Automated facility inspection using robotics and BIM: A knowledge-driven approach

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Abstract

Facility inspection is crucial for ensuring the performance of built assets. A traditional inspection, characterized by humans' physical presence, is laborious, time-consuming, and becomes difficult to implement because of travel restrictions amid the pandemic. This laborious practice can be automated by emerging smart technologies such as robotics and building information model (BIM). However, such automated facility inspection (AFI) entails an autonomy of the robots to adaptively response to the complexity of their environments, which, unfortunately, has rarely been documented. The goal of this research is to propose a knowledge-driven approach that can potentially lead to large-scale automation of facility inspection. It equips facility inspection robots with an ability of unambiguous reasoning for independent decision-making. At the core the approach is an integrated scene-task-agent (iSTA) model that formalizes engineering priori in facility management and integrates the rich contextual knowledge from BIM. Experiments demonstrated the applicability of the approach, which can endow robots with autonomy and knowledge to navigate the challenging built environments and deliver facility inspection outcomes. The iSTA model is publicized online, in hope of further extension by the research community and practical deployment to enable AFI.

Keywords: Facility management; Inspection; Robotic; Building information modeling (BIM); Knowledge formalization; Ontology.

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1. Introduction

Once a built asset is handed over, it is officially put into operation, entering the longest phase of its lifecycle. During this process, facility management is crucial to ensure both functional and structural performance of the facility [1]. Inspection is the cornerstone of facility management [2], which aims to gain up-to-date information of the physical assets to ensure that they are complied with prescribed standards and regulation [3]. To date, facility inspection is conducted manually, where building surveyors or structure and mechanical engineers are dispatched onsite to inspect items indicated by an inspection checklist. This practice is often criticized for its difficult physical presence, low efficiency, and onerous paperwork [3, 4].

Existing manual facility inspection becomes less and less sustainable as major economies are experiencing shrinking population [5], leading to decreasing workforce in the facility management market. The situation is worsened by the on-going COVID-19 pandemic [6], which makes physical onsite inspection more difficult. The series of challenges have forced the academia and industry to think outside of the box, resulting in many computerized tools to support facility inspection. For example, embedded sensing systems, laser scanning, and Radio Frequency Identification (RFID) technologies have been exploited to expedite facility information collection [7-9]. The use of mobile devices (e.g., smart phones, and tablets) for inspection records documentation has become a new norm, freeing inspectors from overwhelming paperwork [3]. While these technologies have undoubtedly helped inspectors, much of the inspection work still needs to be manually accomplished onsite.

The rapid advancement of smart technologies provides abundant opportunities for smarter facility inspection. Particularly, the development of artificial intelligence (AI) and robots has been used to replace humans in a wide range of tasks such as floor cleaning and disinfection [10]. Inspired by these applications, pioneering studies have explored the potential of robots in facility inspection. These include the development of robotic systems for post-disaster asset assessment [11], water utility inspection [12], and building facility management [13, 14]. However, despite the progress achieved, many of the inspection robots still need to be manually controlled by human operators [11]. Some does have a certain level of autonomy, but they are generally confined to relatively simple tasks, failing to independently respond to the dynamic and complex environments.

Another highly potential technology is building information modeling/model (BIM). As a digital replica of a built asset, BIM offers a single source of truth wherein all project-related information is stored, processed, and managed in a central hub [15]. Leveraging the rich information in BIM, traditional inspection process has been augmented to assist human decision-making [4, 16, 17].

BIM can also be linked with robots to allow them better understand of the facility as concerned. Follini et al. [18] leveraged the priori geometric and semantic data in BIM to enable robot perception towards the dynamic and unstructured construction site. Chen et al. [19] proposed a BIM-based global path planning method for ground robot navigation in built environments. Kim et al. [20] studied the viability of using readily-available BIM to model a semantic building world as perceived by a robot. These pioneering studies mainly focuses on devising data interface for construction robot task planning [21]. Nevertheless, much remains unknown on how BIM and robotics can be integrated to equip the robots with a high level of autonomy in facility inspection.

The automation of facility inspection entails an ability to adaptively response to the complexity posed by the tasks (e.g., "inspection of fire doors in a floor") and the changing environments (e.g., "encountering human occupants during inspection"). Robots can be equipped with such an ability via a knowledge-driven approach. Tenorth and Beetz [22] stressed the importance of knowledge processing in enabling autonomous robots to do the right thing to the right object in the right way. Thosar et al. [23] performed knowledge-driven reasoning for tool selection in household environments. To facilitate interoperability across robotic platforms and unambiguous reasoning for independent decision-making, a formal representation of knowledge is necessary [24]. Knowledge formalization is a way to structure the unstructured knowledge, which aims to reach a formal, explicit specification of a shared conceptualization, i.e., an ontology [25]. The robotic research community has been active in developing such knowledge representations, resulting in a series of ontologies [26-28]. However, these ontological knowledge models are mainly for industrial applications [27] or household services [22]. Facility inspection has its uniqueness (e.g., the availability of BIM, and the unique workflow of inspection tasks), which calls for a tailor-made knowledge model to drive automated robotized inspection.

This research aims to propose a knowledge-driven approach that can potentially lead to large-scale automation of facility inspection using robotics and BIM. At the core of the approach is a formalized ontological model encompassing three pillar aspects of facility inspection, namely (a) the scene where a robot operates in, (b) the inspection task, and (3) the robots (agents) themselves. The three aspects of knowledge are seamlessly connected, forming a scalable framework called integrated Scene-Task-Agent (iSTA). The remainder of this paper is organized as follows. Subsequent to this introduction is a literature review. Then, the methodology is introduced in Section 3. Following that, the iSTA knowledge model is presented in Section 4, based on which the knowledge-driven approach for automated facility inspection (AFI) is described in Section 5. The approach is evaluated by experiments in Section 6. Research findings and the strengths and limitations of the study are discussed in Section 7, and conclusions are drawn in Section 8.

2. Related works

2.1. BIM and robotics for facility inspection

Many studies have applied smart technologies such as BIM and robotics to improve facility inspection productivity. BIM has mainly been explored as an information-rich source to support facility inspection. Liu et al. [4] developed a BIM-augmented system for building inspection, which can help users retrieve project information with ease to assist facility condition assessment. Kopsida and Brilakis [16] proposed a registration method to align reality-captured point cloud with BIM for augmented reality (AR)-based inspection. Baek et al. [17] devised a BIM-integrated AR system for facility management using image-based indoor localization. Despite the supportive roles of BIM by providing on-demand, easy-access, and intuitive project information, the process of facility inspection still needs to be manually implemented.

To improve efficiency and productivity, robotics is increasingly used in facility inspection. Torok et al. [11] integrated ground robots with computer vision for post-disaster building inspection. Walter et al. [12] developed a robotic system to inspect wastewater treatment facility. Asadi et al. [13] presented a vision-based mobile robots for facility construction inspection. In these applications, the inspection robots need to be controlled by human operators, making physical presence onsite inevitable. Some research efforts have been made to automate the inspection process. For example, Tan et al. [29] proposed an automatic drone-based method for building envelope inspection. Kim et al. [20] explored the applicability of automated robot task planning/execution. However, the achieved automation is usually confined to simple tasks executed in relatively well-controlled environments. To equip robots with high-level autonomy and independent reasoning, a sophisticated knowledge model for facility inspection is necessary.

2.2. Knowledge-driven robotics and automation

Autonomous task implementation can be realized by various approaches. One is to program all detailed activities involved into the robot. Obviously, this approach is not sustainable owing to the onerous programming efforts to cater to every possible environmental change [30]. The other approach is to represent task implementation knowledge in an interoperable and widely accepted format so that the robotic agents can reuse existing knowledge and conduct reasoning to adaptively adjust to the external world [31]. The process of developing a formal, explicit specification of a shared conceptualization is referred to as knowledge formalization [25]. Because of the promise presented by the knowledge-driven approach, the robotics and automation community has been focusing on knowledge formalization in recent years.

Malec et al. [32] proposed to streamline the reconfiguration of manufacturing robots via the knowledge formalization. The research work later evolved into a set of public-available ontologies called ROSETTA [27]. The IEEE-RAS Ontologies for Robotics and Automation Working Group released core ontology for robotics and automation (CORA) [26], which has now become a basic ontology widely used in industrial, surgical, and service robots. Tenorth and Beetz [22] introduced KnowRob (Knowledge processing for Robots), which soon proved itself one of the most influential knowledge processing system for autonomous service robots in household environments. The authors released a second generation of the system called KnowRob 2.0 in 2018 [28]. Other knowledge formalisms have also been developed for domain-specific purposes, e.g., search and rescue [33], and household service [23].

