International Journal of Hybrid Information Technology
Vol.9, No.3 (2016), pp. 11-22
http://dx.doi.org/10.14257/ijhit.2016.9.3.02

Fast-Optimized Object Detection in Dynamic Scenes Using Efficient Background Weighting

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Abstract

Moving object detection is an important fundamental process in intelligent vision systems and an essential preprocessing step in high-level machine vision applications such as object tracking and moving analysis. This technique helps to detect suspicious events in video monitoring and is a key process for concentration estimation in traffic management. It is also one of the methods used in advanced vehicle control systems to keep vehicle in path and prevent accidents.In this paper, an effective weighted background moving object detection is presented,which is optimized for scenes with dynamic background. The proposed detection is based on real time background subtracting with high accuracy, low computational complexity and a short processing time, which makes it a good candidate for hardware implementation. The proposed algorithm is simulated in MATLAB software. The simulation results in MATLAB on various image sequences and comparison with mixture Gaussian method and median filter algorithm shows the effective weighted background method has better performance in different evaluation criteria that approves its efficiency in dynamic scenes.

***Keywords**: Real-time, dynamic background, motion detection, background subtraction, gray color space*

1. Introduction

Moving object detection is one of the important tasks in machine vision systems with many practical applications such as robotic systems. The robot actions in dynamic environmentsand its interactions with other objectsbecome possible by detection systems. Another application is in security system. Object detection system provides the security of some important places by adding face detection or car plate number recognition unit to moving object detection system and acts as a surveillance system. Furthermore, in a virtual environment, the detection system in computer is able to sense and react to movements. Autonomous cars and vehicles also benefit significantly from the diagnostic systems. Advanced vision system in vehicle is used to find the location of moving objects in path, follow the road and preventing collisions [1].

Background modeling is the first important step in data mining in many video processing applications. High accuracy at the first step leads to better results in moving object detection and in higher stages in video processing. However,background modeling has many challenges because of the inherent variations in video background. These variations include water waves, moving foliage, gradual changes in brightness, the presence of moving objects in most of times and sudden changes in brightness of the scene. There are numerous methods for moving object detection including light flux, frame subtraction and background subtraction. In light flux method, a motion vector is

ISSN: 1738-9968 IJHIT
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calculated for each pixel and the image is considered as a vector field. The motion vector for each pixel shows the brightness variation. The region, in which the brightness variation is observed, is a candidate for moving object. However, this method has a good performance; it has a complex algorithm and due to the large number of images, takes a lot of memory [2]. In frame subtraction, instead of using a constant reference image, consecutive frames are subtracted for moving object detection. This method is capable to match with the changes in dynamic scenes. Frame subtraction has some advantages such as low cost, low complexity computation and simplicity. This method has some problems in detection of the object shape; also, it cannot detect moving objects settled in the scene [3]. Moreover, this method is highly sensitive to the speed of moving object. In background subtraction method, the algorithm uses a background image called as reference image that is stored in the memory. At first, the input video sequence is converted to a number of frames, and then each frame is subtracted pixel by pixel from the background image to detect the moving object [4]. Moving object detection with background subtraction method is classified to adaptable and non-adaptable methods. In non-adaptable method,the background image is loaded online. The main problem of this method is its numerous error. Because when a picture is taken, the immobile objects are considered as a part of background. To avoid such problems, adaptable method is used. In adaptable method, background image is updated with taken frames in the certain times. This approach is more effective because the detection system does not consider constant moving and temporarily immobile object as a part of background. Background subtraction is one of the most widely used methods in moving object detection, because it is a feasible method to implement and has low computational complexity.

