Abstract: Construction robots continue to be increasingly deployed on construction sites to assist human workers in various tasks to improve safety, efficiency, and productivity. Due to the recent and ongoing growth in robot capabilities and functionalities, humans and robots are now able to work side-by-side and to share workspaces. The emerging field of human–robot collaboration has significant potential applications in construction and continues to advance the state of the art in defining the responsibilities of both humans and robots during collaborative work. This paper proposes a new taxonomy for collaborative human–robot work in construction teams. The evolution of construction robots during the last two decades is first reviewed, and relevant bodies of work are categorized into one of five levels of human–robot collaboration: Preprogramming, Adaptive Manipulation, Imitation Learning, Improvisatory Control, and Full Autonomy. The categories of the proposed taxonomy are defined based on the level of robot autonomy and the corresponding human effort in collaborative teamwork. Second, this paper uses the categories of the proposed taxonomy as a contextual framework to identify current challenges and knowledge gaps in collaborative human–robot construction work and recommends directions for future research. DOI: 10.1061/(ASCE)CO.1943-7862.0002154. © 2021 American Society of Civil Engineers.

Author keywords: Human–robot collaboration; Construction robots; Preprogramming; Adaptive manipulation; Imitation learning; Improvisatory control; Full autonomy.

Introduction

Construction work often involves exposure to noise and fumes and is fraught with dangers such as falls, equipment strikes, and electrocution (OSHA 2018). In 2018, the construction industry accounted for 20% of fatal occupational injuries reported in the United States (US BLS 2019). Occupational hazards such as musculoskeletal disorders are also common among workers (Amdt et al. 2005). In addition, according to Global Construction Survey 2015, only 25% of the construction projects between 2012 and 2014 finished within 10% of their original deadline (KPMG 2015); this led to significant extra costs to the construction projects (Shah 2016). It is thus essential to explore methods to relieve human workers from hazardous working conditions and to reduce physically demanding work in construction projects.

Automation and robotics were introduced to the construction industry decades ago to assist human workers in a variety of construction tasks (Bock 2007). The objectives of applying automation and robotics in construction are to increase efficiency and productivity, improve safety and prevent accidents, and reduce health issues from strenuous construction work (Maeda et al. 2004; Saidi et al. 2008; Taylor et al. 2003). Different types of single-task construction robots have been developed over the years for specific construction tasks and have been deployed on factory-like construction sites to assist human workers with physically demanding construction tasks (Bock and Linner 2016). However, the development of such robots has been limited and they have not been broadly employed on real construction sites due to the limitations of the hardware, the quality of the robot actuators, and, importantly, the nature of the unstructured working environments (Feng et al. 2015; Lundeen et al. 2017; Saidi et al. 2008).

Recent advances in hardware, software, and machine learning methods have progressed the general development in robotics, which has in turn increased the performance of construction robots (Balaguer and Abderrahim 2008). In addition, the new paradigm of collaborative robot teams (c-obots) and human–robot collaborative teams has also been introduced and is envisioned to be deployed on future construction sites to assist or relieve human workers from hazardous, dangerous, and repetitive construction tasks (You et al. 2018). By introducing human–robot collaborative teams on construction sites, human workers could potentially transition their current duties to the performance of high-level planning and cognitive work as cobot supervisors, while benefitting from the assistance of the robots in repetitive physical tasks, such as heavy-lifting and precise motion control of tools.

Such rapidly evolving co-robotic capabilities introduce the need for recognizing the relevant state-of-the-art research in the construction discipline, categorizing prior and ongoing work into a logical and encompassing taxonomy, and identifying challenges and knowledge gaps for further research. Everett and Slocum (1994) first proposed a taxonomy of construction field operations.
specifically for automation and robotics research. This taxonomy categorized the construction operation to the level of the basic task, such as “connect,” “cover,” “cut,” and “dig.” Single-task construction robots that existed at the time or were developed later mapped well to a specific basic task in the taxonomy. For instance, robots developed for screwing/bolting identified best with the “connect” basic task (Chu et al. 2013; Jung et al. 2013; Nam et al. 2007). Saidi et al. (2008) further grouped these operations into three types of functional operators: materials handling, materials shaping, and structural joining. In addition, Saidi et al. (2016) also classified construction robots into three general categories based on the level of on-board intelligence: teleoperated systems, programmable construction machines, and intelligent systems.

On the other hand, Tan et al. (2016) proposed a framework for formulating the robot-inclusive environments by measuring the inclusiveness of environments to robots, developing a taxonomy of robot-environment interaction, and identifying design criteria of autonomous robots in indoor and outdoor environments. Bock (2004) identified three modules of construction robots with different tasks in interior assembly—i.e., transportation, drilling and mounting, and assembly—and then proposed a procedure of applying these three robot modules and evaluated it in an office-building construction simulation.

Although the existing taxonomies of construction robotics have reviewed prior studies and categorized them, they have not considered the effect of the human-in-the-loop collaboration. This paper bridges this critical gap and reviews the existing construction automation and robotics studies and applications in the context of a new proposed taxonomy that is based on the level of the human–robot interaction in the performance of work. In addition to the systematic classification of prior and ongoing work, this paper discusses the technical limitations of current construction robots and recommends future research directions in the area of collaborative human–robot construction.

### Research Objective and Methodology

The first objective of this paper is to systematically review and analyze the published articles related to construction automation and robotics and to identify research gaps. Second, a new taxonomy of human–robot collaborative teams in construction is proposed to categorize the existing construction robots and allow researchers and scholars to anchor their ongoing work along the spectrum. Third, existing challenges and future directions of the research in construction robotics are discussed to foster the next-generation human–robot collaborative construction teams.

The methodology of this paper is divided into two phases. First, the literature in general human–robot collaboration is surveyed and used to define the involved levels of robot autonomy. Second, the new taxonomy of the human–robot collaborative teams is proposed, and the relevant construction automation and robotics articles published in the most relevant journals and conferences are selected and reviewed. Fig. 1 illustrates the overview of the research methodology. In the first step, the relevant articles were collected using the search engine tools, including Google Scholar and Scopus. The keywords used to identify the relevant articles were “construction robotics,” “construction automation,” and “building robotics.” All the related articles after 2000 were included in the first step.

Second, we manually screened the selected articles and filtered the most relevant articles for further literature analysis. Most of the literature consisted of journal articles published in *Journal of Computing in Civil Engineering, Journal of Construction Engineering and Management, Automation in Construction, and Construction Robotics,* or conference articles published in *Proceedings of the International Symposium on Automation and Robotics in Construction (ISARC)* and *Proceedings of the Construction Research Congress (CRC).* The filter criteria included robots, automated equipment, control methods, and motion-planning algorithms. Finally, 259 articles were selected during the manual screening process. In the final two steps, the filtered articles were categorized based on the taxonomy and further analyzed.

This paper has three academic contributions. First, the proposed taxonomy allows researchers and scholars to anchor their prior and ongoing research along the spectrum of human–robot collaborative work and helps them identify related research in the field for comparison with their own studies for evaluation. Second, the existing and state-of-the-art research studies in construction robotics are recognized, and how they interact with human workers are analyzed. Level of autonomy and human effort are used to categorize the existing research into the proposed taxonomy. Third, the research gaps between existing work are identified based on the taxonomy. The future research directions are discussed and suggested to foster future studies in human–robot collaboration in construction.

