A DESIGN REUSE METHOD FOR AGRICULTURAL MACHINERY CAD MODEL WITH LIGHT PROPAGATION SIMULATION
/
基于光传播模拟的农机装备 CAD 模型设计重用方法研究

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DOI: https://doi.org/10.35633/INMATEH-58-11

Keywords*: agricultural design reuse, light propagation, agricultural CAD model, Monte-Carlo method*

ABSTRACT

The problem of long design cycle, low efficiency and poor knowledge reusability still exists in China, in the process of agricultural machinery design. The reuse retrieval method designed for agricultural equipment CAD model is proposed to improve agricultural machinery digital design. Since agricultural machinery CAD model has internal coupling and local similarity attributes resulting in low performance of general retrieval methods, the Monte-Carlo light simulation method is utilized to extract CAD model partial features. Firstly, the light propagation process in different mediums was quantitatively analysed with optical parameters. Then how light propagates in complex agricultural CAD model was simulated according to Monte-Carlo method. After that the CAD model feature could be extracted with partial propagation information for design reuse retrieval. Finally, the proposed reuse retrieval method was evaluated on retrieval precision, recall and E-measure with particular agricultural model dataset. The results showed that the accuracy of proposed method was higher than that of general model retrieval approaches. Sphere constrained space and 10000 photon packets were shown to be the optimal feature extraction parameters for agricultural CAD model. The final design application results indicated that the proposed method could particularly satisfy agricultural CAD rapid design requirement, which is more suitable for offline complex agriculture CAD model retrieval. This paper is expected to provide a fine-grained, intelligent and visual method for agricultural machinery CAD management, promoting automatic and intelligent design of agricultural machinery manufacturing industry.

摘要

针对农业机械设计过程中设计周期长、效率低、可继承性差等问题，提出一种针对农机装备的重用检索方法。农业机械 CAD 模型的内部耦合性与局部相似性导致通用检索方法不能满足农机模型检索需求，本文使用蒙特卡罗法提取农机 CAD 模型局部特征以提高农业机械设计重用水平。首先，利用光学特性参数量化分析光传播特性，使用蒙特卡罗法模拟光在农机 CAD 模型中传播过程，然后对光传播特征信息统计分析，完成农机模型特征提取，最终在农机模型库中使用多种重用检索评价标准检测特征提取效果。结果表明：本文提出的方法在检索精度方面高于通用模型检索方法；对于农机 CAD 模型，球形约束空间以及 10000 光子束是最优特征提取参数；该方法能够满足农业机械快速重用设计需求，更适合于离线检索重用。光传播模拟法是一种具有细粒度、智能化和可视化的检索重用新方法，为提高农机制造业的设计自动化和智能化水平增添新动力。

INTRODUCTION

For traditional agricultural machinery design, the problem of long cycle, low efficiency and poor knowledge inheritance and reusability still exists in China. Due to visual and digital advantages of 3D models, three-dimensional CAD became a standard in industrial design, including here the agricultural machinery design process. The design reuse is the process of building new product by reusing previously developed designs. The CAD model retrieval method designed for new mechanical product development is an important component of design reuse technology, which could efficiently shorten mechanical design cycle. It is reported that about 20% machine parts that could be reused directly from the original CAD model dataset and more than half parts need to be adjusted to new design requirement, while only about 20% components need innovative redesign *(Rui et al, 2017).* Therefore the model retrieval reuse method is expected to play an increasingly important role in agricultural machine design.

The CAD model retrieval reuse technology has not been sufficiently utilized in the area of agricultural machinery design, and retrieval method designed for agricultural CAD model has been explored only to a small extent. The core of model retrieval and reuse application is to find and extract 3D model representative feature. The existing feature extraction methods can be divided into three categories, namely mathematical statistics *(Zou et al, 2014; Li et al, 2017)*, model projection *(Ji et al, 2015; Nie et al, 2017)* and topological analysis *(Sfikas et al, 2012; Hong and Kim, 2017)*. There is no doubt that these three methods have improved the accuracy of feature extraction to some extent. However, these approaches are not designed for agricultural CAD model, and feature analyses simply focus on model surface which can not sufficiently reflect internal structure properties of the model.

