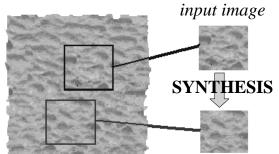




Image Quilting for Texture Synthesis & Transfer

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The Goal of Texture Synthesis



True (infinite) texture generated image

- Given a finite sample of some texture, the goal is to synthesize other samples from that same texture
 - The sample needs to be "large enough"

The Challenge

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



Both?

Texture Synthesis for Graphics

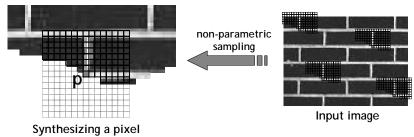
- Inspired by Texture Analysis and Psychophysics
 - [Heeger & Bergen,'95]
 - [DeBonet,'97]
 - [Portilla & Simoncelli,'98]
- ...but didn't work well for structured textures
 - [Efros & Leung,'99]
 - (originally proposed by [Garber,'81])

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

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

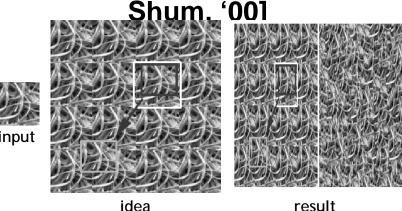
Mark V. Shaney (Bell Labs)

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

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]

Chaos Mosaic [Xu, Guo &

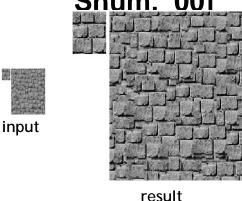


• Process: 1) tile input image; 2) pick random blocks and place them in random locations 3) Smooth edges [Praun et.al, '00]

Image Quilting

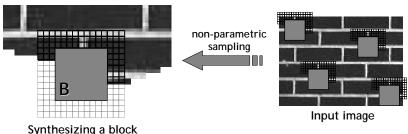
- Idea:
 - let's combine random block placement of Chaos Mosaic with spatial constraints of Efros & Leung
- Related Work (concurrent):
 - Real-time patch-based sampling [Liang et.al. '01]
 - Image Analogies [Hertzmann et.al. '01]

Chaos Mosaic [Xu, Guo & Shum. '001

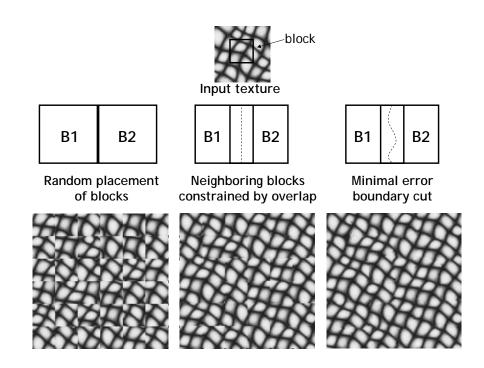


Of course, doesn't work for structured textures

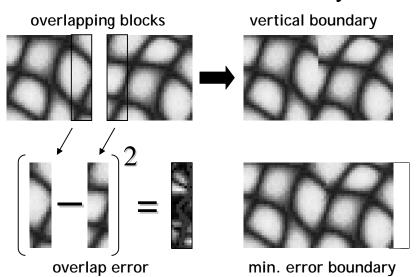
Efros & Leung '99 extended



- 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!



