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Performance Comparison of Background Estimation Algorithms for Detecting Moving Vehicle

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Abstract: Background subtraction is the one of the crucial step in detecting the moving object. Many techniques were proposed for detected moving object however there are few comparative studies carried out to verify their performance. In this paper a performance comparison of different background subtraction algorithms is carried out from the literature as well as through implementation. We investigate some of the techniques which varying from simple techniques such as frame differencing and approximation median filter, to more complicated probabilistic modeling techniques. Our results show that simple techniques such as approximation median filter can produce good results with much lower computational complexity.

Key words: Computer vision · Object detection · Image processing

INTRODUCTION

Detection of moving object from a video sequence is crucial task in video surveillance. In literature many techniques was proposed for object extraction which can be classified into two categories: automatic and semiautomatic [1]. The former works without any human intervention while the latter requires user's interaction. A common approach to identifying the moving objects is by using background subtraction techniques [2], The idea of background subtraction is consists of extracting moving objects as the foreground elements obtained from the image difference between each frame and the so-called background model of the scene. This model is used as a reference image to be compared with each recorded image. Consequently, the background model must be an accurate representation of the scene after removing all the non-stationary elements. It must be permanently updated to take into account the change in the lighting conditions or any change in the background texture. All this should be attainable even when foreground elements are permanently moving around in the scene at different speeds from the beginning of the video stream [3]. Many background subtraction algorithms are proposed from the literature however a problem of detecting moving object in complex environment is still not yet completely solved. Any good background algorithm must have the following characteristics (1) should adapt to various levels of illuminations at different times of the day (2) It must handle adverse weather condition such as fog or snow that modified the background. (3) It must handle the moving objects that first merge into background and then become foreground at a later time [2]. In this paper frame difference algorithm, approximation media filter algorithm and Mixture of Gaussian algorithm for detecting the moving object is examined and compared and the best conclusion are drawn. The rest of the paper is organized as follow. Section 2 the detail steps for background subtraction explanation, Section 3 background subtraction algorithms. Section 4, pro and cons for each algorithm. Sections 5, we will implement algorithms and analyze the results, Section 6 we will conclude our work.

Steps for Background Subtraction: Most of the background subtractions algorithms follow a simple flow diagram defined by Cheung and Kamath [4] shown in Figure 1. The four major steps in a background subtraction algorithm are preprocessing, background modeling, foreground detection and data validation.

Preprocessing: In most computer vision systems, simple temporal and/or spatial smoothing is used in the early stage of processing to reduce camera noise. Smoothing can also be used to remove transient environmental noise

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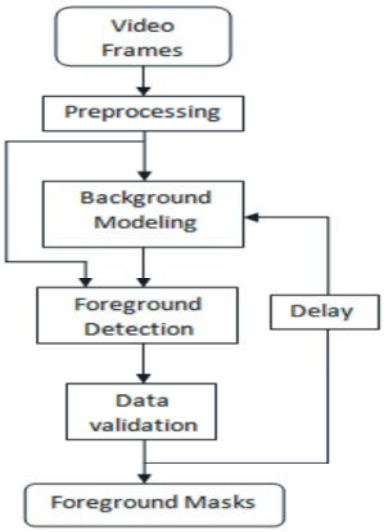

Fig. 1: Generic of Background Subtraction Algorithm [4]

such as rain and snow captured in outdoor camera. For real-time systems, frame-size and frame-rate reduction are commonly used to reduce the data processing rate. If the camera is moving or multiple cameras are used at different locations, image registration between successive frames or among different cameras is needed before background modeling [4]. Another key issue in preprocessing is the data format used by the particular background subtraction algorithm. Most of the algorithms handle luminance intensity, which is one scalar value per each pixel. However, color image, in either RGB or HSV color space, is becoming more popular in the background subtraction literature [4].

Background Modeling: Background modeling is at the heart of any background subtraction algorithm. Much research has been devoted to developing a background model that is robust against environmental changes in the background, but sensitive enough to identify all moving objects of interest. In [2] background modeling techniques are classified into two categories: Non-recursive and recursive.

