#### Data-driven methods: Video & Texture



© A.A. Efros

15-463: Computational Photography Alexei Efros, CMU, Spring 2010

#### Michel Gondry train video

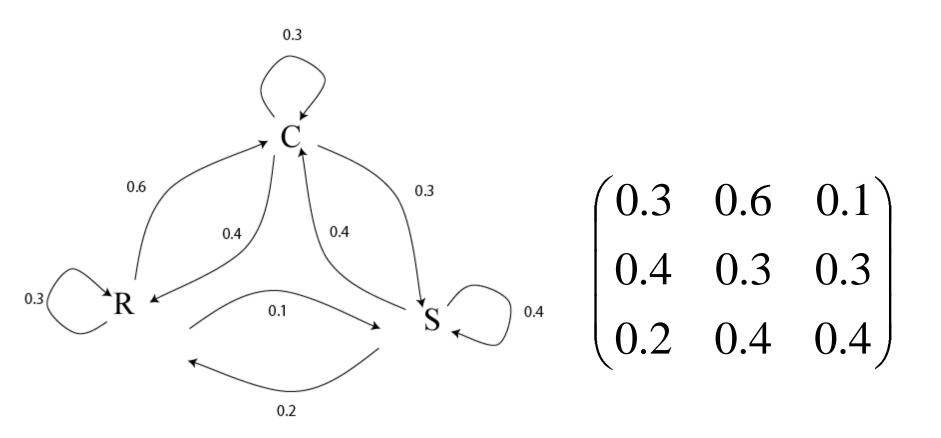
http://youtube.com/watch?v=qUEs1BwVXGA

#### Weather Forecasting for Dummies<sup>™</sup>

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?

[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

Results (using alt.singles corpus):

- "As I've commented before, really relating to someone involves standing next to impossible."
- "One morning I shot<sup>No</sup> 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 clip

#### video texture

# **Our approach**



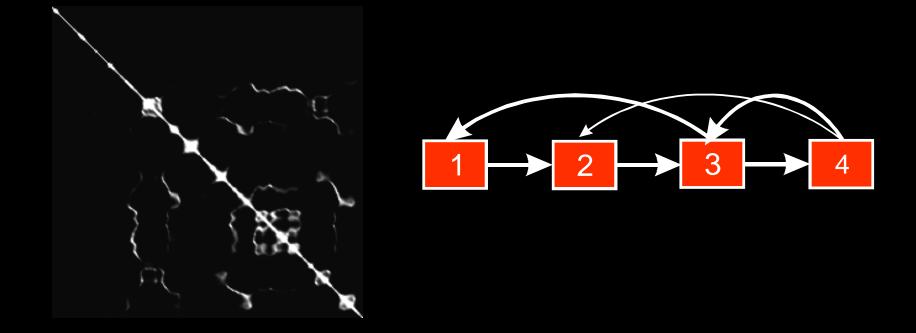
• How do we find good transitions?

