

Implementation of Pixel-wise Background Subtraction

EE20S002

The algorithm implementation input was taken as a video. If input is given in frame images then it was converted to video using Frametovideo.py.

Algorithms

- GMM (refer to the paper Stauffer and Grimson)
 - Implemented algorithm: The Algorithm was implemented as mentioned in the paper. The parameters (Alpha - Learning Rate, K - Number of Gaussian Distribution, Background Threshold) decide the output features.
- Non-Parametric method
 - Implemented algorithm: The Algorithm was implemented as mentioned in the paper. No other parameter was required except the threshold.
- Order-based
 - Implemented algorithm: Video was converted into frames. Each frame (image) was divided into square blocks of some size (say 10 pixels). Random pixel position was chosen in a particular block for the two consecutive frames. Ratio was taken of intensity at those pixel positions, in a specific manner. The difference of the ratio for two consecutive frames was calculated and compared to a threshold. If the difference is less than the threshold then it is considered as background otherwise it is considered as foreground.

Outputs:

1. Jump and Run

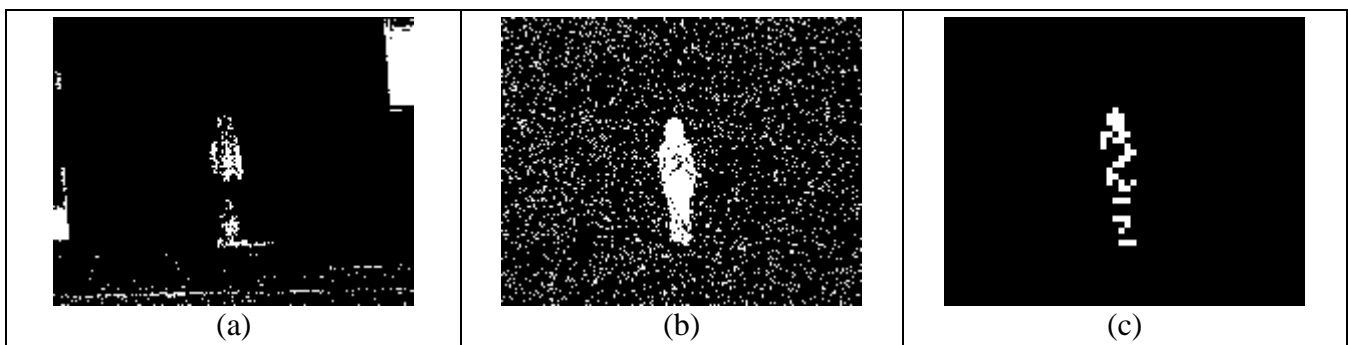


Fig 1: (Left to Right) Output of *Jump.avi* Using Gaussian Mixture Based Model (a), Non Parametric Model (b) and Order Based Model (c).

Jump video had a static background with a little noise. Order Based Model 1.(a) gives resistance to such small noises but the visible shape of the foreground depends on the block size in which we divide the image frame. Non Parametric method 1.(b) doesn't provide the resistance to noise though the shape

of the foreground is much visible. GMM Model 1.(a) do provide better foreground shape but with some false detections.

