Surface Natural Spectrum BRDF Modeling of Commonly Used Materials on Space Targets

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Abstract. This paper measures and analyzes bidirectional reflectance distribution function (BRDF) on material surface of space target under natural light within spectrum range of 400nm-900nm. Through optimization of five-parameter model, the paper carries out modeling and optimal fitting in combination with genetic algorithm and the least square method. Results show the combination of genetic algorithm and the least square method could improve fitting precision of computing results and experimental measurement results, save time, and prove the effectiveness and practical performance of the method.

1. Introduction

In recent years, as more aircrafts are launched, the space debris caused by on-orbit explosion are increased, seriously affecting space environment and safety operation of on-orbit aircrafts[1]. In order to better follow up and recognize space debris, the bidirectional reflectance distribution function (BRDF) is introduced to study and analyze reflectance characteristics and spectrum characteristics on the target surface [2]. Proposed by US Scholar Nicodemust in 1970[3], BRDF is a physical quantity describing reflectance characteristics and spectrum characteristics on the target surface based on geometrical optics, and applied extensively to fields of remote sensing[4], computer graphics[5] and aerospace[6]. At present, two methods are mainly used to acquire BRDF on object surface. One is to acquire data through experimental measurement and the other is to acquire BRDF data through modeling. In actual application, the two methods are usually combined in an effective way. Firstly, experimental measure is applied to acquire some BRDF data, and then corresponding model is selected in combination with experimental data for parameter fitting. Finally, all BRDF data on hemisphere surface of the target could be acquired. The geometric diagram of BRDF can be seen in Fig. 1.
So far, many research institutions at home and abroad have put forward various statistical models for BRDF, which are mainly divided into three types, respectively theoretical model, (semi) empirical model and data-driven model. The theoretical model is proposed based on certain physical principles, such as Torrance-Sparrow model based on geometrical optics [7] and Cook-Torrance model [8], etc.; the (semi) empirical model is a kind of rapid computing model with adjustable parameters, such as Phong model [9], Ward model [10] and five-parameter model [11] which is frequently used in China; data-driven model is a kind of universal model based on machine learning and massive experimental data, for instance, Li Liangchao et al. established BRDF model based on BP neural network [12], and Liu Chenghao et al. established the model based on in-depth neural network [13].

This paper measures the BRDF value of a common space object material within spectrum of 400nm-900nm through experiment, and applies modeling, fitting and optimization with simplified five-parameter model in combination with genetic algorithm and the least quare method. Comparison between experiment measurement data and theoretical data of calculation shows the method is feasible and applicable.

2. BRDF Measurement

2.1 Measurement principles

BRDF is the ratio of spectral radiance. The light source with radiance of $L_r$ irradiates and reflects on object surface panel $dA$, and the spectral radiance of reflected light is $E_I$. The definition formula is:

$$f_r(\theta_i, \varphi_i, \theta_r, \varphi_r, \lambda) = \frac{dE_r(\theta_i, \varphi_i, \theta_r, \varphi_r, \lambda)}{dE_I(\theta_i, \varphi_i, \lambda)}$$  \hspace{1cm} (1)

In the formula, $\theta_i$ and $\varphi_i$ are respectively the incidence angle and incidence azimuth; $\theta_r$ and $\varphi_r$ are reflection angle and reflection azimuth; $\lambda$ is the wave length of light.

Usually, the absolute measurement and comparative measurement may be used to acquire experimental data of BRDF. This paper adopts comparison measurement method, calibrates object material with standard white board, and finally measures BRDF value of samples within spectrum of 400nm-900nm according to hemispherical reflectance of standard board.

2.2 Measurement results

The experiment measures the reflection radiation brightness of yellow multilayer material when the incidence angles are respectively $10^\circ$ and $60^\circ$, and relative azimuth is $0^\circ$; measures once every $5^\circ$. Process BRDF measurement results on sample surface, as shown in Fig.2.
According to the figure, every curve has a prominent peak value, and the value is reduced gradually to both ends. It means the yellow multilayer material has obvious mirror reflection on corresponding position of the peak value, and surface is smooth.

