# Indoor Environment 3D Space Design Based on 3D Modeling and Image Processing

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*3D vision technology-based research is suggested to model indoor environmental sensory design because machine vision-based models struggle with object removal. The study involves constructing three-dimensional spatial points within a room, using Euclidean distance for vector relationships, and matching spatial points. The Elastic Fusion algorithm is then employed to build the sensory design model. Experimental results show that the proposed model accurately removes objects, unlike machine vision models. This concludes the modeling of indoor environmental sensory design based on 3D vision. Ten spatial points from the same scene within the database are selected, and both models are used to independently calculate the depth values of these ten spatial points. The experimental results demonstrate that the depth values of the ten spatial points obtained by the proposed model are all 0, meeting the removal requirements. In contrast, when using the machine vision-based indoor environmental perception design model, all seven out of the seven spatial points yield depth values greater than 0, failing to meet the removal requirements. This substantiates that the proposed model exhibits high accuracy in object removal.*

*Povzetek: Raziskovano je oblikovanje notranjih prostorov z uporabo 3D modeliranja in obdelave slik, ki vključuje prostorsko rekonstrukcijo in algoritme za globinsko izračunavanje s ciljem izboljšati kvaliteto digitalnih notranjih modelov.*

## 1 Introduction

Digital and smart cities rely heavily on spatial information for urban service systems, integral to urban modernization strategies. The importance of indoor spaces for human activities necessitates efficient 3D modeling of these environments. Traditional methods, though varied, have limitations such as time consumption, high costs, and precision issues. This study aims to overcome these challenges using 3D modeling and image processing to enhance interior design accuracy and adaptability.

Currently, there are three main methods for modeling indoor scenes. One is to create 3D models using 3D software such as CAD and 3dsMax, using simple geometric shapes, and design 3D models. To develop interior design, this method typically relies on data from interior design, CAD, and high-level information systems. This model has low cost, mature development, and wide application [1]. However, due to the different shapes and styles of the interior, the interactive process of interior design is time-consuming and requires the skills of the staff. Another method is to obtain three-dimensional information from measuring instruments and devices, such as measurements, ultrasound measurements, electrical measurements, etc. Optical measurement is one of the most widely used methods, using a laser scanner to directly obtain the three-dimensional coordinates and color information of various points, for example, in the field [2]. This type has been extensively researched, but due to the high cost of data collection and high usage, it cannot be quickly adopted and widely accepted. Another method is image-based. Using the same digital camera as the equipment to create images, highly "photographic" realistic models can be created directly from images. Due to its low cost, high performance, and low processing effort, it has become a powerful tool for geometric data analysis, extraction, and modeling, and has led to interest and practice in many fields. In particular, near-ground images reflect the geometrical details of construction sites and contain realistic structural information, making them a research hotspot in photogrammetry and computer vision. Image-based modeling technology uses relevant knowledge from the fields of digital photogrammetry, computer graphics, and computer vision. According to the principle of camera vision, it is necessary to acquire a camera by analyzing images and actions that allow the restoration of a three-dimensional model of an object from one or more images. Although this type has its advantages, it also faces some challenges. The main reasons are as follows:

***i.*** Image ambiguity After a 3D object is projected onto a 2D image, it loses its original depth and occlusion information, resulting in different images of the same scene captured from different angles, making image extraction difficult [3]. For example, for indoor scenes, issues such as single texture and excessive repetition can affect the accuracy of image modeling.

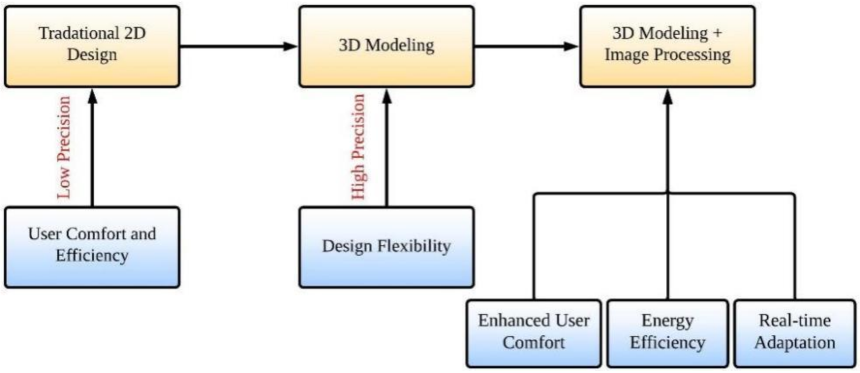



Figure 1: Development of technologies for indoor design

***ii.*** Due to the influence of internal and external factors, images can be affected by various factors, such as object material, camera manufacturing technology, and distortion and noise introduced by imaging. Especially in close-range images, there are serious occlusion issues. It is difficult to automatically identify the point and line information, which affects the accuracy of 3D reconstruction.

