WASHINGTON UNIVERSITY IN ST. LOUIS

School of Engineering and Applied Science

Department of Computer Science and Engineering

Masters Project Examination Committee:
Tao Ju
Robert Pless
Bill Smart

VISUALIZATION TOOLS FOR WEBCAM SCENES

by

David Ross

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ABSTRACT OF THE THESIS

Visualization Tools for Webcam Scenes

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David Ross

Master of Science in Computer Science

Washington University in St. Louis, 2009

Research Advisor: Professor Robert Pless

Webcams are cheap and abundant cameras that are easily deployed, maintained, and archived. The AMOS dataset, which has captured over 1,000 webcams for three years, provides a multitude of diverse scenes, many of which contain interesting variation. The great size of this data makes keeping track of each scene's content impractical. This project explores techniques for automatically visualizing and characterizing these variations over static scenes. The mathematical tool Principal Component Analysis (PCA) is useful for learning common image variations, and can be leveraged to show less common and more interesting variation. With these techniques, it is more reasonable to maintain and use such large sets of scenes.

Acknowledgments

First, I want to thank my advisor, Professor Robert Pless, for four years of teaching, guidance, and support. Without his direction, this project would not have been completed and my four years here would not have been as successful.

I want to thank the graduate students in the Media and Machines Lab, especially Nathan Jacobs and Michael Dixon, for helping me along the way. Very rarely did a question go unanswered with them around. Also, thanks to Tao Ju and Bill Smart for agreeing to be on my presentation committee. I hope you learned something from me for once.

Finally, my utmost gratitude to Washington University, specifically the Computer Science Department. My four years here have prepared me so well for what's ahead.

David Ross

Washington University in Saint Louis
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Contents

List of Figures

Chapter 1

Introduction

Static cameras that observe the same scene for a long period of time can give us valuable information. Given such a sensor, how can we help users to understand the variation in the scene? This project explores automatic visualization tools to quickly show interesting variation. As opposed to natural variation, such as day vs. night or sunny days vs. cloudy day, unnatural variation is less predictable and more interesting. People, cars, and other objects in the scene give more high level semantic information, and to understand a scene is to understand this variation.

1.1 AMOS Dataset

The Archive of Many Outdoor Scenes (AMOS), which is used in this research, consists of over 3,000 webcams, 1,020 of which we have been actively capturing every half hour for the last three years. In this time, we have amassed 35,376,886 images, totally roughly 868 gigabytes of data. Most of the cameras are from the USA, many of which are plotted in Figure 1.1. Clearly, it is impractical to maintain and understand such a large dataset without help. We need to automatically present users with visualizations of this variation.

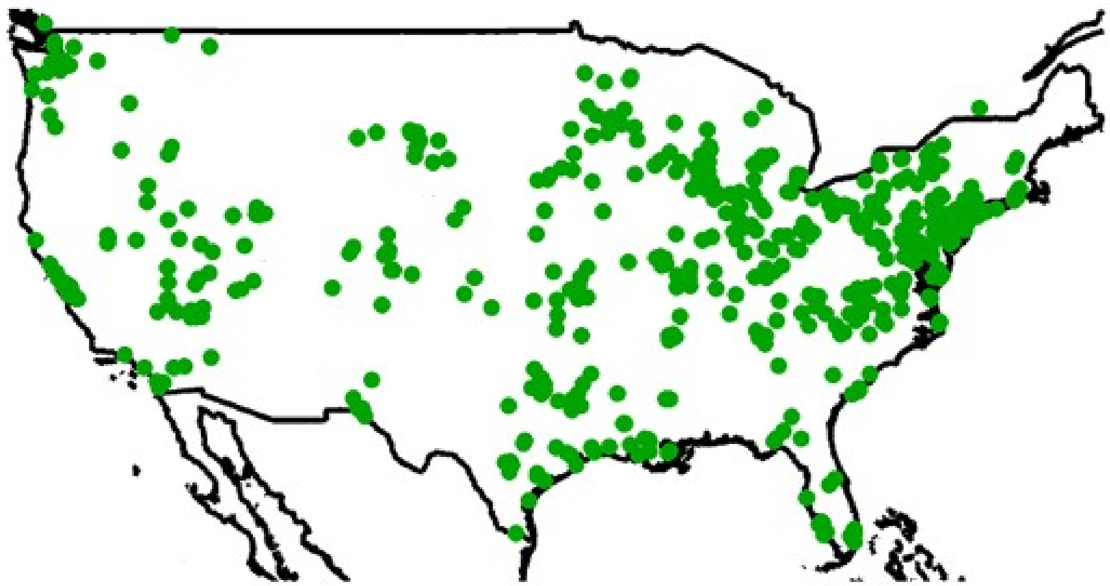


Figure 1.1: Many of the AMOS webcams are located in the United States, as shown in this map.

1.2 Outline of the Paper

We have many images from which we need to find interesting variants. A lot of the variance is natural and controlled - day to night transitions, seasonal changes, and weather are all predictable and learnable. First, we will present the mathematical tool Principal Component Analysis (PCA) as an algorithm to learn this natural variation. Next, we will discuss different inputs to the PCA algorithm to best capture our goal. Finally, we will show several visualization tools and evaluation criteria, and discuss their success in capturing interesting variation.

