# A ROBUST ALGORITHM FOR DYNAMIC OBJECT RECOGNITION FOR VIDEO SURVEILLANCE

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**Abstract -** *To efficiently resolve the problem that the subtraction background model is easily contaminated by slow-moving or temporarily stopped vehicles, the Gaussian mixture model (GMM) is proposed for vehicle detection in complex urban traffic scenes. Using the real-world urban traffic videos, the experiments are conducted by Gaussian mixture model with parameter measurement and compared with adaptive background learning algorithm. The experimental result shows that GMM excels the adaptive background learning method. Matlab software is used which helps to resolve the segmentation process in an optimum manner.*

***Key Words***: Digital Video Processing, background subtraction, foreground segmentation, Video surveillance, Matlab

## 1. INTRODUCTION

The extraction of foreground targets from the complex background is very important for traffic control departments and many applications of city public security, and automatic moving foreground detection of urban traffics has received the attention of a vast research in the fields of video surveillance. Background subtraction (BS) is an effective technique of detecting moving object from image sequences for stationary cameras. In the BS methods, the background models are first computed, after which the input video frames are compared with their current background models, and the regions corresponding to significant differences are then marked as foreground. BS methods can be roughly divided into parametric background model, non-parametric background model and advanced model. Among various BS methods, Gaussian mixture model (GMM) is one classical parametric model because of its robustness and effectiveness over different scenes. However, in the presence of urban traffic scene with fast variations or non-stationary properties, GMM and its improved models still suffer from a tradeoff between robustness to background changes and sensitivity to foreground abnormalities.

Unlike parametric models used in previous approaches, the recent and advanced non-parametric background model methods, visual background extractor (ViBe), pixel-based adaptive segmenter (PBAS) and Self-Balanced Sensitivity SEgmenter (SuBSENSE) have significantly circumvented the difficulties of probability function estimation and dictionary learning. SuBSENSE further combines texture features and colour features with a pixel-level feedback strategy to reduce sensitivity and enhance the generalization capacity. Recently, many new advanced background methods such as self-organizing background subtraction (SOBS) and eigen background have been proposed to achieve good results on various change detection scenarios. However, these approaches need massive calculations. To efficiently resolve the problem that the subtraction background model is easily contaminated by slow-moving or temporarily stopped vehicles, the GMM with CM (GMMCM) is proposed for vehicle detection in complex urban traffic scenes in this paper.

## 2. CONVENTIONAL GMM

The conventional GMM of the pixel in images of complex traffic scenes is established using the Gauss distribution, and the pixel value at position (x, y) with time can be described using the set

$$\{X1 \ldots\ldots Xt\} = I\{(x,y,i)\ ,\ 1 \le i \le t\}$$

Where I(x,y,i) is the pixel's intensity value at position (x,y) and frame I Ɛ [1,t] ( at time t is equivalent to at frame t). A single pixel in images of complex traffic scenes can be modeled by a mixture of $K(3 \le K \le 5)$ Gaussian distributions, and so the probability of observing the current pixel value is

$$f(Xt) = \sum_{j=1}^{k} Wj,t\ \phi\,(Xt \setminus Uj,t\ ,\ \textstyle\sum j,t) \qquad (1)$$

where Wj,t is the weight of the jth Gaussian in the mixture at the current frame t and ϕ(Xt ; Uj,t ,;∑ j,t) symbolizes the Gaussian probability density function with mean Uj,t and variance ∑j,t as follows

$$\phi\,(Xt \setminus Uj,t\ ,\ \textstyle\sum j,t) = \dfrac{1}{(2\prod)^{D/2}\ \left|\sum j,t\right|^{1/2}}\ \exp\{-1/2\ (Xt - Uj,t)^{T} \textstyle\sum j,t^{-1} (Xt - Uj,t)\} \qquad (2)$$

Where D is the dimension of pixel intensity and ∑ j,t (.) = (σ j,t)2I is the covariance matrix.

