# A Survey on Different Background Subtraction Method for Moving Object Detection



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## ABSTRACT

In computer vision application, detecting moving object in a video sequence is considered as a critical task as a moving object detection is very necessary for many video applications like video surveillance, traffic monitoring, object tracking etc. Many different methods have been proposed in recent years to differentiate the moving object and the background. One of the simplest method for detecting moving object from a video sequences is the background subtraction algorithm where the current frame is subtracted from the reference image or background model. In this paper, we review the different background subtraction algorithm developed in recent years.

**Keywords**— Background Modelling, Foreground Detection, Moving Object Detection.

## 1. INTRODUCTION

Analysis and understanding of video sequences become an active research area in the field of computer vision since the last few years due to its growing importance in many video analysis applications like video surveillance, multimedia application is to detect the moving object in the video scene. So the first basic operation is to differentiate the foreground object and background object which can be done in many ways depending upon the data available and whether the object is in motion or not. Detection of moving object from a video sequences does not need any prior information but needs only the multiple consecutives frames of the video sequences. The method mainly used in moving object detection are frame subtraction method, optical flow method, and background subtraction method.

Background subtraction is one of the simplest methods for identifying the moving object from a video sequence. It is a crucial step in many computer vision system. Basically, a background subtraction algorithm needs a stable background which is very complicated in real time application. In this method, the video sequence is divided into different video frames where each video frame is subtracted from a reference or background model. The pixels in the current frame that is different from the background model are considered to be the moving object. For object localization and tracking purpose the foreground object are further processed. As the background subtraction is the first basic step in many computer vision applications, it is important that the extracted foreground pixels must accurately correspond to the moving object of interest. Background subtraction method is very simple algorithm but very sensitive to the change in external environment and it has a poor anti-interference. This method can almost provide the complete object information if the background is known. There are many challenges in developing a good background subtraction algorithm [1]. A background subtraction algorithm must be robust against illumination, should avoid detecting background which is nonstationary like moving leaves, rain, shadow etc. and its internal background model should react quickly to change in background.

The remainder of the paper is outlined as follows. Section II describes the background subtraction algorithm step by step. Section III review various papers related to background subtraction method. Section IV concludes the paper.

## 2. BACKGROUND SUBTRACTION ALGORITHM

Many background subtraction algorithms have been proposed in recent years but identifying moving object in a complex environment is still a challenging problem. Most of them follow a simple flow diagram as shown in Figure 1. Background subtraction algorithm consists of four major steps. They are pre-processing, background modelling, foreground detection, and data validation.

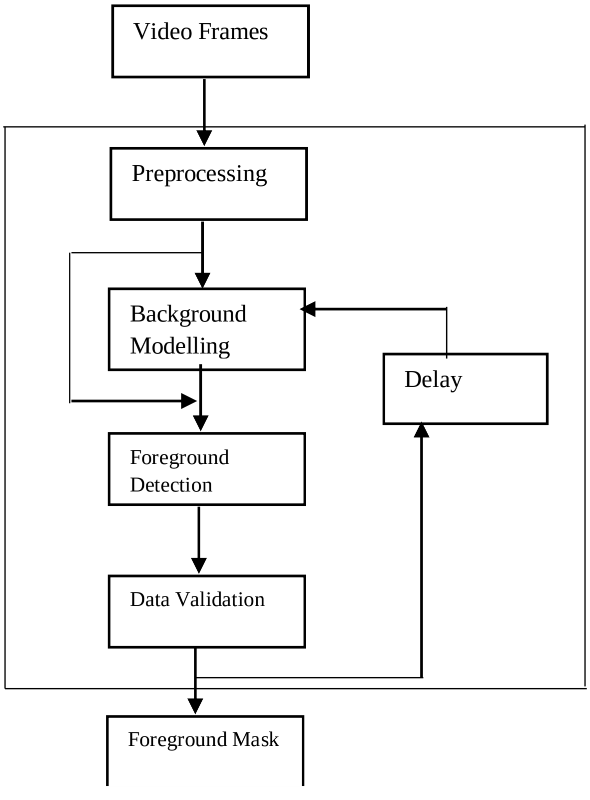


Figure1: Background Subtraction Algorithm

### 2.1 Preprocessing

Preprocessing step changes the raw input video into a format that can be further processed by subsequent steps of background subtraction algorithm. It consist of a collection of simple image processing tasks like removal of noise, smoothening and removing transient environmental noise [1]. This step involves removal of noise, such as rain and snow captured in outdoor camera. To data processing rate is reduced by using the size of the frame and frame-rate reduction are commonly. In the case of multiple cameras, before background modelling image registration between successive frames or among different cameras is needed [2, 3].

