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Conference Paper · September 2019

DOI: 10.1117/12.2534644

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Analysis of different background subtraction methods applied on Drone imagery under various weather conditions in the UAE region

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ABSTRACT

The following paper presents a benchmarking study of the performance of thirty state of the art background subtraction algorithms. In this work, we test the performance of multiple background subtraction methods using drone imageries taken under various weather conditions in the UAE region. This is done by comparing the quality of the foreground mask that is extracted when using these algorithms. Visual Studio and MATLAB has been used to perform the comparison simulations, which would give us a comprehensive background subtraction study to indicate the advantages and disadvantages of each of the algorithms. The algorithms must be robust to stabilization errors, able to cope with insufficient information as a result from various weather conditions such as wind, haze and heat, and able to cope with dynamic backgrounds.

Keywords: Background subtraction, foreground segmentation, comparison, moving detection, unmanned aerial vehicle

1. INTRODUCTION

Background subtraction is a technique that is utilized to extract objects that belong to the foreground model from a given image. Many background subtraction algorithms can be divided into three main stages. Firstly, Background Initialization, there are many ways that a background model can be created, such as fuzzy, statistical and neural methods. The second step is to detect the foreground; this is done by detecting changes in pixel values of the current image by subtracting it from the background model that was previously built. Pixel values that change more than a specified threshold form the foreground mask. On the other hand, if the pixel values difference does not exceed the threshold, they are considered part of the background mask. Finally, the background model has to be maintained, this is performed constantly with a learning rate [1, 2]. This step is done to accommodate for objects that have been stationary for a long time, such as cars in a parking lot. Background subtraction is a crucial step in scene analysis that typically requires object detection, recognition or tracking [3, 4]. This domain has been developing very well as there are numerous proposed and studied methods in the literature. Video surveillance is one of the main applications in which background subtraction is used. This is due to the fact that targets such as vehicles, people or animals need to be detected first before they are tracked and studied.

Small unmanned aerial vehicles (sUAV) such as drones can operate autonomously which enables it to be used for various applications. Generally, sUAV are capable of providing solutions to day to day issues as they are simple to design, fast and cost-effective, this is due to their small size and agility [3]. Many of the sUAV have cameras attached to them in order to provide a ground operator with an aerial view of the area. Thus, surveillance, search and rescue missions, border control, crowd and wildlife monitoring are some tasks that drones are capable of performing, which rely heavily on a good background subtraction algorithm [5]. Nowadays, surveillance is being heavily used all over the world, ranging from statistical applications to security applications. A study of thirty different state of the art background subtraction algorithms is adopted in this research to find the challenges faced by aerial imaging in different weather conditions and the best performing algorithms from the BGSLibrary [2]. Section 2 describes the dataset that is used in this paper, which consists of three different weather conditions taken in the UAE at different times of the year. Section 3 describes the algorithms used in this paper, the best ten algorithms of the results are explained further. In section 4 and 5, the experiment set up and results are discussed respectively. The experiments of the algorithms have been done on Visual Studio 2017, and MATLAB was used to perform the comparison simulations. The results of the best ten algorithms are analyzed for the three different weather conditions.

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Artificial Intelligence and Machine Learning in Defense Applications, edited by Judith Dijk, Proc. of SPIE
Vol. 11169, 111690M · © 2019 SPIE · CCC code: 0277-786X/19/$21 · doi: 10.1117/12.2534644

2. DATASET

The dataset used in this paper consists of full high definition videos (1920 x 1280 pixels) acquired using the DJI Zenmuse X5R camera in Al Lisaili, Dubai from a DJI Matrice 600 Pro drone at an altitude of 100m. The dataset consists of three image sequences varying in size from 1000 to 5000 images. However, only 500 images are taken from each sequence to reduce computation time, but large enough to ensure consistent results. Each of the image sequences have been taken at a different time of the year, under various weather conditions such as temperature, wind speed and humidity levels. Table 1 below shows the details of the datasets. The ground truth for a selected number of frames has been annotated using the MATLAB ground truth labeler. The objects in the images are a combination of both humans and cars. The images consist of a desert background with some objects as such trees, buildings and moving objects such as flags.

