Removal of Construction Machinery Occlusion using Image Segmentation and Inpainting for Automated Progress Tracking

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Abstract –

This study introduces an innovative method for enhancing digital modeling accuracy in construction site monitoring by integrating UAV imaging with advanced machine learning and computer vision algorithms. It focuses on removing temporary elements like construction machinery from images. The method involves two steps: first, using deep learning algorithms, for instance, segmentation to detect and segment construction machinery from UAV images trained on the Aerial Image Dataset for Construction (AIDCON); second, employing image inpainting techniques, utilizing the Places2 dataset and the LaMa algorithm, to fill in the areas left vacant by the removed machinery. Demonstrated on a parking garage construction site in Ankara, Türkiye, the results show high accuracy in machinery segmentation and effective image inpainting, as evidenced by metrics like Normalized Root Mean Square Error (NRMSE), Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). This approach contributes significantly to the field of construction site monitoring by refining digital models and shows potential for broader application in the industry. Future research directions include developing a specialized image inpainting dataset for construction scenarios and extending the methodology to encompass more types of temporary site elements, paving the way for more efficient and accurate project management in construction.

Keywords –

Image segmentation, image inpainting, UAV, point cloud, progress tracking

1 Introduction

In the construction industry, digital modeling of job sites is essential for efficient project management and execution. Automated monitoring systems, frequently incorporating advanced technologies such as UAVs, LiDAR, and machine learning, require accurate data to monitor and compare ongoing construction activities with planned ones. These systems also play a crucial role by enabling the detection of deviations or potential delays. Such systems offer a proactive approach to project management, allowing project managers to address issues promptly and keep the project on track.

In practice, challenges arise due to temporary objects such as machinery, equipment, and materials on the construction site. Such objects can create occlusion in the digital model, obscuring the actual progress of the project. Their presence in the digital representation can lead to inaccuracies in assessing the extent of the completed structure, potentially resulting in misguided decisions and inefficiencies. Therefore, they need to be extracted from the digital models in an automated manner.

Researchers in the field of UAV-based photogrammetry pointed out significant challenges in accurate mapping and calculations due to moving objects such as cars, construction equipment, and temporary facilities [1,2]. These obstacles notably affect computations, leading to the erroneous generation of height differential maps. Their findings underline the necessity for enhanced methods to overcome the inaccuracies introduced by non-terrain objects. Automated monitoring systems can gain a clearer and more accurate view of the construction progress by eliminating these objects from the digital model. This practice is crucial as it allows for a more precise comparison between the current site condition and the project plan. It ensures that the progress tracking is focused solely on the permanent structural developments rather than being skewed by temporary site elements. This leads to enhanced overall efficiency and productivity of the construction project, ensuring it is completed on time and within budget.

Building on the critical need for accurate digital site representation, particularly in light of the challenges posed by temporary objects, it becomes clear that vision-based technological solutions are essential. Image segmentation and image inpainting emerge as crucial techniques in this context. Image segmentation involves dividing a digital image into different segments to distinguish between various elements, such as separating temporary objects like machinery and equipment from permanent structural components [3]. On the other hand, image inpainting is reconstructing missing or obscured parts of images [4]. This technique becomes particularly valuable in construction for filling areas from which temporary objects have been removed, thereby providing a more precise and accurate representation of the actual site conditions.

This study proposes a method that combines image segmentation and inpainting to produce well-represented digital models of construction sites such as point clouds. Initially, image segmentation is utilized to identify and isolate temporary objects within the site images. Following their removal, image inpainting is applied to fill in the resultant gaps, effectively recreating the obscured parts of the construction site. The inpainted images serve as an accurate base for the 3D reconstruction process. By utilizing refined images, point clouds can be generated to accurately reflect the actual state of the construction site, free from distortions caused by temporary objects. This approach significantly benefits the automated monitoring systems, providing them with a more reliable data source for tracking the project's progress. It enables precise tracking and assessment of construction activities, leading to better resource allocation, decision-making, and, ultimately, more efficient and timely completion of construction projects.

