2010 6th International Colloquium on Signal Processing & Its Applications (CSPA)

Background Modelling and Background Subtraction Performance for Object Detection

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***Abstract*— Moving object detection in video applications is usually performed based on techniques such as background subtraction, optical flow and temporal differencing. The most popular literature technique approach to detect moving object from video sequences is background subtraction. This approach utilized mathematical model of static background and comparing it with every new frame of video sequence. In this paper, background subtraction technique using Mixture of Gaussian (MoG) method is conducted for detection of moving object at outdoor environment. Focus is specified at the five parameters of MoG namely background component weight threshold (T_S), standard deviation scaling factor (D), user-define learning rate (α), Total number of Gaussian components (K) and Maximum number of components *M* in the background model (M) to give significant impact in producing the optimize background subtraction process. Experimental results showed that by varying each of the parameter can produce acceptable results that enable us to propose suitable parameter range of each parameter for detection of moving object in an outdoor environment.**

***Keywords*— Background Subtraction, Mixture of Gaussian, Object Detection**

I. INTRODUCTION

There are many challenges in developing a good background subtraction algorithm and researchers has been devoted to develop new invention and improvement techniques to overcome all the limitations. Many aspects involved in order to produce best detection system to detect moving object for outdoor environment. Most methods exist from low to complex computational algorithm and performance, and each with different strengths and weaknesses. Difference technique applied would solved difference issues and challenges face on background subtraction.

The problems encountered in background subtraction are merging of object, distortion of object shape, missing object and classification of background as foreground. However, additional challenges came into account for outdoor environment. The three main challenges on the background subtraction for outdoor are to have robust algorithm to overcome instable changes in illumination due to day and night, avoid detecting non-stationary background objects such as moving leaves, sky, rain, snow, shadows cast and etc. and to ensure internal background react promptly to changes in background as example starting and ending point of moving object such as vehicle.

In this project, we aim to create a robust, accurate and less-complexity background subtraction algorithm in video application to detect moving object for outdoor environment by using MoG background subtraction method. This is done by evaluating each parameter in the MoG approach.

II. BACKGROUND STUDY

Most literatures on background subtraction algorithm consider four major steps namely pre-processing, background modelling, foreground detection and finally is data validation [1]. Fig. 1 depicted the overall view of a generic background subtraction.

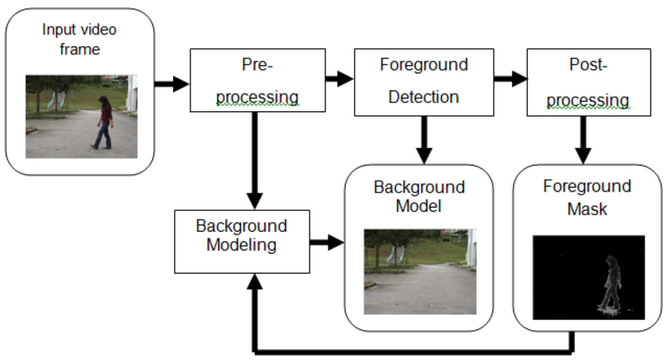


Fig. 1 Flow diagram of a generic background subtraction algorithm [2]

Firstly, pre-processing is the process of changing the raw data which is the input video sequences into a format that can be read for the next phase. In background modelling, the new video frames are updated and calculate the background model where it provides statistical description. Unidentified pixel in the video frame in background model will be output as binary candidate foreground mask at foreground detection step. Data validation stages function as examiner and eliminator where it examines candidate mask and eliminates pixels that are not related with target moving objects and only provide the foreground masks output.

A. *Background Subtraction*

Background subtraction is the method used in computational to separate foreground objects from the background in the sequence of video frames. Non-recursive techniques such as Frame differencing, Median Filter, Linear predictive filter and Non-parametric model proposed by researchers as general is a technique that uses a sliding window approach for background estimation [1,2]. This technique maintain a buffer of previous video frames and estimate a background model based on the statistical properties of these frames that causes this technique consume high memory [2].

Different approach utilized in recursive techniques which is approximated median filter, Kalman filter, Mixture of Gaussian (MoG) do not maintain a buffer for background estimation but updated a single background based on input frame [1]. Recursive can be described as a process of repeating objects in a self-similar way. In addition of that, it maintains a single background model that is updated with each new video frame that makes this technique have minimal memory requirements as compare to non-recursive and computational efficient [2].

