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DEFORMABLE OBJECT REMOVAL VIA EXEMPLAR-BASED ALGORITHM FOR 3D MODEL OF HERITAGE STRUCTURES

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ABSTRACT: Heritage structures are important for tourism and for learning about nations' history. Historical sites around the world are in damaged conditions due to various factors from the environment, man-made activities or natural calamities. To ensure safety and avoid further deterioration, digital re-construction of heritage sites can be used to create 3D virtual models of these structures for archiving and for inspection purpose. This paper presents a technique to reconstruct a high-quality image-based 3D model of a heritage structure. An exemplar-based inpainting algorithm was used for removing deformable obstacles such as trees in 2D images since such obstacles are unwanted in a final 3D model. They also create noise in the 3D modeling process, which makes the final 3D model less accurate. In this paper, an inpainting algorithm is applied to generate implied texture to fill holes that occurred from removing objects so that the generated 3D model does not contain any hole and becomes watertight. The modified exemplar-based inpainting algorithm was implemented on 2D images to remove unwanted objects, and then the image-based 3D modeling technique was applied to create a 3D model that did not contain any unwanted objects. The results show that the final 3D model is more accurate when applied the object removal process and the model provides better visualization for heritage structures.

Keywords: Heritage Structures, 3D Modeling, Unmanned Aerial Vehicle, Digital Reconstruction, Exemplar-based Inpainting

1. INTRODUCTION

Heritage sites are important sources of knowledge for a human to learn about cultural history. Due to various natural events and human activities, many heritage sites have been aging and deteriorating. For example, the bridge of Plaka built by Greek stonemen in 1866, located over the river Arachthos, was damaged by extreme weather and the bridge collapsed on February 1, 2015 [1]. Heritage sites are also facing natural calamities and sabotage, for example, the Buddha's of Bamiyan were destroyed by the Taliban in Afghanistan, or the Vithala temple in India is banned for the visitors in order to avoid further damage to the masterpiece [2]. Many organizations are working hard to preserve these heritage sites and buildings. 3D modeling technology, either by a laser scanning or image-based 3D technique, has been applied to archive heritage sites for use as reference models in the future. The digital models of heritage sites can be used in many applications, including surveying, restoration, and structural analysis [3]. The models also offer the possibility for virtual reality tours of heritage sites to allow people to "walk through" the models with an immersive experience without actually visiting the sites. The virtual environment can offer a deeper understanding of the sites in a holistic way [4]. Virtual reality also enables visitors to remotely view the sites that are no longer accessible or no longer exist. Therefore, it is important to construct 3D models of heritage sites that are as complete as possible. An image-based 3D technique can be used to create highly accurate photo-realistic 3D models of archaeological sites [5]. This technique only requires a digital camera as an acquisition tool, which makes this technique easy and cheap. Currently, Unmanned Aerial Vehicles (UAVs) with high-quality digital cameras are ideal tools for collecting images from heritage sites as they can provide rapid and effective views of sites, and they can collect data from inaccessible areas, such as in post-earthquake zones [6] or from high altitude. Many researchers incorporate the use of image-based 3D techniques with UAVs to obtain complete 3D models of heritage sites [7-9].

Image-based 3D modeling software packages are used to create the 3D models of historical buildings [10]. The software packages rely on automatic control point detection algorithms and Structure from Motion (SfM) to generate 3D models from images acquired with arbitrary camera motions. The software packages can create high-quality 3D models as shown in the previous studies [11-16]. Bhakapong and Chaiyasarn [17] applied an image-based 3D technique to estimate the tilt angle of Wat Yai Chai Monkol from a 3D point cloud model. In his work, the 3D model contained unwanted deformable objects, such as people and trees, which affected the accuracy of the final 3D model. Removing unwanted objects enables 3D models to be more efficient and accurate.

