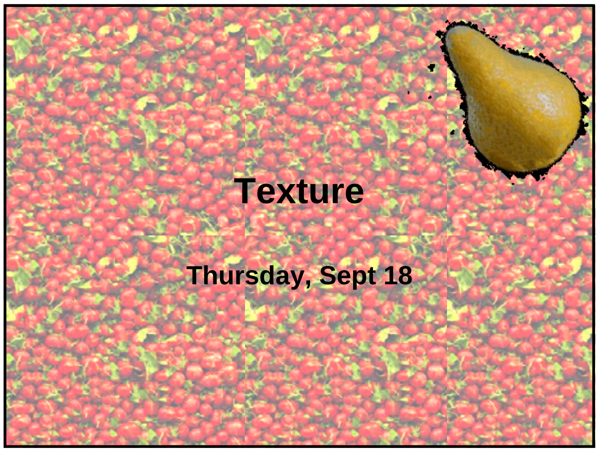
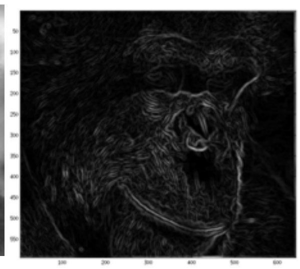



# Review: last time

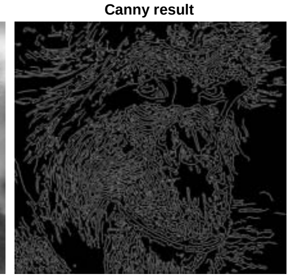
- Edge detection:
  – Filter for gradient
  – Threshold gradient magnitude, thin
- Binary image analysis
  – Connected components to find regions
  – Morphological operators to "clean up"

# Review

Gradient magnitude

# Review


Canny result


What can be done to eliminate some of the finer edges?

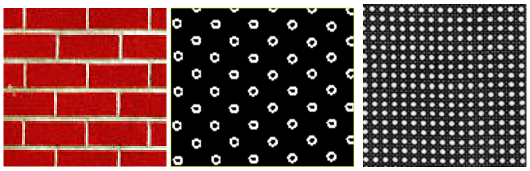
# Review


- Design a system to provide automatic supermarket checkout.
- Assume very limited stock and cooperative customers:

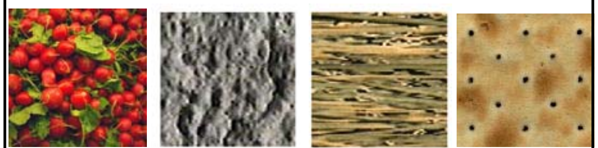

# Texture

What defines a texture?

## Includes: more regular patterns



## Includes: more random patterns



## Scale: objects vs. texture

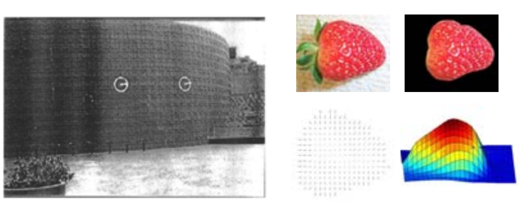
Often the same thing in the world can occur as texture or an object, depending on the scale we are considering.

## Texture-related tasks

- **Shape from texture**
  - – Estimate surface orientation or shape from image texture

## Shape from texture

- Use deformation of texture from point to point to estimate surface shape

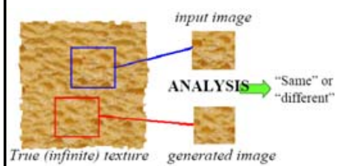


Pics from A. Loh: http://www.csse.uwa.edu.au/~angie/phdpics1.html

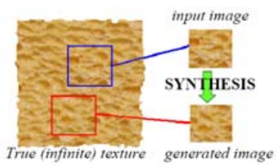
## Texture-related tasks

- **Shape from texture**
  - – Estimate surface orientation or shape from image texture
- **Segmentation/classification** from texture cues
  - – Analyze, represent texture
  - – Group image regions with consistent texture
- **Synthesis**
  - – Generate new texture patches/images given some examples

