On-Board Driver Assistance System for Lane Departure Warning and Vehicle Detection

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***Abstract*—Computer vision and image processing based intelligent transportation systems have become very popular for the last decade. Vehicle manufacturers and automotive industry are interested in vision-based systems. This kind of systems could warn drivers and prevent accidents caused by inattentive driving. This paper introduces a single-board computer system for lane departure warning and vehicle detection. Our system employs the lane departure warning system based on geometrical cues which is implemented widely in the literature. For vehicle detection, we propose a cascade object detector trained by using car rear images. Our main contribution is to implement our system on an embedded single board computer which runs in real time. This system can be mounted into the car with a camera and can be used in practice.**

***Index Terms*—image processing, computer vision, automotive application, single-board computer**

I. Introduction

The inattentive driving especially in long-distance journeys might result in traffic accidents and cause dramatic results such as loss of life and property. These accidents are mainly occurred during the lane departure. In this study, a driver assistance system (DAS) is proposed to minimize occurrence of these accidents. One component of the system called Lane Departure Warning (LDW) is responsible for detecting involuntary lane departures by monitoring the lane lines. This component gives audio alerts on detection of abnormal lane departures. Hence, the control of the vehicle can be provided and the probable accidents can be avoided. Another component of the driver assistance system is the detection of other vehicles along the route. With the information obtained from the camera image, approaching the front vehicle at a certain speed would result in an accident. So, the driver can be alerted and the speed of the vehicle can be reduced if necessary.

The proposed method runs on a single-board computer system which can be easily mounted into a vehicle with a USB web camera. DAS is implemented in MATLAB Computer Vision Toolbox [1]. A straight-forward approach is used to solve lane departure problem. Then a cascade object detector is used for vehicle detection and front car warning. In this research, 300 minutes video recording is used in order to train the cascade object detector. All components of the system are combined for alerting the driver audibly to the possibility of involuntary lane departure and traffic collision. System implementation is embedded into the single-board computer called PandaBoard ES [2]. Camera is mounted on to the rear view mirror, facing towards the road.

The aim of this study is to apply computer vision methods to solve the fundamental problems for developing a DAS which can be used in vehicles on road.

The outline of the paper is as follows. Section II presents the related work in this field. Section III introduces our system, and the dataset used in our experiments. Furthermore, it gives the details of the system components. Section IV discusses our results. Section V concludes all study.

II. Related Work

One of the most important components of the driver assistance system is the lane departure warning subsystem. The Lane departure warning systems mainly consist of four basic steps: image acquisition, image pre-processing, lane detection and lane departure detection. Image acquisition is related with the hardware the system used. Image pre-processing prepares images for line detection by using various approaches and some morphological operations. After image pre-processing, the lines are detected using well-known algorithms. Finally, vehicle position with respect to the lane position is calculated and the lane departure is detected.

The new generation cameras with their smaller size and reasonable prices provide high quality images at embedded systems nowadays. High quality images can capture the details better. However, this issue increases the cost of processing the images. Therefore, some pre-processing of images should be carried out. Different color channels which include the details of images could also affect the processing time, so we should consider these channels in the pre-processing step. Obtaining the gray intensity images by stirring the various proportions of 3-channel image format RGB can be given as an example [3], [4]. In our approach, we use the samples by just cutting the middle part of the images to use the processing power effectively [5].

The pre-processing step prior to the detection of lines needs to be handled carefully. This step should take into account the time of day and without the environmental factors (rain, snow, etc.). However many studies in the

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literature are performed at very limited circumstances (only at night or open air) [6].

Figure 1. Images taken from the camera.

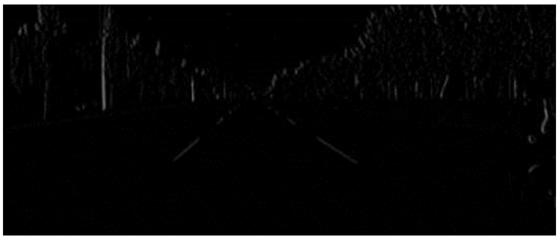


Figure 2. The Filtered image applied on Fig. 1

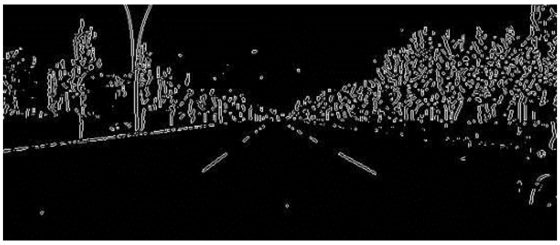


Figure 3. The Sobel edge detector applied on Fig. 2

Figure 4. The lines found after the Hough transformation applied on Fig. 3

Fig. 1 shows an image captured from the camera. Some filters are applied on this figure, and the filtered image is obtained given in Fig. 2. Some approaches that use steerable filters or local filters by sliding windows are proposed in the literature. These filters should be preferred rather than the filters work on the image itself in order to clear the processing image from different structures [6], [7].