B. *Foreground Detection*

Next, foreground is the moving object that separated from the background model or scene after the step of background separation. The method will detect moving object and classify the process of pixels as foreground and background. It detects the foreground and compares the input video frame with the background model, and identifies it pixels from the input frame. However, the detection rate of the foreground depends on the method chosen. Normal approach is to verify the input pixel and compare it with corresponding background estimation. Another popular scheme to detect the foreground is to use threshold based on the normalized statistics. However, limitation of this technique for outdoor environment leads to another approach where two thresholds with hysteresis or known as spatial variability is introduced [1].

There are several more existing method that have been combined with new propose method such as MoG method with gradient-base background subtraction and morphological filter that depends on contour of moving objects [4]. Initial Background model, shadow hi-lite detection and background adaption [5], Background subtraction using Density and Kernel estimation, suppress false detection, updating background for short and long term and shadow detection [3], trackability features and interest of region [6], frame differencing, adaptive median filtering with pre and post processing [2] among others techniques and combination.

III. METHODOLOGY

In this paper, MoG method is chosen due to its low rate of complexity, memory consumption and suitability for outdoor environment along with its robustness and also it can handle multi-modal distributions. In MoG, the background is known as parametric frame of values where each pixel location is represented with number of Gaussian functions as probability distribution function as given in 1.

$$F(i_t = \mu) = \sum_{i=1}^{k} \omega_{i,t} \cdot \eta(\mu, \sigma) \qquad 1$$

where,

η = the *i-th* Gaussian component
μ = intensity mean
σ = standard deviation
$\omega_{i,t}$ = portion of the data accounted by *i-th* component

In addition, for MoG approach, only pixel that is within a scaling factor of background standard deviation is considered as part of background. This can be determined by comparing the pixel value with Gaussian component tracking. MoG approach is more suitable for outdoor environment due to its capability to separate and suppress non-stationary object that classify as noise such as moving leaves, sky and etc. However, illumination will be the drawbacks. Therefore, five main parameters will be evaluated and that will give significant impact. The five parameters are:

i. T_s = Background component weight threshold
ii. D = Standard deviation scaling factor
iii. ρ = Learning rate
iv. K = Total number of Gaussian components
v. M = Maximum number of components *M* in the background model

Furthermore, the advantage of MoG is that it can extend to colour video sequences that can solve the shadows effect [7]. However, this paper will not focus on elimination of shadow but more on focusing that proper selection of MoG parameters for background subtraction purpose can provide enhanced results for detection of moving object in an outdoor environment.

IV. RESULTS & DISCUSSIONS

As mentioned, in the MoG method, there are five parameters that will give significant impact on the results of object detected. In this paper, we evaluated the experiments by varying one of the parameters while others remain fix to observe the results and capabilities of this model to detect moving object. We set T_s= background component weight threshold as 2.5, D= standard deviation scaling factor as 2.5, α= user-defined learning rate as 0.01, K= Total number of Gaussian components as 3 and M= Maximum number of components M in the background model as 3 throughout all experiments as suggested by Ref [7]. Fig. 2 showed the reference parameter test value output.

Firstly, the Total number of Gaussian component K is varied from (1 – 15) in non-uniform interval to observe the results. Refer to Fig. 3 for the output detected on moving object showed that by increasing the number of K, moving object is capable to be detected. However, it is observed that imperfect object detection as K is increased as showed in Fig. 3. On the other hand, the moving object can be detected for K = M. When K = M = {1, 2, 3, 5 or 7} the detection capabilities increased as the value increases as in Fig. 4. Based on this experiment, it is suggested that the typical K ranges from (3 – 7).

Next, as for learning rate (ρ) it decreased as a function of time. It will also give significant impact to moving object detection based on user-define learning rate or alpha (α) chosen. The theoretical proposed value of α is (0 – 1) and in our experiment, if lower value of α is chosen that is between the range of (0.01 - 0.05), good object detection is achieved. However, higher value of α specifically between (0.2 – 0.99) will caused weights and objective function diverged. Fig. 5 illustrated the outcome of foreground object detection for α from 0.005 to 0.05 has attained good moving object detection. Conversely, once the value of α exceeded this range and increased until 0.99 caused degraded output as shown in Fig. 5.