Table 1. Details of the dataset used in this work

Dataset	**April 2018**	**August 2018**	**December 2018**
Number of frames	500	500	500
Minimum number of objects in a frame	5	7	3
Maximum number of objects in a frame	13	7	7
Temperature	28℃	42℃	20℃
Humidity	51%	30%	89%
Wind Speed	25 km/h	20 km/h	15 km/h

3. METHODS USED

As mentioned previously, thirty background subtraction methods were used, which are available at https://github.com/andrewssobral/bgslibrary along with their source codes. Table 2 shows the background subtraction algorithms available in the BGSLibrary that were used [2]. Based on the results which will be discussed later, the following ten algorithms had the best performance.

3.1. Basic methods, mean and variance over time

DP Mean, Weighted Moving Variance (WMV) and Weighted Moving Mean (WMM): for DP Mean The mean of last X frames is used to calculate the background in this method. A threshold is set to compute the foreground mask. This method is able to adapt quickly and is capable of detecting objects that have observable movements between frames. As for the WMM, the same process is performed however the latest frames are weighted greater when calculating the mean, whereas variance is calculated when using WMV [2].

DP Prati Mediod [6]: consists of multiple steps, the first is background bootstrapping, which divides the image into smaller sections. Whenever a satisfactory high amount of pixels within this section remain static, this section is updated in the background model. The foreground is extracted, firstly by updating the background model by using a temporal median, then by using a background differencing technique. Lastly, shadows are removed, objects in the foreground are validated and any ghosts created are suppressed.

3.2. Statistical methods using multiple Gaussians

Mixture of Gaussian (MOG) and MOG2 [7] [8]: is a background segmentation algorithm that uses a distribution of Gaussian Mixtures to model each pixel, each distribution is assigned different weights. The longer a pixel value remains in the scene the larger its weight will be. Hence, the pixels that remain in the scene for longer and remain most static are considered part of the background model. As for the MOG2, it is also a background segmentation algorithm that is Gaussian Mixture based. The Gaussian Mixture Model (GMM) is updated based on Grimson's GMM [9]; however, Zivkovic's [10] is used to determine the amount of Gaussian distributions that would represent the background.
T2F GMM UM and TF2 MRF UM [11]: GMM with uncertain means (UM) is used to model the background. Updates of the fuzzy functions for mean ensure an adaptive background. As for T2F MRF UM, it is an improved version of T2F GMM UM, which includes the addition of Markov Random Field, to improve its performance for dynamic scenes.

3.3. Non-parametric methods

VuMeter [12]: is a kernel density estimation non-parametric background model, which is defined by using a probabilistic approach. Kronecker delta kernels are used to estimate the probability density for 3 colors (Red, Green and Blue). A pixel is considered as part of the background, if it has detected as background in all 3 colors.

Pixel Based Adaptive Segmenter (PBAS) [13]: is a non-parametric method, where an array of previous background models is used to decide if a pixel is foreground or background by using a set threshold, this is done per pixel. The background model is updated overtime to adapt to dynamic backgrounds, this is done for each pixel by using a learning parameter. Both pixel based parameters are updated by using a feedback loop.

Table 2. Background subtraction algorithms used in this study

Method Name	Authors
Basic methods, mean and variance over time	
Adaptive Background Learning	-
DP Adaptive Median	[14]
DP Mean	-
DP Prati Mediod	[6]
Frame Difference	-
Static Frame Difference	-
Weighted Moving Mean	-
Weighted Moving Variance	-
DP Adaptive Median	[14]
Fuzzy Based Methods	
Fuzzy Choquet Integral	[15]
LBFuzzyGaussian	[16]
Statistical methods using one Gaussian	
DP Wren GA	[17]
LB Simple Gaussian	[18]
Statistical methods using multiple Gaussians	
DP Grimson GMM	[19]
DP Zivkovic A GMM	[8]
LB Mixture Of Gaussians	[20]
Mixture Of Gaussian V1	[7]
Mixture Of Gaussian V2	[8]
Type-2 Fuzzy based methods	
T2F GMM UM	[21,22,23]
T2F GMM UV	[21,22,23]
T2F MRF UM	[11]
T2F MRF UV	[11]
Methods that use texture and color descriptors	
LOBSTER	[24]
SubSENSE	[25]
Non-parametric methods	
Independent Multimodal	[26]
KDE	[27]
Pixel Based Adaptive Segmenter	[13]
Vu Meter	[12]
Neural and neuro-fuzzy methods	
LB Adaptive SOM	[28]
LB Fuzzy Adaptive SOM	[29]
Sigma Delta	[30]

