An Adaptive Road ROI Determination Algorithm for Lane Detection

Dajun Ding, Chanho Lee
Soongsil University
Seoul, Korea
dajun.ding@gmail.com, *chlee@soongsil.ac.kr*

Kwang-Yeob Lee
Seokyeong University
Seoul, Korea
kylee@skuniv.ac.kr

Abstract — **Road conditions can provide important information for driving safety in driving assistance system. The input images usually include unnecessary information and road conditions need to be analyzed only in a region of interest (ROI) to reduce the amount of computation. In this paper, a vision-based road ROI determination algorithm is proposed to detect the road region using the positional information of a vanishing point and line segments. The line segments are detected using Hough Transform. The road ROI can be determined automatically and adaptively in every frame. The proposed method is applied to various video images from black boxes, and is verified to be robust.**

Keyword: ROI determination; lane detection; Hough Transform; vanishing point,

I. INTRODUCTION

Driving assistance systems monitor drivers' intent, warn drivers of lane departures, or assist in vehicle guidance [1]. They are usually operated based on the video images and a region of interest (ROI) need to be determined in order to reduce the amount of computation because the images usually include unnecessary information. A region including a driver's face is used to monitor a driver's intent. Lane detection can be used to get the position and orientation of the vehicle with lane data, and a region including roads is necessary to warn a driver of lane departure. The lane data can be also used for locating other vehicles or obstacles in the path of that vehicle which can be applied to further development of the obstacle avoiding system.

Determination of the ROI is important especially in the lane detection because road environment is usually complex and the unnecessary information becomes noise. Isolating the ROI from other region before the computation can reduce the processing time and result in a good performance [2]. The assumptive fixed ROI is popular since it does not require additional computation and is simple [2-4]. However, the assumptive fixed ROI may not work if the angle of the camera is different. The ROI starts from the bottom line since the interior of a car is not included in the input image. Therefore, the assumptive fixed ROI requires an initial calibration after installation of the camera. In addition, the assumptive fixed ROI may be wrong even if the initial calibration has been performed. For example, the position or area of ROI may be changed if uphill and downhill appear in the road.

In order to solve the problem of initial calibration and changing position and area of ROI, adaptive ROI methods are investigated [5-9]. Previous adaptive ROI methods widely use vanishing points. A vanishing point is obtained by extending line segments from lane markings and finding a point that the extended line segments cross. That is, from the driver's perspective, the parallel lane markings will converge at a single point, which is referred to the vanishing point if the lane markings are extended. However, they are susceptible to environmental noises or take much time for computation.

In this paper, we propose a robust method to find the ROI for roads adaptively in the images from cameras of vehicles. The ROI is determined using the positional information of a vanishing point and line segments. The proposed method is implemented using OpenCV library and is applied to various movies which contain lots of false positive vanishing points. It is verified to be robust against the false positive vanishing points and the ROI is determined steadily.

II. ROI ELEMENTS COLLECTION

Our goal is to determine the ROI of rectangular shape in the input images by finding out the region in which the road surface is included. The main texture of the road is usually consistent. We can describe the road surface using some features instead of all pixels of the road surface. The features of the road surface consist of lane markings, paving stones, road boundaries and even other vehicles. They are transformed into collection of line segments with consistent characteristics. They are ROI elements. Line segments from the regions which do not include the road surface are noises in our work although they have the similar description to the elements of the road surface.

We turn color images into grayscale ones in order to reduce the size of pixel data if the input images include color information because any color information is not necessary in the proposed method. All of the appropriate edges in the grayscale images are extracted using Canny edge detection method which is known to be one of the best edge detection algorithms so far as it produces edges

978-1-4799-2827-9/13/$31.00 ©2013 IEEE

that are one pixel wide. The results are too verbose to deal with. We calculate the lengths of all contours of the detected edges and keep edges whose lengths are over 50 pixels in order to remove wispy details. Fig. 1(b) shows the results after the wispy edges are removed.

