

Parallel Priority Region Approach to Detect Background

Sallama Athab, Hala Bahjat, Zhang Yinghui

Abstract—Background detection is essential in video analyses; optimization is often needed in order to achieve real time calculation. Information gathered by *dual cameras* placed in the front and rear part of an *Autonomous Vehicle* (AV) is integrated for background detection. In this paper, real time calculation is achieved on the proposed technique by using *Priority Regions (PR)* and *Parallel Processing* together where each frame is divided into regions then and each region process is processed in parallel. PR division depends upon driver view limitations. A background detection system is built on the Temporal Difference (TD) and Gaussian Filtering (GF). Temporal Difference and Gaussian Filtering with multi threshold and sigma (weight) value are based on PR characteristics. The experiment result is prepared on real scene. Comparison of the speed and accuracy with traditional background detection techniques, the effectiveness of PR and parallel processing are also discussed in this paper.

Keywords—Autonomous Vehicle, Background Detection, Dual Camera, Gaussian Filtering, Parallel Processing.

I. INTRODUCTION

AS computer vision technology develops, a video based traffic environment detection system is widely intended to provide services relating to different modes of transport and traffic management. [1]. At traffic video system is needed to solve background detection problems which have been studied extensively. Real-time background detection is the key issue in traffic video analyses because it is related to object identification, classification, and tracking [2]. Background detection algorithms involve a high computational cost due to many challenges: Firstly, the deal with changes in illumination condition, secondly, separate small motions such as swinging trees and rain and finally a background model must provide a fast response to changes in the background such as the starting and stopping of vehicles [3].

Prior knowledge about the environment helps to reduce calculations and the taken time while an unknown environment need more time to process because of a lack of information (reference background). As static camera system can detect the background using two approaches i.e. parametric and non parametric. In a parametric approach the features are represented using a certain probability distribution which is approximated to real distribution, and parameters are

predictable from the training data. Non parametric approaches predicate directly from the data without assumptions about the distribution. The non parametric method avoids choosing a model for predicating the distribution parameters and stores the complete data [4].

Traditional background detection algorithms process frame pixels regardless to their position in the frame while our method divides each frame into sub areas dependent upon the importance to the driver. This paper discusses two types of changes in sequence frames: the first one is the so called virtual changes caused by the background changing instantly when AV move such as road signs or trees at the side and the arm co-barrier. The second one is the real changes caused by moving object with relative speed to the AV. Temporal differences, Gaussian filters and logical operations are applied to isolate virtual from real movements. The input video frame divides into Priority Regions, and each one is processed in parallel. Regions have their borders modified by adding or removing pixels in order to adjust the region. In this paper the problems to overcome are introduced in Sections III, and IV, a proposed technique is presented in Section V, results and discussion are presented in Section VI and we concluded with future work in Section VII.

II. RELATED WORK

A video traffic monitoring system is normally built by mounting static or dynamic camera. Temporal Difference is caused by the changing environment, and two types of temporal difference methods are used. Parametric approaches are based on two or more background modules that update an intermediate image with the foreground areas which are determined for every frame [2] and Non Parametric methods analyze the input video frame by frame using techniques such as the accumulation of foreground difference [3], [4].

Efficient adaptation allows background variation by using a multi-layered approach which separates the background from the foreground [5], [6]. Gaussian filtering provides steady smoothing, removing noise and maintaining edges. Choosing an appropriate window size for Gaussian Filtering can be make it unclear what is still present in the frame after filtering.

The Gaussian Filtering also turns out to be an optimal smoothing filter for edge detection [4]. Geometric transformations and contour processing algorithms are used to segment lanes, and moving objects are extracted using background modeling [7].

Several crossing lines are draws in the reference background and detections are accordingly performed on these

Sallama Athab, PhD. student, is with Northampton University (e-mail: sallama.resen12@my.northampton.ac.uk).

Hala Bahjet, Dr., is with Technology University, head Information System branch; (e-mail: hala_bahjat@yahoo.com).

Yinghui.Zhan, Dr., is with Northampton University Course Leader for BSc/HND Computing (Graphics&Visualisation).

lines. Detection is done on the pixels located on the detection lines [8]. Minimizing the spatial energy based on suboptimal background labels gives high background possibilities when an object stops or disappears [6].

