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APPLICATION RESEARCH OF ADABOOST REGRESSION PREDICTION BASED ON MACHINE VISION FOR THE BRIGHTNESS OF A SPECIFIED DISTANCE ENVIRONMENT

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Abstract: This paper proposes a decision guidance method based on an environmental brightness prediction model to address the problem of path planning failure and energy waste caused by environmental perception errors in robot recognition of dark areas in the environment. Firstly, by combining machine vision with light intensity sensors and depth cameras, a lightweight dataset containing light intensity, darkness parameters, dynamic parameters, and depth parameters is collected. Secondly, considering the poor accuracy of directly inferring dark areas based on traditional methods of obtaining environmental images and calculating image brightness information, this paper innovatively introduces dynamic parameters and depth parameters, which to some extent consider the impact of short-term environmental changes and spatial distribution on environmental brightness. Thirdly, the Adaboost regression model is used to train the self built lightweight data set. The analysis of feature importance shows that the dynamic and depth parameters account for 30% in total, which confirms the rationality and progressiveness of the introduction of dynamic and depth parameters. Finally, in order to more accurately evaluate the performance of different machine learning methods under the specific objectives of this study, Spearman correlation coefficient and Kendall rank correlation coefficient were introduced to evaluate the performance of the model. The experiment confirmed that the Adaboost model outperformed the decision tree, gradient boosting tree and other comparison models in Spearman (0.826) and Kendall (0.691) correlation coefficients. This method provides a high-precision and high security solution for predicting the brightness of the specified distance environment and identifying the lowest brightness point, with both theoretical value and engineering application potential.
Keywords: Environmental brightness prediction model; Dynamic parameter; Depth parameter; Adaboost regression model; Spearman correlation coefficient

1 INTRODUCTION

In some special fields, robots need to track dark areas in the environment when performing work tasks. Traditional solutions commonly include:1.Laying a network of light intensity sensors, placing multiple light sensors at different positions within the range to measure the light intensity at each position, and determining the dark areas through data analysis. 2.Carry a light intensity sensor on a mobile device and travel multiple times to designated areas for measurement, comparing and determining the degree of darkness using a camera to obtain environmental images and calculate image brightness information to directly infer dark areas.
Reference [1] proposes the use of mobile measurement for rapid evaluation of lighting, which is an efficient and convenient measurement method. However, for electric energy limited robots, obtaining light intensity values through continuous movement can result in low work efficiency and hinder task progress. Reference [2] uses wireless sensor networks to collect light intensity, which can identify points of energy waste and optimize system efficiency. However, sensor networks need to be laid at each working point. If robots need to perform tasks in multiple locations, it will bring great inconvenience and high hardware costs. Reference [3] systematically reviewed the classification and progress of single image shadow detection technology. Learning based methods such as CNN and CRF have high accuracy but high computational costs, making them unsuitable for robot control with limited computing power; The method based on color model is simple and fast, but has a high misjudgment rate.
Due to the recognition errors caused by various factors in traditional solutions, path planning failure and energy waste issues arise. This paper proposes a machine learning environment brightness prediction model based on machine vision parameters to guide robot decision-making during task execution. Deploy cameras on mobile devices and combine them with light intensity detection devices to collect relevant parameters from machine vision images through image processing algorithms. When training the model, place the light intensity detection device at a specific distance in front of the camera. Meanwhile, by collecting samples of light intensity, darkness parameters, dynamic parameters, and depth parameters, a lightweight dataset is constructed for training and optimizing environmental brightness prediction models. Specifically, the reason for placing the light intensity sensor at a specific distance is to efficiently predict the ambient brightness at the specified distance and the lowest point of the ambient brightness. The advantages of camera image processing in indoor dark area prediction models are obvious. It only requires the placement of a light intensity

measurement module at a specified distance in front of the camera during the lightweight dataset acquisition stage. After the model training is completed, it can break away from the dependence of the light intensity measurement module and rely solely on machine vision parameters to achieve environmental brightness prediction at a specified distance, find the lowest point of environmental brightness, improve the search efficiency of the target area, reduce hardware deployment costs, and enhance the overall reliability and robustness of the system.

2 METHODOLOGY

2.1 Light Intensity Measurement

This study aims to accurately measure the actual light intensity in the environment. A simple circuit was built using an STM32 microcontroller and three light intensity sensors, and placed directly in front of a depth camera at a specified distance for measurement (this article sets the specified distance to one meter). When measuring the ambient light intensity, it was found that the range of light intensity was 0-4096. When the sensor was placed under strong light, the data did not reach the expected value of 0. Even in a completely dark environment and after being sealed and obstructed again, the theoretical value of 4096 could not be achieved, and the error remained around 100-150 of the distance range. To eliminate this error, the sensor was subjected to data bias calibration. The deviation calibration values were calculated by measuring the output values of the sensor under zero input, i.e. complete darkness, and full input, i.e. strong light conditions. The formulas are as follows:

$$V_{calibration} = V_{measure} - V_{bias} \tag{1}$$

where $V_{calibration}$ refers to the calibrated voltage, $V_{measure}$ refers to the voltage measured by the sensor, and V_{bias} refers to the bias voltage of the sensor. Measurement errors are reduced through multiple measurements and data processing.

