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Application of Obstacle Identification Algorithm Based on Characteristics to Intelligent Vehicle

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Abstract: This study aims to tackle the obstacle vehicle identification problems when an intelligent vehicle is in motion. The obstacle vehicle identification is realized by using the grade criteria such as gray scales of pixels to determine the characteristics of the shadow cast by the bottom of obstacles ahead of the intelligent vehicle in motion and by analyzing the texture features of the obstacle vehicle. Computer simulation is performed against data for identifying and handling the obstacles. The results show that the obstacle identification algorithm based on characteristics is able to identify obstacles fast and its computing is simple with high reliability.

Key words: Intelligent vehicle, vehicle identification, texture features

INTRODUCTION

The intelligent vehicle that aims at unmanned driving, full-automation and safe driving has been a hot research spot in recent years. One advantage of unmanned driving is safer trip (because Human Caused Error (HCE) can be reduced) and the problem of fatigue driving and difficulty in parking can also be addressed (Huang *et al*., 2003).

Currently, the obstacle identification algorithms mainly fall into these categories, including obstacle identification algorithms based on characteristics, algorithms based on motion and obstacle detecting algorithms based on stereoscopic vision (Tan *et al*., 2008)

The obstacle identification algorithms based on motion principally pre-detect the obstacles by using the mass information among sequential images. The major algorithm is Optical Flow (Yang, 2011). The Optical Flow computes the displacement vector of each pixel (in a successive manner), featuring precision, robustness and more abundant information and it can process the global motion. But it is time-consuming, thus inapplicable for systems requiring realtimeness (Li, 2007)

The obstacle detecting algorithms based on stereoscopic vision is most common method in identifying obstacles. First, two or more video cameras simultaneously shoot the scenes from different angles. Then the parallaxes among the images are obtained by image matching. At last, the actual distance of the obstacle is figured out based on the position of obstacles in the images, the parallaxes and the calibration parameters of the video cameras. The most complex and time-consuming part of such algorithms is the image matching. Due to the requirement of realtimeness in detecting obstacles, the classic per-pixel mapping algorithm is not applicable (Hoffman *et al*., 2004).

To meet the realtimeness requirement of intelligent vehicle in identifying obstacles, this study adopts the simple obstacle identification algorithm based on characteristics and with high reliability and applicability.

PRINCIPLE FOR OBSTACLE IDENTIFICATION ALGORITHM BASED ON CHARACTERISTICS

The obstacle identification algorithm based on characteristics makes use of some significant characteristics in the images of vehicles ahead of the intelligent vehicle to separate the vehicle from the road. The common characteristics include geometrical characteristics, symmetry, color, shadow, corner, horizontal/vertical fringe, texture and vehicle lights and so on.

In this study the shadow cast at the bottom of a vehicle and the difference in vehicle texture are used to identify the obstacles so as to achieve automatic vehicle collision prevention. The basic idea is that firstly the bottom fringe of obstacle is detected by the grade criteria such as the gray scales of pixels on the lane where the intelligent vehicle is driving, considering it is possibly the shadow under the vehicle and then the detecting rectangle is established to further narrow down the area

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that the vehicle occupies. At last the obstacle identification is performed by using the texture features.

OBSTACLE DETECTION

Preliminary obstacle detection: When the intelligent vehicle is in motion on one lane, it takes the area among the lane marker lines as interest area to search obstacle ahead of it (take vehicle obstacles as the research object). Generally, vehicles on the road all have a piece of shadow under them. The area under vehicles cannot be cast by sunshine, so the luminance value of such area seldom varies in a day, yet in the gray scale images the gray value of the area under vehicles is smaller than that of the road surface (Liu and Wen, 2007). Using this characteristic can preliminarily predict areas where obstacle vehicle might exist.

The gray scale of images after filtering is Grade 256. Usually the distribution of gray scale is even or successive on the road surface, while it will change suddenly in the shadow area. Therefore, the approach to detect the vertical fringe that suddenly changes its gray scale is adopted to determine the shadow area.