Chapter 2

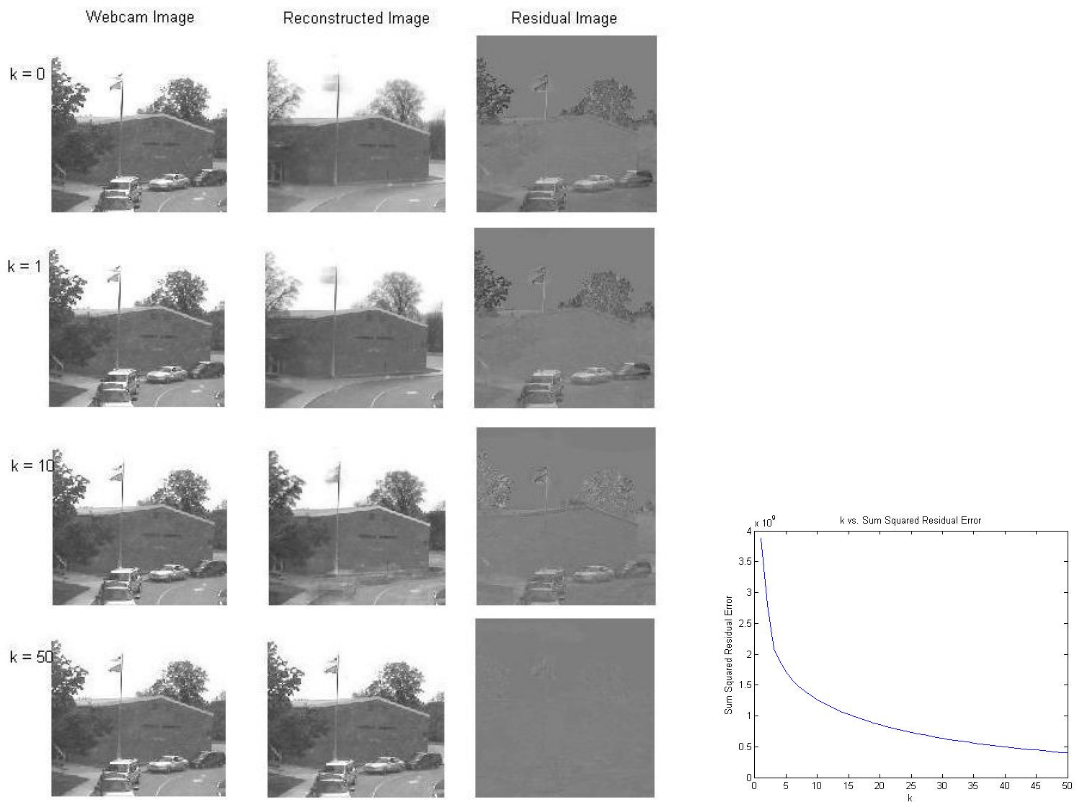
Principal Component Analysis

Principal Component Analysis (PCA) is a powerful tool for

2.1 The PCA method

Given a matrix M, we can use a linear algebra technique called singular value decomposition (SVD) to solve for matrices U, S, V such that $M = U * S * V^T$. For a given k number of components

In situations where dataset sizes conflict with memory constraints, we can use a modified algorithm called Incremental PCA, which allows allows us to... Incremental PCA [reference to Matthew Brand]



(a) (b)

Figure 2.1: Figure 2.1(a) shows the first PCA component of a webcam scene. By adding or subtracting this component, we control how dark or how light the sky is. Figure 2.1(b) shows that a simple thresholding of this image effectively segments the sky from the rest of the image.

Chapter 3

Visualization Tools

The main contribution of this project is automatic methods for visualizing how a webcam scene varies, and for understanding the most important variations. In most natural scenes, we notice changes in lighting, weather, and camera conditions which are interesting, but fail to describe the typical behavior of a scene. The goal of these tools is to learn these variations and to point out changes independent of them. PCA is a commonly used tool, and captures a linear model of consistent image variations. By analyzing the results of certain PCA setups, we can obtain important and interesting information.

3.1 PCA Input

The most obvious way to learn about scenes is to take the PCA decomposition of the entire webcam scene. Unfortunately, our data-set is too large for this to be feasible, so we must limit our inputs. Instead of taking a random subset of the images, if we can intelligently limit the images we give, we can get better inputs.

3.1.1 Temporal Narrowing

The AMOS data-set consists mostly of outdoor scenes. These outdoor scenes vary significantly over the course of a day, going from night to day and back. The change in lighting dominates all other changes across the scene, and causes many images to be completely dark. Instead of wasting

3.1.2 Sky Mask

In many outdoor scenes, even when narrowed to a particular time of day, the most difficult image variation to characterize is the sky. PCA has a difficult time learning changes in sunlight, clouds, and other characteristics of the sky, even among a set of images of one time of day. The variance in the sky dominates the PCA reconstruction, causing it to ignore information that is more interesting in this context.

