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Multi-Source and Multi-Dimensional Data Fusion of Magnetic Levitation Track Transportation Based on Digital Twin

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Abstract. Digital twin (DT) of large-scale transportation infrastructure plays an important role in the development of intelligent transportation system (ITS), and has become the current research hotspot of ITS. Traditional data fusion has done a lot for intelligent transportation infrastructure. However, it still exists many shortcomings. This paper aims at establishing a multi-source and multi-dimensional data fusion model of magnetic levitation track based on digital twin. We proposed a data fusion method that can fuse 2D image data and 3D LIDAR point clouds data together, by using Context Capture and Cloud Compare software. This method combines data advantages so that we can optimize the expression of fine particle accuracy. Firstly, we made the aerial triangulation for the image data that was collected with drone, and then reconstructed the dense point clouds and generated the colorful point clouds; next, we fused the colorful point clouds with the LIDAR point clouds data that has been data processed; and finally, we generated the model and accomplished the fusion process of magnetic levitation track model. We compared the digital twin model with the benchmark model from macroscopic to microscopic perspective, the verification results indicated that the error of track flatness is about one centimeter, and the mean distance between the two models is about 0.124 meters, so the digital twin data fusion model fits well.

Keywords: Magnetic Levitation; LIDAR Point Clouds; Digital Twin

1 Introduction

In recent years, big data, Internet, artificial intelligence (AI) and other new technologies make a deep integration with the transportation industry could be an important trend to accelerate the integration and development of physical transportation infrastructure and cyberspace networks.

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The Internet of Things (IOT), 5G, Building Information Model (BIM), Bei Dou Navigation Satellite System (BDS) and other new technologies have put forward new and higher requirements for the innovative development of railroads in the age of intelligent, which have attracted the attention of governments, railroad transportation enterprises and related research institutions around the world. Magnetic levitation as a large-scale transportation infrastructure is responding to the development of the situation by embedding AI, multi-source and multi-dimensional data fusion, DT and other technologies into the physical world of magnetic levitation transportation construction.

At present, the development and construction [1] of magnetic levitation track transportation has become the research importance of the world, domestic and foreign scholars research on the guiding method [2] of magnetic levitation track, track structure [3-4] and other key technologies [5-7] still maintain a continuous growth trend. In the recent five years, some company launched large-scale project for the construction of a magnetic levitation track, and made effective progress, such as U.S. HTT company in 2018 and China Motor Sifang CoLtd in 2020. However, constructing intelligent magnetic levitation track is still in the preliminary development stage, with the promotion of advanced ITS, the construction of intelligent magnetic levitation track has a long-term and broad prospect.

In this paper, we aim at fusing the 2D image data with the 3D point clouds data to establish a multi-source and multi-dimensional data fusion of the magnetic levitation track model based on DT. We first established a 3D reconstruction model from the collected photographic object by using Context Capture software. This reconstruction model needs the 2D image data and the position information from oblique photography technology of drone. By using Context Capture software, we merged these data into aerial triangulation in Fig. 1, and acquired feature points and dense point clouds, then the dense point clouds could be reconstructed to obtain the 3D reconstruction model. Then, we obtained the multi-dimensional colorful point clouds, which is first generated by the 3D reconstruction model.

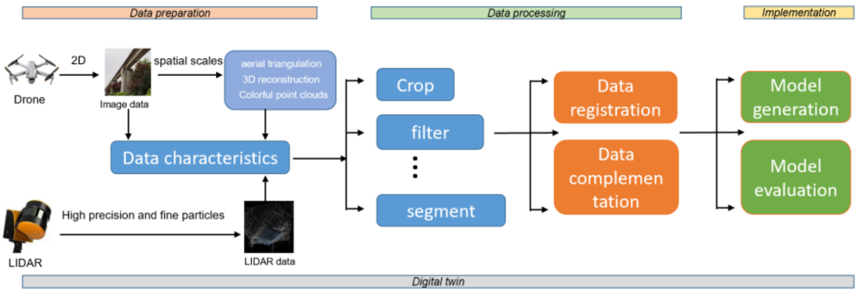


Fig. 1. The research structure of multi-source and multi-dimensional data fusion model.

