

# Moving Area Filter to Detect Objects in Video Sequences from Moving Platform

Sallama Athab, Hala Bahjat

**Abstract**—Detecting objects in video sequences is a challenging mission for identifying and tracking moving objects. Background removal is considered a basic step in detecting moving objects tasks. Dual static cameras placed in the front and rear moving platform gather information which is used to detect objects. Background changes regarding speed and direction of the moving platform, so moving objects so distinguishing moving objects becomes complicated. In this paper, we propose a framework which allows detection of moving objects with a variety of speed and direction dynamically. Object detection technique is built on two levels firstly level apply background removal and edge detection to generate moving areas. Secondly apply Moving Areas Filter (MAF) then calculate Correlation Score (CS) for the adjusted moving area, merging moving areas with closer CS then marking as a moving object. Experiment results are prepared on real scene acquired by dual static cameras without overlap in sense. The results show accuracy in detecting objects compared with optical flow and Mixture Module Gaussian (MMG). An accurate ratio is produced to measure accurate detection moving object.

**Keywords**—Background Removal, Correlation, Mixture Module Gaussian, Moving Platform, Object Detection.

## I. INTRODUCTION

IN most video system applications the first step is detecting objects which separate the foreground from the background. Dealing with real time applications requires massive amounts of computing resources, whereas current real time techniques make limiting assumptions about object or platform movement or scene structure. Background removal is an effective method to detect object in stationary backgrounds [1]. Background subtraction provides many false detection points for a dynamic scene. Moving objects detected in a dynamic environment is still a problem under research. Moving object detection is efficiently handled by Adaptive background removal algorithms when a scene is a dynamic background [2], [4].

There are several challenges that must be confronted when detecting moving objects. It is difficult to distinguish between objects and background. First, both of them have to move closer in speed and direction. Second a quick response to dynamical environment is needed. Previous challenges present serious limitations to real time requirement.

Object detection is the spatial accuracy and temporal coherency of localized independently moving objects detection [3]. Despite its importance, detection of moving objects in dynamic backgrounds is far from becoming highly

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accurate [5]. Motion in video acquired from static cameras placed on moving platforms occurs by moving objects of interest and the background. Optical flow is essential in detection of the moving object task. The drawback of the Optical Flow algorithm is time consumption which make it useless in real time video system applications such as traffic, monitoring. Optical flow regularization acts locally, so does not make use of the large region might which have constant motion [6]. Static camera research is now including background removal, object detection and feature tracking techniques.

This clearly is not sufficient when a static camera is placed on a moving platform. Changes in frames are caused by combined platform and object motion. This paper distinguishes between two types of movement in sequence frames: the first one is called *virtual movement*, caused by background changes when on a moving platform such as a road sign or a tree on the side of the road. Second one is called *real movement*, caused by moving objects with a relative speed to the moving platform. This paper uses the current MAF to isolate virtual movement depending on pixel location and intensity. Real movement is measured by SC. SC measures speed and direction, where change depends on spatiotemporal relation. In this paper object detection algorithms have been built to handle a variety of speeds between platform and objects movement. In this paper the problems to overcome are presented in Section III, proposed technique is presented in Sections IV and V, results and discussion are in Section VI and it is concluded with future work.

## II. REVIEW

Detection of moving objects in a dynamic sense can be considered the lower level of operation in computer vision to get higher level event analyses, so moving objects detection is an essential task for many computer vision applications such as video traffic management and surveillance monitoring systems [2]. Static cameras in moving platforms capturing occurs at time  $t$  this point is moving in time  $t+1$  therefore processing is a function of time. The object of interest is determined by the location filter [7]. Spatial and temporal features based on Pixels are used such as edges and motion information to detect foreground with a scene background that is dynamically changes. Good spatial accuracy is achieved by edges; it is suitable because of the simple computation and storage requirement [8].