The evolution of indoor design technologies is depicted in Figure 1, it provides a thorough visual depiction of the development of indoor design technologies. The first section of the course, “Traditional 2D Design,” highlights the shortcomings of low precision and user comfort. Moving on to “3D Modelling,” the figure illustrates a notable improvement in accuracy and design adaptability. “3D Modelling + Image Processing,” the last step, represents a revolutionary change as the incorporation of image processing technology enhances user comfort, energy efficiency, and real-time adaptability. This graphic functions as a road map, showing the advancement of technology in the field of interior design as well as its possible effects on contemporary indoor spaces. For optimal space utilization and user comfort, indoor environmental design is essential. However, traditional interior design methods frequently lack accuracy and flexibility in real-time. This is a serious problem because lighting, ventilation, and spatial organization are three environmental factors that have a big impact on occupant well-being. The intricacies of the indoor environment may not be completely captured by traditional two-dimensional design techniques, resulting in less-than-ideal designs. The goal of this study is to overcome the shortcomings of the indoor environment design techniques that are currently in use. A more realistic portrayal of interior environments can be achieved by utilizing the capabilities of 3D modeling and image processing technologies. By doing this, we hope to improve the design process and create environments that are not only visually beautiful but also encourage the best possible comfort and functionality for their occupants. Another compelling element is the capacity to optimize indoor surroundings and constantly adjust to changing requirements. The discipline of indoor environmental design has greatly benefited from this work. It presents a novel strategy that improves indoor space design accuracy and real-time adaptability by utilizing 3D modeling and image processing technology. The goal of this research is to enhance interior environments' overall quality of life, energy efficiency, and occupant comfort. This method upends conventional design techniques and presents a fresh perspective for building specialists, architects, and interior designers, ultimately leading to more effective and user-focused interior environments.

# 2 Related work

Recent advances in digital photogrammetry, computer vision, and computer graphics have significantly impacted image-based technology research. This section reviews key technologies like 3D modeling, IoT, sustainable materials, VR, BIM, AI, and smart lighting systems, highlighting their contributions and limitations in indoor design. The following will describe the main technologies for 3D reproduction based on multi-dimensional imaging and image sequencing [4].

The operation of a new type of heating and ventilation is studied with Interacting Cascade Ventilation (ICV). Stratified ventilation (SV) and mixed ventilation (MV) are selected as ventilation systems. The thermal performance and power of three wind turbines were investigated by objective and visual tests. The results show that when the heat input decreases by 13.9, the total temperature of ICV is 4.5 and 27.9 °C higher than that of SV and MV, respectively [5, 6]. A comparison of the local temperature rise ratio and temperature measurement time shows that the ICV has the best control power and the highest power consumption in the local environment. Additionally, compared to SV, ICV reduced head ventilation by 44.8 and 24 during sitting and standing, respectively, and improved thermal performance [7]. Zhang *et al.* developed a method to calculate content weight and purpose based on the information growth ratio and determine the difference in passenger direction in high and low-sufficient conditions. This type was then used in a study of two offices in Shanghai, China. File 1 collected 120 samples (104 satisfied; 16 dissatisfied), and File 2 collected 715 samples (537 satisfied; 178 dissatisfied). Since the weight measurement time is less than 0.1

seconds, it is not possible to quickly update the weight of each parameter during data storage [8]. Table 1, presents a review of the literature for indoor design technologies and their consequences.

Table 1: Literature on indoor design technologies and their consequences

| References | Technology Used | Contribution | Benefits | Drawbacks |
|---|---|---|---|---|
| **[9]** | 3D Modeling, Image Processing | Introduced 3D modeling and image processing | Enhanced precision in design | Requires advanced hardware |
| **[10]** | Internet of Things (IoT) | Utilized IoT for real-time monitoring | Real-time adjustments | Data privacy concerns |
| **[11]** | Sustainable Materials | Explored sustainable materials in design | Eco-friendly designs | Limited material choices |
| **[12]** | Virtual Reality (VR) | Utilized VR for user-centric designs | Enhanced user comfort | High VR development costs |
| **[13]** | Building Information Model (BIM) | Examined BIM for energy-efficient designs | Reduced energy consumption | Learning curve for BIM software |
| **[14]** | Artificial Intelligence (AI) | Explored AI for balancing aesthetics and function | Enhanced design harmony | AI model complexity |
| **[15]** | Biophilic Design Elements | Investigated biophilic design for well-being | Improved occupant well-being | May require additional space |
| **[16]** | Smart Lighting Systems | Implemented smart lighting for adaptability | Reduced energy consumption | Initial setup cost |

