2019 IEEE 4th International Conference on Signal and Image Processing

Research on Monocular Vision Distance Measurement Algorithm Based on Reference Target

Zhengguang Xu
School of Automation and Electrical Engineering, University
University of Science and Technology Beijing, China
Beijing, China
e-mail: xzg_1@236.net

Zhaohui Zhou
School of Automation and Electrical Engineering, University
University of Science and Technology Beijing, China
Beijing, China
e-mail: vlz0517@163.com

Luyao Wang
School of Automation and Electrical Engineering, University
University of Science and Technology Beijing, China
Beijing, China
e-mail: wly199534@163.com

***Abstract*—Aiming at the problem that calculating the distance of the target to be measured relative to the camera for the case where the target has been detected in the intelligent video surveillance, this paper proposes a method for distance measurement only using a single target image without any internal camera parameters. This method firstly calibrates some distance sample points accurately through corner detection and localization, and then builds the mapping model between image ordinate pixel and actual distance through rational function fitting. Combining with artificial bee colony algorithm, the distance model is obtained after parameter optimization, so as to achieve the measurement of monocular image distance. The method requires only one image to be calibrated, and the effects of the imaging model, the imaging system error, and the lens distortion are not separately considered, but are implicitly solved in the regression fitting. The experimental result shows that the algorithm is effective and satisfies the real-time and accurate requirements of distance detection.**

Keywords-component; machine vision; monocular vision distance measurement; corner detectio;, regression analysis; artificial bee colony

I. INTRODUCTION

In recent years, with the rapid development of machine vision, intelligent video surveillance has become a hot issue in the field of machine vision applications. Among them, the machine vision range finding technology provides important parameter information for vision positioning, object tracking, visual obstacle avoidance and vision-based obstacle avoidance, which has the advantages of simple structure, non-contact, high precision and fast data acquisition [1]. The machine vision range finding technology is now generally divided into two types of binocular vision distance measurement [2][3] and monocular vision distance measurement [4-6]. Binocular vision distance measurement is easily affected by mis-matching of feature points, and it is difficult to satisfy real-time requirement with the large amount of calculation. Monocular vision distance measurement is simple, also it has a wide application prospect with high computational efficiency.

At present, the research of monocular distance algorithm mostly adopts a kind of research idea of "sequence", that is, firstly deducing the geometric model of imaging projection, and then calculating the distance. Therefore, they all have some common problems: almost all the work is done on the basis of the simplified pin-hole camera model or lens imaging model; Almost all the geometrical relations of the projection in the study are simplified to the ideal optical path without considering the optical path error of lens distortion existing in the actual imaging. In practice, these assumptions are hard to satisfy.

In this paper, based on a kind of research idea of "inverse" direction, a monocular distance measurement algorithm is designed which is free from the constraint of camera calibration and pitch angle accuracy. This method firstly uses the corner detection algorithm to obtain the corner coordinates of the target image and locates them. Then the data regression analysis method is used to establish the ranging model corresponding to the mapping relationship, and the optimization method of the model parameters is proposed to further improve the accuracy of the range-finding algorithm.

II. MONOCULAR DISTANCE PRINCIPLE

Urbanization road is generally flat and not steep, so the distance measurement is based on the assumption that the road surface is horizontal. If the mapping relationship between the image pixel coordinate and the corresponding distance can be established in advance, the distance of the measured object can be calculated from its bottom pixel coordinates. With reference to the idea of “first detection then modeling” [7], we designed a monocular distance measurement method based on a reference target. As shown in Fig. 1, the height of the reference target is adjustable, the paper on top of target can be replaced according to actual needs, and the difference between adjacent corners is 5cm.

Ranging principle based on reference target is shown in Fig. 2. The reference target is fixedly placed diagonally in front of the camera and a reference target image is acquired. The pixel coordinates of each corner point can be obtained through the corner detection algorithm. Also, the actual distances corresponding to corner points can be measured. Then, we can establish the mapping relationship between

Figure 1. Reference target image

the image pixel coordinate y and the corresponding distance L:

$$L = F(y) \tag{1}$$

When actual ranging is performed, we can obtain the bottom pixel coordinates through moving object detection algorithm, then the distance information can be calculated using (1).

