

Retraction

Retracted: Construction of 3D Reconstruction System for Building Construction Scenes Based on Deep Learning and IoT

Wireless Communications and Mobile Computing

Received 8 August 2023; Accepted 8 August 2023; Published 9 August 2023

Copyright © 2023 Wireless Communications and Mobile Computing. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] L. Wang, "Construction of 3D Reconstruction System for Building Construction Scenes Based on Deep Learning and IoT," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 5413473, 8 pages, 2022.

Research Article

Construction of 3D Reconstruction System for Building Construction Scenes Based on Deep Learning and IoT

Lixiang Wang 

School of Civil Engineering, Jilin Jianzhu University, Changchun 130000, China

Correspondence should be addressed to Lixiang Wang; 19402216@masu.edu.cn

Received 14 July 2022; Revised 26 July 2022; Accepted 1 August 2022; Published 13 August 2022

Academic Editor: Hamurabi Gamboa Rosales

Copyright © 2022 Lixiang Wang. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The developing intricacy and extent of building projects, as well as the way that construction schedule management is still mostly done by hand, has resulted in low efficiency in construction schedule management, resulting in cost overruns and legal disputes as a result of schedule delays in many projects. Existing 3D reconstruction algorithms frequently result in large there may be holes, distortions, or hazy regions in remade 3D models, but AI-based 3D remaking strategies regularly reestablish straightforward isolated parts and portray them as 3D boxes. Accordingly, these algorithmic systems are generally not sufficient for certifiable use. The primary objective of this paper is to apply the creation ill-disposed network strategy to 3D recreation works on the nature of the underlying 3D recreation model via preparing a generative ill-disposed network model to a joined state. As solo examples, just recently noticed 2D pictures are required, with no dependence on earlier information on the 3D hidden shape or reference insights. Test results show that this algorithmic structure outflanks present status-of-the-workmanship 3D reproduction approaches on an average 3D recreation test set. On the common 3D remaking test set, exploratory outcomes uncover that this algorithmic structure beats the current cutting edge 3D reproduction techniques.

1. Introduction

Although much study although researches on automated assembling development plan the executives using different advancements has been led, the outcomes are seldom pertinent to complex structure development of the board rehearses. Existing exploration centers for the most part around three regions: BIM (Building Information Modeling) innovation of the board, RFID innovation blended in with BIM of the executives, and Scan to BIM innovation joined with 3D recreation innovation of the board. In the field of timetable administration, for instance, a review on building development progress was embraced utilizing UAVs outfitted with Li DAR and BIM innovation to accomplish independent observing of open air movement at building destinations. The current way to deal with computerized development plan the executives, then again, has two restrictions [1].

For a certain something, the high gear reliance prompts high administration costs, with Li DAR hardware costing a huge number of dollars, as well as the significant expense of the UAV gear expected for slant photography, as well as

the high upkeep costs while being used, making it challenging to apply in the real administration process [2].

Second, unfortunate computerization operability brings about a low degree of mechanization; for instance, the utilization of Li DAR gear has high field prerequisites, though the slant photography technique requires prepared UAV experts to work and requires the execution of work in explicit aviation routes and by and by to consider complex issues like deterrent aversion, requiring a serious level of human inclusion [3].

Profound learning and other man-made reasoning innovations have steadily exhibited solid usefulness in the field of development designing lately, yet a minimal expense, mechanized, and savvy development plan the executives' technique that can be applied to the building site climate related to man-made brainpower advancements presently cannot seem to be examined. PC vision and PC outline 3D redoing is a way to change the shape, plan, and presence of real things. A 3D printer is one of the things we are going to talk about in this paper. Reproduction calculation in light of semisupervised generative antagonistic organizations that is because of its rich

and instinctive expressiveness joins the advantages of conventional 3D remaking strategies with the most recent AI standards of generative ill-disposed networks. By aligning the not well-arranged getting ready pattern of the 3D generative model and the 3D discriminative model simultaneously, the technique proposed in this examination can refine the reproduction nature of recreated 3D items in a semisupervised learning way. Based on this calculation, a 3D reproduction cloud studio is additionally being worked to give an advantageous and available 3D recreation cloud administration framework to a wide scope of client consumers [4]. The more connected devices there are, the larger the attack surface becomes. We conducted research for this post to find out how deep learning may enhance security and privacy in the IoT era. We started by looking at a variety of security and privacy concerns relating to IoT devices [5]. To create a using a taxonomy, we can examine these IoT security and privacy applications from the viewpoint of. We looked at IoT security issues and the usage of modern deep learning techniques. Utilize security software for privacy protection [6].