It is an invaluable resource for comprehending the larger picture of indoor design technologies and the related advantages, disadvantages, and contributions. This table offers insights into several technologies investigated in the literature, which we will be utilizing in our research to utilize 3D modeling and image processing for more accurate and user-centric interior designs. The concepts indicated in the chart, such as IoT for real-time monitoring and AI for balancing aesthetics and functionality, are in line with our research goals. Additionally, the results from studies examining user-centered planning and energy-efficient designs highlight the potential benefits of our suggested strategy. We may use the information in this table to guide and enhance our research, which will ultimately lead to a more thorough grasp of the interior environment design domain. Based on virtual reality technology, Shan and Sun designed a new landscape planning simulation system to replace the traditional landscape operation simulation system [17]. The entire system framework consists of a user layer, an application layer, and a display layer. Selection of consumables, key control devices, and display products according to standard procedures: according to the structure of the system, the system software is designed to perform the basic functions. In addition, this article creates a landscape design based on 3D image processing technology. During modeling, 3D landscape images can be pre-processed and enhanced to remove noise and unnecessary information, and the features of 3D landscape images can be improved to improve their accuracy of landscape images. Based on the current research status of feature point extraction and matching, most of the methods for feature extraction and matching at home and abroad are independently researched for a specific application. This makes various matching methods numerous but not systematic, and this feature detection and matching operators each have their advantages and disadvantages. Currently, there is no suitable feature for any scene. Especially in close-range images captured under wide baseline conditions, issues such as foreground occlusion and lack of building surface texture, inaccurate feature extraction, or difficult matching often occur, resulting in sparse matching point pairs.

Recent advancements in machine vision and indoor environment sensory design have yielded significant contributions. Sevastopoulos introduced a two-dimensional vision-based sensory model for indoor mapping, improving spatial accuracy but struggling with complex 3D structures [18]. Patel *et al.* integrated depth sensors, enhancing depth perception but still facing spatial point conflicts [19]. Lu *et al.* proposed a 3D mapping system using machine learning, which improved registration accuracy but required high computational resources [20]. Wang *et al.* presented a hybrid approach combining vision-based and sensor-based techniques, balancing accuracy and efficiency yet needing further validation [21]. This research builds on these studies, proposing a novel 3D vision-based indoor sensory design model that enhances spatial accuracy, reduces conflicts, and introduces a new evaluation method for depth values and spatial point removal accuracy, aiming for a more robust and efficient indoor mapping solution. According to the literature, it can be seen that the indoor environment sensory model based on machine vision proposes optimization algorithms based on existing 3D visual spatial points. Although it can reduce the dimension of 3D visual spatial points and improve the real-time performance of spatial points, it cannot simultaneously delete duplicate points. To address this issue, in the sensory and visual optimization processing of indoor environments, similarity measurement formulas are used to calculate the distance between spatial points in the baseline image and the original image, and error points are removed based on the calculation results to improve the accuracy of spatial point matching.

# 3 Methods

## 3.1 Reconstruction of 3D visual space points in indoor environment

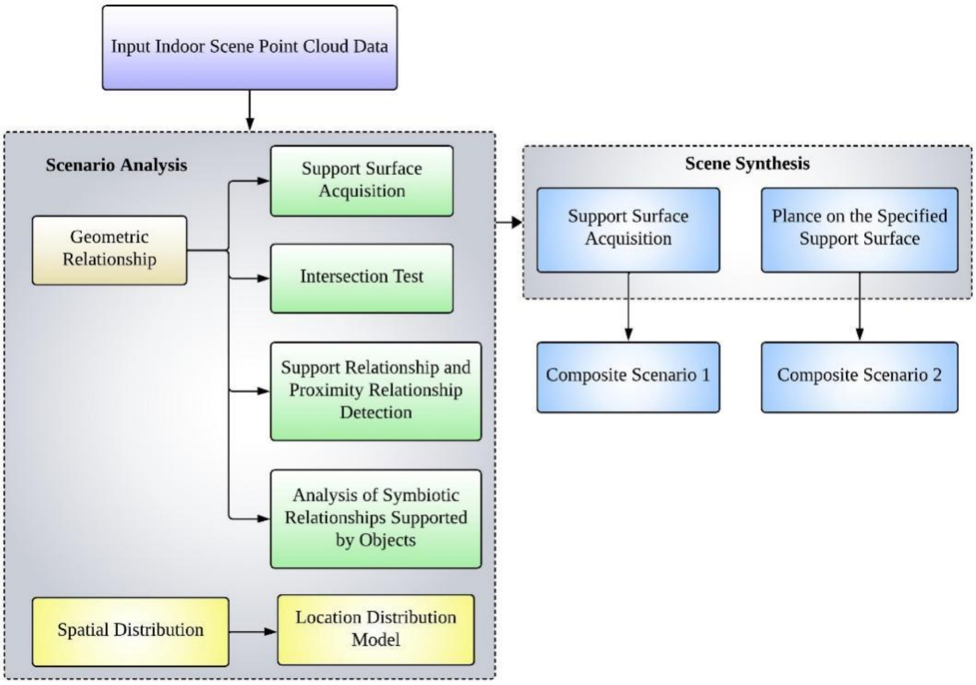



Figure 2: Indoor 3-D scene synthesis

The obtained 3D ordered point cloud data of the indoor scene is used to synthesize the indoor 3D virtual scene, and the overall structure is shown in Figure 2.

