A Novel Approach for Foreground Extraction Technique in Video Surveillance Systems

Anjanadevi B, S Nagakishore Bhavanam, E. Sreenivasa Reddy

Abstract*: *Everything in real word is monitored through surveillance cameras. Video surveillance is a critical tool for a variety of tasks such as law enforcement, personal safety, traffic control, resource planning, and security of assets. The widespread use of surveillance cameras in offices and other business establishments produces huge amount of data every second. The advent of large data is introducing important innovations like availability of additional external data sources, dimensions previously unknown and questionable consistency, poses new challenges to the worldwide spread of data sources (web, e-commerce, sensors). These collections of data sets having video frames which become difficult to process using traditional image processing applications. So, in this paper we propose a new foreground extraction technology using segmentation based on Skew Gaussian Mixture Model. The proposed model is more accurate than traditional approaches.

Index Terms*: *Video Surveillance, Foreground Extraction, Background Subtraction, Illumination Changes, segmentation, Skew Gaussian Mixture Model.

I. INTRODUCTION

The current emerging applications in this area faces various challenges like illumination changes, Dynamic background, video noise etc. The major challenge is to identify moving objects i.e extraction of foreground objects from scene while subtracting the background. In surveillance systems, because, each of the Frame information contains both background and foreground firstly, background subtraction is used to extract foreground objects. [1] Used pixel based method, considering samples of background and foreground intensity values and calculated probability density function for pixel Intensity using kernel density estimation and also tested CMS (Carnegie Mellon image sequences) dataset. Advantages of this method is, it is applicable for non-stationary background and slow foreground. Disadvantage of this method is, it is not applicable when temporal consistency of pixel values are considered. [2] Uses adaptive mixture Gaussian model for (background foreground extraction subtraction), when frame contains noisy data. Advantages of this method is low Cost and faster in computation.

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Disadvantages are, it is applicable in a static camera and intelligent video surveillance using mainly in video frames, extracting foreground from current frame is dependent on change detection between current frame and previous frame.

[3] Focuses on real time video surveillance change detection. Few methods addresses the algorithm for the video surveillance system using segmentation and reconstruction techniques. [4] Addresses the evaluation of some of the background modelling techniques. Background modelling methods are evaluated based on quality and computational cost of the approach. All the methods are classified into three types which are Region-Based, pixel based, mixed. Background subtraction approaches are broadly classified into 2 type's viz., parametric models are Famous Gaussian model & applications based on previously, discussed on GMM and AGMM. Non-Parametric region based method KDE, discussed in [1] and video noise is handled using vibe and sobs in [4] KDE kernel density estimator is applied distribution using kernel function formula:

$$\text{Prob}(p_i) = \frac{1}{s}\sum_{a=1}^{s} \pi_{b=1}^{f} \cdot \frac{1}{\sqrt{2\pi{\sigma_b}^2}} e^{-\frac{(p_a-p_b)^2}{2{\sigma_b}^2}} \quad (1)$$

GMM (Gaussian Mixture Model) Stauffer, et al proposed mode for mixture of N Gaussians to each pixel and finding Probability density Function using,

$$\text{Prob}(P_a) = \sum_{a=1}^{N} \eta(x_i, \mu_{a,t} \textstyle\sum_{a,t}).w_{a,t} \quad (2)$$

N is a number of Gaussians.
$\eta\ (xi, \mu_{a,t} \sum_{a,t})$ – a^{th} Gaussian probability density functions.
Wa,t is its weight at time t.
$\mu_{a,t}$ – mean value of the a^{th} Gaussian in mixture at time t.
$\sum_{a,t}$ is the covariance matrix of the a^{th} Gaussian in mixture at time t. In this case, it is assumed that the covariance matrix is the diagonal matrix, N from 3 to 5. The methods discussed in [4], AGMM, Vibe, SOBS are having their own pros and cons. These methods cannot always produce precise results but shall produce reasonable results for many challenges (like illumination changes, dynamic background, and video noise).In early applications [5], used improved Gaussian mixture model for detecting foreground movable objects. IGMM (Improved GMM used by incorporating a motion based uniform model in GMM background subtraction). Advantage of this method improves foreground detection rate without deteriorating precision. [6] Addressed spatial and temporal independent features developing fast ICA (Independent Component Analysis) algorithm. [7] Describes various image processing techniques for moving object detection and tracking in subsequent frames and even addressed the problem of crowd change detection while using local features with probability density function.