The STM32 controller collects measurement data from three light intensity sensors through ADC and preprocesses these data. The three collected data are first averaged to ensure the average light intensity within their coverage range. In order to avoid instantaneous errors, in this article, five sets of data are obtained from each light intensity collection point. The highest and lowest values are removed, and the remaining data is filtered by the average value. During the data processing, the average filtering technique is applied to reduce noise and errors by averaging multiple measurements. The average filtering formula is:

$$V_{average} = \frac{1}{n}\sum_{i=1}^{n} V_i \tag{2}$$

where $V_{average}$ is the average value, V_i is the value of each measurement, and n is the number of measurements. Reduce measurement errors caused by instantaneous interference through average filtering. The circuit of the measuring device is shown in Figure 1 Light intensity acquisition device circuit.

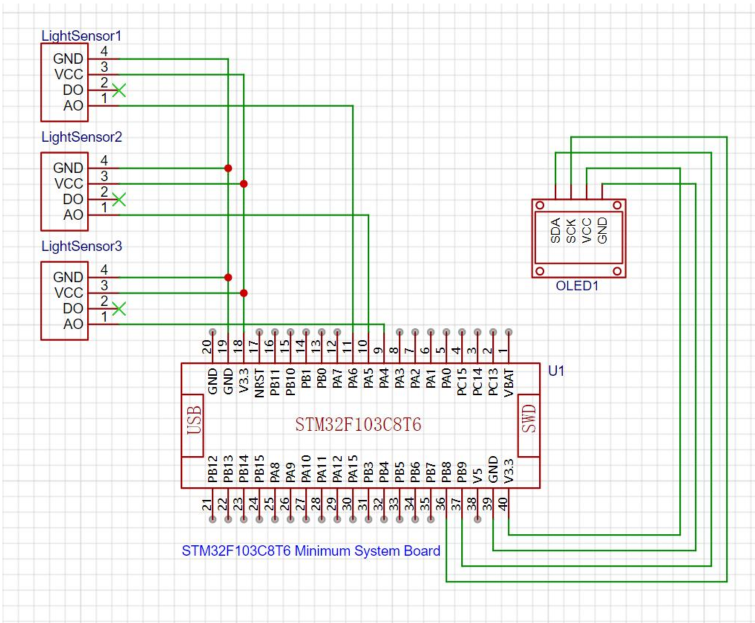

Figure 1 Light Intensity Acquisition Device Circuit

2.2 Machine Vision Parameter Measurement

2.2.1 Measurement of dark parameters

At the same time as collecting the actual light intensity, the depth camera also collects corresponding images. After submitting them to the main control, the images are strictly named according to the requirements and stored in the specified path. The main control runs Python code for image analysis and uses the cv2.imread function to read the image files in the specified path. If the image file is not found, an error message will be printed and the program will exit. In the main function, the cvtColor function converts the image from RGB to grayscale, simplifying the complexity of image processing. Color images consist of three channels: red, green, and blue (RGB), each storing different color information. And grayscale images only contain one channel, representing the brightness information of the image. This conversion step helps simplify calculations by only processing data from a single channel, making it easier to calculate the average brightness of the image. Especially grayscale images represent the brightness information of the image, but do not contain color information. When calculating the average brightness, this article only focuses on the brightness distribution of the image, so grayscale images are more suitable for this purpose.

$$Y = 0.299 \cdot R + 0.587 \cdot G + 0.114 \cdot B \tag{3}$$

where Y represents the brightness component, and R, G, and B represent the intensities of the red, green, and blue channels, respectively.

Convert an image from RGB color space to grayscale color space. Next, use the mean function of the numpy library to calculate the brightness of the grayscale image,

$$mean = \frac{1}{m \cdot n} \sum_{i=1}^{m} \sum_{j=1}^{n} G_{ij} \tag{4}$$

where the grayscale image is a matrix G, G_{ij} represents the grayscale values of the i-th row and j-th column, and m and n represent the number of rows and columns of the grayscale image, respectively.

This function achieves this goal by calculating the average grayscale value of the grayscale image. Finally, the average brightness value of the output image is used as the shading parameter in this paper.

2.2.2 Dynamic parameter measurement

During the process of robot task execution, dynamic changes in the environment are highly likely to have a negative impact on its decision-making process. To enhance the anti-interference and robustness of robot decision-making, this paper innovatively introduces the concept of "dynamic parameters" to effectively filter out irrelevant factors and enhance the reliability of the prediction model. The specific operation is as follows: Firstly, before each decision, multiple frames of RGB images are collected at fixed time intervals, stored according to rules, and converted into grayscale images using OpenCV to simplify the subsequent analysis of brightness differences; Subsequently, the pixel brightness differences of the grayscale images are compared one by one, and the average value is taken. The number of pixels exceeding the set threshold is counted as the dynamic parameter value. The set threshold is selected based on experimental data and experience to ensure effective differentiation between normal environmental changes and sudden disturbances. For example, drastic changes in lighting caused by personnel passing through cameras or other activities may result in captured images lacking real stability, which may lead to decision-making errors in the main control system. This approach incorporates factors that may affect environmental lighting as dynamic parameters [4] into the consideration range of subsequent prediction models, significantly improving the anti-interference ability of the prediction model. Finally, by quantifying the instantaneous changes in the environment, the model can more accurately identify and eliminate measurement related abnormal situations, and take them into account to ensure that environmental information is fully considered in decision-making. The calculation process of dynamic parameters is simple and efficient, significantly improving the overall performance of the system without affecting real-time performance. In summary, dynamic parameters, as an effective anti-interference method, provide solid guarantees for robots to perform tasks in dynamic environments and have important theoretical and practical significance.

