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Real Time Segmentation based Background Subtraction Mechanism Using Morphological Operation and Cascaded Change Detection

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Abstract- The state of the art of all the motion detection techniques that are being employed currently in real time motion sensing systems. The work discusses mechanisms like Optical Flow, Frame differencing, Running Gaussian average as viable mechanisms for motion sensing and also their limitations. The work primarily focuses on Adaptive Gaussian Mixture Models as the preferred mechanism over other options. The work presents simulated results of motion sensing under different ambient conditions and different illumination conditions. The work presents a comparative analysis of all the existing mechanisms with the proposed mechanism.

Keywords: Motion Sensing, Background Subtraction, AGMM, GMM

I INTRODUCTION

It is the human desire that has led to automatic detection systems and intelligent surveillance systems which make lives easier as well as enable us to compete with tomorrow's technology. On the other hand it has pushed us to analyze the challenge sin the field of automated video surveillance in light of the advanced artificial intelligence systems.

The surveillance cameras nowadays are already prevalent in secured commercial locations, with camera outputs being recorded to tapes that are either rewritten or periodically stored in video archiving systems. In order to benefit from this prerecorded digital data, detecting any moving object from the scene is required and that too without engaging any human aid. Real-time segmentation of moving regions in image sequences has been a fundamental step in many vision systems.

II MOTION DETECTION

Motion detection in consequent images the detection of the true moving object in the scene. In real time video surveillance systems, motion detection refers to the capability of the system to detect motion and capture the events and time of occurrence. That also requires a software-based monitoring algorithm which in turn will signal the surveillance camera to begin capturing the event when motion activity is detected. This is also called activity detection. An advanced motion detection surveillance system can analyze the type of motion for triggering an alarm system. In this project, however, the work confines to the robust sensing of activity in prerecorded video feed possibly taken from an associated real time surveillance mechanism and its associated mechanisms (morphological operations, filtering, shadow removal etc.) which in turn can be associated with a hardware based surveillance system. However, the development of that is not the scope of this work.

III PROPOSED METHODLOGY

Background modeling by Gaussian mixtures is a pixel based process.

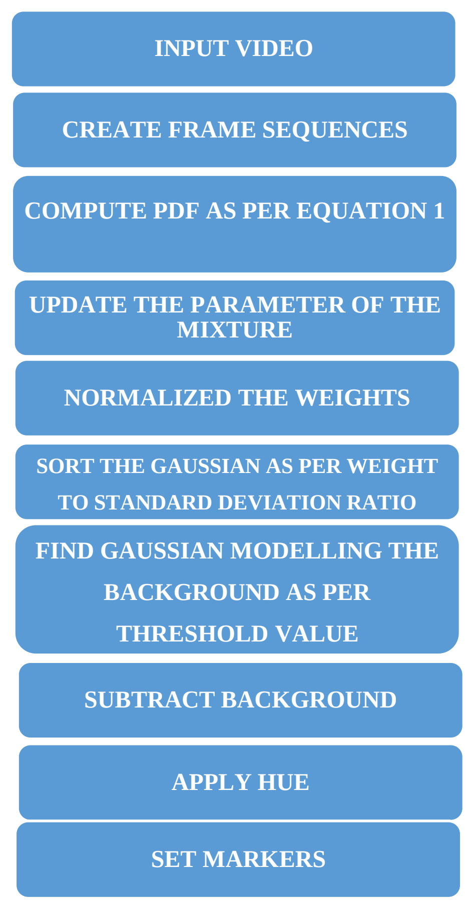

Figure 1 Block diagram Proposed Methodologies

Let x be a random process representing the value of a given pixel in time. A convenient framework to model the probability density function of x is the parametric Gaussian mixture model where the density is composed of a sum of Gaussians. Let p(x) denotes the probability density function of a Gaussian mixture comprising K component densities.

$$p(X) = \sum_{k=1}^{K} \omega_k\, N(X; \mu_{k,} \sigma_k) \quad \text{Eqn.1}$$

Where ω_k are the weights and N(x; $\mu_{k,}$ σ_k) is the normal density of mean μ_k and covariance matrix $\Sigma_k = \sigma_k I$, (I denotes the identity matrix). The mixture of Gaussians algorithm, proposed by Stauffer and Grimson [12] estimates these parameters over time to obtain a robust representation of the background.

