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Foreground Detection application to Outdoor Surveillance

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Abstract: *Visual Monitoring System is the high research area in Today's era. Visual study in computer vision helps to analyze the object actions easily. Computer vision will completely replace 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. Improvement in perception will lead to applications for defence and robotic driving assistance. At the present time researchers are focused on object detection, object tracking, crowd analysis, pedestrian and vehicle identification to look up the security at the public places. The goal of the proposed work is to ensure high level of security in public places using static Pan Tilt Zoom (PTZ) camera and to expand vigorous object detection algorithm for the smart and cautious video surveillance.*

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

1. Introduction

In topical years some compressed-domain analysis techniques have been residential for video surveillance and object-based video encoding. Scene study and behavior of the object understanding in video sequences is a vibrant research field. Many applications in this research area commonly are Visual Surveillance of Motion 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 segment the moving or involved objects from the background without touching or changing the background pixels.

The simple approch toward the model of the background is to genrate a background image which does not contain any moving object. In certain environments, the background is not accessible and can continuously be changed under significant situations like's sudden variations in illumination, fast or slow movement of objects in the scene. So, challenge is to detect such a moving object one must need very vigorous and highly environmental adaptive background models to handle all 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.

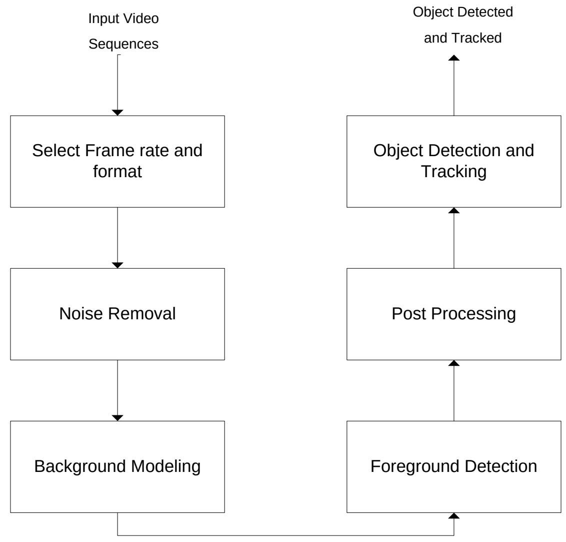

Figure 1. Essential stages for Video Surveillance System

Below Figure. 2 exhibits object detection schemes for the outdoor environments under various constraints. Every object detection approach at least requires certain information likes moving object's size, shapes, classification and its activities in the picture or in the space.

Figure 2. Object Detection

Our assumption is that backgrounds are accessible in a video scene but unfortunately, background pixels do not exist in the problem area hence need arises to generate the background from the initial 25 to 30 frames accordingly to the dynamicity of the scenes. Morphology, image resizing and the edge detection are some of the approaches to set as a preprocessing after the successful background initialization. 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 foreground detection in the activity picture for the outdoor surveillance requires healthy and adaptive background modeling that can simply handle various constraints like dynamic and clutter background, appearance and silhouette.[1] generally, the researchers are adopting either pixel-based background modeling or region-based background modeling. Non adaptive approaches are unable to handle the various constraints for real time analysis. In [2] for the real time object detection analysis, they have used RGB background modeling and erosion and dilation as a pre-processing for suppressing noise and blob labeling for motion detection. They estimate the velocity of the foreground objects and later detect it. [3] Explained conventional approach for the motion detection. They implement background subtraction and tradition GMM approach using learning parameters, which depends on pixel disparity. [4] Proposed exclusive method for the foreground detection by traditional background subtraction and Scale Invariant Feature Transform. [5] They projected morphology as a preprocessing analysis for point processing for providing noise removal, better pixel connectivity and feature based analysis for static pixel detection. [6] They used the single Gaussian the 'Pfinder', which aims to detect pedestrians indoors as model for the background pixels. Such method is incapable 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 nearly all flexible approaches are explained in [7,8], such approaches able to handle different constraints at the cost of large computation. As compared with the model-based approach the data-based methods present excellent response for the computation complexity and at the similar time it also able to accept various static background constraints with the resourceful 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 moving object detection requires dynamic robust and adaptive detection method that additional leads to an exact object tracking. Our proposed approach estimates static pixels - background which capably handles dynamic environments, clutter background and sudden light variations. Similarly it can also 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 modeling, study the behaviors of the non-static pixels in the frames due to flowing leaf's, twinkling of water surface etc., Normally, the Gaussian approach along with constant or variable threshold will sense the foreground in occurrence of the constant background.

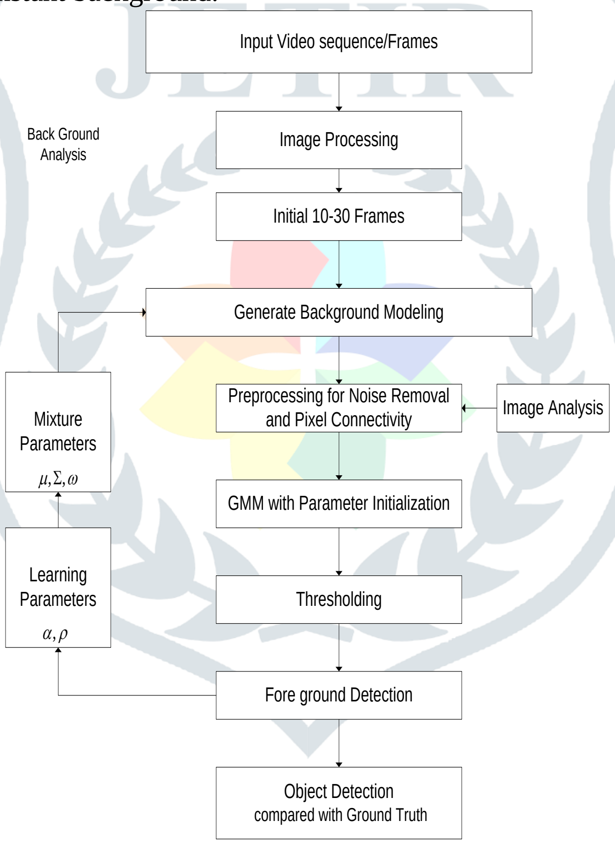

Figure 3. Proposed GMM Algorithm for outdoor object detection

Generally, the background model can estimate by temporal average. However, sequential average cannot use the enlightenment 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,

