To: ICS 2002, Workshop on Artificial Intelligence

Detecting Highway Road/Lane Boundaries at Night

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Abstract

Detecting highway road/lane boundaries is an important task for autonomous vehicle navigation. In this research, we study the case at night in which the bright spots of reflector plates indicate the road/lane borders. Through the brightness and area filtering in the process of detecting the bright spots, the noise interference caused by other vehicles and other light can be eliminated. The filtered bright spots are then sorted based on their locations on ground and approximated by curves of the second order polynomial on the ground coordinates. Based on our scheme, experiments have shown correct and reliable detection of the highway road/lane boundaries under various road scenes and noise environments.

Keywords: ITS, Computer vision, Highway, Lane detection, Night scene

1. Introduction

Detecting highway road/lane boundaries is an important task for autonomous vehicle navigation and driver assistant systems [1-3]. Through the past two decades, many research works have been done in this aspect. Though the autonomous vehicle has run on highway for long-distance testing, research papers were still published in recent years [4-14]. Most of these papers propose schemes for more reliable detection of road/lane boundaries under slightly different environments or conditions. Yet none of them has approached the case of road/lane detection at night, while in practice the autonomous vehicle must face the problem of night driving.

The night scene on highway is quite different from that of daytime. In the aspect of road/lane detection, what the vision system on vehicle can observe from the night scene is some bright spots caused by reflector plates on the road surface, road signs at far place, or by other vehicles. While the bright spots caused by sequences of reflector plates indicate the road/lane boundaries, the light of the lamp poles along the highway and other vehicle(s) nearby may induce more interference in the detection. There are chances that a couple of reflector plates (though just few) are missing due to damage. But even worse, some of them may be occluded by vehicle(s) ahead. In the daytime highway scene, we can easily find the road/lane borders by tracing along the painted solid line, or by searching in the direction of any found dashed line to find its next line segment of the same dashed lane boundary. Unlike the daytime case, the bright spot of the reflector plate itself can hardly give the direction of the boundary. The vision system has to judge from the overview, matching some reasonable principles, to cluster the bright spots that belong to the same boundary curve. And this must be done under the interference of occlusion and noises as well.

In this paper, we present a scheme that can locate the road/lane boundaries from the highway night scene. Our scheme includes the important process of brightness and size filtering in extracting the reflector plates. It eliminates the possible noise interference caused by other vehicles and other light effectively. Through the inverse perspective transform, the acquired bright spots of reflector plates are sorted according to their locations on ground (rather than image). The partitioned reflector spots are then approximated by curves of the second order polynomial on the ground coordinates. And these curves of the best approximation indicate the road/lane boundaries of Highway with respect to our own vehicle. The details of our scheme are described in the following sections.

2. Extraction of Bright Spots

Our vision system uses a color image grabber of resolution 640 x 480 and 8 bits for each pixel in each color frame. To save the processing time and to avoid the motion-caused image discrepancy between the odd/even fields, we choose to process only the single-field image that is of 640 x 240. With such vertical resolution of 240, the image processing still shows satisfactory results. On the other hand, the good horizontal resolution of 640 helps to detect the horizontal locations of the reflector plates more accurately. And this in turn supports more accurate approximation of the highway road/lane boundaries.

Figure 1 shows a sample night-scene image taken from the vision system in our vehicle running on highway. In this picture, two vehicles are present. A nearer one is on the left side, and the other is about hundred meter far ahead. The nearer one shows its rear portion with six indicator-light spots clearly, while the far vehicle shows two bright spots. In addition to the bright spots of the reflector plates, a set of road signs and some tiny spots faraway are also present.

