

# Location of feature points in 3D reconstruction of multi vision color image based on principal component analysis

FENG Huan-ping<sup>1</sup>,ZHANG Li-wei<sup>2</sup>

{aini2125@tom.com<sup>1</sup>, lihaixia09@sina.com<sup>2</sup>}

(1. Hebei Institute Of Communication College,shijiazhuang 051430,China;

2.Hebei Institute Of Communication College,shijiazhuang 051430,China)

**Abstract:** Traditional image feature point location methods, due to the existence of calculation errors, lead to the accuracy of the location of feature points decreased, so based on principal component analysis, a new multi vision color image 3D reconstruction feature point location method is proposed.In this method, the gray level of color image is transformed by principal component analysis, and the color features of the image are obtained according to the gray level difference of local color areas;According to the changing characteristics of environment light coefficient and diffuse reflection light coefficient, the control parameters affecting the three-dimensional light shadow effect of multi vision color image are set;The least square method is used to eliminate the position error of feature points, and according to the confidence degree of association rules between nodes, more accurate feature point positioning results are obtained.Experimental results show that the accuracy of the proposed method is 11.27% higher than that of the traditional method. Therefore, the proposed method is more suitable for feature point location.

**Keywords:** Keywords principal component analysis; multi vision color image 3D reconstruction; feature point location;

## 1 Introduction

At this stage, with the continuous innovation of network technology, the sharpness of image is getting higher and higher, and the effect of light and shadow is getting better and better. More and more people use image to store information, and use three-dimensional technology to pursue image visual effect and experience. However, due to the large number of colors in the color image and the small difference between colors, 3D reconstruction is more difficult. At the same time, because the figures and animals in the picture will show different movements, the plants have extremely irregular outlines, and the solid objects such as

buildings and vehicles will present complex structures, which will also increase the difficulty of 3D reconstruction. In addition, the scene in the figure above will show different light and shadow effects in different environments due to the influence of light, so it is necessary to accurately locate these feature points to achieve the accurate reconstruction of the three-dimensional image<sup>[1]</sup>.

In reference [1], a feature-based 3D reconstruction method based on visual slam anti depth filtering is proposed. A more real-time scene structure is gradually established by using video sequence. The key frame tracking method based on motion model is used to provide accurate relative attitude relationship. Map points are no longer directly calculated by two frame triangulation, but by using the depth inverse filter based on probability distribution. By accumulating and updating the multi frame information, a back-end hybrid optimization framework composed of feature and direct method and a point selection strategy based on adjustment constraints are obtained. This strategy can accurately and effectively solve the camera attitude and structure. However, due to the calculation error of this method, the final positioning result is not accurate enough, and the reconstructed three-dimensional image does not have the stereoscopic feeling of multi vision.

Therefore, aiming at the problems of traditional methods, a location method based on principal component analysis is proposed. In this method, principal component analysis is used to obtain more accurate color features of the image and realize the accurate positioning of feature points.

## **2 Feature point location method for 3D reconstruction of multi vision color image based on principal component analysis**

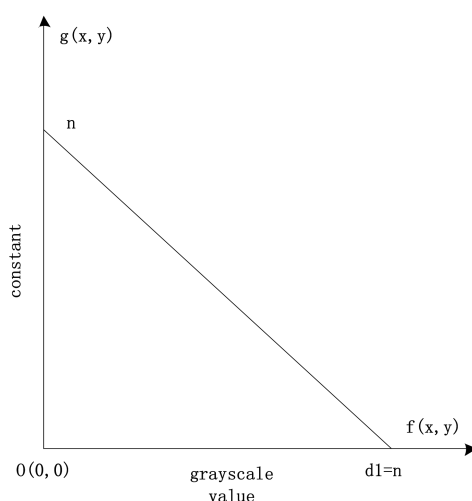
### **2.1 Obtaining color features of image by principal component analysis**