The work starts with the generation of frame sequences from the input video. Then the Probability density functions are calculated for a Gaussian Mixture comprising K component densities. MFCCs are obtained as follows. First, the parameters are initialized with $\omega_k = \omega_0$, $\mu_k = \mu_0$ and $\sigma_k = \sigma_0$. If there is a match, i.e. then the parameter mixtures are updated as per the mentioned equations follow up by normalizing the weights at each iteration to add up to 1. A threshold λ is applied to the cumulative sum of weights to find the set {1...B} of Gaussians modeling the background. Intuitively, Gaussians with the highest probability of occurrence, wk, and lowest variability in the distribution, measured by σ_k, indicating a representative mode, are the most likely to model the background.

Parameters for Simulation

The parameters that have been used in simulation are mentioned and briefly discussed below;

1) Number of Gaussian Densities (K): It represents the number of Gaussian densities used that are used to compute the PDF. Calculations have been done for K=3 and K=4.
2) Background Threshold (λ): A threshold λ is applied to the cumulative sum of weights to find the set {1...B} of Gaussians modelling the background.
3) Covariance (σ): Covariance matrix which is used in calculation of initial pdf.
4) Component Threshold: Normally taken as 10.

IV SIMULATION RESULTS

Car Park Video

1) 520 frame Video.
2) 10 fps.
3) Background: Stable.
4) Illumination Change: Partial.
5) Objects to track: Multiple.

The video consists of multiple objects that are required to be tracked. The system efficiently tracks both the moving car and the pedestrian. It locks on to moving man once the car is stationary, and that the multiple objects have been tracked successfully. The algorithm has seamlessly detected even multiple objects as it can be seen from various images where after subtraction and morphological filtering correct markers have been implanted.

Input frame from video that consist of multiple objects like moving car, stationary car and moving man also. This frame we can see in the Figure 2.

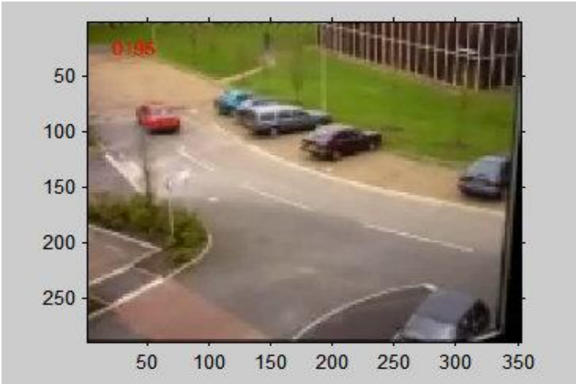

Figure 2 Input Frame

To track the multiple objects we have to extract the best background of this input video and this extracted image is extracted best background image. As we can see from the Fig. 3. False detection is more prominently visible in the initial learning stage that should be removing after using some applications. When some false detection occurred in tracked object image after subtraction frame then we updated the mixture parameter, and the object is traced successfully with few false detection being removed by filtering. As we can see in fig 4.

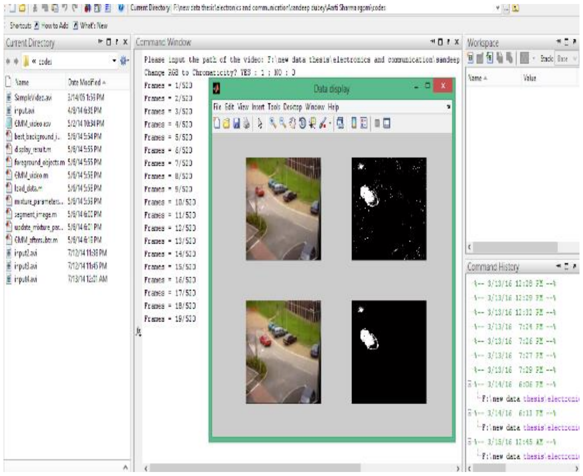

Figure 3 Extracted Best Background Image.