In addition, the major disadvantage of derivative features in background removal is the additional difficulty when dark

areas are dominating the image. Complexity increases when each pixel is modeling independently in background removal Toyama [9]. The adaptive background removal algorithm appropriates in changeable environments. Dynamic background technique is considered as the pixel-level operation. Changes occur at different spatial scales. The background removal algorithm enables us to choose a suitable scale process at frame stages which deals with changes of global illumination [9]-[11].

Motion content in real video sequences often holds extensive types of motion ranging from uniform to random. According to monitoring applications, there must be various degrees of detecting quality. A robust solution is adaptive algorithms. Motion estimation algorithms are crucial for an intelligent choice for search pattern points [12], [13]. Spatial temporal filtering which is proposed to recognize salient motion with the assumptions of single object speed is certainly of value. This method is inoperative for varying speed moving objects [14]. In this paper two levels apply from spatial-temporal relationship. Rapid calculation and fairly certain changes are done. MAF is applied to a certain percent of the candidate moving area after filtering. Moving objects are detected with varying speed movement when measured with SC. The presented work is an approach which takes into account the changing illumination that should be considered as background change, and should not be detected as a moving object.

### III. MOTION DETECTION

Moving objects detected in the video sequence acquired by dual cameras placed in a moving platform need to solve two problems, which are:

Firstly, time consumption in general Optical Flow (OF) algorithms because all examined pixels are equally important. The general procedural steps in computation OF algorithm are:

- Velocities of the local movement are obtained from computed gradients of the spatial-temporal intensity.
- Full velocities result from integrating local velocities by means of correlation measurement.

Second the camera being pleased in a moving platform means everything is moving objects and background, so a wide range of motion speed occurs, slow to high. To detect moving objects there is a need to distinguish between virtual and real movement. In this paper, object detected algorithms focus more on the speed of changes observed in the video sequence, since there is a diversity of motion speed. MAF extracts motion by spatial temporal conditions if MAF is satisfied the area is marked as a candidate for a moving object. Score Correlation measurement is used to show spatial-temporal relation between neighbors moving area. Moving area is separate to a moving object and background according to SC.

Global thresholding technique usually used histogram function to value of the image. Connectivity and intensity thresholds are more efficient since they combine local and

global properties. Calculate min, max, mean, standard division to calculate thresholds:

Global thresholds perform in whole frame by (1)

$$TH = \mu + \alpha * K \quad (1)$$

Local thresholds perform on 8\*8 window size (2)

$$TH = 0.5 * (\mu *_{MIN} + \mu *_{MAX}) \quad (2)$$

where  $\mu$  mean,  $\alpha$  stander division and  $k=0.2$ .

#### A. Moving Area Filter

To speed up the system MAF presented optimized OF with reduced computation time and enhanced performance of detecting objects that have a variety of speeds. The MAF is used to distinguish between virtual and real movement in the video sequence. The moving Area Filter deals with spatial-temporal relation to detect movement which is considered real motion when MAF conditions are satisfied.

MAF procedure steps:

- MAF applies to 8 neighbors, priority to pixel  $(p_0, p_2, p_4)$  or  $(p_4, p_6, p_8)$ .
- If more than 6 pixels have equal value (0 or 1) go to Step 3. Else skip to next block.
- Numbers of transformation from white to black or vice versa is less than 6 in a row go to Step 4. Else skip to next block (Fig. 1).
- Labeled as a moving area if pixel value is equal to one and transforms from zero to one.
- Labeled as a background if pixel value is equal to zero and transforms from one to zero (Fig. 2).

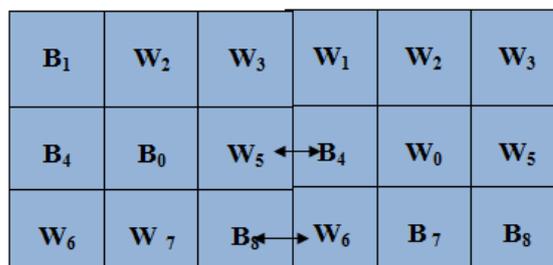


Fig. 1 MAF

#### B. Score Correlation

Spatial-temporal information obtained from smoothing, difference and edge detection are normalized using (3)

$$\text{normlise} = \frac{(x - x_{min})}{x_{max}} \quad (3)$$

where  $x$  is the value of speed and direction. To enhance local performance, normalization performed independently for each moving area detected. Better performance is achieved when spatial-temporal information is integrated based on SC. To determine the relation between adjusted moving areas the correlation measurement is needed. Balance between efficiency and speed is the most important correlation

measurement requirements. Complex relationships between multi features are enabling more efficiency and speed. Wide usage of a method to measure distance is duly simplified.