2.2.3 Depth parameter measurement

The application of predictive models is to predict the ambient brightness at a specified distance ahead. In practical applications, in order to avoid misjudgment caused by special situations within short distances, the system needs to make additional judgments on depth parameters. For example, when the model predicts that the brightness of the specified environment ahead is low but the depth parameter is very small, it may mean that there are very close obstacles or that the robot has reached the edge of a dark area, which affects the prediction of environmental brightness due to the obstruction of light and shadow. In this case, the depth parameter has a dual function: 1.as an influencing variable of the prediction model, it assists in determining whether the environmental brightness is too low or whether it is affected by the small depth parameter in special cases by analyzing the distance information of the front area [5]. Therefore, including it in the scope of subsequent prediction models takes into account the impact of spatial distribution on environmental lighting prediction to a certain extent. 2.If the system decision allows the robot to blindly continue moving towards the target direction, it may lead to collisions or other dangers. Depth parameters can provide a support basis for robots to make safe decisions without moving forward, ensuring the safety and robustness of robots in complex environments.

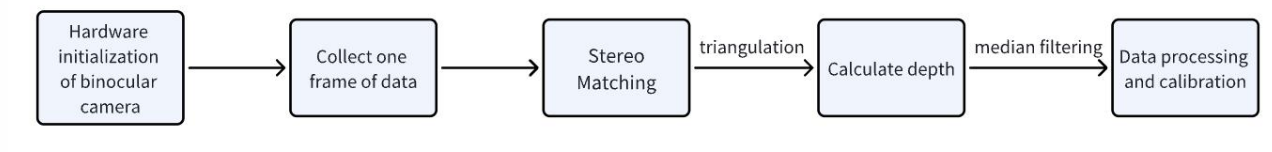

Figure 2 Depth Calculation and Data Processing Process of Binocular Camera

The depth camera used in this article is based on binocular structured light 3D imaging technology. Its data acquisition process is shown in Figure 2 Depth calculation and data processing process of binocular camera. The hardware composition of the depth camera mainly includes two infrared cameras (IR Camera), one infrared projector (IR Projector), and a depth calculation processor (Depth Processor).

1. The infrared projector projects structured light patterns (speckle patterns) onto the target scene.
2. The infrared camera captures an infrared structured light image of a target, and the depth calculation processor receives the infrared structured light image, executes a depth calculation algorithm, and outputs a depth image of the target scene.
3. Match the pre calibrated reference structured light image with the currently collected infrared structured light image to obtain the deviation values of each pixel between the images (d = $|x_L - x_R|$), where x_L and x_R represent the imaging positions of the same object on the left and right camera image planes, respectively. The depth camera is based on the triangulation method [6], which uses the baseline length of the binocular camera (the distance between the optical centers of the two cameras), the focal length of the camera, and the calculated disparity to calculate the depth of each feature point on the object through the principle of triangulation, as shown in Figure 3 Simple schematic diagram of triangulation based on binocular vision. The basic formula for triangulation based on binocular vision is:

$$Z = \frac{f \cdot B}{d} \tag{5}$$

where Z represents the depth of the object point (distance from the camera), f is the focal length of the camera, B is the baseline length of the binocular camera, and d is the disparity [7]. More intuitively demonstrating the principle of triangulation, as shown in Figure 4 Detailed schematic diagram of triangulation based on binocular vision. where a represents the width of the imaging plane, P_L and P_R represent the projection of the target point P on the imaging planes of the IR1 and IR2 infrared cameras, and m and n represent the distance from the image point to the optical center, respectively.

4.Based on the principle of structured light triangulation, calculate the depth value from the deviation value. In the figure, LDM stands for Laser Direct Modulation technology. By calculating the depth of all matched feature points in the image, the depth information of the entire scene can be obtained and a depth map can be generated. A depth map is a two-dimensional image where the value of each pixel represents the depth of the corresponding field point for that pixel.

5.Obtain distance information of various points in the environment and generate real-time depth images on the upper computer. In order to reduce measurement errors of individual points, the system extracts the nearest few points from the depth image and calculates the depth parameters of the current image point through arithmetic mean:

$$average\ depth = \frac{1}{n}\sum_{i=1}^{n} d_i \tag{6}$$

where d_i is the depth parameter of each point, and n is the number of points.

