Combined Depth Camera and MRI for Spatially Encoded Gradient Intensity Calibration and Image Distortion Correction

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Abstract. Magnetic Resonance Imaging (MRI) is a widely adopted modality in clinical diagnostics due to its high-resolution and non-invasive nature. However, the image quality is often compromised by geometric distortions arising from inaccurate settings of the spatially encoded gradient intensity (G_{max}) parameter, adversely affecting diagnostic reliability. To address this challenge, we propose a novel correction method that integrates depth camera data with MRI imaging.

In this study, we first achieve high-precision spatial alignment between the depth camera and the MRI system based on previous calibration research. The depth camera is then employed to capture real-time 3D point cloud data of the human head. By comparing the external contours extracted from MRI images and the 3D point cloud model, we quantify the degree of geometric distortion. Based on this discrepancy, the SEGI parameter is recalibrated, enabling restoration of the true anatomical geometry in the MRI images.

Experiments were conducted on multiple volunteers, during which synchronized MRI scans and 3D surface acquisitions were performed. The Iterative Closest Point (ICP) algorithm was used to ensure accurate registration between the MRI and point cloud data. The proposed method successfully reduced the average contour size error from 11.2% to 2.97%. Additionally, image quality was enhanced, with the signal-to-noise ratio (SNR) increasing from 32.5 dB to 45.2 dB, and spatial resolution improving from 1.2 mm to 0.8 mm. Qualitative evaluations by medical experts also confirmed a significant improvement in anatomical clarity and facial region alignment, contributing to enhanced diagnostic confidence.

This work offers an effective solution for correcting MRI distortions caused by system parameter inaccuracies. Furthermore, the fusion strategy of combining depth camera technology with MRI opens a promising avenue for improving medical imaging accuracy and clinical diagnosis reliability..

Keywords: MRI; depth camera; 3D point cloud; image deformation repair; spatially encoded gradient intensity (G_{max}); Field of View (FOV).

1. Introduction

MRI is a critical imaging modality, especially in diagnosing the brain, spine, and other organs. MRI provides detailed anatomical images through strong magnetic fields and radiofrequency pulses, significantly facilitating early disease diagnosis and treatment [1]. However, image quality often suffers due to incorrect parameter settings, particularly the G_{max} parameter, causing geometric distortions [2]. Therefore, accurate correction of these systematic errors has become essential for improving MRI image quality.

Traditionally, the G_{max} parameter correction in MRI systems relies on scanning standard phantoms—objects of known dimensions—placed precisely within the scanner [3-5]. By comparing the measured dimensions from MRI scans against phantom standards, correction coefficients are calculated to adjust the G_{max} parameter, thus correcting dimensional inaccuracies [6]. Nevertheless, this method has some limitations. Due to limitations in the scanning bed design and coils of MRI equipment, it is often difficult to ensure that the standard analogs are strictly parallel or perpendicular to the three axial planes of the MRI scan, resulting in image acquisition angles that do not correspond to the standard geometries, and consequently, image distortion.

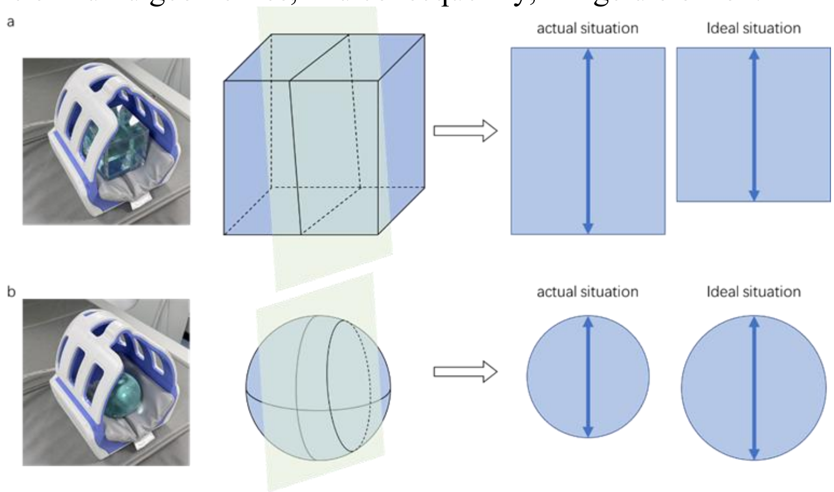

Fig. 1 Inaccurate systematic correction

Recently, depth camera technology has emerged as an effective alternative for MRI image restoration [7]. Depth cameras capture real-time 3D body surface data, providing accurate spatial references that surpass traditional phantom-based approaches in detecting and correcting image deformation, particularly those resulting from equipment misconfiguration or external physical factors [8].

