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Optimum Parameters Selection of Basic Statistical Methods for Effective Object Detection in Video Streams

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Abstract

This paper empirical investigates two basic statistical methods namely Adaptive Median and Adaptive Mean for motion detection in video surveillance for the optimization of parameters namely threshold and the refresh rate of background frame used in these methods. Experimentation shows that the optimum choice of parameters majorly affects the quality of motion detection. The performance of methods for different parameters is measured using precision, recall and f1-score. PR curves are also drawn which are based on precision and recall values to show the effect of different parameters. Test data includes six data sets from differen t scenarios of 'CDNet2012'. Experimental results verify that for every method there are fixed values of parameters with slight variations which gives better result of object motion. These parameter values can be used or adapted for future experimentation on these methods with respect to each scenario.

Keywords; *Object detection, Video surveillance, Adaptive Mean (AM), Adaptive Median (AMD), PR curves.*

I. INTRODUCTION

Frame differencing is the most logical and basic method for determining the motion in a video stream which requires finding the difference of two successive frames for motion/object detection and then thresholding the difference to prevent the spurious noise to be falsely taken as foreground or motion. The choice of thresholding value in different scenario greatly affects the quality of motion detection. There is no fix method to determine threshold value, usually it has to be determined empirically from video sequence. Frame differencing is a crude method which is primarily dependent on frame rate for quality extraction of motion from the frames.

To overcome this limitation, background subtraction (BGS) methods are devised in which a background scene is modeled which is subtracted from the current frame to get moving object. Modeling of background is a tedious process and ideal modeling should be capable of managing dynamicity of scene, detection of ghost objects, sudden illumination and multi modal background. There are many statistical methods for background modeling which range from most basic such as Adaptive Mean (AM) and Adaptive Median (AMD) to highly complex methods based on Kernel Density Estimation (KDE) and Mixture of Gaussians (MOGs). Former methods are faster but lacks the ability to model dynamic scenes and multimodal scenes. The later category of methods is effective but time consuming and hence cannot be used in real time video surveillance, complex methods cannot be used. In AM and AMD methods, in order to handle dynamic scenes, the background needs to be updated periodically either

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through adaptive mean or through adaptive median methods. This updation rate is also called the refresh rate of background frame. There is no predefined method of choosing an optimum frame rate. Hence, there is no alternative but to determine optimum values of threshold and frame refresh rate through empirical investigation every time for a particular scenario.

This paper strives to find optimum and adaptive values of threshold and the background frame refresh rate for the effective detection of objects in video frames through empirically study. Section I of the paper introduces the need of empirical investigation of the methods for finding the optimum parameters. Section II explains the related works. Section III describes AM and AMD object detection methods. Section IV comprises the experimental setup for empirical investigation. Section V discusses the results and is followed by the concluding part of the paper.

II. OBJECT DETECTION METHODS IN LITERATURE

Many literature survey [Yilma z2006, Benezeth2008, Bouwmans2011, Athanesious2012, Parekh2014] critically evaluate and compare different methods of object detection qualitatively on ly. Many of these also failed to use rigorous benchmarks data which provide challenging environment of object detection. The above literature surveys also failed to discus s and evaluate the impact of various algorithmic parameters on efficiency. Our experimentations have used benchmark test data and evaluate methods quantitatively using precision, recall and F-measure so that control parameters values can be determined. In AM and AMD both threshold and background frame refreshing rate are two parameters which need attention. In literature, we didn't find any paper which critically evaluated the effect of these two parameters. Most of the object detection algorithms fixed them empirically based on the test data. In literature, threshold is taken mostly as the tuning parameter. Some of these methods and subsequent improvements are explained below:

Rosin et al evaluated global thresholding techniques for object detection to classify these among; Poisson distribution based modeling, Euler-number which recommends threshold for every block of the image and Entropy-based method that recommends thresholding value based on the rate of change in the picture [Rosin2014]. Various thresholding Techniques were also used by Firdousi to fine tune the methods [Firdousi2014]. Zidek et al categorized threshold values into static versus dynamic thresholding. They also proposed a hybrid thresholding based A multispectral Otsu method based thresholding was also used [zidek2014].