A non-recursive technique uses a sliding-window approach for background estimation. It stores a buffer of the previous L video frames and estimates the background image based on the temporal variation of each pixel within the buffer [2]. Non-recursive techniques are highly adaptive as they do not depend on the history beyond those frames stored in the buffer [2]. Frame difference, median filter, linear predictive filter and Non parametric model are some examples of Non recursive algorithms. For recursive techniques, it does not maintain a buffer for background estimation. Instead, they recursively update a single background model based on each input frame. As a result, input frames from distant past could have an effect on the current background model [2]. Compared with non-recursive techniques, recursive techniques require less storage, but any error in the background model can stay for a much longer period of time. Some examples of algorithms found in this category are: Approximated median filter, Kalman filter and Mixture of Gaussians.

Foreground Detection: It identifies pixels in the video frame that cannot be adequately explained by the background model and outputs them as a binary candidate foreground mask. Foreground detection compares the input video frame with the background model and identifies candidate foreground pixels from the input frame. The most commonly used approach for foreground detection is to check whether the input pixel is significantly different from the corresponding background estimation [4]:

$$|I_t(x,y) - B_t(x,y)| > T$$

Another popular foreground detection scheme is to threshold based on the normalized statistics:

$$\frac{|I_t(x,y) - B_t(x,y) - \mu_d|}{\lambda_d} > T_s$$

where μ_d and λ_d are the mean and the standard deviation of $I_t(x,y) - B_t(x,y)$ for all spatial locations (x,y). T or Ts are foreground experiment which most schemes determined it experimentally.

Data Validation: It examines the candidate mask, eliminates those pixels that do not correspond to actual moving objects and outputs the final foreground mask. The output of a foreground detection algorithm where decisions are made independently at each pixel will generally be noisy, with isolated foreground pixels, holes in the middle of connected foreground components and jagged boundaries. Cheung and Kamath [4] define data validation as the process of improving the candidate foreground mask based on information obtained from outside the background model. Data validation phase is sometimes referred to as the post-processing phase of the foreground mask (pixels).

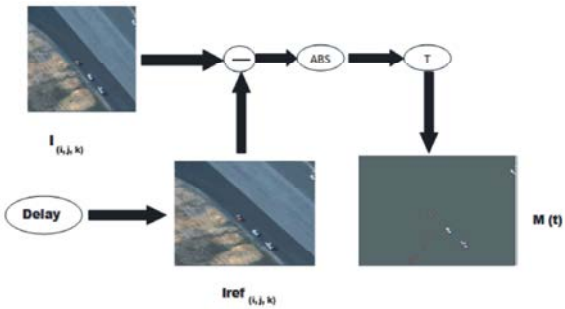

Fig. 2: Frame difference algorithm in operation [8]

Background Subtraction Algorithms: The three different methods studied and implemented use simple background subtraction algorithms, The methods are implemented using MATLAB image processing toolbox. Different methods for detecting moving objects described in this paper are: Frame differencing [5], Mixture of Gaussian [6] and Approximation median filter [6].

Frame Difference Algorithm: Frame differencing is the simplest method in Background subtraction techniques [7].

In Figure 2 a background image without any moving objects of interest is taken as the reference image. Pixel value for each co-ordinate (x, y) for each color channel of the background image is subtracted from the corresponding pixel value of the input image. If the resulting value is greater than a particular threshold value, then that is a foreground pixel otherwise background.

For each frame I and for the reference image Iref, if for a particular pixel, $| I_{val}\text{-}Iref_{val} | > Th$ then that pixel is classified as foreground. That is $I_{(i,j,k)}\text{-}Iref_{(i,j,k)} > Th$ where I (i,j,k) is the co-ordinate (i,j)'s pixel value for k^{th} color channel for the current image I and $Iref_{(i,j,k)}$ is for reference frame.

Approximation Median Algorithm: This method finds the difference of the current pixel's intensity value and the median of some recent pixel's intensity values. It uses a buffer of size n, where n is the number of last frames whose pixel values are considered for calculating the median value for background model. The algorithm is implemented without sub sampling frames for creating an adequate background model. Equation used is as follows. $|I(i,j,k) - Med(i,j,k)| > Th$ then it is classified as foreground. The median value is updated for last n recent pixel values. 'I' represents the current frame and 'Med' is the median of last n frames. For each pixel (i,j), the difference of current frame pixel value with pixel value of median of last n frames decides whether it is foreground or background [9].

Mixture of Gaussian: This method uses a Gaussian probability density function to evaluate the pixel intensity value. It finds the difference of the current pixel's intensity value and cumulative average of the previous values. So it keeps a cumulative average (μ_t) of the recent pixel values. If the difference of the current image's pixel value and the cumulative pixel value is greater than the product of a constant value and standard deviation then it is classified as foreground. That is, at each t frame time, the I_t pixel's value can then be classified as foreground pixel if the inequality:

$|I_t\text{-}\mu_t| > k\ \sigma$ holds; otherwise, it can be considered as background, where k is a constant and σ is standard deviation [9].