# **Finding good transitions**

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

#### Similar frames make good transitions

# **Markov chain representation**

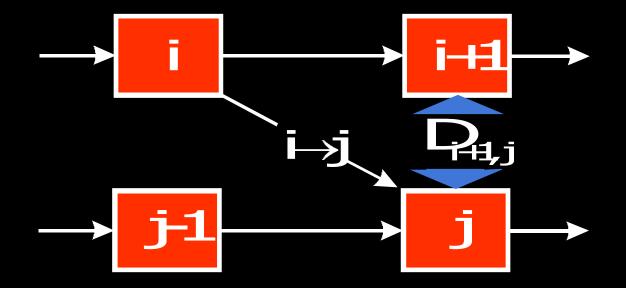


#### Similar frames make good transitions

# **Transition costs**

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

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



# **Transition probabilities**

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

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



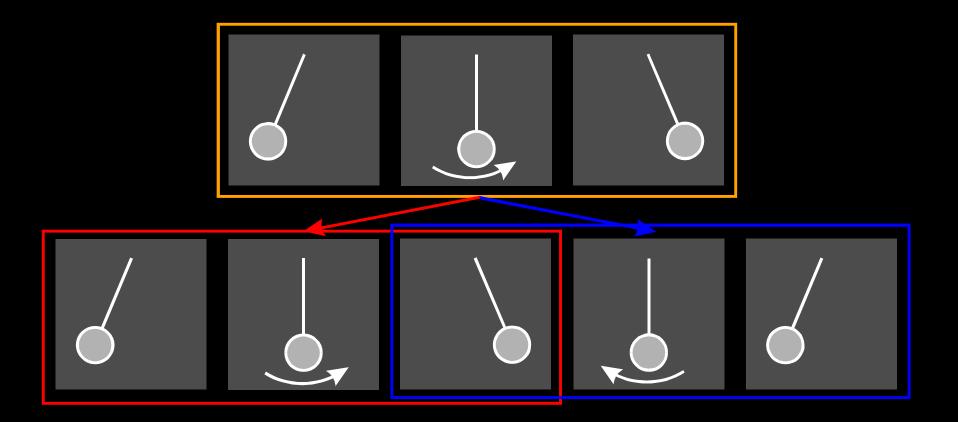
high  $\sigma$ 

low  $\sigma$ 

# **Preserving dynamics**



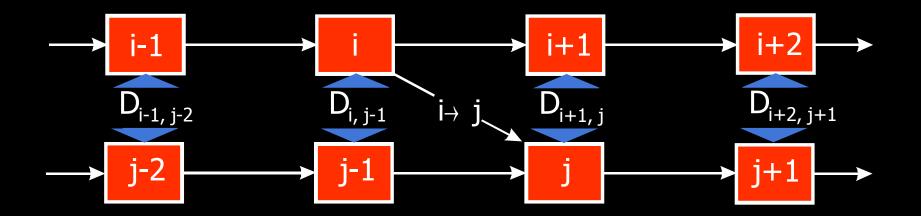
# **Preserving dynamics**



# **Preserving dynamics**

• Cost for transition  $i \rightarrow j$ 

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



# **Preserving dynamics – effect**

• Cost for transition  $i \rightarrow j$ 

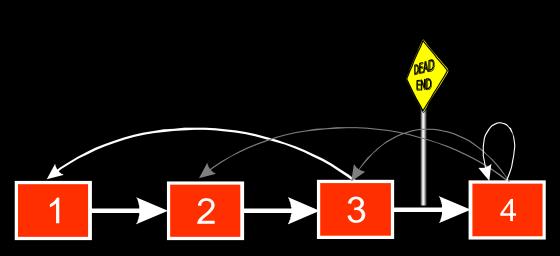
• 
$$C_{i \to j} = \sum_{k = -N}^{N-1} W_k D_{i+k+1, j+k}$$



#### **Dead ends**

No good transition at the end of sequence





- Propagate future transition costs backward
- Iteratively compute new cost

$$F_{i \rightarrow j} = C_{i \rightarrow j} + \alpha \min_{k} F_{j \rightarrow k}$$

- Propagate future transition costs backward
- Iteratively compute new cost

$$F_{i \rightarrow j} = C_{i \rightarrow j} + \alpha \min_{k} F_{j \rightarrow k}$$

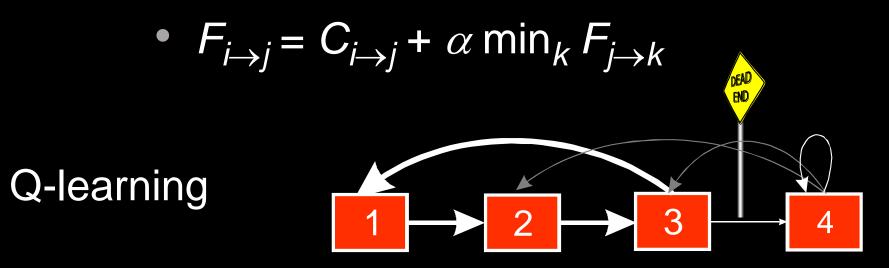
- Propagate future transition costs backward
- Iteratively compute new cost

$$F_{i \rightarrow j} = C_{i \rightarrow j} + \alpha \min_{k} F_{j \rightarrow k}$$

- Propagate future transition costs backward
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$$F_{i \rightarrow j} = C_{i \rightarrow j} + \alpha \min_{k} F_{j \rightarrow k}$$

- Propagate future transition costs backward
- Iteratively compute new cost



# 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**



# slowvariablefastUser 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

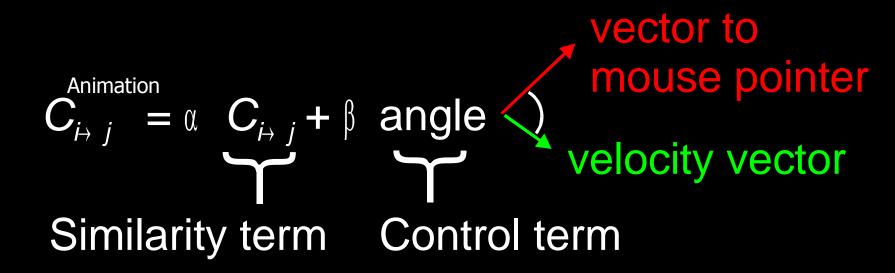


#### blue screen matting and velocity estimation



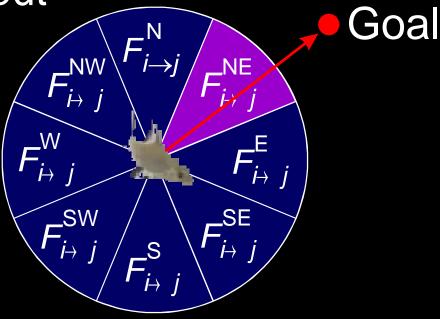
# Video sprite control

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  $\rightarrow$  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