Agricultural machinery CAD models are different from general 3D model due to internal coupling feature and high similarity between partial structures. This is caused by the fact that agricultural machine generally are operated in complex and severe environment and various machinery parts need integration in order to satisfy multifunctional requirement. Based on that, it is necessary to research an agricultural model retrieval method, which could reflect CAD model surface and internal structure properties.

How to penetrate into agricultural CAD model internal structure and extract a comprehensive feature has become a pressing problem to be researched. It is proved that light has particular spreading property and it will interact with substantial particles in propagation medium *(Wang et al, 2016)*. Therefore, CAD model internal and partial feature can be extracted through light propagation phenomenon analysis. Among the simulation methods of light propagation, Monte-Carlo is the most promising one, which being widely used in biological tissues *(Watte et al, 2015; Radosevich et al, 2012)*, paper testing *(Modrić et al, 2009)* and medical diagnosis fields *(Funamizu et al, 2014, Oshima and Sankai, 2011)*. The aim of this paper is to propose a design retrieval reuse method intended for agricultural machinery CAD models with Monte-Carlo light propagation simulation, promoting the design automation of agricultural machinery manufacturing industry.

MATERIAL AND METHOD

Optical phenomenon like scattering, reflection and transmission will stochastically occur as light propagates in a certain space the containing CAD model, which is illustrated in tractor gearbox as shown in Fig.1. The features of the CAD model could be sufficiently represented by different optical phenomena. The fundamental theory in this paper is to simulate light propagation in 3D agricultural machinery CAD model using Monte-Carlo approach *(Giles 2015)* and realize model retrieval reuse.

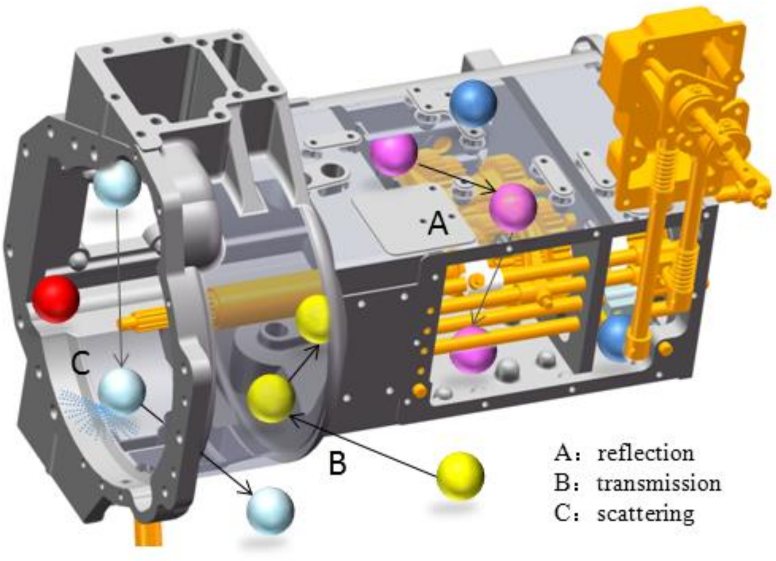


Fig 1 - The illustration of light propagation

1.1 Initialization

The initialization is to make initial condition consistent and compact. Before that, the simulation process has to be simplified due to the complexity of light propagation. (1) The particle property of light is exclusively taken into consideration. The simulation of light propagation is equivalent to tracking photon transfer. (2) The CAD model has the same material and uniform surface. (3) The spreading media between the constrained space and CAD model is regarded as air.