Thispaper presents fast-optimized moving object detection for dynamic scenes using effective background weighting. The proposedmethod is based on real-time background subtracting algorithm and uses gray color space, which leads to process in a short time with an acceptable accuracy. In order to have a valid detection in dynamic backgrounds, a weighting approach is used for background modeling which increases the detection accuracy. Furthermore, if the defined conditions adjustable for dynamic backgrounds are met, the background is updated and this action causes the algorithm to have appropriate performance in scenes with dynamic background. The paper structure is organized as follows, in Section 2 we review the works in the field of background subtraction. Section 3 describes the proposed algorithm and its main blocks. The simulation results and their comparison with other results are presented in Section 4. Finally, the paper is concluded in Section 5.

2. A Review on Background Subtraction Methods

Many researches have been carried out on the background subtraction techniques. Due to the numerous challenges, many of these methods focus on modeling the background. Median filtering [5, 6] is the most commonly used method in background image modeling. The main idea is storing the continuous 'M' frames before the current frame in memory and ranking the value of pixels at the same coordinate for 'M' frames and then chooses the median value as the pixel value of the background model if 'M' is an odd number. If 'M' is even then choose the average of the two middle values. The chosen pixel can be defined as,

$$B_n(i,j) = median\{f_{(n-M-1)}(i,j), \dots, f_{(n-1)}(i,j)\} \tag{1}$$

Where:

$\boldsymbol{B_n(i,j)}$:	Pixel value in the background model,
Median**:**	Getting the median value,
$\boldsymbol{f_{(n)}}$:	Represents frames from *n-M-1* to *n-1*.

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Stauffer [7, 8] proposed a probabilistic model based on Gaussians mixture model for dynamic scenes in real-time indoor and outdoor detection of moving objects. In this probabilistic background model, a mixture of Gaussian presents each pixel that is useful to determine whether each pixel is in the background or foreground. They described their method in following parts: First, K-Gaussian distribution models each pixel as a series of pixels. Modeling of the next pixel is performed using some parameters from previous pixel or initially given (likeω, μ, σ). The probability of a pixel is evaluated as:

$$P(I_t) = \sum_{k=1}^{K} \omega_{k,t}{}^{*}\eta\left(I_t, \mu_{k,t}, \sum k, t\right) \tag{2}$$

$$\eta\left(I_t, \mu_{k,t}, \sum k, t\right) = \frac{1}{(2\pi)^{\frac{|I_t|}{2}}} * \frac{exp\left[-\frac{1}{2}\left(I_t - \mu_{k,t}\right)^T \sum_{k,t}^{-1}\left(I_t - \mu_{k,t}\right)\right]}{|\sum k, t|^{1/2}} \tag{3}$$

Where:

$\omega_{k,t}$: Weight of k[th] Gaussian in mixture,

$\mu_{k,t}$: Mean of k[th] Gaussian component at time t,

$\sum k, t$: Co-variance matrix.

$\sum k, t = \sigma_{k,t}{}^{2*}I$, here σ is variance and I represent identify matrix. Author initializes ω, μ, σ parameters with some fixed initial values. Then, updating the weight, mean and variance with the following equations for each matched Gaussian component.

$$\omega_{k,t} = (1-\alpha)^*\omega_{k,t-1} + \alpha \tag{4}$$

$$\mu_{k,t} = (1-\rho)^*\mu_{k,t-1} + \rho^* I_t \tag{5}$$

$$\boldsymbol{\sigma^2_{\mu_{k,t}} = (1-\rho)^*\sigma^2_{\mu_{k,t}} + \rho^*\left(I_t - \mu_{k,t}\right)^{T*}\left(I_t - \mu_{k,t}\right)} \tag{6}$$

For each unmatched Gaussian component the weightis updated, with the following equations,

$$\omega_{k,t} = (1-\alpha)^*\omega_{k,t-1} \tag{7}$$

Secondly, b distributions were chosen as background if

$$background = argmin_b\left(\sum_{k=1}^{b} \omega_k > T\right) \tag{8}$$

Where, T is a threshold value chosen high for multi-model distribution with repetitive motion in background.

