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Oncoming Vehicle Detection with Variable-Focus Liquid Lens

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Abstract: Computer vision plays an important role in autonomous vehicle, robotics and manufacturing fields. Depth perception in computer vision requires stereo vision, or fuse together a single camera with other depth sensors such as radar and Lidar. Depth from focus using adjustable lens has not been applied in autonomous vehicle. The goal of this paper is to investigate the application of depth from focus for oncoming vehicle detection. Liquid lens is used to adjust optical power while acquiring images with the camera. The distance of the oncoming vehicle can be estimated by measuring the oncoming vehicle's sharpness in the images with known lens settings. The results show the system detecting oncoming vehicle at ±2 meter and ±4 meter using depth from focus technique. Estimation of oncoming vehicles above 4 meter can be done by analysing the relative size of the vehicle detected.

Keywords: monocular vision, liquid lens, depth from focus, oncoming vehicle detection

1. Introduction

The main depth sensors used for on-road vehicle detection are radar, light detection and ranging (Lidar), and stereo camera. Radar and Lidar are both active sensor, where the sensor emit out self-generated energy and receiving back the reflected signal. The sensor determines the object distance by analysing the reflected signal. Radar uses radio waves to measure radial distance and velocity of oncoming vehicles [1], [2]. Long range radar has long sensing distance of up to 250 meter but a narrow field of view of 15 degrees, while smaller range radar has shorter sensing distance but wider field of field. Radar is able to work reliably in most weather and lighting condition. On the other hand, Lidar measure vehicle distance by illuminating the surrounding with pulsed laser light [3]-[5]. With smaller wavelength, Lidar has shorter distance of 50 meter but wider field of view. Compared to radar, Lidar is much susceptible to weather and lighting. However, it is able to sense with higher accuracy and resolution.

Unlike radar and Lidar, camera is a passive sensor which does not require to emit out any signal. Stereo vision extract depth information from two images acquired with two cameras simultaneously. Stereo vision has been used for on-road object detection [6]. In monocular vision, position and distance of vehicles and objects can only be estimated by analysing the object's image size, pixel position and other monocular cues.

Human's monocular vision not only can perceive depth from monocular cues such as occlusions, relative size, aerial perspective, motion perspective and others, but also through accommodation [7]. Accommodation let human sees depth for distances less than 2 meters. This happens when the eye changes optical power of its lens to produce clear image. This paper investigates the application of depth from focus in oncoming vehicle detection. This is done using liquid lens technology [8] to adjust the optical power of the lens.

Extracting depth information from images acquired while varying lens focus or optical power can be done using depth from focus (DFF) [9] or depth from defocus (DFD) [10]. DFF estimates depth from sequences of images of the same scene at different lens settings. Focus measure (FM) operator is used to measure the focus level for every image pixel. On the other hand, DFD uses at least one image to recover the depth image. Our work here make use of the focus measure operator used in DFF to measure the sharpness of an object in the image. The focus measure operator used here is the sum of modified Laplacian (SML) [11].

2. Experiment Setup and Framework

Webcam CCD sensor and liquid lens are assembled together with a flange distance, shown in Fig. 1. The liquid lens is Varioptic's Caspian C-39N0-16 with a C mount, with a flange distance of 17.526 mm. All the parts are connected as shown in Fig. 2. The laptop will communicate with the liquid lens controller to adjust the lens voltage. The webcam will send the acquired video

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images to the laptop. The final assembled camera is shown in Fig. 3.

