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MOVING OBJECT DETECTION USING STATISTICAL BACKGROUND SUBTRACTION FOR A ROTATING CAMERA

Shivprasad Patil

Professor, NBN Sinhgad School of Engineering, Pune, India
Email: sppatil1212@gmail.com

ABSTRACT

In this paper, an algorithm is presented that models the background of a scene observed by a rotating camera. Here, adaptive Gaussian mixtures model is used to estimate the background model. The distribution of each background pixel is temporally and spatially modeled. Based on this statistical model, a pixel in the current frame is classified as belonging to the foreground or background. This method yields improved results in detecting moving objects and building background model in the presence of moving objects.

A test case involving a surveillance system to detect moving objects, especially car as a object is demonstrated successfully. For developing our method, a real time video sequence acquired from a rotating camera is used. Our method can effectively deal with the scenes, such as the outdoor and the cluttered one. The experimental results show our method is quite accurate.

Keywords : Rotating Camera, Background Modeling, Foreground Detection, Adaptive Mixture of Gaussians

INTRODUCTION

In many computer vision applications, robust and real-time foreground detection is a crucial issue. There has been considerable work on object detection and activity monitoring [1]. However, such work assumes non-rotating camera. In contrast, we address the problem of object detection over a wide area through a rotating camera. We propose a background model that can be used to differentiate between the background and the moving objects or foreground.

Background subtraction is a typical approach to detect foreground by comparing each new frame with a developed model of the scene background in image sequences taken from a camera. Usually, motion compensation is required when applying background subtraction to a non-stationary background. In practice, it is difficult to realize it to sufficient pixel accuracy.

Motion detection with a non-stationary viewing sensor has received considerable attention of the researchers. In many computer vision applications robust and real-time foreground segmentation is a crucial issue [1]. The applications include automated visual surveillance [2–4], vehicle-borne video surveillance, object detection and tracking with a pan-tilt camera and others. In these cases, background subtraction cannot be applied directly. Motion compensation is required first to compensate for the motion due to the moving sensor. Usually a motion model of the background is assumed, and motion parameters are estimated. Then the background is registered ideally and the foreground can be detected on pixel level. The underlying assumptions are that the motion model must be sufficiently accurate and the parameters of the motion model are accurately estimated. Also, the sensing lenses are distortion-free. In practice, these assumptions are difficult to realize [5]. Also, these are time-consuming and unsuitable for real-time applications. With the approximation of the motion model, the current and the background image cannot warp and register well. This problem is also encountered when using the temporal difference method.

The use of background modeling for detecting the moving object is very common in many applications. In the scene like video surveillance, the background model can be developed by acquiring a background image which doesn't include stationary object, and such cases are rarely possible. In some situations, the background is not available and/or there is a change in illumination conditions. Also, object is removed or introduced from the scene. Many background modeling methods have been developed, by considering the problems cited above to make them more robust and adaptive. Although most of these methods use only a fixed camera, they provide a good starting point for a rotating camera.

The organization of the paper is as follows. Section II provides a description of related work on background modeling and subtraction. Section III introduces background modeling algorithm of KaewTrakulpong and Bowden [6]. Our proposed technique is based on this algorithm. Section IV presents proposed algorithm of object detection for rotating camera with experimental results. Section V presents conclusions and future work.

Related Work

Though, there are numerous techniques which uses averaging the pixels at a particular location, taking the median of all the pixel values, are of limited usability in practice. Ridder et. al. [3] and others used a Kalman filter-based background model. In this approach, every pixel is modeled by using a Kalman filter. Further it is updated in each frame, depending on whether it is predicted as part of the background or not. However, this approach is not suitable in a changing background or a multi-modal background.

Friedman and Russell [7] have classified the pixels into three distributions. First corresponds to the road color, then shadows present in the scene and lastly, the colors of car. This brings restriction on their work to use into such scenarios, although the method can probably be applied to other scenarios. The most recent survey can be found in [8].

It is found that the most used model is certainly the pixel-wise Mixture of Gaussians proposed by Stauffer and Grimson [2]. It is a good compromise between robustness to the critical situations and the constraints like computation time and memory requirement [8]. In this paper, we proposed techniques for segmenting the foreground when camera is rotating. Our work is based on statistical background modeling and subtraction [6], which is developed from [2]. The general idea is to obtain a per-pixel background model. Further, each pixel in a new image is examined to see whether it is drawn from that pixel's background model or not.

Very few techniques which specifically deal with background models development for rotating camera are available. Exceptions are Ren et al. [9] and Mittal and Huttenlocher [10]. Both have extended Stauffer and Grimson's technique [2] to rotating cameras by incorporating a search for matching pixels within a region in the mosaic to accommodate registration errors. In [9], a probabilistic spatial model is developed to Weight the candidates locations.

Background Modeling

Our work uses the Adaptive Gaussian Mixture Model (AGMM) formulation developed by KaewTrakulpong and Bowden [6]. This scheme is more accurate and learns fast. Also, allows multimodal background modeling. The model can change with time to accommodate shadow and slow lighting variations.