Figure 1 A sample night-scene image on highway

To extract the reflector spots from the image, first we screen pixels in the image based on their brightness. In such a process, we do not care about the color of the bright spots, though the color may help us to distinguish other objects (such as other vehicle's rear lights) from the reflector plates. Hence, we adopt a simple method of checking the sum of the R, G, and B intensities with a certain threshold. If the sum of intensities of a pixel is above the threshold, then this pixel is regarded as a bright pixel. For RGB-color images with each color of 8-bit, using a fixed threshold of 200 gives acceptable result. Yet considering the fact that the nearer spots are usually brighter than the spots faraway, we adopt a variable threshold that depends on the y-coordinate of the pixel in image:

threshold = Max {200, 200+3*(y-150)}

where the origin of the image coordinates system is chosen to be at the upper left corner of the image frame, with the y-axis pointing downward and the x-axis pointing to the right. As mentioned, the image we use is of resolution 640 x 240. Thus the maximum threshold we have here comes near 470 for pixels near the bottom of the image. Figure 2 shows the result of bright-pixel extraction from the image of Figure 1. From experiments on sequences of highway night-scene images, the above simple formula gives satisfactory results.

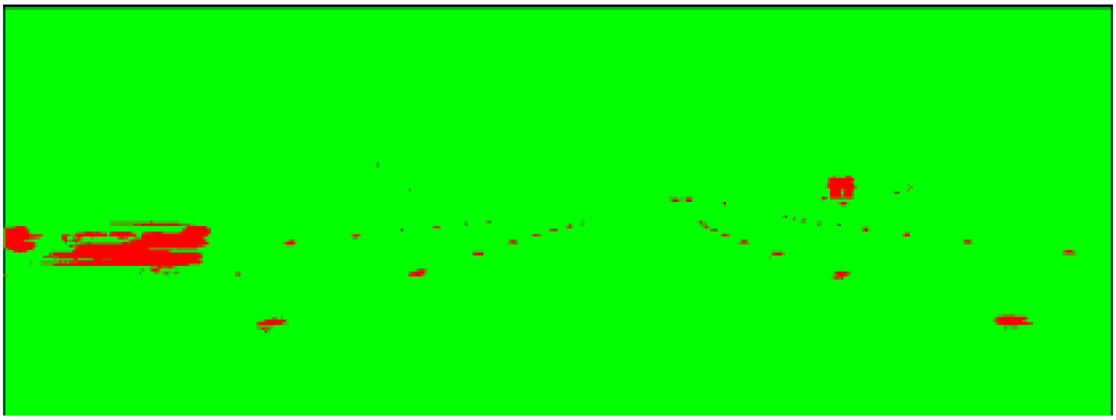

Figure 2 The bright-pixel map extracted from the image of Fig. 1, where the bright pixels are in red while other pixels in green.

Using the technique of blob labeling or region growing, we can easily cluster each group of connected bright-pixels as a region (a bright spot). During this process, the information of spot’s area (pixel count) and reference position (the average image coordinates) of each bright spot can be evaluated at the same time. And for the convenience of latter processing, we store the information of extracted spots according to the sequence of their reference point’s y-coordinate value.

3. Confirmation of Reflector Plates by Area

With the extracted bright spots, the next problem is that the spots caused by other vehicles and noises must be eliminated. In our scheme, we propose to filter the spots based on its area in the image.

The bright spots, caused by the reflector plates, vary in their size in the image due to the different distance and view angle from the camera. Roughly speaking, the area of a reflector spot in the image is inversely proportional to the Z-distance of the reflector plate from the camera. Here the Z-distance is the length of distance projection on the Z-axis, while the Z-axis is the projection of the camera's optical axis on ground.

To evaluate the Z-distance of an object on highway easily, we define a <u>vehicle coordinates system</u> in addition to the image coordinates system. The Z-axis of such a coordinates system is as mentioned above, with its origin defined right under the camera's lens center on ground. While its Y-axis is pointing upward perpendicular to the ground plane, the direction of the X-axis is determined by the left-thumb rule.