In this paper, deformable objects, namely trees, are removed using an exemplar-based inpainting algorithm. The presence of such objects occupies a significant portion in a 3D model, and needs to be removed. The algorithm is applied to images as a preprocessor and then the images are fed as an input to the 3D image-based modeling module to generate a 3D model of a heritage site. The images are acquired by an Unmanned Aerial Vehicle (UAV) from Wat Chai Wattanaram, a temple from Ayutthaya historical park, Thailand as shown in Fig. 1.

Fig. 1 Wat Chai Wattanaram, a temple located in the historic province of Ayutthaya

2. LITERATURE REVIEW

Various projects have been conducted for the digitization of heritage sites all around the world. Amongst these projects, "The Digital Michelangelo Project" was conducted by [18], in which 10 statues by Michelangelo, a huge ancient marble map of Rome and 2 building interiors were digitized by a laser scanner. "The pieta project" was carried out by [19, 20], in which enhanced textured 3D model of a 2.26 meters marble sculpture, made by Michelangelo was created. The authors proposed various ways for the extraction of surface properties, such as color from the acquired images and examined various 3D models representation techniques. "The Minerva Project" was conducted by [21] in which, 3D modeling was performed on a 1.55-meter tall ancient statue by a laser scanner to visualize the changes that occurred during the restoration process. The "Eternal Egypt Project" by [20] developed a virtual museum and digital guide for various monuments in Egypt by using high quality color imaging and thousands of 2D scan data to create a 3D model. Sonnemann et al. [22] conducted a project named "The Angkorian temples project" one of the world's largest religious monuments located in Cambodia in which, thousands of 3D models of heritage structures were reconstructed by using aerial imagery. Padalkar et al. [23] present various techniques for automatically detecting and inpainting damaged regions in heritage monuments to obtained high-quality images to design different virtual reality systems. The authors also explained the worrisome current condition of various heritage sites around the world, which are damaged by natural causes and visitors.

In the recent years, image-based 3D modeling has been applied for 3D reconstruction, which can generate a high quality dense point cloud as a laser scanning point cloud. The image-based techniques are simple, low cost and fast which make them viable alternative to other data acquisition techniques [24]. However, one of the problems with the image-based techniques is the presence of deformable objects in images, which can create noise, resulting in missing regions. Some efforts have been made to address the issues related to 3D model reconstruction [25-27]. Many inpainting techniques have been applied in heritage reconstruction as shown in [28-30]. Inpainting is the art of restoring and modifying the contents of an image. It is used for filling missing regions or removing unwanted information from 2D images by filling it with appropriate color. In in- painting, the missing regions are filled by either propagating information from the neighborhood or from similar regions of different images. Various models have been proposed to address the issue of image in-painting. Interested readers are referred to [31, 32] for explanation. Kuo et al. [33] proposed an improved exemplar-based inpainting algorithm to restore an image to a state, that looks as it has never been altered before. The algorithm worked by assigning different priority level to image patches. The method proposed a scheduling mechanism which freed up the inpainting process from a rigid repair order, for better performance. The exemplar-based algorithm proposed in [31] is modified by incorporating edge information to estimate the confidence and damaged patch values. With edge information, the confidence value and data value parameters damaged patch contour of inpainting points are used for determining the order of filling missing information. In this paper, the same inpainting algorithm is used to remove unwanted objects in 2D images.

3. METHODOLOGY

The outline of the proposed system consists of three modules as shown in Fig. 2. The images are acquired by an unmanned aerial vehicle. After data acquisition, an image-inpainting algorithm is implemented for the removal of unwanted objects from 2D images. Finally, a 3D model is generated by Agisoft, an image- based 3D reconstruction software package. Each module of the proposed system is explained below in detail.

