Research on the forward distance detection algorithm based on the camera switching

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Abstract. In order to promote vehicle active safety and to decrease collision accident, In this paper, an algorithm for detection of vehicle distance in front based on single and double camera switching is presented. This algorithm has done the corresponding difference processing to the day and night two different situations. By switching between single and double cameras, the image of the car bottom shadow, the characteristics of the vertical direction of the vehicle, the characteristics of the car taillight and other features was taken, and the position of the vehicle in front was locked. Finally, the feature information of the vehicle is converted into the distance information. Experiments show that, this system designed in the paper, achieved the anticipated function, can accurately detect multi-lane and short distance vehicle distance, and the efficiency of the system also achieved the real-time requirement.

1. Introduction
In the field of ADAS (Advanced Driving Assistance System) research, vehicle ranging ahead and reflecting road condition information is a key technology in collision warning and fatigue driving warning. In several safety aid systems commonly used today, millimeter scale radar ranging is far away. But it is so expensive that cannot be widely promoted. Ultrasonic ranging is not widely used because of its physical characteristics. Due to the advantages of abundant information data, stable performance and price advantage, machine-vision-based detection has become a hot spot in current research\textsuperscript{[1]}.

At present, the advanced vehicle detection of machine vision is mainly based on the image prior feature knowledge of vehicle tail. Vehicle feature extraction is a key part of vehicle distance detection. In the previous studies, the method of hybrid Gaussian function was used to describe the multi-level background to achieve the purpose of separating vehicle features\textsuperscript{[2][3]}. In literature \textsuperscript{[4]}, vehicle shadow and edge are used as the main features of detection. Variable model is adopted to accurately locate the vehicle ahead, and radar data is integrated to improve the accuracy of the system; The vehicle distance detection is also realized by the vehicle modular method, and the vehicle components are extracted by using the main components of the vehicle feature in \textsuperscript{[5][6]}. And improve the stability of the system by grouping the adjacent areas of the feature. In the literature\textsuperscript{[7][8]}, the Gabor filter is used to obtain the direction angle and the lane line, and the vector division is used to complete the
community division. However, these methods are computationally intensive and require too much CPU to operate in an embedded system.

For the binocular ranging camera system, the key step is feature point matching. Due to the diversity of physical shapes, since the beginning of stereo vision research, the stereo matching of objects is the most difficult, difficult to overcome, and extremely important thing\cite{9,10}. On the one hand, due to the geometry and physical characteristics of the target object, noise interference and distortion, and the physical optical characteristics of the camera itself, it will be integrated into a single image brightness value problem in the camera, that is the problem of gray value. On the other hand, the determination of depth is also one of the difficulties. After obtaining the parallax image through stereo matching, the correlation algorithm can be used to calculate and determine the depth image, and restore the 3D information restored to the original scene\cite{11,12,13}. Among the many factors that affect the accuracy of distance measurement by visual ranging, the main interference is digital quantization (light intensity will be quantized into an integer in the camera), camera calibration error, the use of feature detection algorithms, and the accuracy of matching positioning\cite{14,15}.

2. Vehicle feature detection

This paper proposes a robust solution that distinguishes the detection environment into day and night. In the daytime environment, the gray level is used to analyze the threshold to capture the shadow of the car bottom, and in the case of capturing the shadow of the bottom of the car, the characteristics of the vertical direction of the vehicle are analyzed, and finally the vehicle is locked; in the night environment, first in the YUV The color space filters and normalizes the taillights of the vehicle, and finally completes the vehicle detection under the taillight judgment mechanism. The flow chart is shown in Figure 1.

![Vehicle search algorithm flow chart](image)

**Figure 1.** Vehicle search algorithm flow chart

For the position where the camera is erected, it can limit the detection range of the vehicle during daytime and nighttime road conditions, which can effectively reduce the calculation amount of the system. Therefore, the detection range is limited for two different situations during the day and night, day and night. The scene ROI range is shown in Figure 2.

