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Detection And Analysis of Moving Object in Dynamic Background

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ABSTRACT: In any video surveillance applications moving object detection is an important and basic step. The detected object has been used as an input to higher level tasks such as event detection, object tracking and behavioral analysis. Several challenges such as illumination changes, occlusion, shadow, bootstrap, dynamic background etc. occur while detecting an object. It is very difficult to detect moving object when the background is moving. In this case, false detection occurs in which moving background is also detected as an object. In this paper, different techniques were implemented for detecting moving object fromthedynamic background and their qualitative and quantitative results are obtained.

Keywords: Background subtraction, dynamic background, Gaussian, moving object detection, video surveillance.

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I. INTRODUCTION

In any video surveillance system, the key step is the detection of moving an object from the scene. Moving object detection is the separation of moving foreground objects from background that may be static or dynamic. The dynamic background may be waving trees, rippling water, fountains, outdoor illumination changes, glints and glare of sun etc. Due to different environmental changes detection of moving anobject fromthedynamic background is complicated as compared to static background in the scene. Basic techniques used for detecting moving object are background subtraction, frame differencing, optical flow and temporal differencing. Optical flow is complex, sensitive to noise and also has less speed. Frame differencing method has less complexity but sometimes detects noise as a moving object. In case of background subtraction difference betweencurrent frame and background model is taken. Deviation of pixel intensity in the current frame from that of the reference model is considered as a moving object. Background model should update immediately with variations in the scene. An algorithm is said to be effective if it adapts quickly to the changes in the background.

The method called Gaussian Mixture Model (GMM) is given by Stauffer and Grimson [1]. Here each pixel is modeled as a mixture of Gaussian. Multiple variations in the background are modeled using different Gaussian components. Suppose the background has moving leaves and water fountain during the background modeling, then the intensities of moving water pixels would be represented by one Gaussian curve, while that of leaves would be represented by another Gaussian curve. When combined together, there will be multiple Gaussians with their corresponding weights.

Elgammal et al.[2] Model the background distribution by using Kernel Density Estimation technique. Previous n background values are stored in a buffer. The background probability density function is modeled as the accumulation of the Gaussian kernels which are centered in the latest n background values. Small motions in the background are best handled by this method. In scenes where the background is cluttered and there is periodic motion like waving of leaves, theflow of water etc.; this algorithm is able to give good results.

A novel approach to background subtraction was presented by Marko Heikkila et al.[3], in which the background is modeled using texture features. Feature extraction is done by using local binary pattern (LBP) operator. For external illumination changes, results obtained by LBP are best. In comparison with other methods, the LBP features are computed with higher speed. The method belongs to nonparametric methods, which means that no assumptions about the underlying distributions are needed.

Jing-Ming Guo et al.[4] Introduced a multilayer codebook-based background subtraction (MCBS) model for video sequences to detect moving objects. Frames are divided into blocks of various sizes and different features are extracted from each block. By combining adaptive feature extraction with multilayer block-based strategy moving background is removed which leads to increase in efficiency. The system cannot distinguish foreground and background sharing similar colors.

To handle the illumination changes in the videos an algorithm was proposed by Xiang et al.[5] that combined the local intensity ratio and Gaussian mixture model. The local intensity method was used to eliminate the shadow and then the Gaussian mixture model was used for object detection in a frame. Erosion is then applied to eliminate noise and scattered shadows.

Hong Han et al.[6] combined texture and color information for background modeling. Foreground decision is done by using color information, texture information, and the combination of color and texture information. A new quality measure was given for evaluating the performance ofthemethod on various challenging videos and the result is quite outstanding compared with the other state-of-the-art methods. The memory consumption is low. The method is robust to illumination variations and moving cast shadow problems.

Xiaochun Cao et al.[7] separates moving background from moving objects using the spatial continuity of foreground, and detects intermittent moving objects using the temporal continuity of foreground. TVRPCA algorithm is proposed for detecting irregularly moving objects that correctly detect small objects with continuous movements. Improvement in precision and F-measure by removing the inconsistent movements and gives reduced run time. The algorithm cannot separate foreground objects similar in color tothebackground.

