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MOVING OBJECT DETECTION USING CELL BAESED OPTICAL FLOW FOR STATIC AND DYNAMIC SCENES

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ABSTRACT

In this paper, we propose a moving object detection method which can give warning to drivers and then help to prevent possible traffic accidents. The proposed method is designed to detect moving objects in both situations when host vehicle is stopping (static scene) and when it is slowly driving (dynamic scene). These situations occur alternately in parking lots. The proposed moving object detection method consists mainly of optical flow estimation, background modeling and clustering steps. Amplitude of motion vector is calculated from optical flow technique and used for background modeling. In order to apply effectively background subtraction to motion vectors, we propose a cell based background modeling which accumulates the amplitudes of every vector within a cell and up-dates adaptive threshold value to classify the given vectors into foreground and background. Four different optical flow estimation techniques are considered. Various cell sizes including 1X1, 4X4, 10X10 and 40X40 are applied. The simulations on four kinds of dynamic scenes and three static scenes show that the proposed method achieves good enough moving object detection performances.

Keywords: *Dynamic Scenes, Moving Camera, Moving Object Detection, Optical flow, Adaptive thresholding*

1. INTRODUCTION

When driving in parking lot, drivers do not always recognize pedestrians or other moving vehicles. Drivers should be always careful of every moving object around the host vehicle. This is the reason why vision based moving object detection and warning system is required. It can prevent possible traffic accidents.

Vision based moving object detection has been often applied as a pre-processing in object recognition systems. Many researchers have investigated various moving object detection methods. Most existing methods focused on detecting moving object in static scenes like CCTV (closed circuit television) [1-8]. Static scenes mean that camera position is fixed and then background is not moving. However, moving object detection techniques for static scene cannot be applied ADAS (Advanced Driver Assistance System), because a camera is mounted to vehicle. Therefore, the position of ADAS camera is moving when vehicle is driving. Clearly, moving object detection method in dynamic scenes is required to apply to driving vehicle on which camera is installed [9-16].

In this paper, we propose moving object detection method which is applicable in both static and dynamic scenes, i.e. when the host vehicle is slow driving and when stopping. In the proposed method, optical flow estimation technique is used. In general, the background has very small or zero motion vectors, but moving objects have large motion vectors in the case of static scenes. It is observed that background has relatively smaller motion vector than moving objects even in dynamic scenes. It is also observed that in the case of dynamic scenes the motion vectors on the background have different amplitudes depending on the location in the image. For example, background in the middle part of image has relatively smaller motion than in right/left side, when the host vehicle is driving straight on. Based on these observations, motion vector is obtained in a cell (small block) using optical flow estimation and is used to detect moving objects in the

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successive processes. Assuming that moving objects to be detected includes every object such as pedestrians, vehicles, and bicycles which are oncoming to the host vehicle or crossing in front of the host vehicle. For the simulations, video sequences are captured by a front facing commercial black box camera which is mounted behind windshield of the host vehicle. Dynamic and static scenes are recorded respectively when the host vehicle drives below 20km/h and when stops.

The rest of paper is organized as follows. Section 2 describes the related works. Section 3 explains the proposed method. In Section 4 and 5, simulation results and conclusions follow. Finally, limitation and future works are described in Section 6.

2. RELATED WORKS

2.1 Moving Object Detection in Static Scenes

Many researchers have developed moving object detection methods in static scenes. This technique is often applied to CCTV for detection of moving objects. Background subtraction techniques have been often used. In [3], four different background subtraction methods are implemented to detect moving objects by using median filtering, approximated median filtering, Kalman filter and Gaussian mixture modeling. It is shown that Gaussian mixture model method has better detection performance than the others. Gaussian mixture model [4] is a mixture of K Gaussian distributions representing the distribution of pixel intensities in current frame. In [5], a post-processing is proposed for moving object detection. After background subtraction, stochastic super pixel and Markov Random Fields (MRF) are used to improve the performance. X. Liu et al. is also proposed a post-processing to improve background modeling method in static scene which is including scattered leaves, fountain, and so on. To improve background modeling, they get initial value using Gaussian mixture model for background subtraction method, and Markov Random Fields energy function is used to compensation of background modeling result [21]. Texture feature using Local Binary Pattern (LBP) is utilized for moving object detection in [6]. Input image is divided into small size blocks, and background is modeled on each block by using weighted adaptive LBP histogram. These methods are applicable to static scenes. However, in case of dynamic scenes, backgrounds are changing in each frame. Therefore, these methods that are useful in static scene are not suitable to be used in dynamic scene.

