EIGEN BACKGROUND SUBTRACTION

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Objective

Based on the paper "A Bayesian Computer Vision System for Modeling Human Interactions", we have to apply the partial part on that paper, we chose eigenbackground subtraction part in this work.

Theory of Eigenbackground Subtraction

Eigenbackground method is used to model the background of an image. We built an eigenspace that models the background. The eigenspace model, describes the range of variations in intensity values which has been observed.

If we have frame i with size w x h, where w is the width and h is the height, we must transform that frame into a wh x 1 column vector x_i. This is accomplished by placing the first column into a new vector and then put the second column to the vector after the first one, and so on. If the model is formed by several N frames/images, then the mean of images, m, calculated by :

$$\mathrm{m} = \frac{1}{N}\sum_{i=1}^{N} x_i$$

The mean normalized image vectors are then merged into a wh x N, matrix X :

$$X = [x_1 - m \quad x_2 - m \quad \ldots. \quad x_N - m]$$

All columns on X, according to the frame in the image sequence, all columns lying in wh-dimensional space.

For this reason we calculate the singular value decomposition (SVD) of X :

$$X = U\Sigma V^T$$

where U is an orthogonal wh x wh matrix and V^T is an orthogonal N x N matrix. The singular values of X are contained in the wh x N diagonal matrix Σ, in non-increasing order.

If the first r singular values are non-zero, while the rest values are zero, the first r columns of U gives an orthogonal basis for the column space of X. If the first r singular values are non-zero and the rest values are sufficiently close to zero, then the first r columns of U, form an approximate basis for the column space of X. This is well known as principal component analysis (PCA). We keep only the first r columns U, which in this case is also referred to as eigenbackgrounds ,in the matrix U_r.

Any new image/frame y, now can be projected into the reduced subspace as :

$$\tilde{y} = U_r P + m$$

Since U_r is orthogonal, p is easily obtained as :

$$p = U_r^T (y - m)$$

Moving objects do not have a significant contribution to this model, because they do not appear in the same location in the N sample frames/images and they are typically small. The portions of an image that contains a moving object cannot be well described by this eigenspace model.

By computing and thresholding the absolute difference between the input image and the projected image we can detect the moving objects present in the scene as follows:

$$|y_i - \tilde{y}_i| > T$$

where T is a threshold and y_i is the i-th element of y.

Implementation

- ***Eigenbackground Modelling***:

  We have several frames, which forms a “car” sequence. Then we calculated mean image of wh x 1 column vector (figure 1). After that we calculate SVD of X and took diagonalised matrix with singular values, U_r . Then, we projected new image (1st frame for instance) into reduced subspace (figure 2). Then, by computing and thresholding the absolute difference between the input image (1st frame for instance) we can detect the moving objects present in the scene (figure 3).

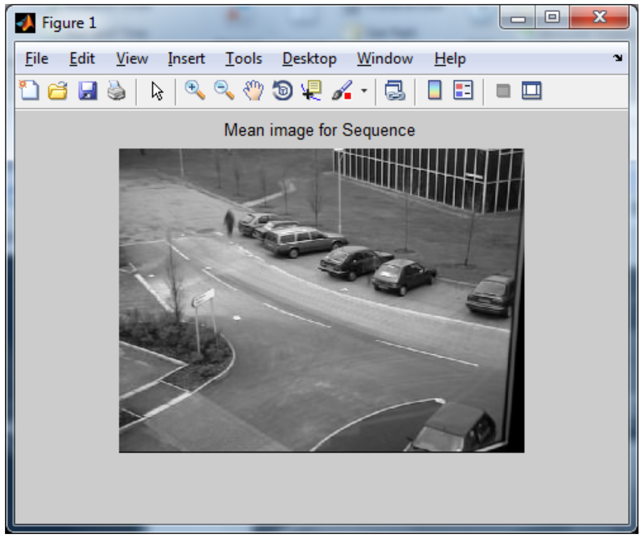

Figure 1.

