A Rear-lamp Recognition System Based on D-S Evidence Theory

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Abstract: In this paper, a recognition system of headlamp language based on D-S evidence theory is proposed. For each recognition, the features of the pictures captured by multiple cameras are extracted and brought into the trained BPA by using the features of HSV color space, which is transformed into the probability of different decision support. Finally, D-S evidence theory is used to calculate the final fusion results. Experiments show that the algorithm effectively improves the recognition accuracy, and can work normally even if a single sensor fails as well as the recognition rate is improved. In addition, the algorithm is simple in calculation and meets the requirement of high real-time performance for unmanned vehicle system

1. Introduction

With the development of driverless technology, road condition perception and analysis is an important part of driverless vehicle. Multi-sensor is used to collect and fuse all kinds of information in the process of vehicle driving, such as lane detection, road detection, obstacle detection in front, signal light and traffic sign detection, etc. hen, decision-making is made according to the fusion result to realize the control of unmanned vehicle. When we are driving normally, we usually predict and judge the state of the vehicle in front by observing the change of the taillight. Similarly, some articles use the method of judging the semantics of the front and rear lights to predict the running state of the front vehicles. In order to improve the recognition accuracy, this paper uses multi-camera to collect information and extract features, then uses Gauss membership function to generate BPA, and finally uses D-S evidence theory to fuse information.

Experiments show that the algorithm can effectively improve the accuracy of the system on the premise of ensuring the real-time performance of the system. In order to improve the recognition accuracy, this paper uses multi-camera to collect information and extract features, then uses Gauss membership function to generate BPA, and finally uses D-S evidence theory to fuse information. Experiments show that the algorithm can effectively improve the accuracy of the system on the premise of ensuring the real-time performance of the system.

2. System Description

After collecting their original pictures by different cameras, the system should use their respective image processing and feature extraction systems, and then carry out information fusion at the decision-making level. The flow chart of the whole system is shown as follows:

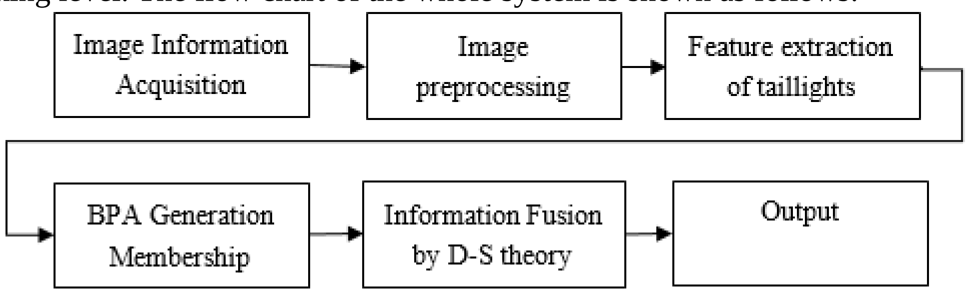

Figure 1. System flow chart

From Figure 1, there are four core parts of the Application layer. After collecting their original pictures by different cameras, the system should use their respective image processing and feature extraction systems, and then carry out information fusion at the decision-making level. Image preprocessing is used to filter the collected images, aiming at removing interference and noise. The second part is the feature extraction of taillights. It is used to find the area of interest in the image, that is, the taillight of the front car, identify its position and extract the feature information of the left and right taillights of the front car. The third part is the decision-making part, which uses BPA generated by Gauss fuzzy numbers to bring the eigenvectors into it and convert them into the support rate of the decision-making framework. The fourth part is the final information fusion. According to the output of the third part, the classical D-S evidence theory is used for decision-level fusion to produce the final results. The pseudo code as follow:

```
STEP1: [color space convert]
IF successfully obtain a frame
THEN RGB color space→ HSV color space
STEP2: [image binaryzation]
FOR (i= first pixel, i<=last pixel, step+1)
IF 171<i. H<180 or 0<i.H<8
IF 100<i. S<255
THEN i. color = black
ELSE i. color = white
END IF.END FOR.
STEP3: [feature extraction]
dilate four times and erodes four times
image segmentation using OTUS
IF Rear-lamp matching =TRUE
THEN record coordinates and draw a rectangle out of it
ELSE record coordinates ← NULL
IF obtain other frames
THEN GOTO STEP1
ELSE D-S fusion, RETURN
END IF.
```