In the AECO (Architecture, Engineering, Construction and Operation) industry, little work has been done in knowledge formalization for robot autonomy. Neythalath et al. [34] proposed a multi-layer knowledge encapsulation model for adaptive robotic manufacturing, which, however, is primarily for industrial robots. Kim et al. [20] explored the applicability of exploiting an IFC-format BIM for construction robot task planning/execution, of which the effectiveness was evaluated in Gazebo simulation environment. However, they focused more on the data interoperability problem between IFC and unified robot description format (URDF), rather than formalizing a general knowledge model for robotized facility inspection.

2.3. Limitations of existing studies

Our literature review reveals three major knowledge gaps in knowledge-driven AFI:

(1) Lack of knowledge formalism for break-down process of facility inspection. Previous efforts mainly focused on representing knowledge of facility management to facilitate data exchange [35], or energy analysis [36]. Only a few has paid attention to activity-level descriptions of facility management tasks, which, however, are either for building renovation [37], or bridge rehabilitation [38]. As a robot needs to understand meaning of task before it can implement it, there is an urgent need to develop a knowledge representation of inspection activities with machine-readable language.

(2) Gap between general robot description and domain-specific needs in facility inspection. There are a number of robot knowledge processing systems proposed by the robotics community. Nevertheless, they are either for industrial robots [27], or for general applications of service robots [28]. Facility inspection has its own characteristics that are distinguishing from existing robot ontology, e.g., the availability of BIM, and the unique workflow of inspection process. These domain-specific needs should be considered to extend existing general-purpose robot knowledge representation.

(3) Absence of an integrated model to synergize knowledge from the diverse domains of built asset,

inspection, and robotics. The automation of facility inspection requires robots to have knowledge about the scene they are to explore, awareness of the inspection tasks they are to implement, and self-knowledge on what they are capable of. However, to the best of our knowledge, an integration of the three aspects of knowledge (i.e., scene, task, and agent) to enable AFI has not never been reported in literature.

3. Methodology

This study uses the Methontology approach [39] to developing a knowledge model that will drive AFI using robotics and BIM. Methontology is a methodological paradigm for building ontologies from scratch. It typically involves six steps, namely specification, knowledge acquisition, conceptualization, integration, implementation, and evaluation.

3.1. Specification

The stage of specification aims at specifying general requirements for the ontology to develop, which usually include purpose, scope, source of knowledge, and intended users. Table 1 summarizes the specification of our knowledge model for AFI. It is acknowledged that certain tasks of high complexity (e.g., measuring designated physical quantity in a narrow pump house) are still difficult to fully automate. Therefore, the ontology in this study is focused only on visual inspection tasks. The scope is confined to the inspection of three items, i.e., fire safety, light system, and interior wall. The primary use is to endow robots with autonomy and domain knowledge for facility inspection. However, end-users can also be extended to facility managers/owners who can use the ontology to query robot inspection records. Researchers and robotic developers in the facility management domain are potential beneficiaries as well, who can reuse the ontology to develop robotized facility inspection applications.

Table 1. iSTA ontology specification

Items	Descriptions
Purpose	To formalize concepts and their interrelation concerning built assets (scene), inspection activities/procedures (task), and robotic platforms (agents) to enable smart facility inspection using autonomous service robots
Scope	To focus on visual inspection tasks, including the inspection of fire resistance system, lighting system, and assurance of the soundness of interior concrete surface
Users	The primary end-user is service robots to allow them implement facility inspection autonomously. Other potential users include facility mangers/owners, and researchers/developers in the area.

Knowledge source	Practitioners, domain experts, facility management handbook, etc.

3.2. Knowledge acquisition

The acquisition of knowledge usually follows methods (e.g., interview, text analysis, and survey) developed in social science [40]. This study adopts the following approaches to eliciting knowledge related to RFI. First, we referred to relevant documentation materials for an informal text analysis. The referred documents include building inspection guidelines, ordinance, and facility maintenance handbooks published over the past two decades in Hong Kong. The analysis allows us to have a general understanding of the basic items on facility inspection checklists. Then, professionals from related domains (i.e., facility management and robotics) were interviewed to gain further insights. The interviewees include a real estate manager, two wardens of student residents, and two robotic engineers. A list of questions were prepared based on the disciplinary background of the interviewees, as listed in Table 2.

It should be noted that specification and knowledge acquisition do not have to be conducted in sequential order. In fact, the two were done simultaneously in this study, where the acquired knowledge can be used to update the specification. For example, the scope initially specified was the general visual inspection tasks. As more and more knowledge solicited (especially via the phone interview with the estate manager), the scope was further refined and updated, which was finally confined to three inspection tasks of “fire safety”, “lighting system” and “interior wall”. We also understand, from the interview that, these tasks were normally performed by the wardens when they do daily patrol in the building. If anomalies are found (e.g., “a flickering light”, “a crack on wall”, or “an unilluminated exit sign”), the wardens should report by taking and uploading photos of the anomalies.

To execute the tasks by robots, according to the robotics engineers, an inspection should to be assigned to different robots on a floor-by-floor basis. This is because different robots have different locomotion capabilities. To make this assignment possible, knowledge of the robots (e.g., “where they are”) is necessary. In addition, the inspection tasks should be broken down into basic activities such as navigation, obstacle avoidance, and photo taking. To plan the navigation path, position information of the facilities to inspect is needed.

Table 2. Interview questions for knowledge acquisition.

Role	Num. of interviewees	Questions

Real estate manager	1	• What are the regular inspection items in operation and maintenance phase of your projects? • Who perform the mentioned inspection tasks? • Which manual inspection tasks do you think will be replaced by robots in the near future? • What is the inspection frequency? • How are the inspection results solicited to support maintenance planning?
Wardens	2	• How do you carry out [xxx] inspection task? • How often is [xxx] inspection implemented? • How do you record and report the inspection results?
Robotic engineers	2	• What information of the scene and the robots would be needed for a robot to implement [xxx] inspection task? • How should the [xxx] inspection task be broken down in order to be implemented by a robot?

* Note: the [xxx] is replaced with specific inspection tasks in the interview.

3.3. Conceptualization

Conceptualization means to structure the obtained knowledge in a conceptual model with a hierarchy of main terms and their relationships [37, 39]. Based on the knowledge acquired by text analysis and interview, this study decided to conceptualize the ontology for AFI from three main branches, that is, the Scene, the Task, and the Agent. Within each branch, corresponding terms and vocabularies are further enumerated to enrich the ontology. For example, under the "Task", there are the "fmTask", "fmActivity", and the "adhocAction", *inter alias*; under the "fmTask", there are then "fmTasFireResist" (fire safety inspection), "fmTasInWallDefect" (interior wall inspection), and "fmTasLightInspect" (lighting system inspection).

3.4 Integration, implementation and evaluation

Integration can facilitate the ontology construction by reusing concepts in existing ontologies. Integration is also an inherent requirement of ontology engineering, which envisions a "shared, common representation and reuse of knowledge" [41]. To take advantages of existing ontologies, we adopted two approaches which are referred to as "vertical integration" and "horizontal integration", respectively. For vertical integration, basic data schemas, e.g., RDF, RDFS, OWL, XSD, and XML, are incorporated at the bottom to provide basic vocabularies such as the concept of "type", "property", and "individual" to support ontology development at higher layers. As for horizontal integration, existing knowledge representations in related domains, e.g., IFC for built environment and CORA for robotic agents, are utilized as backbones of the "Scene" and "Agent" branches [39].

Implementation refers to the realization of the conceptualized ontology with ontology-editing software. In this research, we created the branches of "Task" and "Agent" using the Web Ontology Language (OWL) in Protégé. After an ontology is implemented, next step is to evaluate it. A typical evaluation process includes verification and validation. The former intends to ensure the coherence and correctness of developed ontology, while the latter aims to evaluate whether the ontology can be used to solve the intended engineering problem. After the knowledge model was implemented, we invited the five interviewees at the knowledge acquisition stage to review the ontology for verification. Afterwards, a series of simulation experiments were carried out in a "ROS+Gazebo" environment [41] to validate the effectiveness of the model in enabling AFI.

4. The developed iSTA knowledge model

Using the Methontology approach, a knowledge model is developed for driving automated facility inspection. The model broadly categorizes facility inspection knowledge into three interconnected spheres, i.e., built environments "Scene", inspection "Tasks", and robotic "Agents".

4.1. Ontology of inspection scene

Scene perception is a critical element to form a robot's autonomy. Such perception is traditionally gained progressively via a "learning by doing" approach as the robot explores its environment. BIM provides an unprecedented source of scene information, which can empower robots for value-added applications such as facility inspection.