2 Background

Eliminating occlusion is notably challenging due to the variable geometry of construction surfaces. Various traditional terrain filtering methods have been developed for digital terrain generation, which can also be applied to point clouds of construction. They can be classified based on geometric principles: slope-based, morphology-based, and surface-based methods.

Slope-based approaches [5,6] focus on evaluating the slope in a localized area and categorizing points as ground and non-ground based on a predefined slope threshold. Morphology-based methods [7,8] employ mathematical morphology techniques to effectively identify and remove points that do not correspond to ground surfaces. Surface-based methods take a different approach by gradually selecting points from raw point clouds to construct a ground surface model. This is commonly achieved through the Triangulated Irregular Network (TIN) [9]. Other notable research methods in recent years are the Simple Morphological Filter (SMRF) [10] and the Cloth Simulation Filter (CSF) [11].

While these algorithms have proven effective in various scenarios, they also share certain limitations. Their successful application requires users to thoroughly understand the algorithms and the specific characteristics of the sampled regions. This necessity for specialized knowledge makes these methods more challenging to apply. Moreover, in cases where the sampled region is extensive and features complex terrain relief, the parameters chosen for one site may not be applicable across the entire area without leading to errors in classification. Numerous classical machine learning algorithms have been introduced to enhance the robustness and level of automation in terrain generation. These algorithms aim to provide more adaptable solutions for terrain filtering in varied and complex construction environments.

In computer vision, deep learning has risen significantly in recent years. Deep learning techniques in image inpainting are adept at extracting semantic details from images, making more accurate predictions about missing content. Techniques such as Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) have proven highly effective in capturing nuanced image data. Many studies have successfully employed CNNs to refine image inpainting processes, leading to notable progress [12, 13]. Among the notable variations of CNNs are Fully Convolutional Networks (FCN) [14] and U-Nets [15]. Additionally, the introduction of GANs has been influential, as they are particularly well-suited for image inpainting tasks due to their strong data generation capabilities [16].

To support these advancements, researchers have developed a variety of image inpainting datasets and applications, each specifically designed for different types of images, scenarios, or inpainting challenges. Key datasets such as ImageNet [17], Places2 [18], Paris StreetView [19], and CelebA-HQ [20] have been instrumental in the progress and assessment of image inpainting algorithms. These datasets have provided the necessary diversity and complexity for refining and evaluating inpainting techniques.

Advances in deep learning-based inpainting methods have been significant and widespread, impacting areas including urban modeling, shadow manipulation, construction management, and infrastructure planning. For instance, Kapoor et al. [21] utilized these techniques to create Nostalgin, a tool designed for reconstructing 3D city models from historical photographs by filling in missing data, thus offering a reasonable representation of the past. Similarly, Wei et al. [22] developed a dual-stage GAN method specifically for shadow inpainting and removal, notably improving color retention in shaded areas. In the realm of construction, Bang et al. [23] applied GANs for enhanced detection and reconstruction of construction resources in UAV imagery. Further, Angah and Chen [24] proposed a context inpainting method to eliminate obstructions in construction site images, facilitating the creation of Building Information Models. W. J. Kim et al. [2] enhanced the detection of moving objects by improving background details at a pixel level.

J. Park et al. [25] also introduced a technique to generate vehicle-free ortho-mosaics from UAV images, thereby improving transportation infrastructure management. These diverse applications highlight the adaptability and efficiency of inpainting in tackling complex challenges across various fields. In this study, the objective is to utilize deep learning-based image inpainting techniques to identify and remove construction machinery from images. This approach aims to represent the construction field accurately, which is crucial for the subsequent steps in 3D reconstruction.

3 Method

The study introduces a comprehensive method for enhancing the accuracy of digital models in construction sites by removing temporary elements, such as construction machinery, from UAV-captured images. This methodology unfolds the parts mainly: segmentation of construction machinery through instance segmentation, followed by applying image inpainting techniques to refill the absence of these objects from the images (Figure 1).

