DETECTION OF MOVING OBJECTS IN BAD WEATHER USING DUAL BACKGROUND ILLUMINATION COMPENSATOR IN COMPARISON WITH FRAME DIFFERENCING, SINGLE GAUSSIAN AND GMM TO MEASURE F-SCORE

V. Maneesh Reddy[1] , Karthikeyan P R[2*]

Article History: Received: 12.12.2022 **Revised:** 29.01.2023 **Accepted:** 15.03.2023

Abstract

Aim: By using a background subtraction algorithm the foreground objects are detected. The proposed model performs better comparison algorithms with more f-score and accuracy. The use of this method to detect or have clear images of the objects even in bad weather. **Materials and Methods:** The total number of 29000 images are checked and subtract the background noises and give clear foreground images like pedestrians, cars, skating . By using algorithms in the matlab application. **Result :** The proposed algorithm is tested in four video sequences of various illumination conditions. As the datasets containing both gradual and sudden illumination change. The mean f-scores values of Frame differencing, Single Gaussian, Gaussian mixture method and Entropy model algorithms are 0.3574, 0.0289, 0.6794, 0.3826 respectively. The GMM model provided the best average f-score and it is significantly better than that of the remaining three models ($p<0.0001$), ($\alpha =0.05$), (power=80%). **Conclusion:** The study concluded that the GMM algorithm performed better than the other three algorithms in these four video sequences.

Keywords: Background Subtraction, Illumination changes, Foreground Detection, Vehicle detection, Image Processing, Thermal Infrared Camera.

[1]Research Scholar, Department of Electronics and Communication Engineering, Saveetha School of Engineering'
Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, Tamil Nadu, India. Pin Code: 602105.
[2*]Department of Electronics and Communication Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, Tamil Nadu, India. Pin Code: 602105.

1. Introduction

Background subtraction algorithms are used to detect the moving objects in the surveillance area. Background subtraction algorithms model the background and subtract the current frame of the video with a background model to detect foreground objects. Foreground objects are the moving objects or objects of interest in the scene. In this study, the performance of Single Gaussian, GMM, modified GMM, Frame differencing, DBIC, IISC and Entropy based background subtraction algorithms are evaluated in four video sequences.
Foreground object detection 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 a complex sense of application. (Cao, Yang, and Guo 2016; Bailey 2019)Background subtraction is a process in the area of image processing and computer vision for foreground detection.(Shaikh, Saeed, and Chaki 2014) In order to get the exact location of the object and immediate changes in a video stream to detect the moved objects in a video survillance. (Chen, Zhou, and Yan 2007).

The minimum required sample size for the study is calculated using ClinCalc with Alpha = 0.05 and Power = 80%. The overall performance of the Entropy algorithm is significantly better than the other algorithms (p value<0.001) (Bailey 2019) In an entropy based method the detection of a foreground object is very accurate up to 80%. The frame differencing is a background subtraction algorithm which is proposed to detect the foreground objects with more accuracy and precision and some of the f-score values Consequently, by and (Chen, Zhou, and Yan 2007)large embraced techniques are those of identifying the headlights or the taillights of vehicles at evening time and of getting ready two calculations independently for daytime and evening location. (Tang 2012)In the regular techniques for vehicle recognition by utilization of noticeable light cameras, it is hard to identify vehicles with high precision in awful climates like mist, snow, and weighty downpour.
An entropy based background subtraction algorithm was proposed to detect foreground objects.(Casado, Universitat Autònoma de Barcelona, and Centre de Visió per Computador 2010) A modified GMM algorithm is used as a proposed algorithm and a novel method for efficiently combining background subtraction using this and detecting moving objects with different sizes.

