On The Development of Moving-object Detection Techniques

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ABSTRACT

Moving object detection is considered to be one of the active area of research in the field of computer vision. It is the task of identifying the physical movement of an object in a given region or area. Over last few years, moving object detection has received much of attraction due to its wide range of applications in video surveillance system, such as human motion analysis and event detection, anomaly detection, traffic analysis and security. In addition, it forms a critical step for many complex processes. However, task of detecting object in motion becomes tricky due to various challenges like dynamic scene changes, illumination variations, presence of shadow and so on. To reduce the effect of these problems, researchers have proposed many new approaches. In this paper, we will discuss the major techniques in moving object detection and make use of result of simulation to estimate these methods.

***Index Terms*—Moving object detection, optical flow, GMM, background subtraction, frame differencing.**

I. INTRODUCTION

The most critical task in moving object detection is to segregate region of interest from the background objects in a video. The background can be treated either as static or dynamic. And the camera can be treated as stationary or moving. This motivates researchers to try their best to solve such critical problems in computer vision field.

In recent past, frame difference, optical flow and background subtraction algorithms are employed to detect a moving object out of which background subtraction is one of the popular scheme for moving objects detection in the field of video surveillance.

The basic premise lies in background subtraction algorithm is to set up an initial background with the help of background modeling and then subtracting the current frame from a previous frame to detect the objects in motion. Optical flow estimation yield a two-dimensional vector field i.e. motion field that represent velocities of each point of an image sequence. It initially takes the video frames as input one by one estimates the average flow vectors from them which results in Optical flow vectors. Noise filtering is done to remove the unwanted motion in the background. Then thresholding is done to achieve binary image. There are some uneven boundaries in threshold image which are rectified by morphological operations. Connected components are analyzed to evenly patch the generated white blobs in binary image. Finally, marking of moving object is done with a box which indicates the motion of the objects individually. Frame difference method identifies the presence of moving object by considering the difference between two consecutive frames.

The rest of the paper is organized as follows. Section II presents a review of major techniques on moving-object detection. In section III we conduct simulations with these methods on typical dataset and analyze their performance. Finally, section IV gives the concluding remarks.

II. MAJOR METHODS REVIEW

Not only the background can be treated either as static or dynamic, but also the camera can be treated as stationary or moving. They both have an influence on the result. Different method has different performance in different situations. And the major methods of moving object detection are frame differencing, background subtraction and optical flow.

A. *Frame Differencing*

Frame difference method takes advantage of the difference between two consecutive frames [1]. It makes use of image subtraction operator that obtains output image by subtracting second image frame from first image frame in corresponding consecutive frames. However, Frame differencing method lacks in obtaining the complete contour of the object. As a result of this problem, morphology operations are general used to obtain better results.

B. *Background Subtraction*

Background Subtraction Method is considered to be one of the most reliable method for moving object detection. Background subtraction works by initializing a background model, then difference between current frame and presumed background model is obtained by comparing each pixel of the current frame with assumed background model color map. In case difference between colors is more than threshold, pixel is considered to be belonging to foreground [2]. Performance of traditional background subtraction method mainly gets affected when background is dynamic, illumination changes or in presence of shadow. Numerous methods have been developed so forth to upgrade background subtraction method and overcome its drawbacks. For example, there are Mixture of Gaussians model (GMM), Eigen backgrounds, Kernel density estimation (KDE), Running Gaussian average and Temporal median filter [3].

C. Optical Flow

Optical flow approach of moving target detection is based on calculation of optical flow field of image or video frame [4]. Clustering is performed on the basis of the obtained optical flow distribution information obtained from the image or video frame. This method allows obtaining complete knowledge about the movement of the object and is useful to determine moving target from the background. However, this method suffers from some of drawbacks like large quantity of calculations are required to obtain optical flow information and it is sensitivity to noise.

There are two most used optical flow method, which are Lucas-Kanade optical flow and Horn-Schunck optical flow [5, 6].

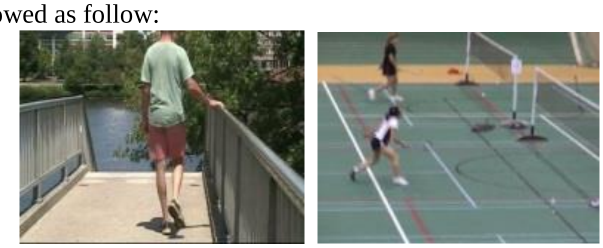
III. EXPERIMENTAL RESULTS

In this section, we will choose the typical method of different techniques in moving object detection to conduct simulations. And then we use the result to estimate their performance in different situations.

