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A Method of Reference Point Range for Field Navigation of Agricultural Robot

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Abstract

The measurement value of the traditional binocular parallax distance is the distance between the reference point P and the center of the baseline of the binocular camera, and for the agriculture robot, because of the needs of ground operations, the cameras are usually installed in certain height from the ground with a certain angle with the horizontal direction, when we have to know the horizontal distance from the navigation reference point to the robot body and thus the next travel pose of the robot can be controlled by real-time. Obviously, the traditional binocular parallax distance measuring methods will no longer apply to this. In this regard, a new method for solving agricultural robot navigation reference point distance measurement is proposed. First, conduct calibration for the binocular system with the improved BP neural network, and secondly, obtain the left and right image coordinates of the navigation reference point (U1,V1) (U2,V2) with the improved SIFT features and input the BP neural networks trained in the calibration, and finally, output the coordinates of the navigation reference point in the world coordinate system (X, Y), and then the horizontal distance between the navigation reference point and the robot body can be expressed as $S=\sqrt{X^2+Y^2}$ *. Experiments show that by this method, the maximum deviation of the actual field experiment test is 0.479cm, with the minimum deviation of 0.032cm, accuracy up to 99%, consuming a total of 55ms. And compared to the traditional binocular parallax distance ranging procedure, the computation is significantly reduced, with certain engineering practicability and feasibility.*

***Keywords**: Reference point range; Field navigation; Agricultural robot; Traditional binocular parallax; BP neural networks*

1. Introduction

Among the distance measurement methods based on the vision sensor, the most commonly used method is parallel binocular stereo vision method, with the central idea of using the principle of binocular parallax [1]. The binocular parallax is constructed by the different image forming position in the image planes of the cameras on both left and right of the same point, by the method of geometry triangle pair wise and using the known baseline b, cameral focal length f of the left and right cameras, and the horizontal coordinate corresponding to the image forming plane of the left and right cameras of the same reference point is x_1 and x_2, and the distance between the reference point P and the center of the baseline of the binocular camera can be calculated according to formulation(1):

$$Z=\frac{f\cdot b}{x_1-x_2} \tag{1}$$

As shown in Figure 1.

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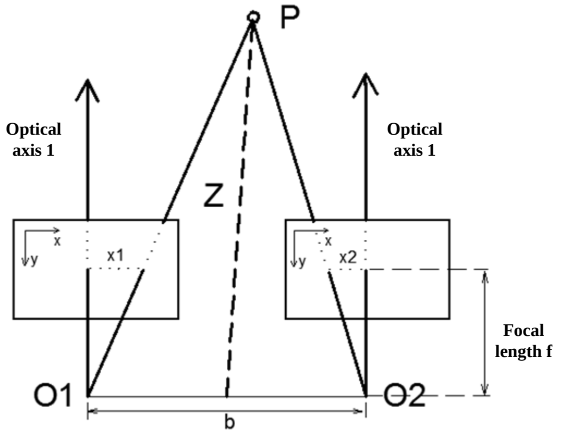

Figure 1. Principle of Binocular Parallax Distance Measuring Method

However, due to the requirements of filed operation, the agricultural robot needs to capture real-time path information of the image operating on the field and traveling forward direction, such as the pesticide spraying robots, weeding robots, and automatic transplanting robots [2. Therefore, their visual sensor devices are often installed at the position with a certain height.

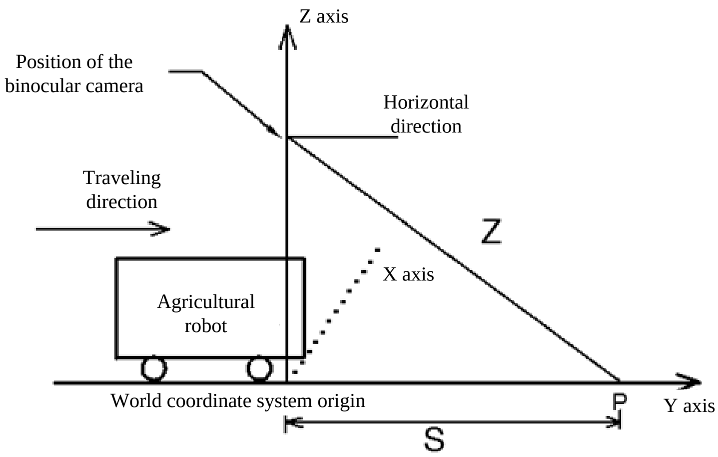

Figure 2. Agricultural Robot Operation Model

In this case, the distance Z in Figure 2 will be obtained if we still use the traditional binocular parallax distance measurement method, while the researchers tend to be more interested in the distance S between the reference P and the robot body, which plays a key role in the control of the position and pose of the agricultural robot operating in the field.