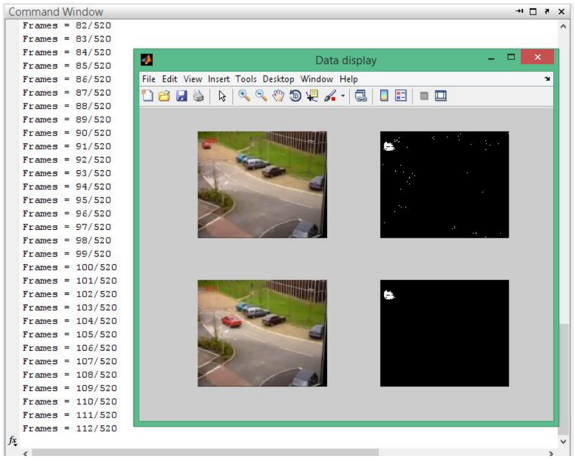

Figure 4 Initial learning phase after filtering

After filtering of image frame of initial learning phase apply hue to detected area for tracking the object. As we can see in the results Figure 5.

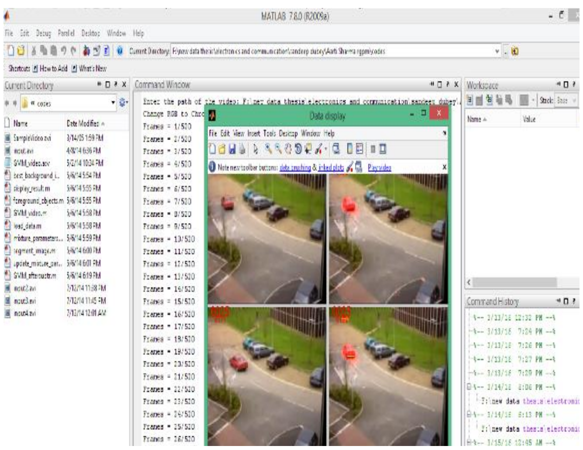

Figure 5 after applying Hue to detected area

Applying Hue to detected area we have to show the object so we marked the object and traced the object successfully. As we can see from the Figure 6.

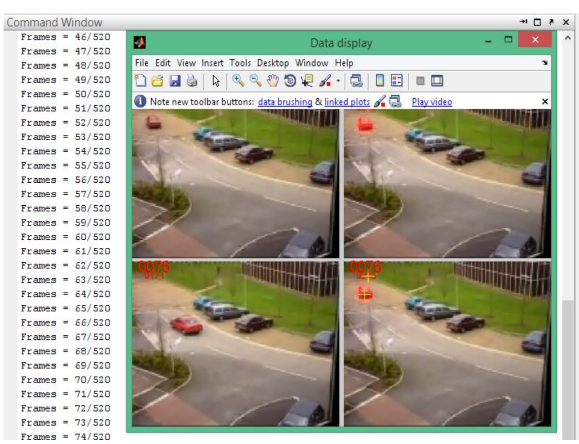

Figure 6 Object Marked and Tracked

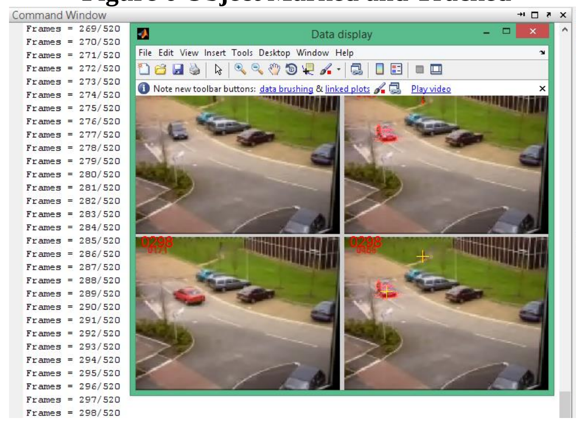

Fig. 7 Multiple Object Detection (Man and car both moving)

