Implementation of Foreground Detection Algorithm Using Modified GMM for Outdoor Surveillance

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Abstract: *Visual Monitoring System is the peak level research topic in Today's era. Visual observation in computer vision helps to analyze object's activities easily. Today's era of computer vision will completely remove traditional human operated Video Surveillance System. A major part of smart video surveillance system is characterized by perception and the robustness of a Smart Video Surveillance System is not only to sense the environment, but also to interpret and act intelligently. Advancement in perception will lead to applications for defence and automated driving assistance. Nowadays researchers are working on object detection, object tracking, crowd analysis, pedestrian and vehicle identification to improve the security at the public places. The objective of the proposed work is to ensure high level of security in public places using static Pan Tilt Zoom (PTZ) camera and to develop robust object detection algorithm for the smart and vigilant video surveillance.*

Keywords: **video surveillance and monitoring, Computer Vision, Background Model, Gaussian Mixture Model, Foreground Detection.**

1. Introduction

In recent years some compressed-domain analysis techniques have been developed for video surveillance and object-based video encoding. Scene analysis and behavior of the object understanding in video sequences is a dynamic research field. Many applications in this research area commonly are Visual Surveillance of Human Activities, Airport surveillance, Maritime surveillance, Store surveillance, Military surveillance, Forest Environments, etc requires initial step to sense the moving objects in the view. So, the most important task is to how to segment the moving or interested objects from the background without interfere the background pixels form the stationary pixels.

The easiest method toward the model of the background is to obtain a background image which does not contain any moving object. In certain environments, the background is not obtainable and can perpetually be changed under significant situations like's sudden changes in illumination or fast or slow movement of objects in the picture. So, ultimately to detect such a moving object one must need very robust and highly environmental adaptive background models to handle such constraints. Some of the various background model categories are: Basic background modeling, Statistical background modeling, Background modeling based on clusters, neural network background modeling, and Background estimation.

Typical system consists of the key components for the real time object detection are pre and post processing before extracting a feature, background image Subtraction and identification of extracted feature. There are couples of approaches for moving object detections are the region-based approach and the boundary-based approach. The region-based approaches are most accepted and especially optical flow and background subtraction are the two common approaches. Background subtraction method detects moving pixels in the scenes by subtracting usual background from the images at the same time this approach takes longer time to predict the background model from the moving scenes.

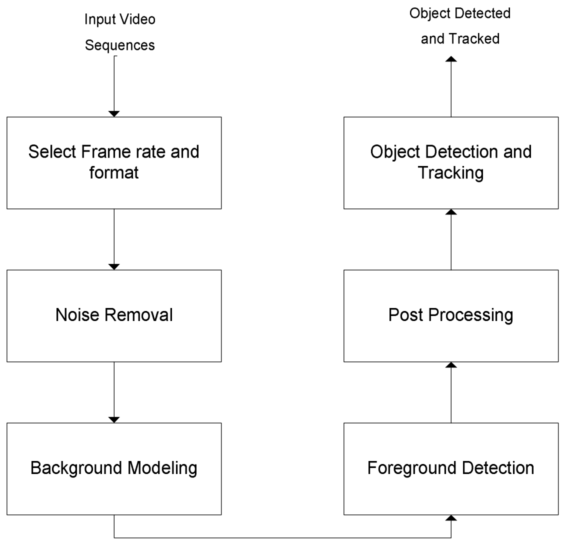

Figure 1. Primitive Steps of Video Surveillance System

Below Figure. 2 shows typical object detection schemes for the outdoor environments under various typical constraints. Every object detection approach at least requires certain information likes moving object's location, shilhouette, classification and its current activities in the scene or in the space