To solve there problems, this paper presents a new method of agricultural robot field navigation reference point ranging. The experiments show that the method in this paper is effective on solving the problem of agricultural robot field ranging**.**

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2. Establishment and Calibration of Agricultural Robot Binocular System

2.1. Establishment of Binocular System

In this paper, the square stool is simulated as the agricultural robot body with the installation height of the left and right cameras of 35.7degrees, the baseline distance of 18cm, IPC CPU of 2.5Ghz and memory of 8G, while make a vertical down lead line with the left camera as the center and the intersection point of the vertical line and the ground is the origin of the world coordinate system O, X axis is to the left along the agricultural robot body , Y axis is vertical to X along the optical axis of the camera and Z axis is vertical to the ground upward, as shown in Figure 3.

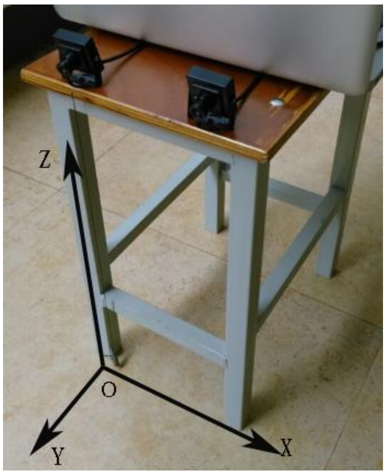

Figure 3. Agricultural Robot Binocular System in this Paper

Because the navigation reference points selected in this paper are all on the ground, the Z plane is always 0, that is, no matter where agricultural robot travels, the world coordinate system is established by this method, and then the world coordinates of the navigation reference point corresponding to the agricultural robot body.

2.2. BP Neural Network Calibration

The operating environment of the agricultural robot is usually in farmland in the unstructured environment and the ground unevenness will cause the difference angle of the robot body and the ground in the travelling, when if the calculation is conducted using the inside and outside parameters of the camera obtained by the traditional camera linear calibration calculation, the calculation amount will be very large, affecting the timeliness of the agricultural robot operations and the inaccurate results will always be obtained due to the machining error of the lens optical system. According to the multilayer neural network mapping theorem, the three-layer neural network structure including the hidden layer can do any precision approximation to any nonlinear function, so in this paper, the BP neural network including the input layer, hidden layer and output layer is selected for the calibration of the binocular system, but because the original BP algorithm is the gradient descent method with the central idea of directing the iterative optimization search direction toward function to the lowering direction and then another problem appears, the training speed of the BP network is slow and the possibility of the minimum value of the stuck area. In order to solve this problem, this paper constructs BP neural network using BP learning algorithm based on Fletcher-Revees conjugate gradient.

(1) Set $k=0, i=0$ and set the maximum learning rate as $C>0$ and optimization purpose value as $\varepsilon>0$, and the initial weight are generated randomly $w(0)$.

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(2) Calculate gradient $g(0) = \nabla E(w(0))$ through local gradient.

(3) Select the search direction.

(4) Calculate the learning speed η_i using one-dimensional search option η_i, holding the following formulation:

$$E(w(i) + \eta_i d(i)) = \min_{0 \le \eta \le C} E(w(i) + \eta d(i))$$

(5) Adjust BP network parameters $w(i+1) = w(i) + \eta_i d(i)$

(6) Set $k = k+1, i = i+1$

(7) With $E(w(i)) < \varepsilon$, the algorithm terminates.

(8) Calculate gradient $g(i) = \nabla E(w(i))$ by local gradient $\delta_j^{(l)}(i)$

(9) Calculate the direction factor $\beta_i = \dfrac{\|g(i)\|^2}{\|g(i-1)\|^2}$

(10) Calculate $d(i)$: in the case of $i < N$, then $d(i) = -g(i) + \beta_i d(i-1)$ and turn to (4); otherwise, $i > 0$, $w(0) = w(i), g(0) = g(i)$, and turn to (3)

2.3. Calibration Experiment

Put a 1100mm×870mm calibration paper in front of the binocular system built in figure 1.1, with the left and right cameras respectively taking the calibration sheet, as shown in Figure4:

Figure 4. Binocular System Calibration in this Paper

Obtain the X corner in the public visual field with Harris corner detection, namely the image coordinates of the calibration point(U1， V1)(U2， V2), and measure the coordinates in the world coordinates system built under the binocular system in 1.1(X,Y), taking (U1， V1)(U2， V2)as output to build BP neural network, with the total calibration of 200 points. Taking 150 points as the training samples save the trained neural network. The experimental results show that the improve BP neural network just need 37 steps for convergence, consuming time of 20ms. The BP network training effect figure is shown in Figure 5 and the calibration results are shown in Table 1.

