PERFORMANCE ANALYSIS OF OBJECT DETECTION USING MODIFIED STATISTICAL MEAN METHOD

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Abstract - Moving object detection is low-level, important task for any visual surveillance system. One of the aim of this project is to, to describe various approaches of moving object detection such as background subtraction, temporal difference. A statistical mean technique is used to overcome the problem in previous techniques. We propose a modified statistical mean technique with noise removing process that is computationally fast, by allowing the parallel processing. This proposed technique, overcome the drawbacks of traditional approach of moving object detection. The noise remove process removes the noise caused due to camera, reflectance noise and gives effective moving objects, as well as provides effective results in the change of light during the day and night, the model of background is changed.

Keywords- Moving object detection, background subtraction, temporal differencing, and statistical mean method

I.INTRODUCTION

Video surveillance is a process of analyzing video sequences. It is an active area in computer vision. It gives huge amount of data storage and display. There are three types of Video surveillance activities. Video surveillance activities can be manual, semi-autonomous or fully-autonomous [10]. Manual video surveillance involves analysis of the video content by a human. Such systems are currently widely used. Semi-autonomous video surveillance involves some form of video processing but with significant human intervention.

Perform simple motion detection [5]. Only in the presence of significant motion the video is recorded and sent for analysis by a human expert. By a fully-autonomous system [10], only input is the video sequence taken at the scene where surveillance is performed. In such a system there is no human intervention and the system does both the low-level tasks, like motion detection and tracking, and also high-level decision making tasks like abnormal event detection and gesture recognition. Video surveillance system that supports automated objects classification and object tracking. Monitoring of video for long duration by human operator is impractical and infeasible. Automatic motion detection which can provide batter human attention [9].There is varieties of applications in video surveillance like access Control, person identification, and anomaly detection. Intelligent visual surveillance (IVS) refers to an automated visual monitoring process that involves analysis and interpretation of object behaviors, as well as object detection and tracking, to understand the visual events of the scene [11]. Main tasks of IVS include scene interpretation and wide area surveillance control. Scene interpretation detects and track moving objects in an image sequence. It is used to understand their behaviors.

II. MOVING OBJECT DETECTION

Moving object detection is the basic step for further analysis of video. Every tracking method requires an object detection mechanism either in every frame or when the object first appears in the video. It handles segmentation of moving objects from stationary background objects [3]. This focuses on higher level processing .It also decreases computation time. Due to environmental conditions like illumination changes, shadow object segmentation becomes difficult and significant problem. A common approach for object detection is to use information in a single frame. However, some object detection methods make use of the temporal information computed from a sequence of frames to reduce the number of false detections [16]. This temporal information is usually in the form of frame differencing, which highlights regions that changes dynamically in consecutive frames. Given the object regions in the image, it is then the tracker's task to perform object correspondence from one frame to the next to generate the tracks. This section reviews three moving object detection methods that are background subtraction with alpha parameter, temporal difference, and statistical methods, Eigen Background Subtraction.

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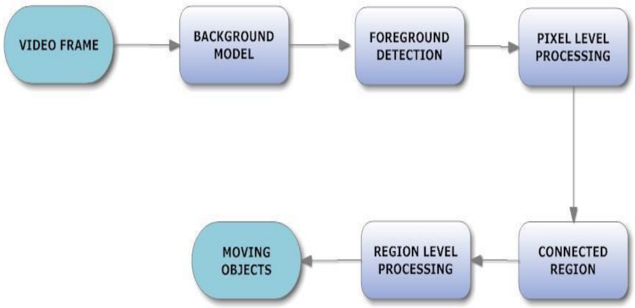

Figure 1: Framework of Moving Object Detection System

The first step is to distinguish foreground objects from stationary background. To achieve this, we can use a combination of various techniques along with low-level image post-processing methods to create a foreground pixel map at every frame. We then group the connected regions in the foreground map to extract individual object features such as bounding box, area, perimeter etc.

2.1 Foreground Detection:

The main purpose of foreground detection is to distinguishing foreground objects from the stationary background. Almost, each of the video surveillance systems uses the first step is detecting foreground objects. This 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 [1].

The first step is the background scene initialization. There are various techniques used to model the background scene. 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 [8].

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 [5]. 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. Hence, some relatively small regions caused by environmental noise are eliminated in the region-level post-processing step [20]. In the final step of the detection process, a number of object features like area, bounding box, perimeter of the regions corresponding to objects are extracted from current image by using the foreground pixel map.

2.2 Pixel Level Post-Processing:

The output of foreground detection contains noise. Generally, it affects by various noise factors. To overcome this dilemma of noise, it requires further pixel level processing. There are various factors that cause the noise in foreground detection such as:

Camera Noise: Camera noise presents due to camera's image acquisition components. This is the noise caused by the camera's image acquisition components. This noise is produce because of the intensity of a pixel that corresponds to an edge between two different colored objects in the scene may be set to one of the object's color in one frame and to other's color in the next frame [16].