Another method is the combination of background subtraction and Kalmanfilter, which operates well for real-time applications, although in this approach moving object detection is highly dependent on current frame [9]. Another algorithm is W4, which operates in gray color space and three parameters including minimum intensity, maximum intensity and maximum absolute difference of consecutive frames are calculatedfor each pixel. This algorithm does not remove the noise of background, but it has a relatively high speed [10].

3. Optimization of Motion Detection Algorithm with Effective Background Weighting

Moving object detection is the main step for video analysis. All the tracking and analysis methods need detection process. Figure (1) shows the proposed optimizedmotion detection algorithm with effective background weighting.

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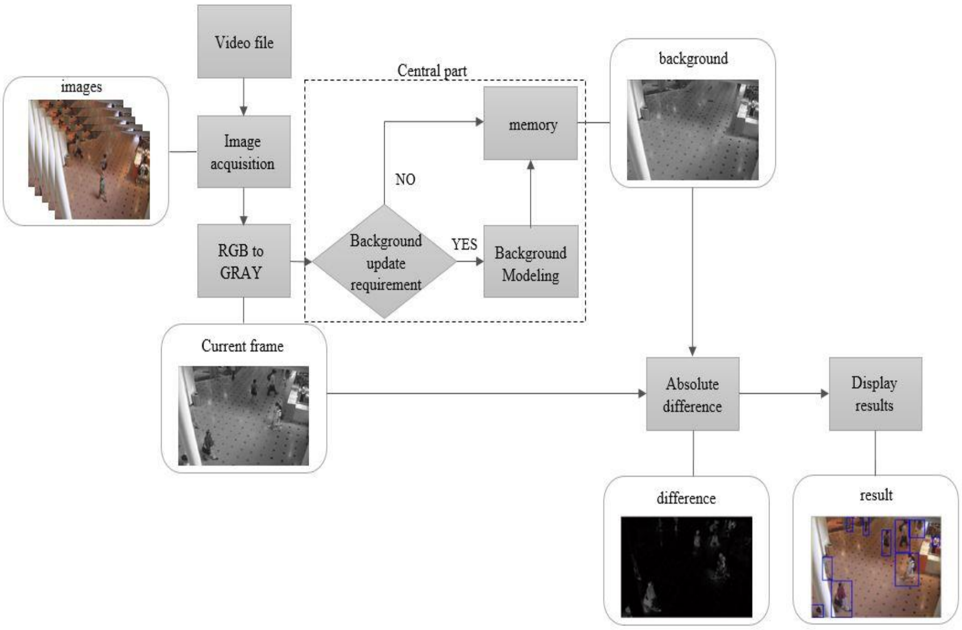

Figure 1. The Proposed Optimized Motion Detection Algorithm with Effective Background Weighting

According to the figure, after converting video files provided by a fixed camera to the individual frames, the color space changes from color to gray. Single-channel color space takes three or four times, less than three-channel color spaces, thus it is useful in pixel level fast processing.

3.1. The Central Part of the Proposed Algorithm

The central part of the proposed algorithm contains memory, background update requirement taking decision and background modeling. At the first step, the algorithm checks the background update requirements and if it is necessary, background-modeling block updates background, otherwise the previous background stored in memory is used.

3.1.1. Background Modeling

The background modeling process is shown in Figure (2). This is one of the most challenging and important part of background subtraction algorithm. We use frame subtraction technique for background modeling. Using this technique, moving parts of a fixed number of frames are specified. Then, all the pixels in these frame bunches are weighted according to their presence or lack of presence in moving parts. Finally, after comparing all the frames in pixel level and considering the weights, the proper pixels for background image are determined. This image is stored as the new background in memory for next steps. This method is persistent against inherent variations in video background like water waves, moving foliage and the presence of moving objects.

