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Detection and Tracking of Multiple Moving Objects for Surveillance and Security System

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Abstract—*In this paper, detection and tracking of moving object with shadow removal, automated counting and alarm generation was proposed. Improved Gaussian mixture model was used for background subtraction and modeling as it robustly deals with lighting changes, repetitive motions, clutter and slowly moving objects. Shadow detection and removal was performed using improved HSV color space method. Morphological operations were used for noise removal in post processing step. Kalman filter was used for tracking of moving objects with occlusion handling. In the last step, automated counting of moving objects and generation of alarm when motion was detected were performed. Experimental results show that proposed approach was able to detect and track moving objects with effective shadow removal and counting.*

1. INTRODUCTION

Video Surveillance System is getting more and more importance nowadays. In many public areas, so many cameras are set at different-different angle, for observing unattended objects, to keep citizen safe. Surveillance systems are getting integrated with intelligent system which can automatically detect and track moving objects. Frequently used techniques to detect moving objects are background subtraction, statistical methods, temporal differencing and optical flow. Background subtraction subtracts the current image from a reference background image, which is updated during a period of time. Statistical method is more advanced method that make use of the statistical characteristics of individual pixels have been developed to overcome the shortcomings of basic background subtraction methods. An adaptive Gaussian mixture model described by Stauffer and Grimson [7] is a statistical method. However, the background subtraction techniques used to extract moving object also detect the shadow cast by it. Shadow cast by moving object make it difficult to detect the exact shape of object and to recognize the object. Shadow detection is a challenging task because shadow differ significantly from the background have same motion as the object casting it and mostly adjacent to casting object.

The aim of an object tracking is to generate the trajectory of an object over time by locating its position in every frame of the video. The efficient tracking of visual features in complex environments is a challenging task for the computer vision applications. Object tracking methods can be divided into three major categories: contour based models [1], region based models [2, 3], and feature point-based models [4, 5]. Multiple objects tracking through occlusion is still one of the most challenging issues in the computer vision. There are a lot of difficulties for a single object tracking like illumination variability, background noise and occlusions. Multiple object tracking is even more challenging due to multi object occlusions.

Mostly used tracking methods are meanshift algorithm, camshift algorithm, Kalman filtering and particle filtering. In [8] meanshift and kalman-based algorithm is used to solve occlusion occur. In [9] acceleration model which is effective solution to fast tracking is used to predict the emergence of target. Meanshift algorithm is an efficient pattern matching algorithm with no parameter estimation, and can be combined with other algorithms. It uses the kernel function histogram model of the target object. Cucchiara [10] proposed probabilistic masks and appearance models to cope with frequent shape changes and large occlusions. Eng [11] developed a Bayesian segmentation approach that fused a region-based background subtraction and a human shape model for people tracking under occlusion.

This paper proposed an approach for detection and tracking of moving objects for surveillance and security system. We used improved Gaussian Mixture Model as an effective way to extract moving objects from a video sequence. However, mixture of Gaussian method also extract cast shadows of moving objects. So we used improved HSV color space method for shadow removal with improved Gaussian mixture Model in order to achieve accurate extraction of the shapes of moving objects. To track moving objects in subsequent images, we use Kalman filter. The tracking stage used kalman filter to model the speed and acceleration of a tracked objects and to predict the position in the current frame and simulate the object trajectories. Finally automated counting and generation of alarm when the motion was detected were performed.

The remainder of this paper is organized as follows: Flow chart of proposed method is presented in Section 2, in Section

3, experimental results are analyzed and conclusions are presented in section 4.

2. PROPOSED APPROACH

In this section, we proposed method for detection and tracking of multiple moving objects with automated counting of moving objects and generation of alarm when motion was detected. The flow chart of our proposed approach is described in fig. 1.