4. EXPERIMENTS

The background subtraction methods are compared using the previously mentioned dataset. The aim is to compare the quality of foreground mask generated by each background subtraction algorithm at the same intervals. From each dataset, frames are picked based on their position in the image sequence, the later they are the better as this allows many background subtraction algorithms to build a reliable background model. However, it is also important to ensure the image includes the maximum number of targets available to test the algorithms under different conditions and scenarios. The foreground model obtained from each of the methods is matched and measured to its corresponding ground truth mask [4]. True positives (TP), true negatives (TN), false positives (FP) and false negatives (FN) can be then evaluated from the comparison results of the ground truth and the reference frame. Hence the image pixels are classified into four categories:

1. TP – Foreground pixels detected as foreground
2. TN – Background pixels detected as foreground
3. FP - Background pixels detected as background
4. FN - Foreground pixels detected as background

This allows us to calculate the following:

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$FalseNegativeRate = \frac{FN}{TP + FN} \tag{3}$$

$$FalsePositiveRate = \frac{FP}{TN + FP} \tag{4}$$

$$F - Score \ = \frac{2 \ \times Precision \ \times Recall}{Precision + Recall} \tag{5}$$

The study was performed on an Intel(R) Xeon(R) CPU with E5-2650 @2.2GHz and 64 GB RAM system. Visual Studio and MATLAB 2018 were used to perform the comparison between the methods. MATLAB was also used to create the background model for each dataset.

5. RESULTS AND DISCUSSIONS

Firstly, we would evaluate the F-score metric as it used to measure the accuracy of the background subtraction algorithms. Better performing background subtraction algorithms tend to have higher F-score than lower performing algorithms. Hence, this would help us filter out and shrink the thirty background subtraction algorithms down to the top ten. To analyze the F-Score, the precision and recall of the algorithms have to be calculated based on the four-pixel classification categories previously mentioned.

True Positive Rate (TPR), True Negative Rate(TNR), False Positive Rate (FPR) and False Negative Rate (FNR) can also be used to evaluate the performance of the background subtraction algorithms. According to [31], (TP>>FN) if and only if the amount of foreground pixels as background is less than the number of foreground pixels detected as foreground, then the TPR will be high. The FNR can be calculated as (1−TPR). As for the TNR, its value would be high, if the amount of background pixels detected as background is more than the number of background pixels detected as foreground (TN>>FP). The FPR can be calculated as (1−TNR). To choose the best background subtraction algorithm for aerial imageries, and different weather conditions. The F-Score must be high, as well as the TPR and TNR. The results of the Precision, Recall and F-Score for the top ten algorithms are shown below in Tables 3-5, which are plotted on Figures 2-4. As mentioned previously, the dataset used takes into account 3 different weather conditions from the UAE region from 3 different months of the year.

It can be noted that the weather conditions for the April and December datasets are somewhat similar, other than the levels of high humidity in the December dataset. This is reflected in the results shown in Figures 2-4, where the evaluation metrics of background subtraction for the April and December datasets are very similar, but most background subtraction algorithms perform slightly better in less humid weather conditions. As for the August dataset, most algorithms had difficulty detecting the targets, hence the evaluation metrics of background subtraction for the August dataset are very poor, this can be seen in Figure 1, which shows a sample of the original frame and the ground truth alongside a few examples of the different BS methods. It can be seen that the size of the targets is much smaller and more blurred out, this is due to the fact that the temperature was 42℃ when the dataset was captured. High heats can amplify the effect of heat waves on the image quality. Tables 6-8 display the results of the TPR, TNR, FPR and FNR, and they are plotted on Figures 5-7, showing the results found for each of the different dataset.

It can be seen that in all three datasets, the results of the TNR are very close to 100% accuracy, while FPR is close to 0%. This is due to the fact that the dataset is of aerial imagery and the majority of the image consists of background pixels. Hence, the main two results that should be taken in consideration are the TPR and FNR. The results of TPR and FNR for the April and December datasets fluctuate around 40%-60%. Background pixels being detected as foreground pixels is caused due to a few obvious reasons, the first is parallax effect. Slight movements of the drone due to changes in wind speeds can cause the camera location to be shifted slightly, this can cause a parallax effect which is very noticeable in buildings and high structures. The second reason is again due to wind, which can cause stationary objects to sway and appear to be in motion, but many algorithms are capable of adapting to such dynamic environments. As for the August dataset, the FNR is mostly always higher than the TPR, this is mostly due to the weather effects previously mentioned such as heatwaves and winds. The small size and number of targets in the frame is another reason why the FNR is high, however this cannot be avoided as the dataset is of aerial imageries and targets would always be a big distance away from the sensor.