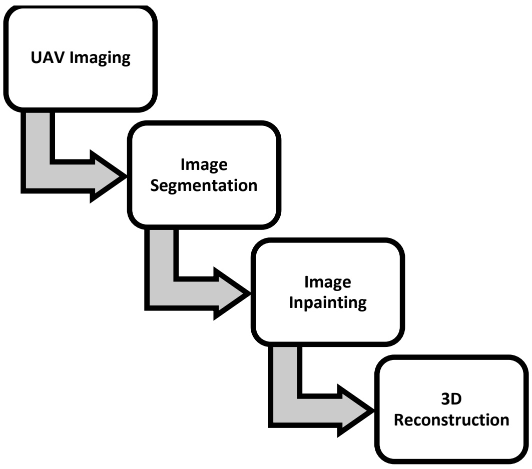


Figure 1. Flowchart of the method

The first stage aims to detect and segment prominent construction machines like excavators, bulldozers, and trucks from the aerial images. Deep learning algorithms, tailored explicitly for instance segmentation, are deployed for this purpose. Instance segmentation offers a more detailed mapping of an image compared to traditional methods. It partitions an image into regions or pixels corresponding to individual objects, producing an exact "mask" for each object. This heightened level of detail in segmentation is essential in accurately identifying and subsequently removing objects from images.

The deep learning model trained by the AIDCON - Aerial Image Dataset for Construction [26] was used to facilitate this process. The AIDCON dataset includes 2155 images captured by UAVs. It provides bird's-eye views of various construction environments annotated at the pixel level, featuring nine categories of construction machinery like dump trucks, excavators, loaders, and dozers. This model smoothly detects and segments construction machinery in the UAV imagery. Subsequently, the identified objects are converted into binary image masks, which are used in the image inpainting process to eliminate these objects from the images.

The second stage involves the application of image inpainting methods. It utilizes the masks generated in the previous stage. The inpainting algorithm effectively fills the pixels previously occupied by the machinery with pixels suitable for the construction site environment. A pre-trained model on the Places2 dataset [18], renowned for its vast collection of diverse images across numerous unique scene categories, is employed. This dataset provides a robust and varied training environment for the model, significantly improving its capability to detect and remove construction machinery in many scenarios. After evaluating various inpainting techniques mentioned in the literature, the Large Mask Inpainting (LaMa) algorithm [27] is used. This algorithm is particularly adept at handling large missing regions, complex geometric structures, and high-resolution images, making it an ideal choice for the study. Combining the pre-trained Places2 dataset and the LaMa algorithm allows us to achieve robust and visually consistent inpainting results.

By merging the strengths of instance segmentation and advanced image inpainting techniques, the method is designed to produce digital models that accurately reflect the actual state of construction sites, devoid of distortions caused by temporary construction machinery. Building on the success of removing temporary construction machinery from UAV images, the study advances into the phase of 3D reconstruction of the current construction sites. Structure from Motion (SfM) [28] and Multi-View Stereo (MVS) [29] techniques are employed to create detailed point clouds. This integration of advanced image processing with 3D reconstruction technologies ensures that the final digital models accurately represent the actual state of the construction sites, significantly enhancing project management and planning capabilities.

4 Results

This section outlines the experiments conducted to assess the effectiveness of the proposed system in construction environments. It offers a detailed examination of how image segmentation, inpainting, and 3D reconstruction techniques can be applied to track construction progress in real-world scenarios.

4.1 Study Area

The field study was conducted at a job site in Ankara, Türkiye, where a parking garage covering more than 9,000 square meters is being constructed beneath a courtyard. This site was selected for its suitability for progress monitoring due to the variety of machinery present.

4.2 Data Collection

This study conducted UAV imaging during two site visits, T1 and T2, offering a detailed overview of the construction progress. Aerial views of the construction site are illustrated in Figure 2 and Figure 3. To enhance the quality of the 3D point cloud and ensure accurate positioning in the 3D reconstruction process, Ground Control Points (GCPs) were measured around the perimeter of the construction site.

Figure 2. Aerial View of Construction Site at T1 Site Visit

The DJI Mavic Pro drone was chosen for the imaging process due to its several beneficial features. Its compact size, prolonged flight capability, and precise positioning make it well-suited for such tasks. The drone flights were maintained at a consistent altitude of 40 meters, which was crucial for ensuring data uniformity and enabling a comparison between different flights. The imaging strategy involved maintaining an 80% overlap for both front and side images, greatly enhancing the data quality and enabling accurate data analysis. This standardized approach to data collection was crucial in facilitating reliable comparisons and drawing meaningful conclusions from the data gathered.