$$\| \sum(S(MA)_i - S(MA)_{i-1})^2 + \sum(D(MA)_i - D(MA)_{i-1})^2 \| \quad (4)$$

where S (MA) is moving area speed, D (MA) is moving area direction (angle) and i is the moving area number. Accomplishment of a high SC between adjusted moving areas is detected as real motion (Fig. 3).

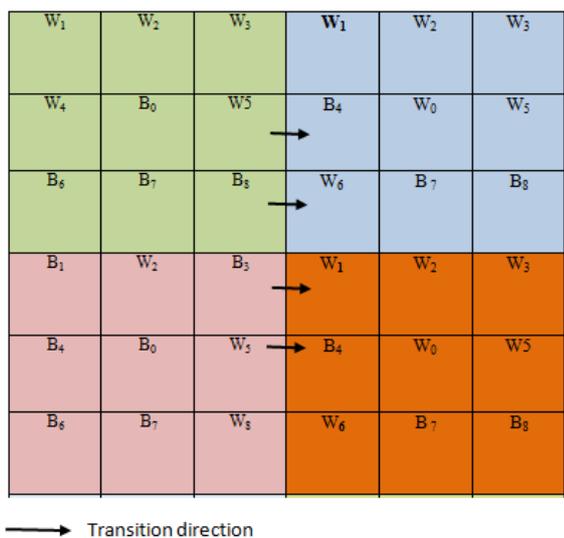


Fig. 2 Detect moving area

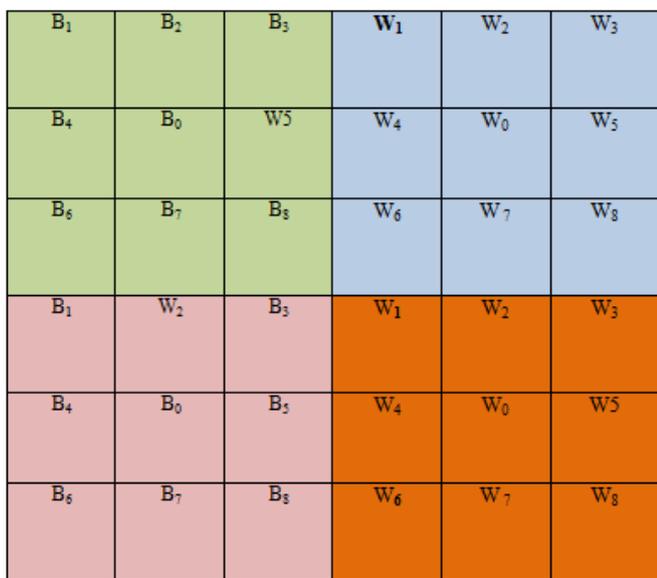


Fig. 3 Merge moving area

CS for the moving area is calculated for comparison between adjusted moving areas (4). It can be confidently marked as a particular moving object is depending on Score Correlation.

#### IV. PROPOSED METHOD

The spatial coherence assumption is the close pixel area that belongs to the same moving object. Our procedure starts by applying Gaussian Filter on sequence frames because Gaussian Filter provides certainty about what still appears in the image. Determining initial edge detection by smoothing three sequence frame is accomplished by using Gaussian filtering then subtracting those frames with global threshold. Background removal applies based on previous differential for the three sequence frames with a global threshold (1). Edge operates apply to increase stability of object detection with the local adaptive thresholding (2) (Fig. 4).