2.3 Experiment data processing

In order to better carry out statistical analysis on sample surface BRDF under natural lights, it is necessary to carry out spectral integral for BRDF of visible spectrum[14]. The calculation formula is as follows:

$$\bar{f}_r = \frac{1}{\lambda_2 - \lambda_1} \int_{\lambda_1}^{\lambda_2} f_r(\lambda)d\lambda$$

(2)

The 400-900nm BRDF value can be acquired through aforesaid formula. Since the data measured in experiment is discrete data, aforesaid formula can be expressed as:

$$\bar{f}_r = \frac{1}{\lambda_2 - \lambda_1} \sum_{i=1}^{n} f_{ri}(\lambda)\Delta\lambda$$

(3)

In the formula, $\Delta\lambda$ is spectral integral, as 1nm; $f_{ri}$ is the BRDF data of the $i^{th}$ wave length.

The group of data acquired by spectral integral calculation can be used as BRDF experimental data under visible light. The modeling and optimization is carried out by genetic algorithm and the least square method.
3. BRDF modeling

3.1 Simplified five-parameter model
The five-parameter model is a BRDF semi-empirical model proposed by Wu Zhensen et al. ADDIN EN.CITE [11] from Xidian University by revising the Torrance-Sparrow model [7]. The expression formula is:

\[
f_r(\theta_i, \theta_r, \varphi_r) = k_b \frac{k_r^2 \cos \alpha}{1 + (k_r^2 - 1) \cos \alpha} \cdot \exp \left[ b \cdot (1 - \cos \theta)^a \right] \cdot \frac{G(\theta_i, \theta_r, \varphi_r)}{\cos \theta_i \cos \theta_r} + \frac{k_d}{\cos \theta_i}
\] (4)

In the formula, the first and second item respectively means mirror reflection component and diffuse reflection; \( G(\theta_i, \theta_r, \varphi_r) \) is a shadowing function, which is decided by shadowing rate of adjacent surface reflection, \( k_b, k_d, k_r \) and \( a \) and \( b \) are undetermined parameters.

The five-parameter model is complex, and the material tested in this paper is of smooth surface. Therefore, in order to simplify the model and speed up calculation, the value of the shadowing function \( G(\theta_i, \theta_r, \varphi_r) \) is taken as 1. The expression of the simplified model shall be:

\[
f_r(\theta_i, \theta_r, \varphi_r) = k_b \frac{k_r^2 \cos \alpha}{1 + (k_r^2 - 1) \cos \alpha} \cdot \exp \left[ b \cdot (1 - \cos \theta)^a \right] \cdot \frac{1}{\cos \theta_i \cos \theta_r} + \frac{k_d}{\cos \theta_i}
\] (5)

3.2 Optimization algorithm
The least square method is a simple and fast mathematical computing method which could be used in curve fitting. The defect is that the fitting results have obvious error due to different initial values set, while the genetic algorithm is favorably adaptive to function optimization by virtue of overall optimization characteristics. The optimal value of function parameters could be searched through the genetic algorithm. The value is set to the initial value of the least square method and calculated again to acquire better fitting precision.

3.2.1 The least square method
The least square method is a kind of mathematical optimization method seeking for functions which could match with data through the quadratic sum of the minimum error. It could simply and rapidly get unknown parameters and fit unknown curves. The least square method is a kind of linear regression algorithm. It follows the principle that the sum of deviation square of each test point and regression equation on y-coordinate reaches the minimum value. For multiple linear regression functions, such as:

\[y = a + b_1x_1 + b_2x_2 + \cdots + b_nb_n\] (6)

In the formula, \( a, b_1, b_2, \) and \( b_n \) are unknown parameters, and can be acquired by the least square method.