Minimal error boundary



Our Philosophy

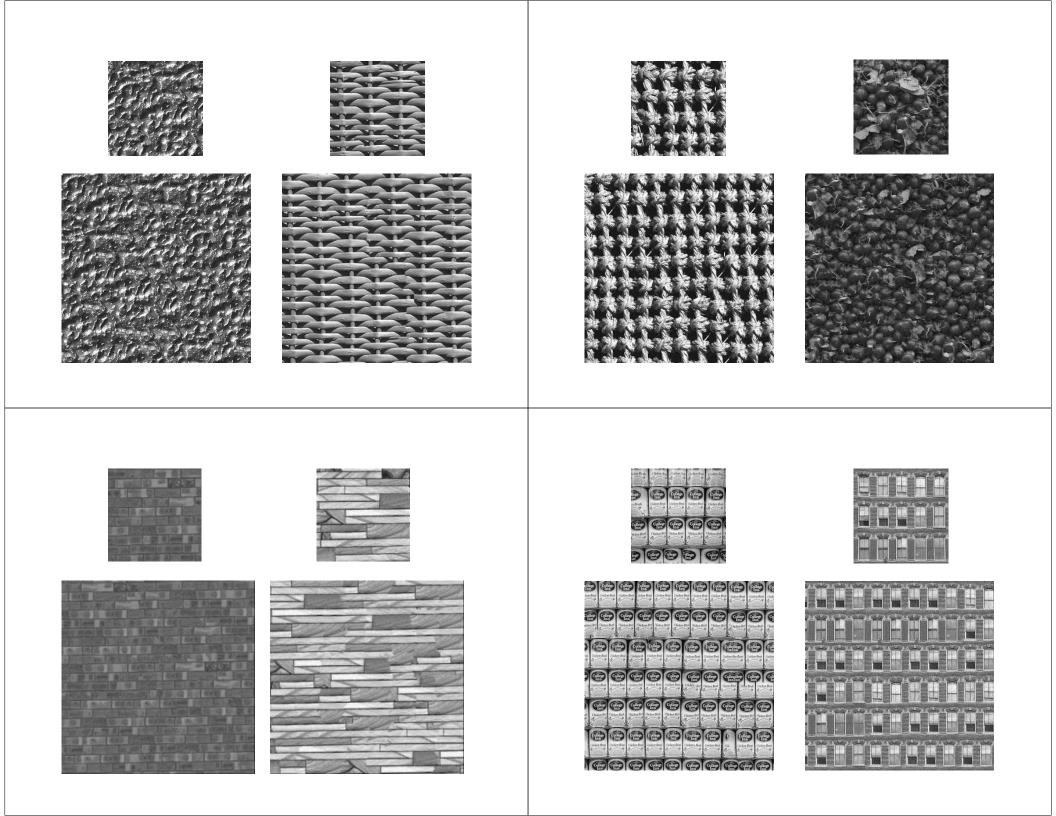
- The "Corrupt Professor's Algorithm":
 - Plagiarize as much of the source image as you can
 - Then try to cover up the evidence
- Rationale:
 - Texture blocks are by definition correct samples of texture so problem only connecting them together