Fortunately, it is fairly easy to learn which regions of an image are most affected by this. In practice, a side effect of the rising and setting of the sun is that the first principal component of most scenes is the sky, as shown in 3.1(a). By thresholding the values of this vector, we can effectively segment the sky from the rest of the image, as shown in 3.1(b).

This simple mask allows PCA to focus on more interesting changes in the image, and most of the results that follow use a simple mask to ignore the sky regions of the images. By setting all pixels in the sky to 0, we can effectively remove this difficulty.

(a) (b)

Figure 3.1: Figure 3.1(a) shows the first PCA component of a webcam scene. By adding or subtracting this component, we control how dark or how light the sky is. Figure 3.1(b) shows that a simple thresholding of this image effectively segments the sky from the rest of the image.

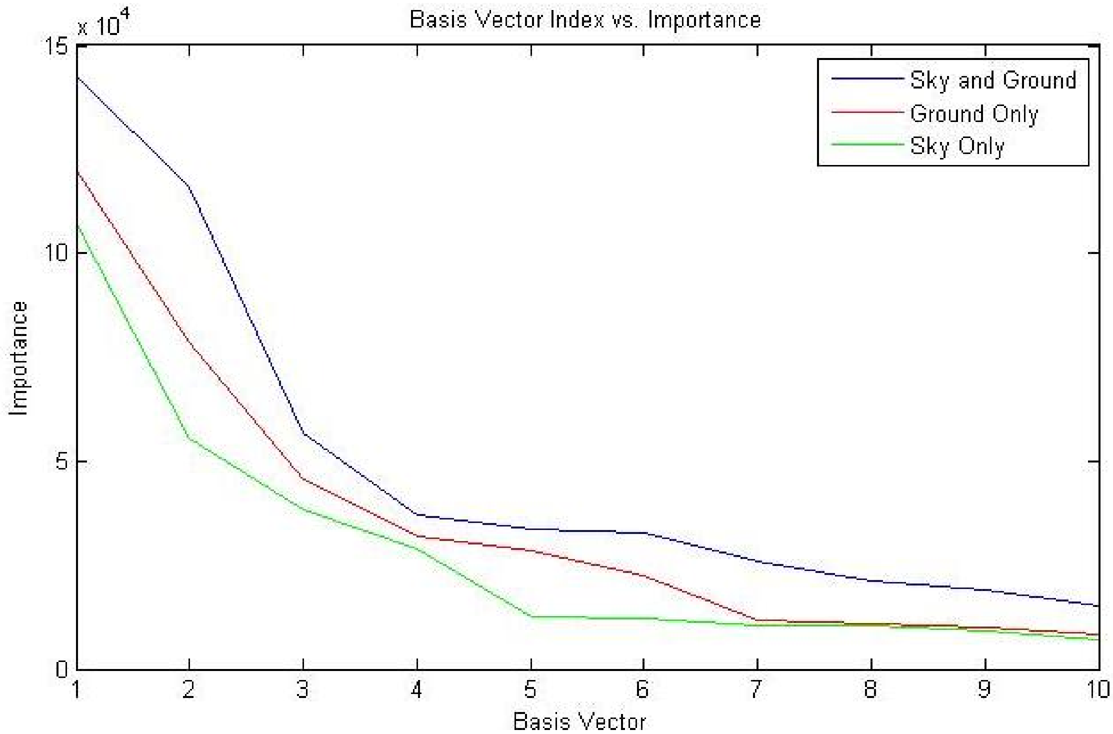


Figure 3.2: Figure 3.1.3 SOME STUFF.

3.1.3 Gradient Image

Webcam images are very high-dimensional - a typical 320 x 240 gray scale image has 76,800 pixels, each of which is a value from 0 to 255. One way to simplify this space without changing the size of the image is to look at the gradient magnitude images of a scene.

The x and y derivatives of an image are approximated as $I_x(x, y) = I(x, y) - I(x-1, y)$ and $I_y(x, y) = I(x, y) - I(x, y-1)$ where the function $I(x, y)$ describes the intensities of an image's pixels. Once we have calculated the derivative images, we define the gradient magnitude of an image to be $G(x, y) = \sqrt{I_x(x, y)^2 + I_y(x, y)^2}$.

The gradient magnitude image highlights edges in an image, as they are image locations where pixel values differ greatly from their neighbors. By performing PCA on the gradient magnitude images, we tend to ignore the potentially noisy surfaces of objects, and instead focus on the locations of the objects. Figure 3.3(a) and Figure3.3(b) show the edges of an interesting webcam image highlighted in a gradient magnitude image.