Thus for an object on the highway road surface, its X- and Z-coordinates on ground can be calculated (transformed) from its x-, y-location on image, assuming that the road surface is flat or on the same ground plane. The transformation formulas are as follows:

$$Z = \frac{H \tan\tau [\,\mathrm{y} - (\mathrm{y}_{\mathrm{size}} / 2\,)] - K_y H}{[(\mathrm{y}_{\mathrm{size}} / 2\,) - \mathrm{y}] - K_y \tan\tau} \tag{1}$$

$$y = \frac{y_{size}}{2} - K_y \frac{(Z \sin\tau - H \cos\tau)}{(H \sin\tau - Z \cos\tau)} \tag{2}$$

where H is the height of camera from the ground plane, τ is the tilt angle of camera (positive when tilt downward), $\mathrm{y}_{\mathrm{size}}$ is the y-resolution of the acquired image, while K_x and K_y are the scaling factors in the horizontal and vertical direction, respectively. Note that these scaling factors are equivalent to another notation frequently adopted in other papers:

$$K_x = f \times S_x \quad \text{and} \quad K_y = f \times S_y$$

with f the focal length of the camera, and S_x and S_y the scaling factors in the horizontal and vertical direction, respectively.

In our experimental setup, the H value is about 1.30 meters and the image y_{size} is known. The scaling factors K_x and K_y are pre-calibrated with all the length measured in units of meter. As to the tilt angle τ of the camera, it is aimed horizontally. Nevertheless, the tilt may vary in a small range due to the uneven road surface and vehicle vibration.

Without knowing the exact tilt angle of the camera, we build an area reference table (in terms of the number of pixels) for the reflector plate with respect to each y-coordinate value of its reference position under the tilt $\tau = 0^\circ$. For each image acquired, we estimate the camera's tilt angle from the previous frame(s). Based on this tilt angle to estimate the y-position of each bright spot if it is in the image taken with camera tilt $\tau = 0^\circ$. Checking the spot's area with the area reference table, we take it as a reflector plate if it matches within the $\pm$30% range of the reference size.

From experiments on a variety of highway night scenes, we find that our scheme works quite well. The bright spots from other vehicle lights, road signs and miscellaneous noises are all filtered out. Figure 3 shows the remaining spots after running the area filtering process on the image of Figure 2. The result is very satisfactory. All the noticeable reflector spots remain and no erroneous spot is taken as the reflector plate.

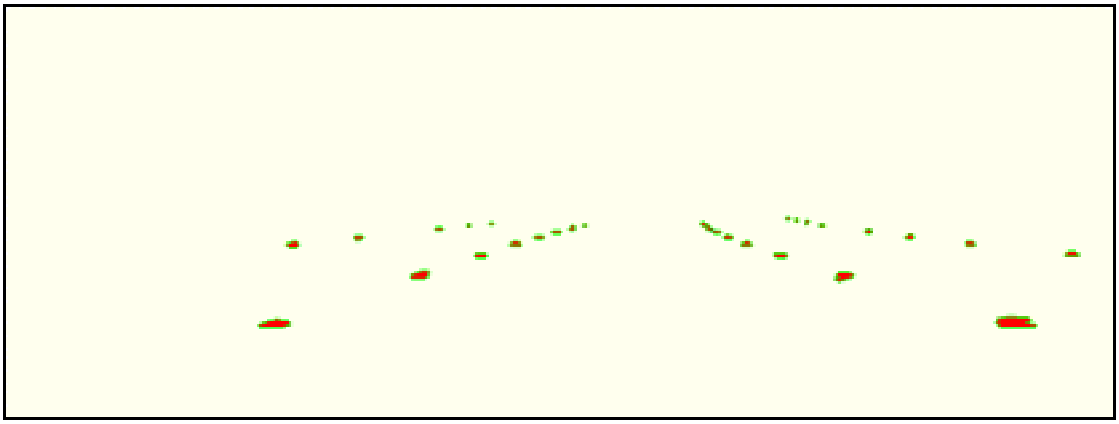

Figure 3 The resultant image after filtering the bright-pixel map by area

After the above filtering by area, the (X, Z) coordinates value of the reference position of each remaining spot is calculated. The (X, Z) position entries of these reflector spots are then stored in a <u>reflector list table</u> in sequence of their Z-position value. This table indicates the positions of reflector spots on ground with respect to the vehicle coordinates system. The reflector plates corresponding to the result of Figure 3's image on ground is shown in Figure 4.

