Point cloud and BIM model registration based on genetic algorithm and ICP algorithm

Chun Liu¹, Meijing Guang¹ and Shanshan Yu¹∗

¹ School of Computer, Hubei University of Technology, Wuhan, Hubei, 40068, China
∗Corresponding author’s e-mail: 101900704@hbut.edu.cn

Abstract. With the rapid development of the construction industry, BIM technology, and 3D laser scanning technology are being used more and more widely, and there are many applications of combining BIM technology with 3D laser scanning technology, such as quality inspection, progress inspection, or digital preservation of ancient buildings. Therefore, this paper proposes a 3D point cloud and BIM model registration scheme based on genetic algorithm and ICP algorithm, firstly, the point cloud data is pre-processed by statistical denoising method for denoising and downsampling, and the BIM model data is converted to format data; then the coarse registration is performed by genetic algorithm, and the accurate registration is performed by ICP algorithm based on KD-tree, and finally, we experimentally verify the feasibility of the algorithm in this paper, and compared with the ICP algorithm, the registration efficiency and accuracy of the algorithm in this paper are greatly improved.

1. Introduction

With the continuous acceleration of urbanization and urbanization, the construction industry has developed rapidly. In the context of the information age, BIM (Building Information Modeling), as the integration of building information, has the characteristics of visualization, coordination, modeling, and complete information. In practical applications, it can effectively improve work efficiency, reduce costs, and have a high degree of visualization. However, the BIM model is a simulation model based on design parameters, and there are often certain differences between the complex real buildings, and they cannot reflect the actual details of the building. Three-dimensional laser scanning technology can achieve a good representation of the actual situation of the building [1], but the point cloud data produced will have a lot of noise. Therefore, the combination of BIM technology and 3D laser scanning technology can have a comprehensive understanding of buildings and can be applied to building quality inspection, progress inspection, or digital protection of ancient buildings.

This paper intends to perform registration analysis on the BIM model and the point cloud data obtained by the 3D laser scanner based on the two-step registration algorithm. The method flow is shown in Figure 1. The method mainly includes (1) data preprocessing, obtaining entity object data and model Object data, point cloud denoising, model data conversion; (2) 3D point cloud and BIM model registration, using genetic algorithm for coarse registration[2] and ICP algorithm to achieve accurate registration; (3) result evaluation to obtain registration result.
2. Related work
In the study of registration method[3], Besl proposed a classic registration algorithm in 1992, called Iterative Closest Point (ICP) algorithm[4]. The traditional ICP registration algorithm has a large amount of calculation, slow convergence speed, and high requirements for the initial position of the point cloud data to be registered[5]. Gelfand[6] et al. proposed an improved ICP algorithm, but the calculation is large and lowly efficiency; Pentland[7] proposed a registration method based on principal component analysis PCA, which speeds up the registration through data dimensionality reduction; Silva[8] and others proposed that genetic algorithm can be used to achieve one-step registration of point clouds, but it is easy to fall into local convergence; Kim[9] et al. matched the point cloud with the CAD model, but the requirements for the model were too high; Bosch[10] proposed a method of 3D laser scanning and 3D building model registration, but it could not be detected. In view of the fact that the above registration methods are not very suitable for the registration of 3D point clouds and BIM models, this paper proposes a point cloud and BIM model registration method based on genetic algorithm and ICP, which can be greatly improved in accuracy and speed at the same time.

3. 3D Point cloud and BIM model registration

3.1 Data preprocessing

3.1.1 BIM format conversion
Because the BIM data format is different from the 3D point cloud data format, it is difficult to perform registration comparisons. Therefore, data conversion of the BIM model is required, and the intermediate format DWG is converted to the STL format. The STL format file consists of the definitions of multiple triangular faces. The definition of each triangular face includes the three-dimensional coordinates of each fixed point of the triangle and the normal vector of the triangular face. The data format required for registration can be obtained by reading the vertices of each triangular patch. The specific process is shown in Figure 2:
3.1.2 Point cloud denoising
A large number of noise points are produced in the process of obtaining point cloud by laser scanner[11]. Therefore, the next step of registration can only be performed after denoising processing. Messy point clouds and discrete points can be directly deleted manually. Other noise points can be statistically denoised[12] to calculate the average distance and standard deviation from each point to the neighboring point.