An operation that performs the same computation on several pieces of data at once is termed data-parallel. Parallel tasks in an algorithm compute data in two ways: the first one dependent with little inherent data while the second one is an independent task.

Parallel processing is a suitable solution for regular algorithm and independency data. Task-parallelism depends upon Data parallelism where multiple threads may simultaneously perform entirely different functions [9].

In this paper traditional background detection algorithms that can use data-parallel operations for real time requirements are modified. Background differencing algorithms works better on slow objects and on other sides, and the speed of change intensity in the background is related with the speed of the AV while objects surrounding the AV have variable speed.

Single threshold for the entire frame pixels may be wasted and is not a robust method for scenes with many moving objects at different speeds. In proposed technique the GF variable depends on the Priority Region which allows for the presenting of different filtering in one scan. In this situation, the reference background image cannot be exactly suited to the AV in a real scene.

Reference background image is changed continuously, and the algorithm enables us to obtain an of the foreground objects. The advantage of TD is rapid calculation, and the advantage of GF is that it is fairly confident about what is still present in the frame after filtering. These two methods can complement each other.

III. PRIORITY REGIONS

Background detection in a video sequence is a task that must be solved in Computer Vision but which involves a high computational cost due to the great amount of data which needs to be scanned many times. Early techniques processed every single pixel regardless of the position in the frame thereby causing massive calculation and processing time.

All of these are real problems for the real-time video processing. In this paper we introduce a novel technique to perform background detection in video sequences by taking advantage of the location information.

Some frame areas like the top left do not require processing (Ignore Region) because it can be ignored by the driver without causing any safety issues. Moving objects surrounding the AV are usually in front of and at the side, and this area is more important than something in the distance. The speed and location information are extremely central to detecting the background.

According to real experience, the driver view shows that the High Priority Region can be considered as the region in front of. It has an of angle 180 degrees which then reduces gradually to 30 degrees for the left and right side until

reaching the Ignore Region which reduces the numbers of examined pixels by about 20 percent from the total processing pixel number.

the high Priority region (HP) covers the driver interest area surrounding the AV. HP Trapezoidal shape; The trapezoidal base is frame width and then it decrements gradually for both the left and right side until reaching the Ignore Priority region (IP) boundaries.

The Ignore Priority region (IP) is the area which the driver neglects when making decision about the path. The IP rectangular shape starts from the left top corner along the frame width, with 20% of the frame dropping down from high rows Fig. 1 (a).



Fig. 1 (a) Ideal Case



Fig. 1 (b) Critical Case

The Medium Priority region (MP) and, Low Priority region (LP) are area that the driver covers with less interest area because the more dominated areas are in the background. MP and LP triangle shapes adjust changes in the HP. MP and LP size according to the road design, i.e. turning right make the right more important than left and vice versa Fig. 1 (b).

The frame is split into relative areas and, each area is processed in a specific method that reduces the overall time consumption. We base our approach upon different schemes for each region depending on priority.

IV. PARALLEL PROGRAMMING

A Parallel Random Access Machine (PRAM) consists of a global access memory (i.e. shared) and a set of processors running the same program. PRAM is synchronous.

We are implementing parallel algorithms to detect the background in a dynamic environment in order to manage real time requirements. We consider a maximum of sixteen execution threads in order fit to an 8-core processor that supports two threads per core and is characterized by a loop on each iteration, i.e. each region, can be executed by one thread.

This loop ends when all of the pixels of the region in the current frame are processed with the reference frame restricted

by the Priority Region area size. Finally, all of the calculated values of the Priority Regions are combined in order to detect the background for the current frame. Previous steps apply to front and rear camera similarity, and it is suitable for independent data and, minimal synchronization.

The objective is to divide the computation among processors so that each processor receives an equal measure of computation Fig. 2 shows the customization of the algorithm to parallel processing.

We have two steps parallel steps, namely decomposing and remapping. When finished this subtask combines the regions results.

