Visualization Tools For Webcam Scenes

A Masters Project by David Ross

Friday, May 24, 2009

With slides by Nathan Jacobs and Robert Pless

Acknowledgement

- Advisor:
  - Robert Pless
- Committee:
  - Tao Ju
  - Bill Smart
- M&M Lab:
  - Nathan Jacobs
  - Michael Dixon
  - and others

Overview

- Introduction
  - Webcams and the AMOS Dataset
  - Problem Motivation
- Principal Component Analysis (PCA)
- Visualization Tools
  - PCA Input
  - Visualization
  - Evaluations
- Conclusion
- Future Work

Introduction

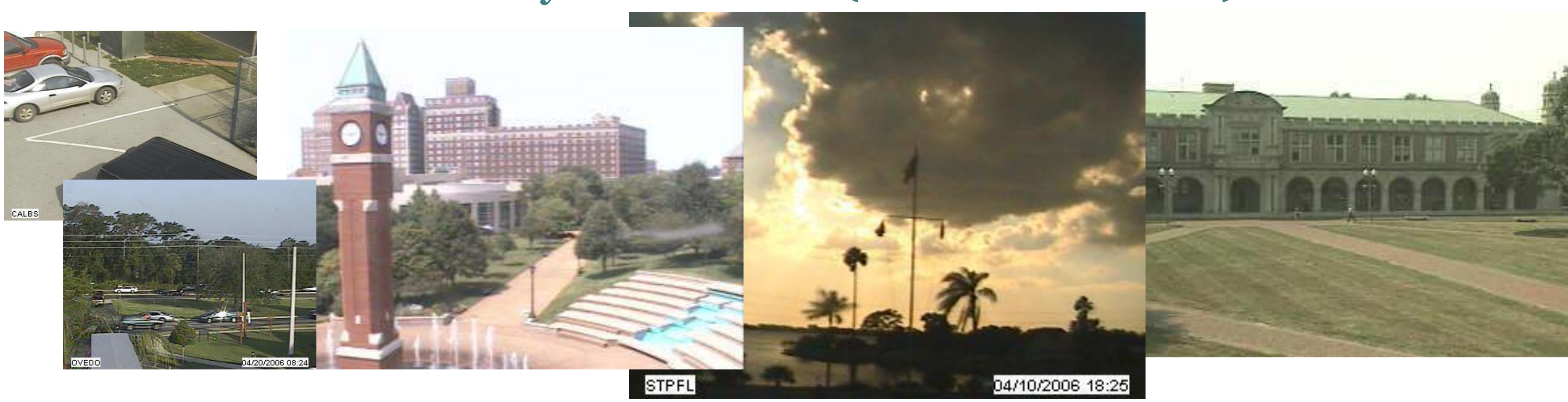
- Given a static webcam scene, how can we make it easier to understand the variation in the scene?
  - Automatic visualization tools to quickly show interesting variation
- Why? Help to maintain and understand massive AMOS Dataset
- Use PCA to learn less interesting variation, analyze PCA error to find more interesting variation

“Interesting” Variation

- Outdoor scenes vary naturally and predictably
  - Day/night
  - Weather
  - Seasonal
- Unnatural variation less predictable
  - People, cars, other objects
  - Camera/image variation
  - Scene changes
- To understand a scene is to understand the latter

AMOS Dataset

- *The Archive of Many Outdoor Scenes (AMOS)*
  - Images from ~1000 static webcams,
  - Every 30 minutes since March 2006.
  - *http://amos.cse.wustl.edu*
- Capture variations from fixed cameras
  - Due to lighting (time of day), and
  - Seasonal and weather variations (over a year).
  - From cameras mostly in the USA (a few elsewhere).



AMOS Dataset

3000 webcams
x 1 years
35 million images

Variations over a year and over a day

Principal Component Analysis

Given: a collection of sample images, $\{I_1,\ldots I_n\}$
Find: A mean image μ, and a collection of principle components $\{B_1, B_2, \ldots B_k\}$, such that:

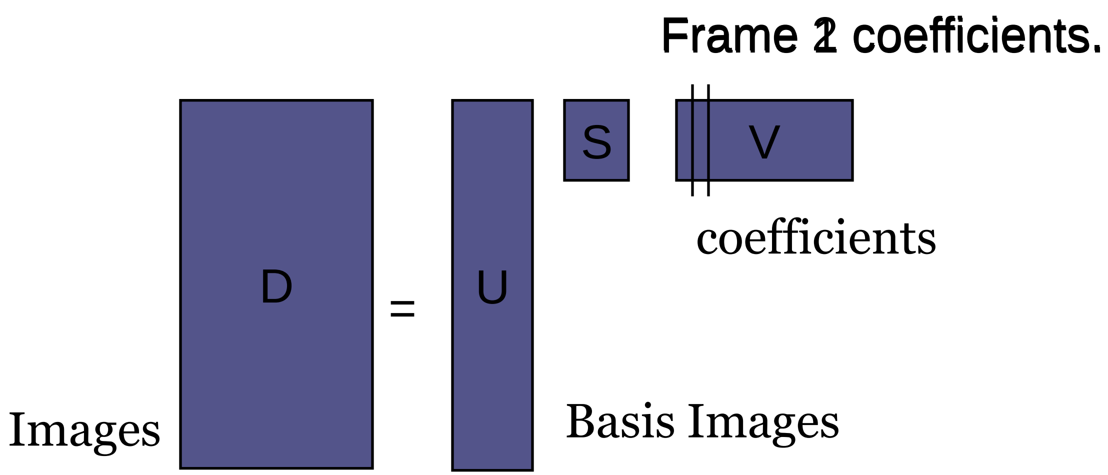
Each sample image I_i can be approximated as:

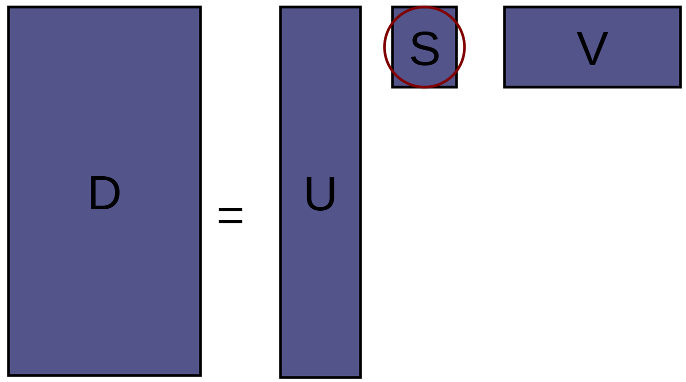
$$I_i \tfrac{1}{4} \mu + c_{1,i} B_{1,i} + c_{2,i} B_2 + \ldots c_{\kappa,i} B_\kappa$$

- $c_1, c_2, \ldots c_k$ are *coefficients*.
- Each image has different coefficients.
- But the whole *set* of images shares principle components.

PCA Math

- Principle component analysis.
  - Images are in a 3D matrix I(x,y,t).
  - Change that matrix into a data matrix D(p,t), listing the pixel values in each frame.
  - Do the "SVD" decomposition:
  - D = U S V



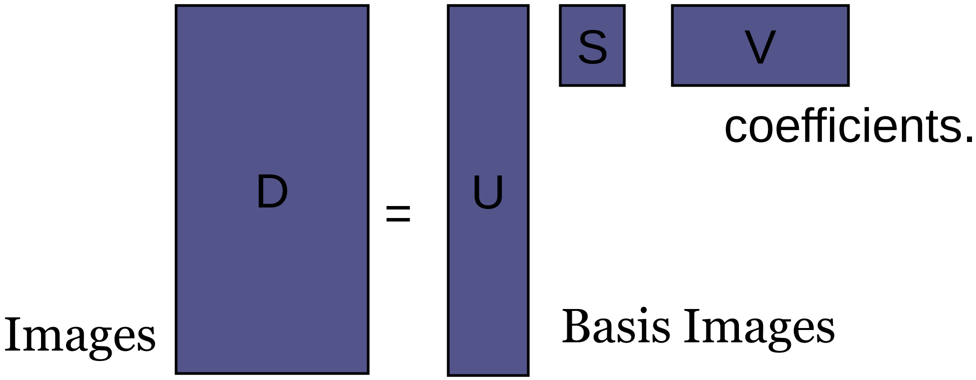


S is a diagonal matrix, so it only has diagonal elements, called singular values.

These numbers are the relative importance of each of the principle components.

If we want we can make the principle components be the columns of U * S, and have the columns of V be the coefficients.

Alternatively, we can keep the columns of U, and make the coefficients be S * the columns of V. This is more common.



Special properties:

U,V are both orthonormal matrices.

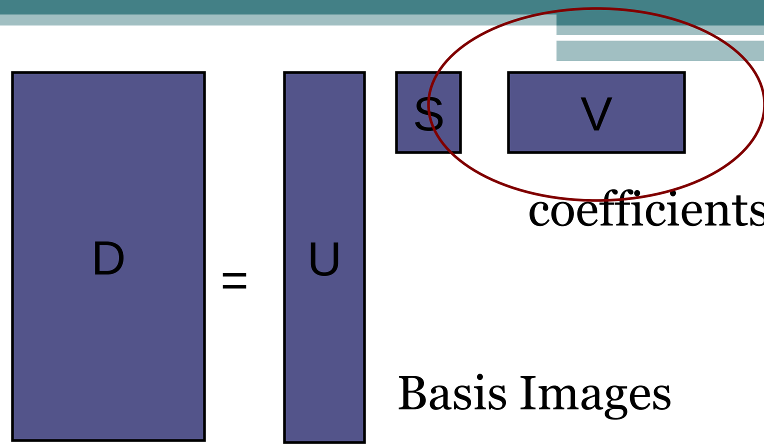
This is cool:

Given a new image W, to get its coefficients v_w, you can use:

$v_w = U^T W$

Then U v_w approximately reconstructs W. Why?

$$
\begin{aligned}
& U v_w \\
&= U (U^T W) \\
&= (U U^T) W \\
&= I W \\
&= W.
\end{aligned}
$$



These coefficients define the appearance of the image.

The U matrix defines the space of possible images within this video.