![Day and night detection ROI range diagram](image)

**Figure 2.** Day and night detection ROI range diagram
2.1 Daytime vehicle feature detection

In this paper, the Jiugongge template is used to analyze the binarized shadow candidate points (the binarized shadow of the vehicle bottom shadow candidate is 255, and the pixel point of the candidate point is not set to 0. Figure 3 shows the Jiugongge template. The center point E of the Jiugongge is the first undercarriage shadow candidate point searched vertically in the ROI range of the daytime scene. The eight connected directions at this point are searched. The whole grouping process is shown in Figure 4. The red square part represents the pixel point with the brightness value of 255, that is, the pixel point which may be the shadow of the bottom of the car. If there is any direction in the eight connected directions of E in Figure 4(a) 255 pixels, this pixel is assigned as the vehicle shadow candidate point, and marked as unavailable, the next round of search is shown in Figure 4(b), then E is Figure 4(b) F, and because there is a point of 255 in the D direction at this time, but it is marked as unavailable in the previous round, so this search only has 255 points in the F direction, so loop until the center point E All eight connected directions are 0, and then exit the group. These searched points are represented as points of the same group. If there is no 255 point in the eight directions of E when starting grouping, then the grouping is directly exited, as shown in Figure 4(c), that is, only the pixel corresponding to E in the community at this time.

![Figure 3. Jiugongge grouping algorithm illustration](image)

The concept of close distance and medium distance is introduced in the article. The definition of close distance is within 15 meters. As shown in Figure 5, the red line in Figure 5 is the boundary line between medium and long distance and close distance.

![Figure 5. Close-up and long-distance conceptual illustration](image)

For the analysis of the bottom shadow of the car, the main feature information is captured by the difference between the bottom shadow and the road surface brightness value. For the close-up bottom shadow, the bottom shadow value is shown in Figure 6, and can be analyzed from Figure 6. In the range shown in the figure, the information of the bottom shadow is sufficient and the brightness value is lower than 35. Considering the climatic factors in the actual scene, the close-up bottom shadow brightness search threshold is set to 40.
When searching for the shadow of the bottom of the car, the order of search in the ROI range is from bottom to top, and the feature points that match the brightness threshold of the bottom shadow are searched column by column, as shown in Figure 7. In the car bottom shadow search ROI range, the pixels whose brightness threshold is lower than 40 are searched, and the cluster width of these pixels is greater than the quarter lane width, and these points are used as the vehicle bottom shadow candidate points, as shown in Figure 8.

(1) Short-distance vehicle shadow candidate points
After searching for the candidate points of the vehicle bottom shadow, it is necessary to further confirm whether these candidate points are the shadow of the bottom of the vehicle. The method adopted in this paper is to judge the road surface and the shadow of the vehicle bottom by the position of the bottom shadow candidate point position down one-half of the lane width. Whether there is a luminance difference in the candidate points, and whether the point cluster is greater than a quarter of the lane width, and if the condition is established, it is determined to be a valid vehicle bottom shadow. The selection of the candidate points for the short-distance bottom shadow is shown in Figure 9.

(2) Medium and long distance vehicle shadow candidate points
The search for the mid-distance bottom shadow candidate points is the same as the close distance. First, the pixels with the brightness difference and the group width greater than the quarter lane width are searched. If this condition is true, the pixels are saved first; The center of the pixel points upward to search for the feature information of the vehicle edge point in the horizontal direction about the width of the lane width. If there is edge feature information, and the number of points accounts for more than 70% of the total number of detection points, it is effective for the shadow of the vehicle bottom. Information data, as shown in Figure 10.
Figure 10. Medium and long-distance vehicle feature detection

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2.2 Night vehicle feature detection
(1) Analysis of color space characteristics of taillights
At night, it is difficult to capture the shadow of the car and the feature points on the edge of the vehicle, which makes it impossible to detect the vehicle at night using the same algorithm during the day. However, at night, the taillight signal of the vehicle is obvious, and the vehicle taillight can be captured to capture the vehicle at night. In order to ensure the real-time performance of the system and improve the computing efficiency, the YUV format image is not converted into other color spaces. The numerical analysis of the vehicle taillights in the YUV color space is shown in Figure 11.

Figure 11. The component values and HSV vector space diagram of the taillights in the HSV color space

After a large amount of experimental data analysis, the taillights will have a halo of red outer ring, and the brightness value of the area surrounded by the red outer ring is close to the saturation value of the brightness value (value is 255). This paper judges the regional community with such characteristics as Vehicle taillights. In the algorithm research of this paper, the information of capturing taillights of the vehicle is finally defined as: \( Y > 200, \ V > 160 \).