Scan the road area vertically from the bottom to the top to compute the average value of the gray scale in each line by Eq. 1:

$$G(r) = \frac{1}{[rb(r) - lb(r) + 1]} \sum_{c=lb(r)}^{c=rb(r)} f(r,c) \qquad (1)$$

In Eq. 1, rb (r) indicates the right coordinate value of Row r in the road area, Ibr indicates the left coordinate value of Row r in the road area, f (r, c) indicates the gray scale value of the pixel (r, c) and G(r) indicates the average gray scale value of Row r in the road area. If the value of G(r) of certain row decreases sharply, it might indicate the position of vehicle ahead of the intelligent vehicle.

G_r records the average gray scale value of each row; t1 is the average gray scale threshold value, which depends on the gray scale values of the lane and the shadow of the obstacle bottom. yy_h_sount records the row where a piece of shadow is. The preliminary obstacle shadow extraction algorithm flow is shown in Fig. 1.

Obstacle location: The role of texture analysis is to retain the area where obstacle vehicle may exist to the most possible extent, not to filter the non-vehicle area. In texture analysis the regional characteristics of images are described, trying to visually and quantitatively describe parameters such as the smoothness and quality of the images (Sonka *et al*., 1999). In the candidate regions where vehicles exist, sharp gray scale change occurs on the fringe of the vehicle.

Figure 2 shows how to calculate the maximum D-value of local reconstructed information images of the road area ahead of a vehicle. The size of the area is 3×3. For the marked pixels in Fig. 2, the output value can be obtained by the maximum value of this area deducting the minimum value of this area, i.e.:

$$15\text{-}3 = 12 \qquad (2)$$

Check whether obstacles exist by texture analysis. The texture analysis steps are as follows:

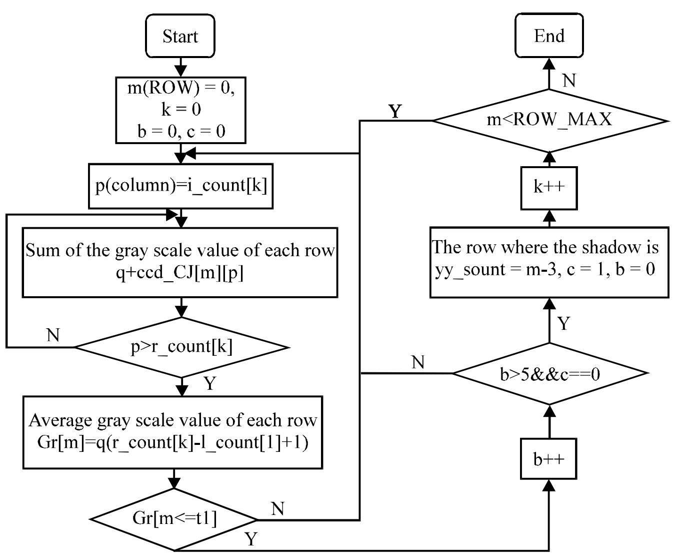

Fig. 1: Obstacle shadow extraction algorithm flow

- Establish a window of 15×15 and make the window glide on the image from top to bottom and from columns to rows
- Sort all the gray scale values in the window in descending order after each gliding
- Replace the original value by the D-value between the maximum value and the minimum value obtained by the sorting
- Make the window slide and repeat steps 2 and 3 until all the images have undergone this process

The algorithm flow is shown in Fig. 3.