Adaptive thresholding was also proposed by [ChangSu2006, [Samanta2012], [Case2010] by statistical techniques. The article [Subudhi2016] proposed a hybrid of spatial and temporal segmentation for proposing dynamic threshold. Hua et al [Hua 2014] also proposed adaptive threshold for bimodal background in Kernel Density Estimation method. Nain et al used histogram based thresholding [Nain2008] where Boufares et al [Boufares2016] proposed wavelet based thresholding for motion detection in AM method. electronically for review.

Table 1. Basic BGS algorithm

Step 1: Create an average image BG with some initial frames.
Step 2: For each of remaining frame say CF
Step 2.1: Find Difference

$$Diff = DIFF\ (CF, BG)$$

Step 2.2: Find foreground $F(Diff > Th) = 1$
Step 2.3: Update BG with the following equations:

(ForAM) $BG = \alpha \times CF + (1-\alpha) \times BG$

whereε is frame refreshing rate.

OR

(ForAMD) $BG\ (Diff > 0) = BG\ (Diff > 0) + \beta;$
$BG\ (Diff < 0) = BG\ (Diff < 0) - \beta;$

III. BASIC MOTION DETECTION METHODS

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Frame Differencing method suggests thresholding the difference of time adjacent frames to obtain moving objects in a video. The difference is shown in equation (1) which is subsequently thresholded by a value Th to obtain moving object or foreground part of the scene.

$$Diff(x,y) = F_t(x,y) - F_{t-1}(x,y) \quad (1)$$

$$M_t(x,y) = \begin{cases} 1 \; iff \; abs(Diff(x,y)) \geq Th \\ 0 \quad otherwise \end{cases} \quad (2)$$

Where F_t is current intensity at (x, y) pixel.Mt is motion detection at (x, y) $andThisa$thresholded value which is usually fixed based on empirical investigation. An optimum threshold is a prerequisite for good results.

The FD method is fast but usually failed due to improper frame rate. It is further improved by modeling a background frame. The background in the starting of object detection process is initialized by some fix number of frames from the video. Now in order to detect moving object difference is calculated between the current frame and the background frame which is further thresholded using equation (2).

$$Diff\ (x,y) = Ft\ (x,y) - B(x,y) \quad (3)$$

The B is background frame which is required to be updated regularly to handle dynamic background scenes as shown in equation (4).

$$Diff\ (x,y) = Ft\ (x,y) - Bt(x,y) \quad (4)$$

where$Bt(x, y)$ is calculated as in eq. (5) for AM and eq. (6-7) in case of AMD.

AM Method:

$$B(x,y) = \alpha \times Ft\ (x,y) + (1-\alpha) \times Bt{-}1(x,y) \quad (5)$$

AMD Method:

$$B(x,y) = Bt{-}1(x,y) + \beta if Diff\ (x,y) > 0 \quad (6)$$

$$B(x,y) = Bt{-}1(x,y) - \beta if Diff\ (x,y) < 0 \quad (7)$$

whereα and β are frame refreshing rate in AM and AMD methods respectively.

IV. RESULTS AND DISCUSSION

The basic methods of object detection have been tested using a standard data set "CDnet2012" (Goyette, Jodoin, Porikli, Konrad, &Ishwar, 2012). The experiments are performed on an Intel i3 3rd generation system with 4GB memory using MATLAB programming. The dataset comprises various scenarios representing different problems related to motion/object detection in video streams such as ghost objects, dynamic background, intermittent motion etc. Out of these scenarios, six sequences have been selected; these are; High_way (HW-baseline), Traffic (camera jitter), Canoe (dynamic background), Sofa (intermittent object motion), copy machine (shadow) and lake-side (thermal imagery) scenes have been chosen from these scenarios. A fixed number of starting frames model a preliminary background. Recall, Precision, F1-measure are calculated by comparing outcome with actual groundtruths. Fifteen thresholds for ten values background frame refresh rates combined to draw P-R curves. Higher covered area of these curves indicates better quality results. F1-score which is a hybrid parameter of precision and recall is used to find out the optimum value of threshold separately for both methods. Precision, which is number of relevant instances out of total retrieved instances and Recall which is relevant instances that are retrieved out o f total relevant instances are found by comparing the motion frame with actual groundtruths.

$$F1 = \frac{2 * Precision * Recall}{(Precision + Recall)} \quad (8)$$

Table 2. Best threshold and frame rates for every scenario with its corresponding F1 score for Adaptive Mean BGS Method