Motion information is obtained from edge velocity and direction for all image pixels. MAF is applied to eliminate virtual motion by isolating a frame into the moving area and background, MAF solved time consumption problems.

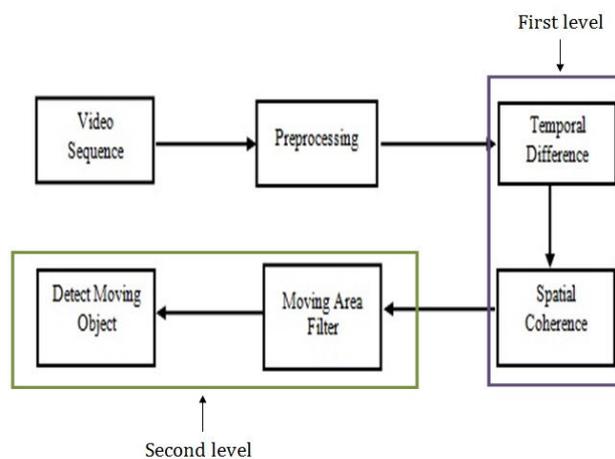


Fig. 4 Basic steps

SC between a pair of two adjusted moving areas is then calculated after normalizing and mapping the coordinates of the centroid of the moving area. SC between the two areas centroid in a period of time is obtained to merge adjusted moving areas that have a closer SC. Moving area SC is estimated by Euclidian distance for speed and direction between adjusted areas. Whereas  $(x_i, y_i)$  represent the spatial position of the center moving areas.

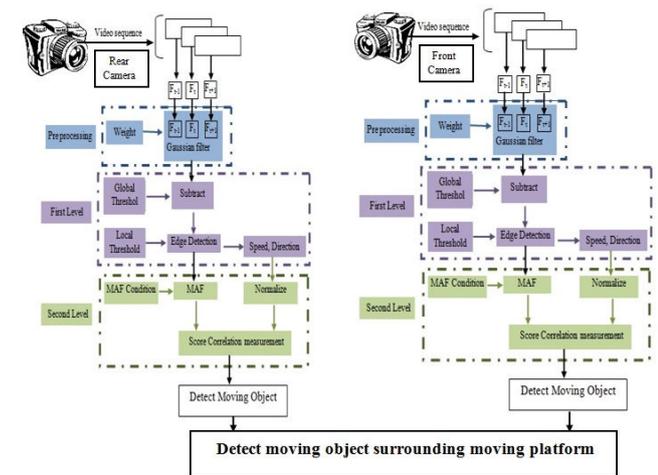


Fig. 5 Method procedure

To detect moving objects in a video sequence acquired by dual cameras placed on a moving platform, we perform these steps:

Step 1. Pre-processing operation

Apply a Gaussian filter with adaptive sigma (weight) depending on frame mean and variance.

Step 2. Temporal difference

Subtract three successive frames to detect initial background using global threshold (1).

Step 3. Apply Soble operator to calculate gradient magnitude and direction at each pixel on the previous step result using local threshold (2).

Step 4. Apply MAF

Step 5. Normalise speed, direction, intensity for moving area (3).

Step 6. Score Correlation (4).

Step 7. Moving objects surrounded by the moving platform is detected from the dual camera simultaneously (Fig. 5).

V. EXPERT RESULT

The proposed method is compared with OF and Mixture Module Gaussian background removal algorithms. Figs. 6 (a)-(c) show the result for one moving object in video 1. While Figs. 7 (a)-(c) shows the result for the complex environment in video 2 that has many moving objects with different shapes, size and color. the green spot in Fig. 6 (a) represents the area processed by MAF which is much accurate compared with MMG and Optical Flow (OF) yellow spots, red spots represent motion in frame. It is clear that there is much more processing time needed in OF and MMG than MAF also MMG needed background model training on a number of frames (about 100-150 frames). Also detected some variables were detected manually such as Gaussian modes mode numbers, variance and threshold to initial background detection. The proposed method can handle quick responses to a variety of video sequences and does not need prior knowledge about background reference. An adaptive threshold is used.

