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Extreme Learning Machine based Bidirectional Reflectance Distribution Approximation

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Abstract— In computer graphics, one of the important aim is generating photo realistic images. Modelling interaction between light and surface of the object is major part of this aim. To achieve this, bidirectional reflectance distribution function is used. Bidirectional reflectance distribution function is calculated by direct measuring, analytical modelling or sampling methods. One of the most common analytic model is Phong illumination, which is based on empirical observation. Phong model considers ambient light, diffuse and specular reflections as in most illumination models. To generate more photo realistic images for each material in the scene; specular, ambient, and diffuse reflection coefficients have to be determined. Instead of searching for coefficients, expert systems can be used for approximating bidirectional reflectance distribution and these pre-trained systems can be utilized for rendering. In this study, extreme learning machine based bidirectional reflectance distribution model is proposed to generate more realistic images. By training proposed structure for each material type, different models were generated. According to the test results, proposed method may be considered as an alternative to interpolation of bidirectional reflectance distribution functions.

Keywords— Image Modelling, Computer Graphics, Extreme Learning Machine, Illumination Models, Bidirectional Reflectance Distribution Approximation

I. INTRODUCTION

Illumination has been one of the main topic in computer graphic from earlier studies to today's studies. For example, virtual reality (VR) is one of the popular topic in computer graphics. Light is an important component of a virtual reality and any artefacts in illumination may lead to odd scenes [1,2]. In addition to requirement of realism, calculations must also be fast to provide real time rendering. To obtain realistic illumination, well description of interaction between material and light is required. When a light energy hit on a surface, it can be absorbed, reflected and transmitted. Transmitted and reflected lights are modelled to simulate light behaviour. Transmitted and reflected lights can be diffuse light or specular light [4]. Traditionally, diffuse reflectance measurements are used for simulating the model. Bidirectional Reflectance Distribution Function (BRDF) is a function utilized for modelling interaction between irradiance (incoming energy) and radiance (outgoing energy). Radiance $R(\theta_e,\varphi_e)$ is estimated by using irradiance function $IR(\theta_i,\varphi_i)$ and BRDF $brdf(\theta_i,\varphi_i,\theta_e,\varphi_e)$, as given in (1) where (θ_e,φ_e) and (θ_i,φ_i) are directions in polar coordinates relative to the surface and from the surface, $d\omega$ is solid angle [3,5,16].

$$R(\theta_e,\varphi_e) = brdf(\theta_i,\varphi_i,\theta_e,\varphi_e)\, IR(\theta_i,\varphi_i) cos\theta_i d\omega_i \quad (1)$$

BRDFs are classified into two classes: isotropic, and anisotropic. Isotropic BRDF means invariant BRDF values with respect to rotation of surface around its normal. On the other hand, anisotropic BRDFs are variant values; they are changed in case of rotation of surface around its normal [16]. There exist many different approaches to model BRDF in literature [7-21]. In [7], BRDF was obtained from a set of measurements. By interpolating and extrapolating new BRDFs were created and reducing dimensionality valid BRDFs were obtained. Besides the directly acquiring models, in some studies samples were obtained from a BRDF using goniospectro-reflectometer; then by utilizing analytical models they were fitted [7-11]. In [8] this type of BRDF measurement approach was proposed. In this study, basis functions were applied for measurement and samples were fitted to analytical model. These approaches require measurement device to obtain BRDF. In [16], another sample based model was proposed. This study uses linear approximation to calculate BRDF. By using $\theta_i,\varphi_i,\theta_e,\varphi_e$ values for a specified surface a response surface model was approximated with linear function by utilizing principal component analysis to reduce the number of parameters. There exist also similar approaches to [16] using halfway vector instead of angles [19-21]. In addition to sample based approaches, in computer graphics analytical methods are also used frequently. Analytical methods are based on observations of the laws of energy conservation and reciprocity, etc.. However, these methods cannot accomplish to exhibit reflectance of all kinds of materials and require search for appropriate model parameters [7,8].

