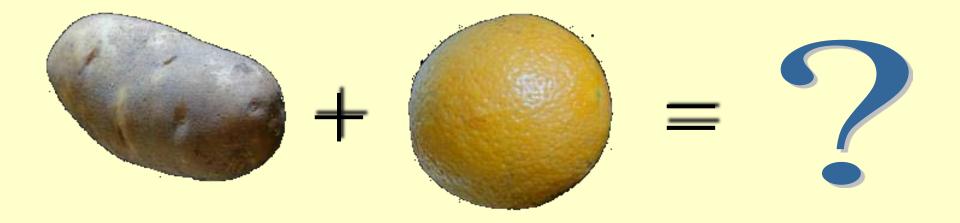
Texture Synthesis

Daniel Cohen-Or

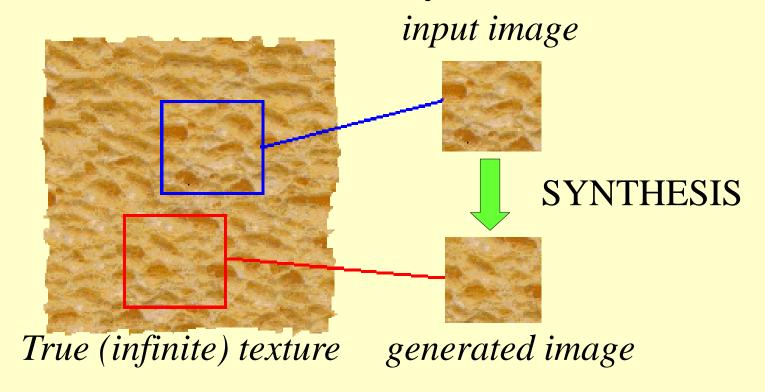








The Goal of Texture Synthesis

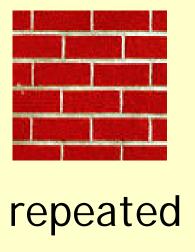


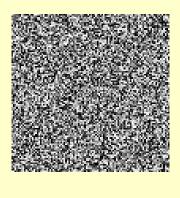
 Given a finite sample (large enough) of some texture, the goal is to synthesize other samples from that same texture.



The Challenge

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







stochastic

Both

Texture Types

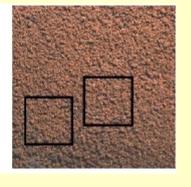




Texture model









Stationary - under a proper window size, the observable portion always appears similar.

Local - each pixel is predictable from a small set of neighboring pixels and independent of the rest of the image.

Non-Stationary



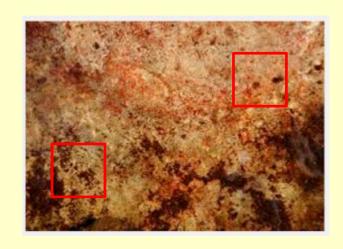


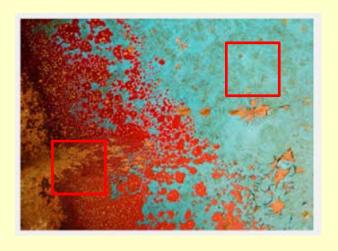


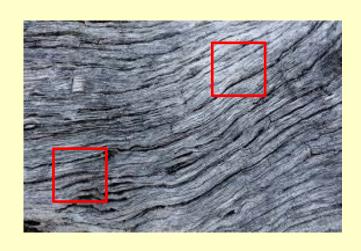


Non-Stationary









Texture Synthesis for Graphics

- Inspired by Texture Analysis and Psychophysics
 - [Heeger & Bergen,'95]
 - [DeBonet,'97]
 - [Portilla & Simoncelli,'98]
- ...but didn't work well for structured textures
 - [Efros & Leung,'99]
 - (originally proposed by [Garber,'81])

"By Example" Texture Synthesis

Input patch boundary.

Input texture example.



Fill boundary with texture.



Texture Synthesis by Non Parametric Sampling

- Generate English-looking text using N-grams, [Shannon,'48]
- Assuming Markov Chain on letters:
 - P(letter | Proceeding n-letters)





Efros & Leung '99

- [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

Unit of Synthesis

- Letter-by-letter: Used to name planets in early 80s game "Elite".
- Word-by-word: M.V. Shaney (Bell Labs) 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".

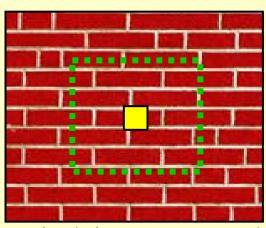
Mark V. Shaney (Bell Labs)

- Notice how well local structure is preserved!
 - Now, instead of letters let's try pixels...

Efros & Leung 99*

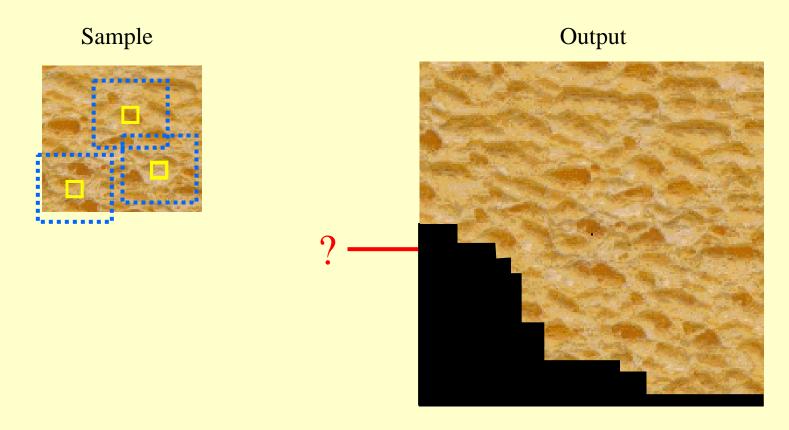
- Assuming Markov property, compute
 - P(p | N(p)).
 - Explicit probability tables infeasible.
 - Instead, search input image for similar neighbourhoods - that's our histogram for p.