A. Dataset

The UCSD Anomaly Detection Dataset: This dataset was acquired with a stationary camera mounted at an elevation, overlooking pedestrian walkways. The crowd density in the walkways was variable, ranging from sparse to very crowded. In the normal setting, the video contains only pedestrians [7]. It is showed as follow:

CDW-2014 dataset: This dataset contains 11 video categories with 4 to 6 videos sequences in each category. The 11 categories: Baseline, Dynamic Background, Camera Jitter, Intermittent Object, Motion, Shadow, Thermal, Bad Weather, Low Framerate, Night Videos, PTZ and Turbulence [8]. It is showed as follow:



B. Simulation and Analysis

We choose Three-Frame difference (Frame difference), Mixture of Gaussians model (Background Subtraction) and L-K Optical flow (Optical flow) to conduct simulation for moving object detection.

Three-Frame difference: The first step of three-frame difference is to make smooth de-noising for three consecutive frames, and then process them by the method of frame difference respectively, i.e. frame k subtracts frame k−1, and we can get a binary image D_1(x, y), frame k+1 subtracts frame k, and we can get a binary image D_2(x, y), and the final step is to make an “AND” operation of D_1(x, y) and D_2(x, y), the result is three-frame difference image D(x, y). We apply this method on dataset and get the result:

We find this method can get the moving object but it lacks in obtaining the complete contour of the object. Therefore, it must combine with morphology operations to get better result.

Mixture of Gaussians model: distribution of each pixel value X is modelled by Mixture of K Gaussian densities in the GMM model, as

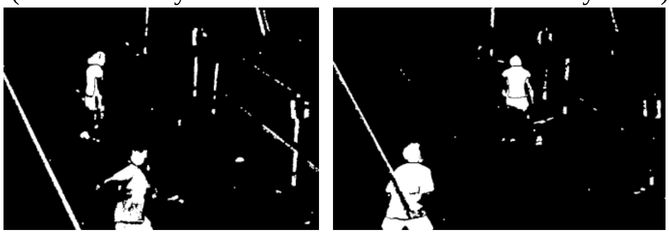
$$P(X_t) = \sum_{i=1}^{K} w_{i,t} . \eta(X_t, \mu_{i,t}, \Sigma_{i,t})$$

Here X_t is YUV color vector of the current pixel, K is the number of Gaussian components, $w_{i,t}$ is a weight associated to the i-th component, m_i is the mean, S_i the standard deviation of pixel values, and η denotes the Gaussian probability density function. Background pixels appear more frequently than the foreground ones, thus the components are arranged in a descending order by the rank $R_K = W_K / \sigma_K$ and the first B components having cumulative posterior probability greater than the threshold T are considered background.

$$B = \arg\min_b \left(\sum_{k=1}^{b} w_k > T\right)$$

For each input video frame, each pixel value is matched against the learned components. If the matching component is among the first B components then it is classified as background, otherwise as foreground. If there is no match at all with any of the existing components, then the least probable Gaussian is reset. We apply this method on dataset and get the result:

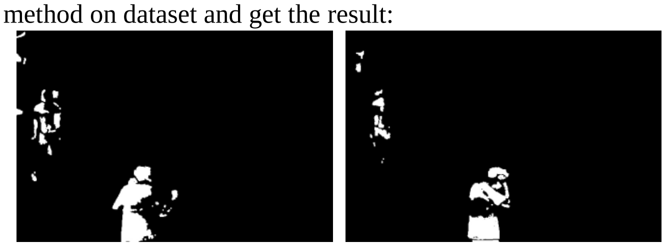
(This scene is dynamic because the tree and river are dynamic)



(This scene is the moving camera situation)

We can find GMM can get good performance in static and dynamic scene. It has a good anti-noise performance but is not good at moving camera situation.

L-K Optical flow: Lucas-Kanade algorithm belongs to sparse optical flow algorithm. Compared with the dense optical flow method, the optical flow vectors of all pixels in the image need to be calculated. LK algorithm only needs to calculate the optical flow vector of the image feature, and has good real-time performance, accurate matching and low complexity in the tracking process. The algorithm assumes that the pixel neighborhood space motion vector is the same. Calculating the flow direction information of the corresponding pixel in the adjacent image, optical flow vector matched via small window local information around the feature points. We apply this method on dataset and get the result:



We can find that optical flow method can get better performance than GMM in moving camera situation. But it also has drawback. It is sensitivity to noise.

Merging Method: The method merging background subtraction and optical flow is a good attempt to solve moving object detection of moving camera. It merges two scores to detect moving objects more accurately in quasi-real time. It designed two scores, anomaly and motion, for real-time application [9]. The anomaly score is calculated based on a background subtraction and depends on the difference in pixel intensities between the current image and the background model. The motion score is calculated from a sparse optical-flow, which is based on the short-term tracking results of sparsely sampled points. The merging method detects moving objects more accurately in quasi-real time.

IV. CONCLUDING

The Frame difference method has a good performance in static scene. The Background Subtraction method get good results in not only static scene but also dynamic scene, but not perform well in moving camera situation. The Optical flow method solve this problem, but the performance is not best. The merging method detects more accurately in quasi-real time.

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