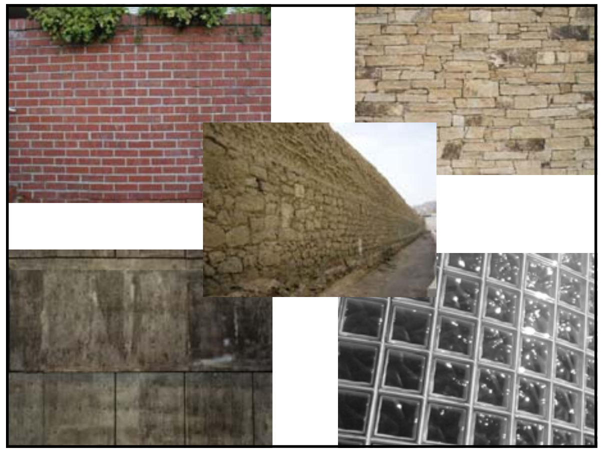
# Analysis vs. Synthesis

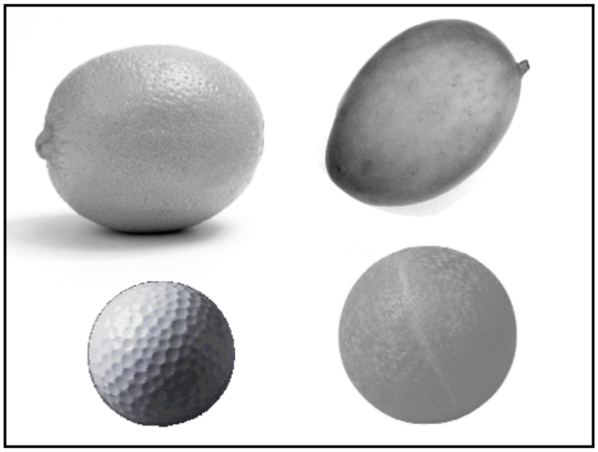


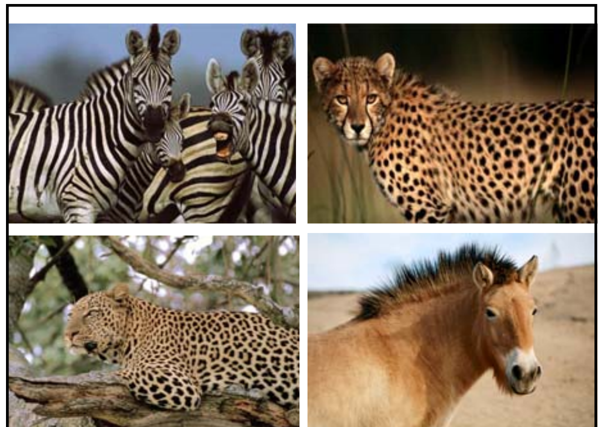

Why analyze texture?




Images:Bill Freeman, A. Efros







http://animals.nationalgeographic.com/

What kind of response will we get with an edge detector for these images?

Images from Malik and Perona, 1990

…and for this image?

Image credit: D. Forsyth

# Why analyze texture?

Importance to perception:

- Often indicative of a material's properties
- Can be important appearance cue, especially if shape is similar across objects
- Aim to distinguish between shape, boundaries, and texture

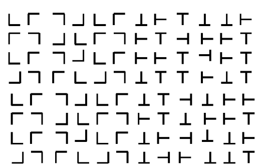
Technically:

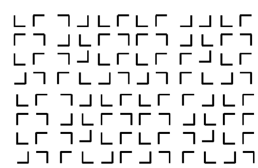
- Representation-wise, we want a feature one step above "building blocks" of filters, edges.

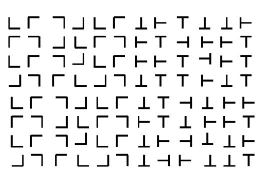
# Psychophysics of texture

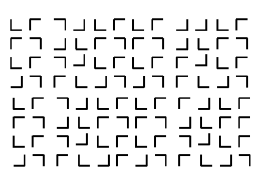
- Some textures distinguishable with *preattentive* perception– without scrutiny, eye movements [Julesz 1975]

Same or different?

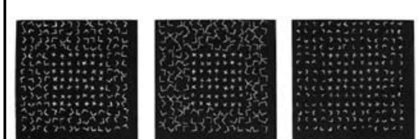








# Capturing the local patterns with image measurements



[Bergen & Adelson, *Nature* 1988]

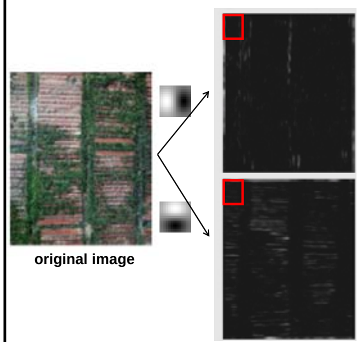
Scale of patterns influences discriminability

Size-tuned linear filters

# Texture representation

- Textures are made up of repeated local patterns, so:
  - Find the patterns
    - Use filters that look like patterns (spots, bars, raw patches…)
    - Consider magnitude of response
  - Describe their statistics within each local window
    - Mean, standard deviation
    - Histogram
    - Histogram of "prototypical" feature occurrences

# Texture representation: example



original image

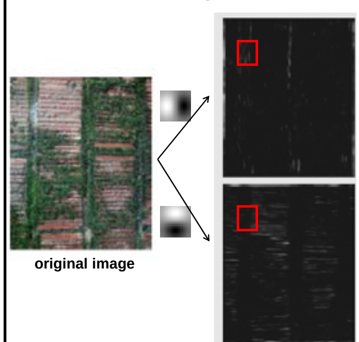
derivative filter responses, squared

| | mean d/dx value | mean d/dy value |
|---|---|---|
| Win. #1 | 4 | 10 |
| | | |
| | | |
| | | |

⋮

statistics to summarize patterns in small windows

# Texture representation: example



original image

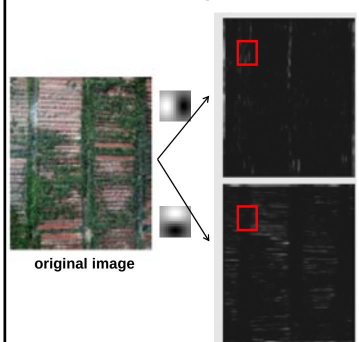
derivative filter responses, squared

| | mean d/dx value | mean d/dy value |
|---|---|---|
| Win. #1 | 4 | 10 |
| Win.#2 | 18 | 7 |
| | | |
| | | |