Obstacle identification algorithm flow is shown in Fig. 4. In the flow, t2 is the threshold value of the D-value of texture, depending on the texture difference of lanes

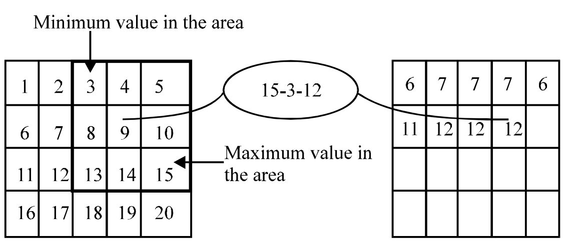

Fig. 2: Calculating the maximum D-value of local images

and obstacles. 11_count and h_count, respectively records the columns and rows of obstacles where the texture difference is significant. Set the threshold values of the length and height of obstacle to KC and KH. If the total number of columns is larger than the threshold value of the length, the total number of rows is larger than the threshold value of the height and the row with shadow exists, the obstacle can be determined to exsit.

SIMULATION RESULTS AND ANALYSIS

Preliminary obstacle detection simulation analysis: Sun cannot cast its light to the area under the vehicle. The gray scale value of this area shows continuity. When a vehicle is on the lane, the gray scale value of the vehicle and the road shows discontinuity; therefore, sharp change occurs in the row average gray scale value of the images. When the target vehicle is far from the intelligent vehicle, these vertical structures are with good cluster characteristic and can serve as clues for vehicle detection. In the preliminary obstacle detection simulation analysis, assume that the lane is extracted accurately and the road surface area ahead of the vehicle is reconstructed, shown as Fig. 5.

