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A 3D MODEL RETRIEVAL ALGORITHM BASED ON BP-BAGGING

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ABSTRACT

Aim at solving the existing problems of 3D model retrieval based on neural network, this paper proposes a new algorithm based on BP-bagging. Through bagging, the algorithm turns the weak classifier into the strong. As to feature extraction, the algorithm projections 3D model into six 2D images by six perspective points. Then transforms the images into frequency domain, gets the high dimension feature by two 1D Fourier Transformation, and compress the high dimension feature to the lower, inputs into the BP-bagging classifier to retrieval the 3D model. Proved by the experiment, the new algorithm is more effective in 3D model retrieval.

Keywords: *3D Model Retrieval; BP-bagging Classifier; Feature Extraction; Compression*

1. INTRODUCTION

The 3D models have important applications in the fields of mechanical design, architectural design, 3D games, animation, virtual reality and e-commerce. The demand of 3D resources is continuously growing. Reusing or modifying the existing models so as to create new model will save a lot of time and costs. The problems of 3D model are not how to construct a 3D model but how to find a 3D model. All kinds of retrieval algorithm are emerged [1, 2]. But the performance or efficiency is not satisfied. The method based on neural network retrieves the 3D model by inputting the feature vector of 3D model into the network classifier which has two problems: One is that the network classifier is a weak classifier for its flaws; the other is that the higher dimension vector can cause lower efficiency and the lower dimension vector can cause lower performance. Therefore, based on BP-bagging, this paper proposes a new retrieval algorithm of 3D mode to solve the contradiction between the efficiency and performance. The flow to realize the algorithm is as follow: (1) Create a stronger classifier by a weak one; (2) Transfer the 3D model to six images by projection; (3) Transform the images into frequency domain by Fourier Transformation; (4)Extract the higher dimension features and then compress them to lower; (5)Retrieval the 3D model by the stronger classifier.

2. BP-BAGGING CLASSIFIER DESIGN

Bagging is a commonly used method to generate multiple classifiers, which is composed of the samples selecting from the training set of basic classifier. The scale of training set is fairly to the original set. The training samples can be selected repeatedly, so some samples may occur several times, and some may never appear.

A. Thoughts of Bagging The basic thoughts of bagging [3, 4]: given a weak classifier and a training set, the weak classifier be trained for T times. The used samples every time in the training set are composed of n samples selected randomly from the original training set. A prediction function h is generated every time, and T prediction functions h_1, h_2, h_3… hn in T times training which are used to predict the sample set. The final predict result h* is generated by majority voting rule. The bagging thoughts include two sides: one is to generate prediction functions; the other is to combine the results of prediction functions.

B. Generating Prediction Functions Bagging provides a method of generating prediction functions [5]. Breiman made a theoretical analysis on classification, pointing out the highest rate of correction that the classification can achieved and the rate of correction that bagging can achieve, shown as Eq.(1) and Eq.(2),

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$$r = \int \max P(j \mid x) P_x(x)$$
(1)

$$r_B = \int_{x \in S} \max P(j \mid x) + \int_{x \in S'} [\sum_j I(\varphi_A(x) = j) P(j \mid x)] P_x(x)$$
(2)

As to the Eq. (1) and Eq.(2), S refers to the corrective input set. S' is the complementary set of S. I (*) is the indictor function.

It can be seen that bagging can make the correction rate of correction set to be in the best state. From the perspective of deviation and variance, Breiman pointed out that the variance of instability prediction functions is larger if deviation is smaller. Bagging reduces the generalization error by reducing the variance.

C. Method of Generating Conclusion There are two methods to generate conclusion [6, 7]: Absolute majority voting and relative majority voting. The method of absolute majority voting refers that the result can be classified as j only when class j gets the most voting and more than half of the total voting. The method of relative majority voting is refers that the result can be classified as j when class j gets the most voting. Assumed that T weak classifiers are generated, the prediction function of each weak classifier can give the correct classification results with probability 1-p, and the mistakes of weak classifiers are not related. The error probability of predictive function of majority voting is shown as Eq. (3)

$$p_e = \sum_{k > T/2}^{T} C_T^k P^k (1-p)^{T-k}$$
(3)

When p<1/2, pe is drab descending with the increase of T, that is to say the more the number of weak classifiers is, the higher the precision is. So the relative majority voting can get better results. Relatively voting is shown as Eq.(4),

$$h^*(x) = \begin{cases} j, m(x \in C_j) \\ = \max m(x \in C_i) > \lambda \bullet K \\ 10, \text{if} \quad \text{not} \end{cases} \qquad (4)$$

Regarding Eq. (4), x is the training samples. $\lambda \bullet K$ is the voting threshold. K is number of network to vote i=0, 1, 2 … 9.

