Robust moving object detection using beam pattern for night-time driver assistance

Rui Zhang, Eunsoo Park, Yongji Yun and Hakil Kim
School of Information and Communication Engineering
Inha University
Incheon, Korea
{rzhang, espark, yjyun}@vision.inha.ac.kr,
hikim@inha.ac.kr

Hyoungrae Kim
School of Robot Engineering
Inha University
Incheon, Korea
hrkim@vision.inha.ac.kr

***Abstract*—Driver assistance is very important in helping the driver in its driving process. Proposed in this paper is a robust method for collision avoidance on the urban road based on the low beam pattern model, which is used to detect objects under night-time condition with an embedded camera. The proposed method consists of two steps. Firstly, the low beam pattern model is computed through perspective transformation and nonlinear regression from the difference signal between the none-beam frame and the beam frame. Secondly, the moving objects are detected by differencing the real-time input video and low beam pattern model. Several night driving videos are adopted in this study and the experimental results demonstrate the feasibility and effectiveness of the proposed method.**

Keywords-beam pattern; night-time driver assistance; object detection

I. INTRODUCTION

The fatal crash rate for night-time driving is much higher comparing to that of day-time, even though the traffic flow at night is substantially lower. Among the nighttime fatalities a large proportion occurs in urban areas rather than in the rural areas [1]. In order to be warned early before accidents, drivers need to look far ahead to see traffic signs, road geometry, other vehicles, pedestrians, and etc. However, this task is difficult at night-time because the vision is severely limited: drivers lose the advantage of color and contrast that are available during the day-time, and depth perception and peripheral vision are also faded away [2]. To help the driver during the night-time driving, objects ahead of the vehicle should be detected and localized in advance from the moving platforms.

Many efforts on the development of detecting and tracking objects have been made [3-5]. Background subtraction algorithm is widely used to obtain moving objects. In [3], a motion-based color background modeling method is proposed. However, this method works poorly in nighttime environment. In [4], a two-step detection/tracking method with a night-vision video camera is presented. The detection phase is performed by a support vector machine and the tracking phase is a combination of Kalman filter prediction and Mean-shift tracking. The detection accuracy of the method is high, however, real-time processing is a challenging problem in this work and an extra expensive infrared camera is needed. A real-time object detecting and tracking system for night-time surveillance is also proposed in [5], however, the proposed method works poorly when the camera is moving.

For the purpose of real-time collision avoidance during night-time driving, in this work, a novel and effective object detection method using a moving camera is proposed. The proposed method has two stages. In the first stage, the low beam pattern model (LBPM) is computed by perspective transformation and nonlinear regression from the difference signal between the none-beam frame (NBF – image with headlight off) and the beam frame (BF – image with headlight on). In the second stage, moving objects are detected by differencing the real-time input video from the LBPM. The system overview of the proposed method is showed in Fig. 1.

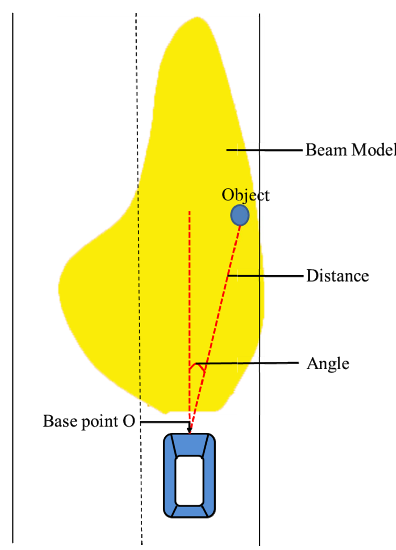

Figure 1. System overview of the proposed method

978-1-4673-0990-5/12/$31.00 ©2012 IEEE

II. PROPOSED BEAM PATTERN BASED OBJECT DETECTION

The proposed method comprises of the following two steps: (1) LBPM analysis and (2) model-based object detection.

A. Low Beam Pattern Model Analysis

The LBPM is computed by a perspective transformation and nonlinear regression over the difference image between NBF and BF. Fig. 2 shows the example of NBF (a) and BF (b) which are taken by a camera mounted inside vehicle, and their difference (c).

According to the headlamp regulations [6] of the International Economic Commission for Europe (ECE), the bird's-eye view is definitely more beneficial to analyze the beam pattern. Therefore, a perspective transformation is adopted by the planar projective transformation [7], which will be described in detail in the next sub-section. And then, interpolation is performed to complete the bird's-eye view.

