UAV Mission Planning Using Swarm Intelligence and 4D BIMs in Support of Vision-Based Construction Progress Monitoring and As-Built Modeling

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ABSTRACT
Inspection planning is a primary element of computer vision- and unoccupied aerial vehicle (UAV)-enabled construction monitoring. Prior to the on-site deployment of camera-mounted UAVs, the inspection objectives need to be identified, and optimal inspection plans must be developed; Such plans should ensure complete data acquisition and minimize the use of UAV’s limited flight time. The image capture configuration must be taken into account since it directly affects the downstream applications of the captured data such as progress detection and as-built modeling. This paper proposes a framework and a novel technique which utilizes four-dimensional (4D) building information models (BIM) and swarm intelligence to automatically generate the UAV inspection mission plans. It computationally supports both static and dynamic site layouts. The inspection objectives, their geometry, and their semantics are automatically extracted from BIM, and the corresponding elements are identified. An optimal inspection plan is developed using artificial intelligence, ensuring complete coverage of inspection targets while minimizing flight duration. The method has been tested in UAV-enabled data acquisition scenarios. It is based on the industry foundation classes (IFC), facilitating OpenBIM and reducing the costs associated with the lack of interoperability, a core challenge in information modeling. Due to the target extraction at element and sub-element levels, it supports computer vision-based construction progress monitoring and automated as-built and as-is BIM development.

INTRODUCTION
The rapid advances in the design of light-weight camera-mounted unoccupied aerial vehicles (UAV) have created unprecedented opportunities for computer vision techniques; the visual assets collected by UAVs facilitate situational awareness at construction sites and provide a clearer view of actual conditions. Project progress tracking and quality inspections have proven to be among the most promising applications of UAV-captured visual data (Irizarry and Costa 2016).

This has initiated recent efforts on computer vision-based application of UAV-captured data for the purpose of surveying (Siebert and Teizer 2014), infrastructure condition assessment (Yan et al. 2016), and construction progress tracking (Hamledari et al. 2017a; Han et al. 2015). Visual data analytics solutions, empowered by UAV-captured visual data, continue to improve the quantitative assessment of as-built and as-is conditions. To increase the accuracy of such vision-based techniques, it is crucial to investigate the design of UAV image acquisition strategies that ensure the high quality of captured data (Morgenthal and Hallermann 2014). The data captured during manually planned inspections suffers from detail, coverage, and accuracy (Zhang et al. 2016); the construction dynamics and changes in the building layouts also increase the need for model-driven and automatic planning of UAV inspection missions.

Successful UAV-enabled visual data acquisition requires the automated design of inspection plans that ensure 1) the customized identification of inspection objectives; 2) the design of optimal inspection plans that minimize the flight time; 3) the consideration of the effect of the data acquisition strategy on future uses of the collected data; and 4) the robust adjustment of the mission plan according to the dynamic changes in the building layout. There is a need for model-driven and goal-oriented approaches toward UAV-enabled data capture. This offers improvements over the haphazard data collection strategies by considering the downstream uses of UAV-captured data.

This paper introduces a novel 4D model-driven technique for the automated design of UAV inspection mission plans in support of computer vision-based construction progress tracking and image capture. First, it discusses the relevant works on UAV inspection planning, the limitations, and the motivation for this research. This is followed by an explanation of the proposed techniques and its applications.

RELATED WORKS
The literature on UAV inspection planning is focused on 1) quantifying the effect of UAV dynamics and photo capture on the accuracy of visual data analytics; 2) minimizing the construction jobsite’s safety hazards using UAV feed; and 3) the design of UAV inspection plan and data acquisition strategies (*this work’s focus*).

**Quality assessment of UAV-captured images.** Robust assessment of the quality of robot-captured data ensures accurate reality capture and streamlines the design of inspection plans. The quality of UAV-captured images were assessed with respect to the robot’s motions and wind (Morgenthal and Hallermann 2014); this helped estimate the reliability of image-based condition assessments based on environmental factors. Others provided quantitative analysis of the effect of UAV’s dynamics and velocity on the accuracy of vision-based construction progress tracking and as-built 4D modeling (Hamledari et al. 2017b). This resulted in a set of recommendations for UAV-enabled image acquisition and the quantification of motion blur effect. The UAV-captured images were proven reliable for the automated generation of as-built 4D BIMs and the in-model integration of as-built and as-is conditions (Hamledari et al. 2017c).