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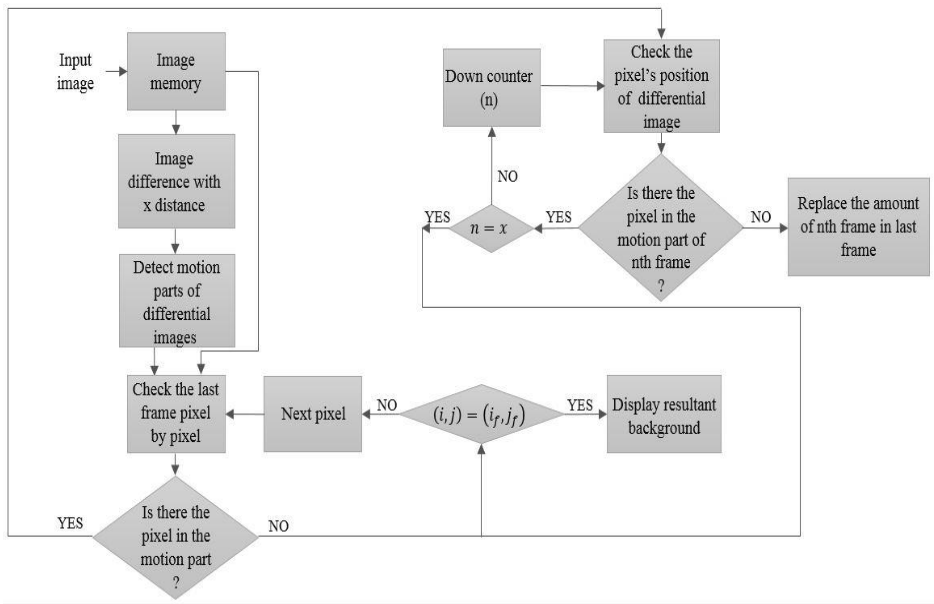

Figure 2. Background Modeling's Block Diagram

3.1.2. Background Update Requirement

To detect moving objects correctly, it is necessary to update background under some conditions. Figure (3)shows background update requirementsprocedure. At the first step, the pixels including moving objects in the current frame and background are removed. Then the absolute difference of the resultant images is achieved. This differential image is enhanced with luminance filter. Then some criteria such as the number of moving objects and their consumed area in the image identify the new background modeling necessity. Background modeling block is responsible produce new background if it is necessary, otherwise the previous background stored in the memory is applied.

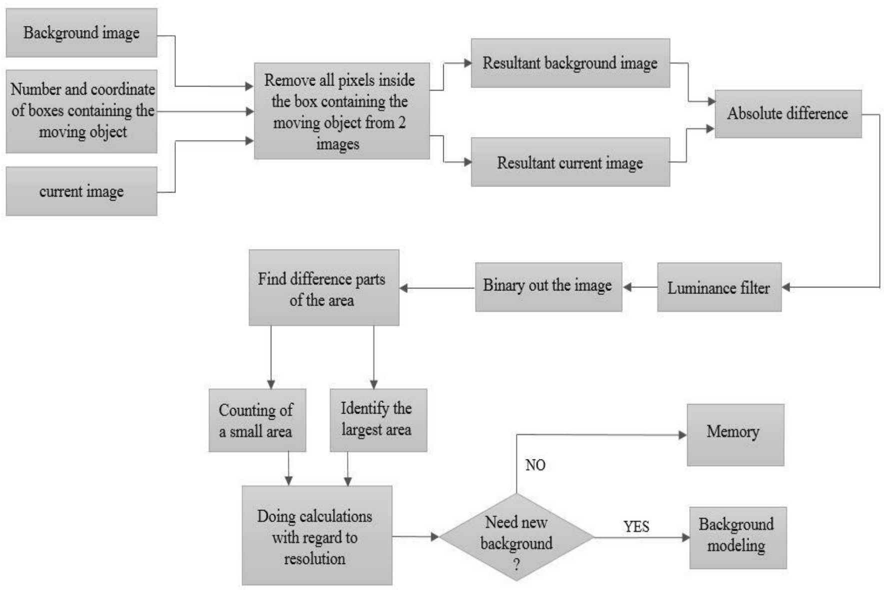

Figure 3. Background Updating Procedure

3.2. Background Subtraction

The equation (9) reflects the difference pixel-by-pixel background image stored in the memory (B) and the current frame (F).