⋮

statistics to summarize patterns in small windows

# Texture representation: example



original image

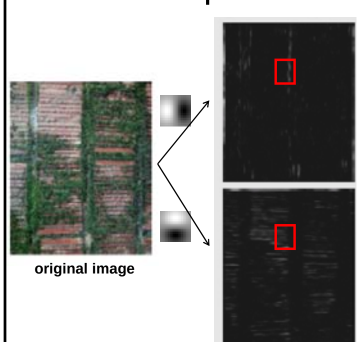
derivative filter responses, squared

| | mean d/dx value | mean d/dy value |
|---|---|---|
| Win. #1 | 4 | 10 |
| Win.#2 | 18 | 7 |
| | | |
| | | |

⋮

statistics to summarize patterns in small windows

# Texture representation: example



original image

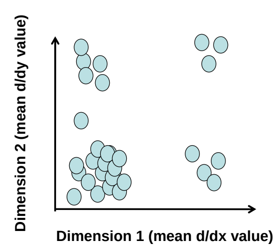
derivative filter responses, squared

| | mean d/dx value | mean d/dy value |
|---|---|---|
| Win. #1 | 4 | 10 |
| Win.#2 ⋮ | 18 | 7 |
| Win.#9 | 20 | 20 |
| | | |

⋮

statistics to summarize patterns in small windows

# Texture representation: example

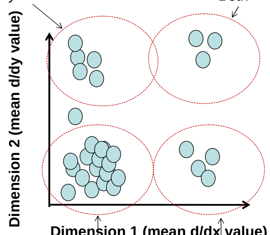



| | mean d/dx value | mean d/dy value |
|---|---|---|
| Win. #1 | 4 | 10 |
| Win.#2 ⋮ | 18 | 7 |
| Win.#9 | 20 | 20 |
| | | |

⋮

statistics to summarize patterns in small windows

# Texture representation: example

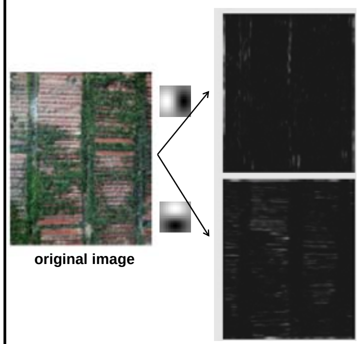



| | mean d/dx value | mean d/dy value |
|---|---|---|
| Win. #1 | 4 | 10 |
| Win.#2 ⋮ | 18 | 7 |
| Win.#9 | 20 | 20 |
| | | |

⋮

statistics to summarize patterns in small windows

# Texture representation: example

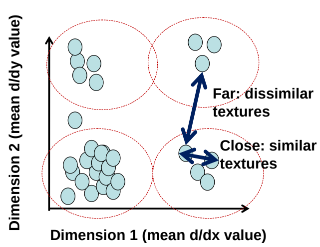


original image

derivative filter responses, squared

visualization of the assignment to texture "types"

# Texture representation: example



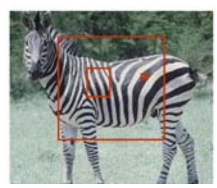

| | mean d/dx value | mean d/dy value |
|---|---|---|
| Win. #1 | 4 | 10 |
| Win.#2 ⋮ | 18 | 7 |
| Win.#9 | 20 | 20 |
| | | |

⋮

statistics to summarize patterns in small windows

# Texture representation: window scale

- We're assuming we know the relevant window size for which we collect these statistics.

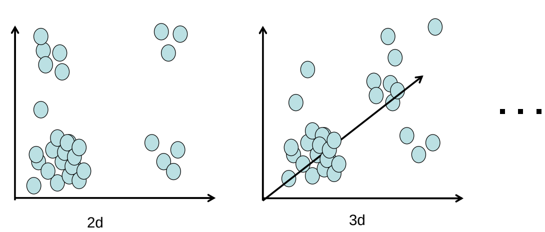


Possible to perform scale selection by looking for window scale where texture description not changing.

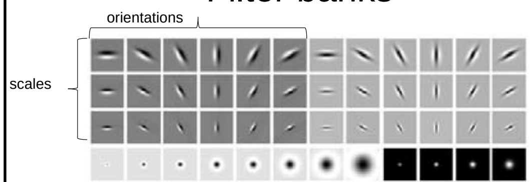
# Filter banks

- Our previous example used two filters, and resulted in a 2-dimensional feature vector to describe texture in a window.
  - x and y derivatives revealed something about local structure.
- We can generalize to apply a collection of multiple (*d*) filters: a "filter bank"
- Then our feature vectors will be *d*-dimensional.
  - still can think of nearness, farness in feature space

# *d*-dimensional features



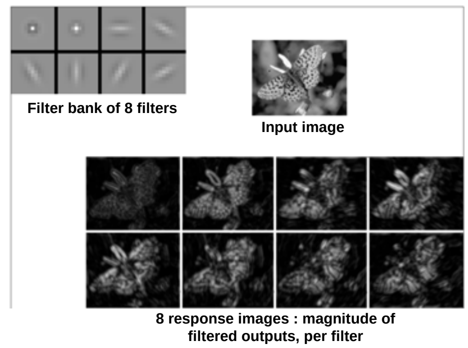
# Filter banks




- What filters to put in the bank?
  - Typically we want a combination of scales and orientations, different types of patterns.