### Background on Human–Robot Collaboration

Human–robot collaboration (HRC) is defined as human(s) and robot(s) contact with each other to establish a dynamic system for accomplishing tasks in the environment (Ajoudani et al. 2018). The goal of HRC is to ease the workload of humans in performing repetitive and physically demanding tasks (Cherubini et al. 2016).

In the manufacturing industry, humans and robots work in the shared workspace performing manufacturing tasks such as welding (Erden and Billard 2014), transporting (Levratti et al. 2016), and assembling (Cherubini et al. 2016; Matsas and Vosniakos 2017; Tsarouchi et al. 2017). In the domestic or healthcare facility, robots are utilized to assist humans with various daily tasks such as picking up objects (van Osch et al. 2014) or rehabilitation, such as walking assistants (Wakita et al. 2013) or arm reinforcement (Huang et al. 2015). These applications are typically deployed in structured environments with dynamic objects and uncertainties (Ajoudani et al. 2018), such as industrial assembly lines with moving workers.

The level of robot autonomy (LoRA) in HRC proposed by Beer et al. (2014) categorizes the HRC into ten levels based on the roles that the human and robot play in the robot primitives—i.e., sensing, planning, and acting, as shown in Table 1. The LoRA is inspired by the taxonomy proposed by Endsley and Kaber (1999), which categorizes human–computer interaction (HCI) systems into ten levels of automation (LOA) based on four generic functions, i.e., monitoring, generating, selecting, and implementing. The ten levels are Manual Control, Action Support, Batch Processing, Shared Control, Decision Support, Blended Decision Making, Rigid System, Automated Decision Making, Supervisory Control, and Full Automation.
Table 1. Level of robot autonomy for HRC and level of robot autonomy in human–robot collaborative construction teams

<table>
<thead>
<tr>
<th>Level of robot autonomy</th>
<th>Sensing</th>
<th>Planning</th>
<th>Acting</th>
<th>Description</th>
<th>LoRA in construction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tele-Operation</td>
<td>H</td>
<td>H</td>
<td>H/R</td>
<td>The robot assists the human with acting—e.g., object grasping.</td>
<td>Preprogramming</td>
</tr>
<tr>
<td>Assisted Tele-Operation</td>
<td>H/R</td>
<td>H</td>
<td>H/R</td>
<td>The robot assists the human with sensing and acting and utilizes the sensing feedback to intervene with the task—e.g., obstacle avoiding.</td>
<td>Adaptive Manipulation</td>
</tr>
<tr>
<td>Batch Processing</td>
<td>H/R</td>
<td>H</td>
<td>R</td>
<td>The human determines the task plan, and the robot executes the plan.</td>
<td>Imitation Learning</td>
</tr>
<tr>
<td>Decision Support</td>
<td>H/R</td>
<td>H/R</td>
<td>R</td>
<td>Both the human and robot generate a task plan, and then the human decides the task plan and the robot executes the plan.</td>
<td>Improvisatory Control</td>
</tr>
<tr>
<td>Shared Control with Human Initiative</td>
<td>H/R</td>
<td>H/R</td>
<td>R</td>
<td>The robot performs all aspects of the task; the human monitors the progress and may intervene with new plans.</td>
<td></td>
</tr>
<tr>
<td>Shared Control with Robot Initiative</td>
<td>H/R</td>
<td>H/R</td>
<td>R</td>
<td>The robot performs all aspects of the task. If the robot encounters difficulty, it can prompt the human for assistance in setting new plans.</td>
<td></td>
</tr>
<tr>
<td>Executive Control</td>
<td>R</td>
<td>H/R</td>
<td>R</td>
<td>The human gives an abstract high-level goal—e.g., navigate to a specified location. The robot performs all aspects of the task.</td>
<td></td>
</tr>
<tr>
<td>Supervisory Control</td>
<td>H/R</td>
<td>R</td>
<td>R</td>
<td>The robot performs all aspects of the task; the human continuously monitors the progress with override capability and may set a new plan.</td>
<td></td>
</tr>
<tr>
<td>Full Autonomy</td>
<td>R</td>
<td>R</td>
<td>R</td>
<td>The robot performs all aspects of the task autonomously without human intervention.</td>
<td>Full Autonomy</td>
</tr>
</tbody>
</table>

Source: Data from Beer et al. (2014).
Note: H = human; and R = robot.

In each level, the computer and human are assigned with these functions to complete a specific task collaboratively. The taxonomy of LoRA preserves the characteristics of HCI while considering the unique aspects of HRC and the differences between HCI and HRC.

In the first level of the LoRA, the human performs all aspects of the task manually without robot involvement. In the lower level of the LoRA, the human performs most aspects of the task with some assistance from the robot. For example, the robot utilizes sensing feedback to avoid obstacles during the tele-operation. The human determines the plan of the task and programs the robot to execute it. In the middle of the LoRA, the human and the robot contribute to the task equally. Both human and robot come up with the task plan, and then the human instructs the robot to proceed with the selected plan.

In the higher level of LoRA, the robot performs most aspects of the task with some human interventions. For example, the robot first plans the task and executes it. If the robot encounters difficulty, the human will intervene with a new plan for the robot. The human can also give an abstract high-level goal to the robot. Finally, in the highest level of the LoRA, the robot performs all aspects of the task without any intervention or assistance from the human, whereas the human only monitors the process to ensure the procedure is correct. Based on these generalized ten levels of LoRA, we propose the following six categories in a taxonomy to organize collaborative human–robot work in construction: Manual, Preprogramming (PP), Adaptive Manipulation (AM), Imitation Learning (IL), Improvisatory Control (IC), and Full Autonomy (FA). Details of each category are described in the section “Interplay between Robot Autonomy and Human Effort.”

Classification of Human–Robot Construction Teams

A taxonomy of collaborative human–robot construction teams is proposed to characterize the existing human–robot collaboration methods in construction by the level of robot autonomy and the human effort in sensing, planning, and acting. The LoRA proposed in Beer et al. (2014) uses ten detailed levels of autonomy to fit broad categories of robots. However, it is not well-suited for the human–robot collaboration in construction. Due to the complexity of construction operations and the need for robots to perform quasi-repetitive tasks, the interactive relationship in human–robot construction teams can be defined as multiplex. It is thus difficult and adds little insight to categorize human–robot collaboration in construction at the level of detail in the LoRA proposed by Beer et al. (2014).