**UAVs promoting safety.** Researchers have assessed the feasibility of UAV-enabled inspections as an active part of construction safety control (de Melo et al. 2017). Vision-based techniques were employed on UAV-captured images to locate cranes (Roberts et al. 2017), helping to reduce their safety hazards on jobsites. The quality of UAV-captured visual data was observed to be a primary factor for UAV use in safety monitoring systems (Kim et al. 2016); this further emphasizes the need for model-driven and automatically planned robotic inspections.

**The design of UAV inspection plans.** The automated model-driven inspection planning was proposed as a primary part of a framework for indoor UAV-enabled construction monitoring (Hamledari 2016). A technique was introduced to generate the UAV waypoints for the outdoor inspection of user-selected elements (Freimuth and König 2016). A user interface was designed to provide assessments of user-specified indoor inspection routes (Ibrahim et al. 2017); the technique evaluated the completeness of 3D point clouds and the route’s proximity to structure based on the location of user-selected waypoints.

Mission planning has also been explored for existing structures (Ramanagopal et al. 2017). UAV missions were designed to support bridge inspection using a set of pre-defined way point patterns (Hallermann and Morgenthal 2014). Other studies offered more customized means of identifying the data acquisition locations. The viewpoint resampling was employed to design customized inspection routes that maximize the coverage and completeness of constructed 3D models for existing structures (Bircher et al. 2016). While tailored to terrestrial laser scanning, scan stations were automatically identified while taking into account the accuracy and the level of detail of the resulting 3D point clouds of target structures (Zhang et al. 2016). Another study further elaborated on the interoperable and IFC-based integration of UAV mission planning modules with progress tracking and automated as-built modeling solutions (Hamledari 2017).

**Identified Limitations and the Need for 4D-based UAV Mission Planning**

This section summarizes the primary limitations that this work aims to address in the area of UAV inspection mission planning.

**Indoor applications.** Unfortunately, the UAV mission planning at indoor sites still remains unexplored (McCabe et al. 2017). There are challenges specifically associated with indoor path and inspection planning. The obstruction of the camera’s line of sight, a common challenge for indoor image-based progress tracking (Bohn and Teizer 2009), affects the data acquisition by camera-mounted UAVs. The robots need to explore the building layout while at times photographing an element from multiple viewpoints (e.g., two sides of a partition). Due to the existence of permanent obstacles and complicated layouts, the straight inspection paths employed for outdoor UAV inspections are not effective indoors. These complexities hugely limit the applicability of manual user interfaces and call for the automated methods tailored to indoor sites.

**Customized target extraction.** There is a need for solutions that provide multi-dimensional and highly customizable query and extraction of UAV inspection objectives. For example, this includes the automated selection of building elements based on geometry, element semantics, schedule items, and schedule performance.

**Consideration of downstream uses of collected data.** The existing literature on UAV inspection mission planning evaluate the completeness of point clouds generated by images. This study, however, addresses the needs of...
vision techniques that identify the progress of building elements directly from the 2D images. Further, the manually planned inspections do not satisfy the requirements for image-to-BIM automation due to the improperly or incompletely captured elements; this work takes into account the accuracy of as-built 3D and 4D modeling techniques to address this.

**Interoperability.** The interoperable design of UAV inspection mission plans increases their ease of use and reduces the costs. It can also facilitate the model-driven communication of data among various stakeholders such as UAV operators, project team, safety managers, and flight regulation bodies.

**THE METHOD**

The proposed method addresses the need for automated and IFC-based 4D model-driven UAV inspection mission planning. This research is motivated by the direct effect of UAV mission planning on the site-to-BIM automation and its role as the first part of a robotic smart construction progress monitoring solution (Figure 1). The UAV inspection plans designed by this method can be used for on-site data acquisition in support of image-based progress tracking and quality control systems.

![Figure 1. The research context: a) 4D BIM-enabled UAV inspection planning; b) robotic visual data capture; c) computer vision-based progress detection; and d) automated generation of as-built 4D BIMs](image)

The method can support both robotic data capture agents and human-centered data collection. This work focuses on the automated and model-driven design of the UAV mission plans based on inspection objectives; the sensor-based plan execution, the online navigation/control, and low-level obstacle avoidance will be elaborated in future works. To maximize its practical use as part of the research context (Figure 1), the method was designed while taking into consideration its effects on the accuracy of downstream applications. In this research, the resulting UAV-captured images are used by techniques previously developed by the authors including computer vision-based progress detection (Hamledari et al. 2017a) automated development of as-built 4D BIMs (Hamledari et al. 2017c; Hamledari et al. 2017b), and automated semantically rich as-built and as-is BIM development (Hamledari et al. 2018). Hence, the design automation for UAV mission planning directly benefits these application domains.