Out of the top ten background subtraction algorithms MOG and DP Mean have provided good results throughout all three datasets. However, PBAS had the best performance between all algorithms in the April and December datasets, but its performance in the August dataset was atrocious as it could not detect any moving targets. Vu Meter had similar performances as PBAS throughout the three datasets.

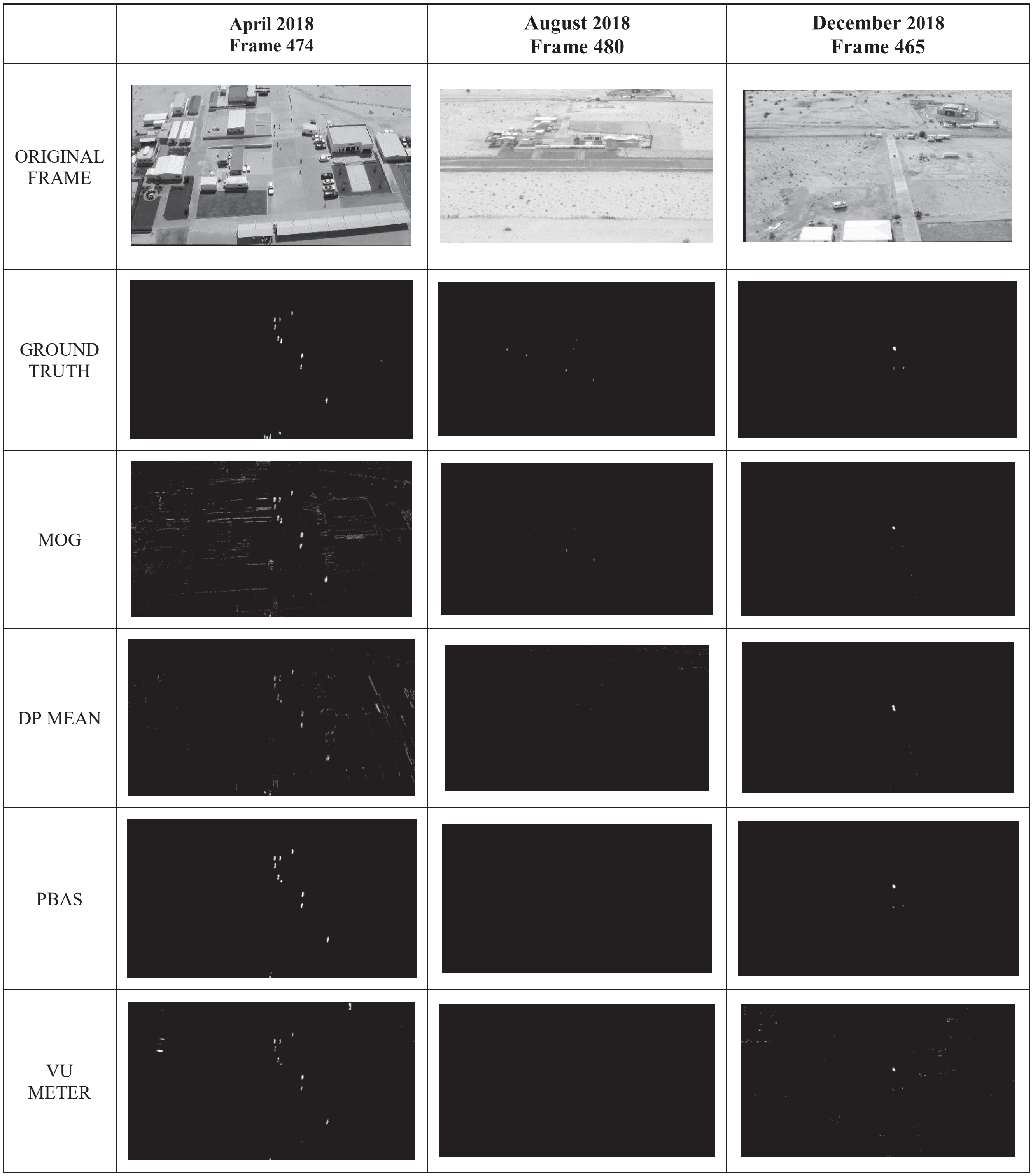

Figure 1. Comparison of foreground masks by different background subtraction algorithms