(2) Description of the taillight capture process
After capturing the characteristics of the vehicle taillights in the YUV space, some of the binarized white spots are retained, and the information of the accurate taillights needs to be searched from these spots. Interference noise will also be captured due to threshold filtering in the YUV space. In order to eliminate these very similar noise disturbances, each spot needs to be grouped. In this paper, the Jiugongge grouping algorithm is used, and then the normalization of each community is carried out, and the size of the community after normalization is compared. The two communities are similar in size and within the limited value, it is considered as the taillight of the vehicle.

In the ROI detection range, the preliminary taillight candidate information captured by the threshold set by the YUV space is searched in the order from left to right. When the first information that matches the characteristics of the taillight is found, the current record is recorded. The location and
area size information, as shown in Figure 12, then continue to search for information that matches the characteristics of the taillights. If it is found, it is judged whether the areas of the two are similar. The similarity is the characteristic information of the effective taillights. If the camera is assumed When the horizontal correction is not made, the tail lights in the picture are not horizontally paired. In this case, it is necessary to search within the entire ROI range.

Figure 12. Search for rear taillights candidate points

If the characteristic area of the taillights is not similar, the taillight candidate point information is updated, and the rightward search is continued until the boundary of the ROI range. If the symmetrical taillight information is still not found after continuously searching for the ROI boundary, it is determined that the noise is cleared. Previously recorded, continue to search up column by column. As shown in Figure 13, if both 1 and 2 meet the characteristics of the taillights, but the areas are not similar, the candidate points are updated to 2, and the symmetrical taillights are searched from 2 to the right.

Figure 13. Rear lights are not similar to the schematic diagram

(3) Taillight feature point normalization comparison
As can be seen from the previous description, an essential step in locking the taillights is to normalize the preliminary information of the taillights and compare the size of the area. In the normalization calculation, a standard size is first determined to standardize the target to be compared. The target refers to the taillight information in this paper. Define the normalized size, that is, the normalization size is normalization size, and the community length and width of the taillight candidate community are recorded as grouplength and groupwidth, and the normalized community length and width are grouplength non and groupwidth non, then the community is normalized. The expression is:

\[
\text{If (Candidate taillight community pixel)} \quad \text{While (Traverse all community pixels)} \quad \text{groupwidth go} \quad \text{grouplength go} \\
\quad \text{grouplength_non} = \text{grouplength/normalization_size} \\
\quad \text{grouplength_non/grouplength/normalization_size}
\]

If the normalized community length and width calculated by the two communities are similar, it is considered to be the taillight of the vehicle taillight, otherwise it is considered to be interference noise.

3. Distance conversion and measure-ment

3.1 Lane line correction mechanism
In order to enhance the stability and robustness of the system, the lane line correction mechanism has been added to ensure that lane line detection can be made under the more vulnerable to the
interference of environment conditions such as light and shade. The algorithm flow chart of lane correction is shown in Figure 14, and the test results of the algorithm in the actual experiment are shown in figure.

![Algorithm Flow Chart](image)

**Figure 14.** Lane line correction flow chart

In Figure 15, figure (a) is the original map of the driving image. As the lane line here is completely damaged, the driver can no longer distinguish the main lane visually. Lane in figure (b), using the modified algorithm, the algorithm for this kind of situation to make the lane line, as shown in figure can see, in the lane line cannot be in a short time detection, algorithm to ride in this short period of time according to the pictures before a couple of reserved the lane line information on the lane line information make general judgment, and for display.

![Lane Line Correction Results](image)

**Figure 15.** Lane line correction results

3.2. Monocular distance model

(1) Establishment of the distance model

When the vehicle is running, the camera shakes and the shooting angle will change, which causes the camera's multiple built-in input parameters to change. From this aspect, its applicability is greatly limited. At the same time, the amount of computation in the actual embedded system is large, which is directly related to whether the system can meet the requirements of real-time processing. Based on the above considerations, this paper adopts a simple and practical monocular ranging method, as shown in Figure 16, which is based on the lane width information. When the vehicle characteristic information is found, a fixed position lane width information is displayed in the screen. For the substrate, the ratio of the lane widths of A and B is calculated, corresponding to the distance conversion table that realizes the measurement, thereby obtaining the actual distance information. The base of the lane line
information is generally set as the base where the lowest position of the detected vehicle is detected, and the calculation formula of the lane ratio mentioned above is expressed as $\frac{B}{A}$.