radishes



rocks

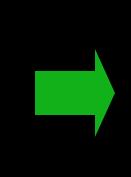


yogurt

## **Texture Synthesis**

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

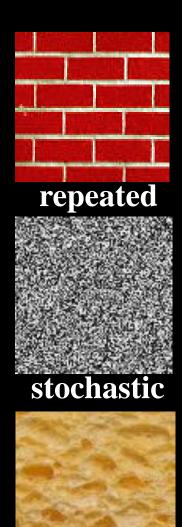






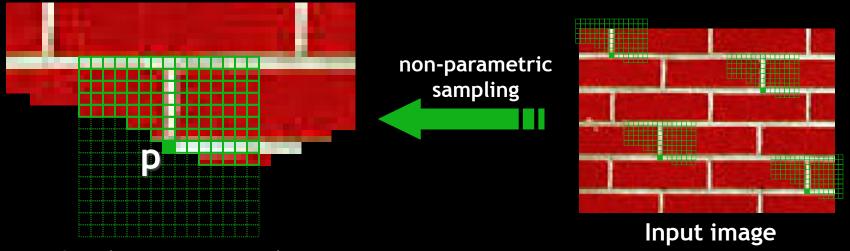
## The Challenge

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





## Efros & Leung Algorithm



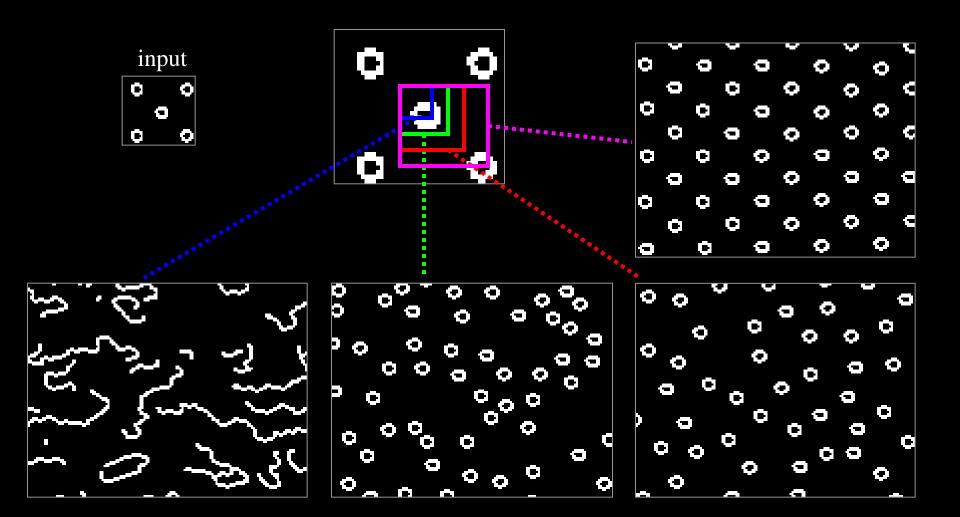
Synthesizing a pixel

- 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

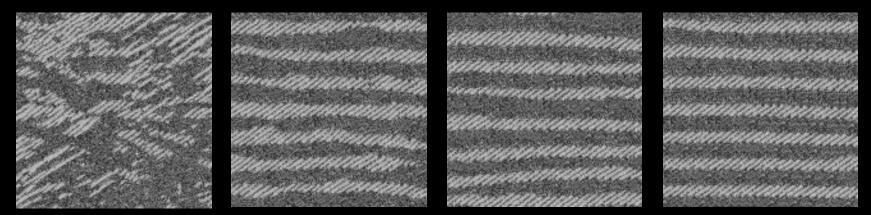
- Growing is in "onion skin" order
  - Within each "layer", pixels with most neighbors are synthesized first
  - If no close match can be found, the pixel is not synthesized until the end
- Using Gaussian-weighted SSD is very important
  - to make sure the new pixel agrees with its closest neighbors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

