

Data-driven Methods: Texture



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15-463: Computational Photography
Alexei Efros, CMU, Fall 2007

Texture

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



radishes



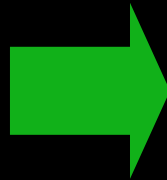
rocks



yogurt

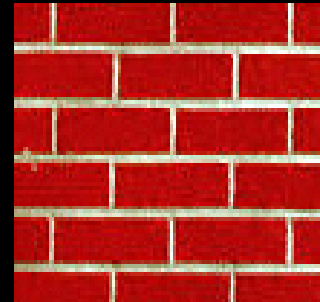
Texture Synthesis

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

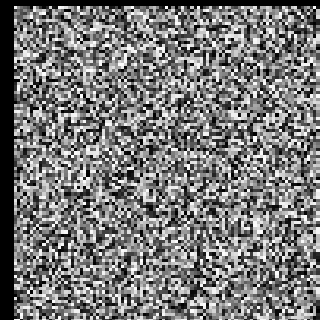


The Challenge

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



repeated

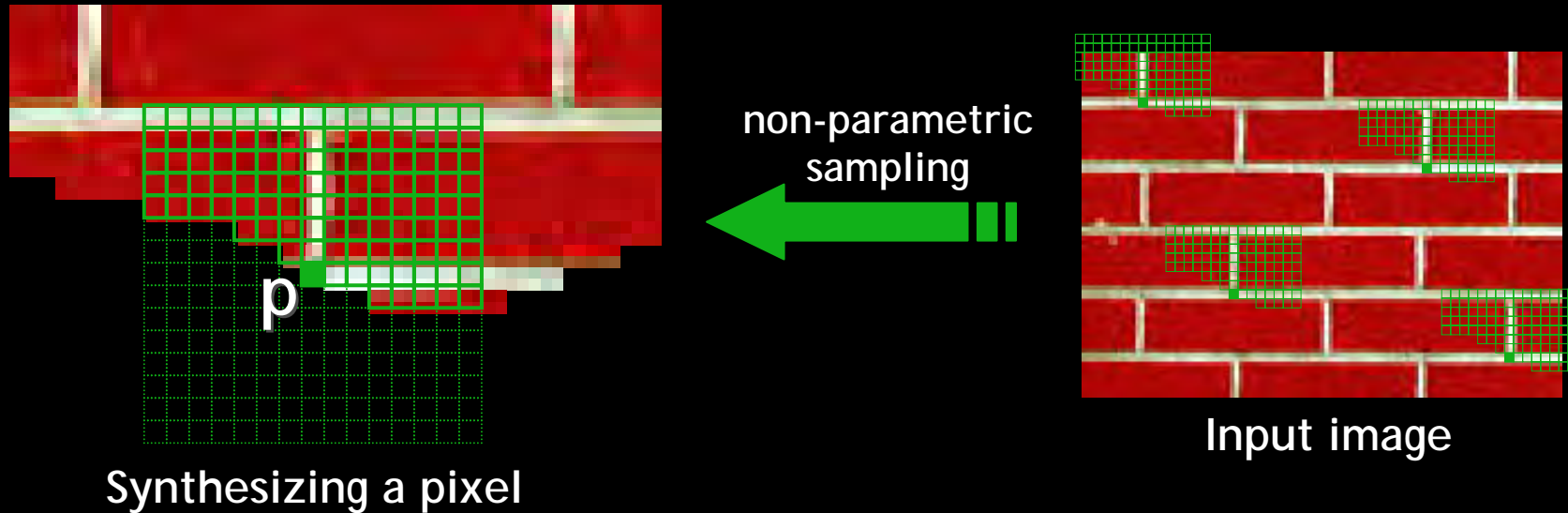


stochastic



Both?

Efros & Leung Algorithm

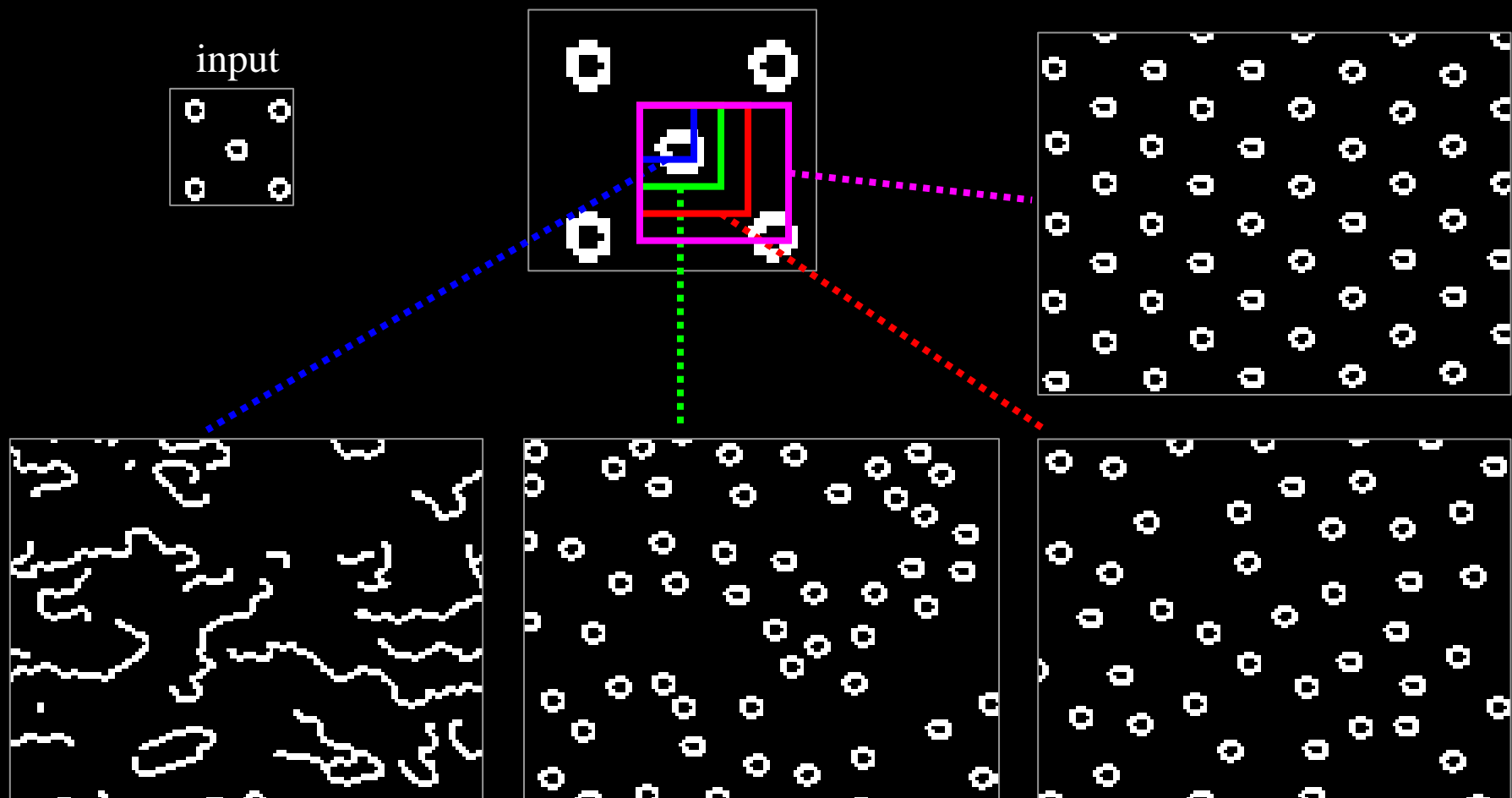


- Assuming Markov property, compute $P(\mathbf{p}|\mathbf{N}(\mathbf{p}))$
 - Building explicit probability tables infeasible
 - Instead, we *search the input image* for all similar neighborhoods — that's our pdf for \mathbf{p}
 - To sample from this pdf, just pick one match at random

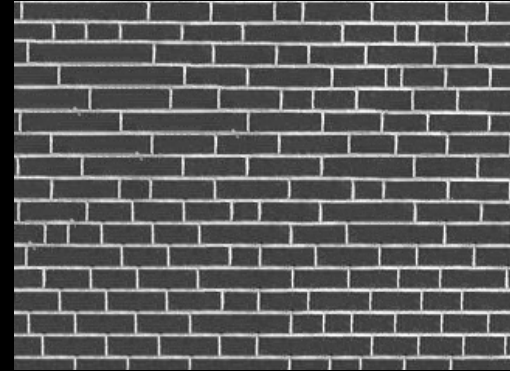
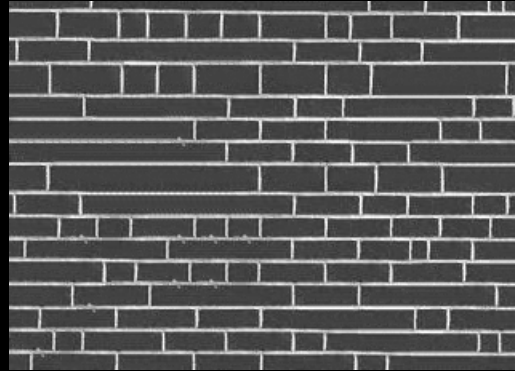
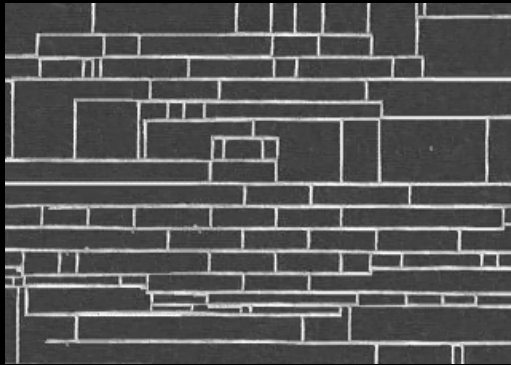
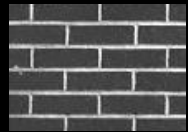
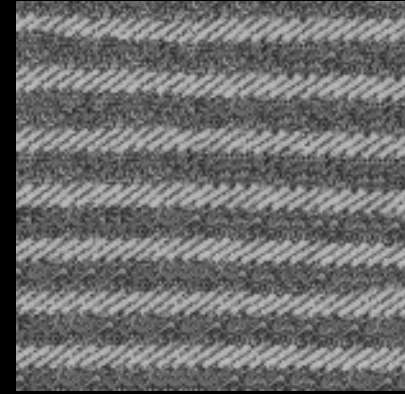
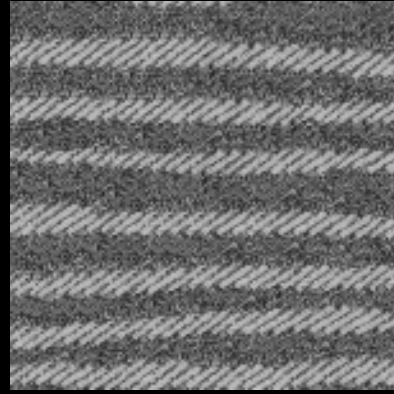
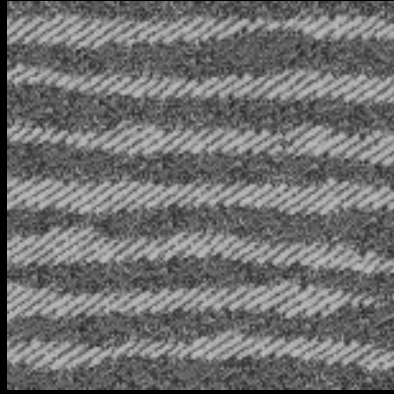
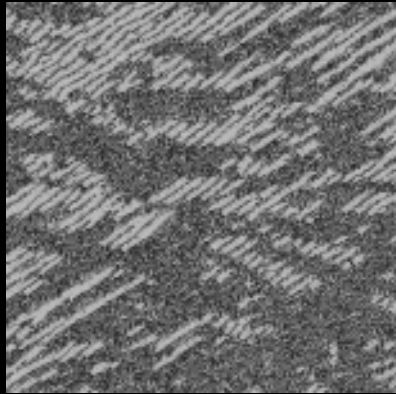
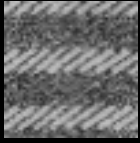
Some Details

- 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

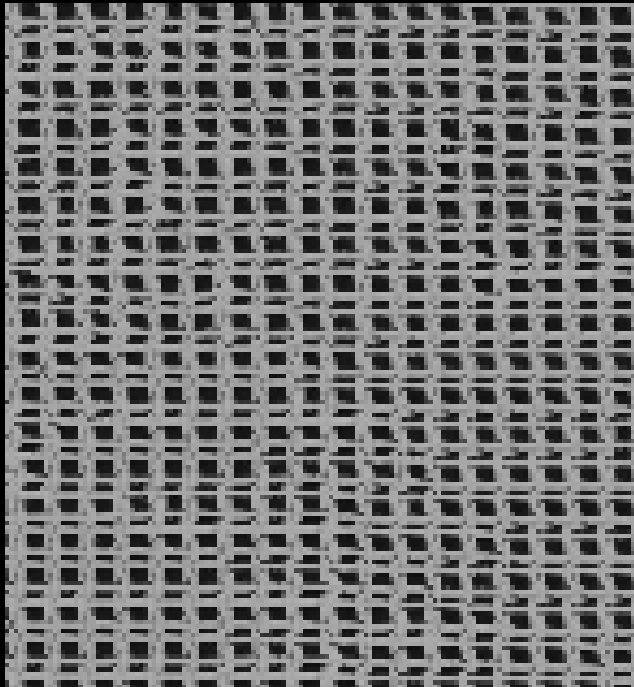
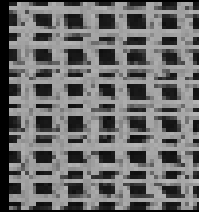


Increasing window size

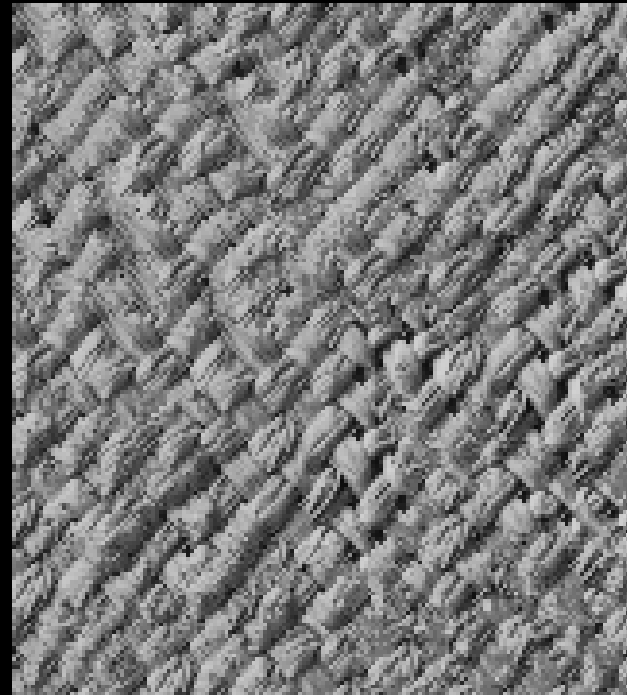
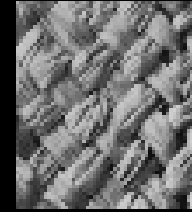


Synthesis Results

french canvas



rafia weave

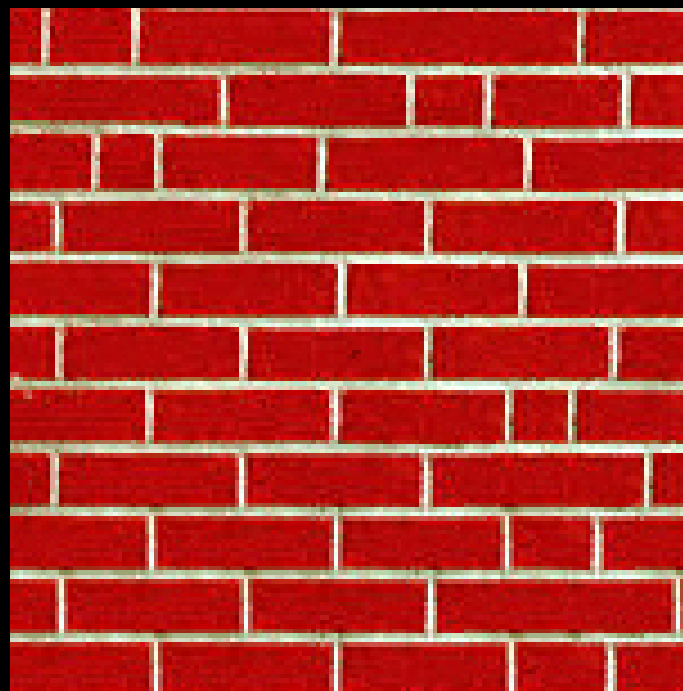
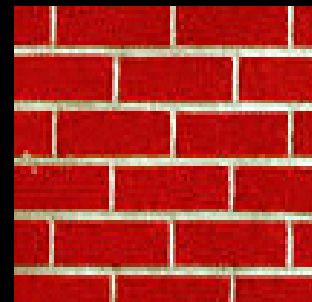


More Results

white bread



brick wall

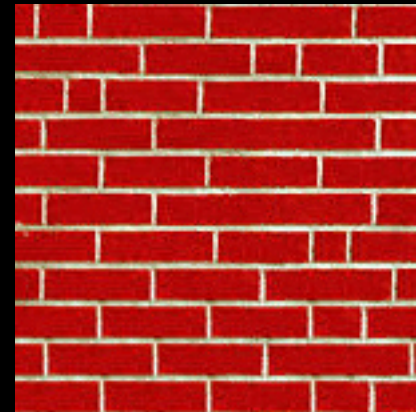
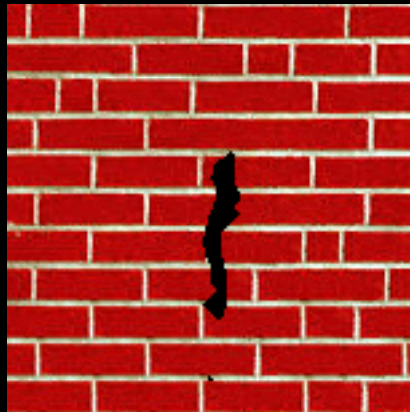