**Figure 16.** Substrate selection and lane width ratio diagram

In the monocular ranging method proposed above, the distance conversion table is important data measured in actual experiments. In the monocular ranging strategy of this paper, the data displayed on the screen is based on this data table, and different road widths correspond to different data tables, and the specific data is shown in Table 1.

**Table 1.** 3 m and 4 m width lane distance search form

| Actual distance (m) | Actual measured lane width – 3 m | Actual measured lane width – 4 m |
|---------------------|----------------------------------|----------------------------------|
|                     | lane width occupied by the screen width | lane width ratio | lane width occupied by the screen width | lane width ratio |
| 4                   | 412 | 69 | 159 | 0.669034 |
| 9                   | 228 | 101 | 173 | 0.410384 |
| 12                  | 209 | 255 | 0.507043 |
| 15                  | 157 | 206 | 0.33333 |
| 18                  | 147 | 218 | 0.286032 |
| 21                  | 137 | 227 | 0.251393 |
| 24                  | 128 | 237 | 0.224852 |
| 27                  | 118 | 247 | 0.203626 |
| 30                  | 108 | 257 | 0.183252 |
| 33                  | 98  | 267 | 0.167893 |
| 36                  | 88  | 277 | 0.155632 |
| 39                  | 78  | 287 | 0.147801 |
| 42                  | 68  | 297 | 0.139602 |

**Figure 17.** Experimental results of single - head distance measurement

(2) Analysis of experimental detection results

The measured results show that the system has extremely stable performance in the daytime, night and road conditions when the distance is more than 10 meters. The experimental results in different situations are shown in Figure 15.

In Figure 17(a), when the distance between the vehicles is too far, the bottom shadow can not be searched, the taillight information is used to calculate the distance. In Figure 17(e), it can be seen that the system can also adopt the previous case when the lane line information is lost. The lane line correction mechanism finds the lane line and calculates the shadow position of the vehicle bottom, and performs the calculation of the distance conversion; when there are complicated road signs in Figure
17(f), the system can still work stably. In Figure 17(c), because the light interference is too strong, the vehicle correction mechanism cannot be correctly started, resulting in an error in the capture of the vehicle, resulting in a large error between the actual measurement and the actual distance. All the types of this situation are used in this paper. The environment rarely appears, and for the most part, the overall system work presented in this paper is stable.

### 3.3 This paper binocular distance model distance detection strategy and evaluation

In the binocular vision ranging strategy of this paper, the parallax of the vehicle in the left and right pictures is first obtained. In order to achieve this goal, the results obtained by the vehicle search algorithm described above need to be obtained, and the left view picture can be obtained through the vehicle search algorithm. Figure 18 (a) The coordinate point \((x_1, y_1)\) of the vehicle, searching for the position of the same vehicle on the right-view screen, and obtaining the coordinate point \((x_2, y_2)\) of the vehicle of Figure 18(b), the disparity value is \(|x_2 - x_1|\) And the parallax calculation in day and night is the same, but the way to capture coordinate points is different.

**Figure 18.** Left and right perspective coordinate points for schematic drawing

After obtaining the coordinate points and calculating the disparity value, the next important step is to convert the real distance. This paper uses the geometric relationship to find the relationship between the parallax and the distance, thus indirectly calculating the distance of the current vehicle. As shown in Figure 19, some geometric relationships between the parallax and the actual distance are calibrated, and according to these relationships, the true distance can be derived, where Object represents an object in a three-dimensional space, and \(d\) represents a target object in the three-dimensional physical space and the true state of the camera. distance \(C_x, C_y\) is the optical center of the camera lens, \(w_1\) and \(w_2\) represent the optical center spacing of the two cameras, \(f\) represents the focal length of the camera, and \(O_x, O_y\) represent the projected position of the object in the three-dimensional physical space in the two-dimensional image.