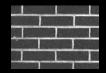
## Neighborhood Window

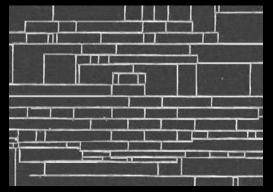


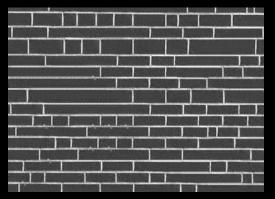
## Varying Window Size







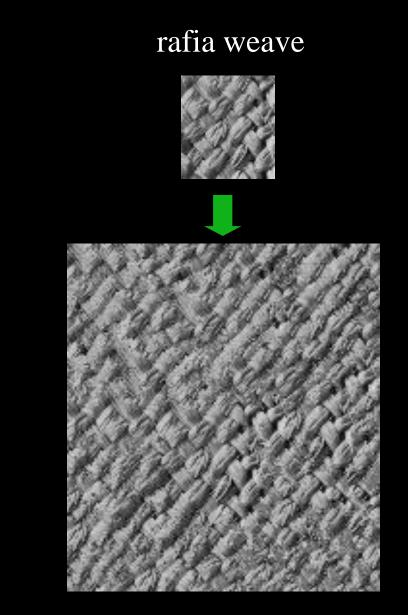




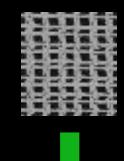
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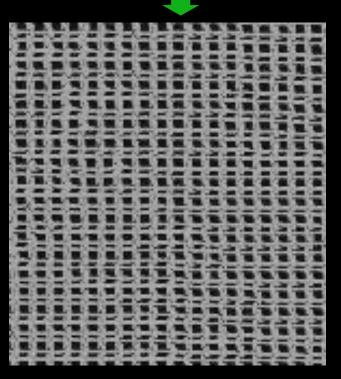
#### Increasing window size

## Synthesis Results



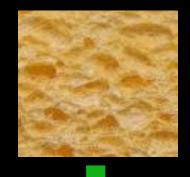
#### french canvas

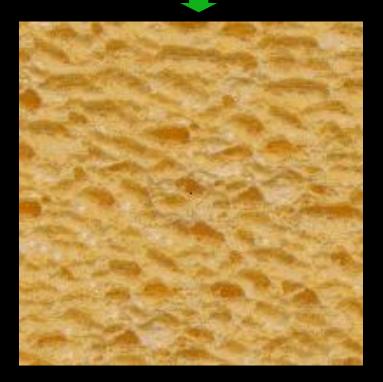




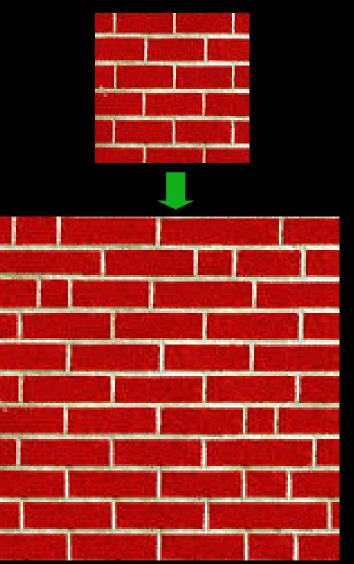
### More Results

#### white bread





### brick wall



## Homage to Shannon

r Dick Gephardt was fai 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

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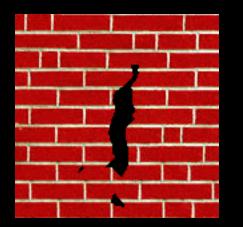
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# Hole Filling

