Development of an Efficient Algorithm in Object Detection for Static and Dynamic Image

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Abstract---The aim of this paper work is to implement an efficient methodology to detect the moving object for static and dynamic images. Moving Object Detection is the most challenging area in video surveillance. Its task is to detect the object of interest in video. The wide application of this is in field like security, criminology etc. Moving object detection are important initial steps in object recognition, context analysis and indexing processes for visual surveillance systems. It is a big challenge for researchers to make a decision on which Detection algorithm is more suitable for which situation and/or environment and to determine how accurately object Detection (real-time or non-real-time) is made. There is a variety of object Detection algorithms (i.e. methods) and publications on their performance comparison and evaluation via performance metrics. In this paper Object Detection process is applied for static and dynamic images. Here Performance of this Object Detection on various classes of test images is reviewed and the possible direction of future research is indicated.

Keywords: Moving Object Detection, Background Subtraction, Mixture of Gaussian[MOG], Optical Flow, SURF.

I. INTRODUCTION

Moving object detection is a basic and important role in video analysis and vision applications. Moving object detection is the first step in video analysis. It can be used in many regions such as video surveillance, traffic monitoring and people tracking. There are three common motion Detection techniques, which are frame difference, background subtraction and optical flow method. Frame difference method has less computational complexity, and it is easy to implement, but generally does a poor job of extracting the complete shapes of certain types of moving objects. Background subtraction method uses the current frame minus the reference background image. The pixels where the difference is above a threshold are classified as the moving object. The Mixture of Gaussians method is widely used for the background modeling since it was proposed by Friedman and Russell. Stauffer presented an adaptive background mixture model by a mixture of K Gaussian distributions. Optical flow method can detect the moving object even when the camera moves, but it needs more time for its computational complexity, and it is very sensitive to the noise. The motion area usually appears quite noisy in real images and optical flow estimation involves only local computation. So the Optical Flow method can't detect the exact contour of the moving object. SURF method is also very efficient for both images. And its speed is more than the other methods.

In this paper we define these four methods for static and dynamic images and also develop other methods for moving object detection for future purpose like particle filter, kalman filter, stereo vision etc.

II. OBJECT DETECTION FOR STATIC IMAGE

Many algorithms are established for object detection. Here two different algorithms are used in this paper for static images and compare with each other. Finally find out better algorithm with its accuracy and speed.

[A] Background subtraction method

[B] SURF (Speeded up robust feature)

A. Background Subtraction Methods

Background subtraction is a commonly used class of techniques for segmenting out objects of interest in a scene for applications such as surveillance. Background subtraction identifies static objects. The concept of background subtraction revolves around the simple technique of subtracting the observed image from the estimated image and thresholding the result to generate the objects of interest. The areas of the image plane where there is a significant difference between the observed and estimated images indicate the location of the objects of interest.

It is simplistic and effective method to remove the background from images in a static image sequence is to simply subtract the background. This is achieved by a simple matrix subtraction operation.

$$F = I - B \quad (1)$$

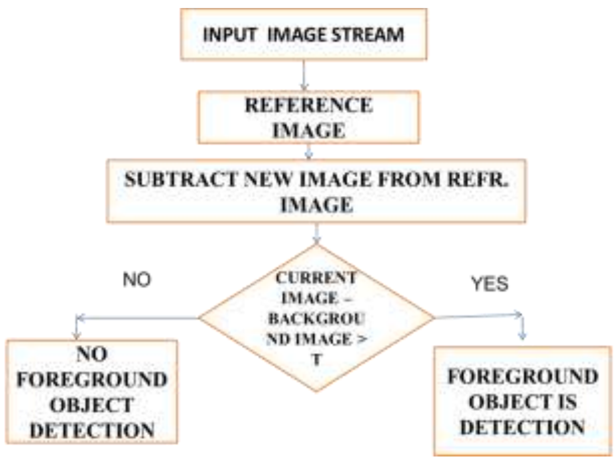

Fig. 1: Object Detection for Static Image

Where, the foreground F is found by removing the background B from the acquired image I. It is necessary to supply the algorithm with a background image, acquired before the tracking loop begins.

