Lane image stitching based on ORB feature matching

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Abstract: This paper proposes an improved lane sequence image stitching technique based on ORB algorithm and the most suture technology for the problem of incomplete image information taken by the lane camera when processing road image。The feature points are first extracted using the ORB method, and then the feature points are purified using an improved GMS method. Finally, the best suture method is used to fuse the overlapping regions of the image.

1. Introduction

In recent years, with the rise of artificial intelligence, intelligent transportation construction has also received increasing attention[1]. However, there are still many problems with the intelligent multi-lane image camera system. The main role of the system

It consists of 1) capturing instantaneous images of offending vehicles, 2) extracting clear license plate information of offending vehicles, and 3) photographing the surrounding environment of offending vehicles when actual problems occur, such as: traffic violations caused by illegal lane changes of vehicles, but lane cameras of intelligent transportation systems usually Only a single lane can be photographed, and the moment of violation can not be completely photographed[2], which makes it difficult for the transportation department to produce strong evidence when the accident is determined. In view of the above problems, I propose to use image mosaic method to solve.

2. Improved GMS algorithm

2.1 ORB feature point extraction

In this paper, a robust, high-speed GMS algorithm is used to extract feature points from the image[3], and a BF algorithm is used to roughly match the feature points of the image. At this time, there are f_n , f_m feature points for the image (Img1, Img2), among which $f_n = f_{n1} \ldots\ldots f_{nn}$ $f_m = f_{m1} \ldots\ldots f_{mm}$, where (f_{ni}, f_{mi}) represents a pair of feature matching.

2.2 GMS algorithm feature neighborhood calculation

The GMS algorithm converts motion smoothness into a probabilistic statistical model estimation problem[4], so that it is more efficient in processing the matching purification problem.

It is assumed that the smoothness of the motion makes the position displacement of the true matching neighborhood range smooth[5], and the motion of the false match is not smooth. From this, the following conclusions are drawn, there must be several matches in the range of correct matches to support its correctness[6], and there are few or no matches in the range of incorrect matches to support it.

Now set $Img1$ $Img2$, the set of matching neighborhood points $\{G_a, G_b\}$ is set to ($G_a = \{G_{a1} \ldots\ldots G_{an}\}$ $G_b = \{G_{b1} \ldots\ldots G_{bn}\}$)Among the i-th group of matches ($\{f_{ai}, f_{bi}\}$), there are matching points $\{f_{a1} \ldots\ldots f_{ak}\}$ in the neighborhood $\{f_{b1} \ldots\ldots f_{bk}\}$.

These matching points will match the feature points[7, and the corresponding neighborhood is G_{bi} ,Count the number of features from G_{ai} to G_{bi} and name it the neighborhood feature score S_i to get the formula (1), (2) where k = 1, ..., M, which represents the feature matching of the k-th feature point If it is in G_{ai}, it is set to 1 if it is not, and it is set to 0 if it is not[8].

$$S_{ik} = \begin{cases} 1, & if \quad f_{bi} \quad in \quad G_{bi} \\ 0, & other \end{cases} \tag{1}$$

$$S_i = \sum_{k=1}^{M_i} S_{ik} \tag{2}$$

3. Improved four-grid feature quantity statistical method

In order to improve the operation efficiency of the algorithm, GMS proposes to divide the image into grids. The GMS algorithm counts the feature quantity of each grid, and at the same time counts the feature scores of the 8 grids that match the neighborhood. The network is often ignored in the actual operation. The feature information of the grid edges and the method of counting the feature scores of eight grids need to be improved. Based on the principles of motion independence and grid symmetry, this paper proposes the feature scores of three grids in the field of statistics and defines the feature scores of four grids as S. , Formula (3)

$$S_i = \sum_{j=1}^{4} S_{i,j} \tag{3}$$

$S_{i,\ j}$ In formula (3) represents the feature score of the j-th grid in the i-th four-grid grid.At the same time, in order to eliminate the statistical impact of image rotation, the statistical effect of image rotation is counted 4 times clockwise to eliminate the effect of rotation. Compared with the traditional GMS nine-grid rotation of 7 times, the efficiency of this method is significantly improved.

$$S_i^L = \max\left\{\sum_{j=1}^{4} S_{i,j}^k, k = 0......3\right\} \tag{4}$$

Where $S_{i,j}^k$ represents the j-th grid feature score obtained after k rotations of the i-th grid, and then calculate the mean value of the feature, Formula

$$M_i = \frac{1}{4}\sum_{j=1}^{4} M_{i,j} \tag{5}$$

Which represents the feature number of the j-th grid in the i-th four-grid grid. Then calculate the feature score threshold amount, the formula is

$$S_T = \mu \ln(\alpha M_i + \beta) \tag{6}$$

Among them, μ, α, β are given by the threshold coefficient GMS algorithm. The μ coefficient is for the case of fewer correct matches and more mismatches in the grid. Generally, it is set to be large. The α coefficient is the weight of the mean of the number of features. Generally, it is set close to 1. The β coefficient is for the logarithmic function input as the base. In small cases, the setting is generally small. After comparing S_i^L, S_T pairs Elimination of mismatches.