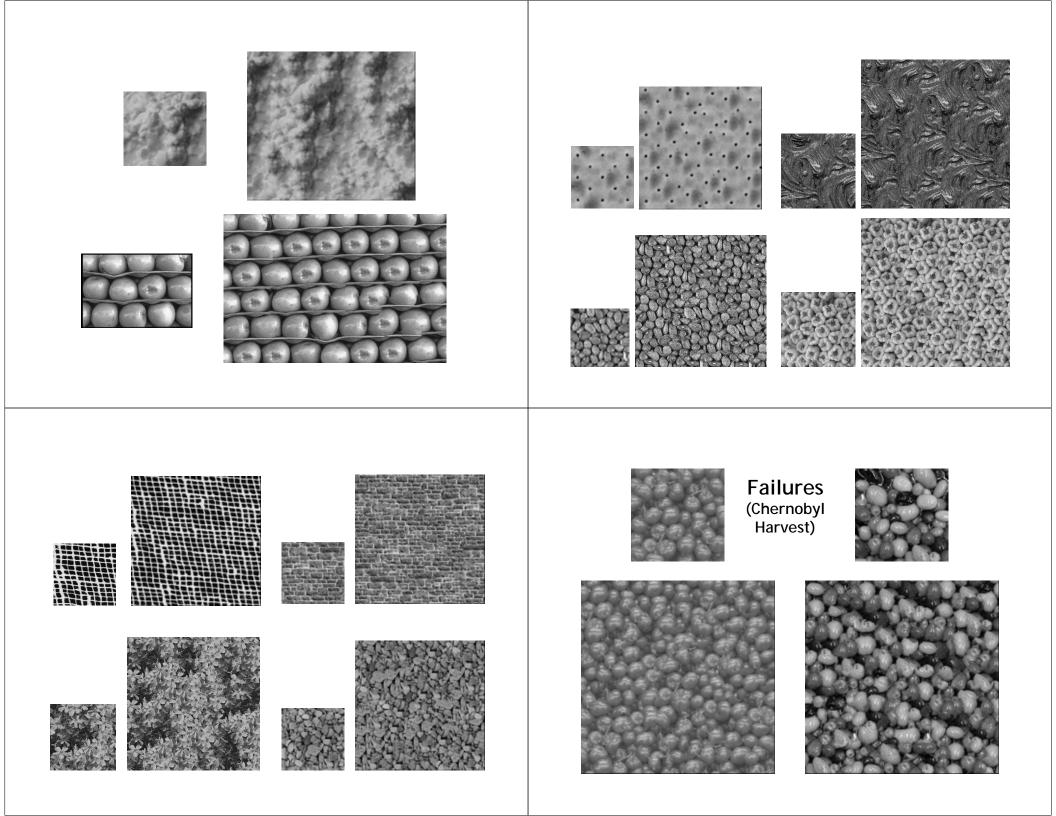
Algorithm

- 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

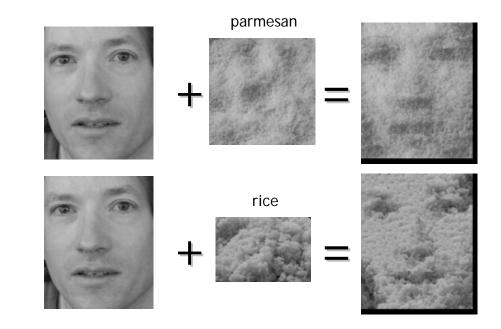


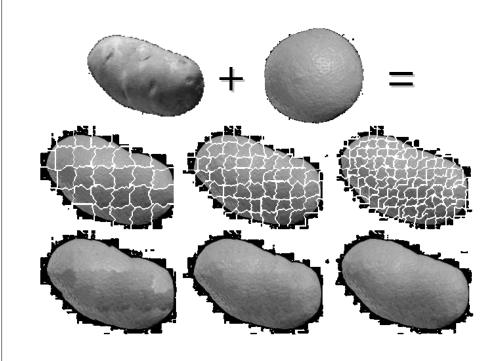


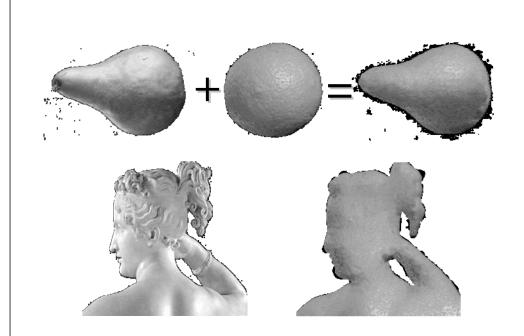
Texture Transfer

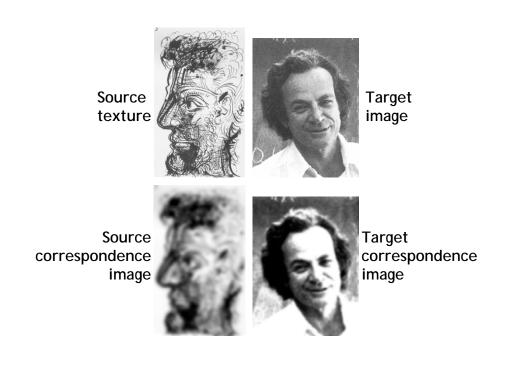
- Take the texture from one object and "paint" it onto another object
 - This requires separating texture and shape
 - That's HARD, but we can cheat
 - Assume we can capture shape by boundary and rough

Then, just add another constraint when sampling: similarity to underlying image at that spot

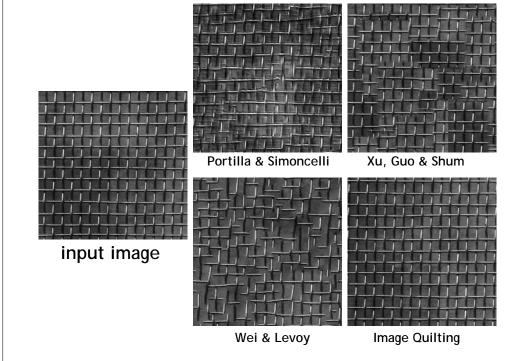


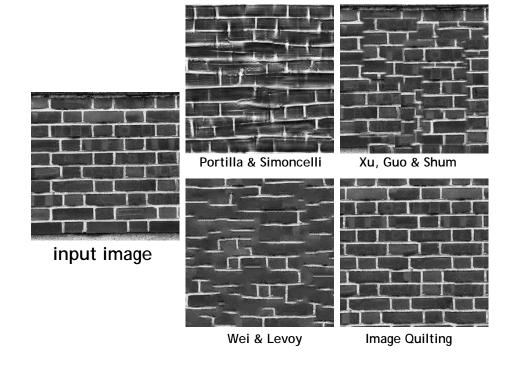












Homage to Shannon!

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Portilla & Simoncelli

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Image Quilting

Conclusion

- Quilt together patches of input image
 - randomly (texture synthesis)
 - constrained (texture transfer)
- Image Quilting
 - No filters, no multi-scale, no one-pixel-at-a-time!
 - fast and very simple
 - Results are not bad