3.1 Data Acquisition

In this study, a Unmanned Aerial Vehicle (UAV)

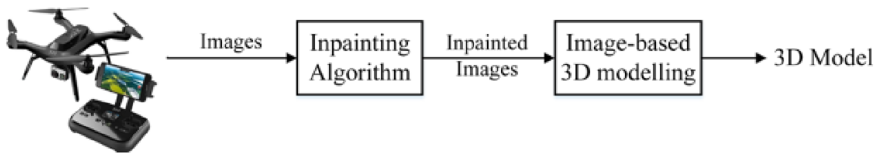
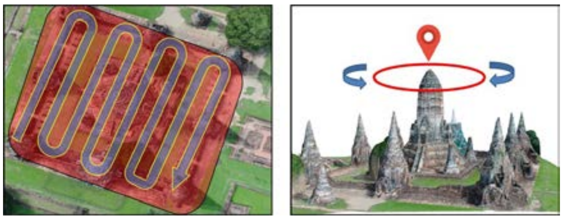


Fig. 2 The outline of the proposed system

was used to collect images from Wat Chai Watthanaram a historic temple, which is located in Ayutthaya, Thailand. The images are collected by a DJI Phantom 4 drone. The specifications of the drone camera is given in Table 1 below. Figure 3(a) demonstrates the first strategy, the sweeping strategy, in which the drone flew in a zig-zag motion to sweep an entire area from a specified height from the ground level. The drone was pre-programmed to take pictures every 2-3 seconds to ensure that an overlap between consecutive images is at least 50%. Figure 3(b) shows the second strategy, the Point of Interest (POI) strategy, in which the drone flew around a fixed object in a circular motion. The acquisition of data is an integral step in digital heritage reconstruction [20]. The data acquisition devices such as 3D laser scans have abilities to accurately create the 3D model of heritage structure with high details. Mostly, scan data of large outdoor structures is not enough to make an accurate 3D model, so various statistical priors are used to fill the missing information.



(a) (b)

Fig. 3 Shows proposed pre-planned flight paths, (a) The sweeping strategy, (b) The POI strategy

Table 1 Specification of a DJI Phantom 4 drone

Specs	DJI Phantom 4
Camera sensor	1/2.3" CMOS, 12.4 Megapixel
Max Speed	20 m/s
Controller range	5 km
Satellite Positioning	GPS/GLONASS
Flight time Approximately	28 min
Weight	1380 g

(a) (b)

Fig. 4 Sample images of study site contain trees, people and site under construction

As shown in Fig. 4, the high-resolution images on high altitude cannot be easily taken by a human, and utilizing the drone for data acquisition around the site clearly provides much more benefits. The total number of collected images is 240, with the dimensions of 4864×3864 pixels. These acquired images contain deformable objects such as people, trees and sites under construction as shown in Fig. 4(b).

3.2 Modified Exemplar-based Inpainting Algorithm

A modified exemplar-based algorithm is applied for filling missing regions of images of the temple. For an image as shown in Fig. 5, the source region is represented S and the target region Ω, which is the area for inpainting. $\delta\Omega$ indicates the connecting boundary of the source and target region where the painting algorithm starts. The proposed method applied the modified exemplar-based algorithms based on the work of Kuo et al. [33], which is summarised in Fig. 6. In the decision-making operation, the first part is the inpainting point assignment, which divides inpainting points (IPs) into four different priorities on the basis of IP parameters. Then, the IP parameters are used in the scheduling mechanism, which selects one of the queues. Finally, a Best Inpainting Point (BIP) will be chosen within this selected queue. The operations determined a Best Inpainting Point (BIP) to start work on. After a BIP has found, the search for its similar region in the source region will begin and the contents from that region will be copied with an irregular patch to restore inpainting patch Ψ_p.

