Study on Illumination Measurement Method of Lighting Environment Based on RBF Neural Network

Yujie Zhang, Si Li (Corresponding author)
School of Electrical and Control Engineering, Shaanxi University of Science and Technology, Xi'an 710021, China
Corresponding author email: 1040828445@qq.com

Abstract—In order to better measure the indoor light environment, evaluate the quality of the indoor lighting environment, and improve the requirements of lighting comfort, a camera image measurement illuminance method based on RBF(Radial basis function) neural network is proposed, and the camera sensor imaging theory is derived and analyzed to obtain the environmental illuminance and camera sensor The relationship between the parameters, the establishment of the RBF neural network model, by building an experimental system platform, collecting data sets to train the network model, fitting the neural network model parameters to obtain the illuminance measurement model, and use the image gray level and the reference point illuminance as the neural network Input and ambient illuminance as output. The prediction result shows that the error between the illuminance value predicted by the neural network and the actual measured value of the illuminance meter is within 10lx, and the relative error is less than 8%, which meets the requirements of lighting building design standards. Therefore, this method can achieve rapid measurement of the illuminance in the environment, and has a relatively high precision.

1. Introduction
With the continuous improvement of lighting demand, lighting comfort is an important part of the lighting environment. In the indoor lighting environment, the level of illumination and unevenness will affect people's movements and vision, thereby affecting the efficiency of work and study [1-2], so the uniformity of the working surface illumination is an important factor affecting office efficiency and comfort. In the indoor lighting environment, the illumination index is the most important content [3].

In the existing indoor lighting environment, traditional photoelectric sensors are used to detect the environmental illuminance, and the measurement of this type of sensor is the average value of a certain range in the environment, and cannot reflect the illuminance distribution in the environment. The demand for comfortable lighting [4-5]. In addition, the main method of illuminance measurement is the illuminance meter measurement method, which has a large workload and complicated operation, and it is easy to cause errors due to irregular operation. Some researchers apply digital cameras to the brightness measurement of the light environment, thereby quickly obtaining the brightness distribution information in a large range [6-7]. According to the literature, when using the camera to measure the illuminance in the environment, it is necessary to know the exposure time and gain in the camera, build a system calibration platform, calibrate the fixed parameters of the camera, and then calibrate the gray value of the digital image through the experimental platform. The relationship between the actual brightness of the environment [8-9], at present, for the use of image sensors to measure the
environmental illuminance, there are methods to obtain the brightness regression curve through least squares polynomial fitting and data linear fitting\cite{10}. In actual application, the exposure conditions and gains need to change with the light environment, so it is necessary to re-calibrate the relational coefficients between the image grayscale and the actual brightness through experiments, which causes great inconvenience in engineering applications. In the measurement process, not only the grayscale of the image, but also the camera's exposure time, gain and other parameters need to be obtained.

2. Radial basis function neural network

RBF neural network is a kind of feedforward neural network with local approximation, which is a three-layer network structure. In Figure 1, it is composed of an input layer, a hidden layer and an output layer. The main idea is to use the radial basis function as the "base" of the hidden unit to form the hidden layer space, and directly map the input vector to the hidden space. It does not need to be connected by right, and it has applications in different fields\cite{11-13}.

![Figure 1. Radial basis function neural network](image)

The input layer is composed of some source points, and the hidden layer uses radial basis function as the activation function, and generally uses Gaussian function as the radial basis function. The relationship between input data and output data is expressed by the following formula:

\[ F(X_i) = \sum_{j=1}^{P} w_j(\Phi |X_i - X_j|) \]  

In the formula, \( P \) means hidden layer size; \( \Phi \) means radial basis function; \( w_j \) means linear combination weight; \( X_j \)-hidden layer radial basis function center. In this article, the Gaussian function is used as the activation function formula that transforms the input signal into nonlinearity as shown below:

\[ F(x) = \exp \left(-\frac{x^2}{2\delta^2}\right) \]  

\( \delta \) means the distance between the input amount and the center, which has a unique maximum value, and will decrease to zero as the increase in; it represents the width of the base around the center, and has a certain relationship with the number of neurons in the hidden layer, The calculation formula is as follows:

\[ \delta = \frac{d_m}{\sqrt{2m}} \]  

\( d_m \) means the maximum distance selected; \( m \) is the number of neurons. The training of the RBF neural network is aimed at the sample set \( x \), and iteratively corrects the center and width of the radial basis function with linear output weights to minimize the error.