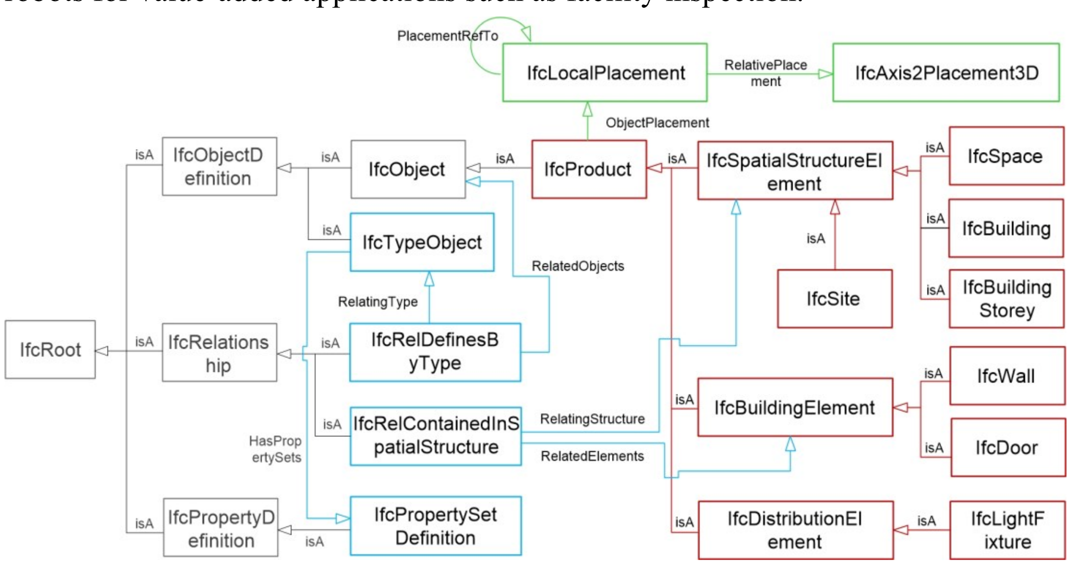


Fig. 1. Graph representation of the iSTA-Scene ontology (A backbone of IFC schema).

This study adopts the IFC schema, the most recognized knowledge formalization in the built environment, as the scene ontology. An open-source IFC2RDF converter is used to translate the original IFC schema to a knowledge graph format [42]. Fig. 1 shows the backbone structure of the IFC schema that is closely related to the inspection tasks in this study (e.g., fire door and lighting inspection). Of the many entities in IFC schema, IfcProduct is of the most interest for robotized inspection (the red boxes in Fig. 1). Under the branch of IfcProduct, the abstract concepts about space (e.g., a floor, or a room) are represented by IfcSpatialStructureElement. This entity is highly relevant, as it will be used to describe the scope of inspection work so that suitable robots can be assigned, and related elements can be retrieved. IfcBuildingElement describes all elements participating in a building system such as walls (IfcWall) and doors (IfcDoor), which will be the entities to inspect in this study. As for the lighting system, we will search the IfcLightFixture for related lighting equipment.

Positions of the building elements are important information, because the robots rely on them for path planning and navigation (the green boxes in Fig. 1). To retrieve element positions, the IfcLocalPlacement entity of the interested elements will be used to progressively obtain their relative positions. For example, the position of an IfcDoor is not explicitly expressed in IFC; Instead, it is represented as local coordinates (i.e., the IfcAxis2Placement3D) in a recursive manner, e.g., position relative to IfcOpeningElement, then to IfcWall, and IfcBuildingStorey, etc. The relative coordinates at different levels will be used to derive global coordinates to guide the robot navigation.

Other than position, relationship between building elements and their type properties are also critical (the blue boxes in Fig. 1). As for the former, how building elements are related to each other in a spatial concept (e.g., a room, a storey) will help determine the elements to inspect based on the given scope (e.g., "inspect all the fire doors on the 3rd floor"). Such inclusion relation is encoded in the schema. For the type property, this information will serve as query constraints when retrieving corresponding elements, e.g., to find all the fire doors under the door category. Such information is defined by the IfcTypeObject, and is connected to specific IfcObject through the IfcRelDefinesByType.

4.2. Ontology of inspection task

Fig. 2 shows an overview of the developed task ontology in the iSTA model. Here, a facility inspection task is conceptualized into three interconnected entities. At the top level is the fmTask class, which divides facility inspection tasks into general categories such as the inspection of the fire resisting system, or the inspection of the lighting system. A fmTask can be broken down into multiple fmActivity, e.g., assignment of suitable robotic agents, path planning to navigate to target positions, and taking photos of elements being inspected. Different fmActivity are chained by the "isFollowedBy" property to indicate the implementation sequence. During the execution of an activity, there may be actions the robots need to implement in an ad hoc manner. For example, in the process of navigating to the inspection target, the robot needs to activate collision avoidance module when encountering unexpected obstacles. Such actions are represented by the adhocAction entity. All the fmTask, fmActivity and adhocAction are related to properties that define their specific attributes.

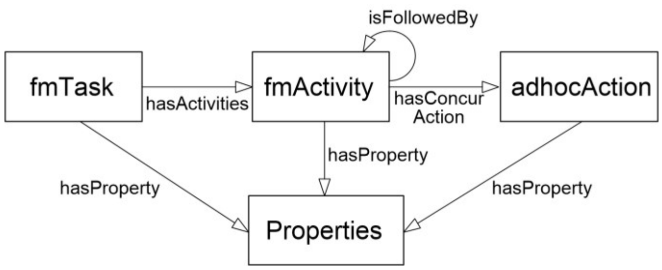


Fig. 2. An overview of the iSTA-task ontology.

Fig. 3 elaborates the tmTask entity. Subclasses of fmTask represent specific inspection tasks such as the inspection of fire door safety, and lighting system. An inspection task has basic properties such as ID ("hasTasID"), starting time ("hasStartTime"), and finishing time ("hasEndTime"), serving as descriptive information for later enquiry. A task is also related to the sensors needed for the inspection, and the scope of the inspection work. Such information will be initialized when a task is assigned. Last but not least, an inspection task is related to its breakdown fmActivity via the "hasActivities" property. Based on our interview with robotic engineers and estate managers, a taxonomy of typical inspection activities and ad hoc actions is established, as explained in Fig. 4. Several activities are required, including the assignment of robots (fmActAsignRobot), search of building elements to inspect (fmActSearIfcEle), path planning (fmActPathPlan), taking photos of the inspection targets (fmActTakePhoto), and navigation (fmActNavigation). Typical ad hoc actions include collision avoidance and obstacle avoidance, which may need to be activated, respectively, during fmActTakePhoto and fmActNavigation. Notice that each activity/action in the ontology corresponds to a module of python code, which will be executed to drive the robot when a command is issued.

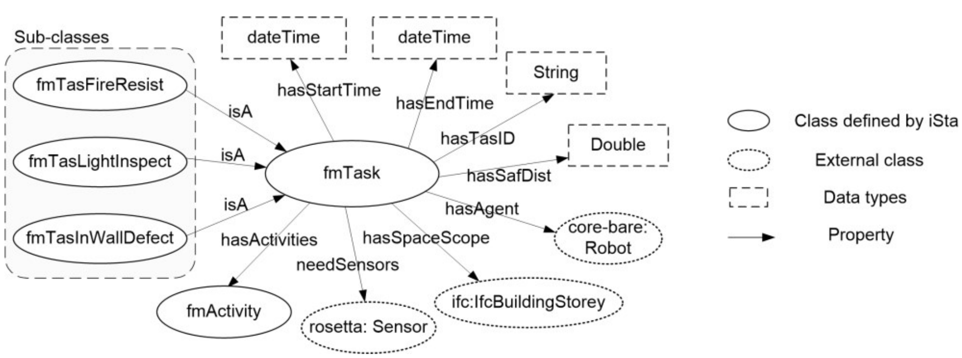


Fig. 3. Ontology entities related to fmTask.

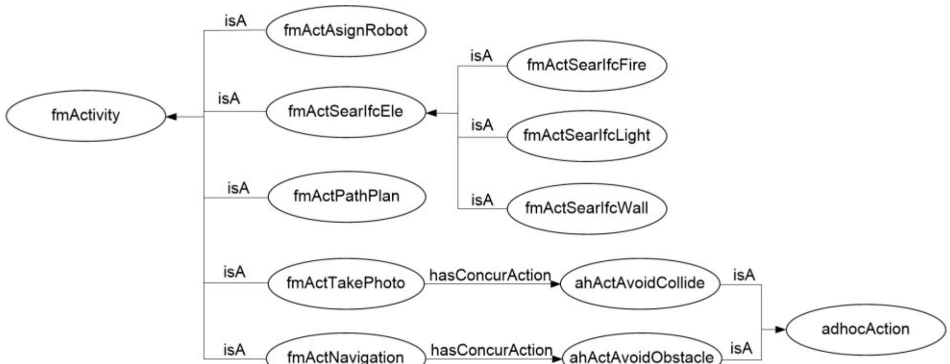


Fig. 4. Subclasses of fmActivity, adhocAction and their connections.