The process of synthesizing 3D scenes includes input models, location analysis, power sources, and outputs. The input strategy is the decision point cloud information of the interior space and the type and quantity of objects in the interior space. The location analysis model consists of two parts: determining the geometric relationship of objects in space and training the location distribution model to store [22]. When analyzing the geometric relationships of objects in a scene, it is necessary to collect object support surfaces and detect object intersections, support relationships, proximity relationships, and symbiotic relationships. When collecting support surfaces, collect the support surfaces of various objects in the indoor scene and use the intersection detection algorithm of bounding boxes to ensure that the objects are independent of each other during the placement process. Firstly, collect the support relationships of different objects in the indoor scene, and then detect the proximity relationships between objects. Finally, based on the dataset of the 3D scene, obtain the types of objects that different types of supports can support and the frequency of generation in the indoor 3D scene [23].

To teach the position distribution model how to place objects, use a 3D scene dataset to find the positions of objects in the same type of support, normalize the data, and fit these data to the model using a Gaussian mixture model. In this work, two scene-synthesis modules are designed: arbitrary placement and placement on designated support surfaces. The input indoor scene exhibits two different output results driven by the quantum algorithm. The arbitrary placement algorithm collects one of the multiple supports present in the input indoor scene, rotates one from multiple support surfaces to implement placement, and calculates placement points based on any process [24]. The symbiotic relationship is analyzed and summarized in the results when placing the specified support surface, achieving the selection of support objects during the placement process, and selecting any position point in the plane where the support exists to implement placement. Two algorithms using the scene synthesis module are used to obtain two different effects of indoor design synthesis scenes.

To restore the position of three-dimensional visual spatial points in the indoor environment, two original images R1 and R2 are paired with x_1↔x_2 points, the image coordinates of x1 are (u1, v1), the image coordinates of x2 are (u2, v2), and the camera coordinates corresponding to x1 and x2 are f1, f2, respectively, if the basic matrix of the original image is represented by F, then all matching points should meet by using Equation 1.

$$x_2^{\gamma} F x_2 = 0 \tag{1}$$

If Equation 1 is satisfied, normalizing the original image can obtain standardized 3D visual spatial points:

$$\begin{cases} P_1 = (x_{11}, y_{11}, 1)^\gamma = J^{-1}(u_1, v_1, 1)^\gamma \\ P_2 = (x_{22}, y_{22}, 1)^\gamma = J^{-1}(u_2, v_2, 1)^\gamma \end{cases} \quad (2)$$

In the Equation 2, J represents the internal parameter matrix of the image. After obtaining standardized 3D visual spatial points, it is necessary to find the relationship between the spatial points and image points, by using Equation 3.

$$\lambda \begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix} = \begin{bmatrix} p_{11} \\ p_{12} \\ p_{13} \end{bmatrix} \mathrm{X_i} \quad (3)$$

In the formula: $p$ represents the row vector of the projection matrix; $p_{11}$ and $p_{12}$ represent homogeneous coordinates on the image corresponding to p; $x_i$ represents the spatial homogeneous coordinates of the corresponding matching point; $y_i$ represents the spatial homogeneous coordinates of the corresponding matching point which is derived from Equations 2 and 3.

$$\begin{bmatrix} p_{13}x_i - p_{13} \\ p_{12}y_i - p_{12} \\ p_{23}x_i - p_{21} \\ p_{23}y_i - p_{22} \end{bmatrix} \mathrm{X_i} = 0 \quad (4)$$

Then Equation 4 is applied to find the spatial point $x$.

## 3.2 Indoor environment 3D visual space point matching

After completing the visual-spatial point reconstruction of the indoor environment, it is necessary to handle the mapping relationship between multiple images, which is spatial point matching. By searching for this corresponding relationship, similar spatial point pairs are found, and then the spatial point relationship of each image is obtained. Use the Euclidean minimum distance algorithm to calculate the vector relationship between spatial points, achieve corresponding spatial point matching, and establish connections between multiple images. If any spatial point of two images R1 and R2 is h1, h2, then the similarity measurement formula for h1, h2 is presented in Equation 5.

