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A Deep Learning Approach to the Classification of 3D Models under BIM Environment

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Abstract

In recent years, the extensive use of BIM has brought a revolutionary change for the construction industry. As an important technology to support BIM, three-dimensional digital technology has become a hot academic research. The 3D geometric model is the main data expression of modes in BIM environment. But because of the complexity of 3D modeling, the maintenance of the 3D model library in BIM environment will spend a lot of time and cost. The traditional CAD 3D modeling has accumulated a large number of 3D models for the BIM project to reuse. Using the 3D model classification technology can quickly classify the existing 3D model, and save a lot of cost. Deep learning is in recent years a new method of machine learning. In this paper, we use Stacked Auto-Encoders (SAE) to classify 3D models under the environment of BIM. Experiments show that, the method proposed in the paper has achieved good results in the 3D model classification, which provides a new idea for the development of BIM.

***Keywords**: Stacked Auto-Encoders, BIM, 3D models classification, feature extraction*

1. Introduction

With the wide application of computer technology in various fields, the traditional construction industry urgently needs a revolution; Building Information Modeling (BIM) emerges as the times require. Building Information Modeling (BIM) is a digital representation of physical and functional characteristics of a facility. A BIM is a shared knowledge resource for information about a facility forming a reliable basis for decisions during its life-cycle; defined as existing from earliest conception to demolition [1]. BIM provides such a technology, method, system and opportunities to provide project stakeholders with timely, accurate, sufficient information during the project life cycle, supporting information exchange and sharing. Thus it can improve efficiency and quality of the project design, construction, operation, maintenance, and continuously upgrade the construction industry productivity. In the view of application, many countries have already applied BIM technology to support processes including cost management, construction management, project management and facility operation.

As an important technology to support BIM, three-dimensional digital technology has become a hot academic research. The 3D geometric model is the fundamental and core data of building information models. But because of the complexity of 3D modeling, the 3D model library is very important for BIM modeling, which makes BIM modeling easily and efficiently. In the process of modeling, a large number of 3D model components can be accumulated for reusing in BIM modeling. These massive 3D geometry models

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provide rich resources for BIM modeling. Accordingly how to manage these components effectively is important, which need to classify and maintain the model library.

The content-based 3D model retrieval technique attempts to extract the feature information of 3D model and establish index, then compare similarity to determine the query results, in order to help the user quickly find the required models. Compared with text retrieval, this retrieval technology has received more and more attention for its high efficiency, reliable characterization method, and its objective, the stability of the retrieval results. As an important step of 3D model retrieval accuracy, 3D model of classification algorithms play a key role. Some 3D model classification algorithms achieve good results. Deep learning is a new method of machine learning in recent years. This method has been applied well in the fields of image and text because it is in accordance with the law of human cognition. This paper proposes a classification algorithm of 3D model based on Stacked Auto-Encoders, and provides a new idea to improve the efficiency of 3D modeling under BIM environment.

2. Related Work

2.1. Building Information Modeling (BIM)

Building Information Modeling (BIM) technology has developed fast in the past ten years. Internationally, building SMART has defined BIM Data Model Standards IFC (Industry Foundation Class) and Process Definition Standard IDM (Information Delivery Manual), providing a standard develop format for BIM data exchange and delivery [2]; USA issued NBIMS (National BIM Standard) to guide the practical application of BIM [3].In China, multiple national science and technology support programs research on BIM theory, methods, tools and standards. According to the research and application of construction in each stage of BIM become more and more [4, 5]. BIM Research Group in School of Software, Tsinghua University has researched the Chinese Building Information Modeling Standard Framework [6] and published the achievements in 2011. Zhang et al. [7] presented the integration of BIM framework for building life cycle, developed a prototype system of BIM data integration and service platform BIMDISP, and verified the feasibility and the feasibility of BIMDISP by the practical application in Engineering. Xue et al. [8] analyzed of BIM in the visual design, parametric design and application of collaborative design and working mechanism, and illustrates the application of parametric design in the design of building structures. Li et al. [9] selected Revit and Project software, to create the 3D building information modeling and schedule information construction is analyzed. Jiang et al. [10] proposed BIM based construction project document management system, and analyzed the necessity and feasibility of the implementation of the system, constructed system framework. Wang et al. [11] summarized the benefit of BIM for project stakeholders during the process of construction through analyzing the results of investigating the 21 construction projects using BIM in North America and Europe.

