3D Building Model Retrieval for Point Cloud Modeling

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ABSTRACT:

Based on the concept of data reuse and data sharing, a 3D building model retrieval approach is proposed to reconstruct point clouds for cyber city modeling and updating. Thanks to age of Web 2.0, an increasing number of models are available on the website like Google Warehouse. A huge database with a great diversity can be easily constructed from the open sources of these platforms. We aim to build a 3D building model search engine for the demand of following application such as quick modeling instead of those with large time-consuming. Spherical harmonics function is chosen as the shape-descriptor to parameterize the models in low frequency domain. The most similar model can be extracted by matching the parameterized spherical harmonic coefficients between models and input data. Point cloud data obtained by airborne LiDAR is inputted as query to search the similar models from database. Properties of point cloud data with incompleteness and noise is also a challenge to this research. A set of data preprocessing procedures will be executed to optimize the retrieval result. The experiment results show the possibility and flexibility of proposed algorithm to effectively retrieve the fittest model from database.

1. INTRODUCTION

In recent years, the research fields on Geomatics have no longer been limited to traditional land-surveying, topographic map production, and photogrammetry. A significant number of investments have been made in new technologies and equipments, Light Detection And Ranging (LiDAR) is one of them. LiDAR can easily and quickly acquire high-accuracy and high-resolution spatial points. By receiving the reflecting signals from ground truth and from objects on earth, abundant points of information called "point clouds" can be acquired.

A great deal of information, including spatial information, can be easily obtained through the internet because of the concept of Web 2.0. Web 2.0 is not a technical standard, but is a term associated with web applications. Briefly, Web 2.0 is a new way of utilizing the internet, promoting the circulation of information and cooperation using web applications. The core of Web 2.0 is its user-oriented mode. Typical Web 2.0 spots include web communities, web applications, social group websites, blogs, Wiki, and so on. These spatial-information websites allow users to build their own models that they can upload to information-sharing platforms. These models are available to the all users around the world, so the idea of data sharing and circulation can promote the completion of these systems and make them more popular.

The purpose of the current study is to obtain the most identical or the precise building model from these information-sharing communities using the point cloud data. Based on the concept of data reusing, the complete or semi-complete models in the internet were reused instead of being rebuilt. The main idea of current research is to retrieve the best model, in terms of accuracy, from millions of models downloaded from the internet using the point cloud acquired by LiDAR as the query input. Then, an efficiently reconstructing the point cloud using the retrieved models is feasible. Applying the concept to point cloud modeling can be regarded as an efficient method for cyber-city modeling, thus providing the basis for the construction of a realistic 3D city. The current study aims to propose a 3D building model retrieval method that can easily and quickly obtain an expected model with the advantage of information sharing. Compared with the related approaches on city modeling, the proposed approach has the capability to flexibly and efficiently refine a city model.

2. RELATED WORK

In 3D model retrieval, characterizing the similarities between two objects is an important priority. A large number of shape-descriptors are applied in the model retrieval algorithm (Vrani et al. 2001; Funkhouser et al. 2003; Kazhdan et al. 2003). The measurement of similarities between 3D shapes has been extensively studied in several fields, such as computer graphics and medical image analysis.

For 3D-object matching, proposed methods also have limitations. Some methods, such as extended Gaussian images, harmonic shape images, and spin images, usually assume that a topologically valid surface mesh or an explicit volume is available. The other popular model-based approaches first decompose a 3D object into a set of features and then calculate a similarity measure between objects based on the differences between the decomposed parts. The methods based on skeletons and super-quadrics work better when models can be segmented into a canonical set of features, but are prone the effects of small perturbations in the model. Finally, the similarity measurement of shapes requires a simple method for comparison on the basis of statistical properties, using geometric statistics to parameterize the features of models (Osada et al. 2002).

Most of the previously mentioned approaches were proposed in the field of computer graphics, which places greater emphasis on how to successfully retrieve similar shapes with the complete data used for indexing. In the current research, the major problem with the input query is a point cloud date that incompletely represents a 3D shape. In addition, point cloud data have a certain amount of noise, so the obtained point cloud generally loses some parts of the shapes because of the field of view (FOV) when scanning. Therefore, most methods based on different shape descriptors are not suitable for this case.

Spherical harmonic functions represent models in the frequency domain. For the abovementioned problems, least square fitting can easily infer the missing part from the neighboring geometry and can significantly ease noise effect. The spherical harmonic function was selected as the shape descriptor in the proposed algorithm, having rotation-invariant and noise-insensitive properties.