Xiang Zhang et al.[8] Proposed a new technique to detect camouflage moving object called as camouflage modeling (CM).Developed a global model for the background and integration with local models for the foreground respectively. With the models, introduce a camouflage degree to compare foreground and background likelihoods for each pixel, based on which camouflaged pixels are identified. Shadow pixels sharing similar color with background are misclassified as foreground pixel.

An interval-valued fuzzy-based moving object detection algorithm is presented by PojalaChiranjeevi et al.[9].considering variable uncertainty over real-valued similarity values, thereby extending real-valued fuzzy integrals to interval-valued. Though method could handle dynamic backgrounds better than its contemporary methods, it still produces some background noise while extracting foreground objects. Processing speed is a bit low as compared to the pixel-based approaches.

Chia-Hung Yehet al. [10]used three different approaches for detecting moving object in surveillance system. First, texture background modeling method only detects the texture of the foreground object but can resist illumination changes and shadow interference. Second, hysteresis thresholding on both texture and color background model is used to generate predominant and supplementary images. Finally, the motion history applies spatial-temporal information to alleviate the cavity and fragment problems in foreground objects. The combined approach thereby offers a three-pronged compensation by leveraging texture, color, and spatial-temporal information.

To cope up with the different dynamic background challenges, adaptive background modeling techniques were widely developed by the researchers. The background is modeled using pixel and block -based features. Algorithms such as Mixture of Gaussian, Kernel density estimation, codebook, background subtraction along with background updating, local binary pattern etc. were invented for making object detection robust in adynamic environment.

II. METHODOLOGY

Three methods frame differencing, a mixture of Gaussian and background updating using background subtraction were implemented and compared on the basis of qualitative and quantitative analysis.

A. Frame Differencing

Frame differencing takes the difference between current frame and previous frame. The result is then compared with the threshold [11] value. Ifthedifference is greater thanthethreshold then pixel belongs to foreground else to the background. Let us denote the intensity value of a pixel $P_{x;\,y}$ at time t as $I_{x;\,y;\,t}$Then according to the method, the difference between the frame at time t and the frame at time t-1 is determined as follows:

$$D=\left|I_{x,y,t} - I_{x,y,t-1}\right| > \tau \qquad (1)$$

For each pixel, the value of D is compared to a threshold τ and classified as follows:

$$P(x,y) = \begin{cases} \text{foreground} & \text{if } D > \tau \\ background & else \end{cases} \qquad (2)$$

B. Mixture of Gaussian

Gaussian probability density function is used to evaluate the pixel intensity value [12]. Difference between current pixel intensity and cumulative average of previous values is compared with the product of deviation and constant value. The pixel is then classified as foreground or background. That is, at each t frame time, if,

$$|\mathrm{It} - \mu\mathrm{t}| > k\sigma \qquad (3)$$

then pixel belongs to the foreground otherwise to the background. Here k is a constant and σ is the standard deviation.

C. Background updating using background subtraction

In this method, the background is updated by classifying stationary and no stationary pixels [13].Pixels that remain stationary for N number of frames are added in the background and accordingly, the background is updated. Initially, frame differencing method is used for every incoming frame.

$$FD_t(x,y) = \left|F_t(x,y) - F_{t-1}(x,y)\right| \tag{4}$$

$$FDM_t(x,y) = \begin{cases} 1 & if\ FD_t > \tau \\ 0 & if\ FD_t < \tau \end{cases} \tag{5}$$

Here, t represents frame at time t, (x, y) gives the pixel position and τ is the threshold value. A pixel with FDM value 0 is a non-moving pixel. If it remains stationary for certain number of frames say N, then that pixel is said to belong to the background. Stationary index for background pixel is incremented by 1. Thus, every incoming frame is subtracted from this updated reference background to detect moving object. Thus, mathematical form of background subtraction is given as.

$$BG_t(\mathrm{x,y}) = \left|F_t(x,y) - BG_n(x,y)\right| \tag{6}$$

$$P(x,y) = \begin{cases} foreground & if\ BG_t \geq \tau \\ background & if\ BG_t \leq \tau \end{cases} \tag{7}$$

Where $F_t(x,y)$the incoming is frame and $BG_n(x,y)$ is the reference background. Thus, three methods frame differencing, mixture of Gaussian and Background updating using background subtraction were studied and implemented in OpenCV-Python.