Our institution is passionate about high quality evidence based research and has excelled in various domains (Vickram et al. 2022; Bharathiraja et al. 2022; Kale et al. 2022; Sumathy et al. 2022; Thanigaivel et al. 2022; Ram et al. 2022; Jothi et al. 2022; Anupong et al. 2022; Yaashikaa et al. 2022; Palanisamy et al. 2022). We have gotten clear pictures in a blanketed and profoundly hazy climate on a street. We have fostered a calculation for moving vehicle location and gives clear pictures with Visual C++ . (Shaikh, Saeed, and Chaki 2014; Gemignani and Rozza 2016)A person on a footpath framework should be aso precise as conceivable that the climate conditions are helpless climate conditions: The location there will be helpless climate conditions which produce noisy images . (Sajid and Cheung 2017)The fluctuation comes with some unwanted things like the shape, clothing or even the stance of the individual, as well as from a few outside variables like the situation, (Rajamanickam and Periyasamy 2019)enlightenment and incomplete impediments. (Onoguchi 2006)**.** The performances of the algorithms are calculated using Precision, Recall and F-Score values. All statistical analysis is performed in the SPSS tool.

2. Materials and Methods

A total of 20900 frames were taken from blizzard, skating, snowfall, wet snow video sequence dataset. The blizzard, skating, snowfall and wet snow video sequences consist of 7000 frames, 3900 frames, 6500 frames and 3500 frames respectively. The datasets are collected from 'Change detection benchmark website'(Wang et al., 2013). The samples calculated using a clincate calculator with (α =0.05), (power=80%).

Out of four video sequences two video sequences are indoor and another two are outdoor, the indoor sequences are Office and pets 2006 ,the outdoor sequences are Highway and pedestrians.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. Frame differencing method uses consecutive frames, Single Gaussian calculates background models from a set of frames, DBIC uses two background models, IISC uses singular value decomposition, GMM estimates three background model from a set of frames, Entropy models background based on variations in illuminations and modified GMM models background based on dynamic nature of the scene.

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 the entropy algorithm uses 100 frames for making a background model.

Statistical Analysis

All statistical analysis is conducted in SPSS 26 (SPSS Inc., 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.

3. Results

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 foreground object detection**.**

In this case of the frame differencing algorithm, the f-score values of Blizzard, skating, snowfall, wet snow are 0.7125,0.1210,0.4175,0.2470 respectively. In this case of single gaussian, the f-score values of blizzard, skating, snowfall, wet snow 2006 are 0.0192,0.0171,0.0040,0.0121 respectively. In the case of Gaussian Mixture Model algorithm the f-score values of blizzard, skating, snowfall, wet snow are 0.8655,0.2745,0.6719,0.4893. In the entropy algorithm, the f-score values of blizzard, skating, snowfall, and wet snow are 0.3543,0.2536,0.6752,0.5548 respectively. All f-score values are in table-1.

The proposed algorithm is tested in four video sequences of various illumination conditions . All the datasets containing both gradual and sudden illumination changes. The SG method each pixel with a gaussian distribution whereas the GMM method each pixel with a mixture of gaussian instead of modeling values of the pixel as one particular distribution.

Foreground 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.

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

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

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

The statistical analysis of Frame differencing, Single Gaussian, GMM, and Entropy 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 0.05 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.

4. Discussion

In this study, we observed that the f-score of the GMM algorithm is significantly better than the remaining algorithms such as Frame Differencing ,Single Gaussian and Entropy. In this analysis, the performance of the four algorithms is analyzed for foreground object detection.In highway video sequence the GMM algorithm performed slightly better than the remaining algorithms. In the office video sequence the GMM algorithm has performed better, the Frame Differencing and entropy has the similar f-score values.In the case of pedestrians video sequence the GMM and entropy performs better than the remaining two algorithms.

In the pets2006 video sequence the GMM and entropy algorithms performance is nearly equal and compared to Single Gaussian and frame differencing algorithms they perform significantly better.(Mohajan et al., 2019). The f-score value of the GMM algorithm is mostly better than the remaining algorithm.The authors used algorithms like Frame Difference, Approximated Median, Single Gaussian, GMM, Sigma-delta.(Elharrouss et al., 2016) 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).

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. The performance of entropy 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.

5. Conclusion

In the present study it is observed that the GMM algorithm performed considerably better than the other algorithm in the four video sequences taken for the study.