Given a new set of coefficients (a new column of V), we can make a new image.

New image = U v

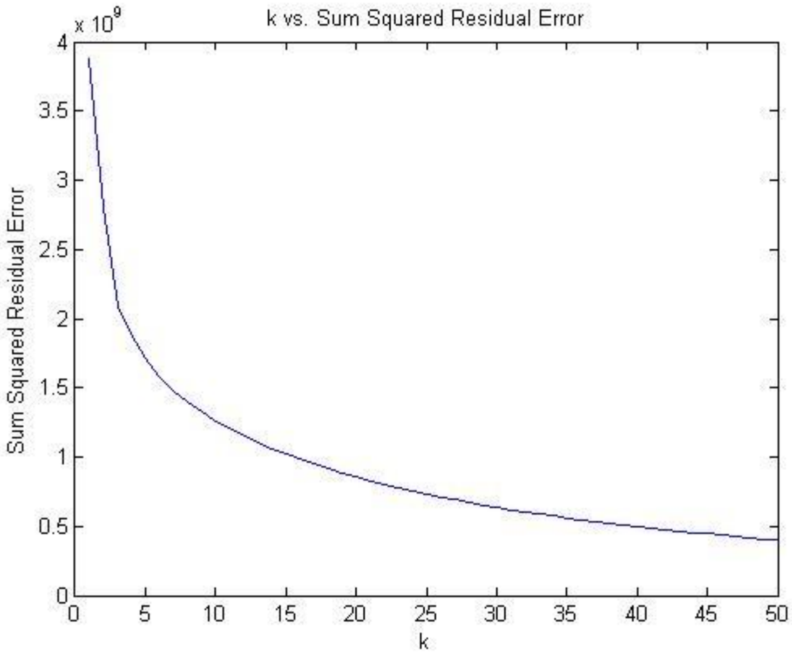
(*this will give us a column vector of the pixel values…*
you have to rearrange it into the shape of the image).

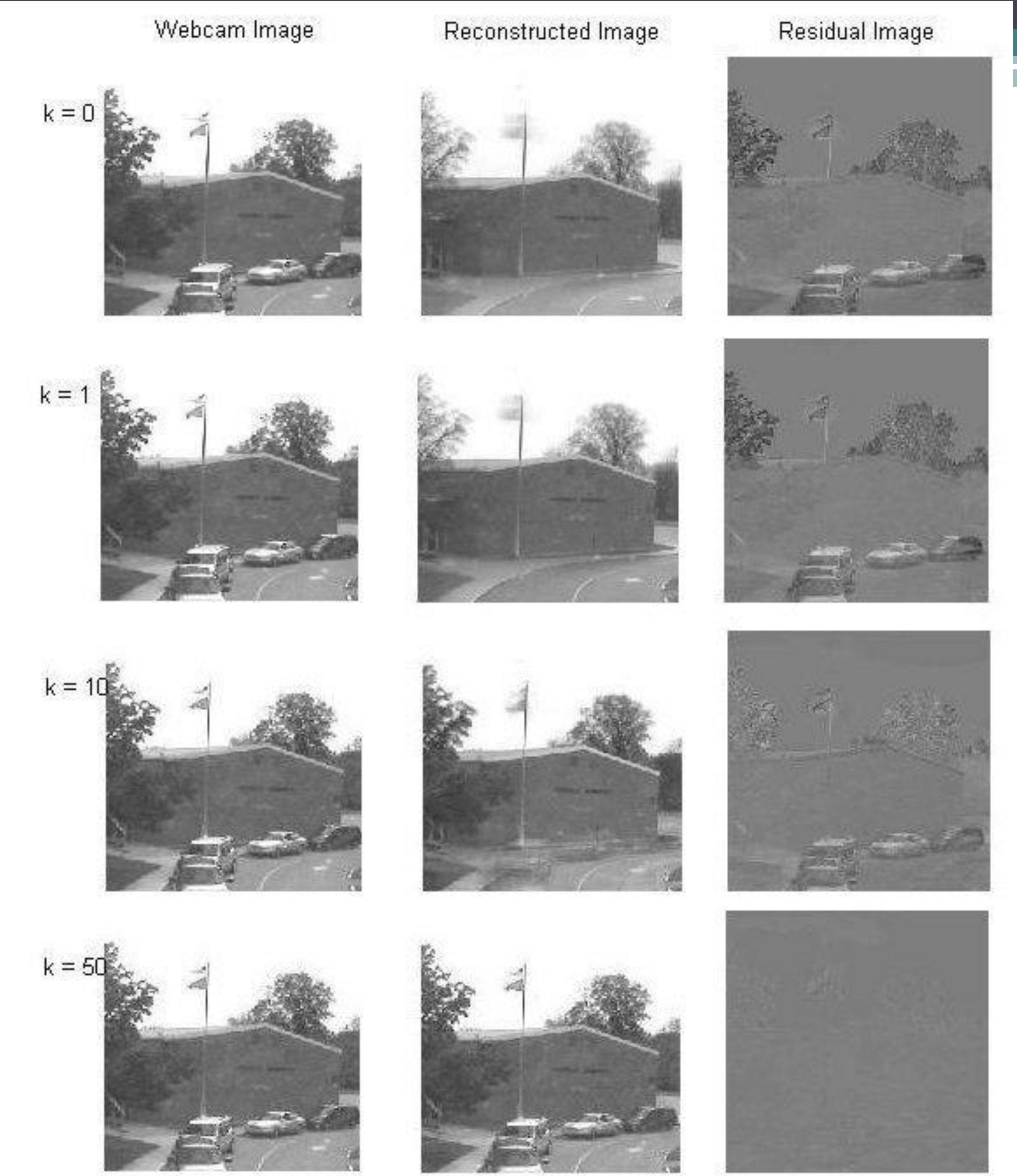
Given a new image W we can find its coefficients