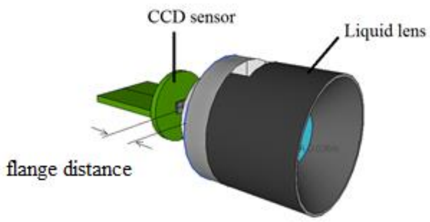


Fig. 1 Webcam CCD sensor and liquid lens assembly

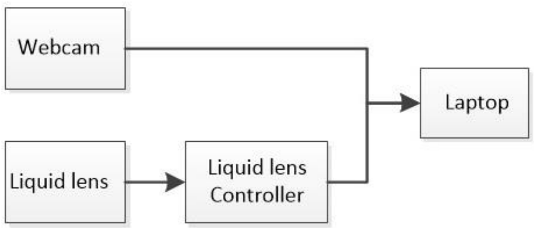


Fig. 2 Parts connection

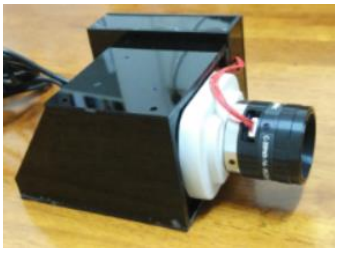


Fig. 3 Assembled camera

The camera is mounted inside the vehicle, looking forward to detect oncoming vehicle. The vehicle is driven towards the oncoming vehicle from distance of 50 meter to 1 meter. Fig. 4 shows the framework for estimating the oncoming vehicle distance at far range and short range. At initial stage, the system will detect and recognize oncoming vehicle. Objects in the image is detected by analysing the detected horizontal lines, and from semantic segmentation using a fully convolutional network (FCN) [12]. Each of the possible objects detected will then be recognized using a deep convolutional neural network called GoogLeNet (R-CNN) [13]. Once oncoming vehicle is detected, its distance will be estimated. For oncoming vehicle with distance of above 4 meter, the position of the vehicle is estimated by processing the vehicle's size and pixel position in the image acquired. For distance of 4 meter and below, the liquid lens is activated to extract the depth information by varying the lens' optical power. The detected vehicle will be tracked using Kalman filter.

For a detected oncoming vehicle, the average SML at the edge location is computed to measure the sharpness of the vehicle image. The edge location is detected using the Sobel edge [14]. The modified Laplacian for a window at pixel is computed as:

$$ML(x,y) = |2I(x,y) - I(x - step, y) - I(x + step, y)| + |2I(x,y) - I(x, y - step) - I(x, y + step)| \quad (1)$$

where I(x,y) is the grayscale image at the pixel (x,y). The *step* is the variable spacing according to the Laplacian operator. The focus measure is the sum of the modified Laplacian of each of the window:

$$SML(i,j) = \sum_{x=i-N}^{i+N} \sum_{y=j-N}^{j+N} ML(x,y) \quad (2)$$

where N = 1 for window size of 3×3. The system will continuously vary the liquid lens' optical power accordingly at each frame to search for the highest average focus measure.