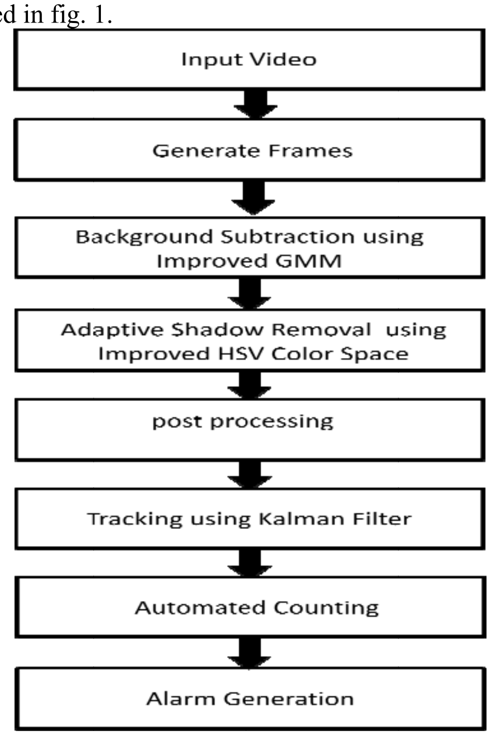


Fig. 1: Flow chart of proposed method

2.1. Improved Adaptive Gaussian Mixture Model

Traditional adaptive Gaussian Mixture Model had some drawbacks such as slow updating rate, slow initialization procedure and time and space consuming. In the proposed approach , an improved Gaussian Mixture Model as described in [12] , was used to save time and space.

Traditional adaptive Gaussian Mixture Model Presented by Stauffer and Grimson [7] used mixture of k Gaussian distributions to describe the history of a pixel. The probability of observing the current pixel value was described as:

$$P(X_t) = \sum_{i=1}^{k} w_{i,t} * \eta(X_t, \mu_{i,t}, \Sigma_{i,t}) \tag{1}$$

where X_t was equal to the intensity of pixel at the position of (x, y) at time t, K was the number of distributions, $w_{i,t}$, $\mu_{i,t}, \Sigma_{i,t}$ were the weight, mean value, and covariance matrix of the i^{th} Gaussian at the time t. Covariance matrix $\Sigma_{i,t}$ was defined as follows :

$$\Sigma_{i,t} = \sigma_{i,t}^{2} I \tag{2}$$

η was a Gaussian probability density function described as:

$$\eta\,(X_t, \mu_{i,t}, \Sigma_{i,t}) = \frac{1}{(2\pi)^{n/2}\,|\Sigma|^{1/2}} e^{-1/2((X_t-\mu_t)^T \Sigma^{-1}(X_t-\mu_t))} \tag{3}$$

Every new pixel intensity was checked against the existing K^{th} Gaussian distribution until a match was found. A match was defined as pixel intensity within 2.5

Standard deviations of a distribution. The parameters of the distribution for matched pixel were updated as follows:

$$\mu_t = (1-p)\mu_{t-1} + p * X_t \tag{4}$$

$$\sigma_t^2 = (1-p)\sigma_{t-1}^2 + p(X_t - \mu_t)^T \Sigma^{-1}(X_t - \mu_t) \tag{5}$$

Where p was another learning rate defined as follows:

$$p = \alpha\eta(X_t \mid \mu_i, \sigma_i) \tag{6}$$

$$w_{i,t} = (1-\alpha) w_{i,t-1} + \alpha * M_{i,t} \tag{7}$$

Where α was the learning rate, and $M_{i,t}$ was 1 for matched pixels and 0 for unmatched pixels. After the Gaussian distributions were ordered by the value of ω/σ, the first B distributions were chosen as the background model, where

$$B = avg\ \min_b\left(\sum_{i=1}^{b} w_i > T_{background}\right) \tag{8}$$

Where $T_{background}$ was the threshold. As described above the traditional GMM have some shortcomings. In order to improve its performance, we do some change in it as given in [12].

Firstly, the original GMM assumed that the R, G and B color channel have the same variation. This is actually not so precise. So, we assume that each channel has its own variation.

Secondly, in order to get a faster adaptation of the mean and the variation value, we use only one learning rate α in the new model. Another aim of using only one learning rate α is to save space and time, and to make the background subtraction more efficient.

2.2. Shadow Detection using Improved HSV Color Space Method

Our method used HSV color space method proposed by Cucchiara [13] for shadow detection with some improvement

.The improved HSV color space method detects shadow more accurately and robustly. In [13], the authors think the *V* component of shadow is smaller than background's, and *S,H* components do not change much, In HSV color space to identify shadow mask for each point (x, y) (previously detected as moving object point). Cucchiara [13] define three constraint on the H, S, V values of pixel (x, y) as follows

$$SP_k(x,y) = \begin{cases} 1 & if\, \alpha \le \dfrac{I_k^V(x,y)}{B_k^V(x,y)} \le \beta \\ & \wedge (I_k^S(x,y) - B_k^S(x,y)) \le \tau_S \\ & \wedge |(I_k^H(x,y) - B_k^H(x,y))| \le \tau_H \\ 0 & Otherwise \end{cases} \quad (9)$$