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

$$|I(x,y) - B(x,y)| > T \quad (2)$$

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

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

(3)

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

B. SURF (Speeded Up Robust Feature)

In this paper, we present our understanding of a cutting-edge image feature scheme known as Speeded Up Robust Features (SURF). SURF is comprised of a feature detector based on a Gaussian second derivative mask, and a feature descriptor that relies on local Haar wavelet responses. This framework shares many conceptual similarities with the most widely used feature detector in the computer vision community, called the Scale-Invariant Feature Transform (SIFT). Interestingly, the authors of SURF have demonstrated experimentally that their new feature scheme outperforms SIFT and other popular feature frameworks, both in terms of speed and accuracy.

We decided to implement SURF for our Computer Vision course project because we were intrigued by the fact that SURF was able to improve its performance all-around without making any compromises. In particular, we built a version of this feature framework from scratch using MATLAB. To quantify this system's performance, we then employed SURF to solve an object recognition task.

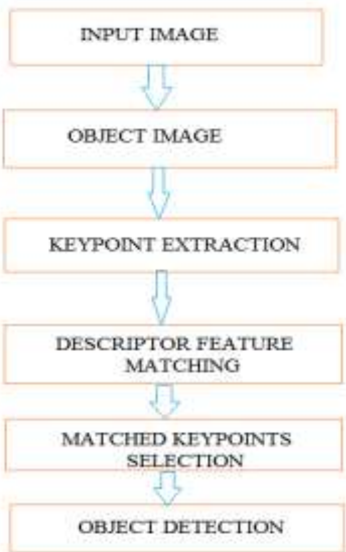

Fig.2: SURF for Static Image

The SURF detector algorithm can thus be summarized by the following steps:

1. Form the scale-space response by convolving the source image using DoH filters with different σ
2. Search for local maxima across neighbouring pixels and adjacent scales within different octaves
3. Interpolate the location of each local maxima found
4. For each point of interest, return x, y, σ, the DoH magnitude, and the Laplacian's sign

III. OBJECT DETECTION FOR DYNAMIC IMAGE

Many algorithms are established for object detection for dynamic images. Here two different algorithms are used in this paper for dynamic images and compare with each other. Finally find out better algorithm with its accuracy and speed.

[A] Background subtraction method

[B] Mixture of Gaussian [MOG]

A. Background Subtraction Method

In video processing applications, variants of the background subtraction (BS) method are broadly used for the detection of moving objects in video sequences. The BS's speed in locating the moving objects makes it attractive for the users. Unfortunately, a simple inter-frame difference with global threshold reveals itself as being sensitive to phenomena of the basic assumptions of BS. These assumptions are based on a firmly fixed camera with a static noise-free background. Real-life systems have camera jitters, illumination changes and etc. . In object detection, usually a scene can be represented by a model called background model. Also, the related algorithm (or method) finds the deviations from the background model for each incoming frame (i.e. frame differencing). A pixel-level background model is generated and maintained to keep track of the time-evolving background. A moving object can be defined as any significant change in an image region compared to the background model. Intra-regions pixels' undergoing changes are marked for further processing. Usually, a connected component algorithm is applied to obtain connected regions corresponding to the objects. Background maintenance is the essential part, which may affect the performance of BS in the time-varying situations.The methods of basic BS employ usually a single reference image corresponding to an empty scene as the background model. This kind of simple model was not suitable for real world's much complex surveillance systems.

All the aforementioned techniques use a single image as their background models, except the non-parametric model and the MoG model . There are some foreground detection approaches and the most commonly-used one is to check whether the input pixel is significantly different from the corresponding background estimate:

$$|I_t(x,y) - B_t(x,y)| > \tau \quad (4)$$

Where $I_t(x,y)$ and $B_t(x,y)$ are used to denote the luminance pixel intensity and its background estimate at spatial location (x,y) and time *t*. In addition, another popular foreground detection scheme is to apply a threshold based on the normalized statistics

$$\frac{|I_t(x,y)-B_t(x,y)-\mu_d|}{\sigma_d} > \tau_s \quad (5)$$

Where μ_d and σ_d are the mean and the standard deviation of $I_t(x,y)-B_t(x,y)$ for all spatial locations (x,y) . In these formulations, τ and τ_c are used to denote the foreground threshold and the statistical foreground threshold, which are experimentally determined by the most of foreground detection schemes. Ideally, the threshold should be a function of the spatial location . For example, the threshold should be smaller for regions with low contrast. Sometimes, this is an advantageous situation for object detection in low contrast scenes.