Background Colored Object Noise: The color of the object may have the same color as the reference background. It's difficult to detect foreground pixels with the help of reference background [16].

Reflectance Noise: Reflectance noise is caused by light source. When a light source moves from one position to another, some parts in the background scene reflect light [16].

We can use low pass filter and morphological operations, erosion and dilation, to the foreground pixel map to remove noise that is caused by the items listed above [3]. Our aim in applying these operations is removing noisy foreground pixels that do not correspond to actual foreground regions, and to remove the noisy background pixels near and inside object regions that are actually foreground pixels. Low pass filters are used for blurring and for noise reduction. Blurring is used in pre-processing tasks, such as removal of small details from an image prior to large object extraction, and bridging of small gapes in lines or curves. Gaussian low pass filter is use for pixel level post processing [8].A Gaussian filters smoothes an image by calculating weighted averages in a filter co-efficient [10]. Gaussian filter modifies the input signal by convolution with a Gaussian function.

2.3 Detecting Connected Regions:

After detecting foreground regions and applying post-processing operations to remove noisy regions, the filtered foreground pixels are grouped into connected regions. After finding individual regions that correspond to objects, the bounding boxes of these regions are calculated.

2.4 Region Level Post-Processing:

As pixel-level noise removed, still some artificial small regions remain just because of the bad segmentation. To remove this type of regions, regions that have smaller sizes than a pre-defined threshold are deleted from the foreground pixel map. Once segmenting regions we can extract features of the corresponding objects from the current image. These features are size, center-of-mass or just centroid and Bounded Area of the connected component. These features are used for object tracking and classification for the further processing in event detection.

2.5. Background Subtraction with Alpha:

Object detection can be achieved by building a representation of the scene called the background model and then finding deviations from the model for each incoming frame. Any significant change in an image region from the background model signifies a moving object. The pixels constituting the regions undergoing change are marked for further processing. Usually, a connected component algorithm is applied to obtain connected regions corresponding to the objects. This process is referred to as the background subtraction [6].

Heikkila and Silven [6] presented this technique. At the start of the system reference background is initialized with first few frames of video frame and that are updated to adapt dynamic changes in the scene. At each new frame foreground pixels are detected by subtracting intensity values from background and filtering absolute value of differences with dynamic threshold per pixel [8] .The threshold and reference background are updated using foreground pixel information. 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 initialized period [6]. The pixels where the difference is above a threshold are classified as foreground. After creating 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. Pixel is marked as foreground if the inequality is satisfied

$$| I_t \quad -_t (x , \ y) | > T \qquad (1)$$

Where T is a pre-defined threshold.

The background image Bt

is updated by the use of a first order recursive filter as shown in equation

$$Bt+1 = \eta \ It + (1 - \eta) \ Bt \ a \qquad (2)$$

Where η is an adaptation coefficient. The basic idea is to provide the new incoming information into the current background image. After that, the faster new changes in the Scene are updated to the background frame. However, formed behind the moving objects. The foreground pixel map creation is followed by morphological closing and the elimination of small-sized regions.

2.6. Statistical Methods:

To overcome the shortcoming of the basic background methods, statistical Methods are used. Statistical methods are used to extract change regions from background. These statistical methods are mainly inspired by the background subtraction methods. It uses characteristics of individual pixels of group of pixels to construct advance background model. That statistics of background are updated dynamically during processing. At each frame this method keeps and updates dynamic statistics of pixels that belongs to background image process [3]. Foreground pixels are background model. This approach is becoming more popular due to its reliability in scenes that contain noise, illumination changes and shadow [8]. One of the example of statistical methods, Stauffer and Grimson [5] described an adaptive background mixture modeled by a mixture of Gaussians which are updated on-line by incoming image data. In order to detect whether a pixel belongs to a foreground or background process, the Gaussian distributions of the mixture model for that pixel are evaluated.

2.7. Temporal Differencing:

Temporal differencing method uses the pixel-wise difference between two or three consecutive frames in video imagery to extract moving regions. It is a highly adaptive approach to dynamic scene changes however, it fails to extract all relevant pixels of a foreground object especially when the object has uniform texture or moves slowly [3]. When a foreground object stops moving, temporal differencing method fails in detecting a change between consecutive frames and loses the object. Let $I_n(x)$ represent the gray-level intensity value at pixel position x and at time instance n of video image sequence I, which is in the range [0, 255]. T is the threshold initially set to a pre-determined value. Lipton et al.[3] developed two-frame temporal differencing scheme suggests that a pixel is moving if it satisfies the following [3]:

$$| I_n \quad I_{n\ 1} (x) | > T \qquad (3)$$

This method is computationally less complex and adaptive to dynamic changes in the video frames. In temporal difference technique, extraction of moving pixel is simple and fast. Temporal difference may left holes in foreground objects, and is more sensitive to the threshold value when determining the changes within difference of consecutive video frames [5]. Temporal difference require special supportive algorithm to detect stopped objects.