Homage to Shannon

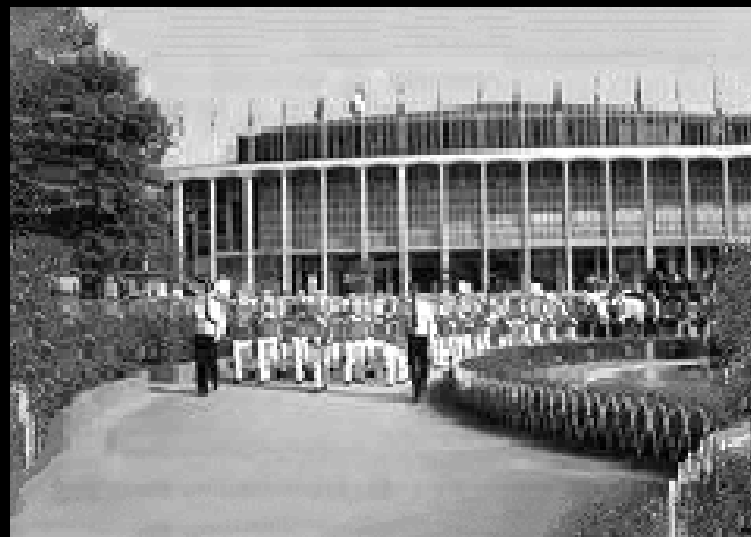
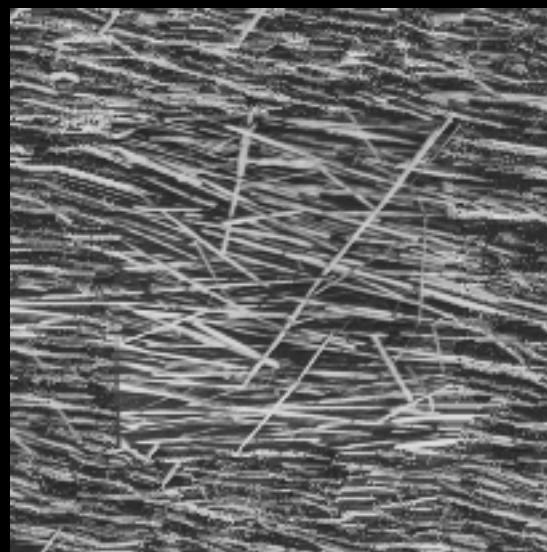
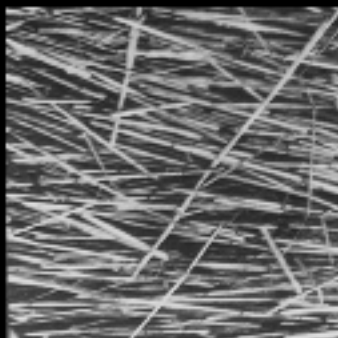
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Hole Filling



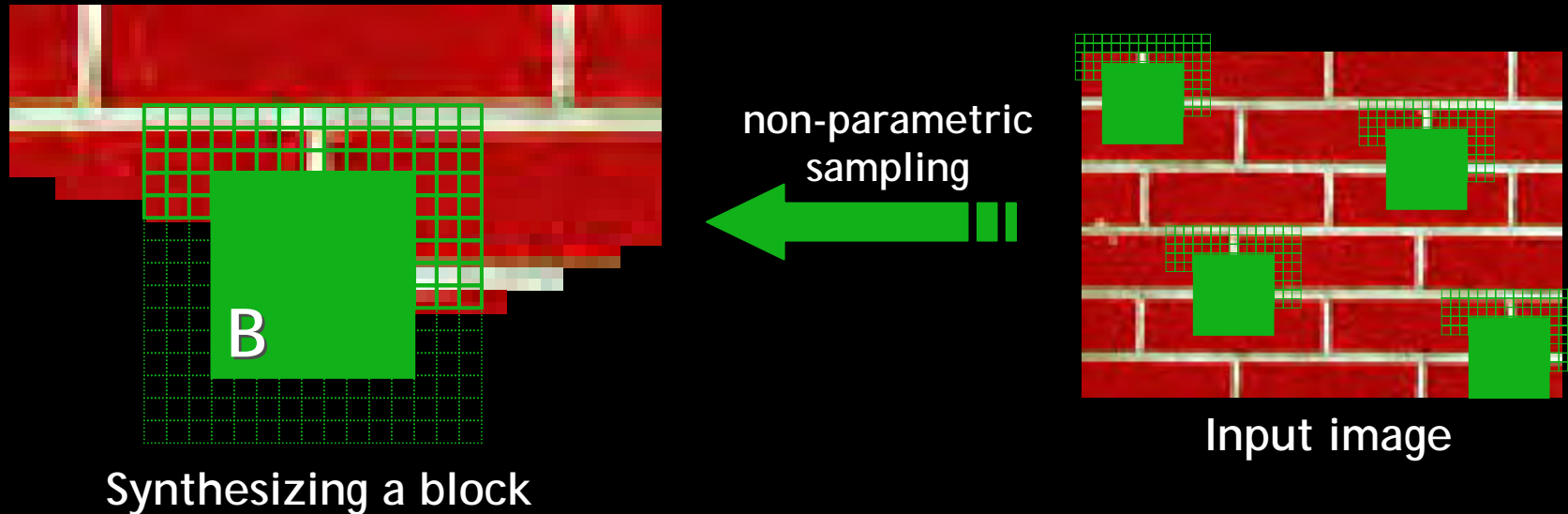
Extrapolation



Summary

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

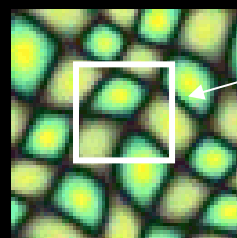
Image Quilting [Efros & Freeman]



- Observation: neighbor pixels are highly correlated

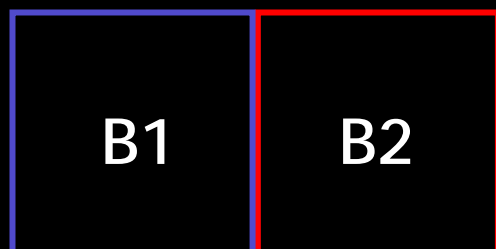
Idea: unit of synthesis = block

- 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!

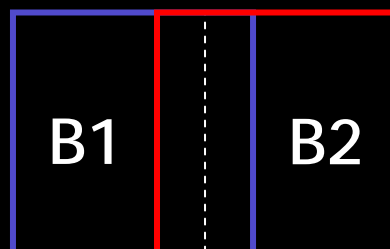


block

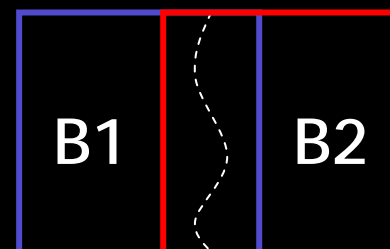
Input texture



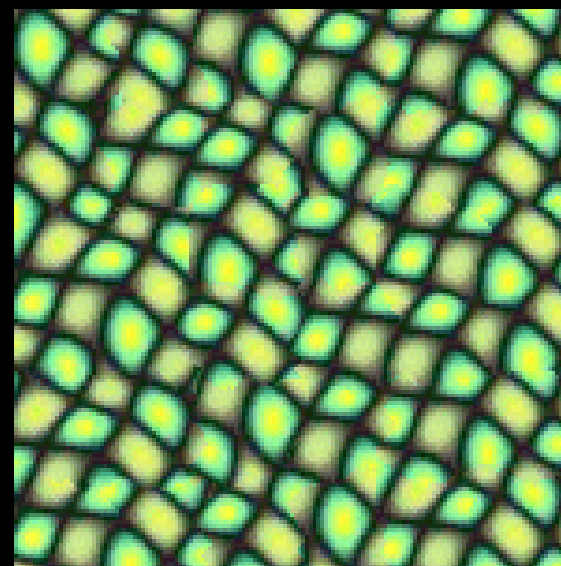
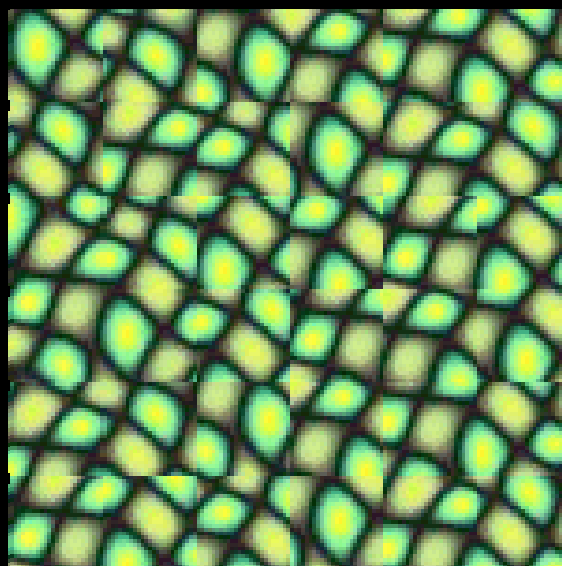
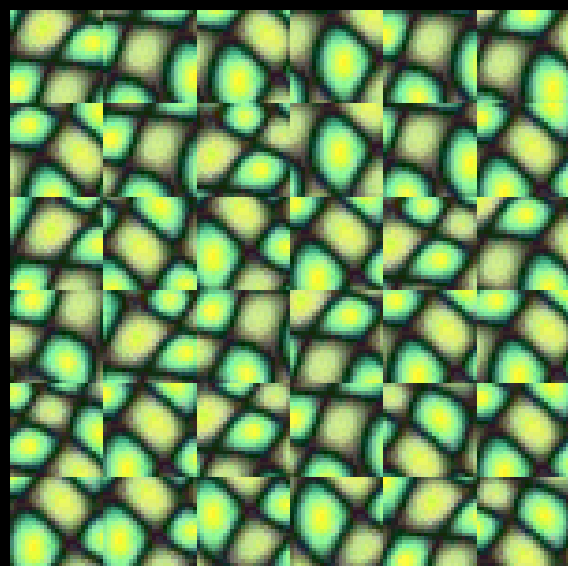
Random placement
of blocks



Neighboring blocks
constrained by overlap

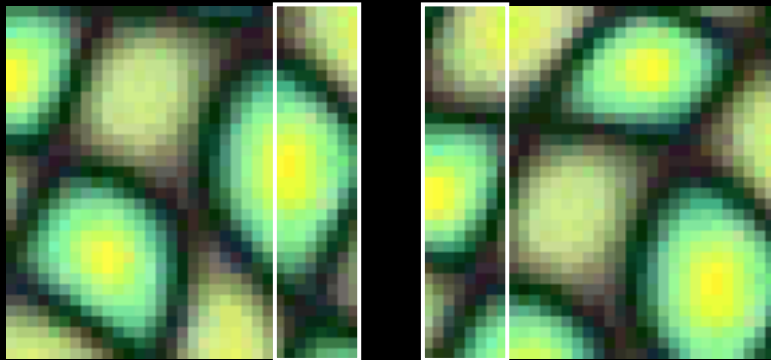


Minimal error
boundary cut

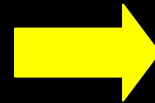
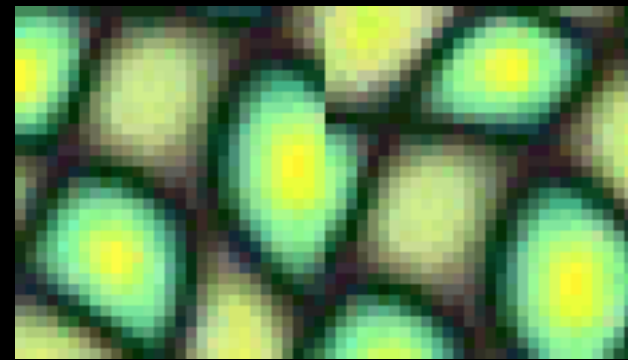


Minimal error boundary

overlapping blocks



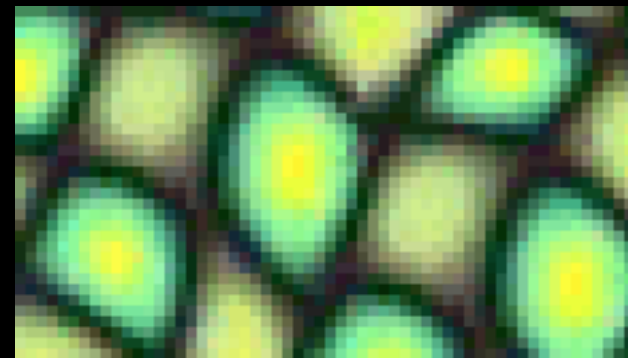
vertical boundary



$$\left[\begin{array}{c} \text{block 1} \\ - \\ \text{block 2} \end{array} \right]^2 = \text{error map}$$

The diagram shows two overlapping blocks of the cell image. A yellow arrow points from the overlap region of the first block to the first block in the subtraction. Another yellow arrow points from the overlap region of the second block to the second block in the subtraction. The result is a vertical strip of the error map, where the error is high (red) at the boundary and low (black) elsewhere.

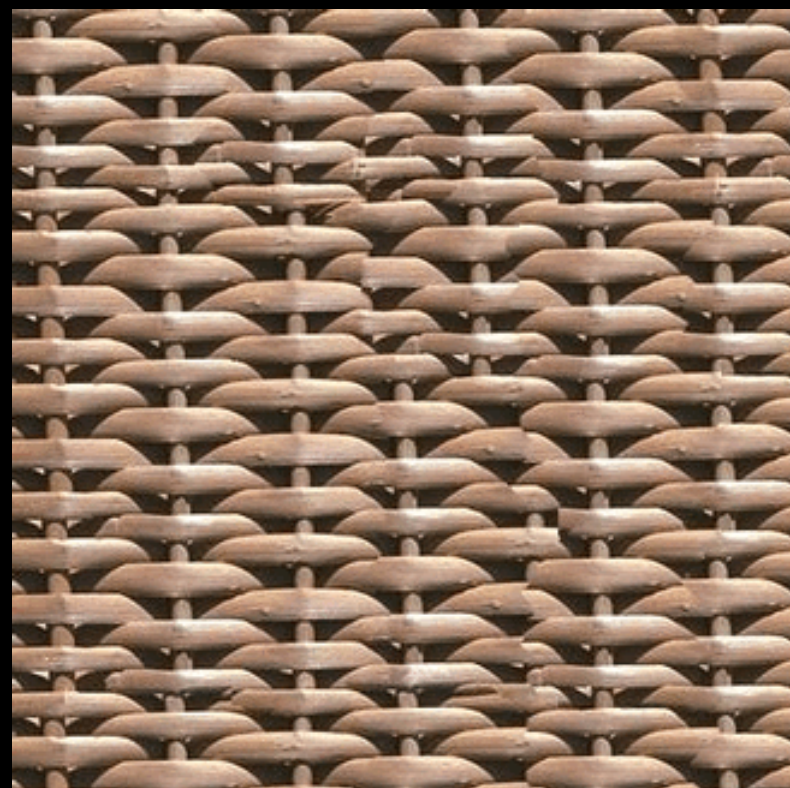
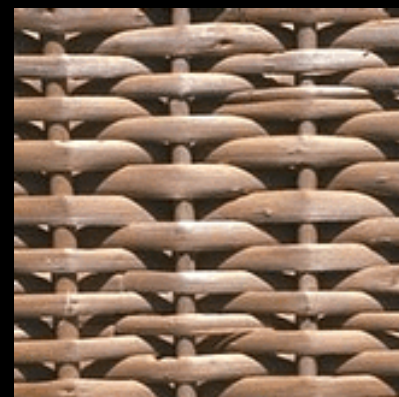
overlap error

