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Addressing Problems with Scene-Based Wave Front Sensing

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Introduction

Scene-Based Wave Front Sensing uses the correlation between successive subimages to determine phase aberrations which blur digital images.[1] Adaptive Optics technology uses deformable mirrors to correct for these phase aberrations and make the images clearer.

The correlation between temporal subimages gives tip-tilt information. If these images do not have identical image content, tip-tilt estimations may be incorrect. Motion detection is necessary to help avoid errors initiated by dynamic subimage content. In this document, I will discuss why edge detection fails as a motion detection method on low resolution images and how thresholding the normalized variance of individual pixels is successful for motion detection.

Motion Detection with Edge Detection

Method

Motion detection is achieved by separating static edges from those that move. This is done by using a reference mask generated by comparing the set of edges in each subsequent frame in time to the current reference mask. Only edges that are consistent in both the current frame and the reference mask are maintained in the updated reference. This prevents the edges of moving objects from being stored in the reference mask. By iteratively updating the reference mask, the algorithm identifies the static sections of the scenes.

Results

6 different edge detection algorithms were used: a high-pass smoothing filter, an ideal high-pass filter, a Butterworth high-pass filter, Prewitt edge masks, Sobel edge masks, and a 2nd derivate zero-crossing filter. While edge and motion detection were successfully achieved on noise-free images with high-contrast edges (Fig. 1a,b), they were less successful when noise was added to the image (Fig. 1c,d).

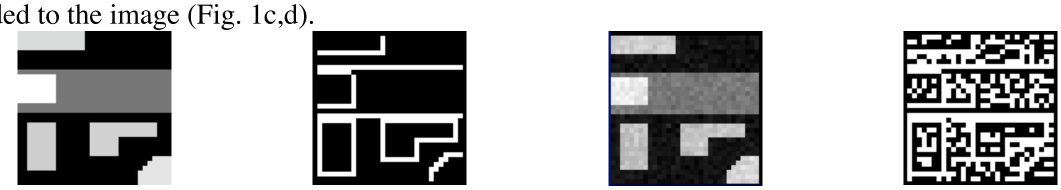


Figure 1: Edge Detection in original and noisy image. A. Original image B. Edges detected in A by High-pass smoothing filter C. Noisy image D. Edges detected in C by High-Pass smoothing filter

The images in Figure 1 have extremely high contrast edges. In reality, most images will not have the same image quality. Edges are not guaranteed to span precisely one pixel, nor are they guaranteed to be large and distinct. For SBWFS, most subimages are 16x16 or 32x32 pixels. Having few pixels define objects within a subimage makes edge detection a weak method of object detection. We can see that edge detection on the same image with 256x256 pixels (Fig. 2a,b) barely finds any objects in the 32x32 pixel image (Fig. 2c,d). The ratio of the number of pixels to the number of distinct objects within the image affects the robustness of edge detection.

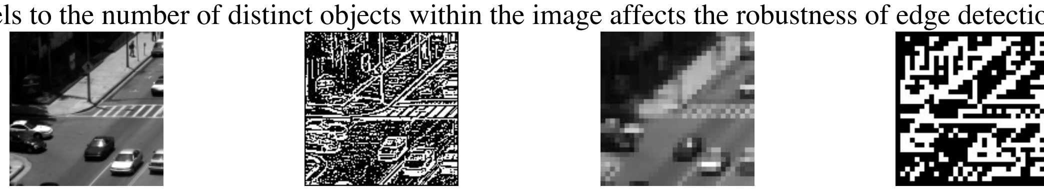


Figure 2: Edge Detection on 256x256 and 32x32 image. A. 256x256 image B. Edges detected in A by High-pass smoothing C. 32x32 image D. Edges detected in C by High-Pass smoothing filter

Conclusions about Edge Detection

No edge detection algorithm ever worked consistently. Image content was a large factor in the success of an edge detection algorithm. While most algorithms are likely to be consistent and successful with more pixels, for the application of SBWFS, it is unrealistic to have images with more than 32x32 pixels. Without a dependable method of detecting edges within each subimage, it is impractical to use edge detection as a way to isolate moving objects from a static background.

