International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 07 Issue: 05 | May 2020 www.irjet.net p-ISSN: 2395-0072

A Review on Moving Object Detection Techniques

Akanksha[1], Nirupma Tiwari[2]

[1]Student, Department of CSE/IT, SRCEM Banmore, Gwalior, India
[2]Professor, Department of CSE/IT, SRCEM Banmore, Gwalior, India

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Abstract: *Detecting citizenry accurately in visual surveillance systems is critical for different application areas which include abnormal event detection, human pace characterization, congestion audit, person identification, gender qualification and fall detection for aged people. The foremost step of the detection process is to find an object that is in motion. Object spotting could be executed using background subtraction, optical flow, and spatio-temporal filtering technique. Once detected, a moving object could be classified as human being using shape-based, motion-based, and texture-based features. An extensive survey of comparison about available techniques for detecting human beings in surveillance videos are explained in this paper.*

Key words: Object detection, background subtraction, optical flow, frame difference, classification methods.

1. INTRODUCTION:

Object detection is the technique of searching the moving entities inside the image sequences. Detection is the initiative towards tracking the moving object within the video. Object classification is the next important step towards tracking. Firstly, for absolute object detection, an adequate and effective scheme is proposed to take out cast shadows/highlights with error corrections supported a conditional morphological reconstruction. Over the recent years, spotting human beings in a video shot of a surveillance system is appealing more attention due to its wide selection of applications in abnormal event detection, human gait characterization, person counting within people gathering, person identification, gender classification, fall detection for aged people, etc.

The shots obtained from a surveillance video are commonly of low resolution. Nearly all the scenes taken by a non-moving camera are with fewest change of background. Objects in outdoor surveillance are often detected in far fields. Most existing digital video surveillance systems believe human observers for detecting specific activities during a real-time video scene. Even so, there are limits in the capacity of humans to supervise concurrent events in surveillance displays.

The detection process can be classified in two steps: object detection and object classification. Object detection follows approaches likewise background subtraction, optical flow and spatio-temporal filtering. Background subtraction is a popular method for object detection where it attempts to detect moving objects from the difference between the present frame and a background frame in a pixel-by-pixel or block-by-block fashion.

The main objective of this paper is to supply a generic review on studies lead within the area of human detection process of a visual surveillance system. A flow chart of the human detection process is presented in figure below.. Various available techniques are reviewed. Details of several benchmark databases are presented. Several major applications are reviewed. We present a review and analyses of recent developments and highlight future directions of research within the area of human detection in visual surveillance. Future directions are discussed. The main contributions of this paper are as follows: Object detection and object classification are discussed during a clearly organized manner consistent with the general framework of visual surveillance. This will help readers, most probably newcomers to the present area, to understand the state of the art in visual surveillance so that the scope of its application in the real world.

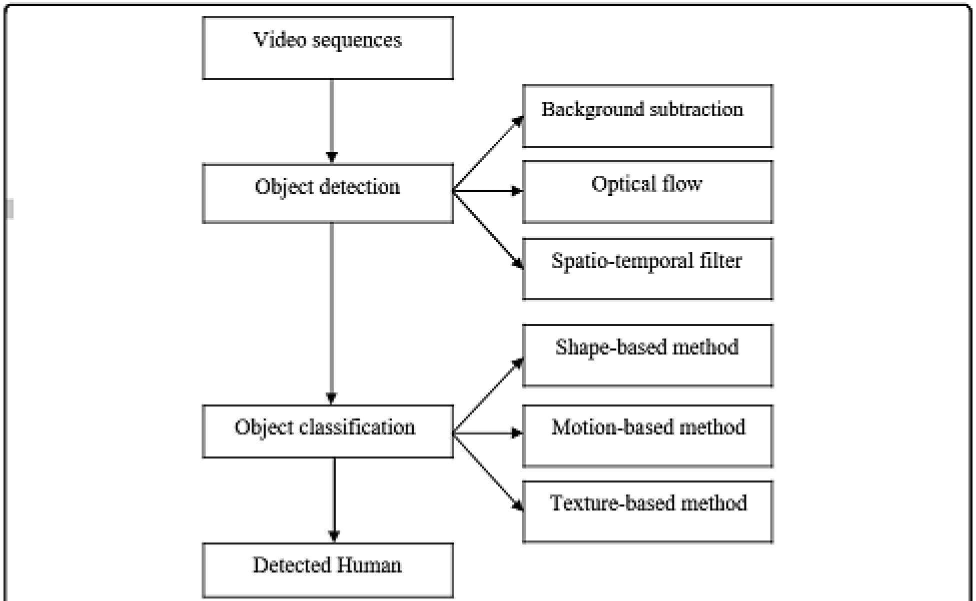

Figure 1 Flow chart of human detection.

