Blind spot monitoring at night-time using rear-view camera

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Abstract: The blind spot monitoring (BSM) is one of the key functions of advanced driver assistance system (ADAS). In this paper, we propose vision-based blind spot detection and tracking algorithm which is applicable at night-time. The feature of highly bright blobs due to the headlights of behind vehicle is employed for the detection of vehicles in blind spot area, because the appearance-based approach that can be used at daytime is not any more appropriate. We calculate the motion vectors of detected blobs to find an approaching vehicle and make headlight grouping to estimate its position by use of the projection map. We can successfully generate an alarm signal by detection and tracking the overtaking vehicle in blind spot area at night-time.

Keywords: advanced driver assistance system; ADAS; blind spot monitoring; BSM; vehicle detection; projection map.


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1 Introduction

As the interest on safety and convenience of driver grows, the demand for the various technologies of intelligent vehicle also increases. Among many advanced driver assistance system (ADAS) functions (Li et al. 2012), the blind spot monitoring (BSM) becomes one of the essential functions. Blind spot area indicates the portion of the road that cannot be seen through either room or side mirrors of a vehicle. Therefore, it is very dangerous for a driver to change lane when an unnoticed vehicle exists in the blind spot area.

Some researchers have adopted active sensors, such as ultra-sound, radar, or light detection and ranging (LIDAR), to detect objects in the blind spot (Mahapatra et al. 2008; Meinel and Dickmann 2013; Domínguez et al. 2011). However, these active sensors usually have a smaller coverage, shorter detecting distance and more expensive in comparison with image sensors. Moreover, they are not adequate to obtain any visual information about the appearance of detected objects. On the other hand, camera have been used for BSM (Jung and Yi, 2015; Beak et al. 2014). Generally speaking, an image sensor has a wider field of view (FOV) and is cost effective over active sensors. And it is the most appropriate sensor for scene interpretation or pattern recognition in spite of its massive amounts of data which require a lot of computational load and complex algorithm. In recent years, researches on sensor fusion have been actively carried out to utilise the merits of each sensor (Kim et al. 2005).

When the rear-view camera is used for BSM, most approaches are based on the appearance of vehicle. The edge and colour of vehicle or its shadow are typical examples of the selected features. Also some kinds of machine learning algorithm such as Support Vector Machine (SVM) or boosting can be employed after histogram of oriented gradient (HOG) or Haar-like features are calculated (Wijnhoven et al. 2011; Yuan et al. 2011). Unfortunately, these features are not effective especially at night-time since the lighting condition is so poor to get sufficient visibility. Figure 1 shows the typical example of the captured frame from rear-view camera at night-time.

We could notice the illumination conditions are quite different from those at daytime. First, there are highly bright blobs due to the intense headlights of the behind vehicle and it is difficult to discern the shape of the vehicle because the intensity level of blobs is
deeply saturated. Therefore, like other researchers (Schamm et al. 2010; Joung et al. 2011; Fernández et al. 2013) we have considered these blobs to be the most outstanding feature and used them to detect a vehicle at night-time. However, we can observe the assumption of symmetry of blobs is not valid any more. This is because the size and position of one lamp are likely to be different from those of the other since the target object of BSM exists not in a driving lane but its adjacent lane as shown in Figure 1. And there may also be redundant blobs reflected from headlight of vehicle or lighting of surrounding buildings. Therefore, careful consideration is required for the detection and tracking of vehicle in blind spot area at night-time.

Figure 1 A typical example of rear-view image at night-time (see online version for colours)

In this paper, the proposed algorithm is discussed in Section 2 and simulation results are given in Section 3. Finally, we present the conclusions in Section 4.

2 The proposed algorithm

The Figure 2 shows the general block diagram of the proposed algorithm. The input is the video sequence captured by rear-view camera and the output is an alarm signal which denotes there is an approaching vehicle in blind spot area.

2.1 Blob detection

In this paper, we make use of the bright blobs to find the headlight of vehicle since those are the most remarkable feature at night-time. Thus the first step is to detect blobs in pre-defined left and right regions of interest (ROI) which are adopted to reduce the computational load. Every input frames are converted to binary images by the use of threshold in order to separate the bright headlight area from background. When there are not any detected blobs, the remaining steps do not need to proceed any further. Figure 3
shows an example of typical pattern of vehicle’s headlight in blind spot area and the results of its binarisation. We can notice a single vehicle may have multiple blobs after thresholding.

Figure 2  Block diagram of proposed algorithm

Figure 3  A typical pattern of vehicle’s headlight and its binarization (see online version for colours)

2.2 Motion vector estimation

Our concern for BSM is not every blob but the approaching ones. Therefore, the moving directions of detected blobs need to be found out. After the bright blobs are detected, the next step is to estimate the motion vectors of them. When a behind vehicle is approaching to ego-vehicle in blind spot, the blobs are getting bigger and have the motion vectors with downward direction in ROIs. Only the blob that has a proper motion vector moves to the next step and others are neglected. Figure 4 shows the result of the second step. The original images are given in the left column. And the results of detected blob with their motion vectors are given in the centre column. The right column shows the remaining blobs after filtering out invalid motion vectors.
Figure 4  The results of the second step (see online version for colours)

Figure 5  The results of headlight grouping and the projection map (see online version for colours)

2.3  Headlight grouping

The third step is to make a group of blobs that correspond to headlight of the same vehicle. The left and right headlights of the same vehicle are parallel and their vertical positions are similar. Thus, we make a projection map along horizontal direction and find the vertical position that has the largest projection value. If two blobs are located at the same height of the vertical position, then these two blobs are regard as headlight of same vehicle. Figure 5 shows the results of headlight grouping step and the horizontal projection map.