3. METHODOLOGY

In the current thesis, a model retrieval approach is introduced for point cloud modeling. The workflow for the proposed system is illustrated in Figure 1, which consists of three main steps, namely, model encoding, model retrieval, and quality assessment. During model encoding, the models in the database are encoded as spherical harmonic coefficients. Before encoding, a series of preprocessing steps for both the models in the database and the input query, i.e., the point cloud, are performed to optimize the spherical harmonic (SH) encoding and the shape retrieval. Models from the database were retrieved in the second step. The input query is the point cloud acquired from an airborne LiDAR. The coefficients of the point cloud are simply matched with that of the models in the database using the SH coefficients. The similarities between the point cloud and the models are estimated using SH coefficients, and the retrieval results can be obtained by sorting the similarities. During quality assessment, the standard root mean square error (RMSE) is used to measure the quality of the retrieved models.

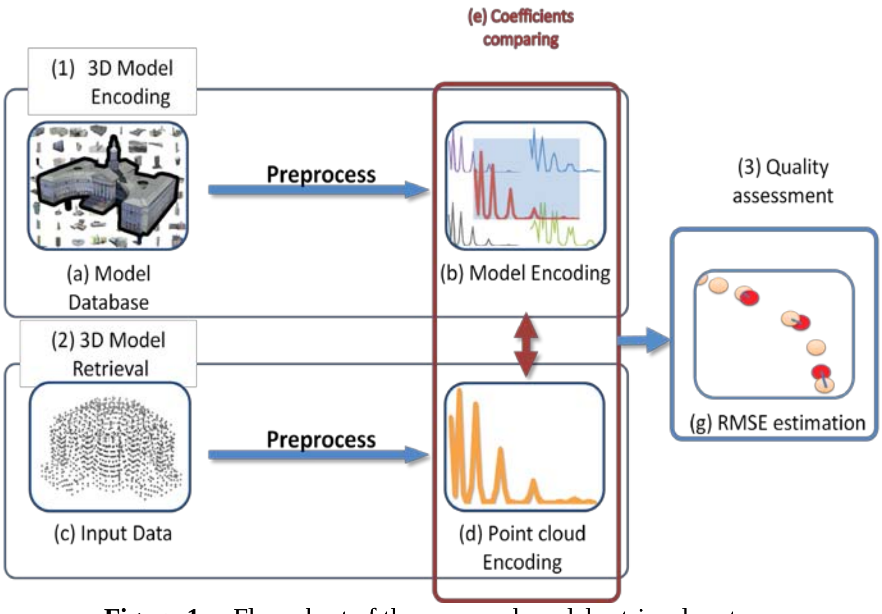


Figure 1. Flow chart of the proposed model retrieval system

3.1 Database Construction

The 3D models in the database were downloaded from Google 3D Warehouse, which can be found in the Google Earth platform. This Web site provides at most 800 spatial distributions of model data in assigned regions (assigned by bbox) by XML*(eXtensible Markup Language). Worldwide model data were collected automatically by changing the value domain of bbox from the XML scanner. A total of 197,359 building models have been automatically download at present, and downloading is still ongoing.

3.2 Spherical Harmonic Functions

The 3D models in the database and the input point clouds are encoded using SHFs, which have the advantages of discrimination, rotation invariance, and insensitivity to noise (Funkhouser et al. 2003).

Spherical harmonic functions are the combination of SH basis functions which are an infinite set of complex function that are continuous, orthonormal, single-valued, and complete on the sphere. SH $Y_l^m(\theta,\varphi)$ of degree l and order m are defined as follows(Shen. et al. 2006):

$$Y_l^m(\theta,\phi)=\sqrt{\frac{2l+1}{4\pi}\frac{(l-m)!}{(l+m)!}}P_l^m(cos\theta)e^{im\phi} \tag{1}$$

where l and m are integers with $|m|\le l$, and P_l^m is the associated Legendre polynomial

Any twice-differentiable spherical function $f(\theta,\phi)$ can be represented by a linear combination of SH $Y_l^m(\theta,\phi)$ as follows:

$$f(\theta,\phi)=\sum_{l=0}^{\infty}\sum_{m=-l}^{l}a_l^m Y_l^m(\theta,\phi), \tag{2}$$

where f is point cloud data or model data in our research; $f(\theta,\phi)$ represents point in point cloud data or model data; a_l^m is unknown which represents the coefficient of basis functions.