Figure 3. Aerial View of Construction Site at T2 Site Visit

4.3 Data Processing

During the T1 and T2 timeframes, the construction site featured a variety of equipment, including dump trucks, excavators, backhoe loaders, and cars. Additionally, a category termed "other" encompassed drilling machines, anchor installation machines, and concrete mixers. The deep learning model previously mentioned was employed to segment construction machinery in both T1 and T2 datasets. The model's performance, measured by the mean Average Precision (mAP) COCO Metrics [30], is detailed for both datasets in Table 1. Additionally, it presents a breakdown of the Average Precision (AP) results, categorized by each type of equipment. AP of the backhoe loader was not present, as it was not visible in the images during the T2 timeframe.

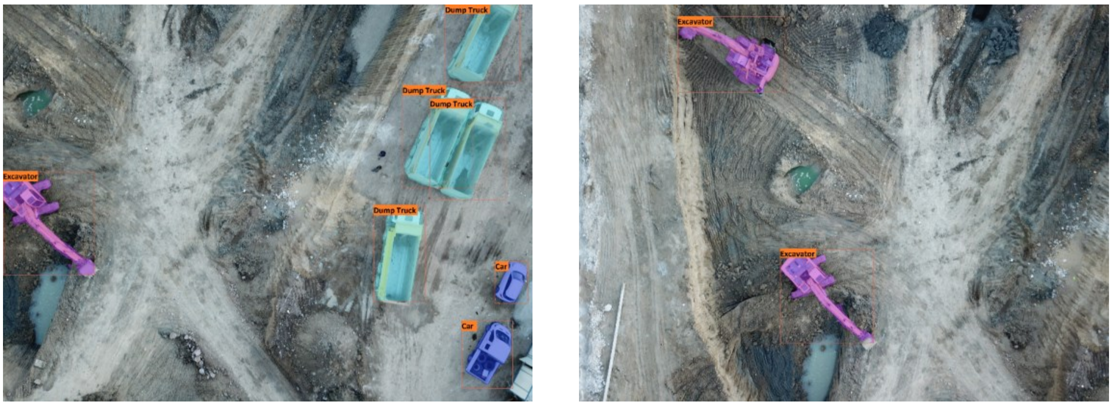
Table 1. Segmentation Results

Dataset	mAP	mAP_{50}	mAP_{75}
T1	67.6	87.3	82.3
T2	64.5	87.2	78.7

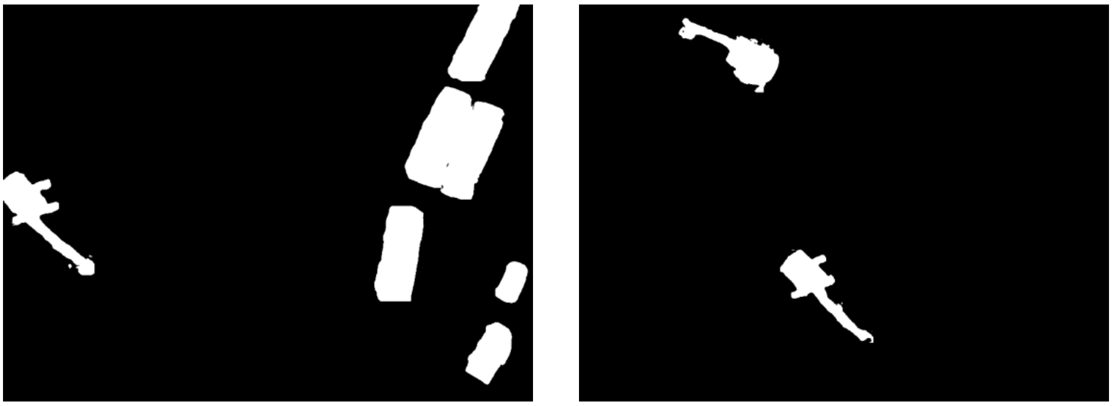
Table 2. Classwise AP Results (IoU=50%) (D.T: Dump Truck, Exc: Excavator, B.L.: Backhoe Loader)