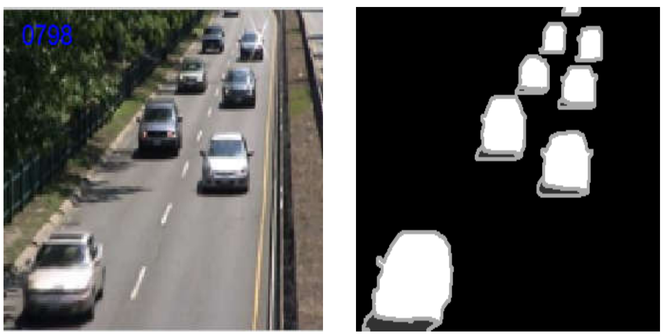

Figure 2. Object Detection

Normally, we assumed that backgrounds are obtainable in a video scene but unfortunately, background pixels do not exist in the problem domain hence we need to generate the background from the initial 20 to 50 frames accordingly to the dynamicity of the scenes. Morphology, image resizing and the edge detection are the various approaches to set as a preprocessing after the successful background initialization. Next, segmentation is required to handle Clutter and dynamic background constraints. Moving object or the motion pixels can be detected in presence of background pixels by means of the thresholding.

2. Related work

Object detection in the motion picture for the outdoor surveillance requires robust and adaptive background modelling that can easily handles various challenges like dynamic and clutter background, appearance and silhouette.[1] generally, the researchers are adopting either pixel-based background modelling or region-based background modelling. Some of them are comfortable with the non adaptive approaches but somehow such method unable to handle the various constraints for real time analysis. In [2] for the real time object detection analysis, they have used RGB background modelling and erosion and dilation as a pre-processing for suppressing noise and blob labelling for detecting the motion in the video sequences. They calculate the velocity of the foreground objects and detects it. [3] explained tradition approach for the motion detection. They adopt background subtraction and tradition GMM approach using learning parameters, which depends on pixel disparity. [4] Proposed unique method for the foreground detection using traditional background subtraction and Scale Invariant Feature Transform. [5] They proposed morphology as a preprocessing analysis for point processing for the providing the noise removal and better pixel connectivity and feature based analysis for static pixel detection. [6] They used the single Gaussian in the system called "Pfinder", which aims to detect people indoors as model for the background pixels. Such method is unable to handle the dynamic environments and hence the outdoor scenes well, as the distribution of the pixel and gray-level value in outdoor video sequences are exhibits multimodalities. Sudden changes in the environments for the outdoor object detection some Non-parametric and most flexible approaches are explained in [7,8], such approaches can handle different constraints at the cost of large computation. As compared with the model-based approach the data-based methods provide excellent response for the computation complexity and at the same time it also able to accept various static background constraints with the ingenious processes of parameter initialization and update like [9]. The self-organizing algorithm for background subtraction proposed by [10] it is the unique and excellent approach for the moment, which continuously senses the static background from the motion pixels in a self-organizing way.

3. Proposed method

Outdoor motion detection requires dynamic robust and adaptive detection technique that further leads to an exact object tracking. Our proposed approach estimates static pixels - background which ably handles dynamic environments, clutter background and sudden changes in illumination. It can deal with the various constraints like motion background, static foreground, entering and leaving objects in a video frames, fast- and slow-moving objects, complex object silhouette etc.

Our proposed approach deals on background static Analysis, parameter initialization for the background modeling and thresholding provides accurate motion detection under various constraints.

Background analysis:

For the background modelling one must have to study the behaviors of the non-static pixels in the frames due to flowing leaf's, twinkling of water surface etc., Generally, the Gaussian approach along with constant or variable threshold will detect the foreground in presence of the constant background.