Here background is updated as the running average:

$$\mu_{t+1} = \mu_t * I_t + (1- \alpha) * \mu_t \quad (1)$$

$$\sigma^2_{t+1} = \alpha\ (I_t- \mu_t)^2 + (1- \alpha)\ \sigma^2 t \quad (2)$$

where α, the learning rate, is typically 0.05, I_t is the pixels current value and μ_t is the previous average.

Implementation and Result Analysis: We have tested the selected algorithm on image sequences on different scenarios like during the clear air, fog, heavy snow and snow. We implement these algorithms with the following parameters. Some of the parameters are fixed and others are variables (test parameters).

Table 1: Shows advantages and Disadvantages of difference background subtraction algorithm

Method	Advantages	Disadvantages
Frame Differencing	Easiest method. It performs well for static background.	It requires a background without any moving objects
Mixture Gaussian	Low memory requirement	It does not cope with multimodal backgrounds
Approximation Median	It performs better than Running Gaussian Average	Its computation requires a buffer with the recent pixel values

Table 2: Shows different parameters used in algorithms [4]

Algorithm	Fixed parameter	Test parameter
Frame difference (FD)	None	Foreground threshold Ts
Approximated median filter (AMF)	None	Foreground threshold Ts
Mixture of Gaussian (MoG)	K = 3 Variance = 36 wo = 0.1	Adaptation rate α Weight threshold Γ Deviation threshold D

For Threshold Ts=25, α= 0.01, Γ= 0.25, D=2.5.

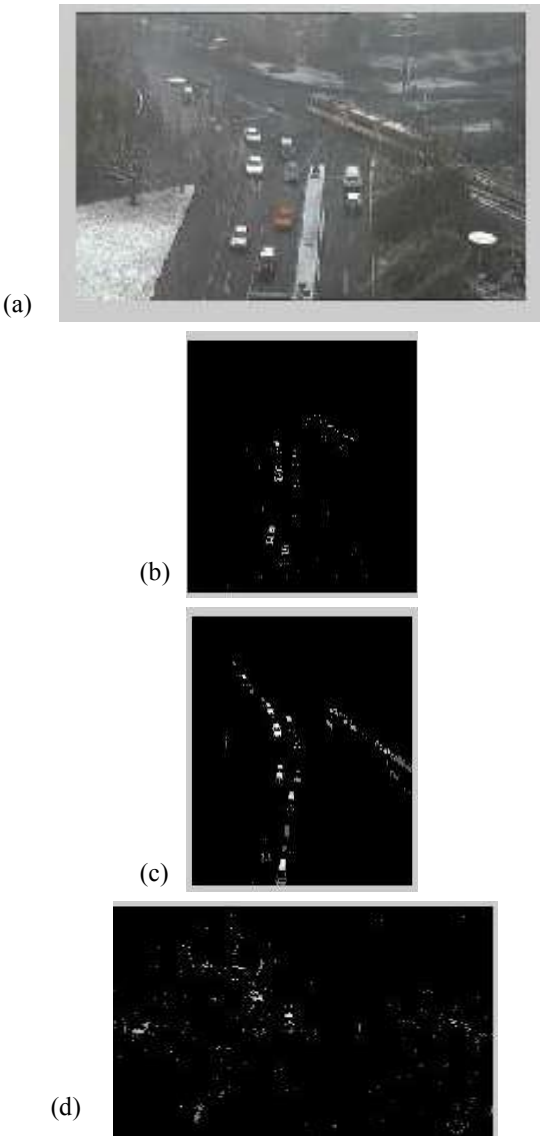

Fig. 5: Foreground image identified by different algorithm (a) original image, (b) FD (c) AMF (d) MoG.