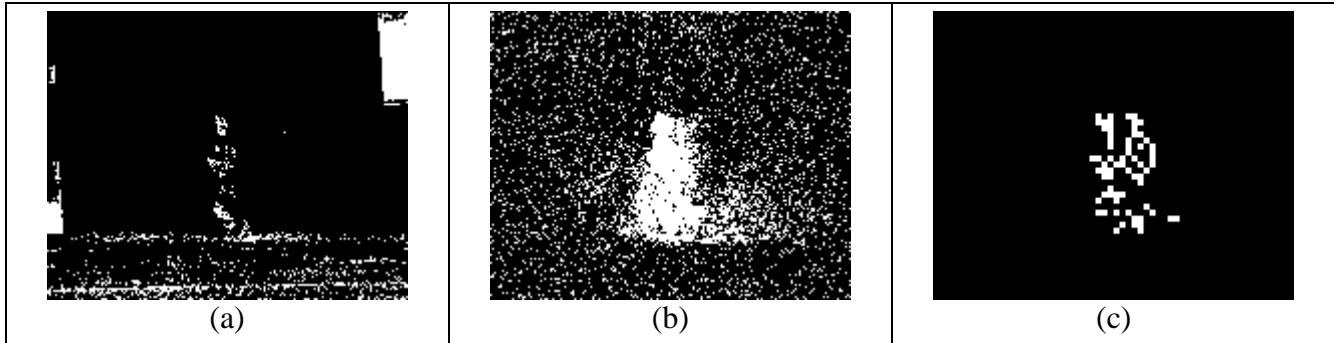


Fig 2: (Left to Right) Output of *Run.avi* Using Gaussian Mixture Based Model (a), Non Parametric Model (b) and Order Based Model (c).

The Run video had a static background with a little noise and shadow. Order Based Model 1.(a) gives resistance to such small noises but the visible shape of the foreground depends on the block size in which we divide the image frame. Shadow visibility depends on the threshold. Non Parametric method 1.(b) doesn't provide much resistance to noise though the shape of the foreground is much visible. False detections are there. GMM Model 1.(a) do provide better foreground shape but with some false detections. Shadow is visible. Gives a better picture of the scene.

2. Highway

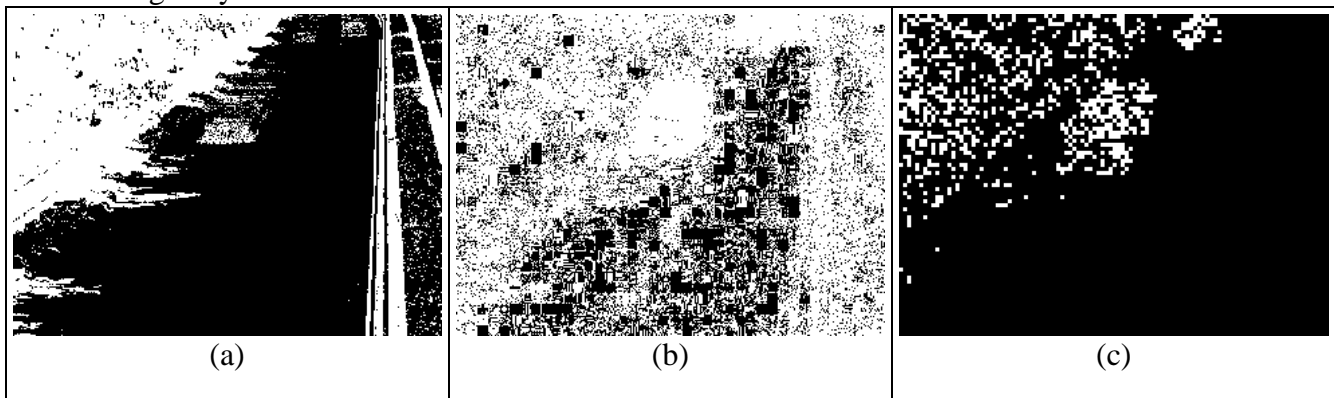


Fig 3: (Left to Right) Output of *Highway.avi* Using Gaussian Mixture Based Model (a), Non Parametric Model (b) and Order Based Model (c).

Highway.avi is full of non static background. With moving leaves, noises and shadow in the background nearly all methods don't provide a good background detection due to the assumption that illumination changes and non static background is not there while implementing the algorithms.