Phong model is frequently used one among analytical methods [1,12]. This model uses ambient, diffuse and specular component together as shown in (2).

Let L_{clr}, k_{amb}, k_{dif}, k_{spec} and Obj_{clr} light colour, ambient, diffusion and specular coefficients respectively, and object colour; L is light vector, N is normal vector and V is view direction, and k_e denotes specular exponent.

$$Phg = L_{clr}\,k_{amb}\,Obj_{clr} + L_{clr}\left(k_{dif}\,(L \cdot N) + k_{spec}\,(R \cdot V)^{k_e}\right) \tag{2}$$

where R is reflection vector and calculated as in (3).

$$R = 2 * (L \cdot N)N - L \tag{3}$$

The main usage of Phong model is simulating shiny materials. On the other hand, by changing the parameter values, appearance of materials may be changed [12]. By discarding object colour (ambient components) BRDF values can be estimated from Phong model as in (4) [16].

$$brdf(\theta_i, \varphi_i, \theta_e, \varphi_e) = \frac{\left(k_{dif}\,(L \cdot N) + k_{spec}\,(R \cdot V)^{k_e}\right)}{cos\theta_i d\omega_i} \tag{4}$$

In [13], instead of calculating reflection vector *R*, angle between normal and halfway vector *(H)* is used. Halfway vector can be computed as in (5). This variation on Phong model is called as Blinn-Phong model and (6) shows specular calculation in this model [1,13].

$$H = \frac{L + V}{\|L + V\|} \tag{5}$$

$$Spec = k_{spec}\,(R \cdot V)^{k_e} \tag{6}$$

More complex models were proposed to obtain photo-realistic images. These methods also use microfacets to model rough surfaces [15,16]. Moreover, different illumination models were proposed for various surface types such as sand, plaster, anisotropic surfaces, etc. [15,17,18]. Due to their computationally benefits, Phong model and Blinn-Phong model have been the two well-known and frequently used models in computer graphic. In [1], polynomial approximation to Blinn-Phong model was proposed to eliminate problems of Blinn-Phong model such as estimating k_e value. That method was compared with Zernike polynomial based BRDF rendering and Blinn-Phong model and it was reported that approximation provided sufficient results.

In addition to these models, there exist studies using neural networks to approximate BRDF [22]. In [23], MLP structures were proposed to model BRDF. Their proposed structure consists of two or more hidden layers. In [24], Kurt and Cinsdikici proposed a solution for memory and measurement noise problems of BRDFs by using Mass Attraction Network and Self Organising Map memory.

In this study, extreme learning machine based approximation to BRDF measurement is proposed. For different materials, rather than using spherical coordinates $\theta_i, \varphi_i, \theta_e, \varphi_e$ as in Phong model dot product of light vector and normal vector; and dot product of view vector and reflectance vector and in addition to these $cos(\theta_i), sin(\theta_i), cos(\theta_e), sin(\theta_e)$ are chosen as input for proposed model. Proposed model was trained with CURET database by utilizing 10-fold cross validation.

II. PROPOSED APPROACH

In this study, extreme learning machine is utilized to model BRDF values for each material separately. $(L \cdot N)$ and $(V \cdot R), cos(\theta_i), sin(\theta_i), cos(\theta_e), sin(\theta_e)$ are used as inputs. Structure has three outputs to represent each channel of BRDF. The reason behind using extreme learning machine structure is to obtain general coefficient by utilizing small set of data within less training time. Proposed model was trained and tested with 10-fold cross validation approach on CURET dataset.

CURET dataset includes BRDF values for 61 different material types with 205 different illumination and viewpoint directions $(\theta_i, \varphi_i, \theta_e, \varphi_e)$. Firstly, light, normal, reflectance, and view vectors were obtained for different illumination and viewpoint directions. Then, for each material and channel structure was trained to obtain material specific coefficients. At last, created structures were trained on database values.