The detected edges are divided into left and right parts. In this step, the slope of a line segment or the angle between the line segment and the horizontal line is an important factor. A line segment survives only if its angle is in a certain range, i.e. R_{left} and R_{right} for lines in the left and the right subsets, respectively (refer to Fig. 1(b)). We have chosen these parameters to be R_{left} = (20, 80) and R_{right} = (100,160). This step eliminates the majority line segments and greatly reduces the processing time of the following steps.

The road surface is determined by line segments of lane marking. The lane marking is detected by fitting straight line model based on edge pixels using Hough Transform (HT) [1-3]. The equation of a lane marking line is obtained using the definition of

$$x\cos\theta + y\sin\theta = \rho \qquad (1)$$

where θ and ρ are estimated to fit the straight line model. The values are finally determined by maximum voting in Hough parameter space.

In order to reduce the influence of the wispy noises, we use Progressive Probability Hough Transform (PPHT) to detect line segments. The decrease of the third parameter of PPHT which is the maximum gap between line segments lying on the same line to treat them as a single line segment will lead to a good result that all line segments are made from relatively solid intact strings instead of broken wispy pixels. The operation removes many line segments that belong to irrelevant details on the scene and greatly reduces the number of features to be processed afterwards. Green lines illustrate the detected line segments by PPHT in the left part while blue lines represent those on the right as shown in Fig.1(c).

(a) Input image (b) Edges after removing wispy segments

(c) Grouping intersection points

Fig. 1. ROI elements collection

After we get the line information, we calculate the intersection points of every line pair selected from the left and the right part respectively as shown in Fig. 1(c). The center coordinate and the radius of the red circle represent the average and the variance of the intersection points, respectively. Obviously, the small variance means the centralized intersection points. Variance is not so crucial when detecting the vanishing point. For example, if there is only one wrong line, the variance will be 0 although the result is wrong. All in all, if the variance is large, the road condition might be too tough to detect a vanishing point with so much noise.

III. ADAPTIVE ROI DETERMINATION

After the ROI element collection, the ROI can be determined adaptively by combining the elements. The elements are comprised of the locations of line segments, vanishing points and the variances of intersections.

In the first step, we analyze the distribution of the line segments to remove the interior of a car by finding out the lower boundary of the ROI for a road. We obtain layer information to describe where the line segments are located. Once we have a line distribution as shown in Fig. 2(a), the layer information will be formed as shown in Fig. 2(b). Similar to the left and right part strategy, the layers are also divided into left and right parts. Although the height of a layer may be different depending on the input image size, we define 20 layers in Fig. 2(b). The gray level stands for the density of the line segments in each layer, i.e. a lighter layer includes more line segments. The calculated layer information is different frame by frame due to the changing road surface. However, the layer information of the interior of a car will be steady. The layers with almost constant values in the lower region may be removed. In some researcher's work, after the vanishing point detection, all of the regions below the vanishing point are set as the ROI [5-9].

The next step is the detection of vanishing points. The total number of intersection points is represented as

$$Num_t = Num_l * Num_r \qquad (2)$$

Num_l and Num_r is the total number of line segments on the left and right half, respectively. In Fig. 1(d), they are 6 and 7. The total number of intersection points is 42.

Even though we apply a slope filter and remove wispy edges, numbers of noisy line segments whose slopes and lengths are similar to those of ROI elements appear frequently. There is one noisy line segment in a yellow ellipse in the middle of the road as shown in Fig. 2(a). Considering the influence of noise, the number of intersection points can be represented as the following:

$$Num_t=(Num_l-Num_{l\_n})*(Num_r-Num_{r\_n}) \qquad (3)$$

where Num_{l_n} and Num_{r_n} are the numbers of noisy line segments in the right and left half, respectively.