2.4  Tracking

When the blobs are grouped in the previous step, we need to track the position of them in order to determine whether a vehicle remains in blind spot area or not. We already have the motion vectors of blobs since they have been calculated at every frame in the second step. And the tracking step can be simply accomplished by observing the motion vectors. Figure 6 shows the tracking process of approaching blobs in the left ROI. As expected, the direction of motion vectors is downward.
Figure 6  The tracking process of approaching blobs, (a) the previous frame (b) the current frame (c) the next frame

(a)  (b)  (c)

2.5 Alarm generation

The final step is to generate an alarm signal. The alarm signal is ON when there exists a paired group of blobs and its moving direction is approaching in left or right ROIs. And the alarm goes to OFF when the blobs completely moves out of ROI. Even the blobs remain in ROI, the alarm also goes to OFF if the moving direction is not approaching during a few frames. We could control the duration of alarm according to the magnitude of motion vector, that is, the larger the motion vector, the shorter the alarm duration.

3 Simulation result

In this paper, we utilised the rear-view camera of two channel black box for vehicle to monitor the blind spot area at night-time. The experiment was performed with Intel Core i7-6700 and NVIDIA GeForce GTX 750. Also, Visual Studio 2013 with OpenCV 2.4.10 was used for simulation. And we used total 57 video clips, of which resolution was reduced to 720 × 480, obtained from on simple motorway and in downtown area with complex background.

Figure 7  The example of TP case by the proposed algorithm (see online version for colours)
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Figure 7 shows the typical example of true positive (TP) case when two vehicles were approaching to ego-vehicle in both lanes. The left and right vehicles are successfully detected and alarms are generated and marked as red dots in upper part of image. The position of ROI depends on the lane width and the pre-defined blind spot area and we set the aspect ratio of ROI as 2:1 as shown in Figure 7.

Table 1 The performance of the proposed algorithm

<table>
<thead>
<tr>
<th>Sequence</th>
<th>TP</th>
<th>FP</th>
<th>FN</th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Downtown</td>
<td>63</td>
<td>8</td>
<td>0</td>
<td>88.7</td>
<td>100</td>
</tr>
<tr>
<td>Motorway</td>
<td>117</td>
<td>6</td>
<td>0</td>
<td>95.1</td>
<td>100</td>
</tr>
<tr>
<td>Total</td>
<td>180</td>
<td>14</td>
<td>0</td>
<td>92.8</td>
<td>100</td>
</tr>
</tbody>
</table>

Notes: TP: true positive, FP: false positive, FN: false negative;
Precision = TP / (TP + FP), Recall = TP / (TP + FN).

Figure 8 The processing speed of the proposed algorithm, (a) in the downtown (b) on the motorway (see online version for colours)
The performance is measured by the precision and recall. The precision is calculated as $\frac{TP}{TP + FP}$ and the recall is calculated as $\frac{TP}{TP + FN}$, where FP and FN denote False Positive and False Negative, respectively. In our simulation, the overall precision was 92.8% and recall was 100%. In these simulation results, all of the vehicles that is approaching to ego-vehicle was detected and give a correct alarm, but few erroneous alarm was generated by the vehicle on the next of side lane. We observed the light of the background could be another cause of erroneous case.

We also measured the processing speed of the proposed algorithm and showed the results for both downtown and motorway sequences in Figure 8. The graph shows the frames per second (FPS) in vertical axis. When a vehicle appears in single ROI, processing speed was over 40 fps and even two vehicles are approaching in both ROI, the processing speed does not fall under 20 fps. In other words, the proposed algorithm can be implemented in real-time.

There were some FP cases by the proposed algorithm. The most frequent cases were generated when a vehicle was approaching in the next of side lane as shown in Figure 9(a). In this case, it is expected that the more accurate adjustment of ROI position can be a solution. If the exact information about the lane is available, this problem can be resolved. Another FP cases occurred when ego-vehicle was changing lanes as in Figure 9(b) because the pre-defined ROI was out of position. The third cases of FP were observed, when the ego-vehicle was driving on a downhill road as shown in Figure 9(c). The position of ROI was also considered as the cause of this problem.

Figure 9 The FP cases, (a) when a vehicle is approaching in the next lane (b) when the ego-vehicle was changing lanes (c) when the ego-vehicle was driving on a downhill road (see online version for colours)
4 Conclusions

In this paper, we proposed a new algorithm for the detection and tracking the overtaking vehicle in blind spot area at night-time. We extracted the feature of bright blobs instead of conventional appearance-based feature and estimated the moving direction of blobs to discriminate the approaching headlights from background noise blobs. After that, the two dominant blobs were paired to comprise the headlight of behind vehicle. Finally, we could generate an alarm signal by considering the position and the speed of paired headlights. Simulation results showed that the proposed algorithm can successfully generate an alarm signal for the overtaking vehicles on motorway without error. However, the precision slightly declined when there were too many erroneous blobs from surround vehicles or nearby buildings in downtown area.

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References