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Object tracking methods are categorized into two types, Region Based and Active Contour Based. In this approach, color descriptors are more efficient than traditional method which uses edge features in illumination changes.

[7] Demonstrated temporal difference used for detection in moving scenes. Disadvantage is, this framework is not suitable for color based tracking and complete occlusion. [8] Addresses GMM based sharable background subtraction. In this approach, each pixel searches best matching model with neighborhood pixel. This method is suitable for dynamic background, camera jitter.

[9] Proposed mean and variance based classification method for background subtraction. Disadvantage of this method is, suffering with camouflage. [10] Explains spatial-based binary similarity descriptor, this works by considering neighborhood of each of the pixel which is analysed. These results obtained using CDNET dataset and also improved by integration of local based binary similarity pattern with PBAS will produce better results on challenges like camera jitter, shadows etc. and can process only static background. The literature clearly signifies that there are still gaps in minimizing the illumination changes, dynamic Background, Camera Jitter. Also, it is understood that the problem of camouflage could not be resolved. However, the major disadvantage is that the back ground subtraction is done based on the pixel intensity, and observed that the pixels of the region follow a bell shaped curve are crude approximation [11]. As it is observed that the sudden illumination changes are prone to change in distribution of the pixels of the image. The change is skewed than is normally distributed. Usually the shape of the pixels is either Mesokurtic or Leptokurtic also called as Symmetric or Asymmetric [12]. So, in order to extract the foreground object from the image, it is essential to propose a method which solves the above issues. Hence, in this paper we propose to use another efficient variant of Gaussian Mixture Model which is Skew Gaussian Mixture Model [11][12]. The rest of the paper is organized as the next section explains about the proposed SGMM, section III presents the results and discussion. Finally, section IV concludes the paper.

II. PROPOSED METHOD

In this method we initially preprocess the image by removing the noise. After preprocessing, the image is applied for K-Means clustering to segment the objects in the image from the background. To find the value of K, the histogram of the input image is drawn and the maximum number of peaks denotes the number of regions in the image which is the value of K. The objects in the image are then extracted. The process of the proposed model is shown in the following fig.1.

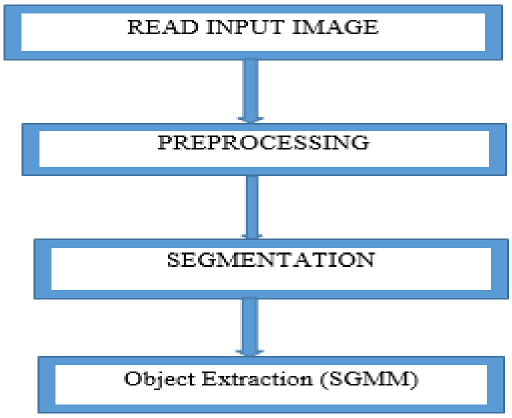

Fig.1: Flow diagram of the Process Model

The pixels of the image regions may not fall under bell curve or a symmetric curve for the regions due to the major problem like sudden illumination change which fall in asymmetric distribution and follow skew distribution. An image is collection of regions so that, segmentation is done based on peaks of image histogram and assuming the pixels in each region/object follow a Skew Normal distribution, where, the probability density function [11][13] is given by

$$f(z)=\sqrt{\frac{2}{z}}\cdot e^{-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^{2}}\left[\int_{-\infty}^{\alpha\left(\left(\frac{y-\mu}{\sigma}\right)\right)}\frac{e^{-\frac{1}{2}\left(\frac{t-\mu}{\sigma}\right)^{2}}}{\sqrt{2\Pi}}dt\right] \qquad (3)$$

The initial estimates of the proposed mixture model μ_i, σ_i and α_i where i=1, 2, , k are estimated using K-Means algorithm. Therefore, the pixel intensities of the given input image is segmented to K component model π_i, i=1, 2...K, assuming that $\pi_i = 1/K$, where K is obtained using K-Means algorithm. The diagram below fig.2 clearly demonstrates the process of implementation of the proposed model with the stages of all the steps.