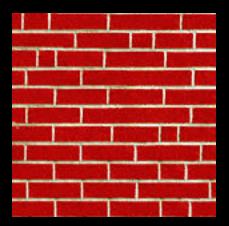




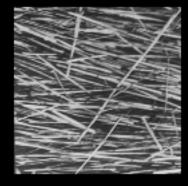


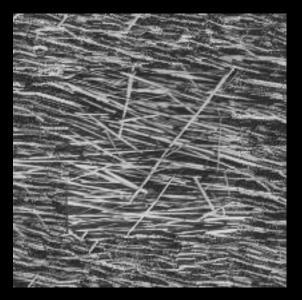




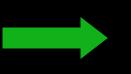


# Extrapolation







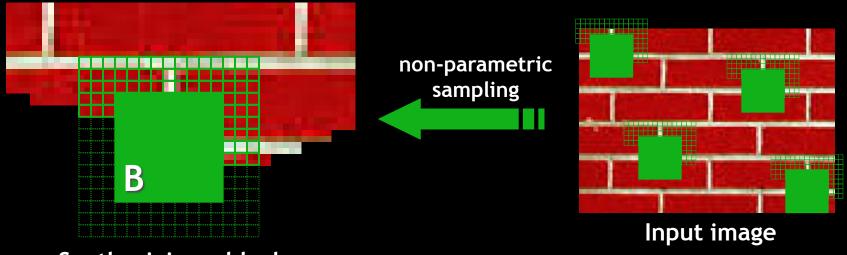




## Summary

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

# Image Quilting [Efros & Freeman]



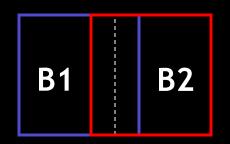
Synthesizing a block

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

### Idea: unit of synthesis = block

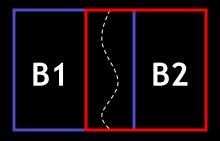
- Exactly the same but now we want P(B|N(B))
- Much faster: synthesize all pixels in a block at once
- Not the same as multi-scale!





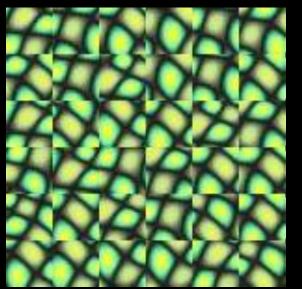
Input texture

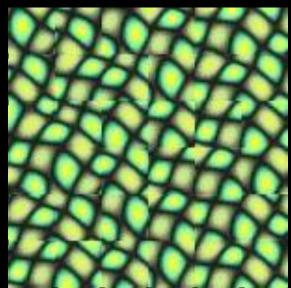
block

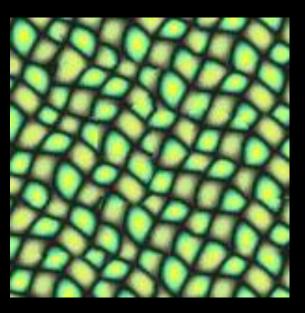


Random placement of blocks Neighboring blocks constrained by overlap

Minimal error boundary cut

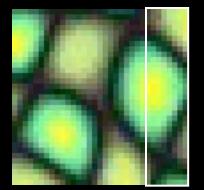


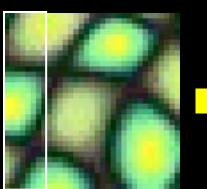




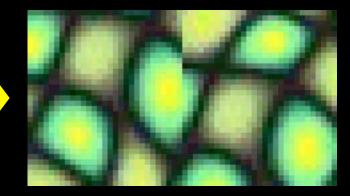
## Minimal error boundary

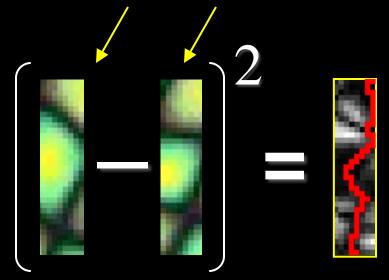
### overlapping blocks





### vertical boundary







overlap error

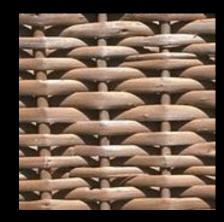
min. error boundary

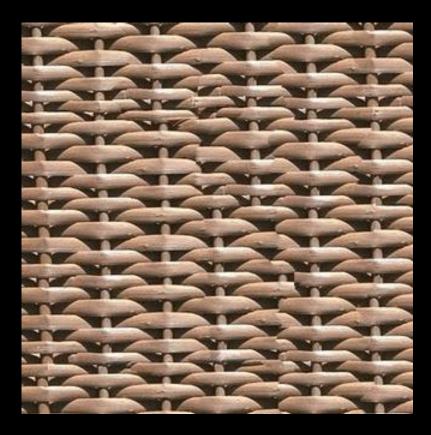
# Our Philosophy

- 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

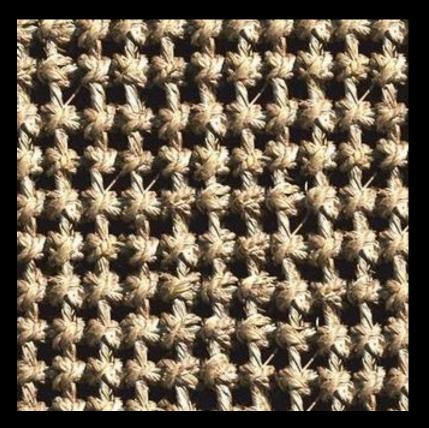






































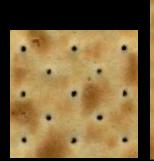


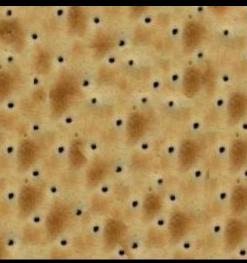
















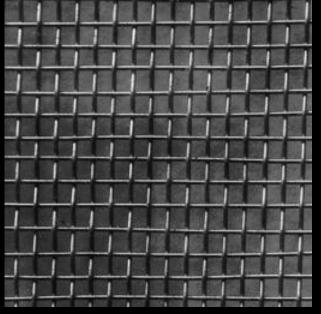


Failures (Chernobyl Harvest)