Then the colorful point clouds and the LIDAR point clouds made the data registration for the preliminary data fusion. However, the colorful point clouds and LIDAR point clouds obtained at this time are both unprocessed point clouds data, so we applied Cloud Compare software to crop, filter, segment, and accurately segment the point clouds data, and then registered these two data; then we deleted and complemented the colorful point clouds and LIDAR point clouds according to their data advantages and disadvantages respectively, the advantage of the part will be complemented, then we merged the processed data into a new point clouds in Fig. 1.

Lastly, we generated the model with the merged point clouds in Fig. 1, and formed the multi-source and multi-dimensional data fusion magnetic levitation track model, and compared the accuracy of the digital twin model points with the benchmark model points, and verified the effectiveness of digital twin model from the three aspects, they are model performance, magnetic levitation track flatness and model fitting effect. The final results have shown that the track flatness error of the digital twin model is about one centimeter, and the fitting mean distance of the two models is 0.124 meters, so the model fit effect meets the requirements and it was verified valid. All above data was collected in the traffic scene of the magnetic levitation test line track of Tongji University in Shanghai.

2 Literature Review

This section briefly introduces the state-of-the-art research status and directions of digital twin and point clouds and image data fusion, and the focus direction of this paper.

2.1 Digital Twin

Digital Twin (DT) was proposed by Professor Grieves [8] in 2002 for product life-cycle management. This initial conceptual model included physical products in real space, virtual products in virtual space, and data and information connections that bridge the two spaces. Subsequent developments in DT theory have also refined and supplemented around this basic model. The NASA definition of the DT reflects its elements and purpose. The elements of the DT [9] include multi-physics field, multi-scale, probabilistic system simulations that use optimal simulation of the system, sensor updates, historical information, etc., with the purpose of mirroring the entire life cycle of the physical twin. Tao Fei et al [10]. in 2018 elaborated the future research scenarios of DT and the current problems to be solved; in 2019, they also proposed the five-dimensional model [11] of DT, which adds two aspects of service and twin data compared with the previous three-dimensional model of physical entity, virtual entity and the connection between these two. In rail transportation direction, Li Feng et al [12]. study the BIM-based track transportation operation management system, the information sources of DT (including information collection from on-board equipment and trackside equipment), elaborate the data processing system, and the data transmission channel, system linkage, etc.

We have compiled the progress of DT development as shown in Fig. 2.

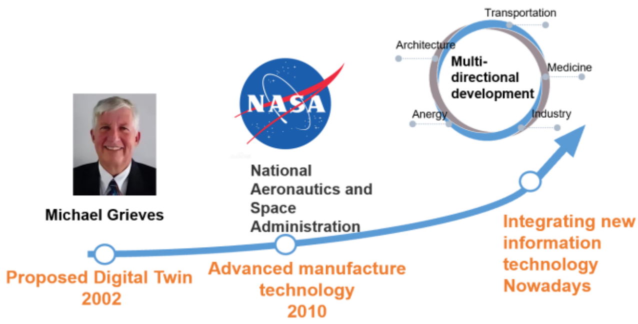


Fig. 2. The evolution of digital twin development.

2.2 Point Clouds and Image Data Fusion

The extensive research in the fields of Cooperative Vehicle Infrastructure System (CVIS), ITS and autonomous driving make the connection between transportation infrastructure and the cyberspace gradually deepen. Data only from a single sensor makes getting higher accuracy in the data detection and the perception of traffic environment more difficult. Therefore, many research scholars have achieved great results on object detection as well as traffic environment perception by fusing 3D data from LIDAR point clouds with 2D image data.

Data fusion technology has been developed into several directions, such as the widely used field of CVIS, depth completion [13], dynamic target detection [14], static road recognition [15-16] (including route recognition and road sign recognition), etc. Data fusion's research methods are also in full bloom. Many scholars have optimized the deep learning algorithms and modified the algorithm parameters to achieve the goal of making the point clouds and image fusion better. Some recently proposed algorithms such as Point-Net [17], ResNet [18-19], RetinaNet [20] are optimized. In this paper, we analyzed the fusion methods and selected the widely used feature-level fusion methods to introduce the current research status of 3D point clouds and 2D image data fusion.

1) Feature-level fusion.