4. Best suture algorithm

This paper uses the best stitching algorithm to fuse lane images. The algorithm is as follows

1) Each line in row 1 corresponds to a suture, and its guideline value

Initialized to the value of the pixel corresponding to the criterion value image.

2) Place 3 in the next line next to the current point of each suture

The criterion value of two points and the criterion value of two adjacent points to the left and right of the current point

For comparison, select the point with the smallest criterion value as the expansion point.

The value point is already a point on the suture line, so the next lowest point is selected. In case

The current point of the suture line is the point of the last line of the overlapping image, then proceed to step

Step 3), otherwise proceed to the next expansion.

3) The one with the smallest average criterion value is selected as the best suture.

Complete image stitching by the above method

5. Analysis of results

(1)Use the matching accuracy rate as the evaluation index of the registration accuracy. The higher the accuracy rate, the higher the algorithm's registration accuracy.

(2)Use variance and root mean square error as the evaluation index.

The three sets of lane images are as follows:

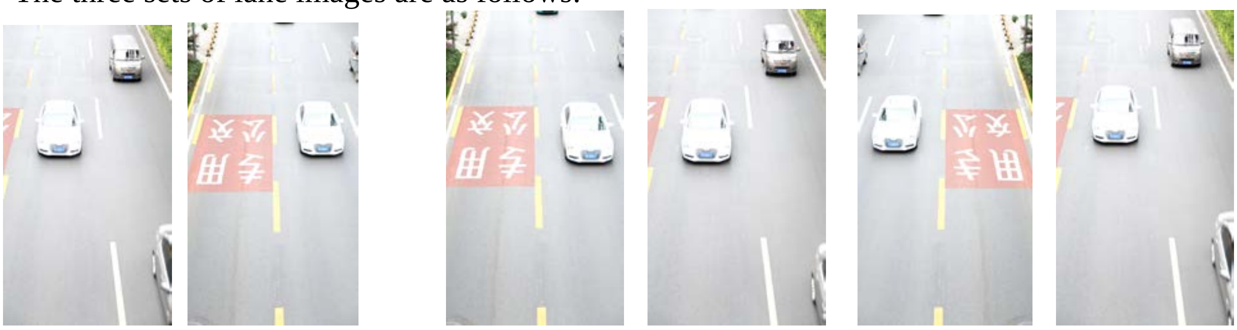

Fig. 1 three sets of lane images

The experiment uses the improved GMS algorithm and SIFT+RANSAC, SURF+RANSAC, ORB+RANSAC algorithm to compare .the results as follows

Table 1 Matching accuracy

algorithm	image		
	first	second	third
Sift+Ransac	82.5%	86%	82%
Surf+Ransac	81.3%	76.8%	74.9%
ORB+Ransac	79.5%	73.2%	68.5%
proposed	85.1%	85.7%	83.7%

It can be seen from the table that the accuracy of the improved GMS algorithm is significantly improved compared to the other three algorithms

The stitched image quality is determined by the Menn square error,The experiment uses the improved GMS algorithm and SIFT+RANSAC, SURF+RANSAC, ORB+RANSAC algorithm to compare the Menn square error.

Table 2 Menn square error

algorithm	image		
	LineImg1	LineImg2	LineImg3
Sift+Ransac	0.4966	0.2959	0.5406
Akaze	0.5311	0.3251	0.6031
Surf+ransac	0.3501	0.2441	0.3911
proposed	0.1948	0.219	0.3622

From the table, it can be concluded that the Menn square error of the improved GMS algorithm is smaller, indicating that the algorithm stitching quality is better.

6. Conclusions

Aiming at the problems of high feature complexity and low image registration accuracy in traditional image stitching algorithms, this paper proposes a Improve the image registration algorithm of GMS. This algorithm uses an improved five-grid feature score statistical method to reduce the computational complexity while reducing the number of grid rotations, and use the size of the image as a constraint to square the image. Points, to obtain the same feature matching accuracy as the GMS algorithm, and greatly improve the operation speed.

Experiments show that the improved GMS algorithm has greatly improved the registration accuracy and the quality of image stitching compared with the traditional algorithm.

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