Frame differencing, a single Gaussian, and modified GMM for foreground object detection on camera jitter movies in comparison to F-Score measurement

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ABSTRACT

Aim: The aim of the study is to evaluate the performance of the novel Modified Gaussian mixture model algorithm in detecting foreground objects on camera jitter videos by comparing it with frame differencing, Single Gausian method, Gausian mixture model in four different scenarios. **Materials and methods:** A total of 6420 frames were taken from Badminton, Boulevard, Sidewalk, Traffic datasets and those video sequences have 1150, 2500, 1200 and 1570 frames respectively.The dataset involves two groups based on indoor and outdoor environments. The indoor group involves 1150 frames and the outdoor group consists of 5270 frames. Precision, Recall and F-Score were calculated to evaluate the performance of all the algorithms. **Results:** The mean F-Score values of frame differencing, single Gaussian, Gaussian Mixture Model and Modified GMM model algorithms are 0.1874, 0.0149, 0.3030 and 0.2927 respectively. The Modified GMM model and GMM model provided better average F-Score and it is significantly better than that of remaining two models ($p<0.0001$, $\alpha=0.05$, power=80%). **Conclusion:** From this study it is observed that the novel Modified GMM and GMM algorithm performed better than the other two algorithms in these four video sequences.

KEYWORDS: Novel Object Detection, Camera Jitter, Novel Modified GMM, Background Subtraction, Frame Differencing, Single Gaussian, GMM.

INTRODUCTION

In recent times, novel object detection on camera jitter videos has become a very useful technique for the detection of moving objects in the area of video surveillance, computer vision, object tracking, optical motion capture and moving object detection under complex scenes (Bloisi 2014). Background subtraction is the useful technique for the novel object detection on camera jitter vedios in many video surveillance applications like traffic, security systems and in many indoor and outdoor video sequences (Takhar et al. 2016). Background subtraction method is used for the detection of foreground objects by comparing the current pixel with a background model (Mahmoudpour and Kim 2016). The dynamic changing objects in outdoor and indoor environments can be detected with the help of background subtraction (Wang et al. 2018). The background subtraction is a building block for many computer vision applications, being the first relevant step for subsequent recognition, classification and activity analysis tasks (Maddalena and Petrosino 2018). The background subtraction algorithms and their performance in different video sequences are analyzed.

For the past five years many research articles have been published on foreground object detection. IEEE has published 32 research articles, science direct has published 89 articles and google scholar has 576 research articles in its database. A novel background subtraction technique is proposed to detect the foreground objects under seven different video sequences and which can perform better in illumination changes of a video sequence (Cheng, Huang, and Ruan 2011). An illumination compensation based background subtraction model is proposed which can perform better under different illumination changes and models the changes in the illumination as a regression function of spatial image coordinates (Paruchuri and Sathiyamoorthy 2011). The authors proposed a method for abnormal event detection for the background subtraction in video sequences (Şengönül and Samet 2021). A novel method for detecting moving objects in a video sequence which need only 2 or 3 frames to update the background model (Huang, Jiang, and Qian 2020). A dual background subtraction technique is used for the detection of static foreground and motion analysis to locate the bounded objects and multiple motion tracking of objects (Xiya, Jingling, and Qin 2012). The authors used a dual background model and finite state machine for the detection of static objects (Heras Evangelio and Sikora 2010).(Bhavikatti et al. 2021; Karobari et al. 2021; Shanmugam et al. 2021; Sawant et al. 2021; Muthukrishnan 2021; Preethi et al. 2021; Karthigadevi et al. 2021; Bhanu Teja et al. 2021; Veerasimman et al. 2021; Baskar et al. 2021)

Many of the existing works failed to detect foreground objects under complex video sequences like illumination changes, command dynamic background, sleeping foreground object etc.In this study the novel Modified GMM based novel object detection algorithm is tested in four scenarios that includes both indoor and outdoor situations.

MATERIALS AND METHODS

The proposed work is carried out in the image processing lab in the Department of Electronics and Communication Engineering, Saveetha school of engineering, SIMATS. The total sample size of 6420 frames with camera jitter were taken for this study, the datasets are from Badminton, Boulevard, Sidewalk, Traffic datasets and those video sequences have 1150, 2500, 1200 and 1570 frames respectively. The datasets are collected from the changedetection.net website (Wang et al. 2014). The sample sizes are calculated using clincalc calculator with (α=0.05), (power=80%).