**Figure 19.** The Geometric Relationship between the Three-dimensional Physical Position of Target and the Projection Position in Two-dimensional Image

From the description of the above geometric relationship, the geometric relations (1) and (2) can be obtained:

\[
d : f = L_1 : O_x \tag{1}
\]

\[
d : f = (L_1 + L_2) : O_y \tag{2}
\]
After finishing, take the dimension to get the formula (3):

\[
d = \frac{f(m) \times L2(m)}{O_x - O_y (pixel)} \times \frac{1}{m_{pixl}}
\]  
(3)

In order to obtain the error between the distance and the actual distance obtained by the parallax conversion, in the actual experiment, the corresponding table of the actual distance and the parallax measurement when the camera spacing is 20 cm is first measured in advance. The distance between the known parameters of the two cameras is 0.22 meters, the focal length is 0.00367 meters, and the experimentally measured data is substituted into equation (3), and the error value of the theoretical distance between the actual distance and the parallax calculation is observed. The specific data is shown in Table 2.

It’s observed from table 2 that after the distance between the two-lens parallax distance conversion exceeds 10 meters, the distance converted from the formula and the actual distance error become more and more larger, which seriously affects the accuracy of the system and poses a danger to the driver. In addition, it can be seen from table 2 that after the distance of the two-lens parallax exceeds 20 meters, there is almost no difference in the parallax value, and the distance cannot be resolved by the parallax value. The single-lens ranging method proposed above cannot accurately measure the distance for too close distance, and the double-lens parallax distance conversion cannot accurately measure the distance at a long distance. Therefore, in order to make the system accurate distance measurement in the far, medium and close distance, the advantages of combining single and double lens distance conversion are integrated. In the long range, the single lens is used for distance conversion, while the close distance is used for double lens parallax distance conversion.

Table 2. Comparison of Theoretical and Actual Distance of Parallax Ranging

| camera spacing - 20 cm | actual distance (m) | parallax (pixel) | theoretical distance (m) | error rate(%) |
|------------------------|---------------------|-----------------|--------------------------|--------------|
| 6                      | 59                  | 6.00            |                          | 7.00%        |
| 9                      | 42                  | 8.37            |                          | 19.58%       |
| 12                     | 37                  | 9.65            |                          | 23.60%       |
| 15                     | 32                  | 11.46           |                          | 32.50%       |
| 18                     | 29                  | 12.15           |                          | 37.85%       |
| 21                     | 27                  | 13.05           |                          | 42.83%       |
| 24                     | 26                  | 13.72           |                          | 47.14%       |
| 27                     | 25                  | 14.27           |                          | 50.83%       |
| 30                     | 24                  | 14.75           |                          | 55.30%       |
| 33                     | 24                  | 14.75           |                          | 59.09%       |
| 36                     | 24                  | 14.75           |                          | 60.54%       |
| 39                     | 23                  | 15.19           |                          | 60.02%       |
| 42                     | 22                  | 15.99           |                          | 60.02%       |

4. Experimental results and analysis

Figure 20 and Figure 21 show the results of the system's distance detection in the single-and-double-lens switching mode, including day and night. As shown in Figure 18, even if only part of the characteristics of the vehicle can be detected within the range of ROI set before the article, the system can accurately detect the distance of the vehicle; as shown in Figure 21, there is a street lamp at night. In the case of reflective road surface, the system can still achieve stable functions.

Figure 20. Daytime distance detection results
Figure 21. Night distance detection results

The strategy of single- and double-lens switching detection distance proposed in the paper is analyzed, and the characteristics of system distance detection are summarized. The results of the analysis by a large number of experimental data analysis systems are shown in Table 3.

Table 3. System distance detection analysis table

| testing scenarios | total number of pictures | correct detection number | error detection number | detection rate  |
|-------------------|-------------------------|--------------------------|------------------------|----------------|
| daytime scene 1   | 4200                    | 4125                     | 75                     | 98.21%         |
| daytime scene 2   | 6050                    | 5952                     | 98                     | 98.38%         |
| daytime scene 3   | 4545                    | 4505                     | 40                     | 99.11%         |
| night scene 1     | 3200                    | 3125                     | 75                     | 97.65%         |
| night scene 2     | 6000                    | 5455                     | 545                    | 90.91%         |
| all scenes        | 23995                   | 23162                    | 833                    | 96.52%         |

When detecting a vehicle, the vehicle is detected by the characteristics of the bottom shadow, the vertical direction of the vehicle, and the taillights. These methods are not only computationally intensive, but also have high accuracy. Based on this, a method based on single and double lens switching is proposed to detect the distance between vehicles. This strategy makes clever use of the geometric relationship between vehicle features and distance, which ensures the accuracy of detection. This greatly reduces the amount of computation of the system.

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