Inspired by these advancements, this study proposes integrating depth camera-derived 3D head point cloud data into MRI deformation correction, replacing conventional phantoms. By comparing the MRI image's outer contour with the actual anatomical contours obtained from the depth camera, dimensional discrepancies are quantified to derive correction coefficients. This approach effectively eliminates errors associated with phantom placement, enhancing image accuracy and reliability.

Previous studies have primarily explored image alignment and multimodal fusion strategies. For instance, Bhushan et al. (2015) improved deformation correction by aligning multimodal images (e.g., CT and MRI) but overlooked external physical factors like phantom placement errors [9]. Recent research has increasingly integrated depth camera data with MRI. Schenkenfelder et al. (2021) combined RGB-D camera alignment with MRI images, significantly improving reconstruction accuracy [10]. Additionally, multimodal fusion approaches employing deep learning techniques have been explored by Kahol et al. (2024), demonstrating effectiveness in deformation correction [11]. Shahzadi et al. (2024) further emphasized accurate 3D alignment using depth cameras to eliminate phantom placement errors [12].

In summary, existing MRI restoration methods partially address image deformation but often remain limited by systematic errors. The fusion of depth camera technology with MRI presents a more accurate and reliable approach, overcoming traditional limitations. This study, therefore, advances MRI image restoration by leveraging depth camera-acquired 3D anatomical data, significantly improving deformation correction accuracy.

2. Methods

2.1 System Architecture

This study proposes an integrated system combining a depth camera with MRI to correct geometric deformations in magnetic resonance images through accurate alignment of 3D point cloud data and MRI images. The architecture includes three modules: data acquisition, data processing and alignment, and image restoration via G_{max} parameter correction [13].

The hardware configuration integrates an MRI scanner, crucial for generating anatomical images, and a depth camera, which compensates for image deformation issues like coil occlusion or incorrect G_{max} parameter settings by capturing real-time 3D surface data, specifically from the patient's head.

In the acquisition phase, a complete 3D point cloud model of the head, including bones and skin, is generated using the MRI system before scanning, serving as a reference. During MRI scans, the depth camera continuously captures facial region point cloud data, which is processed to retain only facial information. To ensure accurate spatial consistency, the captured facial point cloud is aligned with the pre-scan reference model through affine coordinate transformation and the ICP algorithm, minimizing spatial errors.

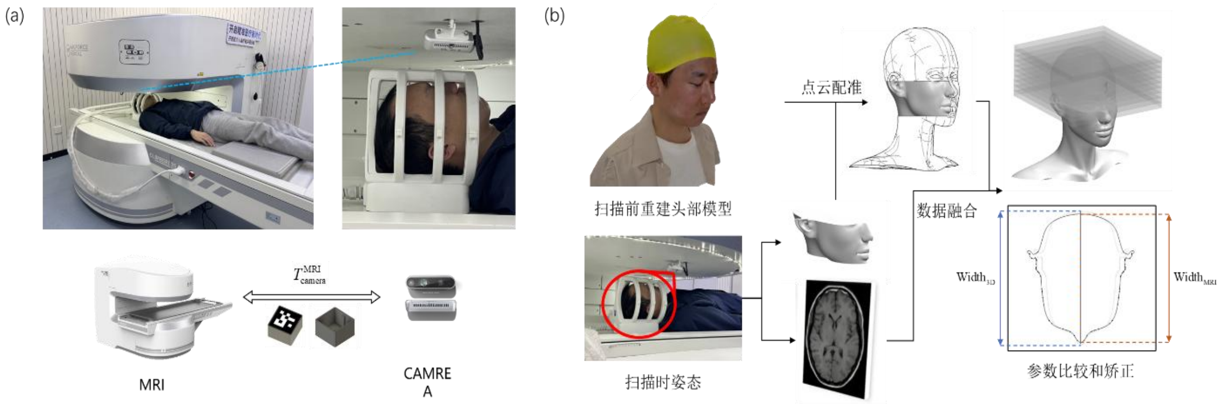

Fig. 2 a. System alignment; b. Deformation correction process

Following alignment, dimensional differences between MRI images and the aligned point cloud model are analyzed within a unified spatial framework. Correction coefficients, derived from these differences, are subsequently used for precise deformation correction, detailed in later sections.