To locate the feature points in 3D reconstruction of multi vision color image, the first step is to obtain the color features of image by principal component analysis. The first step of this method is gray-scale transformation of multi vision color 3D image. In principal component analysis, gray-scale transformation is a very basic image processing method in spatial domain. According to the transformation relationship of gray-scale transformation, the gray value of each pixel in the image is transformed, so as to change the dynamic range of gray-scale of the image, and finally get the method of processing the image. It can enlarge the dynamic range of the image, expand the contrast of the image, make the image clearer and more obvious<sup>[2]</sup>. The grayscale transformation formula is as follows:

$$f(x, y) = D[f(x, y)] \quad (1)$$

Formula:  $D$  represents the gray transformation function, representing the transformation

relationship between the input gray value and the output gray value;  $x$ 、 $y$  represents the horizontal and vertical coordinates of the local gray area;  $f(x, y)$  represents the result of gray-scale transformation. According to the different forms of transformation function, gray-scale transformation can be divided into linear transformation, piecewise linear transformation, nonlinear transformation, and other gray-scale transformation. Because of the segmented linear feature of 3D image, segmented linear transformation is used to preprocess the gray value. The image inversion transform function is shown in Figure 1.



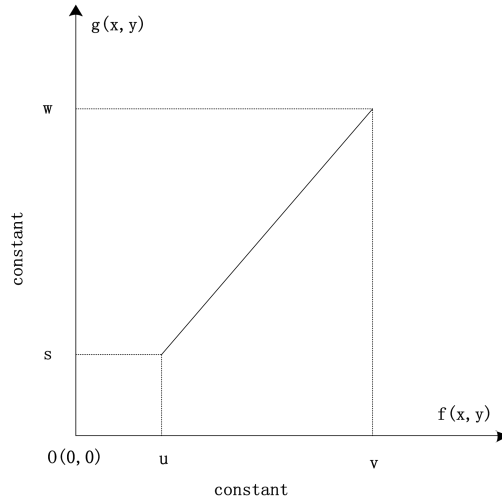
**Figure 1** image inversion transform function

Image inversion transform function image inversion is simply to make black white, make white black, turn the gray value of the original image over, so that the gray value of the output image decreases with the increase of the gray level of the input image. This processing is particularly effective for enhancing white or gray details embedded in a dark background, especially when the amount of color difference in the image is very small. According to the image inversion transformation relationship shown in Figure 1, combined with the tangent form of the linear equation, when there is  $k = -1$  ,  $b = d - 1$  , whose expression is as follows:

$$g(x, y) = kf(x, y) + b = -f(x, y) + (d - 1) \quad (2)$$

Formula:  $g(x, y)$  represents image reversal function;  $k$  is the slope;  $b$  represents a constant change. On the basis of image inversion, the linear gray-scale transformation is

carried out, which transforms each pixel in the image into another pixel value by using the linear relationship, that is, processing each pixel, transforming the image pixel range to the specified range, improving the multi visual effect of the three-dimensional color image<sup>[3]</sup>. In the actual operation, it is assumed that the gray range of the image before and after transformation has been given, as shown in Figure 2 below.

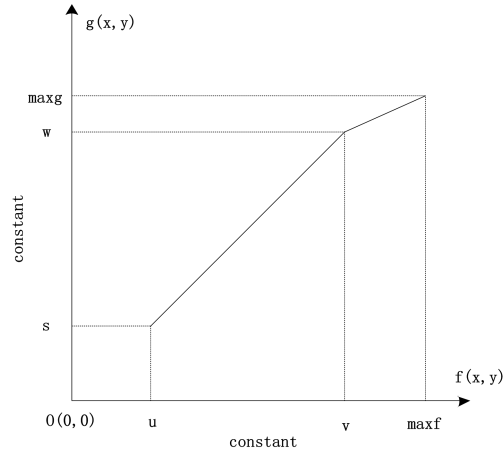


**Figure 2** Schematic diagram of linear gray scale transformation

It is known that the range of gray scale  $f(x, y)$  of the original image is  $[u, v]$ , The range of gray scale  $g(x, y)$  of the transformed image is  $[s, w]$ . Therefore, the following linear transformation is used to realize gray-scale transformation:

$$g(x, y) = \frac{w-s}{v-u} [f(x, y) - u] + s \quad (3)$$

According to the above formula, set the single color range under a certain brightness value in the input image to  $[u, v]$ . Through proportional linear gray-scale transformation, the gray-scale of each pixel in the image is stretched linearly, which effectively improves the visual effect of the image<sup>[4]</sup>. On the basis of the above transformation, the gray scale of the image is divided into two or more intervals, and each interval is transformed linearly to achieve the purpose of segmentation. The following figure 3 is the result of segmented transformation.