Table 3. Background subtraction evaluation metrics, April 2018 dataset

Methods	April 2018		
	Precision	Recall	F-Score
MOG1	0.0837	0.6161	0.1474
DP Mean	0.1720	0.3809	0.2369
PBAS	0.8084	0.6675	0.7312
Vu Meter	0.5341	0.4865	0.5092
DP Prati Mediod	0.2288	0.5881	0.3294
T2F GMM UM	0.9054	0.4195	0.5734
WMM	0.0794	0.5068	0.1373
MOG2	0.0585	0.6164	0.1069
T2F MRF UM	0.9696	0.2911	0.4478
WMV	0.0767	0.5957	0.1359

Table 4. Background subtraction evaluation metrics, August 2018 dataset

Methods	August 2018		
	Precision	Recall	F-Score
MOG1	0.4029	0.3111	0.3511
DP Mean	0.0610	0.2944	0.1010
PBAS	0.0000	0.0000	0.0000
Vu Meter	0.0000	0.0000	0.0000
DP Prati Mediod	0.0691	0.2000	0.1027
T2F GMM UM	1.0000	0.0056	0.0110
WMM	0.0260	0.4056	0.0489
MOG2	0.1332	0.5667	0.2156
T2F MRF UM	0.0000	0.0000	0.0000
WMV	0.0247	0.4611	0.0469

Table 5. Background subtraction evaluation metrics, December 2018 dataset

Methods	December 2018		
	Precision	Recall	F-Score
MOG1	0.7257	0.4587	0.5621
DP Mean	0.4075	0.3790	0.3928
PBAS	0.8813	0.6336	0.7372
Vu Meter	0.2237	0.5972	0.3255
DP Prati Mediod	0.0164	0.4503	0.0317
T2F GMM UM	0.2184	0.1524	0.1796
WMM	0.2999	0.4643	0.3644
MOG2	0.0734	0.7147	0.1332
T2F MRF UM	0.1375	0.1944	0.1611
WMV	0.2372	0.4937	0.3205

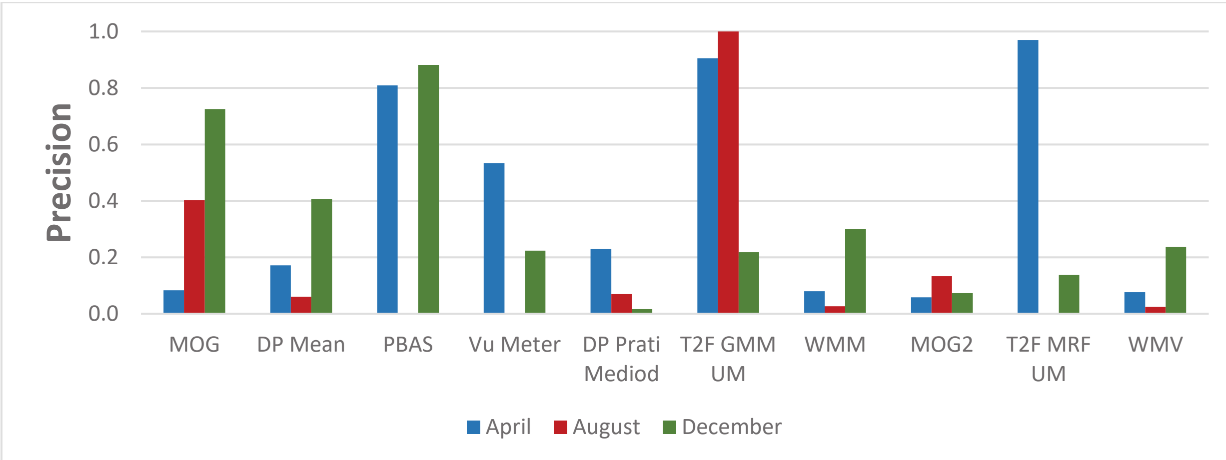

Figure 2. Precision of background subtraction algorithms on the 3 weather datasets

