University of Burgundy

MsCV year 2

Visual Tracking

Tracking a Moving Object I: Background Subtraction

by

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1. Introduction to Visual Tracking

Video tracking is the process of locating a moving object (or multiple objects) over time using a camera. It has a variety of uses, some of which are: human-computer interaction, security and surveillance, video communication and compression, augmented reality, traffic control, medical imaging and video editing. Video tracking can be a time consuming process due to the amount of data that is contained in video.

Background subtraction is a simple and effective technique which is generally used to initialize the tracker. It can be used as an initial step to detect people or vehicles.

It is based on a model of the scene background which is a static image which is then used to track objects in the frames using difference of the frame and background model.

So, here we should estimate a model of background and there are different methods to estimate this background model. The methods include frame differencing (FD), running average guassian (RAG) and Eigen background (EB) models.

2. Background Modeling

2.1 Frame Differencing

In this approach the current background model depends on the previous frames. Its based on history of pixels in previous frames and the history can be mean or median of previous frames.

Let $I_1, I_2, \ldots, I_n$ be the frames of a sequence.

2.1.1 <u>Background model using all frames and applying median</u>

$$bgModel = median(I_1, I_2, \ldots, I_n)$$

$$foreground = | I_i - bgModel | > Threshold$$

2.1.2 <u>Background model from previous 'n' frames without updation</u>

$$(bgModel)_n = median(I_1, I_2, \ldots, I_{n-1})$$

$$(foreground)_{n+1} = | I_{n+1} - (bgModel)_n | > Threshold$$

2.1.3 <u>Background model from previous 'n' frames with updation</u>

$$(bgModel)_n = median(I_1, I_2, \ldots, I_{n-1})$$

$$(foreground)_{n+1} = | I_{n+1} - (bgModel)_n | > Threshold$$

$$(bgModel)_{n+1} = \alpha I_{n+2} + (1-\alpha) (bgModel)_n$$

2.2 Running Average Gaussian

In this method, each pixels history is modeled as a Gaussian probability density function with mean and variance. The rationale of this approach is that of fitting a Gaussian probability density function (pdf) on the last 'n' values of each pixel. This results in two images which hold the mean and standard deviation.

The approach builds the background image during an initialization phase and further only updates its parameters instead of fitting the pdf from scratch at each new frame time for increased speed and accuracy. During this phase the method is provided a temporal sequence of frames taken from a static camera containing no moving objects.

2.3 Eigen Background

Eigen Background model describes the range of variations in intensity values that have been observed by building an eigen space that models the background.

By using principal component analysis, we create an eigen background. A new image can be projected onto this reduced subspace.

The subspace is reduced by taking 'k' number of singular vectors such that

singular values (1:k) / sum(singular values) > 0.95

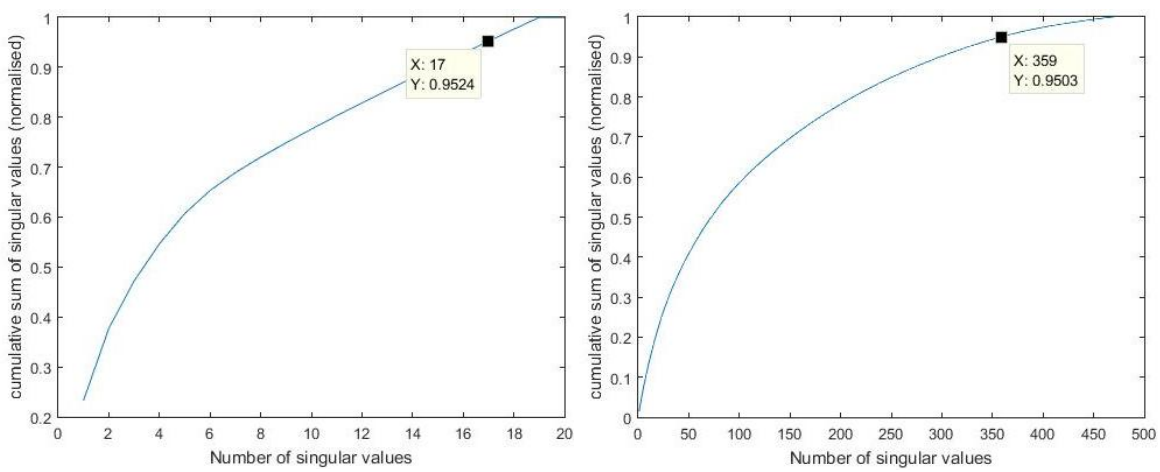

Fig. 1 singular value graph to select 'k' for car and highway sequence

Morphological operations like erosion, filling are applied to clear the unwanted objects. Bounding box (rectangle) is also shown while tracking the car.