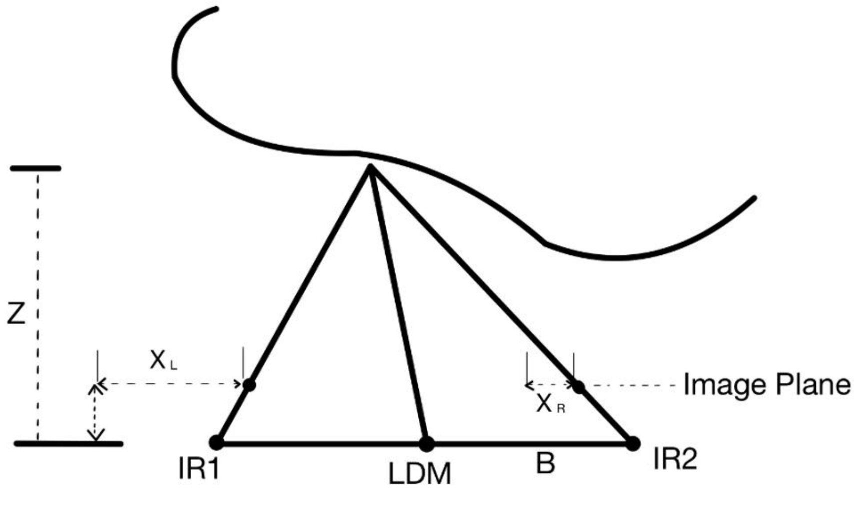

Figure 3 Simple Schematic Diagram of Triangulation Based on Binocular Vision

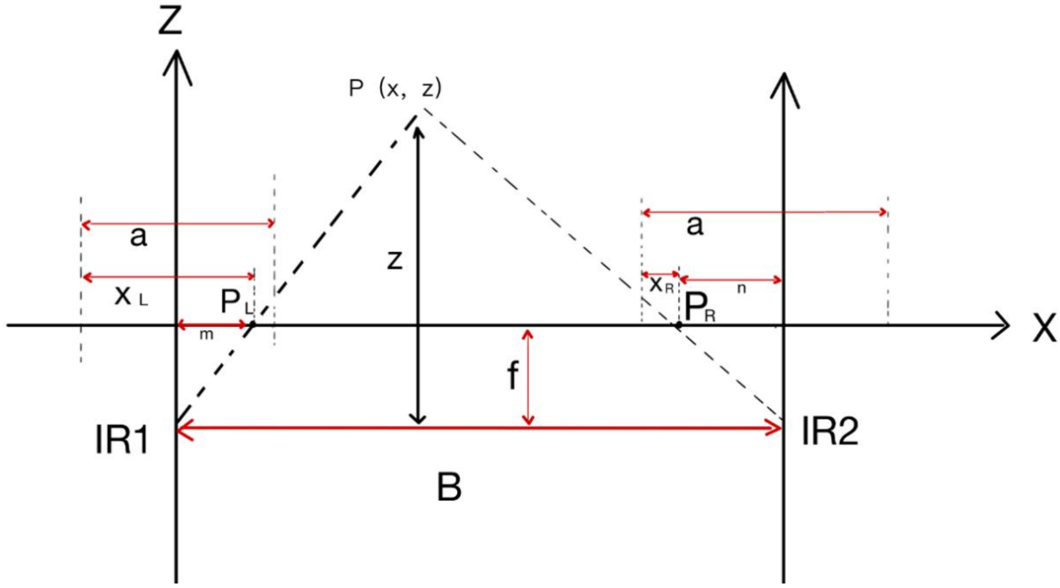

Figure 4 Detailed Schematic Diagram of Triangulation Based on Binocular Vision

2.3 Data Set

During data collection, different points were selected in eight areas and rotated 45 ° with the servo gimbal at each location. One set of data was collected for each rotation, and a total of 8 sets of data were collected for each point. Four parameters were collected in each set of data:

1. Light intensity: Light intensity is the core dependent variable in the prediction model, which is crucial for the recognition and path planning of robots in dark areas. By predicting the light intensity, the robot can determine the direction with the lowest ambient brightness in the surrounding environment. At the same time, the data bias calibration and mean filtering of this parameter during measurement provide reliable basic data for the model, ensuring the accuracy of the prediction results.
2. Shadow parameter: The shadow parameter is the average brightness value calculated based on image grayscale processing. As the core independent variable of the prediction model, its variation has a significant impact on the prediction results. By introducing the dark parameter, the model can roughly capture the distribution pattern of environmental brightness. Simultaneously converting the image from RGB color space to grayscale color space simplifies computational complexity, enabling the model to efficiently process large amounts of image data.
3. Dynamic parameters: Dynamic parameters quantify the instantaneous changes in brightness in the environment by comparing continuous RGB images. As a key independent variable of the prediction model, they can effectively filter out instantaneous changes and abnormal situations in the environment, improve the model's anti-interference ability, and to some extent help the system consider the impact of short-term environmental changes on environmental brightness. This ensures that the model makes decisions based on stable environmental information, enabling the model to better adapt to dynamic changes in the environment and improve the robustness and reliability of predictions.
4. Depth parameter: Depth parameter is the environmental depth information obtained based on binocular structured light 3D imaging technology. As a key independent variable of the prediction model, its spatial position data can quantify the distance information from objects, helping the system consider the impact of environmental spatial distribution on environmental brightness.

By comprehensively considering these four parameters, the model can more accurately predict environmental brightness in complex environments, ensuring the safety and reliability of robots during task execution.