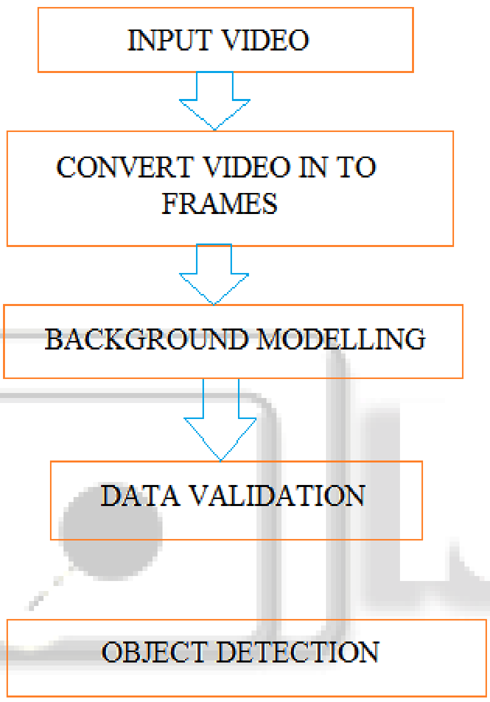

Fig.3: BGS Method for Dynamic Image

$$\frac{|I_t(x,y)-B_t(x,y)|}{B_t(x,y)} > \tau_c \quad (6)$$

where τ_c is used to denote the contrast threshold. The contrast enhancement of bright images, such as an outdoor scene under heavy fog or spot (e.g. sun spot or other flash light source spot) is not possible with this technique. In data validation step, method reviews this candidate mask and eliminates those pixels that do not correspond to actual moving objects, and outputs the final foreground mask.

B. Mixture of Gaussian [MOG]

The background of the scene contains many non-static objects such as tree branches and bushes whose movement depends on the wind in the scene. This kind of background motion causes the pixel intensity values to vary significantly with time. So a single Gaussian assumption for the pdf of the pixel intensity will not hold. Instead, a generalization based on a mixture of Gaussians has been used in to model such variations. the pixel intensity was modelled by a mixture of *K* Gaussian The background of the scene contains many non-static objects such as tree branches and bushes whose movement depends on the wind in the scene. This kind of background motion causes the pixel intensity values to vary significantly with time. So a single Gaussian assumption for the pdf of the pixel intensity will not hold. Instead, a generalization based on a mixture of Gaussians has been used in to model such variations. the pixel intensity was modelled by a mixture of *K* Gaussian distributions (*K* is a small number from 3 to 5). A mixture of three Gaussian distributions was used to model the pixel value for traffic surveillance applications, corresponding to road, shadow, and vehicle distribution. Adaptation of the Gaussian mixture models can be achieved using an incremental version of the EM algorithm. Although, in this case, the pixel intensity is modelled with three distributions, still unimodal distribution assumption is used for the scene background, i.e. the road distribution. Unlike Kalman filter which tracks the evolution of a single Gaussian, the MoG method tracks multiple Gaussian distributions simultaneously. MoG has enjoyed tremendous popularity since it was first proposed for background modelling in . The generalized mixture ofGaussians (MoG) has been used to model complex, nonstatic backgrounds.