In order to complete the LBPM, nonlinear regression by a probabilistic distribution is adopted. From the bird's-eye view beam image, the image formed by the intensity values for each row or column is modeled by a skew normal distribution as illustrated in Fig. 3(b).

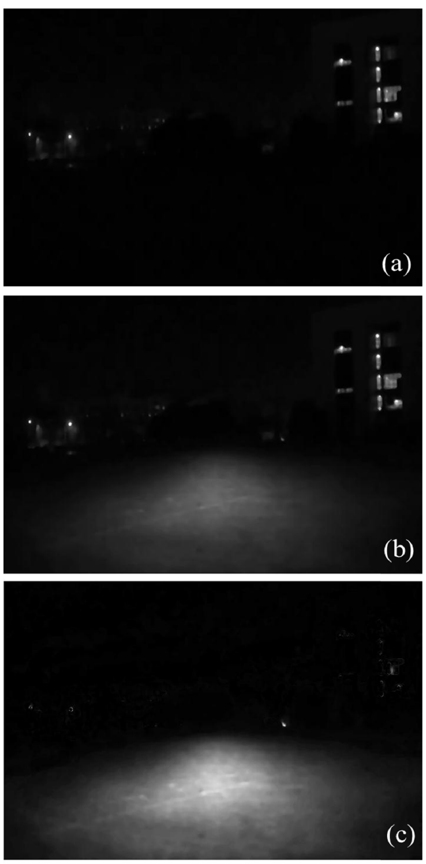

Figure 2. Examples of the (a) NBF, (b) BF and the (c) Difference of (a) and (b)

Let $\phi(x)$ and $\Phi(x)$ be the probability density and cumulative distribution of skew normal distribution, defined as

$$\phi(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}, \quad \Phi(x) = \int_{-\infty}^{x} \phi(t)dt . \tag{1}$$

Then, the skew distribution with location (ε) and scale (ω and ρ) parameters is given as

$$f(x) = \frac{2}{\omega}\phi\left(\frac{x-\varepsilon}{\omega}\right)\Phi\left(\rho\left(\frac{x-\varepsilon}{\omega}\right)\right) . \tag{2}$$

Next, for each line in X direction, the beam image is optimized by nonlinear regression method to obtain the parameters of the skew distribution model, and then the intensity value of each pixel is computed. Fig. 3 shows an example of the intensity profile of X direction and the intensity profile after regression.

The same process is done in the Y direction. Therefore, for the same position of the image, two different values are acquired separately by X direction's nonlinear regression and Y direction's. In order to acquire the model which has the minimal Mean Square Error (MSE), the combination of minimum, maximum and mean of these two values is also computed. Fig. 4 shows the MSE Scores for each method.

In this study, the regression under Y-direction is chosen, which is proved to have the minimum MSE. Fig. 5 shows the result of LBPM.

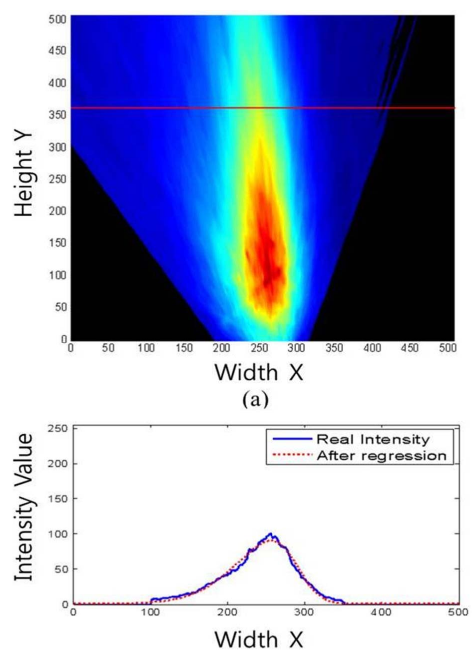

Figure 3. Example of nonlinear regression, (a) bird's-eye view of the difference of NBF and BF, (b) the intensity profile (blue curve) and its fitting result (red dashed curve), where Y = 360 in pixel