III. RESULTS

The three algorithms were implemented in python and tested on different standard dataset for qualitative and quantitative analysis. Standard database changedetection.net is used to test the developed algorithm against the dynamic background. Boats, fall, overpass and canoe video sequences were selected. Boats consist of 7999 frames with size 320x240, fall contain 4000 frames with size 720x480, overpass contains 3000 frames of 320x240 size and canoe contain1189 frames with size 320x240.The results are compared qualitatively and quantitatively.

3.1 **Qualitative Analysis**

The output of three methods namely frame differencing(FDM),mixture of Gaussian(MOG2) and background updating using background subtraction are compared with the ground truth of each sequence.

3.1.1 Boats Sequence

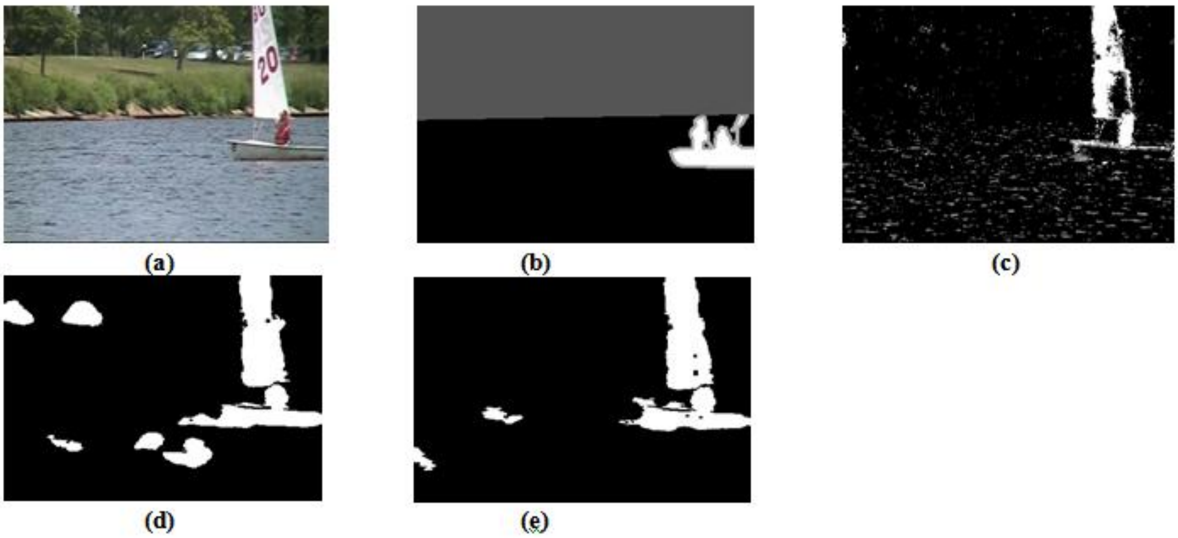

Fig.1 Qualitative analysis on Boats database (a) input frame (b) Ground truth (c) MOG2 (d) FDM (e) Background updating with background subtraction output

MOG is sensitive to noise as seen in fig.1. FDM detects rippling water and vehicle moving in the background also as object. Background updating with background subtraction gives good detection accuracy close to ground truth.

3.1.2 Fall sequence

Fig.2 shows that MOG detects object accurately along with the noise and moving tree.FDM detects boundary and some holes inside the object which is an aperture problem. The third method shows less accuracy in which shadow, as well as moving tree, are also detected as an object.