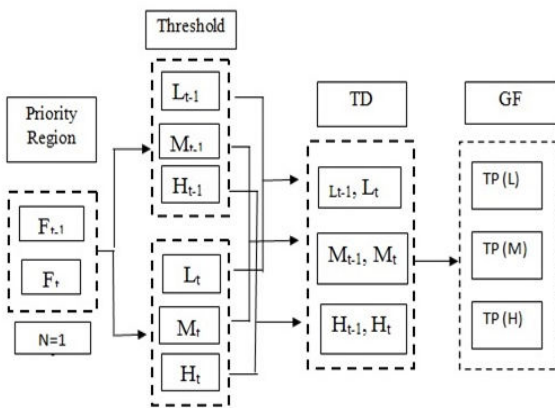


Fig. 2 Block diagram for parallel unit

V. PROPOSED METHOD

In this paper we introduce a novel technique to perform background detection in video sequences by taking advantage of the location information. Temporal difference is required in order to gain the initial interested targets, and additional processing is needed since interesting targets are always accompanied by incorrect foreground information when using of the traditional background differencing algorithm.

This paper combines the TD and GF with different sigma (weight) and thresholds. Instead of multi GF for one frame using different GF for each region in one pass. GF variable depend on Priority Region characteristics and this allows the presenting of different filtering techniques in one scan Fig. 3 shows the proposed technique

We combine local and global thresholds to follow dynamic environment changes local adaptive threshold images yield HPR. The AND operation is used to eliminate unwanted background pixels which generates a background detection image Fig. 3 shows the proposed technique.

Local thresholds perform in HPR with an 8*8 window size (1).

$$TH = 0.5 * (\mu_{MIN} + \mu_{MAX}) \quad (1)$$

Global thresholds perform in the whole MPR and LPR region equation

$$TH = \mu + \alpha * K \quad (2)$$

where μ = mean, α = standard deviation and $k=0.2$ usage of the traditional background differencing algorithm.

This paper combines the TD and GF with different sigma (weight) and thresholds. Instead of multi GF for one frame we are using a different GF for each region in one pass. GF variables depend on Priority Region characteristics and this allows us to present different filtering in one scan Fig. 3 shows the proposed technique. We combine local and global thresholds to follow dynamic environment changes. Local adaptive threshold images yield HPR. The AND operation is used to eliminate unwanted background pixels which generate background detection image Fig. 3 shows the proposed technique.

We propose a method that integrates temporal difference with pixel localization using parallel processing.

Input video is loaded into the CPU frame by-frame. The execution time is set to zero and the video input parameter (region location, frame number) are noted. The time of the execution is started, and for each region in the current frame we subtract symmetrical regions in the previous one, and these steps process independent data. The result is loaded and then ANDs is applied. After processing five sequence frames ($N=3$) where N = the iteration number which means this step processes inherent data. Lastly, the time execution is ended. The results of the process detects these background in video sequences acquired from dual camera.

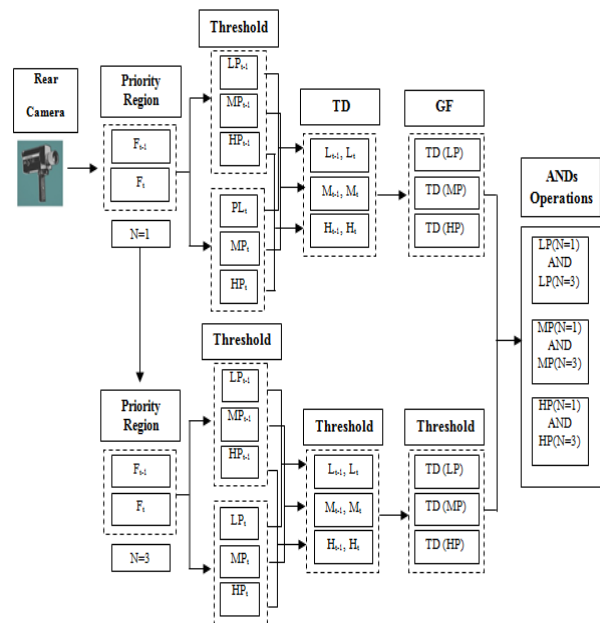


Fig. 3 Proposed technique

Applying the algorithm integrates the Temporal Differencing method and Gaussian Filter for each region with different parameters.

The inefficiency of applying a single Gaussian Filter for real data demanded adaption of the Gaussian Filter by characterizing regions. A linear combination of regions results can deal with very complex densities.

