Fast Lamp Pairing–based Vehicle Detection Robust to Atypical and Turn Signal Lamps at Night

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Abstract: Automatic vehicle detection is a very important function for autonomous vehicles. Conventional vehicle detection approaches are based on visible-light images obtained from cameras mounted on a vehicle in the daytime. However, unlike daytime, a visible-light image is generally dark at night, and the contrast is low, which makes it difficult to recognize a vehicle. As a feature point that can be used even in the low light conditions of nighttime, the rear lamp is virtually unique. However, conventional rear lamp–based detection methods seldom cope with atypical lamps, such as LED lamps, or flashing turn signals. In this paper, we detect atypical lamps by blurring the lamp area with a low pass filter (LPF) to make out the lamp shape. We also propose to detect flickering of the turn signal lamp in a manner such that the lamp area is vertically projected, and the maximum difference of two paired lamps is examined. Experimental results show that the proposed algorithm has a higher F-measure value of 0.24 than the conventional lamp pairing–based detection methods, on average. In addition, the proposed algorithm shows a fast processing time of 6.4 ms per frame, which verifies real-time performance of the proposed algorithm.

Keywords: Vehicle, Detection, Nighttime, Low-light, Lamp pairing

1. Introduction

Recently, autonomous vehicles have been actively studied. Among the technologies that drive autonomous vehicles, environment recognition, such as pedestrian and vehicle recognition, becomes very important in representative advanced driver assistance system (ADAS) technology. In particular, studying automatic vehicle detection techniques has been done for a long time using, for example, the Haar-like feature-based method [1, 2], the histogram of oriented gradients (HoG)-based method [3], the optical flow–based method [4], and the Hough forest (HF)-based method [5, 6]. These techniques usually focus on the daytime environment. Unfortunately, since the images acquired at night have low contrast, it is difficult to obtain useful features for vehicle detection. Therefore, directly applying a conventional daytime vehicle detection technique to the nighttime environment is meaningless in practice.

At nighttime, where the utilization of universal features is limited, the rear lamp of a vehicle may be the only feature available for vehicle detection. In general, rear lamps are always bright at night, and exist in a pair. Therefore, such characteristics are useful for vehicle detection at night. Various lamp pairing–based methods

![Fig. 1. Examples of rear lamps difficult to detect (a) atypical lamps, (b) blinking turn signal lamps.](image)
have been developed for vehicle detection [7-14]. These vehicle detection algorithms basically find the rear lamp of a target vehicle using the brightness and color values obtained from the image. And the target vehicle is detected in a manner that finds a lamp pair satisfying predetermined conditions. Existing lamp pairing–based algorithms detect the back lights of a lamp shape relatively well, but they often fail to detect linear lamps, such as LEDs, as shown in Fig. 1(a). Also, for a vehicle with a blinking turn signal, the conventional lamp pairing–based techniques do not work well because the two lamp shapes are different, as seen in Fig. 1(b). In order to solve this problem, there was an attempt to detect a vehicle through inter-frame motion compensation [15]. However, this technique requires a very large number of computations, because it should adopt computationally heavy inter-frame motion estimation, such as optical flow.

This paper proposes a real-time lamp pairing–based vehicle detection algorithm robust to atypical and asymmetric lamps in the low-light nighttime. First, tone-mapping and Gaussian filtering processes are applied to simplify the shapes of atypical rear lamps. Next, in order to detect asymmetrical lamps due to blinking turn signals, we propose a lamp detection method based on vertical image projection. Through intensive experiments, we confirmed that the proposed algorithm has high accuracy, with average recall of 0.877, precision of 0.933, and F-measure of 0.903, which are better than previous algorithms. In addition, the proposed algorithm has a very fast processing speed of 6.4 ms per frame—enough to guarantee real-time processing.

### 2. The Proposed Algorithm

Fig. 2 describes the overall operation of the proposed algorithm. First, the color format of an input image is converted into the hue, saturation lightness (HSL) format, and the region of interest (ROI) is extracted using only the L channel image. Then, a general lamp and an atypical lamp are detected for the ROI image. After that, an asymmetrical turn signal lamp is detected. Finally, each detected vehicle is tracked via conventional tracking algorithm.