For a data with n points and a user-specified maximum degree l_{max}, we can obtain spherical harmonic coefficients through least squares(Brechbuhler et al. 1995):

$$\begin{bmatrix} y_{1,1} & y_{1,2} & y_{1,3} & \cdots & y_{1,k} \\ y_{2,1} & y_{2,2} & y_{2,3} & \cdots & y_{2,k} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ y_{n,1} & y_{n,2} & y_{n,3} & \cdots & y_{n,k} \end{bmatrix}\begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_k \end{bmatrix}=\begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_n \end{bmatrix} \tag{3}$$

where $y_{i,j}=Y_l^m(\theta_i,\phi_i)$, $a_j\equiv a_l^m$, $j=l^2+l+m+1$, and, $k=(l_{max}+1)^2$. n represents the number of points, i.e., observations, and n is not equal to k.

We represent a 3D or point cloud data in spherical coordinate and encoded by spherical harmonics as follows:

$$SH(f)=\left(\{\|a_0^m\|\}_{m=0}^{0},\{\|a_l^m\|\}_{m=-1}^{0},\ldots,\{\|a_{l_{max}}^m\|\}_{m=-l_{max}}^{l_{max}}\right) \tag{4}$$

Once the coefficient are obtained, these values represents models in a feasible way for model retrieval. In the current implement, a user-specified maximum degree l_{max} is set as ten. All the models in database and input point cloud are encoded as 121 SH coefficients. Based on these 121 coefficients, a similarity measurement is computing the difference of these coefficients, and sort for the several ranks in model retrieval.

3.3 Data Preprocessing

Shape descriptor SHFs have been introduced in last section. Apparently, the achievement quality of model retrieval is dependent on the correctness of the encoded coefficients. Some problems occur in terms of the shape parameterization of SHs due to the properties of the SHFs and of both point cloud and model data. In this section, a set of data preprocessing methods is introduced to deal with the models collected from the internet and point cloud data. The problems encountered are comprehensively discussed. Finally, a procedure for data optimization in SH encoding is determined.

3.3.1 Origin Determination

Models have different origin settings attributable to the different constructing customs of each user. Some users may place the origin at the corner of model, whereas other users customarily place the origin at the center of mass or any other place within the model. The problem that was first encountered was the definition of the coordinate origin because such a huge database contains tens of thousands models built by different users. An unexpected retrieval results from the different definitions of origin. Figure 1 shows a simple test on a rectangle model with five different origins to exhibit this property of SH encoding. The five samples are encoded using SHFs, and each distribution is demonstrated to the left of Figure 1. It’s obviously that the five coefficients are quite different due to the variant relationships between coordinate origin and each model, and this will cause the worse results of model retrieval.

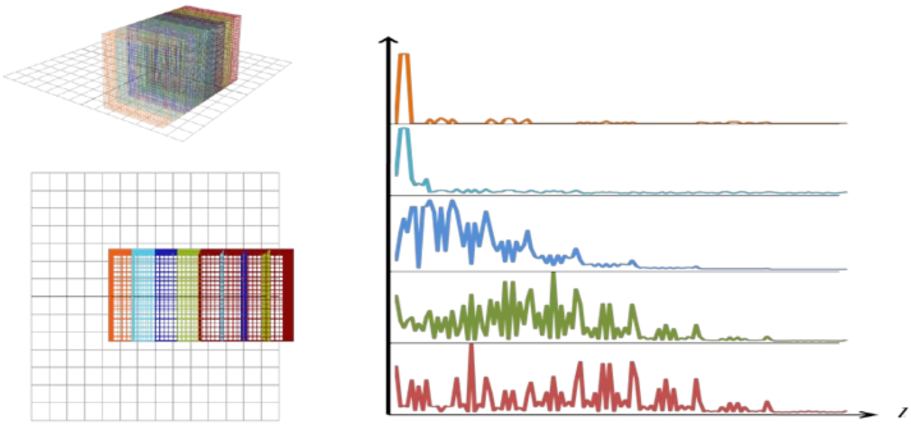


Figure 1. Variation of SH coefficients at different origins. A test is executed for a model with five origins, and the corresponding coefficient distributions reveal the uncertainty of the encoded coefficients.

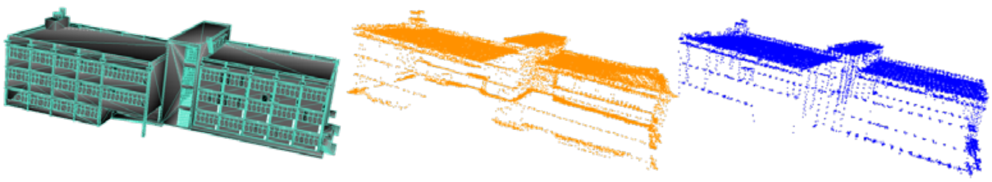
A unified way to define the origin is needed to resolve the problem on one-to-multi SH coefficients. The current study determines the origin based on the center of the bounding box. All the models in the database and input point cloud needs to be redefined the coordinates origin by the stable and general method to ensure the correctness of the SH coefficients representing models and point clouds. This step will make almost the same origin of point cloud and the corresponding models, and thus the expected identical SH coefficients will promote the successful retrieval.

