ISSN:0975-9646

D.B.Bhakte et al, / (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 6 (3) , 2015, 3245-3248

A Study Of Moving Object For Color Detection

Mrs.D.B.Bhakte, Dr.Anilkumar N.Holambe

Department of Computer Science & Engineering Aurangabad
TPCT's COE, Osmanabad, India

Abstract- **A smart visual surveillance system with real time moving object detection, classification and tracking capabilities is presented. The system operates on both gray scale and color video imagery from a stationary camera. The system combines three phases of data processing: moving object extraction, moving object recognition and tracking, and decisions about actions. The extraction of moving objects, followed by object tracking and recognition can often be defined in very general terms. The system is able to detect the natural phenomenon fire in various scenes. Detection of moving object is a challenging task and considered to be a low level task for any video surveillance application. Tracking is required in higher level applications that require the location and shape of object in every frame.**

Keywords- **Video-Based Smart Surveillance, Moving Object Detection, Background Subtraction, Object Tracking, Object Classification.**

I. INTRODUCTION

Moving object detection is the basic step for further analysis of video. It handles segmentation of moving objects from stationary background objects. This not only creates a focus of attention for higher level processing but also decreases computation time considerably. Object classification step categorizes detected objects into predefined classes such as human, vehicle, animal, clutter, etc. It is necessary to distinguish objects from each other in order to track and analyze their actions reliably. Currently, there are two major approaches for moving object classification, shape-based and motion-based methods [1]. Shape-based methods use of the objects' 2D spatial information whereas motion-based methods use temporal tracked features of objects for the classification solution. The next step is tracking, which can be simply defined as the creation of temporal correspondence among detected objects from frame to frame. This procedure provides temporal identification of the segmented regions and generates cohesive information about the objects in the monitored area such as trajectory, speed and direction. The output produced by tracking step is generally used to support and enhance motion segmentation, object classification and higher level activity analysis.

II. MOVING OBJECT DETECTION METHOD

A. Moving Object Detection

Smart video processing has different needs, thus requires different treatment. However, they have something in common: moving objects. Thus, detecting regions that correspond to moving objects such as people and vehicles in video is the first basic step of almost every vision system

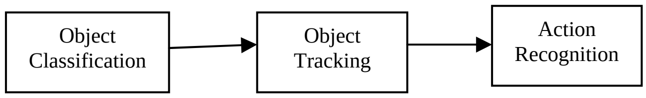

Fig 1: A generic framework for smart video processing.

Since it provides an attention and simplifies the processing on subsequent analysis steps. Due to dynamic changes in natural scenes such as sudden illumination and weather changes, repetitive motions that cause clutter (tree leaves moving in blowing wind), motion detection is a difficult problem to process reliably. The visual surveillance systems' use first step is detecting foreground objects. creates a focus of attention for higher processing levels such as tracking, classification and behavior understanding and reduces computation time considerably since only pixels belonging to foreground objects need to be dealt with. important to pay necessary attention to object detection step to have reliable, robust and fast visual surveillance system. The system diagram for object detection method is shown in Figure 2.

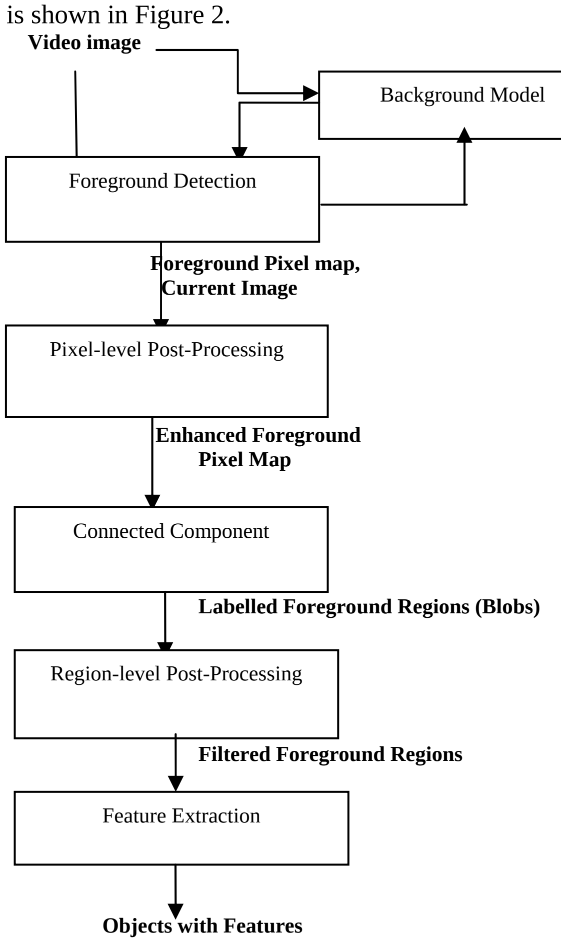

Fig 2: The Object Detection System diagram

Method depends on a six stage process to extract objects with their features in video imagery. The first step is the background scene initialization. In order to evaluate the quality of different background scene models for object detection and to compare run-time performance, The background scene related parts of the system is isolated and its coupling with other modules is kept minimum to let the whole detection system to work flexibly with any one of the background models. Next step in the detection method is detecting the foreground pixels by using the background model and the current image from video. This pixel-level detection process is dependent on the background model in use and it is used to update the background model to adapt to dynamic scene changes. Also, due to camera noise or environmental effects the detected foreground pixel map contains noise. Pixel-level post-processing operations are performed to remove noise in the foreground pixels.