2.2 Moving Object Detection on Dynamic Scenes

Recently, moving object detection systems applicable to dynamic scenes have reported in the literatures [9-16].

First attempts [8-10] use pixel intensity based background modeling with some additional processing to compensate the movement of background. For example, motion compensation based on statistical mix model is applied in [10]. However, these pixel intensity based background modeling methods have still certain limits to overcome the movement of background.

Other technique is using past and future information of frames. A. Shimada et al. [22] proposed bidirectional background modeling method. Background modeling is obtained using information of future as well as past.

Another possible technique is to use optical flow. Yamaguchi, K. et al. use ego-motion estimation and epipolar lines to detect moving objects [11]. Ego-motion is estimated from correspondences of feature points that are obtained by Lucas-Kanade optical flow technique. Epipolar lines are calculated in 3-D space using triangulation. If feature point is away from corresponding epipolar line, it is detected as outlier that belongs to moving object candidates. In [12], optical flow and disparity on certain feature points are extracted by using stereo camera. After generating a graphical structure that connects these feature points using the Delaunary triangulation, moving objects are detected. M. Yokoyama et al. proposed fast detection of moving objects and tracking method, using gradient based optical flow and based on the line which is estimated using edge detection [23]. R. Wang et al. propose Flux Tensor with Split Gaussian(FTSG) model to detect moving objects. Flux Tensor with Split Gaussian model is time-space tensor equation based motion estimation method [24].

It is clear that optical flow is very useful information to detect moving objects on dynamic scenes. Note that sparse optical flow estimation technique is used in [10-12].

3. MOVING OBEJCT DETECTION USING CELL BASED OPTICAL FLOW

In this paper, we propose a moving object detection method which is a combination of optical flow estimation and background modeling. Amplitude of motion vector is calculated from

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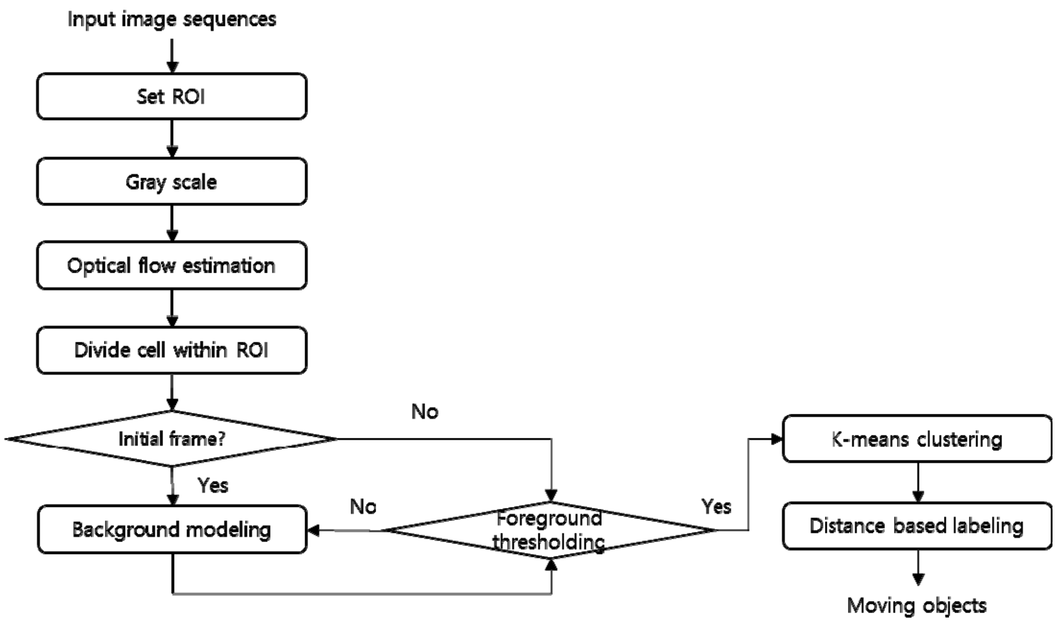