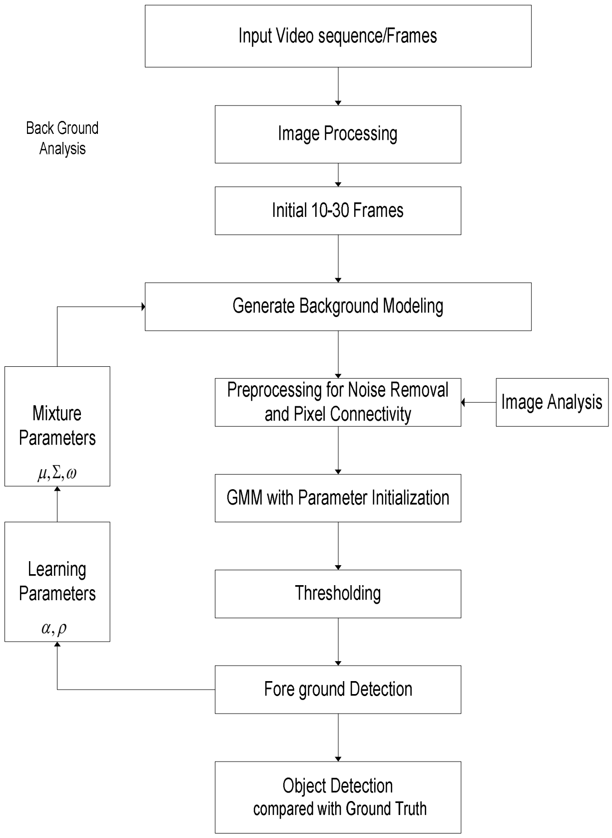

Figure 3. Proposed GMM Algorithm for outdoor object detection

Generally, the background model can evaluate by temporal average. However, temporal average cannot use the illumination variations of the input video frame. With the help of following the background model can be initialized by the running average as,

$$B_t(x, y) = B_{t-1}(x, y) + \alpha((I_t(x, y) - B_{t-1}(x, y)) \quad (1)$$

Where, $B_t(x, y)$ is the current background model,

$B_{t-1}(x, y)$ is the previous background model, $I_t(x, y)$ is the current video frame, and α represents the adaptive parameter.

Gaussian mixture model:

A Gaussian Mixture Model (GMM) is a parametric probability density function represented as a weighted sum of Gaussian component densities. GMM is usually considered as a parametric model for the distribution of probability distribution of continuous measurements. GMM parameters are estimated from training data using the iterative Expectation-Maximization (EM) algorithm or Maximum A Posteriori (MAP) estimation from a well-trained prior model.[11].

A Gaussian mixture model is a weighted sum of K component Gaussian densities as given by the equation,

$$P(X_t) = \sum_{i=1}^{K} \omega_{i,t} . \eta(X_t, \mu_{i,t}, \Sigma_{i,t}) \quad (2)$$

Where,

$\omega_{i,t}$ = weighted associate to current frame Gaussian

K =no. of distributions.

$\mu_{i,t}$ & $\Sigma_{i,t}$ = mean and covariance matrix of the pixel intensities

η = the Gaussian probability density function,

$$\eta(X/\mu,\Sigma) = \frac{1}{\sqrt{2\pi|\Sigma|}} e^{\left\{-\frac{1}{2}(X-\mu)^T \Sigma^{-1}(X-\mu)\right\}} \quad (3)$$

Each pixel is defined as a mixture of gaussian and initializes the various mixture model parameters. The weight, the covariance and the mean matrix is initialized using an EM algorithm or Maximum a Posteriori (MAP) estimation.[5]

Foreground Detection:

Foreground detection consists of classifying pixels as background and foreground by comparing the background and the current images. In general, a simple subtraction is made between these two images to detect regions corresponding to foreground. The goal in visual surveillance is to automatically detect static or moving foreground objects as static foreground objects and moving foreground objects.

First B_{back} Gaussian distributions from K no. of Gaussian distributions will be considered as the background model and B_{back} can be evaluated as,

$$B_{back} = \arg\min(\Sigma_{i=1}^{b} \omega_{i,t} \rangle T) \quad (4)$$

T is to be considered as the minimizing measure of estimating background. Particularly high threshold, foreground pixels with small colour differences will be misclassified and a lower threshold will result in unremovable noise. When using a single or a mixture of Gaussian models, the threshold for every pixel is a fixed multiple of its variance, in which case only temporal features are considered.

4. Results and Discussion

To evaluate our proposed object detection algorithm for the outdoor surveillance, we have performed some of experiments on some of the standard dataset PETS 2009[12] ViSOR [13] and CDnet 2014[14].