2.2 Generation of 3D Point Cloud Head Model

Accurate MRI deformation correction requires generating a high-resolution 3D point cloud model reflecting precise anatomical head structures. This model is created through a pre-scan procedure utilizing a handheld 3D scanner, capturing surface data from multiple viewpoints [14].

The acquired multi-angle scan data are first preprocessed to remove irrelevant noise and artifacts, followed by integration using a 3D reconstruction algorithm to form a complete, accurate head model. An optimization step ensures the inclusion of key anatomical regions, such as the skull, facial contours, and skin surface, while filtering, denoising, and simplifying the model to maintain computational efficiency. Additionally, anatomical details in sensitive regions, like the eyes and ears, are specifically processed to avoid information loss or distortion [15].

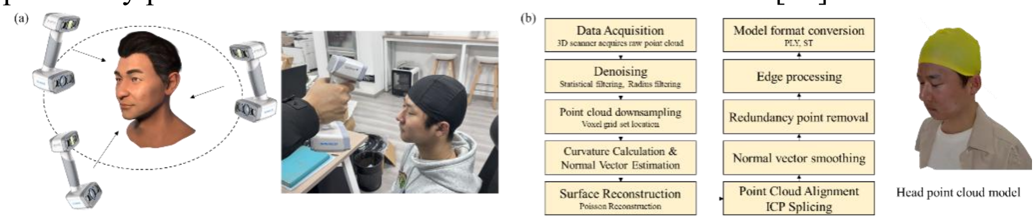

Fig. 3 a. Scanning head point cloud; b. Head point cloud model construction process

The resulting high-resolution head model provides precise benchmark data for aligning with real-time facial point clouds captured by the depth camera, effectively addressing localized data loss due to MRI coil occlusions and ensuring accurate spatial positioning necessary for subsequent deformation correction.

2.3 Depth Camera Acquisition of Body Surface Point Cloud and ICP Alignment

In this study, a depth camera captures real-time 3D point cloud data of the patient's head surface during MRI scanning to address image deformation caused by coil occlusion. By emitting infrared beams and measuring reflected signals, the depth camera rapidly constructs precise 3D geometric structures [16], providing critical spatial references for MRI image restoration.

Specifically, the depth camera, mounted near the MRI scanner, acquires continuous head-surface point clouds focusing primarily on the facial region, due to limited visibility caused by coils and device arrangement. To ensure data quality, filtering, denoising, and view-splicing techniques are applied, alongside RGB-depth image fusion to enhance spatial resolution (Fig. 4).

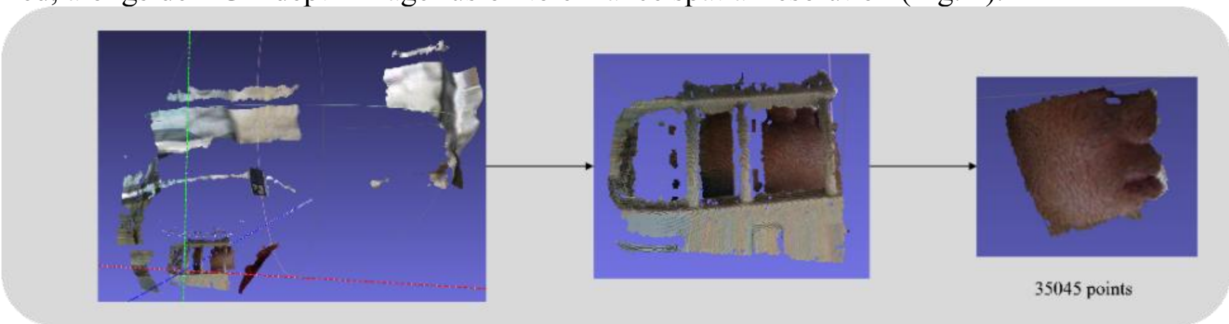

Fig. 4 Point cloud segmentation and facial point cloud extraction

Subsequently, the real-time facial point cloud data is spatially aligned with a pre-generated complete 3D head model using the ICP algorithm [17]. ICP iteratively minimizes Euclidean distances between corresponding points, calculating optimal rigid transformations (rotation and translation):

$$e(R,t) = \frac{1}{N}\sum_{i=1}^{N}\left\|RP_i + t - Q_i\right\|^2 \tag{1}$$

where P_i denotes real-time facial points and Q_i their closest points in the complete model. The algorithm iteratively updates transformation parameters until convergence (Fig. 5).