(a) (b)

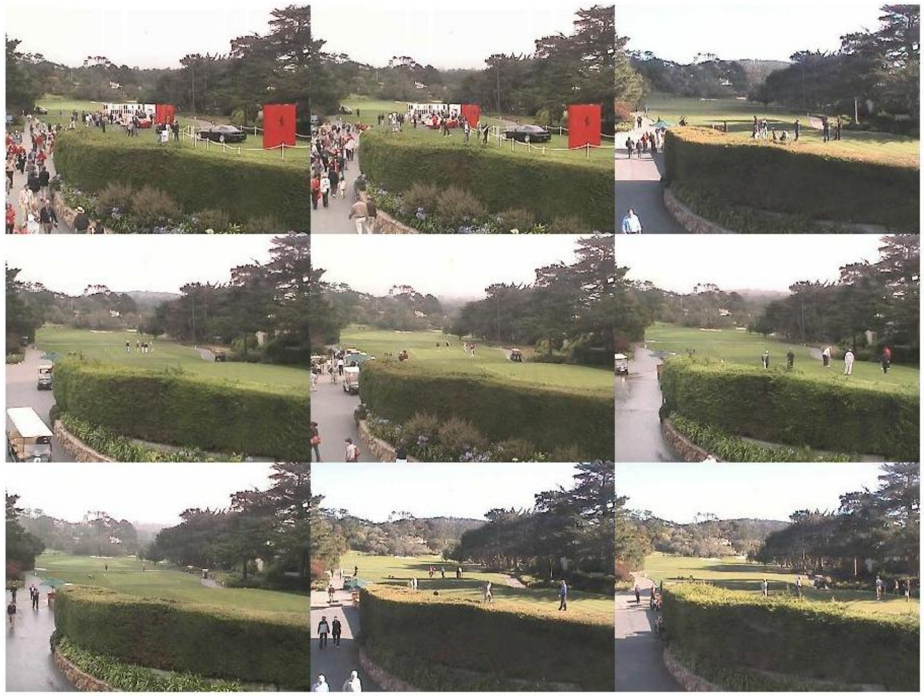
Figure 3.3: Figure 3.3(a) shows a grayscale webcam image. Figure 3.3(b) shows the gradient magnitude image of that frame. Notice the noise is mostly removed and the edges are highlighted.

3.2 Visualizations

In this section, we present several tools to visualize the webcam scene based on criteria we will discuss in the next section.

3.2.1 Image Montage

The simplest way to visualize a webcam scene is to view a montage of several images from that scene. We can easily sort the images along some dimension, and then show the n images with the highest values in that dimension. Figure 3.4(a) Is an example montage of several interesting images from a webcam scene.



(a)

(b)

Figure 3.4: Figure 3.4(a) shows a montage of interesting images from a golf course webcam. Figure 3.4(b) shows a montage of interesting images of the same scene, but attempts to omit similar images.

3.2.2 Well-Separated Set Montage

In several of these montages, we notice that many of the most unusual images are similar to each other. This presents the problem of finding unusual images that are different from the images we have already chosen.

A simple but effective algorithm for this problem uses the L2 norm in image space. If we consider an image as a vector of pixel intensities, such as $v = \{v_1, ..., v_m\}$, the L2 norm of two images v and u is

$$L2\_norm(v, u) = \sqrt{\sum_{i=1}^{m} (v_i - u_i)^2}$$

Given a large set of unusual images $\{x_1, ..., x_n\}$, we compute a distance matrix D where $D_{i,j} = L2\_norm(x_i, x_j)$. Now we iteratively find unusual images by choosing the image that has the largest distance from all of the images we have chosen so far. Specifically, for each remaining image calculate its distance to our set of exemplars, and choose the image whose distance is the smallest. We define the distance of an image x_0 to a set of exemplars $\{x_1, ..., x_n\}$ as

$$d = \min_i (D(x_0, x_i))$$

Then we can choose the image that has the highest value of this distance.

In this way, on each iteration, we pick the image that is least likely to be similar to an image we have already selected. We have found that a good way to seed this process is choosing the image with the highest unusualness score as our first exemplar. 3.4(b) shows how similar images are omitted by viewing results in this way.

3.2.3 Two-dimensional Explorer

Using a simple GUI, we can explore a webcam scene in two dimensions. The GUI, shown in 3.2.3, displays a a plot of image scores for two different criteria, and displays the image corresponding to a mouseovered datapoint. Using this GUI, it is possible to see which criterias are related and which are not, as well as makes it easier to learn how the criteria effects the scene. [I don't really know what to say in this section].

