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SURFACES BY DATABASE METHOD**

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MODELING REFLECTION PROPERTIES OF ROAD SURFACES BY DATABASE METHOD

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Abstract

This paper proposes a new method to model r-tables without an analytical expression, but by database method. A so-called 'knowledge base' for road surfaces is setup, which is constructed by verified r-tables. The data model is trained and built up by some selected r-tables, then predictions are made for the other r-tables in the knowledge base, and prediction errors are then analysed to verify the model. In this paper, 287 r-tables of dry road surfaces is tested. The model is built up by its r-tables with even number indices. The r-tables with odd number indices are then predicted. Results show that 90% of the prediction errors are below 15%, and a great number of examples are distributed around 5%. Only two worst cases are of error around 50%. These results are much better than those we obtained by analytical expression methods. By this database model, if we have a large enough data base with reliable r-tables, covering road surfaces of different materials, service and weather conditions, we can make predictions for most road surfaces with a few measured value, then make a more precise road/street lighting design.

Keywords: Road lighting, Road surface, Reflection, R-table, Model

1 Introduction

For a precise designing of road/street lighting, the reflection properties (described by a reduced luminance coefficient table, short as r-table) of the road surface should be known. Since measurement of a full r-table is costly and time consuming, a better and practical way is to measure finite number of reduced luminance coefficients under several specified angles, then make a prediction for the full r-table by using a model. Extensively investigations have been carried out by scientists, trying to get an analytical expression model with an acceptable prediction precision:

Anisotropic Gaussian model, which was obtained from the theoretical formulation of Fresnel reflection (Ward, 1992).

Schreder model, which was proposed in (Debergh, 2008), and was related with Memphis and Coluroute gonio reflectometer. In this model, interpolation was used to obtain the whole r-table by a small number of measured reduced luminance coefficients at the intersection of the row corresponding to $\tan \gamma$ and of the column corresponding to β as $r_{\gamma\beta}$.

Massart model, which works with the EP-diagram, uses an elliptic plus two nonlinear functions to describe the contour of an EP diagram containing the whole information of a r-table (Erbay, 1974).

S_1 and S_2 index matching model. We also proposed a relatively simple, but not an analytical expression model (Li, 2014). First we compute out the S_1 and S_2 values of a large number of road samples whose r-tables have been known, then for a sample to be predicted, the r-table in the database whose S_1 and S_2 values closest to those of this sample is chosen to be its r-table.

We also made a comparison study for all these four models. For the 287 r-tables we calculated, results showed that, the Anisotropic Gaussian model got an average overall error of 45.0%, the model in Debergh and Embrechts's paper got an average overall error of 41.3%, the Massart model's average overall error was 26.5%. When using the S_1 and S_2 index matching model, the average overall error was 14.2%.

comparing different surfaces. Q_0 , S_1 and S_2 were then introduced to set a categorization label of surface reflection properties. Q_0 as formulated as (3), defines the general lightness level of the road surface, is also called the average luminance coefficient.

$$Q_0 = \frac{1}{\Omega_0} \int_0^{\Omega_0} q d\Omega \quad (3)$$

where

q is the luminance coefficient;

Ω_0 is the solid angle, measured from the point on the surface, containing all those directions from which light is incident that are taken into account in the averaging process.

The specular factor S_1 is defined as ratio of a reduced luminance coefficient which is generally large for specular reflection ($\beta = 0^\circ, \tan \gamma = 2$) to one which is generally large for diffuse reflection ($\beta = 0^\circ, \tan \gamma = 0$).

$$S_1 = \frac{r(0,2)}{r(0,0)} \quad (4)$$

Similarly specular factor S_2 is ratio of the average luminance coefficient to a reduced luminance coefficient at ($\beta = 0^\circ, \tan \gamma = 0$).

$$S_2 = \frac{Q_0}{r(0,0)} \quad (5)$$

As recommended by CIE, road surfaces are categorized by the specular factor S_1 . For dry road surfaces three classes are in use, the R, N and C. For wet surfaces (CIE, 1979), class W is in use and the categorization is made according to a modified specular factor S_1' formulated as equation (6) for $S_{1,wet} > 1$.

$$\log \frac{S_1'}{0.147} = \frac{\log \frac{S_{1,Wet}}{0.147}}{1 - \frac{Q_{0,Wet}}{0.687}} \quad (6)$$

where

$S_{1,Wet}$ is S_1 for the wet conditions;

$Q_{0,Wet}$ is Q_0 for the wet conditions.

For $S_{1,wet} \leq 1, S_1' = S_{1,Wet}$.