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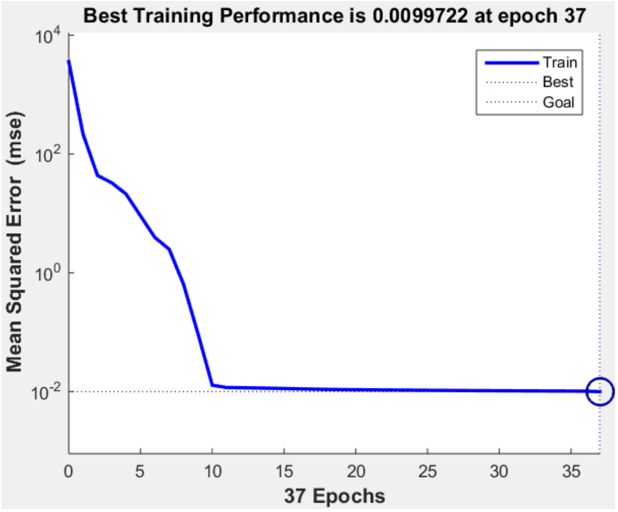

Figure 5. Effort of the Improved BP Neural Network Training

Table 1. Results of the Calibration based on BP

Enter image coordinates				Desired output value /cm		Network actual output /cm	
U1	V1	U2	V2	x	y	X	Y
122	128	257	128	-15	110	-15.0759	109.9041
166	126	303	128	-10	110	-10.0061	109.9866
207	127	343	127	-5	110	-5.1507	109.8904
252	126	388	127	0	110	-0.0618	109.9062
294	126	428	128	5	110	4.9553	109.9778
339	127	472	127	10	110	9.9981	109.7873
381	128	511	127	15	110	14.9335	109.8458
421	128	553	127	20	110	19.8235	110.0839
464	127	591	127	25	110	25.0171	110.0572
503	127	624	127	30	110	30.0457	110.0682

3. Obtaining and Ranging of Field Navigation Reference Point

During walking in the field, the agriculture robot usually selects some objects existing on the road in front as the navigation reference points and the distance and heading angle are calculated on the basis of the reference point, for the preparation of the further traveling pose control. And because there of the great distinction between the soil color and the color of the crops root, so in this paper, the crops roots are selected as the navigation reference points of the agriculture robot. The low-level feature extraction in SIFT method selects those remarkable feature, having image size and rotation invariance, and a certain invariance to the illumination changes, also able to reduce the extraction probability due to occlusion, clutter and noise [3]. This method is particularly applicable to agricultural robot field operating environment, but at the same time, in SIFT method, the step of the generation of feature point description always takes a lot of time because the generation of 128-dimensiona feature description makes the algorithm efficiency greatly lowered. Considering the agricultural robot field operation timeliness problem, the

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requirements of stability, fastness and accuracy are proposed. From the idea of lowering operator dimensions, in this paper, the dimension of the feature description vector in the original algorithm is reduced from 128 to 16, taking the feature point as a circle center, extracting a concentric circle area with the radius from 1 to 4, as shown in Figure 6.

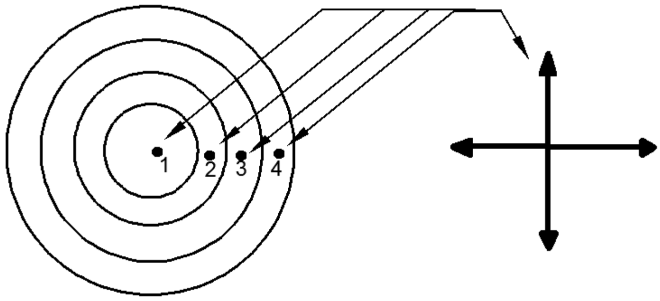

Figure 6. Improved SIFT Feature Descriptors in this Paper

Firstly calculate the modulus values and the direction of each pixel gradient within each circle and then the gradient accumulated value in the 4 directions (0dgeree, 90degrees, 180degrees and 270degrees) in each circle with the gradient histogram statistical method, with weighted using graphical Gaussian window weighting window, which should be ranked in the order of from big to small, and then 1×16 dimensional vector is generated, as the described vector of the feature point.

