Overtaking Vehicle Detection Techniques based on Optical Flow and Convolutional Neural Network

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Keywords: Overtaking Vehicle Detection, ADAS, CNN.

Abstract: As the rise of the intelligent vehicle applications in recent years, the development of onboard vision systems for advanced driving assistance has become a popular research topic. This paper presents a real-time system using a monocular camera mounted on the rear of a vehicle to perform overtaking detection for safe lane change operations. In this work, the possible overtaking vehicle is first located based on motion cues. The candidate is then identified using Convolutional Neural Network (CNN) and tracked for behavior analysis in a short period of time. We also propose an algorithm to solve the issue of repetitive patterns which is commonly appeared in the highway driving. A series of experiments are carried out with real scene video sequences recorded by a dashcam. The performance evaluation has demonstrated the effectiveness of the proposed technique.

1 INTRODUCTION

In the past few decades, advanced driving assistance systems (ADAS) have achieved great advances. They are commonly used to improve the driving safety and traffic efficiency. Recently, the researches on advanced driver assistance systems have gained a great momentum in vehicle safety issues. For examples, lane departure warning system (LDWS), forward collision warning system (FCWS), and lane change assistance (LCA) are some typical applications of ADAS. At the present, many high end vehicles are equipped with ADAS directly from the original manufacturer. Some traffic recorders in the after market such as Mobileye 660 (Mobileye, 2017) and Papago P3 (Papago, 2017) are also equipped with various ADAS functions. The driving recorder or dashcam not only records the traffic conditions but also assists the driver to acquire the traffic information (Dai et al., 2017). The main objective is to provide a safe and comfort driving experience.

There are many kinds of sensors used in advanced driving systems such as radar, lidar, and visual sensor, etc. Among them, the imaging technology using visual sensor has the greatest progress potential in recent years. The visual sensors become cheaper and lighter than ever before. They can provide rich sensing information of the environment and therefore be used to design more functions for driving assistance. Some examples include vehicle identification (Liu et al., 2016), traffic sign recognition (Luo et al., 2017; Shi and Lin, 2017), front collision warning (Lin et al., 2012), parking assistance (Fernandez-Llorca et al., 2014), vehicle speed detection (Lin et al., 2008), and other applications. In the past few years, image processing speed is also greatly improved because of the use of graphics processor unit (GPU). The progress of this hardware makes the image processing task rapid and more suitable for advanced driving assistance systems.

Vehicle drivers usually assess the surrounding traffic before changing lanes, and make turns after checking their rear view and side mirrors. However, even for those who follow the standard procedure, the blind-zone of vehicles is still a source of danger and often the cause of serious accidents. A blind-zone of a vehicle can be described as “an area around the vehicle that cannot be seen directly by the driver by looking forwards or by using any of the vehicles standard rear-view mirrors (internal and external) from the normal sitting position” (Hughes et al., 2009). According to Taiwan Area National Freeway Bureau (MOTC, 2017), the main cause of major traffic accidents in the state roads was the result of “improper conversion la-

Wu, L. and Lin, H.
Overtaking Vehicle Detection Techniques based on Optical Flow and Convolutional Neural Network.
DOI: 10.5220/0006698001330140
In *Proceedings of the 4th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2018)*, pages 133-140
ISBN: 978-989-758-293-6