Matlab code available for these examples:
http://www.robots.ox.ac.uk/~vgg/research/texclass/filters.html

# Example application of a filter bank




# Color vs. texture


Recall: These looked very similar in terms of their color distributions (when our features were R-G-B)

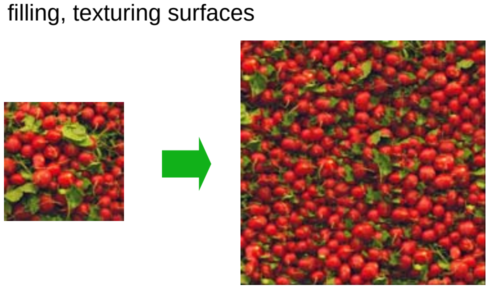
But how would their *texture* distributions compare?

# Texture-related tasks

- **Shape from texture**
  - Estimate surface orientation or shape from image texture
- **Segmentation/classification** from texture cues
  - Analyze, represent texture
  - Group image regions with consistent texture
- **Synthesis**
  - Generate new texture patches/images given some examples

# Texture synthesis

- Goal: 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

Alexei A. Efros and Thomas K. Leung, “Texture Synthesis by Non-parametric Sampling,” Proc. International Conference on Computer Vision (ICCV), 1999.

## Markov Chains

### Markov Chain

- a *sequence* of random variables $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n$
- $\mathbf{x}_t$ is the **state** of the model at time t

$$\boxed{\mathbf{x}_1} \rightarrow \boxed{\mathbf{x}_2} \rightarrow \boxed{\mathbf{x}_3} \rightarrow \boxed{\mathbf{x}_4} \rightarrow \boxed{\mathbf{x}_5}$$

- **Markov assumption**: each state is dependent only on the previous one
  - dependency given by a **conditional probability**:

$$p(\mathbf{x}_t | \mathbf{x}_{t-1})$$

- The above is actually a *first-order* Markov chain
- An *N'th-order* Markov chain:

$$p(\mathbf{x}_t | \mathbf{x}_{t-1}, \ldots, \mathbf{x}_{t-N})$$

Source S. Seitz

## Markov Chain Example: Text

"A dog is a man's best friend. It's a dog eat dog world out there."

Rows: $\mathbf{x}_{t-1}$; columns: $\mathbf{x}_t$; entries: $p(\mathbf{x}_t | \mathbf{x}_{t-1})$

| | a | dog | is | man's | best | friend | it's | eat | world | out | there | . |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| a | | 2/3 | | 1/3 | | | | | | | | |
| dog | | | 1/3 | | | | | 1/3 | 1/3 | | | |
| is | 1 | | | | | | | | | | | |
| man's | | | | | 1 | | | | | | | |
| best | | | | | | 1 | | | | | | |
| friend | | | | | | | | | | | | 1 |
| it's | 1 | | | | | | | | | | | |
| eat | | 1 | | | | | | | | | | |
| world | | | | | | | | | | 1 | | |
| out | | | | | | | | | | | 1 | |
| there | | | | | | | | | | | | 1 |
| . | | | | | | | 1 | | | | | |

Source: S. Seitz

## Text synthesis

Create plausible looking poetry, love letters, term papers, etc.

### Most basic algorithm

1. Build probability histogram
   - find all blocks of N consecutive words/letters in training documents
   - compute probability of occurrence $p(\mathbf{x}_t | \mathbf{x}_{t-1}, \ldots, \mathbf{x}_{t-(n-1)})$
2. Given words $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_{k-1}$
   - compute $\mathbf{x}_k$ by sampling from $p(\mathbf{x}_t | \mathbf{x}_{t-1}, \ldots, \mathbf{x}_{t-(n-1)})$

**WE NEED TO EAT CAKE**

Source: S. Seitz

## Text synthesis

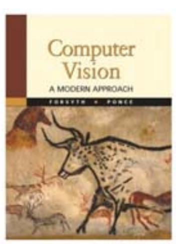
- Results:
  - *"As I've commented before, really relating to someone involves standing next to impossible."*
  - *"One morning I shot an elephant in my arms and kissed him."*
  - *"I spent an interesting evening recently with a grain of salt"*

Dewdney, "A potpourri of programmed prose and prosody" *Scientific American,* 1989.

Slide from Alyosha Efros, ICCV 1999

## Synthesizing Computer Vision text

- What do we get if we extract the probabilities from the F&P chapter on Linear Filters, and then synthesize new statements?




