



Research on Image Stitching for Parking Assistance System

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Abstract. Currently, car parking assistance is limited to the small angle rear view imaging of the reversing radar, which can only provide the driver with a limited range of vision and is prone to safety hazards. It is necessary to stitch the surrounding images captured by the parking monitor by widening the monitoring field of view of the car parking and providing the driver with a complete rear panoramic image through the parking assistance system. In this research, we provide an enhanced SIFT image stitching technique that uses random k-d trees and the k-nearest neighbour matching to optimise SIFT feature matching to improve matching speed, the RANSAC algorithm to reject mismatched pairs to improve matching accuracy, and pre-processing to reduce distortion and eliminate stitching gaps by applying columnar projection and weighted fusion to the stitched images. The experimental findings demonstrate that the suggested approach may increase image stitching speed while also producing stitched and displayed images that are more accurate.

Keywords: Parking Assistance System · Image Stitching · SIFT

1 Introduction

With the increasing automation of cars, people's requirements for parking are not only limited to the simple display of rear view reversing images, but also have a complete and clear knowledge of the overall situation around the vehicle, so that people no longer have blind spots for parking. The parking assistance system enables the driver to have a comprehensive understanding of the surrounding information, reducing the blind spot in the field of vision and ultimately solving the problems of parking, narrow lane meeting and obstacle avoidance, so as to effectively reduce the occurrence of accidents such as cutting. Therefore, this paper studies the image stitching of parking assistance systems to solve the practical problems.

Currently, SIFT is the most widely used image stitching algorithm in image stitching technology, but there are disadvantages such as slow speed, many false matching points and distortions when multiple images are stitched together, so this paper improves the following three aspects and establishes the final parking assistance system: 1) improve the matching speed; 2) improve the matching accuracy; 3) suppress the distortion caused by multiple image stitching.

2 Related Work

In 2006, the concept of panoramic parking was first proposed in a patent by Kato et al. [1] and published in a paper on the subject, attracting widespread attention and research from automotive manufacturers. In recent years, Fen et al. [2] proposed to install angle sensor collection brackets for cameras and generate dynamic offset look-up tables in real time, through which the effects caused by camera shooting can be corrected to achieve parking image stitching. Lee et al. [3] proposed a three-stage approach to achieve accurate and seamless top view image stitching through feature tracking, obstacle filtering and top view generation.

In 2018, Lun Wang [4] proposed the algorithm of "smooth transition fade out and fade in weighted fusion" for the fusion of panoramic images, which achieved the stitching of panoramic images of car parking with good stitching effect, but the efficiency of the image stitching algorithm needs to be further optimised. In 2021, Han Qin [5] proposed to quickly generate the top view based on the projection table and image masking method to achieve the elimination of stitching seams, and to implement the transparent underbody algorithm by multi-threading method to infer the underbody part of the car image. In recent years, most of the panoramic parking assistance systems on the market are seamed stitching systems, which still have visual blind spots. There are few affordable and widely available parking systems, and the stability of the parking system and the effect of the stitched image display need to be further improved and optimised.

3 An Improved SIFT Image Stitching Based Algorithm

3.1 Traditional SIFT Image Stitching Algorithm

A popular stitching technique in the field of image stitching is the SIFT (Scale Invariant Feature Transform) approach, which Lowe first described in 1999 and further developed in 2004. It is a feature-based matching approach with significant resilience for extracted feature points. The SIFT algorithm is a feature-based matching method, which needs to go through the steps of scale space construction, spatial extremum finding, stable key point positioning, stable key point direction information allocation and key point description to achieve the extraction of feature points, and has strong robustness for the extracted feature points. In addition, the SIFT algorithm is a widely used stitching algorithm [7]. However, the algorithm often has the disadvantages of slow stitching speed, poor accuracy and easy distortion for multi-image stitching, so it needs to be further optimised.

3.2 Feature Matching Based on Random k-d Tree Optimisation

The traditional SIFT algorithm uses a violent matcher (BF-matcher) for feature matching. Although the optimal match is found, if the image resolution is high and the number of pixels is large, the time consumed increases as the number of extracted feature points increases by a power function, which greatly increases the overall processing time.

Therefore, FLANN -matcher is used in this study in place of the BF-matcher for a k-nearest neighbour search based on random k-d trees.

k-Nearest Neighbor Algorithm

The k-Nearest Neighbor algorithm is a basic classification and regression method [8]. For a certain set of data, given a new input data, the k data points closest to the new input data are found in the given set of data, and the k data points are counted to find the class with the largest proportion of the k data points, and the new input data is classified into that class.