Statistical denoising method: For the point cloud with noise, set the point cloud set as \( P = \{P_1, P_2, P_3, \ldots, P_n\} \), the point set at any point \( P_i = (x_i, y_i, z_i) \), \( i = (1,2,3,\ldots,n) \), and the set of neighboring points as \( P_j \in Nbhd(P_i) \), \( j = (1,2,3,\ldots,n) \), and calculate the Euclidean distance from \( P_i \) to each point in the neighborhood \( Nbhd(P_i) \). The average value is recorded as \( d_i \). In the statistical denoising method, it is assumed that the Gaussian distribution of \( d_i \) is obtained, and its shape is determined by the mean \( \mu \) and the standard deviation \( \sigma \),

\[
\mu = \frac{1}{N} \sum_{i=1}^{N} d_i \tag{1}
\]

\[
\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (d_i - \mu)^2} \tag{2}
\]

In the formula: \( N \) is the number of point clouds, and \( d_i \) is the average value of the Euclidean distance between \( P_i \) and neighbor \( Nbhd(P_i) \). In the statistical denoising method, the standard range \( [\mu - \alpha \cdot \sigma, \mu + \alpha \cdot \sigma] \) is calculated by setting the number of point clouds \( K \) and the multiple \( \alpha (\alpha = 0,1,2,\ldots) \) of the standard deviation to improve the denoising effect. If the average value \( d_i \) of the Euclidean distance between \( P_i \) and \( Nbhd(P_i) \) in the neighborhood is not within the standard range, the corresponding point will be regarded as a noise point and will be automatically deleted; otherwise, the point will be kept. The denoising effect is shown in Figure 3. Because the amount of point cloud data is too large, the denoised point cloud data is down-sampled at even intervals in order to facilitate the calculation.

Figure 3. (a) Original point cloud (left window) (b) Point cloud after denoising (left window) (c) Original point cloud (right window) (d) Point cloud after denoising (right window)

3.2 Point cloud and BIM model registration

3.2.1 Coarse registration
The genetic algorithm is an excellent random search global optimization algorithm proposed by Holland in the 1960s[13]. The main operations are selection, crossover, and mutation operations [14] to find the optimal rotation and translation matrix. The selection operation is to select \( N \) chromosomes from the parent population as the offspring evolve. The chance of each individual being selected should be proportional to the fitness. The higher the fitness, the greater the probability of being selected. The expected value selection algorithm is used to ensure that individuals with greater fitness have a higher probability of being selected as offspring to evolve. Copy \( \sum M_i \) individual directly to the next generation

\[
M_i = \left\lfloor \frac{F_i}{\sum_k F_k} \times N \right\rfloor \tag{3}
\]
In the formula, $F_i$ is fitness value of the $i$-th individual. The remaining fitness value after copying is

$$F_i' = F_i - \sum_k F_k \times \frac{M_i}{N} \quad (4)$$

All remaining fitness values are used to randomly select the remaining $N - \sum M_i$ individuals according to the fitness ratio. The crossover operation generates two new individuals through the operation of the two chromosomal genes of the previous generation with crossover probability $P_c$. The mutation operation and mutation probability $P_m$ change the value of one or more genes of the chromosome to generate new individuals.

The individuals with the highest fitness are retained and copied to the next-generation group\cite{15}. The fitness value calculation and genetic operations are carried out iteratively to jointly complete the evolution process of genetic algorithms. The termination condition of genetic algorithm evolution needs to satisfy at least one of the following two conditions:

1. Maximum algebra $T_{\text{max}}$: terminate when the evolutionary algebra reaches $T_{\text{max}}$;
2. Fitness threshold $F_{\text{thr}}$: stop when the fitness of the optimal individual reaches the given threshold $F_{\text{thr}}$ or the fitness values of the optimal individual of two adjacent generations are equal;