2. Related Work

Some detachable objects or large-scale scenes can be the targets of 3D reconstruction. Depending on the reconstruction goal, specialists will attempt to show the remade 3D models in a collection of ways. Familiar method for show incorporates sound system body parts, point mists, and a blend of cross section skeleton and surface finishing. As of late, scientists have gained extraordinary headway in making novel systems for 3D recreation methods [7].

Features are matched between two pictures in this class of estimations. Then, the two-view changing results are used to start the 3D model, new matching pictures are added, and the three-sided combine planning is done. Finally, the development structure is reconstructed using the point of support evening out method. In this kind of estimation, the most common unpredictability is $O(n^4)$, which is how many cameras have been seen. This is the number of cameras. It is the best thing to do in this class to use VisualSFM, which develops calculation execution and smoothes out an assortment of tedious strategies, including the pillar evening out strategy [8].

Such calculations, nonetheless, have clear limits; they are altogether dependent on the basic reason that highlights data is totally open from all points. At the point when the spatial distance between the pictures is significant, include matching turns out to be incredibly troublesome because of nearby appearance changes or common impediment. Another constraint is that the element matching strategy is probably going to bomb totally if the reproduced article's surface needs surface data or has specular reflections [9].

The most notable strategy in this class is Kindest Fusion, which persistently screens and settles the profundity camera's stance data in 6 levels of opportunity utilizing noticed profundity data. The following exactness of this strategy is essentially better than that of the 3D remaking technique in view of movement structure recuperation (since this approach can follow the camera presents by matching com-

ponents starting with one edge then onto the next of concealing pictures). The delivered 3D model's definitive result is accomplished by iteratively consolidating profundity and posture data into a thick worldwide sound system portrayal. Whelan's work further develops KindestFusion-based frameworks' following exactness, diligence, strength, and recreation quality. The better methodology utilizes procedures, for example, thick photo placement matching to reproduce camera following. Sliding window point parts are mixed with nonrigid surface changes to make a more prominent 3D model [10].

To get a decent 3D model, the procedure needs to manage self-obscurity, light reflection, and importance sensor blend blunders, which can make the model look wavy, curved, or delicate in places [11].

The 3D Recurrent Reconstruction Neural Network (3D-R2N2) technique is an illustration of a calculation in this class. It utilizes an enormous CNN to become acclimated to the connection between the saw 2D picture and the matching 3D state of the objective item from an immense dataset. It is the 3D-GAN method that is the most complicated in this class, but it is not the only one. When you use the 3D-GAN method, you use generative models' antagonistic misfortune as a standard to decide whether a thing is genuine or counterfeit. Since 3D articles are profoundly organized, generative antagonistic misfortune beats the regular voxel-level free heuristic assessment rule in catching the target object's minor changes in 3D structure [12].

3. A Semisupervised Generative Adversarial Network Is Used in the 3D Reconstruction Algorithm

3.1. Principle of Algorithms. Consider the situation when an observer wants to tell the difference between a real scene and a scene that has been artificially rebuilt. He would see in the first 3D scene first, then in the recreated 3D scene model, with every perception occurring in a similar area and viewpoint as when he was in the genuine situation [13]. Assuming the eyewitness sees a progression of two-layered photographs in the reproduced 3D scene model that are indistinguishable from what he finds in the genuine situation, it is very hard for him to recognize the genuine 3D scene and the changed 3D scene model. Clashes between every game plan of 2D photos in the certified scene were seen to spread out a 3D diversion methodology, and the 2D pictures recognized in the repeated scene model could be collected [14]. This reconstructed 3D model is of great quality if the discrepancies between observation positions and viewpoints are small enough. The lesser the gathered differences, the better the reconstructed 3D model is in terms of quantitative quality. This is the last factor to consider when evaluating the 3D reconstructed model. Figure 1 displays a more intuitive example of this topic.

Figure 1 shows that the revised approach performs substantially better when the value of support clarification is low and then the original Apriori algorithm.