The key contributions of the proposed algorithm are as follows: First, it is possible to detect atypical lamps by simplifying the lamp shapes via tone mapping and Gaussian filtering. Second, it can detect asymmetrical lamps in which a turn signal is on by finding the maximum values in the one-dimensional projected data obtained by the vertical projection.

### 2.1 Detection of General Type Lamp

#### 2.1.1 Generation of General Type Lamp

First, we set the ROI in the input image. The objective is to set an ROI, such as the white box in Fig. 3 centered in the driving lane, except for unnecessary parts, such as the sky. In this paper, the length of the portion of the lane extension that closes to the bottom of the frame is defined as the width of the ROI. In addition, the height of the ROI is 20 pixels above the vertical coordinate of the vanishing point from the bottom of the frame. Assume for convenience that the vanishing point and lane information used in the ROI setting are determined manually.

If the ROI image is obtained, the color format is converted into the HSL format to generate the L channel ROI. Generally, the HSL format is similar to the hue, saturation, value (HSV) format except that the brightness range of the L channel is twice as wide as the V channel, which is effective for detecting rear lamps.

After the L channel ROI is obtained, any vehicle having a normal rear lamp is detected. Note that conventional lamp pairing–based algorithms generally perform binarization of the input image [10] prior to vehicle detection. However, such binary image–based methods rarely handle occasions where the lamp shapes are not maintained after binarization.

In order to compensate for this, we adopt a strategy in which only the pixels above a relatively low threshold are used, and the lamp shape is kept intact by performing tone-mapping on the survived pixels, as in Eq. (1).
where $I(x, y)$ denotes the L value at $(x, y)$ in the ROI, and $I'(x, y)$ denotes the tone-mapping result. In this paper, the threshold is empirically set to 220.

Tone-mapped ROI images may still have outliers rather than actual lamps. To remove these, we apply an erosion filter. Next, adjacent pixels having a distance of two pixels or less among non-zero pixels are grouped into a contour. Finally, the height, width, and size of each contour are measured, and if the measured value satisfies the following conditions, the contour is determined as a lamp candidate (assume that a total of $J$ contours are detected within the ROI):

<table>
<thead>
<tr>
<th>Condition for determining lamp candidates</th>
</tr>
</thead>
<tbody>
<tr>
<td>$h_j \leq \theta_h$</td>
</tr>
<tr>
<td>$w_j \leq \theta_w$</td>
</tr>
<tr>
<td>$\theta_{wm} \leq h_j \cdot w_j \leq \theta_{wm}$</td>
</tr>
</tbody>
</table>

where $h_j$ and $w_j$ indicate the height and width of a bounding box corresponding to the $j$-th contour. Also, $\theta_h$ and $\theta_w$ stand for maximum height and width, respectively, and $[\theta_{wm}, \theta_{wm}]$ is a possible range for the bounding box. These thresholds are the minimum criteria for determining whether each contour can be a lamp candidate. In this paper, we obtained them experimentally, as follows: $\theta_h=90$, $\theta_w=70$, $\theta_{wm}=35$, $\theta_{wm}=2000$.

2.1.2 Lamp Pairing

If lamp candidates are obtained as explained in the previous section, each lamp pair for full vehicle detection is subsequently found. Each pair of lamps is examined to see if the following conditions are met:

<table>
<thead>
<tr>
<th>Condition to determine a lamp pair candidate</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\min(A_j,A_k)/\max(A_j,A_k) \geq \theta^R$</td>
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<td>$</td>
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</tbody>
</table>

The first condition above suggests the minimum for the area ratio of the $j$-th and $k$-th lamp candidates to be considered. The second and third conditions check the distance of the center coordinates of the two lamp candidates, respectively.

Here, $D_x$ and $D_y$ indicate the differences of x and y coordinates of two lamp candidates, respectively. The threshold for the above-mentioned condition were determined via intensive experiments for various images as follows:

$$I'(x, y) = \begin{cases} 
0 & , I(x, y) < \theta_L \\
I(x, y) - \theta_L & , I(x, y) \geq \theta_L 
\end{cases} \quad (1)$$

Then, normalized cross correlation (NCC) matching [7] was applied to pairs satisfying the above-mentioned lamp pair candidate conditions. Only a candidate with a maximum NCC value higher than a pre-determined threshold is selected as the final lamp pair candidate within a given search area. The NCC threshold can be obtained by experiments on actual vehicle lamps, and was set to 0.65 for this paper.

