ATLANTIS PRESS
Atlantis Highlights in Engineering, volume 5
International Conference on Precision Machining, Non-Traditional Machining and Intelligent Manufacturing (PNTIM 2019)

Classification and Retrieval of CAD Three Dimensional Models Based on Neural Network

Mingxia Zhao
State Grid Jibei Electric Power Company Limited Skills Training Center
Baoding Electric Power VOC.& TECH.
College Baoding
Hebei, China
E-mail: 879527755@qq.com

***Abstract*—Several neural networks corresponding to feature space in the paper were formed by Boosting method variant and RBF neural network based on particle swarm optimization (PSO), and these neural networks were integrated, so that the classification information of CAD three dimensional (3D) models was given. In the retrieval of CAD 3D model, the distance of the output results for the classifier and the distance for the feature space were weighted to calculate, which not only considered the difference of between the model's content and features, at the same time, and appended classification information parameters, but also took into account the semantic classified information of model. The experimental results showed that the classification method based on neural network ensemble could effectively improve the classification accuracy of CAD 3D model as well as consider the distance between models in feature space and the distance between models at semantic classification level, so that the 3D CAD model retrieval could be greatly improved accuracy.**

Keywords-Neural Network; Classificationof CAD 3D Model; Retrieval of CAD 3D

I. INTRODUCTION

The classification of CAD 3D model is a basic research topic in the field of 3D model retrieval, which is based on the 3D model itself that has a variety of characteristic parameters to determine its category. Model classification information is helpful to compare the superiority and inferiority of various eigenvalues, organize the model bases and evaluate the retrieval results. the retrieval of CAD 3D model is for a given query model, which retrieve the process of a set of models that matches the intent of the user's query. For purpose of adapting to the current explosive growth of the number of 3D models and the increasing scale and complexity of Internet search engines, CAD 3D retrieval has been transformed from text-based keyword search to content-based retrieval[1]. The retrieval method of content-based 3D model is characterized by applying the model itself contains low-level features. However, humans understand the model content with the high-level semantics in visual sensation, which results in unsatisfactory search results based on content. For the sake of solving the problem of "semantic gap", we must carry out the retrieval research of semantic-based 3D model[2]. Currently, the description and manipulation of 3D model content from the semantic concept level are facing great difficulties in implementation[3].

On behalf of shortening the "semantic gap", some researchers take an overall consideration about model classification information and the similarity of model features. One of the approaches is to apply the classification information obtained by classification learning, which limit the search scope to the same or similar categories, so that the scope of search can be greatly reduced, it will help to improve the efficiency of the search and retrieval results.

For purpose of improving the performance of CAD 3D model and borrowing classified information to enhance the retrieval performance, the method of RBF neural network ensemble was proposed in the paper to classify the 3D models, which solved the problems of high dimension and few samples that encountered in the 3D model classification. Model classification information and feature information were combined to use on the 3D model retrieval. Finally, the classification and retrieval experiments were conducted on 30 models of Princeton model library.

II. 3D Model Classification for RBF-Based Neural Network Ensemble

The RBF network was introduced by Broom head and Lowe[5] into the neural network by observing the local response of biological neurons, which was a kind of forward neural network that could realize arbitrary nonlinear mapping.

RBF network structure included three layers that were the input layer, hidden layer and output layer. Each layer had different functions. The input layer was a combination of source nodes which input the problem variables into the hidden layer. The hidden layer consisted of a set of radial basis functions, which mapped the non-linearly of input layer space to the output layer space. Radial basis function usually took the form of Gaussian function, which was shown in equation(1).

$$\phi_i(x) = \exp\left(-\frac{\|x-u_i\|^2}{2\sigma_i^2}\right) \tag{1}$$

Where x is the input vector, u_i is the center vector of the $i-th$ hidden node, σ_i is the radius of the $i-th$ hidden node, and $\phi(x)$ is the output of $i-th$ hidden node corresponding to the input x. The output of the hidden layer is linearly weighted by the output layer, and the value y_i of the $j-th$ output node is calculated as equation (2).

$$y_i = \sum_{I=0}^{N} w_{ji}\phi(x) \tag{2}$$

Where w_{ji} is the connection weight from the $i-th$ hidden node to the $j-th$ output node, and N is the number of hidden node centers.

The dimension of feature space corresponding to the 3D model was high. The training set samples were too small that compared with the number of dimensions. It was difficult to converge and classify inaccuracy using a single neural network classification. In 1990, the neural network ensemble method was first pioneered by Hansen and Salamon. By its method, we could significantly improve the generalization ability of learning system by training multiple neural networks and synthesizing its results. , we could train a few weak classifiers first when classifying 3D models, and then give the final classification result by the method of neural network ensemble.

