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To cite this article: Jiayu Xu *et al* 2021 *J. Phys.: Conf. Ser.* **2010** 012003

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A Matching Algorithm T-AKAZE for Image Recognition of Hydroelectric Equipment Failure

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Abstract. Aiming at the shortcomings of the current image-based fault identification algorithm for hydropower station equipment, such as low efficiency and poor accuracy, an improved image matching algorithm based on AKAZE, T-AKAZE was proposed. In this paper, AKAZE algorithm is firstly used to obtain image feature points. Then, the improved algorithm T-AKAZE is used for coarse matching of feature points. On the basis of Tanimoto coarse matching, RANSAC algorithm is used for fine matching to improve the algorithm accuracy. In order to verify the matching effect of the improved algorithm, ORB algorithm, AKAZE algorithm and ORB+Tanimoto algorithm were compared and analyzed. The experimental results show that the proposed algorithm has good robustness for image matching of different scales and similarity, and its timeliness also meets the application requirements, which provides convenience for the staff to identify the fault of hydropower station equipment.

1. Introduction

At present, the hydropower station mainly relies on the staff to judge whether the equipment is abnormal through on-site observation and monitoring of video images [1]. However, the method of artificial judgment has the disadvantages of strong subjectivity and low timeliness. With the rapid development of image processing algorithms, image matching, as an important research branch of image processing, has been widely studied and applied in product defect detection, obstacle detection, positioning detection, size measurement and other aspects by virtue of its advantages of simplicity, ease of implementation and small computation [2].

Image matching algorithm is a matching method to extract similar feature points from images. At present, Common Feature matching algorithms include SIFT [3] (Scale Invariant Feature Transform), SURF [4] (Speeded Up Robust Feature) and ORB [5] (Oriented FAST and Rotated Brief) and other matching algorithms based on image features. ORB algorithm has been widely used in real-time feature detection systems in recent years due to its strong robustness and far faster matching speed than SIFT and SURF algorithm. However, FAST feature detection operator in ORB algorithm lacks adaptability to scale changes. When the scale of the image to be detected changes, the detection effect will decrease. Many scholars choose to improve on the basis of ORB algorithm. In literature [6], an improved matching algorithm for multi-scale spatial detection was proposed. The Gaussian pyramid was used to add scale information to the oFAST detection algorithm, thus increasing the adaptability to scale changes and



making the detected feature points more stable. Literature [7] proposed an adaptive Canny operator based on the improved OTSU method, and used the improved Canny operator to extract ORB features of images to achieve stable matching between visible and infrared images. However, all the above studies are based on Gaussian kernel function to construct scale space, which will lead to the loss of image edge information and seriously affect the stability of feature points and descriptors [8]. For this reason, some scholars began to study the construction of nonlinear filtering function. In 2012, a more stable feature detection algorithm KAZE [9] was proposed on ECCV, and then an improved algorithm AKAZE [10] was proposed on this basis. Experiments show that this algorithm can retain the detail part of the image well and has a strong adaptability to scale change. Compared with SIFT algorithm and SURF algorithm, AKAZE algorithm has a faster calculation speed. Compared with ORB algorithm and Brisk [11] algorithm, its repeatability and robustness are also significantly improved [12].

In the process of equipment fault identification in hydropower station, the traditional matching algorithm has high requirements on the scale, size and precision of the collected field images. However, in the practical application process, the acquired images are easily affected by the camera angle and light, and cannot meet the matching conditions, resulting in mismatching, missing matching and invalid matching. Therefore, the matching algorithm with high matching accuracy and strong stability and adaptability has become an urgent problem to be solved. To solve the above problems, this paper proposes an improved algorithm T-AKAZE algorithm based on AKAZE algorithm. The algorithm can match the pictures collected by the intelligent patrol equipment stably. With the matching results, the appearance, meter, defect and internal and external abnormal information of the equipment can be identified effectively, so as to realize the real-time acquisition of the running state of the equipment and the rapid identification of the equipment fault.

