Data-driven methods: Video & Texture



© A.A. Efros

15-463: Computational Photography Alexei Efros, CMU, Fall 2011

Michel Gondry train video

http://www.youtube.com/watch?v=615FUp8a UmU&feature=related

Weather Forecasting for Dummies™

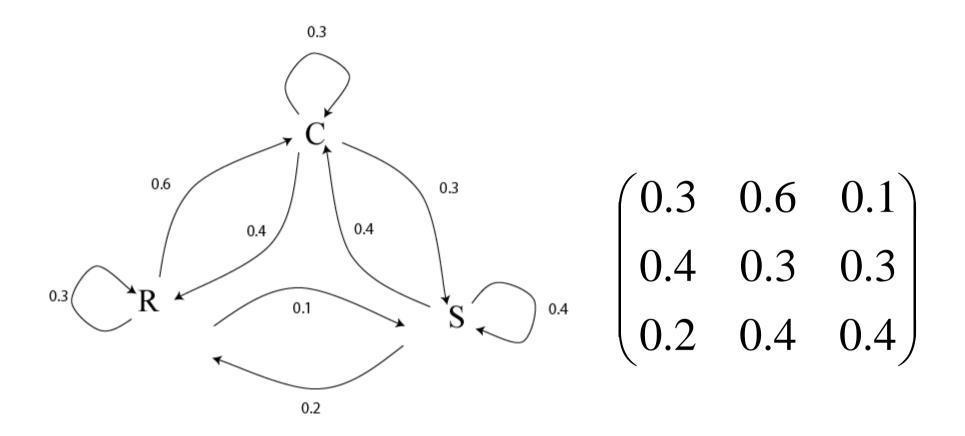
Let's predict weather:

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

The "Weather Channel" algorithm:

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

Markov Chain



What if we know today and yestarday'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"

Video Textures

Arno Schödl Richard Szeliski David Salesin Irfan Essa

Microsoft Research Georgia Tech

Still photos









Video clips









Video textures



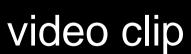






Problem statement









video texture

Our approach

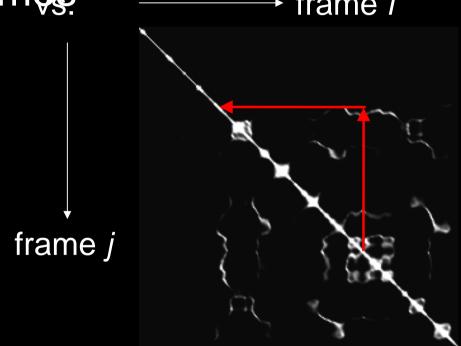


• How do we find good transitions?

Finding good transitions

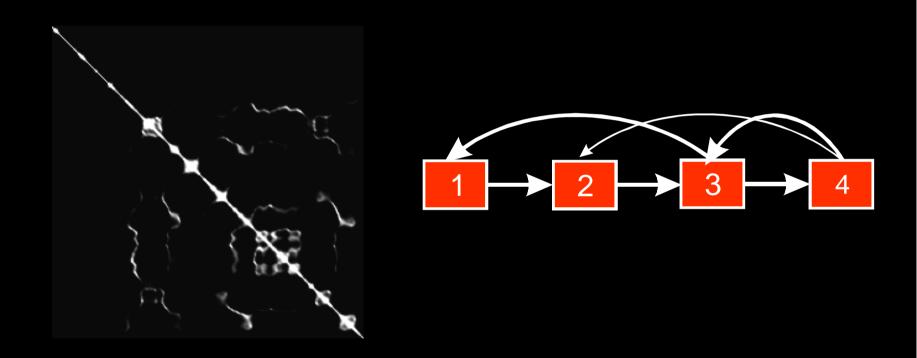
• Compute L_2 distance $D_{i, j}$ between all frames.

frames



Similar frames make good transitions

Markov chain representation

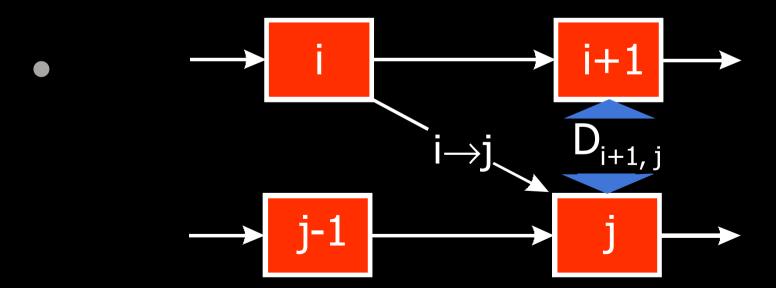


Similar frames make good transitions

Transition costs

 Transition from i to j if successor of i is similar to j

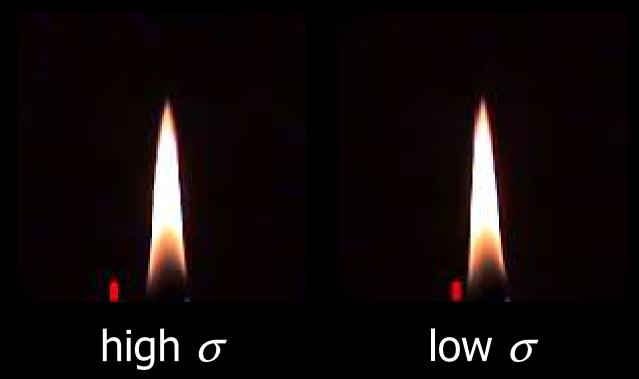
• Cost function: $C_{i \rightarrow j} = \overline{D_{i+1, j}}$



Transition probabilities

•Probability for transition $P_{i\rightarrow j}$ inversely related to cost:

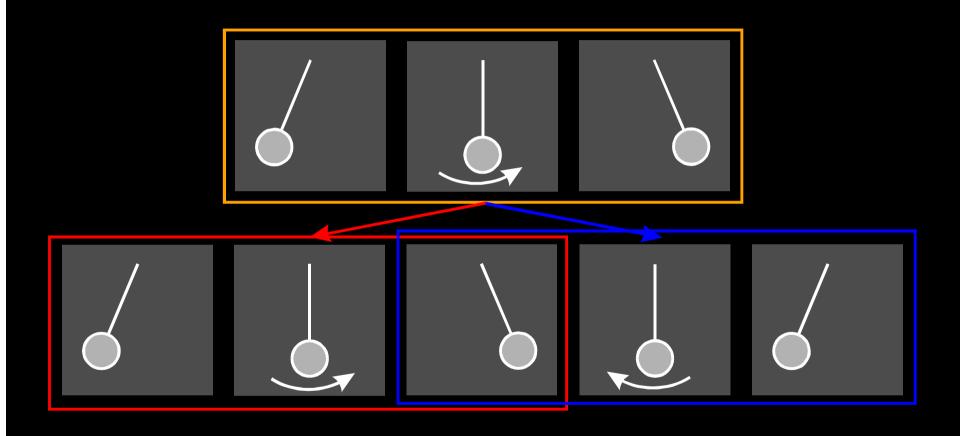
•
$$P_{i \to j} \sim \exp(-C_{i \to j}/\sigma^2)$$