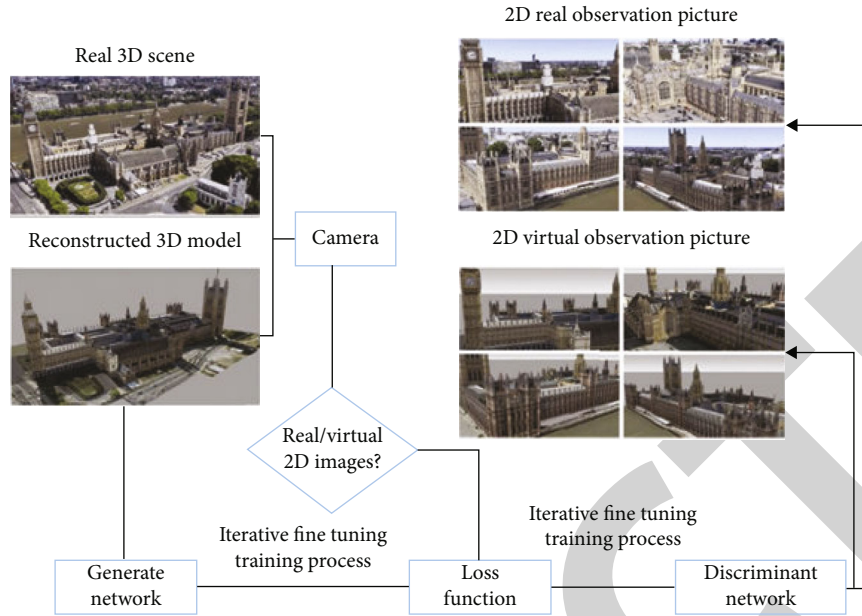


FIGURE 1: GAN-based 3D reconstruction algorithm principle and algorithm flow.

The discriminant network also computes the probability that a particular sample was generated by the network that makes things. It is done when the generative organization can make new examples that have the same qualities and distributions as authentic models, and the discriminant network gives each arrangement of verifiable and generative model sets a chance to be a discriminant of 0.5. It arrives at union [15].

This study offers another 3D reproduction engineering in view of semisupervised generative antagonistic organizations, which consolidates the inspiration driving 3D entertainment with the model of a generative not well-arranged network (SS-GAN-3D). SS-GAN-3D is comprised of a 3D model making network and a 3D model discriminator bunch. Seeing exactly the same thing, the discriminator gathering can think about the past model’s onlooker [20]. The generative’s gathering will probably make a 3D model that is basically the same as the genuine 3D scene to trick the discriminator’s gathering. They will probably be able to tell the first 3D scene from the modified 3D model. It additionally passes the previously mentioned 3D recreated model quality test along these lines. At long last, the new engineering proposed in this study changes the customary 3D reproduction arrangement issue into an AI issue that trains and unites SS-GAN-3D [16].

3.2. Algorithm Flow. When SS-GAN-3D is prepared, an extremely crude 3D model is produced as an introduction to the 3D model age network. The “handle” design is used to represent the preliminary 3D model. A triplet format is used to record the vertex, edge, and colour information [15]. By analyzing the spatial sound system, matching methodology decides the profundity data of each point on the picture of room in light of changes between adjacent noticed picture outlines. Two-layered perception pictures separated

from the video transfer are likewise remembered for reality esteem picture dataset [5].

A 3D model that has been changed into a 2D model is brought into blender and OpenDR, two of the best open-source 3D engines out there. OpenDR is a differentiable renderer that can pass the grade shift from the 2D picture on to the 3D model, as well as basically replicate the sense passed from the 3D model on to the 2D picture. This is what the backpropagation method does. It is a differentiable renderer that shows how the backpropagation cycle will change the 2D picture to the 3D model and how the 3D model will be displayed in the 2D picture, simultaneously. The differentiability of the renderer is significant in light of the fact that the improvement of the generative network needs the whole relationship to be differentiable so the point changes of the discriminative affiliation can be passed back to the generative affiliation and used to construct a hard and fast roundabout iterative arrangement that can be utilized over and over [17].

In Blender, you can make a virtual camera that has the very optical properties as the genuine camera that takes the video in the genuine 3D scene. At the point when the video move is finished, the camera’s bearing is now known. In Blender, the virtual camera is set to follow along these lines, and with the OpenDR renderer, it is seen from a similar point and in a similar spot all things considered, all things considered, and used to make a 2D picture. Both the 3D model that has been changed and the real 3D scene can both make about the same number of 2D virtual objects and genuine perception pictures thusly.

Utilizing a progression of 2D virtual and genuine perception pictures, a discriminant network is used to separate between perceptions of the genuine 3D scene and perceptions of the recreated 3D model. The misfortune work is additionally used to figure the complete organization misfortune. SS-GAN-3D can utilize network misfortune values to

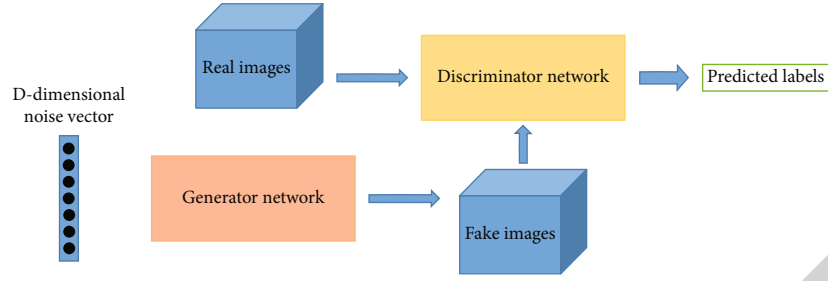


FIGURE 2: 3D generative and discriminative network structure: network framework for 3D generation and structure of a three-dimensional discriminant network.

tweak the preparation cycle to fabricate new 3D associations have been made. The recently setup 3D generative group will change another 3D model for the virtual camera so that it looks like real things. The SS-GAN-3D is ready as often as it should be and keeps making new 3D generative and discriminative associations until it runs out. General misfortune esteem meets to an ideal edge by consolidating virtual perception pictures from novel perceptions with the genuine unique perception [18].