In addition, with the preliminary survey of construction robotics literature, we found that most of the construction robots are in the lower three levels of the LoRA (Tele-Operation, Assisted Tele-Operation, and Batch Processing) and difficult to be categorized in a ten-level taxonomy, especially for the five higher levels of the LoRA (Decision Support, Shared Control with Human Initiative, Shared Control with Robot Initiative, Executive Control, and Supervisory Control) since construction robots are not developed extensively in these levels. We therefore propose a condensed taxonomy of six distinct groups—Manual, Preprogramming, Adaptive Manipulation, Imitation Learning, Improvisatory Control, and Full Autonomy—to adequately classify construction work performed by human–robot teams. Fig. 2 illustrates the taxonomy of construction human–robot collaborative teams depicting the levels of human effort and robot autonomy.
The relative size of the humans and robots in the figure represents the level of effort and autonomy during the process. In the Manual category, the human performs the task without robots on construction sites, which is the existing traditional construction method. The research in the Manual category is not introduced in this paper, but it serves as the foundation to the HRC research and taxonomy. In the Preprogramming category, the human undertakes the majority of the effort to plan the work, and the robot only executes the plan, which maps to the Tele-Operation group in the LoRA described in Beer et al. (2014). In the Adaptive Manipulation category, the human plans the work while the robot adapts to the plan based on the encountered geometry, which represents a combination of the Assisted Tele-Operation and Batch Processing groups in the LoRA.

In the Imitation Learning category, the human plans the work and the robot learns the knowledge of the work and executes it; this is categorized under the Decision Support group, the Shared Control with Human Initiative group, and the Shared Control with Robot Initiative group in the LoRA. In the Improvisatory Control category, the robot plans and executes the work while the human monitors the work and improvises if necessary. In addition, the human can also provide a high-level plan and enable the robot to perform every aspect of the work. We combine the Executive Control group and Supervisory Control group in the LoRA into the proposed Improvisatory Control category. In the Full Autonomy category, the robot performs every aspect of the work without intervention from the human; this also corresponds to the Full Autonomy group in the LoRA. The human only monitors the process in the shared workspace.

Based on reviewed literature studies in the categories of the proposed taxonomy, we discuss each category separately in the following sections. Table 2 summarizes the number of selected articles in each taxonomy category. In the Preprogramming category, 135 articles are included. In the Adaptive Manipulation category, 72 articles are included. In the Imitation Learning category, 3 articles are included. In the Improvisatory Control category, 18 articles are included. In the Full Autonomy category, 31 articles are included.

The Imitation Learning category is found to be generally new to construction robotics research, with the fewest number of articles—e.g., Liang et al. (2020a)—and has been a popular research trend in the general robotics discipline over the past decade (Ravichandar et al. 2020). Imitation Learning, Improvisatory Control, and Full Autonomy are envisioned to be active areas of future research in construction robotics.

**Interplay between Robot Autonomy and Human Effort**

The interplay between robot autonomy and the level of human effort can be represented by a magnitude to indicate the involved distribution between the human worker and the robot in the construction human–robot collaborative team, as shown in Fig. 3. For the Preprogramming method, the human programs the trajectory for the robot or tele-operates it, and the robot is only responsible for the action. Therefore, the robotic autonomy is the lowest and the human effort is the highest in the taxonomy. For the Adaptive Manipulation method, the human still programs or tele-operates the robot, but the robot adapts to the work plan using sensor data. In addition to the acting, the robot is involved in the sensing aspect of the process. Therefore, the human effort is the highest in the taxonomy. For the Adaptive Manipulation method, the human still programs or tele-operates the robot, but the robot adapts to the work plan using sensor data. In addition to the acting, the robot is involved in the sensing aspect of the process. Thus, the robot has a higher level of autonomy than with the Preprogramming method.

For the Imitation Learning method, the robot learns the skill from humans and generates the work plan to complete the task, wherein the human and the robot are equally involved in the process. For the Improvisatory Control method, the robot first explores the possible solution and determines the work plan, then the human supervises the work plan and improvises if necessary. Such collaboration requires a higher level of robot autonomy and lower human effort in the process. For the Full Autonomy method, the robot finds the work plan without support from humans; thus the level of robot autonomy is the highest in the taxonomy and no human effort is involved.
Preprogramming

The first category in the proposed taxonomy, the Preprogramming method, involves programming the construction robot with a predefined sequence of activities to perform the same task repeatedly. This category is the most prevalent form of robotics in industrial work, such as manufacturing assembly lines, which are typically carried out in safety cages with no proximity allowed to humans due to safety concerns (Salmi et al. 2018). Several trajectories can be defined by human workers and provided to the robot in advance, and the human workers can select the trajectory for the robot so that it can react in specific scenarios accordingly. However, robots cannot react to unexpected situations during the process. They must either complete the trajectory and wait for new commands or be interrupted by human workers. One way to overcome unexpected situations is by using tele-operation from human operators. The latency between the remote robot and the human operator needs to be overcome (Khasawneh et al. 2019). The following subsections outline several robotic implementations in construction that can be classified as preprogrammed robotic systems. Fig. 4 illustrates the robotic systems in the Preprogramming category.

PP: High-Rise Building Robots

High-rise building robots are deployed on tall building construction sites and aim to improve the productivity, quality, and safety of high-rise construction. The main challenges of such robots are hazardous working environments (weather, height) and insufficient workspace (Miyakawa et al. 2000). Thus, the climbing mechanisms or construction factories are typically used as the workspace for humans and robots, in collaboration with supporting tower cranes (Bock and Linner 2016; Kim et al. 2009b; Miyakawa et al. 2000). These types of construction concepts have primarily been pioneered by several Japanese companies in the past decades, such as ABCS by Obayashi, Akatuki 21 by Fujita, and FACES by Goyo (Bock and Linner 2016).

The steel structure and the prefabricated, reinforced-concrete structure are two main types of construction methods for the high-rise building robot due to convenient delivery and straightforward assembly (Liang et al. 2017; Wakisaka et al. 2000). Therefore, the robotic bolting device and robotic transportation system are two main functions for structure assembly and transportation (Chu et al. 2013; Jung et al. 2013). The human operator works inside the control cabin and facilitates the structure assembly work by monitoring and tele-operating systems. In addition, the robotic manipulators are used for placing concrete with shuttering (Bock and Volchkov 2000).

PP: Maintenance and Cleaning Robots

The maintenance and cleaning robots in the Preprogramming category are utilized in hazardous or narrow environments such as bridges, tunnels, underwater, post-disaster, or duct systems in buildings. The bridge/tunnel/underwater/post-disaster inspection and maintenance robots remove workers from dangerous underground decks and tunnels and allow them to tele-operate or monitor the process at a remote and safe location (Arai et al. 2015; Chen et al. 2000, 2014; Kim et al. 2011; Moon et al. 2011; Okano et al. 2006; Seo et al. 2007; Zied et al. 2000).

For example, Lorenc et al. (2000) developed the Robotic Bridge Maintenance System (RBMS), which used a robot mounted on a crane to inspect, wash, remove, and apply paint remotely. Moon et al. (2013) developed a bio-inspired underground exploration robot that can dig soils to move underground. Arai and Hoshino (2011) developed an asbestos removing robot system that combined a robotic arm and mobile platform with vacuum suction to relieve manual work. Furthermore, advanced drone technology has recently been introduced for the inspection purpose, combining remote control, path planning, camera and LiDAR, and image-processing methods (Bolourian and Hammad 2020; Phung et al. 2017; Yang et al. 2015).