Check out Yisong Yue's website implementing text generation: build your own text Markov Chain for a given text corpus. http://www.yisongyue.com/shaney/index.php

## **Synthesized** text

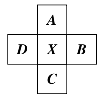
- This means we cannot obtain a separate copy of the best studied regions in the sum.
- All this activity will result in the primate visual system.
- The response is also Gaussian, and hence isn't bandlimited.
- Instead, we need to know only its response to any data vector, we need to apply a low pass filter that strongly reduces the content of the Fourier transform of a very large standard deviation.
- It is clear how this integral exist (it is sufficient for all pixels within a 2k +1 × 2k +1 × 2k +1 × 2k + 1 — required for the images separately.

## Markov Random Field

A Markov random field (MRF)
- generalization of Markov chains to two or more dimensions.

First-order MRF:
- probability that pixel *X* takes a certain value given the values of neighbors *A*, *B*, *C*, and *D*:

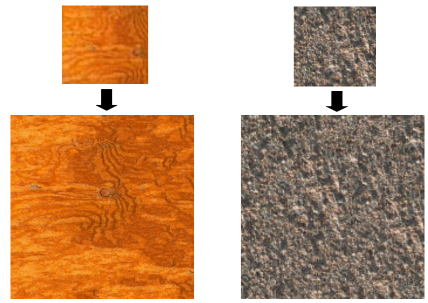
$$P(\mathbf{X}|\mathbf{A},\mathbf{B},\mathbf{C},\mathbf{D})$$




Source: S. Seitz

## Texture Synthesis [Efros & Leung, ICCV 99]

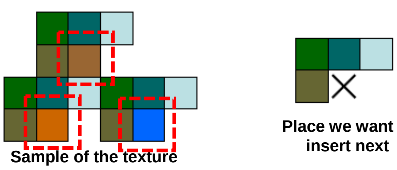
Can apply 2D version of text synthesis



# Texture synthesis: intuition

Before, we inserted the next word based on existing nearby words…

Now we want to insert **pixel intensities** based on existing nearby pixel values.

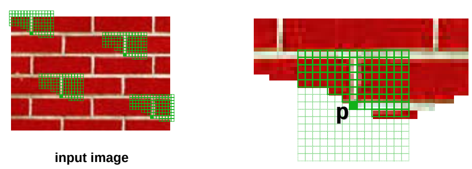


**Sample of the texture ("corpus")**

**Place we want to insert next**

Distribution of a value of a pixel is conditioned on its neighbors alone.

## Synthesizing One Pixel



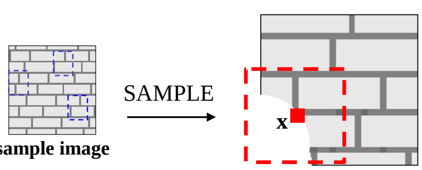

**input image**

**synthesized image**

- What is $P(\mathrm{x}|\text{neighborhood of pixels around x})$ ?
- Find all the windows in the image that match the neighborhood
  - consider only pixels in the neighborhood that are already filled in
- To synthesize **x**
  - pick one matching window at random
  - assign **x** to be the center pixel of that window

Slide from Alyosha Efros, ICCV 1999

## Really Synthesizing One Pixel



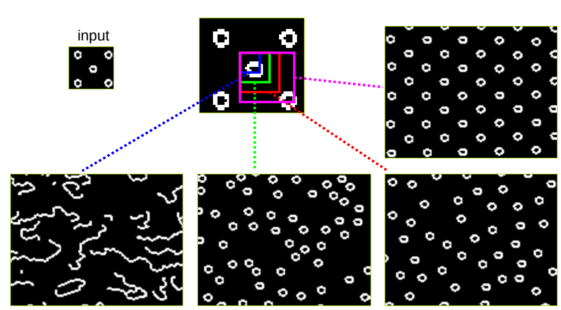

**sample image**

**Generated image**

- An exact neighbourhood match might not be present
- So we find the **best** matches using SSD error and randomly choose between them, preferring better matches with higher probability