2. Techniques:

Human detection during a smart closed-circuit television aims at making distinctions among moving objects in a video sequence. The successful rendering of upper level object motions highly depends on the preciseness of object detection. The detection process occurs in two steps:

1. Object detection
2. Object classification

2.1. Object detection:

An object is usually spotted by segmenting motion during a video image. Most constituted approaches for object detection are background subtraction, optical flow and spatio-temporal filtering method. They are outlined within the ensuing subsections.

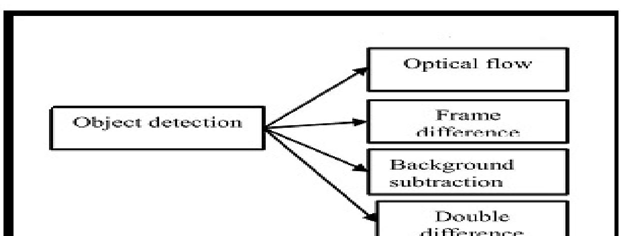

Figure 2: Object Detection techniques.

2.1.1. Background subtraction: Background subtraction could also be a well-liked method to detect an object as a foreground by segmenting it from a scene of a surveillance camera. The camera could be fixed, pure translational or mobile in nature. Background subtraction attempts to detect moving objects from the difference between this frame and thus the frame of reference during a pixel-by-pixel or block-by-block fashion. The frame of reference is usually mentioned as 'background image', 'background model' or 'environment model'. An honest background model must be adaptive to the changes in dynamic scenes. Updating the background information in regular intervals could do Background subtraction is that the foremost generally used method for moving object detection. It are often of two types firstly by considering first frame because the frame of reference or background image. Secondly by considering the standard of „n" frames because the background image. During this background subtraction method every pixel of on-going frame is subtracted with the pixels of the background image. The equation (1) and (2) shows the background subtraction method for the first frame as the background image.

B(a, b)= A(a, b) (1)

where B(a, b) represents background image pixel by pixel. The background subtraction method split the video frames into foreground and background objects, where the foreground object is discovered by matching this frames A(a, b) through the background image B(a, b). The equation used is

C(a,b) = {1 if B(a,b)-A(a,b)>threshold (2)
0 otherwise

where C(a, b) is that the foreground pixel, threshold value are often set manually or can selected automatically as per video input. This method consumes less memory. Accuracy of detection is moderate. But it'll not suit for multimodal backgrounds. results of the background subtraction methods are as depicted in figure 3.

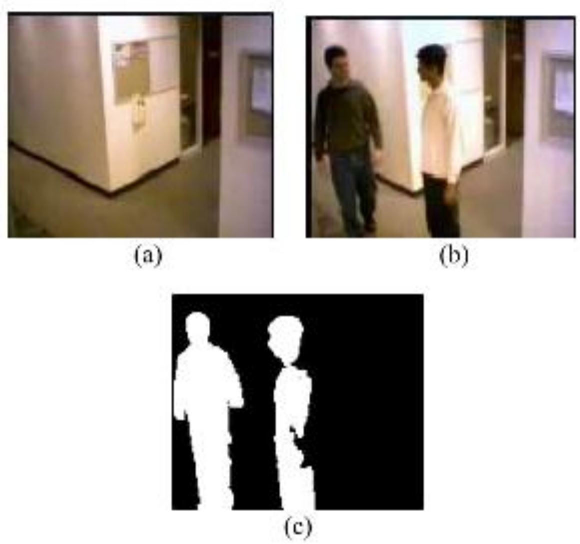

Figure 3: Background subtraction result for hall monitoring video (a) Background model (b) Current frame #89 (c) Resulting frame.

2.1.2. Optical Flow: Optical flow could also be a substitute standard kind of object detection during which the optical flow arena of the image is calculated and grouping of these arenas is completed rendering to appearances of the image. The motion among dual video frames occupied at time t and t+ δt at every individual location is calculated inside the optical flow process. This technique gives the broad information regarding the movement of the thing. And also detects the thing accurately compared thereto of background technique. This method is not widely used because of its huge calculation and it's extremely sensitive to noise. It's not good for real-time occlusion conditions.

2.1.3. Frame difference: The frame difference scheme is additionally mentioned because the temporal difference, during which each current frame pixel is subtracted with its prior frame pixel. If the transformation is superior to the manually set threshold value than that pixel is reflected because the foreground pixel else the pixel is reflected because the background pixel. Equation (3) presents the way for frame difference

$$F(a,b) = \begin{cases} 1, & \text{if}(I_n(a,b) - I_{n+1}(a,b) > T \\ 0 & \text{otherwise} \end{cases} \quad \text{eq}(3)$$

Where I_n is that the prior frame pixel and In+1 is that the pixel value of this frame. T will be the sting value which is manually defined by the user. Calculation of this process is small scaled and lenient . For non-static environments, it's extremely challenging to understand the whole outline of the moving entity. So it's extremely cumbersome to urge accuracy. Results of the frame difference methods are shown in figure 4.