The first step of CAD initialization is shape normalization to ensure each model of the CAD model dataset has the same relative size *(Lin et al, 2011)*. Then the centre of each CAD model gravity is calculated, based on which a new spatial cartesian coordinate system is confirmed. After that, each CAD model is constrained in a certain standard space ranging from sphere or ellipsoid, to cube, and the azimuth angle α and deflection angle β are used to describe the location of different CAD models.

Single photon could not reflect light propagation property. Thus the photon packet consisting of substantial photons is assumed to be the smallest simulation unit. The photon packets uniformly distribute on the surface of the constrained space. Parameters (ux, uy, uz), the cosine value between photon location and coordinate axis (x, y, z), are used to present the photons moving direction. Moreover, the photon packet is endowed with energy w_0 after initialization in order to record photon packet energy.

1.2 Propagation distance

The photon transferring distance before changing direction is defined as moving step-size, which varies with a lot of factors such as the anisotropy, refractive index, scattering coefficient and reflectivity. Nevertheless, it is mainly affected by scattering and absorption coefficient *(Modric et al, 2014)*. Their reciprocal relation can be denoted as

$$\Delta s \ll \frac{1}{\sigma_s + \sigma_a} \tag{1}$$

where Δs is the average step-size; σ_S, σ_a, represent the scattering coefficient and absorption coefficient respectively.

The probability density function of the random variable step-size s follows the Beer's law given as

$$p(s) = (\sigma_a + \sigma_s) e^{-(\sigma_a + \sigma_s)s} \tag{2}$$

Based on the above formula, the step-size is denoted as

$$s = \frac{-\ln \varepsilon}{\sigma_a + \sigma_s} \tag{3}$$

where $\varepsilon \in [0,1]$ is a random variable.

Moreover, when photon moves each step-size in different mediums, there is a fraction of photons being absorbed simultaneously, resulting in photon packet energy reduction.

The energy variation is given by the following formula:

$$w' = \frac{\sigma_s}{\sigma_a + \sigma_s} w \tag{4}$$

where w' is the photon packet energy before moving a step-size and w represent the photon packet energy that suffered the absorption process.

1.3 Scattering direction

In propagation media, the photon packet moving direction would change due to light scattering. Furthermore, the more complex the CAD model, the greater optical property differences at model structural junction are, which could conspicuously lead to scattering. Therefore, the scattering simulation plays a vital role in improving agricultural CAD model feature accuracy. In this section, the scattering direction is expressed by the Henyey-Greenstein phase function *(Hajdek et al, 2014)*

$$\cos\beta = \begin{cases} \dfrac{1}{2g}\left\{1 + g^2 - \left[\dfrac{1-g^2}{1-g+2g\varepsilon}\right]\right\} & g \neq 0 \\ 2\varepsilon - 1 & g = 0 \end{cases} \tag{5}$$

where β is the deflection angle; $g \in [-1,1]$ represents the anisotropy and $\varepsilon \in [0,1]$ is a random variable.

It is essential to point out that $g = 1$ represents light forward scattering. On the contrary, $g = -1$ represents light back scattering.

1.4 Photon termination

When photon packet transfers in the constrained space that contains a CAD model, different optical phenomena would gradually occur. Nevertheless, the simulated photon packet could not spread without limitation. In order to ensure the randomness and effectiveness of light propagation, two approaches are defined. One of the terminated approaches is energy assessment. As mentioned above, photon packet energy reduces with each moving step-size. Photon packet with small energy is of no statistical significance. Therefore, the threshold $w"$ is used to decide photon packet termination.