Fig. 5 uses the example of fire door inspection to elaborate the iSTA-Task ontology. In the middle is a sequence of the inspection activities involved. The task starts with robot assignment. The assigned robot will be updated to relevant properties (e.g., "isAssignedTo" and "hasAgent") for later enquiry. The robot assignment activity is followed by a search of fire door IFC elements from the scene ontology based on the given inspection scope (via the "hasSearchScope" property). The retrieved fire door coordinates, along with initial coordinates of the robot, will be forwarded to entity fmActPathPlan, which plans navigation path for the robot to follow. After path planning, the fmActNavigation and the fmActTakePhoto are implemented recursively to navigate the trajectory sections one by one, and take photo of each fire door. The cycle goes on until all trajectory sections are marked as "finished".

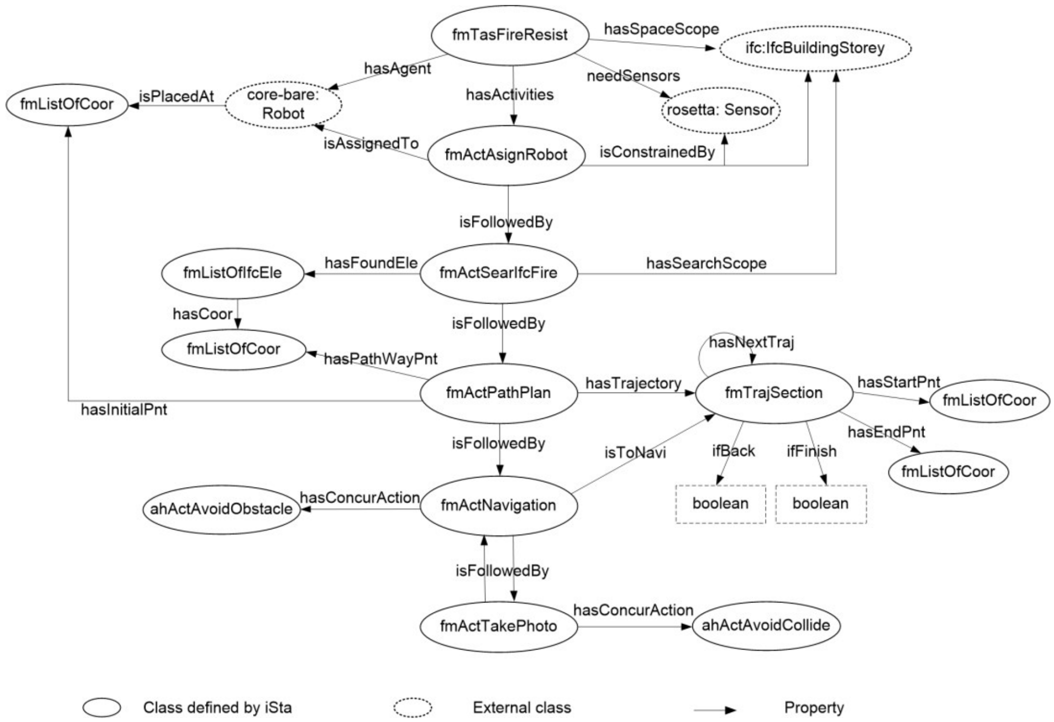


Fig. 5. Graph representation of an example inspection task — Fire safety inspection (fmTasFireResist).

4.3. Ontology of inspection agent

To follow the principle of reusability, this study extends existing robotic ontologies to meet the need of facility inspection, as shown in Fig. 6. The Agent ontology is built upon CORA, the core ontology broadly encompassing main notions across the robotics and automation arena [26, 43]. CORA is a system comprising modularized ontologies in different levels of axiomatization [24], e.g., CORA-BARE, CORAX, RPARTS, and SUMO-CORA. Some later ontologies, e.g., ROSETTA, in downstream subdivision are developed based on CORA.

This research accepts CORA's definition to consider a robot as both a device and an agent, and borrows the "cora-bare: Robot" as the centered entity (see Fig. 6). New properties are added to describe domain-specific information in facility inspection. For example, the "isStoredAt" property reflects in which space the robots are stored so that the one within the inspection scope can be assigned when a new task is issued. The "isPlacedAt" property, on the other hand, stores the current position coordinates of a robot, which would be used as the starting point for path planning. The geometry of a robot is approximated by the bounding box dimensions of a robot, i.e., the properties of "hasRange_length", "hasRange_width", "hasRange_height". Such self-awareness of geometric information is critical for the robots to avoid collision with objects in the environments.

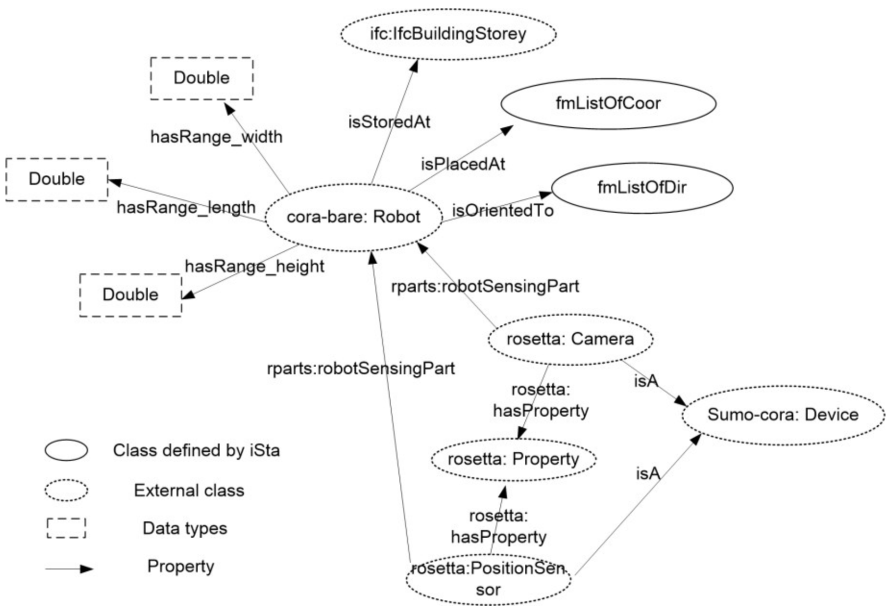


Fig. 6. Graph representation of the iSTA-Agent ontology.

In the domain of facility inspection, the variation among robot instances is mainly determined by the differences of sensors they equipped. This is because agents with different sensors are suitable for different inspection tasks. For example, a robot with RGB cameras is for fire door inspection (just to take photos of the doors), whereas a robot with infrared thermal sensor is needed to detect concealed defects. The “rparts: robotSensingPart” property from RPARTS is used to delineate the relationship between an agent and its forming sensors. After looking into various robotic ontologies, it is found that ROSETTA has a relatively complete description of different classes of sensors. Therefore, the sensing device entities in ROSETTA are included here to represent different sensors.

4.4. Integrating the scene-task-agent ontologies

The aforementioned ontologies are integrated into a unified knowledge model for AFI. The integration is achieved by reusing well-defined entities from one another. Fig. 7 shows the identified entities that are used across ontologies and their connections. It can be observed that the iSTA-Task has borrowed several concepts related to robot agents and building elements/spaces from iSTA-Agent and iSTA-Scene. In the meantime, iSTA-Agent also reused entities (fmListOfCoor and IfcSpatialStructureElement) defined in its counterparts to describe robot position. To make sense of the indexed entities across ontologies, namespaces (or prefixes) of the origin ontologies need to be cited, e.g., the “core-bare” for Robot entity and the “ifc” for IfcSpatialStructureElement entity.

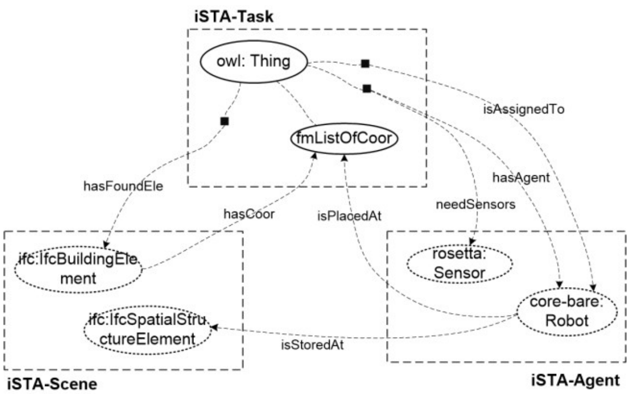


Fig. 7. Schematic diagram showing integration of the scene, task, and agent ontologies.

5. iSTA-driven framework for automated facility inspection

Based on the iSTA knowledge model, an implementation framework for automated facility inspection is developed, as shown in Fig. 8. The framework includes three layers, i.e., the human, the knowledge, and the robot layers. The human layer lies on the top, which is consisted of various actors in facility inspection, i.e., estate managers, inspectors, and engineers. The human staff are not required to carry out the inspection, but only do some periphery works such as setting inspection requirements, and implementing repair works before and after inspection. The robot layer encompasses a variety of robots of different types (e.g., ground robots and drones), which will carry out the inspection. The knowledge layer is made up of iSTA ontologies. It bridges the humans and the robots by receiving inspection instructions on the one hand, and on the other hand, driving the robots to inspect facilities automatically.