3. Illumination measurement based on RBFNN

According to the optical sensitivity characteristic curve of the camera, as shown in Figure 2, the ordinate \( D \) represents the gray value of the digital image, and the abscissa represents the logarithmic value \( \log H \) of the exposure amount \( H \), the gray value of the imaging segment \( B\sim C \) image and the logarithm of the corresponding image exposure are linear. The relationship is as (4):

\[ F(X) = \exp \left(-\frac{x^2}{2\delta^2}\right) \]
In the above formula, $\nu$ is expressed as the gamma, which is the slope of the photosensitive characteristic curve, and $m$ is the intercept of the straight line segment of the photosensitive characteristic curve. The size of the exposure in the camera and the illuminance of the phase have the following relationship:

$$H(x,y) = E_t(x,y) \cdot T$$

$E_t$ means the illuminance of the photosensitive surface, $T$ is the exposure time. In the optical measurement system, the image surface illuminance at the axis of the field of view can be expressed as:

$$E_t(x,y) = \frac{\pi \tau}{4F^2}\cdot B(x,y)$$

(6)

$	au$ is the projection coefficient of the lens, which is related to the lens characteristics and is a constant. $F$ is the aperture coefficient of the camera. In the determined camera equipment, the parameters such as the contrast coefficient $\gamma$, the aperture coefficient $F$, and the lens projection coefficient $\tau$ are the municipal constants, so the image is gray. The degree is related to the exposure time $T$ and the target brightness $B$. Since sensing equipment will generate gain, the relational expressions (4), (5), and (6) are integrated, so the above-mentioned relational expressions are obtained:

$$D(x,y) = G[\gamma \cdot \lg \left(\frac{\pi \tau}{4F^2}B(x,y) \cdot T\right) + m]$$

(7)

Where $G$ is the gain. From the above transformation, we get:

$$B(x,y) = \frac{4F^210^\frac{m}{T}}{\pi \tau} \cdot 10^\frac{D(x,y)}{6\gamma}$$

(8)

Let $\lambda = \frac{4F^210^{\frac{m}{T}}}{\pi \tau}$, be a constant, then the above formula can be reduced to: $B(x,y) = \frac{\lambda}{T} \cdot 10^\frac{D(x,y)}{6\gamma}$. On the surface of the object, the brightness and the illuminance have a linear relationship, that is, the brightness $B$ is equal to the product of the illuminance $E$ and the reflectance $\rho$ of the object surface, $B(x,y) = E(x,y) \cdot \rho$, so the illuminance formula is obtained:

$$E(x,y) = \frac{\lambda}{\rho T} \cdot 10^\frac{D(x,y)}{6\gamma}$$

(9)

From this we can see the relationship between the illuminance and the gray value, the camera parameters $G$, $T$, and the logarithm is taken on both sides, namely:

$$\lg E(x,y) = \frac{\lambda}{\rho T} + \frac{D(x,y)}{6\gamma}$$

(10)

$$\frac{\lg E(x,y)}{D(x,y)} = \frac{1}{6\gamma} + \frac{\lg \rho}{D(x,y)}$$

(11)

From the above relationship, it can be seen that $\frac{\lg E(x,y)}{D(x,y)}$ reflects the change of the camera's internal parameters, the image gray level, and also the change of the reflection coefficient of the working surface. In the same image, the illuminance logarithm of each pixel and the corresponding point gray The ratios of degrees all satisfy this corresponding relationship. Therefore, a reference point is selected in the environment, and the illuminance sensor is arranged to collect the illuminance information of the reference point position, and the reference point variable $\frac{\lg E_0}{D_0}$ is obtained. At the same time, the illuminance meter is used to collect the illuminance $E(x,y)$ of different
positions on the working surface. Define variables \( \theta(x, y) = D(x, y) \cdot \lg E_0 / D_0 \), establish a training data set of image gray \( \{\theta(x, y), E(x, y)\} \), and establish a radial basis function neural network model at the same time, train the neural network to obtain network parameters. Figure 3 shows the flow chart of illuminance measurement based on RBF neural network:

![Figure 3: Flow chart of illuminance measurement based on RBF neural network](image)

### 4. Data set and Network training

#### 4.1. Data set

Randomly select the workstations to be tested in the office desktop environment, use Guarda FX-101 LUX METER to measure the illuminance values of these points to be measured, collect video images through the camera, and obtain a grayscale image of the environment from the video stream. The grayscale processing obtains the grayscale value of the average pixel point of the image corresponding to the range of the station to be tested, and at the same time obtains the measured value \( E_0 \) of the illuminance sensor at the reference point at the moment. According to the data collected at the station to be tested every twenty minutes, the collected data is the corresponding station illuminance information from 9:00 to 18:00 during the day, and a total of 27 sets of data are obtained, 21 of which are used for the sample training set, 6 which are used for the test set samples, and the RBF neural network is created for training and result testing.