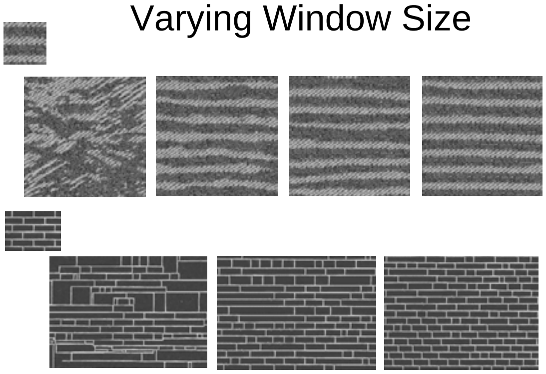
Alyosha Efros, ICCV 1999

# Neighborhood Window




Slide from Alyosha Efros, ICCV 1999

## Varying Window Size



Increasing window size →

Slide from Alyosha Efros, ICCV 1999

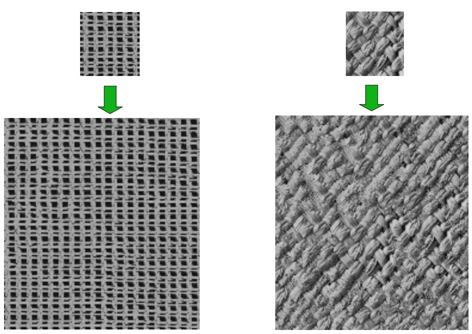
## Growing Texture

- Starting from the initial image, "grow" the texture one pixel at a time

Slide from Alyosha Efros, ICCV 1999

## Synthesis results

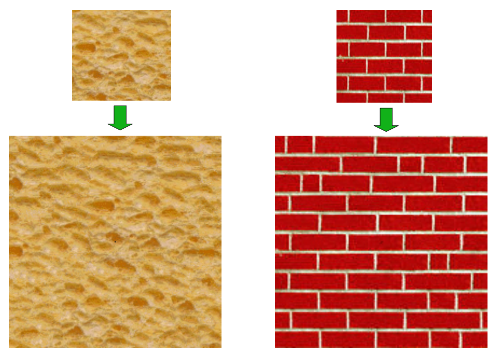
french canvas　　rafia weave



Slide from Alyosha Efros, ICCV 1999

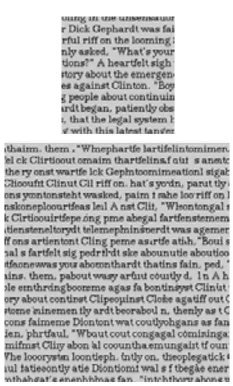
## Synthesis results

white bread　　brick wall



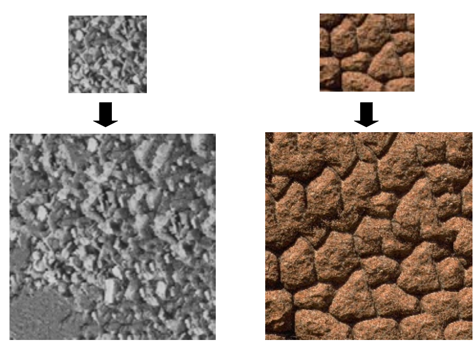
Slide from Alyosha Efros, ICCV 1999

## Synthesis results



Slide from Alyosha Efros, ICCV 1999

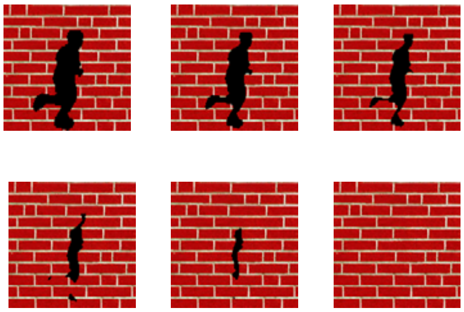
## Failure Cases



**Growing garbage**　　**Verbatim copying**

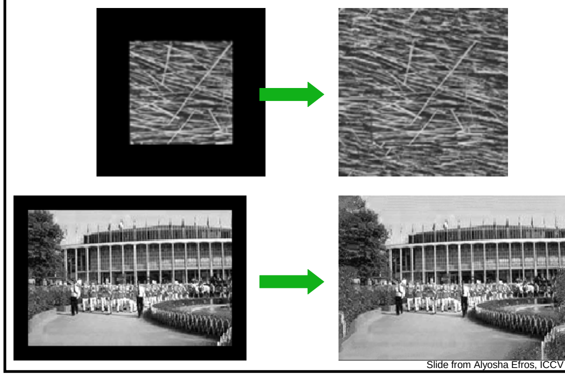
Slide from Alyosha Efros, ICCV 1999

# Hole Filling



Slide from Alyosha Efros, ICCV 1999

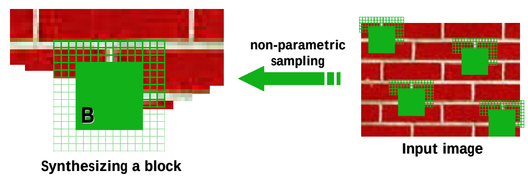
# Extrapolation



Slide from Alyosha Efros, ICCV 1999

- The Efros & Leung algorithm
  - Simple
  - Surprisingly good results
  - Synthesis is easier than analysis!
  - …but very slow

# Image Quilting [Efros & Freeman 2001]

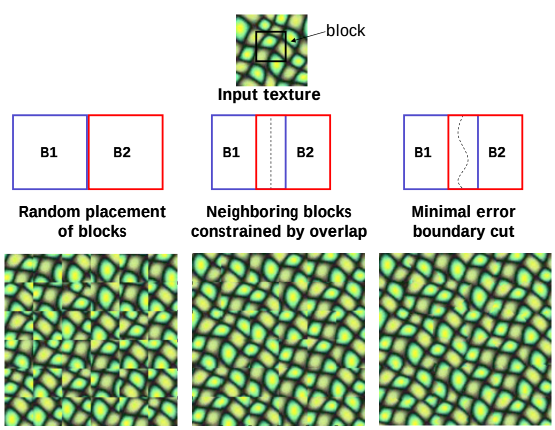



- Observation: neighbor pixels are highly correlated

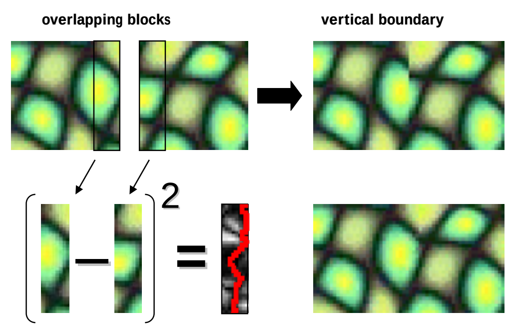
**Idea: unit of synthesis = block**

- Exactly the same but now we want P(**B**|N(**B**))
- Much faster: synthesize all pixels in a block at once

