Frame Difference and Kalman Filter Techniques for Detection of Moving Vehicles in Video Surveillance

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Abstract

Background subtraction is a method to identify object and famous used in moving object detection. The aim is to obtain a clean background and then detect moving objects by comparing it with the current frame. In this paper, kalman filter method and Frame difference has used to detect the objects. The kalman filter has better accuracy than the Frame difference method. Experimental results show that the kalman filter is a good solution to obtain high accuracy, low resource requirements in given video of each technique. The detection of object will be shown in the result.

Keywords: Visual Surveillance, Background Subtraction, kalman filter, Frame difference s

1. Introduction

Nowadays, vision sensor has been introduced in detecting object in day time or night time. Vision sensor can be applied in many areas, such as in medical system, military system, transportation system, robotic and control system, and surveillance system. Using vision, the system can detect, recognize and actuate accurately depend on how good the image have been processing [1],[2],[3],[4].

Background subtraction is a low-level task, it should consider two aspects: accuracy and computational resources (time and memory). Background subtraction performance depends mainly on the background modeling technique [8]. Extensive research has been carried out regarding this task [5]-[7], [8], [9].

In the past, a frame difference using online K-means approximation is one of the most popular methods. In this technique, computation cost and memory requirements are low. However, the foreground segmentation accuracy inevitably decreases due to the loss of color information. To solve the problem of accuracy and resource requirements, this paper proposes a background subtraction method by kalman filter method.It is working on dynamic and static videos. In this paper, we use static videos.

In this paper is organized as follows. Frame difference method in section II. Kalman filter in section III.The simulation results are presented in Section Iv. Concluding remarks are made in Section V.

2. Frame Difference

Background subtraction as the name suggest is the process of separating out foreground objects from the background in a sequence of video frames . Many methods exist for background subtraction, each with different strength and weakness in terms of performance and computational requirements. Background subtraction is implemented using varying complexity.
1) Low complexity-using frame difference method.
2) Medium complexity using approximate median method
3) High complexity using mixture of Gaussian method.

```
fr_bw = rgb2gray(fr);        % convert to grayscale

fr_diff = abs(double(fr_bw) - double(bg_bw));

% if fr_diff > thresh pixel in foreground
for j=1:width
    for k=1:height
        if ((fr_diff(k,j) > thresh))
            fg(k,j) = fr_bw(k,j);
        else
            fg(k,j) = 0;
        end
    end
end
```

Fig.1. Algorithm of the frame difference algorithm

The algorithm is relatively simple.
1. Convert the incoming frame 'fr' to grayscale (here we assume a color RGB sensor)
2. Subtract the current frame from the background model 'bg_bw' (in this case it's just the previous frame)
3. For each pixel, if the difference between the current frame and backround 'fr_diff (j,k)' is greater than a threshold 'thresh', the pixel is considered part of the foreground.

The frame difference technique is low accuracy and it cannot detect the moving vehicle correctly as shown in fig.(2).

3. Kalman Filter

Kalman filters have also been used to perform foreground object detection. In each pixel is modeled using a Kalman filter. In, a robust Kalman filter is used in tracking explicit curves. A robust Kalman filter framework for the recovery of moving objects'. However, the framework does not model dynamic, textured backgrounds. Kalman filter also work on dynamic videos.

The algorithm of kalman filter as shown below

Read the vehicle video
Convert video in to frames i.e I(x,y)
For k=1:totalframes

$$I_k = F_k I_{k-1} + B_k U_k \tag{3}$$
$$P_k = F_k P_{k-1} F^T_k + Q_k \tag{4}$$
$$Y_k = z_k - H_k I_k \tag{5}$$
$$S_k = H_k P_k H^T_k + R_k \tag{6}$$
$$K_k = P_k H^T_k S_k^{-1} \tag{8}$$
$$I_k = I_{k-1} + K_k Y_k \tag{9}$$

End

Presuming a very small process variance, we let Q=1e-5. (We could certainly let Q=0 but assuming a small but non-zero value gives us more flexibility in "tuning" the filter as we will demonstrate below.) Let's assume that from experience we know that the true value of the random constant has a standard normal probability distribution, so we will "seed" our filter with the guess that the constant is 0.

I_k and z_k are the actual state and measurement vectors. I_k and z_k are the approximate state and measurement vectors from eq (3) and (5).

H is the Jacobian matrix of partial derivatives of h with respect to x.

$$H_{[i,j]} = \frac{\partial h_{[i]}}{\partial x_{[j]}}(\tilde{x}_k, 0) \tag{10}$$

The image I_k, represents the estimation of image at frame k given observation up to and including at frame k .Pk is the error covariance matrix that is measure of the estimate accuracy of the state estimate. In the update phase, the current prediction is combined with current observation information to update the state estimate. Typically, the two phases alternate, with the prediction advancing the state until the next scheduled observation, and the update incorporating the observation. However, this is not necessary; if an observation is unavailable for some reason, the update may be skipped and multiple prediction steps performed. Likewise, if multiple independent observations are available at the same time, multiple update steps may be performed typically with different observation matrices H_k . The formula for the updated estimate and covariance above is only valid for the optimal Kalman gain.

4. Experimental Results

In this paper, the experiments can done using MALAB 7.8 in a 2.8 GHz Intel Dual core 860 CPU. The grayscale images are generated from the original color images. Secondly, Kalman filter images are generated from the original color images.

Figure 1 shows the original image in color image. The comparison between frame difference method and kalman filter, kalman filter give better detection. The frame difference more noise and if we do the extraction of image, it makes the extraction lousier. The number of vehicles in given video is 11.

In Figure 2, shows the detection object using Kalman filtering method. The image is smooth, clean and the object is clearly detection. The number of vehicles in given video is 9.In fig.1 big noises are considered as on vehicle. This is the drawback of Gaussian method.
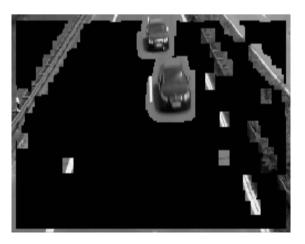

Fig.1. original frame

Fig.2. object detection using frame difference methd
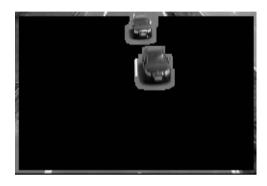
Fig.3. original frame

Fig.4. object detection using kalman filter method

Conclusion

In this paper, kalman filter has better accuracy compare to frame difference method. Furthermore the segmentation has been improve and the object detection more smooth. In future scope is to detect objects using practical filter.

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