The match is found if the pixel value Xt lies within T multiples of the standard deviation from the cluster mean, which is expressed as

$$X_t \in \phi(X_t \setminus U_{j,t}, \Sigma_{j,t}), \text{if } |X_t - U_{j,t}| < T\sigma_{j,t} \quad (3)$$

where T is a constant, normally lying between 2.5 and 3.5. The weight of each model is to be updated by the equation

$$W_{j,t} = (1-a) W_{j,t-1} + ap(W_{j,t-1} | X_{t-1}) \quad (4)$$

If j is the matched Gaussian model,

$$P(W_{j,t-1} | X_{t-1}) = 1 \text{; otherwise } P(W_{j,t-1} | X_{t-1}) = 0$$

For the matched distributions, $U_{j,t}$ and $\sigma_{j,t}$ are updated according to the recursive formulations as

$$U_{j,t} = (1-\beta) U_{j,t-1} + \beta X_t \quad (5)$$

$$\sigma^2_{j,t} = (1-\beta)\sigma^2_{j,t-1} + \beta (X_t - U_{j,t})^T (X_t - U_{j,t}) \quad (6)$$

$$\beta = a\,\phi(X_t \setminus U_{j,t-1}, \Sigma_{j,t-1}) \quad (7)$$

where **a** defines the updating learning rate which controls how fast the model converges to a new one. In the GMM, the very small constant **a** for every pixel is commonly used for background adaptive. Unfortunately, this setting leads to the slow convergence when background needs to adapt to a new cluster. By setting **a** with a large value would improve the convergence speed. Nevertheless, the system will become easier to be perturbed by noise and foreground objects. Therefore, setting global learning rate is not the wise way to acquire robust background. If none of the K distributions match the pixel value, the least probable model is replaced by a distribution with the current value as its mean, an initially high variance and a low weight. Next, the distributions are ordered based on the descending values of w/σ to determine the background. In conventional GMM, the first B distributions satisfying the following criteria are chosen as model of the background

## 3. PROPOSED SYSTEM

Vehicle detection and tracking application play an significant character for inhabitant and military applications such as in highway traffic observation control, management and urban traffic scheduling. Vehicle detection process on road are used for automobile tracking, counts, average pace of each individual vehicle, traffic analysis and vehicle categorizing objectives and may be implemented under dissimilar environments changes.

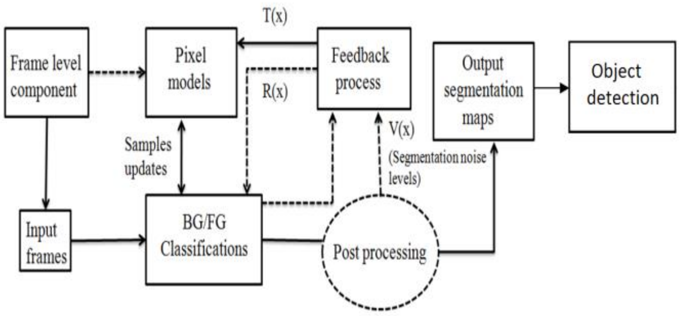


**Fig -1**: Block diagram

### 3.1 Pixel level modeling

Pixel-level modeling, as opposed to region-level or object level modeling, usually allows high-speed parallel implementations to be developed with relative ease due to how the workload is already split and kept isolated at a low level. However, the absence of information sharing between such local models puts the entire burden of spatial (or spatiotemporal) labeling coherence on the method's regularization scheme. To counter this, here pixel-level representations using not only their RGB values, but Local Binary Similarity Pattern (LBSP) features which operate in the spatiotemporal domain.

LBSP features are computed on a predefined 5x5 grid. They can be considered a counterpart to Local Binary Pattern (LBP) and Local Ternary Pattern (LTP) features: instead of assigning binary codes based on whether a given adjoining intensity is lesser or greater than the central reference, they assign them based on similarity (via absolute difference thresholding).

### 3.2 Image segmentation

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super-pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. To be meaningful and useful for image analysis and interpretation, the regions should strongly relate to depicted objects or features of interest.