$$\Delta(i,j) = B(i,j) - F(i,j) \tag{9}$$

The result of this subtraction contains useful information including moving objects and unessential information. According to equation (10), the threshold value in this algorithm removes unessential information and only maintains moving object pixels. Then the subtracted image is converted to a binary image, which is used to find the box around moving object. By inserting this box in the current frame, moving object is determined [11].

$$\Delta(x,y) = \begin{cases} 1, if\ \Delta(x,y) > T \\ 0, if\ \Delta(x,y) < T \end{cases} \tag{10}$$

4. Simulation Results and their Comparison

In this study, we use a personal computer with Corei7 CPU and MATLAB software version 8.1.0 for simulations. To discuss the challenges of this techniques, the algorithm was applied to the various video sequences as Table (1) with different background conditions including the presence of large number of moving objects (sequence1), dynamic background (sequence2), free space (light and climate change) (sequence3) and the presence of moving objects most of the times (sequence4).

Table 1. Under Test Video Sequences

Sampled frame	Sequence type	Image size	Background property	Object size	Object number
	indoor	320 × 256	Static	Small	Many
	Dynamic background	160 × 128	Dynamic	Large	Few
	outdoor	768 × 576	Static	Small	Medium
	The presence of moving objects in most times	320 × 240	Static	Medium	Few

To prove the superiority of the proposed algorithm, the results of the simulation and the results of the mixture Gaussian algorithms and median filter have been evaluated by comparing criteriasuch as false positive rate (FPR), precision (Pr), similarity (Sim), percentage of wrong classification (PWC), F measure (Fm) and accuracy which are shown in equations 11 to 16 [12].

$$FPR = \frac{f_p}{f_p + t_n} \tag{11}$$

$$TPR = \frac{t_p}{t_p + f_n} \tag{12}$$

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$$Pr = \frac{t_p}{t_p + f_p} \tag{13}$$

$$Sim = \frac{t_p}{t_p + f_p + f_n} \tag{14}$$

$$PWC = 100 \times \frac{f_{n+}f_p}{t_p + f_n + f_p + t_n} \tag{15}$$

$$Fm = 2 \times \frac{pr \times TPR}{pr + TPR} \tag{16}$$

Where tp, tn, fp and fn denote the numbers of the true positives, true negative, false positive, and false negative, respectively.

Figures 4 to 7, and tables 2 to 5 respectively show the simulation and comparison results for the proposed method, the mixture Gaussian algorithm and median filter in different image sequences. In each Table, the best performance for each criterion is shown in a rectangle.

Figure (4) corresponds to an image sequence in which a large number of moving objects are always present on the scene. In this sequence, the moving object is detected properly by contrast the compared algorithms' detection is not true and they usually cannot detect accurately or they consider a part of background as the moving object.

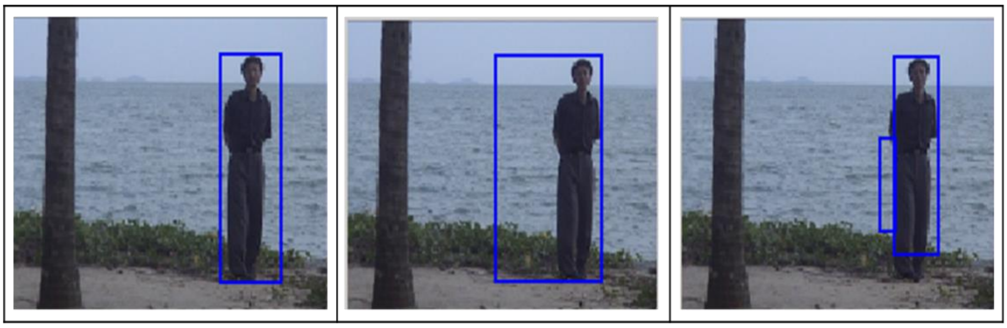
(a) (b) (c)