### 2.2 Background Modelling

Background modelling is one of the most important steps of background subtraction algorithm. The main objective of background modelling is to capture the information about the video frame sequence and updating the information to know the change in the background scene. To detect the foreground, background modelling techniques is very much necessary. Many background modelling technique has been proposed to identify moving object in video sequences over the past few years. Most of the existing background modelling techniques follow the same scheme [4, 5].The first frame or previous frame is used to build a background model. The background model is then compared with the current frame to detect the foreground object then the background model is updated finally. Background modelling is divided into two methods: parametric and non-parametric methods. The parametric model uses an adaptive and statistical background model to detect changes in the video scene by using a multi-dimensional Gaussian. The pixel value in the current frame is compared with the background model in order to classify the pixel as a background. Gaussian model is one of the most famous pixel-based parametric methods .The main task of the non-parametric model is to accurately model the background process non-parametrically. This model should adapt faster to change in the background process and be able to detect targets with high sensitivity which is done by capturing very recent information about the video sequences and continuously updating the information to capture fast changes in the scene background. This non –parametric model estimates the probability of observing pixel value intensity value based on a sample of intensity value.

### 2.3 Foreground Detection

In foreground detection, the input video frame is compared with the background model created in the above step to identify the foreground pixels. One of the most common approaches for foreground detection is to check whether the pixel in the input frame is significantly different from the corresponding background model.

### 2.4 Data Validation

The data validation step is to improve the candidate foreground mask based on the information obtained outside the background model.

## 3. LITERATURE SURVEY

Wren et. al [6] proposed the simplest background subtraction technique by modelling the stationary background at each pixel location with a single 3D Gaussian distribution [7, 8]. Once the background is modeled, every pixel of the input frame that deviates from the model is considered as the foreground pixels. But using a single Gaussian function is not a good model as it cannot deal with an actual dynamic background.

Stauffer and Grimson [9, 10] proposed the Gaussian mixture model (GMM) to eliminate the effect of background texture cause by some environmental condition [8]. In Gaussian mixture model, every pixel is modeled with a mixture of K Gaussian's function. In this model, the current frame is compared with the background model with every Gaussian in the model until a matched Gaussian is found. If the match is found the mean and variance of the match Gaussian is updated.

P. Spagnolo et. al[11] proposed a reliable background subtraction method that integrates temporal image analysis with reference background model. The author addresses the problem of moving object detection using background subtraction, as solving such problem is important in many video analysis applications like video surveillance, traffic monitoring, sports activity etc.

Zivkovic [12, 13] proposed an adaptive GMM algorithm using Gaussian mixture probability density. In this method, recursive method is used to update the parameter efficiently and to select the appropriate number of components for each pixel simultaneously. In this paper, the usual pixel-level approach is analysed.

Lee et. al [14] proposed an effective method to improve the convergence rate without changing the stability of Gaussian mixture model [15] which is achieved by replacing the global static retention factor with an adaptive learning rate. Combining this method with a statistical framework for background subtraction will lead to an improve segmentation performance.

Shimada et. al [16] proposed an algorithm to improve the accuracy and reduce the computational time by creating a background model of a non-stationary scene. The author used a dynamic Gaussian component to control the Gaussian mixture model. This method can automatically change the number of Gaussian in each pixel.

Oliver et. al [17] proposed a non-pixel-level method which uses an eigenspace to model the background. Most of the background subtraction approach of use pixel-based statistics. The method has the ability to learn the background model even when video sequences contain moving foreground objects(robust o unstable background). This approach is less sensitive to illumination. By projecting the current image to the eigenspace, the foreground objects are detected.

Chien et. al [18] proposed a foreground object detection method where threshold based decision method is used. They assume the camera noise to be the zero-mean Gaussian distribution which is the only factor affecting the threshold. But this assumption is hard to satisfy in practice.

Kim et. al [19, 20] proposed a fast algorithm for background modelling and subtraction using codebook. To construct a background model, the codebook algorithm uses a clustering technique where each sample background values at each pixel are clustered into the set of codewords. The background is encoded into the codebook using pixel by pixel basis. The proposed method can handle video containing moving background, illumination variation. This method achieved a robust detection for compressed video.

  

Wang et. al [21] proposed a robust and efficient background modelling method. In this method, the statistical background model at each pixel is used to compute the sample consensus (SACON) of the background sample. SACON is highly effective in background modelling and subtraction. To detect the foreground object, SACON uses both color and motion information.

Elgammal et. al [22, 23] proposed a novel method using kernel density estimation to construct a nonparametric background model. In this method, the pixel in the current frame is matched not only to the background model but also to the nearby pixel location of the background model. The method can handle situations small movement in the background scene.

Russell et. al [24] proposed a block-based incremental background modelling technique to distinguish foreground object from the background model. In this technique, each image region of the incoming frames are compared with a fixed size database of background, if the incoming block is distant more than a certain threshold then it is deemed to be background in the current frame.

Heikkila et. al [25] proposed a novel and efficient background modelling technique using a discriminative texture feature called the local binary pattern (LBP) [26]. Each pixel is modelled as a group of adaptive local binary pattern histogram that is calculated over a circular region around the pixel.