Vision systems such as CCD cameras or laser scanners are usually deployed with the robot to inspect the surface of the bridge/tunnel structure and detect cracks (Chen et al. 2014; Lee et al. 2011; Victores et al. 2011; Yu et al. 2007). Additional sensors or devices include haptic sensors can enhance the tele-operation by creating a human–robot environment interaction (HREI) (Cheung and Chung 2006; Chotiprayanakul et al. 2012), a nondestructive-testing (NDT) device for inspecting bonding quality (Tso and Feng 2003), a total station for shoreline survey with preprogrammed robot paths (Tanaka and Shiraishi 2006), hammering sound wavelet analysis for detecting tile deterioration (Inoue et al. 2009), or a small grinding drill with constant feed rate for infrastructure concrete strength inspection (Inoue et al. 2015) in maintenance robots. The robot path can be planned by the intelligent planner to improve the productivity and quality of the maintenance process (Bai 2007).

Window- and façade-cleaning robots are the second types of maintenance and cleaning robots. Window and façade cleaning is an essential work for buildings that requires workers to stay at a...
narrow and high space to perform the cleaning task. The cleaning robot such as Standard Façade Cleaning Robot (Schaft et al. 2000), Skyscraper Façade Cleaning Robot (Bock et al. 2002a), and Cost-Effective Façade Cleaning Robot (Gambao et al. 2004) are portable robots that can be used on various buildings and integrated into the façade with a preprogrammed trajectory or while tele-operated by the operator.

Maintenance and cleaning robots for a building or factory deal with two different situations. First, the inspection performed at narrow and tight places, such as pipeline or duct systems, typically requires small or specially designed robots in order to fit into the environment (Beckett and Ross 2017). Bio-inspired robots or small robots are suitable for these types of applications (Gambao et al. 2005; Jung et al. 2011; Longo et al. 2005; Lozano et al. 2011; Park and Hong 2012; Popescu et al. 2006; Ragulskis et al. 2008; Schempf and Vradis 2003; Sergiu-Dan et al. 2007; Starý et al. 2020; Tavakoli et al. 2004; Yeo et al. 2000). Second, the maintenance and cleaning performed in wide and large buildings or factories typically requires maneuvering around the space (Lee et al. 2010).

These types of robots are tele-operated along with onboard sensors or cameras supplementing information (Cigola et al. 2005; Jiang et al. 2020; Kuczmarski et al. 2003; Moghaddam and Hadi 2005; Moghaddam and Tafti 2005; Prabakaran et al. 2018; So and Chan 2002) or use virtual guides to assist tele-operation (David et al. 2014). Moreover, a specially designed mechanism—e.g., a flipper from a rescue robot (Chonnaramutt and Birk 2006) or flexible microactuators (FMA) from a microwalking robot (Dinesh et al. 2011)—can help overcome the unstructured and complicated construction environment.

**PP: Assembly Robots**

The assembly task is the basis of a construction project. It requires significant collaboration between humans and construction equipment. The assembly robots are deployed on-site to perform repetitive assembly tasks or to assemble prefabricated or modular components (Terada and Murata 2005), which are usually manipulator-type robots to complete the complex task due to the high degrees-of-freedom flexibility (Gambao et al. 2000; Liang et al. 2019a; Sweet 2016). They are either preprogrammed off-line with the trajectory and monitored by human operators through human–machine interface (Gambao et al. 2000; Iturralde and Bock 2013) or tele-operated by the operator at a remote location (Chi et al. 2012; Chung et al. 2010; Kurien et al. 2018).

Unlike the industrial-assembly robot, the construction-assembly robot has to navigate to different working locations and stations to perform the task (Bruja et al. 2007). Brick or block laying is the first group of the preprogramming assembly robots (Ogbonnah 2003). The robotic arm lays the brick by predefined patterns and the human worker taps the brick and checks the alignment. A fast algorithm and overlap method were developed to generate the brick-laying pattern and plan the manipulation efficiently (Yu et al. 2009). Building information models (BIM) can also be used as the data source and combined with a cable-driven parallel robot or robotic arm to construct the masonry structures (Bruckmann et al. 2016; Ding et al. 2020; Usmanov et al. 2017).

Another group of the preprogrammed assembly robots includes those that fit construction components, such as tile, window panels, or curtain walls (Lichtenberg 2003; Taghavi et al. 2018). The robots are first deployed to the stationary locations—e.g., scaffold structures (Dharmawan et al. 2017)—to fit the tiles or windows by predefined patterns (King et al. 2014) or tele-operation (Chung et al. 2010), then transported to the next location to perform the next round of tasks. The hybrid manipulator that combines pneumatic actuator and servo motor is used to overcome the lifting of heavy panel materials (Choi et al. 2005). Moreover, the building renovation can also be accomplished by combining the stacker crane and the robotic arm to assemble components off-site and later install them on-site (Iturralde and Bock 2018).

Finally, the other group of preprogrammed assembly robots is finishing robots, which conduct tasks such as welding, material laying, and painting. The welding robot is attached to the target column to perform welding work and has several manipulators (Nisita et al. 2000). The concrete laying robot (Jednostroenna Aplikacja Wędrująycym Automatem (JA-WA)) is equipped with an on-site scaffolding track and a mobile robot on the track with a concrete injector to lay concrete on composite walls (Wieckowski 2017). In addition, the concrete-foaming robot is also developed for the façade finish (Lublasser et al. 2018). The painting robot is a robotic arm equipped with an automatic paint-spraying device (Grassi et al. 2007). To optimize the trajectory of the painting robot, a mathematical model is developed by minimizing the overlap of the painted surface (Bruzzi et al. 2016).

**PP: Excavator and Equipment Control**

Excavators and other construction equipment are primary machines deployed on unstructured construction sites to perform heavy construction work. The operator has to be present in the cabin to control such a machine. Accidents usually occur near the machine due to the unstable working environment. For example, excavators might fall into the collapsed trench. The tele-operation techniques are utilized with excavators and equipment to remove the operator from the cabin and control the machine at a safe location (Kimura et al. 2006; Lee et al. 2019).

The first group of research directly mounts (i.e., emulates) a robot inside the cabin to control the machine (Kimura et al. 2006; Lee et al. 2019; Sasaki and Kawashima 2008). These types of robots are portable and can be easily attached to different machines without refitting them. The surrounding environment of the excavator is monitored by laser scanners and cameras and is reconstructed to guide the remote operator (Lee et al. 2019).

On the other hand, the second group of research modifies construction machines to directly control them remotely (Hirabayashi et al. 2006; Kim et al. 2009a; Moon et al. 2009; Okishiba et al. 2019). The tele-operation method can be directly achieved with human arm and inertial measurement unit (IMU) sensors (Kim et al. 2009a), camera to visualize the excavation scene (Okishiba et al. 2019), and haptic sensors with force feedback to augment the information of the construction machine at the remote location (Hirabayashi et al. 2006).