Non-parametric sampling



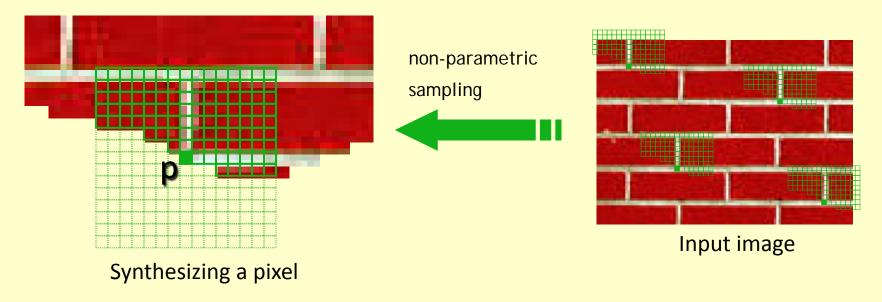
^{*} A.A.Efros, T.K.Leung; "Texture synthesis by non-parametric sampling"; ICCV99. (originally proposed by [Garber, '81])

Efros & Leung 99 - Algorithm



 Causal neighborhood - Neighboring pixels with known values.

Efros & Leung '99

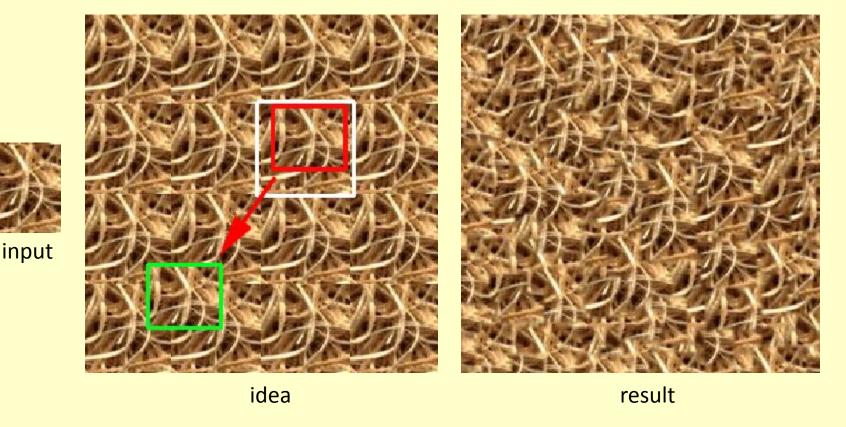


- Assuming Markov property, compute P(p|N(p))
 - Building explicit probability tables infeasible
 - Instead, let's search the input image for all similar neighborhoods — that's our histogram for p
- To synthesize p, just pick one match at random

Efros & Leung '99

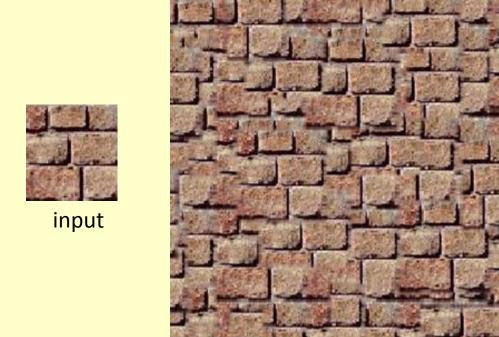
- The algorithm
 - Very simple
 - Surprisingly good results
 - Synthesis is easier than analysis!
 - ...but very slow
- Optimizations and Improvements
 - [Wei & Levoy, '00] (based on [Popat & Picard, '93])
 - [Harrison, '01]
 - [Ashikhmin, '01]
 - PatchMatch [Barnes et al. 2009]

Chaos Mosaic [Xu, Guo & Shum, '00]



 Process: 1) tile input image; 2) pick random blocks and place them in random locations 3) Smooth edges

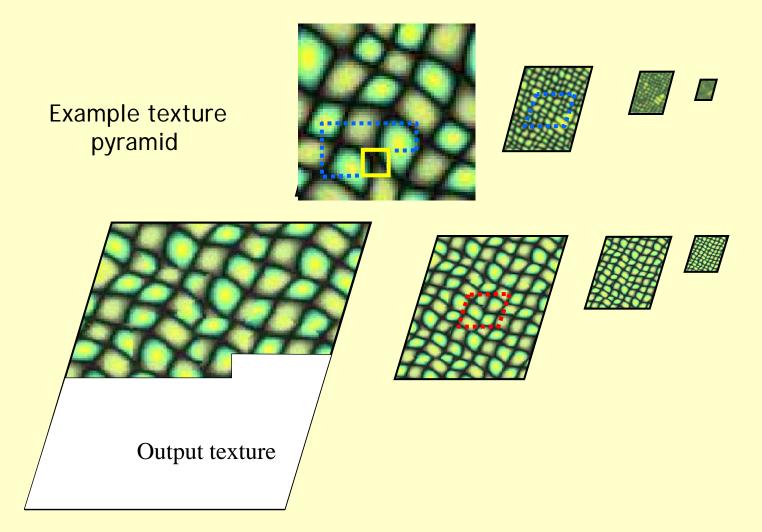
Chaos Mosaic [Xu, Guo & Shum, '00]



Of course, doesn't work for structured textures

result

Multi-Resolution Pyramids*



* L.-Y.Wei, M.Levoy; "Fast Texture Synthesis using Tree-structured Vector Quantization"; SIGGRAPH00.

Extension to 3D Textures

- Motion both in space and time
 - fire, smoke, ocean waves.
- How to synthesize?
 - extend 2D algorithm to 3D.







The Problems of Causal Scanning

- Scanning order:
 - Efros&Leung⁽¹⁾: Pixels with most neighbors.
 - Wei&Levoi⁽²⁾: Raster scan.
- These are "causal" scans.

- (1) A.A.Efros, T.K.Leung; "Texture synthesis by non-parametric sampling"; ICCV99. (originally proposed by [Garber, '81])
- (2) L.-Y.Wei, M.Levoy; "Fast Texture Synthesis using Tree-structured Vector Quantization"; SIGGRAPH00.