3. Main Modules Design

The improvement of recognition accuracy of this system mainly depends on the following two points. First, how to extract the two taillights of the front car simply and efficiently. FIGURE2 shows the flow chart of taillight extraction. It is worth noting that the color space model we choose here is HSV, because Ronan O's Malley [1] et al. collected and counted a large number of automobile taillights. It was found that the distribution of night taillights in HSV space would be more concentrated. Firstly, binary operation was carried out to select the pixels whose ($342° < H < 360°$) or ($0° < H \leftarrow 30°$), $0.45 < S < 0.50$. Due to the variety of styles and colors of vehicle taillights, it is not easy to distinguish all taillights completely by using a threshold. After binarization, the image is corroded twice and expanded twice to further eliminate noise, retain the taillights we are interested in, and finally use OTUS for threshold segmentation.

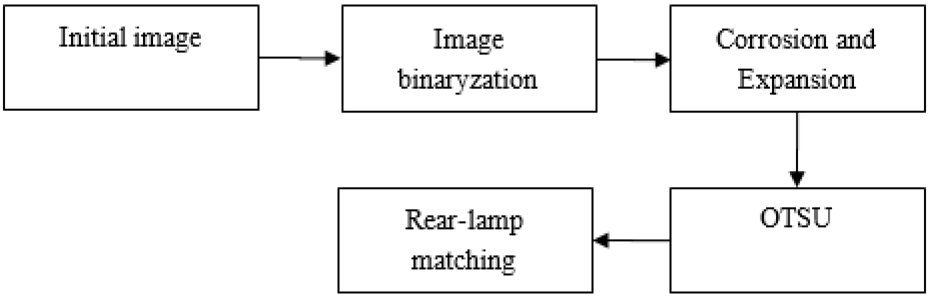

Figure 2. Image processing flow chart

In taillights matching, we think that two headlights are usually located in the same horizontal line (deviation in the horizontal direction is within a certain range) and the centroid distance is within a certain range of two headlights are considered as a set of headlights, matching them into a pair, observing their characteristics and participating in subsequent decision-making. That is to say, as shown in Figure 3, the vertical distance between the left and right lights is less than X-distance, and the horizontal distance is less than Y-distance, where X-distance = k*Y-distance, K takes different values with different systems.

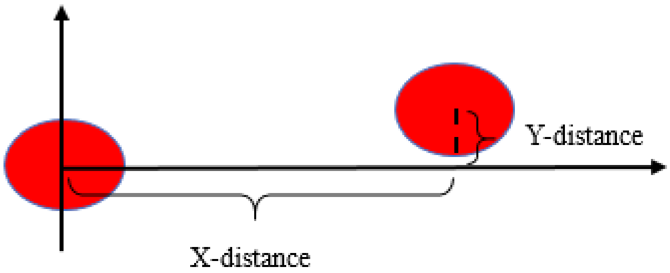

Figure 3. Rear-lamp matching

The second point is information fusion at decision level. The reason why decision-level fusion is adopted instead of pixel-level or feature-level fusion is that unmanned vehicle system requires high real-time performance, while decision-level fusion has strong fault-tolerance, good openness, short processing time, low data requirements and strong analytical ability. The HSV component was detected after successful lamp extraction. In Open CV, H is 0-180, S is 0-255 and V is 0-255. They are used as the basis of recognition. A part of the sample is taken as training set, and the variable is generated by BPA using the membership function of Gauss fuzzy number. According to the generated BPA, the sample data is transformed into the probability of supporting each decision in the recognition framework. Finally, classical D-S theory is used to get the final decision results.