The essence of registration is the rigid conversion process of the coordinate system through translation and rotation. The geometric relationship (Euclidean transformation) between the models $P$ and $Q$ to be registered can be represented by six parameters, which are defined as chromosomes. Each parameter corresponds to a gene in the chromosome\cite{16}. The corresponding relationship is shown in Table 1:

| Translation Genes | Parameter | Rotation Genes | Parameter |
|-------------------|-----------|----------------|-----------|
| x-axis translation | $T_x$     | x-axis rotation | $\alpha$ |
| y-axis translation | $T_y$     | y-axis rotation | $\beta$ |
| z-axis translation | $T_z$     | z-axis rotation | $\theta$ |

3.2.2 Accurate registration

The ICP algorithm is used for accurate registration. The purpose of the ICP algorithm is to find the rotation parameter $R$ and the translation parameter $T$ between the point cloud data to be registered and the reference cloud data \cite{17}. Match each point with the closest point of the target cloud, so as to meet the prerequisites of ICP algorithm, and each point has a corresponding mapping point \cite{18}. The basic principle of the ICP algorithm is to use the least-squares optimization idea \cite{17} to obtain the registration matrix between the point clouds by calculating $R$ and $T$ that minimize the following functions:

$$F(R, T) = \sum_{i=1}^{N} || Q_i - (RP_i + T)||^2 \quad (5)$$

Where $P_i$ is the initial point set of the source data; $Q_i$ is the closest point corresponding to $P_i$ in the target data point set; $R$ is the $3 \times 3$ rotation matrix; $T$ is the $3 \times 1$ translation vector. $F(R, T)$ represents the sum of squared distances between each point in the source point set and the corresponding point in the target point set after the source point set is rotated and translated. When $F(R, T)$ reaches the minimum, it meets the requirement of least squares. In the paper, KD-tree (K Dimension tree) \cite{19} is used for nearest neighbor search to improve the search speed of corresponding points. The time complexity of the improved ICP algorithm added to the KD-tree is $O(N \log N)$, while the time complexity of the original ICP algorithm is $O(N^2)$. Obviously, using KD-tree to find the corresponding points can significantly improve the registration speed of the original ICP algorithm.

4. Experimental analysis

The experimental data in this paper uses Trimble SX10 to scan the building structure point cloud and design model of an embedded artificial intelligence laboratory of a university as the research object to
verify the feasibility and accuracy of the algorithm. The main shape is the ceiling and the windows and walls on both sides. The original point cloud data and BIM model data are shown in the figure.

![Image](figure4.png)

Figure 4. Original 3D point cloud (left) and BIM model (right)

After point cloud preprocessing and BIM model conversion, the number of point clouds to be registered for point cloud \( P \) is 44487, and the number of points after model \( Q \) conversion is 42463. The experiment uses an Intel Core i7-4510U 2.00GHz processor, a notebook computer with 8GB of memory, and compares it with the traditional ICP algorithm and genetic algorithm for verification.

\[
\begin{bmatrix}
0.869 & 0.336 & -0.362 & -17.402 \\
-0.081 & 0.821 & 0.566 & 4.959 \\
0.488 & -0.462 & 0.740 & 0.992 \\
0 & 0 & 0 & 1
\end{bmatrix}
\] (6)

\[
\begin{bmatrix}
0.852 & 0.444 & -0.277 & -17.984 \\
-0.191 & 0.757 & 0.625 & 7.993 \\
0.488 & -0.479 & 0.730 & 1.031 \\
0 & 0 & 0 & 1
\end{bmatrix}
\] (7)

The above is the transformation matrix obtained by the ICP algorithm and our algorithm during registration, including the rotation matrix \( R \) and the translation matrix \( T \). Table 2 shows the results of the ICP algorithm and our algorithm during registration. Our algorithm in this paper exceeds the ICP algorithm in the number of iterations, registration errors, and registration time. The registration effect is shown in Figure 5 and Figure 6.