Figure 1: Block diagram of the proposed method

optical flow techniques and used in background modeling. In general, background modeling has been applied to pixelwise value such as intensity and/or color of image. Motion vector is often calculated in sparse by using optical flow estimation. In order to apply background modeling to motion vector, we propose a cell based background modeling which accumulates the amplitudes of every vector within a cell (small black) and classifies it into background or not by using adaptive thresholding. The meaning of cell in this paper is each columns and rows in the ROI (Region Of Interest). In this paper, we set the ROI where a position with the high probability that moving object will appear. The size of cell can be available to change. However, in this paper, we used fixed size of the cell. Figure 3(a) shows example of cell and ROI. The cell based background modeling can compensate the movement of background when the host vehicle is moving. It allows using both dense and sparse optical flow estimation techniques. Four optical flow estimation techniques are applied and the performances are compared. Figure 1 shows the overview of the proposed method.

Motion vectors are calculated in pre-defined region of interest (ROI) by using optical flow estimation and divided into cell. If motion vector within each cell has smaller amplitude than adaptive foreground threshold value, it is classified to background. Otherwise, it is foreground candidate. The foreground threshold is up-dated in each frame. Given j-th vector in i-th cell at t-th frame, $V_{t,i}(j)$ is classified into background vector $B_{t,i}(j)$ and foreground candidate $F_{t,i}(j)$ as follows;

$$V_{t,i}(j) = \begin{cases} B_{t,i}(j) & for \left\| V_{t,i}(j) \right\| < T_{t,i} \\ F_{t,i}(j) & otherwise \end{cases} \quad (1)$$

where $T_{t,i}$ is foreground threshold value in i-th cell at t-th frame. The threshold value is up-dated at each frame as follows;

$$T_{t,i} = \mu_{t,i} + k\sigma_{t,i} \quad (2)$$

$\mu_{t,i}$ and $\sigma_{t,i}$ are the estimated mean and standard deviation of i-th cell at time t, and k is constant value. The mean and standard deviation are

$$\mu_{t,i} = (1 - \alpha)\mu_{t-1,i} + \alpha \, || \, B_{t,i}(i) \, || \quad (3)$$

$$\sigma_{t,i} = (1 - \alpha)\sigma_{t-1,i} + \alpha\{abs(|| \, B_{t,i}(j) \, || - \mu_{t,i})\} \quad (4)$$

where α is learning rate. The mean and standard deviation are adaptively up-dated by using the vectors that are belong to background using equation (1). Every background vector in cell is

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used to up-date the mean and standard deviation. Assuming that every cell belongs to background

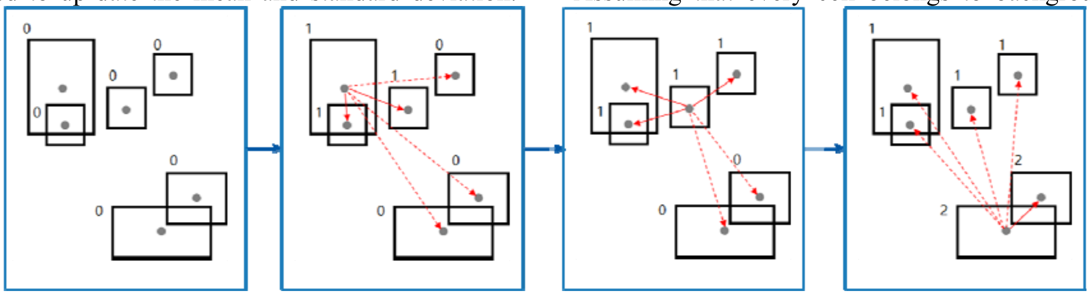

Figure 2: Illustration of labeling technique based on distance of center position between bounding box

for initial frames, every vector is considered as background one and is used to up-date mean and standard deviation using equations (3) and (4) until the number of frames reaches to predefined initial frame number.

After background modeling, foreground candidate vectors are clustered by using K-means clustering algorithm. In this work, we set K to be 10. The position of the motion vector and amplitude are used as features for the K-means algorithm. Each cluster is represented by bounding box which is defined by top-left and bottom-right positions. One moving object can often be indicated by several separated bounding boxes. Therefore, it is necessary to carry out labeling process to regroup clusters to one bounding box. Center point is calculated by using the top-left and bottom-right positions in each cluster. The distance between each pair of clusters is calculated by using the center point. The labeling process is given as bellows;