Preserving dynamics



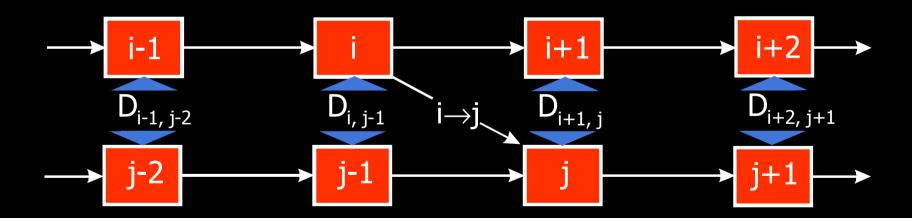
Preserving dynamics



Preserving dynamics

• Cost for transition $i \rightarrow j$

•
$$C_{i \rightarrow j} = \sum_{k=-N}^{N-1} W_k D_{i+k+1, j+k}$$



Preserving dynamics – effect

• Cost for transition $i \rightarrow j$

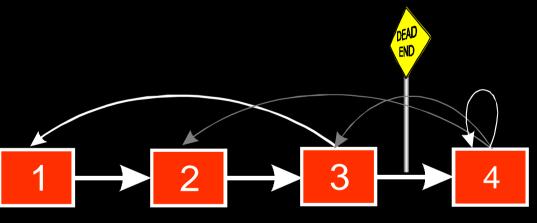
•
$$C_{i \to j} = \sum_{k = -N}^{N-1} w_k D_{i+k+1, j+k}$$



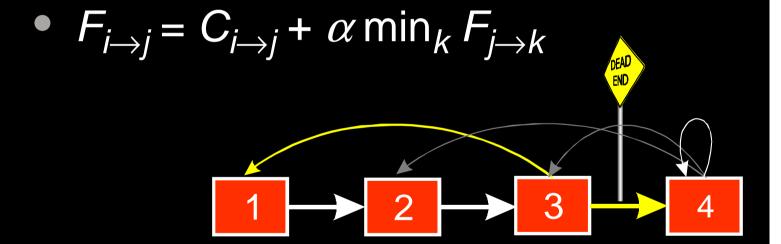
Dead ends

No good transition at the end of sequence

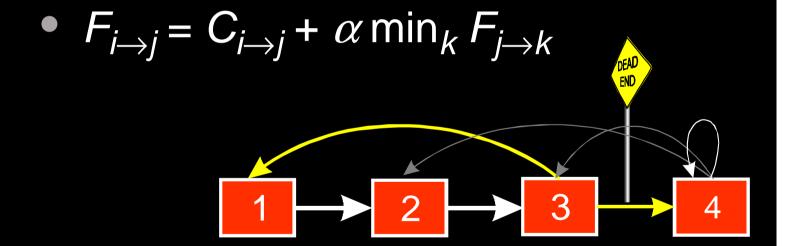




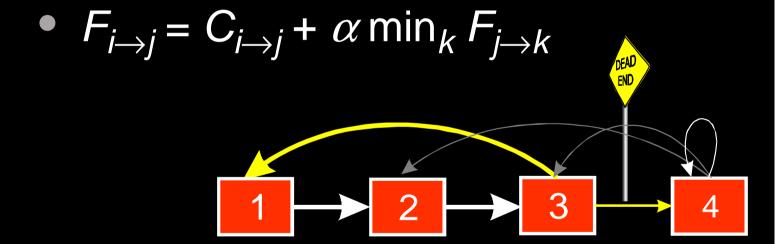
- Propagate future transition costs backward
- Iteratively compute new cost



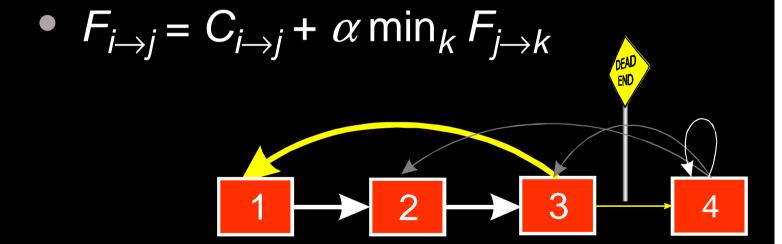
- Propagate future transition costs backward
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- Propagate future transition costs backward
- Iteratively compute new cost



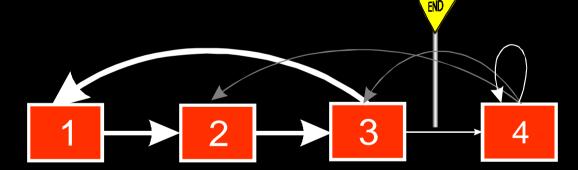
- Propagate future transition costs backward
- Iteratively compute new cost



- Propagate future transition costs backward
- Iteratively compute new cost

• $F_{i \to j} = C_{i \to j} + \alpha \min_k F_{j \to k}$

Q-learning



Future cost – effect



Finding good loops

- Alternative to random transitions
- Precompute set of loops up front



Video portrait



Useful for web pages

Region-based analysis

Divide video up into regions



Generate a video texture for each region

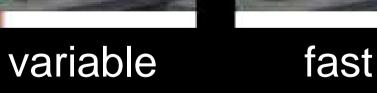
Automatic region analysis



User-controlled video textures



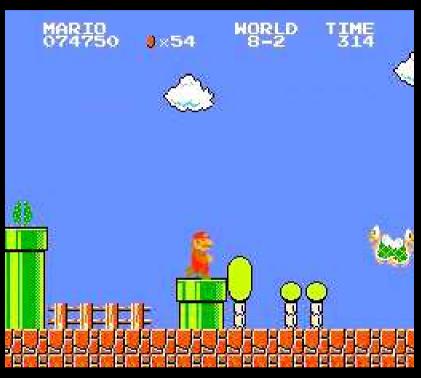




User selects target frame range

Video-based animation

- Like sprites computer games
- Extract sprites from real video
- Interactively control desired motion



©1985 Nintendo of America Inc.