3.3.2 Model Resampling

Models are composed of meshes and vertices. These vertices are the observations of SHFs in Eq. (2) shown in Section 3.2. The unknown coefficients must be solved under the condition that the number of observations is greater than the unknowns because the least square fitting method is used to solve for SH coefficients. Considering that the number of vertices depends on the sophistication of the model, some models with few vertices are sufficiently simple to meet the condition for least square fitting. A model resampling process must be used for all models in the database.

To meet the requirements for the perfect retrieval of a 3D building model, a resampling method should utilize the resampled point cloud as the method for expressing data obtained using an airborne LiDAR. A LiDAR simulator was written to resample models, with the expectation of acquiring a resampled point cloud using the principle similar that used to acquire a real point cloud. The basic concept of LiDAR simulator is to calculate the intersection points between meshes and scanning lines based on parameters containing the initial position, flight length, flight velocity, azimuth, and scanning frequency as real airborne LiDAR. Utilizing these parameters, the scanning intervals can be acquired. Using normal information, each scanning line can intersect all the meshes in this cross-section perpendicular to the flight direction. The resampling also simulate the actual scanning case with four strips to have more dense point information.

Figure 2 shows the resampled point cloud for Department of Geomatics (Dp. of GM) in National Cheng Kung University (NCKU) compared with their real point clouds.



(a) (b) (c)

Figure 2. Comparison between point cloud and resampled point cloud. (a) Model of the Dp. of GM. (b) Point cloud of the Dp. of GM. (c) Resampled point cloud of the Dp. Of GM

3.3.3 Point Cloud Repairing

In Section 3.3.2, the accurate SHs coefficients can be obtained by resampling model using a LiDAR simulator. A phenomenon of point deficiency which exists in the both point clouds and resampled point clouds may affect the SH coefficients. This fact is the fundamental problem causing point cloud incompleteness attributable to scanning occlusion and data breakage, which are the primary difficulties faced in the current research.

The expansion into SH represents a spectral decomposition in file structures corresponding to a resolution of 180/l (Physical geodesy, 2006). Correct SH coefficients are resolved under the rule of resolution because of least square fitting. A point cloud deficiency will lead to the incorrect resolution of SH coefficients. To solve this problem, the missing parts of all the input point clouds and resampled point clouds have to be repaired based on the properties and the resolution rule of SHFs.

In this process, the radius of the building representing degree one of the SH coefficient must be first determined. Radius r is determined by the maximum distance from the points to the origin, and then all the points are transformed into spherical coordinates. A threshold *i* must be set to divide a sphere with radius r into (360/*i*)*(360/*i*) grids. The proposed system sets l_{max} as 10, so the resolution will meet the rule with 18*18 grids. A dense 60*60 grid with intervals of six is chosen for more redundancies to solve SH coefficients in this step. All the grids must have at least one point to ensure the correctness of the SH coefficients. Otherwise, a point is added to the blank grid (θ, ϕ). After refilling the grids, the process is reverted back to the Cartesian coordinate system, and point repairing is completed.

Figure 3 shows the repaired point cloud compared with the original point cloud of the Department of Mechanical Engineering (DP. of ME) in NCKU, as well as the corresponding coefficient distributions. The coefficient distributions are obviously different after repairing, which also proves that the resolution of point distribution would affect the SH coefficients.

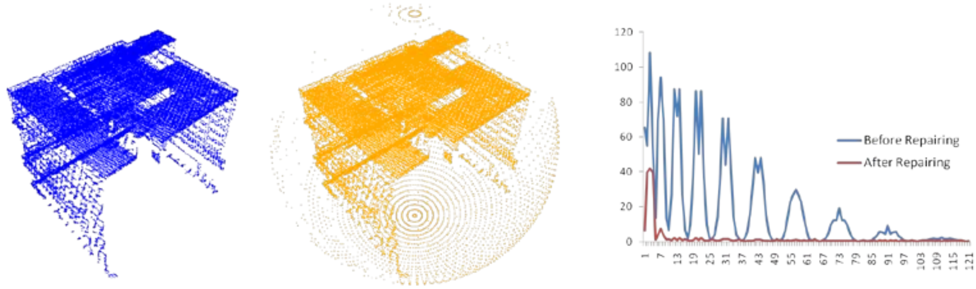


Figure 3. Comparison of point repairing and coefficients. (a) Point cloud of the Dp. of ME. (b) Repaired point cloud of the Dp. of ME. (c) Comparison of coefficients of the Dp. of ME.