2.3. 3D Model Classification

So far, in engineering field, CAD model classification research has achieved certain results. Ip et al. [12] use surface curvature and SVM to classify CAD model. Hou et al. [13] proposed a semi-supervised clustering method based on SVM to semantically organize 3D model. Barutcuoglu et al. [14] proposed a Bayesian framework for hierarchical classification of 3D shape. Given a set of classifier corresponding to the arbitrary shape descriptor, Bayesian framework organically organize classification results together. The framework coordinates those inconsistent prediction results, finally obtains an optimal predicted results. In the experiment, a spherical harmonic descriptor verified that the Bayesian framework can improve the classification accuracy in most categories.

Wei et al. [15] adopts Hopfield neural network to identify the 3D model with color. The color of the surface of 3D VRML model is used as input vectors to the Hopfield neural network. Philipp-Foliguet et al. [16] proposed a framework for indexing and retrieval of 3D archaeological art. The framework includes two parts, support the search and classification of global and local model. The first part use global shape descriptors, the search engine "RETIN-3D" use the strategies to combine SVM classifier and active learning to retrieve similar categories. The second part uses the model local descriptor to improve and enhance the classification results. Wang et al. [17] proposed a new method to automatically select the appropriate descriptors to classification and retrieval of 3D models. Firstly, some shape descriptions were calculated based on histogram to form a feature space, and then automatically select the important descriptors based on sparse theory. Finally, spectral clustering was used to generate new shape descriptor. The method is not only applicable to complete 3D model, also apply to the incomplete 3D model, the deficiency lies in the feature space descriptor must be based on histogram.

2.4. Deep Learning

Deep learning has achieved success in image recognition, speech recognition, and so on in recent years， and get more and more attention. In 2006, Hinton et al. [18] proposed an unsupervised learning algorithm of Deep Belief Network to solve the optimization problem model of deep learning. The core of solving DBN method is greedy layer wise pre-training algorithm. Through optimizing DBN weights under linear time complexity with network size and depth, the problem is decomposed into several simple sub problems to be solved. Bengio et al. [19] and Ranzato et al. [20] proposed the idea of initializing each layer of neural network using unsupervised learning. Bengio [21] gave a comprehensive review on the Deep Learning. He proposed greedy layer wise pre-training and learning process for initializing parameters of the Deep Learning model based on unsupervised learning techniques. From the bottom the input representation of each layer were formed by training each layer neural network. After the unsupervised initialization, each layer of neural network was stacked into deep supervised feed-forward neural network, which was fine tuned by gradient descent. The learning method of deep learning mainly focuses on learning useful data representation, and makes sure that the learned features do not change with the factor change and were robust to sudden changes in the actual data [22]. Paper [23] gives related skills of training Deep Learning model, especially the Restricted Boltzmann Machine (RBM). Bengio [24] gives guidance training method for different types of deep neural networks.

3. 3D Model Feature Descriptors

3.1. Model Coordinates Standardization and Pretreatment

To realize the retrieval and classification of content based 3D model, the key point is to require the extracted 3D model feature description is invariance and robustness to translation, rotation, scale size and orientation transformation. Currently, there are mainly three kinds of methods to realize the feature description invariance: 1) Using principal component analysis and other methods to standardize the 3D model coordinates, calculate the standard coordinate frame, then, extract the corresponding feature under the standard coordinate system. 2) Align coordinate of the two compared 3D models, this method is very time consuming and rarely used. 3) Define and extract invariant features description. But in fact, the invariance of these feature description often is not comprehensive, moreover, most of the calculation of these features is also sometimes need to finish in a normalized coordinate system. Therefore, in order to further improve the accuracy of classification and retrieval, it often also needs to standardize model coordinates.