Mason et. al [27] proposed a novel method to identify regions of the video frame that contain moving objects. In this method, the background model is developed from the initial frame of the video sequence by dividing it into equally sized blocks. For each block in the background grid and the corresponding block of the current frame, histogram is calculated. A comparison between the background and current frame is done on the block by block basis comparing their histogram to know the foreground objects.

Lui et. al [28] proposed a new background modelling approach based on the binary descriptor. This approach constructs the background instances using binary descriptors. It is robust against lighting changes and dynamic background in the environment.

Haung et. al [29] proposed a method of background modelling, where the background is modelled as a sample of the binary descriptor which replaces parametric distributions. Unlike pixel-based method, region-based method, it can reduce the effect of noise but they can get only the rough shapes of foreground objects.

Toyama et. al [30] proposed Wallflower algorithm to solve a problem that occurs at various spatial scales. The algorithm processes images at pixel level, region level, and frames level. The algorithm maintains models of the background for each pixel at the pixel level, the region level components fills in homogeneous regions of foreground objects and the frame level component detects sudden, global changes in the image and swaps in better approximations of the background.

S Azmat et. al [31] proposed an algorithm that focuses on exploiting fine grain data parallelism and optimizing memory access pattern to target a low-cost adaptive background modelling algorithm on low power GPUs. This algorithm has less computational and memory cost but has a comparable accuracy with the Gaussian mixture model.

Haiying et. al [32] proposed a modified Gaussian mixture background model based on the spatial-temporal distribution which uses time and space distribution information. The main concept of this method is based on the optimization of the Gaussian mixture model and combine spatial information which can be obtained by neighbourhood random sampling to create an enhance background model.

Maodi Hu et. al [33] proposed an Adaptive Background Modelling framework, in which multi-channel background model is constructed by Gaussian filters with different variance and by employing boosting like updating rule for channel selection.

Li Sun et. al [34] proposed a new approach for modelling background in complex scenes. To build a background model, the author takes advantage of both temporal and spatial information that can preserve multiple modes. Multiple modes in the background model can reflect the possible temporal variations for the pixel that lie in the background area.

Lu Yang et. al [35] proposed a Pixel-to-Model background modelling method in complex scenes. Each pixel is represented in terms of its local context descriptors. To classify the potential background pixel, Pixel-to-Model distance is employed. To update the background model in the space of local descriptors efficiently, the Pixel-to-Model distances is used .

Soo et. al [36] proposed a fast and reliable method for moving object with moving cameras. A small size background model whose size is the same as the input frame is constructed by a single spatio-temporal distributed Gaussian. This method solves the problem of background adaptation, slow initialization, and large computational problem.

Amith et. al [37] proposed a non-parametric background modelling technique. A single Spatio-Temporal Gaussian is used for modelling the background pixels. The features are extracted from the background region of the previous frame for image wrapping.The proposed background modelling can detect the object from the frame of moving the camera with negligible false alarm.

Alizera et. al [38] proposed a novel technique for background modelling on recursive modelling and non-parametric density estimation. The advantage of this method over the existing techniques is that instead of a global threshold for all pixels in the video scene, different and adaptive thresholds are used for each pixel. This method works robustly on different video scenes without changing any parameter.

Perazzi et. al [39] proposed an efficient method for detecting the salient foreground region using Fiedler Vectors. Salient region is identified by graph Laplacian defined over the color similarity of image super pixel. The method assumes that most of the image boundary are covered by non-salient background. The paper shows that Fiedler vector can compute the salience mask in a very effective and robust way. An SVM-based classifier can train the properties of Fiedler vector to differentiate between the salient and non-salient foreground region.

Kanagamalliga et al [40] proposed a foreground object detection method. The gaussian mixture model is combined with the expectation maximization algorithm for improving the segmentation quality of moving object. The proposed method achieved a fast, simple and high accuracy.

Yuhan L et.al [41] proposed a robust background subtraction method based on the adaptive dictionary learning strategy and penalized splitting approach. The method tries to learn the dictionary via sparse representation for better detection and an efficient splitting method is used to decouple the difference operators, dictionary and sparse coefficients.

Zhou et al [42] proposed a foreground detection method based on improved Codebook. By using the linear transformation, the RGB color space is transformed into the YCbCr color to reduce the illumination changing and improve the convergence. To judge the matching code words, the input pixel values are selected according to colourist and brightness. By using the random discard value method, the codewords that rarely access is deleted and reduced memory consumption.

Yong Xu et.al [43] discussed the advantages and disadvantages of different background modelling techniques in video analysis applications and performance is compared in terms of quality and computational cost.

## 4. CONCLUSIONS

Extracting moving object from a video sequence is the first step in most of the video-based analysis. Different method have been proposed in last few decades. Background subtraction is one of the simplest technique for detecting such moving object from the video sequences. In this paper various step of background subtraction is described and provide a survey regarding recent background subtraction techniques purposed by different authors.

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