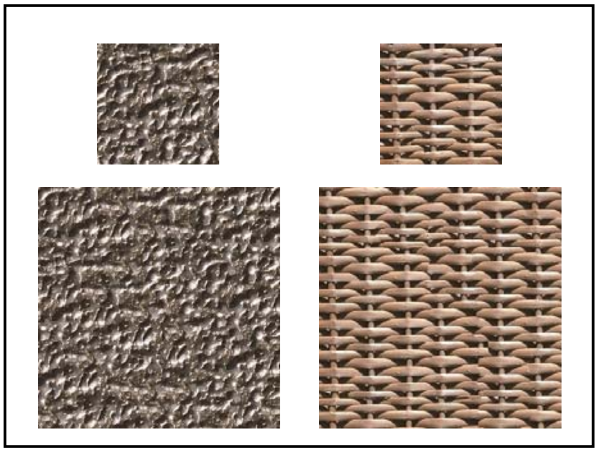
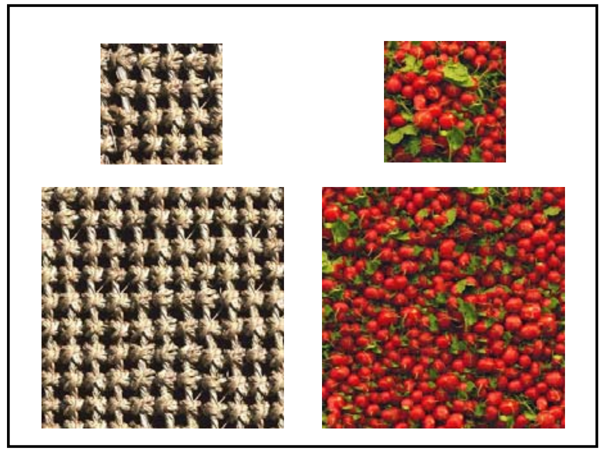
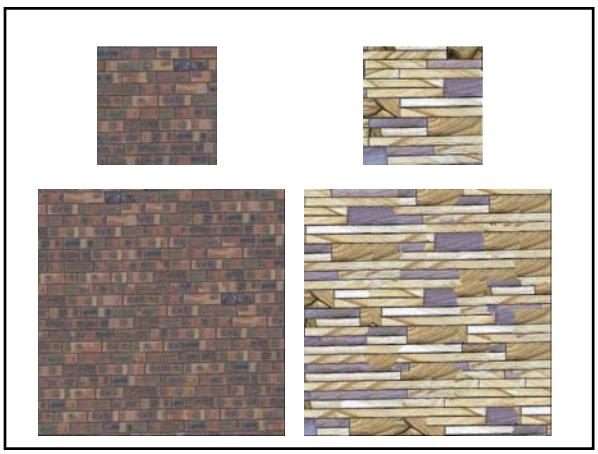
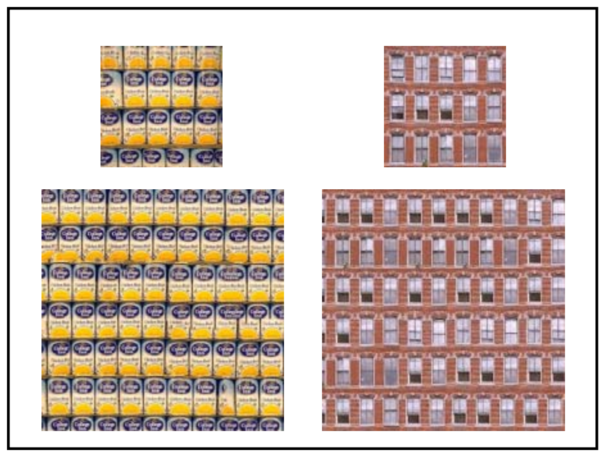
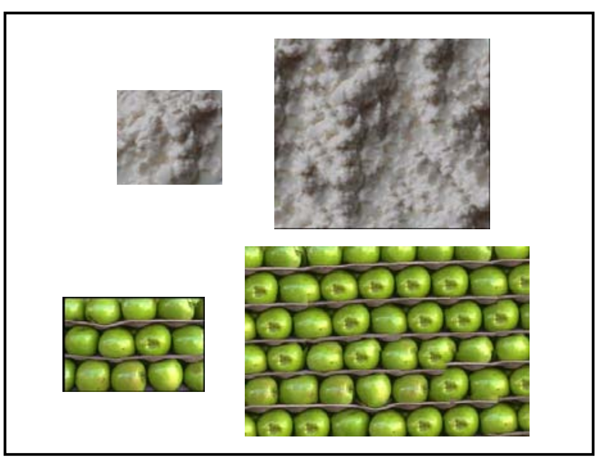
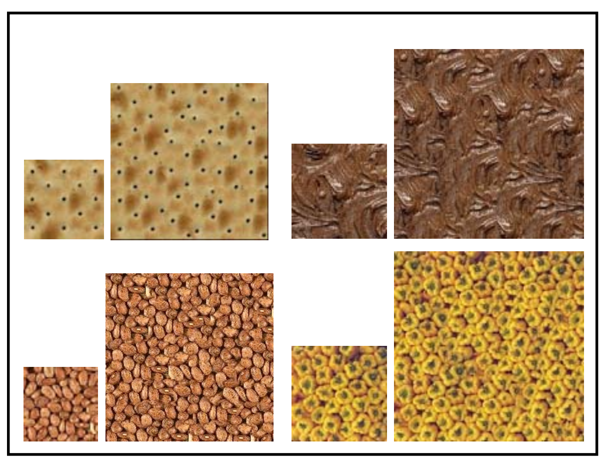
Slide from Alyosha Efros, ICCV 1999