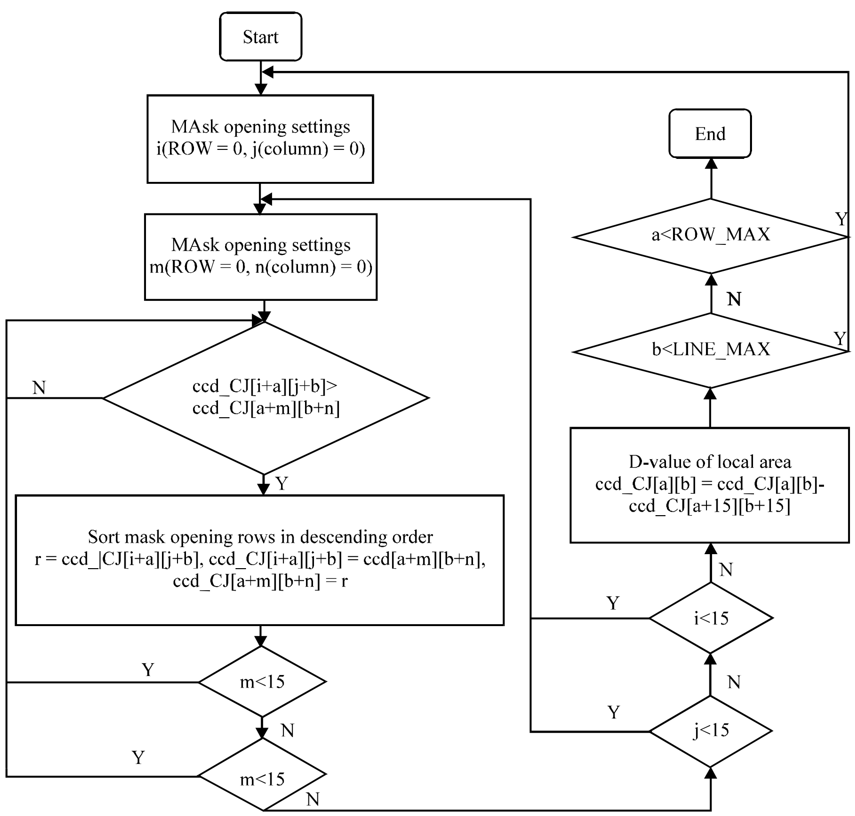

Fig. 3: Obstacle texture extraction flow

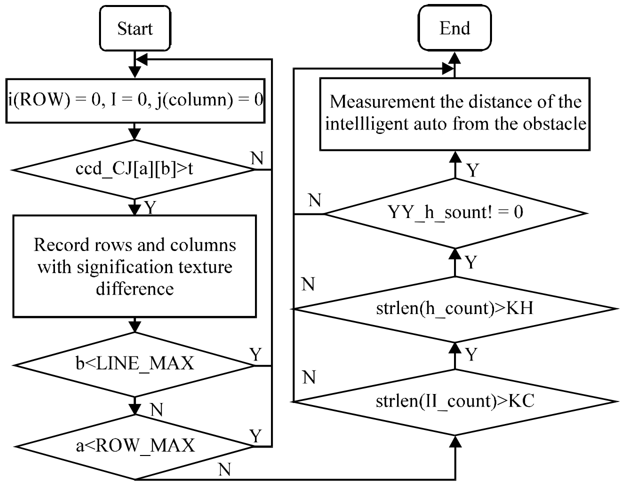

Fig. 4: Obstacle identification algorithm flow

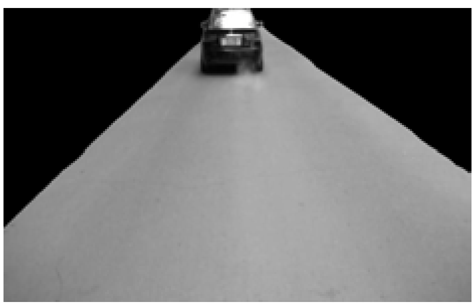

Fig. 5: Reconstructed road surface area ahead of vehicle

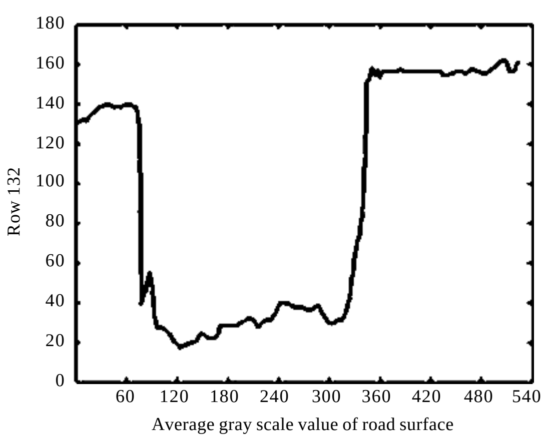

Fig. 6: Change of average gray scale values of road surface

Figure 5 shows the superposition result of the image information of fitted lane marker lines and information within the lanes after median filtering, providing reference for the following obstacle identification.

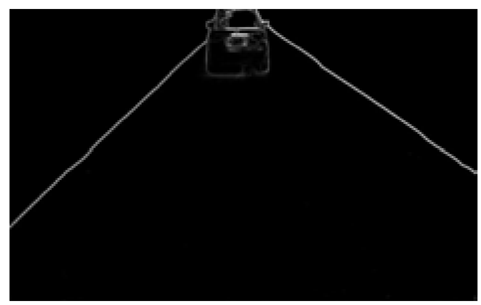

Fig. 7: Image for texture analysis

The change of the average gray scale values of the road surface is obtained based on Fig. 5, shown as Fig. 6.

It can be seen from Figure 6 that a large negative step of the average gray scale value appears under the obstacle. This is because that the bottom of the vehicle cast shadow on the road surface, while the gray scale value of the shadow is far smaller than that of the road surface. Factors causing such negative step include sundries of deep color on the road and pavement patching marks. It is insufficient to determine that vehicle must exist where the negative step appears just based on the aforementioned point. And it can only help the preliminary vehicle detection. To rule out this misjudgment, further obstacle location is needed.

Obstacle location simulation analysis: Figure 7 shows the maximum D-value of the local reconstructed images with texture characteristics of the road surface area ahead of the vehicle.

It can be seen from Fig. 7 that obstacle vehicle does exist.