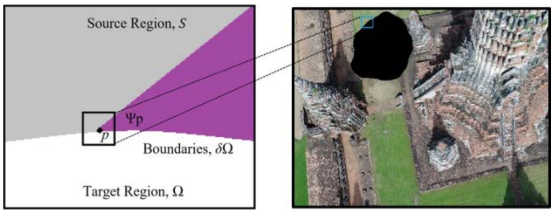


Fig. 5 An illustration filling order in patch-based image inpainting environment

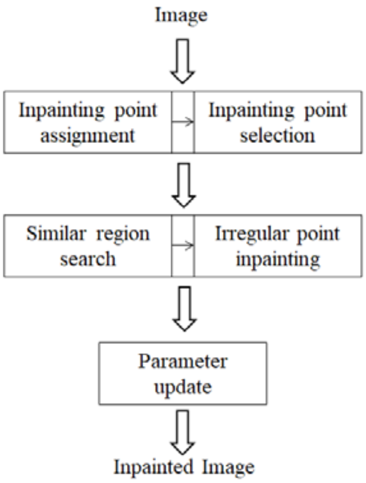


Fig. 6 The workflow of the image inpainting algorithm

3.3 Image-based 3D modeling

Agisoft is an image-based 3D reconstruction system, which takes a set of images as input and the output is a 3D point cloud as shown in Fig. 8. There are three main steps in image-based 3D modeling system such as feature extraction, structure from motion and reconstruction, but there may be more steps in the process in the software package.

3.3.1 Feature Extraction and Matching

In feature detection, the interesting or unique features from an image are extracted. A feature has an image pattern which differs from its immediate neighborhood, which allows the matching of similar features with other images. Examples of the features include corners, blobs, edges, or local image patches with particular properties. In Agisoft, one of the features used in the system is called the Scale Invariant Feature Transform (SIFT) in the feature extraction stage. Once features are detected, feature descriptors are applied to create descriptor vectors to represent the appearances of the features.

The feature descriptors are matched by feature matching algorithms to establish putative correspondences, which are then filtered by robust matching algorithms. In Agisoft, one of the matching algorithms is performed by a brute- force search algorithm and the robust algorithm is Random Smple Consensus (RANSAC) to obtain a fundamental matrix, and the interested reader is referred to [34] for more details.

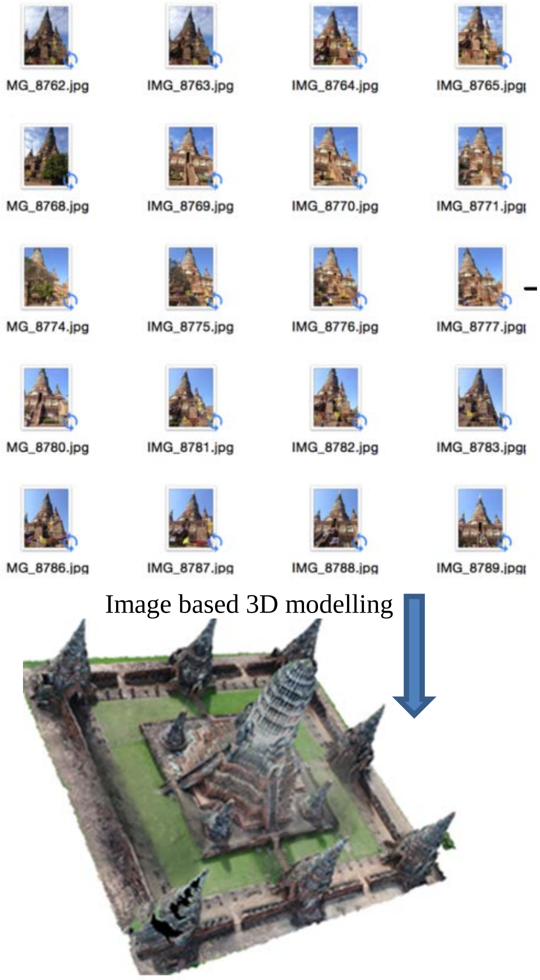


Fig. 8 The outline of an image-based 3D modeling to create a 3D model of a temple

3.3.2 Structure from Motion

The previous module matches images across all images in the database to generate tracks. These tracks are used to initialize the optimizer by triangulation, which estimates the sparse point cloud and camera poses using overlapping triplets of images. The estimation is then refined by Bundle Adjustment (BA). The BA algorithm iteratively adjusts the positions of the 3D coordinates, and the camera poses to minimize the sum of the distances between the re-projections of the reconstructed 3D points through the estimated cameras, and the actual 2D image coordinates.