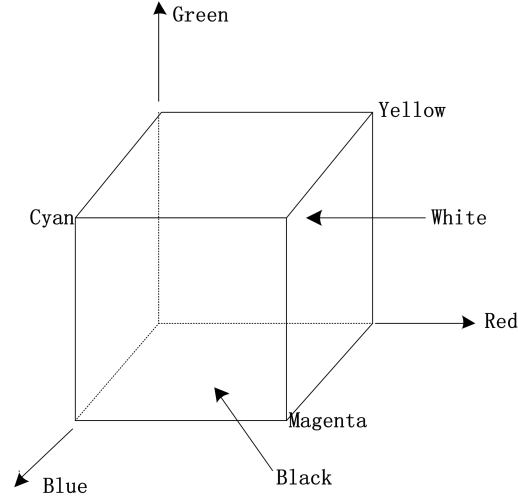


**Figure 3** Schematic diagram of piecewise linear gray scale transformation

With the piecewise linear transformation method, the gray level needed in the image can be stretched and the gray level not used in the image can be compressed at the same time. The mathematical expression is as follows:

$$g(x, y) = \begin{cases} \frac{s}{u} f(x, y), & 0 \leq f(x, y) < u \\ \frac{w-s}{v-u} [f(x, y) - u] + s, & u \leq f(x, y) < v \\ \frac{f-w}{g-v} [f(x, y) - v] + w, & v \leq f(x, y) \leq \max f \end{cases} \quad (4)$$

According to the above content, the color difference enhancement of 3D color image is completed<sup>[5]</sup>. Establish RGB color cube, as shown in Figure 4 below, and obtain image color features by principal component analysis.



**Figure 4** RGB color cube

According to the gray value, the three-dimensional image without obvious color difference is re segmented. The color difference characteristic value of the image can be described by the following algorithm:

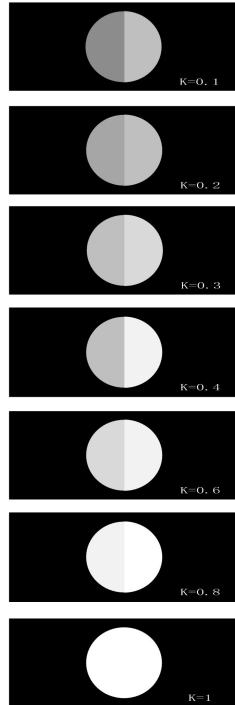
$$\begin{cases} R = Y + 1.041V \\ G = Y - 0.347U - 0.721V \\ B = Y + 1.782U \end{cases} \quad (5)$$

In formula,  $Y$ 、 $U$ 、 $V$  represents the color space value after segmented gray-scale conversion, and obtains the image color characteristics through the above steps<sup>[6]</sup>.

## 2.2 Set up the 3D lighting effect of multi vision color image

Based on the acquired color features of the image, the three-dimensional light and shadow effect of multi vision color image is set up. The illumination model is applied to the 3D image reconstruction algorithm, so it is necessary to set the illumination attributes of the 3D image, including four parameters: ambient light coefficient, diffuse light coefficient, specular light coefficient and specular **index**.

According to the above program setting parameters, analyze the influence of the changes of ambient light coefficient and diffuse light coefficient on the image **effect**. **Figure 5** is a schematic diagram of the light and shadow effect of the image under different ambient light coefficients.



**Figure 5** sketch of light and shadow effect

According to the above diagram of light and shadow effect change, the brightness of the reconstructed image increases gradually with the increase of the ambient light coefficient. However, when the brightness is too large, the inner details of the image cannot be distinguished. When the ambient light coefficient is set to 0.4, the reconstructed color image has the best 3D visual effect. In the same way, obtain the light shadow effect of the change of diffuse light coefficient on the image. After analysis, when the diffuse light coefficient is 0.9, the image reconstruction effect is the **best**<sup>[7]</sup>. According to the above analysis results, set the sampling parameters and reconstruction period. The specific figures are shown in Table 1.