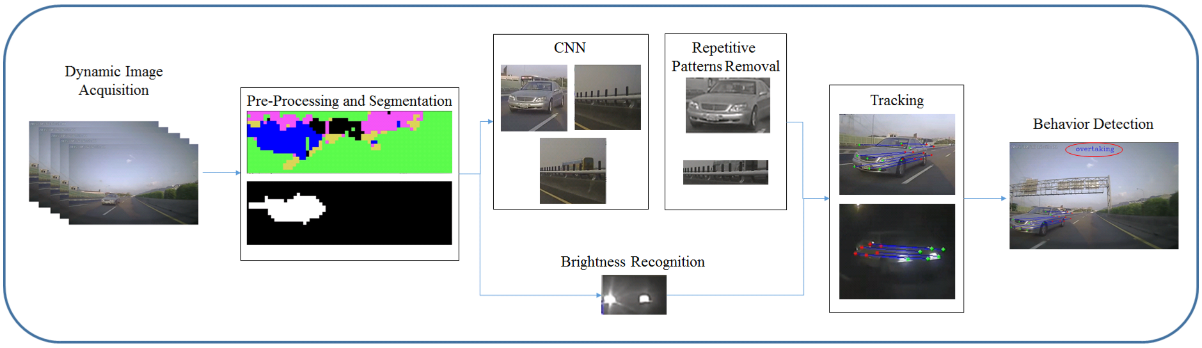


Figure 1: The system flowchart of the proposed overtaking detection technique. It consists of four basic modules: (1) pre-processing and segmentation, (2) convolutional neural network, (3) repetitive pattern removal, and (4) tracking and behavior detection.

nes" followed by "not paying attentions to the state in front of the vehicle".

In order to improve the driving safety, a dashcam can be installed in the rear of the vehicle and used to detect the blind-zone of the overtaking vehicles. It is able to provide the necessary information for the driver about the situation in advance, to avoid the car accident due to an improper turn or lane change. In this work, our experiments contain image sequences acquired from a variety of scenes during day and night. To reduce the cost, a monocular camera is used as the primary sensor. It is also a common approach to analyze the traffic condition using a static camera system.

Because of the vehicle motion and the dynamic change of the scene, the development of onboard camera systems is not a trivial task in terms of the operation efficiency and result accuracy. The image sequence is constantly blurred due to the rapid movement of the vehicle, which introduces unwanted artifacts when the overtaking vehicles approach the camera. Furthermore, the limited field of view of the camera poses additional challenges on vehicle tracking. The vehicle detection is generally more difficult in the urban areas and at night. In the urban areas, the environment is complicated and the vehicles will have various kinds of behavior to respond to. At night, in additional to the complex environment, the image sequences also contain less information due to the illumination condition. In most situations, the feature used for the detection of overtaking vehicles is only the headlights.

2 RELATED WORK

There are many general vehicle detection techniques in the literature. For related work, we mainly survey the vision based approaches for vehicle overtaking and blind-zone detection. The camera system for image acquisition is commonly installed in the front, rear, or sides of the vehicle. For the camera mounted in the front, the overtaking detection is based on the vehicle's motion cues. The advantage of using motion cues is the operation speed. It can still lead to good results even when the vehicle is only partially visible due to occlusion or limited field of view of the camera. Thus, a more complete and continuous trajectory can be obtained. It is, however, easy to be affected by noise and generates erroneous results.

In previous work, Hultqvistet *et al.* (Hultqvist et al., 2014) and Chen *et al.* (Chen and Wu, 2015) proposed efficiency detection overtaking algorithms using optical flow. Their approaches have the cameras placed in the front of the vehicle. As a result, they cannot notify the driver about the occurrence of overtaking in advance. Alonso *et al.* (Alonso et al., 2008) presented a blind-zone overtaking vehicle detection system using optical flow with the cameras installed below the side-view mirror. Wu *et al.* (Wu et al., 2012) proposed an embedded blind-zone security system with a camera mounted below the side-view mirror. First, they detect low-features such as shadows, edges and headlights to locate the vehicle, followed by vehicle tracking and behavior analysis. The cameras below the side-view mirror can detect overtaking vehicles better than others in the blind-zone. However, it requires a pair of cameras which are installed in per external rear mirror and the functions of the cameras are limited than other approaches.

There also exist some techniques with a camera mounted in the rear of the vehicle to detect the overtaking in the blind-zone. It is not only used to inform the driver in advance, but also used by other advanced driving assistance functions. For example, the parking collision avoidance system can use the rear camera to detect the obstacles in the back to avoid collision. Dooley *et al.* (Dooley et al., 2016) installed a fisheye camera in the rear of the vehicle, and used the AdaBoost classification technique and two wheel detection methods to identify the blind-zone vehicles. The vehicles were then tracked by the optical flow technique. Ramirez *et al.* (Ramirez et al., 2014) installed cameras in the front and the rear of the vehicle. They used Deformable Parts Model (DPM) (Pandey and Lazebnik, 2011) to combine optical flow with the mobile information to detect the overtaking vehicles. According to their experimental results, combining these two methods they were able to increase the accuracy of the detection compared to the use of an appearance detector.