Declarations

Conflict of interests

The authors of this paper declare no conflict of interests.

Authors Contribution

Author VKS was involved in data collection, data analysis, manuscript writing. Author KPR was involved in conceptualization, data validation, and critical review of the manuscript.

Acknowledgements

The authors would like to thank the management of Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, Tamilnadu, India for their funding and facilities provided during the period of this research.

Funding

We thank the following organizations for providing financial support that enabled us to complete the study.

1.VELSA TECHNOLOGIES.
2. Saveetha Institute of Medical and Technical Sciences.
3. Saveetha School of Engineering.
4. Saveetha University.

6. References

Bailey, D. (2019). Image Processing Using FPGAs. MDPI.

Cao, X., Yang, L., & Guo, X. (2016). Total Variation Regularized RPCA for Irregularly Moving Object Detection Under Dynamic Background. IEEE Transactions on Cybernetics, 46(4), 1014–1027.

Casado, I. H., Universitat Autònoma de Barcelona, & Centre de Visió per Computador. (2010). Foreground Object Segmentation and Shadow Detection for Video Sequences in Uncontrolled Environments.

Chen, G., Zhou, H., & Yan, J. (2007). A Novel Method for Moving Object Detection in Foggy Day. In Eighth ACIS International Conference on Software Engineering, Artificial Intelligence, Networking, and Parallel/Distributed Computing (SNPD 2007). https://doi.org/10.1109/snpd.2007.350

Chen, P. (2009). Moving Object Detection Based on Background Extraction. In 2009 International Symposium on Computer Network and Multimedia Technology. https://doi.org/10.1109/cnmt.2009.5374629

Gemignani, G., & Rozza, A. (2016). A Robust Approach for the Background Subtraction Based on Multi-Layered Self-Organizing Maps. IEEE Transactions on Image Processing: A Publication of the IEEE Signal Processing Society, 25(11), 5239–5251.

Onoguchi, K. (2006). Moving Object Detection Using a Cross Correlation between a Short Accumulated Histogram and a Long Accumulated Histogram. In the 18th International Conference on Pattern Recognition (ICPR'06). https://doi.org/10.1109/icpr.2006.819

Mohajan, G., Dhar, P. K., Ahmed, M. T., & Shimamura, T. (2019). Moving Object Detection against Sudden Illumination Change Using Improved Background Modeling. In 2019 International Conference on Electrical, Computer and Communication Engineering (ECCE). https://doi.org/10.1109/ecace.2019.8679107

Rajamanickam, K. P., & Periyasamy, S. (2019). Entropy Based Illumination-Invariant Foreground Detection. In IEICE Transactions on Information and Systems (Vol. E102.D, Issue 7, pp. 1434–1437). https://doi.org/10.1587/transinf.2018edl8247

Sajid, H., & Cheung, S.-C. S. (2017). Universal Multimode Background Subtraction. IEEE Transactions on Image Processing: A Publication of the IEEE Signal Processing Society, 26(7), 3249–3260.

Shaikh, S. H., Saeed, K., & Chaki, N. (2014). Moving Object Detection Using Background Subtraction.
Springer.

Tables and Figures

Table 1- Precision,Recall and f-score for the Foreground object detection by Modified GMM in comparison with IISC, DBIC, Entropy algorithms.

Algorithm	videos	precision	Recall	F-score
Entropy	Blizzard	0.9201	0.2837	0.7125
	Skating	0.7961	0.1348	0.1210
	Snowfall	0.6254	0.3569	0.4175
	Wetsnow	0.5423	0.2075	0.2470
IISC	Blizzard	0.0970	0.0193	0.0192
	Skating	0.0765	0.0152	0.0171
	Snowfall	0.0231	0.0067	0.0040
	Wetsnow	0.0365	0.0254	0.0121
DBIC	Blizzard	0.9425	0.7860	0.8655
	Skating	0.7528	0.3548	0.2745
	Snowfall	0.7411	0.8017	0.6719
	Wetsnow	0.6586	0.5464	0.4893
MODIFIED GMM	Blizzard	0.9313	0.2852	0.3543
	Skating	0.6267	0.2016	0.2536
	Snowfall	0.7622	0.7206	0.6752
	Wetsnow	0.6506	0.5252	0.5548

Table-2 Analysis of Variance (ANOVA) for significance with F and df values. P value is less than 0.05 and 95% confidence intervals were calculated.