Eldesokey, A., et al [21]. integrating structural information to study fusion strategies, combining depth and RGB information in a normalized convolutional network framework; Schlosser, et al [22]. integrating LIDAR data by sampling to a dense depth map on point clouds and extracting three features representing different aspects of the 3D scene; C.Y. Wang, et al [23]. extracting image and point clouds data separately by Vgg16 network with 3 depth features at different resolutions, and use a combination of feature concatenation and 1×1 convolution to achieve the fusion of the same resolution features of both data. The data fusion methods used in this paper are essentially a feature-level fusion method, in which the dense point clouds presented after the aerial triangulation processing of image data is matched according to the image features. Data complementation is the process of feature filtering by cloud compare software based on the feature advantages and disadvantages of the point clouds and image data. There are also various fusion methods such as multi-level fusion [24-25], signal-level fusion [26-27] and result-level fusion [28-29].

Nowadays, LIDAR point clouds and image data fusion methods have been very effective in many fields, and the data fusion quality of physical components is very high, and the expression of high-precision information is very effective. However, the data fusion of LIDAR point clouds and image data has not yet achieved typical application results in the micro-expression of major infrastructure and the expression of fine particle accuracy. In this paper, we adopt the method of LIDAR point clouds and image data fusion to explore and research the large-scale infrastructure transportation facilities with prominent geometric characteristics, such as magnetic levitation, and we are devoted to make some exploratory progress in the field of digital twins for related fields, such as urban construction, land resources and other infrastructure researches.

3 Point Clouds and Image Data Fusion Methods

3.1 Point Clouds and Image Data Characteristics

In this paper, we acquired the 2D image data from the Mini-Scan quadcopter drone with WIC-61MP cameras, using the oblique photography method, and obtained the 3D point clouds data by LIDAR from the zeb horizon model of GEO SLAM company, and the collection object is the whole route of the magnetic levitation track, where at Tongji University, Shanghai, in China.

Two-dimensional image is a flat image that does not contain depth information. Two-dimensional means left, right, top and bottom four directions, there is no front and back, only area and no volume. The method of acquiring 2D image data comes from camera, and the method of oblique photography is currently extensively used to acquire image data in the field of real-world modeling. The oblique photography technique is realized by aerial survey system, which consists of different types of drones and sensors [30]. Based on the advantages of the aerial survey system, we could obtain comprehensive information on the location and attitude of surface features. Therefore, we are aware that the quality of vertical and oblique photography image data is relatively high, and in the magnetic levitation track image data of this paper, the data quality of both above the track surface and side of the track are great, but below the track is low, that is because the angle of oblique photography could not completely capture that.

The LIDAR system scans the surface of the magnetic levitation track to obtain the 3D coordinates of the reflected points, and each reflected point is distributed in 3D space, called scanning points. Since the point clouds data are collected on the road surface with handheld LIDAR in this paper, the quality of point clouds data below and beside the magnetic levitation track are higher, while the data on the upper surface of the track are of lower quality. The graphical explanation is depicted in Fig. 3.

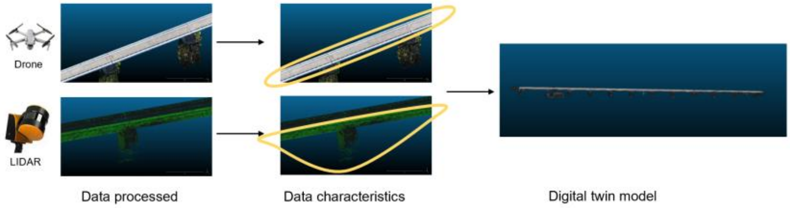


Fig. 3. Point clouds and image data characteristics. The yellow curves mark the data advantages.

3.2 Image Data to Generation Color Point Clouds

1) Feature-level fusion.

We firstly input the 2D image data and its position coordinates from the oblique photography into the Context Capture software, and the position coordinates information include the latitude, longitude and altitude at the time of photography. After adding parameters such as sensor size and focal length, we performed the aerial triangulation (AT) process. The AT could get the dense point clouds linked by the feature points information through the operations of image component, positioning mode and control task. However, the process of AT has a high failure rate, we have done this step many times, analyzing and modifying the parameters, and finally we got a successful dense point clouds by matching feature points. Fig. 4a shows the simulated feature point coordinates of the failed AT case; while Fig. 4b shows the successful (of this paper) case, it can be seen that the coordinates of the model feature points are in line with the overall trend of the track, and the initial trend of the model is better.