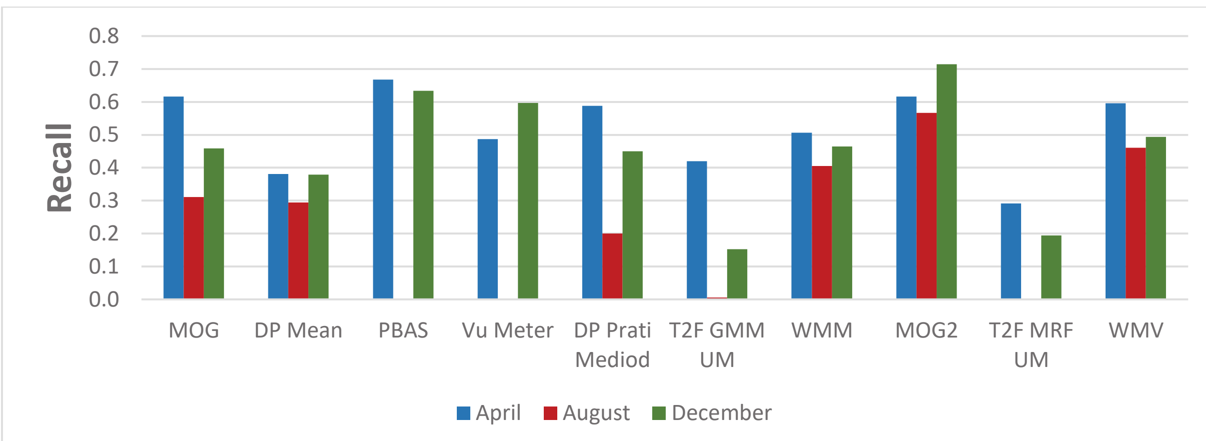

Figure 3. Recall of background subtraction algorithms on the 3 weather datasets

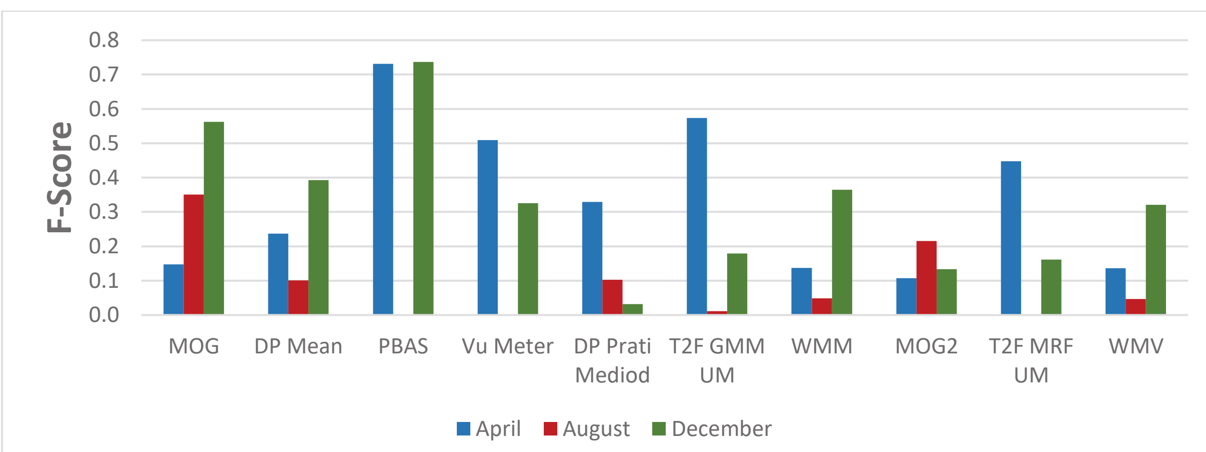

Figure 4. F-score of background subtraction algorithms on the 3 weather datasets

Table 6. The results of TPR, TNR, FPR and FNR, April 2018 dataset

Methods	**April 2018**			
	TPR	**TNR**	**FPR**	**FNR**
MOG1	0.6161	0.9887	0.0113	0.3839
DP Mean	0.3809	0.9969	0.0031	0.6191
PBAS	0.6675	0.9997	0.0003	0.3325
Vu Meter	0.4865	0.9993	0.0007	0.5135
DP Prati Mediod	0.5881	0.9967	0.0033	0.4119
T2F GMM UM	0.4195	0.9999	0.0001	0.5805
WMM	0.5068	0.9901	0.0099	0.4932
MOG2	0.6164	0.9834	0.0166	0.3836
T2F MRF UM	0.2911	1.0000	0.0000	0.7089
WMV	0.5957	0.9880	0.0120	0.4043