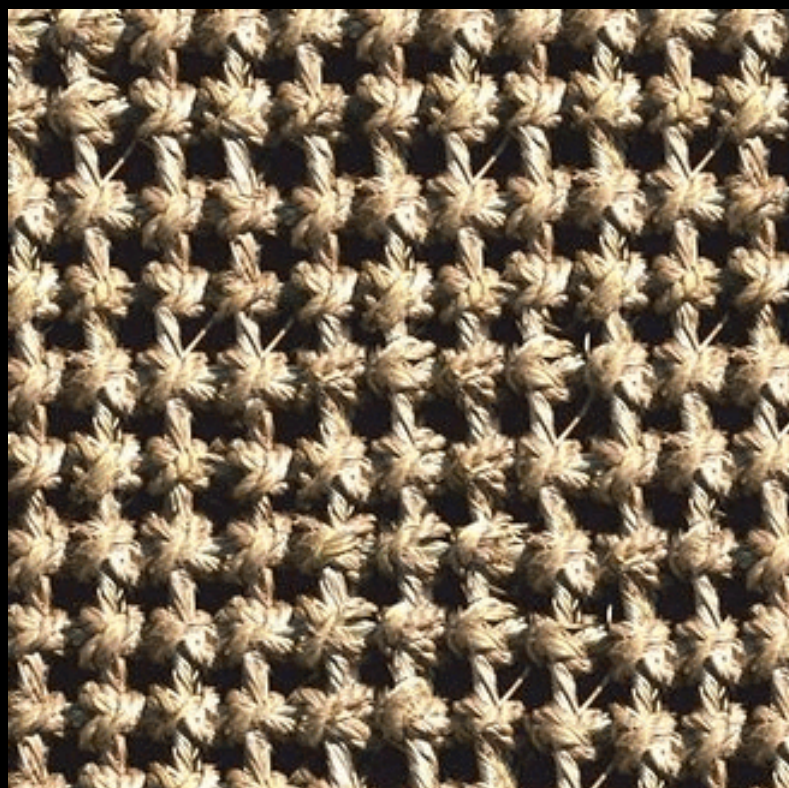


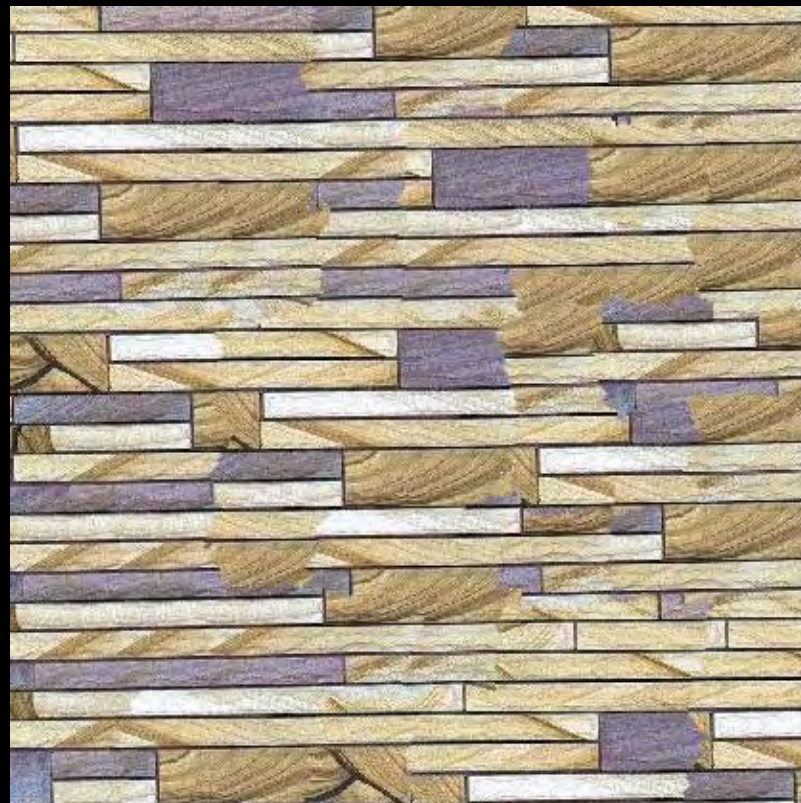
min. error boundary

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

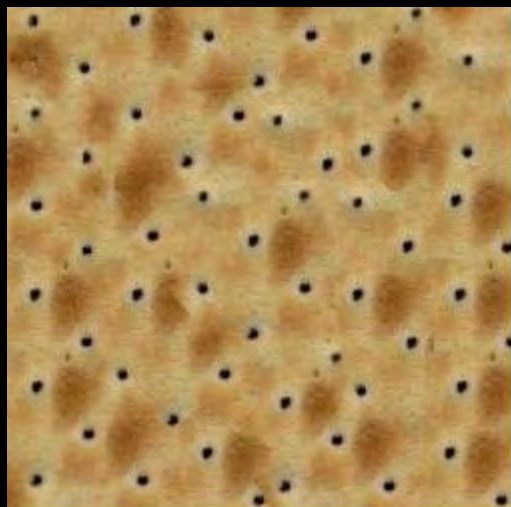








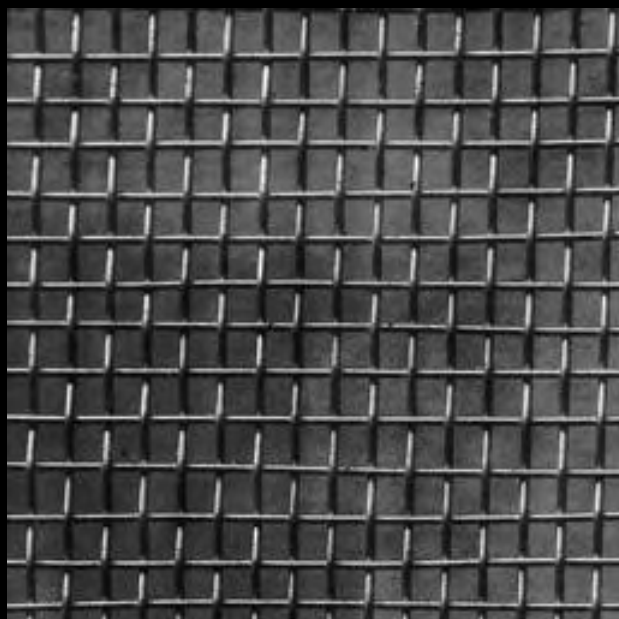




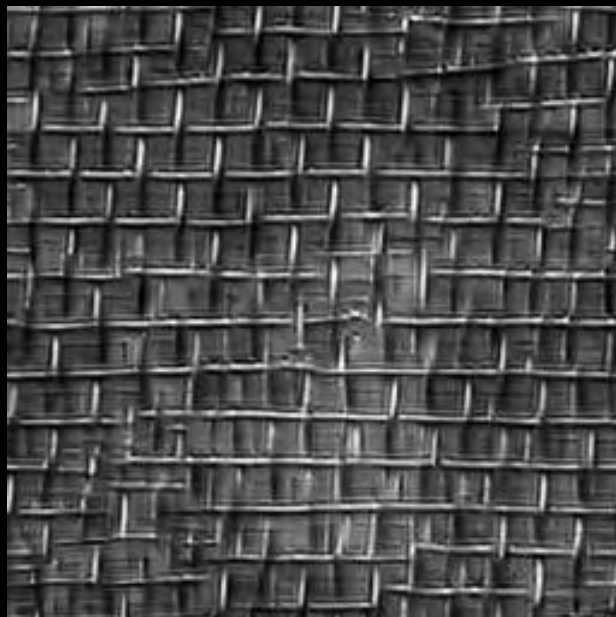


Failures (Chernobyl Harvest)

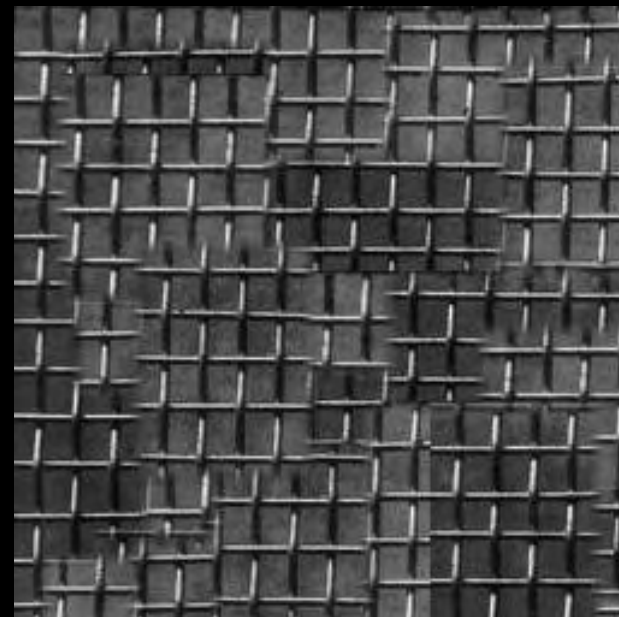




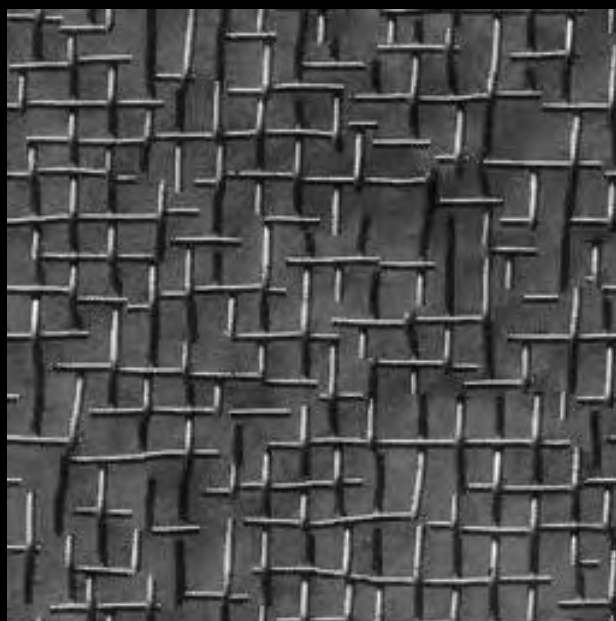
input image



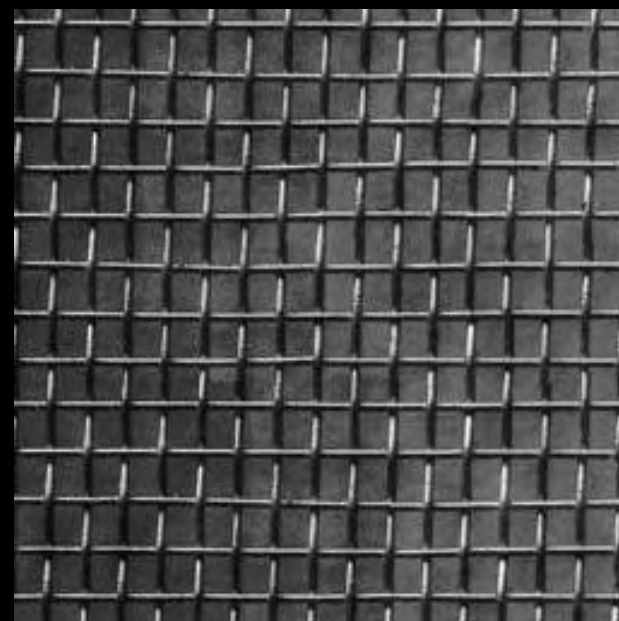
Portilla & Simoncelli



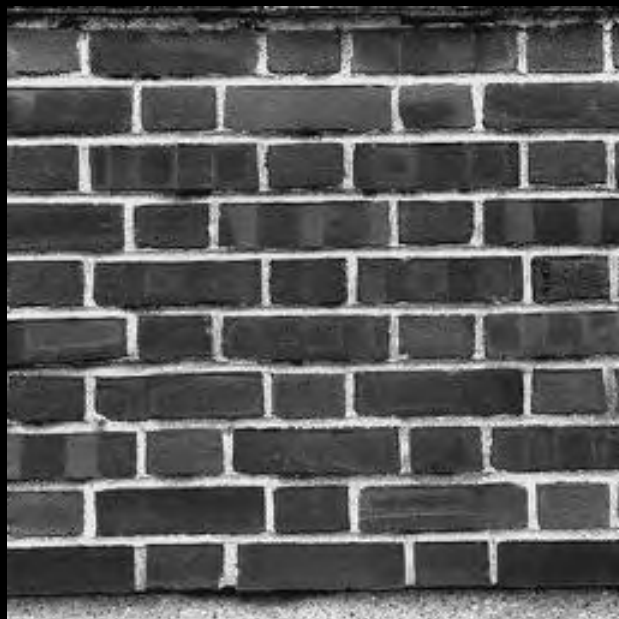
Xu, Guo & Shum



Wei & Levoy



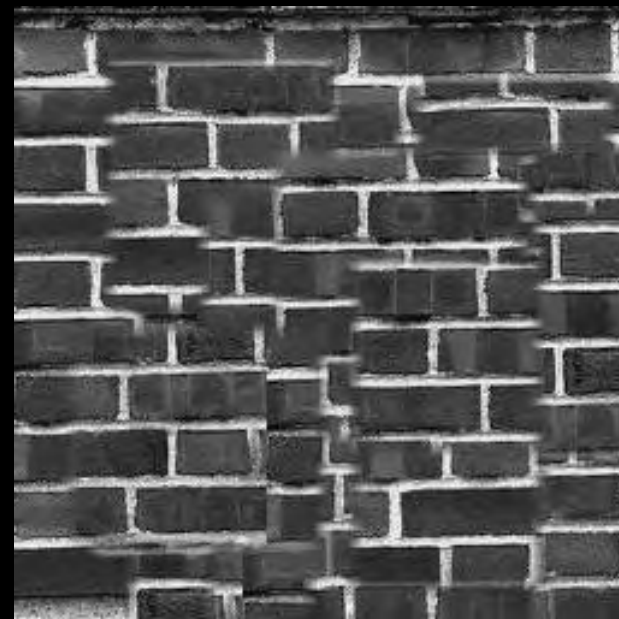
Our algorithm



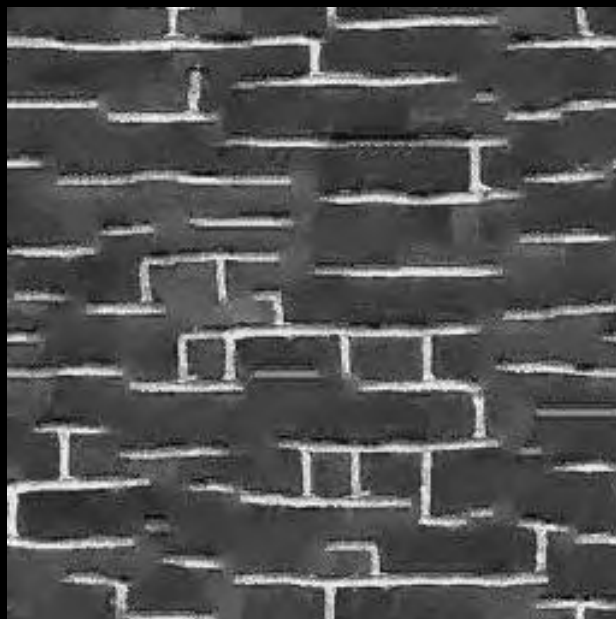
input image



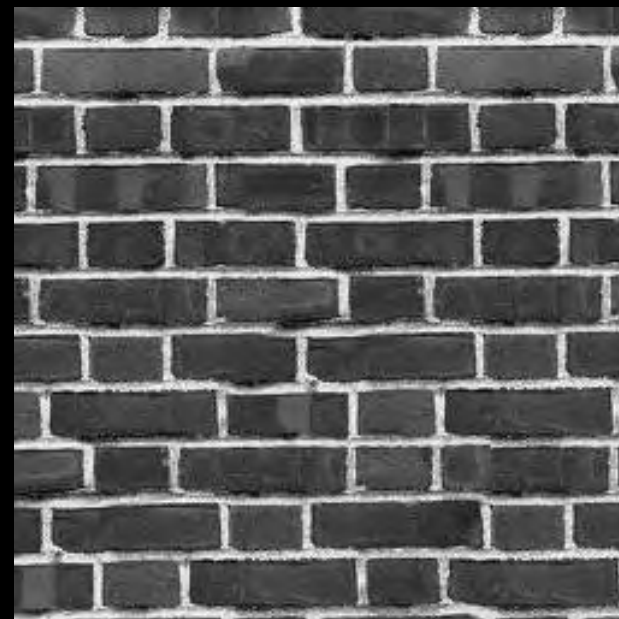
Portilla & Simoncelli



Xu, Guo & Shum



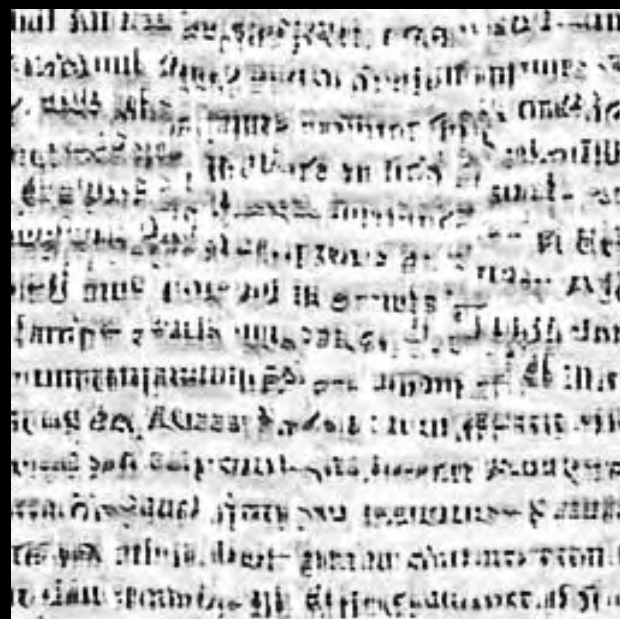
Wei & Levoy



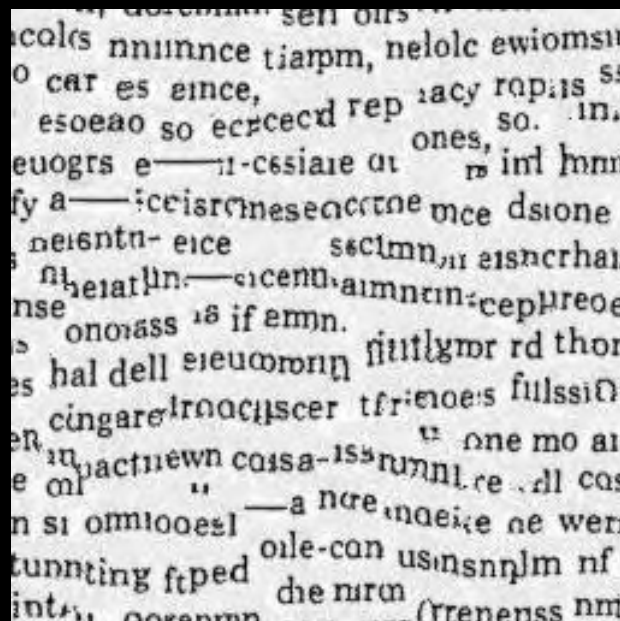
Our algorithm

end of a visual cortical neuron—the in
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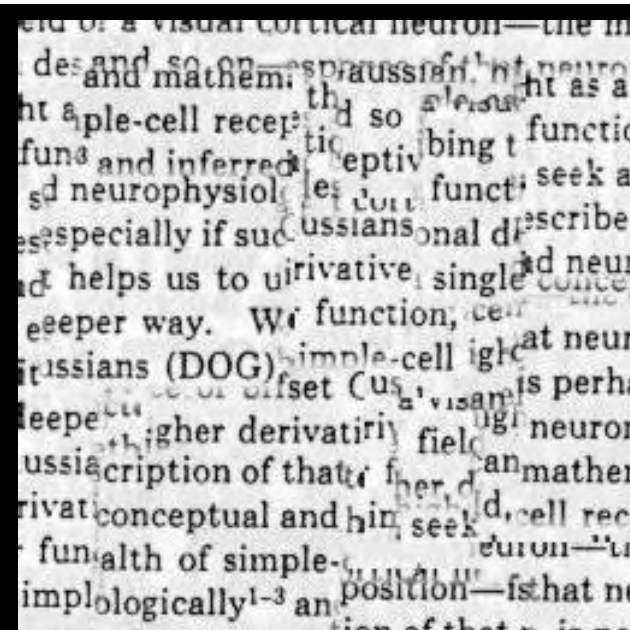
input image



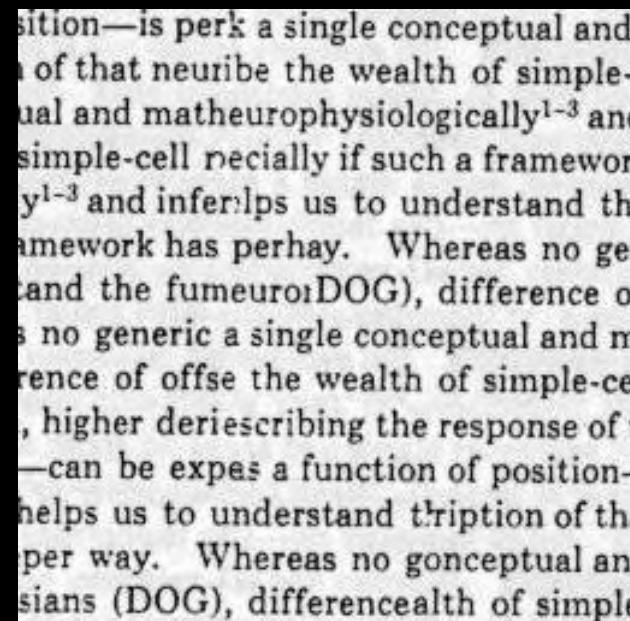
Portilla & Simoncelli



Wei & Levoy



Xu, Guo & Shum



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.

This section shows a sampling of the duplication of soldiers.