2.4 Prediction Model

2.4.1 Model selection

Adaboost is an adaptive boosting machine learning method, whose core idea is to iteratively train multiple weak learners and adjust sample weights based on the errors of the previous learner, gradually optimizing model performance. In regression tasks, Adaboost regression prediction achieves high prediction accuracy, strong robustness, and prevents overfitting by weighting and combining multiple weak regression models.

2.4.2 Model building process

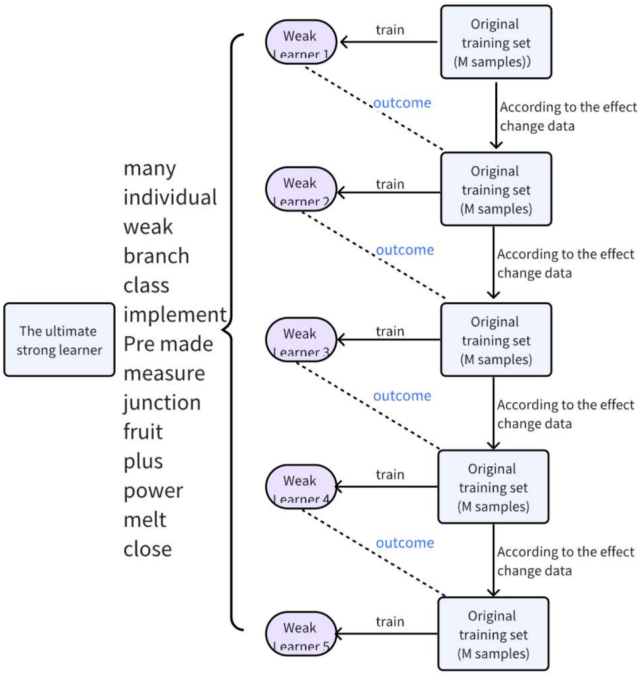

Figure 5 Schematic Diagram of AdaBoost Algorithm

The AdaBoost algorithm iteratively trains multiple weak learners and adjusts sample weights based on their performance, ultimately combining these weak learners into a strong learner to improve the overall performance of the model. As shown in Figure 5 Schematic diagram of AdaBoost algorithm.

Specifically, x_i and y_i are used to represent the sample points and their class labels of the original sample set D. Use w_k (i) to represent the weight distribution of all samples at the kth iteration. The specific steps of AdaBoost algorithm [8] are as follows:

1. Initialization: The input parameters are training set D={x_1, y_1, ..., x_n, y_n}, maximum cycle count k_{max}, sampling weight w_k(i)= $\frac{1}{n}$, i=1, ..., n;
2. The iteration counter k is assigned a value of 0;
3. Counter k increases by 1;
4. Train the weak learner C_k using W_k(i) sampling weights;
5. Evaluate the training results of the weak learner C_k and record them in the error matrix E_k;

$$\alpha_k \leftarrow \frac{1}{2} ln \frac{1-E_k}{E_k} \tag{7}$$

$$W_{k+1}(i) \leftarrow \frac{W_k(\mathrm{i})}{Z_k} \times \begin{cases} e^{-\alpha_k}, if h_k(x^i) = y_i \\ e^{\alpha_k}, if h_k(x^i) = y_i \end{cases} \tag{8}$$

6. Stop training when k = k_{max};
7. Return results C_k and α_k, k=1, ..., k_{max} (population of weighted classifiers);
8. End;

where in line 5 that the current weight distribution must take into account the error rate of classifier C_k. In the 7th line, Z_k is just a normalization coefficient that allows W_k (i) to represent a true distribution, while h_k (x_i) is the label (+1 or -1) given by the component classifier C_k for any sample point x_i. When h_k (x_i)= y_i, the sample is correctly classified. The iteration stop condition in line 8 can be replaced with determining whether the current error rate is less than a threshold.

The final overall classification decision can be obtained by weighted average of each component classifier:

$$g(x) = \left[\sum_{k=1}^{k_{max}} \alpha_k h_k(x) \right] \tag{9}$$

In this way, the final judgment rule for the classification result is:

$$H(x) = sign\big(g(x)\big) \tag{10}$$

3 Model Results and Comparison

The feature importance analysis of Adaboost regression model provides key insights for a deeper understanding of the model's decision-making mechanism. By quantifying the contribution of each feature in the prediction process, this article not only reveals the relative importance of each feature to the model output, but also provides important

theoretical basis for optimizing model performance. As shown in Figure 6 Importance of environmental brightness model features, the importance of environmental brightness model features.
Specifically, the analysis of feature importance shows that the "dark parameter" dominates in model construction, with a feature importance of up to 70.00%, far higher than other features. This discovery indicates that the 'dark parameter' is a core influencing factor in predicting light intensity, and its variation has a significant impact on the prediction results.
In contrast, the feature importance of "depth parameters" and "dynamic parameters" is 13.30% and 16.70%, respectively. Although their contribution is not as high as that of "dark parameters", they together contribute nearly one-third of the influence. This indicates that both "depth parameters" and "dynamic parameters" play important roles in the model prediction process that cannot be ignored. In particular, the "dynamic parameters" and "depth parameters" introduced in this article together account for 30% of the importance of model features, highlighting their crucial role in predicting environmental brightness.