Moreover, transmission and internal reflection would occur when photon packet transfers to the surface of the constrained space. If photon packet escapes out of the constrained space through transmission, it is supposed to be terminated. The Fresnel parameter *(Periyasamy and Pramanik, 2014)* $R(a_i)$ is used to decide internal reflection, which is formulated as

$$\begin{cases} \alpha_i = \cos^{-1}(|u_z|) \\ n_i \sin\alpha_i = n_t \sin\alpha_t \\ R(\alpha_i) = \dfrac{1}{2}\left[\dfrac{\sin^2(\alpha_i-\alpha_t)}{\sin^2(\alpha_i+\alpha_t)} + \dfrac{\tan^2(\alpha_i-\alpha_t)}{\tan^2(\alpha_i+\alpha_t)}\right] \end{cases} \tag{6}$$

where:

n_i represents the refractive index inside the constrained space;

n_t denotes the outside refractive index.

If the random variable $\varepsilon \in [0,1]$ is greater than $R(a_i)$, the photon packet escapes out of the constrained space. Otherwise, the photon packet is reflected back into the constrained space.

1.5 Feature analysis and extraction

The photon moving information in CAD model can be sufficiently recorded from the process of the initialization to termination. This particular optical information is a comprehensive feature of CAD model.

Table 1

The statistics of light propagation information

statistics	index
angle	maximum deflection minimum deflection angle distribution
distance	total distance average distance distance distribution
energy	remaining energy energy distribution

A single photon packet transferring data is a random event. According to probability theory, the effective optical information can be obtained after substantial photon packets propagation simulation. The essential optical statistics are given by Table 1. The statistics finally form a matrix that can represent the partial and entire features of CAD model. Thereafter, the similarity value between different models can be obtained by calculating the Euclidean distance of the feature matrix.

RESULTS

In order to test the proposed retrieval method, an agricultural machinery CAD model dataset was established. The dataset is mainly composed of the ESB international engineering models *(Jayanti et al, 2006)* and typical agricultural machine components derived directly from various combine-harvesters, tractors, seeders and cultivators. The part of agricultural machinery models is shown in Fig.2.

Fig. 2 - The illustration of agricultural machinery CAD models

According to the simulation process given in Fig.3, the light propagation in agricultural CAD model was simulated in Matlab 2016. The involved optical parameters of CAD model include the anisotropy $g = 0.12$, the scattering coefficient σ_S = 12 mm^{-1} and the absorption coefficient σ_a = 0.03 mm^{-1}.

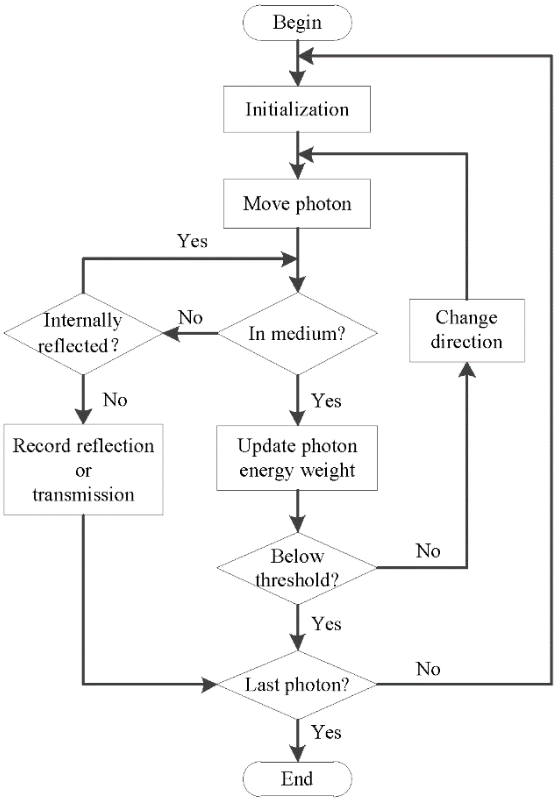


Fig 3 Light propagation simulation process

In addition, the precision-recall curve and E-measure *(Lian et al, 2013)* are used to evaluate the proposed method. The precision is the percentage of retrieved model that are relevant, while recall is the percentage of relevant models that are retrieved. The E-measure is a composite measure of precision and recall for a fixed number of retrieved models. The E-measure is defined as

$$E = \frac{(e^2+1)\cdot Precision \cdot Recall}{Recall + e^2 \cdot Precision} \tag{7}$$

where:

e denotes the correlation coefficient between the precision and recall. In this test the parameter e was 0.5.

