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Foreground Detection for Indoor Visual Monitoring System

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Abstract – Visual Monitoring System, background examination and modeling, segmentation and foreground detection under tough environments are the most considerable task. In this paper, we propose a novel performance approach for the GMM based indoor motion segmentation approach under different challenges. Generally, In a Computer vision or visual monitoring systems, a scene frequently requires the detection of non stationary objects as a prime requisite. Generally, researcher are focused on region based, pixel based or block based approach for the non stationary object detection, but amongst all the approaches the pixels based approach provides quicker result at the expenditure of sensitivity. It also depends on the object appearance and the shape. A enormous portion of the surveillance room depends on the image awareness, interpretation and recognition. We propose an competent and adaptive robust approach to detect the moving object in indoor environments. We have experienced our proposed approach with the various standard dataset and tested results with the accessible ground truth. The experimental results illustrate the robustness and flexibility to take the challenges for the indoor environments.

Key words: Background modeling, GMM, Thresholding, foreground Detection.

I. INTRODUCTION

For the robust and adaptive visual monitoring system, detection of motion in the video scenes and the detection of the stationary objects is the prime and significant feature for the monitoring system. Especially for the indoor surveillance the dependence on the PTZ static camera plays an essential role. For the outdoor surveillance, normally we rely on assured challenges like light variation, water repelling, and tree's leaf weaving and static backgrounds. While same is not happen with the indoor scenes. Generally, the indoor scenes are suffered with the low light, clutter background and occlusions. For the efficient motion segmentation and detection background analysis and background modeling is a major concern.

Background can be approximate and modeled using the combine of adaptive and non adaptive approaches. Non adaptive model is approximate using only few frames however at the same time it cannot handle the motion background so, it is very responsive to the background environments and pixels. While adaptive takes longer time to estimation the background model but at the same time is also robust to maintain the background against the various background motion. Adaptive approach provides accurate segmentation and motion detection.

Motion detection used to segment the non static objects from the stationary background. Literature review identifies that temporal difference, background subtraction and optical flow are a few of the most important strategies for the foreground detection. Amongst all temporal difference shows sense the detection using pixel difference in consecutive video frames. It requires less memory compared to others and also provides robustness in terms of the sensitivity like illumination variation. The majority researchers are focus either on temporal or spatial pixel and require intensity information for detecting the foreground in indoor environment.

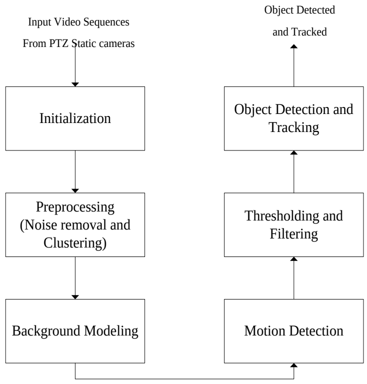

Figure 1 Basic Flow of Visual Monitoring System

Figure 1 shows the typical access flow of the visual monitoring system. Usually for the indoor object detection system needs robust static PTZ camera as an input source and the captures scenes are needs to be initiated with the help of frames organization strategies. Input scenes are normally available with the dataset noises so needs to eliminate dataset noise with the help of pre-processing noise removal filters. Certain background investigation requires generating and main the background model in every frame and at the same time it needs to be robust and adaptive to handles various environmental and other dataset challenges. All time the non static objects are to be recognized and extracted from the video frames for the further motion segmentation detection technique. With the help appropriate thresholding technique can be capable to sense the foregrounds and one again some sort of filtering as post processing is required to remove the noises from the foreground and increases the detection efficiency.
Figure 2 shows usual indoor object detection schemes with the clutter and illumination challenges. In every frame the variation or steady changes in light will leads to increases the false positives and hence it will influence the detection efficiency and hence precision and recall.

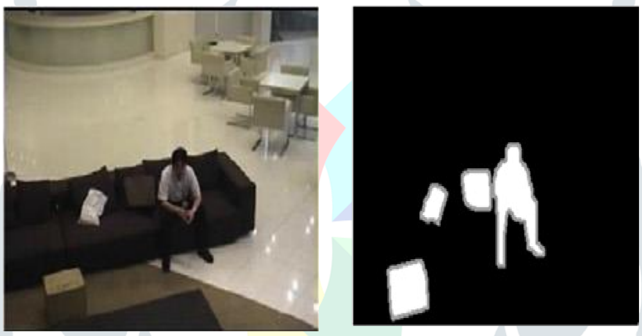

Figure 2 Indoor Object Detection

We propose an adaptive light or intensity sensitive background modeling for the indoor object detection system. Primarily, we need to generate precise background modeling which does not consist of the non stationary foregrounds as, it will maintain for the every frames under the intensity variations or any other situation.