III. SIMULATION RESULTS

The simulated results of moving object tracking using Matlab has been shown below in the figure2&3

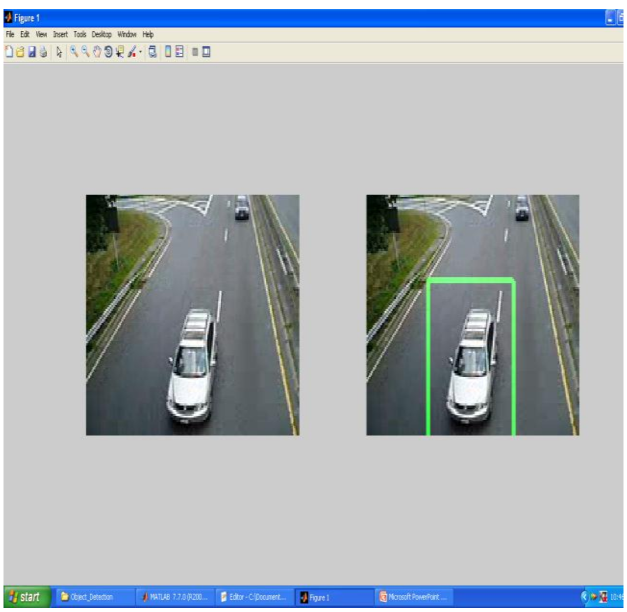

Figure 2: Motion of the moving object

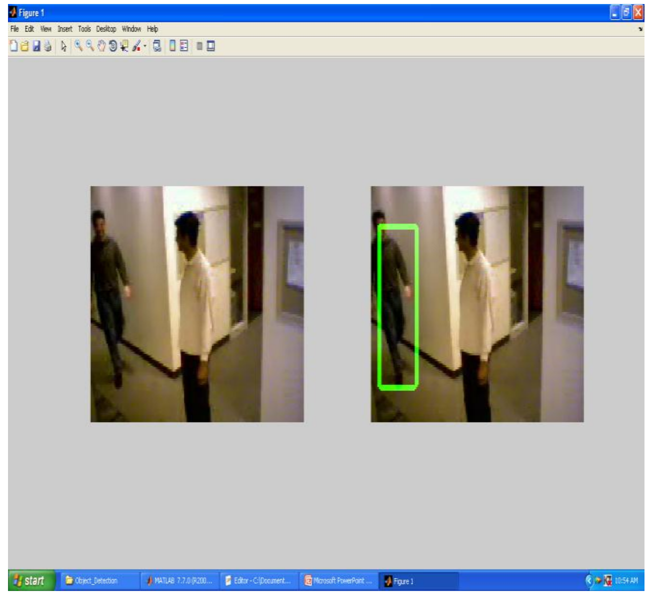

Figure 3: Tracking of the moving person

In the figure2, modified statistical mean method is used to track the moving vehicle. In figure3, the same algorithm has been used to track the moving person

PERFORMANCE ANALYSIS

Video	Processing Time per frame	Number of frames	False Negative Rate	Tracking Accuracy
Traffic.avi	0.1198	120	0.1917	0.8083
Vipmen.avi	0.0818	283	0	0.98

In the above table Performance Parameters Like Processing Time Per Frame, Number Of Frames, False Negative Rate, Tracking Accuracy are analysed for both the videos.

TRACKING PARAMETERS

Performance Parameters	Proposed Method	Multiple Candidate Regeneration
Features used	Temporal Differencing	Candidate features
Time cost	0.08ms	0.1ms
Image Resolution	640*480	640*480
Tracking Accuracy	0.98	0.92

In comparison with Multiple Candidate Regeneration (MCR) algorithm, tracking parameters like time cost and tracking accuracy are improved in the proposed method

IV. CONCLUSION & FUTUREWORK

To analyze images and extract high level information, image enhancement, motion detection, object tracking and behavior understanding researches have been studied. In this paper, we have proposed a real-time object tracking system, which is based on the modified statistical mean method mechanism and we have studied and presented different methods of moving object detection, used in video surveillance. We have described background subtraction with alpha, temporal differencing, statistical methods. Detection techniques into various categories, here, we also discuss the related issues, to the moving object detection technique. The drawback of temporal differencing is that it fails to extract all relevant pixels of a foreground object especially when the object has uniform texture or moves slowly. We presented detail of background subtraction method in deep because of its computational effectiveness and accuracy. This article gives valuable insight into this important research topic and encourages the new research in the area of moving object detection as well as in the field of computer vision. Here research on object tracking can be classified as point tracking, kernel tracking and contour tracking according to the representation method of a target object. In point tracking approach, statistical filtering method has been used to estimating the state of target object. we propose a unified approach of tracking and recognition with matching of stored video in the database and noise removing process that is computationally fast, by allowing the parallel processing for object detection. This proposed technique overcomes the drawbacks of traditional approach of moving object detection.

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