3.3.3 Dense Reconstruction

The sparse 3D model from SFM can be re-created to obtain a denser point cloud model. This is done by the algorithm called Patch-based Multi-

View Stereo (PMVS), which takes a set of images and camera parameters from SFM, and then reconstructs a sparse model to a dense 3D point cloud. PMVS algorithm is the backbone of most dense cloud algorithm.

4. EXPERIMENTS AND RESULTS

4.1 Inpainting Algorithm

The inpainting algorithm discussed in section 3.2 is implemented on the image dataset. The images in the dataset contain obstacles such as trees, people, and some areas under construction. Binary masks are applied to the original images so that unwanted areas are specified for the inpainting algorithm. The binary mask are applied manually as shown in Fig. 9(b) and Fig. 10(b).

(a) (b) (c)

Fig. 9 (a) Typical image (b) binary mask (c) typical results

The result of the algorithm is shown in Fig. 9(c) and Fig. 10(c). Tthe binary mask is applied to the regions containing trees and people. As shown in Fig. 9(c), the trees and people have been inpainted. Similarly, Fig. 10(a) only contains a tree, a binary mask is applied in order to specify the tree region in the image. The algorithm is implemented on 240 images in the dataset. The inpainted images are then given to Agisoft to create a 3D model.

4.2 Image-based 3D Modelling

The images were collected using a drone and a digital camera from Wat Chai Wattanaram in Ayutthaya. Two types of collection strategies are applied as explained in Section 3.1. The model created from the sweeping strategy provides an overview of an entire site, and the model from the POI strategy is used to obtain detail information from each stupa in the site.

(a) (b) (c)

Fig. 10 (a) Image of study site, (b) binary mask, (c) typical results

4.2.1 Sweeping Strategy

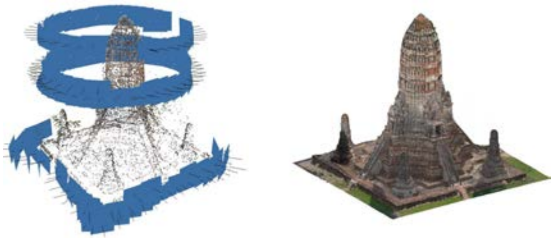
Figure 11 shows the 3D model of study site created from the sweeping strategy. As shown in Fig. 11(b), the model provides a good representation of the entire, such that users can set a sense of space when inspecting the site. However, the model from this strategy cannot provide detail information for close-up inspection. To obtain the detail of the model, the POI strategy is used as explained in the next section.

(a) (b)

Fig. 11 The 3D point cloud, (a) Sparse point cloud, (b) Dense point cloud

4.2.2 POI Strategy

Figure 13 shows example images taken from the drone using the POI strategy. This type of strategy can provide more detail about the structure, and the main benefit is that it can provide the detail on the top of the structure, which is difficult to access using other types of instruments, such as laser scanners. Figure 12(a) shows a sparse 3D model and image locations of the main stupa in Wat Chai Wattanaram, obtained from the POI strategy. It can be seen that images were taken in a circular motion by the drone from two heights, whereas the images on the ground level were obtained manually. Figure 12(b) shows the dense 3D model of the temple, which is sufficiently good for visualization. This model can be combined with the model from the sweeping strategy.



(a) (b)

Fig. 12 The 3D point cloud (a) Sparse point cloud, and (b) Sense point cloud

4.2.3 Model Comparison

The 3D model obtained from non-inpainted images is shown in Fig. 14(a) and Fig 14(c). As shown in Fig. 14(a), the model contains more noise due to deformable objects in the scene, including trees, people and areas under construction. The model obtained after the removal of unwanted objects by the proposed inpainting algorithm as shown in Fig. 14(b) and Fig. (d). The model is improved and implied texture enables the model to be complete without holes. The final reconstructed model is shown in Fig. 15, and the processing parameters of both the models are summarized in Table 2 below.

