

Deriving Fabrication Information from BIM for Automated Robotic Task Planning

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Abstract: Construction robotics enables the integration of multiple technologies (e.g., Building Information Modelling, Artificial Intelligence and Additive Manufacturing), thus presenting an opportunity for further productivity gains for the construction industry. However, a key obstacle lies in generating fine-grained information required for robots to plan autonomous tasks. To achieve reliable robot-based construction automation, information about the product design to be built and the status of construction progress must be available to the robot systems in real time. Building Information Modeling (BIM) holds promise in converting high-level building information into the requisite level of detail for robotic operations. One approach is to enrich the data from Industry Foundation Classes (IFC) models with construction data and convert it into a robotic format for robot task planning. We propose leveraging and extending the data extracted from BIM models to integrate with Robotic Operating Systems (ROS), a prevalent framework for robot control. The framework is evaluated through robotised bricklaying realised by *MoveIt*, and visualised using *Rviz*.

Keywords: Building Information Modeling (BIM), Construction Robotics, Construction Simulation, Task Planning



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1 Introduction

The Architecture Engineering and Construction (AEC) industry seeks to enhance efficiency and productivity by adopting Industry 4.0 concepts and technologies [1]. Various technologies, including data analytics, artificial intelligence, Building Information Modeling (BIM), digital twins, and (autonomous) robotics, are increasingly used during the preparation phase or off-site operations [2]. Robotics, in particular, have the distinct capability to integrate and harness these technologies on-site.

One of the prerequisites for robotics operation is providing detailed task information. Typically, robots are programmed with specific movements and actions in controlled environments like factories. This approach demands significant effort, and the tasks and their sequence are often non-reusable due

to the unique and dynamic nature of construction projects. On-site operations thus cannot rely only on a predefined set of task instructions. Much attention, therefore, is paid to developing methods for autonomous, even adaptable [3], task-planning. BIM models are becoming increasingly commonplace in practice, and the information contained within these files provides a valuable source from which the robotic operations can be derived.

The information captured in BIM is of a higher degree of abstraction. A building and its components are described as 'concrete wall, beam, column,' which is sufficient information for human labourers to perform their tasks. A robot, on the other hand, is (as of yet) unable to reason about the necessary sequence of operations for building a 'construction element.' This results in a gap between the provided information and the detailed information a robot requires. The level of detail needed also varies based on the type of robotic system (gantry, arm), construction element (wall, floor, column), and construction method (precast, in-situ, additive manufacturing). The effort to create such operational information makes it impractical for designers and engineers to manually include this level of detail in their projects. The focus of this work is therefore on converting high-level BIM information into fine-grained construction data to bridge this gap. This data is thereafter used to realise robotic task planning, exemplified by brick-laying for walls. While commercial brick-laying robots are available [4], our aim specifically targets data refinement, independent of a robot type.

Our workflow involves extracting data from IFC models to generate precise coordinates for brick placement forming overall wall structures. This process is achieved by using a BIM parsing tool for data access. The generated coordinates are based on the conversion of the wall into a boundary representation (BREP). These BREPs undergo various operations and arithmetic calculations informed by brick-laying heuristics to produce accurate brick placement coordinates. These coordinates are then transferred as inputs for the robotic motion planning, with each set of coordinates corresponding to unique actions that require their own inverse kinematics (IK) solutions to calculate movement trajectories. This method effectively translates high-level BIM data into precise construction information, enabling task planning for brick-laying scenarios. Several case studies have been conducted to test the validity and robustness of both coordinate generation and robotic motion-planning. The cases are differentiated by altering the wall's dimensions and construction method – dry-stacking or using a mortar bond.

An overview of the state-of-the-art for BIM-to-task is presented in section 2. Following that, section 3 addresses the data transformation from IFC to robotic task-planning. The case studies and their results are outlined in section 4. The implications of the proposed procedure, as well as a conclusion and recommendations, are deliberated in section 5 and section 6, respectively.

2 Related Work

Building Information Modelling (BIM) is increasingly recognised and used in conjunction with robotics to derive task information. The information contained in the BIM file is used for tackling autonomous

navigation [5], object detection [6], or to adjust a task plan based on detected material deviations [3]. Such applications target specific tasks but lack a holistic approach that includes both the tasks and the construction environment. Holistic robotic task planning requires simulation environments with detailed models of robots and assets. These environments enable safe testing, validation, and debugging of algorithms and behaviours. Accurate construction site descriptions allow for visualisation and analysis of robotic processes before implementation.