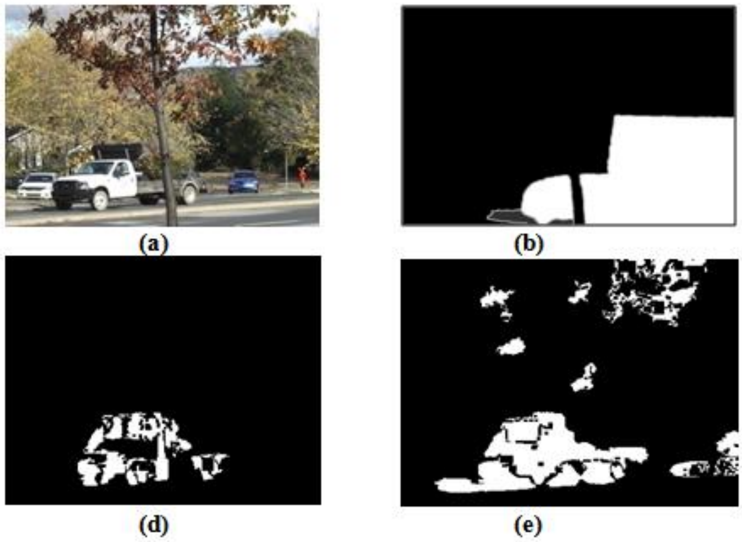

Fig.2 Qualitative analysis on fall database (a) Input frame (b) Ground truth (c) MOG2 (d) FDM (e) Background updating with background subtraction output.

3.1.3 Overpass sequence

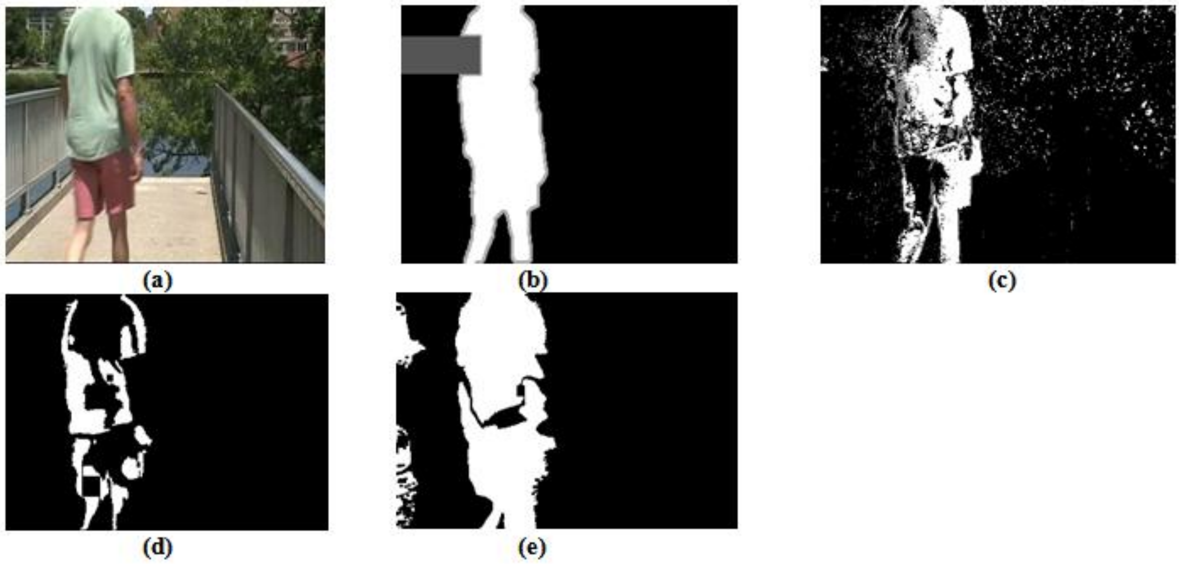

Fig.3 Qualitative analysis on overpass database (a) Input frame (b) Ground truth image (c) MOG2 (d) FDM (e) Background updating with background subtraction output.

MOG and background subtraction detect anobject near to the ground truth as seen in fig.3. .In case of MOG come noise is also detected in the form of moving tree. FDM shows aperture problem and only boundaries of the object are detected.

3.1.4 Canoe sequence

The background subtraction method presents significant improvement in qualitative results as shown in fig.4. Objects moving in the background are eliminated easily. The qualitative evaluations reveal that results are better as compared to another state of art methods.