The Problems of Causal Scanning

- Can grow garbage.
- No natural means of refining synthesis.
- Cannot be parallelized.
- Problems are made worst for synthesis of 3D space-time volumes (a.k.a. video)...

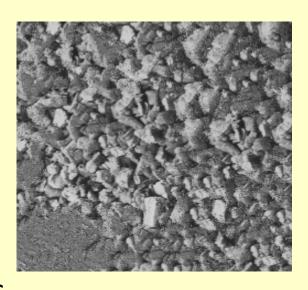
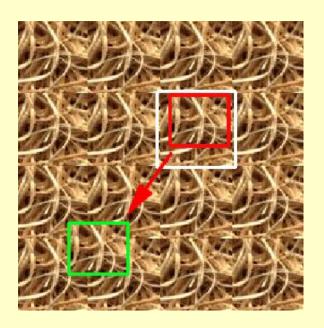


Image Quilting

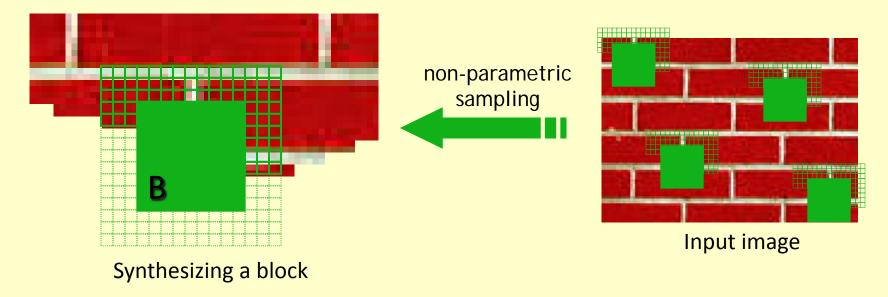
Observation: neighbor pixels are highly correlated

Idea:

 let's combine random block placement of Chaos Mosaic with spatial constraints of Efros & Leung.

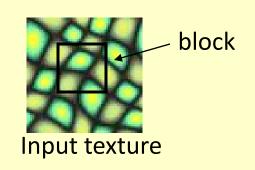


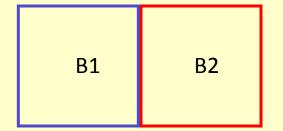
Efros & Leung '99 extended



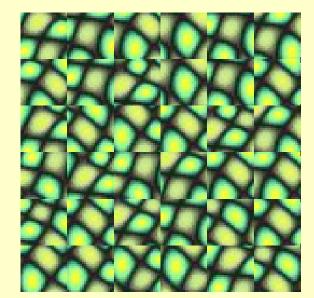
<u>Idea:</u> unit of synthesis = block

- 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!



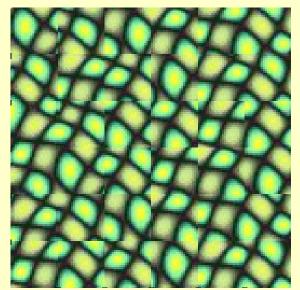


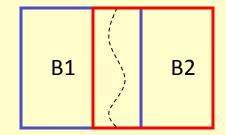
Random placement of blocks



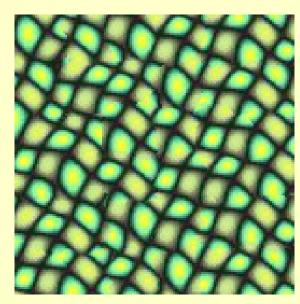
B1 B2

Neighboring blocks constrained by overlap





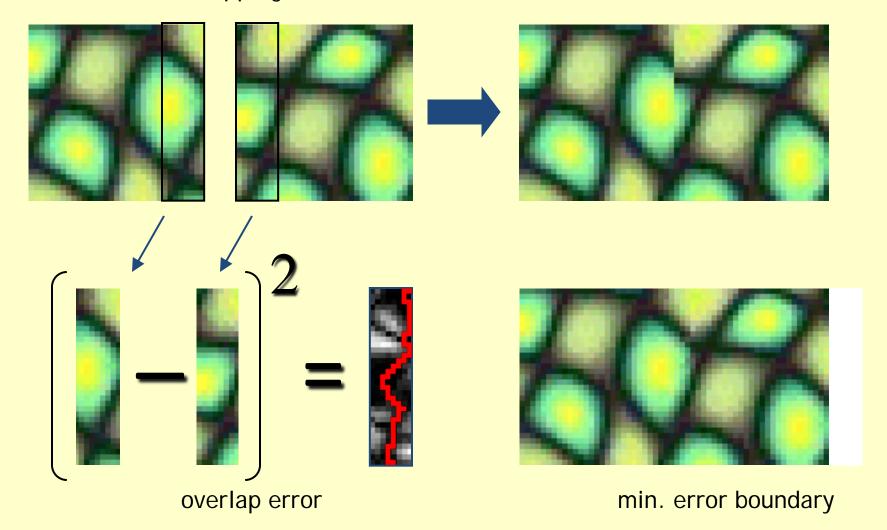
Minimal error boundary cut



Minimal error boundary

overlapping blocks

vertical boundary

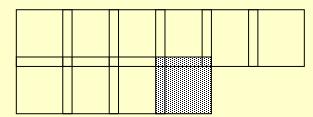


Our Philosophy

- 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

Image Quilting Algorithm

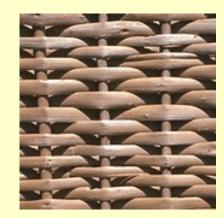
- Pick size of block and size of overlap
- Synthesize blocks in raster order