Methods	Basic_AM Method

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Scenarios	Best F1 score	Best Threshold	Best Frame Refresh Rate
High_Way	0.819430	30	0.0005
Traffic	0.698303	55	0.0005
Canoe	0.767960	40	0.0005
Sofa	0.605116	20	0.0005
Copy Machine	0.652236	30	0.0010
Lake Side	0.614307	10	0.0010

Table 3. Best threshold and frame rates for every scenario with its corresponding F1 score for Adaptive Median BGS Method

Methods	Basic_AMD Method		
Scenarios	Best F1 score	Best Threshold	BestFrame Refresh Rate
High_Way	0.877347	25	0.25
Traffic	0.698213	55	0.10
Canoe	0.767244	40	0.10
Sofa	0.602394	20	0.010
Copy Machine	0.667587	20	0.25
Lake Side	0.674375	10	0.10

Table 2 and Table 3 displays best threshold and best frame rates for every scenario with its corresponding best F1 score for AM and AMD background subtraction methods respectively. If we analyze the table, it is clearly seen that no one fix value of threshold and frame rate can be fixed for all scenario. We have taken only one data set from one scenario. So, instead of fixin g a fix value for parameters, it is suggested to define a range of parameters. Based on the analysis of whole data, one more thing, we have observed from results, is that F1 score is continuous with parameters i.e. it is either decreasing or increasing with increase or decrease of parameter values. So a range may be safely defined for each scenario. These range values are given in table3.

Table 3. Range of threshold and frame rates values for each scenario for BGS Method

Scenarios	Range Threshold	Range Frame Refresh α	Range Frame Refresh β
High Way	25-35	0.0005-0.001	0.1-0.25
Traffic	55-60	0.0005-0.001	0.1-0.25
Canoe	40-45	0.0005-0.001	0.1-0.25
Sofa	20-25	0.0005-0.001	0.1-0.25
Copy Machine	20-30	0.0005-0.001	0.1-0.25
Lake Side	10-15	0.0005-0.001	0.1-0.25

