## Data-driven methods: Video \& Texture


(C) A.A. Efros

CS194: Intro to Computer Vision \& Comp. Photography Alexei Efros, UC Berkeley, Fall 2020

## Michel Gondry train video

http://www.youtube.com/watch?v=0S43IwBF0uM

## Class Choice award!



## Weather Forecasting for Dummies ${ }^{\text {TM }}$

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:
- $P(R \mid S), P(S \mid S)$, etc.
- Predict the state with highest probability!
- It's a Markov Chain


## Markov Chain



What if we know today and yestarday's weather?

## Text Synthesis

[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


## 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"


## Video Textures

## Arno Schödl

## Richard Szeliski

## David Salesin

 Irfan EssaMicrosoft Research. Georoia Tech

## Still photos



## Video clips



## I



## Video textures



## Problem statement


video clip

video texture

## Our approach

- How do we find good transitions?


## Finding good transitions

- Compute $L_{2}$ distance $D_{i, j}$ between all frames


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 $\mathrm{P}_{\mathrm{i} \rightarrow \mathrm{j}}$ inversely related to cost:

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

high $\sigma$
low $\sigma$

## Preserving dynamics



## Preserving dynamics



## Preserving dynamics

- Cost for transition $i \rightarrow j$

$$
C_{i \rightarrow j}=\sum_{k=-\mathrm{N}}^{\mathrm{N}-1} w_{k} D_{i+k+1, j+k}
$$



## Preserving dynamics - effect

- Cost for transition $i \rightarrow j$

$$
C_{i \rightarrow j}=\sum_{k=-N}^{N-1} W_{k} D_{i+k+1, j+k}
$$



## Dead ends

- No good transition at the end of sequence



## Future cost

- Propagate future transition costs backward
- Iteratively compute new cost
- $F_{i \rightarrow j}=C_{i \rightarrow j}+\alpha \min _{k} F_{j \rightarrow k}$



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Q-learning


## Final result



## Finding good loops

- Alternative to random transitions
- Precompute set of loops up front


## Video portrait



- c.f. Harry Potter


## Region-based analysis

- Divide video up into regions

- Generate a video texture for each region


## User-controlled video textures


slow

variable

fast

User selects target frame range

## Video-based animation

- Like sprites computer games
- Extract sprites from real video
- Interactively control desired motion



## Video sprite extraction



> blue screen matting and velocity estimation


## Video sprite control

- Augmented transition cost:


## vector to mouse pointer <br> 

Control term

## 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 / Discussion

- Some things are relatively easy



## Discussion

- Some are hard



## "Amateur" by Lasse Gjertsen

http://www.youtube.com/watch?v=JzqumbhfxRo
similar idea:
http://www.youtube.com/watch?v=MsBMGp1HDM\&feature=share\&list=PLFFD733D0FF425290

## Hyperlapse Videos

https://www.youtube.com/watch?v=Wt Y04xn84M
"Do As I Do" (ICCV 2003)

## https://youtu.be/UMJcpLIAwKg

Efros, Berg, Mori, Malik, "Recognizing Action at a Distance", ICCV 2003

## 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

repeated

stochastic


Both?

## Efros \& Leung Algorithm




Input image

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 $\mathbf{p}$
- 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

$\square$


## More Results

white bread

$\pm$


## Homage to Shannon <br> oning in une unsenseruou

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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]




Input image

Synthesizing a block

- Observation: neighbor pixels are highly correlated Idea: unit of synthesis = block
- Exactly the same but now we want $P(B \mid N(B))$
- Much faster: synthesize all pixels in a block at once
- Not the same as multi-scale!


Random placement of blocks



Neighboring blocks constrained by overlap


Minimal error boundary cut


## Minimal error boundary

overlapping blocks

vertical boundary

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)




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## input image













 v, 4all :

## Portilla \& Simoncelli

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## Xu, Guo \& Shum

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## 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 Jacobs ${ }^{2}$
Nuria Oliver ${ }^{2}$

Brian Curless ${ }^{3}$
David Salesin ${ }^{2,3}$
${ }^{1}$ New York University
${ }^{2}$ Microsoft Research
3University of Washington

## Image Analogies



A


B


A'


B'


## Image Analogies

Goal: Process an image by example


Hertzmann et al. SIGGRAPH 2001

## Non-parametric sampling




B
B'


## Blur Filter



## Edge Filter



## Artistic Filters



A


B


A'

$B^{\prime}$

## Colorization



## Texture-by-numbers



A



B'

## Super-resolution



A

$A^{\prime}$


## Super-resolution (result!)



B


B'