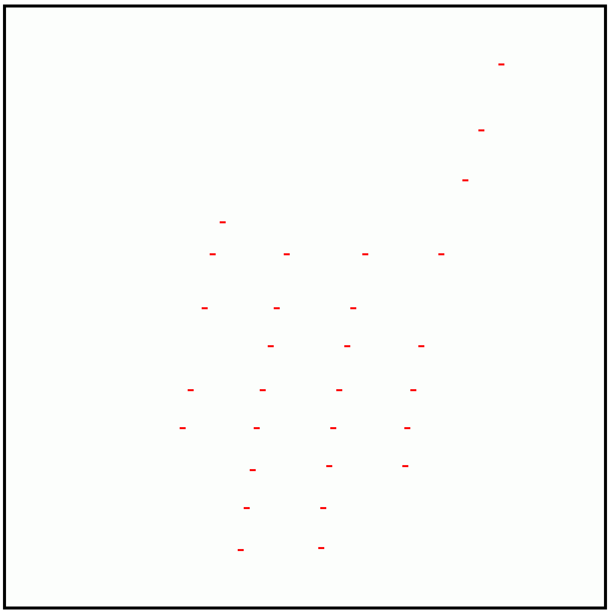

Figure 4 The distribution of reflector plates on highway road surface as detected by our filtering scheme and inverse perspective

transform

Shown in Figure 5 is another highway night-scene image in which more lights are interfering with the reflector plates. Through the brightness filtering, the bright-pixel map of Figure 6 is extracted. And after the spot-size filtering, we have the image of reflector plates as shown in Figure 7. From the resultant image, we can see virtually all the noise spots have been removed except two tiny spots remain on the right side of image. The rightmost reflector plate near the lower right corner of the image is not kept, because it is linked with a large area of bright road borderline.

Figure 5　Another sample of night-scene image on highway

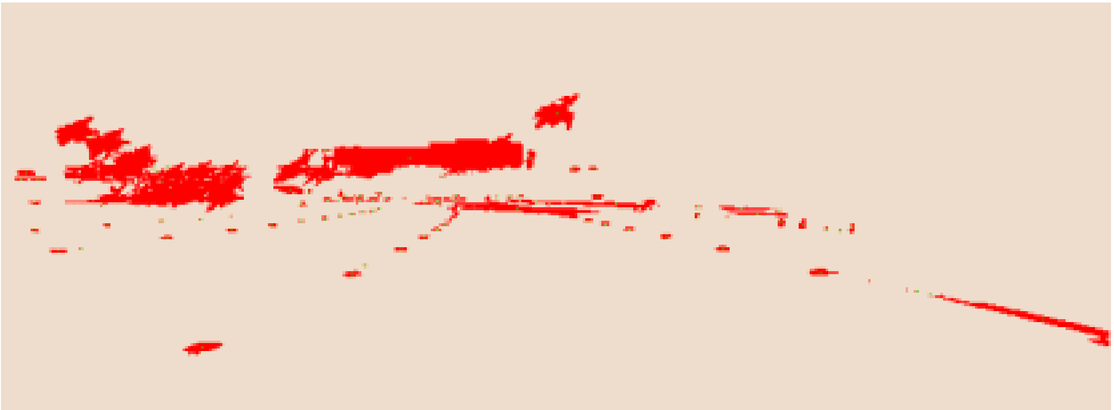

Figure 6　The bright-pixel map extracted from the image of Fig. 5, where the bright pixels are in red.