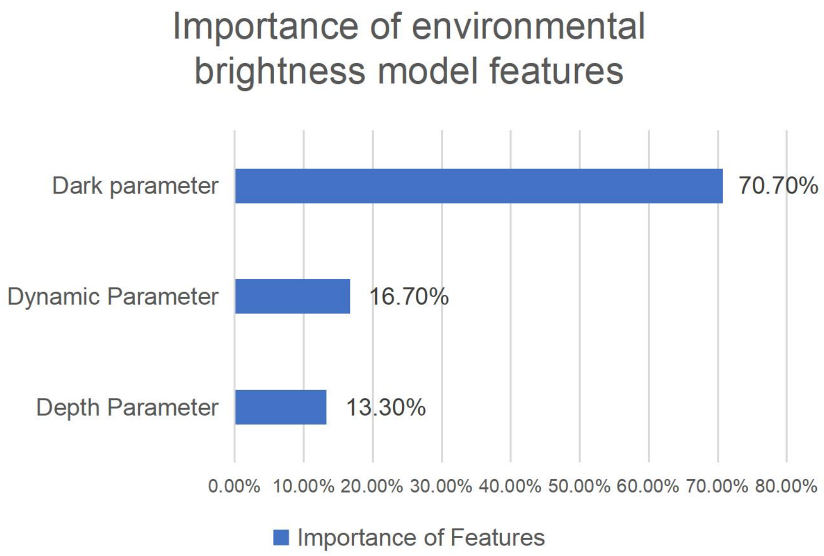

Figure 6 Importance of Environmental Brightness Model Features

This analysis further reveals the limitations of traditional methods for obtaining environmental images and calculating image brightness information to directly infer dark areas. Traditional methods fail to fully consider the impact of dynamic environmental factors such as changes in lighting and object movement on brightness distribution, resulting in limited prediction accuracy. In contrast, this article successfully captured the dynamic changes and spatial distribution characteristics of environmental brightness by introducing "dynamic parameters" and "depth parameters", significantly improving the predictive performance of the model.
Specifically, "dynamic parameters" can reflect the temporal variation of environmental brightness, while "depth parameters" can capture the impact of spatial position relationships of objects in the scene on brightness distribution. The introduction of these features enables the model to have a more comprehensive understanding of the distribution pattern of environmental brightness, thereby making more accurate predictions. The research results indicate that "dynamic parameters" and "depth parameters" have important contributions in model prediction, which further confirms the necessity of dynamic environmental features in predicting environmental brightness.
In order to visually demonstrate the predictive effect of Adaboost regression model on environmental brightness using dark parameters, dynamic parameters, and depth parameters, this paper visualizes the predicted values and true values of eight directions at one point, and compares them with the effects of decision tree regression prediction, gradient boosting tree regression prediction, BP neural network regression prediction, and linear regression prediction using four other machine learning methods. The specific results are shown in Figures 7 to 11.