3.2.2 Genetic algorithm
The genetic algorithm is a kind of random search algorithm referring to natural selection and nature genetics mechanism in the biosphere. Different from the traditional algorithm which solves problem based on a single appraisal function gradient, the genetic algorithm is independent from gradient information, and searches for optimal solution by simulating natural evolution [15]. With the advantage of overall optimization, the genetic algorithm is difficult to be trapped in local optimal during searching, and could find out the overall optimal solution with large probability. Meanwhile, it provides the ability of parallel computing, and could rapidly and reliably solve difficult problems. It is extensively applied to function optimization [11], image processing [16], data mining, machine learning and automatic control, in which function optimization is the typical application field of the genetic algorithm. Main steps of the genetic algorithm are:

1. Select operation
Select the superior individuals from groups and eliminate inferior ones. According to roulette wheel selection method, individual i’s probability of being selected is:

\[P_i = f_i / \sum_{j=1}^{n} f_i\] (7)
In the formula, \( n \) is the size of group, and \( f \) is the adaptation of individuals.

(2) **Crossover operation**

After selection probability of individuals is calculated, the matching individuals will be selected in several rounds; the individuals selected will be matched at random for crossover operation. The crossover operator exchanges certain genes at random of two individuals from crossover rate drop group to generate new gene groups.

(3) **Mutation**

Mutation is endow the genetic algorithm with local random searching ability. When the crossover operator approaches to the optimal solution, mutation may be used to speed up converging toward the optimal solution and could maintain group variety and prevent early convergence. During crossover operation, individuals in the group will be judged with certain mutation probability to decide whether it will be mutated. For individuals mutated, the mutation position will be selected at random.

(4) **Fitness assignment**

When the fitness of optimal individual reaches the given threshold, the algorithm will end, and output the optimal solution calculated finally.

3. 3 **Fitting results**

The experimental data of two groups BRDF of yellow multilayer materials from different incidence angles is used for modeling and analysis in combination with the genetic algorithm.

Fig. 3 (a) (b) are the BRDF fitting value of yellow multilayer material fitted by the genetic algorithm and the least square method when the incidence angle is respectively 10° and 60°.

The results of two groups of experimental data in combination with the genetic algorithm and the least square method have favorable fitting effects for BRDF value measured in experiment. The secondary optimization data and experimental measurement data through the least square method after optimization with the genetic algorithm have higher fitting precision. After modeling and analysis of BRDF data when the incidence angle of 10° and 60° the calculation results of unknown parameters can be seen in Table 1. According to data in the table, the initial value of the least square method after overall optimization of the genetic algorithm has higher fitting precision than that of the genetic algorithm, and the operation time is far shorter.
### Table 1 Modeling result of yellow multilayer material sample

|       | $k_b$      | $k_d$    | $k_r$    | a        | b        | MSE       | Time(s)  |
|-------|------------|----------|----------|----------|----------|-----------|----------|
| 10°   | GA         | 15.6549  | 0.0419   | -3.9463  | 0.4403   | -93.2121  | 0.0014   | 459.05  |
|       | LS         | 13.4743  | 0.0999   | -313.9974| 0.4678   | -107.5540 | 0.0002   | 16.42   |
| 60°   | GA         | 17.9727  | 0.0522   | -472.7850| 0.6248   | -88.3508  | 0.4950   | 460.89  |
|       | LS         | 20.0585  | 0.1080   | -886.0283| 0.9717   | -886.0283 | 0.1634   | 16.69   |

### 4. Conclusion

This paper, based on experimental measurement of BRDF on material surface, adopts the genetic algorithm and the least square method to carry out modeling, fitting and parameter optimization for BRDF experimental data of yellow multilayer material in natural light band. The analysis results show the five-parameter model in combination with the genetic algorithm and the least square method has higher fitting precision compared to that of separate calculation with the genetic algorithm. Moreover, the computing speed of the least square method is faster. The combination of these two methods could acquire smaller fitting error and faster fitting speed.

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