1. Calculate center point of each bounding box
2. Calculate the distance of center points between *m*-th and *n*-th bounding box

$$d_{m,n}=\sqrt{(x_m-x_n)^2+(y_m-y_n)^2} \qquad m,n\in(0,K) \tag{5}$$

3. If $d_{m,n}$ is shorter than the pre-defined threshold value and *n*-th bounding box has no label, then, the label of *m*-th bounding box assigns to *n*-th bounding box.
4. If $d_{m,n}$ is shorter than the pre-defined threshold value and *n*-th bounding box has label, then, the label of *m*-th bounding box assigns to all bounding boxes which have the same label as *n*-th bounding box.
5. Step 3~5 are iterated until there are no $d_{m,n}$ which is shorter than the threshold value
6. Finally, every bounding box is labeled

Figure 2 shows illustration of the labeling process. Bounding box represents cluster, the number indicates label, and arrow is the distance between clusters. If the distance is longer than the threshold, it is indicated by dot line. Figure 3 shows example images of the proposed method.

4. EXPERIMENTAL RESULTS

For simulations, video sequences are captured by a forward-facing commercial black box camera mounted behind the windshield of host vehicle. Dynamic and static scenes are recorded respectively while the host vehicle drives at below 20 km/h and when stops. For dynamic scene, we test on four situations of which each includes different moving object such as bicycle, motorbike, pedestrian, and vehicle. In the case of static, we test on three video clips of which each includes motorbike, pedestrian, and vehicle. Ground truth data is manually obtained for evaluation.

For the simulations, the method is implemented with learning rate α=0.001 and constant value k =3. For the purpose of analyzing the detection performances according to the size of cell, four sizes such as 1x1, 4x4, 10x10, and 40x40 are examined. To analysis the performance according to the optical flow estimation techniques, Lucas-Kanade [17], pyramidal Lucas-Kanade [18], Extended Salient Motion Map (ESMM) [19], and Farneback techniques [20] are applied respectively. Pyramidal Lucas-Kanade is a sparse optical flow, and the others are dense ones.

The performance of moving object detection is evaluated by recall, precision, and

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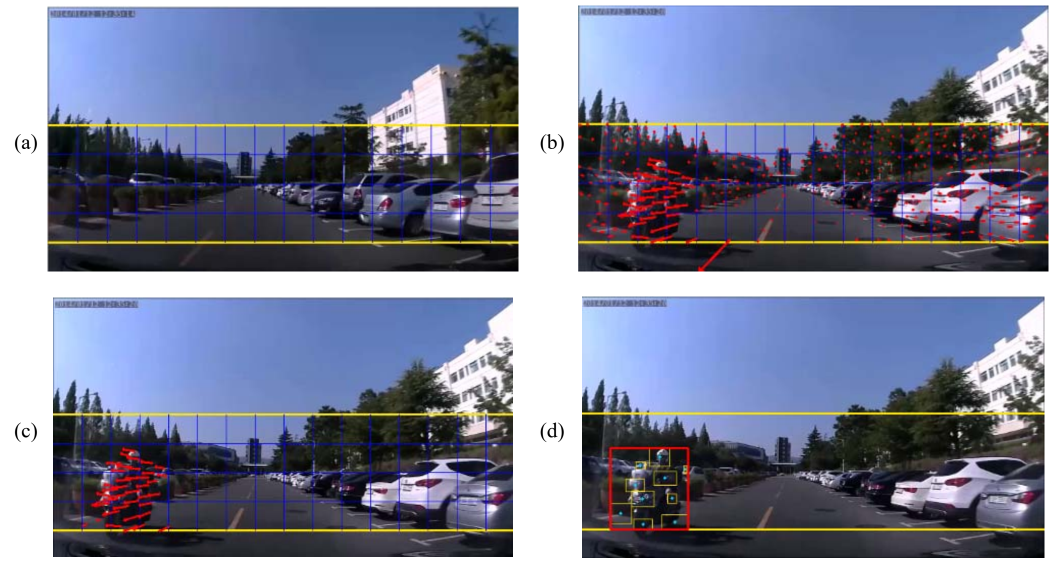
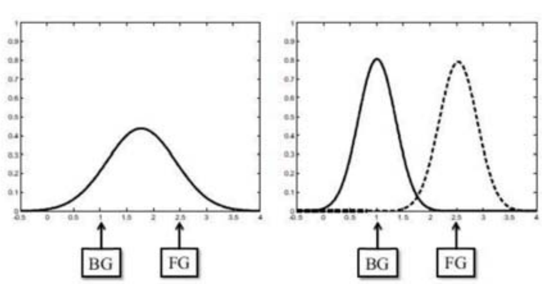