$$v = U^T W$$

PCA – dependence on k

- Image reconstruction is sensitive to k parameter
- As k approaches the number of images, error decreases
  - 189 images, k = 0-50




Webcam Image
Reconstructed Image
Residual Image
k = 0
k = 1
k = 10
k = 50

Incremental PCA

- Too many images to fit into memory at once
- Can iteratively update our U, S, and V matrices for new images
  - Good estimate for U and S
  - V coefficient for early images not updated well for later changes to U and S
    - Can fix S and V on a second pass
    - $(S * V_x)_{fixed} = (I_x - I_{mean}) * U$

But what do we take PCA of?

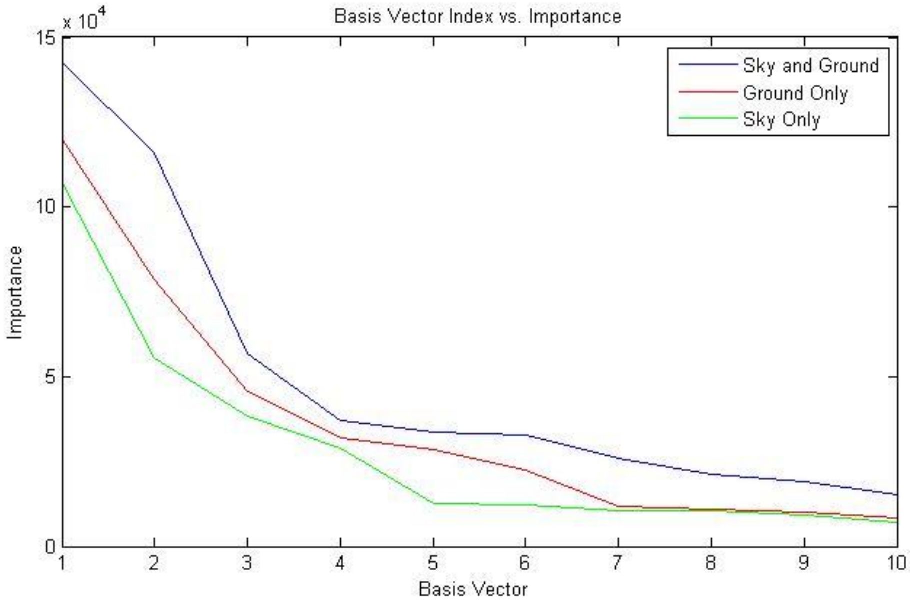
- Daytime images
- Sky Mask
- Gradient Magnitude Images

Daytime Images

- Could take PCA of the entire set of images from one camera
  - Not interested in how image varies from day to night
  - Camera noise in low light
- Choose only daytime images
  - Input images have least natural variation

Sky Mask

- Sky is another source of unnatural variation
  - Sun, clouds, hard to model
  - Not what we are interested in, so why waste effort?



Sky Mask - algorithm

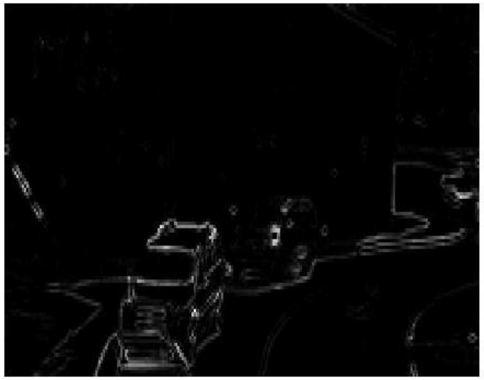
- Luckily, we can mask it away
  - 1st PCA Component of most natural scenes (all times of day) is the sky
  - Simple thresholding can accurately segment the scene

Gradient Magnitude Images

- Can take the gradient magnitude of images
  - Ignores changes in overall image intensity while retaining the scene structure

$$I_x(x,y) = I(x,y) - I(x-1,y) \qquad I_y(x,y) = I(x,y) - I(x,y-1)$$

$$G(x,y) = \sqrt{I_x(x,y)^2 + I_y(x,y)^2}$$



Not that useful

How do we display results?