Line detection is usually performed on pre-processed image by applying edge detection algorithms or spline fitting approaches. Perspective conversions also will be applied to obtain bird's-eye view. Edge detection approaches are mainly Sobel edge detector (Fig. 3), Canny edge detector and LoG edge detector [4]. Hough transforms (Fig. 4) or RANSAC [5], [7], [8] are mainly used for lines fitting on the edge after the edge detection step. In the road bends or turns, spline fitting approaches will follow the edge detection step [8], [9], [10].

Methods which use perspective conversion are bird's-eye view, inverse perspective mapping and warp perspective mapping. Some of these methods are dependent on the camera parameters, but some of them are independent [5]. They decrease the line detection cost of the system, however it increases the perspective calculation cost.

The lane departure detection can be performed with geometrical calculations with respect to the detected lanes. The directions of vehicles direction can be estimated by using a reference line, the distance between detected left/right lane lines. Then, the departure warning can be triggered based on this estimation.

There are many studies about on-road vehicle detection systems. A detailed review [11] on these studies is given by Sun et al. They analyze hypothesis generation (HG) and hypothesis verification (HV) steps. The main objective of HG methods is to find the vehicle position quickly.

HG approaches can be classified into three categories: knowledge based, stereo-based and motion-based. In the knowledge based methods, the representative features of vehicles such as symmetry, color, shadow, geometrical properties, texture, and vehicle lights are used. The stereo-based approaches mainly use transformation and mapping techniques with the calibrated camera images. The aim of the motion-based methods is to separate vehicles and background from each other. Optical flow is used heavily in motion-based systems and it is very useful for detecting vehicles in opposite lane.

The input of the HV step is the candidate location found in the HG step. Main approaches can be classified into two groups: template-based and appearance-based. In template-based methods, the predefined patterns of vehicles are used, and then the correlation is applied. However the system learns the characteristics of vehicles from a training set, and a classifier is employed for detecting the region as a vehicle in the appearance-based methods.

III. Driver Assistance System

A. Hardware

The DAS used in the vehicle consists of following components: single-board computer, USB webcam, speaker and cabling between components and for power supply. Pandaboard ES [2], single-board computer used in our system, is shown in Fig. 5. Although there are several similar devices such as Beagleboard®, Hackberry®, Raspberry® and the like in the industry, we prefer to use this single board computer because it is small enough to mount in a vehicle (for example into glove compartment) and powerful comparing to other boards. It has dual-core ARM cortex at 1.2 Ghz each, 1 GB RAM, USB and audio ports used for input and output to the system. The operating system (Ubuntu®, Linux®), which runs on the board, boots from a microSD card.

In this study, a Standard USB webcam (Logitech® Webcam C270) supports 320x240 pixel resolution is used for real-time image acquisition. It is easy to setup on board and it has sufficient frame rates and resolutions. Speakers are also mounted into the vehicle for alerting the drivers on the detection of the involuntary lane departure and the possibility of traffic collision.

Figure 5. Pandaboard ES [2]

B. Dataset

Training and testing are carried out by using a dataset including approximately 300 minute video recording. It was recorded in the roads in Turkey during the daytime. In order to test the lane departure warning system, highways are used due to the clarity of the road lanes.

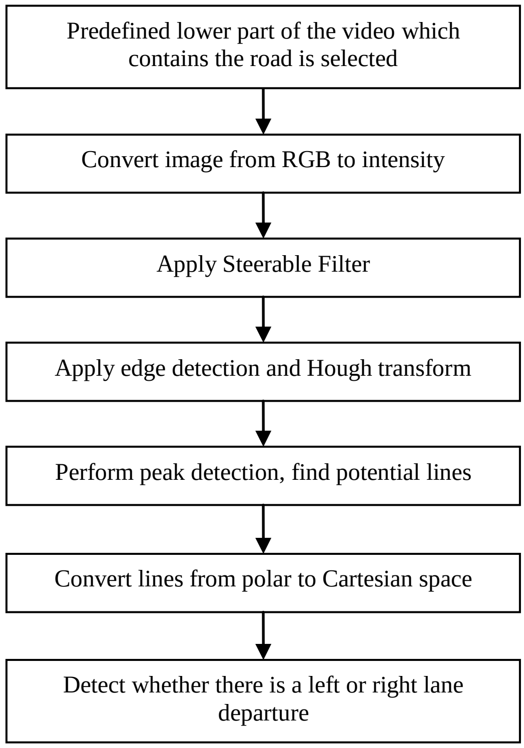
Training the cascade object detector is accomplished by using the scenes in the city traffic which have many vehicles. The rear images of vehicles are cropped and 510 rear images are obtained. Some sample images from our dataset are shown in Fig. 6. A 40 minute video recording is used for testing object classifier.

Figure 6. Rear image dataset samples

C. Lane Departure Warning

In our system, well-known approaches used for LDW implementation with some modifications and optimizations. We prefer to use this methods because processing in real-time is very important for such systems. Also it is easy to install the codes on to the target hardware. It also works fine on our highway video recordings.