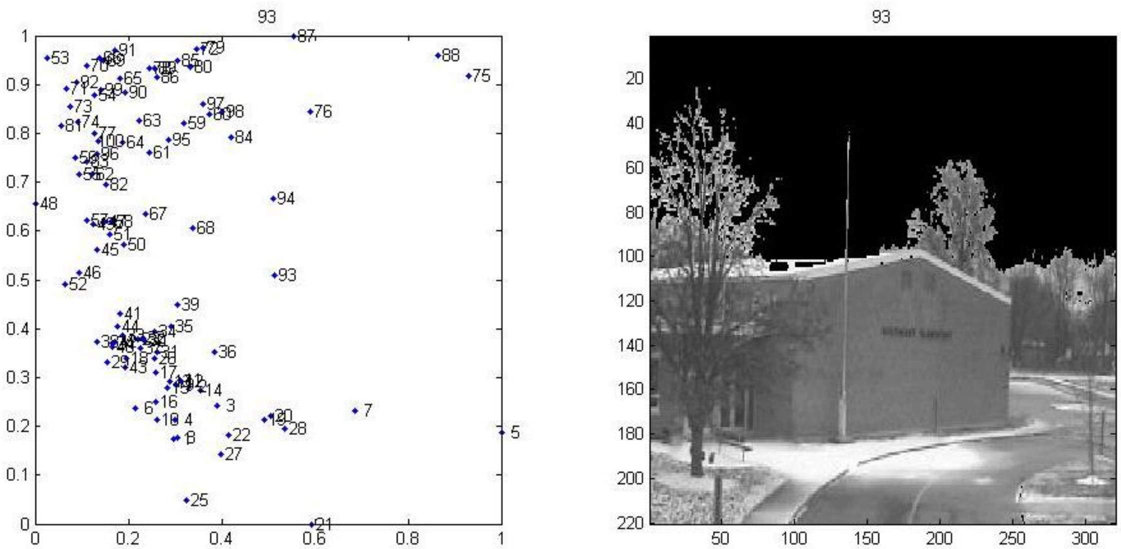


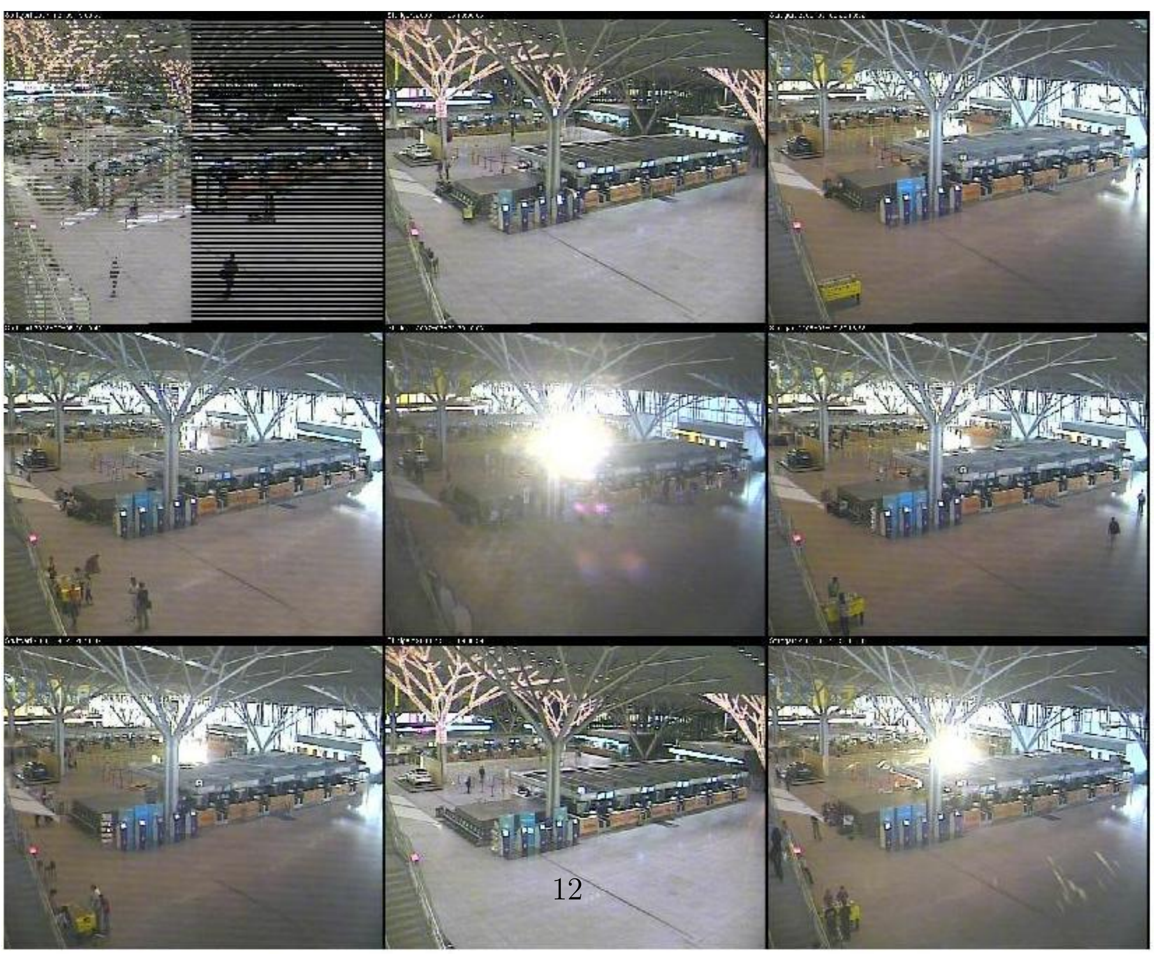
Figure 3.5: Figure 3.2.3 shows a webcam scene displayed using the 2D GUI.