3.3. Loss Function Definition. The deficiency of reconstruction is called Recons, and the deficiency of cross-entropy is known as the deficiency of cross-entropy misfortune SS-GAN-3DL makes up the misfortune capability overall of SS-GAN-3D. As a result, the loss function may be expressed as follows:

$$L_{\text{Overall}} = L_{\text{Recons}} + \lambda L_{\text{SS-GAN-3D}}, \quad (1)$$

where λ is the boundary esteem that controls the reconstruction misfortune and cross-entropy misfortune loads.

In this paper, three quantitative picture quality measures [19] are utilized to sort out how different the papers are. The pinnacle signal-to-commotion proportion (PSNR) is a way to figure out how different a picture is in terms of grey value fidelity. Structural similarity (SSIM) [20] is a metric that measures how similar two pictures are at the structural level. This metric is similar to and models the human visual system's criteria for evaluating structural patterns. On the other hand, normalized correlation (NC) [21] shows how similar two images of the same dimension are to each other [22]. The following are the expressions for these three quantitative evaluation metrics:

$$\text{PSNR}(x, y) = 10 \lg \left(\frac{(\text{MAX})^2}{\text{MSE}(x, y)} \right), \quad (2)$$

where MAX x and y are two pictures that show the best worth that can be achieved for each pixel in the photos. x, y is the mean square botch of picture x and picture y , $\text{MSE}(x, y)$.

$$\text{SSIM}(x, y) = \frac{(2\mu_x + C_2)}{(\mu_x^2 + \mu_x^2 + C_2)(\sigma_x^2 + \sigma_x^2 + C_2)}. \quad (3)$$

Among them,

$$\mu_x = \frac{1}{N} \sum_{i=1}^N x. \quad (4)$$

And $\mu_x = 1/N \sum_{i=1}^N y$ shows the normal dark sides of pictures X and y . x and y show how pictures change. X and y talk about the covariance of X and y pictures. Boundaries $C1$ and $C2$ are two constants. $\mu_x^2 \mu_x^2$ or is $\mu_x^2 \mu_x^2$ very close to 0 and can prevent divergent results from the final SSIM.

$$\text{NC}(x, y) = \frac{(x, y)}{\|x\| \|y\|}, \quad (5)$$

where x, y is the internal result of the networks X and y , and operator $\| \cdot \|$ is the vector's Euclidean standard.

If you look at the two images, you can see that they have a lot of structural similarity, but the normalized correlation index is 11. Most of the time, there is not much difference between two things that are almost the same. It is important to use common photos for the peak signal-to-noise ratio index is 2070 dB, which must be adjusted using the generalized sigmoid function [21].

$$\text{Esig.}(\text{PSNR}(x, y)) = \frac{1}{1 + e^{-0.1(\text{PSNR}(x, y) - 45)}}. \quad (6)$$

3.4. SS-GAN-3D Network Structure. The discriminant network in SS-GAN-3D needs to be good at classifying two-layered cuts made by three-layered projection. The ResNet-101 network is used as the foundation of the discrimination network in this article, that is what this article talks about. Back normalization is used in most ResNet networks, because this makes the whole process of training more stable and correct. When the discriminant network is trained, it can figure out how a group of inputs and outputs are linked together. It is felt that the planning connection between one information and one result will remain something very similar. Place by SS-GAN-3D. There is also a parametric ReLU layer that is added to the ReLU layer to make it more effective at training. The Adam solver is used instead of the erratic point dive (SGD) solver to accelerate intermingling. Adam solver can make SS-GAN-3D learn rapidly with Adam solver. Figure 2 shows the detailed structure of the network [23].