Each pixel in the scene is modeled by a mixture of K Gaussian distributions. The pixel distribution can be represented as a mixture of K Gaussians:

$$f(I_t = x) = \sum_{j=1}^{K} w_{j,t}\, \eta(x, \mu_{j,t}, \sigma_{j,t}) \qquad (1)$$

Where $w_{j,t}$ is the weight parameter of the jth Gaussian component. $\eta(x, \mu_{j,t}, \sigma_{j,t})$ is the jth Gaussian component with intensity mean $\mu_{j,t}$ and standard deviation $\sigma_{j,t}$.

Normally, the value of K varies from three to five, depending on the computational power and available storage.

The K distributions are ordered based on the fitness value w_k/σ_k. First M distributions are used as a model of the background of the scene where M is estimated as:

$$M = arg_m min\left(\sum_{j=1}^{m} w_j > T\right) \qquad (2)$$

The threshold T is the minimum fraction of the background model. Background subtraction is performed by marking a foreground pixel which is away from any of the M distributions by more than 2.5 standard deviations.

The updating of the parameters which are matched is done with following update equations [7],

$$\hat{W}_k^{N-1} = \hat{W}_k^{N} + \frac{1}{N+1}\left(\hat{P}(\omega_k / X_{N+1}) - \hat{W}_k^{N}\right) \qquad (3)$$

$$\hat{\mu}_k^{N+1} = \hat{\mu}_k^{N} + \frac{\hat{P}(\omega_k / X_{N+1})}{\sum_{i=1}^{N+1} \hat{P}(\omega_k / X_i)}\left(X_{N+1} - \hat{\mu}_k^{N}\right) \qquad (4)$$

$$\sum\nolimits_k^{N+1} = \sum\nolimits_k^{N} + \frac{\hat{P}(\omega_k / X_{N+1})}{\sum_{i=1}^{N+1} \hat{P}(\omega_k / X_i)}\left(X_{N+1} - \hat{\mu}_k^{N}\right)\left(X_{N+1} - \hat{\mu}_k^{N}\right)^T - \sum\nolimits_k^{N}) \qquad (5)$$

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If none of the distributions matches the pixel value then least significant component of the mixture model is replaced by a distribution with low weight, high variance and current value as its mean.

Detecting Foreground Objects

In the first phase, we have used very simple technique of the frame differencing for detection of moving object. Intention is, to find out to what extent we get good results with minimum cost of computation. In this, we calculated a perspective transform matrix from four corresponding points from every two successive frames. This is required for the compensation of camera motion. Further, incoming frame is warped with computed perspective transform matrix. This transformed frame is subtracted from the previous frame to get the moving object detected.

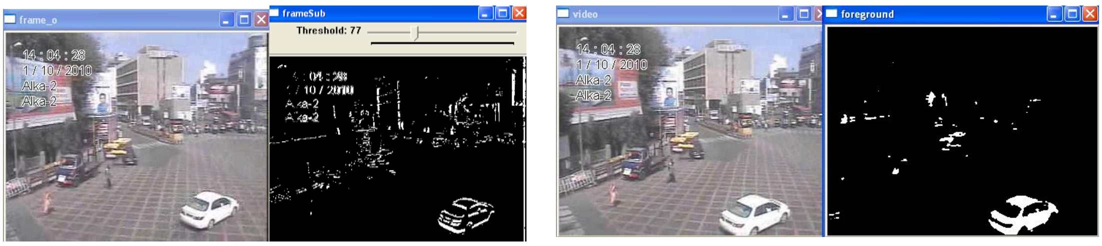
In the next phase, we build a statistical background model. Our background model is based on Kaew Trakulpong and Bowden's algorithm. Initially, we build background model for N frames that comprises one complete rotation of the camera. We estimated value of N, from cameras fps (frame rate per second). Onwards, based on this statistical model, a pixel in the current frame is classified as belonging to the foreground or background with reference to corresponding background model.

RESULTS

This project needs real-time analysis of the video stream for object detection. We used the free available Open CV-library, which is implemented in C and C++ Code.

The library offers a broad range of computer vision functions and allows an easy link to our rotating camera prototypes. The sequence shown here are 352x272 images. We used an adaptive mixture of five Gaussian components.

Figure 1 shows foreground segmentation results with motion compensation by using perspective transform and adaptive statistical mixture model.



(a) (b)

Figure 1. Car as a detected object. (a) Frame differencing using Adaptive perspective transform. (b) With proposed algorithm.

CONCLUSION AND FUTURE WORK

In this paper, we proposed a statistical background subtraction algorithm, which takes care for motion compensation of rotating camera, for detection of moving object. The dataset used is a video clip, coming from a rotating camera. Result is compared with frame differencing algorithm. Our results are more accurate than existing one.

There is still much work required before our system can termed as a complete one. Robust operation requires mechanism for handling occlusion and illumination changes.

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