Video sprite extraction

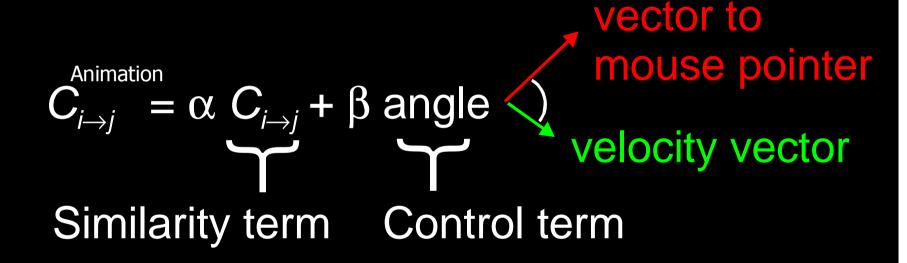


blue screen matting and velocity estimation



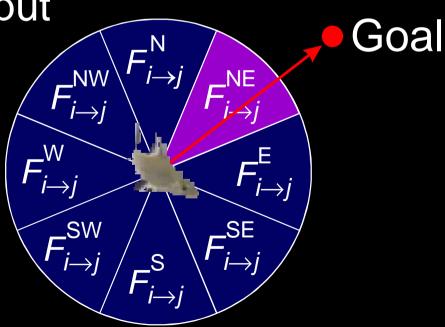
Video sprite control

Augmented transition cost:



Video sprite control

- Need future cost computation
- Precompute future costs for a few angles.
- Switch between precomputed angles according to user input
- [GIT-GVU-00-11]



Interactive fish



Summary

- Video clips → video textures
 - define Markov process
 - preserve dynamics
 - avoid dead-ends
 - disguise visual discontinuities



Discussion

Some things are relatively easy









Discussion

Some are hard



"Amateur" by Lasse Gjertsen

http://www.youtube.com/watch?v=JzqumbhfxRo

Texture

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







rocks



yogurt

Texture Synthesis

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

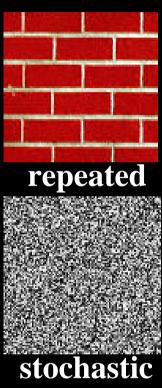






The Challenge

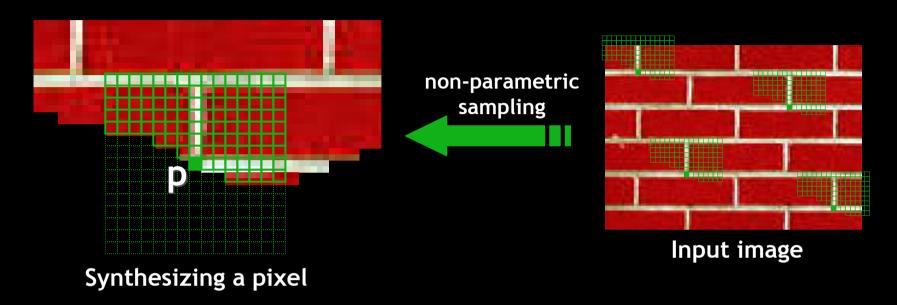
• Need to model the whole spectrum: from repeated to stochastic texture





Both?

Efros & Leung Algorithm

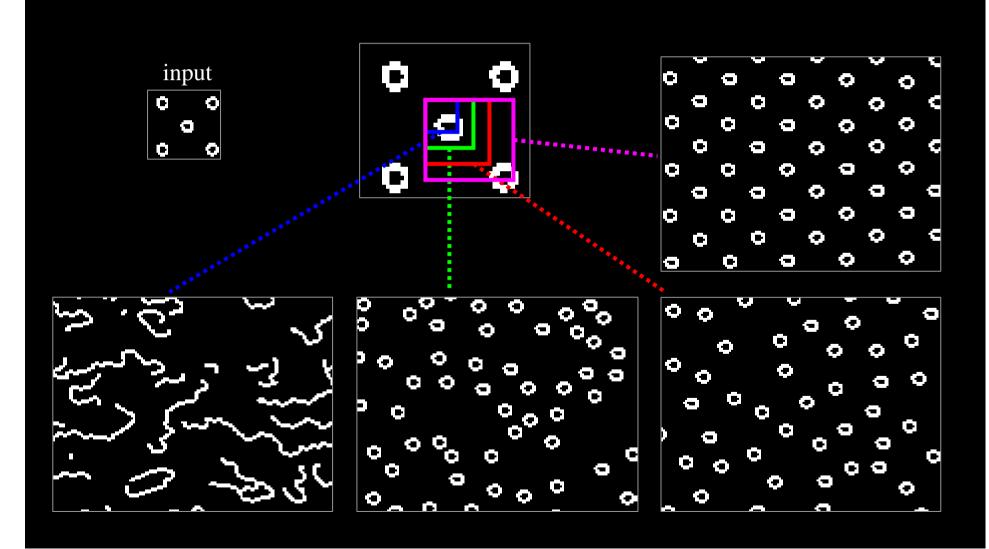


- Assuming Markov property, compute $P(\mathbf{p}|N(\mathbf{p}))$
 - Building explicit probability tables infeasible
 - Instead, we search the input image for all similar neighborhoods that's our pdf for p
 - To sample from this pdf, just pick one match at random