Once we get the filtered foreground pixels, in the next step, connected regions are found by using a connected component labeling algorithm and objects' bounding rectangles are calculated. The labeled regions may contain near but disjoint regions due to defects in foreground segmentation process. some relatively small regions caused by environmental noise are eliminated in the region-level post-processing step. In the final step of the detection process, a number of object features are extracted from current image by using the foreground pixel map. These features are the area, center of mass and color histogram of the regions corresponding to objects.

B. Background Subtraction

A background subtraction is used technique for motion segmentation in static scenes [2]. It attempts to detect moving regions by subtracting the current image pixel-by-pixel from a reference background image that is created by averaging images over time in an initialization period. The pixels where the difference is above a threshold are classified as foreground. After creating a foreground pixel map, some morphological post processing operations such as erosion, dilation and closing are performed to reduce the effects of noise and enhance the detected regions. The reference background is updated with new images over time to adapt to dynamic scene changes. different approaches to this basic scheme of background subtraction in terms of foreground region detection, background maintenance and post processing. In [3] Heikkila and Silven uses the simple version of this scheme where a pixel at location in the current image is marked as foreground if

$$|I_t(x,y) - B_t(x,y)| > \tau \qquad 1.1$$

is satisfied where a predefined threshold is. The background image is updated by the use of an Infinite Impulse Response (IIR) filter as follows:

$$B_{t+1} = \alpha I_t + (1-\alpha) B_t \qquad 1.2$$

The foreground pixel map creation is followed by morphological closing and the elimination of small-sized regions. Although background subtraction techniques perform well at extracting most of the relevant pixels of moving regions even they stop, they are usually sensitive to dynamic changes when, for instance, stationary objects uncover the background (e.g. a parked car moves out of the parking lot) or sudden illumination changes occur.

III. Object Classification Method

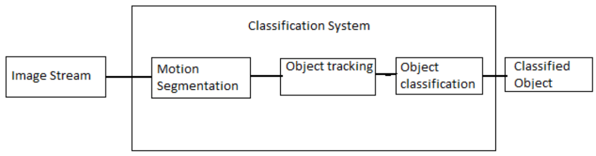

Fig 3: Flow diagram of common classification systems

A system that observes an outdoor environment by a single static camera is developed and tested. The goal is to track objects like walking people or moving vehicles in view of the camera and to determine their type and position. In Figure 1.3 the flow diagram of the system is shown. The motion segmentation step detects the moving objects using the current image in the image stream. This output (the moving objects) is required by the object tracking algorithm that provides the motion history of each object. A particular characteristic of the tracking algorithm is its ability to track objects with complete knowledge about their shape or motion. The output of the tracking algorithm is used by the classification system. Our classification algorithm is a modified version of the system presented in Javed and Shah [4]. The algorithm uses on the motion history of each object and by determining the type of motion. Motion type is determined by any repeated, recurrent motion of the object's shape. This property is used to classify between people and vehicles. The motion segmentation, tracking and classification steps are dependent on each other. Moving regions detected in video may correspond to different objects in real-world such as pedestrians, vehicles, clutter, etc. It is very important to recognize the type of a detected object in order to track it reliably and analyze its activities correctly. Currently, there are two major approaches towards moving object classification which are shape-based and motion-based methods [1]. Shape-based methods make use of the objects' 2D spatial information whereas motion-based methods use temporally tracked features of objects for the classification solution.

A. Shape-based Classification

Shape-based classification is the bounding rectangle, area, silhouette and gradient of detected object regions. The approach presented in [5] makes use of the objects' silhouette contour length and area information to classify detected objects into three groups: human, vehicle and other. The method depends on the assumption that humans are, in general, smaller than vehicles and have complex shapes. Dispersedness is used as the classification metric and it is defined in terms of object's area and contour length (perimeter) as follows:

$$Dispersedness = \frac{perimeter^2}{Area} \qquad 1.5$$

Classification is performed at each frame and tracking results are used to improve temporal classification consistency. The classification method developed by Collins et al. [6] uses view dependent visual features of detected objects to train a neural network classifier to recognize four classes: human, human group, vehicle and clutter. The inputs to the neural network are the dispersedness, area and aspect ratio of the object region and the camera zoom magnification.

B. Motion-based Classification

Some of the methods in the literature use only temporal motion features of objects in order to recognize their classes [7, 8]. In general, they are used to distinguish non-rigid objects (e.g. human) from rigid objects (e.g. vehicles). The method proposed in [7] is based on the temporal self-similarity of a moving object. As an object that exhibits periodic motion evolves, its self-similarity measure also shows a periodic motion. The method exploits this clue to categorize moving objects using periodicity. Optical flow analysis is also useful to distinguish rigid and non-rigid objects. A. J. Lipton proposed a method that makes use of the local optical flow analysis of the detected object regions [8]. It is expected that non-rigid objects such as humans will present high average residual flow whereas rigid objects such as vehicles will present little residual flow. Also, the residual flow generated by human motion will have a periodicity. By using this cue, human motion, thus humans, can be distinguished from other objects such as vehicles.