		Sum of groups	df	Mean square	F	significance
Blizzard	Between groups	4.209	3	1.403	11.315	0.000
	Within Groups	14.385	116	0.124		
	Total	18.595	119			
Skating	Between groups	1.019	3	0.340	10.279	0.000
	Within	3.832	116	0.33		

	Groups					
	Total	4.850	119			
Snowfall	Between groups	0.283	3	0.094	5.023	0.003
	Within Groups	2.179	116	0.019		
	Total	2.463	119			
Wetsnow	Between groups	0.183	3	0.061	2.889	0.039
	Within Groups	2.449	116	0.021		
	Total	2.632	119			

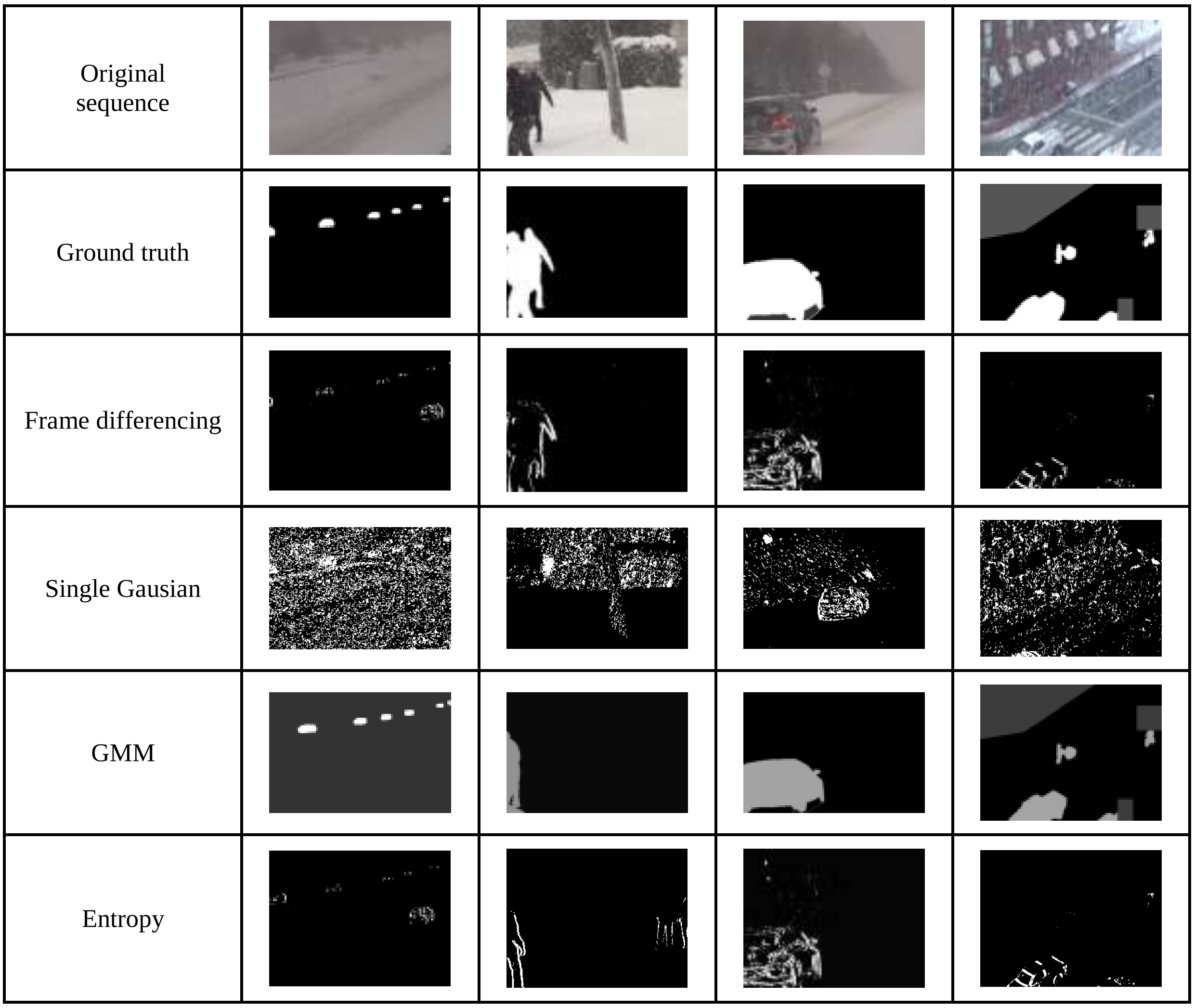