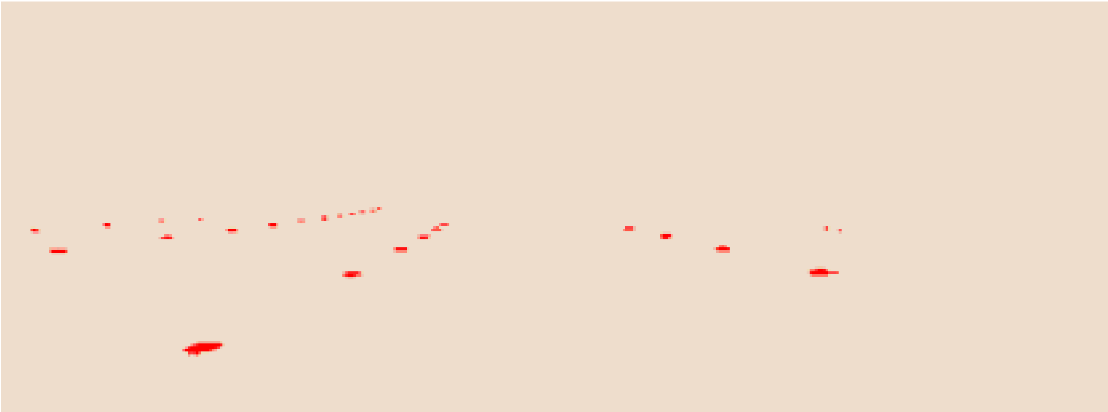

Figure 7　The resultant image after filtering the bright-pixel map of Fig. 6 by area

Figure 8 show the third sample of highway night-scene image from which the bright-pixel map of Figure 9 is extracted. And after the spot-size filtering, we have the image of reflector plates shown in Figure 10.

Figure 8　The third sample image of the highway night scene

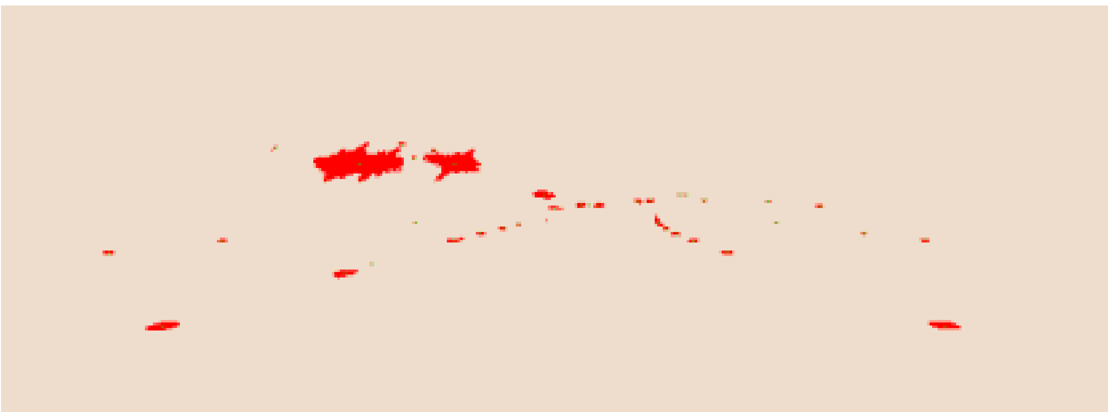

Figure 9　The bright-pixel map extracted from the image of Fig. 8

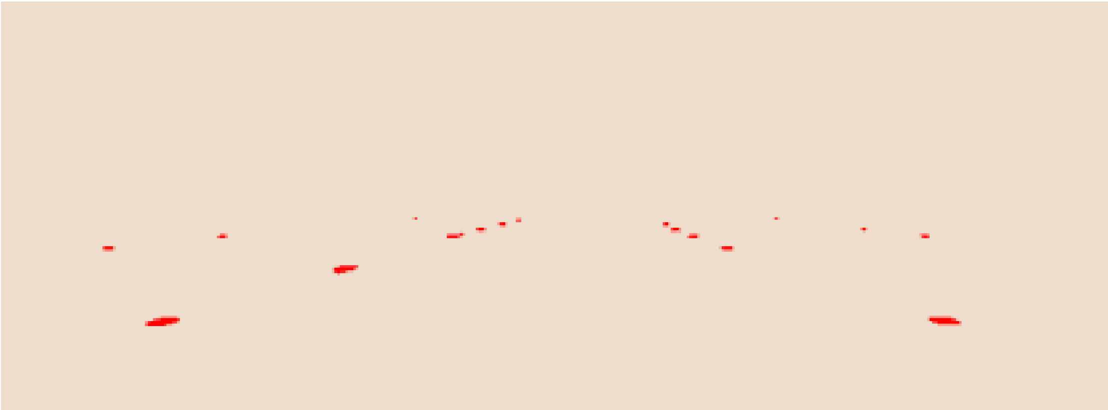

Figure 10 The resultant reflector-plate image after filtering the bright-pixel map of Fig. 9 by area

From the resultant image of Figure 10, we see that our filtering scheme does remove all the noise spots so well. Two tiny spots slightly above the real road border are gone, because their areas are slightly larger than expected. As in many other tests, the extraction by our scheme is quite successful.