![Image](figure5.png)

Figure 5. ICP registration results (left) and Our algorithm registration results (right)

![Image](figure6.png)

Figure 6. ICP registration window results (left) and Our algorithm registration window results (right)
The results of the experiment are shown in Table 2. Therefore, our algorithm has a great improvement in global search and very local search, improves the registration accuracy and convergence speed, and makes the registration more efficient.

| Algorithm   | Iteration times | Registration error/cm | Registration time/s |
|------------|-----------------|-----------------------|---------------------|
| ICP        | 27              | 0.929                 | 46.632              |
| GA+ICP     | 13              | 0.243                 | 15.863              |

5. Conclusion

Aiming at the registration between the 3D point cloud and the BIM model, this paper proposes the genetic algorithm coarse registration and the ICP algorithm accurate registration method, which can complete the registration work well, including the preprocessing of the point cloud and the data of BIM model. The improvement of the genetic algorithm enable the coarse registration and the accurate registration to cooperate well, so the registration accuracy and convergence speed have been greatly improved, and it can be better applied to various scenarios.

References

[1] Golparvar Fard, A., et al. (2011) Evaluation of image-based modeling and laser scanning accuracy for emerging automated performance monitoring techniques - ScienceDirect. J. Automation in Construction., 20: 1143-1155.
[2] Salvi J, Matabosch C, Fofi D, et al. (2007) A review of recent range image registration methods with accuracy evaluation. J. Image and Vision computing., 25: 578-596.
[3] Pottmann H, Leopoldseder S, Hofer M. (2004) Registration without ICP. J. Computer Vision and Image Understanding., 95: 54-71.
[4] Besl P J, McKay N D. (1992) Method for registration of 3-D shapes. C. Sensor fusion IV: control paradigms and data structures. International Society for Optics and Photonics., 1611: 586-606.
[5] Yang J, Li H, Campbell D, et al. (2016) Go-ICP: A globally optimal solution to 3D ICP point-set registration. J. IEEE transactions on pattern analysis and machine intelligence., 38: 2241-2254.
[6] Gelfand N, Mitra N J, Guibas L J, et al. (2005) Robust global registration. C. Symposium on geometry processing., 2: 5.
[7] Pentland A P. (2009) Local shading analysis. J. IEEE Transactions on Pattern Analysis and Machine Intelligence., 6: 170-187.
[8] Silva L, Bellon O R P, Boyer K L. (2005) Precision range image registration using a robust surface interpenetration measure and enhanced genetic algorithms. J. IEEE transactions on pattern analysis and machine intelligence., 27: 762-776.
[9] Kim C, Son H, Kim C. (2013) Fully automated registration of 3D data to a 3D CAD model for project progress monitoring. J. Automation in Construction., 35: 587-594.
[10] Bosché F. (2012) Plane-based registration of construction laser scans with 3D/4D building models. J. Advanced Engineering Informatics., 26: 99-102.
[11] Cheng L, Chen S, Liu X, et al. (2018) Registration of laser scanning point clouds: A review. J. Sensors., 18: 1641.
[12] Rusu R B, Marton Z C, Blodow N, et al. (2008) Towards 3D point cloud based object maps for household environments. J. Robotics and Autonomous Systems., 56: 927-941.
[13] Gao R, Zhang J, Shang Y, et al. (2012) An Improve Genetic Algorithm Based on Fixed Point Algorithms. J. Journal of Computers., 7: 1109-1115.
[14] Brindle A. (1980) Genetic algorithms for function optimization. J. Alberta: University of Alberta.
[15] Forrest S. (1996) Genetic algorithms. J. ACM Computing Surveys (CSUR)., 28: 77-80.
[16] Chow C K, Tsui H T, Lee T. (2004) Surface registration using a dynamic genetic algorithm. J. Pattern recognition., 37: 105-117.

[17] Xu G, Du S, Xue J. (2016) Precise 2D point set registration using iterative closest algorithm and correntropy. In: International Joint Conference on Neural Networks. New York. pp: 4627-4631.

[18] Masuda T, Sakaue K, Yokoya N. (1996) Registration and integration of multiple range images for 3-D model construction. In: Proceedings of 13th international conference on pattern recognition. Vienna, Austria. pp. 879-883.

[19] Vanco M, Brunnett G, Schreiber T. (1999) A Hashing Strategy for Efficient k-Nearest Neighbors Computation. In: Proceedings Computer Graphics International CGI-99. Canmore, Alta. Canada. pp. 120-128.