International Journal of Science, Engineering and Management (IJSEM)
Vol 3, Issue 2, February 2018

Overview of Background Subtraction Algorithms

[1] Prachi A. Joshi, [2] Dr.R.A.Khan, [3] S.C.Nandedkar
[1][2][3] Deogiri Institute of Engineering & Management Studies

Abstract-: **Understanding the human activity from the video is proved to be important research area in computer vision since last few years. Background subtraction is a widely used technique for detecting moving objects in videos from static cameras. This approach is said to be the fast way of localizing moving objects in a video frame shot by the static camera which can be used for various computer vision applications. The mentioned technique is used for calculating the foreground mask performing a subtraction between the current frame and a background model, containing the static part of the scene. Here regions of interest are objects like humans, cars, text etc. in its foreground. The objective here is of detecting the moving objects from the difference between the current frame and a reference frame, frequently called as background model or image. Background subtraction algorithms are more popular nowadays because of its computational efficiency in applications like video surveillance, traffic monitoring, human-computer interaction etc. The conditions like moving background, temporarily stationary objects, objects shadows, illumination variation can affect the background subtraction. This paper focuses on the comparative study of different background subtraction algorithms.**

***Keywords*: Background Subtraction, Human Computer Interaction, Object Detection, Regions of interest, Traffic Monitoring, Video Surveillance, Frame Difference, Mean Filter, Approximate Median Filter, Mixture of Gaussian Model, Running Gaussian Average.**

I. INTRODUCTION

Background subtraction is critical step in many computer vision applications since it is applied for detecting moving objects in video frame. The applications like video surveillance, traffic monitoring etc. requires analysis and understanding of video sequences for further processing. The basic operation implemented here is separating moving objects from the given static information. The moving objects can be called as "foreground" and static information is called as "background". Motion detection in an object using background subtraction seems to be easy at first but can be imperfect in case of low quality camera, noisy environment etc. Also gradual or sudden illumination changes, animated background like water waves, moving trees or camera jitter can generate the false positives in background subtraction. A robust and efficient background subtraction algorithm should be able to handle these situations. This paper compares some popular background subtraction algorithms representing different challenges.

II. BACKGROUND SUBTRACTION ALGORITHMS

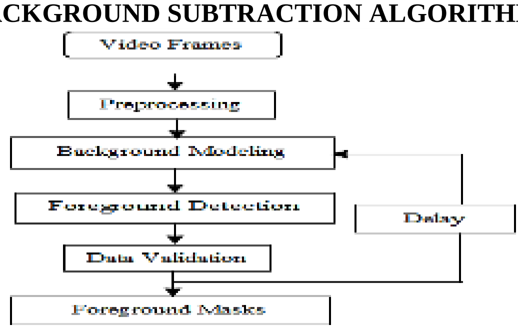

Fig 1: Generic of Background Subtraction

A. Frame differencing technique

Frame difference is simple form of background subtraction. This technique works on subtraction of current frame from previous frame. If this difference in pixel values for a given pixel is greater than threshold Θ then the pixel is assumed to be part of foreground.

$$|frame_i - frame_{i-1}| > \Theta \quad (1)$$

Formula (1) shows threshold Θ is fixed value and plays crucial role in detection effect as it decides the sensitivity of the complete detection system [1]. An advantage of frame differencing is that this method adapts changes in background faster than other methods as background is only the previous frame. Disadvantage is if an object stays still for more than one frame period, then it also becomes part of background generating an error. The only challenge of this technique is determining threshold value as each different video depends on different thresholds [1].

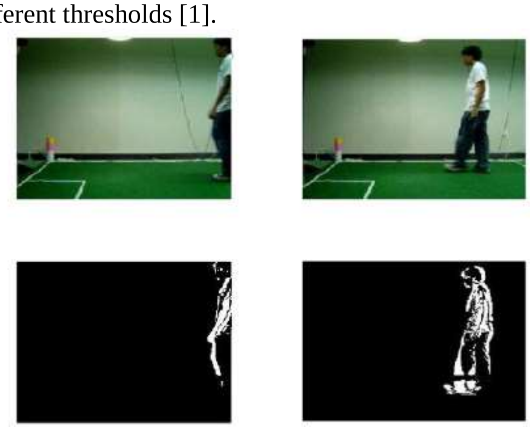

Fig 2: Results of frame difference method [1]

ISSN (Online) 2456 -1304

International Journal of Science, Engineering and Management (IJSEM)
Vol 3, Issue 2, February 2018

Mean filter

In mean filter, background is the mean of previous n frames means for calculating the image containing only background, a series of preceding images are averaged [2]. Here the background image is calculated at time instant t by,

$$B(p,q,t) = 1/n \sum_{i=1}^{n} V(p,q,t-i) \quad (2)$$

Here, the mean is referred to finding means of corresponding pixel in the given images. n depends on video speed and amount of movement in the video [2]. After finding B (p, q, t), we can subtract it from the image P (p, q, t) at time instant t and threshold it.