**PP: Additive Manufacturing and Digital Fabrication**

Additive manufacturing and digital fabrication are construction methods that directly obtain the geometric information from a digital model—e.g., BIM—and then control the machine—e.g., a robotic arm—to manufacture or assembly the structure (Bechthold et al. 2011). These types of methods are either established in off-site factories for prefabrication (Pires 2000) or deployed on-site for in situ fabrication (Dierichs et al. 2019). Contour crafting (CC), or 3D printing, is the first type of method in this category; it is a layered manufacturing technique that has the potential to directly construct a building or component with different designs, embedded with all conduits for mechanical, electrical, and plumbing (Khoshnevis 2004).

Concrete is the most common material used in CC and 3D printing due to its fluidity and solid characteristics during and after the fabrication (Carneau et al. 2020; Herrmann et al. 2018; Jeon et al. 2013; Li et al. 2020; Lim et al. 2011; Panda et al. 2017; Shakor et al. 2017; Vantyghem et al. 2020). Steel and clay are other types of
materials for robotic 3D printing (Kerber et al. 2018; Kontovourkis and Tryfonos 2020). In terms of the robot type, since the fabricated construction components are large, the workspace of the robot is larger than the traditional robot application. In addition to the robotic arm on the track system, the cable-driven parallel robot (Boscher et al. 2007; Izard et al. 2017; Vuorenp 2017), gantry robot (Gardiner et al. 2016), or truck-mounted concrete pump robot (Krause et al. 2018) are utilized due to their large-scale workspace.

Robotic fabrication is the second type of method in this category and includes the robot assembling or cutting components to build the structure (Andreani et al. 2012; Yang et al. 2019). The robot fabrication assembly can handle complex designs such as timber structures, carbon-fiber winding ceiling structures, or specific concrete elements (Hasan et al. 2019; Heikkilä et al. 2015; Jovanović et al. 2017; Reinhardt et al. 2019; Willmann et al. 2016). The trajectory is planned based on the designed model and can also be performed by multiple robots to complete the task (Shahmiri and Tryfonos 2020). The human worker collaborates with the robot fabrication process through the stationary monitor or augmented reality goggles (Kyjane et al. 2019). Finally, a new concept of robotic refabrication is proposed to disassemble a prefabricated structure and fabricate it into a new design by comparing the two designs and removing unnecessary components (Kasperzyk et al. 2017).

**PP: Road and Infrastructure Construction Robots**

Road and infrastructure construction robots are required to work in a broad workspace to perform construction tasks such as underground utilities or road work. They are either manually delivered to each construction location and then execute the preprogrammed work (Lee et al. 2006b) or are tele-operated by an operator (Belotti et al. 2005). Control, position, and data transmission are three principal segments of the robot because of the long distance between the robot and the operator control station (Gatti and Malaguti 2003). The underground utility construction robot and the pavement robot are two types of road and infrastructure construction robots.

First, the underground utility construction robot removes workers inside the trench for pipeline installation to prevent cave-in accidents (Bernold 2007). The tele-operated robotic manipulator is applied for large concrete pipe installation with motion control and feedback to the human–machine interface (Bernold 2007; Bernold and Li 2002). Furthermore, the underground drilling robot with remote control and monitoring system also eliminates the requirement of the operator having to control the work from inside the equipment cabin (Belotti et al. 2005).

Second, pavement robots are typically applied for road striping or crack sealing. The road stripe work includes stripe removal and painting. For example, Ham et al. (2006) developed a road-stripe-removing robot with a high-pressure water jet system and a semi-automatic controller to inject high-pressure water on the road stripes. Lee et al. (2006b) developed an automatic pavement-sign-painting robot with omnidirectional wheels for extending the workspace and a paint spray system with pavement signs database for end-effector path planning. The painting process also expands to temporary marking, such as equipment installation location marking on power-plant construction sites (Kitahara et al. 2018).

On the other hand, the crack-sealing robot is deployed at the crack location and tele-operated by the operator to seal pavement cracks with a computer vision algorithm to locate the crack and plan the trajectory (Lee et al. 2006a). In order to identify the pavement crack, infrastructure inspection robots are utilized to assist the crack seal construction; these are typically unmanned aerial vehicles (UAV) or mobile robots with cameras (Shaghlii and Khalafallah 2018; Tseng et al. 2011).

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**Adaptive Manipulation**

The authors propose the term Adaptive Manipulation to describe robotic methods that use sensors to measure the physical environment, adapt to the encountered geometry, and generate work plans for the robots. This is the second category in the proposed taxonomy in Fig. 2. The human worker performs the planning of the construction work and assigns specific construction tasks to the robot. The robot utilizes sensors to collect the workspace geometric information to reconcile any mismatches between the as-designed and the as-built workspace geometry. Therefore, the robots can adapt their work plan and perform construction tasks (Lundeen et al. 2018). Several research studies in the recent past have focused on this level of the taxonomy, such as Adaptive Manipulation by Lundeen et al. (2017, 2019) or vision-guided manipulation by Feng et al. (2015). The following subsections outline several robotic implementations in construction that can be classified as Adaptive Manipulation robotic systems. Fig. 5 illustrates the robotic systems in the Adaptive Manipulation category.

**AM: Excavator and Equipment Control**

The control methods in Adaptive Manipulation are mainly feedback control—i.e., using sensor feedback to control the excavator or construction equipment. One of the purposes is energy consumption minimization (Rachkov et al. 2002), another is vibration and sway reduction (Cheng et al. 2015; Ha et al. 2000), and the other is unskilled operation assistance (Araya and Kagoshima 2001). The force sensor, the pressure sensor, and the position sensor are used to measure the force from the bucket, the hydraulic pressure, and the position of the boom, stick, and bucket as the input to the controller (Cho et al. 2004; Ha et al. 2000; Szalek and Szlagowski 2001; Tang et al. 2009).

The control algorithms include a sliding controller with an equivalent control, a switching control and a tuning control (Ha et al. 2000), fuzzy logic control (Rachkov et al. 2002; Santos et al. 2000; Szalek and Szlagowski 2001), feedforward and feedback control (Araya and Kagoshima 2001; Choi et al. 2007; Činkelj et al. 2010; Sun et al. 2013; Tang et al. 2009; Wang et al. 2016), virtual decomposition control (Koivumäki and Mattila 2015), impedance force control and explicit proportional-integral-derivative (PID) force control (Jung and Jeon 2004), and engine constant-work point, double-work-point and dynamic-work-point control (Xiao et al. 2008).

Another direction of research in this subcategory analyzes the mathematical model of construction robots for controlling and motion-planning purposes (Bock et al. 2002b). For instance, kinematic and dynamic model of the wood-processing robot (Bock et al. 2002c), the mechatronic slip robot (Bock et al. 2004b), the robotic crane (Lytle et al. 2004), nuclear decommissioning multi-arm mobile robot (Bakari et al. 2006), reinforced concrete box culvert (RCBC) chipping robot (Cho and Lee 2017), tunnel inspection undactuated hammering robot (Takahashi et al. 2017), and the autonomous underwater vehicle (Choi et al. 2007) are examined and further applied for control strategies or tele-operation assistance.