- Image montage – show most interesting images
  - Highest value of some score

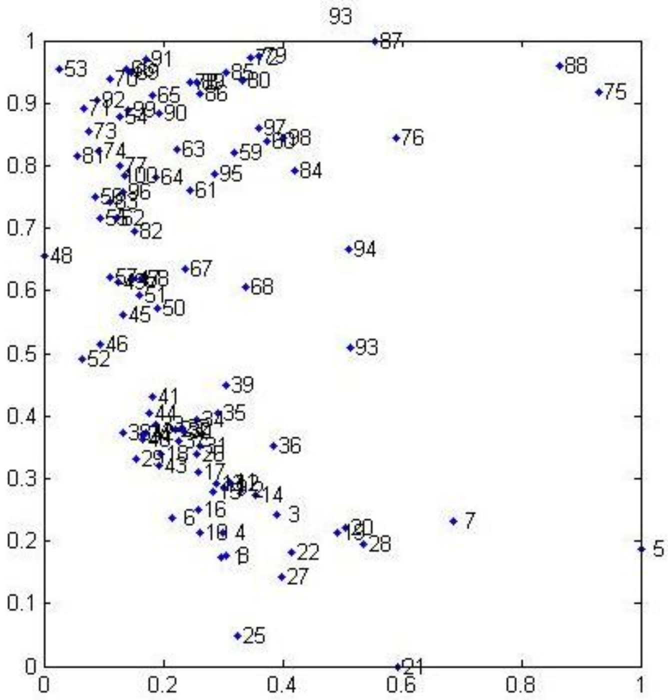
- Well-Separated Set Montage
- 2D GUI

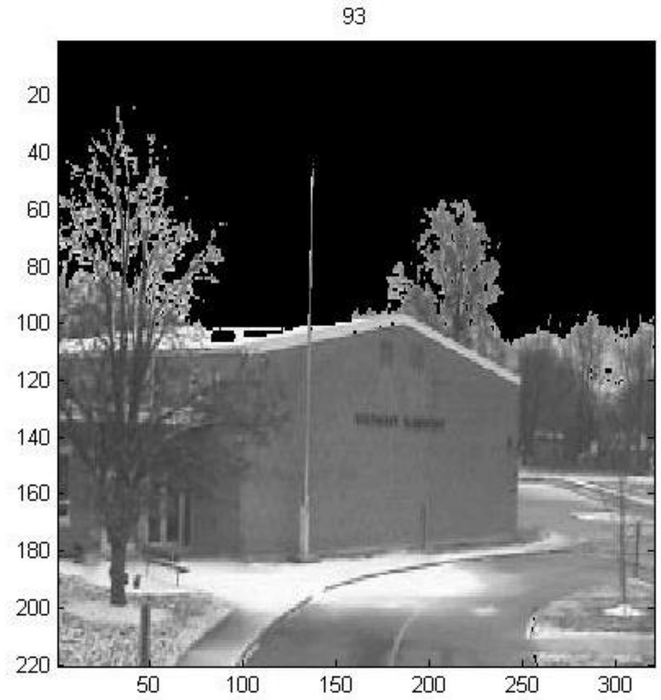
Well-Separated Set

- Image montages often have similar images
  - same parked cars, same crazy golf course scene
- Want to show the n most interesting and unique images
- Algorithm:
  - Pick N > n interseting images to set S
  - Seed with S = {most interesting image}
  - Iterate
    - Create by-pixel difference Matrix D
    - Choose image i that has highest distance to set S
    - S = {S i} $d = \min_i(D(x_0, x_i))$
- Used for all montage visualizations

2D GUI

- Explore two dimensions at once (example later)