**Table 1** matching table of sampling parameters and reconstruction period

Match group	Sampling parameters	Rebuild cycle
A1	2048	0.02
A2	1024	1.1
A3	512	2.3

A4	256	3.1
A5	200	4.1
A6	128	4.5
A7	100	5.1
A8	64	11.7
A9	32	21.9
A10	16	28.3
A11	8	32.5
A12	4	34.5
A13	2	38.7

According to table 1, the sampling period increases with the decrease of sampling parameters. This is because the smaller the sampling parameter, the more pixels emitted by 2d pixel points in the plane, and the slower the reconstruction. When the sampling parameter is less than 64, the speed of the increase of sampling time is more obvious. According to the above analysis results, the control parameters of 3D light and shadow effect of multi-vision color images were set by using the illumination model. Since the surface of the object in the image will reflect light with different intensity, the intensity formula of diffuse reflected light at a certain point in the image is as follows:

$$p = \mu_i p' \quad (6)$$

Formula:  $p'$  represents the intensity of ambient light;  $\mu_i$  represents nodes at different locations;  $i = 1$  represents the diffuse reflection coefficient of ambient light at the node;  $p$  represents the light intensity after the diffuse reflector interacts with the ambient light. As far as an ideal diffuse reflector is concerned, there are reflection rays of equal intensity in all directions, but the intensity of the light on the surface of the object also depends on the intensity and direction of the incident ray. This phenomenon is described quantitatively by Lambert's law. Suppose that the intensity of diffuse light is directly proportional to the cosine of the incident angle when a certain direction of light is irradiated on the Lambert mirror, then the control parameters of image shadow effect are obtained:



$$\sigma_a = p \ln e + \sqrt{\frac{\sin \beta^2 - 1}{\varepsilon \cos \beta}} \quad (7)$$

Formula:  $\sigma_a$  represents the control parameter with control intensity of  $a$ ;  $e$  represents the base value of the exponential function;  $\beta$  represents the incidence angle of the light source, whose value ranges from  $0^\circ$  to  $90^\circ$ ;  $\varepsilon$  represents the light intensity index generated by the interaction reflection between the diffuse reflector and the incident light in a certain direction. Through the above process, the control parameters of 3D light and shadow effect of multi-vision color images are set<sup>[8]</sup>.

### 2.3 Eliminating error to realize the feature point location of 3D reconstruction

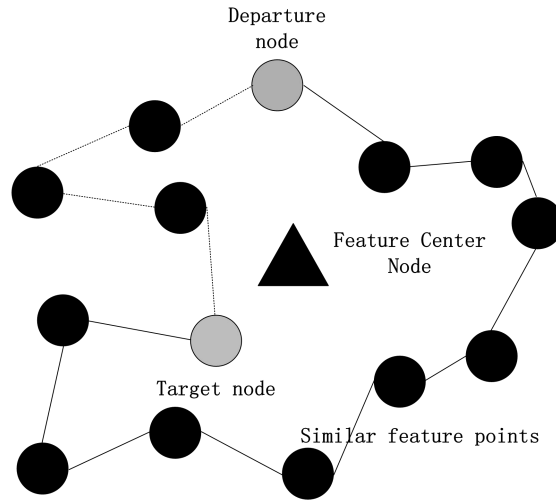
According to the set light and shadow effect control parameters, the least square method is used to set the position coordinates of the image feature points to achieve the accurate positioning of the reconstructed 3D image. Assuming that the center of the feature point is  $c$  and there are  $n$  anchor nodes from the center. Within the determined defect target range, each coordinate can be represented by  $a_1, a_2, \dots, a_n$ , so there are  $a_n = \{(x, y) | (x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$  for each anchor node; Set an unknown node as  $a_k$  and its coordinate as  $(x_k, y_k)$ . Assume that the node is the real coordinate of the feature point, then the relationship between the unknown node and the anchor node is:

$$\begin{cases} (x_k - x_1)^2 + (y_k - y_1)^2 = d_1^2 \\ (x_k - x_2)^2 + (y_k - y_2)^2 = d_2^2 \\ \vdots \\ (x_k - x_n)^2 + (y_k - y_n)^2 = d_n^2 \end{cases} \quad (8)$$

Formula:  $d_1, d_2, \dots, d_n$  represents the estimated distance between the unknown node and the anchor node. The coordinate boundary obtained by this formula is adjusted according to the control parameters, and the adjusted equation is:

$$\lambda = s_1 \times \left( 2 \times \frac{\sigma_a d}{s_0} + q \right) \quad (9)$$

Formula:  $\lambda$  represents the adjusted value, which is usually between  $(0,1)$ ;  $s_1$  represents the traversal times of image code phase;  $s_0$  represents the total spatial step size during image positioning;  $d$  represents the frequency step of image feature data;  $q$  is the non-zero constant of change<sup>[9]</sup>. Figure 6 shows the boundary conditions of the location region of feature points.