Figure 3: Example images of the proposed method
(a) cells within ROI (yellow line), (b) optical flow indicated by red arrow,
(c) foreground threshold, (d) labeling results indicated by red bounding box

F-measure. Figure 5 shows the detection performance comparison of the proposed method according to the size of cell and optical flow estimation techniques. From the viewpoint of F-measure, pyramidal Lucas-Kanade optical flow with cell size of 10x10 shows relatively stable and better performance both for dynamic and static scenes. F-measure reaches to around 0.782 and 0.947 in dynamic and static scenes. This shows the effectiveness of the proposed method. Dense optical flow techniques show lower detection performance. The reason is that, dense optical flow has more data in a cell than pyramidal Lucas-Kanade optical flow which is sparse optical flow. For example, if cell size is 10X10, the number of optical flow data is 100. While pyramidal Lucas-Kanade optical flow has less data than 100 in a cell. When mean and standard deviation are calculated in case of pyramidal Lucas-Kanade optical flow technique, the value of mean and standard deviation for amplitude of optical flow in a cell can be greater than dense optical flow technique used. Therefore, adaptive threshold value will be greater than dense optical flow technique used in each cell, so it can classify foreground and background well. Cell size does not have significant effects on the detection performances in static scenes, while it does in dynamic case. Performance decreases as cell size increases, when using dense optical flow. More very small motion vector is used to up-date the mean and standard deviation, larger the size of cell is. This is the reason why the foreground threshold gets smaller, and then more background region is classified to false foreground.

To evaluate the performance of our proposed method, background modeling with motion compensation proposed by Yi et al. [10] method is tested on the same video clips. Yi et al. proposed moving object detection method is based on Dual-mode Single Gaussian Model (SGM). We compared Dual-mode Sigle Gaussian Model based method with our proposed method, because it is also cell and optical flow based method. Yi et al. [10] also used pyramidal Lucas-Kanade optical flow technique for motion compensation. Figure 4 shows conceptual diagram of Dual-mode Single Gaussian Model.



(a) (b)

Figure 4: conceptual diagram of Single Gaussian Model (a) and Dual-mode Single Gaussian Model (b).

For fair comparison, ROI is set on the same region in the image. Then, morphological filtering, and our proposed labeling processes are applied. The simulation results are listed in Table 1. This table shows also the performance of the proposed method when using pyramidal Lucas-Kanade optical flow with cell size of 10x10. The proposed method has better performance in terms of F-measure than Dual-mode Single Gaussian Model based moving object detection method in both static and dynamic scenes. Some examples of detection result are shown in figure 6 and figure 7. The proposed method shows less false detected moving objects than Dual-mode Single Gaussian Model, especially in dynamic scenes. It may be caused by the fact that pixel intensity based modeling is more sensitive to intensity changes. Figure 8 shows other false detection example of the previous method in dynamic scenes, where stopped vehicles on the right-side parking lot are detected as moving objects. The proposed method shows also this kind of error, but less than the previous method.

5. CONCLUSTION

In this paper, we propose a moving object detection method which is a combination of optical flow estimation and background modeling. Amplitude of motion vector is calculated from optical flow and used in background modeling. In order to apply background subtraction to motion vector, we propose a cell based background modeling which accumulates the amplitudes of every vector within a cell and up-dates adaptive threshold value to classify given vector into background or not. One sparse optical flow estimation technique (Pyramidal Lucas-Kanade optical flow technique) and three dense optical flow estimation techniques (Lucas-Kanade, Extended Salient Motion Map, and Farneback optical flow technique) are applied and various cell sizes (1X1, 4X4, 10X10, and 40X40) are tested.

Through the simulations, 10X10 cell size and pyramidal Lucas-Kanade optical flow estimation technique shows better performance than other cell size (1X1, 4X4, and 40X40) and dense optical flow technique applied method. For evaluation of our proposed moving object detection method, we compared performance with Dual-mode Single Gaussian Model method [10] in both static and dynamic background. Through the simulation, we show that optical flow is very useful clue for moving object detection.