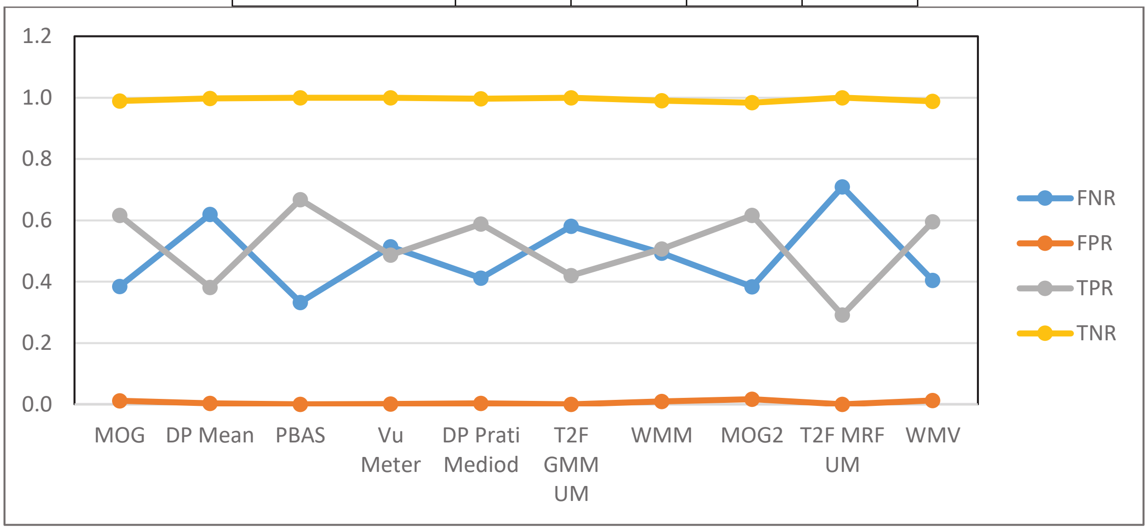

Figure 5. The results of TPR, TNR, FPR and FNR, April 2018 dataset

Table 7. The results of TPR, TNR, FPR and FNR, August 2018 dataset

Methods	**August 2018**			
	TPR	**TNR**	**FPR**	**FNR**
MOG1	0.3111	1.0000	0.0000	0.6889
DP Mean	0.2944	0.9996	0.0004	0.7056
PBAS	0.0000	1.0000	0.0000	1.0000
Vu Meter	0.0000	1.0000	0.0000	1.0000
DP Prati Mediod	0.2000	0.9998	0.0002	0.8000
T2F GMM UM	0.0056	1.0000	0.0000	0.9944
WMM	0.4056	0.9986	0.0014	0.5944
MOG2	0.5667	0.9997	0.0003	0.4333
T2F MRF UM	0.0000	1.0000	0.0000	1.0000
WMV	0.4611	0.9984	0.0016	0.5389

