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Model and Simulation of Camouflage Evaluation Indicators for Computer Information Technology based on Eye Tracking Mechanism

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Abstract

The rapid development of data mining algorithms provides a foundation for the construction and simulation of eye tracking evaluation models. Mature eye tracking devices have been applied in various fields such as medical, commercial, aerospace, and military, and eye tracking data is also considered an important indicator of human subjective perception. The effectiveness evaluation of target camouflage directly affects the battlefield survival capability. The eye tracking mechanism can capture human eye movements and reflect an individual's attention allocation towards the target. Analyzed the detection probability model in the evaluation of camouflage effects, and established a relationship between the two based on the analysis of eye tracking data. This article uses data mining algorithms to extract the relationship model between relevant parameters, and combines the subjective detection probability model with objective eye movement data to find the relevant relationship, construct relevant mathematical models, analyze the error between reality and prediction, and provide theoretical guidance for practical applications.

Keywords: Model, Simulation, Data mining, Eye Tracking Mechanism, Detection Probability

1. Introduction

There is a close relationship between data mining and camouflage effect evaluation. As a powerful data analysis tool [1], data mining [2] can deeply explore the patterns and patterns behind data, providing strong data support for the evaluation of camouflage effects [3]. Through data mining, we can analyze the differences in data before and after camouflage, evaluate the effectiveness of camouflage measures, and optimize camouflage strategies [4]. Meanwhile, the evaluation of camouflage effects also provides an important feedback mechanism for data mining [5], helping us continuously improve data mining algorithms and models, and enhance the accuracy and efficiency of data mining [6]. Therefore, data mining and camouflage effect evaluation mutually promote the development and application of camouflage technology.

As an important medium for human beings to receive information from the outside world, the eye acquires 80% to 90% of all information [7]. The study of the process of information acquisition by the eye has been initiated as early as the Ancient Greek period [8]. After entering the age of information technology, research on eye behavior has gradually matured, developing into a system called eye tracking technology independently. The origins of eye-tracking technology can be traced back to the early 1900s, when scientists began studying the relationship between human eye movements and mental activity. As research becomes deeper, the importance of eye movement information in cognitive, psychological and behavioral research is gradually realized. Eye-tracking technology can record an individual's eye movements and gaze position at different times and tasks, which is a common method of responding to an individual's visual attention allocation [9]. Quantify the process of shifting attention when the human eye observes a target by detecting changes in attention when observing the outside world to obtain relevant data [10]. Early eye-tracking devices were mainly simple devices based on optical principles, which can only record basic eye movements. However, with the enhancement of science and technology, eye tracking technology has gradually developed from simple optical principles to a combination of various technologies, as a result of which the application fields are becoming increasingly extensive, covering human-computer interaction, psychology, neuroscience, medical diagnosis, advertising design and etc.

The study of camouflage effectiveness evaluation is one of the ways to improve battlefield survivability. The detection probability model in the evaluation of camouflage effect is analyzed and the relationship between the two by combining the analysis of eye-tracking data is established. In this paper, a subjective detection probability model is combined with objective eye movement data to find the correlation, and a relevant mathematical model is constructed, analyzing the error between the real and the predicted, and providing theoretical guidance for practical usage.

2. Detection Probability

2.1 Detection probability model

The formula [11] for the detection probability P is shown in (1):

$$P = \frac{N}{M} \tag{1}$$

Where M is the total number of observers and N is the number of total observers who found the target. The detection probability $P \leq 1$, the smaller the value of P, the better the camouflage effect.

2.2 Detection probability test chart production

32 background images that match the real environment were selected, numbering as Chart 1 to 32. Meanwhile, 32 personnel or vehicle targets are chosen, which are similar in color to the background, and subsequently are placed in rectangular squares randomly. When setting up, it is necessary to conform to the size and position of people and vehicles in the real environment, and to make the target blend into the background through color mixing so that it is not easy to be detected. When setting targets, 2 targets are randomly placed without repetition in each background image, and the number of target appearances is not greater than 2 in all background images. According to the order from left to right, from top to bottom for Target 1 and Target 2, respectively, and the test chart as shown in Figure 1.