Reference Parameter	Result of Object Detected
Video Frame Input	
K=3, M=3, D=2.5, α=0.01, Ts=2.5	

Fig. 2 Result of moving object detection for reference parameters of MoG.

Test Parameters		
K	Result of Object Detected	Performance of Detection
Video Frame Input		
3		Good
4		Good
5		Good
7		Good
10		Average
15		Average

Fig. 3 Results of moving object detection when Total number of Gaussian components, C varies from (1-15) in non-uniform interval.

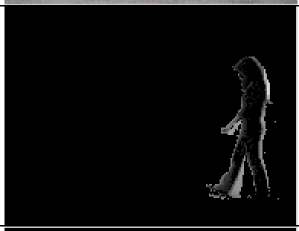
Test Parameters K=M	Result of Object Detected	Performance of Detection
Video Frame Input		
1		Poor
2		Good
3		Good
5		Good
7		Good

Fig. 4 Results of moving object detection when Total number of Gaussian components, K matches with Maximum number of components M in the background model, M.

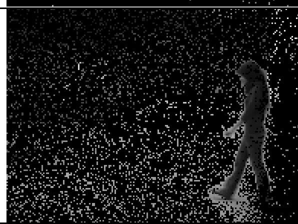
Test Parameters α	Result of Object Detected	Performance of Detection
Video Frame Input		
0.005		Good
0.01		Good
0.05		Good
0.06		Poor
0.10 – 1.0		Poor & Worsen

Fig. 5 Results of moving object detection when learning rate, α varies from (0.005 – 1) in non-uniform interval.

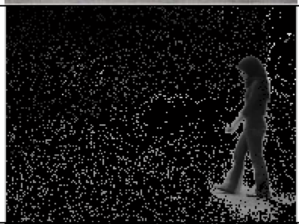
Test Parameters		
D	Result of Object Detected	Performance of Detection
Video Frame Input		
1.0		Worse
1.5		Poor
2.0		Average
3.0		Good
3.5 - 15		Average
16 - 20.0		Worst

Fig. 6 Results of moving object detection when D = standard deviation scaling factor varies from (1 – 20) in non-uniform interval.

Test Parameters		
T_S	Result of Object Detected	Performance of Detection
Video Frame Input		
0.1		Worse
0.15		Poor
0.20		Average
0.30 – 0.55		Good
0.6		Average
0.65 and above		Poor & Worsen

Fig. 7 Results of moving object detection when background component weight threshold, T_S varies from (0.1 – 0.75) in non-uniform interval.

Further, the standard deviation scaling factor is varied and observed. Based on the outcome in Fig. 6, when D is in the range of (1 - 1.5), the results of object detection is considered as worst due to flawed foreground. Incremental of D from 3.5 to 20.0 resulted as the object to be classified as background.

Based on the result showed, we proposed that acceptable D is from 2.0 to 3.0 since if D is too low or high the foreground is defective. In addition, background component weight threshold, T_s is also tested. Based on literature [7], proposed T_s is 0.25 or 0.75. However, in this paper we experimented that the value from (0.1 – 0.75) in non- uniform interval is observed as the best range of T_S that can be proposed. Fig. 7 showed that the best range that can still be acceptable for moving object detection is in the range of (0.2 – 0.55).

Therefore, based on the overall experimental results, MoG method can be utilized as one of the option for moving object detection in an outdoor environment using acceptable parameters range as tabulated in Table 1.

TABLE I

PROPOSED MoG PARAMETER RANGE

Test Parameters	Parameter Range Ref [7]	Proposed Parameter Range
Total number of Gaussian components (K)	(3 – 5)	(3 – 7)
Maximum number of components M in the background model (M)	3 (no range)	(3 - 7)
User-Define learning rate (α)	(0 – 1)	(0.005 – 0.05)
Standard deviation scaling factor (D)	2.5 (no range)	(2 – 3)
Background component weight thresh (T_s)	0.25 or 0.75	(0.2 – 0.55)

V. CONCLUSIONS

As a conclusion, the five parameters in MoG are evaluated for moving object detection specifically in an outdoor environment. Suitable parameter ranges for each parameter has been proposed for detection of moving object that can be selected by researchers when employing the MoG method for background subtraction process with less computationally, simple and more practical aspects.

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