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A Background Subtraction Based Moving Object Detection around the Host Vehicle

Hyojin Lim, Cuong Nguyen Khac, Ho-Youl Jung

***Abstract*—**In this paper, we propose moving object detection method which is helpful for driver to safely take his/her car out of parking lot. When moving objects such as motorbikes, pedestrians, the other cars and some obstacles are detected at the rear-side of host vehicle, the proposed algorithm can provide to driver warning. We assume that the host vehicle is just before departure. Gaussian Mixture Model (GMM) based background subtraction is basically applied. Pre-processing such as smoothing and post-processing as morphological filtering are added. We examine "which color space has better performance for detection of moving objects?" Three color spaces including RGB, YCbCr, and Y are applied and compared, in terms of detection rate. Through simulation, we prove that RGB space is more suitable for moving object detection based on background subtraction.

***Keywords*—**Gaussian mixture model, background subtraction, Moving object detection, color space, morphological filtering.

I. INTRODUCTION

CAR accidents are often occurred at the parking lot. When a driver is taking the car out of parking lot, he/she could not always recognize some moving obstacles rear-side of his/her car. It causes serious car accident. Driver should always check out rear-side whether moving objects such as balls, peoples, motorbikes, or vehicles exists or not. Through the room mirror and side-view mirror, the driver can miss to identify the objects even when driver watch carefully rear-side. Clearly, camera based moving obstacle detection system is required for driver to safely take his/her car from parking lot. In this paper, we focus only on moving object detection method which is helpful for driver to avoid from car accident at the parking lot. This system can provide warning to driver, when moving obstacles are detected.

Many moving object detection algorithms have developed for static scene that is captured by fixed-position camera. Background subtraction, optical flow methods have often used in various moving object detection applications [2], [3]. While dynamic scene moving object detection methods have recently reported in the literatures, such as generalized background subtraction using super pixel [4], [5]. Where, dynamic scene means that the background as well as foreground is moving. However, dynamic scene moving object detection method requires higher computational complexity, and then is not suitable to real-time system.

In this paper, we consider only static scene moving object detection, assuming that the host vehicle is just before departure. One of well-known moving object detection method, GMM (Gaussian Mixture Model) based background subtraction is basically applied. Pre-processing such as smoothing and post-processing as morphological filtering are added to reduce noisy effects.

We examine "which color space is better for moving object detection?" The color space selection is very important to implement a real-time system with low computational cost. General automotive cameras provide YCbCr or RGB format, but it is necessary to select one color space prior to implementing embedded system and to avoid to carrying out color space transform in the system. Memory space saving issue is also important. In this research, three color spaces including RGB, YCbCr, and Y are applied and compared, in terms of detection rate.

This paper outline is as follows. The proposed algorithm is briefly introduced in Section II. In Section III, we show the simulation results that are tested on five cases. Finally, we conclude in Section IV.

II. OUTLINE OF THE ALGORITHM

The proposed moving object detection algorithm consists of seven steps as shown in Fig. 1. First, input video is converted to other color space, for example RGB to YCbCr. The color space conversion step can also omit according to the selection of camera type or embedded system performance. Second, smoothing process to reduce noise and make blurring image. Third, background subtraction based on Gaussian Mixture Model (GMM) to get moving object candidates. Forth, binary image is obtained by thresholding. In fifth step, the image is processed by morphological filtering such as open-closing, to reduce small size noisy and to merge separated blobs belonging to one object. In sixth step, the candidate blobs are labeled to independent object by bounding box.

A. Smoothing

Smoothing process is popular method in order to reduce noise and make blurring images. Nowadays some researchers introduce this pre-processing for background subtraction based on GMM simply [2]. In this paper, we use 5X5 averaging box filter for the reason of real-time processing. The averaging box filter takes the least computational cost compare with the others (e.g. Gaussian filter), so we use this filter for smoothing process.

Hyojin Lim, Cuong Nquyen Khac, Ho-Youl Jung (Corresponding author) are with the Department of Information and Communication Engineering, Yeungnam University, Gyeongsan, 712-749, Republic of Korea (e-mail: hjlim@ynu.ac.kr, cuongnguyenkhac@hotmail.com, hoyoul@yu.ac.kr).

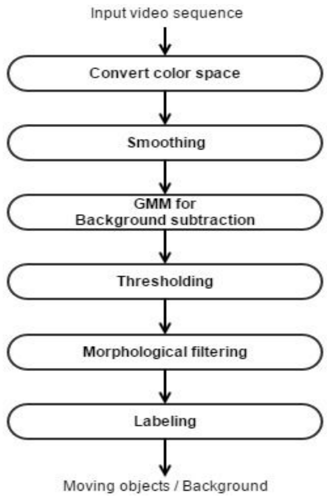

Fig. 1 Flow chart of followed algorithm

B. Gaussian Mixture Model

The GMM is a mixture of K Gaussian distributions representing the distribution of pixel intensities in current frame. It means that the probability of intensity within frame at time t is modeled as:

$$P(x_t) = \sum_{k=1}^{K} w_{k,t} \times N(x_t, \mu_{k,t}, \Sigma_{k,t}) \tag{1}$$

where, $w_{k,t}, \mu_{k,t}, \Sigma_{k,t}$ are weight estimation, mean, and covariance matrix of Gaussian k^{th}, respectively. In this paper, we assume the color R, G, B that are independent. Thus, the covariance matrix of Gaussian k^{th} is referred from standard deviation as (2):

$$\Sigma_{k,t} = \sigma_{k,t} \times I\,. \tag{2}$$

The new pixel intensity x_t is estimated with respect to each Gaussian component to find the nearest distribution where it should belong to. Then, the new parameters $w_{k,t}, \mu_{k,t}, \Sigma_{k,t}$ are updated. By using the Gaussian Mixture Model, the set of background pixels are characterized adaptively follow temporal domain. Therefore, it is useful to use GMM to eliminate all of possible background pixels. In another word, GMM based background subtraction is robust against such illumination changing [1]. This is the reason why we use adaptive GMM for background subtraction in this paper.

C. Morphology

As a GMM for background subtraction, the result image has a lot of noise and the moving object candidates are become separately, because GMM is one kind of probability methods for background subtraction. Morphology filtering has two kinds of basic operations which are erosion and dilation. In this paper, to merge these moving object candidates and to reduce noise, we choose open-closing filtering. Opening (erosion + dilation) and closing (dilation + erosion) filters are successively applied to the binary image. Here, 3X3 kernel for structure element is used.

III. Experimental Results

For the simulations, video sequences are captured by a rear-facing commercial black box camera mounted inside the host vehicle. These are recorded at parking lot, assuming that the host car is just before departing for rear-side. Five video sequences are recorded by different scenarios such as approaching bicycle, motorbike, human, truck, and basketball. Each video sequence consisting of 100 frames is tested in the simulation and the ground truth data is manually obtained. Examples are shown in Fig. 2. Each row shows different scenario and each column shows moving object detection results when using RGB, YCbCr, and Y space in order from left to right. Red bounding box indicates the detection result.

The moving object detection performance is evaluated by detection rate as given by

$$detection\ rate = \frac{\#TP}{\#TP + \#FN} \tag{3}$$

where, $\#TP$ means the number of TP (True Positive) blob that is detected correctly as a moving object, and $\#FN$ indicates the number of FN (False Negative) that is not detected.

Sometimes, the proposed GMM based background subtraction detects several separated candidate bounding boxes for one moving object. In this case, we defined that one blob candidate which is within the ground truth is TP and the other candidates that are also within the ground truth are counted as $\#overlap$. For example, the first-row second column of Fig. 2, it shows two detected bounding boxes (Red box) within the ground truth (Green box). One of them is TP and the other one is counted as $\#overlap$.

If $\#overlap$ is greater than zero, one object is detected as more than one objects. This leads to increase the computational cost. Especially for the real-time system, low computational cost is important. Therefore, the performance is also evaluated by the overlapping rate that represents the average number of detected bounding box belonging to one object. The overlapping rate is defined as (4):

$$overlapping\ rate = \frac{\#TP}{\#TP + \#overlap} \tag{4}$$

where, $\#overlap$ means the number of the overlapping blobs that are detected except for TP as belonging to one moving object.