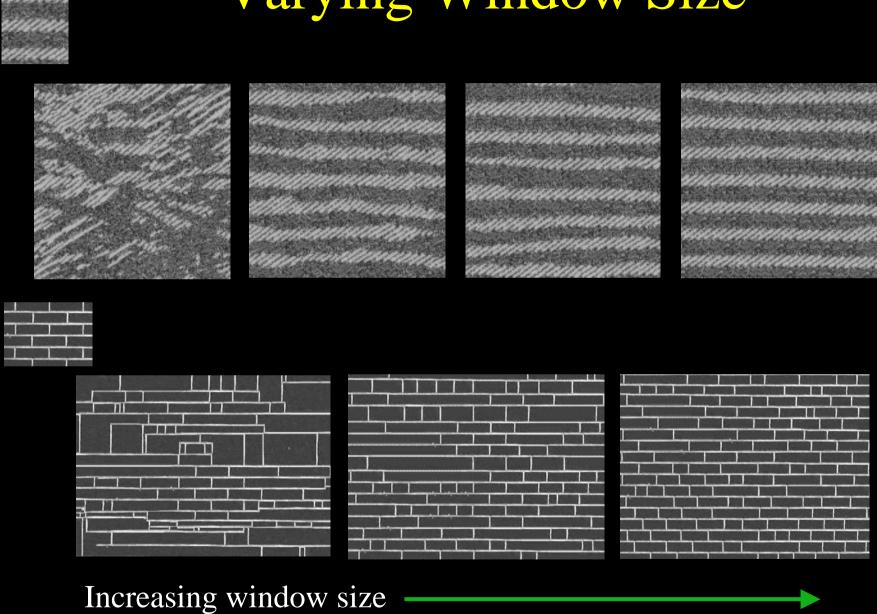
Some Details

- 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

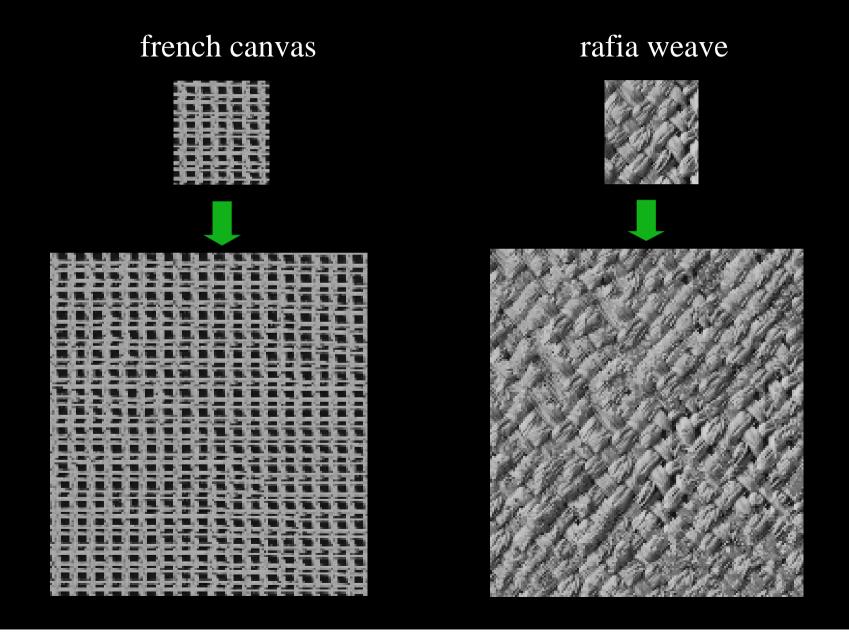
Neighborhood Window



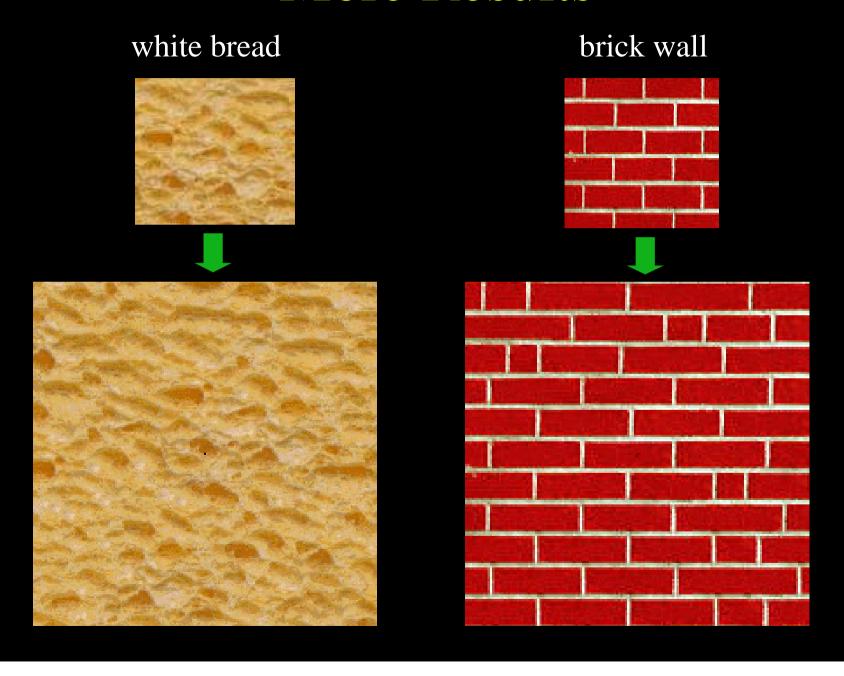
Varying Window Size



Synthesis Results



More Results



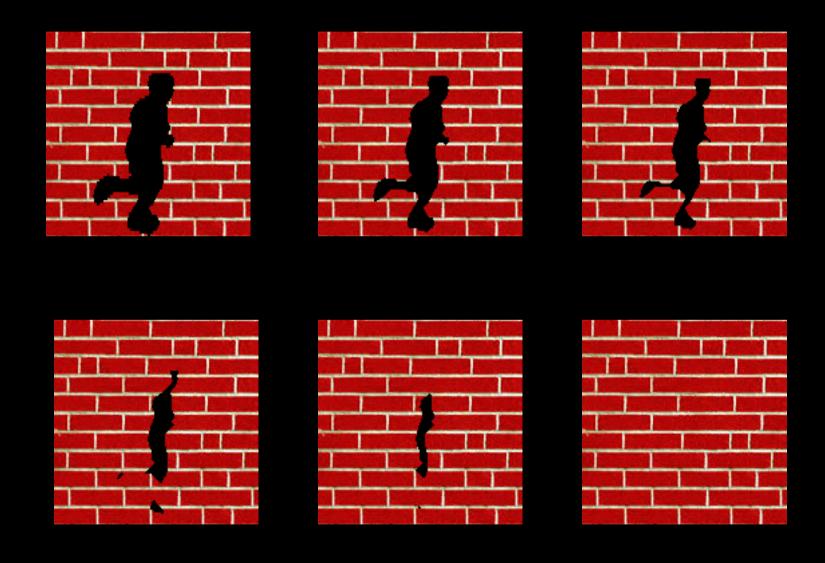
Homage to Shannon

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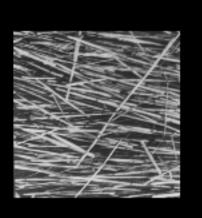
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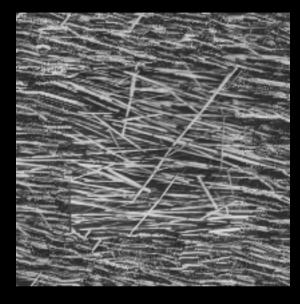
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Hole Filling