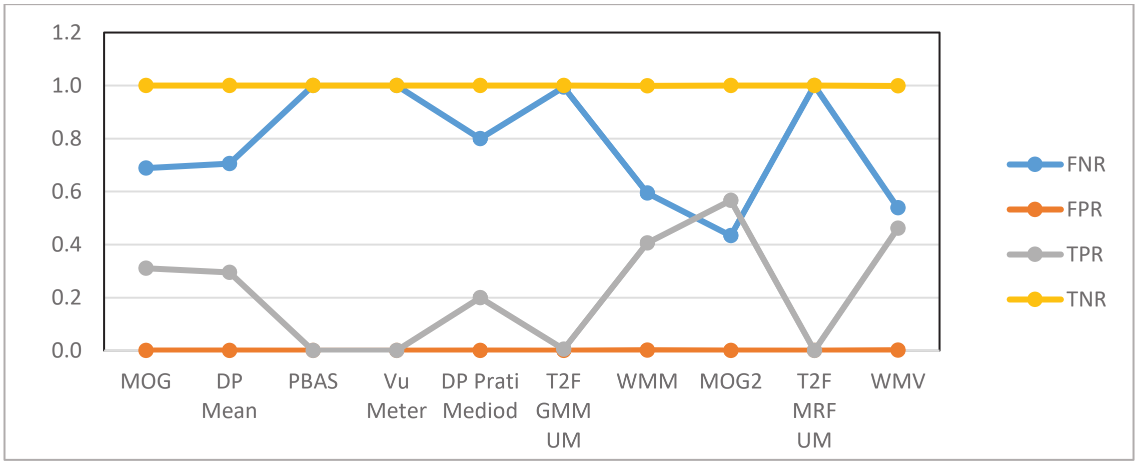

Figure 6. The results of TPR, TNR, FPR and FNR, August 2018 dataset

Table 8. The results of TPR, TNR, FPR and FNR, December 2018 dataset

Methods	December 2018			
	TPR	TNR	FPR	FNR
MOG1	0.4587	0.9999	0.0001	0.5413
DP Mean	0.3790	0.9998	0.0002	0.6210
PBAS	0.6336	1.0000	0.0000	0.3664
Vu Meter	0.5972	0.9993	0.0007	0.4028
DP Prati Mediod	0.4503	0.9903	0.0097	0.5497
T2F GMM UM	0.1524	0.9998	0.0002	0.8476
WMM	0.4643	0.9996	0.0004	0.5357
MOG2	0.7147	0.9968	0.0032	0.2853
T2F MRF UM	0.1944	0.9996	0.0004	0.8056
WMV	0.4937	0.9994	0.0006	0.5063

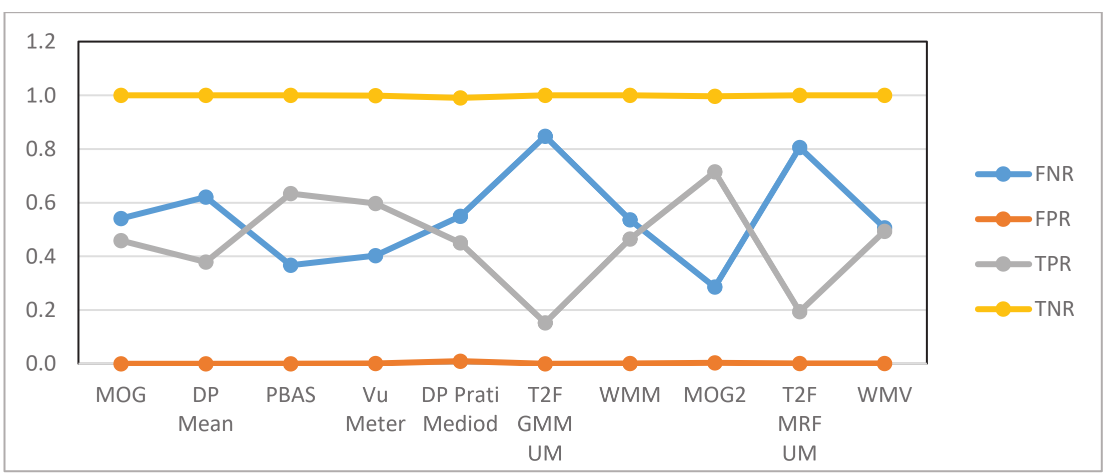

Figure 7. The results of TPR, TNR, FPR and FNR, December 2018 dataset

6. CONCLUSION

In this article, background subtraction methods from the literature are presented, compared and analysis against each one another, thanks to the BGSLibrary. The algorithms were tested on images taken from a drone in different weather conditions throughout the year, to get a better understanding into the difficulties faced by the background subtraction methods. This is accomplished by extracting and evaluating the foreground mask of each background subtraction algorithm. thirty background subtraction algorithms were tested on 3 different aerial datasets; the experimental results of the best ten algorithms are presented, where the algorithms are compared by using 7 evaluation measures. One of the main challenges faced by the algorithms is the small size of the targets in the images. This can be seen in the low results of the top ten algorithms. Another issue that many algorithms could not overcome is the effect of heat waves on the images, this can be seen in the results of the August dataset, as many algorithms failed to detect any moving targets.

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