We use the existing technology to standardize 3D model. To ensure the model is translation invariant, translational transform methods were used to align the centroid and origin coordinate of model. To ensure the rotation invariance, PCA was used to rotate the model to the uniform rotation angle. In order to ensure the scale invariance, the 3D models were scaled up to a uniform scale. Reflecting transformation executed in order to guarantee mutual consistency of two 3D models in the mirror.

3.2. Feature Extraction

The basis of ray based feature extraction algorithm to extract features of 3D model process is as follows: Firstly, the model is standardized pretreatment, move the center to the origin of coordinate, scale model to the unit size, and to make all model's direction and rotation angle consistent. Spherical parameterization for the model use the surrounded spherical ball with the center at the origin, projecting a series of uniform sampling ray from the origin to the spherical warp, weft direction respectively, calculate the intersection point of each ray and the model surface. For each ray, using the maximum value from the model origin to surface intersection as the sampling value of the direction, sampled values of all direction constitute the feature vector. The process of calculation method based on ray show in Table 1. The inputs of function include the 3D mesh model, the ray number N along warp and the ray number M along weft. The outputs are distance of each direction from the intersection of ray and model surface to the model centroid.

Table 1. Ray Based Feature Extraction Algorithm

```
Ray-based
{
    for(i=0;i<N; i++)
    {
        φ=2iπ/N ;
        for(j=0;j<M; j++)
        {
            θ=2jπ/M ;
            for(k=0;k< The total number of triangles; k++)
            {
              Calculate intersection of ray with direction(θ,φ) and triangle k;
              If intersection exist, then calculate and save the distance from the origin to the
              intersection point;
            }
        }
    }
}
```

4. 3D Models Classification using SAE

Stacked auto-encoders network was proposed by Bengio [19], it is a multilayer neural network which was conducted by auto-encoder. Auto-encoder was successfully used for dimensionality reduction, and achieve low dimensional feature of the raw data. Adding a Softmax classifier to the last auto-encoders form a SAE which can use the learned feature for classify tasks.

4.1. Stacked auto-Encoders Network (SAE)

The auto-encoder (AE) is a simple network that tries to produce at its output what is presented at the input. As exemplified in Figure 1a, the most basic AE is in fact a multi-layer perceptron that has one hidden layer and one output layer, with two restrictions: the weight matrix of the output layer is the transposed of the weight matrix of the hidden layer; and the number of output neurons is equal to the number of inputs.

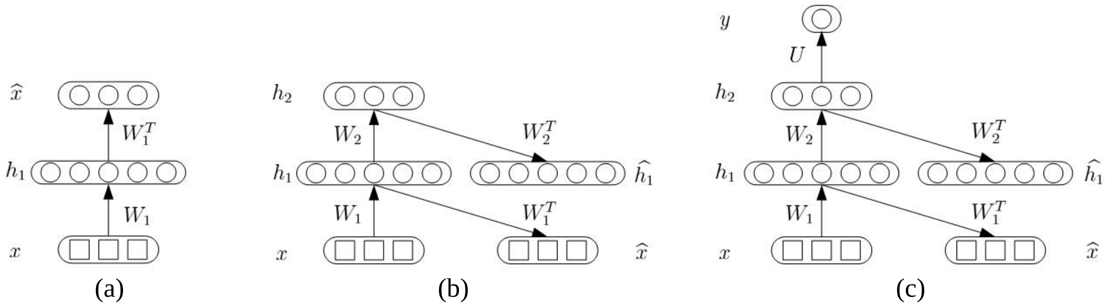

Figure 1. (A) An Auto-Encoder. (B) Pre-Training of Hidden Layers of A Deep Network Using Auto-Encoders. (C) A Pre-Trained Deep Network with An Additional Output Layer. [19]