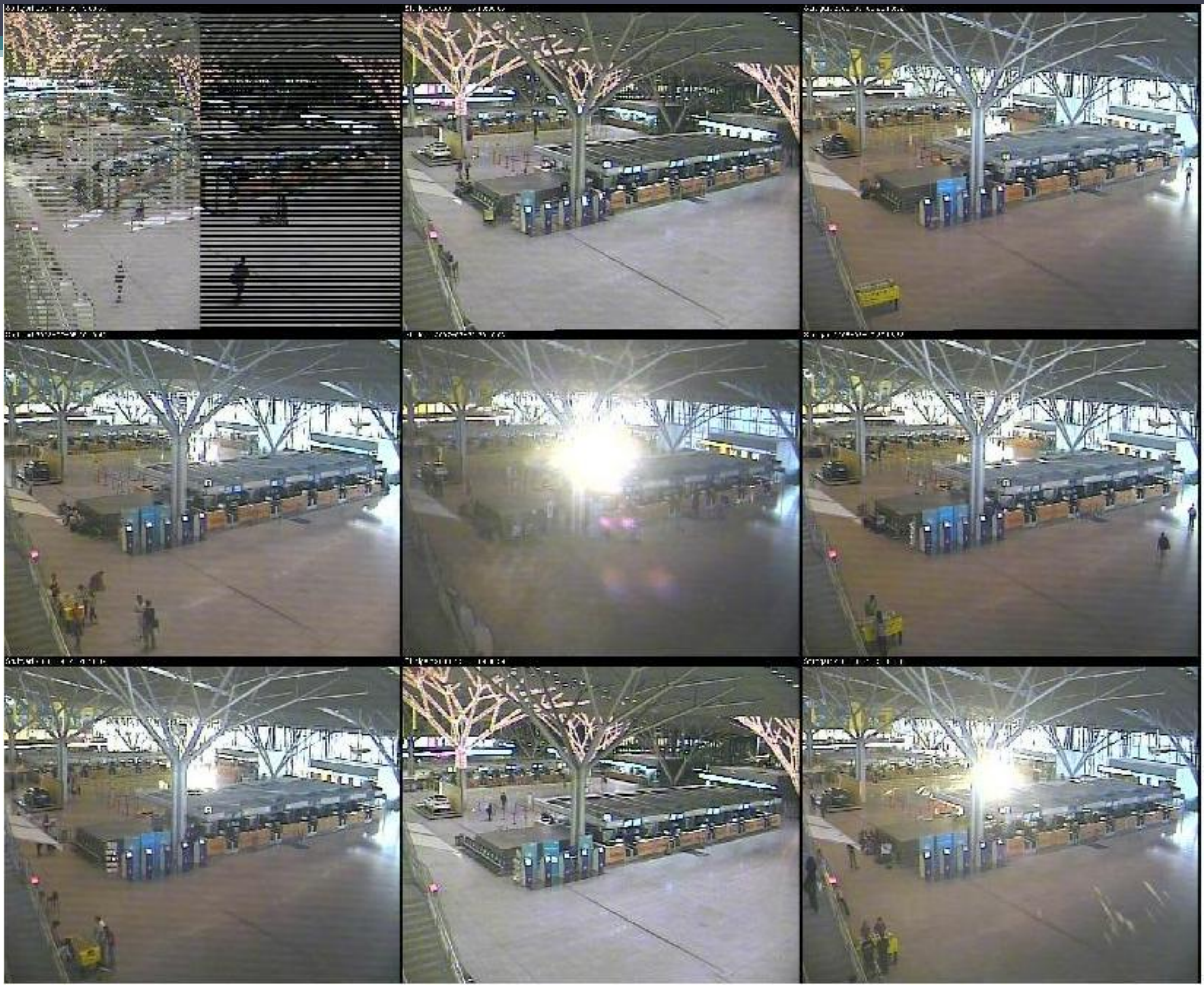


How do we evaluate images?

- PCA will capture the uninteresting variation, need to analyze the error to find interesting variation
  - Coefficient Vector Magnitude
  - Reconstruction Error
  - Variance Model
  - Distribution of Residuals

PCA Coefficient Vector Magnitude

- D (:,x) ~= U S V(x,:)
- S * V(x,:) is a vector of dimension k corresponding to the linear combination of U columns that best approximates D(:,x)
- D is mean subtracted so
- ||SV(x,:)|| gives a measure of how far from the mean image is each image



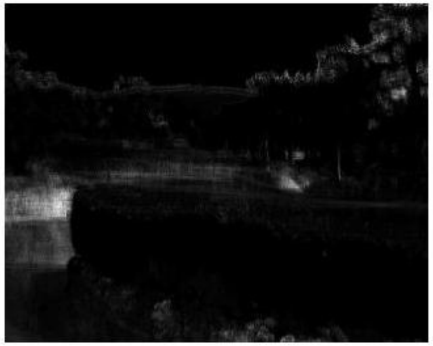
Residual Error

- PCA gives a reconstructed image
- $I_{residual} = (I - I_{mean}) - I_{recontsructed}$
- Sum of the squared residual values gives a good measure for "how much variation did we not capture"

Variance Model

- Can estimate the variance image of a scene by averaging sum squared residual at each pixel across all images

webcam 2



webcam 33

webcam 194

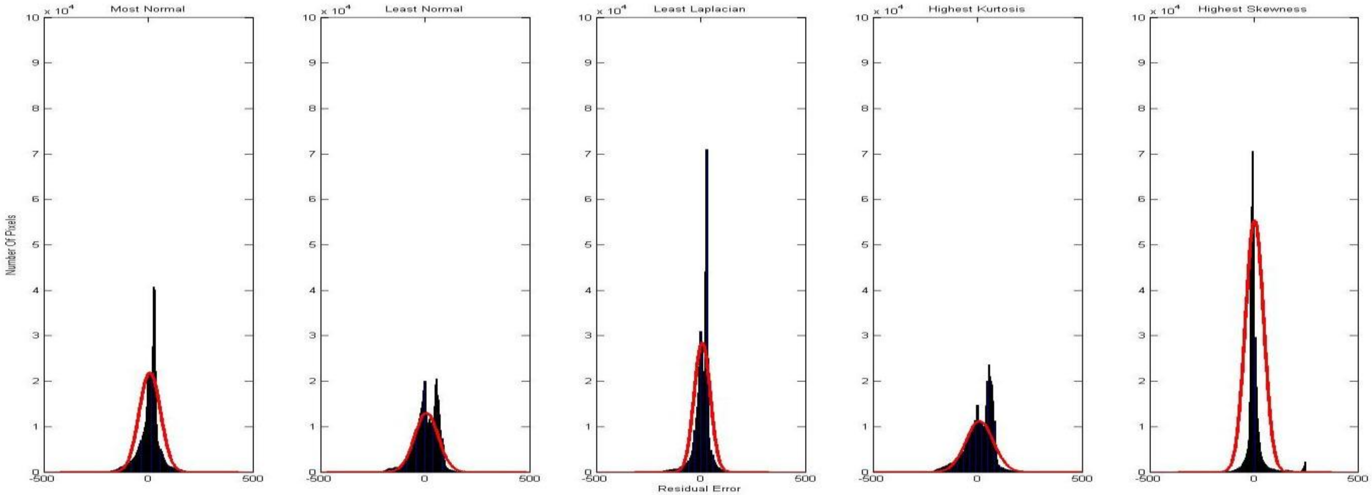
webcam 1042

Z-score Image

- To find which variation is most unusual, can calculate the z-score at each pixel
- Z-score(x,y) = Residual(x,y) / Variance(x,y)
- Now we have a more context-based system for evaluating how interesting variation is
- Most marketable contribution
  - security

