Learning to Find Signals in Image Sequences

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Abstract

Webcams are cheap sensors that capture a potentially large amount of information about a scene. Here we automate the process of converting a series of images from a webcam into other signals of interest; with a focus on weather and climate. We test our algorithms on the AMOS database, which archives images from nearly 1000 webcams over the last three years.

1. Introduction

There are a vast number of webcams that continually capture images and make them available on the internet. Current properties of the local environment often directly affect these images; whether it is cloudy or sunny is visible by the presence of shadows; wind speed and direction is visible in smoke, flags, or close up views of trees; particulate density is reflected in haziness and the color spectrum during sunset. In this paper we explore several techniques to automatically extract such time varying environmental properties from a long time sequence of interest. This allows the large set of webcams *already* installed across the earth to act as sensors an improve our understanding of local weather patterns and variations.

The challenge is images may vary more due to other causes that due to the variations related to the signal of interest. We consider wind-speed as a driving example; its effect is limited to locations in the scene that are affected by wind (flags and vegetation), but much larger changes in the overall image appearance may arise due to clouds casting shadows on the scene, and the motion of the sun throughout the day. Thus we explore efficient mechanisms to learn features that are invariant to other scene variations, as well as tools to condition our feature set on the known causes of image variation.

Finally, in order to make these visual sensors effective over long time periods, we need to continually adapt; both to changing appearances of the scene (ie, tree that lose their leaves, changing both their visual appearance, and the magnitude of their motion as a function of wind speed), and changing priors on the magnitude of wind-speed (which may be, for example, smaller in the winter than in the summer.

This is a figure

Figure 1. Intro figure

2. Algorithms

Dump of potential things to try.

1. Try CCA between signal of interest and the image, or features extracted from the image, or (to make it more likely to work, on selected parts of the image).

2. Try CCA between signal of interest and the "residual" of what is left after projecting image onto PCA basis.

3. Is this the type of problem where one could run GPLVM (Gaussian Process Latent Variable Model), where the latent variable is the current windspeed, and we define a set of features who expression is varied depending on the windspeed?

2.1. Rough Paper Writeup

Local environment properties often directly affect the images we collect from the webcams; whether it is cloudy or sunny is visible by the presence of shadows; wind speed and direction is visible in smoke, flags, or close up views of trees; particulate density is reflected in haziness and the color spectrum during sunset. We explore techniques to automatically extract such time varying environmental properties from a long time sequence of interest. This allows the large set of webcams *already* installed across the earth to act as sensors an improve our understanding of local weather patterns and variations.

We will independently consider two weather signals for our driving examples: wind-speed and vapor pressure. These two signals represent two very different casses. The effect of wind-speed is limited to locations in the scene that are affected by wind (flags and vegetation) while the effect of vapor pressure on the scene may result in larger, more universal changes to the image. The challenge with both is that images may vary more due to other causes that due to the variations related to the signal of interest. Thus we explore efficient mechanisms to learn features that are invariant to other scene variations, as well as tools to condition our feature set on the known causes of image variation.

We begin by running Principal Component Analysis (PCA) on the set of images to extract the 10 most significant components of the n images. This allowed us to express each image as a vector of 10 numbers rather than a 320 x 240 pixel image. If M is an array where each row is one image, then PCA decomposes M into three matrices U, S, and V such that:

$$USV \approx pca(M) \tag{1}$$

Where U stores the basis vectors, S is a singular matrix, and V is a 10xn matrix containing the value of each basis for each image.

Next, we will use Canonical Coefficient Analysis (CCA) to correlate a given weather signal over time with the principal components of the images from the same time range. CCA is a multivariate regression method which helps to determine the relationship between groups of data. In our case, we are looking to find the relationship between the principal components for each image and the weather data from the same time. [**explain CCA more?**] The weather data is obtained from the Historical Weather Date Archives (HDWA), which is maintained by the National Oceanic and Atmospheric Administration (NOAA) [**CITE**]. Given this data, CCA looks to find two matrices A and B such that:

$$AX \approx BY \tag{2}$$

Where X and Y are the image PCA compoeenents and the weather signal, respectively. In other words, A and B represent a way for us to derive weather data from a an image and vice versa. So, given a new image i and its principal components V_i on the existing basis vectors U, we can predict the value of the weather signal y as follows:

$$y = AV_iB^{-1} \tag{3}$$

We now consider two examples to verify our methods. The first example will use a camera containing a flag to predict wind speed. Wind speed is made up of two components: magnitude and direction. Since images are two-dimensional, we can only make successful predictions of the wind speed when it is blowing in a direction orthogonal to the camera. After running CCA, we can project the A matrix back onto the image basis vectors U in order to get a visual representation of the CCA bases. This clearly shows us that the analysis cued in on the flag as the key indicator of wind speed. Sorting the images by their CCA values one can clearly see that the flag moves from left to right, which further verifies the CCA. These results can be used to predict the magnitude of the wind speed vector in m/s with a reasonable degree of accuracy. However, the direction of this wind vector is still unknown. It can be determined by finding the vector which minimizes the residual between the predicted and actual wind directions. [**more on direction?**]

The second example will consider a different webcam and will attempt to find vapor pressure. What makes predicting this signal different than wind speed is that we do not have a local feature such as a flag to easily correllate with our weather signal. In this case we are more concerned with some overall change in the image to correllate with the weather signal. [**explain why gradient magnitude image is used**]. The results of CCA indicate that vapor pressure is very strongly correllated with cloud cover, which makes sense and further verifies our method. We can now use these basis vectors to predict the vapor pressure in millibars from a new image.