6. LIMITATION AND FUTURE WORKS

In this paper, we proposed a moving object detection method using optical flow estimation and background modeling, which is useful in both static background scene and dynamic background scenes. However, our proposed method in this paper has some limitation. Our proposed method must set the number of initial frame to accumulate amplitude of motion vector, and it is used for modeling of background. And then, the proposed moving object detection method cannot detect moving objects which are moving in the same direction with host vehicle, because the moving object has smaller amplitude of motion vector, then our proposed method classify to background.

For the future works, we are going to use Gaussian mixture model based on information of optical flow for modeling of background instead of using adaptive threshold technique, and we are going to evaluate that which methods are good at detection of moving objects.

In this paper, we only used amplitude of motion vector. Therefore, it is necessary to consider a combination of color information with amplitude of motion vector using the proposed algorithm instead of using only amplitude of motion vector.

7. ACKNOWLEDGMENTS

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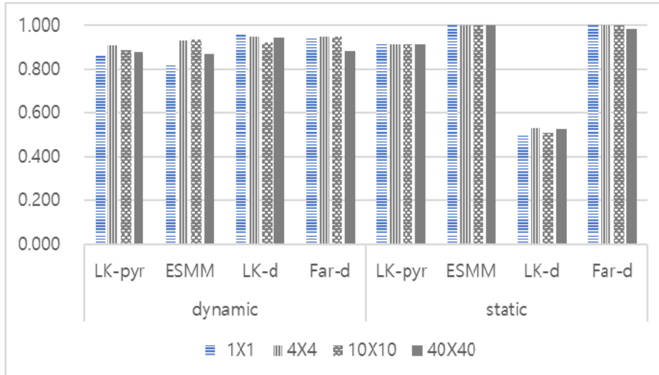
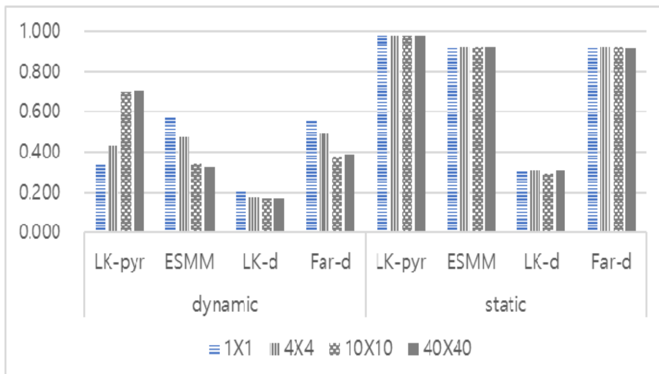
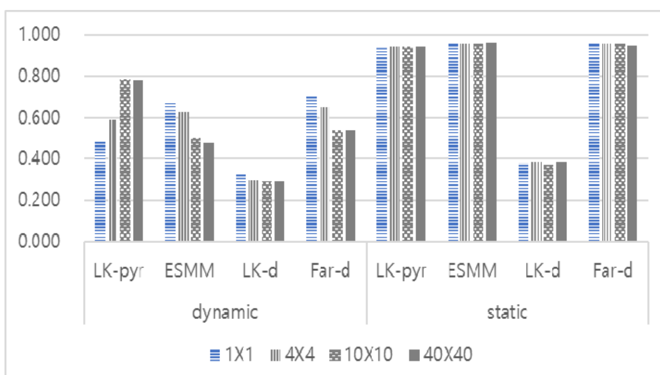


(a) recall



(b) precision



(c) *F-measure*

Figure 5: Moving object detection performances of the proposed method according to the size of cell (1x1, 4x4, 10x10, 40x40) and optical flow estimation techniques (dense Lucas-Kanade indicated by LK-d, pyramidal Lucas-Kanade by LK-pyr, Extended Salient Motion Map by ESMM, and Farneback by Far-d)

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Table 1: Performance comparison between the proposed using pyramidal LK optical flow with cell size of 10X10 and Dual-mode SGM method (D-SGM)[10]

Background	System	Recall	Precision	F-measure
Dynamic	Proposed	0.888	0.698	0.782
	D-SGM	0.850	0.391	0.536
Static	Proposed	0.916	0.979	0.947
	D-SGM	0.936	0.817	0.873