Figure 1-Test Chart

2.3 Detection probability experiment and analysis

50 school students were included into this experiment. Before starting, introduction to the experimental procedure and the precautions were given to each tester. They were informed that there are a total of 32 test charts with 0-3 targets in each chart. The playback time of each test chart is 10s, and there is a 5s break between the test charts to avoid interference. During the experiment, respondents were required to maintain independent judgement. During the experiment, it was ensured that the experimental environment is quiet without noise, and the light intensity is moderate, to reduce the subjective error kindled by the different environments. Testers were not allowed to view the experimental material in advance of the start of the experiment, and testers were only

allowed to observe each test chart once. The tester recorded on the test paper of the order and number of targets he/she finds during the test. Subsequently, the detection probability of each figure is calculated with Equation (1) to obtain the results, and the detection probability of some charts is shown in Table 1.

Table 1-Detection Probability of Test Charts

Test Chart	Chart 1		Chart 2		Chart 3		Chart 4	
Detection Probability	Target 1	Target 2	Target 1	Target 2	Target 1	Target 2	Target 1	Target 2
	0.4	0.04	0.4	0.04	0.56	0.42	0.18	0.28
Test Chart	Chart 5		Chart 6		Chart 7		Chart 8	
Detection Probability	Target 1	Target 2	Target 1	Target 2	Target 1	Target 2	Target 1	Target 2
	0.26	0.64	0.1	0.12	0.16	0.02	0.1	0.44

After excluding test charts with particularly high and low detection probability, the other charts were selected randomly. The detection probabilities of the selected Charts 3, 4, 5, 8, 12, 20, 22, 23, 24, 25, 28, and 31 were used as samples for the following experiments.

3. Analysis and Selection of Eye Movement Indicators

3.1 Definition of eye movement indicators

With current technology, eye-tracking technology is the most intuitive and effective way to objectively reflect human thinking. According to recent studies on eye movement, eye movement indicators can be divided into four main categories, including fixation index, saccade index, and regression following parameter and pupil interest index. Fixation index: Fixation is the process of aligning the central fossa of the eye to an object, is the relative static state of the eye between two saccades, and the eye retention time should be greater than 100 ms, including the sequence of fixation points, the first fixation time, the duration of fixation and the number of fixations. Saccade index: Saccade refers to the jump of fixation point, including the first saccade, saccade number, saccade amplitude. Regression refers to the return of the fixation point to the area that was scanned again or several times, which is a cognitive supplement or processing of the previous area. Pupil change generally refers to pupil diameter change [12]. In this paper, 27 eye movement indicators such as Number of Glances, Total Glance time and Mean Glance Duration are selected as research objects, and then indicators that have a greater impact on the detection probability are screened through data analysis.

3.2 Eye movement experiment

Ten students were invited for this experiment. During the experiment, the tester sat in front of the device and kept about 50cm away from the screen. The distance between the tester and the screen was maintained by fixing the seat of the subject. In the experiment, the tester's head was required to always remain straight ahead. During the experiment, the experimental environment was quiet without noise and the light intensity was moderate. The eye movement experiment of each tester was carried out independently. Testers were not allowed to view the experimental material in advance of the start of the experiment, and testers were only allowed to observe each test chart once. The test subjects were tested randomly. After obtaining the consent of the tester, the whole process of the experiment was informed. Dikablis Glass 3 (DG3), a glass-based eye tracking system was applied in the experiment. The sampling rate of the DG3 eyeglass eye tracker was 60Hz, while the accuracy is 0.1°-0.3°. Binocular capture is possible during sampling. The test data consisted of a display, a personal computer (Lenovo legion Y7000), and a desktop computer (Lenovo ideacentre AIO 520-271KL).

3.3 Eye movement data analysis

A total of 6480 data were obtained from 27 eye movement index values obtained by 10 subjects observing 2 targets in 12 test charts. The data were divided into 12 groups according to 12 test charts, and each group was further divided into two groups of target 1 and target 2, totaling 24 groups of initial data. The process of observing the target was replayed for each group of testers. After the invalid data was cleared, correlation analysis was carried out for each group of data [13], as shown in Figure 2.