**Figure 6** constraint conditions of coordinate region of feature points

The black circle in the figure represents the approximate feature range of the image feature points, that is, the constraint conditions that limit the location of feature points. Combining the contents of formula (9), formula (8) is rewritten into the form of  $\lambda x = \omega$ , and the least square method is used to solve the equation, and the objective function  $Min \|\lambda x - \omega\|^2$  is obtained. The specific formula is as follows:

$$P = \lambda \begin{bmatrix} x' \\ y' \end{bmatrix} \quad (10)$$

Formula:  $x'$  and  $y'$  represent the abscissa and ordinate of the feature points of the reconstructed image;  $P$  represents the feature points. Thus, the location of the feature points in 3D reconstruction of multi-visual color images is realized. The correlation confidence between feature points is calculated as follows:

$$CL(P) = \frac{\zeta_{support}(P_1 \cup P_2)}{\zeta_{support}(P_n)} \quad (11)$$

Formula:  $CL(P)$  represents confidence;  $\zeta$  represents the association rule of feature points;  $P_1$  and  $P_2$  represent any two adjacent random feature points in all feature points  $P_n$ .

When the above calculation results are greater than 0.96, it proves that the positioning is accurate. When it is less than the reference value of the standard, it indicates that there is error in the positioning result, and the deviant data need to be removed and repositioned. Through the above content, based on principal component analysis, the feature point location of 3D reconstruction of multi-vision color image is realized<sup>[10]</sup>.

### 3 Experiment and analysis

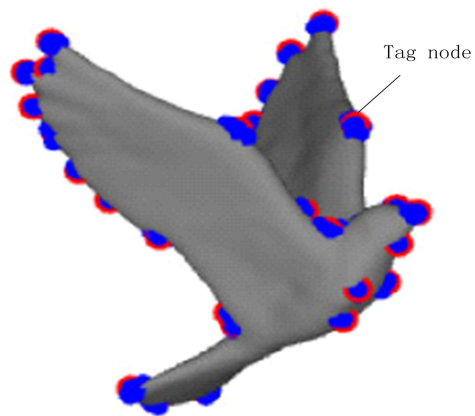
In order to prove the reliability and feasibility of the proposed positioning method, a comparative experiment was proposed for this study. Based on the experimental test results, the accuracy of feature point positioning results was analyzed during 3D reconstruction of multi-vision images. At the same time, the traditional image feature point localization method is introduced to compare the differences between the two methods.

This experiment adopted the evaluation system as the test software, and loaded the software into the experimental test computer, whose operating system is Windows 10, the memory capacity is 8G, the hard disk capacity is 500G, and the browser version is IE11.0, which meets the test requirements of this experiment. A relatively complex photo was randomly selected as the experimental test object, as shown in figure 7 below. Two feature positioning methods were used to reconstruct the image in three dimensions.

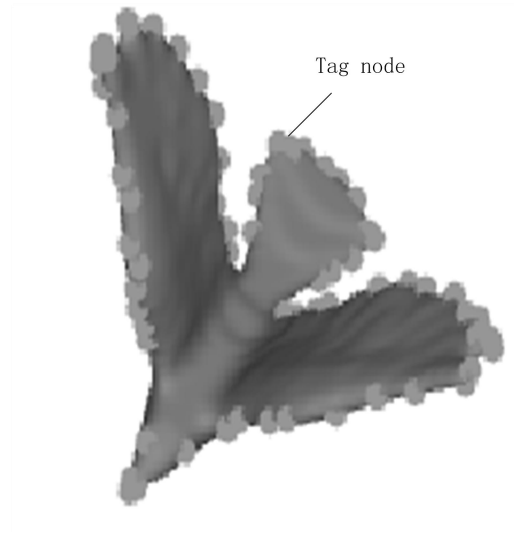


**Figure 7** experimental subjects

Two positioning methods are used to mark the contours and features of objects such as pigeons, ground, trees, grass and buildings. Figure 8 below shows the marking results of pigeons with different flight attitudes.