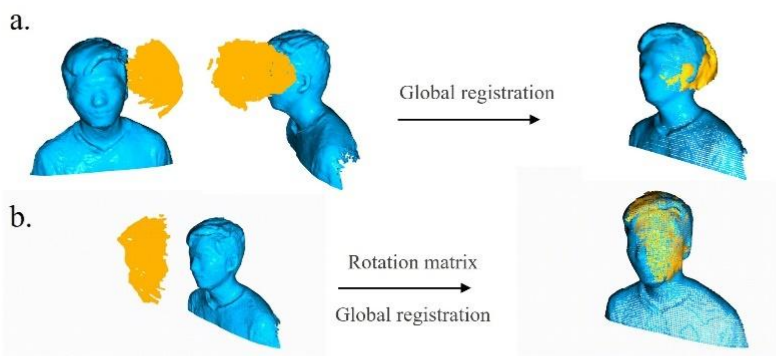

Fig. 5 a. Initialized alignment: getting the point cloud data initially aligned; b. ICP alignment

ICP-based alignment ensures accurate positioning of the head model within MRI coordinates, effectively eliminating spatial errors due to device positioning discrepancies and significantly enhancing image restoration accuracy and spatial consistency.

2.4 MRI and Point Cloud Outline Comparison and G_{max} Parameter Correction

To accurately correct MRI deformation, we first quantitatively compare the MRI outer contours with corresponding sections from the 3D point cloud head model. Initially, the MRI head contours are extracted using a Canny edge detection algorithm. Meanwhile, the 3D point cloud model contours are projected onto a 2D plane aligned with MRI image slices through coordinate transformation [18], ensuring spatial correspondence.

We then calculate maximum dimensions along X, Y, and Z axes for both contours:

- MRI contour dimensions:

$$W_{MRI}^{x,y,z} = \max(C_{MRI}^{x,y,z}) - \min(C_{MRI}^{x,y,z}) \quad (2)$$

• 3D model contour dimensions:

$$W_{3D}^{x,y,z} = \max(C_{3D}^{x,y,z}) - \min(C_{3D}^{x,y,z}) \quad (3)$$

Next, the deformation ratios ($r_{x,y,z}$) are computed as:

$$r_{x,y,z} = \frac{W_{MRI}^{x,y,z}}{W_{3D}^{x,y,z}} \quad (4)$$

These ratios indicate deformation extent: ratios smaller than 1 imply an excessively large G_{max} and reduced FOV, while ratios greater than 1 indicate the opposite.Considering the inverse proportional relationship between FOV and G_{max} , expressed by:

$$FOV_x = \frac{\gamma \cdot g_x \cdot \Delta t}{G_{max_x}} \quad (5)$$

we correct the G_{max} parameter using:

$$G_{max\,corr}^{\;x,y,z} = G_{max\,orig}^{\;x,y,z} \cdot \left(\frac{1}{r_x}, \frac{1}{r_y}, \frac{1}{r_z} \right) \quad (6)$$

(a) (b)

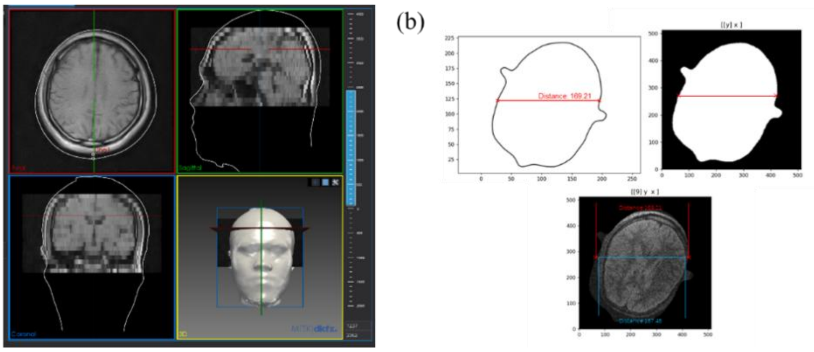

Fig. 6 a. MRI images and the 3D point cloud model registered in the same coordinate system; b. Comparison of MRI contours and point cloud contours

Through this correction, MRI images accurately reflect real anatomical geometry, significantly enhancing spatial accuracy and image quality for subsequent clinical analyses.