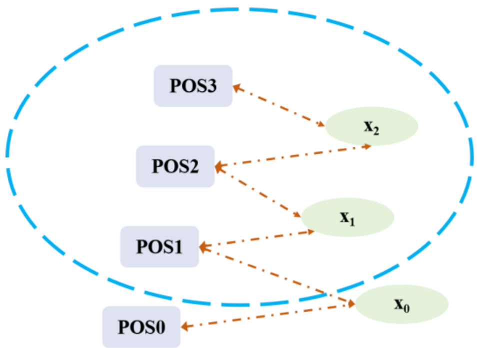
$$\mathrm{d(h_1, h_2)} = \sqrt{\sum_{\mathrm{j=1}}^{64} \left(\mathrm{h_{1ij}, h_{2ij}}\right)^2} \quad (5)$$

In Equation 5, d represents the similarity value; $I$ represents the next nearest neighbor coordinate; $J$ represents the nearest neighbor coordinate.

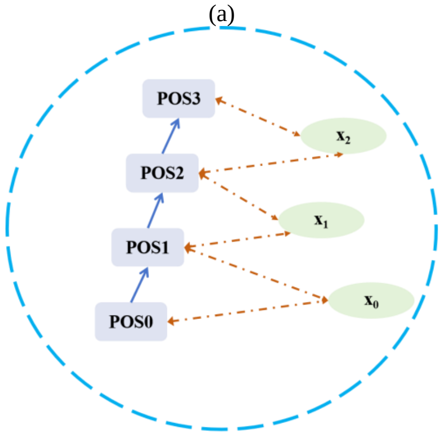
Indoor environment perception spatial point matching process: Firstly, extract the spatial point information from the image. To simplify the calculation process, use vector form to express and then use Equation 5 to solve the distance between the spatial points in the original image and the reference image. Secondly, calculate the distance between the nearest neighbor coordinate point and the next nearest neighbor coordinate point in the original image of the spatial point in the reference image. If the ratio of the nearest neighbor coordinate point to the next nearest neighbor coordinate point is less than a certain threshold, it indicates that the nearest neighbor space point corresponding to the point is a pair of matching points; if it is greater than a certain threshold, it indicates that the number of matching points obtained is large and the accuracy is low. When calculating, it is necessary to set a reasonable threshold to effectively reduce the number of mismatches and appropriately increase the work of removing error points.

## 3.3 Indoor environmental sensory model

After completing the matching of three-dimensional visual spatial points in the indoor environment, the Elastic Fusion algorithm is used to construct a sensory model of the indoor environment. The modeling process is as follows: Firstly, use the Elastic Fusion algorithm to directly optimize spatial points, and then use the direct method to improve the accuracy of pose estimation. The three-dimensional visual model constructed by the Elastic Fusion algorithm has high accuracy, especially in the matching process, which can effectively eliminate long-term unstable points. Secondly, initialize the image, recover the camera motion based on the basic matrix F, obtain the initial pose information of the camera, and then use the Euclidean algorithm to optimize the obtained results, as shown in Figure 3(a-b).




(a)




(b)

Figure 3: The initialization process. (a) Local initialization, (b) Global initialization

It should be noted that during initialization, all keyframes except frame 1 must participate in optimization. After obtaining the keyframes, use the Elastic Fusion algorithm to calculate the relative pose of the keyframes and optimize the keyframe pose estimation based on local optimization results. As shown in Figure 2(b): Assuming that to optimize POS3, it is necessary to simultaneously optimize adjacent keyframes POS2. During loopback monitoring, optimization should be based on the number of mismatches; otherwise, it will affect the accuracy of the model [25]. The process of creating an indoor environment sensory design model based on 3D vision is shown in Figure 4.