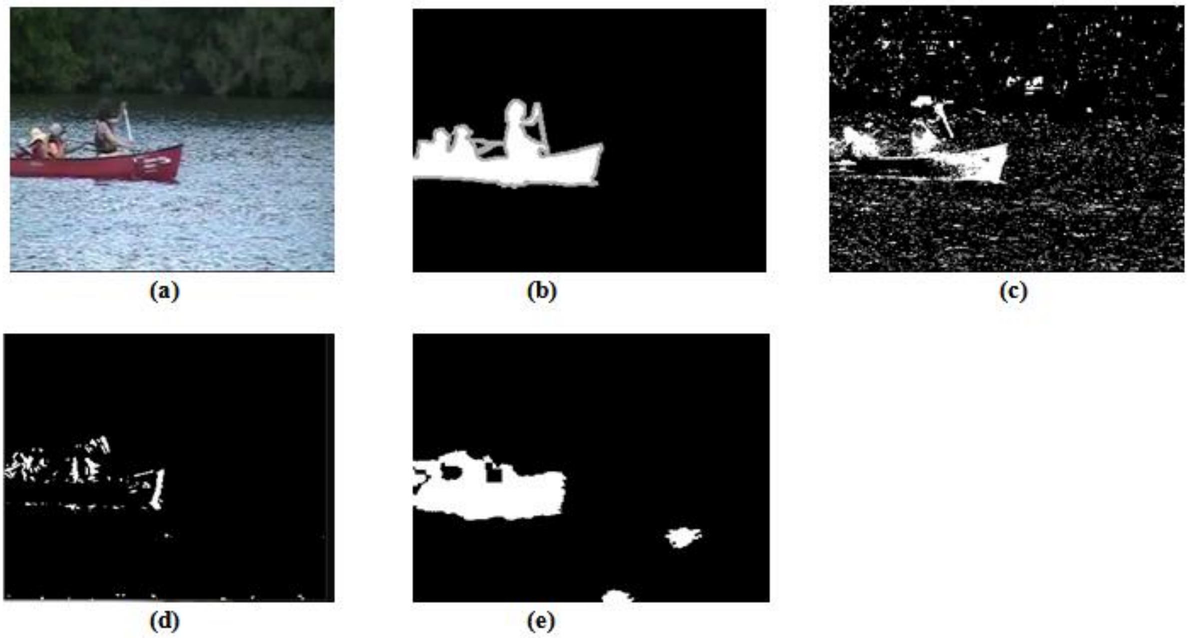

Fig.4 Qualitative analysis on Canoe database (a) Input frame (b) Ground truth (c) MOG2 (d) FDM (e) Background updating with background subtraction output.

3.2 Quantitative Analysis

Three parameters have been evaluated for performance analysis. Performance evaluation tells how well the algorithm detects the target with fewer false alarms. Three performance parameters recall, precision and f-measure were calculated. Recall (Detection rate) gives the percentage of corrected pixels classified as background with respect to the total number of background pixels in the ground truth.

$$Recall = \frac{Number\ \ of\ correctly\ \ identifying\ \ pixel}{Number\ \ of\ foreground\ \ pixels\ in\ ground\ \ truth.} \quad (8)$$

Precision gives the percentage of corrected pixels classified as background with respect to the total pixels classified as background by the method:

$$Precision\ = \frac{Number\ \ of\ correctly\ \ identifying\ \ pixel}{Number\ \ of\ foreground\ \ pixels\ detected\ \ by\ algorithm} \quad (9)$$

A good performance is said to be obtained when the recall is high without affecting Precision.

The F-Measure (or effectiveness measure) is determined as follows:

$$F\ measure = \frac{2*recall\ *precision}{recall\ +precision} \quad (10)$$

The F-Measure characterizes the performance of classification in Precision-Detection Rate space. The aim is to maximize F closed to one.

3.2.1 Boat sequence

From fig.5 it can be stated that, the recall value of background subtraction method is very good as compared to FDM and MOG .MOG has higher precision than FDM and background subtraction method. Effectiveness measure of background subtraction method is better than MOG and FDM.