3 PROPOSED METHOD

In this paper, we propose a real-time system that uses a monocular camera mounted in the rear of a vehicle to detect overtaking and assist the driver to change lanes. The monocular camera is installed at the height of about 1 meter from the ground. In our main method the architecture contains (1) pre-processing and segmentation, (2) convolutional neural network, (3) repetitive pattern removal, and (4) tracking and behavior detection, as illustrated in Figure1.

3.1 Pre-Processing and Segmentation

In order to increase the speed of operations, we usually use only about half size of the original image by removing unnecessary regions such as the sky, buildings or traffic signs located in the upper part of the image. Thus, the region of interest (ROI) is first defined before performing the image segmentation algorithm. To obtain the motion clues in an image, the settings on the tracking points are very important. Chen *et al.* (Chen and Wu, 2015) use Canny edge detection to extract the edges in the image, and then use the optical flow to calculate the edges of the motion clues. Ramirezet *et al.* (Ramirez et al., 2014) detect the strong corners, and then use the optical flow to calculate the corners of the motion clues. Although using edges or corners as tracking features can derive more robust results, it may increase the amount of extra computations. Further, it is hard for us to determine the number of tracking feature when the image is complicated, which will also cause the uncertainty of computing time.

To avoid the above problems, we set a fixed number of tracking points in a fixed location. First, we set a tracking point per 10×10 pixels in an ROI. Second, we use the pyramid model of Lucas-Kanade optical flow (Lucas and Kanade, 1981) to calculate the optical flow information of the tracking points. Third, according to the direction and measurement of the tracking output, we divide it into five different categories: (i) road and sky, (ii) land marking, (iii) overtaking vehicle, (iv) object further away, (v) uncertain region.

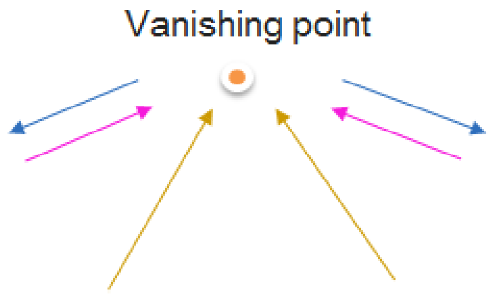


Figure 2: Directional classification diagram. The yellow lines represent the land marking. The blue lines illustrate the objects (vehicles) approaching from the sides. The pink lines illustrate the objects (vehicles) moving further away.

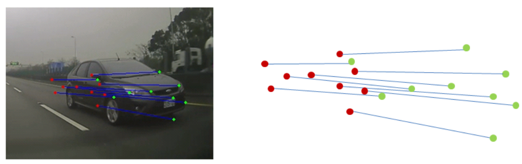
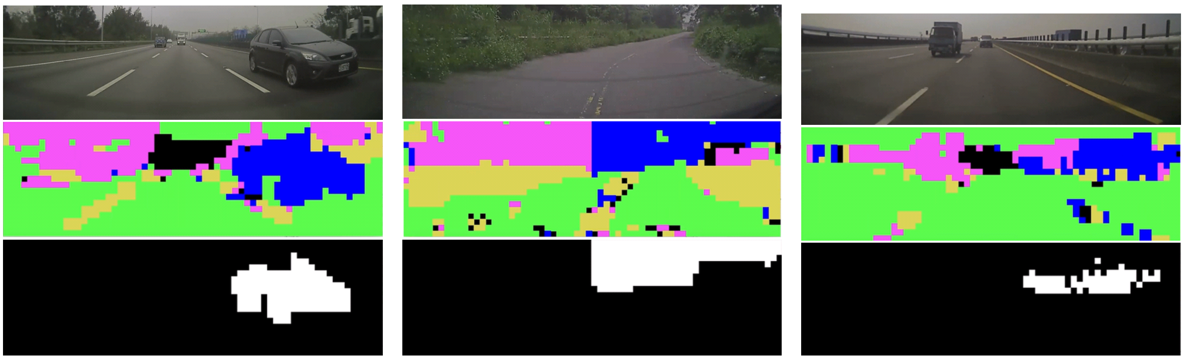


Figure 3: The optical flow in the x-direction.