3 Model

In this paper we come up with an idea that is borrowed from the popular data science nowadays. To do this, we build up a so-called 'knowledge base', which is constructed by reliable sources. Since each r-table consists of 580 real numbers, in our formulation each of the r-table is described by a vector $r_i \in \mathbf{R}^{580}$. Suppose we have N known r-tables, then the knowledge base \mathbf{R} is basically a matrix of size 580-by-N of the form

$$\mathbf{R} = [r_1 \ r_2 \ \dots \ r_N] \quad (7)$$

The Modelling task is to predict the full r-table according to a small number of observed values of the r-table, for a considered road surface. To insure the modelling precision, these observed values should represent the characteristics of the considered road surface. In our previous study on modelling (Li, 2014), we found that some of the points were of the most importance, of which their angle indices in the r-table were

$$i_{column} = [1 \ 3 \ 6 \ 11 \ 14], \quad j_{row} = [2 \ 3 \ 4 \ 5 \ 15] \quad (8)$$

By using these 25 reduced luminance coefficients, the prediction errors were the smallest. So a measurement device based on model prediction method was built to measure the reduced luminance coefficients of these points. In this paper, we still use these 25 points.

First we reduce the dimension of the knowledge space. We define the projection operation $\mathbf{P} : \mathbf{R}^{580} \rightarrow \mathbf{R}^{25}$, which projects each r-table into a vector of 25 real numbers, i.e. taking values at the points with indices in Equation (8). Then a deflated knowledge base matrix $\hat{\mathbf{R}}$ of size 25-by-N is setup. To make a model prediction for a considered road surface, denote its 25 measured values as vector $\hat{\mathbf{r}}$, then we solve the following least square problem for \mathbf{w}

$$\min_{\mathbf{w}} \|\hat{\mathbf{r}} - \hat{\mathbf{R}} \cdot \mathbf{w}\|_2 \quad (9)$$

where

\mathbf{w} is a vector with N weighting factors of the considered road surface for that knowledge base.

This problem has an explicit solution

$$\mathbf{w} = (\hat{\mathbf{R}}^T \cdot \hat{\mathbf{R}})^{-1} \cdot \hat{\mathbf{R}}^T \cdot \hat{\mathbf{r}} \quad (10)$$

provided that the deflated knowledge base $\hat{\mathbf{R}}$ has full column rank, so that the inverse part $\hat{\mathbf{R}}^T \cdot \hat{\mathbf{R}}$ is non-singular. Finally we can make the model prediction by

$$\tilde{\mathbf{r}} = \mathbf{R} \cdot \mathbf{w} = \mathbf{R} \cdot (\hat{\mathbf{R}}^T \cdot \hat{\mathbf{R}})^{-1} \cdot \hat{\mathbf{R}}^T \cdot \hat{\mathbf{r}} \quad (11)$$

where

$\tilde{\mathbf{r}}$ is the predicted r-table vector with full 580 values;
 \mathbf{R} is the knowledge base defined in Equation (7).

4 Verification

With the reliable r-tables we have at hand, we then perform some numerical experiments to verify the precision of our modelling method. First 287 verified r-tables of dry roads are used. We choose r-tables with even number indices to setup the knowledge base \mathbf{R} , and try to build up a model to predict the r-tables with odd number indices, assuming their reduced luminance coefficients with indices defined in Equation (8) have been measured but others have been not. After the predicted full r-table vector $\tilde{\mathbf{r}}$ of a road surface is obtained, the relative prediction errors on Q_0 , S_1 , S_2 and r-table are calculated and plotted in Figure 2, in which the relative error on r-table is defined as

$$\text{Err}(\|\mathbf{r}\|) = \frac{\|\tilde{\mathbf{r}} - \mathbf{r}\|_2}{\|\mathbf{r}\|_2} \quad (12)$$

where

\mathbf{r} is the real full r-table vector of that road surface, obtained from the 287 r-table database.