As can be seen from the Figure 4 and 5 for Ts=25 in both cases (during heavy snow and fog). Approximation median (Figure 4, 5(c)) performed better compare to frame

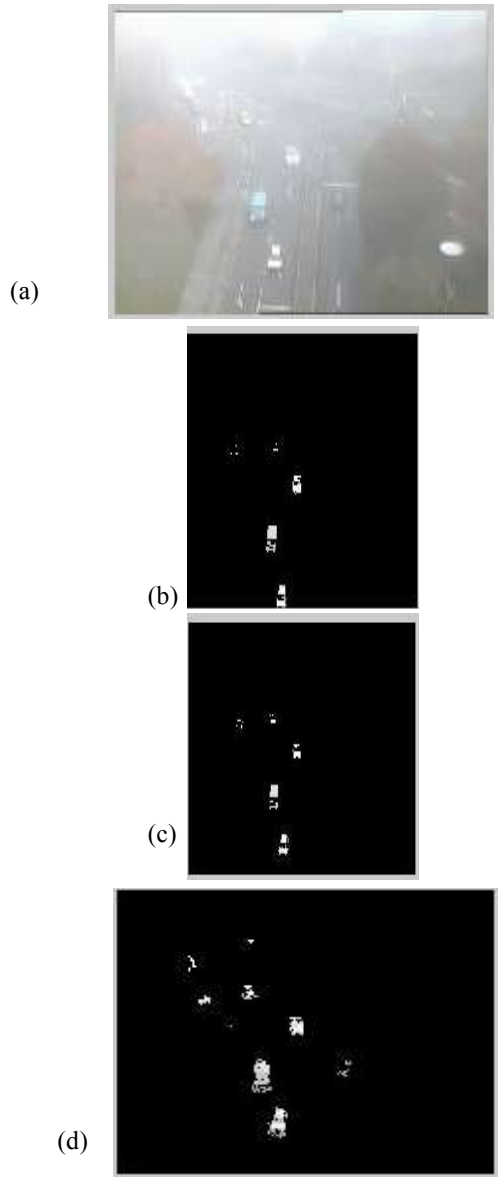

Fig. 6: Foreground image identified by different algorithm (a) original image,(b) FD(c) AMF (d) MoG. For threshold Ts=40, α= 0.01, Ã= 0.4, D=2.5

difference (Figure 4(b)) and Mixture of Gaussians (Figure 4(d)), However Frame difference algorithm has a major flaw that is when values (such as the side of a car) objects with uniformly distributed intensity; the interior pixels are interpreted as part of the background. Another problem is that objects must be continuously moving. If an object stays still for more than a frame period (1/fps), it becomes part of the background [8]. Mixture of Gaussians shows unaccepted result because it detects not only vehicles but also detect particles of the snow as moving object. The main advantages of frame difference

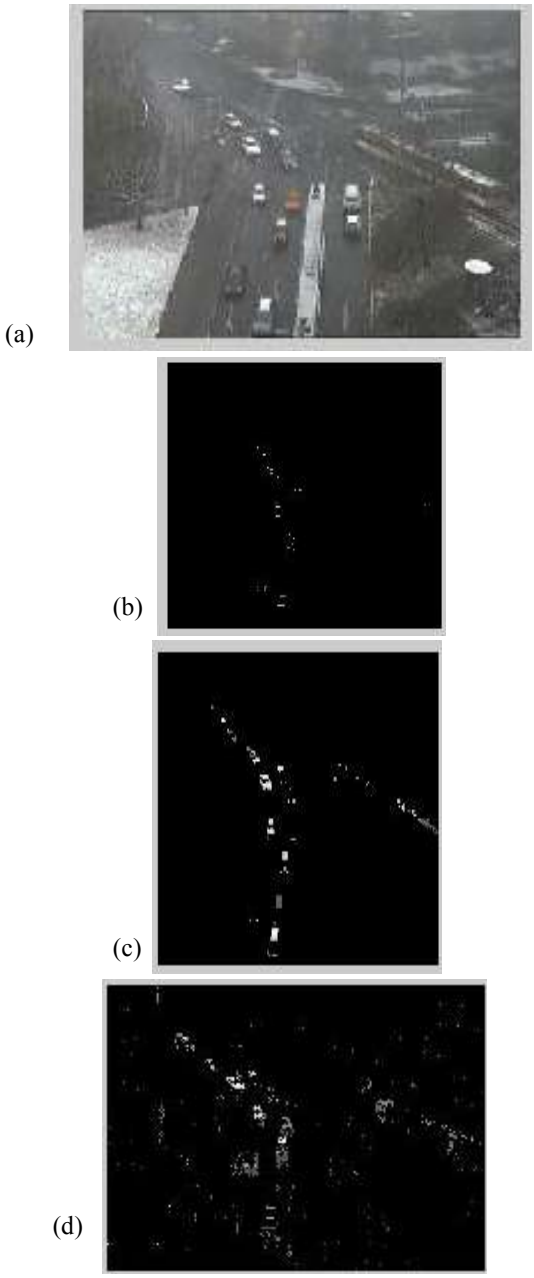

Fig. 6: Foreground image identified by different algorithm (a) original image,(b) FD(c) AMF (d) MoG, For threshold Ts=2, α= 0.01, Ã= 0.02, D=2.5