2. AKAZE algorithm

Multi-scale detection and description algorithm such as the common SIFT, SURF, and some improved algorithm based on ORB is achieved by constructing Gaussian scale space [13], but were unable to avoid a potential problem, Gaussian filter can't keep the edge information, and all the details of the scale and the noise will be smooth to the same level [14]. For this reason, some scholars proposed AKAZE algorithm for the limitation of Gaussian kernel function scale space. This algorithm can effectively solve the above problems by constructing nonlinear filtering scale space. The main steps of the AKAZE algorithm are as follows:

2.1. Construction of nonlinear scale space

The nonlinear diffusion filter describes the brightness changes of the image in different scale Spaces. As shown in Equation (1):

$$\frac{\partial L}{\partial t} = \text{div}[c(x, y, t) \cdot \nabla L] \quad (1)$$

In Equation (1) : div is the divergence operator, ∇ is the gradient operator, L is the image brightness matrix, $c(x, y, t)$ is the diffusion conduction function, and t is the scale parameter. The conduction function is shown as follows:

$$c(x, y, t) = g(|\nabla L_\sigma(x, y, t)|) \quad (2)$$

In Equation (2) : ∇L_σ is the gradient image of the original image L after Gaussian smoothing filtering, and g can be customized according to requirements.

Same as the KAZE algorithm, the number of floors O and towers S are established. Where o and s represent the corresponding discrete index identifiers. Then, the Gaussian scale of each sub-layer is calculated. Since the nonlinear diffusion filtering performs operations with time as a unit factor, the scale factor needs to be converted into a unit of time. As shown in Equation (3) :

$$\sigma_i(o, s) = \sigma_o 2^{o+\frac{s}{2}} \quad t_i = \frac{1}{2} \sigma_i^2 \quad (3)$$

This paper chooses the FED algorithm to solve the nonlinear diffusion equation. Compared with additive operator splitting algorithm (AOS), this algorithm can approximate Gaussian filter well, and can construct nonlinear scale space faster. The solution is shown in Equation (4) :

$$L^{i+1,j+1} = (I + \tau_j B(L_i)) L^{i+1,j} \quad (i > 0, j = 0, 1, 2, \dots, n-1) \quad (4)$$

$$\tau_j = \frac{\tau_{\max}}{2 \cos^2 \frac{\pi(2j+1)}{4n+2}} \quad (5)$$

Where, I is identity matrix, τ_j is constant step size, $B(L_i)$ is the conduction matrix of image coding, $L^{i+1,j}$ is the number of steps to perform diffusion, τ_{\max} is the threshold of the maximum stride length without violating the solution stability condition, and n is the number of dominant diffusion steps.

2.2. Feature point detection

Searches for Hessian local maxima after normalization of different scales. The calculation of Hessian matrix is shown in Equation (6) :

$$L_{Hessian} = \sigma(L_{xx}L_{yy} - L_{xy}L_{yx}) \quad (6)$$

Where: σ is the scale parameter; L_{xx} 、 L_{yy} 、 L_{xy} 、 L_{yx} are the second derivative of the image after Gaussian filtering.

2.3. M-LDB feature description and feature point matching

In this paper, M-LDB descriptor is used to describe the feature points. The experimental results show that M-LDB is more robust than LDB in the rotation invariance and scale invariance, and reduces the computation in the process of descriptor generation.

3. Improved AKAZE algorithm based on Tanimoto

3.1. Tanimoto algorithm

Tanimoto is a common similarity measurement method, as shown in Equation (7) :

$$T(A, B) = \frac{A \cdot B}{\|A\|^2 + \|B\|^2 - A \cdot B} = \frac{\text{Features included in both A and B}}{\text{Total features of A and B}} \quad (7)$$

In Equation (7), A and B represent two sample sizes. The larger the proportion of common features, the greater the similarity between the two vectors. In this paper, Tanimoto similarity determination principle is used to determine the obtained descriptor pairs, and the matching point pairs that meet R_x are retained. After M-LDB description, two groups of feature point descriptors A and B can be obtained. Firstly, a feature point a_n in A is selected to carry out similarity measurement with all feature points in B , as shown in Equation (8) :

$$T = \frac{N_{C1}}{m + n - N_{C1}} \quad (8)$$

Where: N_{C1} is the number of the same elements in two sets of vectors, and $m = n$ is the number of bits of binary descriptor. If the calculated result T is greater than the threshold value R_x , the pair of feature points is considered to be a correct matching pair, and the pair of feature points is retained.