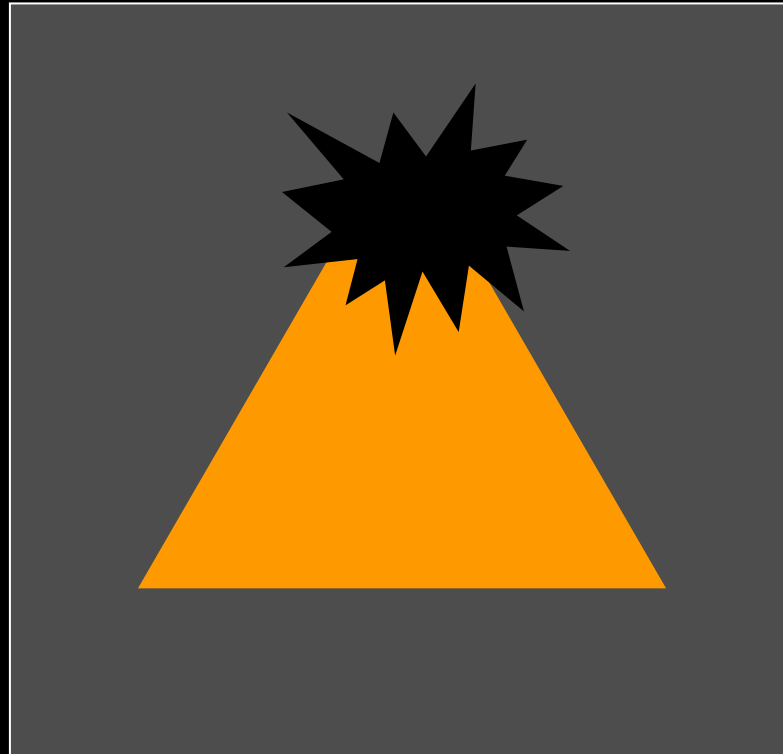
Original photograph

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

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

lines/curves/colors

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

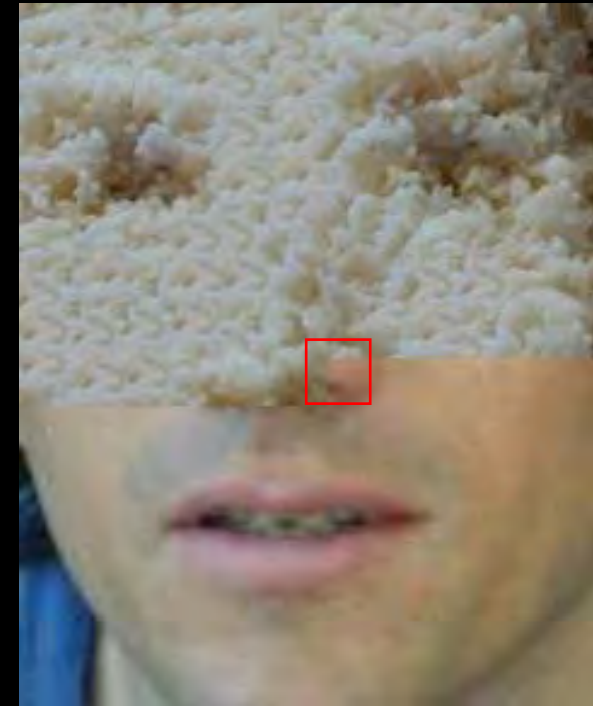


Texture sample



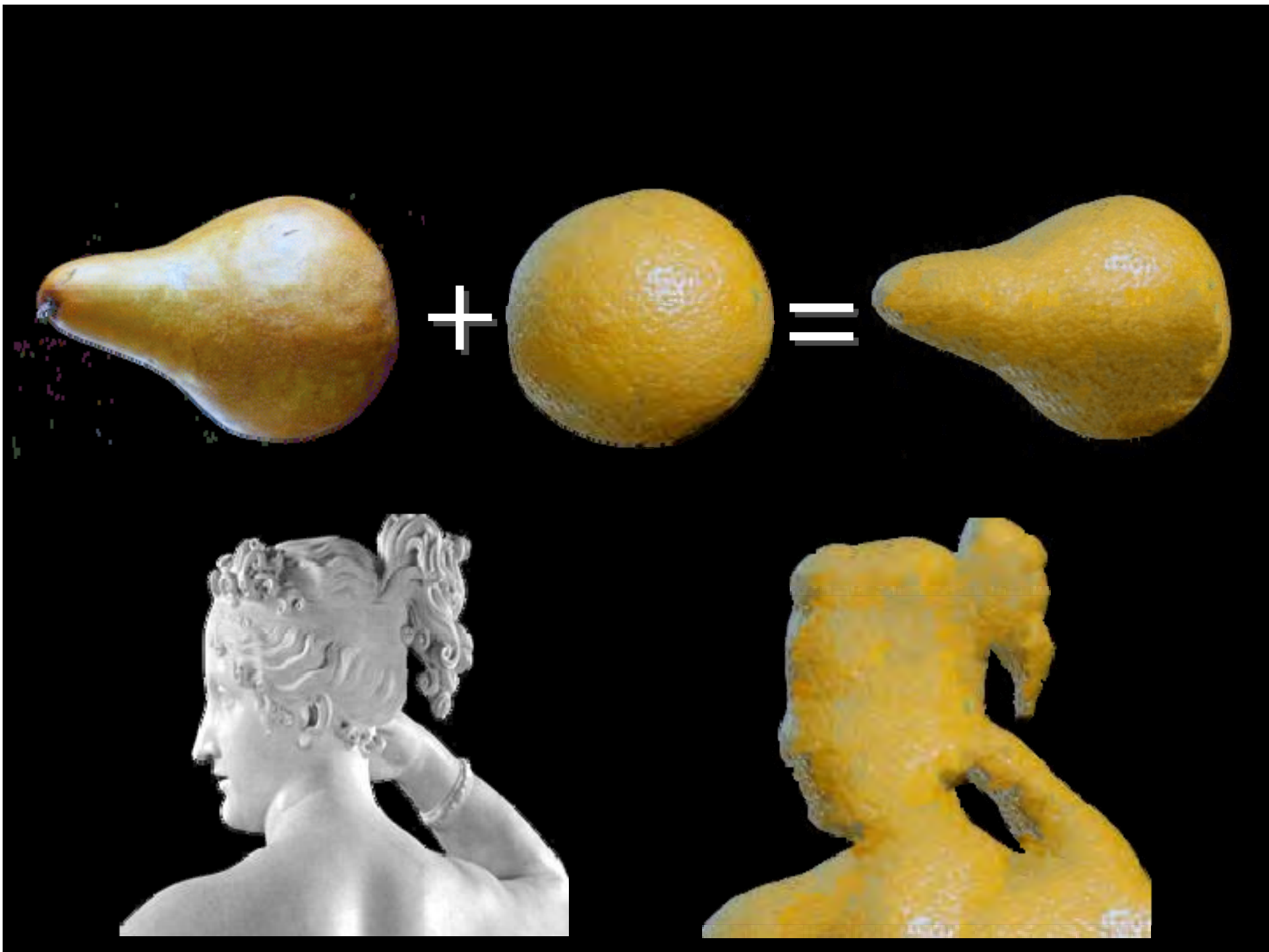
Texture Transfer

- 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”



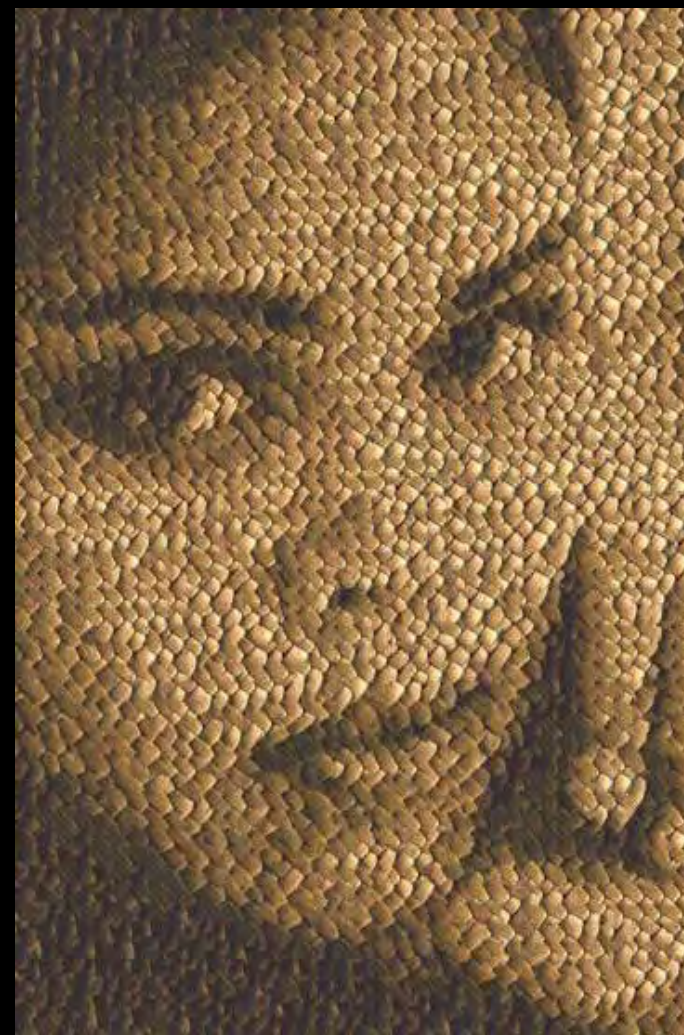


Image Analogies

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



A'



B



B'



Blur Filter



Unfiltered source (A)



Filtered source (A')



Unfiltered target (B)

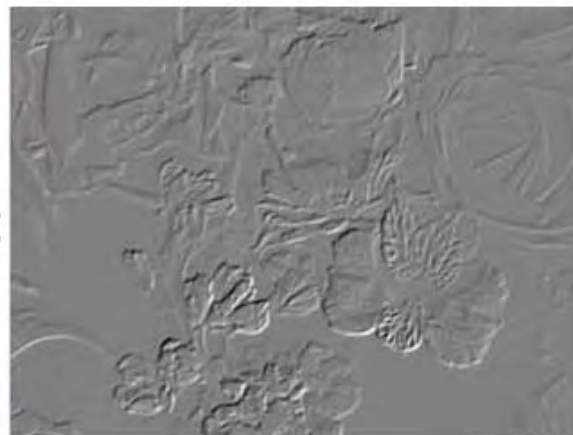


Filtered target (B')

Edge Filter



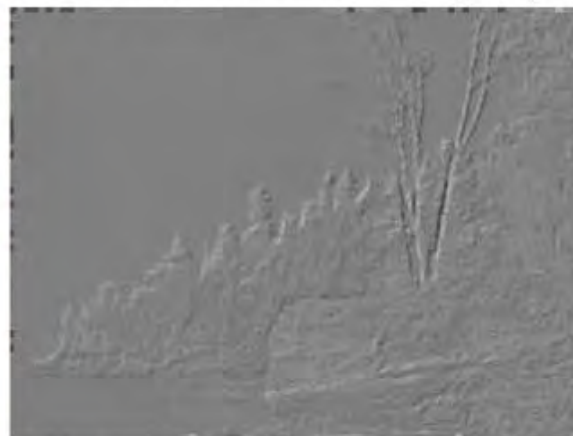
Unfiltered source (A)



Filtered source (A')



Unfiltered target (B)



Filtered target (B')

Artistic Filters



A



A'



B



B'

Colorization



Unfiltered source (A)

▪
▪



Filtered source (A')

▪ ▪
▪ ▪



Unfiltered target (B)

▪
▪



Filtered target (B')

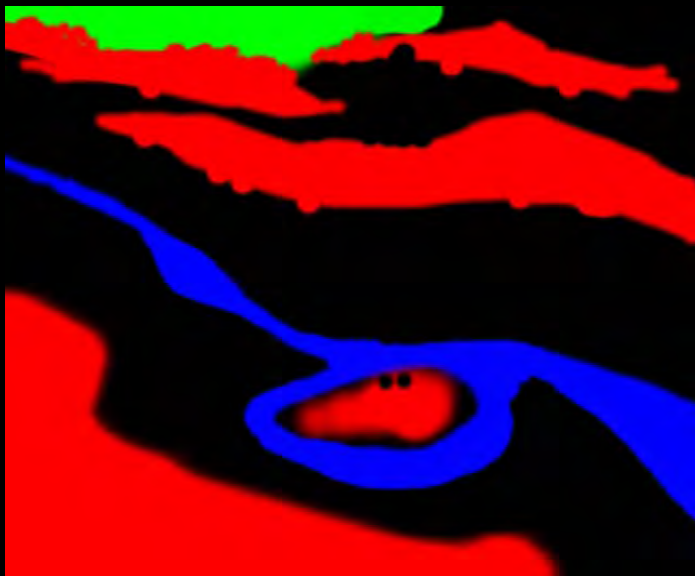
Texture-by-numbers



A



A'



B



B'

Super-resolution



A



A'

Super-resolution (result!)



B



B'

Scene Completion Using Millions of Photographs

James Hays and Alexei A. Efros
Carnegie Mellon University







Efros and Leung result



Criminisi et al. result



Criminisi et al. result



Scene Matching for Image Completion



[Search Images](#)[Search the Web](#)[Advanced Image Search](#)
[Preferences](#)

Strict SafeSearch is on

Images

Showing:

All image sizes

Results **1 - 20** of about **908,000** for **alley** [\[definition\]](#) with **Safesearch on**. (0.07 seconds)

Change **Alley** Aerial Plaza with its The Printer's **Alley** sign looking ...
300 x 400 - 21k
en.wikipedia.org



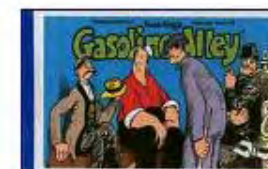
Looking west past Printers **Alley**.
679 x 450 - 469k - jpg
franklin.thefuntimesguide.com



More Bubble Gum **Alley** photos
can be ...
679 x 450 - 464k - jpg
franklin.thefuntimesguide.com



Gasoline **Alley** gang
692 x 430 - 177k - jpg
newcritics.com



2007 **Alley** Loop Sponsors
300 x 453 - 51k - jpg
www.cbnordic.org



Earl G. **Alley** ...
550 x 413 - 98k
infopedia.nlb.gov.sg



Gun **Alley** 8.5x11 Full Color Ink
Wash ...
321 x 383 - 19k - jpg
www.msstate.edu



Grace Court **Alley**
732 x 549 - 98k - jpg
www.bridgeandtunnelclub.com



Richard B. **Alley**
450 x 361 - 29k - gif
www.ncdc.noaa.gov



Also, Chicken **Alley** is reported to
...
4902 x 460 - 1048k - jpg
sflwww.er.usgs.gov