2.1 Number analysis of simulated photon

The amount of photon packet plays a vital role in deciding the performance of CAD model feature. Insufficient photon packet would result in inadequate character information, so that the defining feature cannot be sufficiently extracted. However, the feature extraction consuming time would inevitably increase with too many simulated photon packets, reducing the efficiency of the proposed method. Fig.4 shows the variation of feature accuracy and efficiency with different amount of photon packets.

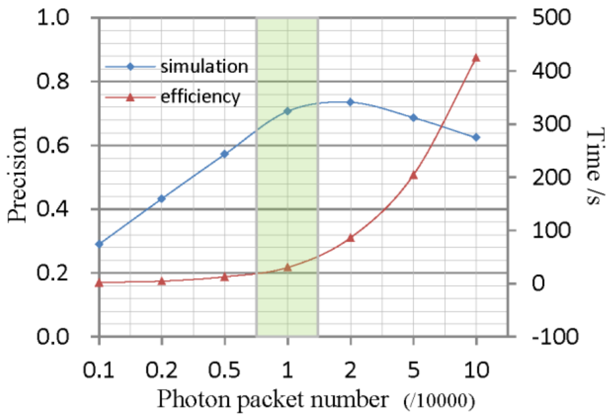


Fig 4 The curve of simulation numbers analysis

As shown in Fig.4, the feature extraction time gradually improves with increasing photon packets participating in simulation. The precision curve increases until photon number reaches to 10 thousands times. After that, it slightly decreases. This is because photon propagation density increases inside the model as the photon number increases, and feature statistic is more sufficient, resulting in precision increase. However, the model feature statistics gradually become saturated and tend to be normally distributed, which reduced model feature discrimination. Consequently, the retrieval precision decreases to some degree. Based on the two above discussions, it is proved that 8,000 to 10000 photon packets are the optimal simulation number. Within this variation range, the feature extraction consumed about 40 seconds, indicating that the proposed feature extraction method is more applicable for offline CAD model retrieval and application.

2.2 Constrained space analysis

The constrained space is another pivotal factor that would influence feature extraction and retrieval accuracy, since photon packet launch location and light reflected angle all depend on the surface of the constrained space. Fig.5 shows photon packet distribution in different constrained spaces including sphere, cube and spheroid.

Table 2

The results of feature extraction

index \ space	sphere	cube	spheroid
average precision	0.68	0.66	0.62
average recall	0.24	0.26	0.23
E-Measure	0.35	0.37	0.34
precision variance	0.12	0.16	0.21
recall variance	0.08	0.11	0.17

As shown in Fig.5, the constrained space indeed leads to various photon distributions with the spheroid in particular. To quantitatively analyse the effectiveness of the constrained space, 10 kinds of large different models were selected for comparison experiment. According to the results shown in Table 2, the sphere performs better than spheroid in the aspect of retrieval accuracy. In terms of stability, the sphere space dominates the first position. Furthermore, CAD model rotation and deformation would not change the relative position in sphere space. Therefore, the rotational normalization is not compulsory, which could productively lower algorithm complexity. Based on retrieval performance and method application, the sphere space was determined as the best constrained space.