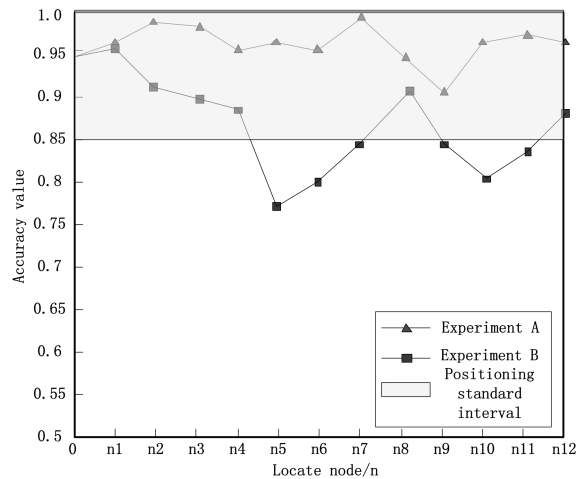
**(a)** the pigeon contour mark with attitude A



**(b) the pigeon contour mark with attitude B**

**Figure 8** schematic diagram of feature point marking

In this experiment, the test results of the proposed feature point positioning method were taken as experiment group A, while the test results of the traditional feature point positioning method were taken as experiment group B. Test run the experimental test software for 30min, and there are no data anomalies or system hardware problems, so the experiment can start. Figure 9 shows the comparison results of this experiment.



**Figure 9** comparison results of experimental tests

According to the above test results, the positioning accuracy of the proposed positioning

method in group A is above the standard value, and the average accuracy is 95.56%. However, in the positioning results of feature points in group B of the traditional positioning method, 6 groups of data were outside the standard value, and the average positioning accuracy was only 84.29%. Therefore, the feature point positioning method based on principal component analysis can obtain higher accuracy of feature points.

#### **4 Conclusion**

In order to solve the problem of low accuracy of traditional positioning methods, a method of locating feature points in 3D reconstruction of multi-vision color images is proposed. Through principal element analysis of image color difference features and image light and shadow effect, accurate positioning of feature points during the reconstruction of 3D image is realized to enhance the 3D visual effect of the image. However, the proposed positioning method, the analysis process is more, the calculation steps are relatively complex, so need to pay special attention. In the future research, some calculation steps can be simplified to improve the positioning efficiency of the method.

#### **References**

- [1] Zhang Yi, Jiang Ting, Jiang Gangwu, et al.: 3D reconstruction with inverse depth filter of feature-based visual SLAM. *Acta Geodaetica et Cartographica Sinica*. 48(06):708-717 (2019) ,
- [2] Chen Guojun, Cao Yue, Yang Jing, et al.: Real-Time Reconstruction of Multi-Angle 3D Human Faces Based on Morphable Model. *Journal of Graphic*. 40(04):659-664 (2019)
- [3] Wang Shaoyang, Li Dahua, Gao Qiang, et al.: Research and design of 3D vision inspection system based on structured light in rectangular steel production line. *Laser Journal*. 39(11):22-28 (2018)
- [4] Miao Huicui, Wang Jihua, Zhang Quanying.: Concave-convex Manufacturing Features Recognition Based on 3D Reconstruction of Single View. *Computer Science*. 46(07):280-285 (2019)
- [5] Guo Weiqing, Wu Xiaogang, Tang Yiping.: Research of 3D Reconstruction Based on Monocular Multi-view Panoramic Visual Perception. *Journal of Chinese Computer Systems*. 40(07):1525-1531 (2019)
- [6] Yue Pengfei, Zhao Lanpu, Zhang Wei.: Visual Image Special Target Detection Simulation of Low Pixel Monitoring System. *Computer Simulation*. 35(07):452-455 (2018)
- [7] Sun Yanli, Yang Na, Zhang Zhengtao, et al.: Structural Damage Identification Study Based on Kernel Component Analysis and Support Vector Machine. *Journal of Basic Science and Engineering*. 26(04):888-900 (2018)
- [8] Zhang Hongyun, Zhao Quanhua, Li Yu.: Geometric feature extraction of scattered targets from remote sensing images based on irregular mark point process. *Control and Decision*. 34(09):1840-1846 (2019)
- [9] Shao Jinda, Yang Shuai, Cheng Lin. UAV Image Matching Algorithm Based on Improved SIFT

Algorithm and Two-stage Feature Matching. *Computer Science*. 46(06):316-321 (2019)

[10] Hu Gaorui, He Yibin, Chen Yuchen, et al.: Research on 3D Reconstruction Technology Based on 2D Image. *Machinery*. 46(08):27-31 (2019)