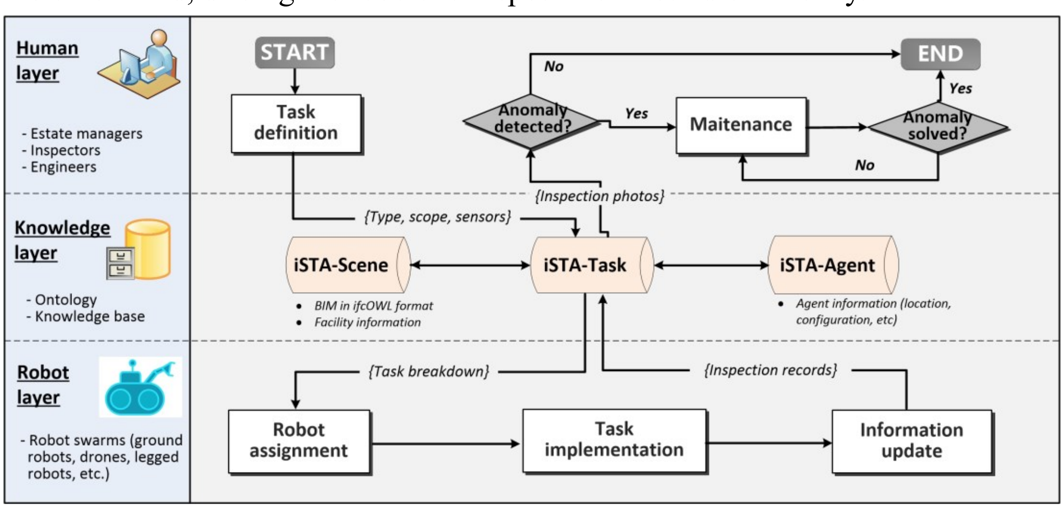


Fig. 8. An implementation framework for automated facility inspection driven by iSTA knowledge model.

The entire workflow starts by a human facility manager specifying the task type, space scope, and sensors required by the inspection to conduct. The specified task information is forwarded to the iSTA-Task ontology in the knowledge layer, where knowledge on the breakdown workflow of the task will be retrieved. The iSTA-Scene and iSTA-Agent complement the iSTA-Task ontology by providing contextual knowledge of the facility and information of the robots. Once proper robots have been assigned based on the given inspection type, scope, and required sensors, the robot will execute inspection activities step by step as indicated by iSTA-Task. As the inspection goes on, the generated inspection data (e.g., inspection ID, assigner, datetime, and photos) will be updated to the iSTA-Task. After finished, the inspection photos will be checked if there is any anomaly of the facilities. The checking can either be down manually or automated with computer vision technologies. If no anomaly is detected, the inspection task is ended, and can be closed. Otherwise, engineers of relevant disciplines should be sent to the site to address the problem (e.g., "to fix a flickering light") until the anomaly is solved.

6. Experiments

The proposed knowledge-driven approach was evaluated by a series of simulated experiments. The target facility to inspect is a "J" shape, three-floor office building, as shown in Fig. 9 (a). The simulation was implemented in an open-source 3D robotics simulator called Gazebo (version 9.0.0). The Gazebo environment has been integrated with robot operating system (ROS) for robot programming and control. The simulation was run on Lenovo-R720-15IKBN with an Intel Core i5-7300HQ CPU and a Intel HD Graphics 630 GPU.

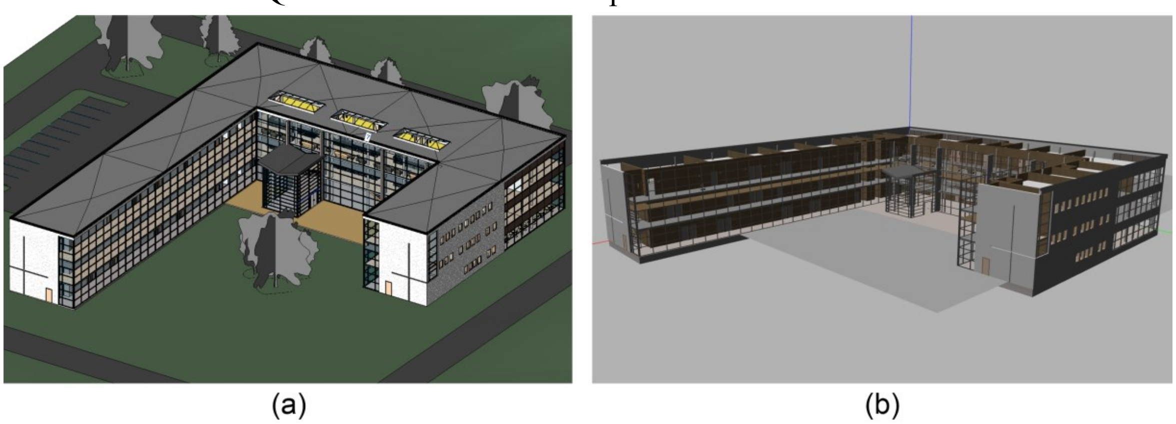


Fig. 9. (a) BIM model of the pilot project; (b) The scene model after imported to Gazebo.

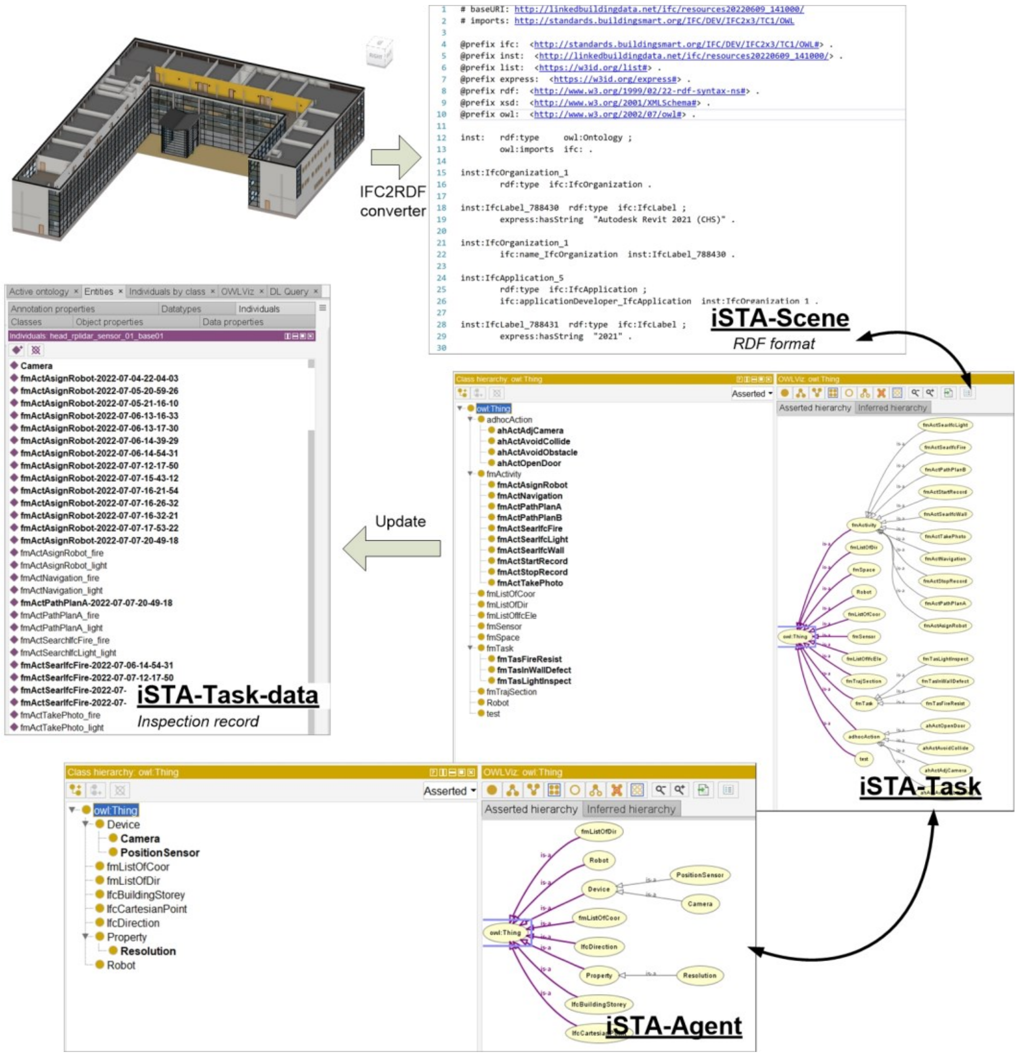


Fig. 10. Instantiation of the iSTA model based on the case building.