The particle swarm optimization (PSO) algorithm in the paper was used to train the individual RBF neural network, which did not need to pre-set the number of hidden nodes, and used a particle of containing the number of hidden nodes and central parameter information to represent configuration information of neural network. The function was taken into account two aspects that were the classification accuracy and the number of hidden nodes, which transformed the training of RBF neural network into the optimization problem of fitness function for PSO algorithm. For the convenience of follow-up, we used PSO to train RBF neural network, which was abbreviated as PSO-RBF method.

A. Generation of individual neural networks

Research results in neural network Ensemble showed that obtaining good integration results was necessary to reduce the error of individual neural network and increase the difference between neural networks. In the generation of different individual networks.Boosting.M2 algorithm in terms of performance and adaptability was widely accepted and used in the paper, and algorithm of individual neural network was generated by based on Boosting.M2 and

PSO-RBF Methods, which the algorithm 1 was shown as follows.

Algorithm 1.Algorithm of individual neural network was generated by based on Boosting.M2 and PSO-RBF methods

Input: The original data sets $S=\{(x_1,y_1),...,(x_n,y_n)\}, y_i \in Y=\{1,...,C\}$,individual neural network training algorithm PSO-RBF;

Output: Neural Network Sets E ;

Initialization: The neural network sets E is initialized to an empty set, which the weight vector $w_{i,y}^{l}=D(i)l(C-1)$, where $D(i)=1/N, i=1,...,N, y\in Y-\{y_i\}$;

Step1:For $t=1,...,T$ looping;

Step1.1:For $i=1,...,N$ looping, equations (3), (4), (5);

$$W_i^t=\sum_{y\neq y_i} W_{i,y}^t \tag{3}$$

$$q_t(i,y)=\frac{W_{i,y}^t}{W_i^t}, where\ \ y\neq y \tag{4}$$

$$D(i)=\frac{W_i^t}{\sum_{i=1}^{N} W_i^t} \tag{5}$$

Step1.2: According to the weight distribution D_t, the sample is extracted by roulette method, the PSO-RBF algorithm is used to train an individual neural network, and the neural network h_t is added to E, which is $E=E\cup h_t$; $h_t: X\times Y\to[0,1]$ is returned by the result of training sets.

Step1.3: ε_t is calculated h_t-based by equation (6);

$$\varepsilon_t=\frac{1}{2}\sum_{i=1}^{N} D_t(i)\left(1-h_t(x_i,y_i)+\sum_{y\neq y_i} q_t(i,y)h_t(x_i,y)\right) \tag{6}$$

Step1.3:Setting $\beta_t=\varepsilon_t/(1-\varepsilon_t)$;

Step1.3:The weight vector is updated by equation (7);

$$w_{i,y}^{t+1}=w_{i,y}^{t}\beta_t^{\frac{1}{2}1+h_t(x_i,y_i)-h_t(x_i,y)}, where\ i=1,...,N, y\in Y-\{y_i\} \tag{7}$$

Step: Return to the neural network sets E , the end.

B. Neural network ensemble

In the process of classifying the three-dimensional model, first, the training samples were selected by boosting method; then the RBF neural network was trained by the PSO-RBF method on the selected training samples; finally, the data were classified by the method of multiple RBF neural network ensemble.

The result of neural network ensemble was to combine the output results of individual neural networks. Using the above representation, the set of individual neural networks was E , and the capacity was T . For the input data x_i , the actual output of the $t-th$ neural network corresponding to the class $y(y\in Y)$ was denoted as $h_t(x_i,y)$, and w_t is the weight of corresponding to the $t-th$ neural network. Therefore, the output after the neural network ensemble was equation (8) in the case of input x_i ;

$$f(x_i,y)=\sum_{t=1}^{T} w_t h_t(x_i,y) \tag{8}$$

where $w_t=\log(1/\beta_t)$.

The features of 3D model was extracted by based on content, which had diversity and complexity; the same type of model in the feature space might vary widely, a single neural network was difficult to have sufficient optimization ability and generalization ability. The categories of 3D model were realized by using the method of neural network ensemble, which was helpful to improve the ability of optimization and generalization of the classification system by applying the difference of each neural network.

III. INTEGRATING 3D MODEL RETRIEVAL OF CLASSIFIED INFORMATION

The integration of classification information for retrieval was to reduce the gap between content features and high-level semantic retrieval, which was different from the past in the form of integration. In the paper, we applied the classification information as a parameter to calculate the similarity. The similarity measure between the models included the two parts of feature distance and classified information quantification, which took into account both the content feature and the semantic classification information, so that it improved the retrieval performance of 3D model.