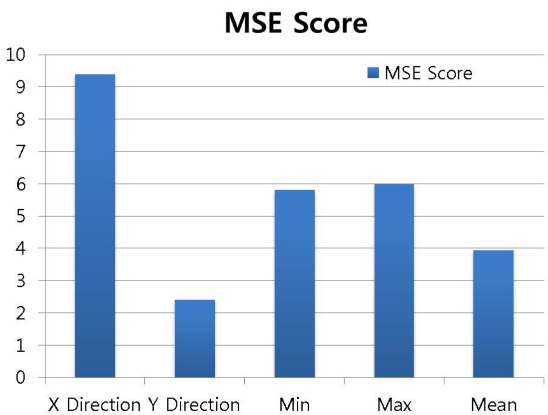

Figure 4. Comparison of the MSE scores of different methods

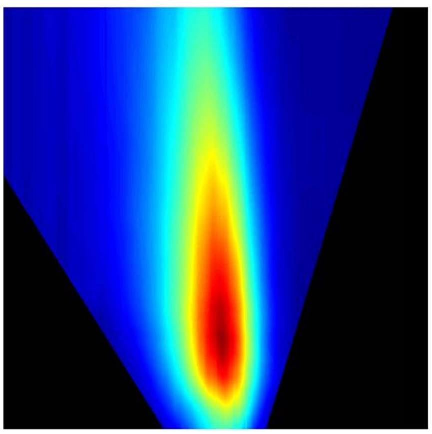

Figure 5. Demonstration of the LBPM

B. *Model-based Object Detection*

In order to compute the difference image between input test video and LBPM, input frames should firstly be transformed to bird's-eye view. The key point of the perspective transformation is to compute the homography matrix $\mathbf{H}$, in which the 2D projective transformation method [7] is adopted in this study.

A planar projective transformation is a linear transformation on homogeneous 3-vectors represented by a non-singular 3×3 matrix. Let the coordinates of the matching points be (x, y) and (x', y') respectively, where the mathematic relationship is given as

$$\begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = \mathbf{H}\begin{pmatrix} x \\ y \\ 1 \end{pmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & 1 \end{bmatrix}\begin{pmatrix} x \\ y \\ 1 \end{pmatrix}, \qquad (3)$$

An example of 2D projective transformation is shown in Fig.6. As the total number of degrees of freedom in homography matrix $\mathbf{H}$ is eight, and each point-to-point correspondence accounts for two constraints, it is necessary to specify four points in order to fully compute the $\mathbf{H}$.

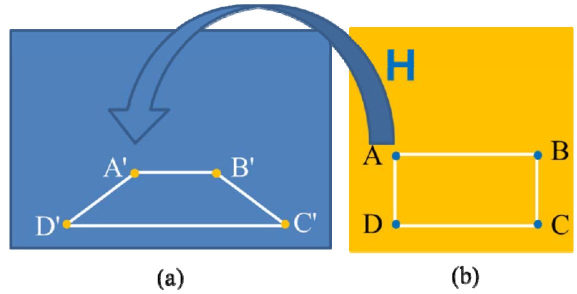

Figure 6. An example of 2D projective transformation, (a)The original plane with perspective distortion, (b)The original plane

Therefore, A' , B' , C' and D' four points which all on the ground are chosen in Fig. 6(a). Let $K \in \{A, B, C, D\}$ where the image coordinates of these four points are indicated by

$$P_{K'} = (X_{K'}, Y_{K'}), \qquad (4)$$

Then, in Fig. 6(b), based on base point O, the world coordinates of these four points A , B , C , D can be measured and defined as

$$P_K = (X_K, Y_K). \qquad (5)$$

Next, from (3), four points corresponds lead to such linear equation (6) and given as

$$P_{K'} = \mathbf{H} P_K \qquad (6)$$

Lastly, the inverse of the homography matrix $\mathbf{H}$ is computed and then applied for the perspective transformation.

For extracting objects, considered as the regions of rapid intensity change in one frame, Laplacian filter is adopted to perform the edge detection. The edge mask is then obtained by thresholding the edge image where the threshold is adaptively obtained by Otsu's method [8]. The binary mask is then processed with a morphological open operator to remove small connected regions. Fig. 7 shows some intermediate results of frame 110 of video 1 from our experiments.

Once an object is extracted, the bottom coordinates of the detected object in image plane can be obtained and denoted as $(\mu_1, \ \nu_1)$. According to homography matrix $\mathbf{H}$, the world coordinates of the points can be computed, defined as $(X_1, \ Y_1)$. Therefore, the distance and angle from the object to the camera-assisted car can be computed by (7)

$$\text{Distance} = \sqrt{(X_1)^2 + (Y_1)^2}, \quad \text{Angle} = \arctan((\mu_1)/(\nu_1)). \qquad (7)$$

Finally, these can be used to remind drivers with an alarm to deal with night-time vehicle-object collision. However, the distance is an approximation, since the objects' bottom points detected in the proposed method will affect the results.