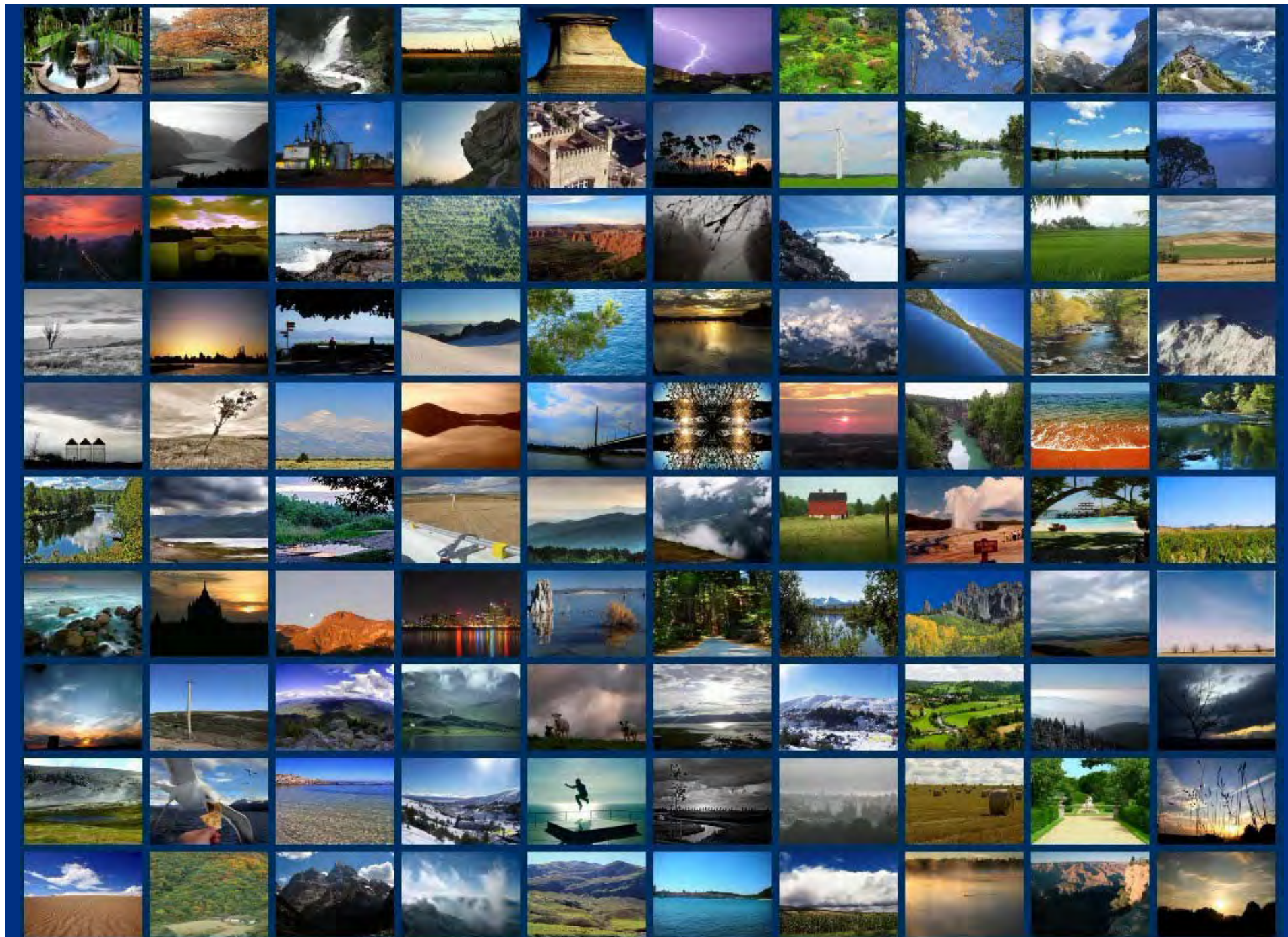


Also, Chicken **Alley** is reported to
...
450 x 337 - 82k
phidoux.typepad.com



Ego **Alley**
500 x 375 - 48k - jpg
dc.about.com

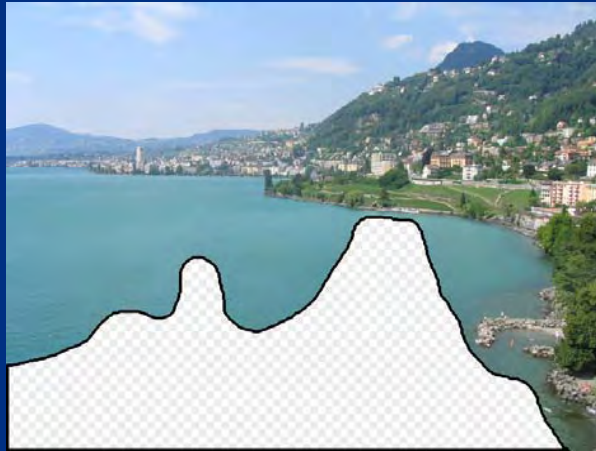




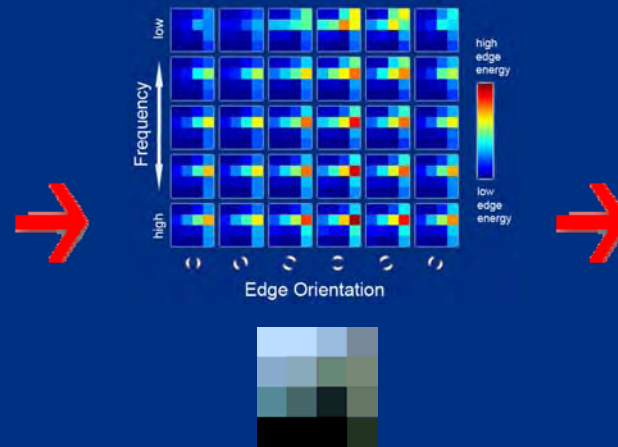


Scene Completion Result

The Algorithm



Input image



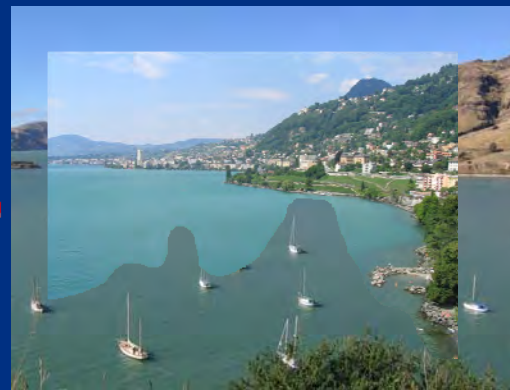
Scene Descriptor



Image Collection



20 completions



Context matching
+ blending



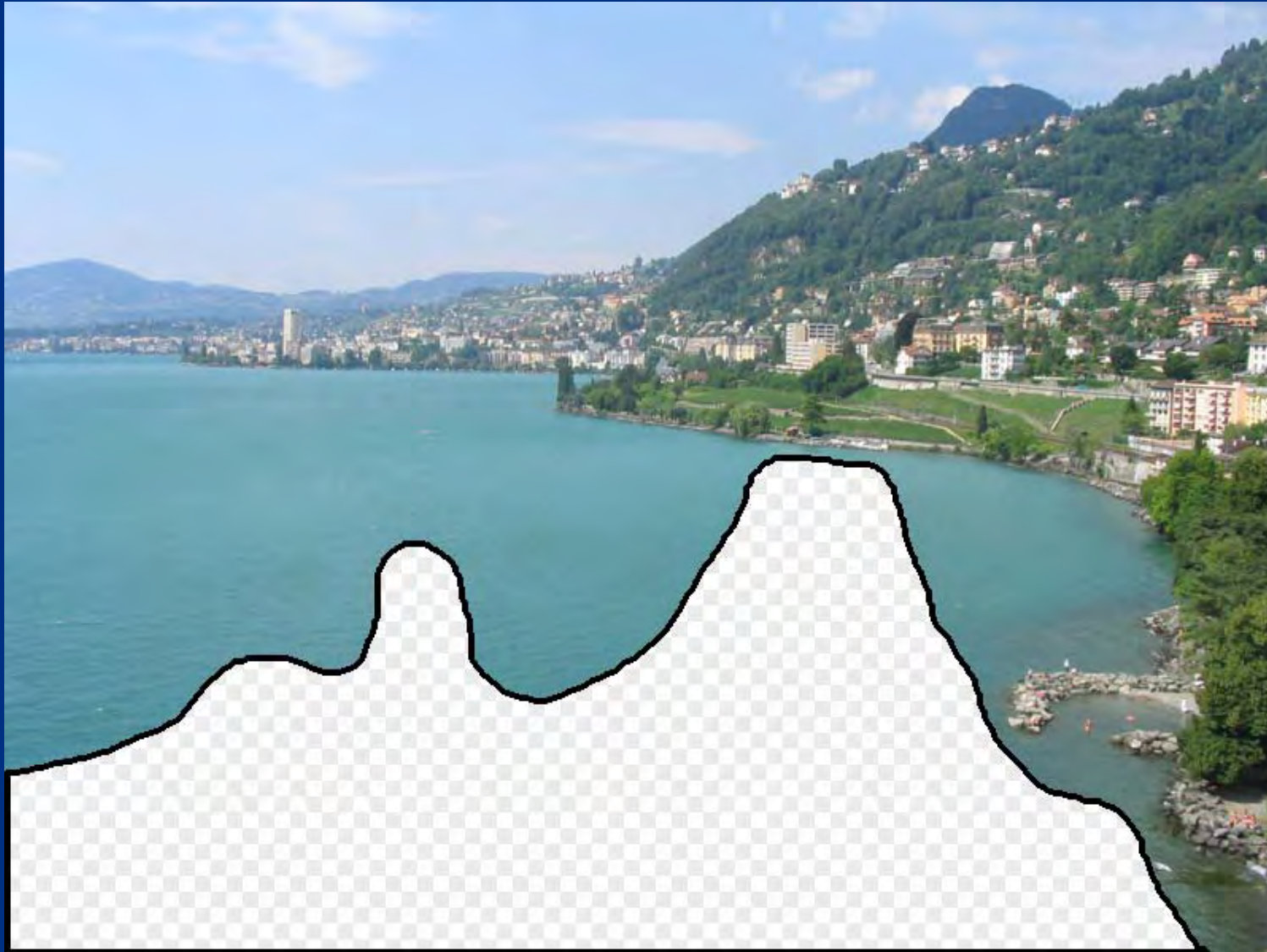
200 matches

Data

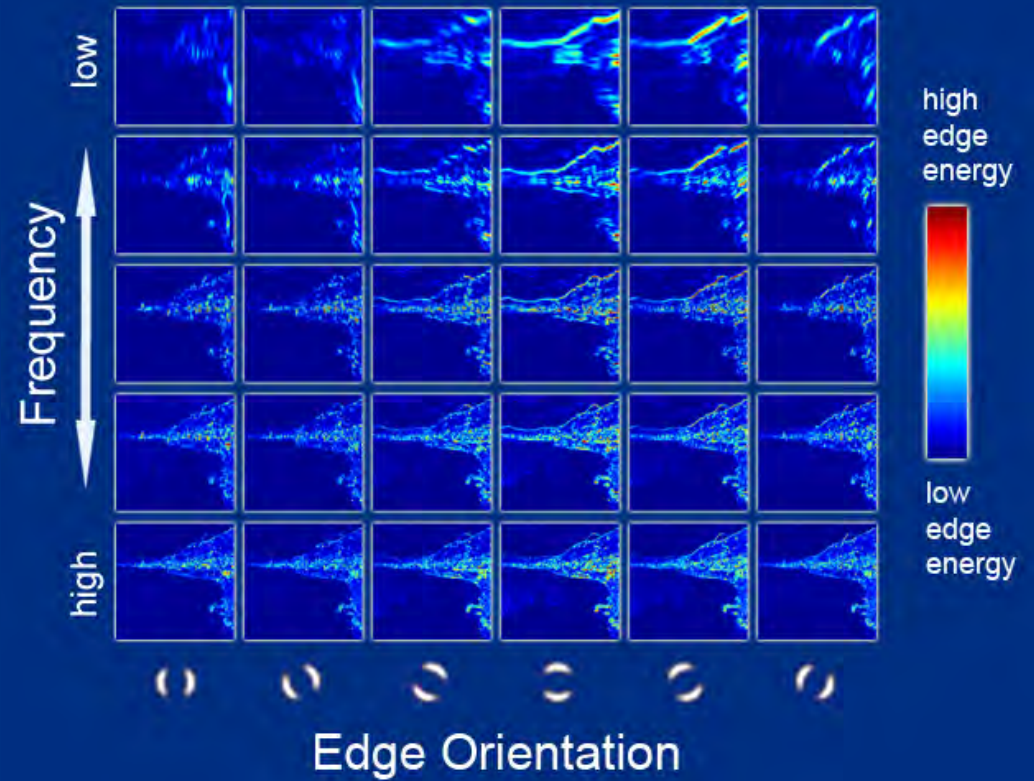
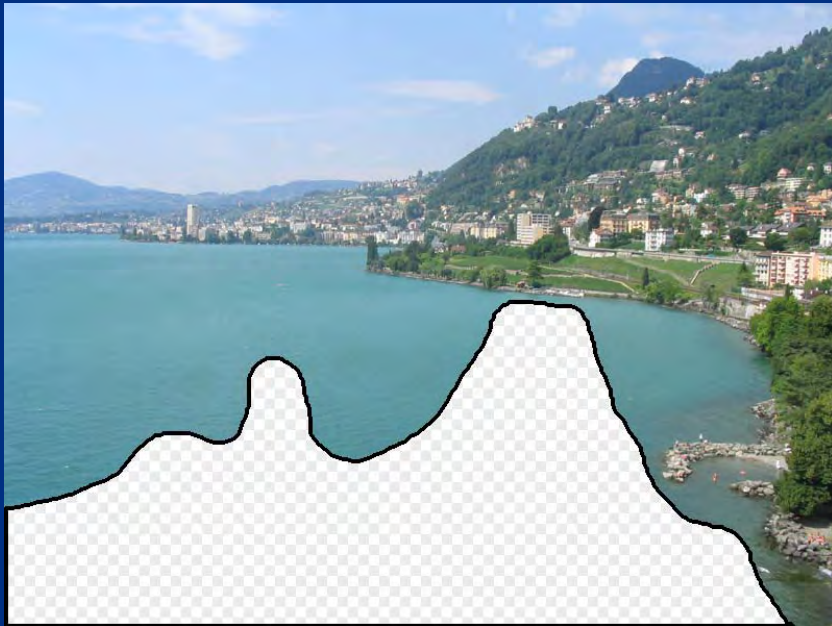
We downloaded 2.3 Million unique images from Flickr groups and keyword searches.



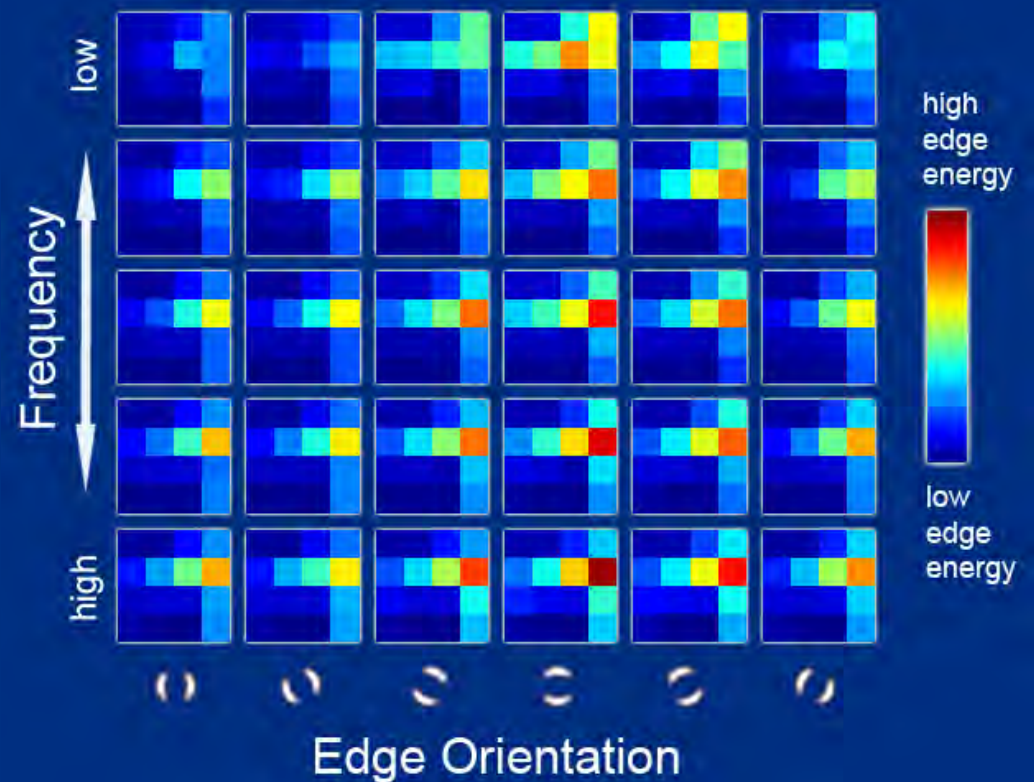
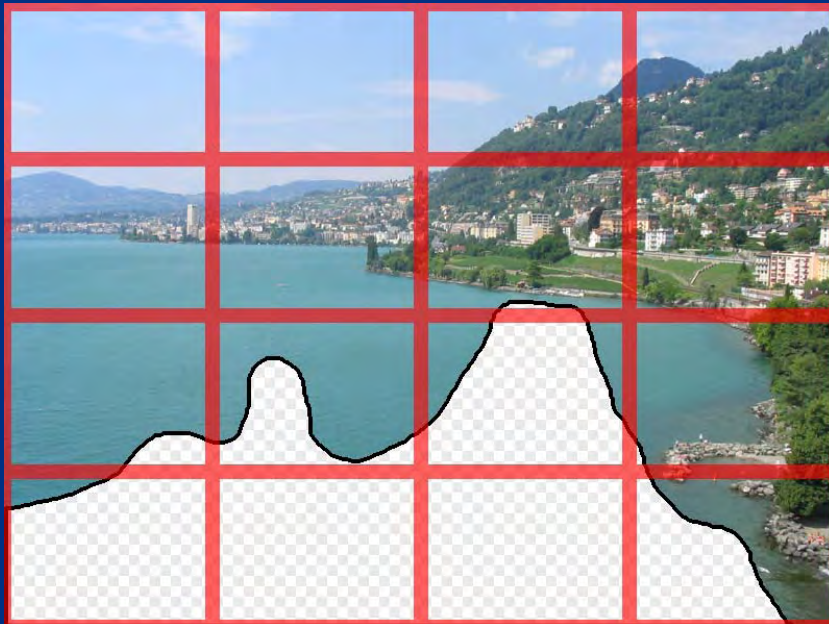
Scene Matching



Scene Descriptor

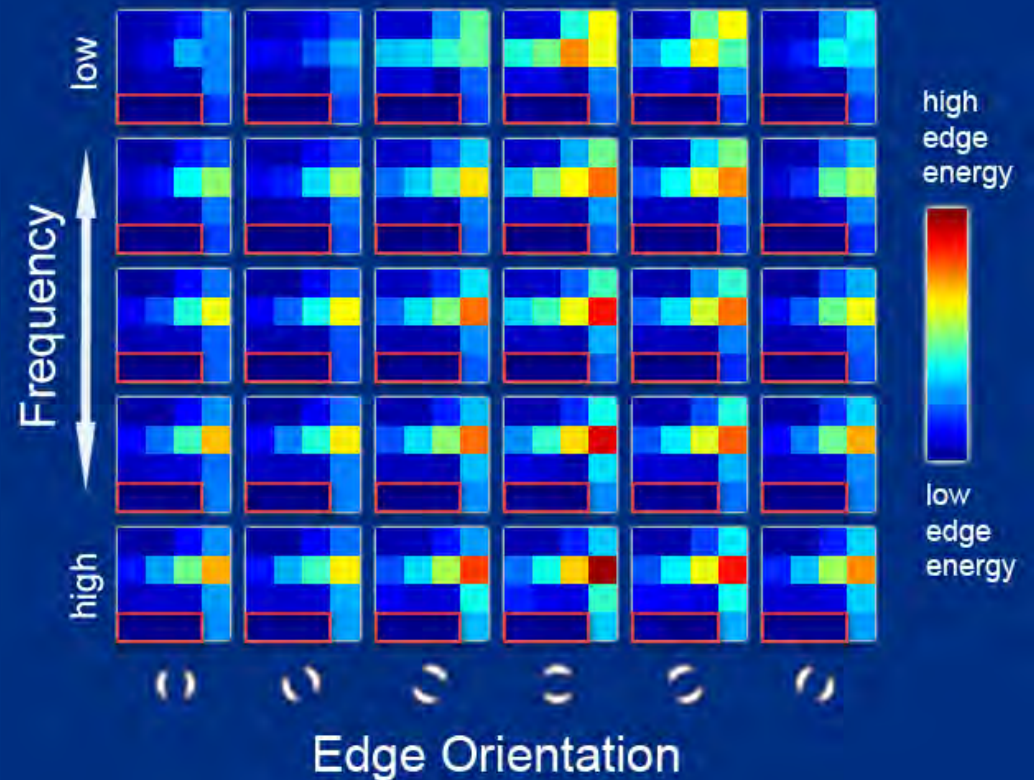
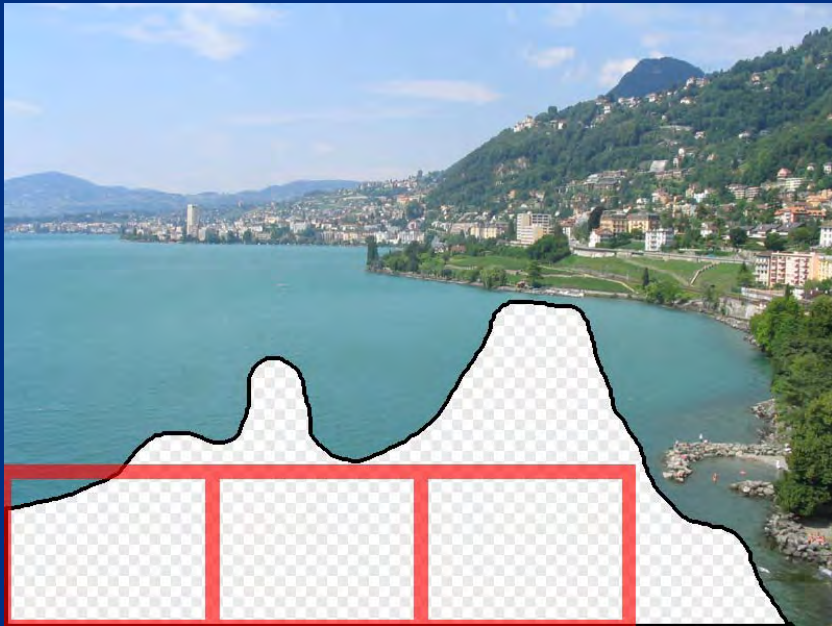