Data	D.T.	Exc.	B.L.	Car	Other
T1	97.8	98.9	96.3	97.5	45.9
T2	92.8	96.4	-	96.5	63.1

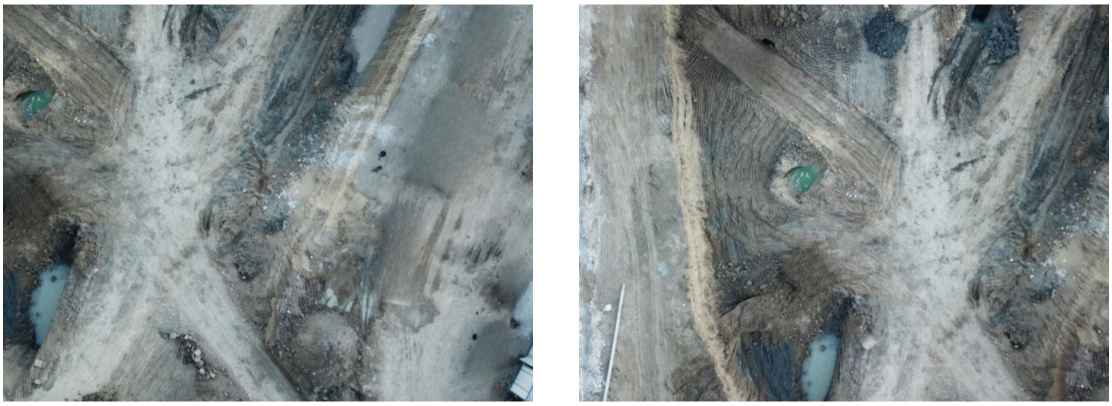
The outcomes of the segmentation stage lay the groundwork for advancing to the subsequent phases, which involve the removal of construction machinery and the creation of 3D surface models. Following the segmentation stage, image masks were created (Figure 4). These masks accurately define the boundaries of each piece of machinery detected in the images, preparing them for the next phase of the process. The LaMa inpainting algorithm, which has been trained using the Places2 dataset, was then employed on these images.



(a) Segmentation of Machinery from Images



(b) Creation of Image Masks



(c) Inpainting image masks

Figure 4. Eliminating Occlusion from the Images

The effectiveness of the inpainting process was assessed using several established image comparison metrics. These include the Normalized Root Mean Square Error (NRMSE) [31], Peak Signal-to-Noise Ratio (PSNR) [31], and Structural Similarity Index (SSIM) [32]. The results of these evaluations are detailed in Table 3.

Table 3. Inpainting Results

Dataset	NRMSE	PSNR	SSIM
T1	0.019	37.628	0.900
T2	0.018	32.595	0.901

Table 4. 3D Reconstruction Results

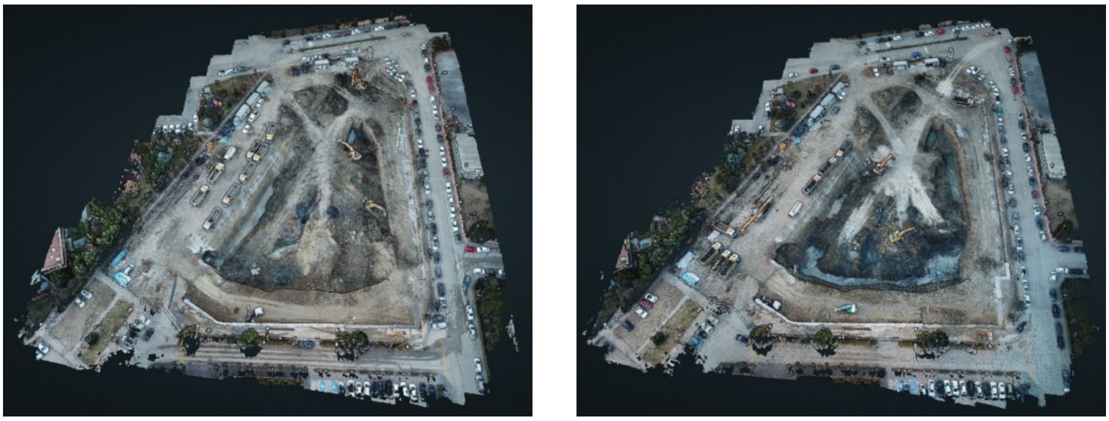
	T1	T2
Processed Images	230 of 230	230 of 230
Sparse P. Cloud	314,299	313,065
Dense P. Cloud	32,491,933	32,012,587
GSD	1.3 cm	1.3 cm
GCP Error	16.7 cm	14.4 cm