3. Experiment and Results

To evaluate the proposed MRI deformation correction method integrating a depth camera, experiments were conducted with volunteers of varying body sizes, genders, and ages to verify the accuracy and robustness of the approach. MRI image quality before and after G_{max} parameter correction was compared quantitatively and qualitatively.

3.1 Qualitative Analysis

Qualitative evaluation by medical experts demonstrated clear improvements in MRI image clarity, especially in facial regions, following correction. Experts reported enhanced anatomical accuracy and better morphological consistency, significantly increasing diagnostic reliability (see Fig. 7).

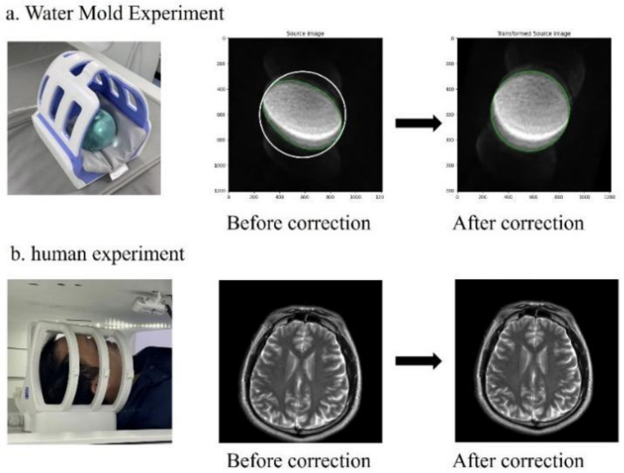

Fig. 7 a. Water mold experiments; b. Human experiments

3.2 Quantitative Analysis

Quantitative assessment showed the average dimensional discrepancy between MRI images and the 3D head point cloud decreased from 11.2% to 2.97% after G_{max} parameter correction. Specifically, differences reduced notably in X (12.5% to 3.7%), Y (9.8% to 2.2%), and Z (11.3% to 3.0%) directions.

Additionally, corrected images exhibited significant improvements in signal-to-noise ratio (from 32.5 dB to 45.2 dB) and spatial resolution (from 1.2 mm to 0.8 mm), enhancing tissue boundary clarity (Table 1).

Table 1. Quantitative analysis results of image quality

Evaluation index	Before correction	Before correction
Signal-to-noise ratio (SNR, dB)	32.5	45.2
Spatial resolution (mm)	1.2	0.8
Structure matching degree	Low	High

3.3 Algorithm Performance

The proposed algorithm demonstrated sufficient efficiency for clinical use, with an average point-cloud alignment time of 2.5 minutes and G_{max} parameter correction time of 1 minute. Robustness tests confirmed the effectiveness across diverse patient demographics (Table 2).

Table 2. Algorithm performance evaluation

Evaluation index	Calculation time (minutes)	Applicability
Point cloud alignment	2.5	Good
Parameter correction	1.0	Good
Applicable population	-	Suitable for all age groups

In summary, the proposed correction method effectively reduces MRI image deformation, enhances image quality, and provides reliable support for clinical applications.

4. Summary

This study proposes a deformation correction method integrating depth cameras with MRI imaging to effectively repair MRI distortions caused by improper system parameter settings through precise spatial alignment and gradient G_{max} parameter adjustments. Experimental results confirmed that the proposed method significantly reduced dimensional errors in the MRI images, particularly improving the accuracy of head contour alignment and anatomical consistency.

Comparisons of MRI images before and after correction revealed substantial reductions in dimensional discrepancies across the X, Y, and Z axes, demonstrating the effectiveness of using 3D point cloud-based contour comparisons for identifying and correcting parameter-induced distortions. Furthermore, the derived correction coefficients provided accurate G_{max} parameter adjustments, leading to improved imaging quality, robustness, and adaptability compared to previous methods.

However, this method has certain limitations. Depth camera data acquisition may suffer from incomplete or biased information due to perspective occlusions, patient posture variations, or larger head sizes, potentially affecting alignment accuracy. Additionally, since the current approach relies primarily on external head contours, correcting complex internal deformations requires further development. The ICP alignment algorithm used may also experience slower convergence or reduced accuracy in cases of substantial noise or complex occlusions. Future work could explore advanced alignment methods, such as deep learning-based techniques, to enhance accuracy and processing efficiency.