Finally, we put the bounding box on the selected lamp pair(s) and examine whether the bounding box width of each lamp pair is within a certain range. The lamp pair is determined to be that of a generic vehicle if the following conditions are met: $\theta_{nw} < W_n < \theta_{nw}$. Here, $W_n$ indicates the width of the bounding box, and $[\theta_{nw}, \theta_{nw}]$ is the possible range of $W_n$. Actually, $[\theta_{nw}, \theta_{nw}]$ was determined by calculating the range of possible vehicle widths under normal road conditions. In this paper, we calculated it on a frame basis by using the vanishing point and the coordinate of the bottom of the lane. Also, the vanishing point and the bottom lane coordinate of the first frame of each video sequence were considered as those of the video sequence.

2.2 Detection of Atypical Lamps

The detection process of atypical rear lamps is mostly the same as described in Section 2.1. The only difference is that a Gaussian filter is applied to the ROI image obtained through tone mapping in order to change the incomplete lamps into their semi-complete forms. The reason the atypical lamp is not detected well is that the contour of an atypical lamp can be divided into several segments, as shown in Fig. 4(c). Conventional lamp pairing–based algorithms use a morphological filter to combine scattered lamp shapes, but they have a long computational time. On the other hand, even if only tone-mapping and Gaussian filters are applied instead of binarization and morphological filters, the shape of the LED lamp is preserved, as shown in Fig. 4(b). In this paper, we use a general 3x3 Gaussian filter.

2.3 Detection of Turn Signal Lamps

Among the remaining lamp candidates, except for the already detected lamps, turn signal lamps are detected as follows. First, the process in Section 2.1.2 is performed, except for the first condition, because if the turn signal is blinking, the resulting area difference between
corresponding lamps can increase significantly.

In order to detect blinking turn signal lamps, vertical projection-based matching is implemented, instead of NCC matching defined in Eq. (2):

\[ H(x) = \sum_y L(x, y) \]  

(2)

\( L(x, y) \) denotes a tone-mapped and Gaussian-filtered result for a lamp candidate, and \( H(x) \) denotes a vertically projected value. Fig. 5 shows the vertical projection results of a pair of lamps when a turn signal is blinking and not blinking. Figs. 5(e) and (f) are vertical projection images generated by using the vertical projection of each lamp pair. As can be seen, when the turn signal is on, the gap between the minimum projection value \( M_m \) of the small lamp and the maximum projection value \( M_M \) of the large lamp becomes greater. Using this phenomenon, if the ratio of the maximum projected value of two lamps in a pair is above threshold \( \theta^p \), the turn signal lamp is considered to be on (see the following condition).

**Condition to detect turn signal lamp**

\[ M_m / M_M > \theta^p \]

In this paper, \( \theta^p \) was experimentally set to 0.3.

### 3. Experiment Results

Test images for evaluation were obtained directly from an expressway, and an LG G5 smartphone and a Sony digital single-lens reflex camera were used as acquisition devices. The image resolution is 1280x720 with a frame rate of 30 Hz. As shown in Table 1, a total of 11,783 frames were used as a test set.

The experiment was conducted on a desktop with an i7-6700K CPU and 32GB of RAM. The evaluation was done in terms of recall, precision, and F-measure [22] as follows:

\[ \text{Recall} = \frac{TP}{TP + FN} \]  

(3)

\[ \text{Precision} = \frac{TP}{TP + FP} \]  

(4)

\[ F\text{-measure} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \]  

(5)

where TP and FP are true positive and false positive, respectively, and FN indicates false negative. In particular, F-measure values, the harmonic mean of precision and recall, are well-known as the basis for judging overall performance.