4. Reflector-Point Clustering

From Figure 4, we can see a rough outline of the road/lane borders on highway. However, this is only a display to the human visual system. The computer vision system does not recognize the road/lane boundaries at this stage yet. To align the reflector points properly on sequences of smooth curves, an algorithm that depends on the following analysis is proposed.

According to Taiwan Area National Freeway Bureau, the lane width (between painted border) is about 3.65 meters on our highway, and about every 10 meters there is a painted line segment along the dashed lane border. Thus the distance between two consecutive reflector plates along the same lane border should be about 10 meters or multiple of 10 meters if some reflectors are missing. Since our camera is heading in the vehicle direction while the vehicle is roughly heading in the direction along the lane on highway, the Z-distance between consecutive reflector plates is about the same as above or only slightly less. Even under the situation of lane change, the Z-distance between two consecutive reflector plates (10-meter away) usually should be 9.5 to 10 meters.

In our clustering algorithm, we first locate the Z-nearest reflector point (usually it is along the lane border right next to our own vehicle) from the reflector list table. This point is used as the initial point for clustering. Then we search for all the reflector points of about 40 meters far away in Z-distance. If some are found, then each of these points will go through the "matching process" with the initial point until one is found to be matching. If no reflector points of about 40 meters can be found or none of them can match the initial point, then the reflector points of about 50 meters far away in Z-distance will be tried. If this does not work out, then we locate the next nearest reflector point as our new initial point and go through the same process as described above. The process goes on until either one matching group (at least three reflector points along a borderline) is found or all the possible matching fails.

The matching process, serving the core portion of this clustering algorithm, is to check the alignment error along the reference line between the initial point and the reflector point 40 or 50 meters away in Z-distance. For each segment distance of around 10 meters, we try to find a nearest point from the group of about the same Z-distance (within 3 meters of error). If the X-distance error of the nearest point from the reference line is larger than 1.5 meters, then the reflector point matching the reference line at this Z-distance is missing and the error does not count. In the other case with X-distance error less than 1.5 meters, then the error is squared and accumulated. After adding up all the squared errors, we divide the sum by the number of valid reflector points (in between the two end points). If the result is below a threshold (the error tolerance), then this group of reflector points is “matched”. And from the position and direction of the matched group, we can easily find all other reflector points along the same lane border. After a cluster of reflector points is found, other clusters can be easily located by shifting the X-coordinate for about 3.7 meters. From experiments, we find that this algorithm works quite well.

5. Road/Lane Border Approximation

For each group of the clustered reflector points, we use the 2nd-order polynomial to form a smooth curve, that is, to approximate each individual road/lane border. Figure 11 shows such a curve approximation for the reflector points shown in Figure 4. Note that the scaling is not the same for the horizontal and vertical axes. The deviation in the X-direction is more enlarged. From Figure 11, we may see the clustering is correct and the curve is quite smooth.