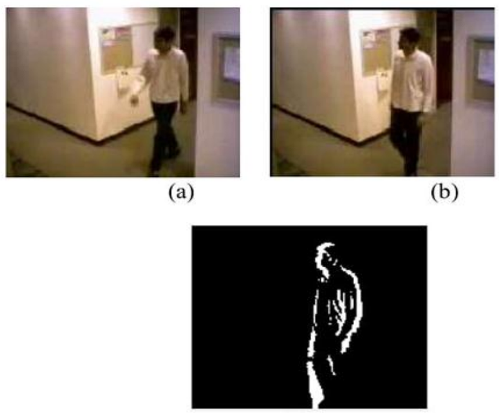

Figure 4: Frame difference result of hall monitoring video. (a) frame #47 (b) frame #48 (c) Resulting frame.

2.1.4. Double difference: The frame difference scheme is additionally mentioned because the temporal difference, during which each current frame pixel is subtracted with its prior frame pixel and immediate next frame pixel. If the renovation is kind of defined threshold value then that pixel is reproduced because the foreground pixel else, the pixel is replicated because the background pixel.

$$C_n(a,b) = D_n(a,b) - D_{n+1}(a,b) \quad (4)$$

$$C_{n+1}(a,b) = D_{n+1}(a,b) - D_{n+2}(a,b) \quad (5)$$

$$DD(a,b) = C_n(a,b) - C_{n+1}(a,b) \quad (6)$$

Where Cn(a, b) is that the resulting foreground pixel. Dn denotes this frame of the video sequence. Dn+1 indicates subsequent frame. Similarly in equation (5) Dn+1 is that this frame, Dn+2 is that subsequent frame. Finally DD(a, b) specifies as output of double difference frame pixel value.

$$R(a,b) = \begin{cases} 1, & \text{if } DD(a,b) > Th \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

where Th is that the edge value. If the pixel of absolutely the difference is larger than the sting value than the pixel is reflected as black otherwise it's reflected as white pixel. This method produces accurate movement of the objects. But it consumes large memory and it takes longer to calculate.

2.2. Object Classification:

The quoted moving object could be of different types like human, vehicles, trees, floating clouds, birds and other non stationary objects. Strategies to represent moving objects are depicted in figure5.

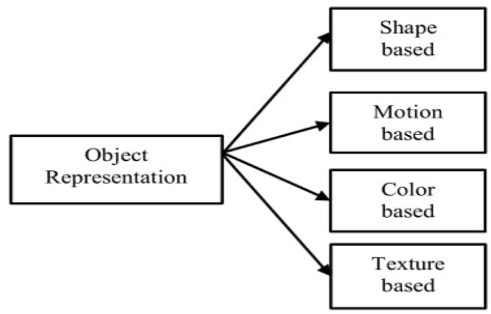

Figure 5: Object Representation Methods.

2.2.1. Shape-based classification: Unalike imageries shape data of motion regions like Depictions of points, Blob and boxes are approachable for categorizing objects in motion. Combination of image and scene object restraint like blob region of image, misleading feature ratio of blob rectangle box area will form the input feature for network of images. Ordering is executed on every blob at each frame and outputs are retained as histograms.

2.2.2. Motion-based classification: Non rigid object motion exemplifies an interrupted asset, since it's been used as a strong indication for dynamic object organization. Optical flow process could also be a convenient method for object grouping. Residual flow could even be cast-off to scrutinize inflexibility and periodicity of moving objects. We can predict that some unbending entities may explain atomic or atomlike lasting flow whereas nonrigid objects as citizenry have complex average residual flow and even exhibit an intermittent component.

2.2.3. Texture-based classification: Texture based system counts the existences of gradient alignment in confined parts of a picture , then calculates the knowledge on a condensed grid of consistently opened up cells and uses overlapping narrow disparity standardization for enhanced accuracy. Texture features are vital to live the intensity divergence of surfaces and are discerning with object pattern demonstration.

3. LITERATURE REVIEW:

Tie Liu (2010) gave an alternate approach for spotting objects by template matching from the massive database collection. The go up was appropriate for multi-scale contrast backgrounds and used a color spatial method to detect objects. But this approach was proved to fail to detect multiple objects in a given user scenario and also a failure when the objects were in non-linear motion. This problem of failed detections was effectively overcome in the proposed system by training the system to identify the objects through an effective system learning technique and the objects in non-linear motion are tracked using the proposed particle grouping approach.