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**Fig. 5.** Robotic systems in the Adaptive Manipulation category.
The other direction of research in this subcategory is obstacle avoidance. The robots are programmed with a planned path to complete the task or remotely controlled by an operator at first and then avoid obstacles during the navigation (Boeing 2013). The location of the robot is first measured by global positioning system (GPS) on the outdoor construction site (Navon et al. 2004). Then, the onboard sensors such as cameras or range sensors detect the obstacles and determine the safe navigation points (Bone et al. 2013; Chen and Tsai 2000). A path-planning algorithm—e.g., SensBug—is employed to generate an effective path for the robot to avoid complex obstacles (Kim et al. 2003). The sense-and-act algorithm has also been developed for the mobile construction robot to sense the surroundings and modify the plan based on the data (Kahane and Rosenfeld 2004).

### AM: Assembly Robots

The assembly robots with adaptive capabilities are either tele-operated with direct feedback to the operator—e.g., intuitive remote controller with a force-reflecting joystick (Lee et al. 2007)—or use sensor readings to adjust the preprogrammed trajectory—e.g., quality assurance (QA) of the robotic floor tiling by computer vision algorithm (Navon 2000). Planning, sequential and movement control, and environment recognition are three main functionalities of the Adaptive Manipulation assembly robot (Feldmann and Koch 2000). The motion-planning algorithm is applied to determine the new trajectory of the robot to complete the task based on sensors (Bock et al. 2003; Lundeen et al. 2019). In such human–robot collaboration assembly tasks, large or heavy components such as glass or curtain walls can be installed in an easier way with coworker guidance and the physical effort of the robot (Gil et al. 2013).

The vision sensors such as cameras or laser scanners are the first types of sensors applied. The position of the grasped components or the target joint are recognized and compared with the planned trajectory (Iturralde et al. 2019; Lundeen et al. 2017). The fiducial markers attached to the components can help the robot locate them precisely (Feng et al. 2015). The force sensors are the second types of sensors applied to measure the contact force between the component and the robot or between the robot and the coworker (Gamboa et al. 2012; You et al. 2004). The controllers are developed to revise the planned trajectory based on the force data or the coworker’s intention for the human–robot collaborative assembly task (Devadass et al. 2019; Yousefizadeh et al. 2019). The IMU sensors are the third type of sensors applied to measure the heading of the robot. With the developed controller, these types of methods can direct the swarm robotics—e.g., Firberbots—to build a structure in parallel (Kayser et al. 2018). Finally, the wearable robot has been developed to assist workers with additional force (Naito et al. 2007; Seo et al. 2016).

### AM: Maintenance and Cleaning Robots

The infrastructure-inspection robot and the cleaning robot are two types of Adaptive Manipulation robots in this category. Similar to the preprogrammed robots, they are programmed with trajectories and then use onboard sensors—e.g., infrared (IR) sensors, ultrasonic sensors, laser sensors, and cameras—to collect data and adjust the plan and avoid obstacles (Sooraksa et al. 2000). The robots can also be programmed to keep a constant distance from the reference objects—e.g., walls—and follow them to complete the inspection task (An et al. 2004).

In the tunnel inspection task, the speed of the robot is maintained by control algorithms to collect high-quality visual inspection data (Sient et al. 2015). In the pavement-stripe-removing and painting tasks, the robot is installed on a truck and equipped with a vision system to position the paint spray on the detected mark to repaint (Woo et al. 2008), or it is equipped with light-emitting diode (LED) and IR sensors to track the line and then utilize dry ice to remove the stripes (Bernold et al. 2010).

Vertical-moving robots make up most of the maintenance and cleaning robots since they can maneuver on the side surface of the infrastructure or buildings to perform their tasks. The climbing mechanisms, with sensor feedback and control algorithms, are designed and developed to overcome the unstructured environment. For example, the parallel mechanism with several ultrasonic sensors can locate itself and climb along an unknown structure (Aracil et al. 2000), or the bio-inspired robot (INCHWorm) with cameras can move vertically on the wind-power blade for cleaning purposes (Jeon et al. 2012).

Vacuum suction mechanisms are mounted on the window cleaning or maintenance robot to provide its climbing ability (Miyake et al. 2006; Rachkov et al. 2005; Tun et al. 2018). With the supplement of sensors (accelerometer sensors, encoders, lidar sensors, IMU sensors, inductive sensors, pressure sensors, flow sensors) and control algorithms, the robot is able to navigate on the window or various walls surfaces and maintain its location (Miyake et al. 2006; Rachkov et al. 2005), or to transit from one window panel to another by crossing over the metallic panel (Vega-Heredia et al. 2019). Similarly, a magnetic cylinder mechanism is embedded on the steel-bridge inspection robot to climb on the steel structure and capture 3D data by image sensors, encoders, and IR sensors (Pham et al. 2016).

Cable-suspended mechanisms or rail-based systems are the other types of window-cleaning robots. These are applied to high-rise buildings with sensors, control algorithms, and human-machine interfaces to monitor the robots (Hortig et al. 2001; Joo et al. 2019; Kim et al. 2017; Lee et al. 2018). Force sensors and IR sensors are deployed to measure the force and position of the robot; they then input to a position-based impedance controller to avoid unexpected objects on the exterior of the building (Kim et al. 2017). The parallel manipulator with load-cell sensors is developed to improve the robot cleaning performance on a scaffold (Joo et al. 2019).

Finally, UAV systems have improved the performance of infrastructure and building inspections since they have low geometry restrictions (Wang and Cheng 2019). Several studies have been conducted on control algorithms for UAVs to maintain their altitude—e.g., fuzzy logic control algorithms (Bulgakov et al. 2014) or dynamic control algorithms (Metni and Hamel 2007). The distance-measuring sensors or the IMU sensors are used to measure the location and the orientation of the UAV to assist the operator in approaching the structure and contacting it stably for contact inspection (González-deSantos et al. 2020).

The visual sensor plays an important role in the UAV inspection to capture the image of the surface or reconstruct the 3D model (Kim et al. 2019c). The visual servoing control is developed to keep the target in the view field of the camera (Metni and Hamel 2007). The reconstructed 3D model includes obstacle information, which can be utilized for the mobile robot on-site navigation and further enhanced with detailed geometric information collected by the mobile robot (Kim et al. 2019c).

### Imitation Learning (IL)

In the third category of the taxonomy, the robot Imitation Learning method, is defined as robots learning a specific task by observing demonstration from human experts (Argall et al. 2009; Liang et al. 2020a). The format of the demonstration can involve directly controlling the robot—e.g., kinesthetic or tele-operating (Abu-Dakka et al. 2018; Calinon et al. 2006)—or indirectly recording observations using sensors—e.g., camera or tactile sensors (Duan et al. 2017; Edmonds et al. 2017; Liu et al. 2018).
When applying robots for complicated construction tasks, it is difficult to preprogram or automatically plan the trajectory due to the discrepancy between the design model and actual workpieces (Lundeen et al. 2017). Even with the feedback from sensors, the human still needs to assist the robot with additional guidance. Stumm et al. (2018) developed a new human–robot collaboration strategy for on-site robotic assembly, called haptic programming. The robot performs the assembly task by preprogrammed trajectory and the human adapts to the plan based on the environmental and material conditions. The robot utilizes haptic technology to record human performance and applies it to future assembly tasks.