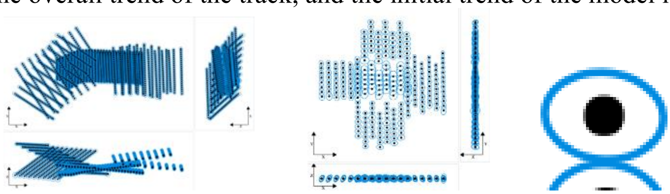
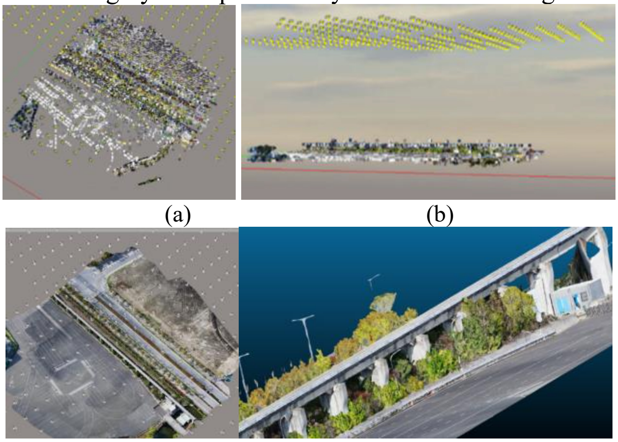


Fig. 4. Example of a figure caption. Feature points coordinates. (Top view (XY plane), side view (ZY plane) and front view (XZ plane) of computed photo positions (black dots). Blue ellipses in Figure 2c show the position uncertainty).

2) Dense Point Clouds.

After AT, we acquired the model with dense point clouds, and the contours and features of the physical objects are clearly reflected, so that the shape of the digital twin model can be understood initially, we could judge if the model fusion method is correct quickly. Fig. 5 shows the collective state presented by the dense point clouds of the oblique photography image data, from the top view and the front view respectively, and we could roughly see a preliminary formed track at higher level.



(a) (b) (c) (d)

Fig. 5. Three-dimensional reconstruction process of magnetic levitation track. (a) top view of dense point clouds; (b) front view of dense point clouds, we can see the initial shape of the track at higher level; (c) top view of 3D model; (d) colorful point clouds figure.

3) Three-Dimensional Reconstruction and Generate Color Point Clouds.

We adopt the method of adaptive block-cutting and set the filling holes, colors, textures and so on, to reconstruct the 3D track model as shown in Fig. 5c, these operations are all handled by the Context Capture software, and then we generated colorful point clouds from the reconstructed 3D model as shown in Fig. 5d. These colorful point clouds reserve the color characteristics of the image data, so we obtained the first apart of multi-source and dimensional data preparation.

(a) (b)

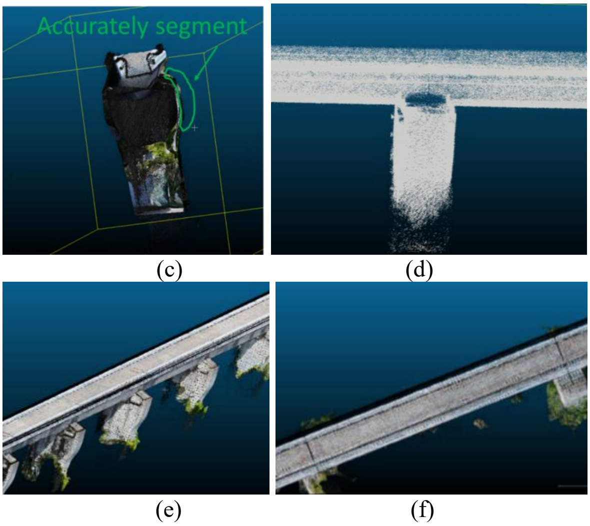


Fig. 6. Three-dimensional reconstruction process of magnetic levitation track. (a) top view of dense point clouds; (b) front view of dense point clouds, we can see the initial shape of the track at higher level; (c) top view of 3D model; (d) colorful point clouds figure.