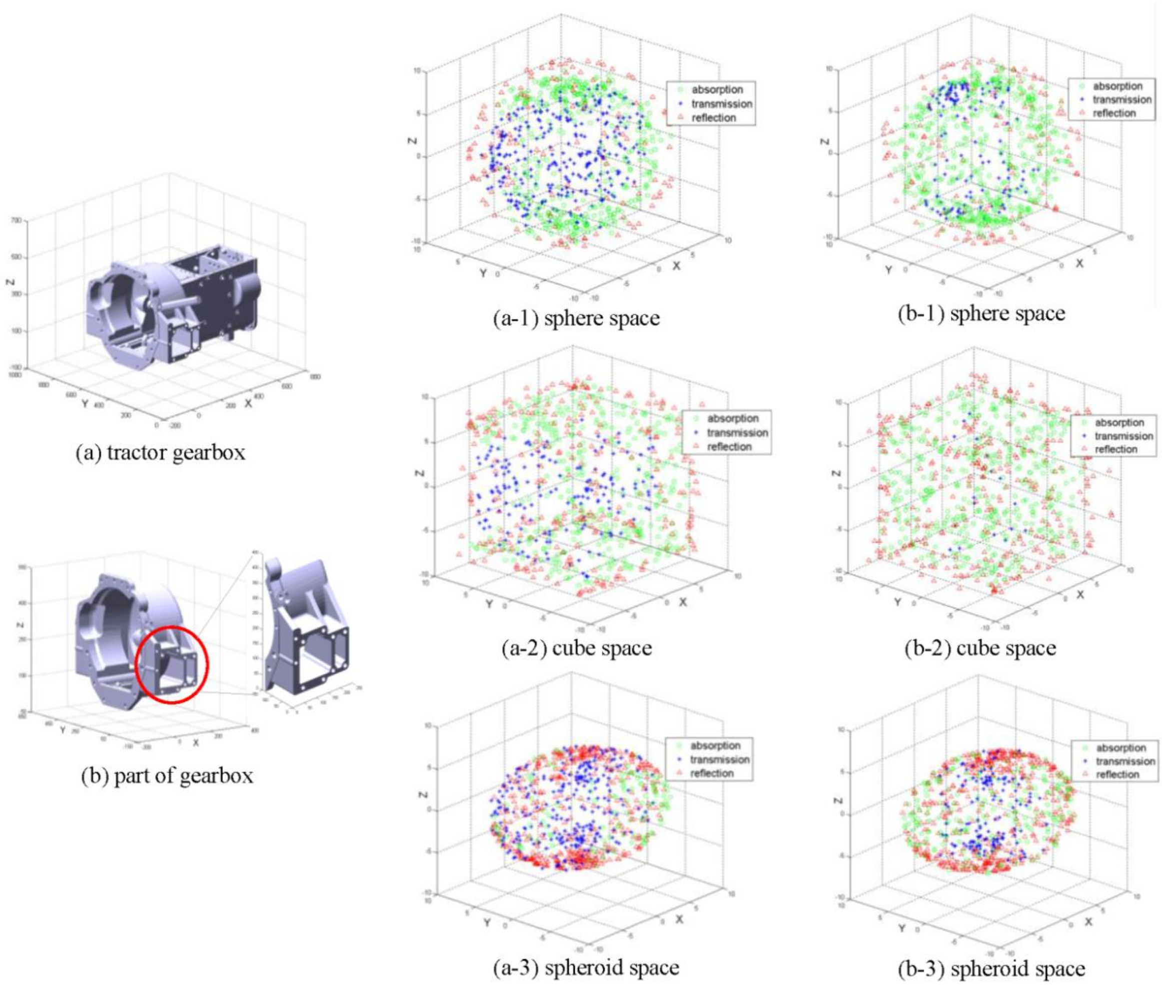


Fig. 5 - The photon distribution in different constrained spaces

2.3 Retrieval comparison

Based on the above discussion, the sphere space and 10 thousands photon packets are defined as the optimal feature extraction parameters. With optimal parameters, three frequently used methods were chosen to verify retrieval performance, which include the D2 method, the distance-angle method and the wavelet transform method *(Masoumi et al, 2016)*. Fig.6 shows the comparison results obtained by calculating the average retrieval value of 10 different agricultural machinery CAD models.