Where I_k^V (*x, y*) is the intensity value for component V of the HSV color space at coordinate (*x, y*) in the frame K. $B_k^V(x, y)$ the background V component at coordinate (x, y) and K^{th} frame time. $I_k^S(x, y)$ foreground S component, $B_k^S(x, y)$ background S component. $I_k^H(x, y)$ foreground H component. $B_k^H(x, y)$ background H component. α, β, τ_S, τ_S are manually defined parameters. Improved HSV color space method uses $\left(\dfrac{I_k^V(x,y)}{B_k^V(x,y)}\right)^2$ instead of $\dfrac{I_k^V(x,y)}{B_k^V(x,y)}$ in the condition described in equation (9).this improved the robustness and accuracy of shadow detection.

2.3. Post Processing

The detected moving objects in the previous phase may lead to have a connectivity problem and it may also have some holes which may be useless for object representation. Therefore here we need to have some post processing which will reduce the problem of handling holes and the connectivity of pixels within object region. Mathematical morphological analysis is one of post processing approach which leads to enhance the segmented image in order to improve the required result. In the proposed method we have used the erosion and dilation iteratively so that an object will clearly appear in foreground while the rest useless blobs will be removed. Morphological operations are useful to obtain the useful components from the image.

2.4. Tracking Using Kalman Filter

In the proposed approach multiple objects tracking was performed using Kalman filtering which uses Stable Marriage Problem (SMP) implemented algorithm which is adapted to perform data association.

In reference [14]**,** Kalman filter is an optimal solution for the discrete data linear filtering problem. Kalman filter is a set of mathematical equations which provide an efficient computational solution to sequential systems. The filter is very powerful in several aspects: it supports estimation of past, present, and future states (prediction), and it can do so even when the precise nature of the modeled system is unknown. The filter is derived by finding the estimator for a linear system, subject to additive white Gaussian noise. Given a discrete-time process described by the following equations.

Dynamic model:

$$x_{k+1} = Ax_k + w_k \quad (10)$$

Measurement model:

$$z_k = H_k x_k + v_k \quad (11)$$

Where x_k is *n*×1 system state vector, w_k is *n*×1 process noise vector, z_k is *m*×1 measurement vector, and v_k is *m*×1 measurement noise vector. Both w_k and v_k are assumed to be uncorrelated zero-mean Gaussian white noise. The KF algorithm represents a feasible linear measurement update for the estimate and error covariance. KF can be organized into time update and measurement priori estimates for the next time step.

The measurement update equations incorporate a new observation into a priori estimate from the time update equations to obtain an improved posteriori estimate.

As mentioned in [4], In order to find match between two sets of targets (previous frame) and objects (current frame measurements) used SMP algorithm adapted to the perform data association introduced in [14]. After extracting current frame objects positions (first set) and previous targets positions estimated by Kalman filter for current frame, we create cost matrix of two sets based on Euclidian distance of two set positions and apply SMP algorithm to this cost matrix to find the most stable match between targets and measurements. KF handle occlusion very effectively.

2.5. Automated Counting and Alarm Generation

Automated counting of moving objects is one of the important feature of proposed system. An efficient mechanism are used to performed automated counting of moving objects and it is very useful in traffic monitoring system.

In proposed system, a mechanism is provided to raise an alarm in case of motion is detected in the video stream. This property makes proposed system act as an effective surveillance system.

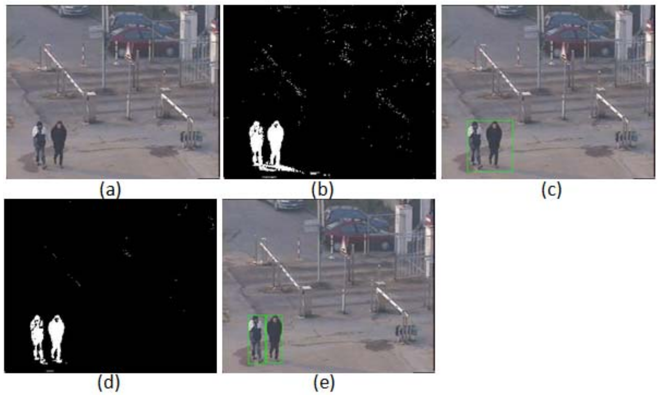
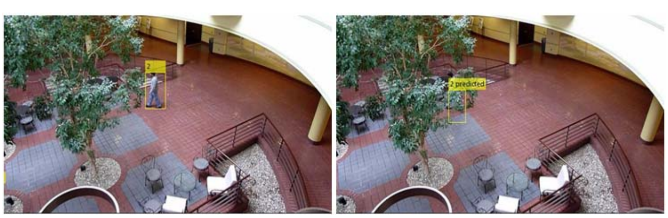