Once these construction machines were digitally eliminated from the images, the next step involved converting the 2D images into a 3D point cloud. This transformation required using the SfM-MVS technique to achieve a three-dimensional site representation. SiteEye, a robust photogrammetry software [33], was chosen to manage UAV photogrammetry in this study. SiteEye was selected from a range of available software known for its comprehensive capabilities in photogrammetry. The results of the photogrammetric process using SiteEye are visualized in Figure 5 and summarized in Table 4. The table indicates that all 230 images from each image set were processed successfully, demonstrating the effectiveness of this approach in creating accurate 3D models of the construction site.

5 Discussion

The current research introduces a novel approach for monitoring construction site progress, fusing UAV imaging with advanced machine learning and computer vision algorithms. This innovative method addresses several limitations in traditional techniques for generating point clouds at construction sites. The discussion will highlight the significant contributions of the study, the challenges faced, and potential avenues for future research.

- **Performance of the Construction Machine Segmentation Model:** A pivotal success of the proposed approach is the performance of the deep learning model in segmenting construction machinery. This model exhibited reasonable accuracy, especially for frequently encountered construction vehicles like dump trucks, excavators, backhoe loaders, and cars. The AP scores, often surpassing 90%, attest to the efficacy of deep learning algorithms in machinery segmentation within construction site imagery. This achievement is vital to integrating machine learning technologies into construction site monitoring. It is essential to acknowledge that flight parameters such as height, overlap, and camera angle substantially impact the resolution, coverage, and geometric accuracy of UAV images. These factors significantly influence the detectability of construction machinery and the quality of the areas inpainted subsequently. For example, flying at a higher altitude may lead to low-resolution images, complicating fine-grained segmentation tasks. In the study, a flight altitude of 40 meters resulted in a ground sampling distance of 1.3 cm, sufficiently identifying the construction machinery targeted in the images.
- **Advancements in the Automation of Construction Machine Removal:** The study marked a significant stride in the automated removal of construction machinery using image inpainting techniques. The encouraging results from the evaluation metrics—NRMSE, PSNR, and SSIM—underscore this success. For instance, dataset T1 showed an NRMSE of just 0.019 and an SSIM score of 0.900, indicating good structural similarity in the inpainting process. These results were closely mirrored in dataset T2. These metrics validate the effective implementation of image inpainting algorithms for removing construction machinery, thus aiding in the precise generation of digital terrain models.
- **Interoperability and Versatility of the Method:** A noteworthy aspect of the method is its compatibility with various photogrammetry software. The construction machine-removed images are designed to be georeferenced and processed independently, making the output of the proposed method adaptable for integration with different third-party photogrammetry applications. This flexibility enhances the method's potential for widespread adoption, particularly in automated progress monitoring for construction sites.
- **Potential for Future Research - Specialized Image Inpainting Dataset and Removal of More Types of Site Occlusion:** Looking ahead, developing a dedicated image inpainting dataset tailored to scenarios commonly encountered in automated construction site monitoring presents a research opportunity. Such a specialized dataset could enhance the performance of image inpainting algorithms, a critical component of the proposed method. Improved algorithms will further refine automated progress monitoring, making it more efficient and reliable. Future research also offers the potential to expand current methodologies by removing various site occlusion types. While the current focus is on construction machinery, extending this to elements like workers, unused materials, and temporary structures could greatly enhance site management. This would improve the digital representation of construction sites, providing a clearer view of progress and conditions, thereby facilitating more efficient and accurate



(a) 3D Reconstruction with Original Images

(b) 3D Reconstruction with Inpainted Images

Figure 5. Resultant Point Clouds

project management. Developing comprehensive models and datasets is crucial to advancing automated monitoring in the construction industry.