6.1. Implementation of the iSTA model

The proposed iSTA knowledge model was instantiated based on the case building. Fig. 10 shows an overview of the resulted iSTA model. To obtain the iSTA-Scene knowledge base, the Revit model of the case building was first exported to an IFC format (2×3 Coordination View 2.0). The IFC file was then processed and converted to an RDF format [42], which describes an entity as a triple that includes a subject, a predicate, and an object. As for iSTA-Task and iSTA-Agent, we created their representations from scratch in Protégé. Instances of different types of inspection tasks and robotic agents were manually input, which will serve as knowledge bases of the inspection workflow and the available robots for later query operations.

Note that in iSTA-Task, the instances only store high-level specification of the entities. For example, the workflow for fire door inspection “fmTasFireResist” needs to be specified by instances of different “fmActivity” connected by the “isFollowedBy” property. Once put into use, it is expected a further instantiation at lower level is needed, e.g., the inspection task/activity that happened at July 30, 2022, or other times. As such instances would continuously accumulated as more and more inspections are carried out, we designate a separate knowledge base called “iSTA-Task-data” to store these instances, which would keep the original iSTA-Task as concise as possible. iSTA-Task-data forms a database wherein all historical inspections are kept in records for future analysis or retrieval.

6.2. Implementation of iSTA-driven facility inspection

Simulated scenarios were carried out to validate the iSTA-driven AFI approach. With the approach, a human expert does not need to be physical onsite or control a robot for the inspection. Rather, he (or she) is only required to designate the scope (e.g., “the 3^{rd} floor”) and the type (e.g., fire safety inspection to ensure all fire doors are closed) of the inspection work. Such scope/task designation can be realized via a computer user interface at a central control room. The designation command will be sent to a central server where the iSTA model is hosted. On receiving the command, knowledge related to the task workflow, inspection scene, and available agents will be extracted to automatically inform the inspect operation without human intervention.

Suppose a command for “inspecting all fire doors on the 3^{rd} floor” is issued, then the branch of “fmTasFireResist” in the iSTA knowledge graph will be activated. As indicated by the knowledge graph (see Fig. 5), the first activity is to assign the task to a suitable robotic agent. There are three robots in total in our experiments, which are, respectively, stored at the three floors of the building, all equipped with high-resolution cameras. The robotic agent information has been keyed in and represented in the iSTA-Agent graph (as shown in Fig. 11 (c)). According to the required working scope (i.e., “the 3^{rd} floor”) and the needed sensor (i.e., “camera”), the task was assigned to “SahayakBot_01”.

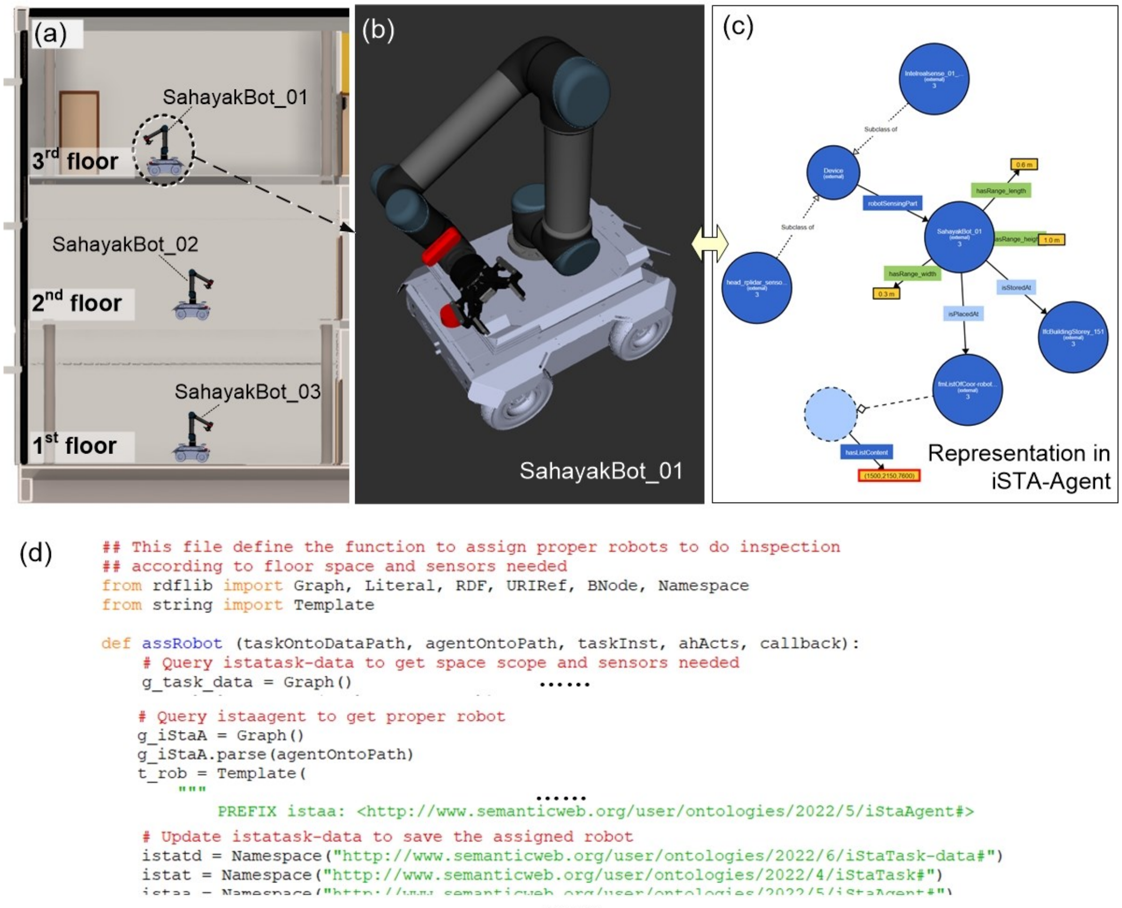
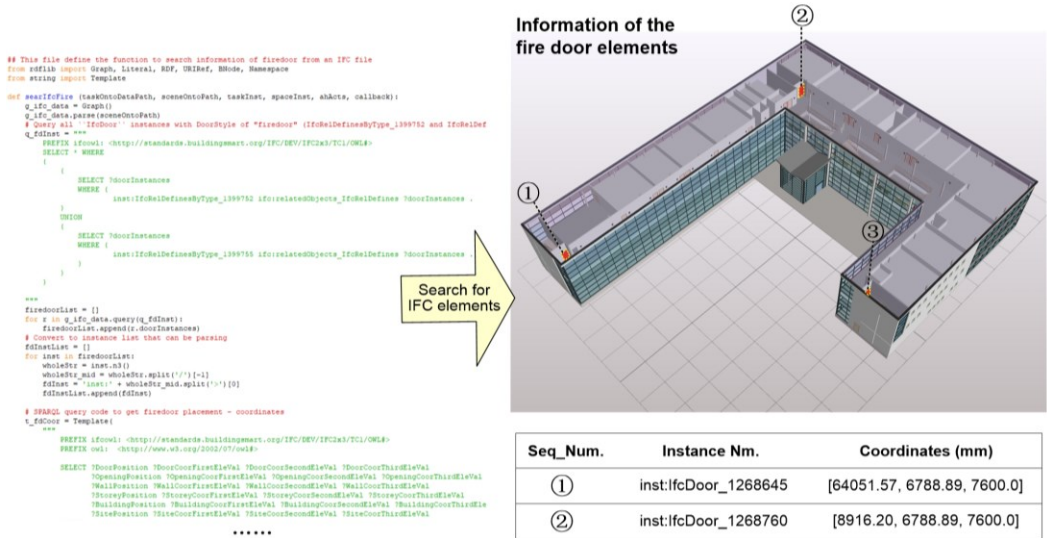


Fig. 11. Implementation of robot assignment: (a) Robots placed at different floors ready for task assignment; (b) A close look of the robot in the third floor; (c) Corresponding graph representation of the robot in iSTA-Agent ontology; (d) Python code for robot assignment.

Once an inspection robot is assigned, next step is to retrieve information of the elements of interest from the iSTA-Scene ontology. Fig. 12 shows the query code corresponding to the "fmActSearthIfcFire" entity, and the retrieved information of all fire doors on the third floor. There are three fire doors in the range of inspection, of which the coordinates have been retrieved and shown at the button right corner of Fig. 12. Based on the given element coordinates and the robot initial position (i.e., the "isPlacedAt" property), path planning (i.e., the "fmActPathPlan" activity) is then executed to compute the robot navigation trajectory. Fig. 13 presents the planned path for the robot to inspect the fire doors one by one. The instantiated "fmTrajSection" entities and their related properties have also been shown in the figure. For example, it can be observed that robot has finished navigating along "fmTrajSection_01", as its related "ifFinish" is filled with "True". Similarly, the property "ifBack" of the trajectories indicates that the black dash line is the trajectory path that leads the robot to its original position.