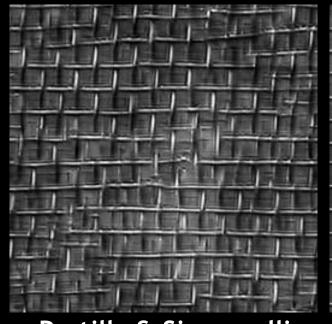




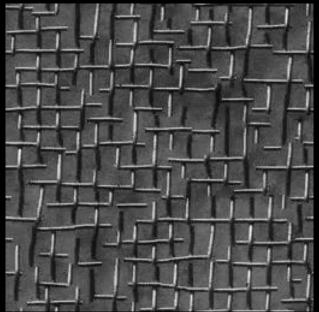


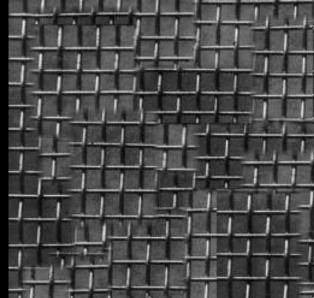


input image

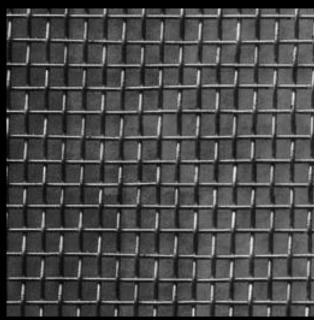


Portilla & Simoncelli



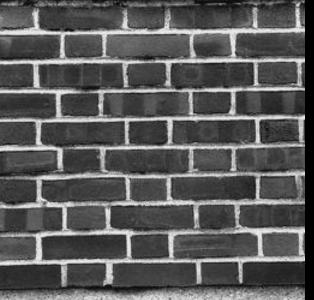


Xu, Guo & Shum



Wei & Levoy

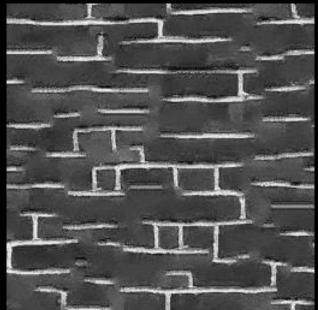
Our algorithm



input image

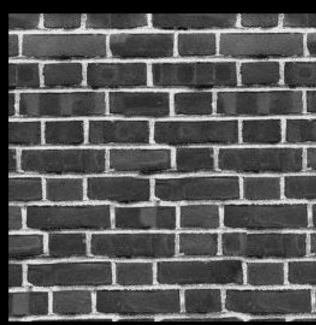


Portilla & Simoncelli





Xu, Guo & Shum



Wei & Levoy

Our algorithm

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### input image

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#### Portilla & Simoncelli

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#### Wei & Levoy

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#### Xu, Guo & Shum

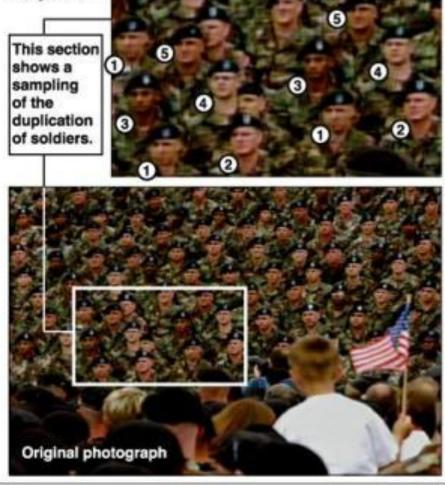
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#### Our algorithm

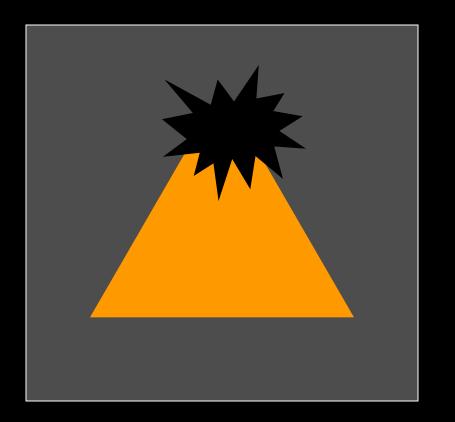
## Political Texture Synthesis!