3. Results and Discussions

3.1 Frame Differencing

3.1.1 Background model using all frames and applying median

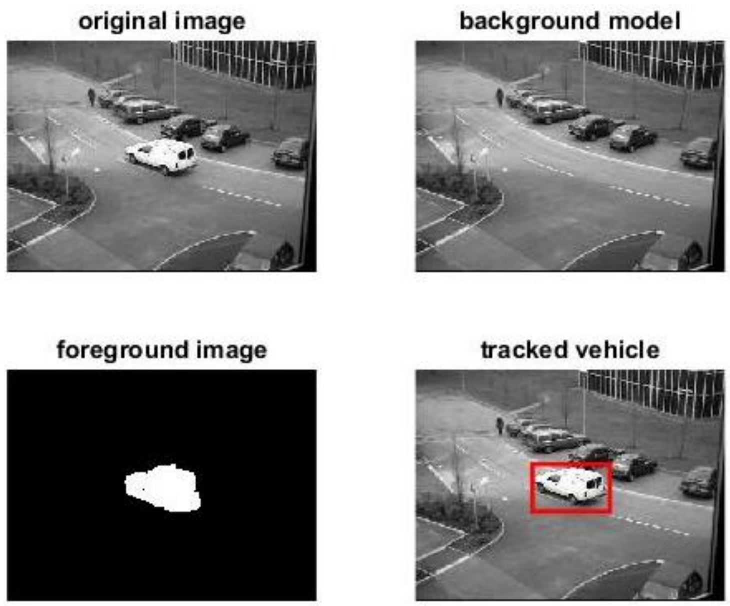

Fig. 2 Result of frame differencing as in 2.1.1 on car sequence

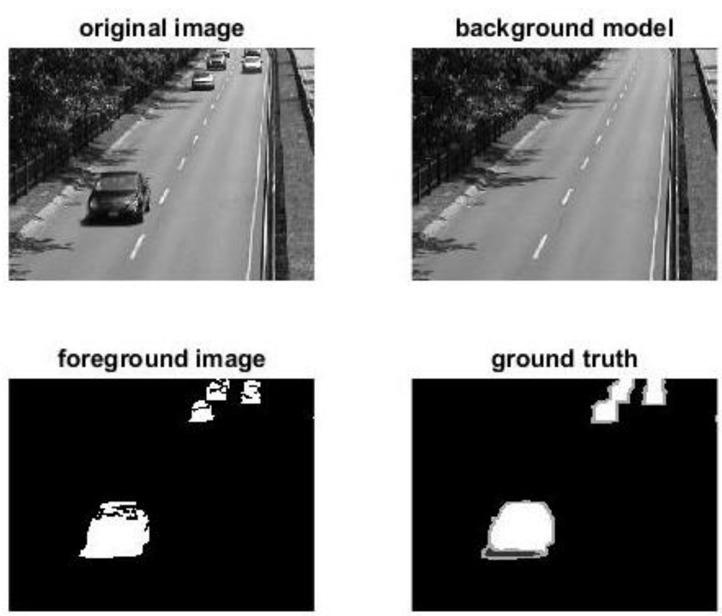

Fig. 3 Result of frame differencing as in 2.1.1 on highway sequence

3.1.2 Background model from previous 'n' frames without updation

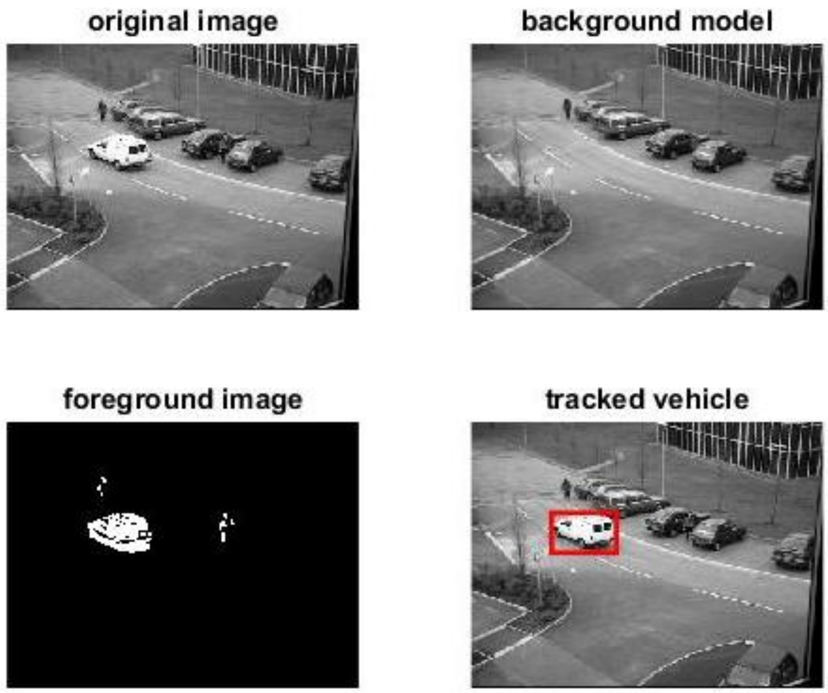

Fig. 4 Result of frame differencing as in 2.1.2 on car seqeunce

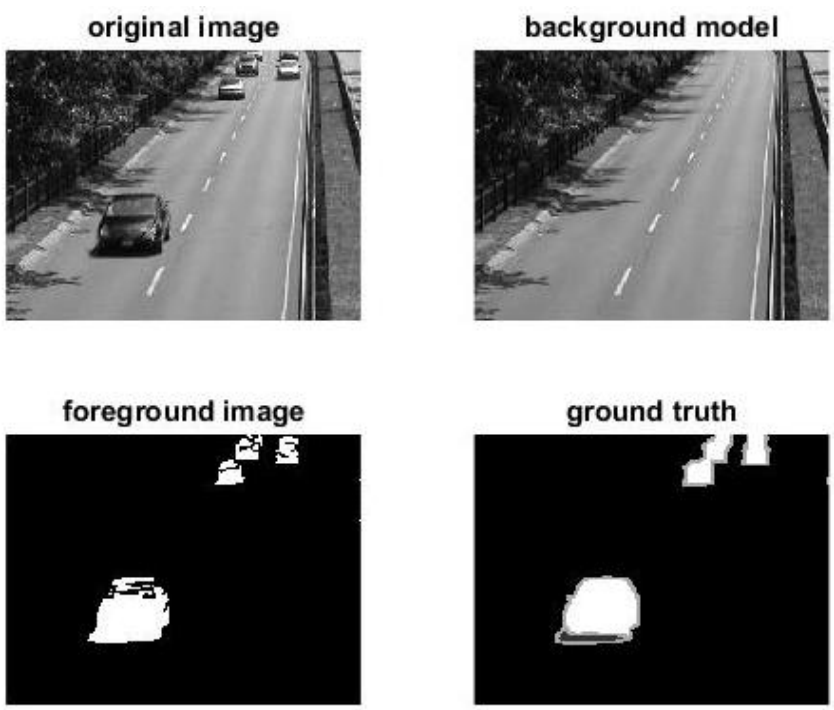

Fig. 5 Result of frame differencing as in 2.1.2 on highway sequence

3.1.3 Background model from previous 'n' frames with updation

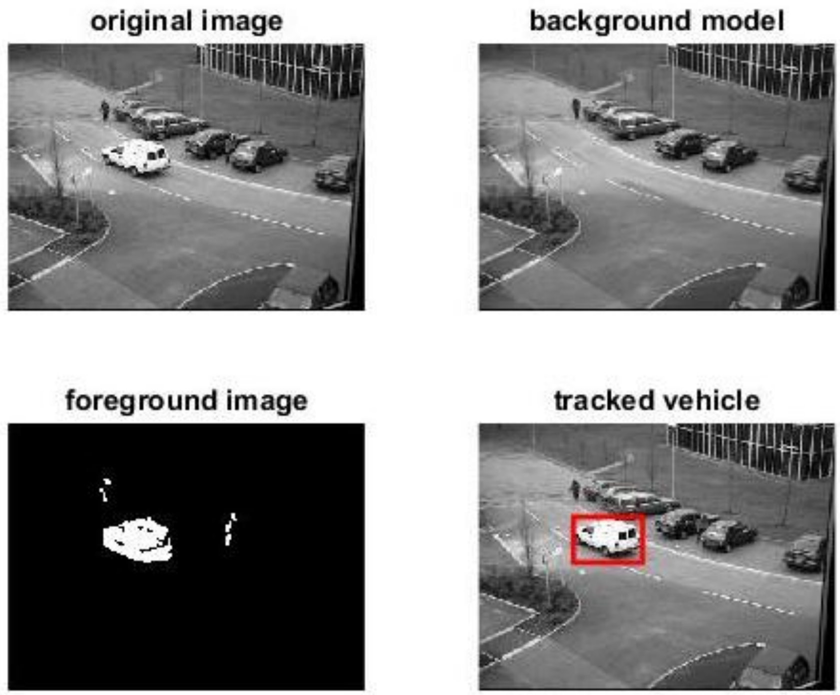

Fig. 6 Result of frame differencing as in 2.1.3 on car sequence

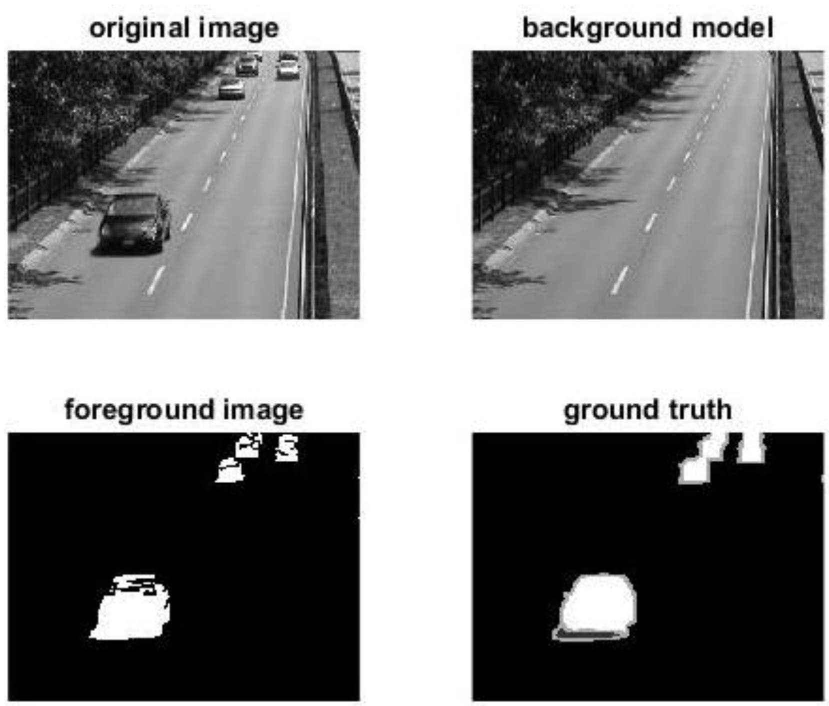

Fig. 7 Result of frame differencing as in 2.1.3 on highway sequence

3.2 Running Average Gaussian