The earliest example of such a holistic approach is by Kim et al. [7]. The authors use geometric BIM data and a predefined construction schedules for task planning, which in turn is used to generate robot motions. The construction site or objects, at least the relevant parts of it, need to be included in such holistic approaches. The researchers therefore take the geometric data, exported as an IFC schema, and convert this into a Simulation Definition Format (SDF) to set up a simulation in the Gazebo environment¹. This step enables the authors to model the geometries in a robotic simulation environment, and accurately represent (a part of) the construction site. As the test-case is robotic painting, only walls are converted and modelled. The case study shows that the proposed method of using BIM for robot task planning can merge the fields of construction and robotics to effectively plan the operations of autonomous robots in construction projects.

Zhu et al. [8] take a different approach, where they derive the required construction information directly from the construction elements themselves. The researchers propose a method that enables task planning in a Multiple Robot Coordination (MRC) setting for prefabricated construction. IFC elements are enriched with construction status (e.g., InTransit) and required actions (e.g., NeedToTransfer) to form *Smart Construction Objects* (SCOs). The SCOs are able to communicate and update their status and requirements, which get published to the robots. Discrete Event Simulation (DES) is used to divide into the construction task in three sub-tasks (events): transport, positioning, and assembly, each assigned to a set of robots specifically suited for that task. The simulation results verified the method, and showed the benefit of using a multiple robots simultaneously.

Slepicka et al. [9] take a similar component-oriented approach for which they introduce the Fabrication Information Modelling (FIM) methodology. FIM is used to generate precise robotic execution instructions within the context of Additive Manufacturing (AM), leveraging both semantic and geometric BIM data. To ensure integration and avoid data conversion losses, the authors utilised the IFC data schema. Much like in 3D printing, an element is created by following a print path layer by layer. In similar fashion to Zhu et al. [8], the path planning process can be viewed as a discretised event within the broader task of "constructing a wall." The authors developed a software prototype that generates the print path from IFC data, which is then used by a custom script to produce the robot controls for printing a model-sized wall element.

The geometric representations and semantic information contained in BIM models provide a rich basis from which robotic operations can be derived. There are numerous formats in which BIM data can be

¹<https://gazebosim.org>

expressed, of which the non-proprietary formats provide the most flexibility. The Industry Foundation Classes (IFC) format is most notable and prevalent, modelled on the EXPRESS modelling language. The IFC format is widely supported and accommodates various geometric representations of the same object, reflecting the diverse modelling approaches of different BIM authoring tools. IFC gets increasingly mapped onto other formats, such as the Resource Description Framework (RDF), XML, and JSON [10]. IFC and RDF follow a graph data model, whereas XML and JSON have a tree-like structure. Graphs differ from trees in that they provide the flexibility and expressiveness to model complex, interconnected relationships and facilitate advanced analyses. In contrast, trees offer a simpler and clearer structure for organising hierarchical data. Pauwels et al. [10] demonstrated that either data structure has the potential to enable autonomous robotic navigation.

3 Methodology

The workflow proposed in this work explores the conversion from high-level BIM objects into operational information suited for robotic task planning for brick walls. BIM objects and their geometric information are represented using IFC, from which target locations are generated for each brick. The targets serve as the input for the inverse kinematics (IK) solvers that finally realise the robotic movements and thus task planning. The complete methodology is presented in Figure 1, and discussed in detail below.

The geometric information of the building elements captured in a particular building information modelling software can be stored in the IFC format. In this paper, Autodesk Revit, as one representative of BIM authoring tools, is used to generate walls and export the corresponding IFC models. To effectively process and manipulate the diverse representations that IFC accommodates, we utilise a dedicated software library that ensures robust interoperability and data handling. This library enables the parsing of IFC files and extracting and modifying necessary information. The data first needs to be preprocessed to extract relevant geometric features, after which arithmetic calculations informed by brick-laying heuristics are performed. Brick dimensions and the inclusion of a mortar gap, together with these heuristics, yield a set of coordinates to be used by the robot. The resulting set of coordinates then correspond exactly to the wall placement as modelled in the design environment.

The extracted coordinates are used to set up the robot task planning system in our simulation framework [11], which is based on the Robot Operating System (ROS)². The bricklaying task consists of a sequence of actions, each corresponding to the placement of a single brick. The framework assigns an ID to each brick, and uses a task node to generate it as an entity in the scene with an initial pose (location). Upon successful placement, a new task for picking and placing a brick is added to the motion plan to generate the necessary actions for the new brick.