3.2. Improved AKAZE algorithm

In order to meet the application conditions of the actual scene and ensure the matching accuracy, this paper proposes an improved AKAZE algorithm based on Tanimoto. The flow chart of the algorithm is shown in Figure 1, the main steps are as follows:

1) First, the nonlinear method is used to construct the scale space, and the FED is used to quickly calculate the nonlinear diffusion equation. Then, the Hessian matrix was used to calculate the local maximum value to get the feature points. Finally, the M-LDB descriptor was used to complete the image feature points description.

2) Tanimoto algorithm is used to calculate the T value of feature point pairs, determine the similarity, and conduct rough matching. This step improves the matching accuracy and carries out detailed screening of possible mismatched point pairs.

3) The KNN algorithm is used to simply and roughly match the selected matching points, and then the RANSAC algorithm is used to eliminate the wrong matching point pairs in Step 2. Finally, the matching results are displayed in the reference image and detection image.

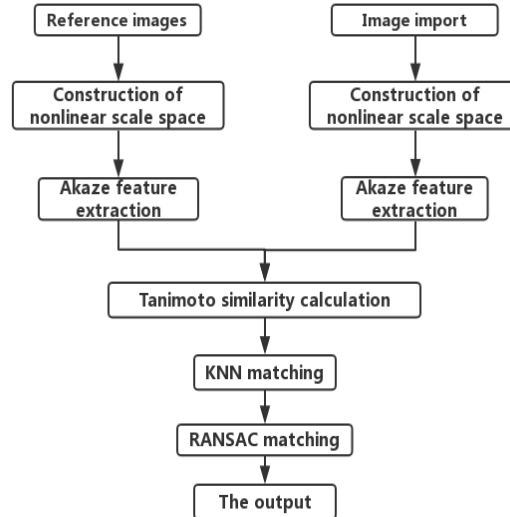


Figure 1 T-AKAZE algorithm flow chart.

4. Experimental results and analysis

This paper uses VS2010 and OpenCV4.5.1 as the operating platform. With the Intel(R) Core(TM)i7-8700 CPU, 8 GB RAM, Windows10 system computer. It also uses a phone camera with a resolution of 2310×1080 pixels.

In order to verify that the T-AKAZE algorithm has high matching accuracy and good adaptability to scale and rotation changes. The proposed algorithm and ORB algorithm, AKAZE algorithm and ORB+ Tanimoto algorithm were tested for matching stability and adaptability to scale change respectively by using the method of control experiment. The test images are shown in Figure 3. (Note: For the convenience of introduction, the experimental graphs of the three groups are labeled as Group A, Group B and Group C)

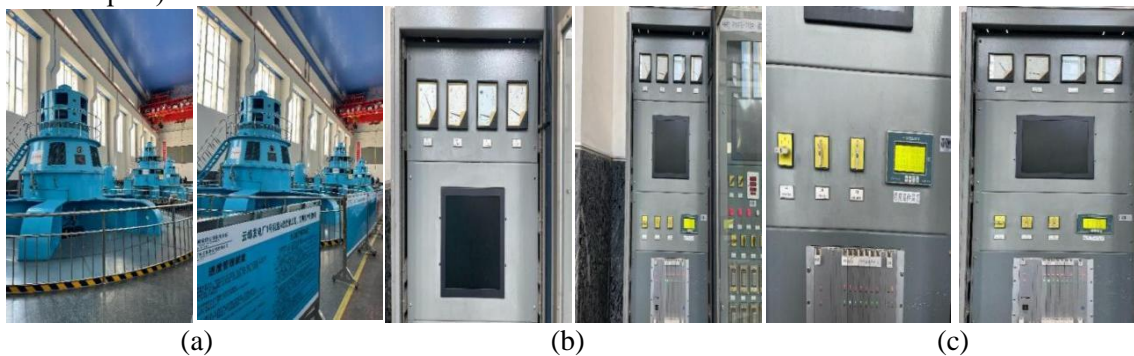


Figure 2 Test image.