3.3 Characteristics of Image Reconstructions and Residuals

Once webcam scenes are projected onto a PCA basis, there are many different ways to analyze the results. In this section, we will present several different criteria for evaluating this appearance model of a scene, the meaning behind each criteria, and results.

[I don't love the term criteria, but I think it encapsulates the idea of this section...]

(a)



(b)

Figure 3.6: Figure 3.6(a) shows the mean image of an airport webcam scene. Figure

3.3.1 PCA Basis Coefficient Vector Magnitude

For each image in a scene, PCA gives a vector of coefficients that correspond to the best linear combination of basis images to reconstruct that image. From this vector, we can assign each image a score equal to the magnitude of this vector. For a vector $v = (v_0, v_1, ..., v_n)$, the vector magnitude is

$$||v|| = \sqrt{\sum_{i=0}^{n} v_i^2}$$

This effectively gives us a measure for how far from the mean image in our basis space each image is. Figure 3.6(a) shows the mean image of a webcam scene and Figure 3.6(b) shows several images from that webcam scene that are especially far from the mean.

3.3.2 Residual Error

Given an image and a PCA basis, we can project the image onto the basis and see how well we can reconstruct the image.

[Figure of subplot with image, reconstruction, and residual]

[figure of montage sorted be residualSSD, showing some noisy images and some with real foreground objects]

3.3.3 Variance Model

We can estimate the variance image of a webcam scene as the average of the square of each residual image. This image gives a good summary as to where most activity occurs in a webcam scene. Several examples are shown in Figure 3.3.3.

Figure 3.7: Figure 3.3.2 show a webcam scene image, the reconstruction of that image from a PCA basis, and the residual image.

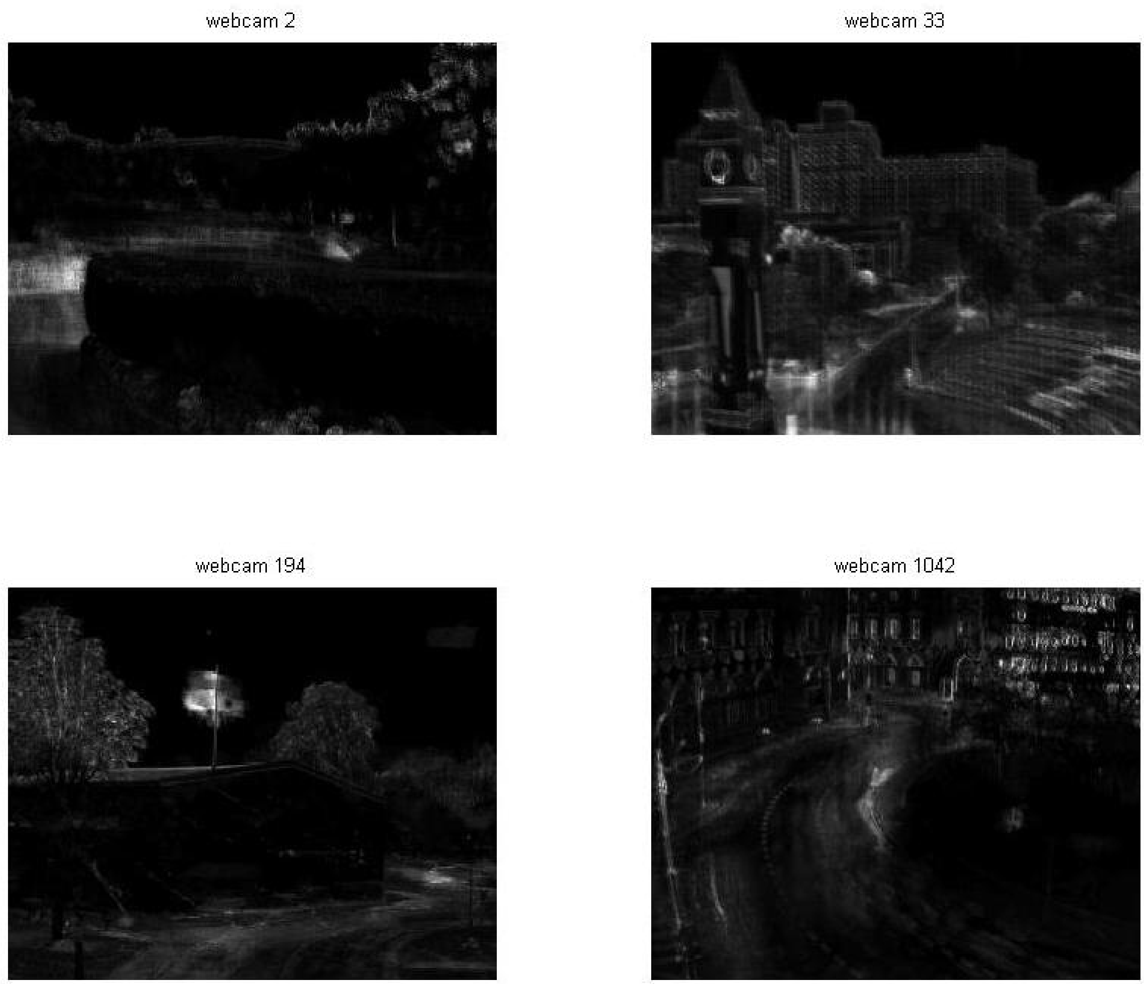


Figure 3.8: Figure 3.3.3 shows estimated variance images from several webcam scenes.