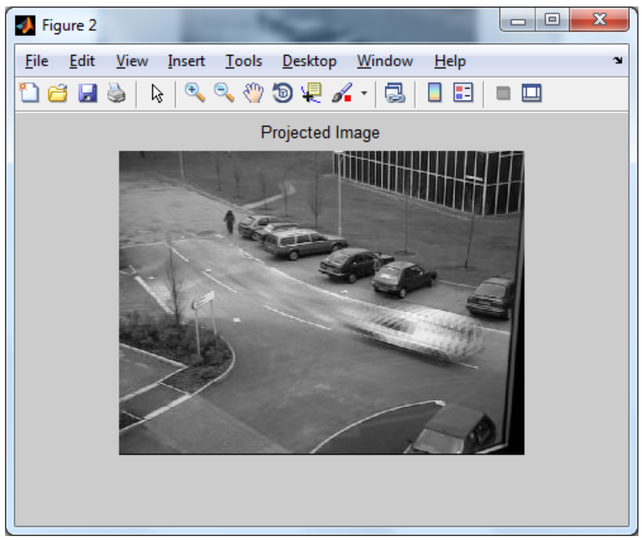

Figure 2.

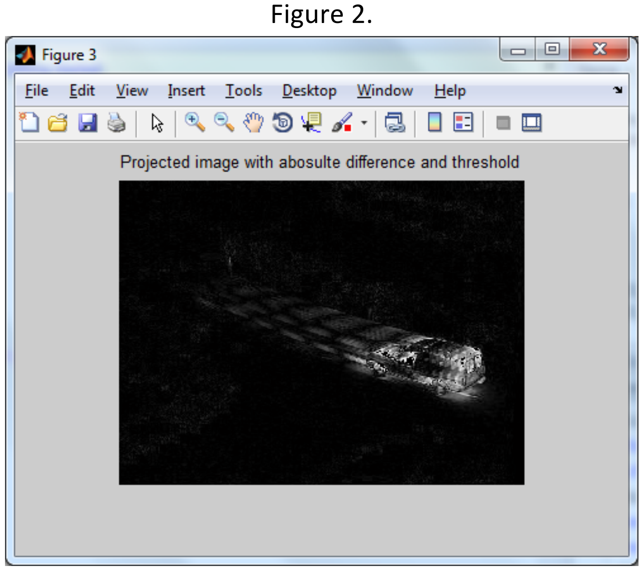

Figure 3.

Figure 4: Tracking without Kalman filter

- ***Tracking with Eigen background and Kalman Filter***:
  After we have a method to detect object present in the scene, we develop tracking that use eigenbackground method with Kalman Filter. Kalman Filter can handle occlusions.
  Here are the results of our tracking :

Figure 5: Tracking with Kalman Filter

Tracking results:

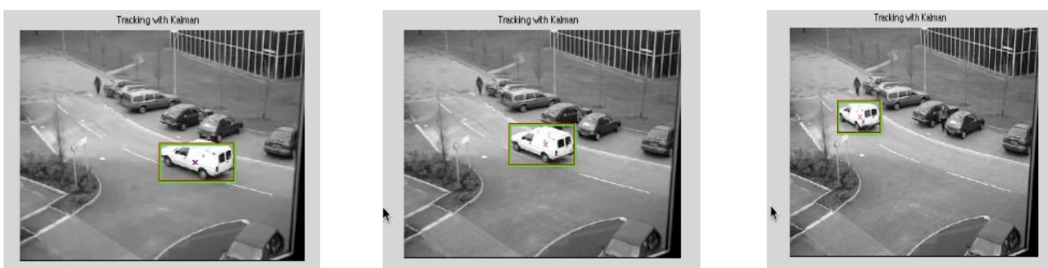

Figure 6

Conclusion:

The tracking for the car sequence works well with the paper proposed in [1]. Here we use the eigen background subtraction followed by kalman filter to get the accurate tracking results. In order to deal with multiple objects or to get better accuracy Synthetic agents are used in this paper [1]. Here we use only kalman filter, which deals only with linear systems with Gaussian noise.

References:

[1] A Bayesian Computer vision System for Modeling Human Interactions by Nuria M.Oliver et al.

[2] Background modeling and subtraction for object detection in video by Niel Joubert.

[3] Visual tracking notes and Lab practicals by Désiré Sidibe.