# Minimal error boundary



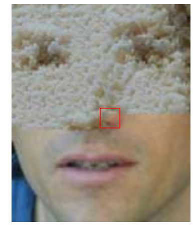

Slide from Alyosha Efros

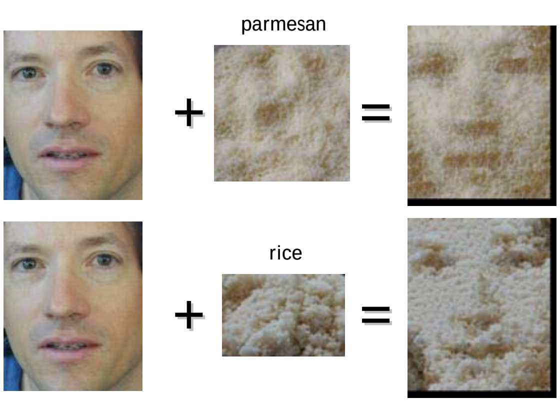







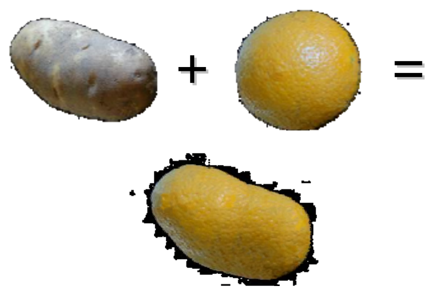
## Failures
(Chernobyl Harvest)

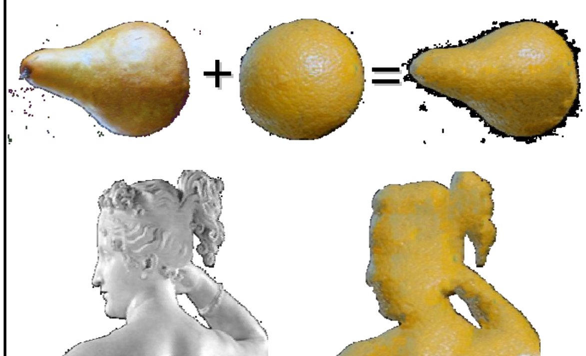
## Texture Transfer

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






## (Manual) texture synthesis in the media

## (Manual) texture synthesis in the media



http://www.dailykos.com/story/2004/10/27/22442/878

http://thelede.blogs.nytimes.com/2008/07/10/in-an-iranian-image-a-missile-too-many/

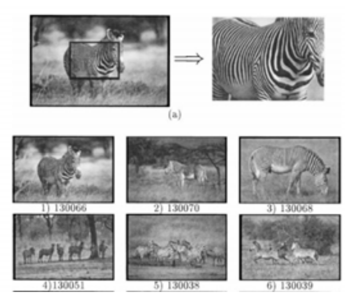
## Example uses of texture in vision

## Synthesizing textures when constructing 3d models of archaeological sites

Figure 12. The Nymphaeum at the upper agora of Sagalassos with differently textured pillars. Overview of one half of the building (symmetric)

Figure 14. Nymphaeum pillars and back wall fragments in detail

A. Zalesny et al., Realistic Textures for Virtual Anastylosis




## exture features for image retrieval

Y. Rubner, C. Tomasi, and L. J. Guibas. The earth mover's distance as a metric for image retrieval. *International Journal of Computer Vision*, 40(2):99-121, November 2000,


Characterizing scene categories by texture

L. W. Renninger and J. Malik. When is scene identification just texture recognition? Vision Research 44 (2004) 2301–2311

Segmenting aerial imagery by textures

http://www.airventure.org/2004/gallery/images/073104_satellite.jpg

## Summary

- Texture is a useful property that is often indicative of materials, appearance cues
- **Texture representations** attempt to summarize repeating patterns of local structure
- **Filter banks** useful to measure redundant variety of structures in local neighborhood
  - Feature spaces can be multi-dimensional
- Neighborhood statistics can be exploited to “sample” or **synthesize** new texture regions
  - Example-based technique

## Next

- Next week: Segmentation and grouping
  - Read F&P Chapter 14

- Reminder:
  - Problem set 1 due Monday 5 PM