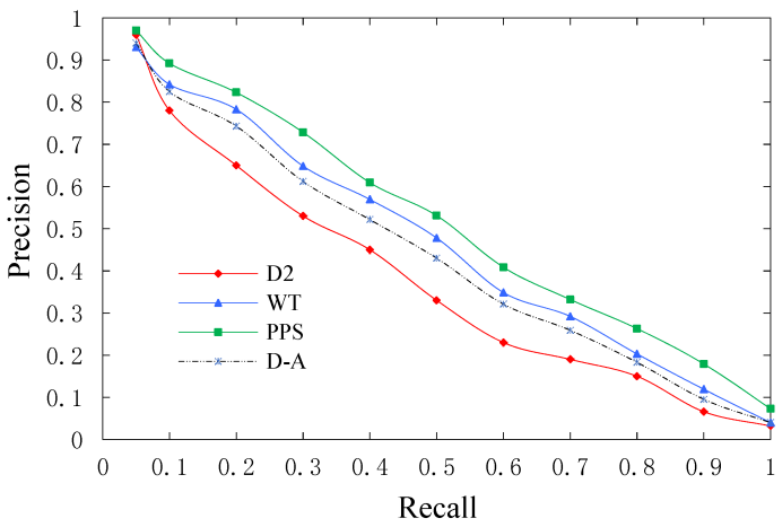


Fig 6 - The recall-precision curve

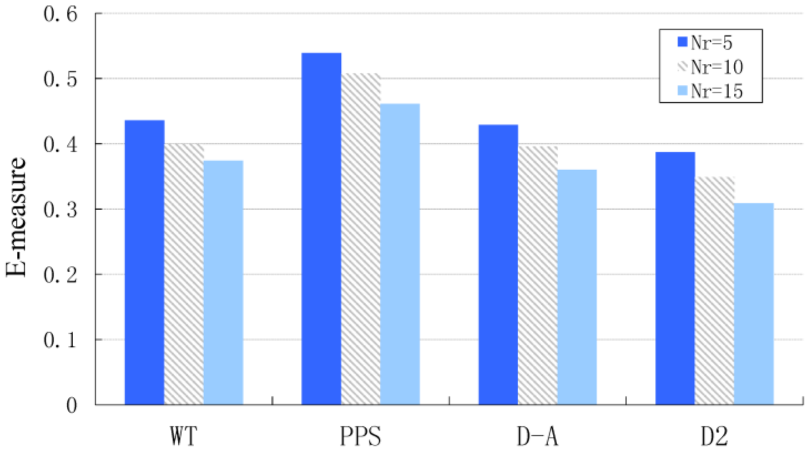


Fig. 7 - The E-measure results for complex model

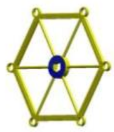
As shown in Fig.6, it is indicated that the retrieval performance of wavelet transform is approximately the same as that of our proposed method, better than the D2 shape and the distance-angle approaches. This is because the extracted feature by the D2 and distance-angle methods merely depends on CAD model surface information. However, our method and wavelet transform focus on model global feature, which could organically integrate model internal and surface attributes. Fig.7 presents the retrieval results of the shape complex and multi-cavity models. It can be seen that the E measure value of our proposed method is much higher than that of wavelet transform. This is mainly attributed to rotation normalization. As it is mentioned above, there is no need of rotation normalization for our proposed method. However, the wavelet transform is quite sensitive to shape deformation caused by rotation normalization, which reduced feature discrimination to some extent. Based on the above discussion, it is proved that our proposed method could extract the optical features of agricultural machinery CAD models, which is more suitable for complex CAD model feature extraction.

2.4 Design retrieval application

There are two retrieval modes of the proposed retrieval method that includes hand drawing model search and regular CAD model retrieval. Assuming that a new furrower of cultivation equipment requires redesign and a reel of wheat combine harvester needs modification, the first step is to select the query model or to draw a simplified model according to design requirement. After inputting query model, the relevant CAD models could be correspondingly retrieved from agricultural model dataset as shown in Table 3.