Let x be the input vector with $x_i \in (0,1)$. For a layer with weights matrix W, hidden biases column vector b and input biases column vector c, the reconstruction probability for bit i is $p_i(x)$, with the vector of probabilities $p(x) = \mathrm{sigm}(c + W\mathrm{sigm}(b + W'x))$. The training criterion for the layer is the average of negative log-likelihoods for predicting x from $p(x)$. For example, if x is interpreted either as a sequence of bits or a sequence of bit probabilities, we minimize the reconstruction cross-entropy:

$$R = -\sum_i x_i \log p_i(x) + (1 - x_i)\log(1 - p_i(x)).$$

The deep networks we used for classification had an architecture similar to that shown in black in Figure 1c, with a layer of inputs, two or more hidden layers, and an output layer with as many units as classes (or a single output unit, if only two classes exist). The hidden layers of such a network can be pre-trained in an unsupervised way, one at a time, starting from the bottom layer. In order to be pre-trained, a hidden layer is seen as belonging to an AE. Once a given AE has learned to reconstruct its own input, its output layer is no longer needed and its hidden layer values become the input to the next level, as shown in Figure 1b. The next level is in turn pre-trained as an individual AE, and the process is repeated until there are no more hidden layers, as in Figure 1c.

The goal of unsupervised pre-training is to bring the network's weights and biases to a region of the parameter space that constitutes a better starting point for a supervised training stage than a random initialisation. In this context, the supervised training stage is usually called fine-tuning and can be achieved by conventional gradient descent, based on a training set of paired input and target vectors. It should be noted that the output layer weights *U* are not involved in the pre-training stage, so they are randomly initialised and learned only in the supervised stage.

4.2. SAE Based 3D Model Classification

The characteristics of input data can be obtained by ray based feature extraction algorithm, and SAE has good classification efficiency. Therefore, we proposed a 3D model recognition and classification method based on SAE algorithm. The main process of the algorithm is described in Table 2.

Table 2. SAE Based 3D Model Classification Algorithm

Step 1 Choose appropriate training and testing set.
Step 2 Process 3D model feature description, and represent the data set using matrix.
Step 3 Treat the first layer as an auto-encoder model, using unsupervised training to minimize the reconstruction error.
Step 4 The output from the hidden unit of auto-encoder model as input of another layer.
Step 5 Initialize the parameters of each layer in step 4.
Step 6 The output of the last hidden layer is used as an input to a supervised layer, and initialize the parameters of the layer.
Step 7 Adjust all parameters of deep structure neural network according to the rule of supervision. Stack all the auto-encoder models to form the stacked auto-encoder network.

5. Experiments

The main content of this section is to verify the effectiveness of the proposed algorithm in some public data sets. First of all, a public 3D model library was chosen as data set. Then, the experimental results were showed in Table 4. Finally, we gave the analysis of the algorithm according to the experimental results.

5.1. Dataset

The 3D shapes retrieval and analysis team of Princeton University combined the experimental database of computer graphics and image processing laboratory of Germany University of Leipzig, and also get 3D model through network crawling, establish a standard experimental database after converting those models into a uniform format. This database includes 1814 models, covering most types of models of common nature in daily life.

PSB model database is using artificial classification according to the natural attribute of the model. The previous experiments demonstrated the different classification method has different impact on retrieval results. So the models provide coarse to fine hierarchical classification to ensure that the number of each species is balanced. To prevent certain types of model too much to impact fairness of assessment, the 1814 models are divided into training set and testing set, each 907 models. In the division, not only the total is average, each type also tries to ensure uniform. The purpose of division is to adjust parameters of method using training set, then, do searching test using the test set, to determine the stability of parameter adjustment.

Figure 2. Some 3D Models of PSB Database

5.2. Feature Description

The features of the 3D model were extracted use the ray-based feature extraction algorithm before classifying the 3D models. In our experiments, we set the parameter N equal to 12 and the parameter M equal to 3. Then each 3D model was described with 36 dimension features. We choose four 3D models (specifically, M420, M421, M798, and M799) to show the features description. The features description of the four models is shown in Table 3.