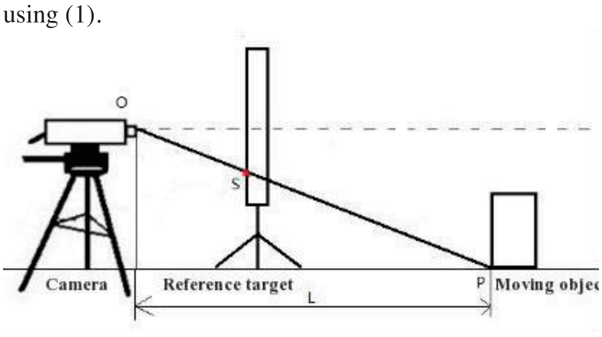

Figure 2. Ranging principle based on reference target

III. Establishing the Mapping Model Between Pixels and Actual Distance

Since the whole measurement process is based on the mapping relationship between the target ordinate and the actual distance based on the reference target, the establishment of the mapping relationship becomes the key issue affecting the measurement.

The coordinates of the reference target point and its corresponding actual distance obtained by corner detection and localization are shown in Fig. 3. The mapping relation can be approximated as a curve. Next, we need to establish the mapping relation between the image pixel value and the actual distance, that is, the regression analysis of these two sets of variables.

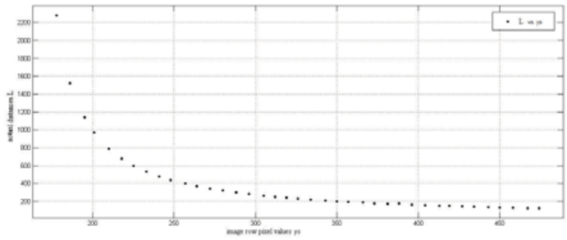

Figure 3. Mapping relation between image row pixel values and actual distances

A. Back-Propagation Neural Network

The Back-Propagation (BP) neural network was proposed by Rumelhart et al. in 1986. It is a multi-layer feed forward network trained by error inverse propagation algorithm and is one of the most widely used neural network models.

The BP neural network model is mostly a three-layer topology, which is the input layer, the hidden layer and the output layer used as the adjustment map. The three-layer BP network structure is shown in Fig. 4.

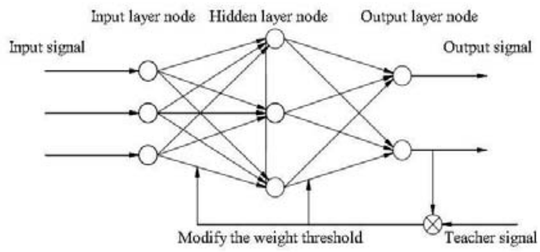

Figure 4. Three-layer BP neural network structure

The establishment of the BP neural network model mainly consists of two parts: forward propagation and back propagation. The network of the number of input nodes n and the number of output nodes m is regarded as a mapping from the n-dimensional European space, and the weights and thresholds are continuously learned and adjusted by the least squares principle and the gradient search technique. If the output of the output layer differs greatly from the expected expectation, the error signal is reversely transmitted to each network layer unit of the network, and the mean and error of the network are reduced to an acceptable level by modifying the weight and threshold of each layer of neurons [8].

B. Random Forest

Random forest (RF) algorithm is an algorithm based on classification tree proposed by Breiman and Cutler in 2001 [9]. This algorithm needs simulation and iteration and is classified as a method in machine learning. Compared with the neural network, the RF reduces the computational amount by repeatedly classifying or regression the data. At the same time, the RF improves the prediction accuracy on the premise that the computational amount is not significantly improved, which is praised as one of the best algorithms at present [10].

As shown in Fig. 5, the RF algorithm first uses the Bagging sampling technique to generate n sets of new sample data sets from the original training set. The size of each training subset is approximately two-thirds of the original training set, and each sampling is random and put back into sampling. Secondly, for each node in the n sets of training subsets obtained in the first step, some attributes are randomly selected to be segmented, and n fully grown decision trees are generated to form a forest. Each decision tree does not need pruning. For the regression problem, the prediction results of the n decision subtrees are usually used as the final output of the RF algorithm.

