

**COL-780**  
**ASSIGNMENT-1 REPORT**

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**2019CS10369**

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# 1 Method Used

My entry number is **2019CS10369** and ends with 69. So my Y=1 and I used the background subtraction method with constant weights for past N values. For the aggregation of foreground pixels, I used the integral images.

## 1.1 Gaussian Mixture Models

Stauffer and Grimson used the Mixture of Gaussians (MOG) to model dynamic backgrounds. The recent history of the intensity values (in RGB color space) of each pixel  $X_1, \dots, X_t$  is modeled by a mixture of K Gaussian distribution. The probability of observing the current pixel value is given by the formula:

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

where  $K$  gives the number of Gaussian distributions,  $\omega_{k,t}$  is the weight of the  $k^{th}$  Gaussian in the mixture at time  $t$  having mean  $\mu_{k,t}$  and covariance matrix  $\Sigma_{k,t}$  and  $\eta$  is a Gaussian probability density function.

For computational reasons it is assumed that the red, green and blue color components are independent and have the same variances. The authors propose the value of K from 3 to 5. K-means algorithm is used in the original paper to update the values of weights, means and co-variances of the mixture of Gaussians in an online fashion.

## 1.2 Gaussian Mixture Models with Constant Weights for past N frames

The main difference between this method and the original method proposed by Stauffer and Grimson is in the update equations for weights, mean and co-variances of the GMMs. Instead of comparing all frames in time  $t$ , only N-recent window samples are processed which increases the processing speed of the algorithm. The N-recent window update equations give priority to recent data therefore the tracker can adapt to changes in the environment effectively.

The update equations of the N-recent window version are:

$$\begin{aligned}\omega_{k,t} &= \omega_{k,t-1} + \frac{1}{N}(M_{k,t} - \omega_{k,t-1}) \\ \mu_{k,t} &= \mu_{k,t-1} + \frac{1}{N}\left(\frac{M_{k,t}X_t}{\omega_{k,t}} - \mu_{k,t-1}\right) \\ \Sigma_{k,t} &= \Sigma_{k,t-1} + \frac{1}{N}\left(\frac{M_{k,t}(X_t - \mu_{k,t-1})(X_t - \mu_{k,t-1})^T}{\omega_{k,t}} - \Sigma_{k,t-1}\right)\end{aligned}$$

## 2 Design Choices Made

I chose the value of N to be 10 and set the fps of the video to be 10 frames per second. I set the number of Gaussians to be 4 and initialized their mean-values to be 0 and Variance to be 225 with an initial weight of 0.01 for the four Gaussians used.

### 3 Instructions to run the code

Use the command `python3 Code.py arg1 arg2 arg3` to run the code where arg1 and arg2 are input and output paths respectively and arg3 is the number of Gaussians to be used in the mixture model.

### 4 Observations

For the first 5-8 frames, we cannot see any clear background in any method for all five datasets and it gradually improves with the next frames.

But I could see that my friend's model which uses the Gaussian Mixtures with decaying weights( $Y=0$ ) performs better background subtraction than my model. This could be because, with decaying weights, the recent frames are more weighted than in my case where past and present frames have equal weights for mean and variance.

The code works well with the datasets HighwayL, IBMTest and HallAndMonitor. But the datasets, Candela and Caviar have subtle lighting changes and camera changes and in these cases the Gaussian mixture model does not work properly to detect background for certain frames.

I have added the outputs of each frame and the final videos after background subtraction and foreground aggregation at this [link](#).

## 5 Results

The model performs pretty well on HighwayL and IBMTest2 datasets.



(a) HighwayI



(b) IBMtest2

Figure 1: Sample output of a frame for HighwayI and IBMtest2 Datasets

In the case of HallandMonitor dataset, the model performs better on earlier frames and does not perform well on the later frames.



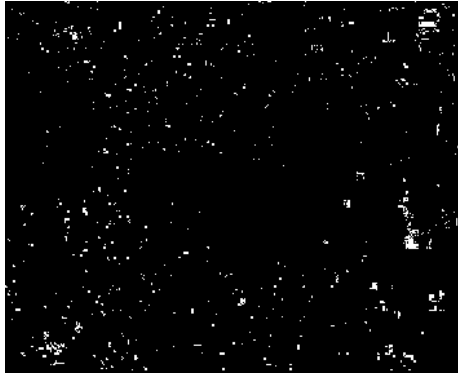
(a)  $t=4$  sec



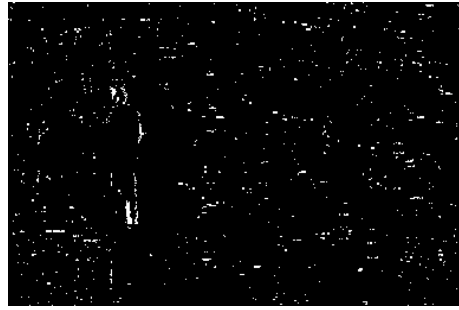
(b)  $t=20.7$ sec

Figure 2: Sample output of frames for HallandMonitor Dataset

The model does not perform well on Candela and Caviar datasets.



(a) Candela



(b) Caviar

Figure 3: Sample output of a frame for Candela and Caviar Datasets

## 6 References

1. [Stauffer-Grimson Paper](#)
2. [Improved Adaptive Background Mixture Model](#)
3. [OpenCV Tutorials](#)