Fig. 2: Experimental results of campus video sequence for outdoor scene a) Original image. b) Background subtraction using Gaussian Mixture Model Result. c) Object Segmentation error because of shadow. d) Result after shadow removal process. e) Final result with segmented object

3. EXPERIMENTAL RESULTS

The system is tested in typical indoor and outdoor environments for handling various situations, background modeling, shadow detection, occlusion and counting. In order to evaluate the tracking performance of our system, we used three video sequences (campus, atrium and intelligent room). Campus and atrium video sequences are outdoor sequence with multiple moving objects while intelligent room video sequence is indoor sequence with single moving object. All three sequences have shadows of moving objects with different backgrounds. Campus video Sequence is used to demonstrate the capability of system in tracking in presence of shadow for outdoor environment as shown in figure 2. Figure 2 show that objects were merge in a single blob due to shadows but after shadow removal process they were segmented into different blobs. In atrium video sequence as shown in figure 3 prediction of person occluded by tree are performed successfully. Figure 4 shows tracking results with occlusion handling while in figure 5 automated counting of moving persons were performed.



(a) (b)

Fig. 3: Tracking results for atrium video sequence in outdoor environment (a) Result before occlusion (b) Result after occlusion by tree

Tracking of single moving person with shadow removal was performed in intelligent room video sequence as shown in figure 6. These results show that our proposed method successfully performed tracking with occlusion handling, shadow detection and counting.

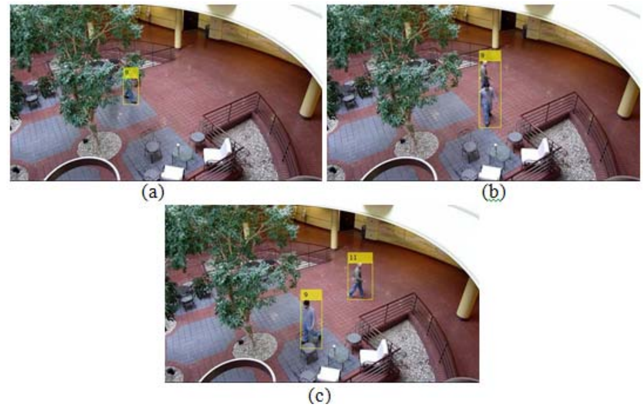


Fig. 4: Tracking with occlusion detection results for atrium video sequence (a) Result before occlusion (b) Result at the time of partial occlusion (c) Result after occlusion detection

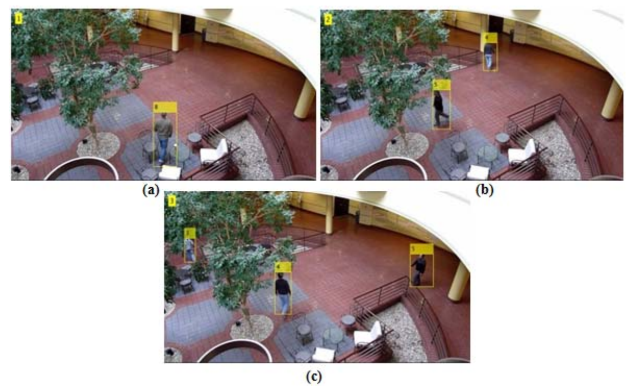


Fig. 5: Automated counting results of atrium video sequence. The system correctly count number of persons in the scene.

4. CONCLUSIONS

We have proposed an approach for detection and tracking of multiple moving objects with shadow detection, alarm generation and automated counting. Detection of moving objects were performed using improved Gaussian Mixture Model, which can effectively detects different situations like sudden illumination change, fake motions. Proposed approach uses improved HSV color space method for shadow detection and morphological operations for noise removal from the background subtracted images. The tracking process is done using a Kalman filter with occlusion handling. Experimental results shows that the system can deal with difficult situations such as shadow and illumination changes. It shows the effectiveness and robustness of the proposed approach.

Fig. 6: Tracking results for intelligent room sequence in indoor environment with single person

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