D. Choosing Weak Classifier Bagging weak classifier can be the nearest neighbor classifier, decision tree and neural network. The BP neural network is not stable. The effect for bagging is very remarkable to the unstable learning algorithm. So, BP neural network is selected as the weak classifier. Most of the topology of BP network is forward feed network with three layers: input layer, hidden layer and output layer. Every layer is fully connected, and the neurons in each layer are non-connected. The number of neurons in input layer is fairly to the dimensions of feature vector. The output of neurons in hidden layer and output layer is shown as Eq. (5),

$$O_j = f_j(Net_j) = f_j(\sum \omega_{ij} x_i + \theta_j) \qquad (5)$$

As the above shown, fj refers to excitation function. At present, the most application is Sigmoid function, $f(x)=1/(1+e^{-x})$, θ_j refers to the threshold of neurons j. x_i refers to the input of neurons j. ω_{ij} refers to the connection weight.

3. FEATURE EXTRACTION

Feature extraction is the most important and it is the key in 3D model retrieval which is directly related to the efficiency of the whole retrieval algorithm.

A. Perspective Projection The first work is pretreatment to adjust the gravity of 3D model to the coordinate's original point, so the three directions with most information is adjusted respectively to the three main directions of 3 D coordinate system. At the same time, size normalization, coordinate proportion and rotating normalization are realized. The adjustment effect is shown in Figure1.a. After pretreatment, a tetrahedron is used to surround the 3D model to get the most information while not lose the information on the surface. We can get six images of the 3D model by perspective project from six perspective points that the 3D model crossed with the 3D coordinate. The 3D model is transformed from 3D space into six images in 2D space with size of M=N=64. The Six respective is K, L, M, K', L', M' as shown in Figure1.b. The attribute f (a, b) of each point (a, b) of the image is the closest distance, as shown in Eq. (6),

$$f(a,b) = \sqrt{A^2 + B^2} \qquad (6)$$

As in the above formula (6), A is the shortest vertical distance from (a, b) to the surface of the model. B is the distance of (a, b) to the centre of the image.

B. Feature Vector Extraction

(1) Extraction High Demission Vector The images are processed by twice 1D Fourier Transformation, as show in Eq.(7),

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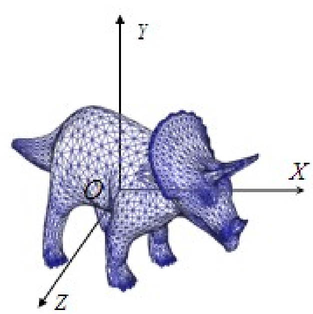
$$F(p,q) = \frac{1}{M}\sum_{x=0}^{M-1}\left(\frac{1}{N}\sum f(x,y)e^{-j2\pi py/N}\right)e^{-j2\pi px/M} \quad (7)$$

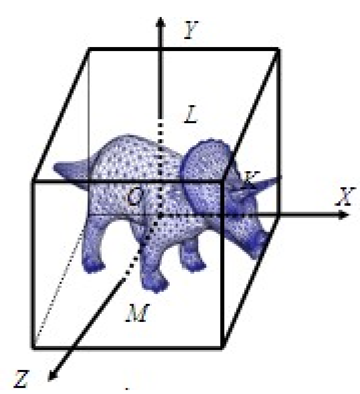
After the transform, the images transformed from airspace to frequency domain. Selecting1/8 of the low frequency area of the image, the high dimension vectors is generated (6×64/8×64/8=384), as shown in expression (8),

$$\begin{aligned}&(v_{00}^1, v_{00}^2, \cdots v_{00}^6, v_{01}^1, v_{01}^2,\\ &\cdots v_{01}^6, \cdots, v_{07}^1, v_{07}^2, \cdots v_{07}^6,\\ &v_{10}^1, v_{10}^2, \cdots v_{10}^6, v_{11}^1, v_{11}^2, \cdots v_{11}^6,\\ &\cdots, v_{17}^1, v_{17}^2, \cdots v_{17}^6,\\ &\cdots,\cdots,\cdots,\cdots,\cdots,\cdots,\cdots,\\ &\cdots,\cdots,\cdots,\cdots,\cdots,\cdots,\cdots,\\ &v_{70}^1, v_{70}^2, \cdots v_{70}^6, v_{71}^1, v_{71}^2, \cdots v_{71}^6,\\ &\cdots, v_{77}^1, v_{77}^2, \cdots v_{77}^6,)\end{aligned} \quad (8)$$

v_{xy}^i refers to the value of energy of the image.