3.3 Point Clouds Data Processing

The point clouds data processing above both colorful point clouds and LIDAR point clouds process. These two kinds of point clouds data processing are carried out in parallel and use similar methods, so this paper only introduces the steps of LIDAR point clouds data processing. The main functions include crop, segmentation, accurately segment and data filter.

1) Data Segmentation.

We firstly cropped point clouds data as shown in Fig. 6a, this step could get the part of point clouds data that we want to fuse, and they were extracted from the whole scanned magnetic levitation track point clouds data; according to the characteristics of track model above, we then segmented other point clouds on both sides of the track, such as arch bridges, rivers and other long-distance obstacles as shown in Fig. 6b; lastly, we accurately segmented obstacles around the track that are more difficult to separate, such as shrubs, street lights, etc. as shown in Fig. 6c. And this step requires certain technical skills, such as contouring segmentation from the side of the track, accurately segmentation from the lateral direction of the track, and other methods of operation.

2) Data Filtering.

We filtered the data obtained from accurately segmentation as shown in Fig. 6d, and applying bilateral filter, cloth simulation filter (CSF) algorithm and gradient filter three methods successively, setting the maximum number of iterations, grid sizes, filter threshold, spatial standard deviation and other physical parameters, by this way, we have achieved multi-layer filter, and complemented the advantages and disadvantages between these algorithms, so the filtering effect could be optimized best. Data filtering algorithm and ending condition are as Table 1.

Table 1. Comparison of Three Data Filtering Methods

Data Filter Algorithm	***Preparation***	***Algorithm***	***Algorithm and Condition***
bilateral filter	None	Euclidean distance	spatial standard deviation
CSF filter	None	Invert point clouds, calculate the surface distance	The maximum number of iterations
gradient filter	Calculate the gradient	Euclidean distance	filter threshold

3) Data Registration.

In this paper, we applied the Iterative Closest Point (ICP) algorithm to register the colorful point clouds and LIDAR point clouds after the data processing above. We obtained the first set of colorful point clouds P = $\{p_1, p_2 ... p_n\}$, and the second set of LIDAR point clouds Q = $\{q_1, q_2 ... q_n\}$, where the coordinates of P and Q correspond to the pre and post movement coordinate systems, respectively. Without error, the conversion formula for converting P coordinates to Q coordinates as (1):

$$\begin{vmatrix} q_1 & 0 & \cdots & 0 \\ 0 & q_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & q_n \end{vmatrix} = R \begin{vmatrix} p_1 & 0 & \cdots & 0 \\ 0 & p_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & p_n \end{vmatrix} + t \tag{1}$$

while the above feature matching algorithm does not always hold, due to the inconsistency of the total number of these two kinds of point clouds, so the minimization objective function is set as (2):

$$\frac{1}{2}\sum_{i=1}^{\mathrm{n}} \| \begin{vmatrix} \mathrm{q}_1 & 0 & \cdots & 0 \\ 0 & q_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & q_n \end{vmatrix} - R \begin{vmatrix} p_1 & 0 & \cdots & 0 \\ 0 & p_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & p_n \end{vmatrix} - t \|^2 \tag{2}$$

where the solution of R and t can be solved by Singular Value Decomposition or other methods.

4) Data Complementation.

After registering these two kinds of point clouds, we can clearly understand the advantages and disadvantages of their respective data. According to the above, the LIDAR point clouds data are of higher data quality below and on the side of the track, while above the track is of lower quality, due to the equipment collection or other reasons. Therefore, according to this data feature, we complemented the colorful point clouds and LIDAR point clouds data to get the final two groups of point clouds data, and finally merged these two as shown in Fig. 6e and Fig. 6f, the above are the process of point clouds data processing.