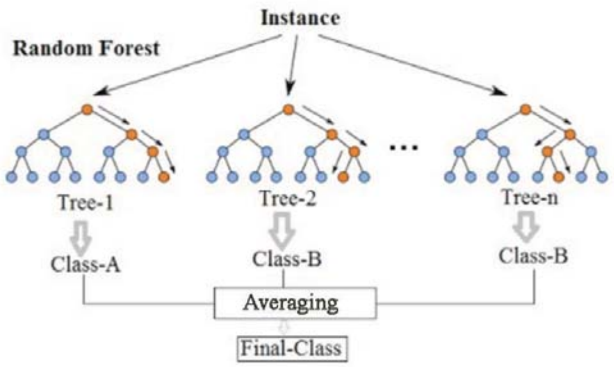

Figure 5. Schematic of RF algorithm

RF is an integrated algorithm that is insensitive to outliers in the dataset. It does not require excessive parameter tuning. Compared with single decision tree, RF usually has better generalization performance, that is, good convergence of generalization error [11]. At the same time, it can effectively avoid the occurrence of overfitting by randomly selecting training samples and randomly selecting m attributes [12].

C. Curve Fitting

As shown in Fig. 3, the mapping relation between the ordinate pixel value and the actual distance can be approximated as a curve. In this paper, the fitting experiment of ys-L data is carried out respectively with exponential function and rational function, and the fitting effect is shown in Fig. 6.

As shown in Fig. 6, fitting data with rational function is better than fitting data with exponential function, and the range-finding model can be obtained by rational fitting as shown in (2):

$$L = \frac{p_1 y + p_2}{y + q_1} \tag{2}$$

where y represents the midpoint ordinate pixel of the bottom of the object to be measured, L represents the distance between the moving object and the camera. p_1、p_2 and q_1 are the parameters in the model.

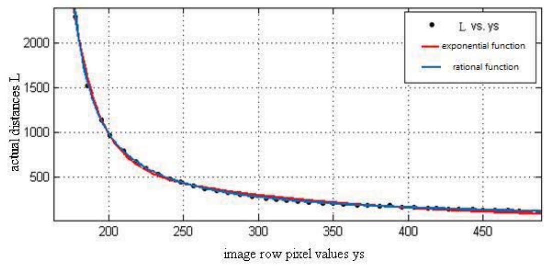

Figure 6. Curve fitting effect

In this paper, the BP neural network, RF algorithm and rational function fitting method are used to establish the mapping model between the corner ordinate pixel and its actual distance. The model prediction distance and its relative error with the actual distance are shown in Fig. 7.

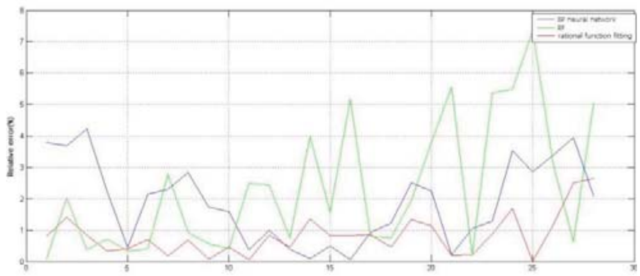

Figure 7. Comparison of range-finding effects between different models

According to the analysis in Fig. 7, the distance measurement error obtained through the mapping model constructed by BP neural network and RF algorithm is relatively large. This is because the training data is composed of corner ordinate pixels and their corresponding actual distances, which data quantity and feature quantity are less, while machine learning must be based on a large amount of data. Therefore, in this paper, the rational fitting method is adopted to perform regression fitting of the corner ordinate pixel and its corresponding actual distance, so as to establish the mapping model required for ranging.

IV. Ranging Model Parameter Optimization

Experiments show that the parameters of the ranging model obtained by rational fitting method are not an exact value, but a range value. Therefore, based on the existing ranging model, this paper makes further parameter optimization based on artificial bee colony (ABC) algorithm.