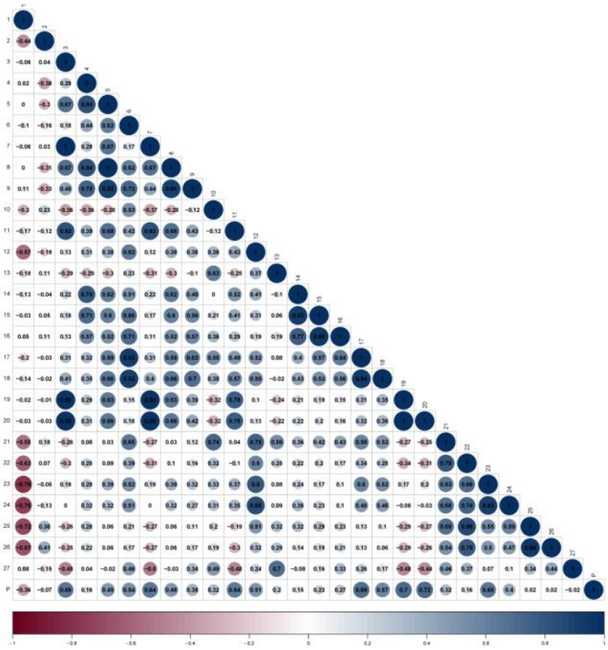


Figure 2-Correlation Analysis of Target 1

To understand the distribution of correlation coefficients more clearly, different colors and circle sizes are used to distinguish. The correlation table for reference is shown in Table 2. The common eye movement indicators, the meaning of eye movement indicators and the eye movement data within the scope of correlation analysis were comprehensively considered. After comprehensive screening of target 1 and target 2, the following 9 eye movement indicators were selected as the main eye movement indicators of this experiment.

Table 2-Correlation Range

0.8-1.0	Extremely strong correlation
0.6-0.8	Strong correlation
0.4-0.6	Moderate correlation
0.2-0.4	Weak correlation
0.0-0.2	Very weak correlation or no correlation

At the same time, the eye movement index X1~X9 was set as the dependent variable for the construction of the following model, and the detection probability P was set as the independent variable to find the relationship between the two. Some data are shown in Table 3.

Table 3-Selected Eye Movement Data

Eye movement indicator name	Substitution	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Number of Glances	X1	5.20	12.70	5.40	5.90	6.60	8.80
Total Glance time	X2	0.58	1.16	0.43	0.51	1.31	1.85
Glance Rate	X3	0.49	1.21	0.51	0.56	0.62	0.84
AOI Attention Ratio	X4	5.49	10.99	4.10	4.90	12.45	17.46
Maximum Glance Duration	X5	0.35	0.50	0.27	0.36	0.75	0.92
Glance Location Probability	X6	11.38	11.19	4.27	7.38	5.94	9.48
PERCLOS average	X7	2.44	0.44	0.96	1.26	0.89	1.30
Mean saccade angle left	X8	6.14	2.84	4.16	0.99	3.53	4.10
Mean saccade angle right	X9	6.09	2.96	3.66	1.18	3.68	4.80
Detection probability	P	0.56	0.18	0.10	0.58	0.24	0.36

4 groups were randomly selected as the test group, and the other 20 groups were used to construct the relational model.

4. Construction and Test of Relational Model

Regression analysis is a statistical analysis method to determine the interdependent quantitative relationship between two or more variables, and it is a predictive modeling technique [14]. In this paper, multiple linear regression model and multiple nonlinear regression model are constructed to fit the relationship model between eye movement index and discovery probability.

4.1 Multiple linear regression model

The general form of the linear regression equation constructed in this paper is shown in (2):

$$P = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9 \qquad (2)$$

Among them, $\beta_1, \beta_2, \cdots, \beta_5$ is partial regression coefficient, α is the constant term of the regression equation.

Linear regression data were analyzed by SPSS, as shown in Table 4.

Table 4-R-square test

Test		
Test	R-square	Durbin-Watson
Value	0.488	2.520

R square =0.488, Durbin-Watson coefficient is 2.520, indicating that 9 eye movement indicators can basically explain the detection probability of dependent variable. The linear regression model obtained through the standardization coefficient is shown in (3) :

$$P = 0.319 + 0.364X_1 - 1.832X_2 - 4.024X_3 + 0.228X_4 - 0.708X_5 - 0.001X_6 + 0.046X_7 - 0.106X_8 + 0.142X_9 \quad (3)$$