System detects and tracks road lanes in video frames. It detects unintended lane departure and gives a warning. Briefly systems detects lane lines in the current frame. Then match the current lanes with previously detected ones. After that algorithm finds left and right lanes (shown in Fig. 7). Finally warning message appears if vehicle moves across either of the lane. Details of the algorithm will be explained below:



Common sub steps that is used in lane detection by many related studies [3], [4], [5] are used in our method. Hough transform is a generalized method in line detection thus, we applied this method to detect highway lines. Additionally we applied steerable filtering [12] to enhance input image and making edge details clear. In the first step of lane detection, RGB frames are converted into grayscale images by taking the mean of 3 channel. Then edge detection is applied on preprocessed frame. Preprocessing step includes steerable filtering which sharpens the edges in the image. To find lines in edge map Hough transform [13] is applied. The lines that have a theta and rho values greater than a predefined threshold are selected locally. The first line that has a theta value greater than 80 degree is selected as right lane and the line that has a theta value smaller than -80 degree is selected as left lane. After points are selected in Hough transform, Cartesian coordinates of these point are calculated and drawn on frame.

In our work, algorithm is modified for real-time on-board usage with low memory usage. Video input is live USB webcam capture instead of video source file. Image resolution is reduced to 320x240 pixels for speeding up the processing frame rate. Road lane types like broken or solid is ignored.

As mentioned above, step forward toward board implementation of such systems in vehicles is used. Because implemented system is simple and fast enough to use in a low powered board system.

Figure 7. Lane Detection

D. Vehicle Detection and Tracking

Vehicle detection component of our study uses appearance based method which is trained by our rear car image dataset. Object categories whose aspect ratio does not change significantly can be detected by cascade object detector. Vehicle seen from one side is a good example for that type of object. After detection step, detected vehicles are tracked with Kalman Filter [14]. Once vehicle is detected, its locations is predicted with Kalman Filter. For each frame cascade detector is applied and a new tracker is created for new detected non-tracked vehicles.

Vehicle detector consist of two steps: learning and detecting. Learning part contains cascade classifier in other words. Cascade classifier composed of many stages where each stage is an ensemble weak learner. Each stage is trained using boosting. Boosting provides the ability to train a highly accurate classifier by taking a weighted average of the decisions made by the weak learners.

Feature types experimented in training stages are Haar features [15], Local Binary Patterns [16] and Histogram of Oriented Gradients [17]. Detection performance of Haar and LBP features are under 60% which is a lower rate compared to HOG features. Also their false positive error is higher than HOG features that cause system to give wrong alerts. For this reason HOG features are used for training object detector.

Cascade object detector detects vehicles in images by sliding a window over image. The detector then uses a cascade classifier which is trained using dataset to decide whether the window contains the object of interest. The size of the window varies to detect objects at different scales, but its aspect ratio remains fixed. The detector is very sensitive to out-of-plane rotation, because the aspect ratio changes for most 3-D objects.

Detected vehicle is represented by a bounding box (shown in Fig. 8). Size of the bounding box determines the distance to the front vehicle. In experiments, if area of the bounding box is 1/9 of the scene area, front vehicle is dangerously close to our vehicle. In this situation warning signal is produced.

Figure 8. Detected vehicles using cascade object detector.

E. Implementation

All of the system components are implemented in MATLAB [1]. Implementation is installed on the Pandaboard hardware with target installer. This process converts MATLAB to C code which is suitable for ARM processor architecture.

Input of the system is webcam mounted in a vehicle, so system is modified with live capture. Output of the system is driver warning with sound in case of lane departure and near vehicle detection. So all of the image drawings used in lane departure and vehicle detection are discarded while installing on board because these stages increases the cost of the system. These drawings are only used in debugging and testing on PC.

IV. Experimental Results

The implemented system was tested on video images recorded by authors in a vehicle. 320x240 pixels resolution was used in video recordings. The vehicle was moving with a speed between 30 and 90 km per hour. Lane departure warning system detects lanes with 90% success in Turkish highways. Changing lighting condition and occlusion of lanes by other vehicles affects the lane detection performance.

Vehicle detection system detects vehicles with 85% accuracy. Some objects in the road also detected as false positive which has a rate 9%. That would be the main obstacle toward commercial success of such systems. Incorrectly detected objects along the road are not vehicles but they are also dangerous objects to crash while driving your car.

Processing time of a frame is approximately 0.1 seconds on the single-board computer. Hence the system process nearly 10 frames in a second. This processing time is enough to alert the driver on lane departure and vehicle detection when the speed of the car is averagely 70 km per hour.

V. Conclusion

This paper presents an implementation of well-known methods for lane departure warning and vehicle detection in a combination with driver assistance system. The main contribution of this study is to embed the system into a single-board computer system, so it can be used in real life.

In the future work, the other embedded boards which are dedicated to image processing can be used for more specific and industrial solutions. Another likely development is to make our system work on various weather and light conditions (such as rainy, snowy, cloudy weathers, and nights). Different types of cameras such as night vision cameras, infrared cameras or depth sensors can be used in these conditions.

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