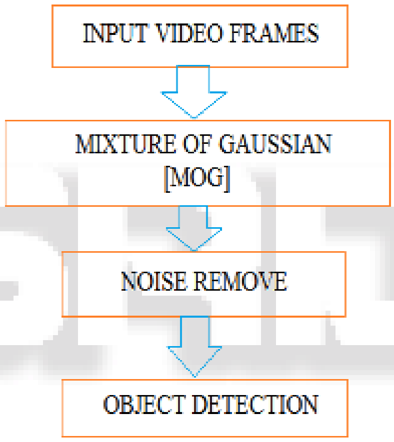

Fig.4: Mixture of Gaussian Method for Dynamic Image

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 (μt) 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 pixel's value can then be classified as foreground pixel if the inequality:

$|I - \mu| > k\sigma$ holds; otherwise, it can be considered as background, where k is a constant and is σ standard deviation

Here background is updated as the running average:

$$\mu_{t+1} = \mu_t * I_t + (1-\alpha) * \mu_t$$
$$\sigma^2_{t+1} = \alpha\,(I_t - \mu_{t})^2 + (1-\alpha)\,\sigma^2 t \quad (7)$$

where , the learning rate, is typically 0.05, I is the pixels current value and μ is the previous average.

IV. EXPERIMENT RESULTS FOR STATIC IMAGE

A. *Background Subtraction Method*

Fig.5: Input Image

Fig.6: Background Frame

Fig. 7: Output Image

B. *SURF(Speeded Up Robust Feature) Method*

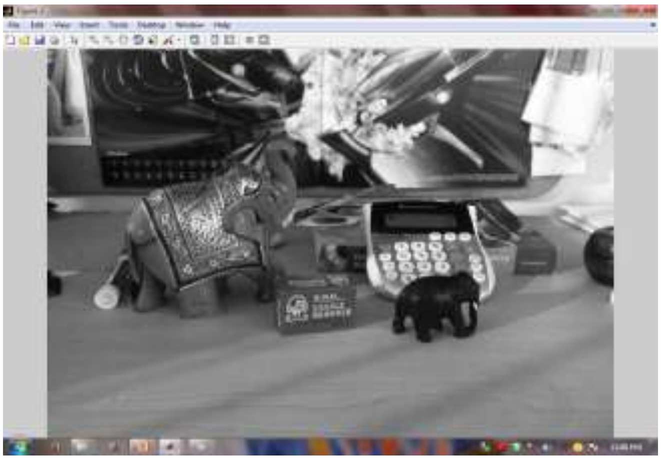

Fig.8: Input Image

Fig.9: Interested Object Image

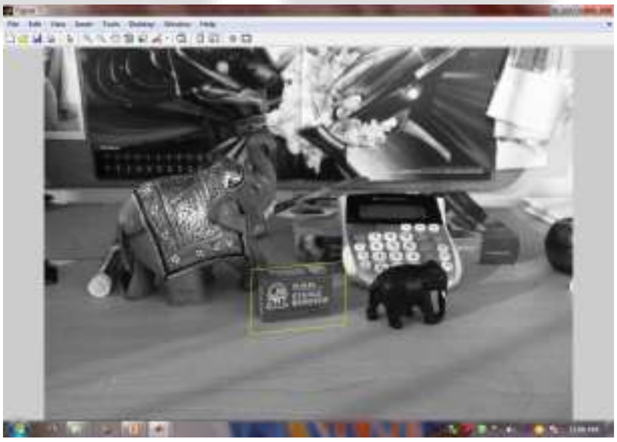

Fig.10: Output Image

Algorithms	Parameter
Background Subtraction	Threshold Value Ts
SURF Method	Extract Feature Points , Sigma = 1.6

Table 1: Paremeter for Static Image

Algorithms	Advantages	Disadvantages
BGS Method	Better Result For Static Images	Its Require Reference Images