Out of four video sequences one video sequence is indoor and other three are outdoor, the indoor sequence is of Badminton, the outdoor sequences are Boulevard, Sidewalk and Traffic datasets. From each dataset we have randomly selected 30 frames and calculated the precision, recall and F-Score values. In those datasets some of the groundtruth images are not provided.

In this proposed work the Matlab 2021 has been used with a core i5 processor and 8GB RAM. The algorithms used are entropy model, frame differencing, single Gaussian and GMM algorithms, for all the algorithms programming is done in MATLAB. In frame differencing the background subtraction is done based on the previous frame, in single Gaussian first100 frames were taken to make the background model, in GMM algorithm background is subtracted from the previous frame with some predefined parameter values, whereas entropy algorithm uses 100 frames for making a background model.

STATISTICAL ANALYSIS

All statistical analysis is conducted in SPSS 26 (Chicago, Illinois, USA). Descriptive statistical analysis (mean, standard deviation and standard error) is carried out on various algorithms. An Analysis of variance (ANOVA) test was performed to compare the various algorithms. Independent variables in the study are input features from each algorithm. The dependent variables are the precision, recall and F-Score.

RESULTS

In the case of the frame differencing algorithm, the F-Score values of Badminton, Boulevard, Sidewalk and Traffic datasets are 0.2151, 0.2002, 0.1375 and 0.1970 respectively. In the case of the single Gaussian algorithm, the F-Score values of Badminton, Boulevard, Sidewalk and Traffic datasets are 0.0189, 0.0196, 0.0060 and 0.0151 respectively. In the case of the Gaussian Mixture Model algorithm, the F-Score values of Badminton, Boulevard, Sidewalk and Traffic datasets are 0.4666, 0.2745, 0.2719 and 0.1993. In the case of the novel Modified GMM algorithm, the F-Score values of Badminton, Boulevard, Sidewalk and Traffic datasets are 0.3173, 0.3636, 0.1952 and 0.2148 respectively. All F-Score values are tabulated in Table 1.

Novel object detection results depend on the four metrics namely: True positive(TP), True negative(TN), False positive(FP), and False negative(FN). The performance of the algorithms are calculated using the formulas given below.

$$Recall = \frac{TP}{FN+TP} \quad (1)$$

$$Precision = \frac{TP}{FP+TP} \quad (2)$$

$$F\text{-}\ Score = \frac{2(recall)(precision)}{(recall)+(precision)} \quad (3)$$

Figure 1 gives the information about the images of four video sequences which includes original images, ground truth images and output images of all four algorithms in novel object detection.

The statistical analysis of frame differencing, single Gaussian, GMM, and novel Modified GMM algorithms with 95% CI are shown in Table 2. Analysis of Variance (ANOVA) for significance with F and df values. P value is less than 0.0001 and 95% confidence intervals were calculated and shown in Table 3. Fig 2 gives the information about the performance of all four algorithms in terms of F-Score in four different video sequences.

DISCUSSION

In this study, we observed that the F-Score of the GMM and MOdified GMM algorithms are significantly better than the remaining algorithms such as frame differencing, single Gaussian. In this analysis, the performance of the four algorithms is analyzed for novel object detection on camera jitter videos (Aslam and Sharma 2017). In the Badminton video sequence the GMM algorithm performed slightly better than the remaining algorithms (Karthikeyan Panjappagounder Rajamanickam and Periyasamy 2019). In the Boulevard video sequence the GMM algorithm has performed better, the frame differencing and MGMM has the similar F-Score values. In the case of Sidewalk video sequence the GMM and MGMM performs better than the remaining two algorithms. In the Traffic video sequence the GMM and MGMM algorithms performance is nearly equal and compared to single Gaussian and frame differencing algorithms they perform significantly better (K. P. Rajamanickam and Periyasamy 2019).