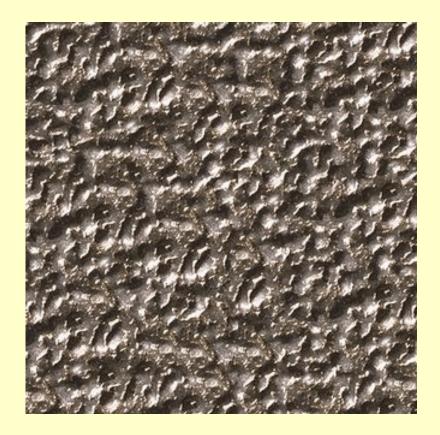


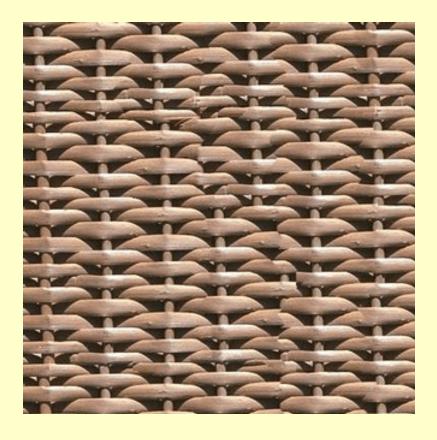
- Search input texture for block that satisfies overlap constraints (above and left)
 - Easy to optimize using NN search [Liang et.al., '01]
- Paste new block into resulting texture
 - use dynamic programming to compute minimal error boundary cut

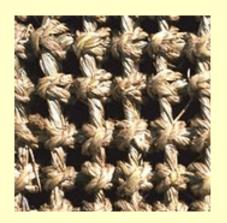
<u>Video</u>



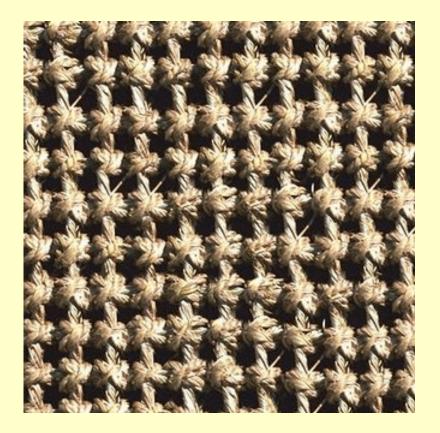










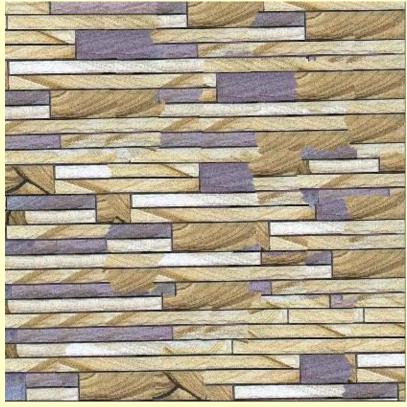
















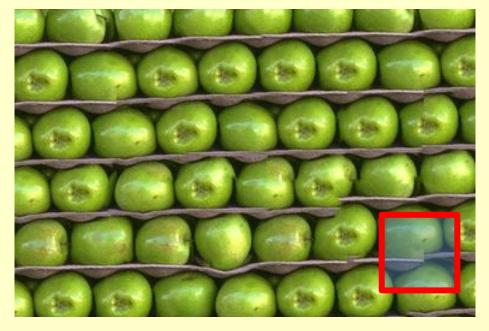




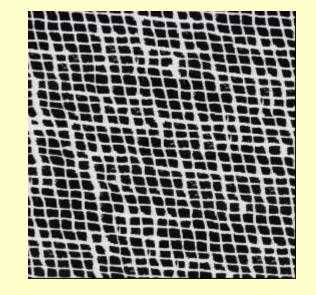






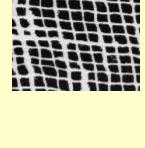




















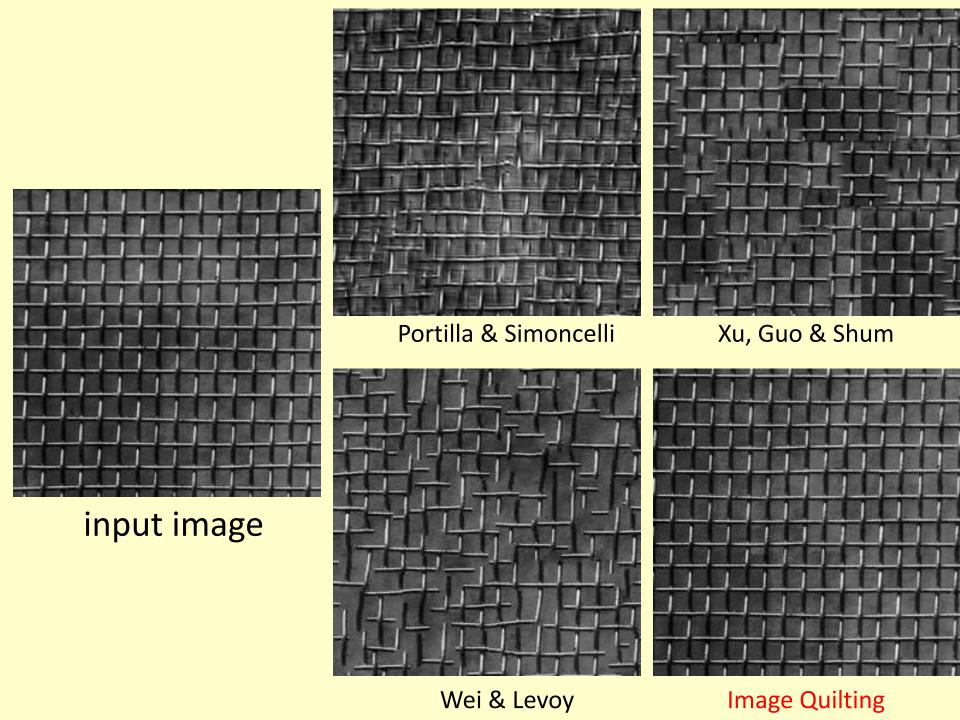


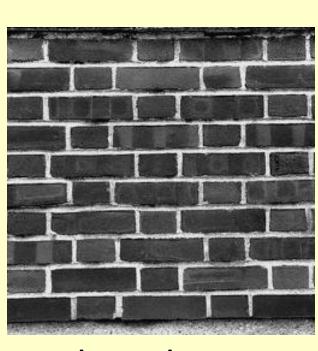
Failures (Chernobyl Harvest)