When a vehicle is moving forward, there will be a large amount of optical flow around the vehicle. However, the road and sky are relatively smooth, and the optical flow is small. Therefore, if the optical flow of a feature point is very small, we can assign the point to the road and sky region. If the optical flow in the y-direction is very large and moves to the vanishing point, then the point is assigned to the land marking. The points are considered as the overtaking vehicle if the optical flow in the x-direction is large and moves far away from the vanishing point. Otherwise, if the optical flow in the x-direction is large and moves towards the vanishing point, it indicates that some object is moving further away. These conditions are illustrated in Figure 2. We use the uncertain region to conclude the situations not in one of the above criteria.

Here we only use the x-direction of the optical flow to distinguish the overtaking vehicle from the object moving further away, and discard the y-direction of the optical flow. The main reason is that the y-direction of the optical flow in two adjacent frames is very small, and the approaching vehicle will be deformed (see Figure3). Thus, it is difficult to use the y-direction of optical flow to distinguish the direction of the object motion.

Overtaking vehicles are continually approaching,



(a) (b) (c)

Figure 4: The accumulation of tracked points and image segmentation used to detect the approaching vehicles.

so the space correlation between two vehicles is used to filter out the noise. We accumulate every tracking point of the approaching object to a grayscale image and binarize it. Then, a 10×10 mask is used to dilate each tracking point, to make a connection between the points, and filter out the small connection areas. An illustration of these rules is shown in Figure 4(a). The top is the original image, the middle is the result of a single frame, and the bottom is the binarized result from multiple frames.

When the vehicle makes turns or there are repetitive patterns in the image, the segmentation results might not be correct, as illustrated in Figures 4(b) and 4(c) respectively. In the urban area, there are a variety of curved roads. This makes the vehicle move in a more complicated way, so the optical flow of the rear objects and background will be away from the vanishing point. Another common problem is the repetitive patterns in the images. When a vehicle is in fast motion, another image point close to the original image point might be identified as the original image point. With this continuous appearance, a repetitive pattern will be generated and false targets will be tracked by the optical flow algorithm. Since the repetitive patterns usually appear for a period of time in the same image region, it is difficult to filter out the wrong features using the spatio-temporal correlation of the image pixels. Figure 5 shows some repetitive patterns commonly seen in Taiwan's highway and local road. To deal with this problem, we use the convolutional neural network to identify the segmented area and remove the non-vehicle objects to avoid the false segmentation to produce false positives.

3.2 Convolutional Neural Network

The convolutional neural network architecture used in this work is CaffeNet (BLVC, 2017). It is a replication of the model described in the AlexNet publication (Krizhevsky et al., 2012) but with some differences. This network was originally designed to classify 1000 different categories of objects in the ImageNet database. We performed fine-tuning using our data in BVLC CaffeNet model and changed the output to 6 categories. It contains the front of the car, the rear of the car, the motorcycle, repetitive patterns, background and lane marks. Some of the images are shown in Figure 6. The images are segmented by the algorithm described in Section 3.1. The deep learning framework, Caffe (Jia et al., 2014), is used to train and evaluate the neural network. We added CaffeNet to our system to identify the segmented area and remove the non-vehicle objects.

Figure 5: Common repetitive patterns in Taiwan.

3.3 Repetitive Pattern Removal

In some situations, wrong segmentation, especially when the algorithm is confused with a vehicle on the opposite lane. As a result, the segmentation and CNN identification are erroneous at the same time. This kind of error is due to the feature points of the optical flow tracking on the repetitive patterns, but CNN recognizes the vehicle in the opposite lane. One such example is shown in Figure 7. To solve this problem, we consider the case that a moving vehicle is in the opposite lane and the repeated pattern occurs due to the separation poles. As shown in Figure 8, they make the optical flow disorder, resulting in forward and backward optical flow inconsistency.