The F-Score value of the GMM and Modified GMM algorithms are better than the remaining algorithms. The authors used algorithms like frame difference, Approximated Median, single Gaussian, GMM, Sigma-delta, ISBS, ViBe and Illumination invariant under various illumination conditions in three different video sequences and concluded that GMM performs better in two out of three video sequences which is similar to our study (Karthikeyan, Sakthivel, and Karthik 2020). In another study the authors used GMM, Vibe, VIbe+ and some deep learning methods like BMN-BSN, BSUV.net under different video sequences and concluded that their proposed algorithm is performing better than the GMM algorithm (Huang, Jiang, and Qian 2020). A texture-based self-adaptive algorithm is compared with SPAS, KDE, SOBS and GMM algorithms where the texture-based self-adaptive algorithm performance is better than the remaining algorithms (Goyal and Singhai 2018).

The F-Score values depend on the precision and recall values. If the frames of the video sequences have better precision and recall values then the F-Score values will also become better. In this comparison it is observed that the single Gaussian algorithm has very less F-Score values, the frame differencing and the GMM algorithm has performed better than the single Gaussian algorithm (Zhang, Liu, and Li 2010). The performance of novel Modified GMM and GMM algorithms seems to be similar in two out of four video sequences.In future studies the performance of the algorithms is to be tested with more video sequences which includes more illumination changes and dynamic background.

CONCLUSION

In the present study it is achieved that the GMM and Modified GMM algorithms with mean F-score values 0.3030 and 0.2927 are comparatively better than the other algorithms such as frame differencing and single Gaussian with 0.1874 and 0.0149 mean F-scores respectively in the four video sequences taken for the study.

DECLARATION

Conflict of interests

No conflict of interests in this manuscript.

Authors Contributions

Author GGNMR was involved in data collection, data analysis, manuscript writing. Author PRK was involved in conceptualization, data validation, and critical review of manuscript.

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Tables and Figures

Table 1 Precision, Recall and F-Score for the foreground object detection by frame differencing, single Gausian, GMM, MGMM algorithms.

Algorithm	Videos	Precision	Recall	F-Score
Frame Differencing	Badminton	0.5748	0.6226	0.2151
	Boulevard	0.5920	0.3923	0.2002
	Sidewalk	0.4476	0.2369	0.1375
	Traffic	0.8216	0.5780	0.1970
Single	Badminton	0.7066	0.4794	0.0189

Gaussian	Boulevard	0.7880	0.2815	0.0196
	Sidewalk	0.7995	0.6859	0.0060
	Traffic	0.8034	0.3961	0.0151
Gaussian Mixture model	Badminton	0.7587	0.2993	0.4666
	Boulevard	0.8706	0.4242	0.2745
	Sidewalk	0.8699	0.6929	0.2719
	Traffic	0.8988	0.0666	0.1993
MGMM	Badminton	0.6045	0.5508	0.3173
	Boulevard	0.5714	0.1937	0.3636
	Sidewalk	0.7475	0.0512	0.1952
	Traffic	0.8217	0.5757	0.2148

Table 2 Statistical analysis of frame differencing, single Gaussian, GMM, and MGMM algorithms with 95% CI.

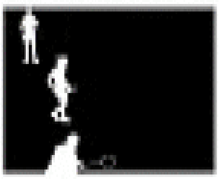
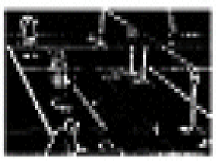
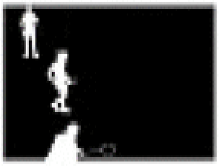
Algorithm	Videos	F-Score mean	Std.Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Frame Differencing	Badminton	0.2151	0.02894	0.00542	0.0132	0.0654	0.37	0.52
	Boulevard	0.2002	0.0117	0.01345	0.1452	0.6541	0.15	0.22
	Sidewalk	0.1375	0.00592	0.01983	0.0032	0.0557	0.32	0.44
	Traffic	0.1970	0.1407	0.01995	0.0649	0.1123	0.09	0.23
Single Gaussian	Badminton	0.0189	0.0907	0.00123	0.3213	0.3745	0.25	0.46
	Boulevard	0.0196	0.04755	0.00103	0.0454	0.0654	0.19	0.34