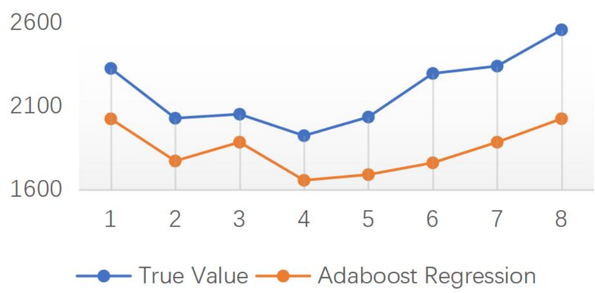

Figure 7 Adaboost Regression

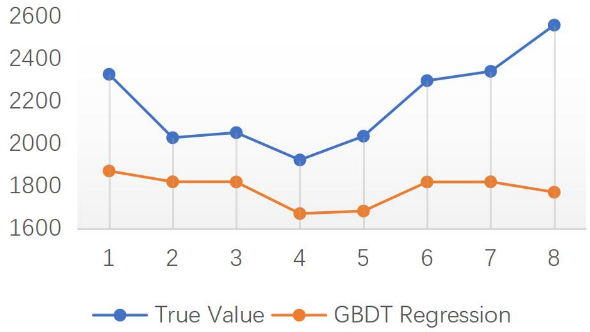

Figure 8 GBDT Regression

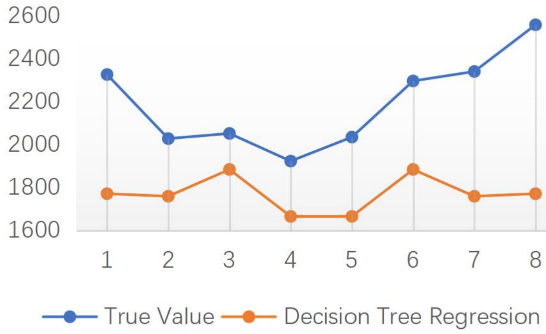

Figure 9 Decision Tree Regression

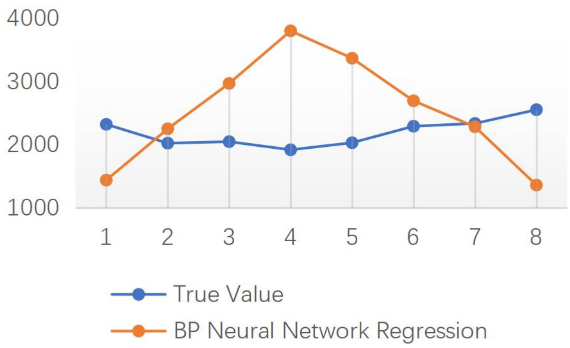

Figure 10 BP Neural Network Regression

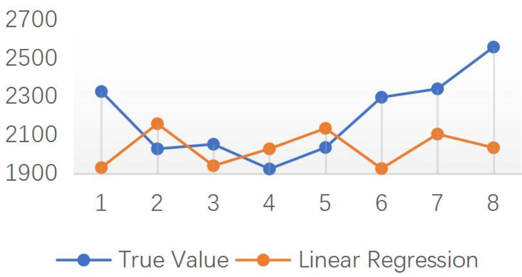

Figure 11 Linear Regressio

According to the above visualization analysis, it can be seen that due to the pursuit of lightweight dataset samples, the performance measurement parameters of commonly used traditional machine learning regression prediction models are poor. Specifically, traditional performance evaluation metrics such as mean square error (MSE), mean absolute error (MAE), etc. mainly focus on the numerical error between predicted values and true values, but these metrics fail to fully reflect the performance of the model under the specific objectives of this paper.

The core goal of this article is to accurately identify the lowest point of environmental brightness in the sample through a predictive model, but traditional indicators have obvious limitations in evaluating whether the model can achieve this goal. Traditional indicators such as MSE and MAE mainly focus on the numerical differences between predicted values and true values, while ignoring the relative order and distribution characteristics of predicted values. For this article, accurately identifying the lowest point of environmental brightness not only requires the numerical accuracy of the predicted values, but also requires the model to correctly sort the brightness values of the samples. However, traditional indicators cannot evaluate the monotonicity and ranking ability of the model, which are crucial in this article. For example, if the model can correctly sort the brightness values of the samples, even if there is a certain error between the predicted values and the true values, the model can still effectively identify the lowest point of environmental brightness. In addition, traditional indicators have not been optimized for the specific goal of this article, which is to identify the lowest point of environmental brightness, resulting in a deviation between their evaluation results and the actual application effect of the model. Therefore, relying solely on indicators such as MSE or MAE cannot comprehensively evaluate the monotonicity and ranking ability of the model, nor can it directly measure the effectiveness of the model in identifying the lowest point of environmental brightness. This article introduces Spearman correlation coefficient and Kendall rank correlation coefficient for performance evaluation under specific objectives.
Spearman correlation coefficient is the Pearson correlation coefficient calculated by converting the raw data into rank. Measure the monotonic relationship between predicted values and true values. Sensitive to non-linear relationships, it can capture correlations even if the predicted values are not linearly related to the true values.

$$\rho = \frac{Cov\big(R(x),R(y)\big)}{\sigma_{R(x)}\sigma_{R(y)}} \tag{11}$$

where R (x) and R (y) are the ranks of x and y, Cov is the covariance, and σ is the standard deviation.
The Kendall rank correlation coefficient measures the consistency of the rank of two variables. More emphasis is placed on consistency than Spearman correlation coefficient. In the case of a small sample size, Kendall rank correlation coefficient is usually relatively stable.

$$\tau = \frac{C\ -\ D}{\frac{1}{2}n(n-1)} \tag{12}$$

where C is the number of harmonious pairs, D is the number of discordant pairs, and n is the sample size.
Spearman and Kendall rank correlation coefficients are both ranking based indicators [9] that can measure the monotonic relationship between predicted values and true values, even if they are not linear.
By using Spearman and Kendall rank correlation coefficients simultaneously, the model can be evaluated from different perspectives:
1. Comprehensive evaluation of monotonicity and consistency: Spearman correlation coefficient focuses more on the monotonicity between predicted values and true values, while Kendall rank correlation coefficient focuses more on consistency. By combining these two indicators, the ranking ability of the model can be evaluated more comprehensively.
2. Robustness assessment of outliers: Kendall is more robust to outliers, while Spearman is more sensitive to outliers. By comparing two indicators, it is possible to determine whether there are outliers in the data that affect the model.
Through Spearman correlation analysis and Kendall's tau-b correlation analysis, the true values were compared with the predicted values of various machine learning models (including Adaboost regression, decision tree regression, gradient boosting tree regression, BP neural network regression, and linear regression). The results showed that the Adaboost regression prediction model was significantly better than other models in both correlation indicators [10], as shown in Figure 12 Spearman correlation analysis thermal matrix and Figure 13 Kendall's tau-b correlation analysis thermal matrix.
Specifically, the Spearman correlation coefficient between Adaboost regression predictions and true values is 0.826, and Kendall's tau-b correlation coefficient is 0.691, both of which are higher than other models, demonstrating significant advantages in sorting ability and monotonicity. The Spearman correlation coefficient measures the monotonic relationship between predicted and true values, while Kendall's tau-b correlation coefficient further verifies the consistency of the ranking. Compared to Adaboost regression model, decision tree regression, gradient boosting tree regression, BP neural network regression, and linear regression perform worse in both indicators, indicating their limitations in ranking and monotonicity. Therefore, the Adaboost regression prediction model performs the best in the performance evaluation under the specific objectives of this article, and can more accurately reflect the distribution characteristics of the true values, providing important basis for the prediction task of the lowest point of environmental brightness.