3. Pets

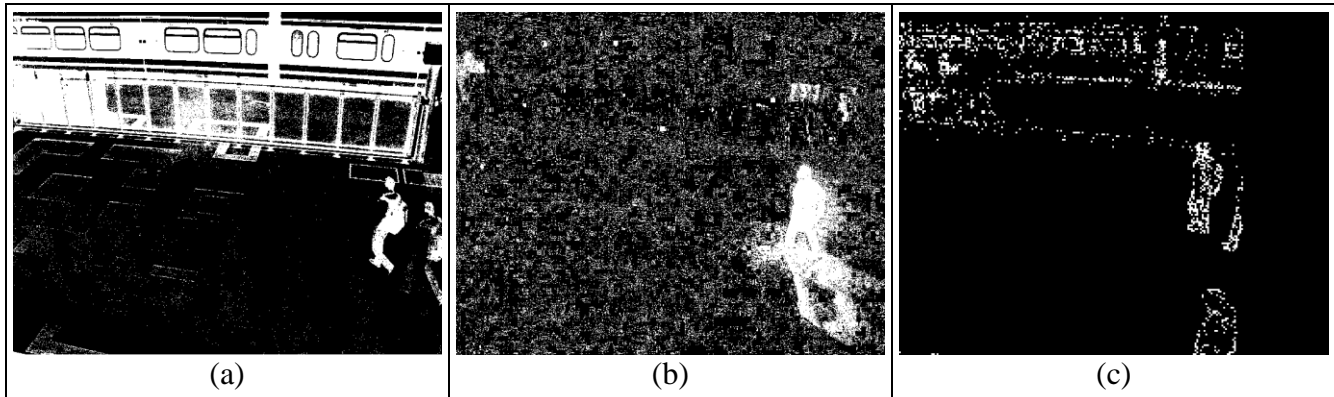


Fig 4: (Left to Right) Output of *Pets.avi* Using Gaussian Mixture Based Model (a), Non Parametric Model (b) and Order Based Model (c).

Though the background is static this video does have multiple shadows which ideally should not be shown in foreground. Here Order Based Model 4.(a) is much better in getting the shape of the foreground and least false detection.

4) Canoe

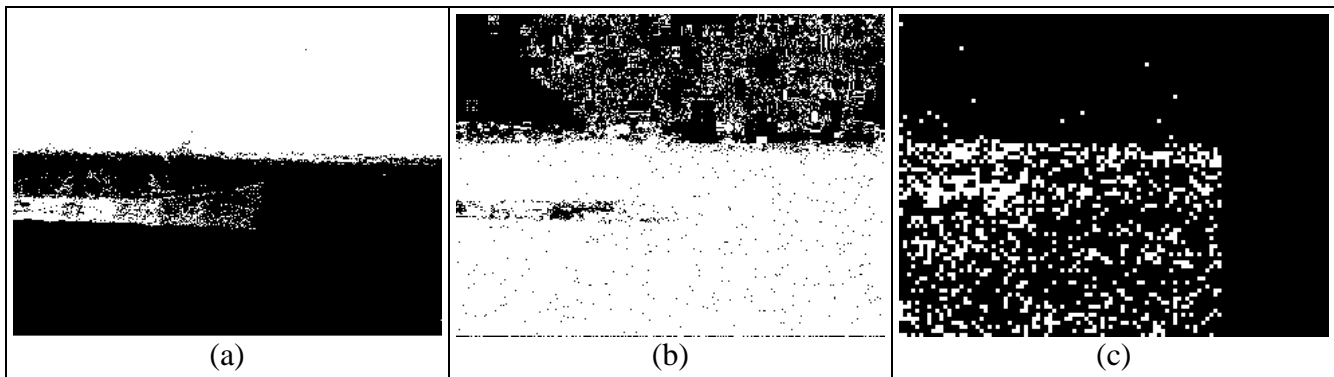


Fig 5: (Left to Right) Output of *canoe.avi* Using Gaussian Mixture Based Model (a), Non Parametric Model (b) and Order Based Model (c).

Order based Method 5.(c) completely fails in the background detection for canoe.avi, due to the water movement which leads to change in intensity difference frequently in consecutive frames thus detected as foreground. GMM 5.(a) proved to be best among the three algorithms with a better picture of foreground compared to the other two. The noise in the waves was the other issue in detection of false background.

The link to Outputs and Gif of the outputs:

https://drive.google.com/drive/folders/1Z_B49x5CwLJqKucD9XLS0cUCrg0yD1KQ?usp=sharing