We scan an input frame by sliding a 41*41 sized block window from top left to bottom right with a step of 15 pixels to find a candidate region including vanishing points. Whenever the number of intersection points in a block is more than the threshold value, the block is represented by a green box as shown in Fig. 2(c). The threshold value is determined by the variance of the distribution of intersection points. We can set both Num_{l_n}

and Num_{r_n} to 0 when the variance is close to 0, which means the intersection points are concentrated. Num_{l_n} and Num_{r_n} increase as the variance increases. We set the minimum threshold in one block to (Num_l-2)* (Num_r-2), that is, two false line segments are included in both left and right part in the worst case. Four 41*41 blocks in green boxes covers 28 intersection points in Fig.2(c) in which one wrong line segment exists in the left part. The centers of all blocks in green boxes are calculated and stored as a vanishing point for the next frame.

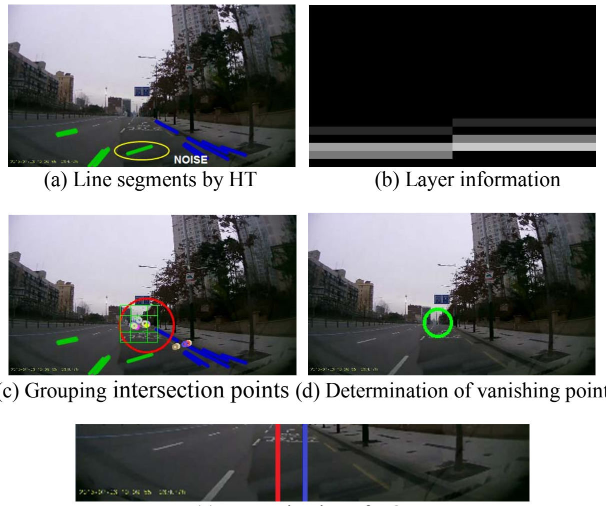
The procedure to obtain a vanishing point is applied to each frame. If the environment of the input frame is tough, it is difficult to find out the correct vanishing point. The noisy line segments do not appear consistently in tens of frames while the surface conditions of a road do not change much in several seconds which correspond to hundreds of frames. If we collect ROI elements for large number of frames and remove intersection points which appear only in a few frames, most of the intersection points are concentrated in a small area including the true vanishing point. We trace 100 past frames to make the proposed algorithm more robust.

When a car is running on the road, the vanishing point is stable and cannot be changed rapidly from frame to frame. If a vanishing point detected in a frame has a totally different position from that of the last frame, it is highly probable that the vanishing point is affected by noisy line segments and it would be better to discard it. Instead, the previous vanishing point is used for the current frame. In our work, the vanishing point is abandoned if the difference of the position is larger than 50 pixels of Euclidean distance. The vanishing point is represented as the center of the green circle in Fig. 2(d).

The coordinates of vanishing points from 100 frames are integrated to get the final result. The upper bound of the ROI is determined by the y coordinate of average vanishing points, and the lower bound is determined by the results of layer image analysis. The detected ROI is shown in Fig. 2(e). The blue line represents the physical center of the frame while the red one represents the x coordinate of the vanishing point that can be used for lane detection. Since the environment of a road changes little, we can use the same ROI to the following frames without applying the proposed algorithm. The proposed algorithm is applied again when lanes are not detected for a certain number of frames.

The information of road surface is usually obtained from the video of a camera installed at a fixed position of a car. The resolution of the video is usually higher than the required one for the lane detection. Our experiments show that correct ROI can be detected with video of relatively low resolutions as long as the lines can be detected. We resize an input video and turn its resolution into a standard size. The original input video has the resolution of 1920*1080. It is resized to a resolution of 427*240, which is much smaller by about one twentieth.

The proposed detection algorithm is implemented using C++ and OpenCV library. The platform for implementation is a desktop PC with an Intel Core2 CPU of 2.83 GHz. The average calculation time for determining ROI in one frame is shown in Table1. The vanishing points are obtained in more than 10,000 frames. The average calculation time is about 22ms and more than 40 frames per second can be processed. A previous work has reported the computation time of 158.2ms, with the image size of 320*240 and a 1.8 GHz CPU [5]. If we estimate the computation time after equalizing the conditions, our computation time is 16ms and that of the previous work is 100ms. The results show that the proposed algorithm is very efficient. Another previous work has reported fast computation time of 12ms using quite simple algorithm with an angle filter. However, it fails in detecting lanes for videos with complex environments.



