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Multi-Object Tracking Using ST-MRF, GMM, Modified Running Average and Camshift - A Comparative Study

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Abstract-- Video-based object tracking in static or in dynamic scenes is one of the challenging problems with vast variety of applications, is currently one of the most active research topics in computer vision. This paper mainly focuses on performing survey on tracking moving objects in video scenes in both pixel-domain and compressed-domain with detailed descriptions of tracking strategies and examining their pros and cons. Survey of tracking methodologies in both pixel and compressed domain for object recognition and tracking includes modified running average, Gaussian Mixture Model, Spatial-temporal MRF and Camshift. Experimental result has been evaluated for different video sequences with different conditions such as noise; illumination changes, shadow, scale change in the objects etc. estimate the performance of these algorithms. Result obtained has better accuracy, good performances and with the consumption of less processing time according to the evaluation criteria.

Keywords: Spatio-temporal Markov-Random field, GMM, motion detection, video surveillance, RA, objects tracking, Camshift

INTRODUCTION

Tracking moving objects by analyzing video sequences is one of the active research topics in the field of computer vision. There are two major areas in detecting and tracking objects in motion, distinguished by the domain in which they operate: pixel domain and compressed domain [1]–[2]. In this paper a compressed realm MRF tracking movement based objects using spatial and time information is proposed and the same method can be used even for other older video format is presented.

MRF [9] method mainly uses information such as space, temporal dependence information to track object in subsequent frame, coding each block of frame, motion vector of individual frame etc. for precise tracking [4]. Modified RA method [3] for background model with temporal changes in each video frames to track objects. CAMshift [11] is based on an adaptation of Mean Shift that makes use of continuously adaptive probability distributions computed for each frame. It is one of the simplest methods and supplies reliable and robust results, if the colors in the background differ significantly from those in the target object. Finally, Gaussian Mixture Model (GMM) [10] method based on background modeling method to extracting moving objects and for trajectory prediction is discussed. The rest of the paper is organized as follows: Section 2 describes various approaches for object tracking. In Section 3 the results and discussion finally, conclusions are summarized.

DESIGN AND IMPLEMENTATION

The design of the proposed motion detection approach for static-camera surveillance system includes object tracking algorithms followed by the designing of the GUI with process flow diagram shown in Figure 1.

Method comprises of preprocessing to eliminate background noise besides the moving objects and parameters such as the outline for the display of tracking box are up for the users to make a decision.

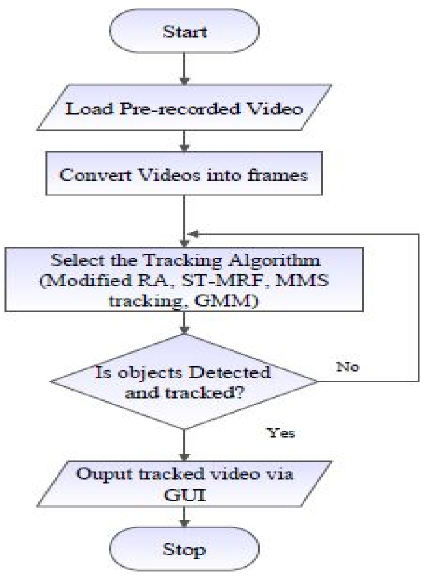


Figure1: Processing flow diagram of object tracking system

MOVING OBJECT DETECTION AND TRACKING TECHNIQUES

Project is implemented using MATLAB using modular design and the aim of the object tracking is to generate the trajectory in the video sequence from one frame to another.

A. Modified RA Tracking Module

A novel method for tracking motion based objects in videos using static camera. Method [3] includes three main steps and he processing flow diagram for Modified RA module is shown in Figure 2.