![Figure 4: Experimental reality](image)

#### 4.2. Network training

Based on the illuminance measurement model of the RBF neural network, the collected image gray value and the reference point illuminance value are processed by data to get \( \theta(x, y) = D(x, y) \cdot \lg E_0 / D_0 \), which is used as the network input, and the output is the illuminance \( E(x, y) \). Use MATLAB to create RBF neural network and conduct training and testing. The specific implementation method is as follows:

1. Import the acquired sample data set into MATLAB;
2. Randomly select parts as training data set and test data set, and process the data;
3. Write software in MATLAB to create RBF neural network;
4. Start running to train the RBF neural network;
5. Judge the training result of the network model according to the mean square error;
6. Obtain the calculation error between the estimated value and the test value.

The training process in this article is carried out in the MATLAB software. By calling the function in the software, the training result will stop when the error is within the required range or the maximum number of iterations. The input of the radial basis function neural network is the parameter.
quantity, and the output is the illuminance of the position to be measured. The training results are shown in Figure 5:

![Figure 5. Neural network convergence curve](image)

According to the convergence curve, when the mean square error of the initial setting target reaches 100, the minimum number of neurons is 21 to meet the error range, so the final neural network model is output.

5. Experimental measurement analysis

After the trained neural network model is obtained, select the positions to be measured for several workstations in the environment, obtain the average gray scale of the workstation range from the collected images, and then obtain the illuminance and gray scale of the reference point, and calculate the variable θ, as the input of the neural network, the illuminance estimation output is obtained. Figure 6 is a comparison between the predicted illuminance of the desktop neural network and the actual measured illuminance of the illuminance meter in an office environment.

![Figure 6. Simulation results](image)

### Table 1. Illumination error analysis table

| Measured value E₀ (lx) | Predictive value E (lx) | Absolute error ΔE (lx) | Relative error (%) |
|------------------------|-------------------------|------------------------|-------------------|
| 92                     | 86.6                    | 5.4                    | 5.86              |
| 120                    | 120.4                   | 0.4                    | 0.33              |
| 160                    | 164.2                   | 4.2                    | 2.75              |
| 156                    | 161.1                   | 5.1                    | 3.26              |
| 84                     | 88.9                    | 4.9                    | 5.83              |
| 134                    | 144.1                   | 10.1                   | 7.53              |
| 90                     | 92.5                    | 2.5                    | 2.78              |
| 125                    | 117.2                   | -7.8                   | -6.24             |
| 127                    | 123                     | -4                     | -3.14             |
| 125                    | 126.7                   | 1.7                    | 1.36              |

Note: The relative error is the absolute error calculated by the measured illuminance E₀.

Figure 6 shows that the RBF neural network predicted value has a small difference with the predicted value in the environment, and the accuracy is high. Table 1 is a comparison table of the error between the predicted value and the actual measured value.

According to Table 1, it can be seen that the absolute error between the predicted illuminance value E of the neural network and the actual measured illuminance value E₀ of the illuminance meter is within 10Lx, and the relative error does not exceed 8%. According to the provisions of the architectural lighting design standard GB50034, the design illuminance value The accuracy can be satisfied if the standard value is not more than 10%, so it can be seen that the RBF neural network is feasible in the contrast measurement method using the image sensor.
6. Conclusion
Through the analysis and research on the principle of using image sensors to measure environmental illuminance, it is proposed to apply RBF neural network to illuminance measurement, which provides new ideas and new methods for rapid measurement of illuminance distribution. In practical applications, first obtain the data set to perform the neural network. The network model is trained, and then in the measurement, only the image gray scale and the reference point illuminance are needed. After the data is processed, it is input into the network, and then the environmental illuminance can be output.

After verification and analysis of experimental data, it is feasible to train the RBF neural network to obtain an illuminance detection model. At the same time, for traditional illuminance (brightness) detection methods, the use of neural networks is convenient. The traditional detection methods need to calibrate the camera parameters. At the same time, the cost of using precision instruments is relatively high. In this article, only the measured value of the illuminance sensor is needed to reflect the changes in the internal parameters of the camera, and the illuminance model between the variable $\theta$ and the environmental illuminance is established to achieve a rapid estimation of the environmental illuminance and improve the feasibility of engineering application.

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