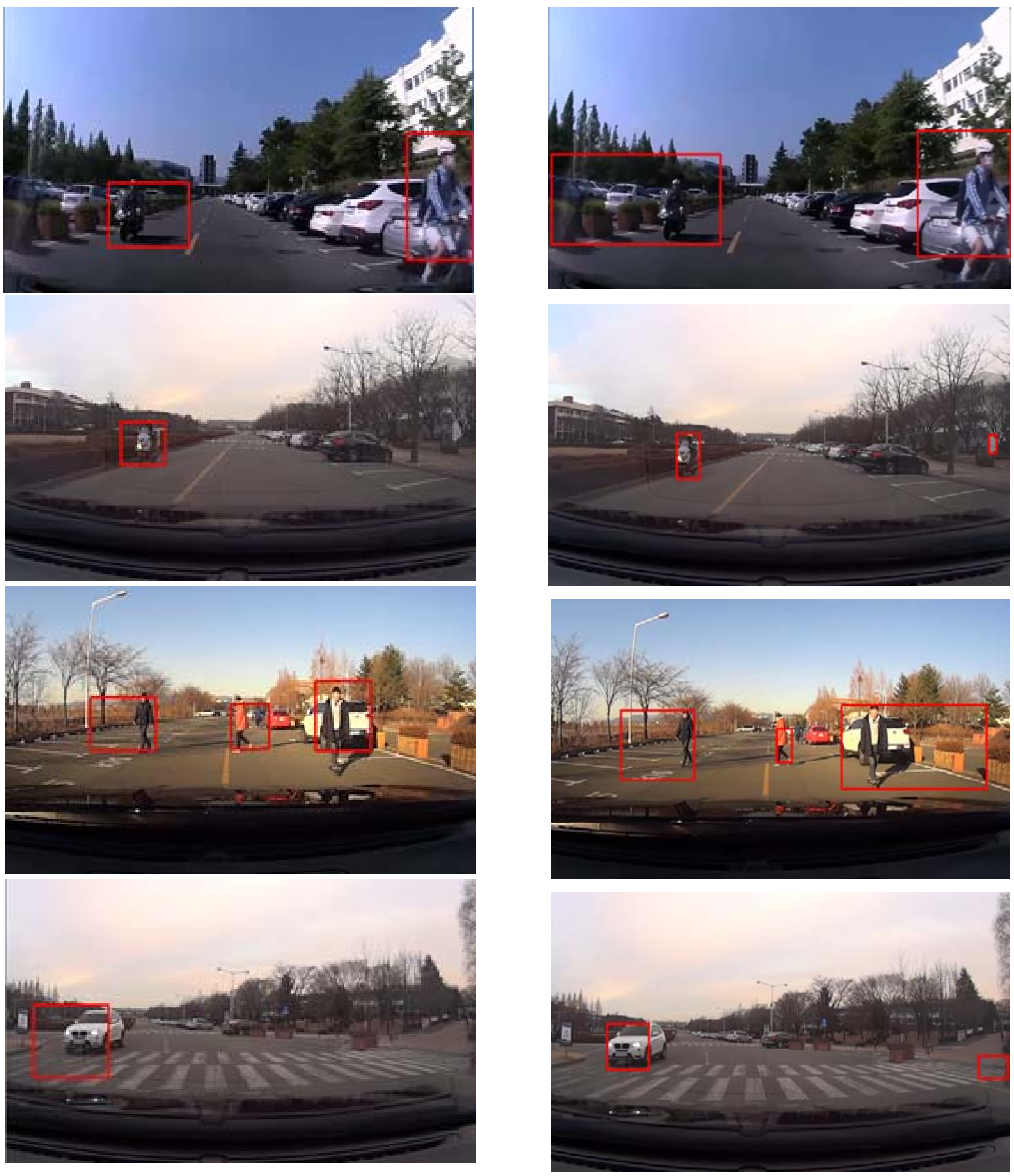

Figure 6: Examples of moving object detection of the proposed (left column) and Dual-mode SGM method[10] (right column) tested on dynamic scenes