Such knowledge will inform the inspection robot to execute the planned path step by step, and finally returning to the initial starting point.



Seq_Num.	Instance Nm.	Coordinates (mm)
①	inst:IfcDoor_1268645	[64051.57, 6788.89, 7600.0]
②	inst:IfcDoor_1268760	[8916.20, 6788.89, 7600.0]
③	inst:IfcDoor_1272194	[33870.89, 45889.10, 7600.0]

Fig. 12. Implementation of IFC element searching (using fire door search as an example).

Following the workflow indicated by iSTA-Task, the navigation activity "fmActNavigation" will be activated immediately after the "fmActPathPlan". Fig. 14 (a) shows that the robot is navigating from fire door ① to fire door ② along the planned trajectory "fmTrajSection_02". Rviz, a ROS graphical interface, was used to visualize the process from the robot's perspective. The costmap in Fig. 14 (b) presents a 2D description on the difficulty of traversing different areas of the scene, wherein the pink and wathet regions represent the sensed obstacles and corresponding inflated areas. An inflated area is defined as a buffer zone around the obstacles that should be avoided by the robot planned path. The robot has a depth camera in the front of its base platform, which can scan the environment ahead of the robot (image in the middle of Fig. 14 (b)).

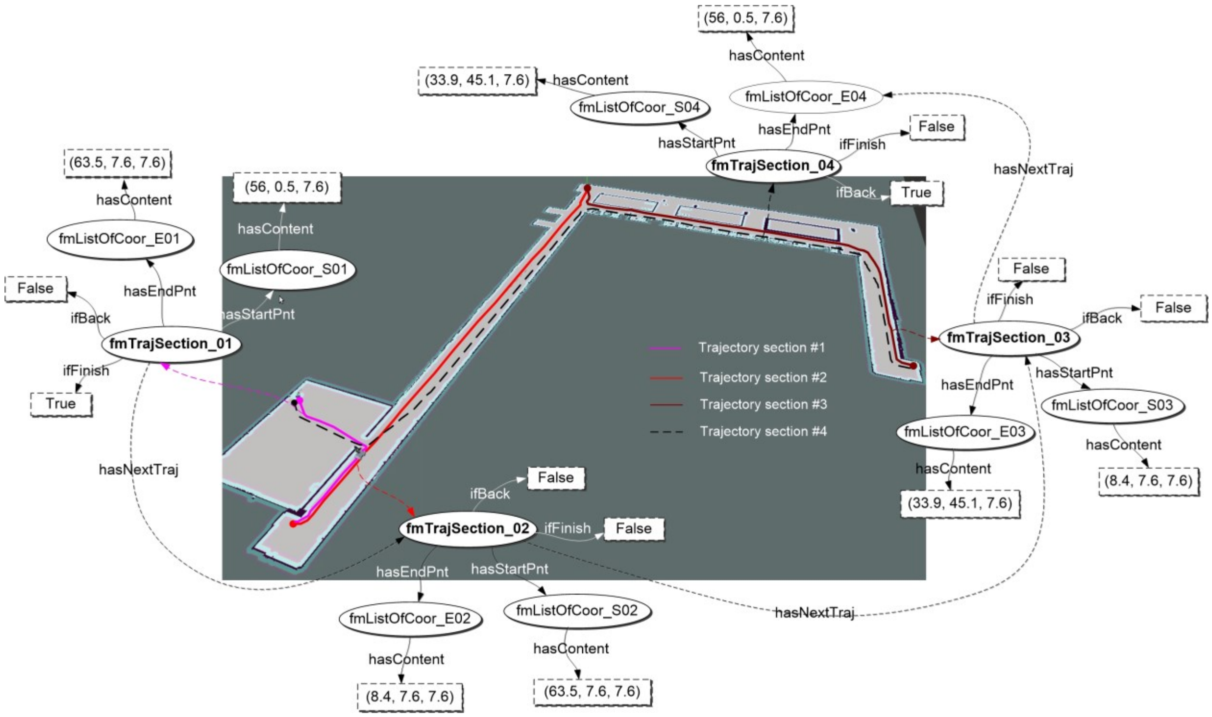


Fig. 13. Implementation results of path planning.

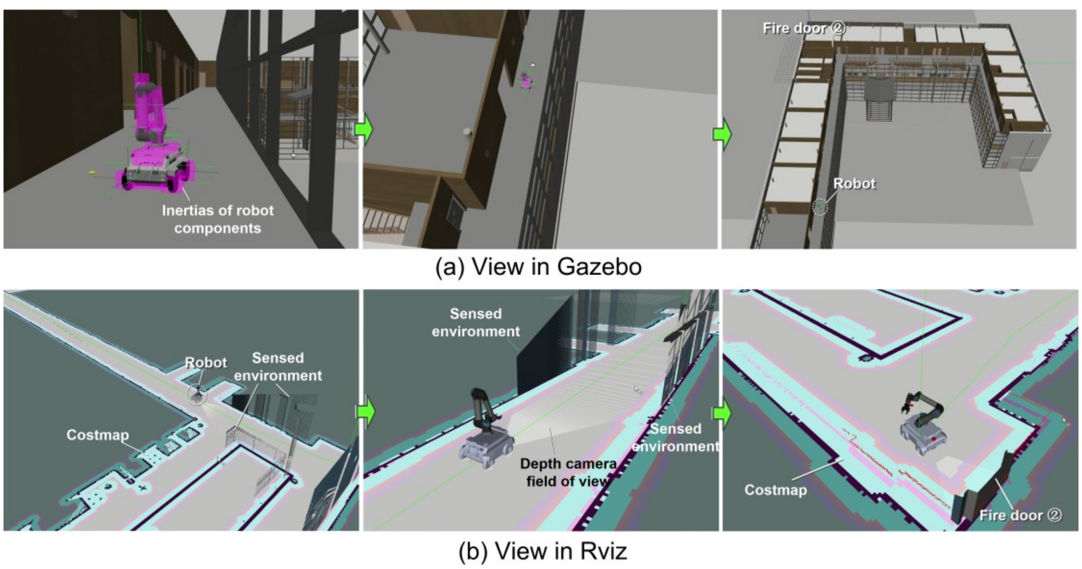


Fig. 14. Robot navigation to inspect fire door #2.

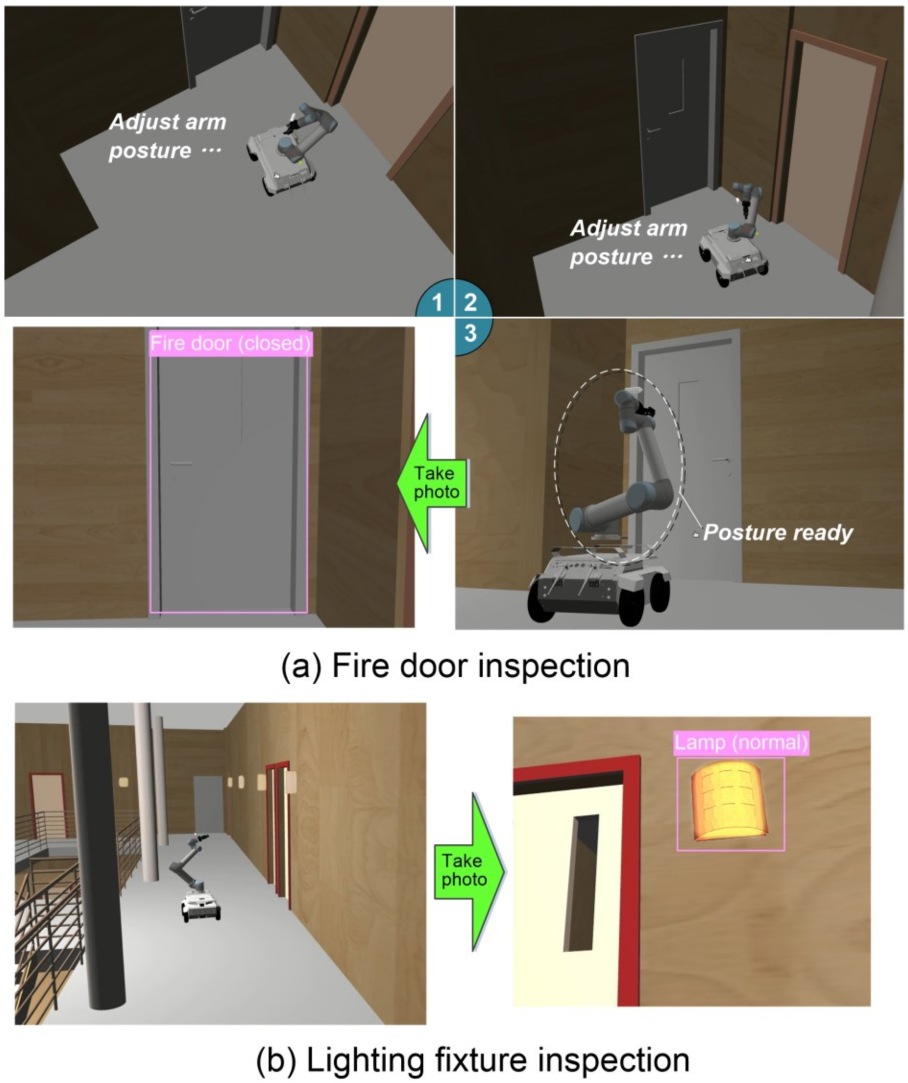


Fig. 15. Photo taking for visual inspection of (a) fire door, and (b) lighting fixture.