II. RELATED WORK

In this fragment, we explain the literature review and the study in the field of background modeling and foreground detection. We have considered some approaches which are pertaining to the motion segmentation in various situations. [1] They have initial considered the well known GMM approach for the background modeling. They have proposed that the pixel are exhibits the multimodality. They have proposed K-means algorithm for the background modeling. The background modeling is initialized with the help of mixture weight, mean and the covariance matrix. [6] proposed backgorund model for the
Independently at every pixel location (i,j). The background model uses the Gaussian probability density function on
the final n pixel's values. They have projected signe Gaussian approach. [43-10.p] they have projected a new approach for the background modeling. They have planned the Hue-
Saturation-Value (HSV) color space model in place of the RGB traditional model.such an approach isolate the intensity and chromatic pixel information and leads to adopt the challenges like illumination variations and clutter background.
[2] They have proposed the precision to background variations is not as pleasing as them especially to some occurrence such a abrupt light changes. [3] They have proposed conventional GMM approach for the background analysis and frequently update the model learning parameters. The proposed approach deals with the slow light changes and occlusions particularly in the indoor environments. Such an approach is suffered with the computational complexity. [4] They have proposed a novel segmentation spatio-temporal adaptive GMM algorithm using traditional GMM and using the spatial and temporal dependency. The effectiveness of the motion segmentation or the object detection can be further improved by adopting the some shadowing removal techniques since it eventually removes the false positives and consequently increases the detection efficiency. [7] Proposed a new kernel estimator approach for the background modeling. The proposed approach deals fine adjacent to the dynamic backgrounds. The approach estimates the pixel PDF using the novel estimator named as a Kernel. [8] Proposed an enhanced approach of the established GMM to adopt the mixture parameters and to be trained the parameters using definite algorithm. Such an algorithm easily adopts the scene changes.

III PROPOSED METHOD

Indoor foreground detection requires robustness and flexibility in the background modeling which can be simply adopt the environments variations. Our proposed approach estimates static and non static pixel by estimating the background investigation. Proposed approach capable to estimate the object motion and hence ably detect the object motion for indoor environment under various situations.

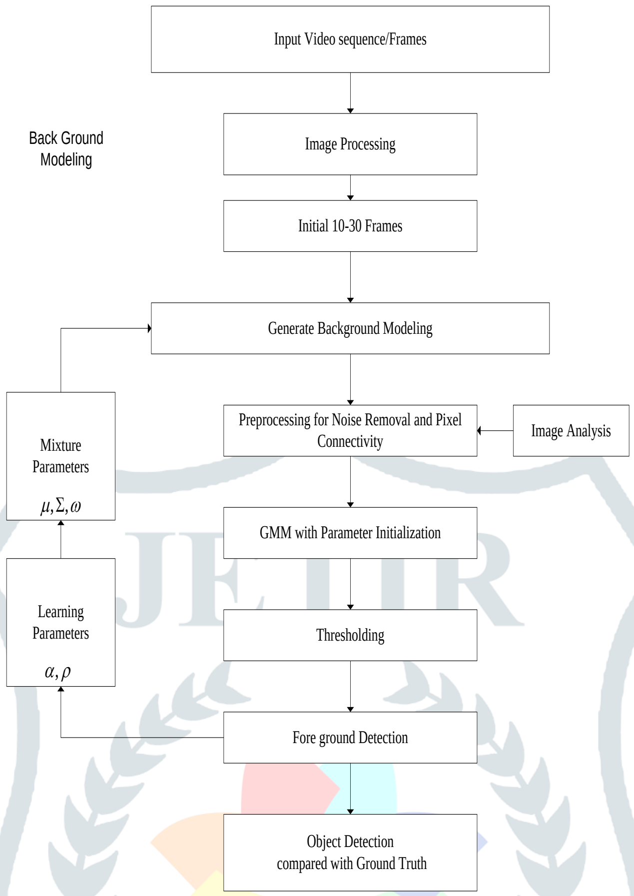

Figure 3 Proposed GMM Algorithm for Indoor Object Detection

It usually deals with the unusual challenges such as non static background, static foreground and change in intensity in a video frames. Our projected algorithm deals with the stationary background analysis, parameter initialization for the background modeling and adaptive thresholding provides precise foreground detection under diverse environments.

Background Modeling:

For the indoor surveillance generally the challenges are like clutter background, low illumination and occlusions plays a vital role while generating or developing the background model. In general, the background modeling can estimation with the help of simplest background subtraction advance. Conversely, temporal average cannot use the light variations of the input video frame $I_t(x,y)$. With the help of following the background model can be estimated by the following eq.

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

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

$B_{t-1}(x,y)$ is the previous background model, $I_t(x,y)$ is the current video frame and where α exhibits the adaptive learning 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 typically considered as a parametric model for the distribution of probability distribution of continuous measurements. GMM parameters are approximate from training data using the iterative Expectation-Maximization (EM) algorithm or Maximum A Posteriori (MAP) estimation from a well-trained priori model.[5].