Extrapolation







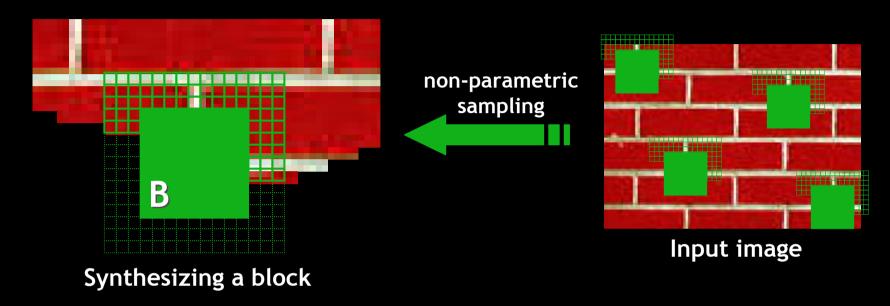




Summary

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

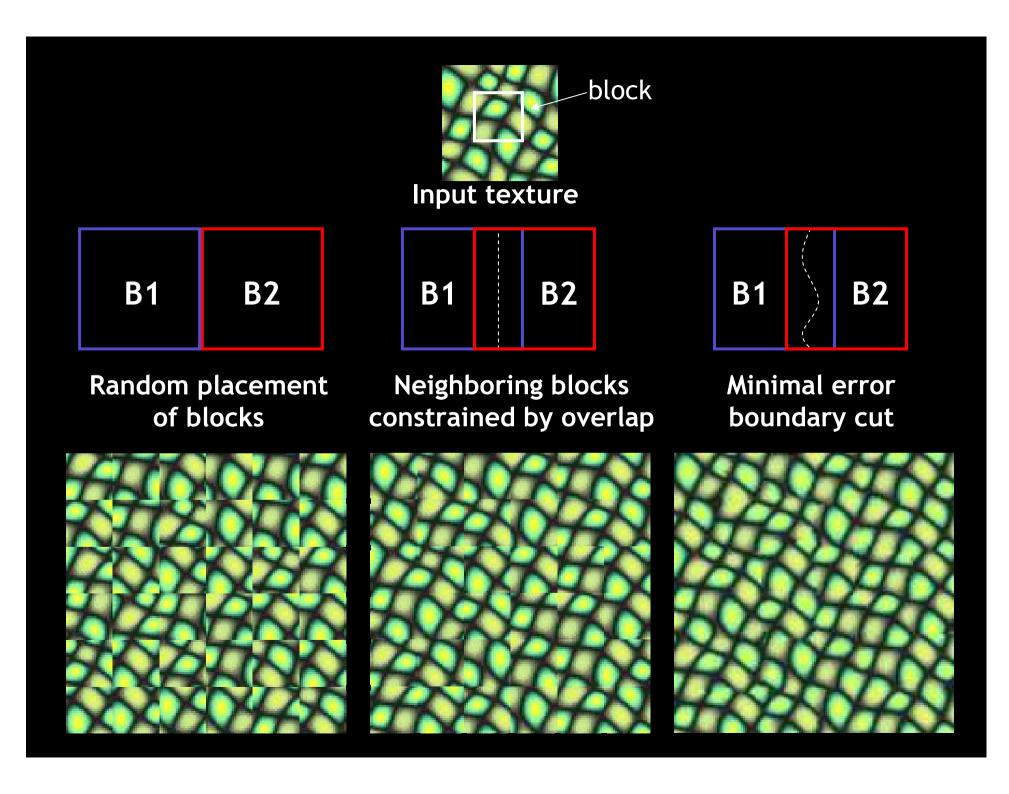
Image Quilting [Efros & Freeman]



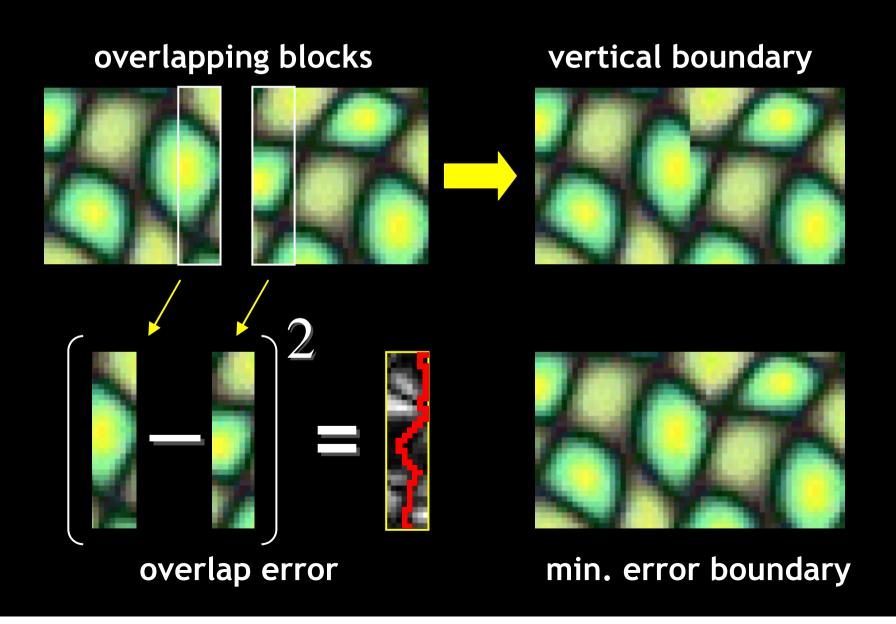
• Observation: neighbor pixels are highly correlated

<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!



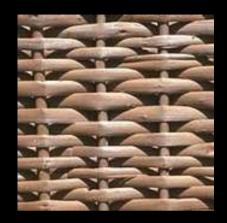
Minimal error boundary



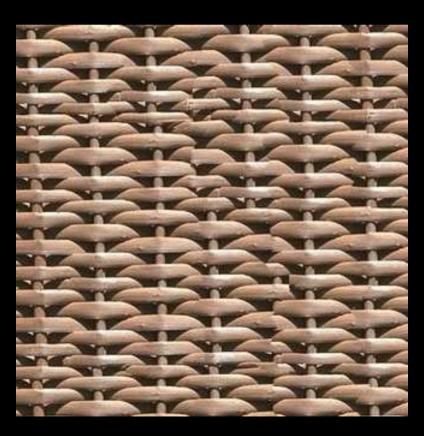
Our Philosophy

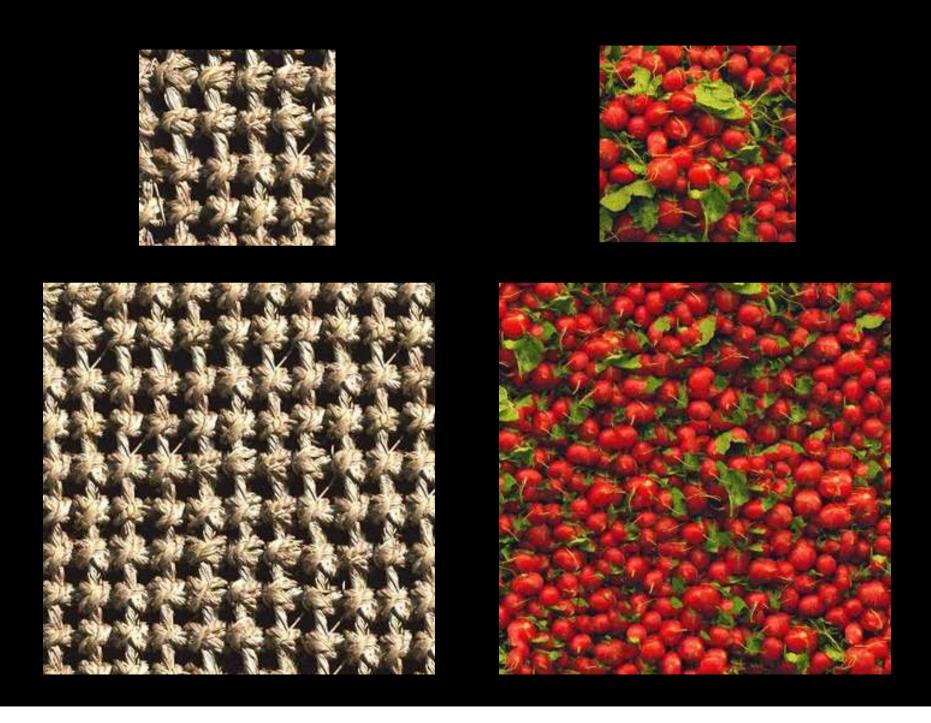
- The "Corrupt Professor's Algorithm":
 - Plagiarize as much of the source image as you can
 - Then try to cover up the evidence
- Rationale:
 - Texture blocks are by definition correct samples of texture so problem only connecting them together