Figure 4. The Simulation Results of (a) the Proposed Method (b) Median Filter Algorithm and (c) Mixture Gaussian Algorithm on Sequence 1

Table 2. FPR, TPR, Pr, Sim, PWC, Fm and Accuracy for Sequence 1 (The Large Number of Moving Objects)

Method	FPR	TPR	Pr	Sim	PWC	Fm	Accuracy
Proposedalgorithm	$\boxed{0.0874}$	0.9391	$\boxed{0.7533}$	$\boxed{0.5935}$	1.1500	$\boxed{0.7450}$	$\boxed{0.9195}$
Median filter [11]	0.1404	$\boxed{0.9453}$	0.3767	0.3760	3.8400	0.5467	0.6515
Gaussian mixture model [10]	0.0931	0.7715	0.6050	0.4084	$\boxed{1.0900}$	0.58	0.8991

Figure (5) includes the simulation results of an image sequence in which the scene has a dynamic background. The proposed algorithm again has an accurate detection. Whereas the median filter considers a large part of background as a moving object due to the existence of dynamic background. Mixture Gaussian algorithm also cannot extract the background completely and therefore fails to detect moving object correctly.



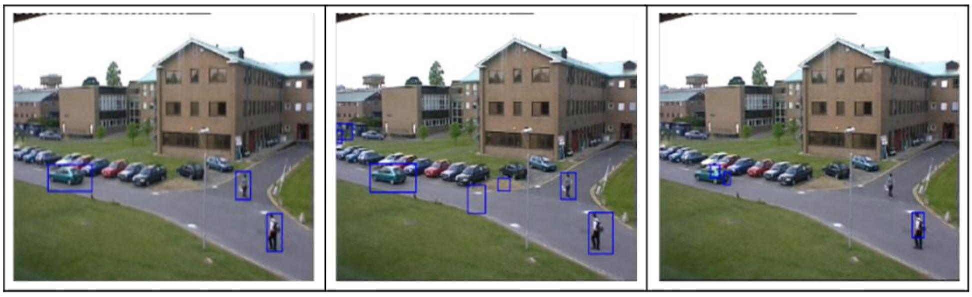
(a) (b) (c)

Figure 5. The Simulation Results of (a) the Proposed Method (b) Median Filter Algorithm and (c) mixture Gaussian Algorithm on Sequence 2

Table 3. FPR, TPR, Pr, Sim, PWC, Fm and Accuracy for Sequence 2 (Dynamic Background)

Method	FPR	TPR	Pr	Sim	PWC	Fm	Accuracy
Proposed algorithm	0.0503	$\boxed{0.9889}$	$\boxed{0.8544}$	$\boxed{0.7044}$	$\boxed{1.4800}$	0.8262	$\boxed{0.9851}$
Median filter [11]	0.1516	0.8897	0.4414	0.4414	3.5400	0.5901	0.8646
Gaussian mixture model [10]	$\boxed{0.0500}$	0.921	0.7044	0.7960	2.5500	$\boxed{0.8865}$	0.9545

As shown in Figure (6), the proposed algorithm in an image sequence taken from the free space detects the moving object correctly. While the two other algorithm fail to detect moving object in sequences due to the variant light and climate conditions.