Statistical Distribution of Residual Images

- Can treat R(x,y) as a sample from an underlying PDF
  - Expect noise to be Gaussian, objects to be non-Gaussian

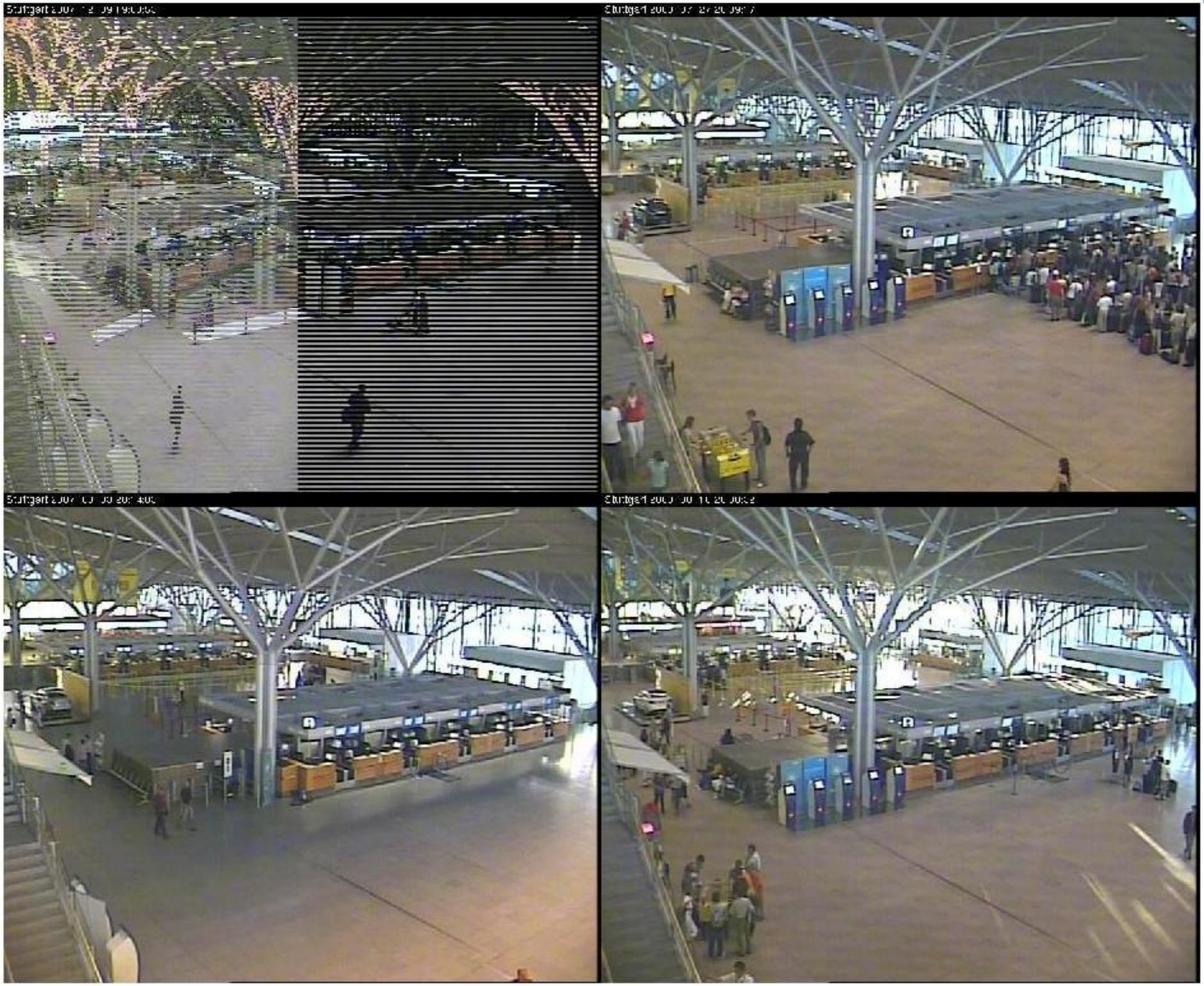



Webcam Image
Reconstructed Image
Residual Image
Most Normal
Least Normal
Least Laplacian
Highest Kurtosis
Highest Skewness

Normal Distribution

- If we expect R(x,y) to sample from a normal distribution, we can easy estimate that and then evaluate each value using