The framework's motion planning node receives these tasks with their IDs, divides the required motion into actions (e.g., open hand, move to pick, pick object) and sub-actions (e.g., allow collision, attach the brick to the gripper), and generates plans for the robot's gripper and arm for each stage. Arm

²<https://www.ros.org/>

manipulators may have multiple IK solutions per stage, achieving the same end-effector pose [12]. The simplest and fastest solution is preferred, but joint limits and collision avoidance may prevent this. We use MoveIt³, a platform for motion planning and IK calculation, to compute the IK for every stage, providing possible and lowest-cost solutions. Optimal planning is beyond the scope of this paper and will be further investigated in future publications. This process, visualised using ROS visualisation (Rviz)⁴, continues until the overarching task is complete and the wall is constructed.

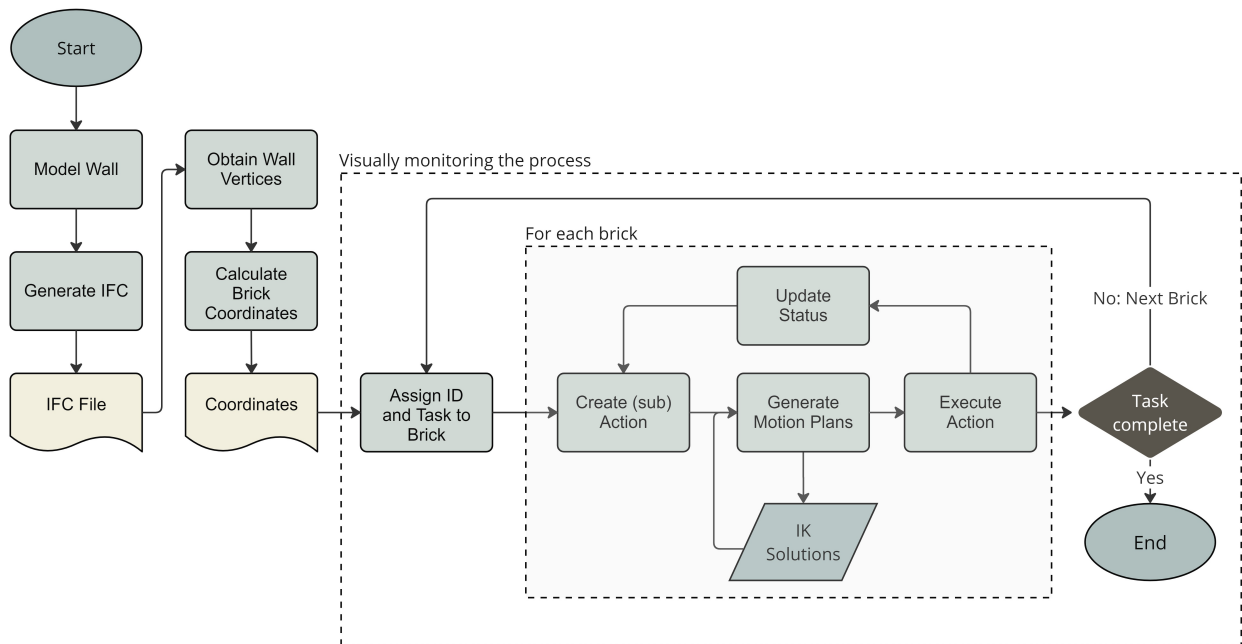


Figure 1: Flowchart of the robotic bricklaying process, from wall modelling to task execution.

4 Case Study

Several experiments evaluated different aspects of the proposed workflow discussed in section 3. Walls of varying length and height were modelled in Autodesk Revit resulting in two variations to analyse robotic constructability limits. A further distinction is made by altering the mortar thickness, resulting in a dry-stacked wall and a wall with a regular mortar joint. The latter aims to test the transformation from IFC geometry to brick coordinates.

The process starts with modelling a simple wall inside the BIM authoring tool. After exporting the projects as an IFC, the file gets imported and opened using the software library `IfcOpenShell` to extract information. The information undergoes several steps to obtain the wall's vertices and direction vector. In addition to the wall's dimensions, the brick dimensions and potential mortar gap determine the brick coordinates. The latter are parameters that can be altered inside the Python script. Running the script will save the xyz coordinates in a dictionary, with the key being the wall's unique ID, obtained from the IFC model. The coordinates are then used in our simulation framework [11] for robot operations. We

³<https://moveit.ros.org/>

⁴<http://wiki.ros.org/rviz>

used a *Panda*⁵ robotic arm, which has a reach of 850mm, to execute the construction. The framework assigns a specific ID for each brick, and based on the initial position and the target position from IFC, it creates a task (pick-place) for each brick. Furthermore the motion planning, creates required robot's actions and sub-actions for the brick's task. Then the framework executes the lowest cost and possible plan for each action. Figure 2 shows the execution of the simulation for two different scenarios.