The k-nearest-neighbour algorithm uses a brute force search when classifying data, which takes too long. The k-d tree solves this problem and further improves the performance of the k-nearest-neighbour algorithm.

Construction of Random k-d Trees

A random k-d tree, which is basically a balanced binary tree, is a data structure that partitions a k-dimensional data space [9].

Every point in a random k-d tree is a k-dimensional node, and each non-leaf node is partitioned by one dimension. The following equation calculates the separation between two points a and b in an N-dimensional Cartesian space:

$$d = \sqrt{(x_1^1 - x_2^1)^2 + (x_1^2 - x_2^2)^2 + \dots + (x_1^N - x_2^N)^2} \quad (1)$$

In general, the nearest neighbour search only needs to detect a few leaf nodes, and the matching obtained is not necessarily the optimal solution but a near-optimal solution, which is good for images with a large number of pixels that do not require as much precision.

In this study, the following formula is used to determine the Euclidean distance between the feature points of the two pictures that will be stitched together:

$$d_{12} = \sqrt{\sum_{k=1}^n (x_{1k} - x_{2k})^2} \quad (2)$$

where $a(x_{11}, x_{12}, \dots, x_{1n})$ and $b(x_{21}, x_{22}, \dots, x_{2n})$ are the image's feature points that will be stitched together.

The average time complexity of this nearest neighbour search can be controlled to $O(\log N)$, which can greatly reduce the matching speed to achieve the total time reduction.

3.3 SIFT Algorithm Based on RANSAC Optimization

In the feature matching of the traditional SIFT algorithm, there is often a mismatching phenomenon [10], that is, the feature points in the two images cannot be correctly matched together due to occlusion and other reasons, that is, there are some mismatched points. If these errors are not correct, proper processing of matching points will affect the subsequent homography transformation, resulting in reduced splicing accuracy or even splicing failure. This paper mainly uses the Random Sampling Consistency Algorithm (RANSAC) supplemented by dynamically adjusting the ratio of the nearest neighbor

and the second nearest neighbor to achieve the purpose of eliminating false matching points.

Dynamic Adjustment of Matching Feature Pair Thresholds

In Lowe's paper, it is proposed that the ratio of nearest neighbours to second nearest neighbours (Lowe's rate) can be used to reduce unqualified matches. In this paper, the dynamic input threshold is used to adjust the accuracy of the required matches and reject the matches that do not meet the requirements.

RANSAC Algorithm for Rejecting False Matches

In SIFT, the main objective of RANSAC is to find an optimal single-response matrix. Since there are eight unknown factors in the single-response matrix, at least eight linear equations must be solved in order to determine the position of each point. A set of point pairs can be given in two equations, each of which has at least four sets of matching point pairs [11].

$$s \begin{bmatrix} X' \\ Y' \\ Z' \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \quad (3)$$

When (x, y) represents the corner position of the target image, (x', y') denotes the location of the scene image's corner point, and s specifies the scale parameter. The surrogate function is shown below:

$$\sum_{i=0}^n \left(x'_i - \frac{h_{11}x_i + h_{12}y_i + h_{13}}{h_{31}x_i + h_{32}y_i + h_{33}} \right)^2 + \left(y'_i - \frac{h_{21}x_i + h_{22}y_i + h_{23}}{h_{31}x_i + h_{32}y_i + h_{33}} \right)^2 \quad (4)$$

RANSAC randomly selects 4 matches from the original matching set, fits a model, and then calculates the distance between this model and the remaining matches. If it is less than the set threshold, the match is added to the inlier set of the model, and the cost function is calculated. After iterating several times, the model with the largest number of interior points and the smallest cost function is used as the final result, and those matches that are not in the center of the model's interior points are discarded.

3.4 Ptimisation of the Visual Effect of Distortion in Multi-picture Stitching

Traditional SIFT algorithms often fail to achieve satisfactory results when stitching multiple images [12]. In the stitching process, the images are easily stretched to produce serious distortions, which can cause a lot of information loss, and the stitching marks at the seams can be obvious and lead to poor visual effects. In a parking assistance system, this will undoubtedly result in the driver not being able to grasp the view of the side of the body, thus affecting the driver's judgement, so it must be optimised.

Treatment of Image Distortion

This phenomenon is caused by the vertical distortion caused by the use of a planar single-strain transformation without considering spatial consistency when stitching [13]. For

this phenomenon, this paper adopts the method of selecting the main image for stitching and pre-processing the image by first making a columnar projection before stitching, through these two means then stitching can achieve better results.

