Front Collision Warning based on Vehicle Detection using CNN

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Abstract— **Front Collision Warning(FCW) is a critical safety function [illegible] Advanced Driver Assistance System(ADAS). Recently, many researches related to FCW systems which use monocular camera image processing have been introduced. In this paper, we propose an FCW system for highway environment based on vehicle detection using Convolutional Neural Network(CNN) as a classifier. Adaptive Region-of-Interest(ROI) is set using lane detection to enhance speed and detection performance of the system. We measure the distance between our vehicle and the detected vehicle in front by calculating the ratio between the lane width of the position of the detected vehicle and our vehicle, respectively. Time-to-Collision(TTC) is used as a collision warning index. For FHD(1920x1080) black-box camera images taken in highway environment, the detection rate of the proposed CNN is 99.1%, and the execution time of the system is 19.8ms per frame.**

Keywords; FCW; Vehicle Detection; CNN; Lane Detection;ADAS;

I. INTRODUCTION

As Advanced Driver Assistance System(ADAS) has emerged as a major field of interest to engineers, many researches and applications related to the area have been introduced to the public. Moreover, ADAS has become a requirement, not a recommendation to vehicle manufacturers. Euro New Car Assessment Program(NCAP) is a representative program which requires ADAS functions as a safety indicator for manufactured vehicles. Front Collision Warning(FCW) is one of the safety functions required for Euro NCAP. FCW provides the user a visual or voice warning when collision with the vehicle in front is expected. For most FCW systems, Time-to-Collision(TTC) is used as a collision warning index[1].

The FCW system is usually composed of two stages; the vehicle detection stage and distance measuring stage. In the vehicle detection stage, Hypothesis Generation(HG) is performed to find candidates for cars, and Hypothesis Verification(HV) to verify the candidate, respectively[2]. To calculate TTC, we measure the distance between the detected vehicle in front of the user's current lane[3]. Warning signals are provided to the user based on TTC result.

Many previous researches have been made related to on-road vehicle detection. Most of the early works used a combination of feature extraction and machine learning. The various combinations of the two are well organized in [4]. For recent works, Convolutional Neural Network(CNN)s are being applied to vehicle detection systems[5]. Compared to its predecessors, CNN-based vehicle detection doesn't require a feature extracting phase since the network itself learns its own features.

In this paper, we propose an FCW system with FHD black-box images taken in highway environment. CNN is used for vehicle detection, and CalTech rear-viewed vehicle database (1999) is used to evaluate the detection rate of the CNN algorithm. An adaptive Region-of-Interest(ROI) setting stage using lane detection is added before the vehicle detection stage to enhance speed and detection performance of the system. TTC is calculated using the distance measured by the method proposed in [6] to provide warnings.

II. FCW ALGORITHM

A. Algorithm Flow

The entire algorithm flow for the FCW is shown in Fig. 1.

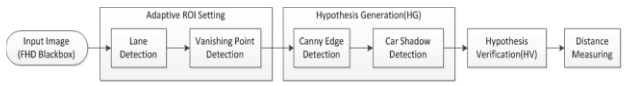


Figure 1. Algorithm flow

Adaptive ROI setting is performed by detecting the lane the driver is currently in, and the Vanishing Point(VP) of the image is determined using the two lanes. After the ROI is set, we use Canny edge detection and car shadow detection for HG. HV is performed using a pre-trained CNN. Distance measuring and collision warning is performed using the verification result and the detected lanes.