**The System’s Architecture**

The method (Figure 2) receives as input an IFC-based 4D BIM along with the user-specified inspection parameters, which include a description of inspection objectives (i.e., the type of building elements or schedule tasks that need to be inspected), the date and time of the inspection, the takeoff and landing locations (optional), and other customizable restrictions on the navigable 3D space. The inputs are passed to a parser that extracts the geometrical and semantic information for the modeled building elements. This is achieved by querying the subtypes of IfcElement and the data instances within the model that are related to them (e.g., schedule).
The method 1) develops a spatial understanding of the building floor layout at the date and time of the inspection; 2) extracts the building elements satisfying the user-specified description of objectives; 3) maps the elements to the 3D navigable space on the building floor; 4) generates a series of image capture locations on the building floor that ensure full coverage of identified elements and satisfy the requirements of computer vision and model updating algorithms; and 5) designs an optimal inspection plan that results in a visit to each data capture location while satisfying safety requirements and minimizing the flight duration. The resulting inspection plan determines the sequence in which the image acquisition needs to proceed; it consists of multitude of paths, each of which connect two consecutive data capture locations.

4D-based Identification of Navigable Spaces at Dynamic Sites

To take into account the dynamic nature of indoor construction, this work automatically time stamps the 4D models based on the date and time of the inspection. This is achieved with the investigation of task-object and task-control relationships within the IFC data model. The instances of IfcScheduleTimeControl can provide the necessary information with respect to the duration and the scheduling of tasks related to each element. Based on this analysis and a comparison of the time of inspection and schedule items, the site’s layout can be generated and adjusted for each inspection date.

Figure 3 depicts a 2D representation of the building layout of the same jobsite at two different dates; it is observed that the construction’s dynamics can be captured using this 4D-enabled time stamping process. The same approach is employed for the quantification of changes in the navigable height of the building floor at each location. In other words, the 4D use helps identify to what extent the installation of elements constrains vertical movements of the robotic data collection agent.
Customized and Multi-Dimensional Extraction of Inspection Objectives

The next step automatically extracts the inspection objectives, i.e. the building elements that need to be photographed by the UAV. In this work, the project team members can either 1) provide a description of target elements (e.g., elements behind schedule); 2) identify the task items in the schedule and the associated elements that need inspection; or 3) identify the spaces on the building floor that need inspection. Users can extract target elements using a series of nD filters that focus on geometry, semantics (e.g., element type), schedule, resources, and schedule performance. To enable such extraction of elements, the algorithm iterates over data instances within the model that are related to the building element (e.g., through subtypes of IfcRelationship). The queried element is included in the UAV mission plan if it meets the user-specified conditions. Examples are provided in the “case studies” section.

Identification of Image Acquisition Strategy

A series of locations are identified for UAV-enabled image capture to ensure full coverage of extracted target elements. For each element, the number of locations and their placements are selected in coordination with the computer vision algorithms that employ the resulting images. The vision-based algorithms employed in this work rely on the extraction of progress directly from 2D images; hence, locations are selected such that both sides of large elements, such as partitions, are captured. More importantly, in cases where the modeled element (e.g., a partition) spans several spaces (Figure 4a), the program identifies locations along its length to ensure its full coverage. The intervals for image capture are selected such that all workstations along that element are visited. This process is less challenging for elements such as outlets or columns with relatively small dimensions. For a larger element, the program iterates over its neighboring building elements and identifies their intersections and spatial relationship. This is used for the optimal placement of image capture locations. This process can be adjusted based on the employed computer vision algorithm.