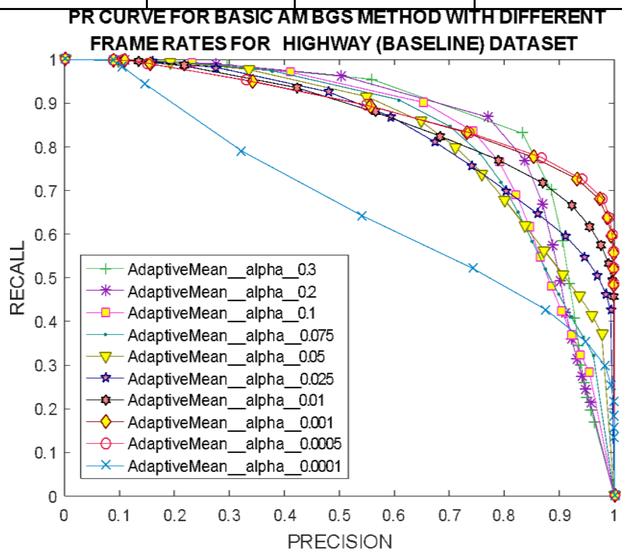

Fig 1: Results of AM object detection methods for Highway data set

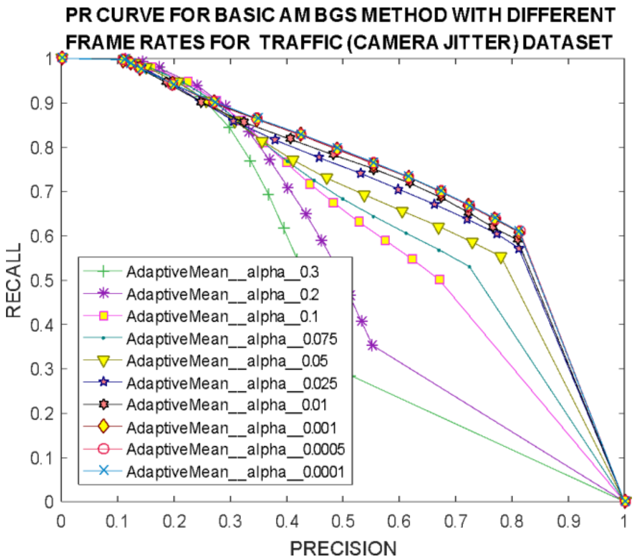

Fig 2: Results of AM object detection methods for Traffic data set

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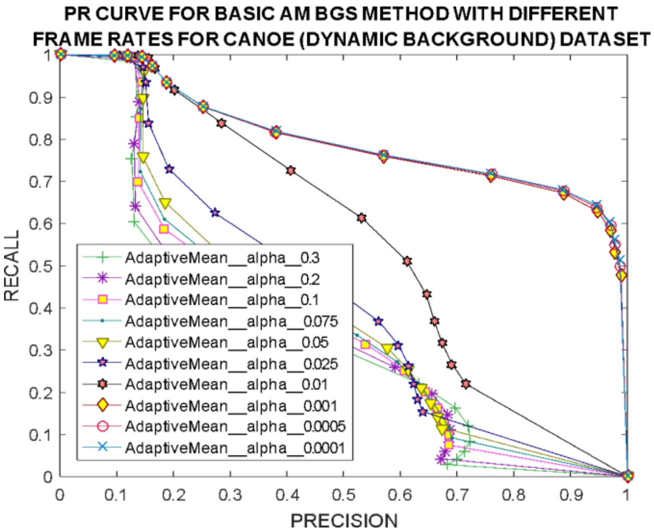