	Sidewalk	0.0060	0.84085	0.00109	0.6835	0.7231	0.24	0.48
	Traffic	0.0151	0.70503	0.00547	0.5032	0.5398	0.43	0.59
Gaussian Mixture model	Badminton	0.4666	0.0176	0.00575	0.0023	0.0423	0.31	0.61
	Boulevard	0.2745	0.11925	0.02408	0.0537	0.1003	0.03	0.47
	Sidewalk	0.2719	0.0715	0.00899	0.0171	0.575	0.04	0.17
	Traffic	0.1993	0.19657	0.02029	0.1741	0.2005	0.37	0.71
MGMM	Badminton	0.3173	0.01532	0.13758	0.0007	0.0333	0.08	0.09
	Boulevard	0.3636	0.3583	0.03126	0.0224	0.697	0.46	0.61
	Sidewalk	0.1952	0.17052	0.01426	0.1032	0.1198	0.11	0.25
	Traffic	0.2148	0.09326	0.01614	0.2143	0.2653	0.33	0.55

Table 3 Analysis of Variance (ANOVA) test for significance, with F and df values. The value of P with 95% confidence intervals is less than 0.0001.

Videos		Sum of groups	df	Mean square	F	Significance
Badminton	Between groups	10.157	4	0.3385	795.865	0.0001
	Within Groups	0.354	110	0.003		
	Total	10.511	114			
Boulevard	Between groups	8.943	4	2.981	38.517	0.0001
	Within Groups	1.128	110	0.002		

	Total	10.071	114			
Sidewalk	Between groups	6.743	4	2.244	835.174	0.0001
	Within Groups	0.326	110	0.005		
	Total	7.069	114			
Traffic	Between groups	4.327	4	0.3602	224.167	0.0001
	Within Groups	0.440	110	0.009		
	Total	4.767	114			

Original sequence				
Ground truth				
Frame differencing				
Single Gausian				
GMM				

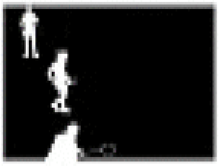
Entropy				
MODIFIED GMM				

Fig. 1 Foreground detected by various algorithms in four video sequences. Images of video sequences, from left to right: Badminton, Boulevard, Sidewalk, Traffic datasets .

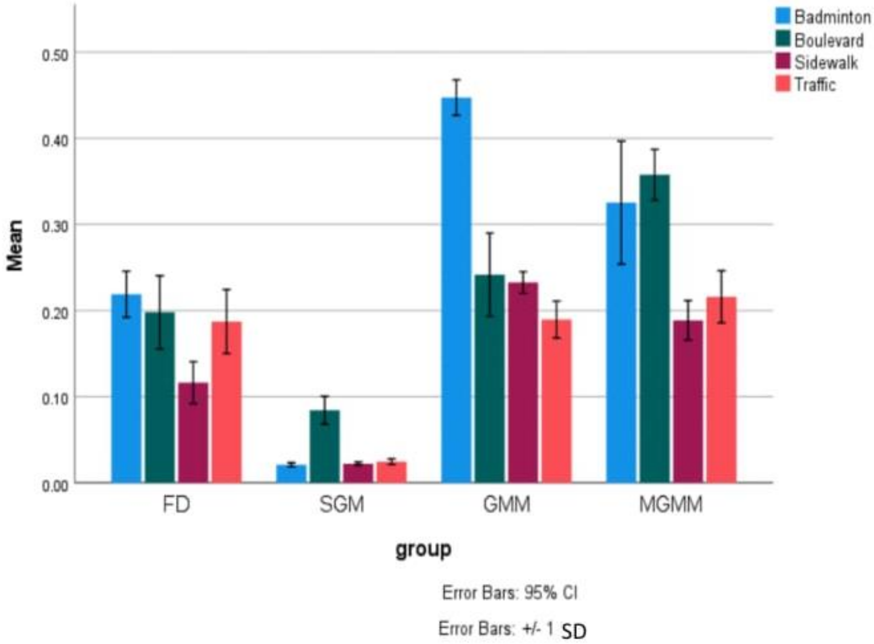


Fig. 2 The mean F-Score values of four video sequences in frame differencing, single gaussian, Gaussian Mixture model and MGMM model. Novel Modified GMM algorithm performs significantly better than other algorithms ($p<0.0001$). X axis represents the algorithms, Y axis represents the mean F-Score values. Error bars represent 95% CI and +/- 1 SD.