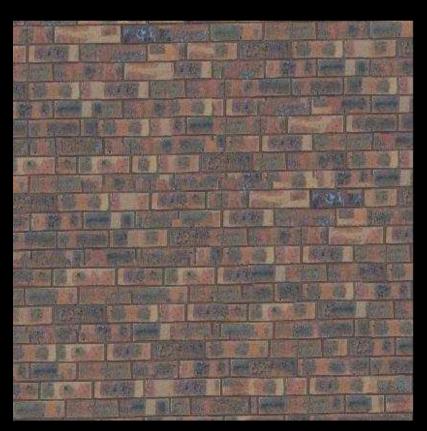




















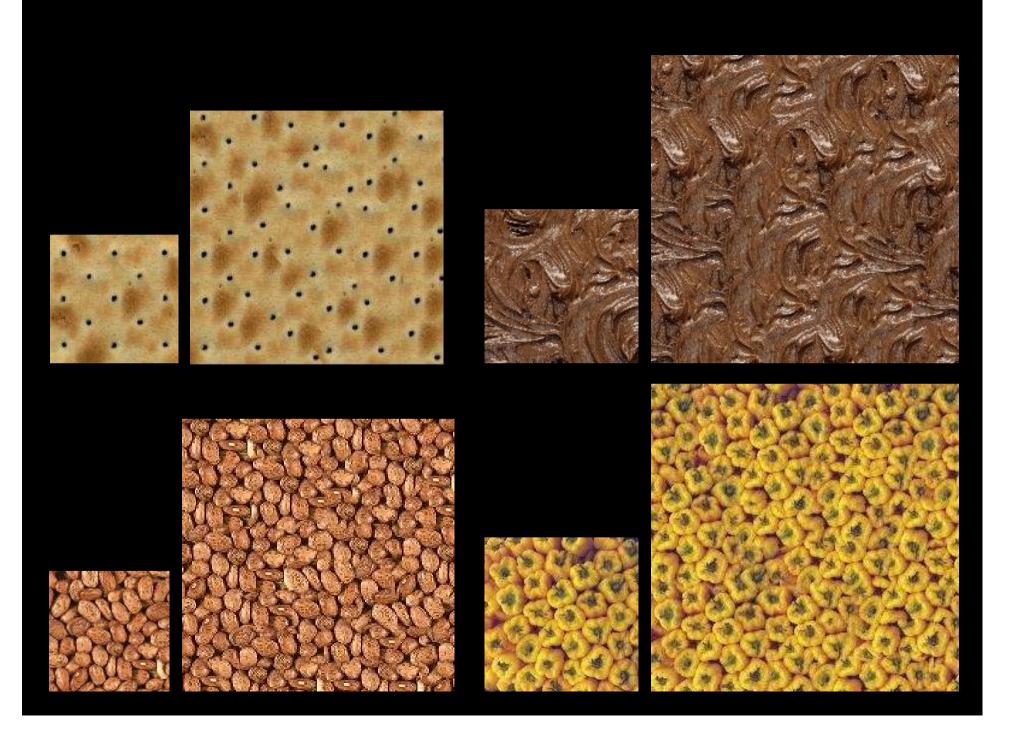












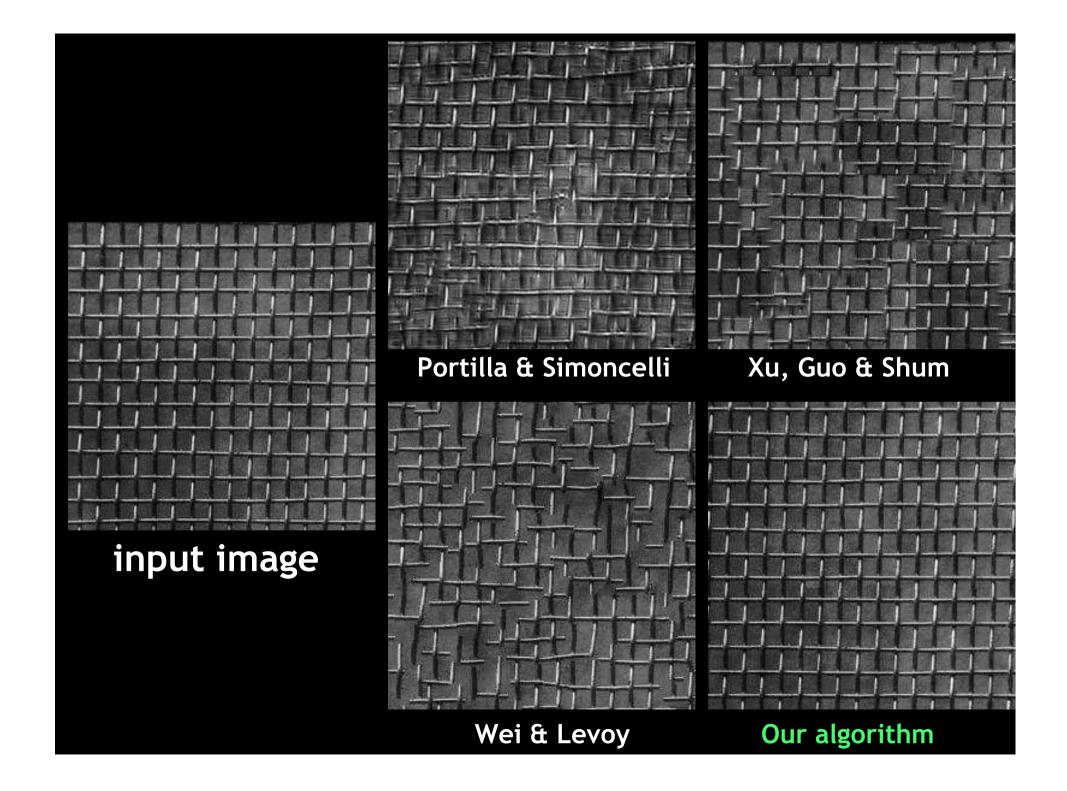


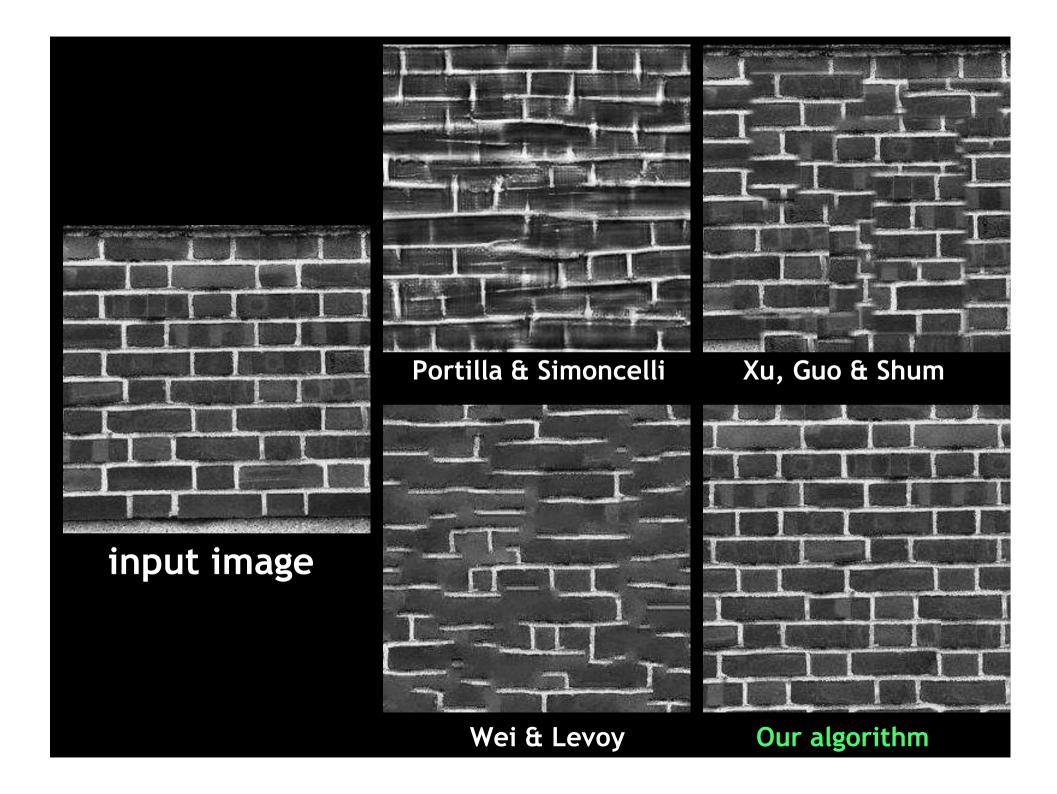
Failures (Chernobyl Harvest)











describing the response of that neuron that as a function of position—is perhap functional description of that neuron seek a single conceptual and mathematically the wealth of simple-cell recepted neurophysiologically and inferred especially if such a framework has the it helps us to understand the function leeper way. Whereas no generic most ussians (DOG), difference of offset Crivative of a Gaussian, higher derivation function, and so on—can be expected imple-cell receptive field, we noneth

input image

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Portilla & Simoncelli

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Xu, Guo & Shum