Fig 3: Results of AM object detection methods for Canoe data set

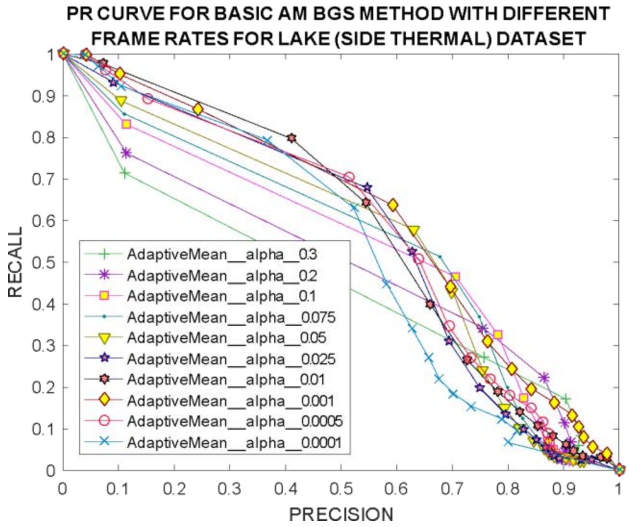

Fig 6: Results of AM object detection methods for Lake Side data set

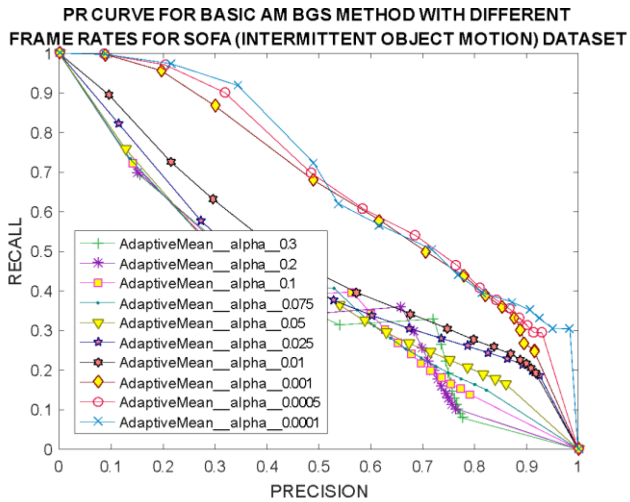

Fig 4: Results of AM object detection methods for Sofa data set

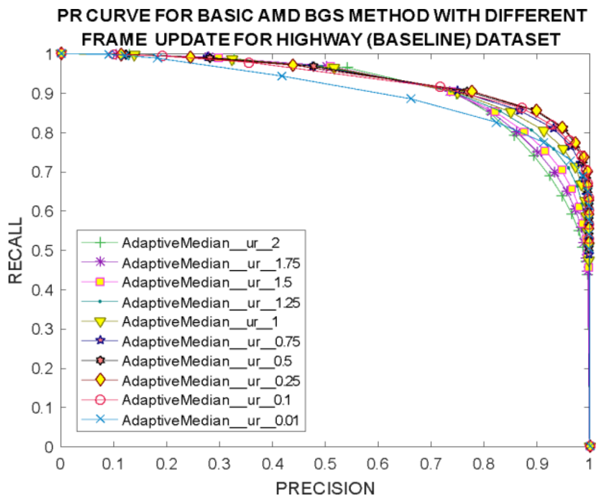

Fig 7: Results of AMD object detection methods for Highway data set

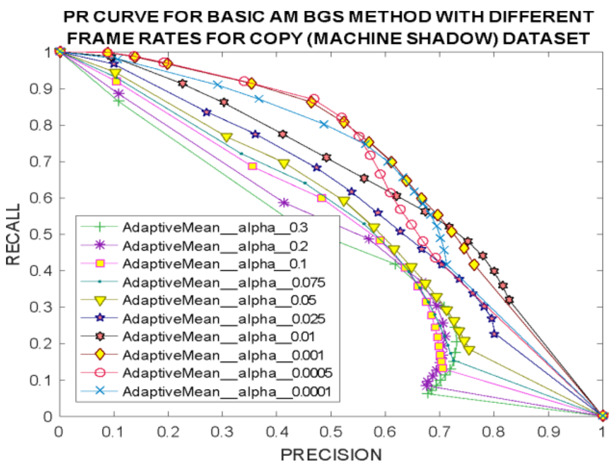

Figure 5: Results of AM object detection methods for Bus Station data set

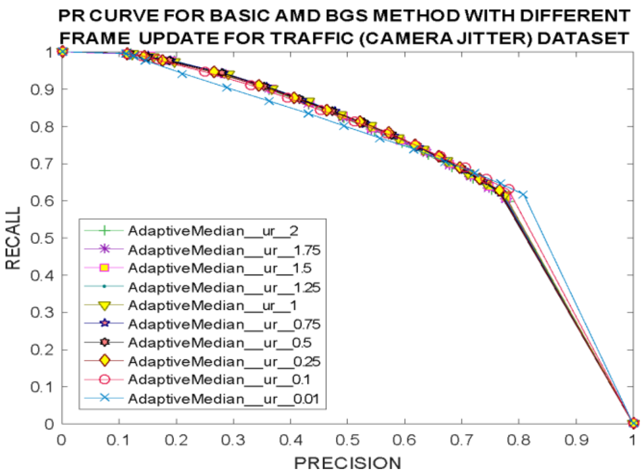

Fig 8: Results of AMD object detection methods for Traffic data set

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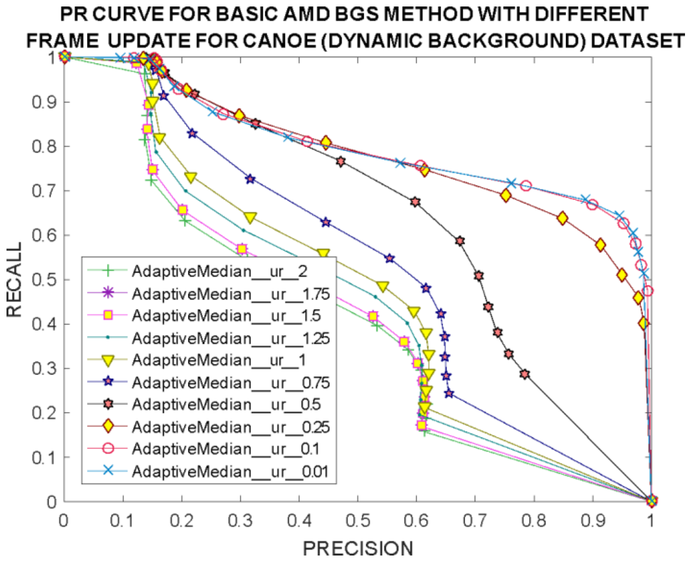