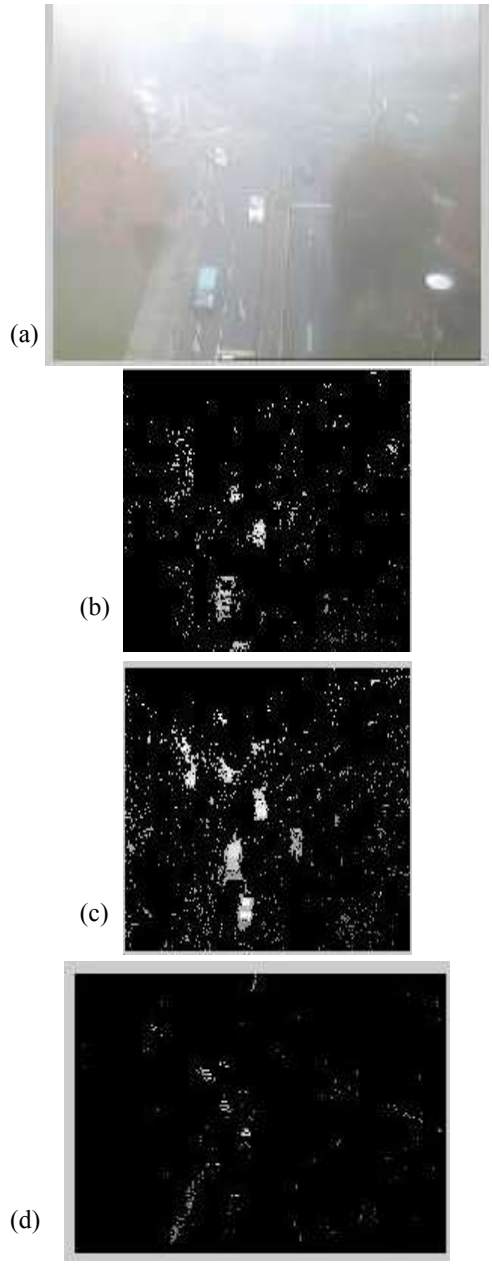

Fig. 7: Foreground image identified by different algorithm (a) original image, (b) FD (c) AMF (d) MoG

techniques are highly adaptive in modest computational load as well as in background model [8]. When we change the value of threshold to higher values (Ts=40) the performance of both frame difference and Mixture of Gaussian degrade dramatically while the approximation median still has shown the reasonable results as it revealed in figure 6 (c) and (b). For lower value of threshold Ts=2 the performance of all algorithms are not acceptable, the object are not well detected a lot of salt noise introduced. In general from the Figure 5, 6, 7 (c) approximate median method does a much better job at separating the entire object from the background. This is because the more slowly adapting background incorporates a longer history of the visual scene, achieving about the same result as if we had buffered and processed N frames. We do see some trails behind the

larger objects. This is due to updating the background at a relatively high rate (30 fps). In a real application, the frame rate would likely be lower (say, 15 fps) [8].

Mixture of Gaussian algorithm (Figure 5, 6, 7(d)) is very good at separating out objects and suppressing background noise such as waving trees. However, there are several points where the method breaks down, allowing most of the background to seep into the foreground. These points correspond to relatively rapid changes in illumination [8].

To determine the threshold value is one the critical challenge for this method. The threshold is typically found empirically, which can be tricky. But from our experiment it shows that the threshold which provides the best result is 25 for both Frame difference and Approximation median algorithm while for Mixture of Gaussian the best weight threshold is 0.25.

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CONCLUSION

It is clear shown that the simplest method is arguably the most robust. While it has major flaws and is probably not suitable for most applications, frame differencing does the best job of subtracting out extraneous background noise. The second most robust method, approximate median, gives us significantly increased accuracy for not much more computation. It had a little trouble with quickly changing light levels, but handled them better than mixture of Gaussians. And Mixture of Gaussians, the most complex of the methods, gives us good performance, but presents a tricky parameter optimization problem.

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