6 Conclusions and Future Work

This study introduces a method combining UAV imaging, machine learning, and computer vision algorithms to improve the digital modeling of construction sites. The focus was on removing temporary elements like construction machinery from images to enhance the accuracy of these models. The approach was tested in a real-world setting on a construction site, demonstrating its practical application. Key findings include the effective use of deep learning for segmenting construction machinery, resulting in high AP scores. This success illustrates the potential of deep learning in construction site monitoring. Additionally, image inpainting proved valuable in creating accurate digital representations of the site after removing temporary objects.

The method's compatibility with various photogrammetry software suggests its potential for broader application in the construction industry. Future research directions could involve developing a specialized image inpainting dataset for construction scenarios and extending the methodology to include more types of temporary site elements. In conclusion, this research contributes to the field of construction site monitoring by offering an innovative method for improving the precision of digital models, with implications for more efficient and accurate project management in the construction industry.

Acknowledgments

This research is funded by a grant from the Scientific and Technological Research Council of Türkiye (TUBITAK), Grant No. 122M055. TUBITAK's support is gratefully acknowledged.

References

[1] Cho, J. W., Lee, J.-K., and Park, J., Large-scale earthwork progress digitalization practices using series of 3D models generated from UAS images, Drones, vol. 5, no. 4, 2021.

[2] Kim, W. J., Hwang, S., Lee, J., Woo, S., and Lee, S., AIBM: Accurate and instant background modeling for moving object detection, IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 7, pp. 9021–9036, 2021.

[3] Xuehui, A., Li, Z., Zuguang, L., Chengzhi, W., Pengfei, L., and Zhiwei, L., Dataset and benchmark for detecting moving objects in construction sites, Automation in Construction, vol. 122, no. October 2020, p. 103482, 2021.

[4] Bertalmio, M., Sapiro, G., Caselles, V., and Ballester, C., Image inpainting, in Proceedings of the 27th annual conference on Computer graphics and interactive techniques, 2000, pp. 417–424.

[5] Vosselman, G., Slope based filtering of laser altimetry data, International Archives of Photogrammetry and Remote Sensing, Vol. 33, Part B3/2, vol. 33, no. Part B3/2, pp. 678–684, 2000.

[6] Wang, C. K. and Tseng, Y. H., Dem generation from airborne lidar data by an adaptive dual-directional slope filter, International Archives of Photogrammetry Remote Sensing and Spatial Information Sciences, vol. XXXVIII, pp. 628–632, 2010..

[7] Zhang, K., Chen, S. C., Whitman, D., Shyu, M. L., Yan, J., and Zhang, C., A progressive morphological filter for removing nonground measurements from airborne LIDAR data, IEEE Transactions on Geoscience and Remote Sensing, vol. 41, no. 4 PART I, pp. 872–882, 2003.

[8] Chen, Q., Gong, P., Baldocchi, D., and Xie, G., Filtering airborne laser scanning data with morphological methods, Photogrammetric Engineering and Remote Sensing, vol. 73, no. 2, pp. 175–185, 2007.

[9] Axelsson, P., DEM generation from laser scanner data using adaptive TIN models, International archives of photogrammetry and remote sensing, vol. 33, no. 4, pp. 110–117, 2000..

[10] Pingel, T. J., Clarke, K. C., and McBride, W. A., An improved simple morphological filter for the terrain classification of airborne lidar data, ISPRS Journal of Photogrammetry and Remote Sensing, vol. 77, no. October 2017, pp. 21–30, 2013.

[11] Zhang, W. et al., An easy-to-use airborne lidar data filtering method based on cloth simulation, Remote Sensing, vol. 8, no. 6, p. 501, 2016.

[12] Liu, G., Reda, F. A., Shih, K. J., Wang, T. C., Tao, A., and Catanzaro, B., Image inpainting for irregular holes using partial convolutions, in Proceedings of the European conference on computer vision (ECCV), 2018, pp. 85–100.

[13] Yu, J., Lin, Z., Yang, J., Shen, X., Lu, X., and Huang, T., Free-form image inpainting with gated convolution, Proceedings of the IEEE/CVF international conference on computer vision, vol. 2019-Octob, pp. 4470–4479, 2019.