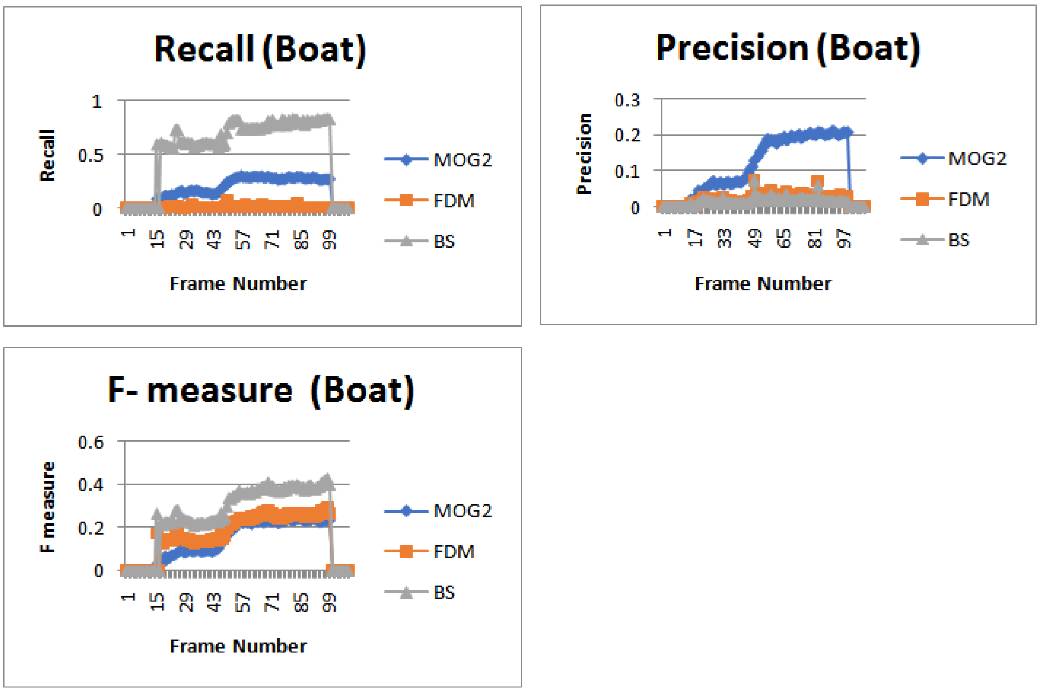

Fig.5 Recall, precision and f-measure plot for Boat sequence

3.2.2 Fall Sequence

The detection rate of background subtraction method is very good close to 1 as seen from fig.6.Detection rate of MOG is also very high as compared to FDM. Background subtraction method is more precise for fall sequence as compared to boatsequence. All three methods have nearly equal effective measure for fall sequence. Good results are obtained as compared to boats sequence.