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

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,

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

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 the pixels as background and foreground by comparing background and current frames. In general, a easy subtraction is made among these couple of frames 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,

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

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 estimate our projected object detection algorithm for the outdoor surveillance, we have performed experiments on very famous and standard datasets PETS 2009[12], ViSOR [13] and CDnet 2014[14].

Figure 4 is a crowded outdoor standard sequence from PETS 2009. The sequence having dare like clutter background and occlusions. It is also suffered with the near far moving objects with the different object shapes. Our proposed algorithm clearly indentified and skillfully detects the crowded people in presence of different constraints. Second row shows the best background and third exhibits the corresponding foregrounds for the video frames. Figure5 is also an outdoor multiple light variation crowded standard sequence ViSOR.

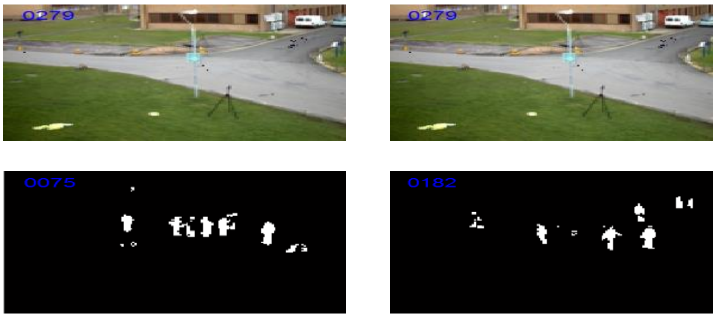

Figure 4. Outdoor sequence PETS 2009

The sequence having challenge like clutter background, occlusions with the moving and stationary objects and light variations. Our proposed approach is capable to detect moving foregrounds in presence of various constraints. Second row shows the best background and third represents the corresponding foregrounds for the video frames. Our proposed algorithm fails to implement on fully occluded objects and those objects which similar in appearance.

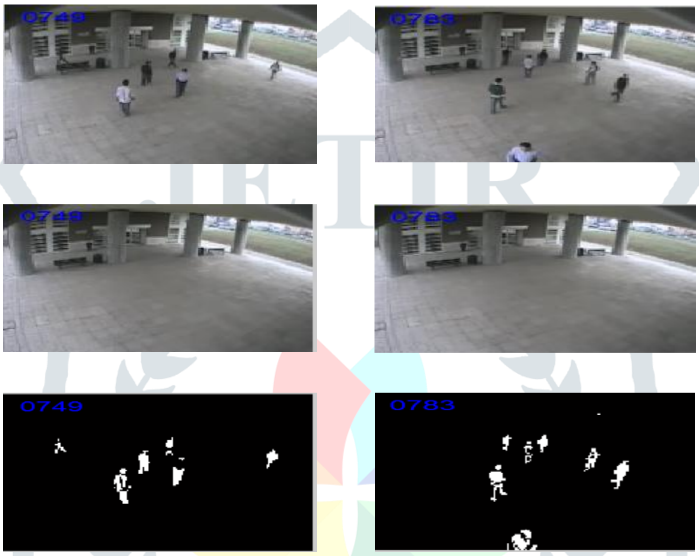

Figure 5. Outdoor sequence ViSOR

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 capable to detect moving foregrounds in presence of all constraints. Our proposed algorithm fails to implement on moving background and the final result is being compared with the ground truth.

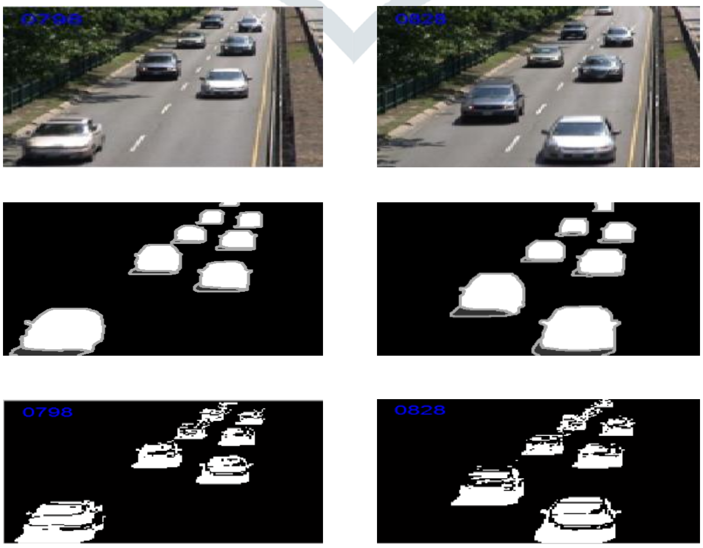

Figure 6. Outdoor sequence CDnet

5. Conclusion

Our proposed algorithm shows the statistical probabilistic approach to estimate the background. Our proposed approach results are validates using standard datasets. All the datasets are suffered with the various constraints like clutter background, illumination variations, moving background pixels, partial and fully occluded moving and static objects and similar appearance. This approach nearly handles all variations and capably detects the outdoor moving foregrounds under diverse 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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