3.4 Data Fusion Model of Digital Twin

The digital twin model is a virtual model of the physical track through digital modeling. The virtual model can simulate the shape of the track in the real environment in all directions, and can also be derived to develop a real-time sensing and feedback process. We calculated the normal vectors of the merged colorful and LIDAR point clouds, and adjusted the orientation of the point clouds normal by using the least squares fitting plane algorithm and the least-cost spanning tree, and then we performed poisson surface reconstruction to generate the model, but the model is not optimistic enough at this point, which is due to the default parameters of the system and the target model requirements. The larger the octree depth parameter (also the deeper the depth), the better the result, but it also requires more running time and memory. We set octree depth equals 12 as the optimal state value. Due to the error when calculating the normal vectors, the boundary will bulge when the model is generated, so we set the boundary to dirichlet mode instead of the system default free. Finally, we obtained the digital twin model of magnetic levitation track in Fig. 7.

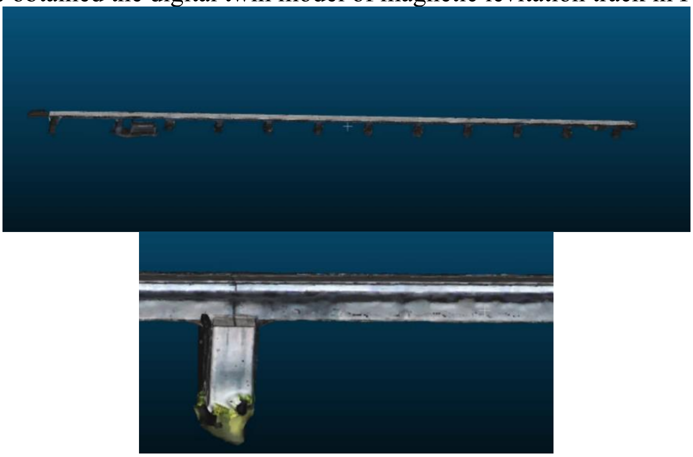


Fig. 7. Digital twin model of magnetic levitation track

4 Implementation

In this chapter, we briefly analyzed the digital twin model accuracy, and then evaluated the quality of the model from three aspects. They are model performance, magnetic levitation track flatness and model fitting effect.

4.1 Model Performance

Last chapter, we have shown the shape of the digital twin model of the magnetic levitation track. From a macro point of view, the entire track is in a good shape and the overall trend is smooth enough. Fig. 8a shows the top view direction above the track.

From a mesoscopic point of view, the digital twin model presents the texture information of the track surface, rail joints, etc., which is very similar to the real-world track shape. In addition, we also introduced a bottom view of this track, a partial front view of this track as shown in Fig. 8b.

(a) (b)

Fig. 8. The shape of the digital twin model

4.2 Magnetic Levitation Track Flatness

To explore the digital twin magnetic levitation track flatness, we firstly selected several points randomly on the surface of the track and selected three points with the larger spacing of them p_1 (x_1, y_1, z_1), p_2 (x_2, y_2, z_2), and p_3 (x_3, y_3, z_3) as shown in Fig. 9.

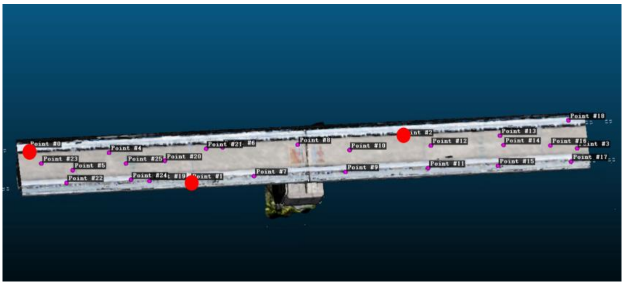


Fig. 9. The shape of the digital twin model

We calculated the normal vector composed of three points as (3):

$$\vec{\mathrm{n}} = \mathrm{p}_1 p_2 \times p_1 p_3 = \begin{vmatrix} i & j & k \\ x_2 - x_1 & y_2 - y_1 & z_2 - z_1 \\ x_3 - x_1 & y_3 - y_1 & z_3 - z_1 \end{vmatrix} = ai + bj + ck = (a, b, c) \tag{3}$$

Then substituted one of the three coordinates to solve the unknown d as (4):

$$\mathrm{d} = 0 - a \times x_1 - b \times y_1 - c \times z_1 \tag{4}$$

And solved the plane equation consisting of these three points as (5):

$$\mathrm{ax} + by + cz + d = 0 \tag{5}$$

Next, we calculated the distance from the remaining points to this plane as (6):

$$\mathrm{distance} = \frac{\left|\mathrm{ax}_{\mathrm{n}} + by_n + cz_n + d\right|}{\sqrt{a^2 + b^2 + c^2}} \tag{6}$$

The mean distance from each point to this plane is 0.013 meters and the standard deviation is equal to 0.025. We could be aware that the distance between the points and the plane is very small, and the distribution of the points is relatively uniform, so it can be interpreted that the points on the surface of the digital twin track almost on the same plane, the flatness above the track is excellent, and the error can reach centimeter-level accuracy.