A. Extreme Learning Machine

Extreme Learning Machine (ELM) is a machine learning method that is used for single hidden layer structures. Generally, for hidden layer random nodes are applied. Since it does not need tunning for hidden layer, it provides generalization at faster learning speed. In addition to speed, by providing small norm of weights, ELM provides better generalization performance than traditional neural networks. ELM provides both interpolation and approximation capabilities [25].

An example ELM structure for one output is given in Fig. 1.

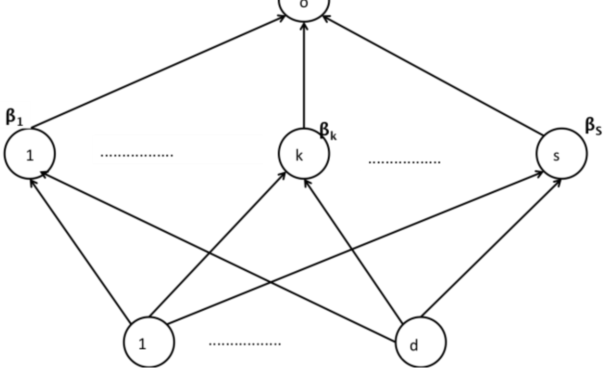

Fig. 1. An ELM structure [25]

Output of ELM is calculated as in (7) where x_i is d dimensional ith input, (ω_k, b_k) pair is randomly generated weight and bias value for node *k*, *f(x)* is activation function.

$$o_i = \sum_{k=1}^{s} \beta_k\, f(\omega_k * x_i + b_k) \tag{7}$$

Let t_i as target value for input x_i. There should be (ω_k, b_k) and β_k such that (8) is satisfied.

$$\sum_{k=1}^{s} \beta_k\, f(\omega_k * x_i + b_k) = t_i, \qquad 1 \le i \le N \tag{8}$$

There exits N equations that can be represented as in (9) where T is $Nx1$ dimensional target vector, β is $sx1$ dimensional vector, F is Nxs size matrix representing output of hidden nodes.

$$F\beta = T \tag{9}$$

Training of ELM structure is finding least-square solution β^{opt} of linear system given in (9). If number of hidden neurons is equal to number of training samples, F will be square matrix and β^{opt} is calculated as in (10). However, if they are not equal, Moore–Penrose generalized inverse of matrix F is used to calculate β^{opt} as in (11) where F^{M-P} is Moore–Penrose generalized inverse of matrix *F*.

$$\beta^{opt} = F^{-1}T \tag{10}$$

$$\beta^{opt} = F^{M-P}T \tag{11}$$

B. Converting from Spherical Coordinate to Cartesian Coordinate

In CURET database spherical coordinates are provided, to calculate vectors utilized in this study firstly spherical coordinates were converted to Cartesian coordinate to represent vectors [16].

Let $L = (L_x, L_y, L_z)$, conversion is implemented as in (12) [16].

$$\begin{aligned} L_x &= cos\varphi\ sin\theta \\ L_y &= sin\varphi\ sin\theta \\ L_z &= cos\theta \end{aligned} \tag{12}$$

III. TEST AND RESULTS

In this study, a neural network based BRDF illumination approximation model was aimed. $\theta_i, \varphi_i, \theta_e, \varphi_e$ values were utilized in proposed approach and $(L \cdot N)$ and $(V \cdot R), cos(\theta_i), sin(\theta_i), cos(\theta_e), sin(\theta_e)$ were used as inputs. Proposed method was evaluated on CURET database by 10-fold cross validation approach. Following tables show root mean square error (RMSE), mean absolute error (MAE), and correlation evaluation results, respectively. To provide legibility of tables, test results were given for different 15 materials of CURET's 61 materials. Table I shows RMSE results of proposed method.