A. High Priority Region (Hp) Processing Steps

Steps apply to double sequences HPR in (F_{t-1} , F_t)

- 1- Compute mean and standard deviations of HP then calculate threshold value in (1)
- 2- Apply GF to Smooth and remove noise with sigma value (0.12), generate Gaussian kernels with window size (8*8).
- 3- Subtract HP region detect Temporal Difference.
- 4- Apply Sobal operator to approximate first order differentiation.
- 5- For three iteration above steps detect which object still, disappear by ANDs operation.

B. Medium Priority Region (Mp), Low Priority Region (LP) Processing Steps

Steps apply to double sequences MP in (F_{t-1} , F_t)

- 1- Compute mean and standard deviations of regions then calculate threshold value in (2).
- 2- Apply GF to Smooth and remove noise with sigma value (0.3), generate Gaussian kernels with window size (16*16).
- 3- Subtract MP and LP regions to detect Temporal Difference.
- 4- ANDs operation for MP and LP regions to detect stable pixels and removes virtual movement.
- 5- For three iterations the above steps detect which objects are still out of view by utilizing the ANDs operation.

C. Ignore Priority Region (IP)

This region is not processed at all as it has no effect on driver decisions.

VI. EXPERIMENTAL RESULT

We implemented and tested the Parallel Priority Regions to detect the background for a traffic video acquired by dual cameras placed in the front and rear of the AV, and they work in a synchronized fashion. When Paralleled Priority Regions is applied to a frame, time complexity is reduced for two reasons. Firstly, it reduces the number of pixels that are examined in one scan and forms a certain area of the frame (Ignore Region) area without processing it that the driver dose not consider when making decisions.

Secondly each region is processed in Parallel. We compare the Gaussian Mixture Model and Optical Flow with the Parallel Priority Region technique in order to detect the background. The results are examined on real video with a variable car speed front and rear cameras were placed inside the car in the middle of its longitudinal axis's. both cameras have the same properties which are Number of Pixels Approx. 18.9 Megapixels, Dimension (W x H x D)=121.6x86.6x93.3 mm, Focal length 35 mm equivalents, Image Sensor type

(7.76mm) Exmore R CMOS sensor, Video Out type HD. The speeds of the car are 20-30 miles an hour.

The video length is 25 sec, frame rate 15fps, video1 and video2 are acquired by front, and rear camera synchronization Table I shows the time affected.

TABLE I
COMPLEXITY TIME

Algorithm	Video1 Time	Video2 Time
GMM	40:35	54:11
OF	42:24	57:72
PPR	25:19	34:36

From Table I, PPR reduces time by 0.596 and 0.624 from OF and GMM respectively after complete calculation of the detection region. It is easy to find that the LPR and MPR regions rarely changes while the HPR changes frequently. The road surface for the main MPR and LPR is relatively smooth in traffic scenes, while the HPR (e.g. vehicles) always has clear and definite visible changes so it requires more time for processing than other regions as shown in Table II.

Time in Table II represents the average for both video 1 and video 2. The time taken by a sequential algorithm is simply proportional to the number of steps it must take for sequential computers.

TABLE II
PARALL STEP

Operation	Frame No.	Regions	Time
Threshold	F_t	HP	12:56
		LP	6:33
		MP	10:50
Temporal Different	F_{t-1}	HP	12:03
	F_t	LP	4:54
		MP	9:11
Gaussian Filter	F_{t-1}	HP	15:33
	F_t	LP	8:02
		MP	11:45
ANDs	F_{t-1}	HP	14:12
	F_t	LP	6:55
		MP	8:54

The proposed technique is archived in real time by using parallel processes for each region and applying the appropriate treatment for each region and its execution time compared with the sequence of dependencies among the operations Fig. 4 shows the result for sequence frames acquired by the rear camera.