Figure 4 is a crowded outdoor standard sequence from PETS 2009. The sequence having challenge like clutter background and occlusions. It is also suffered with the near far moving objects with the different silhouette. Our proposed algorithm indentified and ably detects the crowded people in spite of various constraints. Second row shows the best background and third represents the corresponding foregrounds for the video frames. Figure5 is also an outdoor multiple illumination variation crowded standard sequence ViSOR.

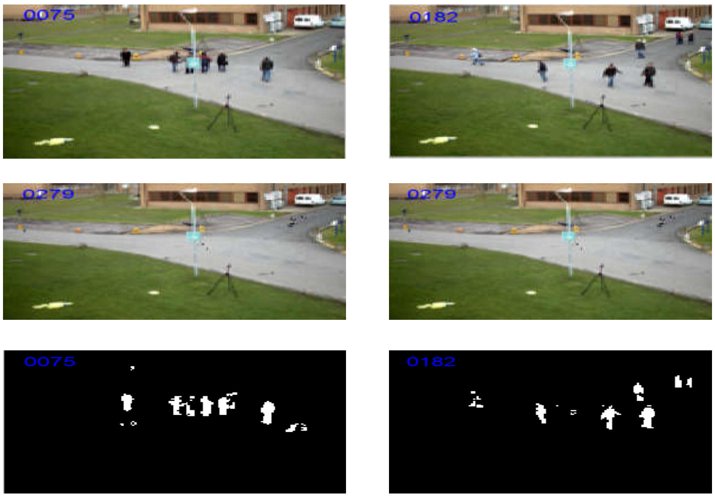

Figure 4. Outdoor sequence PETS 2009

The sequence having challenge like clutter background, occlusions with the moving and static objects and illumination variations. Our proposed approach is able to detect moving foregrounds in spite of all constraints. Second row shows the best background and third represents the corresponding foregrounds for the video frames. Our proposed algorithm does not work on fully occluded objects and those objects which similar in appearance.

Figure 5. Outdoor sequence ViSOR

Figure 6 is also a very famous outdoor standard sequence CDnet 2014. The sequence having challenge like clutter background, trees leaf's weaving, shadow high illumination and moving pixels appearance similar with the static. Our proposed approach is able to detect moving foregrounds in spite of all constraints. Our proposed algorithm does works on moving static background and the final result is being compared with the ground truth.

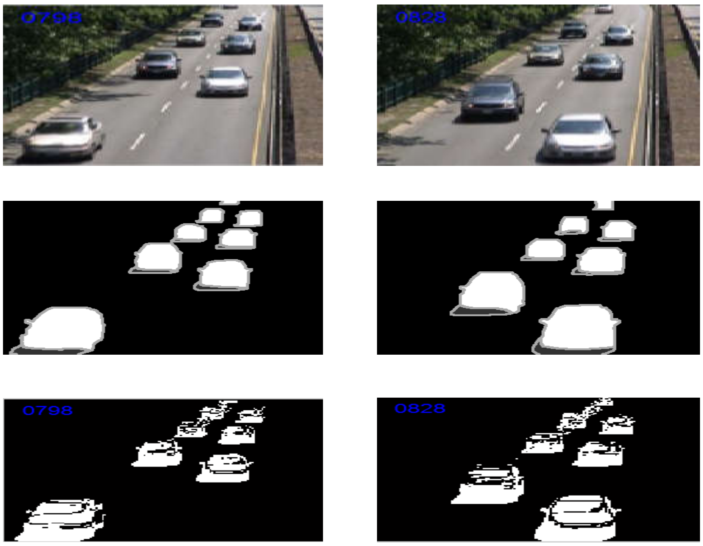

Figure 6. Outdoor sequence CDnet

5. Conclusion

Our proposed algorithm shows the probabilistic approach to generate the background analysis. Our proposed approach results are validates using standard datasets. All the datasets are suffered with the various challenges like clutter background, illumination variations, moving background pixels, partial and fully occluded moving and static objects and similar appearance. This approach almost handles all constraints and ably detects the outdoor moving foregrounds under various challenges except fully occlusion and similar appearance. Proposed algorithm provides robustness and adaptability to visual surveillance system for the outdoor object detection.

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