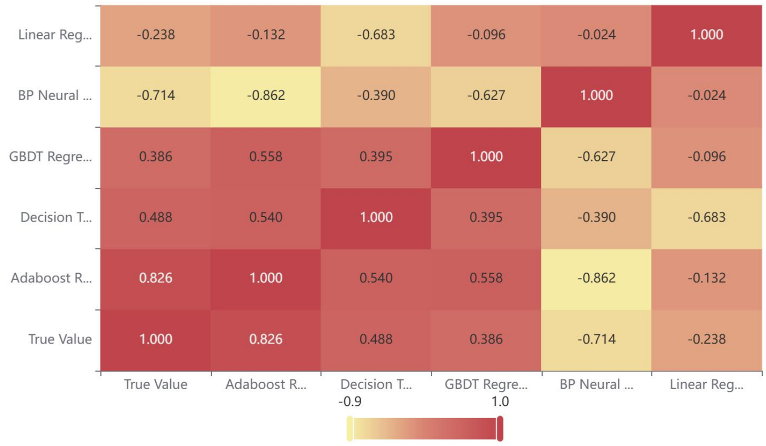

Figure 12 Spearman Correlation Analysis Thermal Matrix

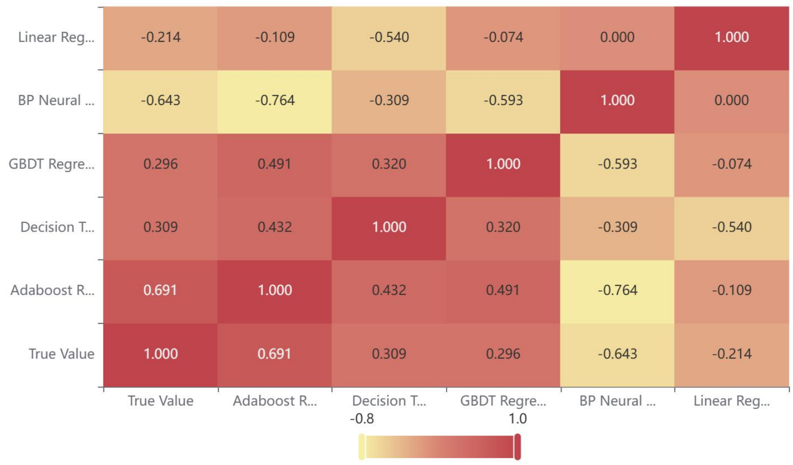

Figure 13 Kendall's tau-b Correlation Analysis Thermal Matrix

4 CONCLUSION

This article proposes a decision guidance method based on an environmental brightness prediction model to address the problems of path planning failure and energy waste in robot recognition of dark areas in the environment. By combining machine vision image processing technology, light intensity sensors, and depth cameras, a multi parameter lightweight dataset (including light intensity, shading parameters, dynamic parameters, and depth parameters) is collected, and the measured light intensity values are subjected to data bias calibration and average filtering to ensure data accuracy. This article innovatively introduces dynamic parameters and depth parameters to consider the impact of short-term environmental changes and spatial distribution on environmental brightness, effectively avoiding misjudgment and collision risks.

1. Multi parameter fusion: Traditional methods rely solely on environmental images to calculate brightness information, which results in significant errors. This article introduces dark parameters, dynamic parameters, and depth parameters to capture the characteristics of environmental brightness from multiple dimensions, significantly improving the accuracy and robustness of the prediction model.
2. Data processing optimization: In response to measurement errors in light intensity sensors, data bias calibration and average filtering techniques have been proposed to effectively reduce measurement errors and ensure data reliability.
3. Application of Adaboost regression model: Adopting the Adaboost regression model and utilizing its adaptive enhancement mechanism to optimize prediction performance. The analysis of feature importance shows that the contribution rate of dark parameters reaches 70%, and the dynamic and depth parameters account for 30%, which verifies the rationality and progressiveness of the introduction of these parameters.

In order to more accurately evaluate the performance of different machine learning methods under the specific objectives of this article, Spearman correlation coefficient and Kendall rank correlation coefficient were introduced as evaluation metrics. The experimental results show that the Adaboost model outperforms comparative models such as decision trees and gradient boosting trees in terms of Spearman (0.826) and Kendall (0.691) correlation coefficients, verifying its significant advantage in predicting the lowest point of environmental brightness [11]. This indicates that the Adaboost regression model can not only accurately capture the distribution characteristics of environmental brightness, but also effectively identify the lowest point of environmental brightness, providing reliable decision support for robot navigation in complex environments.

In summary, this article provides an innovative and efficient solution for predicting environmental brightness, which provides important technical support for autonomous navigation and decision-making of robots in complex environments. Future research will continue to revolve around this direction, continuously optimizing and improving relevant technologies and methods.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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