$$|P(p,q,t) - B(p,q,t)| > \Theta \quad (3)$$

where Θ is threshold. An advantage of mean filter method is that this method is pretty fast. But there is global threshold Θ for all pixels where Θ is not function of time t and also the static nature of Θ makes this method inappropriate for solving real life problems

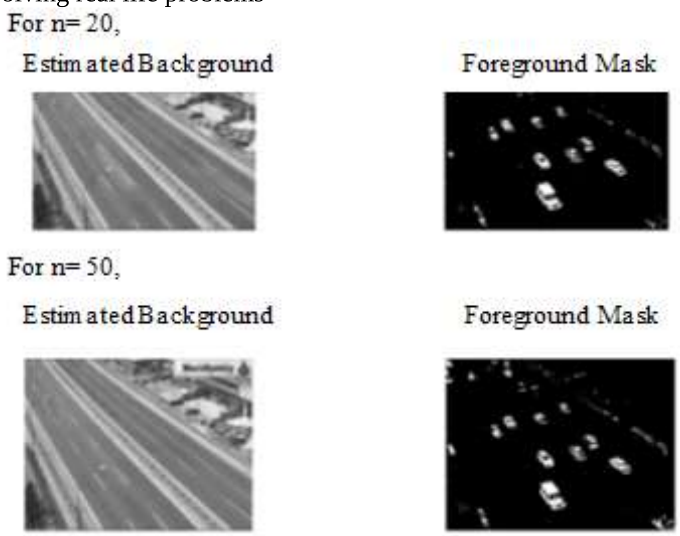

Fig 3: Results of mean filter [2]

C. Approximate Median Filter

The approximate median filter algorithm is adaptive, dynamic, non-probabilitsitc and intuitive [3]. This method is based on difference two video frames. This difference is then used for determining method to update the background [4]. Basically, this algorithm is implemented without sub sampling frames for creating adequate background model [5]. An Advantage of approximate median filter is it is pretty fast method. But it may not give the appropriate result in case of if the scene contains many, slowly moving objects. Also, median background models have relatively high memory requirements [2]. Equation 4 shows approximate median updates in the reference frame of each video sequence. The succeeding background frame B_{i+1} is dependent on the intensity value of both the frame, present frame P_i and background frame B_i. Hence, here the background converges to an estimate point where half the input pixels are greater than the background and remaining half are less than background achieving approximately the median.

$$B_{i+1}(p,q) = Fi(p,q) + 1 \quad F_i(p,q) > B_i(p,q) = Fi(p,q) - 1 \text{ otherwise} \quad (4)$$

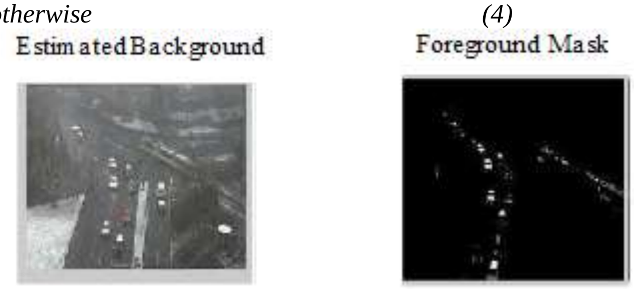

Fig 4: Result of approximate median filter [5]

D. Mixture of Gaussians (MOG)

Mixture of Gaussians is one of the high complexity approach used in background subtraction. It can handle multi model distributions. Here the background is not frame of values; it is simply parametric [6]. A simple heuristic determines which intensities are of background. So, the pixels which do not match to these are foreground pixels [7]. A pixel is matched by its mean to nearest Gaussian component and then its parameters are adjusted. It makes this method suitable for adapting the changes in background [8]. In this method, the probability of occurrence of a color at given pixel s is given by, [9]

$$P(I_{s,t}) = \sum_{i=1}^{K} w_{i,s,t} \cdot N(\mu_{i,s,t}, \Sigma_{i,s,t}) \quad (5)$$

where $N(\mu_{i,s,t}, \Sigma_{i,s,t})$ is the i^{th} Gaussian model $w_{i,s,t}$ is its weight. Number of Gaussians K, the weight $w_{i,s,t}$, the mean μ and the covariance matrix $\Sigma_{i,s,t}$ are main parameters of MOG. The challenge with MOG is that this model deals with the movement in the background because of multimodality in representation step. Another limitation of this model is pixel-wise aspect prevents to handle some critical situations [7].