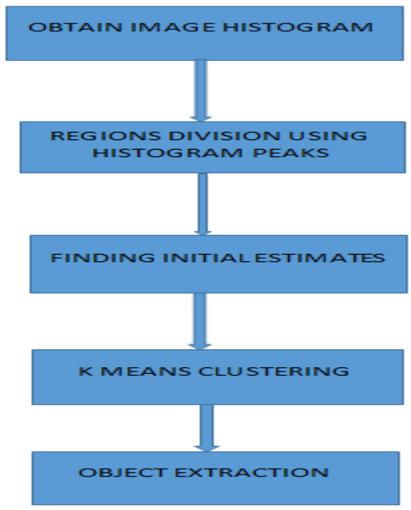

Fig.2: Flow diagram of the proposed Model

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III. RESULTS & DISCUSSIONS

The experimentation is carried out using MATLAB in a system with Core i5 processor and 8GB RAM with 1 TB HDD. The dataset used is from the standard CDNET. The experimentation is done on different image sets. The results a as shown in fig.3

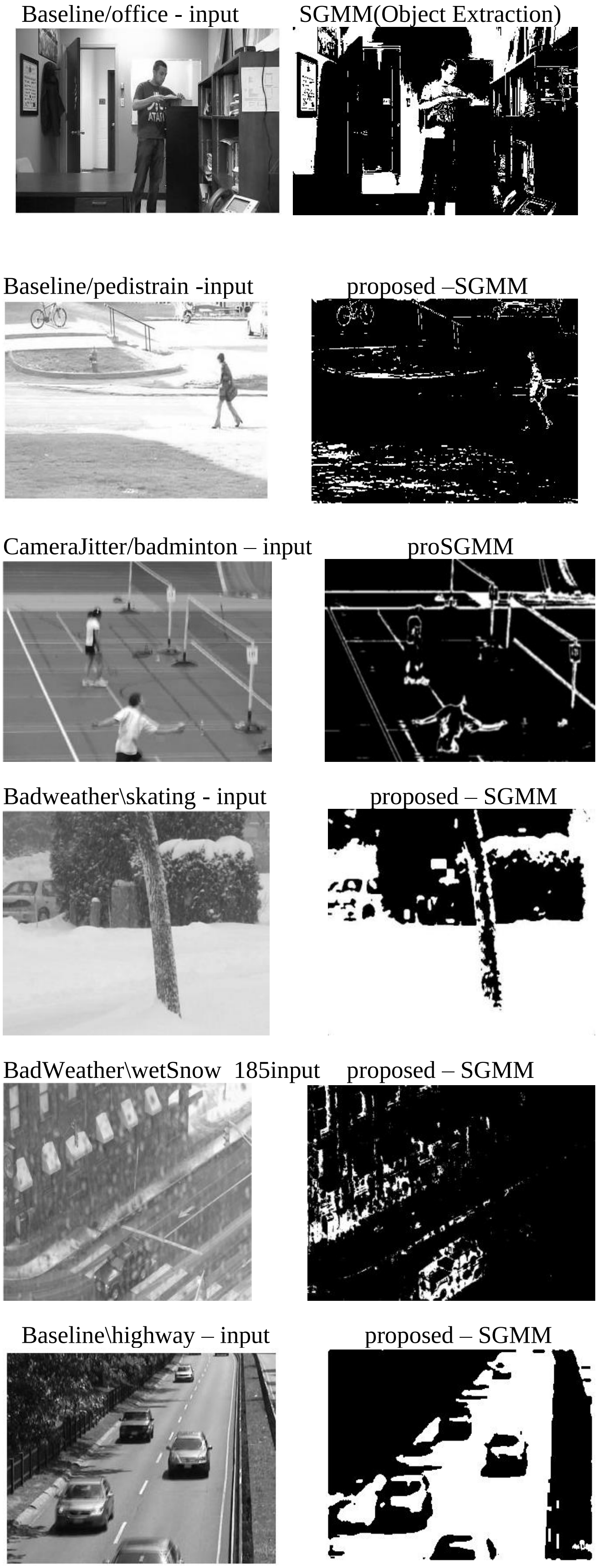

Fig.3: Foreground Object Extraction with input images and Output Images

The accuracy of the proposed model has been compared with the widely used Gaussian Mixture model. The experimentation has been carried out on the CDNET dataset with different databases. The accuracy of the proposed model is observed to much more effective than the existing model GMM. The below Table 1 and Graph of the accuracy values in fig. 4 clearly shows that the proposed model is better than the existing models.

Table 1: Comparison of Proposed model with GMM

CD_NET DATA_SET	GMM	SGMM
baseline_office (frame - 881)	0.4639	0.7413