This concept can be further extended to robot learning from human performance or demonstration, which is similar to the apprenticeship learning modality already prevalent in the construction industry for human-to-human training (Grytnes et al. 2018). The Imitation Learning method utilizes the demonstration data from human experts to guide the robot, while the robot tries to mimic the human behavior and explores the environment to find the optimal policy (Argall et al. 2009). The robot first extracts and learns the knowledge from the demonstration data and then applies it to the encountered situation. The human workers switch their role to that of a supervisor of the robot, where they first demonstrate the task several times and then monitor the robot’s performance during the execution.

IL methods offer a promising opportunity to deploy robots on construction sites. The traditional robot programming methods require an exhaustive specification of robot actions by programmers and are difficult to adapt to unknown geometry in the workplace, where the IL methods require task-specific experts for demonstration (Ravichandar et al. 2020; Torabi et al. 2019). Thus, in the construction industry, instead of replacing any human workers on-site, the skilled human workers have to continually train construction robots and work with them to supervise the process. IL research is one of the current trends in the robotics community. As indicated by Ravichandar et al. (2020), the number of publications in the IL area has been consistently growing in the past decade. Fig. 6 illustrates the robotic systems in the Imitation Learning category.

In the authors’ previous studies, a specific type of IL technique called the robot Learning from Demonstration (LfD) method was developed and evaluated for complex construction assembly tasks (Liang et al. 2019a). The robot learned the knowledge of one construction task—i.e., ceiling tile installation—based on videos of the human demonstration, and then performed the task in a virtual simulator to validate the feasibility of applying the LfD method in field construction (Wang et al. 2020). The context translation model (Liu et al. 2018) was adapted to translate the task context from the source demonstration video to the target scenario—i.e., the image of the robot with the tile at the starting pose and the target ceiling grid. The context was extracted and translated by several encoders, decoders, and autoencoders (Vincent et al. 2008), and then defined reward functions for reinforcement learning methods were used to determine the robot control policy (Schulman et al. 2015).

**Improvisatory Control**

The Improvisatory Control method, which is the fourth category in the proposed taxonomy, allows robots to perform all aspects of a task while human workers play roles as supervisors. The robots first come up with the work plan based on the sensed data, and then the human workers confirm the plan and let the robot execute the task if accepted. When the quality of the work plan is unacceptable or robots are unable to generate the work plan, the human worker will take over and control the robot manually to improve the manipulation. The robot will learn the improvised knowledge, which is similar to the construction improvisation process used for training human apprentices (Hamzeh et al. 2018). Thus, the Improvisatory Control method is the online learning version of the Imitation Learning method.

Even though the Improvisatory Control method is at a higher level in the proposed taxonomy, the research in this category has generally been for single-task robots operating in a continuous space. Such tasks do not involve a combination of materials or construction methods and are usually monolithic in product. For example, an autonomous drilling robot focuses on rocky wall consolidation under human supervision (Molfino et al. 2008). Knowledge transfer is not involved between human workers and robots in the Improvisatory Control category. Thus, the Imitation Learning category in taxonomy has remained unexplored in construction robotics due to the complexity of the tasks and materials from a co-robotic perspective. The following subsections outline several robotic implementations in construction that can be classified as Improvisatory Control robotic systems. Fig. 7 illustrates the robotic systems in the Improvisatory Control category.

**IC: Assembly and Earthmoving Robots**

The assembly and earthmoving robots in the Improvisatory Control category are capable of performing construction assembly tasks autonomously under human supervision remotely (Molfino et al. 2008) or projecting information by augmented reality (Tavares et al. 2019). The human worker monitors the situation of the robot and determines when to intervene by tele-operation if necessary (Molfino and Zoppi 2012). For example, a shotcreting robot equipped with profile measuring equipment can measure the surface and determine the shotcreting nozzle path. If operators are not satisfied with the shotcreting quality, they can switch to manual control mode and manipulate the robot by optimized control joysticks (Cheng et al. 2001).

The drilling robot (Roboclimber) for rocky walls consolidation can automatically operate the task with a drilling rig, a feeding system, a manipulator for loading and unloading the rods, and storage for rod allocation (Molfino et al. 2008). The unmanned rolling compaction system (URC) includes an unmanned roller with an automatic driving system, a wireless communication system, and a real-time remote monitoring system (Zhang et al. 2019). The URC is capable of automatic navigation while sending the information of the current status to the remote monitoring system, where the operator can provide commands to support the navigation.

Structure decommissioning robots are equipped with a cutting tool to automatically cut structures such as contaminated structures or offshore oil piles (Matteucci and Cepolina 2015; Molfino and Zoppi 2012). The control system with onboard sensors, such as tensioner sensors and cameras, are used to provide feedback for

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**Fig. 6.** Robotic systems in the Imitation Learning category.

**Fig. 7.** Robotic systems in the Improvisatory Control category.
the robot and monitor the performance by remote operators with tele-operating functionalities.

The other types of assembly and earthmoving robots in this category are semi-automatic robots—that is, the human operates the robot to complete the parts of the work that are usually too complicated for the robot, and the robot completes the rest of the work autonomously. Bock et al. (2004a) developed the large-panel mounting robot, which can be controlled by the operator to grasp the panel, then utilizes sensors and control algorithms to install the panel. Liu et al. (2019) developed the floor-tiling robot, which consists of laser sensors, an industrial robot, a mobile platform, and controllers, to locate itself and place the tile. The operator can control the mobile platform to the next location.

Bryson et al. (2005) developed the pavement robot (RoboPaver), which is capable of autonomous navigation based on GPS, laser, IR sensors, and position controller (Bryson et al. 2005). The intelligent concrete construction system on the RoboPaver allows remote control of the paving operation. Kilpeläinen et al. (2011) developed a multipurpose pavement repairing robot (ROADMOTO), which is equipped with GPS to locate itself and conducts road repair operations automatically. The control system of the ROADMOTO also offers the ability of tele-operation for the operator.

On the other hand, the new concept of human–robot collaboration in construction was proposed where the human worker delivers some of the critical work beforehand to support the autonomous robot. In the welding process, the human operator first connects the beam by tack weld so that the industrial robot can conduct seam welding later (Tavares et al. 2019). In the integrated design-fabrication process (Sharif et al. 2016), the human worker first designs the model and plans the path. The robot then uses sensors to obtain the point cloud of the environment and reflects the designed model and the planned path by adaptive control.

IC: Maintenance Robots

The maintenance robots in the Improvisatory Control category are divided into two types: navigation robots and bridge and offshore plant-maintenance robots. The navigation robots are applied for construction site security or building inspection. The autonomous navigation is realized by wireless sensor networking technology to track the location of the robot (Cho and Youn 2006), and laser scanners are used for path planning and obstacle avoidance (Wang and Kwok 2007). The operator can monitor the navigation and tele-operate the robot with superimposed information in the augmented reality goggle for efficient inspections. The UAV plays the role of an external eye for the navigation robot, which observes the blind spot and constructs a human–UAV collaboration team with unmanned ground vehicle (UGV) for on-site data collection (Asadi et al. 2020).