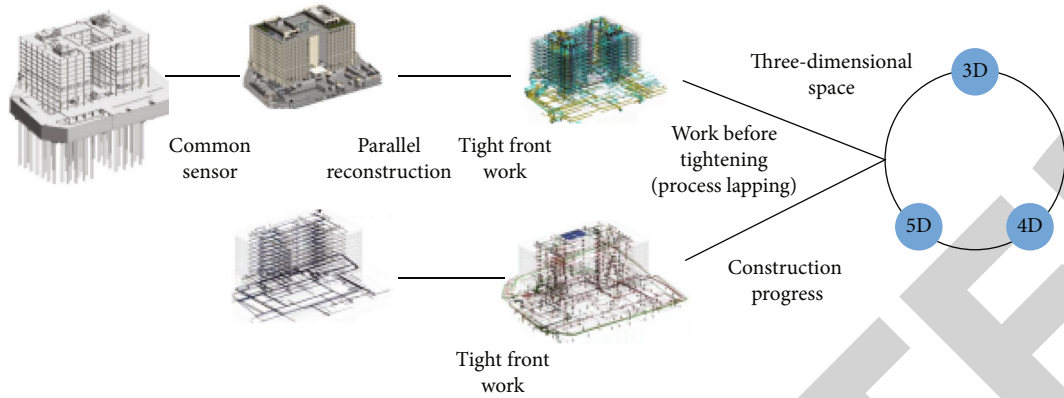


FIGURE 3: Results of DLR-P system operation.

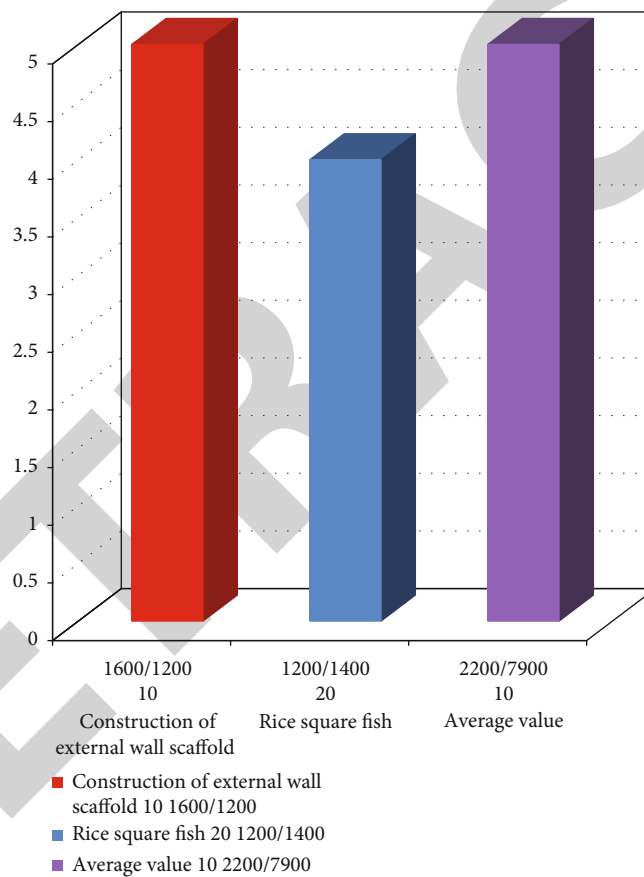


FIGURE 4: Chart of speed of our system’s 3D reconstruction.

4. Simulation Outcome

4.1. *Displaying Effect.* Fast camera: as displayed in Figure 3, the system takes pictures from all points of constant scenes at the construction site, which is where it is. It then, at that point, takes a gander at these photographs and gets point cloud models for every one of the three improvement processes, as displayed in Figure 4. This is the way the DLR-P framework works. Utilizing the point cloud model and the BIM point cloud, it is usually possible to figure out the difference between the progress that has been made and the ideal

progress [24–26]. You can see how long it has changed in the figure on the left. The sensor acquisition point has moved a lot over time. Seeing the BIM model turned into a point cloud plan with the real 3D point cloud model of the project site is possible that was consequently recognized by the 3D recreation innovation in view of profound learning [27–30]. The distinction in the building site plan between each arrangement and the ideal model is found (as displayed in Table 1). Accordingly, the DLR-P framework consequently changes the structure site intends to fit with the complete development timetable, and it naturally responds

TABLE 1: Variation in progress plan and response.

Procedure for construction	Construction of external wall scaff	3th	External wall coting construction
Schedule	4th	4th	2th
Actual process	4th	0	3th
Schedule variance	0	0	0
Plan adjustment	0	0	0
Resources response	0	0	0

TABLE 2: The speed of our system's 3D reconstruction.