1) Background Extraction: Method includes rapid and then accurate matching to get the entire background pixel for background extraction. Bt(x, y) and Ct(x, y) is the last background and the present incoming video frame used for further calculation. For every pixel (x, y), t (count of frame) the value of the corresponding present background Bt(x, y) is computed using:

$$B_t(x, y) = B_{t-1}(x, y) + t\,(C_t(x, y) - B_{t-1}(x, y)) \qquad (1)$$

2) Block-Based Entropy Evaluation: Absolute difference $\Delta_t(x, y)$ between the estimated background model $B_t(x, y)$ and present frame $C_t(x, y)$ is taken. After considering the absolute difference for each block (i, j) block-based entropy evaluation procedure is applied which results in bock E(i, j). Motion block M(i, j) is set as 1 if entropy bock E(i, j) exceeds threshold indicating moving pixels and is set as 0 otherwise.

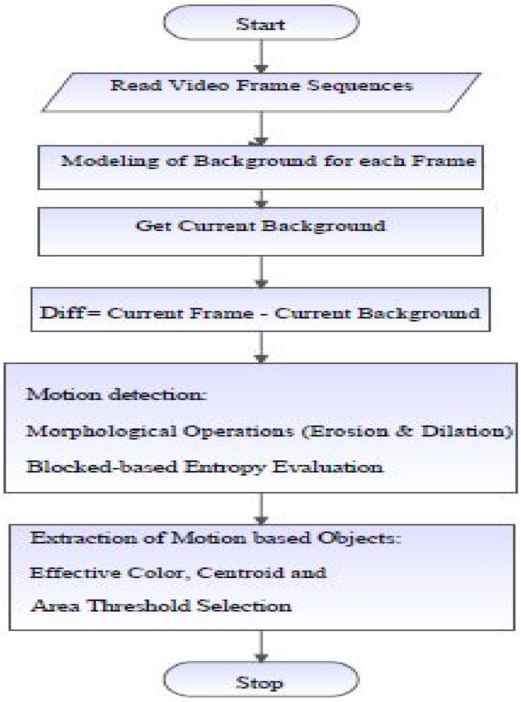


Figure 2.Flow chart of Modified RA Module.

3) Processing of Moving Blocks: Gray-level illumination changes is used for finding blocks containing objects in movement with the help of suitable threshold value to get binary object mask.

B. GMM Tracking Module

Proposed GMM based algorithm [10] uses GMM for detection of foreground and for tracking moving objects is done using blob analysis. It is a parametric PDF indicating total of Gaussian component densities. A block diagram of GMM module is shown in Figure 3.

Blob analysis involves recognition and study of region of connected pixels in binary images. In this paper for detecting blob mainly two information is used Bounding Box Output Port and Minimum Blob Area. Bounding Box Output Port property returns Bounding Box coordinates and Minimum Blob Area gives number of pixel in the particular blob area which is considered as 150 pixels in this paper.

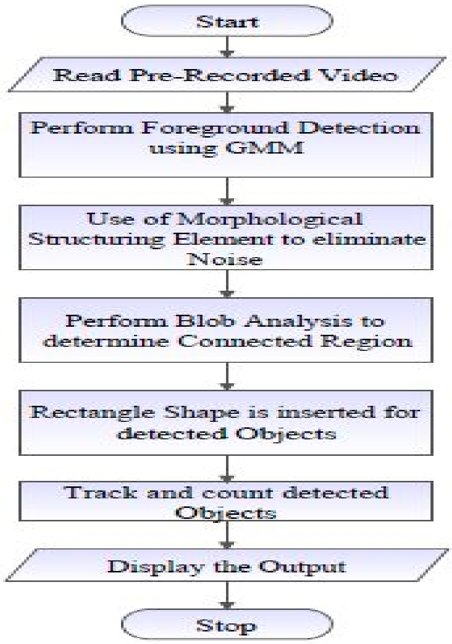


Figure 3.Flowchart of the GMM module.

Here Background Subtraction is used to detect foreground objects which includes four steps.

- Preprocessing is done to get rid of device noise.
- Computation of background model.
- Detection of foreground entities by indentifying all pixels belong to foreground with respect to background model pixels.
- Finally, confirmation of the data and improving the foreground mask.