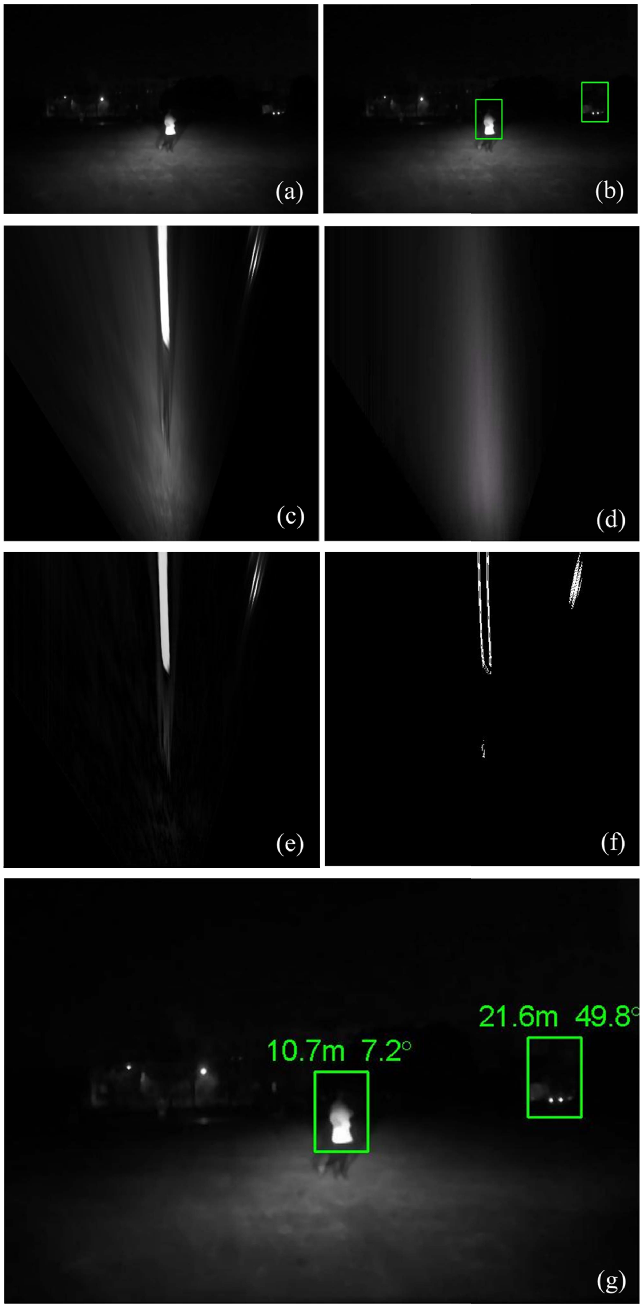

Figure 7. Intermediate results of object detection. (a) frame 110 of video sequence 1, (b) the result of detection, (c) the bird's-eye view of image (a), (d) beam model frame, (e) the difference image between (c) and (d), (f) the result after using laplation filter and threshold, (g) the result with distance and direction

III. EXPEIMENTS AND DISCUSSIONS

A Sony digital camcorder video camera DCR-SX83 is mounted in the middle of the front window of a car which is measured by the center of two headlights. The size of the recorded image sequences is 720×480 and the system is implemented in MATLAB.

Several different video sequences under real night driving conditions are acquired. Fig. 8 shows some results of detection from our experiments. Fig. 8a, b, c show some results of correct detection, while due to the occlusion, in Fig. 8d, the result is incorrect as one object is missing. In order to evaluate the performance for each video sequence, the evaluation scheme proposed in [9] is performed. Assuming that the number of misses is indicated by m_t and the number of false positives is indicated by f_{p_t} for each frame t, and then Multiple Object Detection Accuracy (MODA) for the entire sequence is calculated by:

$$\text{N-MODA} = 1 - \frac{\sum_{t=1}^{N_{frame}} \left(c_m(m_t) + c_f\left(f_{p_t}\right)\right)}{\sum_{t=1}^{N_{frame}} N_G^{(t)}}, \qquad (8)$$

where c_m and c_f are the cost functions for the missed detects and false positives, and $N_G^{(t)}$ is the number of ground truth objects in the t^{th} frame. Table I shows the result of performance evaluation for the proposed method.