#### 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.

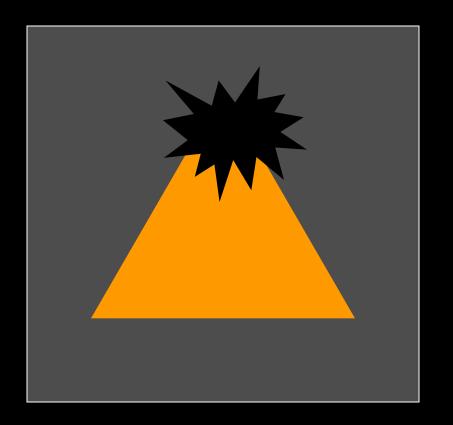


## Fill Order



• In what order should we fill the pixels?

## Fill Order

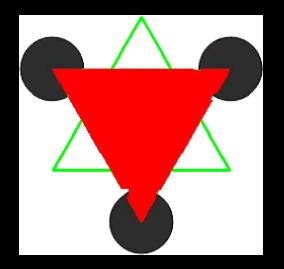


• In what order should we fill the pixels?

- choose pixels that have more neighbors filled

Criminisi, Perez, and rosema. "Select that are continuations of a proc. CVPR, 2003.

## **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



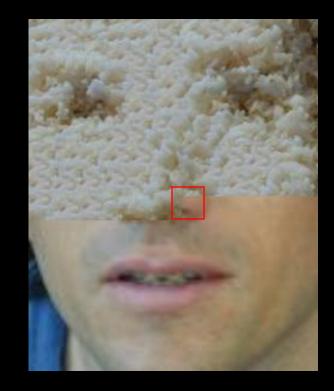


Texture sample

## **Texture Transfer**

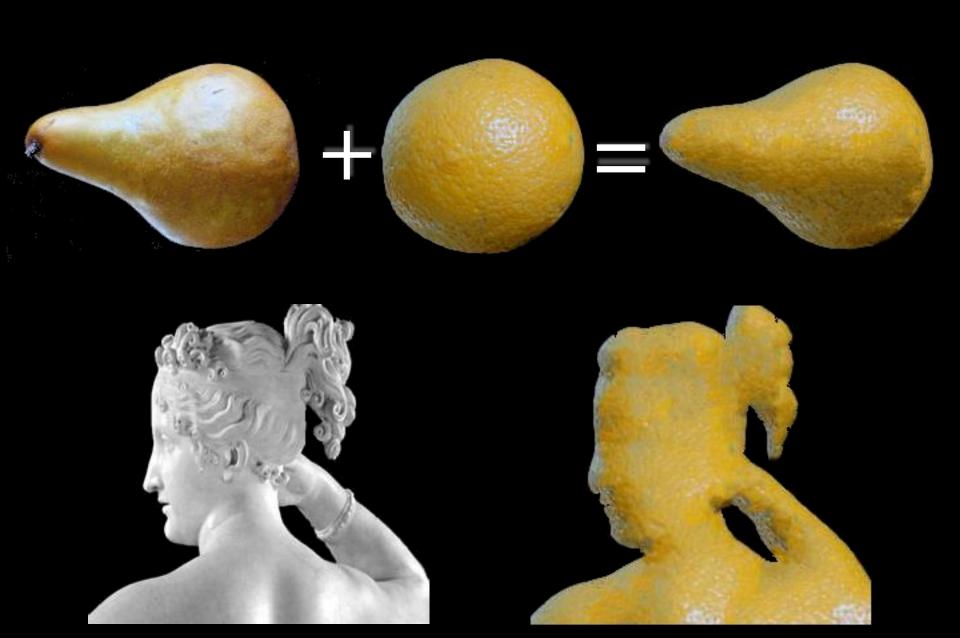
• Take the texture from one image and "paint" it onto another object





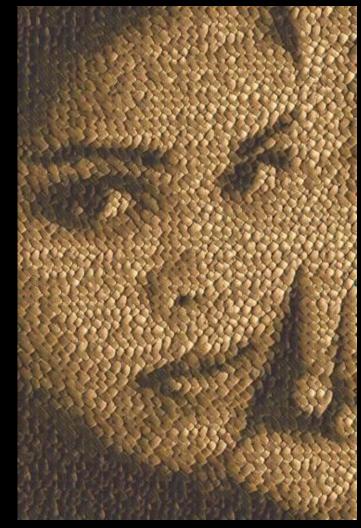
Same as texture synthesis, except an additional constraint:

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









# Image Analogies

Aaron Hertzmann<sup>1,2</sup>

Chuck Jacobs<sup>2</sup>

Nuria Oliver<sup>2</sup>

Brian Curless<sup>3</sup>

David Salesin<sup>2,3</sup>

<sup>1</sup>New York University
<sup>2</sup>Microsoft Research
<sup>3</sup>University of Washington

## Image Analogies





A









## **Blur Filter**



Unfiltered source (A)



Filtered source (A')



Unfiltered target (B)

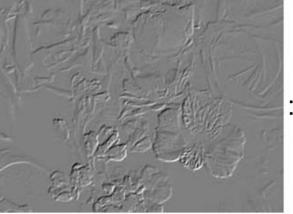


Filtered target (B')

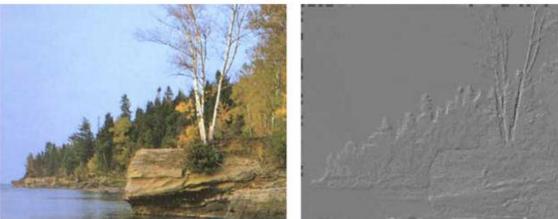
## Edge Filter



#### Unfiltered source (A)



#### Filtered source (A')



#### Unfiltered target (B)

Filtered target (B')

# Artistic Filters

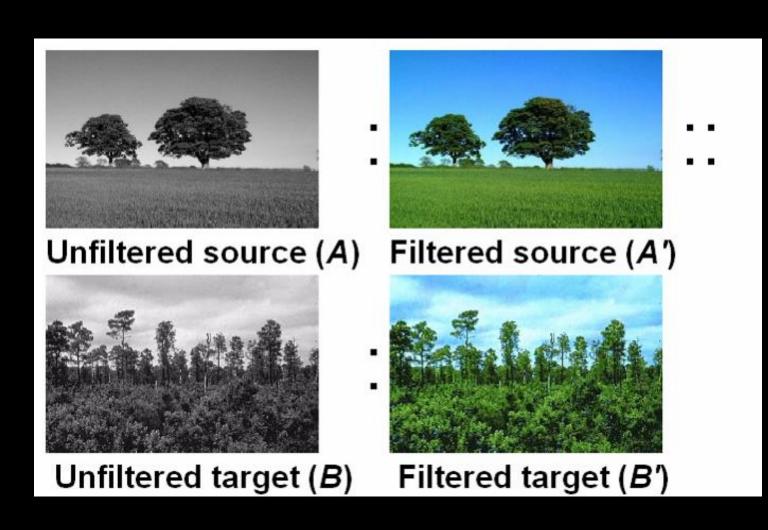




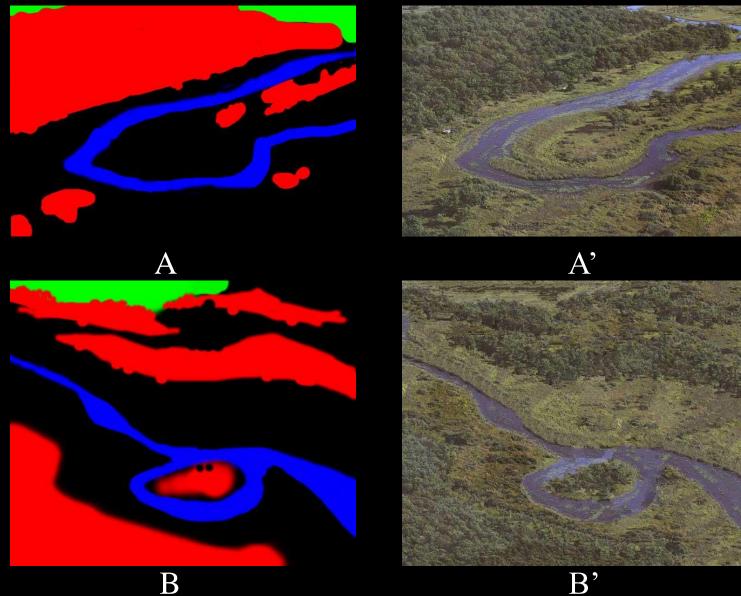


B'

### Colorization

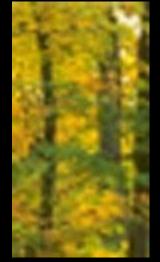


# Texture-by-numbers



# Super-resolution









A'

A

# Super-resolution (result!)