4.3 Model Fitting Effect

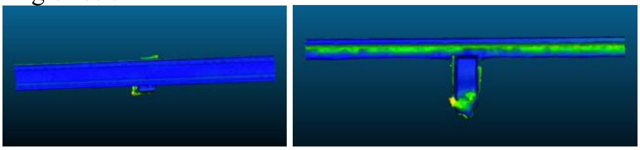
From a microscopic point of view, we selected a real 3D model of magnetic levitation track as the evaluation reference object. This model was made by 3DSMAX software, and it used the image data to be the texture map, and used the coordinates of the track to be standard reference points, then generated this model (to distinguish it from the digital twin model described above, we call this model made with 3DSMAX software as the benchmark model) as shown in Fig. 10a. We exported the benchmark model file as an obj format file, and loaded it into the cloud compare software, preprocessed the model to keep the track part only, and adjusted the benchmark model and the digital twin model to the same size, finally registered them, so that the two track surfaces are on the same level for accurate analysis, the benchmark model has been tinted to green in Fig. 10b.

(a) (b)

Fig. 10. a: Benchmark model; b: The registration of benchmark model and digital twin model.

We calculated the mean distance and standard deviation between the benchmark model and the digital twin model, by setting the parameter of the maximum distance as an independent variable and applying unsigned distance option. The calculated mean distance is 0.124 meters and the standard deviation is 0.120, which meet the fitting requirements. Therefore, these are able to prove the mean distance between the two is enough small, and the fitting effect of the digital twin model is very good.

We added the scalar field (SF) to the digital twin model, and finally formed the micro-fitting results of each part of the digital twin model. From the top view, we can see the fitting effect of the track surface is very good as shown in Fig. 11a, while in the front view the effect below the track is relatively poor as shown in Fig. 11b, it may be caused by too many data obstacles, and the image data forms some errors when modeling. Finally, we synchronized the probability distribution map of the SF, and found that the fitting effect of the data meets the requirements except for a small part of the model, which SF is yellow-green and has some error as shown in Fig. 12. Therefore, we can conclude that from the microscopic level, the digital twin model has a great fitting effect.



(a) (b)

Fig. 11. Digital twin model with the calculated SF

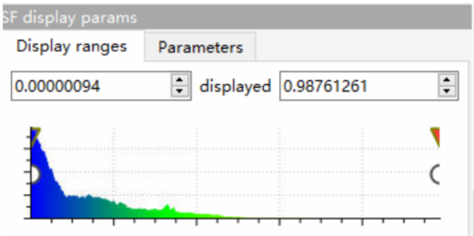


Fig. 12. SF points distribution

5 Conclusions

We have proposed a method for the data fusion of 2D image data with 3D LIDAR point clouds data, and established a magnetic levitation track transportation data fusion model by using Context Capture and Cloud Compare software, and all above background is based on digital twin technology. Our specific contributions are as follows:

- We applied two levels of high-precision micro-expression and large-scale transportation infrastructure macro-expression to express the digital twin of magnetic levitation track transportation.
- We fused the multi-source and multi-dimensional data in feature-level fusion method, and converted the 2D image data into colorful point clouds data and 3D LIDAR point clouds data fusion as a new breakthrough.
- Our method has indicated the digital twin data fusion model fits well, by comparing with the benchmark model. And our model has proven the effectiveness from a macroscopic to microscopic perspective, and the model error is compressed to about one centimeter.

Although we have fitted the data fusion model well in this paper, the development of the two software of Content Capture and Cloud Compare is not enough, and it faces the problem of deeper study and optimization of algorithms. In the future, our research will be based on the state-of-the-art background of data fusion, such as applying point cloud library for analysis, and will expand more algorithms to reach a higher level of data fusion network.

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