4. EXPERIMENT

4.1 Experimental data

A small experimental database comprising 1423 models, 1403 randomly selected models and 20 models corresponding to input point clouds, was used to conduct the experiments on building model retrieval. All of the input point cloud data, which contains 17 point clouds, are airborne LiDAR data obtained from the NCKU Photogrammetry and Remote Sensing Laboratory of the Department of Geomatics.

4.2 Model retrieval

Figure 4 shows some retrieval results and the corresponding RMSE values of each retrieved ranks, and the perfect retrievals are marked with a red star.

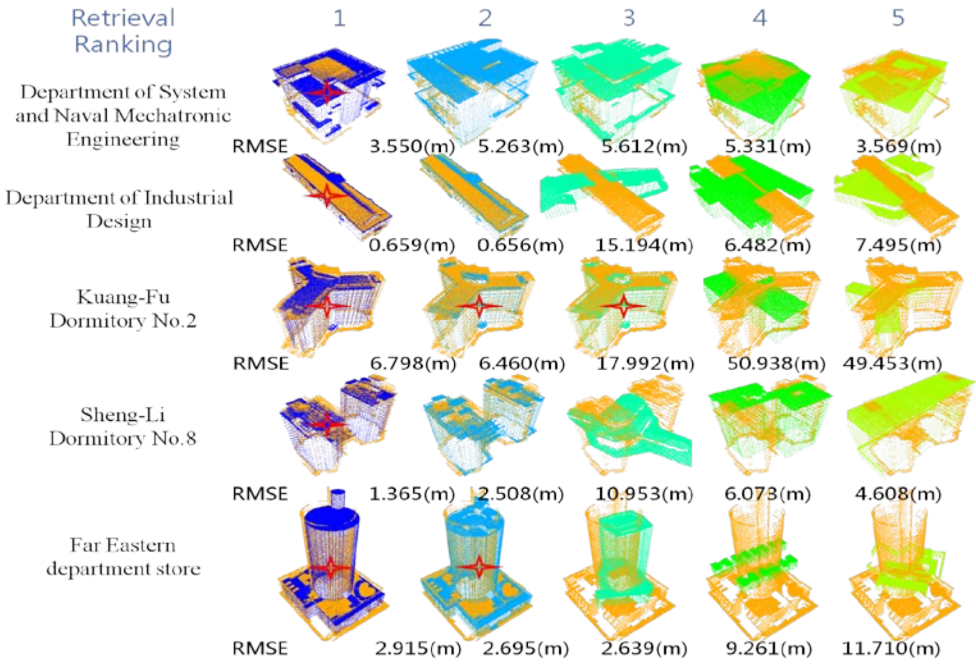


Figure 4. Retrieval Results from 5 input point clouds and RMSE of each retrieved ranks.

Among the seventeen cases of building retrieval, eleven models were perfectly retrieved, and four were within the first three ranks, whereas one falls into rank no. 5, and one retrieves nothing. As shown in Figure 5, except retrieving the expected models, most of the retrieved models in other ranks are in accordance with the shape and size of the input point cloud by the proposed method. On the other hand, only four exact models are retrieved in rank no.1 without the optimization step of point cloud repairing.

5. CONCLUSION

The current thesis introduced a novel 3D building model retrieval algorithm based on the concept of data reusing for the efficient modeling of point clouds acquired from an airborne LiDAR. A database containing abundant massively 3D models has been constructed by automatically downloading models in the information-sharing platform, Google Warehouse. This database provides the basis for the successful retrieval of the most suitable models.The proposed approach utilizes SHFs as shape descriptors to represent 3D models and point clouds into a set of coefficients. Using these coefficients, the similarity between models and input point clouds can be easily obtained by matching the coefficients.

In the current research, the greatest difficulty is dealing with point clouds that have the inherent characteristics of incomplete shape and noise. The resolution of this problem is the main contribution of the proposed approach compared with the related methods for 3D model retrieval. Optimized preprocessing were proposed to mitigate these problems. The model retrieval results and the analysis of each data preprocessing step demonstrate the capability of the proposed approach for retrieving models from a huge database and the flexibility of the turning parameters to meet various requirements of input. From the experiments discussed in Section 4, the proposed algorithm was shown to effectively mitigate the difficulty of handling point clouds and was found to have good performance in terms of 3D building model retrieval.

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