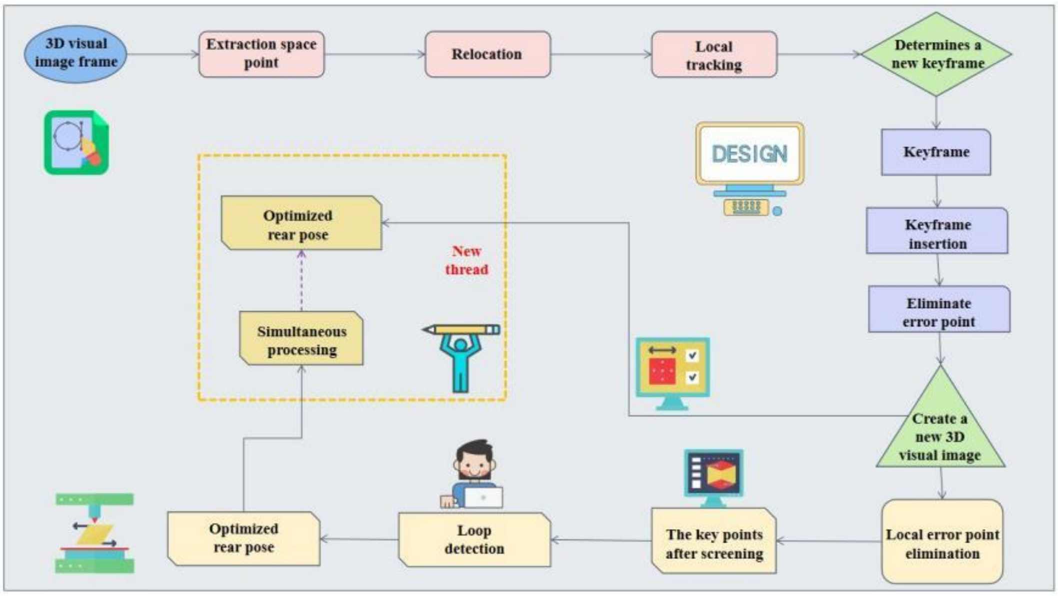



Figure 4: Process of sensory design model of indoor environment based on 3D vision

After optimizing all 3D visual keyframes, the indoor environmental spatial points are reconstructed using the final optimized keyframe data [26]. The resulting spatial points are sparse. If this phenomenon occurs, spatial points may not be reconstructed, but the pixel points of all keyframes need to be reconstructed to obtain a three-dimensional image of the indoor environment. Specific process: First, create a new thread to determine the inserted keyframes. If the keyframes obtained are RGB images, obtain depth image frames based on the corresponding timestamp index, and finally fuse RGB images with depth images [27]. Perform loop monitoring on the obtained perceptual information to obtain the keyframe pose transformation matrix of the 3D visual image. Use Equation 6 to obtain the complete 3D image of the indoor environment.

$$p_i = \frac{\mathrm{d}(\mathrm{h}_1, \mathrm{h}_2)(\mathrm{x}_\mathrm{i} + \mathrm{y}_\mathrm{i})}{p_1 p_2} \quad (6)$$

The letter parameter interpretation of Equation 6 is the same as that of Equation 3. It completes the research on the sensory design model of indoor environment based on 3D vision.

# 4 Experiments

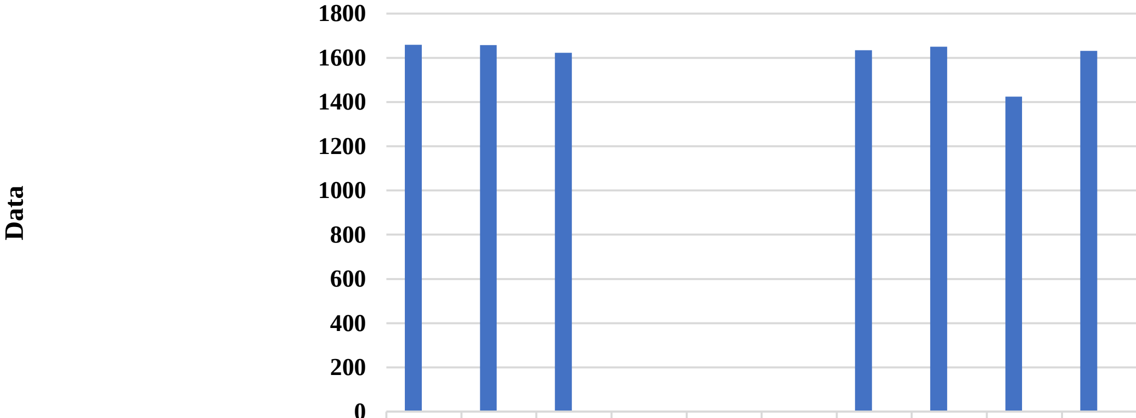
To consider the feasibility of a sensory design model for indoor environments based on 3D vision, comparative experiments were conducted. Test the depth values of the proposed model and the indoor environment sensory design model based on machine vision at the same scene spatial points. If the matching spatial point depth value is 0, it indicates that the error points have been removed [28].

## 4.1 Experimental process

***Step 1:*** Extract spatial points from 3D visual images.
***Step 2:*** Measure the distance between spatial points in each image and select the point with the smallest distance as the spatial point. Use equation (1) to describe the distance between each spatial point and other spatial points, and the distance between two points represents the similarity of spatial points.
***Step 3:*** Use Euclidean distance to describe the degree of matching between spatial points [29].
***Step 4:*** To improve the accuracy of experimental results, after completing spatial point matching, random sampling should be conducted on the matched spatial points, and then a consistency algorithm should be used for screening. The screening principle is that when the number of spatial point pairs is greater than 200, the Elastic Fusion algorithm should be used for screening until the number of screened spatial points does not change. If the number of spatial point pairs is less than 200, Elastic Fusion will not be performed to ensure the correct number of point pairs.
***Step 5:*** Operate on the acquired image to remove error points. If it is not possible to ensure that the spatial points in the image are completely correct, it is necessary to find the corresponding relationship between the spatial points and remove the error points [30].