4.1. Matched stability experiment

In order to verify the stability of the algorithm in this paper, ORB algorithm, AKAZE algorithm and ORB+ Tanimoto algorithm are compared to visually display the matching effect.

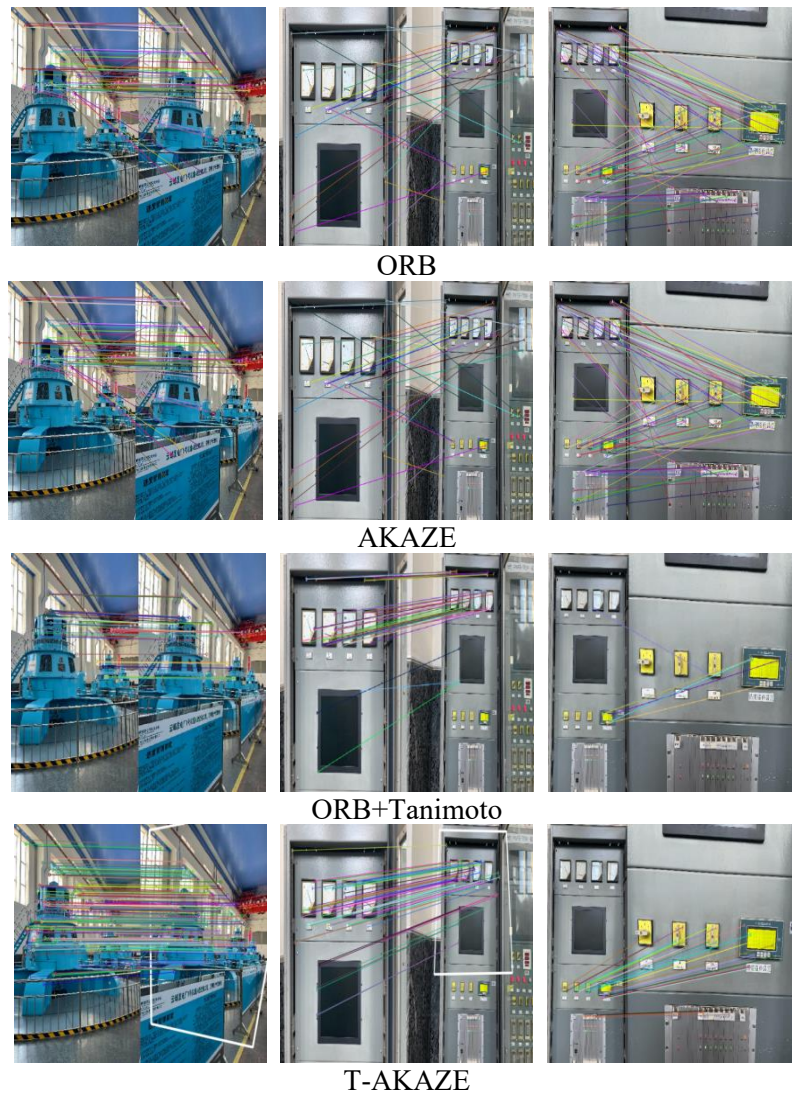


Figure 3 Matching effect comparison.

The intersecting lines in the figure are the wrong pairs of matching points. Experimental results show that the proposed algorithm can extract the most matching point pairs under the premise of ensuring accuracy, and has a good matching effect.

As shown in Table 1, the matching accuracy of this algorithm is 47% higher than that of the traditional ORB algorithm, about 28% higher than that of AKAZE algorithm, and 6% higher than that of ORB+Tanimoto algorithm. Experimental results show that the matching accuracy of the proposed algorithm is more than 98%, and the matching effect is stable.