4. Result and Analysis

The laptop running the algorithm is configured as follow: CPU-Intel(R) Core(TM) i5-5200U CPU @ 2.20GHz, graphics card-AMD Radeon R7 M270, memory-6GB, hard disk-1TB. Figure 4 and Figure 5 show the frequency statistics of S and H components of the taillight successfully extracted. It can be found that the components of H and S of taillights are concentrated on the binarization threshold mentioned above(($342° < H < 360°$) or ($0° < H < 30°$) $0.45 < S < 0.50$)). However, if RGB color space is used, it will be affected by illumination and other environmental factors, so a reasonable threshold can not be set very well. Figure 6 is the result of image segmentation; from which we can see that many noises have been successfully filtered out.

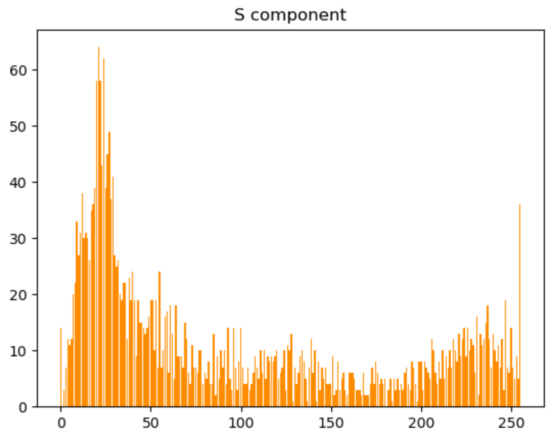

Figure 4. S component

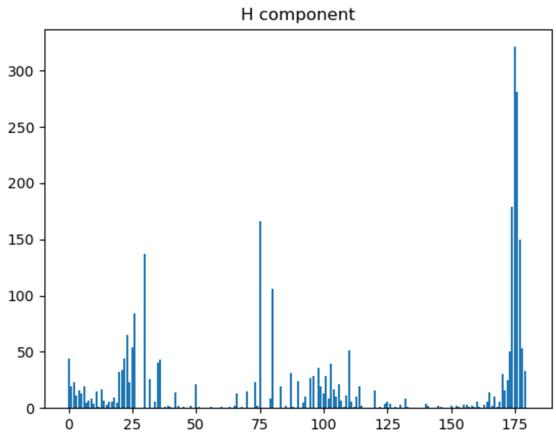

Figure 5. H component

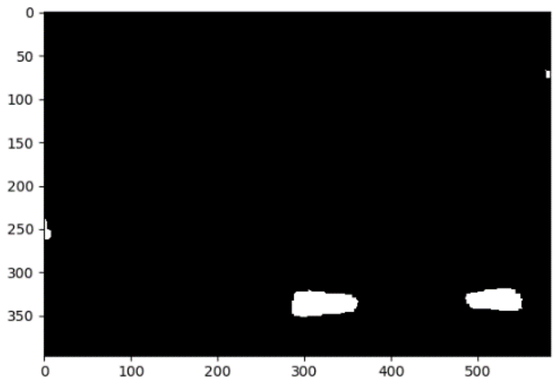

Figure 6. Segmented image

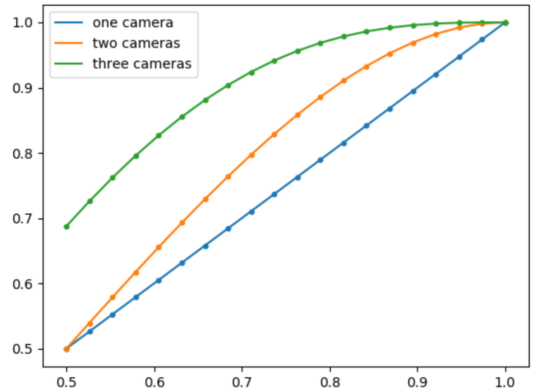

Figure 7. Comparison curve

As shown in Figure 7, in the system where a few cameras make decisions together, we can see that with the increase of sensor reliability, the recognition success rate of multi-sensor system is significantly higher than that of single-sensor system.

5. Conclusion

In this paper, a multi-source recognition system of headlamp language based on D-S evidence theory is proposed. It improves the existing algorithm, introduces multi-sensor information fusion to participate in decision-making, improves the accuracy of system recognition and guarantees the real-time performance of the system on the premise of small amount of calculation.

Acknowledgements

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