Table I

Material Types.	**Evaluation Results - RMSE**		
	Red	**Green**	**Blue**
1- Felt	0.0416	0.0323	0.0131
2- Polyester	0.0271	0.0212	0.0101
9-Frosted Glass	0.0692	0.0458	0.0214
12-Rough Paper	0.0344	0.0225	0.0099
13-Artificial Grass	0.0059	0.0051	0.0017
15- Foil	0.0702	0.0490	0.0230
16- Cork	0.0173	0.0174	0.0068
21-Sponge	0.0135	0.01294	0.0053
23-Lettuce Leaf	0.0316	0.0228	0.0113
25-Quarry Tile	0.0309	0.0301	0.0141
39-Human Skin	0.0114	0.0091	0.0050
41-Brick_b	0.0485	0.0378	0.0173
44-Linen	0.0298	0.0206	0.0080
46-Cotton	0.0418	0.0306	0.0160
55-Orange Peel	0.0483	0.0425	0.0260

Table II shows MAE results of proposed method.

Table II

Material Types.	Evaluation Results - MAE		
	Red	**Green**	**Blue**
1- Felt	0.01880	0.0142	0.0063
2- Polyester	0.0115	0.0089	0.0044
9-Frosted Glass	0.0314	0.0211	0.0098
12-Rough Paper	0.0160	0.0104	0.0047
13-Artificial Grass	0.0029	0.0025	0.0008
15- Foil	0.0362	0.0253	0.0118
16- Cork	0.070	0.0069	0.0027
21-Sponge	0.0066	0.0058	0.0023
23-Lettuce Leaf	0.0139	0.0102	0.0050
25-Quarry Tile	0.0134	0.0130	0.0059
39-Human Skin	0.0053	0.0042	0.0023
41-Brick_b	0.0205	0.0161	0.0072
44-Linen	0.0135	0.0094	0.0036

Table III shows correlation results for proposed method. Correlation results show that proposed method provides correlation with BRDF values obtained from CURET database in the range of (0.92 and 0.98).

Table III

Material Types.	Evaluation Results -Correlation		
	Red	**Green**	**Blue**
1- Felt	0.9696	0.9717	0.9747
2- Polyester	0.9810	0.9795	0.9827
9-Frosted Glass	0.9633	0.9638	0.9650
12-Rough Paper	0.9817	0.9810	0.9813
13-Artificial Grass	0.9855	0.9847	0.9864
15- Foil	0.9274	0.9270	0.9289
16- Cork	0.9845	0.9818	0.9839
21-Sponge	0.9906	0.9886	0.9894
23-Lettuce Leaf	0.9358	0.9375	0.9416
25-Quarry Tile	0.9562	0.9516	0.94961
39-Human Skin	0.9762	0.9744	0.9775
41-Brick_b	0.9363	0.9355	0.9325
44-Linen	0.9754	0.9754	0.9758

According to the test results, proposed method approximates BRDF with extremely small errors. Therefore, it can be considered as an alternative approach to other approximations with its high accuracy. Since proposed method based on ELM, its generalization ability will be higher than interpolation and it can be utilized for precise calculations. In addition to these, thanks to ELM's fast training, new material types can be presented easily.

IV. CONCLUSIONS

In this study, ELM based BRDF approximation for materials provided by CURET database was aimed. The main reason of using ELM is its fast training and generalization ability. Firstly, database information transferred into Cartesian coordinate. Secondly, light, reflectance, normal, viewpoint vectors and $(L \cdot N)$ and $(V \cdot R)$ components were calculated. Lastly, by utilizing 10-fold cross validation for each material ELM structures were trained and tested separately.

According to the test results, ELM provided high accuracy for BRDF approximation. In addition to its generalization ability, its fast training allows to present new material types easily.

Consequently, proposed method can be considered as efficient alternative to other approximation methods due to its fast training and generalization ability.

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