Firstly, we define the function R to represent the accuracy of the distance measurement model. R is the weighted sum of squared errors of the distance measured and the distance measurement model:

$$R = \sum_{i=1}^{m} w_i \left(\hat{L}_i - L_i \right)^2 \tag{3}$$

where $\hat{L}_i$ represents the measured distance, L_i represents the actual distance, and W_i represents the weight. As the distance corresponding to the remote unit relative error is larger than that of the proximal end, if the unweighted weight is only used to represent the accuracy of the distance model by the sum of deviation squared, the accumulated sum of the total difference squared will be smaller, but the data points with the error greater than 1% will be larger.

Since the unit pixel point at the far end of the image corresponds to a larger distance, the corresponding relation between the vertical coordinate and the distance of the image referring to the target corner can be expressed as piecewise linear function. The slope of piecewise linear function is taken as the reference and the normalization method is used to weight:

$$w_i = 1 - \frac{k_i}{\sum_{i=1}^{m} k_i} \tag{4}$$

where k_i represents the absolute value of the slope of the linear function in each segment.

ABC algorithm is an intelligent search method which imitates the honey bee collecting behavior, proposed by Karaboga et al. [13] in 2007.The algorithm has few control parameters, is easy to implement, has strong global optimization ability, and has fast convergence speed, and is suitable for solving multivariable function optimization problems [14], [15].

As a meta-heuristic random search algorithm, ABC seeks the optimal solution by performing random and targeted evolution on the population of candidate solutions. Among them, the food source represents a possible solution to the optimization problem, and the quality of the quality depends on the fitness value of the function. The $i - th(i = 1, 2, \ldots, SN)$ food source is represented by $x_i = \left(x_i^1, x_i^2 \cdots, x_i^D \right)$, and D is the dimension of the search space S. After initialization, the optimization process is divided into three phases according to the type of bee:

Hire bee stage. At this stage, the hiring bee searches for a neighborhood near the food source according to (5), generates a candidate food source v_i^j, and selects a better food source through a greedy mechanism.

$$v_i^j = x_i^j + \varphi_i^j \left(x_i^j - x_k^j \right) \tag{5}$$

where φ_i^j is a random number between [-1, 1] and is used to control the neighborhood radius of x_i^j. A and B are randomly selected: $k = 1, 2 \cdots, SN$, $j = 1, 2 \cdots, D$, and $k \neq i$.

Observation bee stage. After the hiring bee completes the exploration, the observation bee selects a food source for further exploitation based on the information shared by the hiring bee, and the probability that the food source is selected is according to (6).

$$P_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \tag{6}$$

where fit_i is the fitness function value of the $i - th$ food source. For the purposes of this paper, the correspondence between fit_i and the accuracy R of the ranging model is shown in (7).

$$fit_i = \frac{1}{1 + R_i} \tag{7}$$

Scout bee stage. When the adaptive value of the hired bees corresponding to the food source has not been updated for $limit$ consecutive times, indicating that the food source has been exhausted, the corresponding hired bees will abandon the food source and become the scout bees, and generate a new food source randomly, as shown in (8).

$$x_i^j = x_{lb}^j + rand \times \left(x_{ub}^j - x_{lb}^j \right) \tag{8}$$

where $rand$ is a random number between (0, 1), x_{lb}^j and x_{ub}^j are the lower and upper bounds of the j-th dimension component.

After $maxcycle$ iterations of the stage of hire bee, observation bee, and scout bee, the optimal illuminating source is output, otherwise iterating again until $maxcycle$ iterations are reached.

V. Experiments and Results

To verify the feasibility and accuracy of the method, we write the program according to the above method and perform the experiment after debugging. The height h of the camera from the ground is 88.5cm. The distance between the target surface of the reference target and the camera is 51 cm.

The difference between adjacent corner points is 0.8cm. The image resolution is 640X480.

A. Parameter Optimization Experiment

As shown in Fig. 8, the image of the object to be measured moving to different grid boundaries of near and far is taken based on the 60cm grid on the laboratory ground, and the actual distance L_i from the object to the camera and the vertical coordinate pixel y of the middle point of the object base are recorded. Thus, the sample points required for parameter optimization are obtained.

