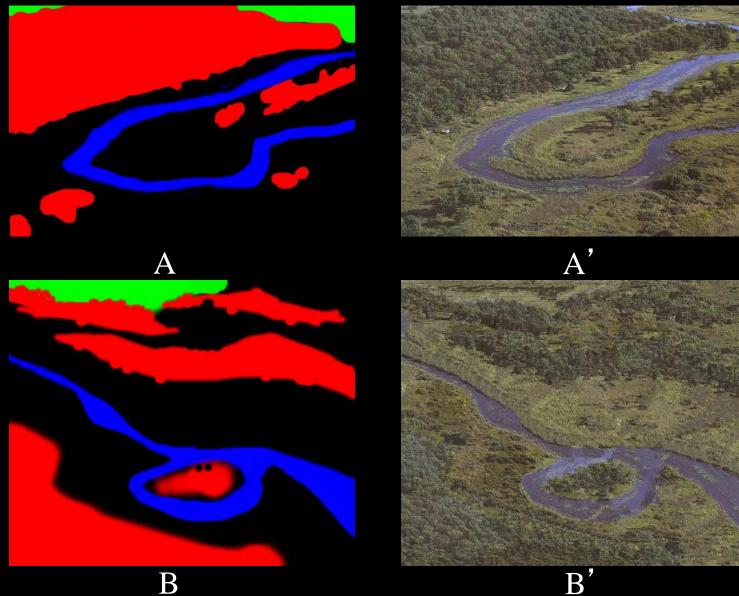


B

Colorization

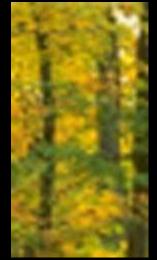


Texture-by-numbers



Super-resolution











A

Super-resolution (result!)





Video Textures

Arno Schödl Richard Szeliski David Salesin Irfan Essa

Microsoft Research, Georgia Tech

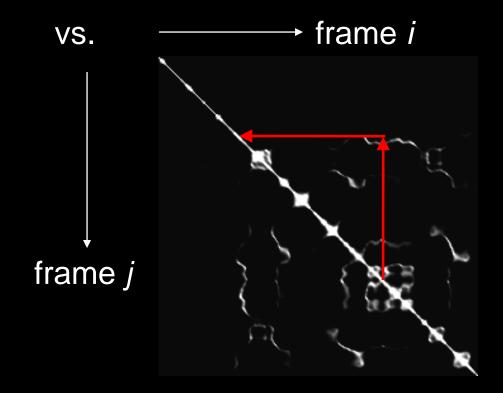
Our approach



• How do we find good transitions?

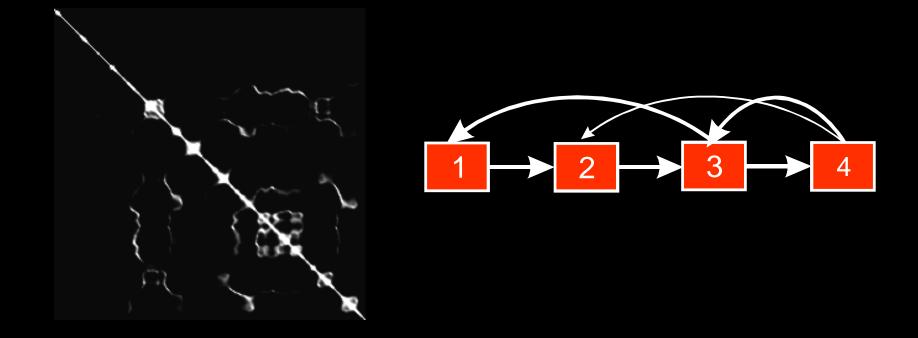
Finding good transitions

• Compute L_2 distance $D_{i,j}$ between all frames



Similar frames make good transitions

Markov chain representation



Similar frames make good transitions

Example