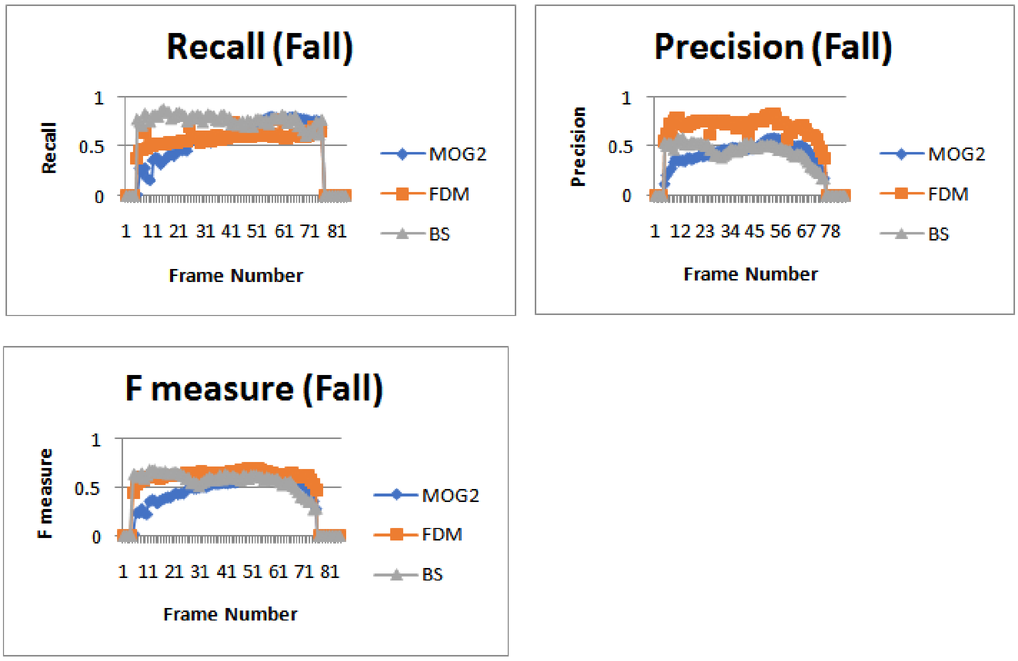

Fig.6 Recall, precision and f-measure plot for Fall sequence

3.2.3 Overpass sequence

Overpass database gives best results as compared to boats and fall sequence. The recall rate is closed to 1 for background subtraction shown in the below fig.7 .FDM gives the best precision result close to1 as compared to MOG and Background subtraction method. Background subtraction method has good detection accuracy.

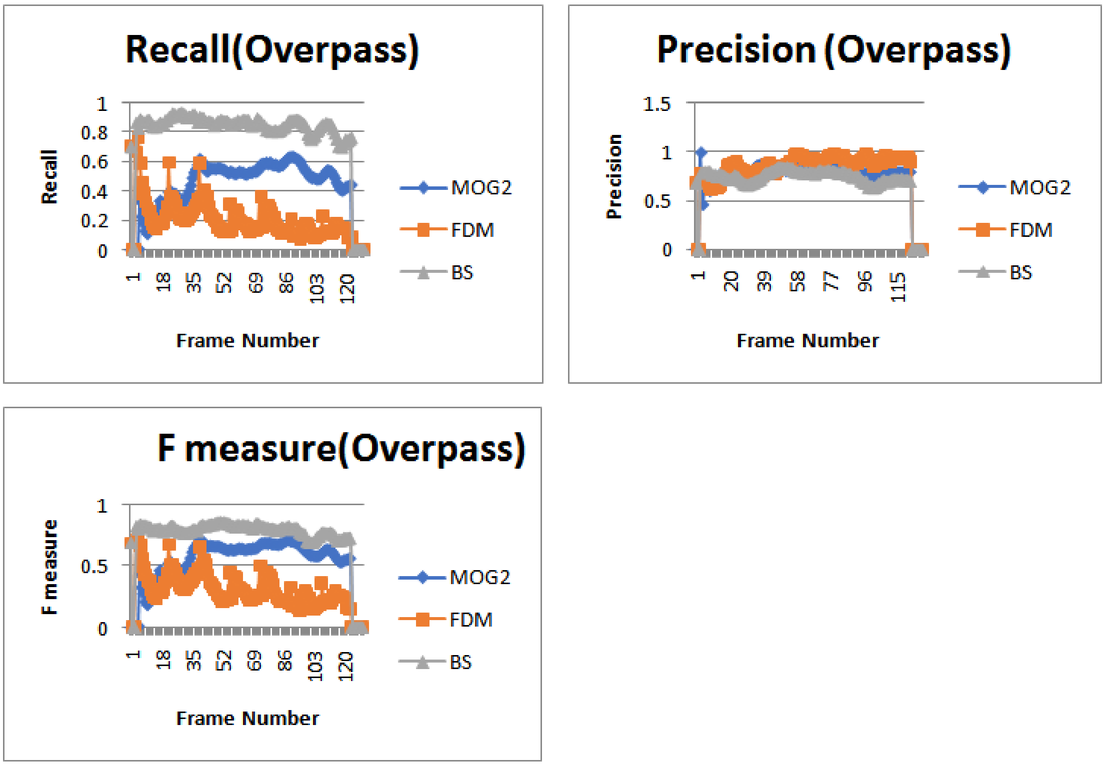

Fig.7 Recall, precision and f-measure plot for Overpass sequence

3.2.4 Canoe sequence

Recall rate for canoe sequence for background subtraction is good as compared to other databases as shown in fig.8.FDM is more precise in canoe sequence as compared to MOG and Background Subtraction.F-measure is close to 1.Background subtraction with background updating gives the best result than other two methods.