The specific formula for the columnar projection is as follows:

$$x' = r \sin \frac{\theta}{2} + r \sin(\arctan(\frac{x - \frac{W}{2}}{r})) \quad (5)$$

$$y' = \frac{H}{2} + \frac{r(y - \frac{H}{2})}{k} \quad (6)$$

$$k = \sqrt{r^2 + (\frac{W}{2} - x)^2} \quad (7)$$

$$r = \frac{W}{2 \tan(\frac{\theta}{2})} \quad (8)$$

Where W denotes the width of the original picture, H the height of the original image, and θ is the projection angle.

Handling of Image Seams

For the seams generated by the traditional SIFT stitching method, this paper adopts the means of image weighting fusion for processing, and its specific formula is as follows:

$$I(x, y) = \begin{cases} I_1(x, y) \\ (1 - \alpha)I_1 + \alpha I_2 \\ I_2(x, y) \end{cases} \quad (9)$$

That is, I_1 is the stitched picture, I_2 is the stitched image, and α is the weighting factor

$$\alpha = \frac{W_d}{W} \in (0, 1) \quad (10)$$

where W is the width of the stitched image's overlapping area and W_d is the distance of the pixel point in the stitched image's overlapping area from the left overlapping border.

4 Analysis of Experimental Results

4.1 Experimental Results

As illustrated in Fig. 1, three photos to be stitched in two scenarios were chosen for this work. The stitching results are presented in Fig. 2, where (a), (b) are the classic SIFT algorithm stitching results and (c), (d) are the modified SIFT algorithm stitching results in this article.

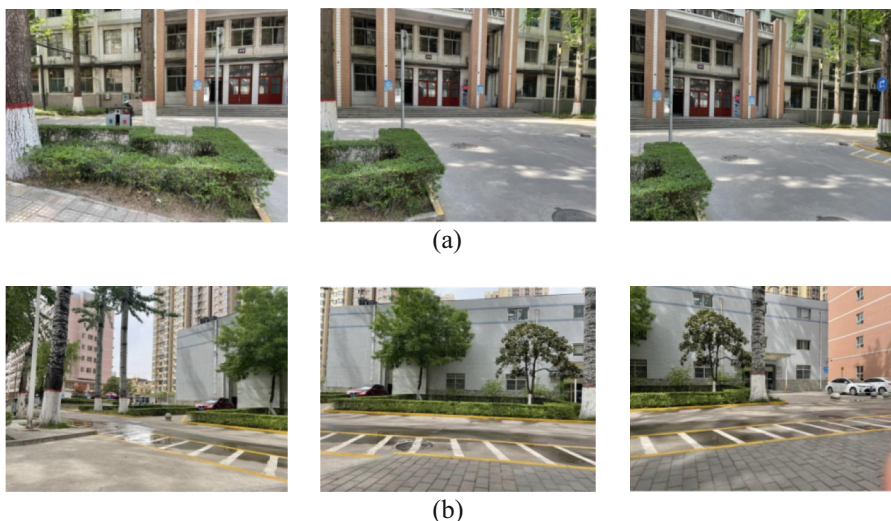


Fig. 1. Pictures waiting to be stitched together



Fig. 2. Comparison of the splicing results between the traditional SIFT algorithm and Algorithm in this article

4.2 Image Quality Evaluation Metrics

Zhou Wang et al. [14] proposed SSIM, a structural similarity-based assessment tool, in 2002. The system assesses picture quality in three ways: brightness, contrast, and structural similarity. Compared to PSNR, the SSIM evaluation criteria are more similar to those of the human visual system, and the final scoring formula of SSIM is:

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_x\sigma_y + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_1)} \in (0, 1) \quad (10)$$

where μ_x is the mean of x , μ_y is the mean of y , σ_x is the variance of x and σ_y is the variance of y , $\sigma_x\sigma_y$ is the covariance of x and y [15], and the closer the SSIM score is to one, the greater the similarity, and the closer it is to zero, the greater the dissimilarity.

As shown in Table 1, the improved SIFT algorithm evaluates the middle and rightmost images better than traditional SIFT method while keeping the evaluation of the leftmost camera basically unchanged. In addition, its total assessment is substantially higher than that of the classic SIFT technique, proving that the improvement of SIFT in this paper is effective in terms of visual effects in terms of objective evaluation.

Table 1. SSIM quality evaluation for stitched images

Description	Classical SIFT	Improved SIFT
Left camera	0.89	0.87
Front camera	0.22	0.33
Right camera	0.21	0.34
Overall rating	0.44	0.52

The real-time requirement of the method is another indicator for the picture stitching outcomes. Table 2 compares the running times of the classic SIFT method, the enhanced SIFT algorithm, and the SURF technique in this research.