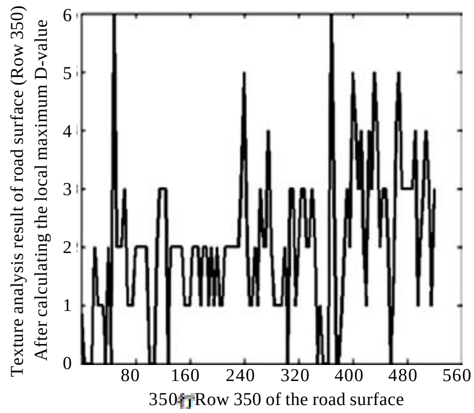

Fig. 8: Analysis result of road surface texture

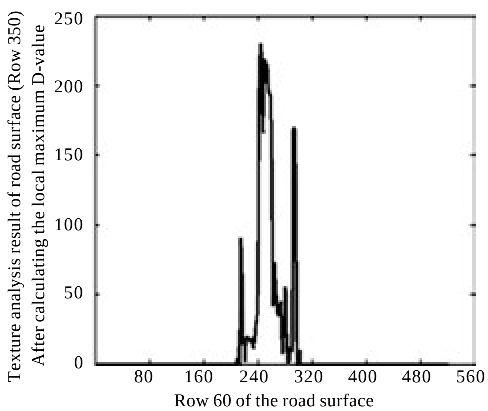

Fig. 9: Analysis result of obstacle vehicle texture on the lane

Figure 8 shows the texture analysis result of road surface (Row 350) after calculating the local maximum D-value. It can be seen from Fig. 8 that the local maximum D-value of road surface fluctuates within 0~6.

Figure 9 shows the texture analysis result of the obstacle vehicle (Row 60) on the lane after calculating the local maximum D-value. It can be seen from Fig. 9 that the local maximum D-value on the road surface is 0, while that of the obstacle vehicle ranges from 0~225. This can tell that the texture of road surface is consistent and the texture difference of the obstacle is significant. Based on this characteristic the detection rectangle is established for the final obstacle vehicle location.

CONCLUSIONS

The gray scale value of pixels of the shadow in the image of the vehicle bottom ahead ranges from 0~225. The obstacle fringe was identified by the grade criteria such as the gray scale value of pixels. The threshold value method was adopted to extract the characteristics of the shadow under the vehicle to determine the preliminary detection area of the vehicle. The detection rectangle was established by the texture feature analysis to realize the final obstacle vehicle location.

The lane detection and vehicle identification algorithms are theoretically approaching the requirements of realtimeness and robustness. However, the rationality of the parameters in the system such as the threshold value of the texture difference deserves more long-distance test run verification so as to optimize the algorithms and enhance the robustness and realtimeness of the system. In addition, the lane detection algorithm cannot identify curves, roads without lane marker lines, lane changing situations and roads with large curvature. For those crowded road conditions, the lane detection algorithm cannot accurately identify several target vehicles. In the future research, identification algorithms under special working conditions need to be further studied to enhance the robustness of the system.

REFERENCES

Hoffman, C., T. Dang and C. Stiller, 2004. Vehicle detection fusing 2D visual features. Proceedings of the IEEE Intelligent Vehicles Symposium, June 14-17, 2004, Italy, pp: 280-285.

Huang, X.Y., L. Zhu, J. Yang and Q. Li, 2003. Application of TMS320C6201 to Intelligent active security system. J. Chongqing Univ., 26: 83-86.

Liu, Z.Q. and H. Wen, 2007. Monocular vision-based vehicle collision warning System. Comput. Appl., 27: 2056-2058.

Li, Y.P., 2007. State of arts of vision based techniques for vehicle detection. Foreign Electron. Meas. Technol., 26: 21-32.

Sonka, M., V. Hlavac and R. Boyle, 1999. Image Processing, Analysis and Machine Vision. CL-Engineering, USA..

Tan, B.H., L.X. Ren and L. Zhang, 2008. State-of-art vechicle collision avoidance system based on video image processing. J. North China Inst. Aerosp. Eng., 18: 7-10.

Yang, Y.M., 2011. Moving objects tracking based on improved optical flow method. Comput. Digital Eng., 39: 108-110.