C. Camshift Module

The Continuously Adaptive Mean Shift Algorithm (CamShift) [11] uses continuously adaptive probability distributions and is based on an adaptation of Mean Shift Tracking method. CamShift can easily identify dynamic change in the background color probability which differ significantly from those target objects. Here initially moving object is detected in video sequence by plotting a rectangle region.

A block diagram of Camshift module is shown in Figure 4.

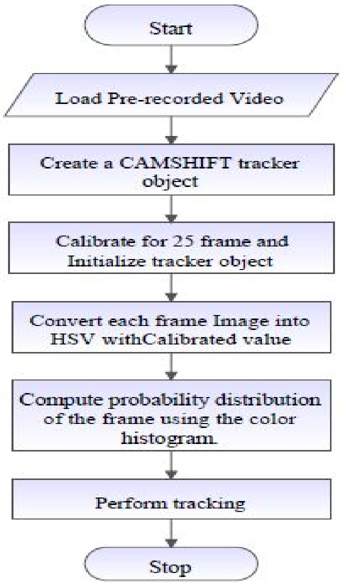


Figure 4. Flow chart of Camshift Module.

For target model and candidate model color Probability Density Function of the objects is calculated. It is Histogram-based object tracking method that uses histogram of pixel values to identify the tracked object. Step method uses input image, histogram-based tracker object to compute bounding rectangle box for tracking object. Step method returns angle, first-order and second-order moments as the object defined by equations below:

$$M20 = \sum_x \sum_y x^2 * I(x, y) \tag{2}$$

$$M02 = \sum_x \sum_y y^2 * I(x, y) \tag{3}$$

$$M11 = \sum_x \sum_y x * y * I(x, y) \tag{4}$$

D. ST-MRF Module

In MRF (Markov Random Field) tracking using spatial and temporal dimension tracking [4] of pre-recorded video is done. Initially, preprocessing of the video is done to remove noise by using Gaussian filter. GM [6] estimation is done to estimate the camera movement and GM compensation is done to remove GM which includes intra-coded block processing. After preprocessing tracking is performed using MRF method which uses spatial and time information. MRF [5] make use of markov property to track rigid object by using compactness behavior of the moving object which will not get dispersed in frame sequence. A block diagram of MRF Tracking method using spatial and temporal information is shown in Figure 5.

In proposed MRF [7-8] based method compact space information for tracking moving rigid object in frame sequence, MV temporal continuity information is used find movement similarity between blocks in the frame in use by the objects. Video is taken as input and converted into frame; next frame is divided into 4X4 blocks. Blocks are labeled based on presence of object such as non-object and object blocks as 0 and 1 respectively.

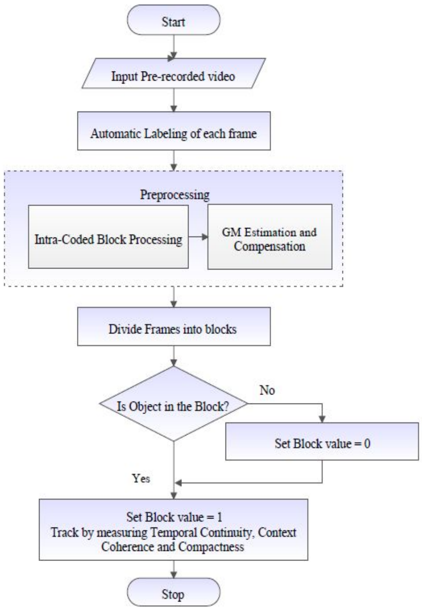


Figure 5.Flow chart of ST-MRF tracking module

Suppose the block labeling is done for frame 'x' and previous frame 'x-1' then tracking between the frame is done using motion information which is denoted by : $f_x=(m_x, b_x)$ where m_x denotes MV for inter calculation between previous and current frame and bx(t) denotes block coding mode where t=(x,y) represent block position in the frame. Labeling is done using MAP (Maximum A Posteriori) criterion where block is selected with maximum posterior probability:

$$P\ (w^x \mid w^{x-1}, f_x) \tag{5}$$

Temporal continuity and spatial continuity is measured between previous frame labeling and candidate current frame labeling ψ which is the powerful cue for object tracking and represents compactness of rigid moving object.