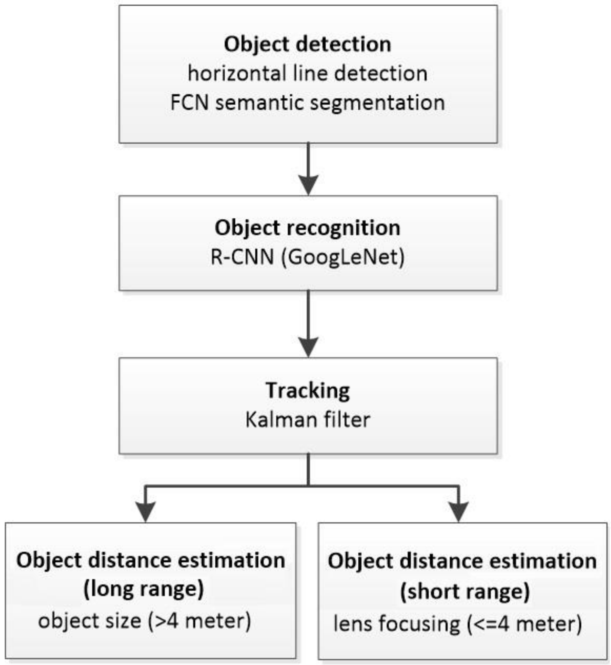
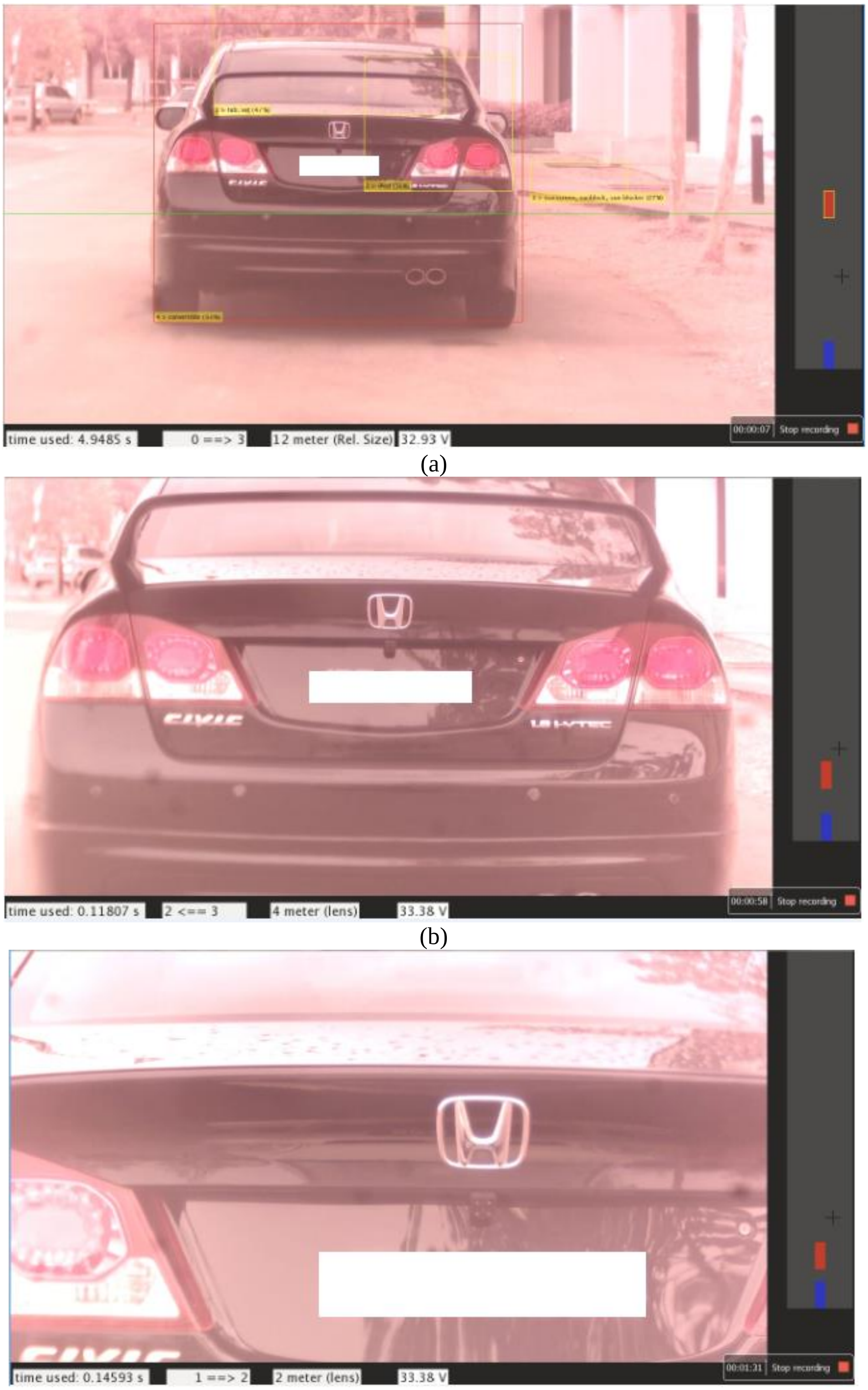


Fig. 4 Framework for oncoming vehicle detection with variable-focus liquid lens.

3. Results and Discussion

Fig. 5(a) shows the results of detection and recognition of an oncoming vehicle. The distance of the vehicle is estimated by analysing the position and size of the vehicle in the image. When the vehicle comes closer and reach ±4 meter zone, the liquid lens is activated to focus on the vehicle to sense the distance of the vehicle. Fig. 5(b) and (c) shows the oncoming vehicle is detected by the liquid lens at ±4 meter and ±2 meter respectively.

Our framework is implemented in MATLAB on an Intel i5-3360M 2.8 GHz CPU with 4 GB memory. Image resolution of 1280×720. Computation time for vehicle detection and recognition is around 5 second per frame. While focus measure algorithm uses around 0.15 second per frame. At least 3 frames are required to determine the distance of the detected vehicle.



(a)

(b)

(c)

Fig. 5 (a) Vehicle detected and recognized at estimated distance of 12 meter. (b) vehicle detected at distance of 4 meter. (c) vehicle detected at distance of 2 meter.

During the image acquisition, the intensity of each image sequences varies and cause the focus measure at each frame to be different even when the vehicle is static. This pose a problem when sensing object at longer distance as the room for such deviation becomes smaller. This is due to the reciprocal nature of the lens.

4. Summary

In this paper, the framework for oncoming vehicle detection with variable-focus liquid lens has been presented. The use of depth from focus is able to estimate the vehicle distance correctly for short range distance. This shows that the application of variable-focus liquid lens for on-road vehicle detection is possible for short range. Long range detection can be done by analysing the relative size of detected vehicle and short range detection with depth from focus. For future work, better focus measure can be research to increase the distance sensing interval. The speed up of computation with GPU can also increase the sensing capability.

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