Once the robot get to the end of a trajectory section, the photo-taking activity (i.e., the "fmActTakePhoto" entity) will be activated to take photo of the target for visual inspection. Fig. 15 shows the example scenarios of fire door and lighting fixture inspection. On activation, the "fmActTakePhoto" will first adjust the robot arm's posture to point the camera towards the target (e.g., a fire door or a lamp). Then, a photograph of the target will be captured and stored. Computer vision algorithms such as deep learning (DL) can be used to process the captured photograph to determine if the inspected elements are compliant with relevant ordinance (e.g., "the fire door is kept close"). If anomalies are detected, the corresponding competent department should be notified to address the issue in due time.

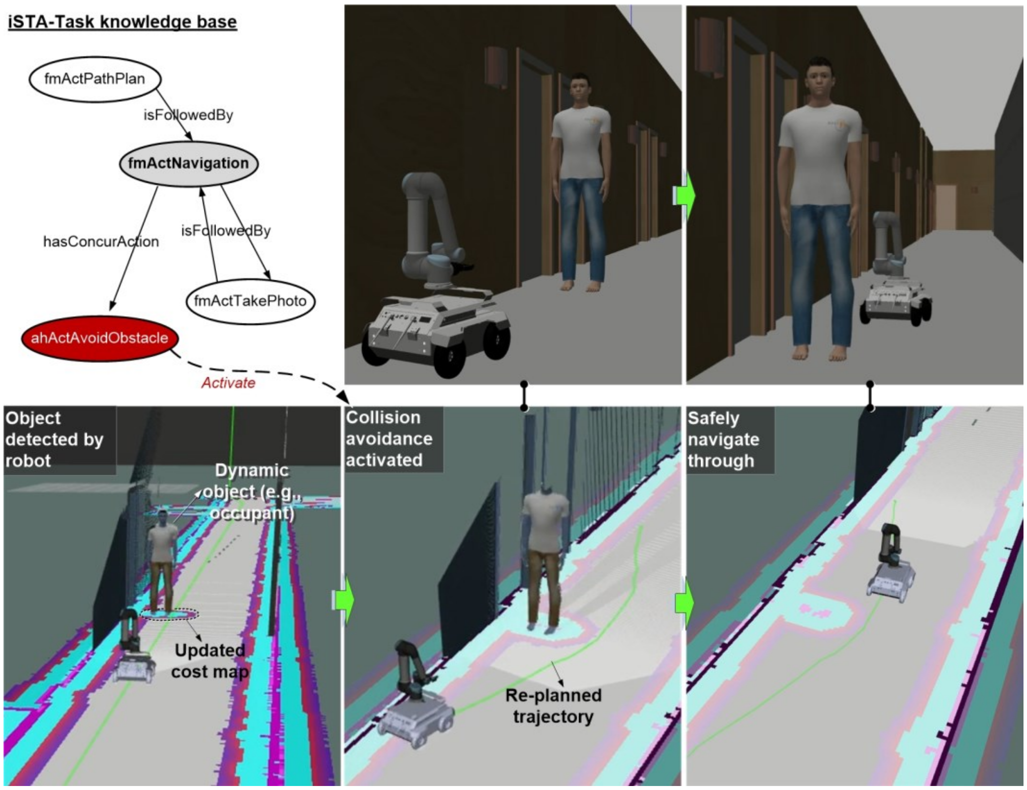


Fig. 16. Knowledge-driven collision avoidance during robot navigation.

It is worth-mentioning that the inspection robots are operated in a dynamic environment, with possibility to come across facility occupants. The iSTA knowledge model can inform the robot how to deal with such situation. Fig. 16 simulates a scenario where the robot encounters a human in the corridor. As we mentioned before, the "fmActNavigation" has a property called "hasConcurAction", which directs to the "ahActAvoidObstacle" entity. This means the collision avoidance will be executed when needed during the navigation. When the robot detects an unexpected obstacle (i.e., a human in this case), the costmap will be updated accordingly, and the collision avoidance mode will be activated. Then, the moving trajectory is re-planned based on the updated costmap to bypass the obstacle. As shown in Fig. 16, the robot is successfully guided by the re-planned trajectory to safety navigate through the human. The autonomy to avoid collision allows the inspection robot to co-exist with humans in dynamic environment.

7. Discussion

As the built environments age [44], the importance of facility inspection has never become so stringent. In face of the global pandemic, traditional manual inspection, characterized by its requirement on physical presence, can no longer sustain itself. Potential automation of facility inspection by the use of robotics and BIM presents a way out. Such automated facility inspection requires the robotic agents to be able to independently react to the changes and complexity of their tasks and environments [22]. While pre-programming the robots with "if …, then …" rules can give them a certain level of adaptivity in a controlled environment, it is not suitable in an open, dynamic scenario like facility inspection. The proposed knowledge-driven approach presents an alternative to achieve AFI by equipping the robots with an ability of unambiguous reasoning for independent decision-making.

The study contributes to the knowledge body from three aspects. First, a knowledge-driven approach is developed to endow robots with knowledge processing and reasoning capability to carry out inspection independently. It opens a new venue to counteract the diminishing productivity in facility management by the application of robotics, BIM and other automation technologies. Second, the developed iSTA framework represents the first of its kind for knowledge modelling in the arena of robotized facility inspection. The iSTA model is a symbolic representation [23] of knowledge covering all spheres (i.e., the facility "scene", the inspection "task", and the robotic "agent") of facility inspection. It is built based upon the reusability principle, and thus can take advantage of existing IFC-formatted BIM to enable scene perception. Third, the iSTA model is made publicly available (github.com/civilServant-666/iSTA). It can help researchers and developers train their robots for automated facility inspection. In addition, it can be further enriched by the research community with formalized knowledge about other tasks in facility inspection.

Despite the advantages, future research is suggested to further develop the proposed approach. Firstly, the iSTA model represents a knowledge base of high-level concepts (tasks, activities, inspection targets, etc.) in facility inspection. However, not all knowledge in an inspection can be engineered in a "top-down" manner like iSTA modelling. For example, it is difficult to handcraft all features/patterns to teach a robot how to distinguish if a fire door is closed based on the collected photo. Such abilities, nonetheless, can be easily acquired in a "bottom-up" manner by learning from data using deep neural networks. The "top-down" knowledge engineering and "bottom-up" neural nets represent two schools of thoughts in AI, that is, symbolism and the connectionism. There is a growing trend of convergence between the symbolism and connectionism [45] in recent years. For the automation of facility inspection, future research should seek to integrate the symbolic iSTA knowledge model with the connectionism-based DL techniques to make use of advantages of both approaches. Secondly, although effectiveness of the proposed approach has been validated, further efforts are needed to enrich the iSTA model to enable robotic agents to take up more facility inspection tasks in more complicated environments. The iSTA model is intended to provide a high-level conceptual structure upon which further specification and extension can be developed in a relatively straightforward way. Therefore, it is hoped that future research can further develop the iSTA model with more detailed task description (e.g., object manipulation), and knowledge on more challenging tasks (e.g., pump house inspection).

8. Conclusions

In recent years, there is growing momentum to boost facility management productivity by the applications of automation and robotics technologies. Examples of these applications include robots that are increasingly seen in floor cleaning, disinfection, and indoor guidance. In line with the ongoing trend, this research proposes a knowledge-driven approach that can potentially lead to large-scale automation of facility inspection using robotics and BIM. With the Methontology approach, a knowledge model is developed. It encompasses three pillar aspects of facility inspection, i.e., knowledge of the scene where a robot operates, knowledge of the inspection task to carry out, and knowledge of the robots (agents) themselves. BIM is leveraged as a readily-available source of facility information to form the scene knowledge base. The three aspects of knowledge are seamlessly integrated, forming a scalable framework called iSTA. An implementation framework for automated facility inspection is devised based on the iSTA model.

A series of simulated experiments were carried out to demonstrate the applicability of the proposed approach. It is shown that the iSTA knowledge model can endow robotic agents with autonomy and knowledge to navigate the challenging built environments and deliver facility inspection outcomes. Via the automation based on robotics and BIM, the efficiency and productivity of facility inspection have been improved. We publicized the iSTA model online, hoping that it can be further enriched and can help developers deploy their robotic systems for automated facility inspection.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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