IV. Object Tracking Method

Tracking is a significant and difficult problem that arouses interest among computer vision researchers. The objective of tracking is to establish correspondence of objects and object parts between consecutive frames of video. It is a significant task in most of the surveillance applications since it provides cohesive temporal data about moving objects which are used both to enhance lower level processing such as motion segmentation and to enable higher level data extraction such as activity analysis and behavior recognition. Tracking has been a difficult task to apply in congested situations due to inaccurate segmentation of objects. Common problems of erroneous segmentation are long shadows, partial and full occlusion of objects with each other and with stationary items in the scene. Tracking in video can be categorized according to the needs of the applications it is used in or according to the methods used for its solution. Whole body tracking is generally adequate for outdoor video surveillance whereas objects' part tracking is necessary for some indoor surveillance and higher level behavior understanding applications. There are two common approaches in tracking objects as a whole, one is based on correspondence matching and other one carries out explicit tracking by making use of position prediction or motion estimation. On the other hand, the methods that track parts of objects (generally humans) employ model-based schemes to locate and track body parts. Some example models are stick figure, Cardboard Model, 2D contour and 3D volumetric models. W4 combines motion estimation methods with correspondence matching to track objects. It is also able to track parts of people such as heads, hands, torso and feet by using the Cardboard Model which represents relative positions and sizes of body parts. It keeps appearance templates of individual objects to handle matching even in merge and split cases. Amer [9] presents a non-linear voting based scheme for tracking objects as a whole. It integrates object features like size, shape, center of mass and motion by voting and decides final matching with object correspondence. This method can also detect object split and fusion and handle occlusions.

V Color Detection

Generally fire regions in video images have similar colors. This suggests the idea of detecting fire region pixels based on their color values. In order to achieve this, we create a fire color lookup function (FireColorLookup) which given an RGB color triple returns whether it is a fire color or not.

The FireColorLookup function uses a fire color predicate formed by several hundreds of fire color values collected from sample images that contain fire regions. These color values form a three dimensional point cloud in RGB color space . The problem now reduces to represent this fire color cloud in RGB color space effectively and deciding on the type of a given pixel color by checking whether it is inside this fire color cloud or not. We decided to represent the fire color cloud by using a mixture of Gaussians in RGB color space. We used the idea presented in [10]. In this approach, the sample set of fire colors F C = {c1, c2, . . . , cn} is considered as a pixel process and a Gaussian mixture model with N (= 10) Gaussian distributions is initialized by using these samples. In other words, we represent the point cloud of fire colored pixels in RGB space by using N spheres whose union almost covers the point cloud. The sample fire color cloud and the Gaussian distributions

VI. Conclusion

Thus we have studied Moving Object Detection, Tracking and Classification and Color Detection for Smart Video Surveillance.

REFERENCES

[1] L. WANG, W. HU, AND T. TAN. RECENT DEVELOPMENTS IN HUMAN MOTION ANALYSIS. PATTERN RECOGNITION, 36(3):585–601, MARCH 2003.

[2] A. M. McIvor. Background subtraction techniques. In Proc. of Image and Vision Computing, Auckland, New Zealand, 2000.

[3] J. Heikkila and O. Silven. A real-time system for monitoring of cyclists and pedestrians. In Proc. of Second IEEE Workshop on Visual Surveillance, pages 74–81, Fort Collins, Colorado, June 1999.

[4] O. Javed and M. Shah, *Computer Vision - ECCV 2002*, ser. Lecture Notes in Computer Science. Springer Berlin/Heidelberg, 2002, vol. 2353/2002, ch. Tracking And Object Classification For Automated Surveillance, pp. 439–443.

[5] A. J. Lipton, H. Fujiyoshi, and R.S. Patil. Moving target classification and tracking from real-time video. In Proc. of Workshop Applications of Computer Vision, pages 129–136, 1998.

[6] R. T. Collins et al. A system for video surveillance and monitoring: VSAM final report. Technical report CMU-RI-TR-00-12, Robotics Institute, Carnegie Mellon University, May 2000.

[7] R. Cutler and L.S. Davis. Robust real-time periodic motion detection, analysis and applications. In IEEE Transactions on Pattern Analysis and Machine Intelligence, volume 8, pages 781–796, 2000.

[8] L. Wixson and A. Selinger. Classifying moving objects as rigid or non-rigid In Proc. of DARPA Image Understanding Workshop, pages 341–358, 1998.

[9] A. Amer. Voting-based simultaneous tracking of multiple video objects. In Proc. SPIE Int. Symposium on Electronic Imaging, pages 500–511, Santa Clara, USA, January 2003.

[10] C. Stauffer and W. Grimson. Adaptive background mixture models for realtime tracking. In Proc. of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, page 246252, 1999.