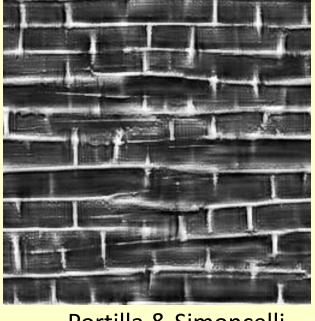




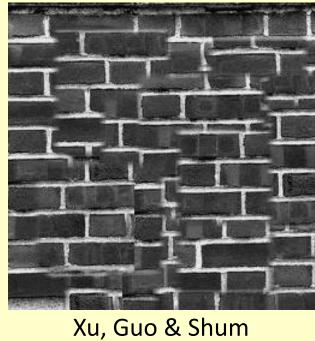


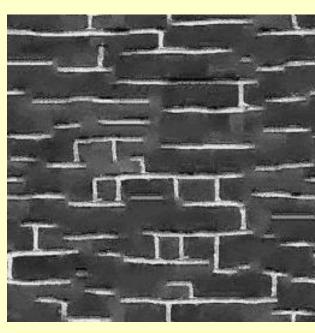


input image



Portilla & Simoncelli





Wei & Levoy

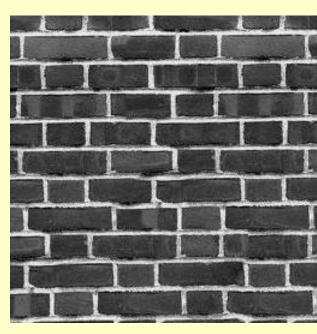


Image Quilting

Homage to Shannon!

or a visual corrical neuron-the in describing the response of that neuro: ht as a function of position—is perhap functional description of that neuron. seek a single conceptual and mathem: scribe the wealth of simple-cell recer id neurophysiologically1-3 and inferred especially if such a framework has the it helps us to understand the function leeper way. Whereas no generic mos ussians (DOG), difference of offset (rivative of a Gaussian, higher derivati function, and so on-can be expected imple-cell receptive field, we noneth

input image

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Portilla & Simoncelli

Sell Oils ...

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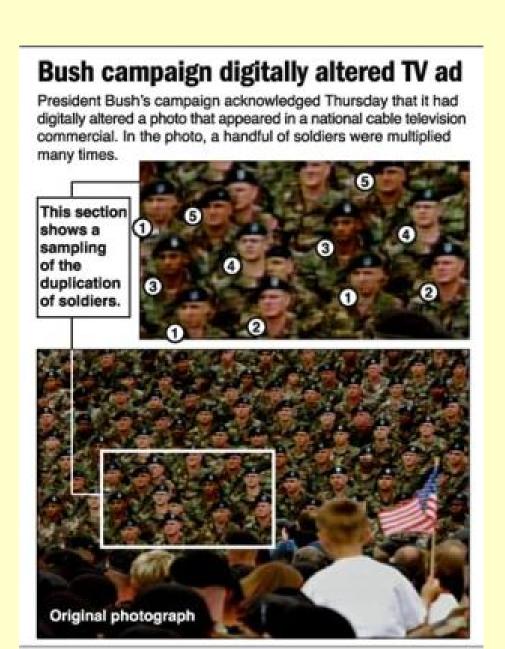
Xu, Guo & Shum

sition—is perk a single conceptual and of that neuribe the wealth of simpleual and matheurophysiologically1-3 and simple-cell necially if such a framewor y1-3 and inferrips us to understand th mework has perhay. Whereas no ge and the fumeuroiDOG), difference of no generic a single conceptual and n rence of offse the wealth of simple-ce , higher deriescribing the response of -can be expas a function of positionhelps us to understand thription of th per way. Whereas no gonceptual an sians (DOG), differencealth of simple