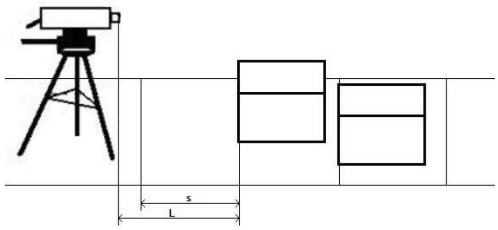

Figure 8. Parameter optimization experiment diagram

The ABC algorithm is used to optimize the initial parameters of the ranging model. The optimization results are shown in Table I.

TABLE I. PARAMETER OPTIMIZATION DATA

	p1	*p2*	*q1*
Initial parameter	0.51	38023	-161.45
Optimized parameter	0.6851	38040	-161.2

B. Ranging Experiment

Keep the camera still, let the object move in front of the camera, and record the actual distance value. In order to compare the parameter optimization effects, the model parameters before and after optimization are input into the system program respectively. Some experimental images are shown in Fig. 9, and the ranging results are shown in Table 2. The relative error comparison of ranging is shown in Fig. 10.

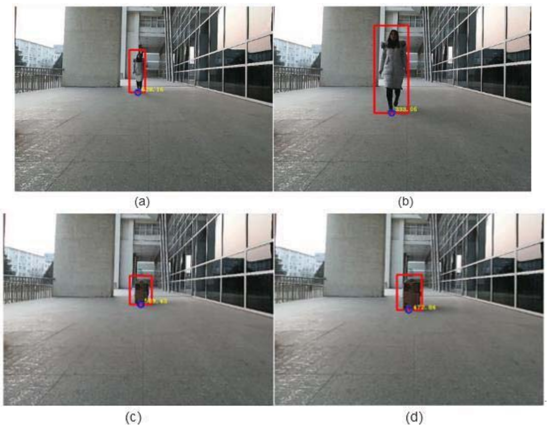

Figure 9. Part of experimental images

TABLE II. RANGING RESULT AFTER PARAMETER OPTIMIZATION

Number	*Actual Distance/cm*	*Calculated Distance Before Parameter Optimization/cm*	*Calculated Distance After Parameter Optimization/cm*	*Relative Error/%*
1	120	119.03	119.22	-0.65%
2	150	147.89	148.07	-1.29%
3	180	178.51	178.65	-0.75%
4	210	209.30	209.41	-0.28%
5	240	240.97	241.01	0.42%
6	270	271.88	271.86	0.69%
7	300	300.58	300.48	0.16%
8	330	332.24	332.05	0.62%
9	360	359.76	359.46	-0.15%
10	390	391.77	391.37	0.35%
11	420	419.76	419.24	-0.18%
12	450	446.24	445.59	-0.98%
13	480	482.22	481.39	0.29%
14	510	516.86	515.87	1.15%
15	570	574.70	573.31	0.58%
16	630	635.20	633.40	0.54%
17	690	695.95	693.73	0.54%
18	750	753.47	750.75	0.10%
19	810	820.86	817.53	0.93%
20	870	879.87	875.92	0.68%
21	1025	1027.03	1021.41	-0.35%
22	1085	1087.38	1080.99	-0.37%
23	1145	1155.04	1147.75	0.24%
24	1205	1184.65	1192.47	-1.04%
25	1265	1264.90	1273.85	0.70%
26	1325	1309.54	1319.30	-0.43%
27	1445	1408.61	1420.00	-1.73%

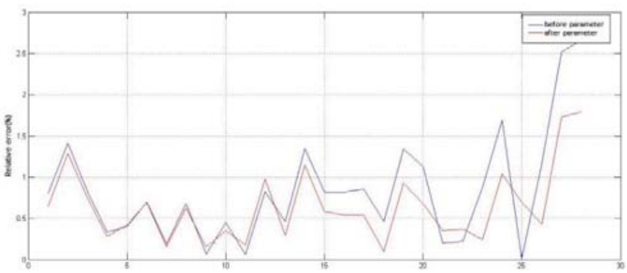
Figure 10. Comparison of ranging effects before and after parameter optimization