Given that the feature vector space of 3D model was R^D, the category was $y \in \{1,...,C\}$, the feature vector of any two models u and v were represented as $x_u = \left[x_{u,1},\cdots,x_{u,D}\right]^T$ and $x_v = \left[x_{v,1},\cdots,x_{v,D}\right]^T$; the input of the neural network ensemble was x_u, and the output of the neural network ensemble was expressed as $f\left(x_u, y\right)$;the input of neural network integration was x_v ,and the output of neural network integration was expressed as $f\left(x_v, y\right)$; so that the similarity distance $\delta(u,v)$ between u and v could be expressed by the distance $d\left(x_u, x_v\right)$between feature vectors and the weighted sum of classification information. The similarity distance was expressed by equation (9) and to calculate;

$$\delta(u,v) = \frac{d\left(x_u, x_v\right)}{d_{\max,x}} + \lambda \frac{d\left(f\left(x_u, y\right), f\left(x_v, y\right)\right)}{d_{\max,f}} \qquad (9)$$

Where $d(\cdot,\cdot)$ represents the distance between two vectors, $d_{\max,x}$ represents the maximum distance of any two models in the model base,which was calculated by $d(\cdot,\cdot)$ in the feature space; $d\left(f\left(x_u, y\right), f\left(x_v, y\right)\right)$ represents the distance between two model classification results calculated by $d(\cdot,\cdot)$, $d_{\max,f}$ represents the maximum distance calculated by $d(\cdot,\cdot)$ for the classification information of any two models in the model base, and λ is the parameter that balances the proportion of both.

IV. Experiment Analysis

A. Classification experiment of CAD 3D model

The Princeton University 3D Model Retrieval and Analysis team had built a standard experimental database PSB. The database contained a total of 1814 models, which covered a variety of common models in nature and everyday life. Its database was divided into a training subset and a testing subset, which each subset contained 907 3D models, where the training subset included 90 categories and the testing subset included 92 categories. The training subsets were applied for the preliminary testing and modification of the search algorithm, while the test subset was used to evaluate the advantages and disadvantages of different algorithms, because the categories of training subset and testing subset were not exactly the same. In order to validate method proposed by the paper, we selected 30 categories that had both training subsets and testing subsets as experimental data, which included 369 models of training sets and 370 models of testing sets.

The feature algorithm was extracted based on the shape distribution, which its basic idea was statistical characteristics of the point distribution on the surface of statistical model. Therefore, its feature value did not depend on the standardization process, thus could overcome the instability of the standardization process and have better robustness. The research results of Osada R et al. pointed out that the D2 distribution method achieved good retrieval results in several pattern distribution methods. Therefore, we adopted the D2 method to calculate the 64-dimensional feature sets of 739 models. Because of having the higher feature dimensionality of 3D models, the feature dimension reduction should be used to reduce the size of feature data sets, which reduced the interference of irrelevant or redundant features for the prediction results of neural networks, and improved the predictive ability of neural networks and the differences between individual networks. Therefore, we employed the feature dimensionality reduction method of literature on the 64-dimensional feature sets to obtain the 15-dimensional SD feature sets as the experimental data.

About 30 neural network ensembles were applied by according to the usual settings. A total of 10 experiments were run, and the average result was used as an evaluation of the classification performance of 3D model. The comparison results of PSO-RBF method, RBF neural network ensemble and k -nearest neighbor classification method were listed as table 1.

The classification method of k -nearest neighbor was calculated based on the essential attributes of feature sets, such as the distance between feature vectors. It could be seen that the neural network ensemble classification method improved the classification ability of the nature of feature sets, which compared with the k -nearest neighbor classification method. The k -nearest neighbor method was to calculate the proportion of correctly classified models in the k - nearest models to the distance query model. Here, we set the change k , k was set to the number of models in the model base that were of the same type as the query model. The k -nearest neighbor classification results of all the query models were averaged as the classification performance evaluation values of k -nearest neighbor on the model base.

TABLE I. THE COMPARISON RESULTS OF SEVERALCLASSIFICATION METHODS

Algorithm	**Classification accuracy on training sets**	**Classification accuracy on testing sets**
k -nearest neighbor	42.09%	39.85%
Average value of individual network	60.54%	54.26%
Average value of ensemble network	95.21%	84.61%
Best ensemble network	97.89%	86.54%
Worst ensemble network	92.86%	82.74%

As could be seen from Table 1, the average values of individual network in the training set and the testing set were 60.54% and 54.26% of the classification accuracy, respectively; which were 42.09% and 39.85% higher than 43.83% and 36.16% obtained by the k-nearest neighbor classification respectively. It showed that the PSO-RBF method could effectively improve the classification performance of 3D model, but the neural network obtained by training was still a weak classifier.