Scene Descriptor



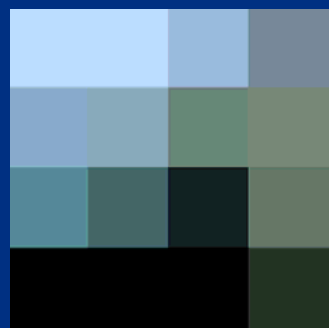
Gist scene descriptor
(Oliva and Torralba 2001)

Scene Descriptor

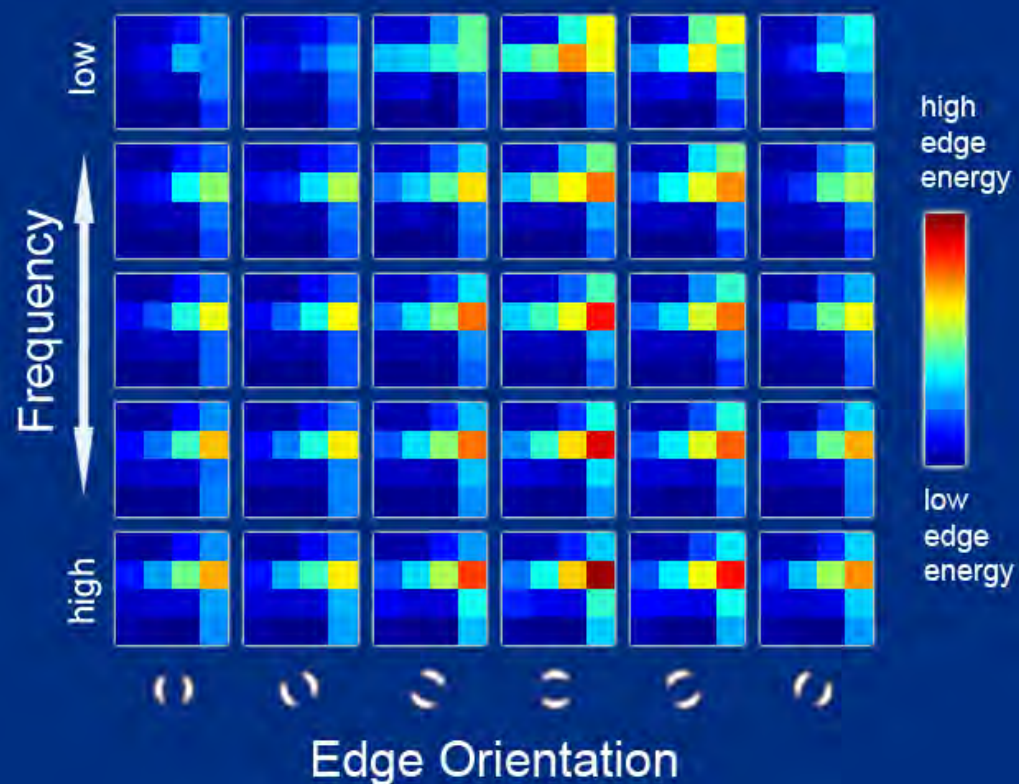


Gist scene descriptor
(Oliva and Torralba 2001)

Scene Descriptor

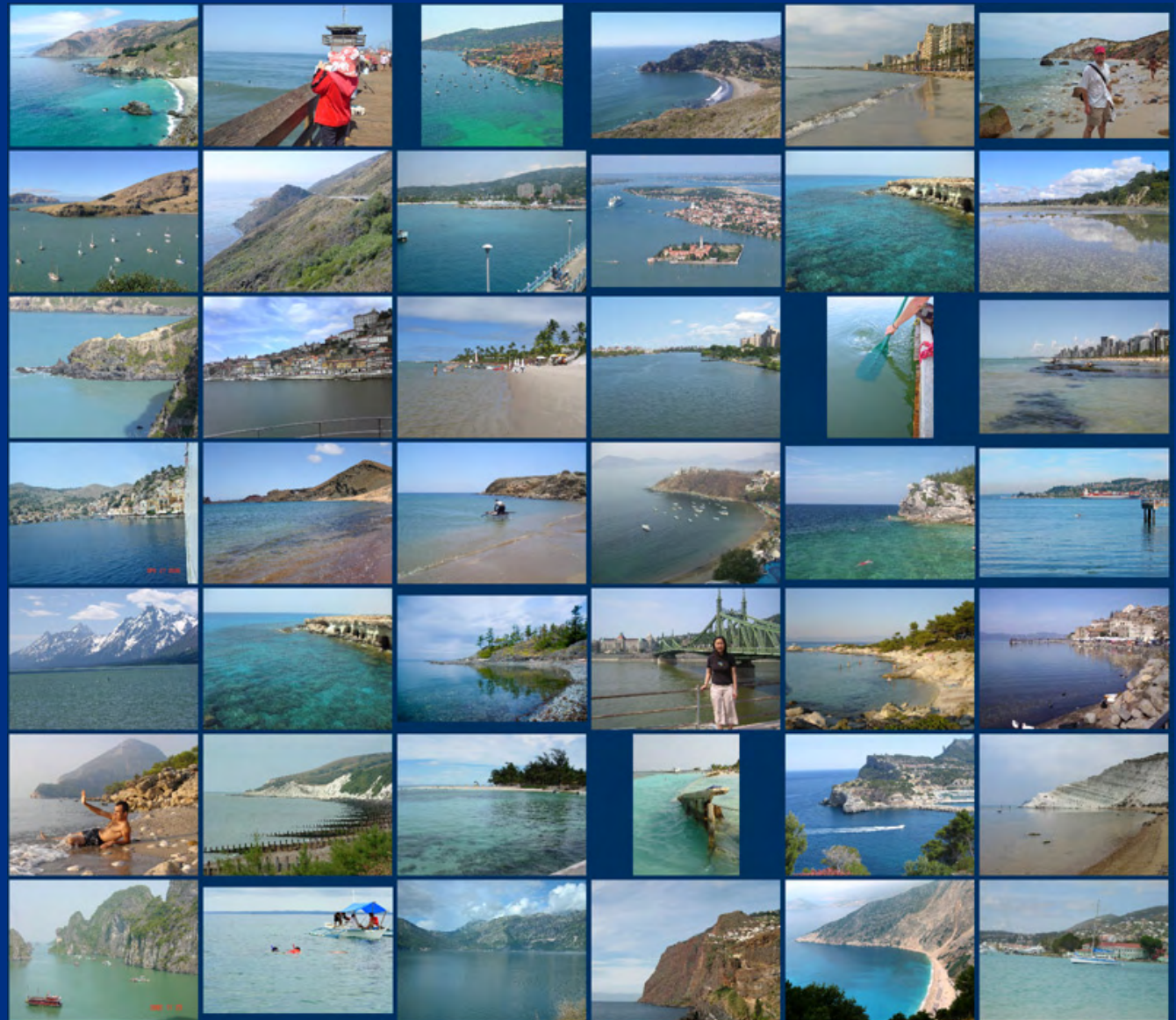


+



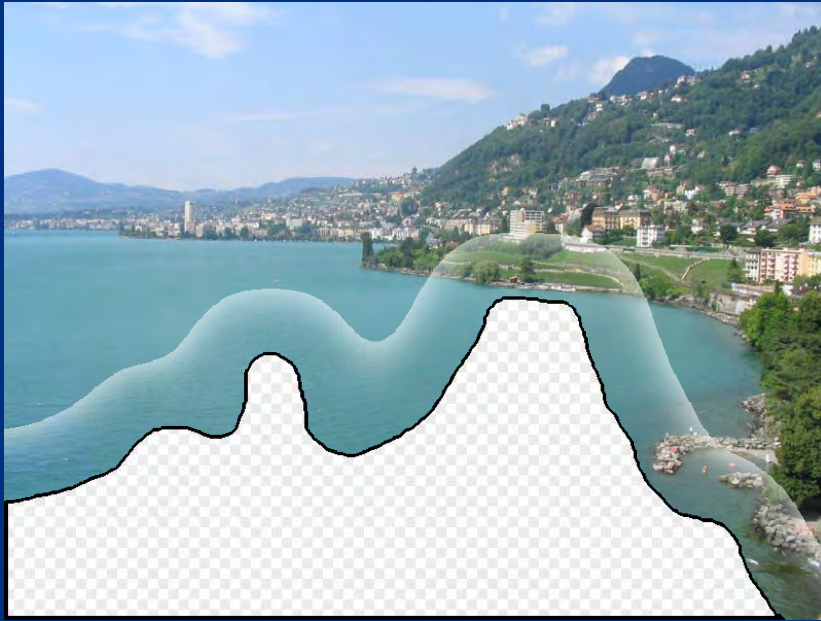
Gist scene descriptor
(Oliva and Torralba 2001)





... 200 total

Context Matching

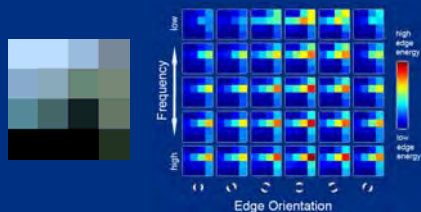






Result Ranking

We assign each of the 200 results a score which is the sum of:



The scene matching distance



The context matching distance
(color + texture)



The graph cut cost

Top 20 Results



























... 200 scene matches

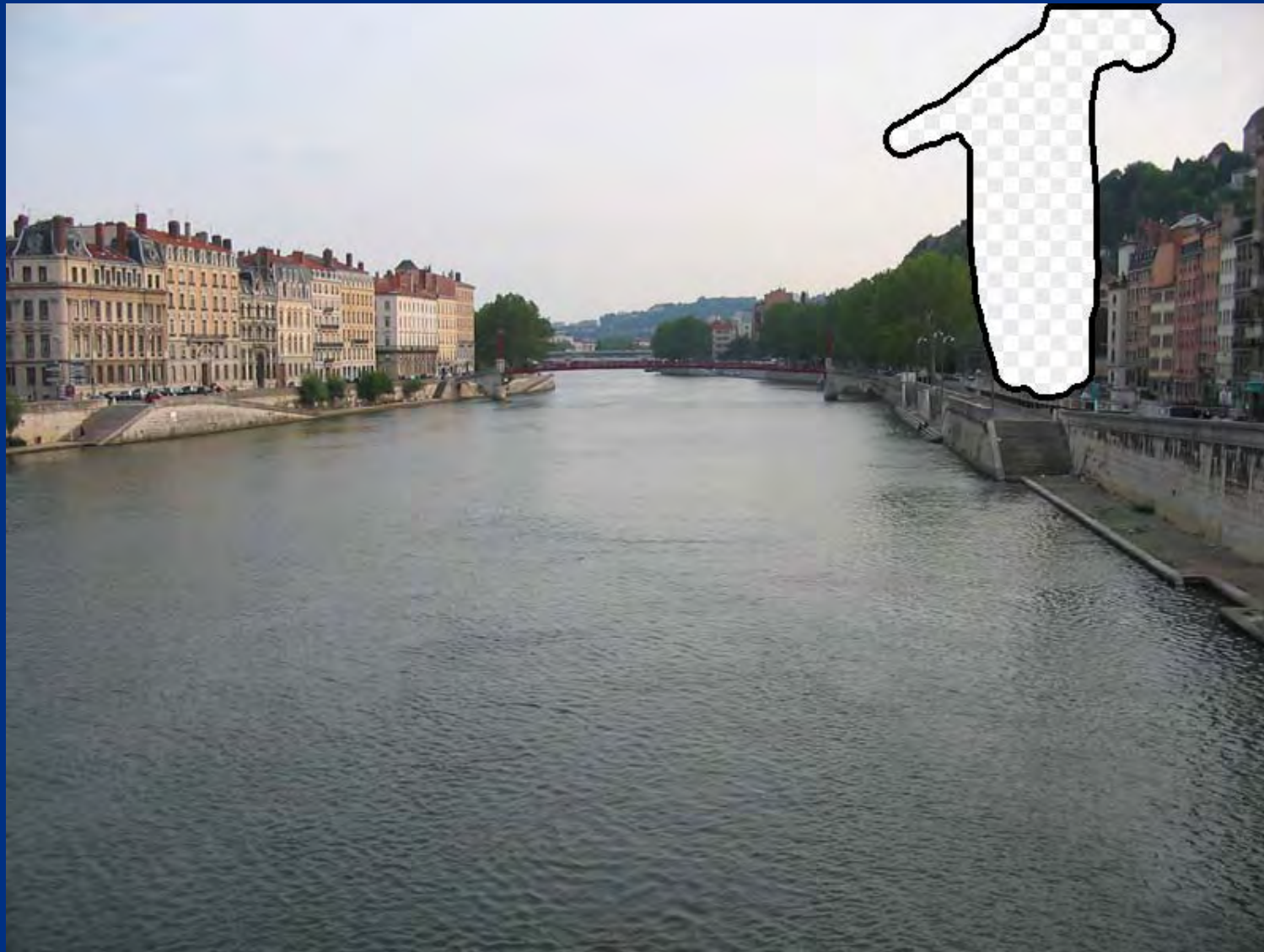


... 200 scene matches

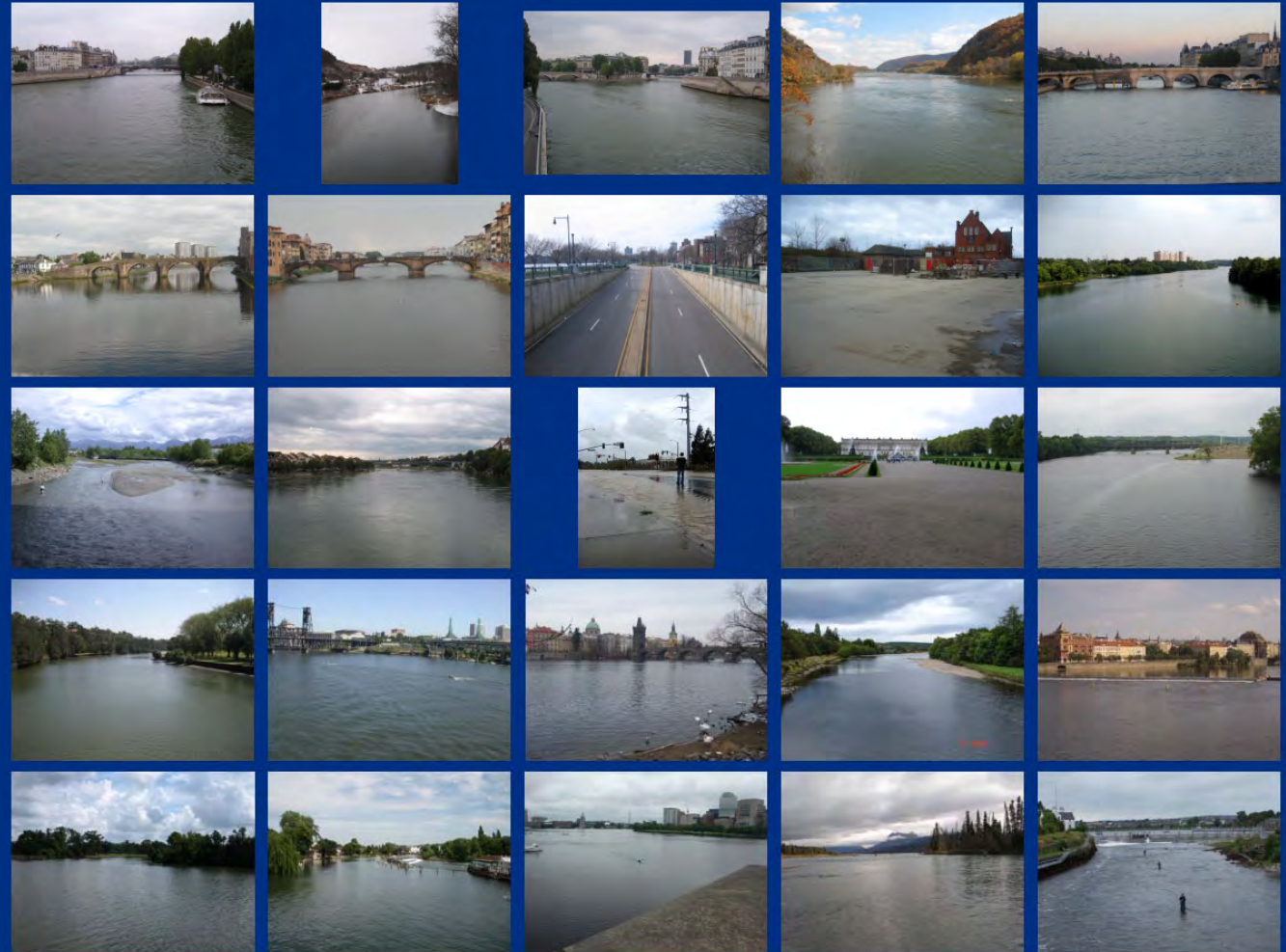
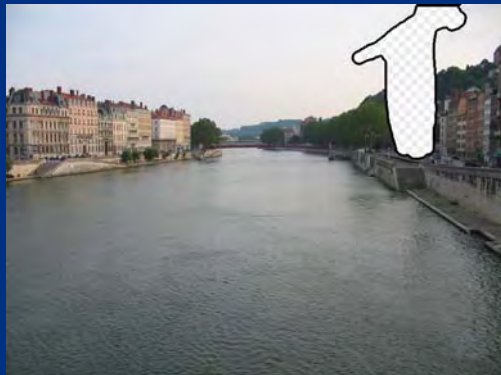