Scott McCloskey et al (2011), provided a kernel based method to detect objects even in the presence of partial occlusions. The blur kernel method was used to examine large partial occlusions when the foreground object was out of focus. The key merit of this method was that it provided an exact solution for partial occlusions through background mapping. However, the possibility was only through a gradation of hypothesis made on background intensity such as the static nature of the background, the illumination changes, the color of the objects, etc. Also it had been found viable just for self occlusion. A better solution to this problem was to utilize a lively appearance model to detect the objects occupation dynamically changing background. And also the distance formulation technique based on bus topology is used to detect the presence of partial and complete occlusions with high accuracy in proposed MLP based object tracking.

Aniruddha Kembhavi et al (2011), gave an object detection method using color probability maps to capture the colour statistics of vehicles and their surroundings. Partial Least Squares (PLS) to project the data onto a much lower dimensional subspace was the method highlighted and executed. The advantage of this method was that PLS enables in the selection of a small subset of feature data. But the detector's performance goes down with 38 decreasing illumination and acquisition angle. The proposed MLP based object tracking system is made racy by optimum selection of unique features and also by performing the adaptive boosting strong classification method.

Liyuan Li et al (2003), contributed a method for detecting foreground objects in non stationary complex environments containing moving background objects. A Bayes decision rule was used for classification of background and foreground changes supported inter-frame color co-occurrence statistics. An approach to store and fast retrieve color co-occurrence statistics was also established. In this method, foreground objects were detected in two steps. First, both foreground and background changes are excerpted using background subtraction and temporal differencing. The periodic background changes were then diagnosed using the Bayes decision 39 rule based on the learned color co-occurrence statistics. Both short-term and long term strategies to learn the frequent background changes were used.

An algorithm centralized on holding stationary foreground regions as said by Álvaro Bayona et al (2010), which was useful for applications such as the detection of abandoned/stolen objects and parked vehicles. This algorithm used two steps. Firstly, a sub-sampling scheme based on background subtraction techniques was implemented to obtain the stationary foreground regions. This detects foreground changes at different time instants in the same pixel locations. This was done by using a Gaussian distribution function. Secondly, some modifications were introduced on this base algorithm such as thresholding the previously computed subtraction. The main aim of this algo was to reduce the measure of stationary foreground detected.

The background subtraction method by Horprasert et al (1999), was able to manage with local illumination changes, such as shadows and highlights, even globe illumination changes. In this method, the background model was statistically modeled on each pixel. A computational color mode, including brightness deformation and chromaticity contortion was used to distinguish shading background from the ordinary background or moving foreground objects. The background and foreground subtraction method used the following approach. A pixel was modeled by a 4-tuple [Ei, si, ai, bi], where Ei- a vector with expected color value, si - a vector with the standard deviation of color value, ai - the variation of the brightness distortion and bi was the variation of the chromaticity distortion of the ith pixel. In the next step, the difference between the background image and the current image was evaluated. Each pixel was then divided into four categories: original background, shaded background or shadow, highlighted background and moving foreground object.

Schweitzer et al (2011), derived an algorithm which used both upper and lower bound to detect 'k' best matches. Euclidean distance and Walsh transform kernels are used to calculate match measure. The positive things contain usage of priority queue which improves quality of decision as to 40 which bound-improved and when good matches exist inherent cost was main and it improved performance. But there were brakes like deficit good matches that lead to queue cost and the arithmetic operation cost to higher. The proposed methods don't use queue thereby avoiding the queue cost rather than using template matching.

Qian Zhang et al. 2011 proposes adaptive background penalty with occlusion reasoning to separate the foreground regions from the background in the first frame. Multiple cues are employed to fragment individual objects from the group. To spread the segmentation through video, each and every object area is independently tracked by uncertainty refinement and motion compensation and therefore the motion occlusion is tackled as a layer transition.

In the year 1994, S. H. Courellis and V. Z. Marmarelis [170] introduced an artificial neural network for motion detection with non-linear spatio-temporal features. System structure was fairly simple and straightforward, and the process was carried out in three layers. The input to the network is moving spots and edges with a number of velocity profiles. The network uses the principle of directional selectivity to diagnose the direction of motion, by selectively activating output nodes. Further in 1995 [163] Scott A. Nichols and W. Brian Naylor developed the Advanced Exterior Sensor (AES) program for highly adaptive video motion detection and tracking.

4. CONCLUSION:

Within diverse detection methods Background subtraction is the easiest method which offers complete information. New researchers prefer texture and color for representing objects. Object tracking is often achieved via numerous algorithms which use point, shape, and feature techniques. We have some efficient algorithms which can reduce calculation time. And also decreases the value, used for tracking the entities for various kinds of the sequence of frames consisting of differentiated appearances. These are the basic techniques which are commonly used. These techniques work well for static cameras. Despite the very fact that amid the foremost recent centuries, has seen a big advancement against object detection and tracking.

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