Figure 3.9: Figure 3.3.3 shows several images from the same scene as 3.3.2, but with more atypical objects.

One we have this variance image, we can attempt to isolate independent pixels in a z-score image. We define our z-score image as

$$Z(x, y) = \frac{R(x, y)}{V(x, y)}$$

where $R(x, y)$ is the residual value of the pixel and $V(x, y)$ is the variance value of the pixel. By summing the per pixel z-score for an particular image, we can infer how atypical the residual of that image is. Figure 3.3.3 shows several images that contain atypical objects. Such a tool can be used to quickly highlight unusual behavior in a scene.

3.3.4 Statistical Distribution of Residual Images

We can also try to learn about an image reconstruction by treating its residual image as samples from an underlying probability density function. If image deviations are due mostly to noise, we predict that these deviations will be normally distributed, but as shown in 3.10(a), this is not always the case. We have found that these distributions vary in the same way as webcam scenes, and analyzing them in the right way tells an interesting story.

1. **Gaussian Likelihood**

   The most obvious way to do this is to treat each residual image pixel as a sample from a normal distribution. We can easily estimate the mean and variance of this PDF and then, for each residual value, use the normal distribution equation

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

2. **Laplacian Likelihood**

   Many of the residual images have a majority of pixels that are very close zero. This causes the histogram to look very similar to a laplacian distribution.

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

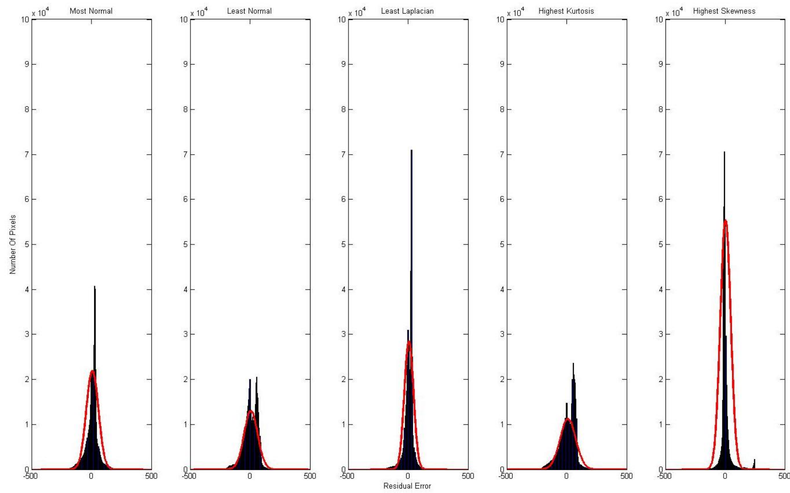
3. **Kurtosis**

   The kurtosis of a real-valued random variable is a measure of its peakedness. Larger values of kurtosis means more variance is due to less frequent extreme deviations rather than frequent less extreme deviations. It is defined as