(a) (b) (c)

Figure 6. The Simulation Results of (a) the Proposed Method (b) Median Filter Algorithm and (c) Mixture Gaussian Algorithm on Sequence 3

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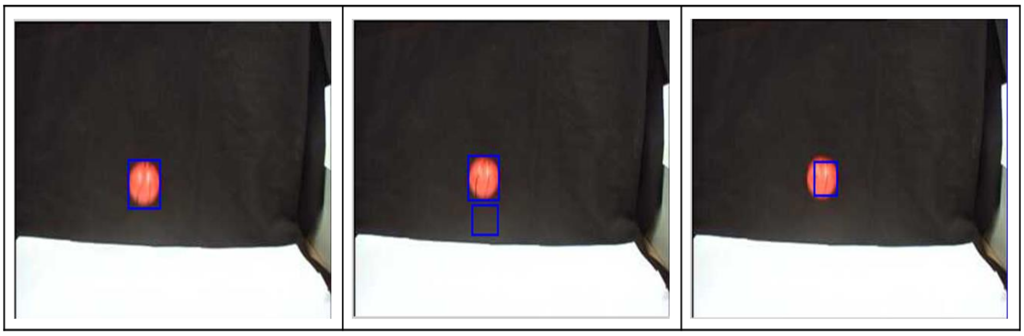
Table 4. FPR, TPR, Pr, Sim, PWC, Fm and Accuracy for Sequence 3 (Outdoor)

Method	FPR	TPR	Pr	Sim	PWC	Fm	Accuracy
Proposed algorithm	$\boxed{0.0081}$	$\boxed{0.9187}$	0.8666	$\boxed{0.7187}$	$\boxed{1.7919}$	$\boxed{0.8065}$	$\boxed{0.9937}$
Median filter [11]	0.0272	0.8753	0.4455	0.4455	2.6595	0.5905	0.9734
Gaussian mixture model [10]	0.0093	0.5334	$\boxed{0.8675}$	0.4939	1.9449	0.6606	0.9737

Figure (7) also shows that the proposed algorithm detects correctly in the continuous presence of moving objects. While the median filter algorithm detects a part of moving object and the mixture Gaussian algorithm considers a part of background as the moving object.



(a) (b) (c)

Figure 7.The Simulation Results of (a) the Proposed Method (b) Median Filter Algorithm and (c) Mixture Gaussian Algorithm on Sequence 4

Table 5. FPR, TPR, Pr, Sim, PWC, Fm and Accuracy Sequence 4 (The Presence of Moving Objects in Most Times)

Method	FPR	TPR	Pr	Sim	PWC	Fm	Accuracy
Proposed algorithm	$\boxed{0.0017}$	$\boxed{0.9975}$	$\boxed{0.8931}$	0.7746	$\boxed{1.4239}$	$\boxed{0.9424}$	$\boxed{0.9783}$
Median filter [11]	0.0741	0.8538	0.6683	0.5997	2.9744	0.7497	0.8903
Gaussian mixture model [10]	0.0038	0.6074	0.8194	$\boxed{0.7857}$	1.6855	0.6977	0.9231

According to the simulation results, the median filter detection shown in the part (b) of Figures 4 to 7, is wrong or not complete true in some situations because of considering a part of the background as a section of moving object. Additionally, the mixture Gaussian method has some problems in spaces with light and climate changes according to section (c) of the resulted figures. However, the proposed method results presented in Figures 4 to 7 Section (a), show its feasibility using efficient background weighting and updating to detect large number of moving objects correctly; while at the same time can detect continuous presence of moving object in the background. It is also capable of detecting moving object detection in dynamic backgrounds and is robust on light and climate changes.

Figure (8) compares false positive rate and wrong classification metrics for three methods. The minimum value for these two metrics is the optimum situation. Figure (9) compares true positive rate, precision, similarity and F-measure metrics in which the maximum value is the best. All bar charts in Figures 8 and 9 approve the efficiency of the proposed algorithm related to two other methods. We calculated the improvement percentage of the proposed algorithm to other methods from equations 17, and reported in Table 6.