Motion Detection using Image Statistics

Method

Motion detection is achieved by thresholding the normalized variance of each pixel. Pixel-by-pixel operations on a finite number of stored frames allows for motion detection in $O(n^2)$ time and $O(n^2)$ space for an nxn image.

Image motion can cause edges to initiate false alarms. To only detect truly moving pixels, we categorize pixels as stationary, edge, or moving. Based on the probability model and the expectation for the mean-normalized variance of these types of pixels, a motion detection threshold was established. We approximate the expectation of the mean-normalized variance as the expectation of the sample variance divided by the expectation of the sample mean. This approximation proved to be quite accurate.

Models

The pixel value of a stationary pixel is the sum of Poisson read-noise and the realization of a Poisson process with parameter equal to the static noise-free pixel value. An edge is modeled as one pixel wide with intensity equal to a realization of a random variable that shifts from a mean equal to the average of the intensity levels on each side of the edge. Each shift is a zero-mean Gaussian random variable with variance on the order of .01 pixels. A moving pixel begins at some intensity level and increases with constant slope k, for n samples.

Chart 1 shows that the expectation for moving and edge pixels depend on range and background levels (L is the background level). The expectation for stationary pixels is not shown because it is always lower than the expectation for edge and moving pixels. Chart 1 shows that, for the same background levels, the expected normalized variance for moving pixels is over 5 times larger than that for edge pixels. To minimize false alarms and misses the threshold is set to 1.25 times the maximum expected normalized variance of edge pixels.

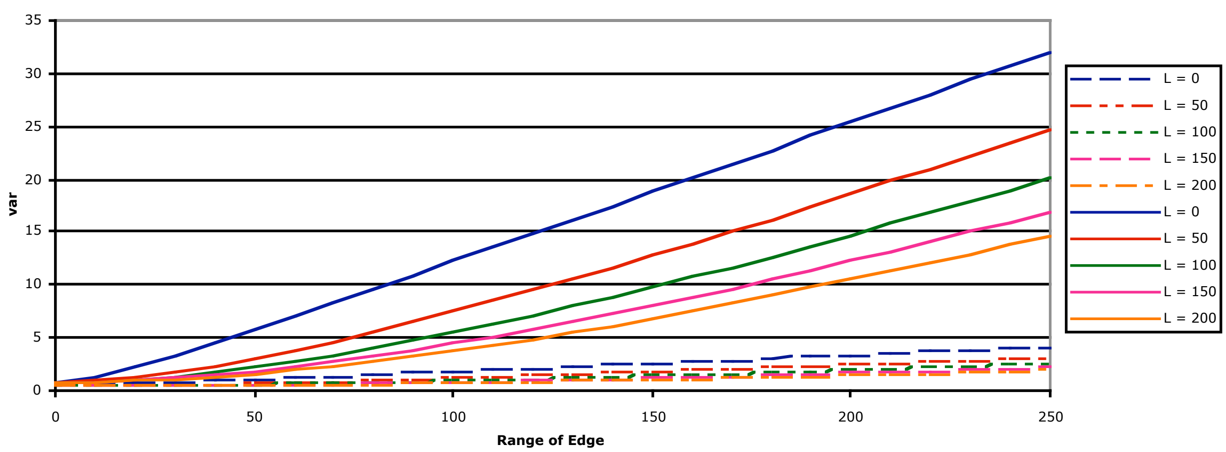


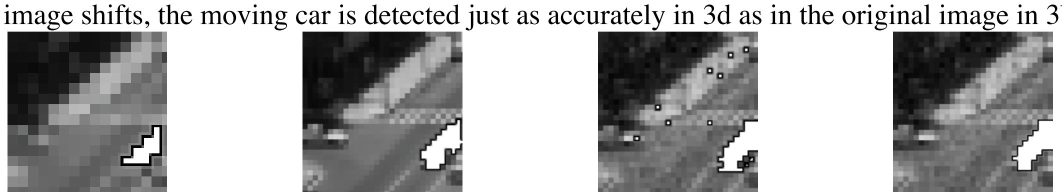
Chart 1: Expected normalized variance for edge and moving pixels. Edge pixels are dotted lines. Moving pixels are solid lines.