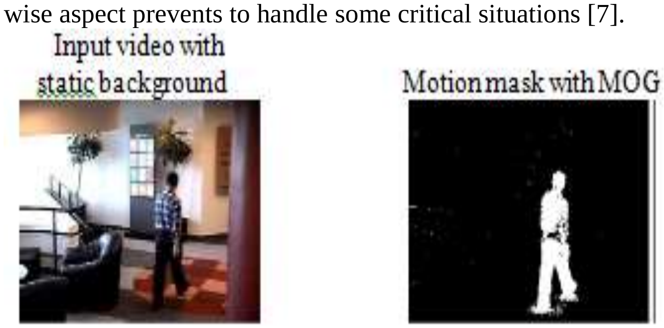

Fig 4: Results of MOG [9]

E. Running Gaussian Average

This approach is divided into three parts [10] building background model, performing background subtraction and updating background model. The background model is built individually for each color channel R, G, B. and once for intensity image. This technique fits the Gaussian probability density function (pdf) on last values of each pixel. The purpose of this approach is to build background image in an initialization phase and later only updating its parameters rather fitting the pdf from scratch at each new frame time for improved speed and accuracy [10]. During initialization, the mean is estimated for each pixel and the standard deviation is as,

$$\sigma^2=1/(N-1)\sum_{t=1}^{N}(x_t-\mu^2) \quad (6)$$

where N is number of initilization frames,x_t ispixel value at frame t and µis the estimated mean.In background subtraction part,current frame is subtracted from previously estimated mean. Here the resultant difference image shows how much value of current frame is updated in comparison of mean image in corresponding channel. This approach uses two threshold values for normalizing every channel. The result of confidence normalization step shows confidence of each pixel classified as foreground. If value of resultant differene is less than threshold then the corresponding pixel's value gets updated because of camera noise and considered it belonging to the background. For intermediate values, the confidence is scaled linearly as, [10]

$$C=[(D-m\sigma)/(M\sigma-m\sigma)]*100 \quad (7)$$

where D is difference value, mσ and Mσ are thresld values. Cucchiara et al. [11] stated that background model should reflect sudden changes such as start or stop of objects to allow detection of only actual moving objectswith high reactivity.So new variable is intriduced α as learning rate of a model [10]. The runnig average at each pxel for each new frame is given by,

$$\mu_t=\alpha x+(1-\alpha)\mu_{t-1} \quad (8)$$

where α is learning rate of model, x_t is pixel value at frame t and μ_t is mean computed up to frame t. The runnig standard deviation σ_t is computed as,

$$\sigma_t^2=\alpha(x_t-\mu_t)^2+(1-\alpha)\sigma_{t-1}^2 \quad (9)$$

So here background model consists for each pixel of two parameters μ_t and σ_t instead of buffer with last n pixel values [10].

III. COMPARISON OF BACKGROUND SUBTRACTION ALGORITHMS

Table 1: Comparison of background subtraction algorithms [5]

Algorithm	Advantage	Disadvantage	Fixed Parameter	Test Parameter
Frame Difference	Performs well with static background	Requires background without any moving objects	None	Foreground threshold Ts
Mixture Gaussian	Low memory requirement	Not suitable for multimodal backgrounds	K=3 Variance=36 wo=0.1	Adaption rate, weight threshold, Deviation threshold
Approximate median filter	Performs better than Running Gaussian Average	Requires buffer with recent pixel values	None	Foreground threshold Ts

REFERENCES

[1] Mr. Deepjoy Das and Dr. Sarat Saharia, "Implementation and Performance Evaluation of Background Subtraction Algorithms", International Journal on Computational Sciences & Applications (IJCSA) Vol. 4, No. 2, April 2014

[2] Birgi Tamersoy," Background Subtraction", The University of Texas at Austin, September 2009

[3] A. Singh, S. Sawan, M. Hanmandlu, V. K. Madasu, and B. C. Lovell, "An abandoned object detection system based on dual background segmentation," in Proceedings of the 6th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS '09), pp. 352–357, IEEE Press, September 2009

[4] Farah Yasmin, Aini Hussain, Wan Mimi Diyana Wan Zaki, Halimah Badioze Zaman and Nooritawati Md Tahir, "Enhancement of Background Subtraction Techniques Using a Second Derivative in Gradient Direction Filter", Journal of Electrical and Computer Engineering, Volume 2013, Article ID 598708,12 pages

[5] Mahmoud Abdulwahab Alawi, Othman O. Kalifa and M.D. Rafiqul Islam, World Applied Sciences Journal 21, PP 109-114, 2013

[6] Seth Benton, “Background Subtraction Part 1 Matlab Models”, August 2008

[7]https://en.wikipedia.org/wiki/Background_subtraction

[8] Lucy Morgan, “Background Subtraction”, Maths and Stats, Lancaster University

[9] Yannick Benezeth, Pierre-Marc Jodoin, Bruno Emile, Laurent, Christophe Rosenberger, “Comparative study of background subtraction algorithms”, Journal of Electronic Imaging, Society of Photo Optical Instrumentation Engineers, 2010

[10] Cerman Martin, “Background Subtraction Using Running Gaussian Average: A Color Channel Comparison”, Seminar aus BVME 183.165

[11] Cucchiara, R., Piccardi, M., Prati, A.,” Detecting Moving Objects, Ghost and Shadows in Video Streams”, IEEE Transactions on Analysis and Machine Intelligence 25(10), PP 1337-1342, 2003