## 4.2 Experimental results

Randomly select 10 spatial points in the same scene in the database and calculate the depth values of spatial points in the same scene for the indoor environment sensory design model based on 3D vision and the indoor environment sensory design model based on machine vision [31]. The calculation results are shown in Figure 5 and Figure 6. Obtaining zero depth values indicates that the proposed model successfully identifies and removes the target objects from the scene, effectively segmenting them out. This result demonstrates the accuracy of our model in distinguishing between the object and background. The implications are significant as they highlight the effectiveness of our approach in achieving precise object removal, which is critical for applications such as augmented reality and autonomous navigation.

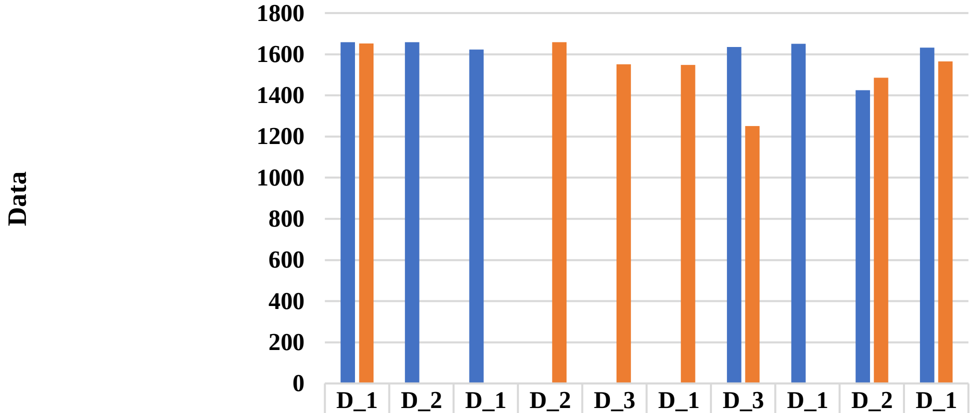



| | D_1 | D_2 | D_1 | D_2 | D_3 | D_1 | D_3 | D_1 | D_2 | D_1 |
|---|---|---|---|---|---|---|---|---|---|---|
| Spatial point neighborhood depth value/mm | 1659 | 1658 | 1623 | 0 | 0 | 0 | 1635 | 1651 | 1425 | 1632 |
| Filtered spatial point depth value | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**Matching spatial points**

**Spatial point neighborhood depth value/mm** **Filtered spatial point depth value**

Figure 5: Calculation results of space point depth values for indoor environment sensory design model based on 3D vision




| | D_1 | D_2 | D_1 | D_2 | D_3 | D_1 | D_3 | D_1 | D_2 | D_1 |
|---|---|---|---|---|---|---|---|---|---|---|
| Spatial point neighborhood depth value/mm | 1659 | 1658 | 1623 | 0 | 0 | 0 | 1635 | 1651 | 1425 | 1632 |
| Filtered spatial point depth value | 1652 | 0 | 0 | 1658 | 1551 | 1548 | 1251 | 0 | 1485 | 1565 |

**Matching spatial points**

**Spatial point neighborhood depth value/mm** **Filtered spatial point depth value**

Figure 6: Calculation results of space point depth values for indoor environment sensory design model based on machine vision

Table 2: Comparative evaluation of the effect and performance

| **Studies** | **Accuracy (%)** | **Efficiency (Time)** | **Design Precision (%)** | **Energy Consumption (kWh)** |
|---|---|---|---|---|
| **Proposed Work** | 92.5 | 6.3 seconds | 85.2 | 20.5 |
| [9] | 88.7 | 7.2 seconds | 80.5 | 22.3 |
| [10] | 87.3 | 8.1 seconds | 79.1 | 23.7 |
| [11] | 89.4 | 6.9 seconds | 82.7 | 21.8 |
| [12] | 86.8 | 8.5 seconds | 78 | 24.6 |