[14] Long, J., Shelhamer, E., and Darrell, T., Fully convolutional networks for semantic segmentation, in Proceedings of the IEEE conference on computer vision and pattern recognition, 2015, pp. 3431–3440.

[15] Ronneberger, O., Fischer, P., and Brox, T., U-Net: Convolutional networks for biomedical image segmentation, in Medical image computing and computer-assisted intervention–MICCAI 2015: 18th international conference, Munich, Germany, October 5-9, 2015, proceedings, part III 18, 2015, pp. 234–241.

[16] Goodfellow, I. et al., Generative adversarial networks, Communications of the ACM, vol. 63, no. 11, pp. 139–144, 2020.

[17] Russakovsky, O. et al., Imagenet large scale visual recognition challenge, International Journal of Computer Vision, vol. 115, no. 3, pp. 211–252, 2015.

[18] Zhou, B., Lapedriza, A., Xiao, J., Torralba, A., and Oliva, A., Learning deep features for scene recognition using places database - supplementary materials, Advances in neural information processing systems, vol. 27, 2014..

[19] Pathak, D., Krahenbuhl, P., Donahue, J., Darrell, T., and Efros, A. A., Context encoders: Feature learning by inpainting, in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 2536–2544.

[20] Karras, T., Aila, T., Laine, S., and Lehtinen, J., Progressive growing of GANs for improved quality, stability, and variation, in 6th International Conference on Learning Representations, ICLR 2018 - Conference Track Proceedings, 2018, pp. 1–26.

[21] Kapoor, A., Larco, H., and Kiveris, R., Nostalgin: Extracting 3D city models from historical image data, in Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2019, pp. 2565–2575.

[22] Wei, J., Long, C., Zou, H., and Xiao, C., Shadow inpainting and removal using generative adversarial networks with slice convolutions, in Computer Graphics Forum, 2019, pp. 381–392.

[23] Bang, S., Baek, F., Park, S., Kim, W., and Kim, H., Image augmentation to improve construction resource detection using generative adversarial networks, cut-and-paste, and image transformation

techniques, Automation in Construction, vol. 115, no. September 2019, p. 103198, 2020.
[24] Angah, O. and Chen, A. Y., Removal of occluding construction workers in job site image data using U-Net based context encoders, Automation in Construction, vol. 119, no. April 2019, p. 103332, 2020.
[25] Park, J., Cho, Y. K., and Kim, S., Deep learning-based uav image segmentation and inpainting for generating vehicle-free orthomosaic, International Journal of Applied Earth Observation and Geoinformation, vol. 115, no. June, p. 103111, 2022.
[26] AIDCON Authors, Aerial Image Dataset for Construction (AIDCON). On-line: https://ai2lab.org/aidcon/ Accessed:09/04/2024
[27] Suvorov, R. et al., Resolution-robust large mask inpainting with Fourier convolutions, in Proceedings of the IEEE/CVF winter conference on applications of computer vision, 2022, pp. 2149–2159.
[28] Wu, C., Towards linear-time incremental structure from motion, in Proceedings - 2013 International Conference on 3D Vision, 3DV 2013, 2013, pp. 127–134.
[29] Furukawa, Y. and Ponce, J., Accurate, dense, and robust multiview stereopsis, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 32, no. 8, pp. 1362–1376, 2010.
[30] Lin, T. Y. et al., Microsoft COCO: Common objects in context, in Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part V 13, 2014, pp. 740–755.
[31] Eskicioglu, A. M. and Fisher, P. S., Image quality measures and their performance, IEEE Transactions on Communications, vol. 43, no. 12, pp. 2959–2965, 1995.
[32] Wang, Z., Bovik, A. C., Sheikh, H. R., and Simoncelli, E. P., Image quality assessment: From error visibility to structural similarity, IEEE Transactions on Image Processing, vol. 13, no. 4, pp. 600–612, 2004.
[33] SiteEye Authors, SiteEye: Cloud-based Photogrammetry and Project Management. On-line: https://www.siteeye.co, Accessed: 09/04/2024.