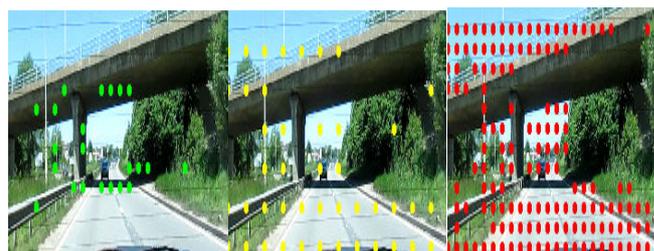


Fig. 6 (a) video 1 MAF (b) video 1 MMG (c) video 1 OF

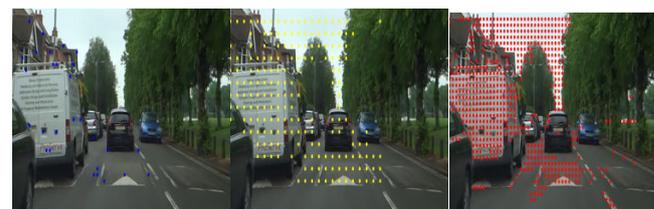


Fig. 7 (a) video 1 MAF (b) video 1 MMG (c) video 1 OF

Figs. 7 (a)-(c) show the result on a complex environment.

In Fig. 7 (a) blue spots represent the examined area to detect moving objects on a dynamic background and it is clear that our method uses less pixels numbers. Blue spots show that the proposed method enables detection of real movement and ignores virtual movement, while the MMG and Optical Flow results have more miss detection. MAF chooses pixels to examine in artificial rule.

From Figs. 6 and 7 background size relative to the whole image size is efficient on time complexity. When the background size is larger MAF applies to less of area and eliminates pixels which belong to the background.

An accurate ratio is produced to measure accurate detection of moving object (5). Table I shows the result of accurate ratio.

$$\text{Accurate ratio} = \frac{\text{number false detection pixels}}{\text{total pixels numbers of image}} \quad (5)$$

Real video is acquired by dual static cameras placed in the front and rear of a car and also in the middle of it is longitudinal axis. They work simultaneously.

TABLE I  
ACCURATE RATIO CAMORRISM

Video	Algorithm	Accurate ratio average
Video1	Optical flow	0.16
	MMG	0.11
	Proposed method	0.087
Video2	Optical flow	0.2
	MMG	0.13
	Proposed method	0.095

Dual cameras have the same properties which are Number of Pixels 18.9 Megapixels. Dimension (WxHxD) =121.6x86.6x93.3mm. Focal length 35mm. Speeds of the car are between 20-60 miles per hour. Video length is 25 seconds. Frame rate is 15fps. Video1 and Video2 are acquired by front,

and rear cameras simultaneously. Video1 and Video2 contain vehicles which are moving with a variety of velocities. These vehicles are labeled in real-time as moving areas in the image sequence. Average speed is about 15fps at size 360 X 240. The method runs with 8GB multi processor CorTM-i7. The success of the proposed algorithm when detecting moving objects is established for a variety of real environments with less time computing and high accuracy. In the experiment the results achieved were very encouraging results that could be used in real time applications.

## VI. CONCLUSION

The proposed method handles two problems time firstly, the time consuming computation of Optical Flow for moving objects with a variety of speeds; secondly isolating virtual and real movement. Object detection techniques were built on two levels, the first level applied Gaussian smoothing and Sobel operator techniques which are used in this work for the computation of Optical Flow vectors. The second level detected multiple movements with respect to the computed features. The extracted movements are detected using MAF centered moving area information.

SC was applied to merging adjusted moving areas to remove virtual motion information presented in the image. Real videos are tested to validate the developed algorithms. The moving object detection performance, in terms of their accuracy and computation time, is analyzed and compared with the traditional algorithms.

Since this approach solves eliminates unwanted motion and detects different motion speed for the scene flow, it can be used for motion analysis in existing 2Dtracking based methods or to define scene flow descriptors. In future work adding depth information should be added to the predicate stable area.

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