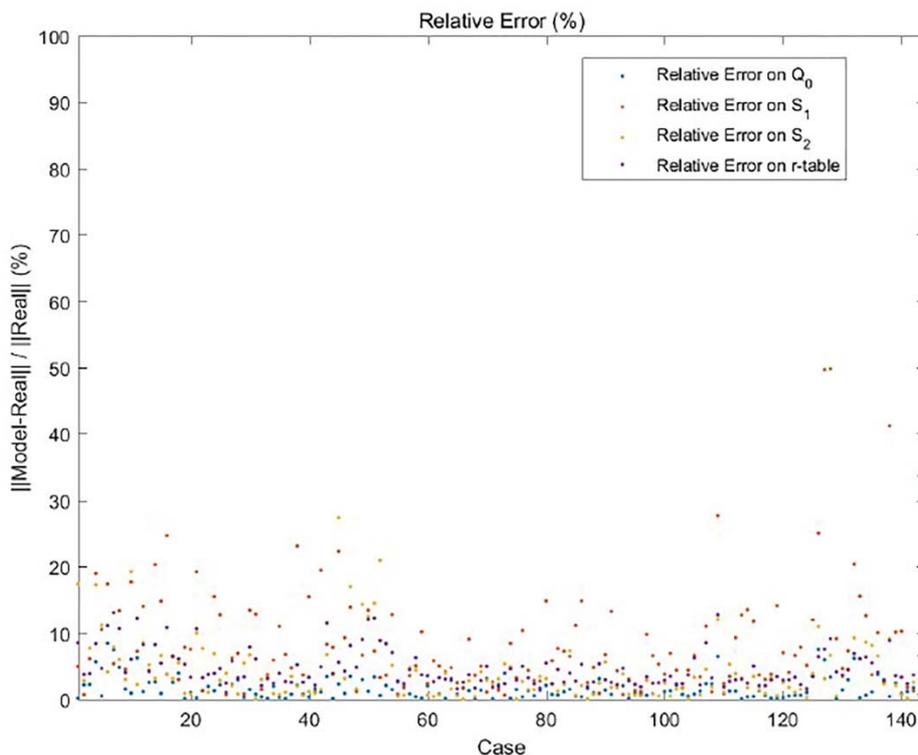


Figure 2 – Relative model prediction errors on Q_0 , S_1 , S_2 and r-table, using half of the 287 r-tables as database to predict the other half

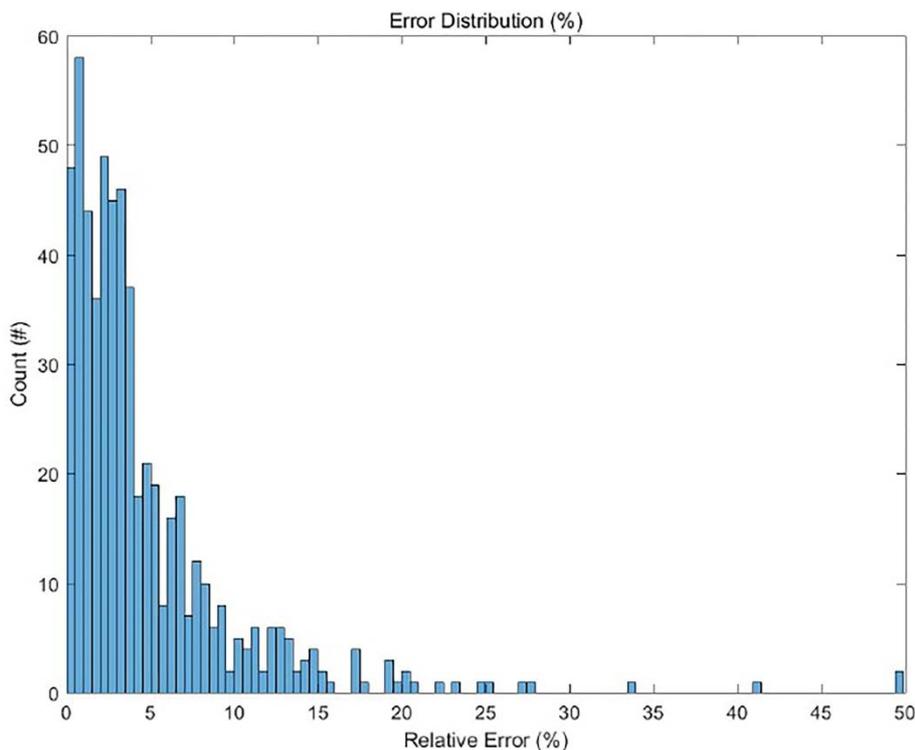


Figure 3 – Histogram of all the relative prediction errors in Figure 2

Figure 3 make a histogram of all the relative errors in Figure 2. We find that 90% of the prediction errors are below 15%, and a great number of them are distributed around 5%. Only two worst cases are around 50%.This is better than the results of all the four models.

5 Summary and outlook

The database model proposed in this paper is adequate for a precise road light calculation, for the 287 r-tables of dry road surfaces tested in this paper. Our next step is to gather and verify more r-tables to expand our database, to make further verification for our model. Moreover, more r-tables covering road surfaces of different materials, service and weather conditions, especially wet road surfaces need to be modelled. Previous study showed that wet road surfaces were very difficult to model. Besides gathering verified wet r-tables (Frederiksen, 1976, Sorensen, 1974), we also setup a measurement system to obtain wet r-tables (Li, 2017, Wang, 2018), so that we can make predictions for wet road surfaces.

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