### 3.3 Post processing

The term post-processing is used in the video processing for quality-improvement image processing methods used in video playback devices, (such as stand-alone DVD-Video players), and video players software. This helps reduce or hide image artifacts and flaws in the original film material. It is important to understand that post-processing always involves a trade-off between speed, smoothness and sharpness. De-noising, De-blurring, contrast adjustments etc is carried out in this technique.

### 3.4 Feedback scheme

So far, we have seen how R, the maximum sample distance threshold, and T, the model update rate, are the two most important parameters in our method. They essentially control its precision and sensitivity to local changes and can determine how easily moving elements are integrated in the model. In global values were determined empirically for both and used frame-wide. This kind of approach is flawed, as using a global strategy to control model maintenance and labeling decisions implies that all pixels will always present identical behavior throughout the analyzed video sequence. In reality, this assumption almost never holds since an observed scene can present background regions with different behaviors simultaneously, and these can vary over time. Moreover, even if it were possible to fix parameters frame-wide and obtain good overall performance, finding an optimal set of values for a specific application requires time as well as good knowledge of the method and dataset.

### 3.5 Matlab software

Matlab (matrix laboratory) is a multi-paradigm numerical computing environment and fourth-generation programming language. It is being developed by the mathworks. It allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces and interfacing with programs written in languages including C, C++,Java, Fortran and python. The MATLAB platform is optimized for solving engineering and scientific problems. The matrix-based MATLAB language is the world's most natural way to express computational mathematics. Built-in graphics make it easy to visualize and gain insights from data. Although MATLAB is intended primarily for numerical computing, an optional toolbox uses the MuPAD symbolic engine, allowing access to symbolic computing capabilities.

## 4. RESULTS AND DISCUSSIONS

We use three classical measures based on the numbers of true positive TP pixels (correctly detected foreground pixels), false positive FP pixels (background pixels detected as foreground ones), false negative pixels FN (foreground pixels detected as background ones), and TN true negative pixels (correctly detected background pixels). True positives (TP =intersection between segmentation and ground truth), false positives (FP = segmented parts not overlapping the ground truth), false negatives (FN = missed parts of the ground truth) and true negatives (TP = part of the image beyond the union segmentation + ground truth).

$$\text{Recall} = \frac{TP}{TP + FN} \qquad (8)$$

$$\text{Precision} = \frac{TP}{TP + FP} \qquad (9)$$

$$\text{F - Measure} = \frac{2 \times (\text{Recall} \times \text{Precision})}{(\text{Recall} + \text{Precision})} \qquad (10)$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \qquad (11)$$

**Table -1:** Comparison of parameters at various frame levels by Adaptive background learning method and Gaussian mixture model method

| Frames | Precision | | Recall | | F - measure | | Accuracy | |
|---|---|---|---|---|---|---|---|---|
| | Adaptive method | Gaussian mixture model method | Adaptive method | Gaussian mixture model method | Adaptive method | Gaussian mixture model method | Adaptive method | Gaussian mixture model method |
| 566 | 0.9963 | 0.9935 | 0.9396 | 0.9821 | 0.9671 | 0.9878 | 0.9366 | 0.9759 |
| 625 | 0.9893 | 0.9855 | 0.9487 | 0.9822 | 0.9686 | 0.9838 | 0.9400 | 0.9685 |
| 890 | 0.8623 | 0.8656 | 0.8621 | 0.9264 | 0.8622 | 0.8950 | 0.7693 | 0.8179 |
| 1675 | 0.8889 | 0.8876 | 0.8701 | 0.9550 | 0.8794 | 0.9201 | 0.8009 | 0.8617 |

## 5. CONCLUSIONS

The system can be effectively used in complex video surveillance scenarios presenting many different challenges simultaneously. A number of improvements in the present image segmentation and video processing techniques are being implemented in this work.

More sophisticated processing operations are carried out to obtain an effective processed video which also helps to eliminate larger noise. Gaussian mixture model gives optimum parameter values such as recall, precision, F-measure and accuracy compared to the adaptive background learning method. Also the method is relatively simple and operates at the pixel level. The moving object detection on various climatic conditions can be carried out as part of the future work.

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