Wei & Levoy

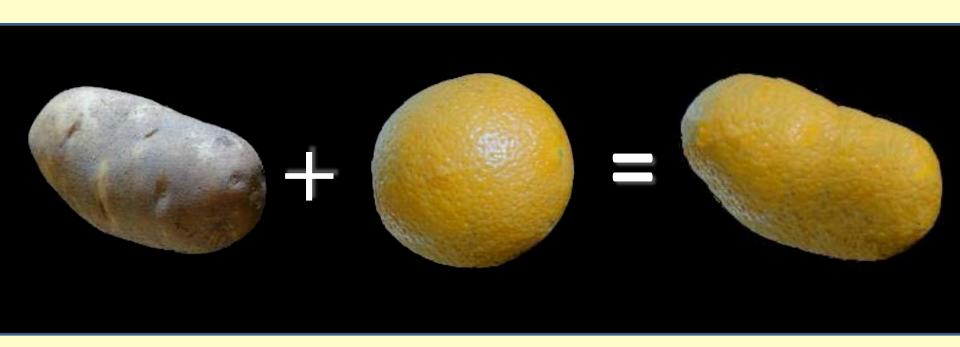
Image Quilting



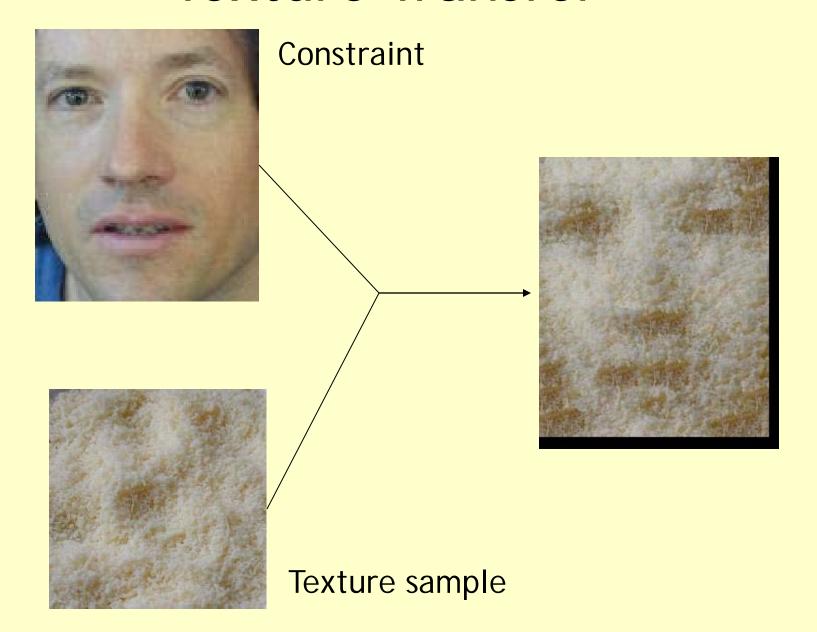


Application: Texture Transfer

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



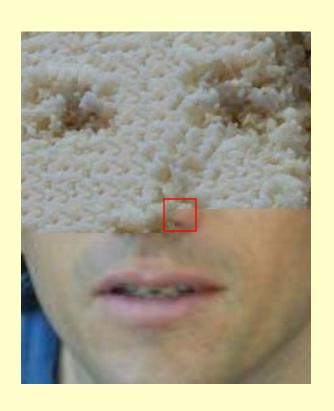
Texture Transfer



Texture Transfer

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



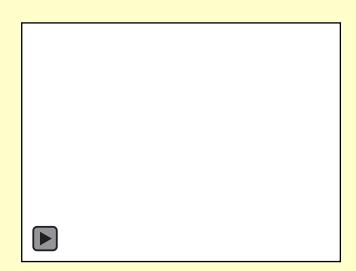


Same as texture synthesis, except an additional constraint:

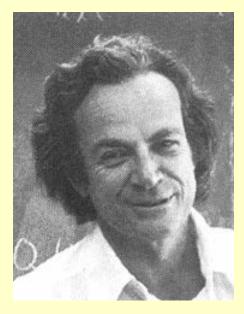
- 1. Consistency of texture
- 2. Similarity to the image being "explained"









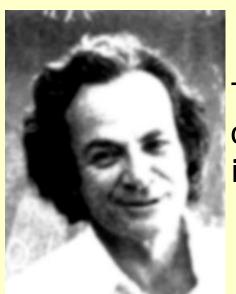


Target image

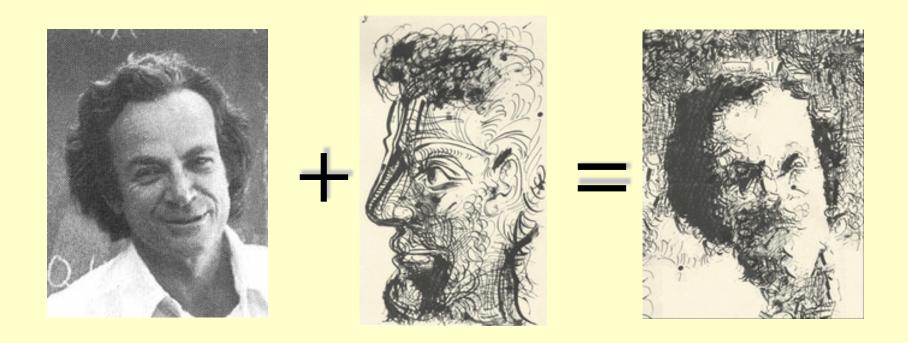
Source correspondence image

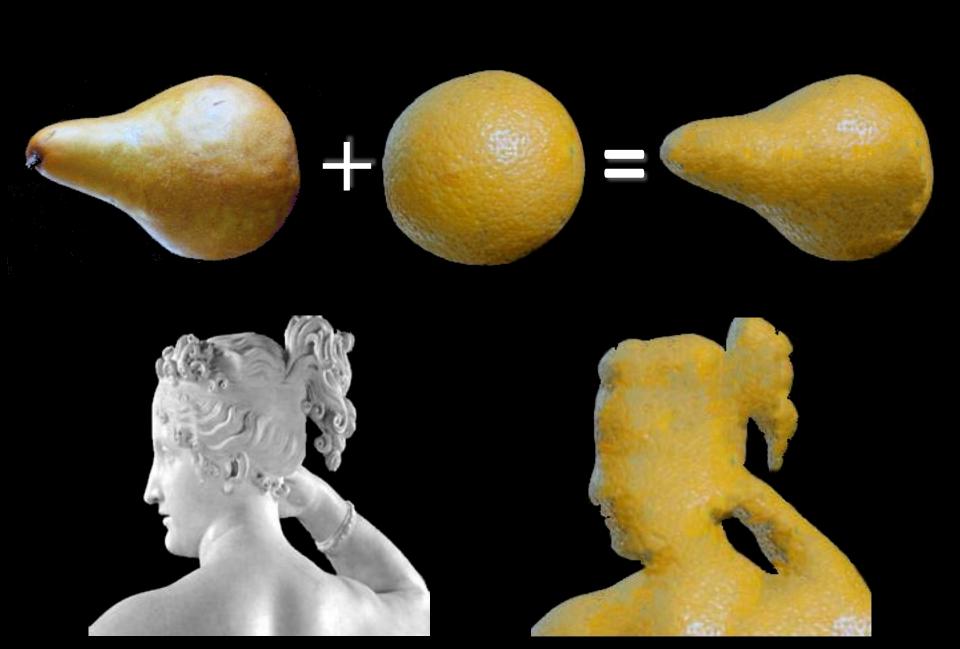
Source



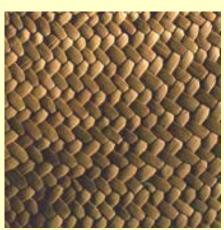


Target correspondence image









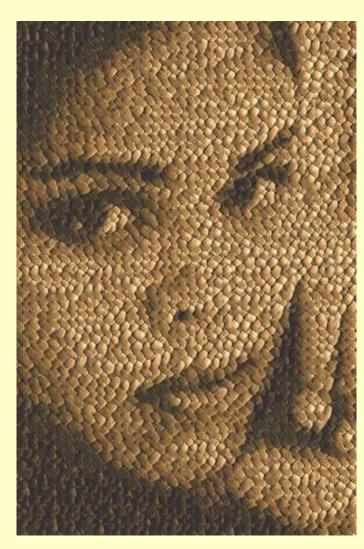


Image analogies (filter by example)