$$= \frac{|A-B|}{B} * 100 Theimprovementpercentage \tag{17}$$

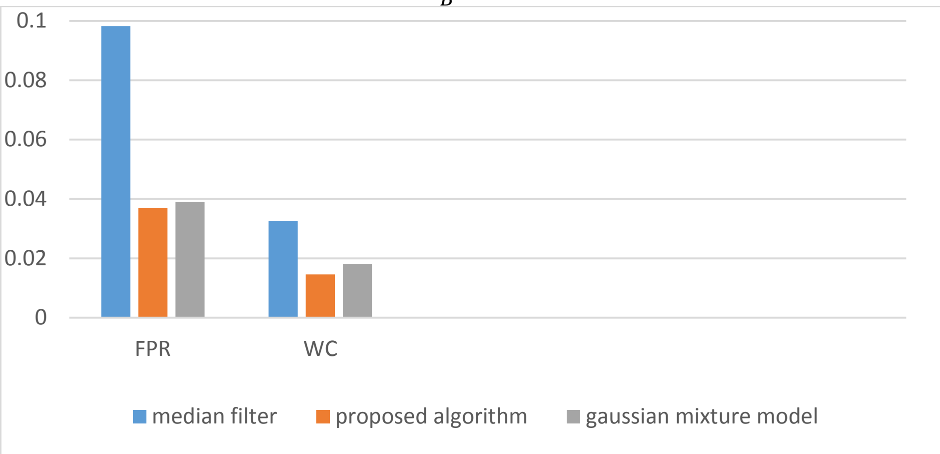


Figure 8. False Positive Rate and Wrong Classification Metrics Comparison

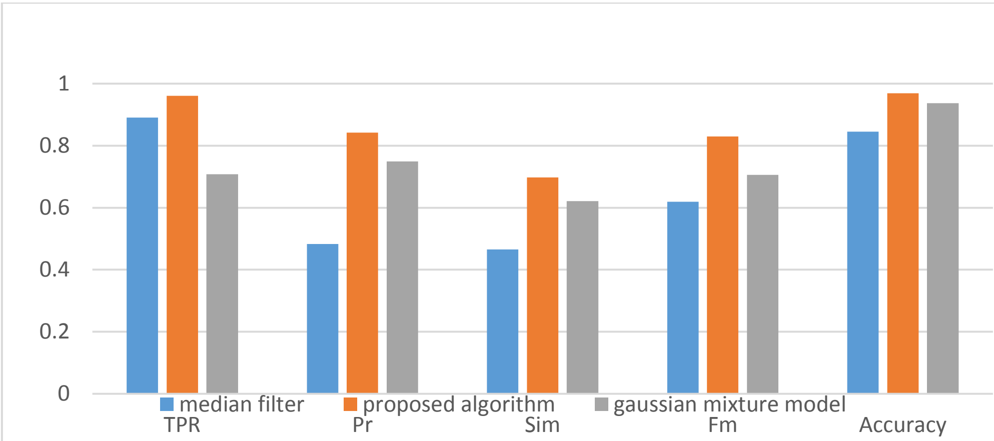


Figure 9. True Positive Rate, Precision, Similarity, F-measure Metrics Comparison

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Table 6. The Improvement Percentage of the Proposed Algorithm to Two other Methods

Criterion	The improvement percentage in the proposed algorithmUsing Efficient Weightingcompared to	
	Median filter	Mixture Gaussian
FPR	5.38	62.46
TPR	35.67	7.85
Pr	12.4	74.34
Sim	12.36	49.87
WC	19.33	55.07
Fm	17.53	34.02
Accuracy	3.37	14.71

5. Conclusions

In this paper, a fast-optimized moving object detection method using effective background weighting based on background subtraction has been proposed. The proposed method guaranties high performance in dynamic scenes and scenes with light and climate variations through the process of checking update requirements and new background modeling. This method has low computational complexity and needs less time to process, thus is a good candidate for implementation. The efficiency of the proposed algorithm has been approved by examine on various image sequences obtained from a fixed camera. The result of the proposed method compared with its counterparts are provided by figure, comparison table and histogram, which approves the accuracy of the effective background weighting algorithm and shows the proposed algorithm superiority to the other compared methods.

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