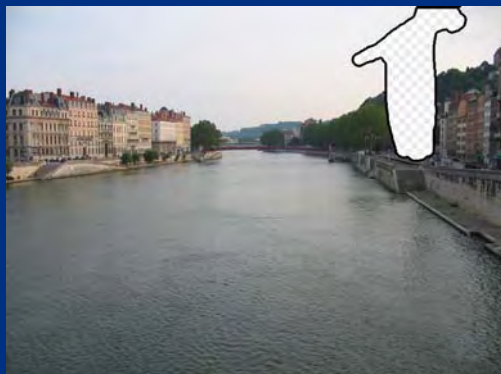




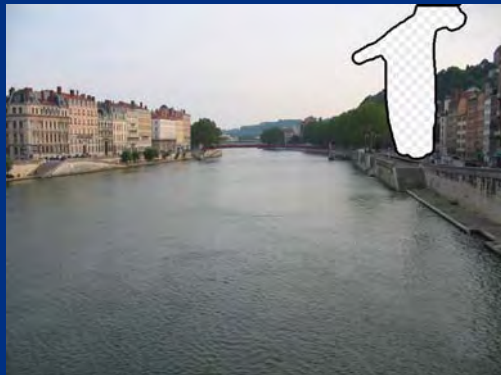




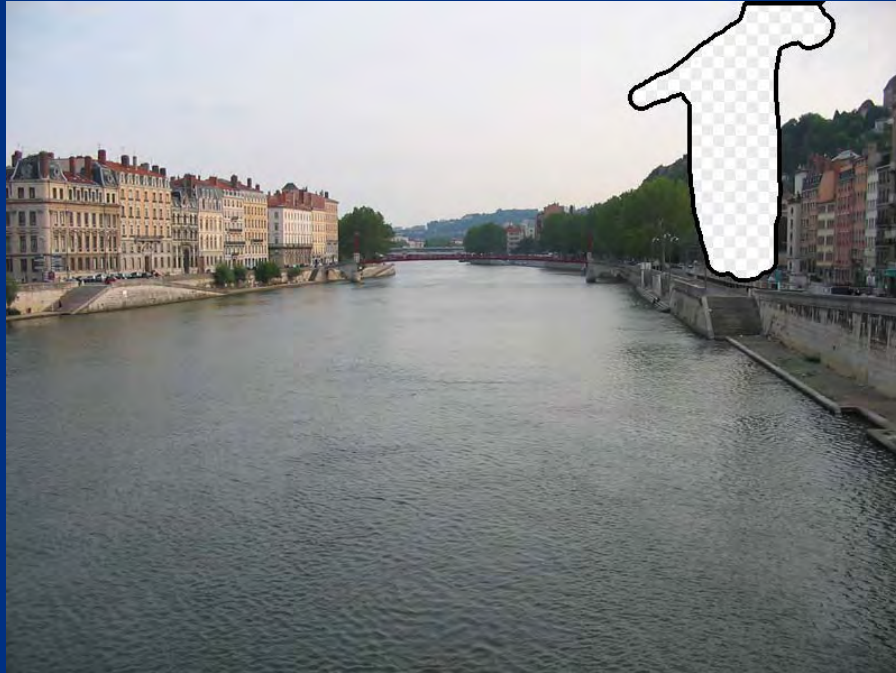
... 200 scene matches



... 200 scene matches



... 200 scene matches

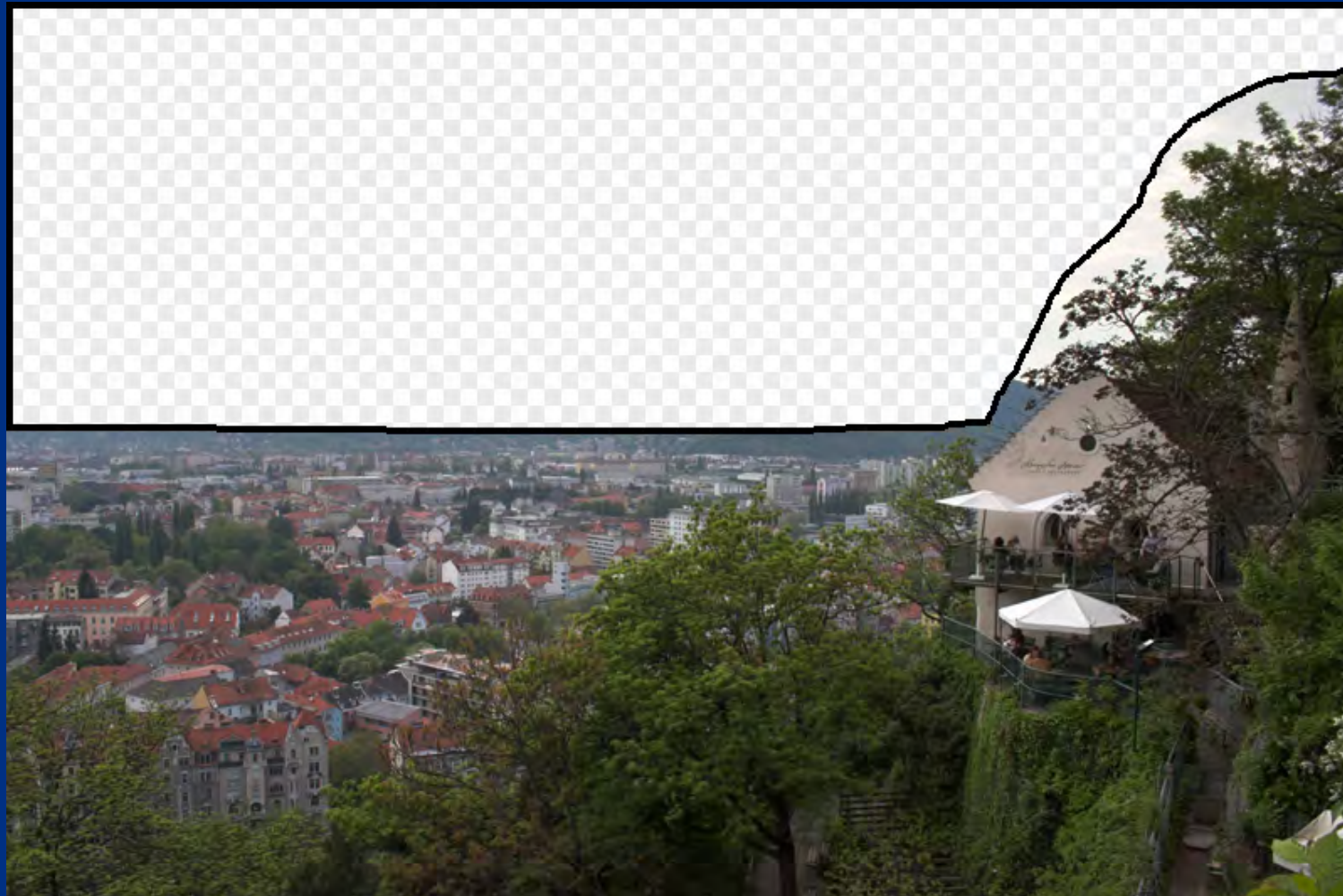












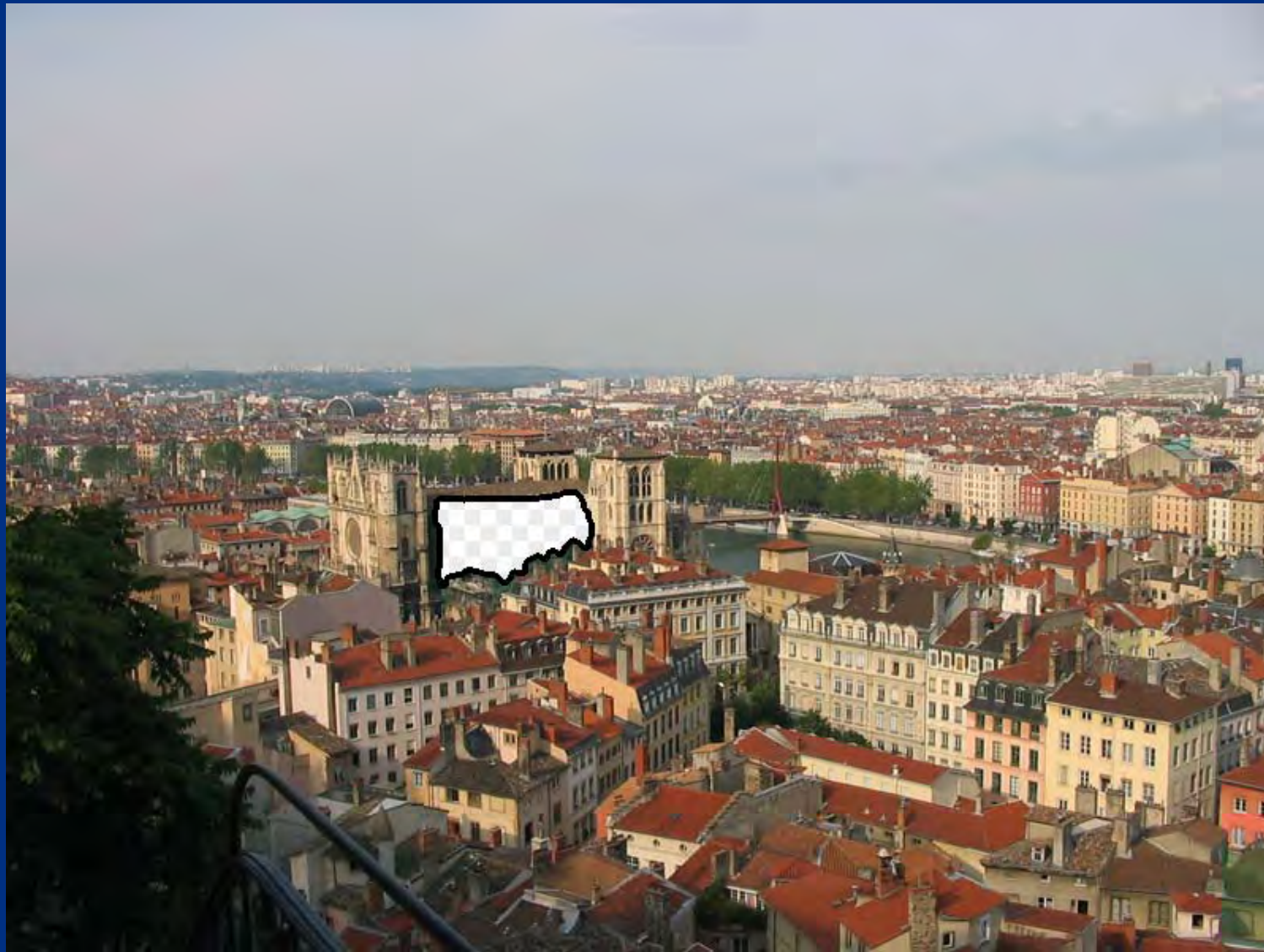




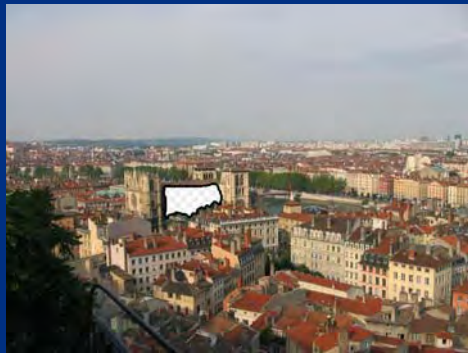




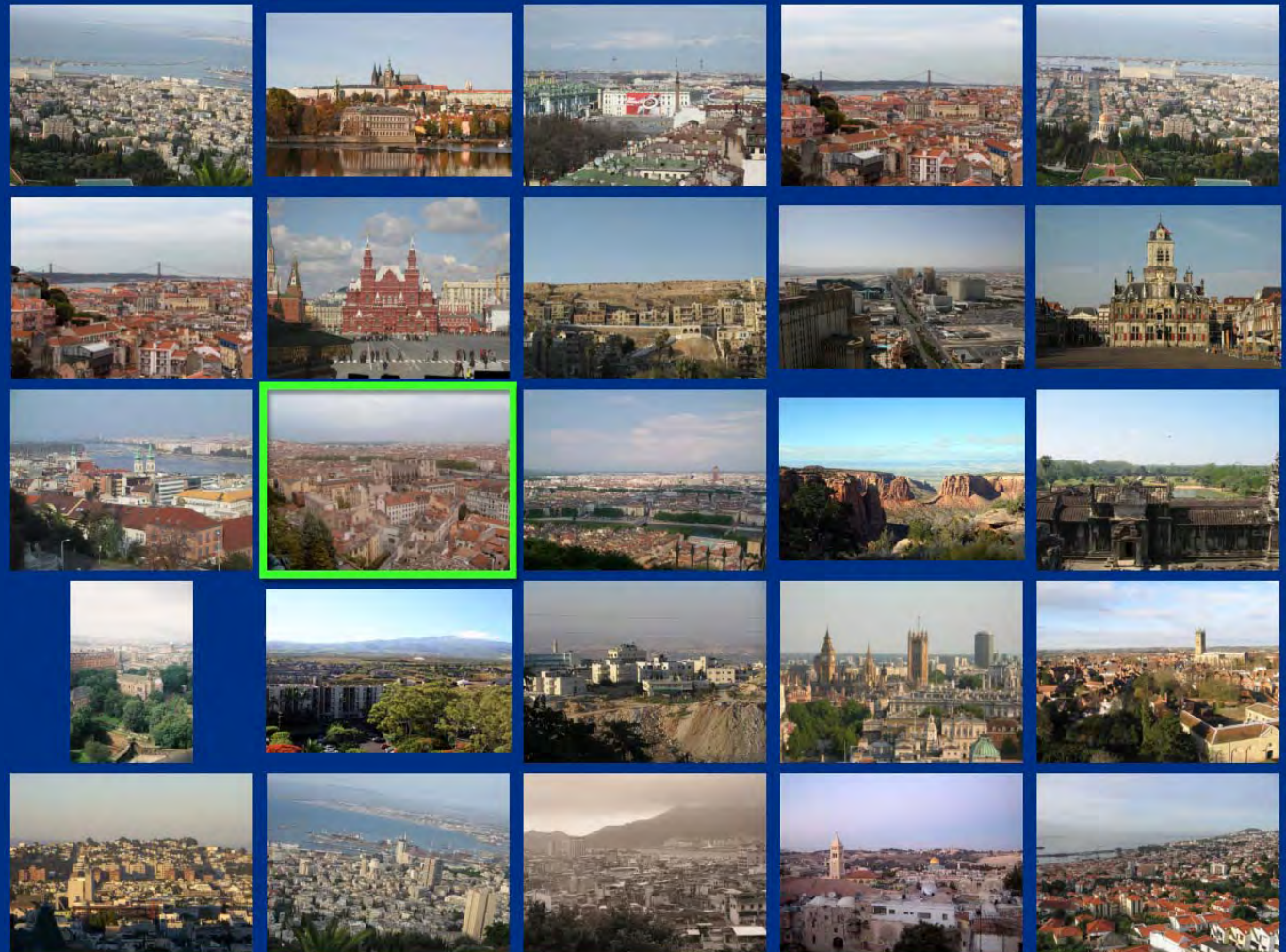
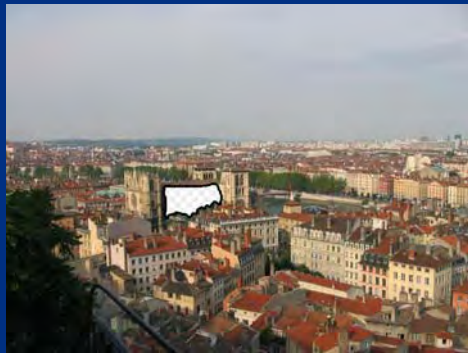