(a) Line segments by HT (b) Layer information

(c) Grouping intersection points (d) Determination of vanishing point

(e) Determination of ROI

Fig. 2. Determination of adaptive ROI

TABLE.1 CALCULATION TIME ACCORDING TO PROPOSED ALGORITHM

Calculation Step	Time(ms)
Resize	5.54
Processing(Canny+ Smoothing)	5.53
Hough Transform	9.17
Vanishing analysis	0.79
Layer image	0.48
Result display	0.35
Total ROI detection time	21.86

In our experiment, there are three kinds of errors. They are no result, wrong result, and multiple results. The errors are caused by the lack of correct road data and by the influence of noises. We show the error cases in Fig. 4. The green boxes in Fig.4 means the result of clustering intersection points and the red circle means the average coordinates of intersection points. The upper right picture in Fig. 4 corresponds to no result since the green boxes are not shown. The lower right picture corresponds to multiple results, and there are 3 vanishing points.

Table2 shows the instantaneous detection ratios of vanishing points for 1500 frames in three different road conditions. The correctness of detecting a vanishing point is determined in each frame. The instantaneous detection ratio in the city road seems to be low. The value reflects the simple statistics of detecting a vanishing point in each frame. However, the proposed algorithm traces 100 frames before decision of the final vanishing point. If the average ratio is over 50%, we can get the correct result. Table2 shows that we have the correct vanishing points in all cases. That is, averaged final detection ratio is 100% for hundreds of video samples we have tested. The previous works showed detection ratios of 91.4% [6] and 96% [7].

The proposed algorithm works fine when changing lanes and the lane markings are blurred. We also applied the lane detection algorithm on some road conditions with curved lanes. Most curved lanes especially in highway can be approximated to segmented straight lines near a car. Fig.5 shows the experimental results of detecting vanishing points for various road conditions such as highway, curve lanes, city road, weak lane markings, complex background and solid or dashed lane markings.

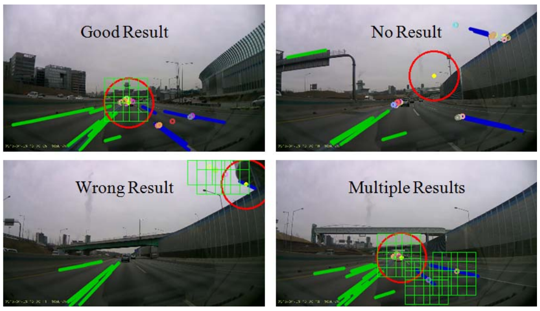


Fig. 4. Error cases of detecting vanishing point

TABLE.2 DETECTION RATIO IN ONE FRAME

Road	Total	Missing	Wrong	Multiple	Ratio
Highway	500	5	1	1	98.6%
Country road	500	10	11	8	94.2%
City road	500	6	19	32	88.6%

IV. CONCLUSIONS

In this paper, an adaptive ROI determination algorithm for lane detection is proposed. The proposed algorithm obtains intersection points using line segments and finds candidate regions by scanning distribution of intersection points to find a vanishing point. It traces the vanishing points for 100 frames to find correct one. The experimental results show that it works efficiently and correctly in various road conditions.

ACKNOWLEDGEMENT

This work was sponsored by ETRI SW-SoC R&BD Center, Human Resource Development Project. The EDA tools were supported by IDEC.

REFERENCES

[1] McCall J C, Trivedi M, "Video-based lane estimation and tracking for driver assistance: survey, system, and evaluation," Intelligent Transportation Systems, IEEE Transactions, 2006, pp. 20-37.

[2] Lin Q, Han Y, Han H, "Real-time lane departure detection based on extended edge-linking algorithm," Second International Conference Computer Research and Development, IEEE, 2010, pp.725-730.