SURF Method	Less Time Require, Higher Accuracy	Complexity In Calculation

Table 2: Advantage & Disadvantage For Static Image

V. EXPERIMENT RESULTS FOR DYNAMIC IMAGES

A. *Background Subtraction Method*

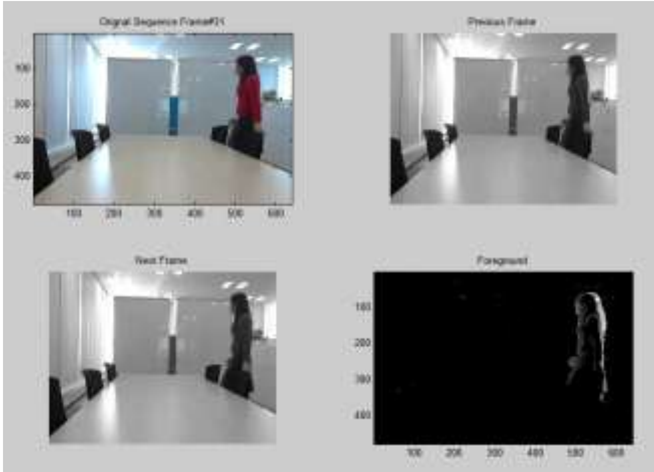

Fig.11: Frame no. 31st

Fig.12: Frame no. 55th

B. *Mixture of Gaussian [MOG]*

Fig.13: Frame no. : 12th

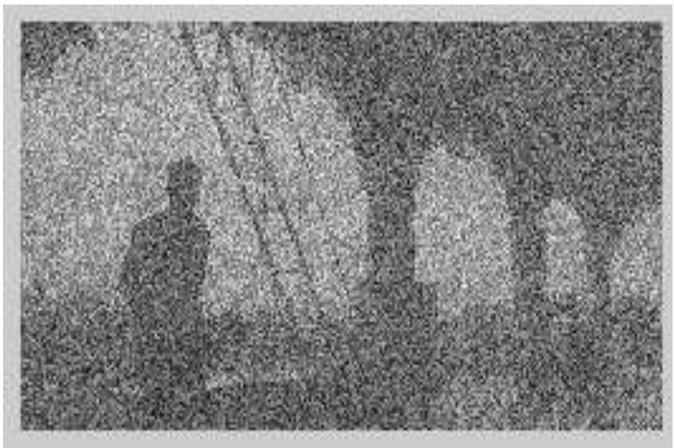

Fig. 14: Gray scale

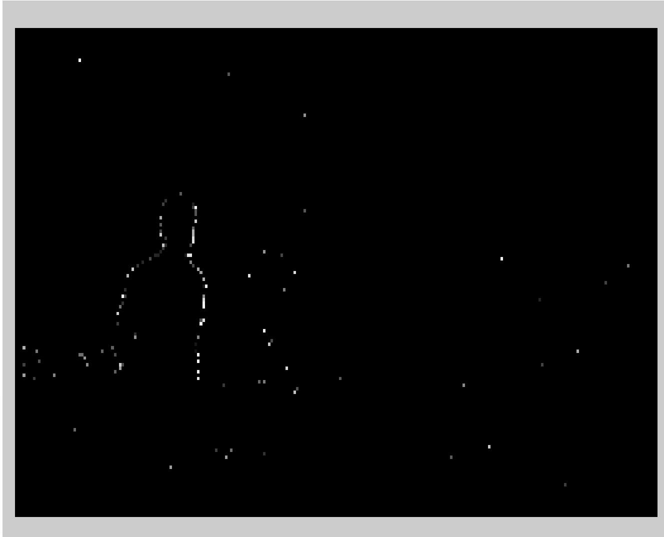

Fig. 15: Object Detect

Algorithm	Fixed Parameter	Test Parameter
Background Subtraction	None	Foreground Threshold Ts
Mixture Of Gaussian(MOG)	K=3 Variance = 36	Adaptation Rate Weight Threshold Deviation Threshold

Table. 3: Parameter for Dynamic Image

Algorithm	Advantages	Disadvantages
BGS Method	Easiest method, it performs well for Static Background.	Its requires a background without any moving object
MOG	Low memory requirement	It does not cope with multimodal backgrounds

Table. 4:Advantage & Disadvantage for Dynamic Image

VI. CONCLUSION

In this paper, the work is completely done by using MATLAB. Here i implement object detection methods for static and dynamic images. Two methods are implement for static and dynamic object detection. for static object BGS and SURF algorithm is used.BGS method is give better result for static image but it sensitive to the change in intensity. Where SURF gives better result for all type of objects and also increase in speed for matching pairs then other feature detector.

There are two algorithms for dynamic objects.one is BGS method but which is not suitable for dynamic images. Because of contineous change in intensity with its background. so its not give better result then MOG algorithm. MOG method is suitable for dynamic images. Also it has been detected multiple object. and it give better result then the BGS method.

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