a



b

Figure1 Perspective Project

(2)Vectors Compression High dimension vector can cause low efficiency. In order to improve the retrieval speed and not to lose the vector information, a straight line is selected by Fisher Criterion to project the image vector [8-10]. This method can ensure that the projection differentiate is the best. So, the high vector of each image is mapped into 1D vector, and six images can get one 6D vector (v_0, v_1, v_2, v_3, v_4, v_5).

4. 3D MODEL RETRIEVAL

The method of 3D model recognition is to input the feature vector into the classifier, which turns out three results: satisfied models set, less satisfied models set and dissatisfied models set.

A. Network Topological Structure As the feature vectors of the model is 6D, the number of network node of input layer is 6. According to the relationship that the node number of hidden layer is twice of that of the input layer, the hidden layer takes 12 nodes [11-12]. The output layer takes 3 nodes according to the demand of output.

B. Classification Algorithm Based on BP-bagging The feature vector of 3D model will be inputted into BP-bagging classifier to realize classification retrieval. The procedures are as follow:

Step1: Assumed that the sample training set is D={x (i)}, i =1, 2 …, N. The total times of training are N and the initial value of training number i is 0. A basic classifier is generated after once training. So, the total N basic classifiers are generated after N times training.

Setp2: The training subset D_i is composed of k samples drawn out from the sample training set in the ith training. Training the classifier with training set D_i, and the ith classifier is generated.

Step3: The samples are sorted by the classifier. We can get the sorted result by integrating with absolute majority voting. Among the results, the satisfied sets are the models that we need. We can get some modes in the less satisfied models set by feedback.

5. EXPERIMENT VALIDATION

In order to test the efficiency and performance of the algorithm, the feature vector is input into BP-bagging classifier to realize 3D model retrieval. Three kinds of 3D models are selected from the model lib: table models, rabbit models, lamp models, whose number are larger, and the models are more similar, by which we can well test the performance and efficiency of the algorithm.

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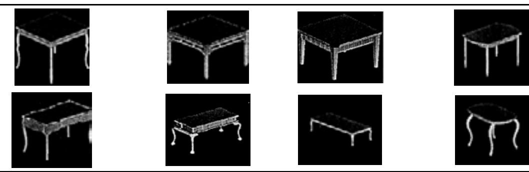
A. Experimental Results the experimental result of tables is provided; the others are similar to this. Table 1 gives the experimental results. The result is sorted according to the similarity.

Table1 Performance Test

Example model	Retrieval results
	

The results are ordered by similarity. It can be seen from the table that the algorithm can get perfect performance.

Table 2 provides four times: pretreatment time, feature extraction and compression time, retrieval time, and the total times.

Table 2 Times Test (Unit: Second)

Pretreatment	Feature Extraction	Retrieval Time	Total Times
0.007	0.009	0.008	0.024

The above table indicates that the algorithm is more effective. The times are shorter than the similar algorithms [1, 2]. Especially the retrieval time is much reduced. Therefore, a conclusion can be drawn that the algorithm performs better and which is more effective.

B. Experimental Analysis. Seen from table 1 and table 2, the BP-bagging strong classifier takes on a good effect: the high dimensional features vectors guarantee the retrieval performance, and the effective compression improves the retrieval speed.

6. CONCLUSION

This paper introduces bagging to construct BP-bagging classifier. The high dimensional features vector guarantees the retrieval performance, and the effective compression improves the retrieval speed. This algorithm realizes the retrieval of 3D model with high speed and good performance. The effect is perfect. More important, the algorithm solves the contradiction of performance and efficiency. There is no doubt that further works are necessary. For instance, feedback mechanism can be introduced to provide interactive interface. If the trivial results are not satisfactory, the user can give a parameter to retrieval further.

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