The proposed algorithm was compared with two previous algorithms: Gall et al.’s method based on the Hough forest (HF) [5] and the lamp pairing method.
proposed by O’Malley et al. [10]. These two algorithms were chosen because we could easily get the C code. The C code released by the authors was employed for the evaluation of the two benchmarking methods. The initial ROI for each algorithm was preset. Gall et al. [5] used scale factors of {0.34, 0.49, 0.7, 1.0}. And O’Malley et al. [10] set γ to 0.65. The parameters of the proposed algorithm were set experimentally according to the environment in which the data were acquired. For parameter setting, we used a separate set of 5,000 images taken under the same conditions as test image acquisition.

Table 2 shows that the performance obtained by Gall et al. [5] is not acceptable because of limited edge information at night. And we can see that O’Malley et al. [10] provided high precision values, but recall rates are significantly low. However, the proposed algorithm yields outstanding and balanced recall and precision values compared to Gall et al. [5] and O’Malley et al. [10]. Therefore, we find the proposed algorithm superior to the previous works in terms of F-measure, which shows comprehensive performance.

Fig. 6 qualitatively compares the results of several

<table>
<thead>
<tr>
<th>Method</th>
<th>Set #</th>
<th>Recall</th>
<th>Precision</th>
<th>F-measure</th>
<th>Process Time (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gall et al. [5]</td>
<td>1</td>
<td>0.289</td>
<td>0.773</td>
<td>0.421</td>
<td>47.885</td>
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<td></td>
<td>2</td>
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<td>0.752</td>
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<td></td>
<td>3</td>
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<td>4</td>
<td>0.260</td>
<td>0.545</td>
<td>0.352</td>
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<tr>
<td></td>
<td>5</td>
<td>0.472</td>
<td>0.539</td>
<td>0.503</td>
<td>42.926</td>
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<tr>
<td></td>
<td>Avg.</td>
<td>0.259</td>
<td>0.657</td>
<td>0.344</td>
<td>48.588</td>
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<tr>
<td>O’Malley et al. [10]</td>
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<td>0.615</td>
<td>0.973</td>
<td>0.754</td>
<td>4.276</td>
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<tr>
<td></td>
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<tr>
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<td>Avg.</td>
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<tr>
<td>Proposed</td>
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<td>6.967</td>
</tr>
<tr>
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<td>0.848</td>
<td>0.961</td>
<td>0.901</td>
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</tr>
<tr>
<td></td>
<td>Avg.</td>
<td>0.877</td>
<td>0.933</td>
<td>0.903</td>
<td>6.352</td>
</tr>
</tbody>
</table>

Fig. 6. Performance from several algorithms (a) Gall et al.’s [5], (b) O’Malley et al.’s [10], (c) the proposed.
algorithms. We can see that the proposed algorithm detects vehicles more reliably than the previous methods. This can be seen in Fig. 7 in more detail, which provides enlarged parts of Fig. 6. From Fig. 7(a), we find that Gall et al. [5] failed to detect a dark vehicle. However, as shown in Fig. 7(b), the proposed algorithm succeeds in detecting even dark vehicles. In addition, we observe that O’Malley et al. [10] failed to detect vehicles with amorphous lamps and turn signal lamps. However, the proposed algorithm detects a vehicle with an irregular lamp, as shown in Fig. 7(d), and also detects the vehicle even when the turn signal is on and the lamp pair is asymmetric, as shown in Fig. 7(f). Even with this high performance, the proposed algorithm provides an average processing time of 6.35 ms, which is very fast and can be processed in real time.

4. Conclusions

This paper proposes a real-time nighttime vehicle–detection algorithm that is especially robust to atypical lamps and flashing turn signals. As shown in the experiment results, the proposed algorithm appropriately responded to vehicles with irregular lamps that could not be handled by conventional algorithms, and to vehicles on which turn signals are blinking. The processing speed is very fast and can be used in various fields requiring real-time application.

However, due to the nature of lamp pairing–based vehicle detection, it is not possible to respond to vehicles with either the rear lamp turned off or a one-sided vehicle. Also, if there is another light source near the back ramp in the image, the proposed algorithm does not detect the vehicle. In the future, it is necessary to investigate the possibility of vehicle detection regardless of lamp shape by, for example, employing deep learning.

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References


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