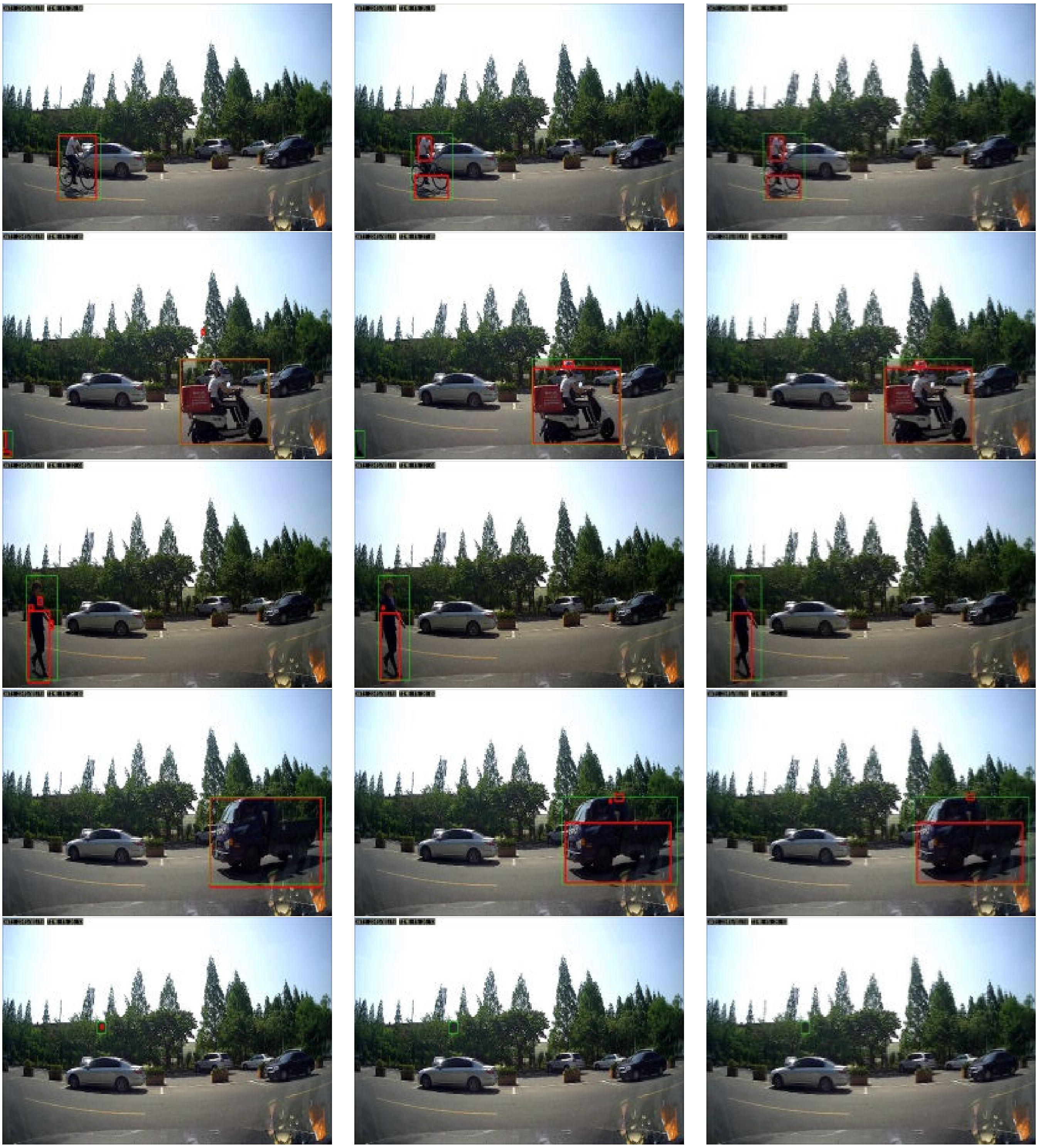

Fig. 2 Examples of detection result tested on five different scenario videos (from top to bottom: bicycle, motorbike, human, truck, and basketball) by using three different color spaces (from left to right: RGB, YCbCr, Y), where green color bounding box indicates ground truth and red is detection result. One bicycle is detected as two objects within the ground truth in the first-row second column, even though there is one moving object

Table I shows the detection performance tested on five different video sequences, in terms of detection rate and overlapping rate, when using different color spaces. The number of FP (False Positive) that is detection error is also compared. From the viewpoint of detection rate, the use of RGB color space shows in average slightly higher performance than that of YCbCr and Y component only. In particular, RGB space outperforms in the case of small objects such as basketball. The detection rate performance is very important, as it is directly related to car accident. RGB space shows also higher overlapping rate, compared to others. However, RGB space has some disadvantage that false positive occurs more frequently compared other two space. It is a trade-off between detection rate and false detection.

TABLE I
PERFORMANCE COMPARISON TESTED ON FIVE DIFFERENT SCENARIO VIDEOS BY USING THREE DIFFERENT COLOR SPACES

Image	Color space	Total object (#)	TP (#)	FN (#)	Detect rate	FP (#)	Overlapping rate
bicycle	RGB	110	104	6	0.945	9	0.512
	YCbCr		95	15	0.893	3	0.325
	Y		95	15	0.893	3	0.326
Motor bike	RGB	120	120	0	0.100	19	0.393
	YCbCr		110	10	0.916	2	0.333
	Y		109	11	0.908	3	0.346
Human	RGB	91	91	0	1.000	3	0.326
	YCbCr		90	1	0.989	1	0.415
	Y		90	1	0.989	1	0.489
truck	RGB	99	96	3	0.969	45	0.252
	YCbCr		94	5	0.949	10	0.315
	Y		95	4	0.959	13	0.333
Basket ball	RGB	137	112	25	0.817	2	0.974
	YCbCr		71	66	0.518	1	0.922
	Y		71	66	0.518	1	0.922
Total	RGB	557	523	34	0.939	78	0.408
	YCbCr		460	97	0.826	17	0.379
	Y		460	97	0.826	21	0.399

IV. CONCLUSION AND FUTURE WORK

In this paper, we implement moving object detection method which is helpful for driver to avoid from car accident at the parking lot. The method consists of smoothing, GMM based background subtraction and morphological filtering. Considering real-time implementation, we examine “which colour space has better performance for detection of moving objects?” Three colour spaces including RGB, YCbCr, and Y are considered and tested. Through the simulation tested on various scenarios, we prove that the use of RGB space is more suitable in such moving object detection applications.

In this research, we could find the disadvantage; for one moving object, the proposed sometimes detects more than one moving objects. Even though we used smoothing filter for pre-processing and the morphological filter for post-processing to solve the disadvantage, the result shows separated blobs even for one object. To improve the performance, we are going to investigate to detect objects with exact the number of them.

ACKNOWLEDGMENT

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