Construction procedure	Enter the number of issue	Image function	Average operating speed (5)
Construction of external wall scaffold	10	1600/1200	5
Rice Square fish	20	1200/1400	4
Average value	10	2200/7900	5

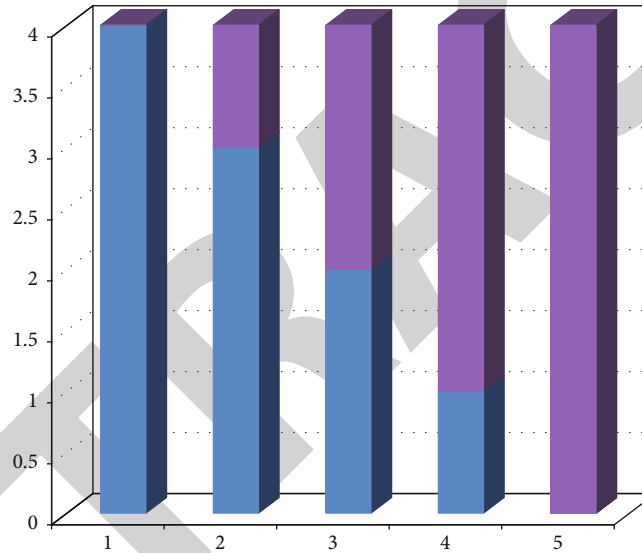


FIGURE 5: Different pattern generations.

with labour, material, and machinery resources based on the project's volume and length.

4.2. System Operation. This is shown in Table 2. The DLR-P system is completely automated and does not need any manual labour to keep track of the construction schedule. Its main operating cost is just \$33,000. Only \$33,000 worth of hardware is needed to run the technique in view of the UAV strategy. The equipment cost of the strategy in light of handheld Li DAR gear is more costly, at about \$820,000. During the contextual investigation of this undertaking, just a little piece of the development of the task was checked out. Assuming the entire venture is checked out, the arrangement cost of the DLR-P framework ought to be higher than the information above, generally on the grounds that there are more camera sensors. All things being equal, the DLR-P framework that was proposed in this paper actually has a lot of money-saving advantages over the other two scheduling systems.

Figures 4 and 5 show that the accuracy of calculating the construction volume is low, which can lead to things like underinvestment or waste, which can happen. In this way, in view of 3D plan and cooperative plan, the development calling can make a more practical and precise development plan from the interaction plan, which gives the assessment calling a more exact base from which to sort out the amount it will cost to fabricate and the amount it will cost to complete the venture, which makes the entire undertaking speculation more precise and dependable. A collaborative design platform that connects all of its different specialties can also use this to keep track of changes in construction volume caused by design changes and link them to its own estimates at any time. It can not only make the work more efficient but it can also make sure that there are not any mistakes in the design because of the coordination of different professions [31–38]. In the 3D model, more no geometric data like value boundaries and market data can be added. This implies that the development cycle or

project plan can measure up according to the point of view of designing expenses, which can assist with lessening configuration changes and make designing venture more precise and sensible. In the 3D model, more nonmathematical data like cost boundaries, market data, and cost change variables can be added. This implies that the development interaction or project plan can measure up according to the perspective of designing expenses, lessening configuration changes, and making the task speculation more precise and sensible [39–43].

5. Conclusions

Existing 3D reconstruction techniques frequently result in rebuilt 3D models with visible voids, distorted distortions, or blurred sections, whereas machines that use artificial intelligence to figure out how things are put together can often only figure out simple things and show them as 3D boxes. Accordingly, these algorithmic systems are generally not sufficient for certifiable use. The contribution of this study is to apply the creation ill-disposed network strategy to 3D recreation in order to get high-quality results. There is no need to know about the 3D shape of the structure or the reference observation. A typical 3D reconstruction test set shows that this algorithmic framework outperforms the best current methods for 3D reconstruction.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