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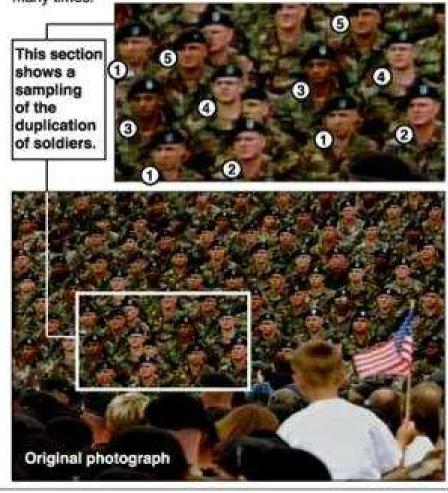
Wei & Levoy

Our algorithm

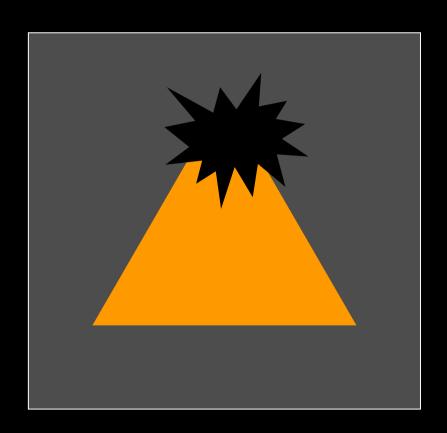
Political Texture Synthesis!

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

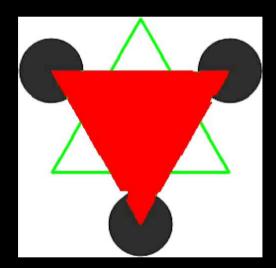


- In what order should we fill the pixels?
 - choose pixels that have more neighbors filled

Criminisi, Perez, chopse mixels that are continuations of," Proc. CVPR, 2003.

1:..../-----/- 1---

Exemplar-based Inpainting demo



http://research.microsoft.com/vision/cambridge/i3l/patchworks.htm

Application: Texture Transfer

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



Texture Transfer



Constraint



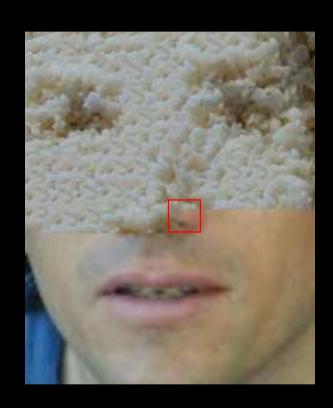


Texture sample

Texture Transfer

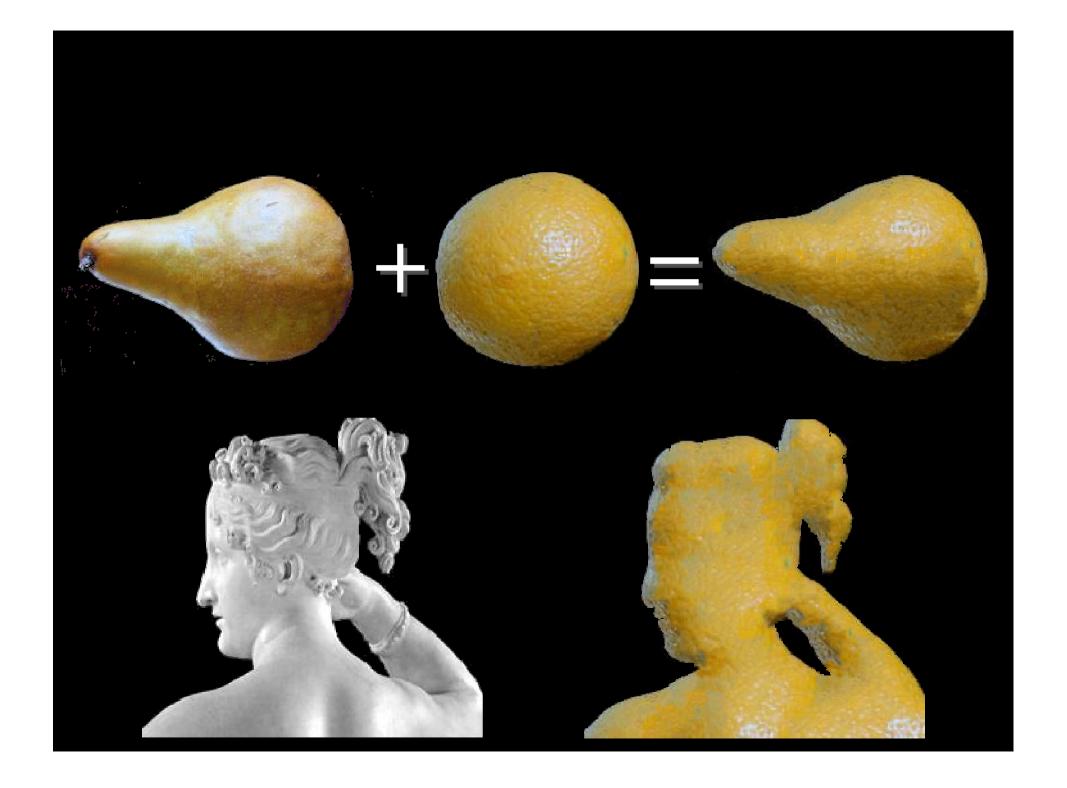
• Take the texture from one image and "paint" it onto another object