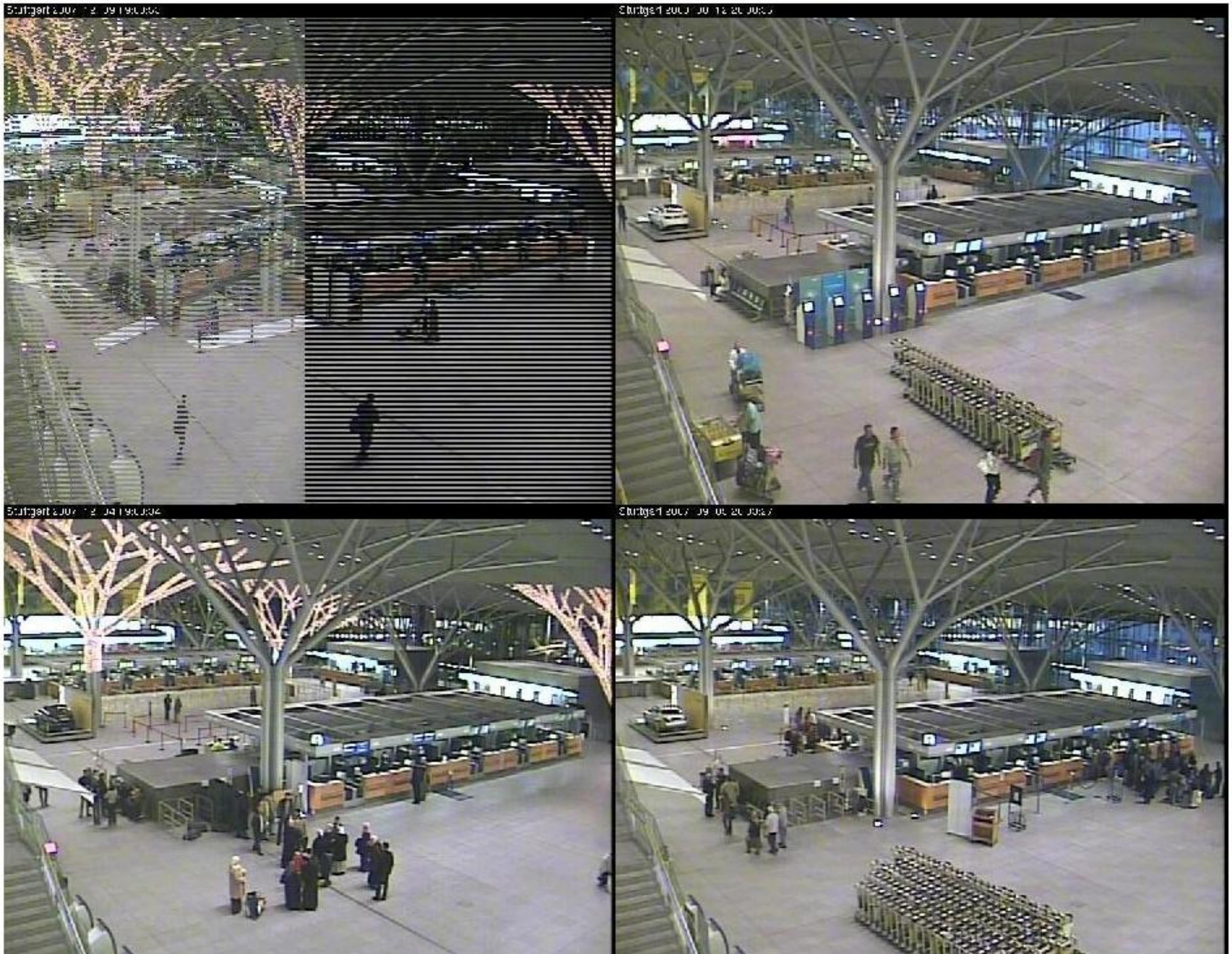
$$f(x|\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{(x-\mu)^2}{2\sigma^2}}$$



Laplacian Distribution

- Many histograms look more like Laplacian Distributions, so we can do the same algorithm but for the Laplacian distribution

$$f(x|\mu,\beta) = \frac{1}{2\beta} e^{\frac{-|x-\mu|}{\beta}}$$



Bonus – Kurtosis and Skewness

- Statistics for "non-Guassiannesss"
- Skewness measures asymmetry
  - No good results

$$\gamma_1 = \frac{\mu_3}{\sigma^3}$$

$$\mu_k = \int_{-\infty}^{\infty} (x-\mu)^k f(x)dx$$

- Kurtosis measures unlikely deviation

$$\gamma_2 = \frac{\mu_4}{\sigma^4}$$

  - Tends to mirror the residual sum squared error scores
- The effect of small objects is dominated by the noise over the rest of the image

Conclusion

- AMOS Dataset too big to keep track of interesting variation in each scene
- Developed automatic visualization tools to help
  - Use PCA to learn less interesting variation
    - Daytime images, sky mask -> useful
    - Gradient images -> not useful
  - Interesting images from evaluating PCA error
    - Reconstruction error and Variance Models -> useful
    - Statistical models -> mixed results

Future Work

- Interface with AMOS site
- Object Extraction
- User customizability

Questions?