baseline_pedistrain	0.0237	0.9307
camerajitter_badminton (frame - 185)	0.3246	0.9272
badweather_skating(fr -185)	0.3699	0.9033
badweather_wetsnow(fr -185)	0.378	0.9999
baseline_highway(fr - 881)	0.3152	0.758
PTZ_intermittenpan(fr - 881)	0.3457	0.8971
PTZ_twopositionPTZcam	0.4075	0.9511

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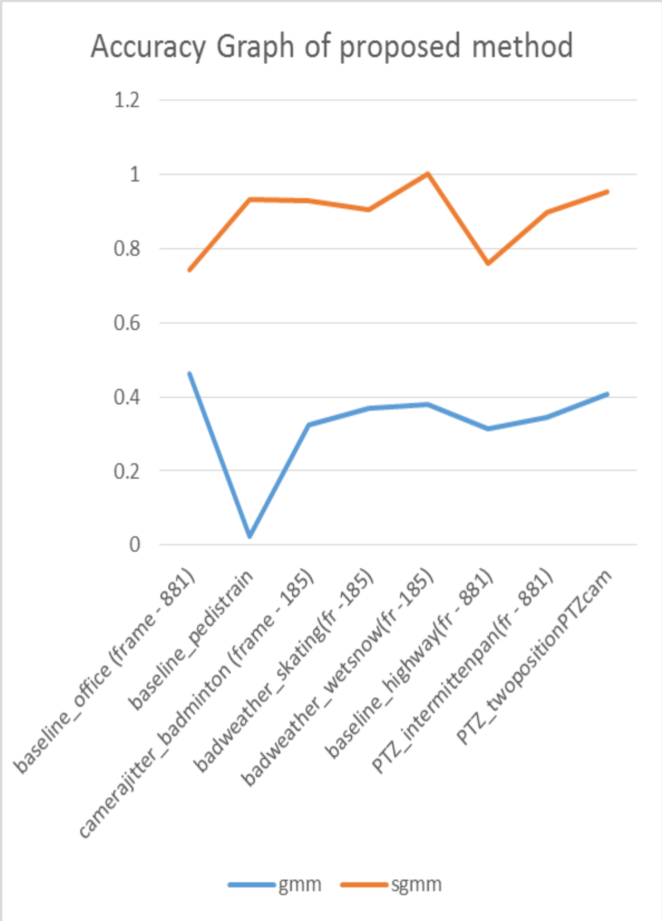

Fig. 4: Graph showing performance of proposed model with GMM

IV. CONCLUSION

The literature clearly demonstrates that the techniques still have gaps in addressing the illumination changes, dynamic background subtraction with high computational cost. Hence, to address these issues, it is essential to use statistical models like Skew Gaussian Mixture Model addresses the certain issues of the Surveillance System. The experimental results obtained clearly depict that the proposed model is efficient than the existing models. Further, the major focus is detecting the moving object with bounding boxes.

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