EXPERIMENTAL RESULTS

Proposed algorithm is implemented in MATLAB and tested on various video sequences. Different sequences, that represent typical situations critical for video surveillance systems because of its capacity in simulating various tracking conditions, including illumination changes, pose variations, occlusions, and distraction.

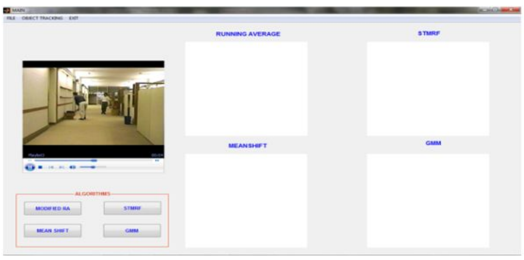


Figure 6. GUI for object detection and tracking system

The result has been presented with qualitative results obtained with the proposed methods. Figure. 6 illustrated a sample of the GUI display of the proposed object detection and tracking system implemented using MATLAB GUI development environment. The opening experiment is started with indoor Hall monitor sequence mp4 with 210 frames of spatial resolution 352×240 attained at a frequency of 25 fps (frames per second) to test the ability of the proposed methods. The view has a room with man entering the room, leaves a bag on the floor and a man comes out of the room. This is easy sequence example with quit constant lighting situation but strong shadows cast by moving objects can be observed in the entire sequence. Based on the proposed moving objects detection and tracking algorithm, the experiments are conducted and results are shown in Figure 7, 8 and will be labeled with different color rectangles. The results of processing time (sec) for different methods are shown in Table 1 and 2.


(a)


(b)


(c)


(d)


(e)

Figure 7. (a) Frame to be tested, Tracking results of the moving objects (b) by Modified RA method (c) by MMS tracking method (d) by GMM tracking method (e) by ST-MRF tracking method

Table 1.The result of processing time (sec) for different methods

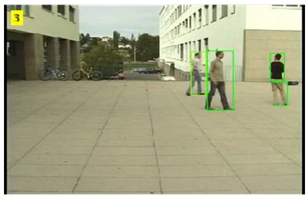
Method	Processing Time (Sec)
Modified RA	12.291505
MMS tracking	100.420769
GMM tracking	56.652406
ST-MRF tracking	67.567901

The second experiment is on a sequence with 275 frames of spatial resolution 360 × 288. In this video, one or more person is tracked moving in the campus, captured at a frequency of 25 fps.


(a)


(b)


(c)


(d)


(e)

Figure 8. (a) Frame to be tested, Tracking results of the moving objects (b) by Modified RA method (c) by MMS tracking method (d) by GMM tracking method (e) by ST-MRF tracking method

Table 2.The result of processing time (sec) for different methods

Method	Processing Time (Sec)
Modified RA	8.291505
MMS tracking	50. 144745
GMM tracking	42.839094
ST-MRF tracking	33.176994

CONCLUSION

In this paper four different visual surveillance methods has been explored and implemented for moving objects recognition, counting number of objects and tracking. GMM, Modified RA, MRF based spatial and temporal information, Camshift tracking has been studied for their performance by using different video datasets. By the experimental test sequences produced with four different methods it is shown that the performance of methods is not unique, robust and changes based on different condition, such as illumination changes, type of object being tracked, shadow, background motion, tracking non-rigid objects, and etc. Upon study of experimental results it is shown that four discussed method is better compared to different methods presented in the literature survey in terms of elapsed time, precision and other metrics.

Result shows feasibility and usefulness of the proposed method however, in some situation identify the moving objects is still difficult. The features extracted in this case are not enough to be used to identify the moving objects. This problem can be improved by a better feature selection method in the future.

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