ADVANTAGES OF SUBSPACE ESTIMATION TECHNIQUES OVER GAUSSIAN MIXTURE MODELS FOR BACKGROUND SUBTRACTION OF NOISY VIDEOS

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ABSTRACT

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Index Terms— One, two, three, four, five

1. INTRODUCTION

In the field of video surveillance, the user typically wishes to extract meaningful and salient information from a video sequence in a completely automatic fashion. In several instances, the video sequences are captured using stationary cameras leading to a relatively static scene layout. The absence of camera motion implies that the background of the video sequence exhibits very little variation while dynamic changes in the scene represent the objects of interest. In such a case, the most common approach is to perform background subtraction to separate said dynamic regions (i.e. foreground) from the background of each frame.

When performing background subtraction, some naïve methods include frame differencing and approximate median [1]. While these algorithms are simple to use and quite efficient, the most popular technique, by far, is adaptive Gaussian Mixture Models (GMMs) [2, 3]. These works posit that each pixel in the background image can be represented by a probability distribution formed by a mixture of Gaussians. If a pixel greatly deviates from its corresponding model, then the pixel is labeled foreground. While the number of Gaussians used at each pixel is usually fixed, there has been some work [4] that adaptively selects the number of mixture components.

Although background subtraction via Gaussian Mixture Models enjoys widespread use in the computer vision community, it is not without drawbacks. As opposed to the frame differencing and approximate median techniques, GMMs possess several parameters that must be individually tuned. This implies that the algorithm is innately sensitive to different scene configurations. Therefore it should be no surprise that GMMs tend to perform rather poorly on noisy videos where the foreground objects are not immediately distinguishable.

When dealing with noisy video sequences, we advocate the use of low-rank subspaces for background subtraction. Given that each of the video sequences was obtained using a stationary camera, the high level of temporal redundancy between the frames suggests that the backgrounds lie on a low-dimensional subspace. Therefore, foreground activity can be thought of as sparse deviations from said subspace. In this paper, we consider two different subspace estimation algorithms and show empirically how they both achieve superior performance to GMMs on noisy traffic video sequences.

The first method, Robust Principal Component Analysis (RPCA or Robust PCA) [5], attempts to decompose a data matrix (or video sequence) into a low-rank matrix and a sparse matrix via a convex optimization problem. While typically performed in batch on purely intensity videos, we describe how performing Robust PCA on each of the color channels of video and subsequent post processing via wavelet de-noising leads to additional performance gains. If a user requires a real-time alternative, we also consider the newly proposed Grassmannian Robust Adaptive Subspace Tracking Algorithm (GRASTA) by He et al. [6] that learns the aforementioned low-rank subspace by subsampling the video frames and proceeds in an online fashion.

The remainder of this paper is organized as follows. Section 2 will describe the improvements made to the batch Robust PCA algorithm. Section 3 will present our experimental setup and findings. Section 4 will describe our conclusions and directions for future work.

2. METHOD DESCRIPTION

Traditionally, when given a video sequence, Robust PCA

Up until now, there has been very little work that investi-

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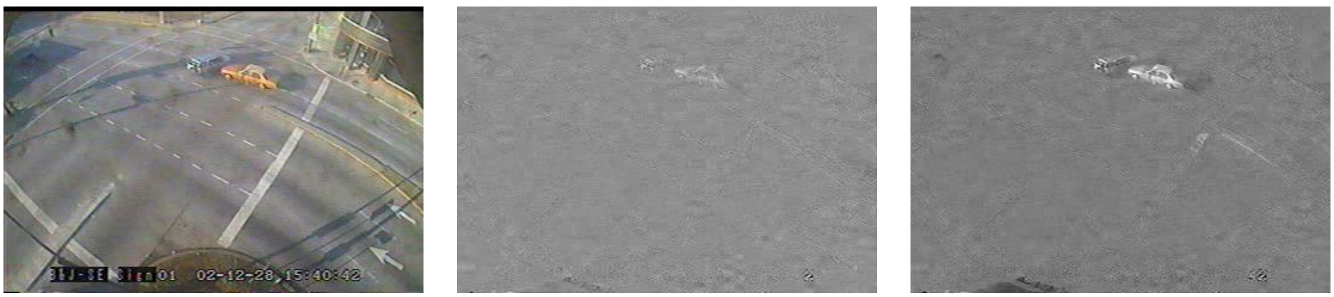
(a) Original Image (b) Intensity Sparse Image (c) Red Channel Sparse Image

Fig. 1. Visual Comparison of Robust PCA on Intensity and a Color Channel



(a) Original Image (b) Robust PCA Sparse Image (c) Reduced Robust PCA Sparse Image

Fig. 2. Reduced Frames Comparison

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3. EXPERIMENTAL RESULTS

(Cite Toyota Dataset?)

4. CONCLUSIONS

5. REFERENCES

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