A to A' like B to B'

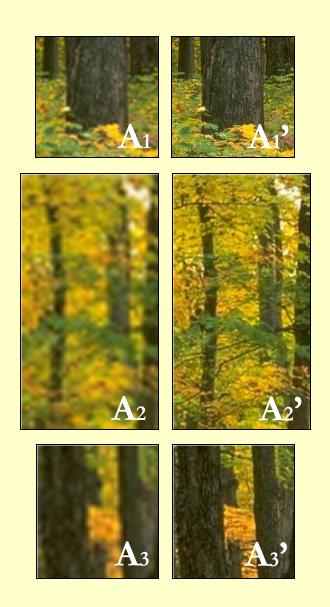






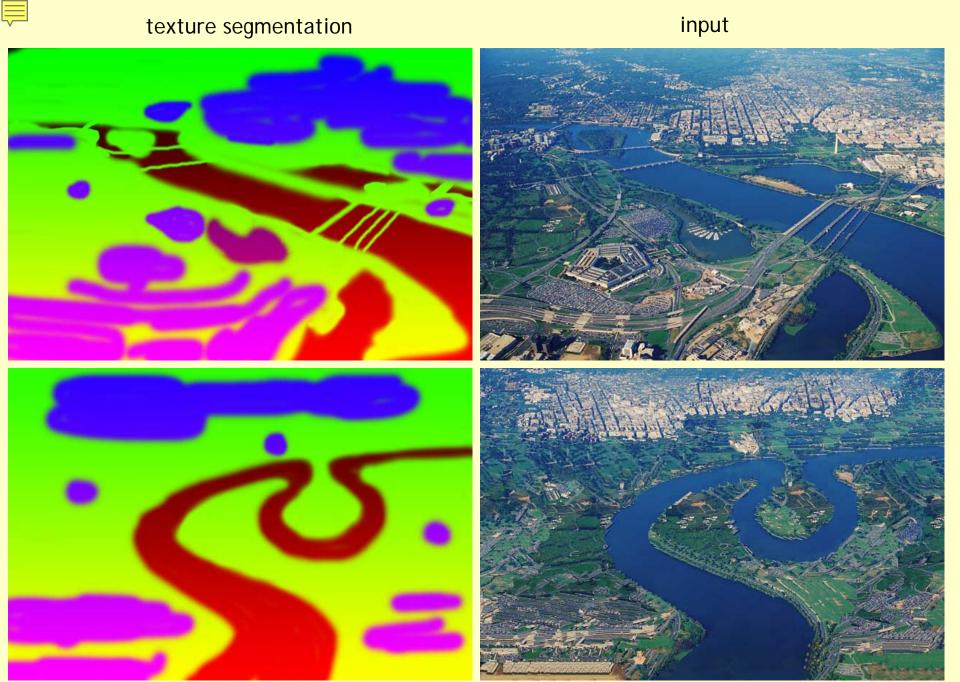


$A_1,...,A_n : A_1',...,A_n' :: B : B'$









drawing with color coded textures

output



Applications - Artistic Filters (Cont.)

Target Pairs:

Source Pair:











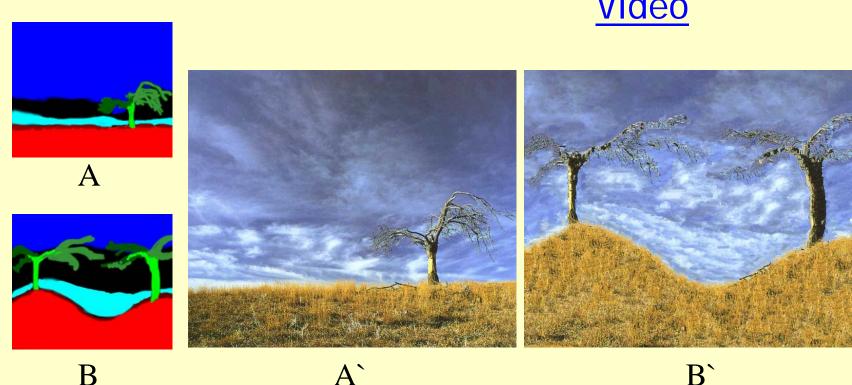




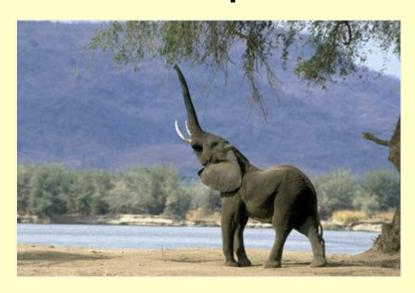
"Texture By Numbers"

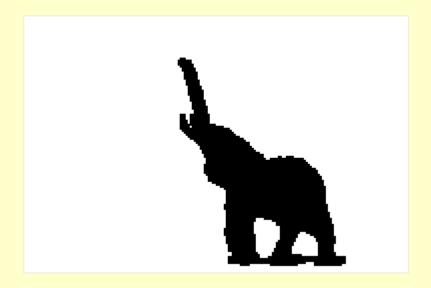
 By color-labeling source image parts a realistic synthesized image can be created

Video



Fragment-based Image Completion (SIGGRAPH'03)



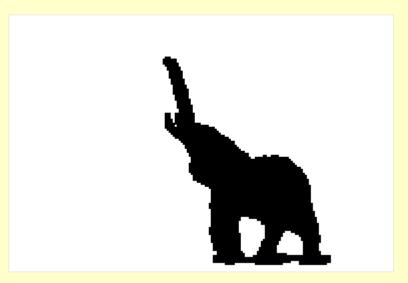


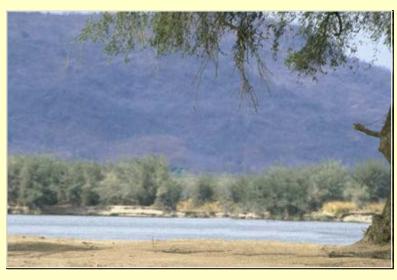


Fragment-based Image Completion (SIGGRAPH'03)