Table 2. Running time comparison results for conventional and improved SIFT algorithms

Size of the images	Classical SIFT	Improved SIFT	SURF
800 × 600	16.34	15.23	15.10
1280 × 720	30.12	29.34	29.67
1920 × 1080	89.33	87.67	87.88
4032 × 3024	702.39	450.83	449.99

From Table 2, we can see that when the image size is small, the improved SIFT algorithm proposed in this paper does not have obvious advantages over the traditional SIFT, and the stitching time of both is basically the same, but as the scale of the image to be stitched increases, the time of the traditional SIFT increases significantly faster than the improved SIFT algorithm in this paper. When the size of the image to be stitched reaches 4032 × 3024 pixels, the stitching time of the improved SIFT algorithm is reduced by 36.1% compared with that of the traditional SIFT algorithm. In summary, the improved SIFT algorithm proposed in this paper has a significant improvement over the traditional SIFT algorithm when stitching larger size images.

5 Design of a Parking Assistance System Based on Image Stitching

In this article, the design of the image stitching based parking assistance system is divided into three parts: dynamic selection of stitching conditions, display of images to be stitched, display of successful stitched images and display of matching features.

This paper uses the Python GUI library tkinter to write the GUI interface, and the final designed system interface is shown in Fig. 3 below: where lowe's rate is an input box to dynamically adjust the value, BFmatch and FlannMatch are radio boxes to select the feature matching means, and stitch is a button to the button to start stitching.

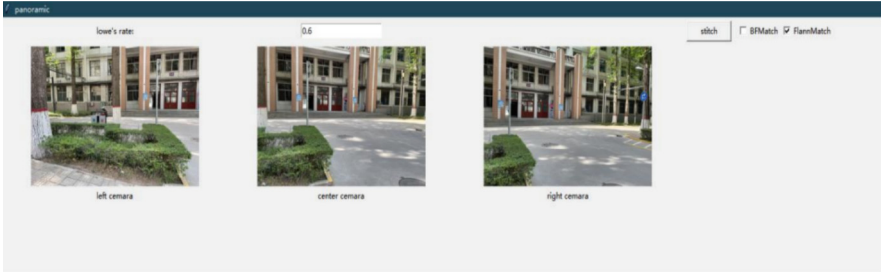


Fig. 3. Pictures waiting to be stitched together

After entering lowe's rate, selecting the feature matching method and clicking the stitch button to start stitching, the ending up shown in Fig. 4.

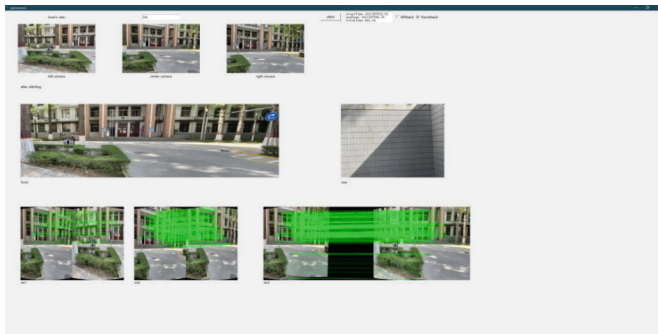


Fig. 4. Operational results of the parking assist image stitching system

The runtime in the top right corner shows the total time spent on the stitching, while the bottom three images show the stitching results and feature matching, with front showing a panoramic view of the three camera images taken from the front of the car at different angles, and rear showing a photo taken from the rear of the car, and the bottom three images showing the feature matching during the stitching.

6 Conclusion

This research addresses the shortcomings of current parking assistance systems and proposes an improved SIFT image stitching method based on random k-d tree optimisation for feature matching, dynamic threshold setting by RANSAC to reject mis-matching,

and optimisation of multi-image stitching distortion, and designs a parking assistance system based on image stitching to provide drivers with a panoramic parking view and reduce safety hazards. The experimental findings suggest that the proposed enhanced SIFT picture stitching technique is more successful, more accurate and faster, and meets the requirements of users for parking assistance systems.

Acknowledgment. This work was supported in part by the Special Project of Technological Innovation and Guidance in Shaanxi Province under Grant 2022QFY01-03, in part by the Natural Science Foundation in Shaanxi Province under Grant 2022JQ-476, and in part by the Natural Science Foundation of Deduction Department in Shaanxi Province under Grant 2022JK0474, and by Science and Technology Program in Xi'an city under Grant 21XJZZ0055.

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