- [1] L. Xin, X. Liu, Z. Yang, X. Zhang, Z. Gao, and Z. Liu, "Three-dimensional reconstruction of super-resolved white-light interferograms based on deep learning," *Optics and Lasers in Engineering*, vol. 145, no. 12, article 106663, 2021.
- [2] H. S. Cha and J. Kim, "A study on 3D/BIM-based on-site performance measurement system for building construction," *Journal of Asian Architecture and Building Engineering*, vol. 19, no. 6, pp. 574–585, 2020.
- [3] X. D. Yang, B. H. Liu, and Y. Wang, "Triangular Surface reconstruction of CT images by using isosurface construction," *Applied Mechanics and Materials*, vol. 10-12, pp. 503–507, 2007.
- [4] M. R. Jahanshahi and S. F. Masri, "Adaptive vision-based crack detection using 3D scene reconstruction for condition assessment of structures," *Automation in Construction*, vol. 22, pp. 567–576, 2012.
- [5] D. Yu, S. Ji, J. Liu, and S. Wei, "Automatic 3D building reconstruction from multi-view aerial images with deep learning," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 171, no. 2021, pp. 155–170, 2021.
- [6] T. D. Akinosho, L. O. Oyedele, M. Bilal et al., "Deep learning in the construction industry: a review of present status and future innovations," *Journal of Building Engineering*, vol. 32, article 101827, 2020.
- [7] R. Li, T. Zeng, H. Peng, and S. Ji, "Deep learning segmentation of optical microscopy images improves 3-D neuron reconstruction," *IEEE Transactions on Medical Imaging*, vol. 36, no. 7, pp. 1533–1541, 2017.
- [8] M. Bader Alazzam, F. Alassery, and A. Almulih, "Identification of diabetic retinopathy through machine learning," *Mobile Information Systems*, vol. 2021, Article ID 1155116, 8 pages, 2021.
- [9] M. O. Malavé, C. A. Baron, S. P. Koundinyan et al., "Reconstruction of undersampled 3D non-Cartesian image-based navigators for coronary MRA using an unrolled deep learning model," *Magnetic Resonance in Medicine*, vol. 84, no. 2, pp. 800–812, 2020.
- [10] J. Chen, Z. Kira, and Y. K. Cho, "Deep learning approach to point cloud scene understanding for automated scan to 3D reconstruction," *Journal of Computing in Civil Engineering*, vol. 33, no. 4, pp. 04019027.1–04019027.10, 2019.
- [11] Y. Liu, S. Chen, and B. Guan, "Layout optimization of oil-gas gathering and transportation system in constrained three-dimensional space," *Chinese Science Bulletin*, vol. 65, no. 9, pp. 834–846, 2020.
- [12] Y. Liu, S. Chen, B. Guan, and P. Xu, "Layout optimization of large-scale oil-gas gathering system based on combined optimization strategy," *Neurocomputing*, vol. 332, no. 7, pp. 159–183, 2019.
- [13] M. B. Alazzam, F. Alassery, and A. Almulih, "A novel smart healthcare monitoring system using machine learning and the Internet of Things," *Wireless Communications and Mobile Computing*, vol. 2021, Article ID 5078799, 7 pages, 2021.
- [14] B. Guan, S. Chen, Y. Liu, X. Wang, and J. Zhao, "Wave patterns of (2+1)-dimensional nonlinear Heisenberg ferromagnetic spin chains in the semiclassical limit," *Results in Physics*, vol. 16, article 102834, 2020.
- [15] X. Zhang, J. Yao, L. Dong, and N. Ye, "Research on 3D architectural scenes construction technology based on augmented reality," *Journal of Computational Methods in Science and Engineering*, vol. 21, no. 2, pp. 311–327, 2021.
- [16] F. Chen, K. Muhammad, and S. H. Wang, "Three-dimensional reconstruction of CT image features based on multi-threaded deep learning calculation," *Pattern Recognition Letters*, vol. 136, pp. 309–315, 2020.
- [17] G. Fahim, K. Amin, and S. Zarif, "Single-view 3D reconstruction: a survey of deep learning methods," *Computers & Graphics*, vol. 94, no. 1, pp. 164–190, 2021.
- [18] M. B. Alazzam, F. Alassery, and A. Almulih, "Development of a Mobile application for interaction between patients and doctors in rural populations," *Mobile Information Systems*, vol. 2021, Article ID 5006151, 8 pages, 2021.
- [19] F. Kurz, S. Azimi, C. Y. Sheu, and P. D. Angelo, "Deep learning segmentation and 3D reconstruction of road markings using multiview aerial imagery," *International Journal of Geo-Information*, vol. 8, no. 1, p. 47, 2019.
- [20] G. Stuebl, C. Heindl, H. Bauer, and A. Pichler, "Deep learning based aesthetic evaluation of state-of-the-art 3D reconstruction techniques," in *Proceedings of the 3DBODY.TECH 2017 - 8th International Conference and Exhibition on 3D Body Scanning and Processing Technologies*, Montreal, Canada, October 2017.