In practical clinical applications, rapid and precise acquisition of point cloud data remains challenging. Future research may address this by optimizing hardware configurations and improving acquisition protocols, while also exploring the applicability of this method in other imaging modalities like CT and X-ray.

References

[1] Brown R W, Cheng Y C N, Haacke E M, et al. Magnetic resonance imaging: physical principles and sequence design[M]. John Wiley & Sons, 2014.

[2] Hsu Y C, Hsu C H, Tseng W Y I. Correction for susceptibility-induced distortion in echo-planar imaging using field maps and model-based point spread function[J]. IEEE Transactions on Medical Imaging, 2009, 28(11): 1850-1857.

[3] O'Callaghan J, Wells J, Richardson S, et al. Is your system calibrated? MRI gradient system calibration for pre-clinical, high-resolution imaging[J]. PLoS One, 2014, 9(5): e96568.

[4] Stupic K F, Ainslie M, Boss M A, et al. A standard system phantom for magnetic resonance imaging[J]. Magnetic resonance in medicine, 2021, 86(3): 1194-1211.

[5] Wang D, Doddrell D M, Cowin G. A novel phantom and method for comprehensive 3-dimensional measurement and correction of geometric distortion in magnetic resonance imaging[J]. Magnetic resonance imaging, 2004, 22(4): 529-542.

[6] Jafar M, Jafar Y M, Dean C, et al. Assessment of geometric distortion in six clinical scanners using a 3D-printed grid phantom[J]. Journal of Imaging, 2017, 3(3): 28.

[7] Frohwein L J, Heß M, Schlicher D, et al. PET attenuation correction for flexible MRI surface coils in hybrid PET/MRI using a 3D depth camera[J]. Physics in Medicine & Biology, 2018, 63(2): 025033.

[8] Yuan Y, Ge Z, Lai B, et al. Three dimensional deformation measurement method based on image guided point cloud registration[J]. Optics and Lasers in Engineering, 2023, 161: 107399.

[9] Bhushan C, Haldar J P, Choi S, et al. Co-registration and distortion correction of diffusion and anatomical images based on inverse contrast normalization[J]. Neuroimage, 2015, 115: 269-280.

[10] Schenkenfelder B, Fenz W, Thumfart S, et al. Elastic registration of abdominal MRI scans and RGB-D images to improve surgical planning of breast reconstruction[C]//2021 Annual Modeling and Simulation Conference (ANNSIM). IEEE, 2021: 1-12.

[11] Kahol A, Bhatnagar G. Deep learning-based multimodal medical image fusion[J]. Data Fusion Techniques and Applications for Smart Healthcare, 2024: 251-279.

[12] Shahzadi I, Tamersoy B, Frohwein L J, et al. Automated patient registration in magnetic resonance imaging using deep learning-based height and weight estimation with 3D camera: a feasibility study[J]. Academic Radiology, 2024, 31(7): 2715-2724.

[13] Qi F, Hao X, Guo Z, et al. A fast co-registration scheme between camera and MRI for MRI-guided surgery[C]//2024 46th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, 2024: 1-4.

[14] Chen J, Wu X, Wang M Y, et al. 3D shape modeling using a self-developed hand-held 3D laser scanner and an efficient HT-ICP point cloud registration algorithm[J]. Optics & Laser Technology, 2013, 45: 414-423.

[15] Han X F, Jin J S, Wang M J, et al. A review of algorithms for filtering the 3D point cloud[J]. Signal Processing: Image Communication, 2017, 57: 103-112.

[16] Ha H, Lee J H, Meuleman A, et al. Normalfusion: Real-time acquisition of surface normals for high-resolution rgb-d scanning[C]//Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2021: 15970-15979.

[17] Marani R, Reno V, Nitti M, et al. A modified iterative closest point algorithm for 3D point cloud registration[J]. Computer‐Aided Civil and Infrastructure Engineering, 2016, 31(7): 515-534.

[18] Yang Q, Chen H, Ma Z, et al. Predicting the perceptual quality of point cloud: A 3d-to-2d projection-based exploration[J]. IEEE transactions on multimedia, 2020, 23: 3877-3891.