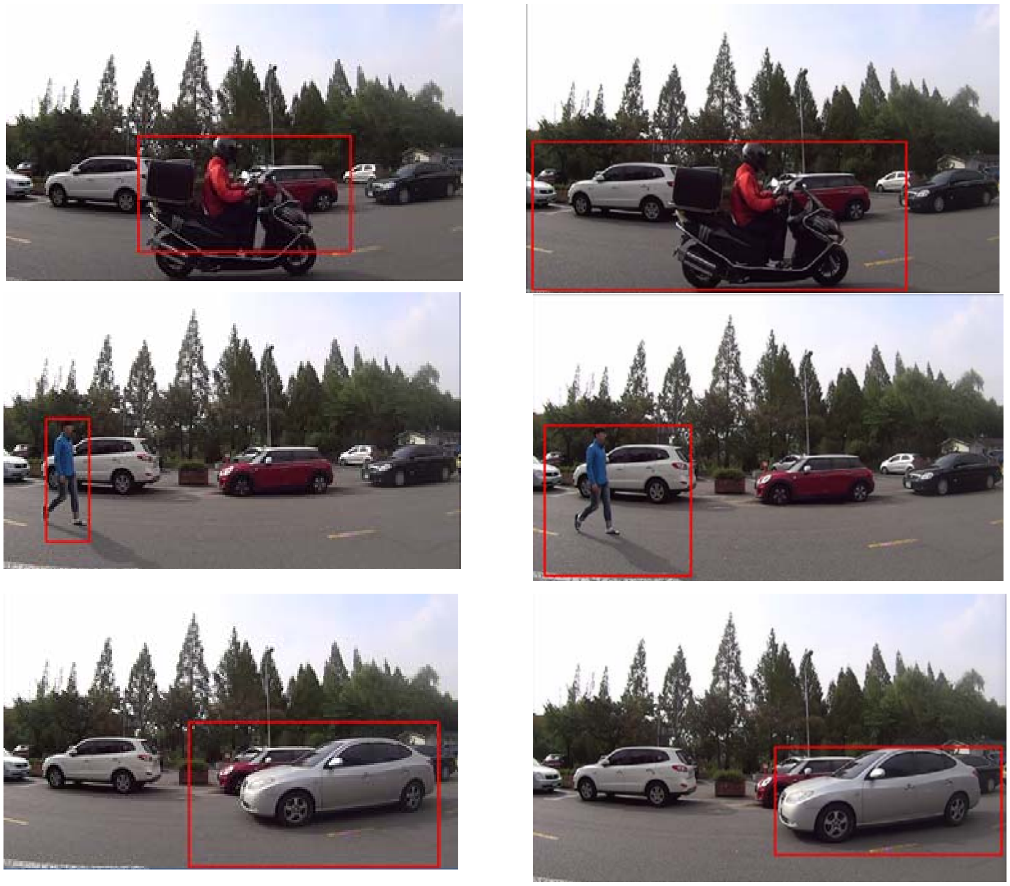

Figure 7: Examples of moving object detection of the proposed (left column) and Dual-mode SGM method[10] (right column) tested on static scenes

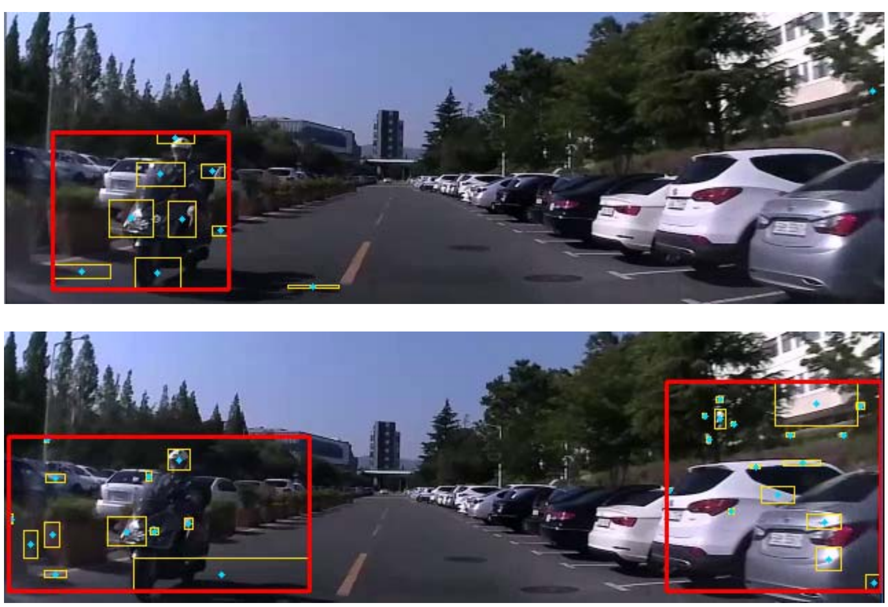

Figure 8: False detection example of Duel mode SGM method[10] (bottom) and the result of the proposed (top) in dynamic scenes