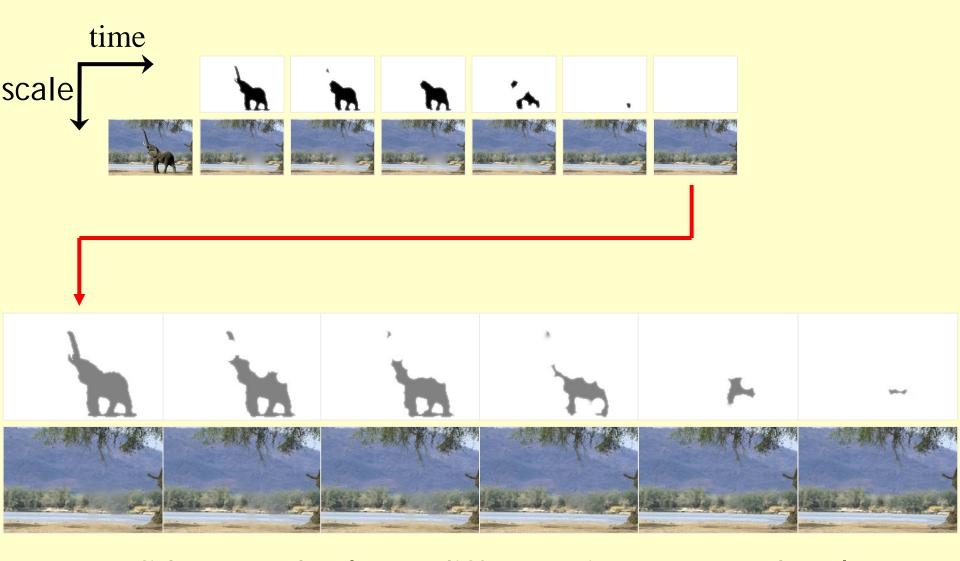








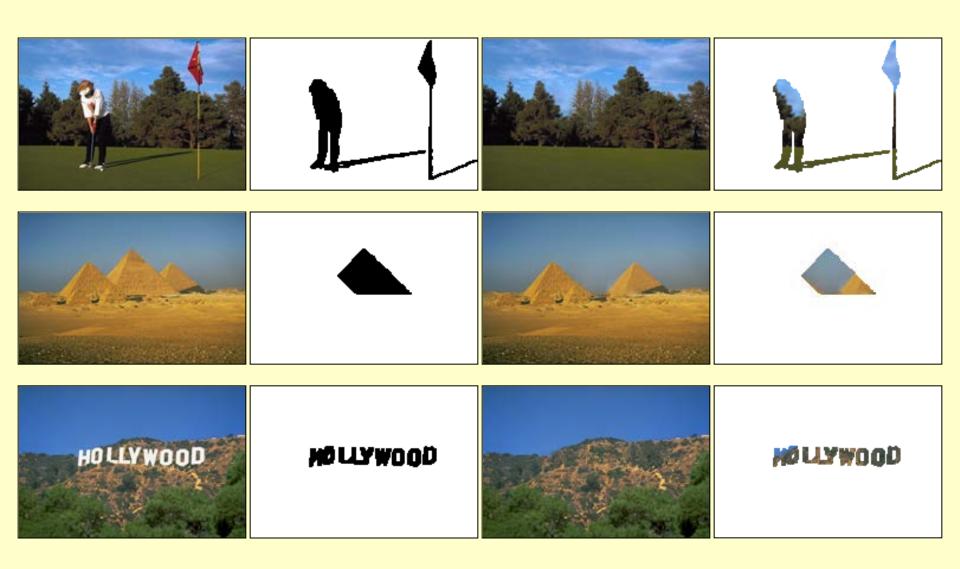
Completion process



confidence and color at different time steps and scales



Results





Results



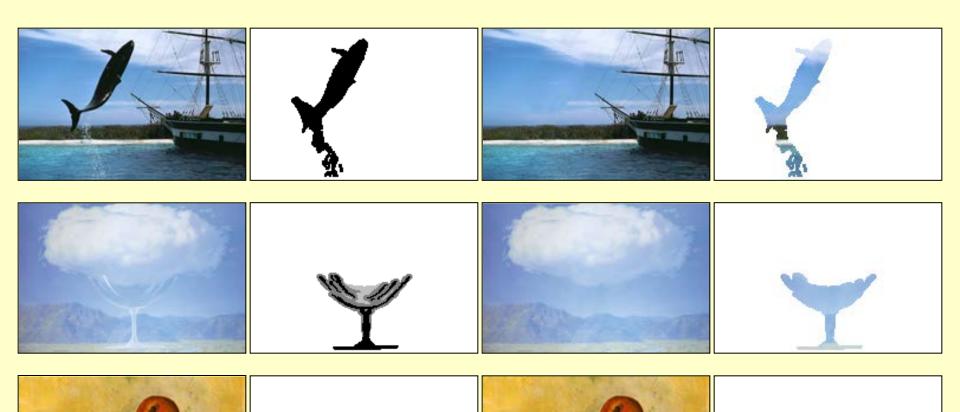
input image



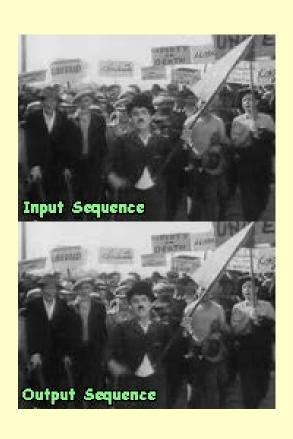
completion



Results



Video Completion







. Wexler E. Shechtman M. Irani; "Space-Time Video Completion"; CVPR'04.

Thank You