Figure 6: Some sample images in the training data used in this work.

Figure 7: The use of segmentation and CNN at the same time can still be erroneous for repetitive patterns.

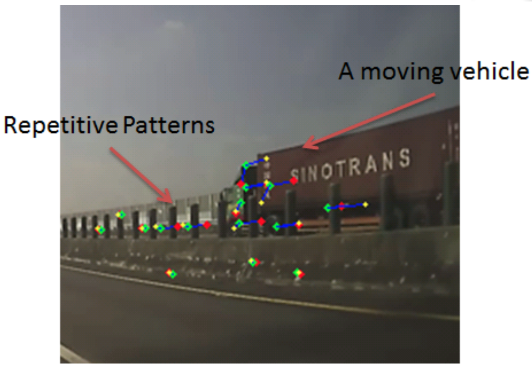


Figure 8: An illustration of messy optical flow when repetitive patterns occur.

We use multiple feature points to determine whether the segmented region contains repetitive patterns. First, “good features to track” is used to detect the feature point $P(t)$ on the frame at time t (Shi and Tomasi, 1994). Then, its succeeding $P(t+1)$ is found by referring to the forward optical flow $f_t^+ = (u^+, v^+)$ from the frame at t to the frame at $t+1$. That is,

$$P(t+1) = P(t) + f_t^+(P(t))$$

Similarly, generated from the backward tracking, the point $P'(t)$ is related by the backward motion,

$$P'(t) = P'(t+1) + f_{t+1}^-(P'(t+1))$$

where $f(t+1)^- = (u^-, v^-)_(t+1)$ is the backward optical flow from the frame at $t+1$ to the frame at t.

Ideally, if the feature point $P(t)$ does not belong to a repetitive pattern and the optical flow is correctly estimated, then we have

$$P(t) - P'(t) = 0$$

However, from our experience, there are some errors in the real situations, i.e.,

$$P(t) - P'(t) \leq \varepsilon$$

where ε is the error between $P(t)$ and $P'(t)$, and is very small. If most of the feature points on the target are within ε, we will classify this object as a vehicle. Otherwise, it is classified as a repetitive pattern and thus eliminated.

3.4 Tracking and Behavior Detection

After the segmentation using CNN and the repetitive pattern removal, we track the object rather until it disappeared in the image or no overtaking. Continue the previous step of “repetitive pattern removal” and the detection of feature points, we use Lucas-Kanade optical flow for continuously tracking in order to

- detect the movement of objects for a period of time,

Figure 9: An example result of the overtaking vehicle detection and tracking.

- overcome the shape, size and scale of the object changes as it approaches the camera,
- get the operation speed quickly,
- have a more complete trajectory which can be provided at the edge or part of the field.

A tracking result is shown in Figure9.

We expect that CNN is able to identify and remove the repetitive patterns, and have the correct overtaking detection. However, the camera resolution is too low, and the image segmentation is not good enough for identification due to some errors. To further reduce the false detection, we assess whether the direction of tracking has continued to stay away from the vanishing point for a period of time to help us effectively remove the wrong detection.

3.5 Night Time

In general, the appearance of the vehicle at night cannot be clearly obtained from the camera because the brightness of the image is too low. The camera usually captures the information of the headlights. If only the brightness is used to grab the headlights, it can be easily disturbed by other background lights. Furthermore, the headlights of the vehicles in the sides do not have the symmetry property, which makes the overtaking detection at night a difficult issue.

We present a method that uses motion cues to combine the brightness information to capture the overtaking vehicles. The steps of overtaking detection at night includes: (1) pre-processing and segmentation, (2) brightness recognition, (3) tracking, and (4) behavior detection. First, we use ROIs to remove the image regions which are not important. Second, the headlight areas are segmented when they approach the vehicle by the algorithm described in Section 3.1. Figure 10 shows a typical result. Third, the low brightness areas are removed by binarization. Finally, we track the brightness region and analyze its behavior by the method given in Section 3.4. If it continues to keep away from the vanishing point, it is considered as the headlights of an overtaking vehicle.