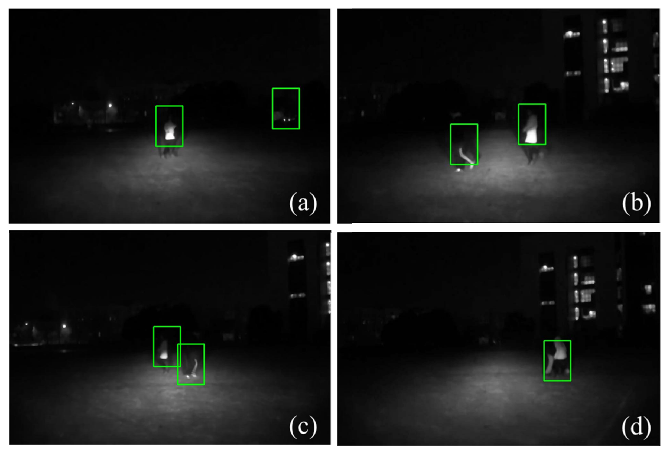

Figure 8. Detected objects in different video sequences. (a) video sequence 1, frame 105, (b) video sequence 2, frame 163, (c) video sequence 3, frame 177, (d) video sequence 4, frame 165.

TABLE I. THE PERFORMANCE EVALUATION OF SEVERAL VIDEO SEQUENCES WITH MOVING CAR

No. of Sequence	Average Time (per frame)	MODA (%)	Missing Rate (%)	False Positive (%)
1	0.35 ms	89.4	10.6	0
2	0.42 ms	90.0	9.1	0.9
3	0.63 ms	72.3	27.7	0
4	0.37 ms	88.8	8.3	2.9
Average	0.44 ms	85.1	13.9	1.0

IV. Conclusions and Future Work

In this paper, a new night-time object detection method for collision avoidance on the urban road is proposed. Beam pattern is obtained by differencing the NBF and BF, and then LBPM is processed by nonlinear regression and perspective transformation. Next, with the LBPM, object detection is performed robustly. For reminding driver whether it has some objects ahead of the car or not, distance and the angle from objects to the camera-assisted car is computed. The method is evaluated on different video sequences under real night driving conditions. One advantage of the system is that works in real time.

The results are encouraging. More improvements must be done in the stage of object extraction to reduce the false detection rate. Therefore, as a future idea, the probability model and motion-based compensation method is going to be introduced into the system to detect objects more accurately.

Acknowledgment

This work was supported by Ministry of Knowledge Economy (MKE) and IDEC Platform center (IPC) at Hanyang Univ.

References

[1] U.S Department of Transportation. “2010 Motor vehicle crashes: overview,” U.S. National Highway Traffic Safety Administration,2010.

[2] Antonio Lopez, Jorg Hilgenstock, Andreas Busse, Ramon Baldrich, Felipe Lumbreras and Joan Serrat, “Nighttime vehicle detection for intelligent headlight control,” ACIVS 2008, LNCS 5259, pp. 113-124,2008.

[3] Ming-Yu Shih, Yao-Jen Chang, Bwo-Chau Fu and Ching-Chun Huang, “Motion-based ackground modeling for moving object detection on moving platforms,” ICCCN 2007, pp.1178-1182, 2007.

[4] Fengliang Xu, Xia Lir and Kikuo Fujimura, “Pedestrian detection and tracking with night vision,” IEEE transction on intelligent transportation system , Vol.6, No.1, March 2006.

[5] Kaiqi Huang, Liangsheng Wang, Tieniu Tan and Steve Maybank, “A real-time object detecting and tracking system for outdoor night surveillance,” Pattern recognition volume 41, Issue 1, Pages 432-444, January 2008.

[6] ECE R112 Rev.2. Uniform provisions concerning the approval of motor vehicle headlamps emitting an asymmetrical passing beam or a driving beam or both and equipped with filament lamps and/or light-emitting diode (LED), 2002.

[7] Richard Hartley and Andrew Zisserman, “Multiple view geometry in computer vision,” pp.50-57,2003

[8] WANG Hongzhi and DONG Ying, “An improved image segmentation algorithm based on otsu method,” International Symposium on Photoelectronic Detection and Imageing 2007: Related Technologies and Applications, Vol.6625, 2008

[9] Rangachar Kasturi, Dmitry Goldgof, Padmanabhan Soundararajan, Vasant Manohar, John Garofolo, Rachel Bowers, Matthew Boonstra, Valentina Korzhova, Jing Zhang, “Framework for performance evaluation of face, text and vehicle detection and tracking in Video: data, metrics, and protocol,” IEEE transctions on pattern analysis and machine intelligence, VOL.31, No.2, February 2009.