The experimental results show that the relative error between the distance and the actual distance of the ranging algorithm is further reduced by optimizing the parameters of the ranging model. When the distance between the camera and the object to be measured is within 100~1325cm, the optimized range error is basically controlled within 1.0%. When the distance is greater than 1400cm, the measurement error increases. The reason is that the farther the moving object is from the camera, the larger the corresponding distance to the unit pixel is, and the smaller the proportion of the moving object in the image is, which leads to that a smaller error caused by the object detection will form a larger range error. In general, the above method can meet the accuracy requirements of ranging within the range of effective ranging.

VI. CONCLUSION

In this paper, a single reference target image is used to obtain the corner coordinates of target image and its corresponding actual distance through corner point detection and localization. By using the method of data regression analysis, the distance model corresponding to this mapping relation is established to realize the distance information extraction of monocular vision image. Three common regression analysis methods are studied experimentally. Finally, the rational fitting method is used to establish the mapping model between pixel and actual distance. The ABC algorithm is used to optimize the model parameters, which further improves the accuracy of the ranging algorithm. This method only needs to collect a target image. The operation is simple and does not need to consider the influence of the imaging model, the imaging system error and the lens distortion, etc. The experiment shows that the idea of the algorithm is effective and can meet the real-time and accuracy requirements of ranging.

This paper only studies and experiments the distance measurement algorithm in the case of horizontal straight path, but does not take into account other conditions such as curves, ramps, etc., and the effective range of distance measurement is small, so there is much room to improve in our work.

REFERENCES

[1] Guo, L., Xu, Y., Li, K., and Lian, X., "Study on real-time distance detection based on monocular vision technique," Journal of Image and Graphics, 11(1), 74-81 (2006).

[2] Wang, H., Xu, Z., Xie, K., et al., "Binocular measuring system based on OpenCV," Journal of Jilin University, 32(2), 188-194 (2014).

[3] Sun, W., Chen, L., Hu, B., et al., "Binocular vision-based position determination algorithm and system," Proc. CDCIEM 2012, 170-173 (2012).

[4] Huang, G., Li, G., Wang, B., et al., "Evolution for monocular vision measurement," Acta Metrologica Sinica, 25(4), 314-317 (2004).

[5] Yu, N., Huang, C., and Lin, J., "Target location and ranging based on monocular vision robot," Computer Measurement & Control, 20(10), 2654-2660 (2012).

[6] Wu, G., and Tang, Z., "Distance measurement in visual navigation of monocular autonomous robots," Robot, 32(6), 828-832 (2010).

[7] Shen, Z., and Huang, X., "Monocular vision distance detection algorithm based on data regression modeling," Computer Engineering and Applications, 43(24), 15-18 (2007).

[8] Liu, S., "Research and application on MATLAB BP neural network," Computer Engineering and Design, 24(11), 81-83 (2003).

[9] Breiman, L., "Random Forests," Machine Learning, 45(1), 5-32 (2001).

[10] Iverson, L., Prasad, A., and Matthews, S., "Estimating potential habitat for 134 eastern US tree species under six climate scenarios," Forest Ecology and Management, 254(3), 390-406 (2008).

[11] Dong, S., and Huang, Z., "A Brief Theoretical Overview of Random Forests," Journal of Integration Technology, 2(1), 1-7 (2013).

[12] Corani, G., "Air quality prediction in Milan: feed-forward neural networks," Ecological Modelling, 185(2), 513-529 (2005).

[13] Karaboga, D., and Basturk, B., "A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm," Journal of Global Optimization, 39(3), 459-471 (2007).

[14] Qin, Q., Chen, S., Li, L., and Shi, Y., "Artificial bee colony algorithm: a survey," CAAI Transactions on Intelligent Systems, 9(2), 127-135 (2014).

[15] Chen, J., Shen, Y., and Lu, X., "Artificial bee colony algorithm based on information feedback and an improved fitness value evaluation," CAAI Transactions on Intelligent Systems, 11(2), 172-179 (2016).