4.2 Multivariate nonlinear regression model

Multiple regression analysis is usually used to study problems where causality involves dependent variables and two or more independent variables, and the regression law is graphically represented as various curves of different shapes. A multivariate multiple nonlinear regression model suitable for discovering the relationship between probability and eye movement indicators is constructed in this paper. Due to the small amount of data, only the quadratic nonlinear regression model is constructed when the model is constructed, which general form is shown in (4):

$$\begin{aligned} P = {} & \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9 + \beta_{10} X_1^2 + \\ & \beta_{11} X_2^2 + \beta_{12} X_3^2 + \beta_{13} X_4^2 + \beta_{14} X_5^2 + \beta_{15} X_6^2 + \beta_{16} X_7^2 + \beta_{17} X_8^2 + \beta_{18} X_9^2 + \beta_{19} X_1 X_2 + \\ & \beta_{20} X_1 X_3 + \beta_{21} X_1 X_4 + \beta_{22} X_1 X_5 + \beta_{23} X_1 X_6 + \beta_{24} X_1 X_7 + \beta_{25} X_1 X_8 + \beta_{26} X_1 X_9 + \beta_{27} X_2 X_3 + \\ & \beta_{28} X_2 X_4 + \beta_{29} X_2 X_5 + \beta_{30} X_2 X_6 + \beta_{31} X_2 X_7 + \beta_{32} X_2 X_8 + \beta_{33} X_2 X_9 + \beta_{34} X_3 X_4 + \beta_{35} X_3 X_5 + \\ & \beta_{36} X_3 X_6 + \beta_{37} X_3 X_7 + \beta_{38} X_3 X_8 + \beta_{39} X_3 X_9 + \beta_{40} X_4 X_5 + \beta_{41} X_4 X_6 + \beta_{42} X_4 X_7 + \beta_{43} X_4 X_8 + \\ & \beta_{44} X_4 X_9 + \beta_{45} X_5 X_6 + \beta_{46} X_5 X_7 + \beta_{47} X_5 X_8 + \beta_{48} X_5 X_9 + \beta_{49} X_6 X_7 + \beta_{50} X_6 X_8 + \beta_{51} X_6 X_9 + \\ & \beta_{52} X_7 X_8 + \beta_{53} X_7 X_9 + \beta_{54} X_8 X_9 \qquad (4) \end{aligned}$$

Among them, $\beta_1, \beta_2, \cdots, \beta_5$ is partial regression coefficient, α is a constant term in the regression equation.

When regression is performed, it can be converted to a linear regression model. In this way, the nonlinear regression problem can be transformed into a linear regression problem to complete the parameter estimation, model fitting and application. Let $X_{10} = X_1^2$,..., $X_{18} = X_9^2$, $X_{19} = X_1 X_2$,..., $X_{54} = X_8 X_9$. Then it is transformed into a multiple linear regression model, as shown in $P = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_{54} X_{54}$.

Linear regression data are analyzed by SPSS, as shown in Table 5.

Table 5-R-square test

Test		
Model	R- square	Durbin-Watson
Value	1.000	1.957

R square =1.000, Durbin-Watson coefficient is 1.957, which means that 9 eye movement indicators can explain the discovery probability of dependent variable, indicating that the multivariate nonlinear model constructed by 9 eye movement indicators meets the requirements. The nonlinear regression model acquired by the standardized coefficient is shown in equation (5):

$$P = 5.045 - 3.925X_3 + 0.869X_4 - 11.546X_5 - 0.109X_6 - 2.839X_7 + 0.421X_8 - 1.437X_9 + 0.004X_1^2 - 2.184X_2^2 + 1.937X_5^2 + 0.002X_6^2 + 0.773X_7^2 + 0.779X_3X_5 - 0.047X_3X_6 - 0.887X_3X_7 + 0.338X_3X_8 + 0.574X_3X_9 - 0.049X_4X_8 + 5.129X_5X_7 - 1.672X_5X_8 + 1.73X_5X_9 - 0.06X_7X_8 + 0.084X_8X_9 \tag{5}$$

4.3 Neural Network Model

Neural network is an artificial intelligence model inspired by the structure of neurons in the human brain. It consists of a large number of artificial neurons (nodes) that communicate information to each other through connections (weights) to enable the learning and recognition of complex patterns. Its structure usually includes an input layer, a hidden layer and an output layer. The input layer is to receive the raw data, the hidden layer is for information processing and feature extraction, while the output layer is to produce the final prediction results. In a neural network, each neuron receives the output from the previous neuron, and after the weighted sum of these inputs, activates the correlation function for processing to produce an output. These outputs serve as input to the next neuron, and so on, constantly adjusting the weight of the calculation to bring the prediction closer to the actual result until the final result is obtained. Neural networks are outstanding in processing large-scale, complex data and nonlinear problems, and therefore are widely applied in image recognition, speech recognition, natural language processing, predictive analysis and other analysis fields [15]. SPSS was used to train 20 groups of neural network models, and then the discovery probability was predicted by 4 groups of data.