As shown in Table 2, for non-inpainted images, the number of created points was 94,393 points, while for the inpainted images, 87,772 was created. The re-projection error is improved from 0.180482 to 0.178738. Similarly, the max re-projection error is improved from 0.545285 to 0.539829. The effective overlap is also increased from 13.0711 to 13.4847, while the matching time in alignment parameter phase is decreased from 17 minutes 32 seconds to 11 minutes 16 seconds. The results reveal that model obtained using the proposed method is efficient and required less computational time. Image based 3D modelling techniques are cost effective and perform fast in 3D scanning measurement of heritage sites. The proposed method works well to remove noise caused by deformable objects preserving the quality of the models.

The proposed method can be used to create 3D virtual models of various heritage structures for archiving and for inspection purpose. The inpainted images can be used as an input to these systems. However, the proposed method still needs improvement in the selection of inpainting region. Automatic inpainting area selection is required instead of manual binary masks. The state of the art deep learning object detection techniques can be used for the detection of regions to be inpainted.

Fig. 13 Example images of Wat Chai Wattanaram taken from the drone with the POI strategy

5. CONCLUSION

In this paper we have addressed the problem of noise in 3D models of heritage sites, which is produced due to numerous deformable objects such as trees, people and under construction sites. These objects also affected the resolution of 3D models which results in false identification of various objects. We have presented an image inpainting based innovative approach for the occlusion removal in 3D reconstruction. Both qualitative and quantitative results of the proposed system shows that the quality of the 3D model is improved. It can be concluded that the RMS re-projection error, max re-projection error and matching time of the 3D model is improved by the proposed inpainting algorithm. It can also be concluded that the proposed system can help in preventing heritage sites from further harm by making various walkthrough systems for virtual environments in which the visitor will be able to observe fine details of the historic sites.

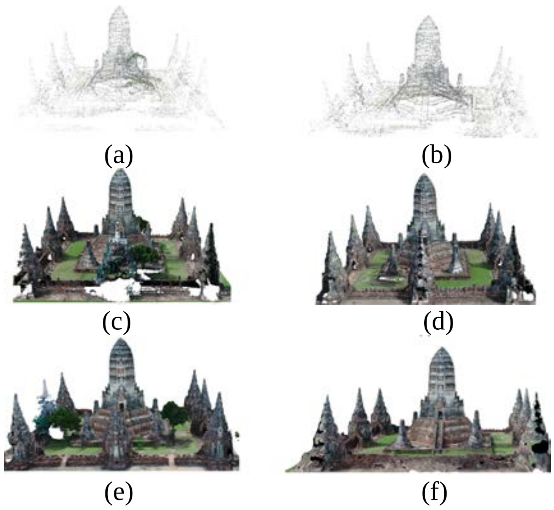


Fig. 14 (a) 3D sparse point cloud (b) A 3Dsparse point cloud with the application of the proposed algorithm, (c) 3D dense point cloud, (d) 3D dense point cloud with the application of the proposed algorithm (e) 3D texture model without the inpainting algorithm and (f) 3D texture model with the application of the proposed inpainting algorithm

Table 2 Processing parameters

Process	Before	After
Reconstructed Points	94,393	87,772
RMS re-projection error	0.180482 (0.58627 pixels)	0.178738 (0.58623 pixels)
Max re-projection error	0.545285 (31.7398 pixels)	0.539829 (18.2844 pixels)
Mean key point size	3.04729 pixels	3.0667 pixels
Effective overlap	13.0711	13.4847
Matching time	17 minutes 32 seconds	11 minutes 16 seconds

5. ACKNOWLEDGMENTS

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