Table 3. The Feature Description of 3D Models

Model	Feature description											
	0.4944	0.2164	0.3733	0.1650	0.3878	0.2493	0.3487	0.2461	0.4328	0.2949	0.4818	0.3003
M420	0.1710	0.1422	0.2956	0.2390	0.3804	0.3002	0.3481	0.3661	0.3225	0.3809	0.3149	0.3743
	0.0532	0.0674	0.1070	0.1049	0.1430	0.1363	0.1724	0.1645	0.1974	0.1904	0.2191	0.2142
	0.5606	0.1043	0.3577	0.2605	0.4029	0.2682	0.4013	0.3194	0.4437	0.3273	0.4752	0.3206
M421	0.2258	0.1321	0.3169	0.2195	0.3923	0.2846	0.3727	0.3360	0.3482	0.3482	0.3563	0.3555
	0.0774	0.0223	0.1557	0.0348	0.2081	0.0452	0.2508	0.0546	0.2872	0.0631	0.3187	0.0710
	0.6869	0.4397	0.7375	0.6143	0.6480	0.6322	0.5952	0.6985	0.5771	0.6075	0.7588	0.5665
M798	0.6156	0.3060	0.8638	0.2413	0.9874	0.5271	1.1002	0.7759	1.1262	0.9076	1.1840	1.0073
	0.0681	0.0908	0.0973	0.1156	0.1242	0.1221	0.1710	0.1855	0.1845	0.2006	0.1951	0.1908
	0.7411	0.4343	0.6335	0.4016	0.5482	0.4006	0.5287	0.4099	0.5231	0.4423	0.5927	0.4995
M799	0.4942	0.6016	0.7796	0.7854	0.8315	0.7663	0.7134	0.7469	0.8022	0.8783	0.8809	0.9454
	0.1524	0.0702	0.3360	0.2667	0.3658	0.3709	0.3531	0.4220	0.3939	0.4377	0.4815	0.5288

5.3. Experimental Results and Analysis

The initial parameters in SAE algorithm set as: The learning rate is equal to 0.1; the rate of decline is equal to 0.3; cycle number equal to 30. In the algorithm, the hidden layer unit is a feature representation of input data. Therefore, hidden layer unit numbers can be preset to 10, and then increase according to the accurate rate.

Precision (P) is used the as evaluation standard to evaluate the performance of 3D model classification accuracy: $P = \mathrm{a} / (\mathrm{a+b})$, a represents the number of models that has been correctly judgment to the class, b represents the number of models that has been wrongly judgment to the class.

Experiments were taken to compare the algorithm of this paper with several commonly used algorithms; SAE achieved better performance than KNN, NN and SVM on the classification accuracy. The Table 4 lists the average accuracy of several different algorithms.

Table 4. The Accuracy of Four Algorithms

Algorithm	Accuracy (%)
KNN	83.5
NN	77.0
SVM	78.0
SAE	88.0

The number of hidden layer unit has a greater impact on the accuracy of the results of the classification in SAE algorithm. Since the number of the hidden layer unit determines whether the data characteristics can be correctly represent. If the number of the hidden unit layer too little, then the feature vector are mostly 1, only a small part is 0, that unable to correctly describe the characteristic. On the contrary, if the number of elements is too much, the feature vector is too sparse to describe the characteristics of data effectively. It can be seen from the figure that when the input unit is 36 dimensional, the optimal classification results can be get when the hidden units is 25. Then more hidden units will only increase the training time, but will not improve the accuracy of classification. At present, there is no method of quick setting the number of hidden units, only through experience and continue to experiment to find the optimal number of hidden units, and that is the next research direction.

6. Conclusions

A method of SAE based 3D model classification under BIM environment was proposed. Deep learning is a new research direction of Computer Science in the field of machine learning, which commitment to let the machine learning to master the ability to simulate the human learning and analysis, cognate Image, sound and text data. Ray based 3D model feature extraction algorithm was used to extract feature, then combine SAE to classify the models. SAE algorithm was compared with several commonly used the classification method, the experimental results show that, on the premise of large number of samples, SAE algorithm performed better than other classification algorithms.

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