4 IMPLEMENTATION AND EXPERIMENTAL RESULTS

To evaluate the performance of our overtaking detection method in the real world scenarios, we use a dashcam to capture the dynamic images. Our dashcam is installed in the rear of the vehicle at about 1 meter about ground. The original image size is 1200×800, and the sub-image region for process is 600×200. We test our algorithms on a PC with ubuntu 16.04 operating system, 4.0 GHz Intel CPU, and ASUS GTX 1080 GPU. The execution time is divided into three parts tabulated in Table 1.

There are totally 7,587 images collected in our training data. The image sequences are segmented using the algorithm described in Section 3.1 and marked manually for each image. Similarly, the validation data of 2,770 images are collected from 80-minute video sequence and marked manually. The recognition results for each category are tabulated in Table 2. In our vehicle recognition module, it does not matter if overtaking is identified or not since a subsequent tracking stage will be performed. However, a serious false alarm will occur if the background is recognized as overtaking. This usually happens when making turns with a vehicle in the background as shown in Figure 11.

It is not easy to evaluate the accuracy and efficiency of the real image sequence at the present time. In particular, the algorithms for detecting vehicles by motion cues do not have good benchmarks for performance evaluation. There are totally 50 image sequences collected in our database. It contains 20 highway image sequences, 15 city image sequences and 15 night image sequences. Each image sequence is about two minutes. If we detect the vehicle before it is disappeared in the image sequence, the overtaking detection is successful. Otherwise, it is called missed. It is considered as failed if the approaching vehicle is not detected. The evaluation is tabulated in Table 3 and some result images are shown in Figure 12.

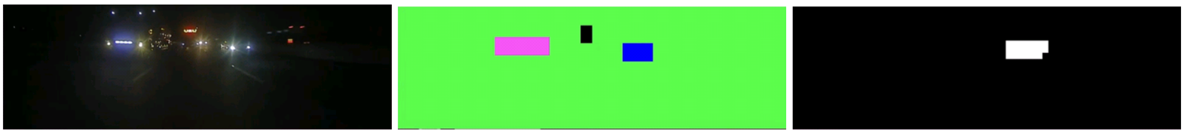


Figure 10: Overtaking vehicle detection and tracking at night using the headlights.

Table 1: The execution time for individual stages of the algorithm.

	Segmentation	CNN	Repetitive Patterns Removal	Entire Time
time	6ms	3ms	1ms	6-10ms

Table 2: The recognition results for each category and the recall.

	Background	Lane mark	Locomotive	Repetitive pattern	Front of vehicle	Back of vehicle
Groundtruth	375	252	545	408	480	710
Background	322	1	2	0	1	11
Land mark	2	249	0	2	0	0
Locomotive	0	0	524	1	0	0
Repetitive pattern	25	2	0	405	0	3
Front of vehicle	13	0	16	0	470	34
Rear of vehicle	13	0	3	0	9	662
Recall	0.858	0.988	0.961	0.992	0.979	0.932

Table 3: The experimental results and performance evaluation.

Scene	True overtakes	Detected	Missed	False
City	102	102	0	13
Highway	79	79	0	1
At night	42	37	5	4

Figure 11: The false alarm might happen if the vehicle makes turns with another behind.

Figure 12: Some overtaking vehicle detection results. High traffic, local traffic and night are shown in the top, middle, and bottom, respectively.

5 CONCLUSIONS

This paper presents a real-time system to detect overtaking and assist in driving lane change based on visual cues from a dashcam . We use the motion cues and combine with CNN to detect the vehicle appearance. Compared to the low-order features and weak classifier it is faster and more robust. It is more suited for light and complex environments. In addition to improving the limitation and shortcomings of the existing methods, the proposed technique can maintain the operational efficiency and provide more complete overtaking information. The performance evaluation has demonstrated the effectiveness of the proposed techniques.

ACKNOWLEDGMENTS

The support of this work in part by Create Electronic Optical Co., LTD, Taiwan and the Ministry of Science and Technology of Taiwan under Grant MOST 104-2221-E-194- 058-MY2, is gratefully acknowledged.

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