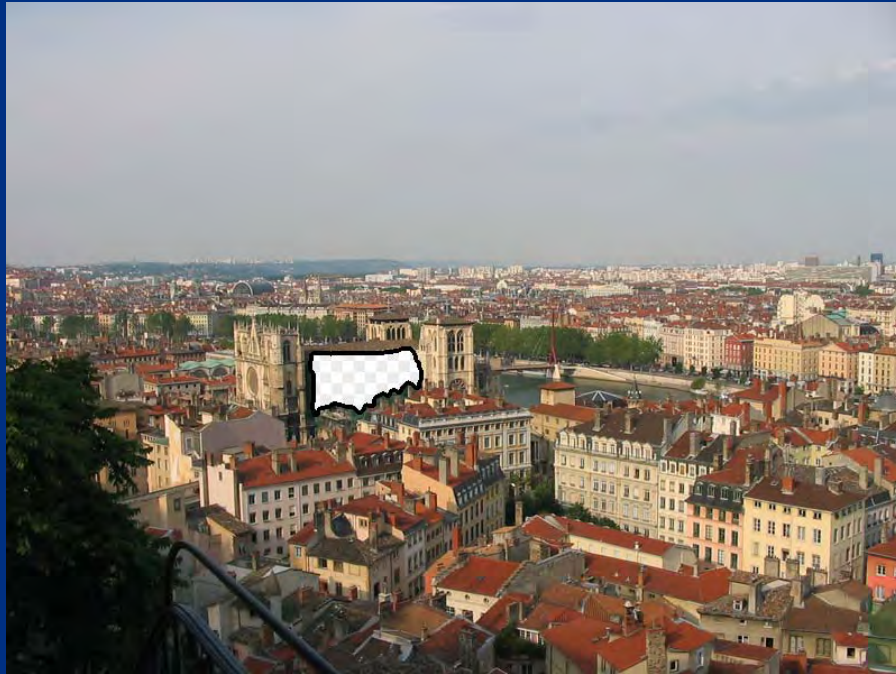




... 200 scene matches



... 200 scene matches





Failures



Failures



Failures



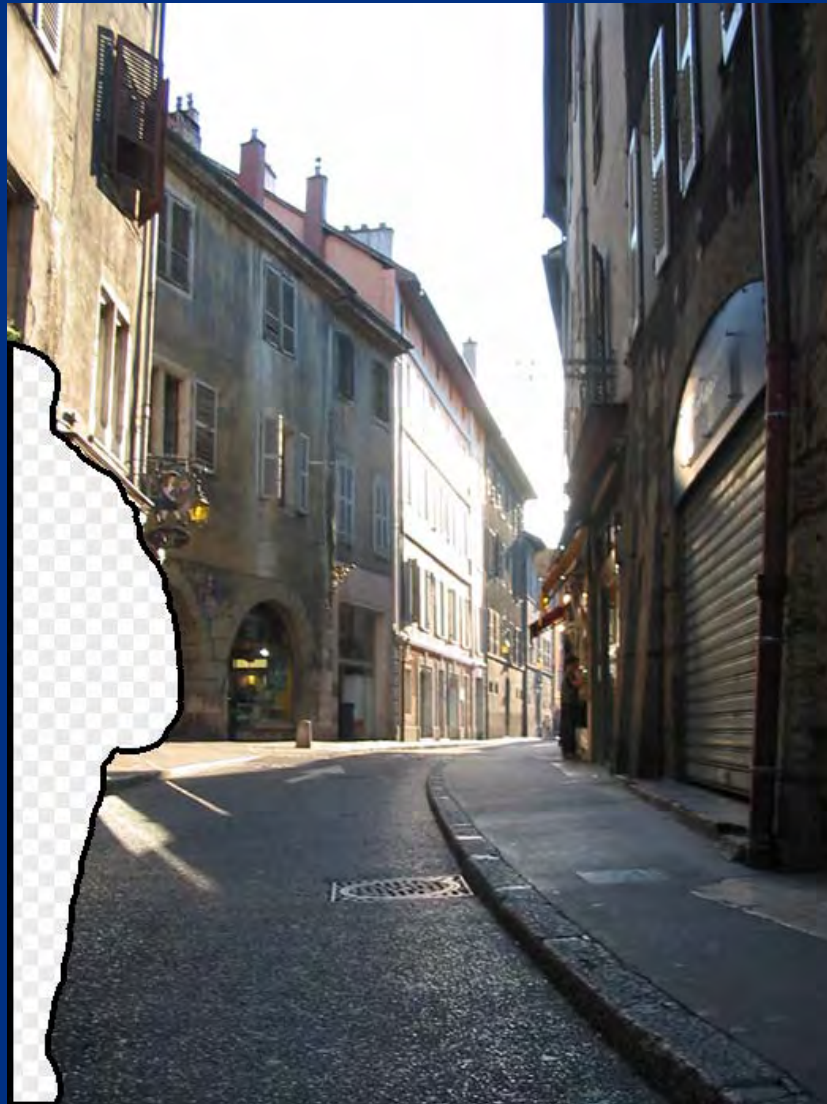
Failures



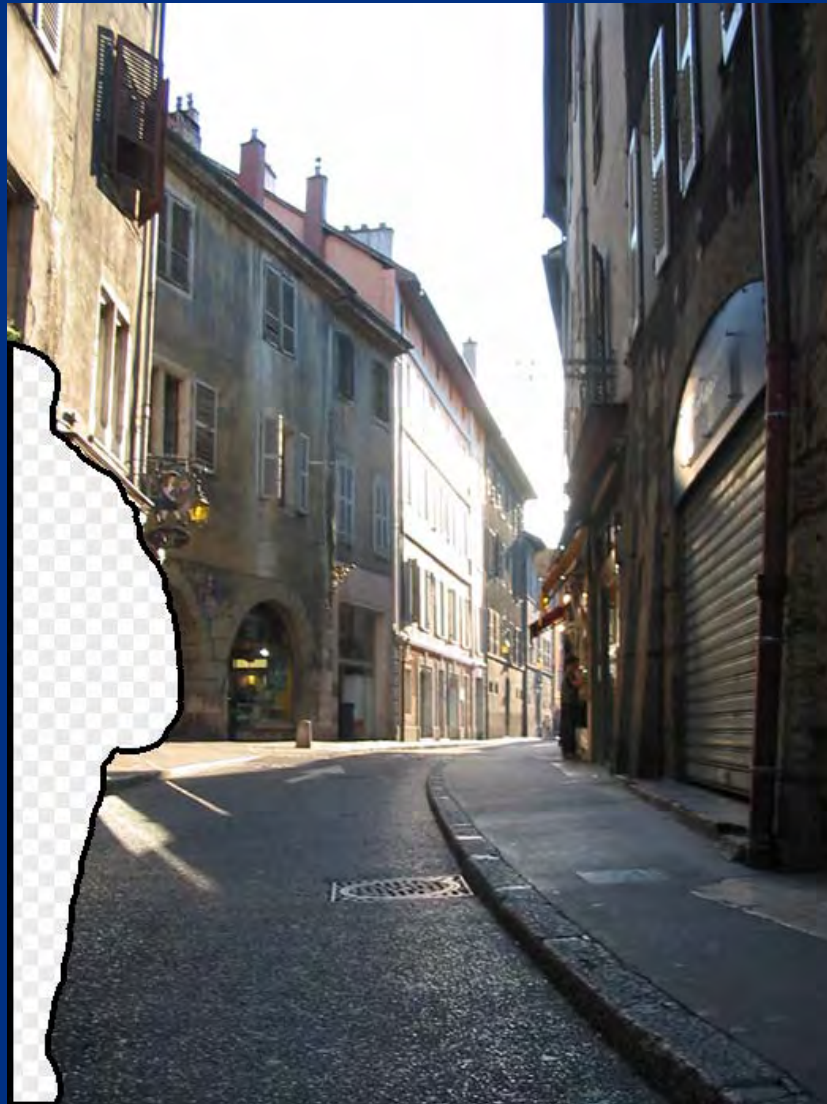
Failures



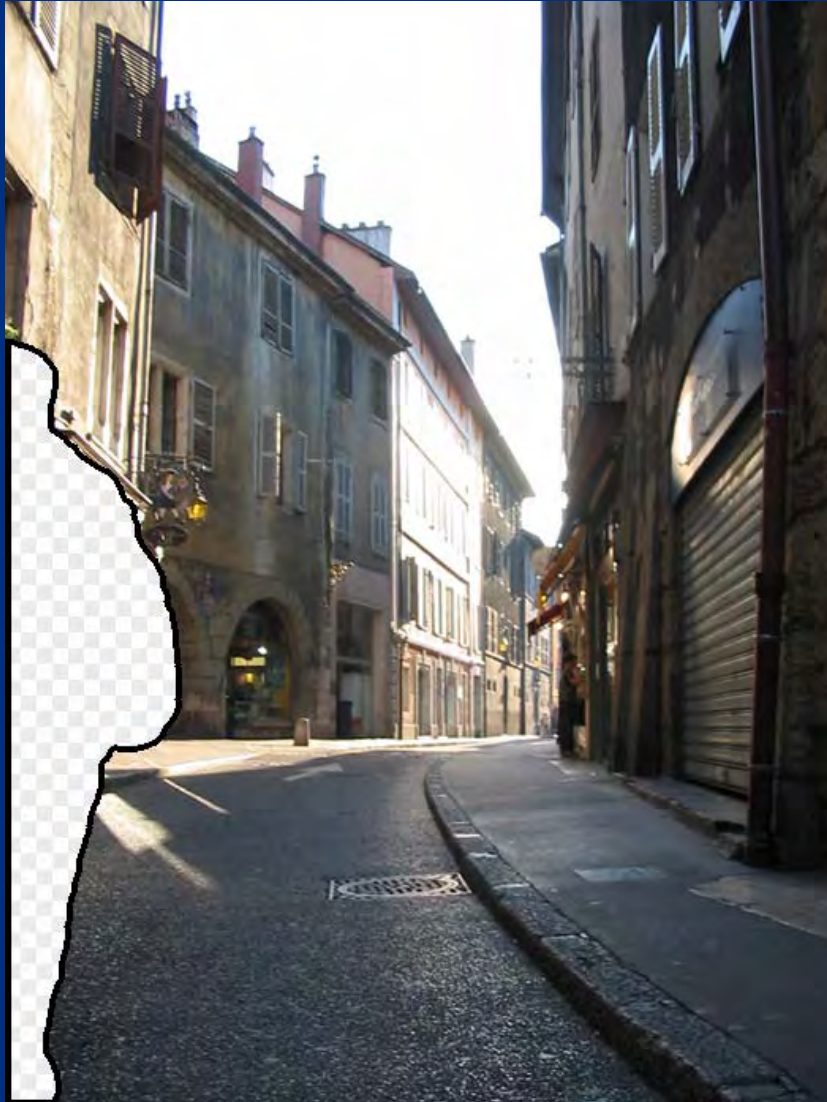
Failures



Failures



Failures



Failures



Failures



Failures



Failures



Evaluation





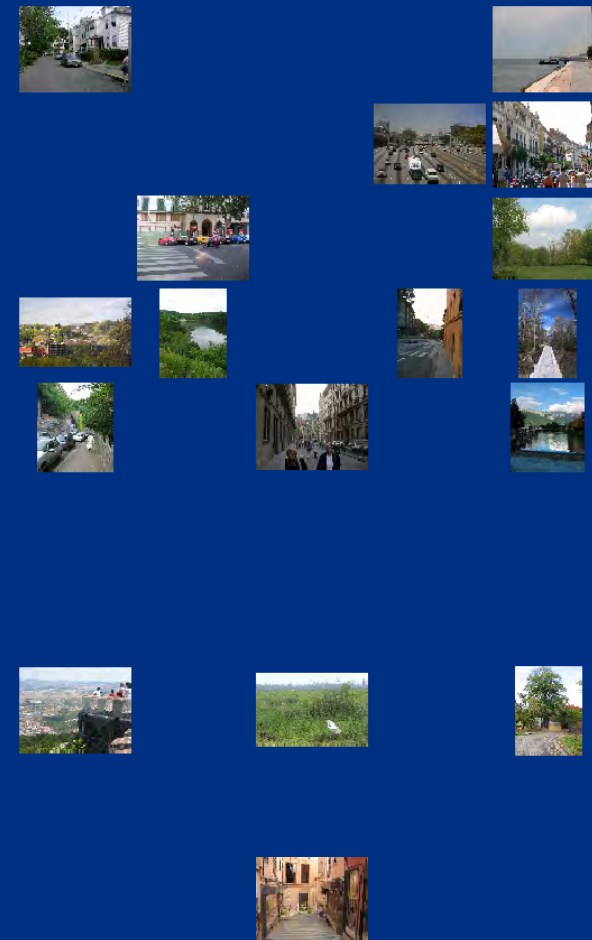


Original Images



Criminisi et al.

Single result



Scene Completion

Each result
selected from 20



Real Image. This image
has not been manipulated

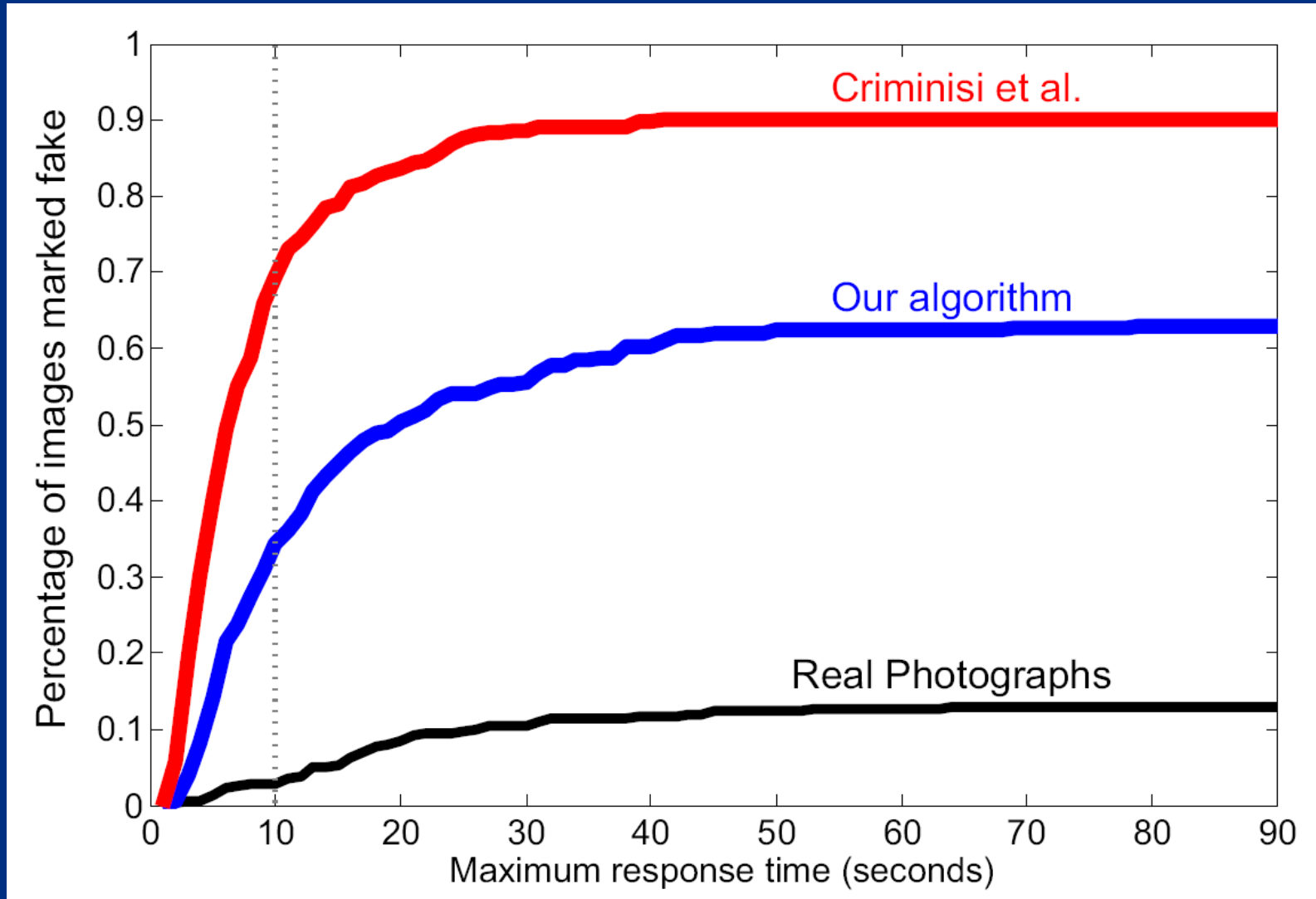
or

Fake Image. This image
has been manipulated





User Study Results - 20 Participants



Why does it work?

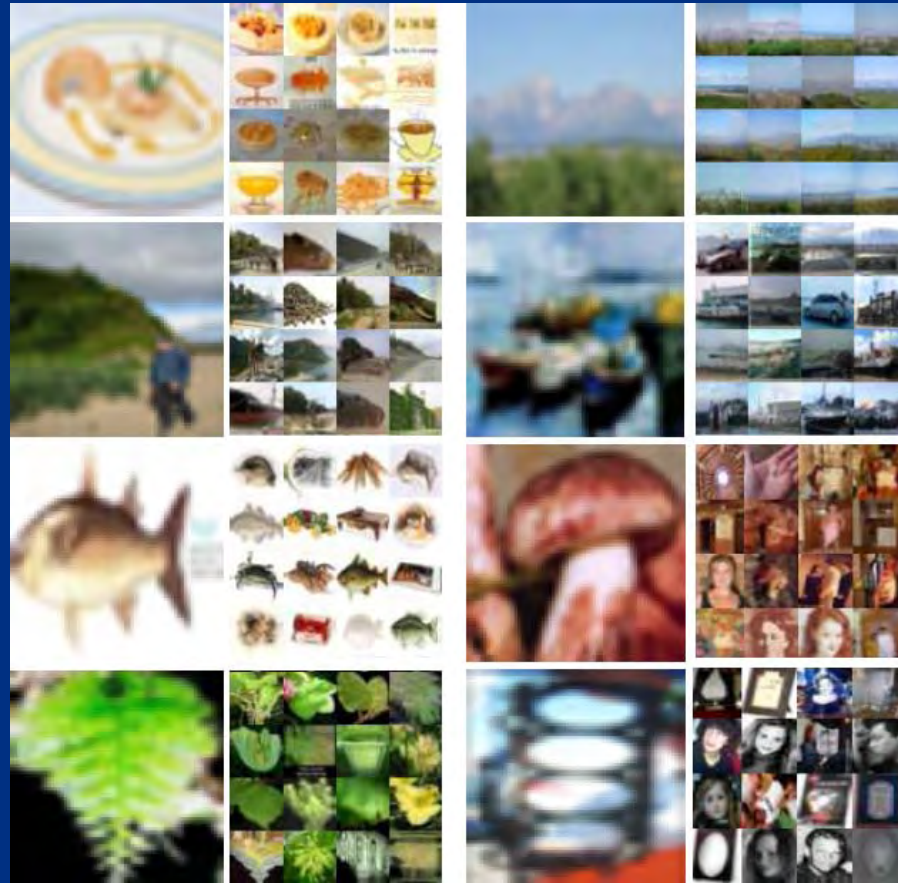




10 nearest neighbors from a
collection of 20,000 images



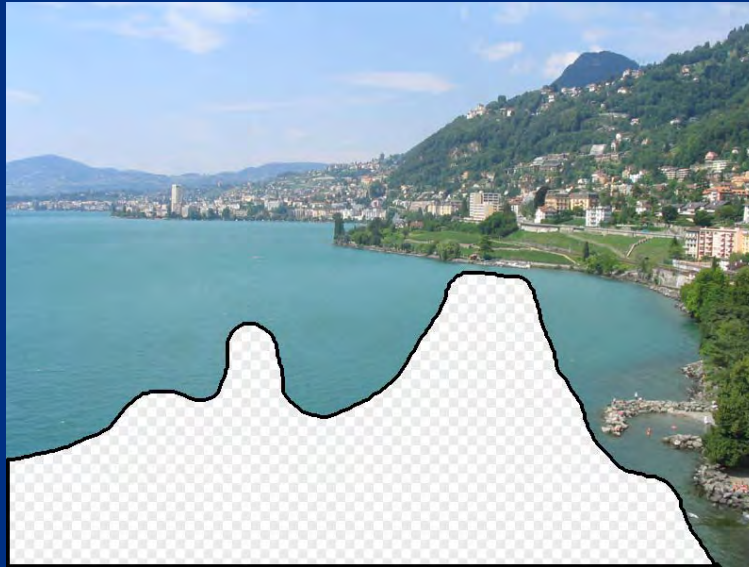
10 nearest neighbors from a
collection of 2 million images



Database of 70 Million 32x32 images

Torralba, Fergus, and Freeman. Tiny Images.
MIT-CSAIL-TR-2007-024. 2007.

The Small Picture



Pixels



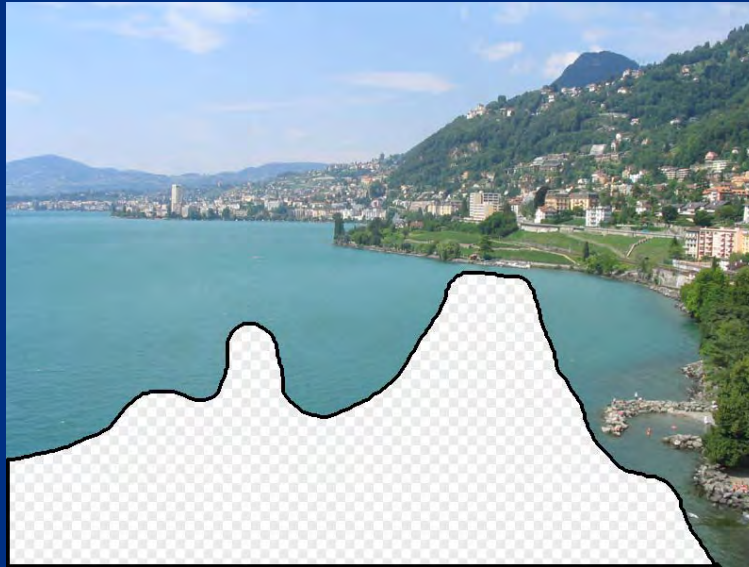
Image Collection

Pixels + Semantics

What Next? Small Picture

- Add outline of what we just presented
- We presented a very different hole-filling technique
- Sometimes works better than old stuff, but not always.
- Value in reusing original material. Just need semantics.
- Hybrid solution.

Hybrid Solution?



Pixels



Image Collection

Semantics

The Big Picture



Sky, Water, Hills, Beach,
Sunny, mid-day

Brute-force Image Understanding