The average classification performance of individual neural network ensembles in the training set and the testing set was 57.27% and 55.93% higher than that of individual neural networks, respectively, which showed that the method proposed by RBF neural network ensemble in the paper could greatly improve the classification performance. The best ensemble network in 10 experiments had been achieved a high classification accuracy of 97.89% and 86.54%, and the worst ensemble network had been achieved the classification accuracy of 92.86% and 82.74%. It showed that neural network ensemble was more suitable for 3D model classification than individual neural network, which was an effective method for 3D model classification.

B. *Retrieval experiments of 3D model*

This experiment was still employed the model sets of classification experiment to facilitate the utilization of classification results for the following retrieval experiments. We made use of the best ensemble neural network to give the output results from classification. Figure 1 showed the results of integrating the classification information method and feature method on the testing sets; which its results were that the retrieval performance of the 3D model was mainly described by using the rate-of-completeness check-up map, the average precision of the first 50%, the average precision, R-Precision, BEP, and nearest neighbor retrieval performance evaluation index. The results given by the paper were a retrieval of all the models in the testing model base, and the average values of all the search results were calculated as the index value of retrieval performance evaluation.

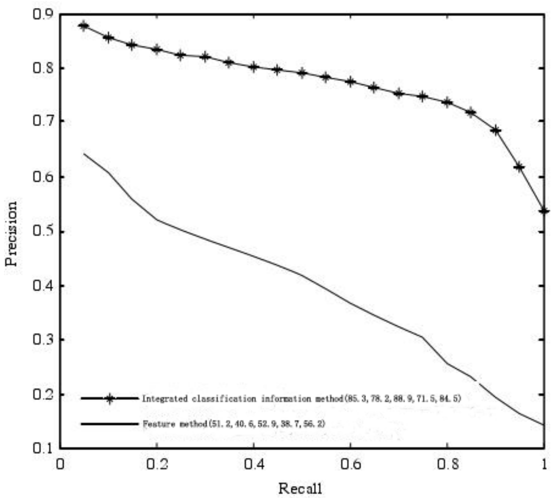

Figure 1. The results of integrating the classification information method and feature method on the testing sets

It could be seen from Fig. 1 that the curve of rate-of-completeness check-up of the integrated classification information method lied far above the curve of the characteristic method, which indicated that the method of integrating classification information significantly improved the retrieval performance. The five performance index values of the integrated classification information method were respectively 66.6%, 92.61%, 68.05%, 84.75% and 50.53% higher than the five performance evaluation indexes that did not include the classification information method. The larger the recall ratio was, the greater the difference between the curve of rate-of-completeness check-up of integrating classified information and the curve of the characteristic method was. It indicated that the larger the retrieval model number required to be returned, the larger effect the classification information was.

V. CONCLUSIONS

There mainly studied the CAD 3D model classification method based on RBF neural network integration and the retrieval method of integrating classification information in the paper. When solving the classification problem of CAD 3D model, the RBF individual neural network was integrated with the boosting method by specific to the complexity of 3D model feature space. We used RBF neural network automation design method based on PSO. The experimental results on 30 models showed that RBF neural network integration could greatly improve the classification performance of CAD 3D model. In the retrieval process of integrated classification information, the distance of the output results for the classifier and the distance for the feature space were weighted to calculate, which not only considered the difference of between the model's content and features, at the same time, and appended classification information parameters, but also took into account the semantic classified information of model. The experimental results showed that the method of integrating classification information greatly improved the retrieval performance.

REFERENCES:

[1] Gao Boyong, Zheng Herong, Zhang Sanyuan. An overview of semantics processing in content-Based 3D model retrieval [C]//2009 International Conference on Artificial Intelligence and Computational Intelligence, Vol I, 2009: 54-59.

[2] Wei Wei, Yang Yubin, Lin Jinjie, et al. Color-Based 3D model classification using Hopfield neural network [C]//International Conference on Computer Science and Software Engineering (CSSE 2008). Wuhan, Hubei, China, 2008: 883-886.

[3] Broomhead D S, Lowe D. Multivariable functional interpolation and adaptive networks [J]. Complex System, 1988, 2(1): 321-355.

[4] HL K, Neural P S. Network ensembles [J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 1990, 12(10): 993-1001.

[5] Kennedy J, Eberhart R. Particle swarm optimization [C]// Proceedings of IEEE International Conference on Neural Networks, Piscataway, 1995: 1942-1948.