Table 3

The retrieval results of furrower and reel

Query model		Retrieval correspondences found in agricultural library					
		1	2	3	4	5	6
	Furrower						
	Similarity	89.41%	85.48%	84.35%	80.14%	77.83%	71.16%
	Reel						
	Similarity	92.22%	88.63%	87.51%	82.09%	76.14%	75.85%

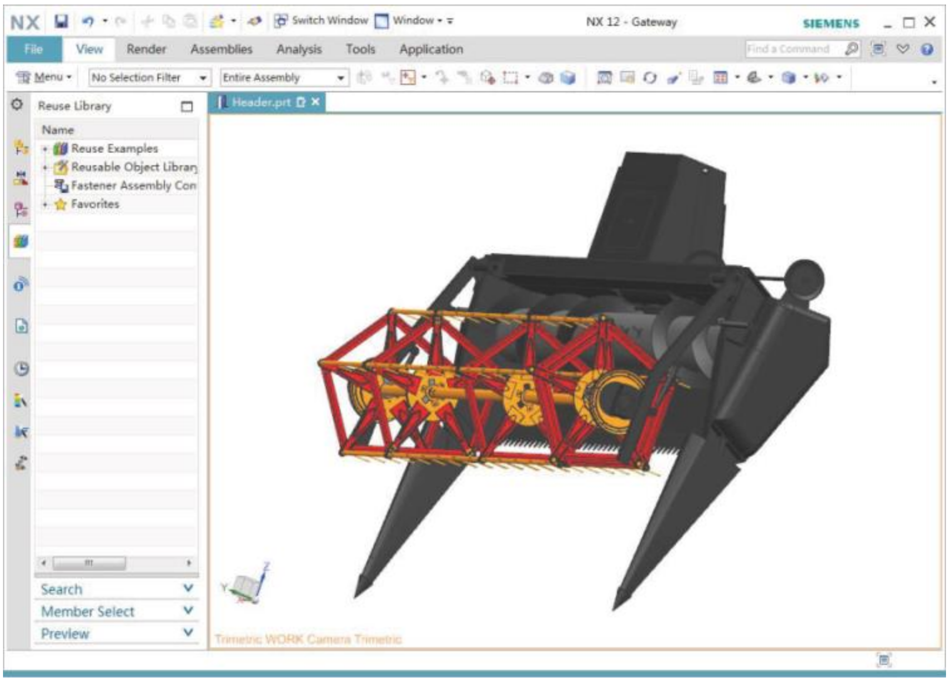


Fig. 8 - Rapid design results of combine harvester header

In the case of furrower retrieval results, 6 relevant models were retrieved according to the similarity value between query model and dataset models. Among them, the first 5 models are agricultural machinery CAD model and the last one belongs to the ESB dataset, indicating that the proposed method and the model dataset could particularly satisfy agricultural model retrieval requirements.

Fig.8 shows the rapid design results of combine harvester header with the first retrieved reel model in Table 3. With increasing agricultural machinery CAD models and design knowledge, the retrieval reuse method could be more efficient.

CONCLUSIONS

(1) The light propagation simulation technology could be effectively applied in feature extraction of agricultural CAD models. Through light propagation simulation, the internal coupling and local features of agricultural machinery CAD models could sufficiently be extracted.

(2) In retrieval accuracy aspect, the proposed method performs better than traditional approaches. For agricultural machinery CAD model dataset, the sphere constrained space and 10000 photon packets are the optimal feature extraction parameters.

(3) The proposed method could particularly satisfy agricultural CAD rapid design requirement, which is more suitable for offline complex agricultural CAD models. In the near future, the proposed method should be improved in retrieval efficiency to satisfy online and larger dataset retrieval requirement.

ACKNOWLEDGMENT

This work was supported by the project of national key research and development (2017YFD0700102) and the funds of Shandong “Double Tops” with grant number of SYL2017XTTD14.

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