B. Adaptive ROI Setting

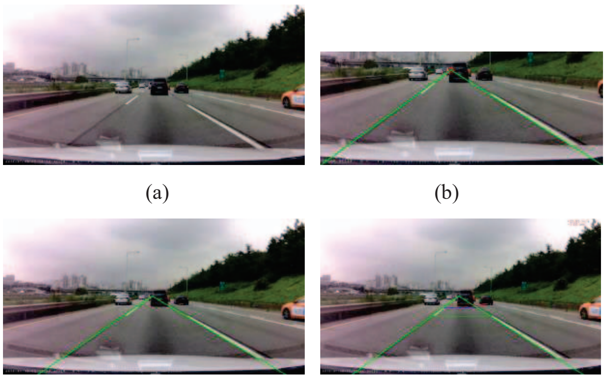
This stage is performed for three reasons; to reduce computation time, to eliminate hypothesizes outside the current lane, and to detect VP using lanes. Lane detection is performed using line Hough transform, and the VP of the image is set as the intersection point of the two lanes. Fig. 2 (b) shows the result of this stage. Since FCW systems only require cars in front of the current driving lane, we can reduce the number of candidates

C. Hypothesis Generation / Hypothesis Verification

We find car-like candidates by using edge figures and car shadows. Since we restrict the scanning area in the previous stage, the number of HGs is fewer than 5 in most highway cases. We verify the extracted candidates using a CNN similar to Lenet[7]. Fig. 2(c) shows the verification result of the provided input image.

D. Distance Measuring / Warning

In order to measure the distance between the user's vehicle and the vehicle in front, we use the "width-ratio" model proposed in [3]. With the measured result, TTC is calculated every 0.5 seconds to provide the user visual warning signals when collision is expected 3 seconds later[1].



(a) (b) (c) (d)

Figure 2. FCWS. (a) Input image, (b) Adaptive ROI result, (c) Verification result, (d) Full system result

III. RESULTS AND DISCUSSION

The proposed system provides the user the position of the vehicle in front, the distance between the vehicles, and collision warning based on TTC. We checked the vehicle detection rate of the CNN in order to verify the system. 2,128 vehicle rear samples were collected from Korean highways and [8], and 5,130 non-vehicle samples were collected from [9] and slices of Korean highway roads, respectively. The training time of the CNN was 1200 seconds. For general vehicle detection cases, we used the CalTech 99 rear-viewed vehicle dataset which is composed of 126 samples, and achieved 100% detection rate. For actual FCW environment, we counted the number of true positive and false positive results for 3140 frames. We achieved a 99.36%(3120 true positive results) precision rate for daytime highway environment images. Table 1 shows the detection rate values for our CNN and other vehicle detection methods compared in [2].

Due to the lack of additional sensors such as LIDAR or RADAR, we couldn't check the distance error of our system's result and the ground truth distance. Instead, we assumed that the result of [6] is accurate up to 30 meters. For collision warning, the TTC of people in general researched in [1], which varies from 1.1 seconds to 1.8 seconds, is used. Our system provides warning for cases when TTC is less than 3 seconds. The 1 second redundancy is given since the proposed system isn't an Automatic Emergency Braking(AEB) system, but a user-aiding warning system. The execution time for the proposed system was 19.8ms per frame in Intel i5 3.4GHZ CPU environment. The basic outline of the entire system is shown in Fig. 2(d).

TABLE I. TRUE POSITIVE RATE FOR CALTECH DATASET

Methods	True Positive Rate
PCA + SVM	86.59%
Gabor + SVM	90.24%
Wavelet + SVM	90.24%
Wavelet + Gabor + SVM	91.06%
Haar-like + Cascaded AdaBoost	92.38%
Haar-like + AdaBoost	92.89%
Haar-like + AdaBoost + SVM	94.41%
Proposed System	100%

IV. CONCLUSION

In this paper, we developed an FCW system using CNN for vehicle detection. We added an adaptive ROI setting stage to reduce execution time and eliminate redundant vehicle-like candidates. A Lenet-like CNN is used for vehicle detection. We achieved a 100% detection rate for the CalTech 99 dataset and 99.36% for actual daytime highway environment test images, respectively. The system can measure distance up to 30 meters from the user vehicle, and sends out warning signals when TTC is below 3 seconds. The execution time of the system, which is 19.8ms, indicates that the system can be executed in real-time in PC environment.

ACKNOWLEDGMENT

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