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

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

Where,

$\omega_{i,t}$ = mixture weight associated 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,

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

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:

The detection of the motion or the categorization among the stationary and non stationary objects is approximated by purely comparing the background modeling pixels with the moving objects. Usually various foregrounds are available similar to static foreground and moving the foregrounds. The essential step in all visual monitoring system is to sense and categorize the stationary and non stationary pixels in every successive frames and by way of the foreground mask, which is to be evaluated with the help of thresholding recognize the foreground objects as follows,

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,

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

T represent the thresholding value. Considering the minimum value as a static threshold to estimate or classify the foreground and background pixel. High threshold values will miss the foreground pixels and leads to false negatives while the lower threshold values will definitely identifies the foreground objects but at the same time it will also allows some background pixel to be considered as a foregrounds so it will leads to false positives.

IV. EXPERIMENT RESULT

In this section the qualitative assessment for the proposed indoor object detection algorithm has revealed. Our proposed algorithm has been tested on some of the standard dataset PETS 2006[9] ViSOR [10] and CDnet 2014[11].

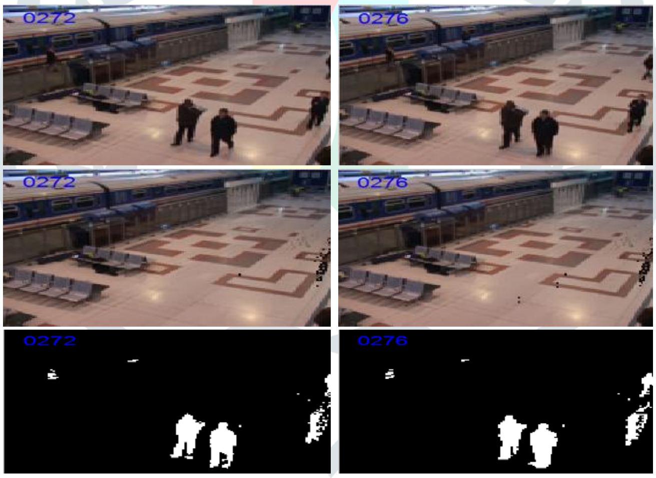

Figure 4 Indoor sequence PETS 2006

Figure 4 illustrate a crowded indoor standard sequence from PETS 2006. The sequence having test like clutter background, reflecting surface, like form and occlusions. Our proposed algorithm secret and able to detects the crowded people against certain challenges. Second row shows the most excellent background and third represents the corresponding foregrounds intended for the video frames. Figure5 is an indoor challenging dataset commencing the standard sequence ViSOR. The sequence having challenge like clutter background, major fully occlusions among the stationary objects, a very low light with a similar approaches. Our proposed algorithm detects moving foregrounds in spite of all challenges. Second row shows the best background for the each video frame and third represents the resultant foregrounds for the video scenes. Our proposed algorithm does work on fully occluded objects as clearly shown in the frame no.146 where only head movement is detected as a foreground and at a same time background model exhibits no foreground pixels.

Figure 5 Indoor sequence ViSOR

Figure 6 is also a very famous indoor standard sequence CDnet 2014. The sequence having confront like clutter background, reflecting surface, similar appearance and occlusions with the stationary object. Our proposed algorithm provides excellent foreground and compared it the accessible ground truth.

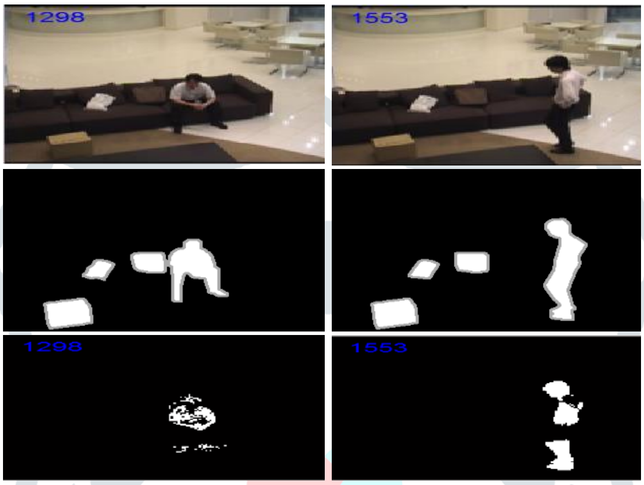

Figure 6 Indoor sequence CDnet2014

V. CONCLUSION

This paper explained the new execution for the detection of indoor objects. Indoor object detection has been carried out with the help of conventional probabilistic GMM approach. Background modeling is estimated with the modified GMM and eventually the foreground can be detected with the help of motion segmentation by foreground mask. Our proposed algorithm is being experienced with the standard challenging datasets. All the datasets are suffered with the various constraints like clutter background, low illumination, similar appetence, reflecting surface and occlusions. Proposed approach proven to all various challenges and capable to detects the indoor moving foregrounds. The developed algorithm is robust against partial occlusions and low illumination variations.

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