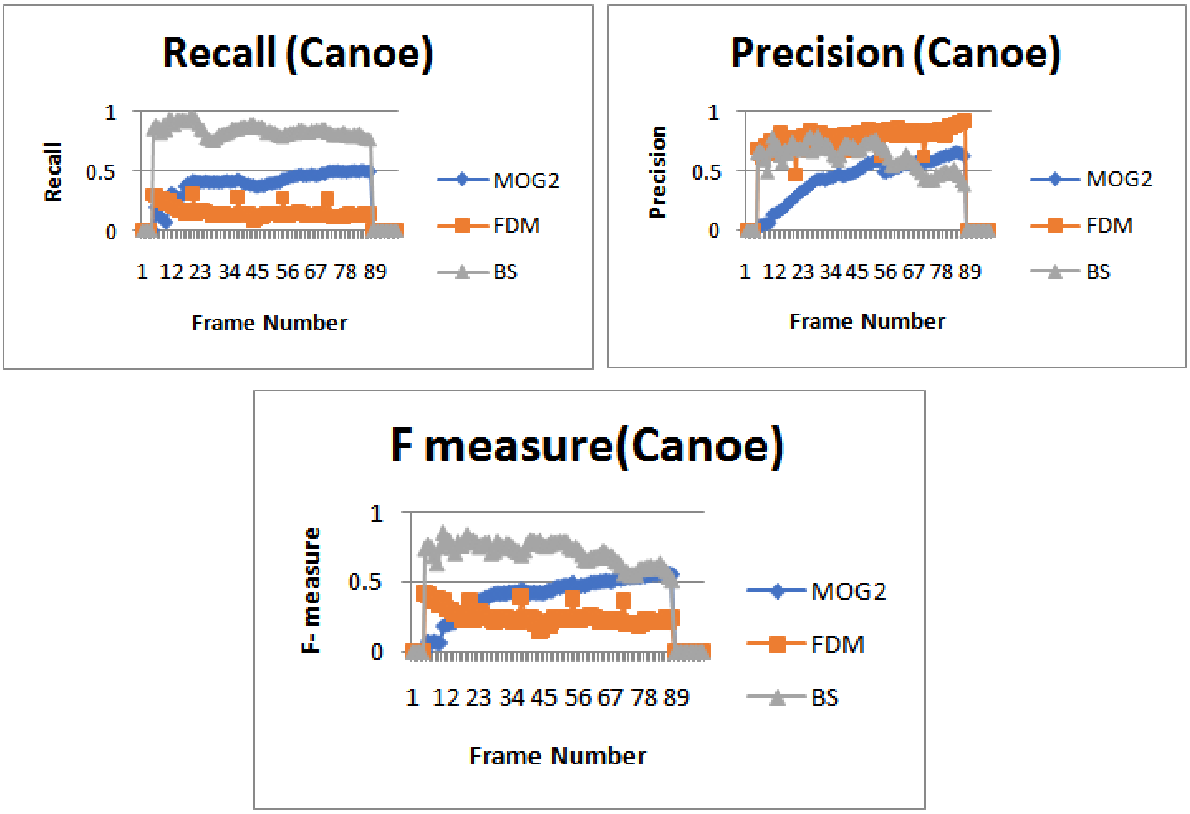

Fig.8 Recall, precision and f-measure plot for Canoe sequence

FDM shows the poor result in case of canoe sequence due to slow moving object. FDM fails to detect an object having an uniformcolor.MOG is sensitive to noise.MOG detects small moving objects in the background for boats sequence. As compared to MOG and FDM, background updating technique shows good results. The value of F-measure of background updating is high in all cases except fall due to the strong dynamic background. F measure for background subtraction is closed to about 85%.This clearly shows detection accuracy of this method is higher than state of art algorithms, MOG and FDM.

IV. CONCLUSION

Moving object from the dynamic background is detected by implementing three algorithms such as a mixture of Gaussian, frame differencing and background subtraction using background updating technique. The testing is done in dynamic background scenario which consists of waving trees and rippling water mostly. A mixture of Gaussian algorithm detects object accurately but is sensitive to noise. Frame differencing algorithm fails to detect an object having an uniform color. Only edges of the object are detected. Aperture problem is also detected in FDM. Background subtraction is able to deal with changing background efficiently. It is having the higher recall, precision and F measure value close to 1 for fall, overpass and canoe sequences than the other method. Though poor results are obtained for boats sequence, the background updating with background subtraction is still more robust to noise and works better in the dynamic background. In as urveillance system, these methods are very useful to detect moving objects in the outdoor environment.

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