Same as texture synthesis, except an additional constraint:

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







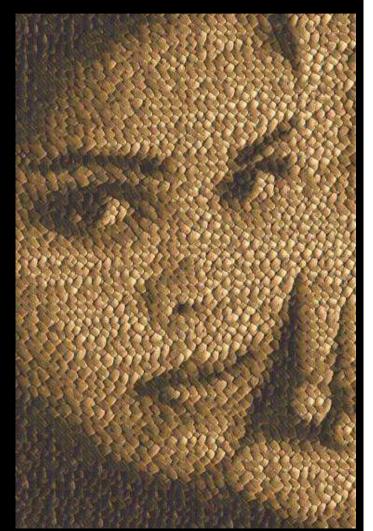


Image Analogies

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'



B B'



Blur Filter



Unfiltered source (A)



Unfiltered target (B)

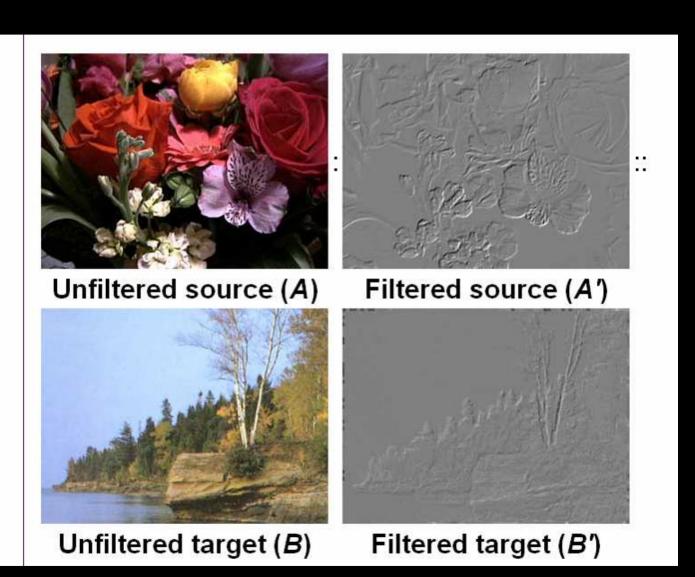


Filtered source (A')

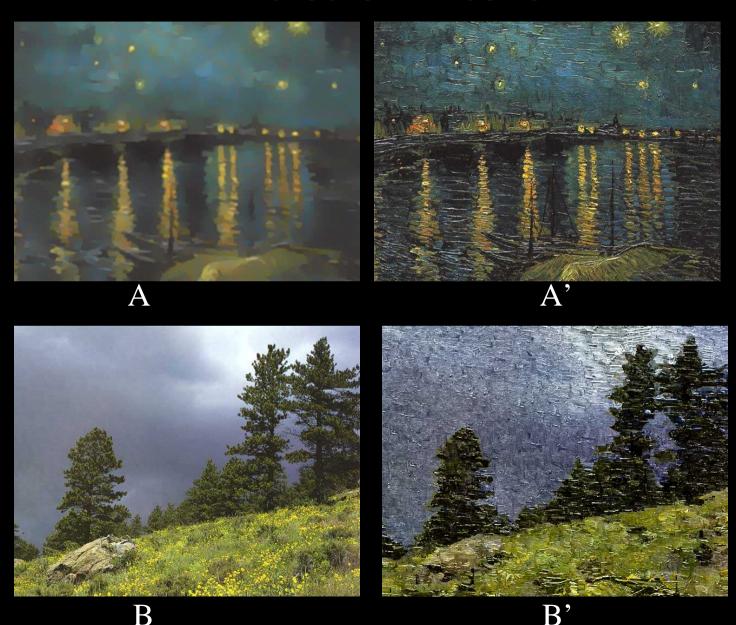


Filtered target (B')

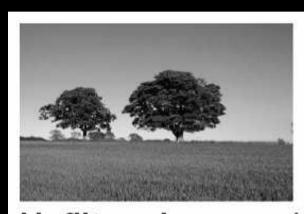
Edge Filter



Artistic Filters



Colorization



Unfiltered source (A)



Unfiltered target (B)

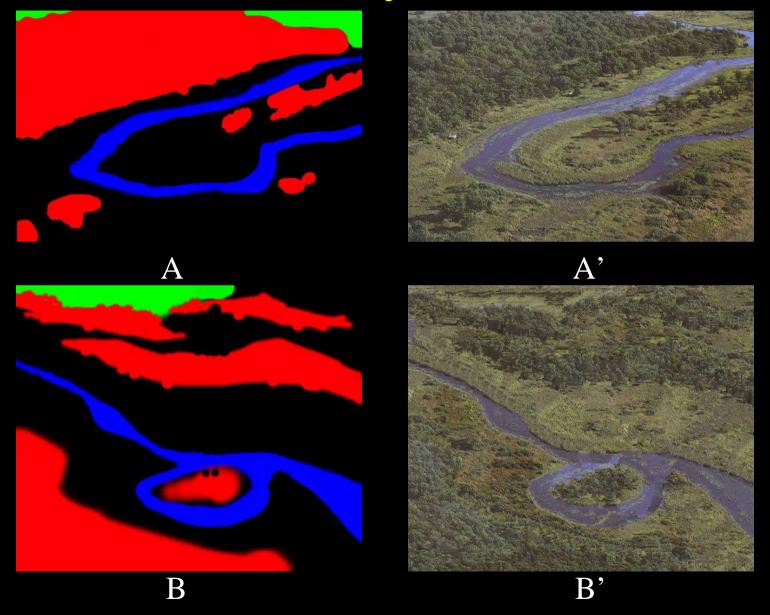


Filtered source (A')



Filtered target (B')

Texture-by-numbers



Super-resolution







A

Super-resolution (result!)





B'