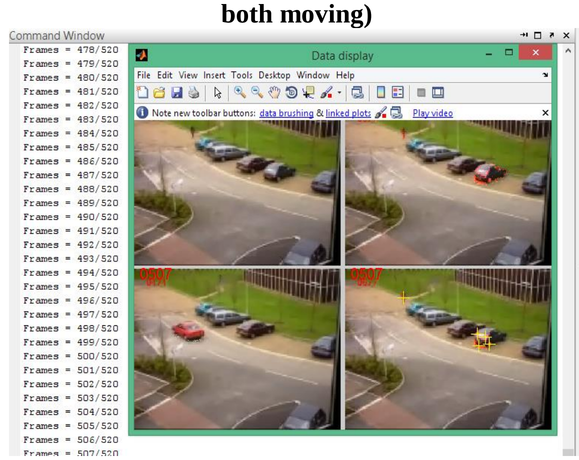

Fig. 8 Car Stationary and man moving

The video consists of multiple objects that are required to be tracked. The system efficiently tracks both the moving car and the pedestrian. It locks on to moving man once the car is stationary. However the initial learning phase was slightly slower than previous videos owing to the initial visibility in this video is very poor as the illumination change is significant and the camera is at a significant distance away from the object.

V COMPARISON OF PAST AND PRESENT WORK

Evaluation Value True Positive and False Negative Recognition

Parameter	True Positive Rate Value		False Negative Rate Value	
Algorithm / Variance	EM Algorithm	AGM Algorithm	EM Algorithm	AGM Algorithm
0.012	0.65	0.85	0.12	0.12
0.012	0.6	0.81	0.20	0.20
0.012	0.57	0.70	0.30	0.30
0.012	0.40	0.60	0.40	0.40

Using the value of evaluation of performance of proposed algorithm (AGM Algorithm) and past work algorithm (EM Algorithm) we conclude that the mean of true positive is 85% with variance 0.012 and the mean of false negative rate is 0.12. We can also see from the graph which has plotted between true positive recognition and false negative Recognition rate.

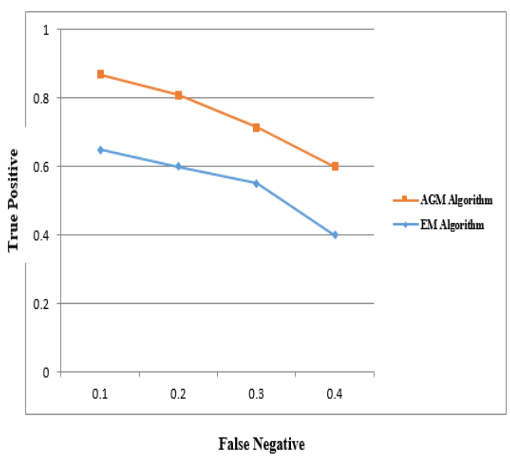

Figure 9 Line Chart of Evaluation of Performance of Algorithm

VI CONCLUSION

This paper has presented a detailed account on the state of the art in the field of Motion Detection through Computer Vision. The work discussed all the technologies like Optical flow, Gaussian average etc. and the mathematical concepts involved in the algorithms. The paper discussed at length the advantages using Gaussian Mixture models and presented the use of Adaptive GMM as an enhanced tool for motion sensing. The results showed the effectiveness of AGMM in detection of motion in videos with varying light intensities and poor visibilities. The work showed satisfactory performance in terms of its detection capabilities and learning rate performance.

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