Table 1 Comparison of image matching accuracy of the four algorithms.

| Image group | Matching accuracy (%) | | | |
|-------------|-----------------------|-------|--------------|---------|
| | ORB | AKAZE | ORB+Tanimoto | T-AKAZE |
| Group A | 63.33 | 75.68 | 98.86 | 99.02 |
| Group B | 74.36 | 80.23 | 96.55 | 99.50 |
| Group C | 63.64 | 75.44 | 83.34 | 98.23 |
| The average | 67.11 | 77.12 | 92.92 | 98.92 |

As can be seen from Table 2, compared with the AKAZE algorithm, the average time consumption of the proposed algorithm increases by 0.03s. However, the running speed of this algorithm is significantly faster than the similar improved algorithm ORB+Tanimoto, and the time consumption is reduced by 0.1s compared with ORB algorithm, which can meet the requirements of timeliness.

Table 2 Comparison of time consuming of 4 algorithms (unit: s).

| | ORB | AKAZE | ORB+Tanimoto | T-AKAZE |
|-------------|--------|--------|--------------|---------|
| Group A | 0.1925 | 0.0519 | 1.9131 | 0.0748 |
| Group B | 0.2098 | 0.0768 | 1.9149 | 0.1197 |
| Group C | 0.1829 | 0.0539 | 1.8061 | 0.0958 |
| The average | 0.1951 | 0.0609 | 1.8780 | 0.0968 |

4.2. Scale adaptation experiment

In order to verify the application effect of this algorithm in hydropower stations, recall rate (Recall) is used as an evaluation index to verify the matching performance of this algorithm under different changing conditions. The recall rate is the ratio of the number of pairs of correctly matched feature points to the number of pairs of all matching points in the image. The calculation formula is shown in Equation (9) :

$$\text{Recall} = \frac{\text{correct matches}}{\text{correspondences}} \times 100\% \quad (9)$$

The experimental data diagram is shown in Figure 4:

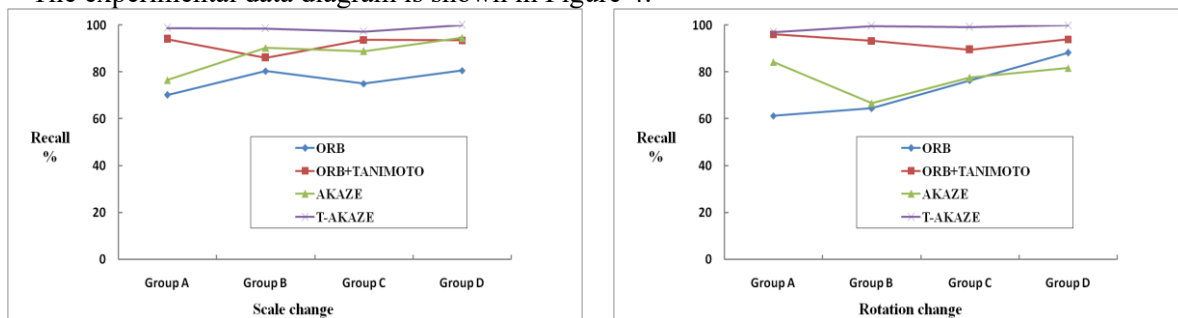


Figure 4 Recall rate of 4 algorithms.

When rotation changes, the recall rate of the proposed algorithm is about 11 percentage points higher than that of the AKAZE algorithm and 22 percentage points higher than that of the ORB algorithm. When the scale changes, the recall rate of the proposed algorithm is significantly higher than that of the traditional OEB algorithm and AKAZE algorithm. Compared with the ORB+Tanimoto algorithm, the recall rate of the proposed algorithm is increased by about 6 percentage points and basically remains at 98.96%. From the above, it can be seen that the T-AKAZE algorithm proposed in this paper has strong adaptability to various changes of images and is suitable for the matching and recognition tasks of complex changes.

5. Conclusion

Aiming at the problem of fault identification of hydropower equipment based on image processing, this paper proposes an improved image matching algorithm T-AKAZE based on AKAZE. Experimental results show that the accuracy of the proposed algorithm is 28% higher than ORB algorithm and 16% higher than AKAZE algorithm. Compared with ORB+Tanimoto algorithm, the matching time is 50% higher, and has good scale adaptability. In the following research, the algorithm will be further applied in the image-based fault detection system of hydropower equipment.

Acknowledgments

This research was supported by the Science and Technology Project of Jilin Province 20180201065SF.

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