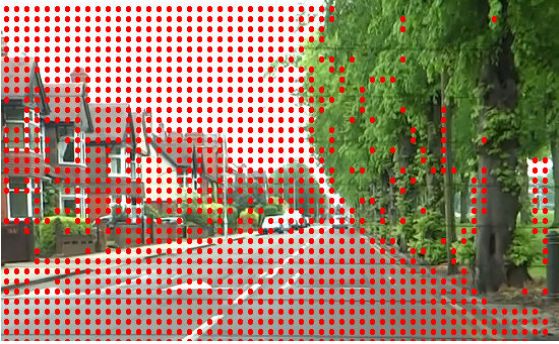


Fig. 4 (a) Traditional algorithm rear camera



Fig. 4 (b) Proposal algorithm rear camera

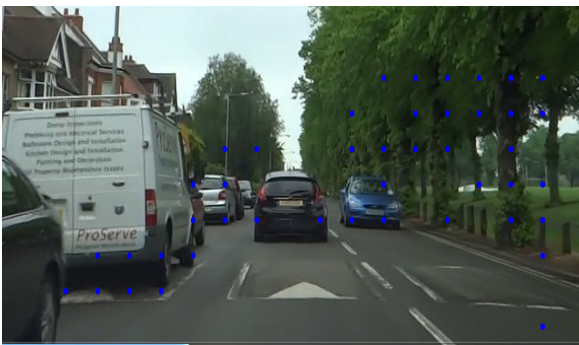


Fig. 5 Proposal algorithm front camera

Fig. 4 (a) traditional background detection result where a red spot represents the fact that Pixel location changing occurs between two successive framers. Fig. 4 (b) shows the result of the proposed technique by using blue spots. Objects move and the background changes speed at similar speed to the AV which causes false detection shown in Fig. 5 so we need produce another feature to detect real movement in the scene.

VII. CONCLUSION AND FUTURE WORK

Background detection in traffic monitoring systems is problem which is still under research. There are many challenges in perfecting the efficiency of background detestation algorithms i.e. changes in illumination, background

model response to changes in the background and high time computation.

We present a novel technique called Priority Regions which consider the frame location in the process. the frame is divided into regions depending on their importance and; separate regions allows the processing of each one in parallel and using different parameters depending on the region characteristics.

Comparing the time complexity of the Parallel Priority Region system with GMM algorithms and Optical Flow Results shows that PPR reduced time.

We propose simple techniques to detect the background from combined Temporal Differencing and adaptive Gaussian Filtering with a global, local threshold.

Over 0.59 from the cooperation notes make this motion feature more sensitive to background change than GMM.

Our experiments show that novel techniques like PPR can produce much lower computational complexity. In future work improvement, motion feature used for updating region boundaries, depend on displacement and direction between the sequence frames. The PR area resized shapes automatically according to the roads design.

REFERENCES

- [1] C. Stauffer and W. Grimson, "Adaptive background mixture models for real-time tracking", in: IEEE Computer Society Conference on Computer Vision and Pattern Recognition, vol. 2, 1999, pp. 246–252.
- [2] O. Javed, K. Shafique and M. Shah, "A hierarchical approach to robust background subtraction using color and gradient information", in: Proceedings Workshop.
- [3] A. M. Elgammal, D. Harwood and L. S. Davis, "Non-parametric model for back- ground subtraction", in: Proceedings of the 6th European Conference on Computer Vision-Part II, 2000, pp. 751–767.
- [4] A. Elgammal, David H. and L. Davis "Non-parametric Model for Background Subtraction", Computer Vision Laboratory, University of Maryland, College Park, MD 20742, USA, 2000.
- [5] E. Monteiro, B. Vizzotto and C. Diniz "Parallelization of Full Search Motion Estimation Algorithm for Parallel and Distributed Platforms".
- [6] D. Park and H. Byun "A unified approach to background adaptation and initialization in public scenes", Department of Computer Science, Engineering.
- [7] J. M. Geusebroek, A. W. M. Smeulders, and J. van de Weijer, "Fast anisotropic gauss filtering," IEEE Transactions on Image Processing, vol. 12, no. 8, pp. 938–943, 2003.
- [8] Y. Zhang, Chenyao Geng, Danya Yao, Lihui Peng, "Real-time Traffic Object Detection Technique Based on Improved Background Differencing Algorithm".
- [9] M. McNaughton, "Parallel Algorithms for Real-time Motion Planning" 2011, University Autonomous Driving Collaborative Research Laboratory, CMU-RI-TR-xx-xx.