Figure 9: Results of AMD object detection methods for Canoe data set

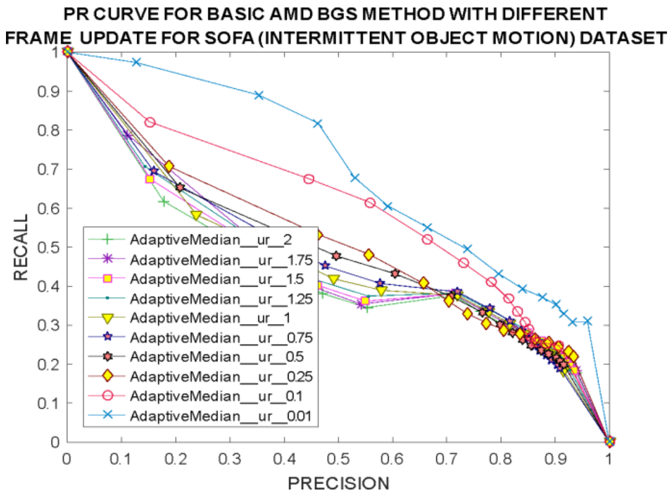

Figure 10: Results of AMD object detection methods for Sofa data set

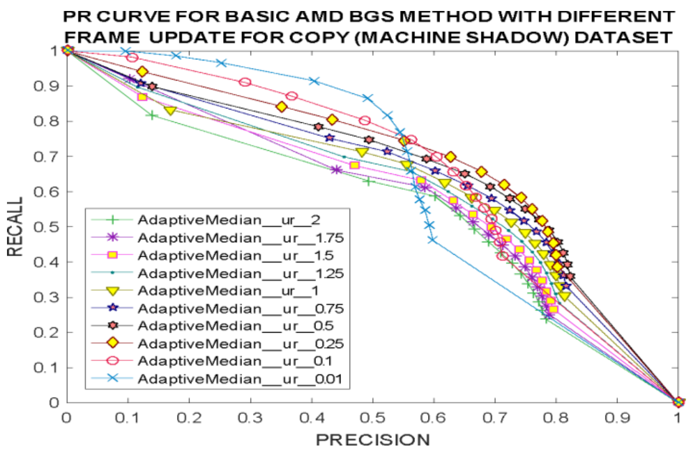

Figure 11: Results of AMD object detection methods for Copy Machine data set

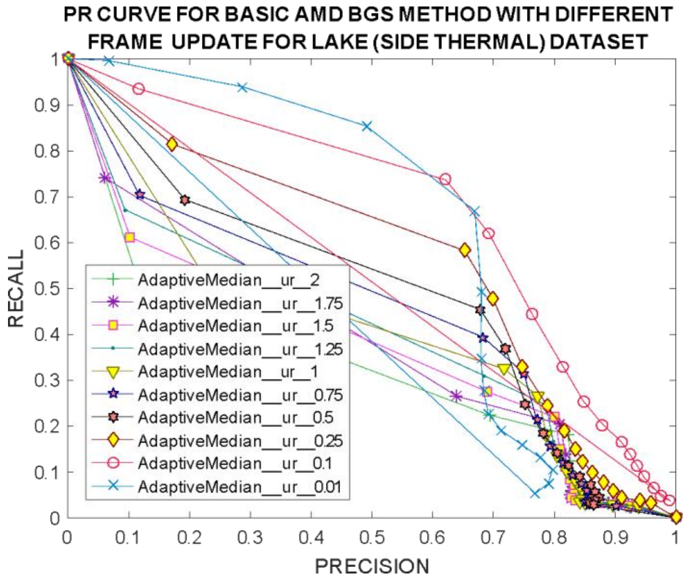

Figure 12: Results of AMD object detection methods for Lake Side data set

V. CONCLUSION

This paper proposes an empirical evaluation method for determining the parameters' values for BGS based edge detection methods AM and AMD. Two parameters global threshold value and the background frame refresh rate from AM and AMD have been identified and empirically evaluated to fix their values. Experiments have found that one threshold value can't be fixed for all data sets in a scenario but a narrow range of these values can be defined for both BGS methods. One range of threshold values for AM and AMD both has been defined but frame refresh rates for both methods can't agree on one range because of its inherent different approach of background refresh rate. So, two separate ranges for refresh rate have been defined. These value ranges can be effectively used in future for fine tuning object detection methods.

As the values are still in a range, more experiments are required to determine or model a fix value automatically based on scenario, data set properties. An adaptive value can also be a solution but need more experimentation on different types of scenario before generalization.

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