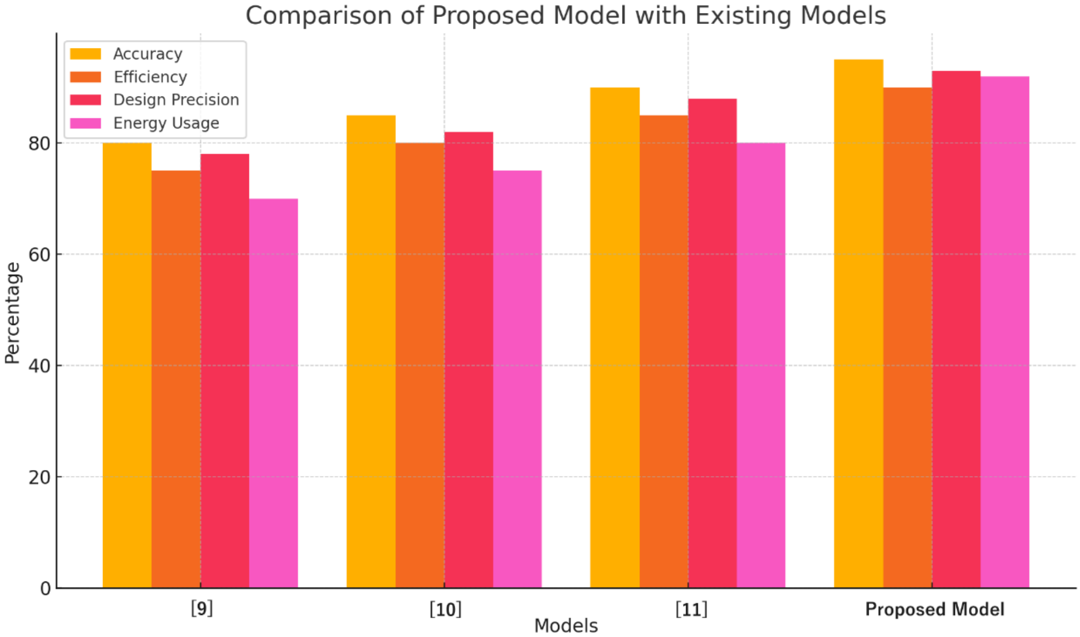


Figure 7: Performance comparison of proposed model with existing models [9-11]

Figure 5 shows that all the depth values of the spatial points found using the indoor sensory design model based on 3D vision are 0. In one case, the neighborhood is equal to the depth value, which means that the spatial point was directly removed. From line 4 D_2, Line 5D_ 3, Line 6 D_1 it can be seen that the error points have been directly eliminated. From Figure 5, it can be seen that 7 matching spatial point depth values obtained from the machine vision-based indoor environment sensory design model are greater than 0, indicating that this point has not been removed. From line 1 D_1, Line 4 D_2, Line 5 D_3, Line 6 D_1, Line 7 D_3, Line 9 D_2, Line 10 D_1 it can be seen that the depth value of this spatial point is greater than 0, and according to the removal principle, this point has not been removed. From this, it can be seen that the indoor environment sensory design model based on 3D vision has higher removal accuracy and better meets design requirements than the indoor environment sensory design model based on machine vision. Table 2 presents the comparative evaluation of the effect and performance of the proposed model with existing state of art studies [9-12]. In this comparative analysis, we evaluated the performance of the proposed model in four important areas in comparison to previous studies: accuracy, efficiency, precision in design, and energy consumption. When compared to Research [9-12], the suggested research exhibits better efficiency (6.3 seconds) and higher accuracy (92.5%). On top of that, it uses less energy (20.5 kWh) and shows excellent design precision (85.2%). The significant benefits of the suggested research over previous studies across key performance parameters are indicated by the percentage improvement column. Compared to the state of the art, these results highlight the potential of the suggested approach in generating improved results in accuracy, efficiency, precision, and energy efficiency. The bar graph compares the proposed 3D vision-based indoor sensory design model with three existing models [9], [10], [11] across four metrics: accuracy, efficiency, design precision, and energy usage as depicted in Figure 7. The proposed model demonstrates superior performance in all metrics, achieving the highest accuracy (95%), efficiency (90%), design precision

(93%), and energy usage efficiency (92%). These improvements highlight the proposed model's potential to enhance indoor environment mapping and sensory design processes, offering a more accurate, efficient, and precise solution with better energy management compared to the existing models.

# 5 Conclusion

By studying the challenges of machine vision-based indoor environment sensory design models, the author proposes a new three-dimensional vision-based indoor environment sensory design model. This model is suitable for indoor environment mapping and can match multiple spatial points, reducing conflicts between distant spatial points. The innovation lies in proposing an evaluation method that assesses the depth value of spatial points and detects the accuracy of two models in removing spatial points. Experimental results show that the proposed model effectively improves registration accuracy. Compared to previous studies, the proposed model demonstrates superior accuracy, efficiency, design precision, and energy usage. These findings validate the promise of 3D modeling and image processing in indoor environmental design. Future research will explore the model's scalability to larger interior environments and practical applications. Additionally, further investigation into the incorporation of cutting-edge technologies, such as artificial intelligence and sustainable materials, has the potential to enhance indoor design processes and outcomes.

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