[3] Gaikwad V, Lokhande S, "An improved lane departure method for Advanced Driver Assistance System," Computing, Communication and Applications (ICCCA), IEEE, 2012, pp.1-5.

[4] Zhe X, Zhifeng L, "A robust lane detection method in the different scenarios," Mechatronics and Automation (ICMA), 2012 International Conference on, IEEE, 2012, pp.1358-1363.

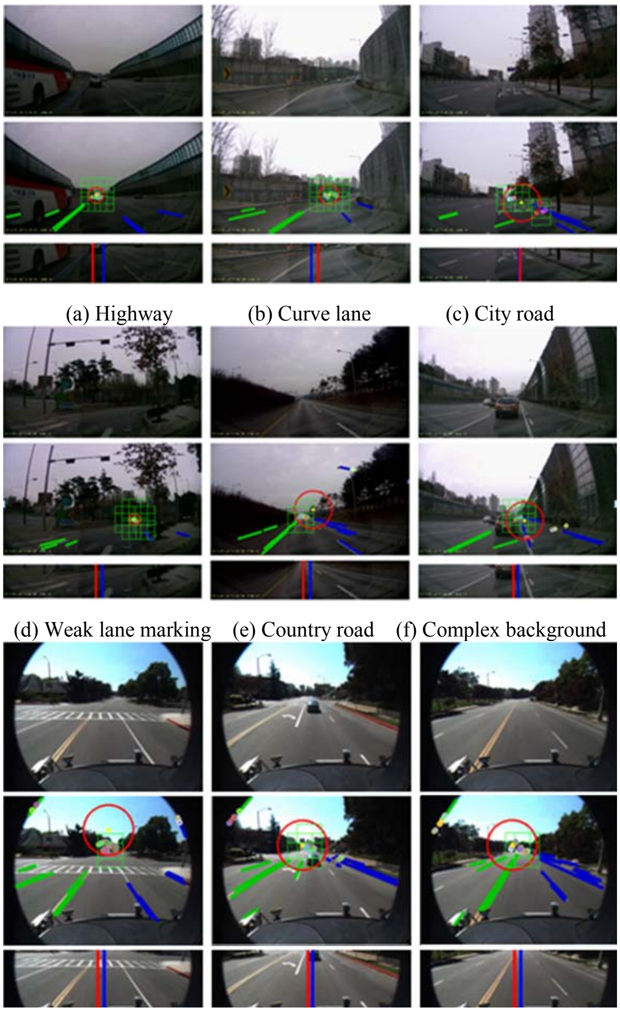
[5] Wang C C, Huang S S, Fu L C, "Driver assistance system for lane detection and vehicle recognition with night vision," Intelligent Robots and Systems(IROS 2005), IEEE/RSJ International Conference on, IEEE, 2005, pp.3530-3535.

[6] Benligiray B, Topal C, Akinlar C, "Video-Based Lane Detection Using a Fast Vanishing Point Estimation Method," Multimedia (ISM), 2012 International Symposium on, IEEE, 2012, pp.348-351.

[7] Kong H, Audibert J Y, Ponce J, "Vanishing point detection for road detection," Computer Vision and Pattern Recognition (CVPR 2009), International Conference on, IEEE, 2009, pp.96-103.

[8] Wu Q, Zhang W, Chen T, et al, "Prior-based vanishing point estimation through global perspective structure matching," Acoustics Speech and Signal Processing (ICASSP), 2010 International Conference on, IEEE, 2010, pp.2110-2113.

[9] Wang H, Chen Q, "Real-time lane detection in various conditions and night cases," Intelligent Transportation Systems Conference (ITSC06), IEEE, 2006, pp.1226-1231.



(a) Highway (b) Curve lane (c) City road

(d) Weak lane marking (e) Country road (f) Complex background

(g)Two solid lanes (h) Two dashed lanes (i) One dashed lane

Fig. 5. Experiment results in various road conditions