Importance analysis of independent variables: The largest influence on the independent variable is 100%, and the importance of the remaining variables is analyzed relative to the maximum deformation importance. With the importance of independent variables and the importance of normalization, it can be seen that X8 has the greatest influence on the detection probability under this neural network model, and X4 has the least influence, which is shown in Table 6.

Table 6-Importance of Independent Variable

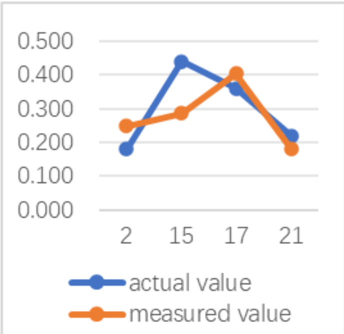
Importance of Independent Variable		
	Importance	Importance of Normalization
X1	0.087	42.2%
X2	0.080	38.9%
X3	0.074	36.0%
X4	0.054	26.3%
X5	0.138	67.0%
X6	0.080	39.0%
X7	0.122	59.6%
X8	0.206	100.0%
X9	0.159	77.3%

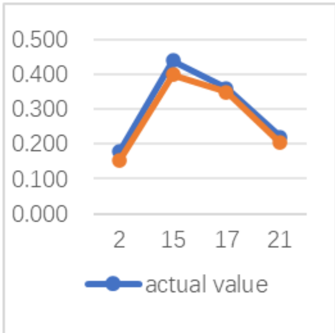
4.4 Analysis and Test of Relational Model

The reserved 4 groups were brought into the multiple linear regression model, multiple nonlinear regression model and neural network model respectively as test groups to test the error between the predicted value and the actual measured value, as shown in Table 7 and Figure 3. Figure 3 shows the errors of various models, with the horizontal axis representing the number of groups and the vertical axis representing the errors. The minimum error value is 0 and the maximum error value is 1. Figures 3 (a) and 3 (d) represent the line and bar charts of the error of the multiple linear regression model. Figures 3 (b) and 3 (e) represent the line and bar charts of the error of the multiple nonlinear regression model. Figures 3 (c) and 3 (f) represent the line and bar charts of the neural network model error.

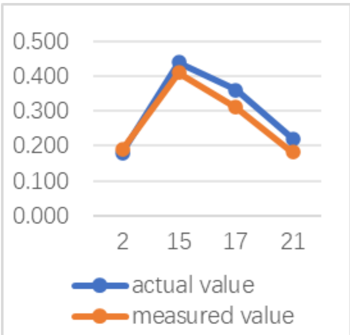
Table 7-Error Analysis

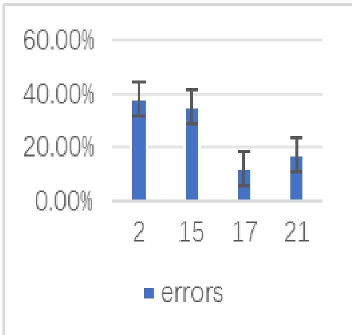
	Multiple linear regression model			Multivariate nonlinear regression model			Neural network model		
	Measured value	Predicted value	Error	Measured value	Predicted value	Error	Measured value	Predicted value	Error
2 groups	0.180	0.249	38.12%	0.180	0.154	14.43%	0.180	0.190	5.56%
15 groups	0.440	0.286	35.10%	0.440	0.399	9.26%	0.440	0.410	6.82%
17 groups	0.360	0.405	12.36%	0.360	0.349	3.03%	0.360	0.310	13.89%
21 groups	0.220	0.182	17.46%	0.220	0.204	7.25%	0.220	0.182	17.46%



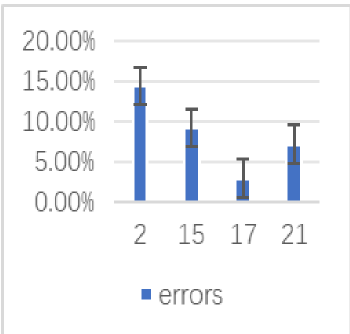


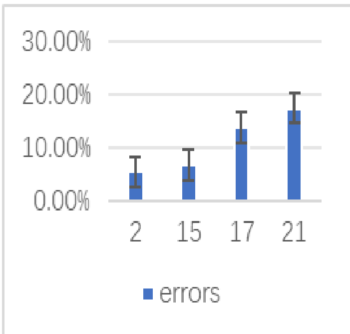
(a) Error of line chart of multiple linear model (b) Error of line chart of multiple nonlinear model