Figure 4. Plan optimization: a) image capture locations for a set of 9 partitions; b) 2D representation of a UAV inspection plan developed for targets in Figure 4a and based on the user’s preferred takeoff and landing locations

Swarm Intelligence-based UAV Plan Optimization

In the next step, an inspection plan is developed that satisfies the data capture and safety requirements and minimizes the flight duration. The safety requirements are specified by users and include, but are not limited to, restrictions on the aerial robot’s horizontal/vertical distance to elements, flight restrictions during specific times and spaces, and proximity to workforce. This acts as a preventive safety measure for use in the planning phase, and it minimizes potential collisions and supplements the on-site sensor-based navigation. The algorithm first calculates the shortest distance between each pair of image capture locations; this work employs the Dijkstra algorithm but other solutions can be used. This results in the calculation of the distance matrix, which holds the shortest distance connecting each pair of target locations.
The ant colony optimization (ACO) is employed to design an inspection plan that minimizes flight duration while granting one visit to each image capture location. Each potential sequence at which data capture locations can be visited is represented by a state. The ACO iteratively switches between the set of possible states. Equation 1 describes \( p_{xy} \), the probability of a switch from the state \( x \) to \( y \). The \( \tau_{xy} \) and \( \eta_{xy} \) are respectively the trail level (an indication of how effective that switch has previously been) and the a priori desirability of the transition \( x \to y \). The denominator includes the sum of \( (\tau_{xz})(\eta_{xz}) \) for all possible transitions, where \( z \) is the new state. Completing this process for a series of ants at each iteration results in the selection of the final optimal inspection plan. The trail levels are updated after all ants complete an iteration (Equation 2, where \( \tau_{xy}^{k} \) is the trail level deposited by the \( k \)th ant).

Figure 4b illustrates an ACO solution for the set of inspection target locations shown in Figure 4a. The UAV takeoff and landing locations were arbitrarily chosen by the users, and the image capture locations were identified by the program as explained in the previous section. The developed inspection mission plan is used during the on-site data capture and low-level robot navigation. Additionally, the algorithm also outputs a geometrical description of the navigable space such as the navigable elevation range at each location on the building floor. The UAV mission plan is updated during the on-site flight and based on the aerial robot’s sensory identification of obstacles (Figure 2). The 3D navigable space is continuously updated and used to modify the distance matrix and correspondingly the outcome of ACO.

\[
p_{xy} = \frac{(\tau_{xy}^{k})(\eta_{xy}^{k})}{\sum_{z}(\tau_{xz}^{k})(\eta_{xz}^{k})} \quad \text{Eq. 1}
\]

\[
\tau_{xy} \leftarrow (1 - \rho)\tau_{xy} + \sum_{k} \Delta \tau_{xy}^{k} \quad \text{Eq. 2}
\]

**CASE STUDIES**

The method was implemented and tested in multiple UAV-based data collection scenarios. Different choices of input BIMs were used for the purpose of evaluation including both 3D (static layout) and 4D models (dynamic layout). In each test, the users 1) arbitrarily chose the takeoff and landing locations, 2) stated the date and time of robotic inspection, and 3) described the inspection objectives. Examples of such descriptions include:

- Partitions that are behind schedule
- Electrical outlets of type “standard duplex”
- The work associated with the “subcontractor A”
- All elements that are associated with the “Task A” and “Task B”

For each set of target elements, the experiment was successfully repeated by changing other parameters such as the inspection time, the terminal locations, and the safety requirements. Figure 4 shows the results of one such experiment for 9 partitions.

Future works include the integration of this UAV mission planning solution with online execution strategies relying on sensor data and the direct and in-BIM integration of the UAV mission plans; the latter empowers model-driven and effective communication of the designed plans among project stakeholders. It also facilitates BIM-based collaborations on UAV inspection mission design and contributes to the model-driven integration of project information (Fischer et al. 2017).

**CONCLUSION**

This paper introduced an automated and model-driven technique for the design of UAV inspection mission plans in support of indoor computer vision-based construction progress tracking. The solution designs image capture plans for static and dynamic site layouts while maximizing the accuracy of downstream uses of the collected data, satisfying safety requirements, and minimizing the aerial robot’s resource use. The inspection objectives and their corresponding building elements are extracted based on users’ customizable target description. An optimal plan is designed using swarm intelligence, ensuring full data capture for identified elements while minimizing the flight time. The generated inspection plan is used for on-site execution, where it will be updated based on UAV’s in-flight feed and the identified obstacles. The technique is completely based on the non-proprietary IFC schema, promoting
interoperability and OpenBIM; this software-independent approach maximizes the practical use of the method among all stakeholders in UAV-enabled inspections.

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