Fig. 1- Foreground detected by various algorithms in four video sequences. Images of video sequences, from left to right: Blizzard, Skating, Snowfall,Wet Snow.

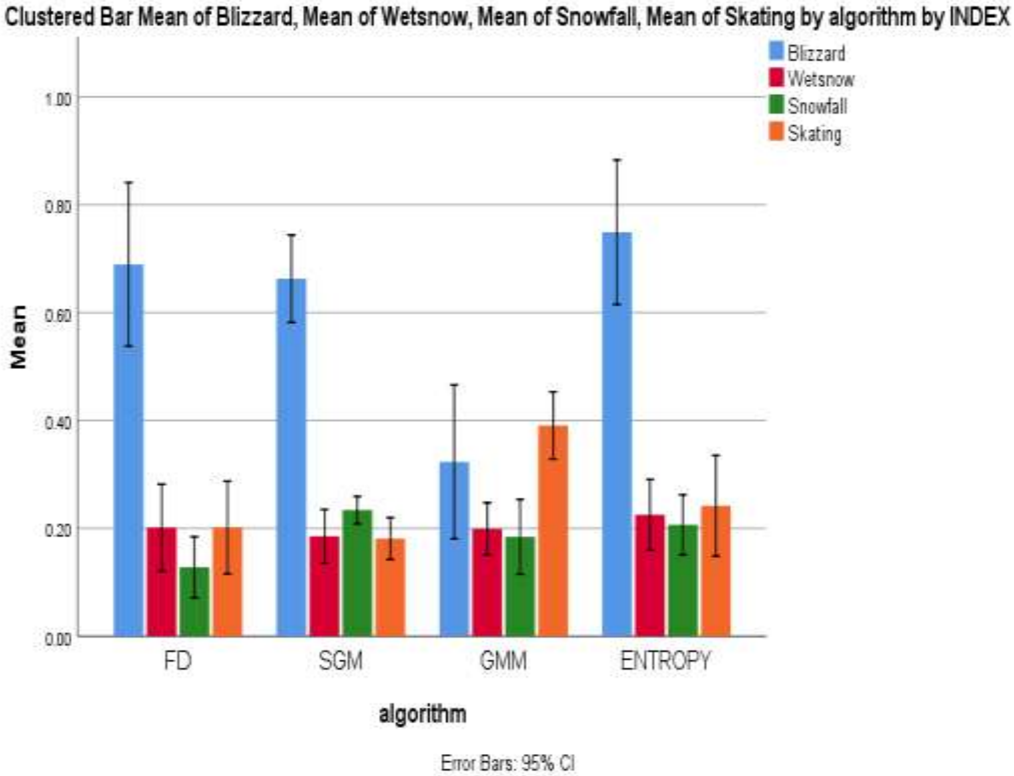

Fig. 2- The mean f-score values of four video sequences in frame differencing,single gaussian,Gaussian Mixture model and Entropy model.GMM algorithm performs significantly better than other algorithms ($p<0.05$). X axis represents the algorithms, Y axis represents the mean f-score values. Error bars represent 95% CI and +/- 1 SD.