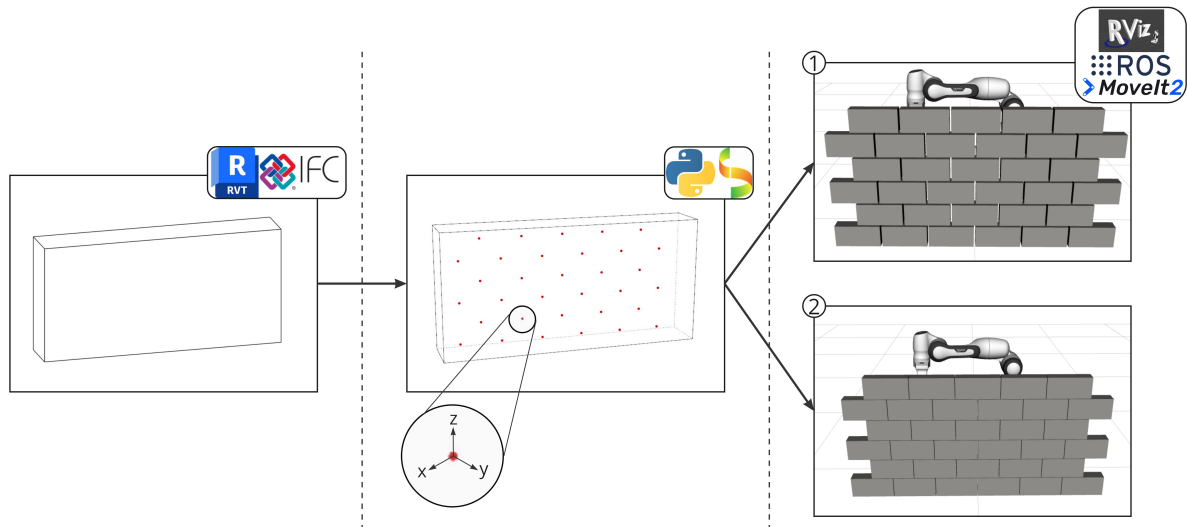


Figure 2: Visualised schematic of the wall-building process.

On the right-hand side of Figure 2, we see that the IK solutions could be computed successfully for dry-stacking and using a mortar joint of up to six rows. Collisions with previously placed bricks prevented higher placements.

5 Discussion

The proposed workflow generates fine-grained instructions from high-level BIM data for brick-laying. By taking the available geometric information from BIM files and fashioning a method tailored to the construction material and technique, this approach shows promise for further automation. The experiments indicate robustness and scalability in this construction method's coordinate generation and consequential task planning parts. While currently designed for brick-laying, this workflow can be extended for other construction methods and materials, such as 3D concrete printing. This extension would require generating different types of information suited to those specific methods, materials and robotic systems.

There are several limitations still that require further development of the workflow. In the overall data flow, every conversion step from IFC to task planning requires manual effort. Using different data models, for example, graphs combined with queries, can link various data formats and streamline the process to a certain degree. More specific to the brick-laying case, details like cornerstones and cases with adjacent walls are to be included. For a more realistic simulation scenario, bricks should

⁵<https://robodk.com/robot/Franka/Emika-Panda>

be placed in a material stockpile rather than spawned at a single location. In addition, the simulation revealed a practical limitation regarding the construction size; we could construct up to six rows before the inverse kinematic solutions became unfeasible without colliding with already placed bricks. This emphasises the need for incorporating robotic systems with diverse characteristics, like maximum reach, or that can cooperate to jointly overcome such challenges.

6 Conclusion and Future Work

This study showcases a workflow that effectively leverages the data contained in BIM files for robotised construction activities. The simulation framework utilises this enriched data for the robot's task planning system, successfully demonstrated in several case studies for robotic bricklaying. By leveraging advanced technologies such as ROS, MoveIt for motion planning and inverse kinematics calculations, and Rviz for visualisation, the framework offers a versatile platform for planning, simulating, and executing complex tasks with arm manipulators in a construction environment. Further development, including various construction methods, materials, and robotic systems, enables the generation of detailed operational information, making it possible to embed this level of detail into construction projects.

In the future, we plan to use different data models capable of capturing and linking various data representations without requiring numerous conversion steps. Specifically, we will investigate using a linked building data approach to link construction elements with the generated construction information. Analogous to that step is the incorporation of different arm manipulators and construction methods.

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