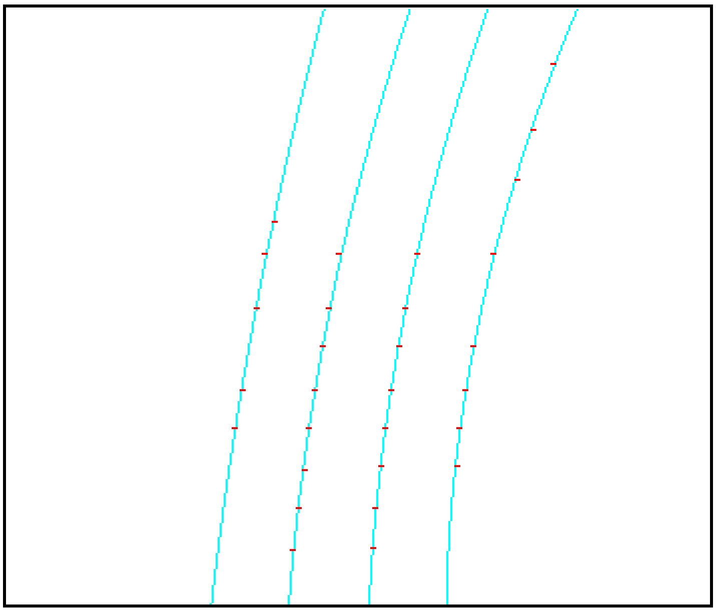

Figure 11 The curve approximation of the highway road/lane border based on the reflector points obtained in Figure 4

Figure 12 shows another highway road/lane border approximation on ground for the reflector points shown in Figure 10. Note that quite a few reflector points are missing in Figure 10, but it does not affect our algorithm. The clustering still works well and the curve approximation is quite smooth.

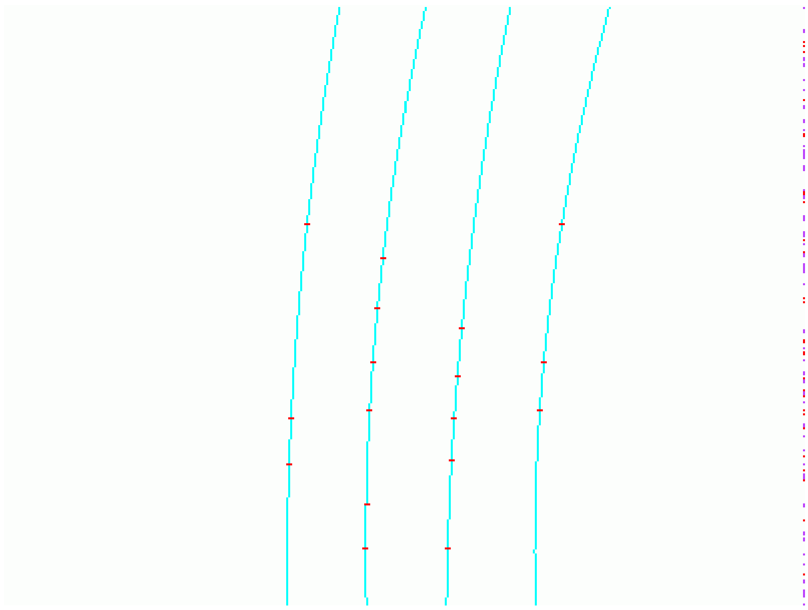

Figure 12 The curve approximation of the highway road/lane border based on the reflector points obtained in Figure 10

In practice, however, the highway road surface is not necessary on the same plane. The highway may go up and down slightly from place to place. And there are slight depression or small bumps on the road surface that causes the vehicle vibration. These would slightly affect the tilt angle of our camera, which may need to be re-estimated from frame to frame. Besides, the highway may be slanted to one side because of curving or slightly slanted on both sides for the sake of water drain. And the image processing may cause some round-off error in the pixel positioning and the inverse prospective projection. All these may make the lane width between the individually approximated road/lane border curves look inconsistent. And to solve this problem, we adopt to use a single set of three parameters to generate all the road/lane borders (keeping the lane width constant) and to minimize the errors from the overview.

7. Conclusion

In this paper, we present a scheme that detects the highway road/lane boundaries from the night scene. Through the brightness and area filtering in extracting the bright spots, the noise interference caused by other vehicles and other lights can be avoided. Experiments confirm the success of our method. Only the spots of reflector plates in the image are extracted. And no noticeable reflector plates are missing from the extraction. In the latter processing with our clustering algorithm and 2^{nd}-order polynomial curve approximation, the reflector points are corrected aligned and road/lane border curves are quite smooth and consistent. Our proposed scheme is efficient and effective.

Acknowledgement

This work was supported by the National Science Council, ROC, under grant NSC 90-2215-E-194-010.

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