(c) Error of line chart of neural network model (d) Error of bar chart of multiple linear model





(e) Error of bar chart of multiple nonlinear model (f) Error of bar chart of neural network model

Figure 3-Error Analysis

It can be seen from the line chart that the trend of measured curve and predicted curve is basically the same, which indicates that the multiple linear regression model constructed is more accurate. The three models all have errors. In order to further reduce the errors of the three models, the three models are ranked, and the new predicted value is obtained by weighting the prediction results of the three models according to their proportion, as shown in Table 8. The construction formula is shown in $P = \beta_1 P_1 + \beta_2 P_2 + \beta_3 P_3$

Table 8-Rank of the Three Models

Model	2 groups	Rank
Neural network	5.56%	1
Multiple nonlinear regression	14.43%	2
Multiple linear regression	38.12%	3
	15 groups	Rank
Neural network	6.28%	1
Multiple nonlinear regression	9.26%	2
Multiple linear regression	35.10%	3
	17 groups	Rank
Multiple nonlinear regression	3.03%	1
Multiple linear regression	12.36%	2
Neural network	13.89%	3
	21 groups	Rank
Multiple nonlinear regression	7.25%	1
Multiple linear regression	17.46%	2
Neural network	17.46%	2

We believe that the smaller the error between the predicted value and the actual value, the closer the construction of the relationship model is to the reality. The weighted analysis results of the experimental data are shown in Table 9.

Table 9-The Proportion of the Three Models

Model	Add the weights of each group	Total score	Rank	The proportion of the model
Multiple nonlinear regression	2+2+3+3	10	1	1/2
Neural network	3+3+1+2	9	2	1/3
Multiple linear regression	1+1+2+2	6	3	1/6

The constructed formula is shown in $P = 1/6P_1 + 1/2P_2 + 1/3P_3$.

The results of error analysis conducted again are shown in Table 10.

Table 10-Error Analysis

	Measured value	Predicted value	Error
2 groups	0.180	0.182	0.99%
15 groups	0.440	0.384	12.75%
17 groups	0.360	0.345	4.08%
21 groups	0.220	0.193	12.36%

It if found that after synthesizing the three models and calculating according to a certain proportion, the error is obviously reduced, indicating that the detection probability and eye movement index cannot be determined only by one relationship model, as there is a complex relationship structure between them, and our model can only effectively explain part of the data.

5. Conclusion

Using eye tracking mechanism to evaluate camouflage effect can quickly, accurately and objectively improve the evaluation rate of camouflage effect evaluation, which has an immeasurable role in the future battlefield.

The relationship model constructed in the experiment has important reference value for the real environment. In this paper, a target is set on the background to simulate the real environment to measure the detection probability, and the influence of multiple eye movement indicators on the detection probability is analyzed, the main influence is selected, and the relationship between the detection probability and its model is built.

(1) After screening the measured eye movement data, it is found that each eye movement index has a significant positive and negative correlation with the detection probability. For example, the more the Number of Glances, the greater the discovery probability and the more the PERCLOS average number, the smaller the discovery probability.

(2) Through the analysis of R-square and Durbin-Watson coefficient, the selected 9 eye movement indicators such as Number of Glances, Total Glance time and Glance Rate can explain the influence on the detection probability.

(3) By calculating the predicted values of the detection probability of the three models, and comparing with the measured values, it is found that the best fitting error of the predicted values of the multivariate nonlinear regression model is about 8.49%, the error of the neural network model is about 10.932%, and the error of the multivariate linear regression model is about 25.763%.

(4) With the error analysis, it is concluded that the eye movement index has a significant impact on the discovery probability, and there is a complex relationship between them. Considering the prediction errors of the three relational models comprehensively, the model is further optimized, and a relational model considering the influence of the three models is constructed by weighting the ranking size. The error analysis of the predicted value again is about 7.546%, and the error reduction of the new model is more obvious than that of the previous three models.

Mining can help evaluate the effectiveness of camouflage measures more accurately. Through in-depth mining and comparative analysis of data before and after camouflage, the degree to which camouflage measures alter data features can be revealed, thereby determining the effectiveness of camouflage. Secondly, data mining can also help us optimize camouflage strategies. By exploring the key influencing factors and patterns during the camouflage process, we can find effective ways to improve the camouflage effect.

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