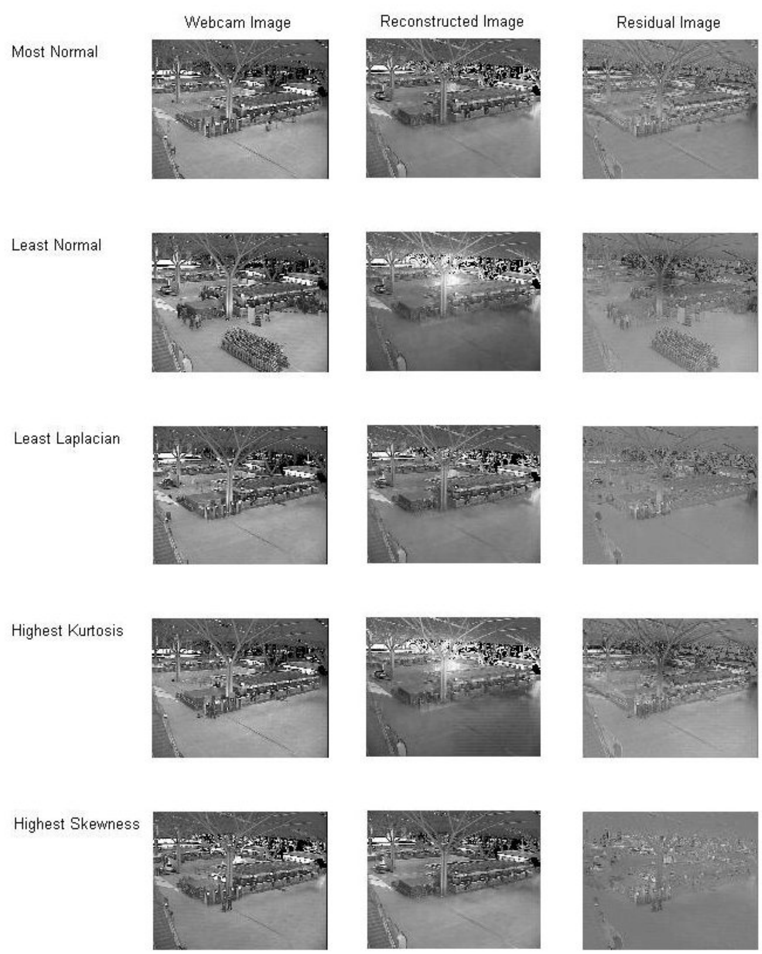
$$\gamma_2 = \frac{\mu_4}{\sigma^4}$$

   where μ_4 is the fourth moment about the mean and σ^4 is the estimated standard deviation to the fourth power. For a function $f(x)$, the k^{th} moment about the mean is defined as

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

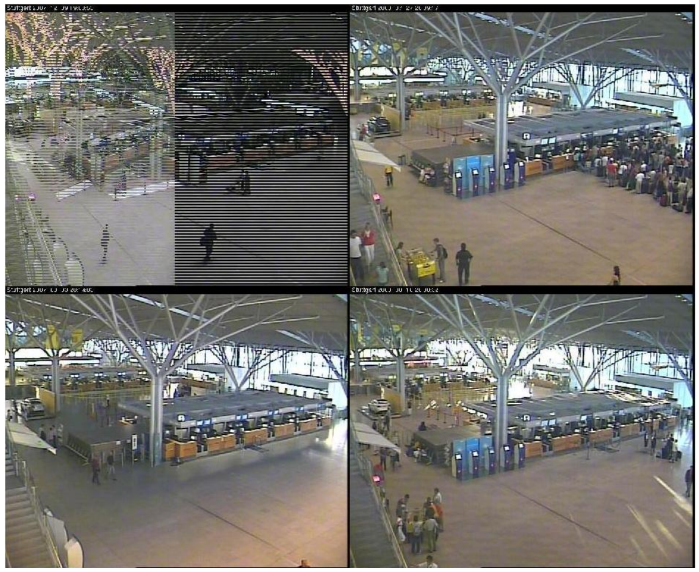


(a)

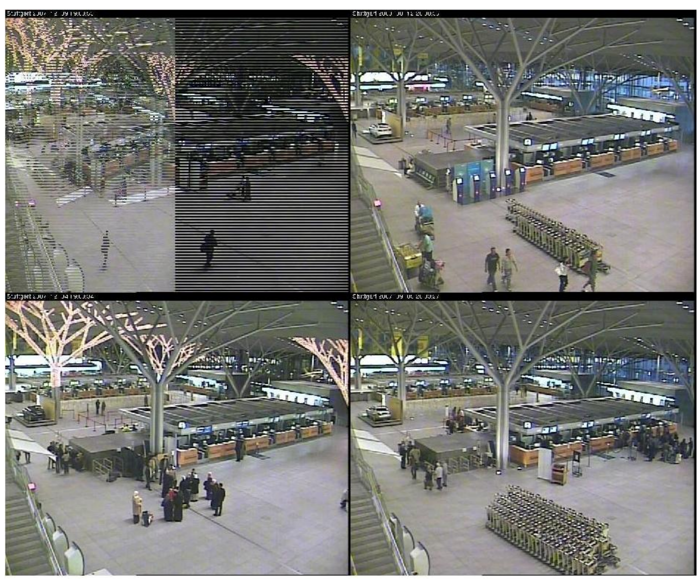


(b)

Figure 3.10: Figure 3.10(a) shows several residual image histograms and the the best approximation of a normal distribution fitting the data. Figure 3.10(b) does not.



(a)



(b)

Figure 3.11: Figure 3.11(a) shows a montage of interesting images from an airport scene that were labeled very non-guassian. Figure 3.11(b) shows a montage of interesting images from an airport scene that were labeled very non-laplacian.

We can use this measure

4. **Skewness**

   The skewness of a random variable is a measure of asymmetry. Higher skewness values mean deviations on one side of the mean do not have corresponding deviations on the other side. It is defined as

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

   where μ_3 is the third moment about the mean and σ^3 is the cube of the standard deviation.

   This measure can be used

Chapter 4

Conclusion

The original goal of this project was to find clean mathematical tools to catalog the objects found in a particular webcam scene. Cameras vary in sufficiently difficult ways to make this hard, so we investigated general tools for visualizing these variations.

The tools presented in this project are useful in

4.1 Future Work

The AMOS website

Although the original goal of the project was not met, these visualization tools give information that would be helpful for the original problem.

[Customizable Visualizations]

Another area that this work could be expanded in is user interaction. A tool with which a user could specify what type of information he or she is interested in would be very powerful.

References

[1] Matthew Brand. Incremental singular value decomposition of uncertain data with missing values. In *In ECCV*, pages 707–720, 2002.

Note: Use month and year in which your degree will be conferred.

Visualization Tools for Webcam Scenes, Ross, M.S. 2009