For SBWFS, most subimages are 16x16 or 32x32 pixels, which means most moving objects, such as cars, are likely to be on the order of 3 to 5 pixels. A reasonable number of frames to look at is 5 because a car with a size of 5 pixels would take 5 frames to fully traverse a single pixel. More frames would detrimental, because if the AO system must wait for more frames, it might not be able to correct the phase aberrations quickly enough. Also, in order to use SBWFS to find slopes, the frames must be correlated, which is unlikely when frames are separated by many time steps.

Results

By thresholding the normalized variance of individual pixels, motion detection is successfully achieved. For noise-free images, the motion detection is extremely accurate for 32x32 and 16x16 images (Fig 3a,b). These images are of a car driving down a street. The white with black border isolate the pixels of the moving car which have a normalized variance over the threshold.

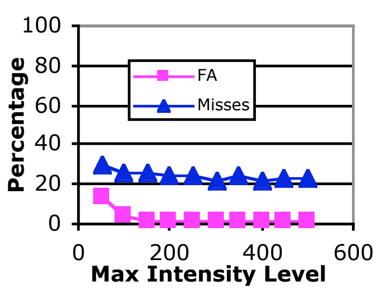
The threshold is based on the *expected* values, so false alarms become quite regular for noisy and shifted images, especially as the SNR decreases. Figure 3c shows 8 randomly dispersed false alarms. It is unlikely that a single stranded pixel with high normalized variance is part of a moving object. We lowpass filter an image mask where moving pixels are equal to 1 and non-moving pixels are equal to 0 to find clumps of high variance pixels (Fig. 3d). Despite the noise and image shifts, the moving car is detected just as accurately in 3d as in the original image in 3b.



A. 16x16 image **B.** 32x32 image **C.** 32x32 noisy/shifted image with no lowpass filter **D.** 32x32 noisy/shifted image with lowpass filter

Figure 3: Motion Detection of a car driving on a street. The white with black border highlight the pixels detected as moving.

Illumination and background levels significantly affect SNR and, hence, the performance of motion detection. The percentage of false alarms is defined as the number of pixels falsely marked as moving divided by the total number of non-moving pixels in the noise-free version of the same frame while the percentage of misses is the number of pixels not marked as moving divided by the number marked as moving in the noise-free version. Motion detection is very consistent with exposure level, only degrading for fewer than 50 counts per pixel (Chart 2a). When the background level increases beyond the illumination level, false alarms increase rapidly (Chart 2b). Fortunately, beyond this point, motion detection is not necessary since images may be too degraded to use.



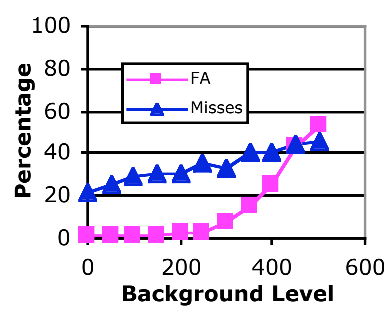


Chart 2: Percent of False Alarms/Misses due to A. Changing Illumination B. Changing Background

Image shifts cause the variance of a pixel to increase. For groups of stationary pixels, these increases are not large enough to initiate a false alarm. However, shifted edge pixels and moving pixels can be large enough. Fortunately, this phenomenon does not hurt our usage of this motion detection algorithm. If images have enough motion to cause so many false alarms, SBWFS will be unsuccessful for slope estimation.

Conclusions about Image Statistics

Using a threshold on the mean-normalized temporal variance of individual pixels proved to be an efficient and effective method for motion detection. While many standard image-processing techniques failed on our low-resolution images, this method successfully detected moving objects on 16x16 and 32x32 images.

Conclusion

While edge detection was unsuccessful for motion detection in subimages used for SBWFS, pixel-by-pixel image statistics was very effective on our low-resolution images. This efficient motion detection algorithm can help allow for tip-tilt information to be extracted even with temporal image motion.

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[1] Poyneer, L., "Scene-based Shack-Hartmann Wave-Front Sensing: Simulation and Analysis," submitted to Applied Optics