Fig.8 Result of RAG on car sequence

Fig.9 Result of RAG on highway sequence

3.3 Eigen Background

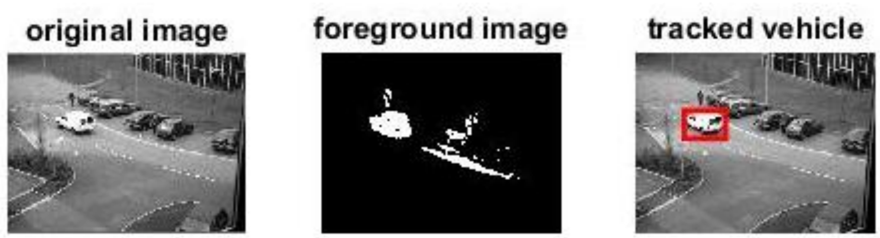

Fig.10 Result of Eigen Background on car sequence

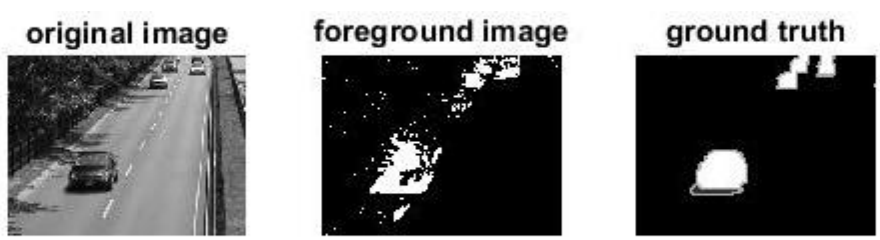

Fig.11 Result of Eigen Background on highway sequence

TABLE 1 Metrics of different methods used

	Frame Differencing			Running Average Gaussian	Eigen Background
	Method as in 2.1.1	**Method as in 2.1.2**	**Method as in 2.1.3**		
Precision	0.995	0.995	0.98	0.879	0.635
Recall	0.6565	0.655	0.66	0.35	0.572
F-Score	**0.79**	**0.79**	**0.78**	**0.50**	**0.604**

3.4 Discussion on Results

Background subtraction is very sensitive to the changes in the external environment and has poor anti- interference ability. However, it can provide the most complete object information in the case background is known.

Frame differencing calculation is simple and easy to implement. For a variety of dynamic environments, it has a strong adaptability, but it is generally difficult to obtain complete outline of moving object.

The methods we used do not maintain a buffer for background estimation. Instead, they recursively update a single background model based on each input frame. As a result, input frames from distant past could have an effect on the current background model. Compared with non-recursive techniques, recursive techniques require less storage, but any error in the background model can linger for a much longer period of time.

4. Conclusion

Background subtraction is simple tool to initially track the objects in the video. The significant step in this approach is to estimate the background model to subtract from the original frame to get the foreground object. Three different approaches to estimate the background model are studied in this lab and out of three, frame differencing approach produce good results (Tab. 1) with the given highway sequence.