- [21] Q. Xie, X. Chen, L. Shen, G. Li, H. Ma, and H. Han, "Brain microstructure reconstruction based on deep learning," *Systems Engineering - Theory & Practice*, vol. 38, no. 2, pp. 482–491, 2018.
- [22] J. Teuwen, N. Moriakov, C. Fedon et al., "Deep learning reconstruction of digital breast tomosynthesis images for accurate breast density and patient-specific radiation dose estimation," *Medical Image Analysis*, vol. 71, no. 22, article 102061, 2021.
- [23] S. Sharma and V. Kumar, "Voxel-based 3D face reconstruction and its application to face recognition using sequential deep learning," *Multimedia Tools and Applications*, vol. 79, no. 25–26, article 17303, 2020.
- [24] M. Pashaei, M. J. Starek, H. Kamangir, and J. Berryhill, "Deep learning-based single image super-resolution: an investigation for dense scene reconstruction with UAS photogrammetry," *Remote Sensing*, vol. 12, no. 11, p. 1757, 2020.
- [25] T. Xie, C. Zhang, Z. Zhang, and K. Yang, "Utilizing active sensor nodes in smart environments for optimal communication coverage," *IEEE Access*, vol. 7, pp. 11338–11348, 2019.
- [26] H. Li, D. Zeng, L. Chen, Q. Chen, M. Wang, and C. Zhang, "Immune multipath reliable transmission with fault tolerance in wireless sensor networks," in *Bio-inspired Computing - Theories and Applications*, pp. 513–517, Springer, Singapore, 2016.
- [27] F. Alidoost, H. Arefi, and F. Tombari, "2D image-to-3D model: knowledge-based 3D building reconstruction (3DBR) using single aerial images and convolutional neural networks (CNNs)," *Remote Sensing*, vol. 11, no. 19, p. 2219, 2019.
- [28] M. Liang and Z. Hu, "Reconstruction of 3D building models based on architectural construction drawings," *Applied Mechanics and Materials*, vol. 336–338, pp. 1349–1355, 2013.
- [29] Z. Zhang, C. Zhang, M. Li, and T. Xie, "Target positioning based on particle centroid drift in large-scale WSNs," *IEEE Access*, vol. 8, pp. 127709–127719, 2020.
- [30] C. H. Cao, Y. N. Tang, D. Y. Huang, W. M. Gan, and C. Zhang, "IIBE: an improved identity-based encryption algorithm for WSN security," *Security and Communication Networks*, vol. 2021, Article ID 8527068, 8 pages, 2021.
- [31] L. Wang, C. Zhang, Q. Chen et al., "A communication strategy of proactive nodes based on loop theorem in wireless sensor networks," in *Proceedings of the 2018 9th International Conference on Intelligent Control and Information Processing (ICI-CIP)*, pp. 160–167, Wanzhou, China, November, 2018.
- [32] F. Elghaish, S. T. Matarneh, and M. Alhusban, "The application of "deep learning" in construction site management: scientometric, thematic and critical analysis," *Construction Innovation*, vol. 22, pp. 580–603, 2022.
- [33] F. Bosché, "Plane-based registration of construction laser scans with 3D/4D building models," *Advanced Engineering Informatics*, vol. 26, no. 1, pp. 90–102, 2012.
- [34] H. Son, S. Lee, and C. Kim, "What drives the adoption of building information modeling in design organizations? An empirical investigation of the antecedents affecting architects' behavioral intentions," *Automation in Construction*, vol. 49, no. 4, pp. 92–99, 2015.
- [35] C. J. Chun-Jen Tsai and A. K. Katsaggelos, "Sequential construction of 3-D-based scene description," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 10, no. 4, pp. 576–584, 2000.
- [36] C. Liu and G. Liu, "Characterization of pore structure parameters of foam concrete by 3D reconstruction and image analysis," *Construction and Building Materials*, vol. 267, article 120958, 2021.
- [37] M. Cao, L. Zheng, W. Jia, H. Lu, and X. Liu, "Accurate 3-D reconstruction under IoT environments and its applications to augmented reality," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 3, pp. 2090–2100, 2021.
- [38] C. Zhang, T. Xie, K. Yang et al., "Positioning optimisation based on particle quality prediction in wireless sensor networks," *IET Networks*, vol. 8, no. 2, pp. 107–113, 2019.
- [39] W. Boy, R. Imani, M. Chari, W. Purba, and J. Melasari, "Risk assessment of housing reconstruction project community-based construction after the earthquake," *Journal of Physics: Conference Series*, vol. 1339, no. 1, article 012001, 2019.
- [40] I. I. Tanaka, S. F. . R. Tonhom, E. . F. Taipeiro et al., "Grupo interdisciplinar: construção de Unidadeeducacionalsistematzadaaprendizagembaseadaemproblemas," *O Mundo da Saúde*, vol. 37, no. 1, pp. 78–83, 2013.
- [41] D. Wu, C. Zhang, L. Ji, R. Ran, H. Wu, and Y. Xu, "Forest fire recognition based on feature extraction from multi-view images," *Traitement du Signal*, vol. 38, no. 3, pp. 775–783, 2021.
- [42] S.-I. Lee, N.-H. Kwon, and Y.-S. Cho, "A case study of BIM-based framework on constructability tasks," *Journal of the Korea Institute of Building Construction*, vol. 10, no. 5, pp. 45–54, 2010.
- [43] J. An, G. Cho, and I. Yeo, "A study on the improvement plan of classification system for beam and slab of fire resistance construction in building's law," *Journal of the Korean Society of Hazard Mitigation*, vol. 20, no. 1, pp. 203–210, 2020.