The above improved SIFT feature vector generation can greatly enhance the speed of obtaining the image coordinates(U1,V1)(U2,V2)of the left and right camera image capture during the agricultural robot, which then are entered in the trained BP neural network in 1.2. At this time the neural network will output the world coordinate values(X,Y)of the navigation reference point corresponding to the robot body, then the horizontal distance of the navigation reference point and the robot body can be expressed as \ $S=\sqrt{X^2+Y^2}$.

4. Experiment and Results Analysis

This paper takes a farmland within Guangxi Technology University on the afternoon of Jun, 9th, 2015. Move the agricultural robot binocular system calibrated in 1.2 into the field, capture crops image at the two positions A and B with the left and right cameras and select the root of each crop as the navigation reference point of the agricultural robot. Measure the straight line distance between the each crop root and the intersection point of the left camera vertical line and the ground when the agricultural robot is at the different positions. Figure 7 shows the matching images by classical SIFT features:

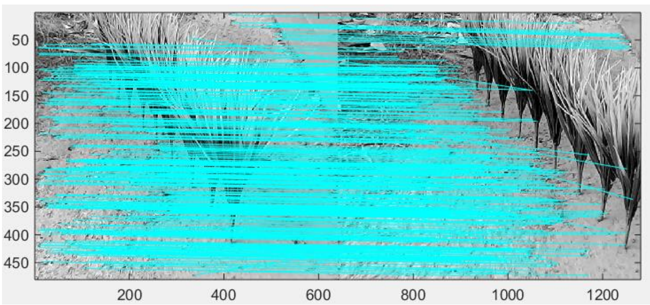

Figure 7. Matching Images by Classical SIFT Features

Figure 8 shows the matching images by improved SIFT algorithm in this paper, greatly reducing the number of the unwanted matching points, only taking 35ms. Table 2 is the

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ranging result of the navigation reference point when the agricultural robot is at position A. Table 3 is the ranging result of the navigation reference point when the agricultural robot is at position B. There are 16 groups of results in table 1 and 2, from which we can know by this method, the maximum error of the measured distance and the actual distance is 0.479cm and the minimum error is 0.032cm with the average error of 0.14cm.

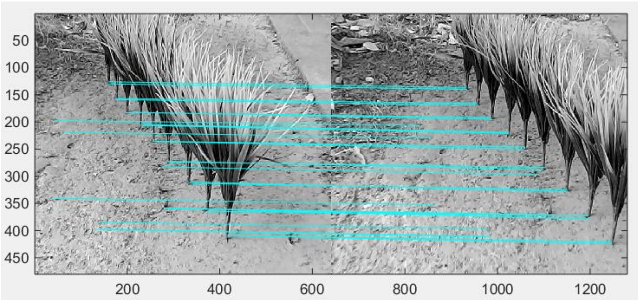

Figure 8. Matching Images by Improved SIFT Algorithm

Table 2. Results of ranging in position A

Neural network output world coordinates /cm X	Y	Measured distance by the method in this paper/cm	Actual distance/cm	Error /cm
19.225	56.326	60.032	60	0.032
21.125	61.247	65.122	65	0.122
23.445	66.765	70.113	70	0.113
27.453	69.063	75.166	75	0.166
29.921	75.564	80.041	80	0.041
34.757	78.394	85.189	85	0.189
39.223	82.822	90.112	90	0.112
41.997	86.313	95.179	95	0.179

Table 3. Results of Ranging in Position B

Neural network output world coordinates /cm X	Y	Measured distance by the method in this paper/cm	Actual distance/cm	Error /cm
19.421	62.986	65.054	65	0.054
24.321	65.667	70.038	70	0.038
26.578	70.324	75.121	75	0.121
29.987	75.311	80.231	80	0.231
33.323	79.697	85.122	85	0.122
37.355	82.487	90.153	90	0.153
43.364	85.811	95.124	95	0.124
48.451	87.726	100.479	100	0.479

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5. Conclusion

This paper presents a new method of agriculture robot ground navigation reference point ranging based on binocular system. This method is applicable to the camera installation position at any angle and height, calibrating the agricultural robot binocular with the improve BP neural network and then the left and right image coordinates of the reference point can be obtained with the improved SIFT feature matching and the trained BP neural network saved during calibration is output, and then the world coordinates of the navigation reference point corresponding to the agricultural robot are output, and finally the horizontally straight line distance between the reference point and the robot body can be obtained. Experimental results show that in a certain field of view, the total time of field navigation reference point ranging is 55ms with the accuracy up to 99%, able to meet the operational requirements of the agricultural robot in most cases.

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