The bridge and offshore plant-maintenance robots are mounted on specially designed trucks for maneuvering on roads and train bridges (Oh et al. 2009; Sutter et al. 2018). The vision system on the end-effector of the robot manipulator is programmed to automatically detect cracks (Oh et al. 2009) or associate photos with the bridge three-dimensional model (Sutter et al. 2018). The operator utilizes the human–machine interface to monitor the status of the robot and intervene if necessary.

In addition, collaborative robots can increase the efficiency of the maintenance work, especially for the offshore plants. The single-user multi-robot (SUMR) tele-operated system has been developed to enable a single user to tele-operate a number of robots to conduct maintenance work or to allow an autonomous mode between robots to overcome the limitation of the tele-operation (Eom et al. 2014).

Full Autonomy

In the Full Autonomy category (the fifth category in the proposed taxonomy), the robot can perform a specific task fully autonomously without any human intervention. The Autonomous ground vehicle (AGV) is an example of a fully autonomous construction robot that can operate in unstructured, expandable, and harsh environments or indoor GPS-denied environments (Czarnowski et al. 2018; Madhavan and Durrant-Whyte 2004). The localization and mapping methods are developed using sensors such as laser scanners to navigate in the environment and identify landmarks.

Even though the Full Autonomy method is at a higher level in the proposed taxonomy, the research in this category is generally for single-task robots operating in a continuous space—such as autonomous excavators, which do not involve a combination of construction methods or materials—and without knowledge transferring from human workers. For example, the autonomous excavators focus on digging and dumping soil on construction sites based on sensor readings and site planning. Thus, the Imitation Learning category in the taxonomy has remained new to construction robotics due to the complexity of construction tasks from a cobotic perspective, and requires knowledge transferring from human workers. The following subsections outline several robotic implementations in construction that can be classified as Full Autonomy robotic systems. Fig. 8 illustrates the robotic systems in the Full Autonomy category.

FA: Maintenance Robots

The maintenance robots in the Full Autonomy category are usually equipped with several sensors—e.g., lidar, GPS, laser, sonar, camera, and IMU—to autonomously navigate inside buildings or construction sites in order to collect data such as 3D model reconstruction, wall defect detection, embankment inspection, or building retrofit evaluation (Gramegna et al. 2005; Kamiyama et al. 2018; Mantha et al. 2017; Wang and Luo 2019). The recent evolving simultaneous localization and mapping (SLAM) techniques have enhanced mobile robot navigation ability, especially for the indoor GPS-denied environment, by building the map of the environment and locating itself (Asadi et al. 2018; Kim et al. 2018b; Nemoto and Mohan 2020; Xu et al. 2020). A 3D point cloud of the environment is created in real-time to determine the navigation path (Kim et al. 2018b; Xu et al. 2019).

Vision-based scene understanding methods or methods based on convolutional neural networks (CNN) have been applied to identify the context of the environment—such as cracks, nails, screws, or walls (Asadi et al. 2018; Kucuksubasi and Sorguc 2018; Wang et al. 2019)—and to then generate a semantic model of the building (Adán et al. 2020). In addition to the vision-based scene understanding methods, fiducial markers or laser positioning units can help in accurate localization (Mantha et al. 2018; Nahangi et al. 2018; Tsuruta et al. 2019).

The Full Autonomy bridge- and tunnel-inspection robots can autonomously navigate on a bridge or along a tunnel to collect...
visual and acoustic data via cameras, laser profilers, and several nondestructive evaluation sensors (NDE) to inspect the bridge and tunnel structural deformation (La et al. 2014; Menendez et al. 2018). Similar to the mobile robot in indoor or construction environments, SLAM algorithms—such as the adaptive Monte Carlo localization method—were applied for navigation inside the tunnel or under the bridge deck (Peel et al. 2018). The operator can retrieve the status of the inspection from the remote station while the robot is inside the tunnel or bridge deck.

FA: Autonomous Excavators
The autonomous excavator has been advancing toward Full Autonomy due to advancements in sensors, actuators, and perception and control methods (Kim et al. 2019b). To achieve automatic excavation, the pose of the excavator and the condition of the soil surface need to be tracked by computer vision and point cloud modeling methods to provide information to the controller and planner (Liang et al. 2019b; Niskanen et al. 2020). Control methods including a velocity-field controller and PID controller have been proposed with the input of the pose and the main control valve (MCV) (Kim et al. 2019b; Wang et al. 2018). Data communication between sensors, planner, and controllers is an important aspect of realizing autonomous excavators (Kim et al. 2018a).

FA: Additive Manufacturing and Fabrication
The additive manufacturing and fabrication robots in the Full Autonomy category are mainly in situ fabrication mobile robots (Giffthaler et al. 2017; Hack et al. 2020). Cameras, fiducial markers, and laser scanners are deployed to localize the mobile robot and to match workpieces with the digital model (Cebollada et al. 2018; Dawod and Hanna 2019). The trajectory and the path of the robot are determined based on the design layout and the scanned data (Dawod and Hanna 2019). In addition to a single mobile robot, a team of multiple collaborative robots has been developed for printing a large structure or laying fiber concurrently (Vasey et al. 2020; Zhang et al. 2018b). Such a robotic system has to optimize the placement of robots in the workspace and ensure each robot navigates to the desired location accurately.

Recently Advanced Construction Robots
Recently advanced robotics technologies have increased robot hardware performance and software computational ability. This in turn promotes the application of construction robots. This section discusses recently advanced construction robots and their applications, including UAVs and construction-robot startup companies.

Unmanned Aerial Vehicles
Unmanned aerial vehicles, or drones, have been applied to construction sites for assisting in project progress due to their commercialization and affordability. A UAV mounted with a camera can provide additional and broader range of viewpoint from top or unreachable places. This can be utilized for proximity monitoring, highway pavement inspection, or bridge inspection (Kim et al. 2019a; Yang et al. 2015). In addition, the maneuverability of UAVs helps reduce blind spots and occlusion on construction sites. For example, UAVs can team up with UGVs to provide an external view (Asadi et al. 2020).

One of the UAV applications on construction sites is 3D reconstruction. The UAV is equipped with a camera or lidar to collect data and reconstruct the 3D point cloud (Jiang et al. 2020; Kim et al. 2019c). Such point clouds can be used for as-built 3D model updating or robot path planning. Since the UAV requires batteries and has limited operating time, it is important to maximize the coverage of the UAV in the route. Research on path-planning algorithms improves the performance of the UAV in bridge inspection, maximizing coverage and minimizing flight time (Boolourian and Hammad 2020; Phung et al. 2017).

Navigation and localization is another research topic improving UAV performance on construction sites or indoor environments. SLAM is the most well-known algorithm for autonomous or semi-autonomous UAV navigation (Kucuksubasi and Sorguc 2018). The UAV onboard sensors can extract features of the environment or markers and match them with the model to locate itself (Nahangi et al. 2018; Wang and Cheng 2019). Finally, the control method is also important to ensure the UAV follows the correct route (Metni and Hamel 2007). For example, the UAV has to keep a constant distance from the structure for contact inspection (González-deSantos et al. 2020). In the robot laying process, the quality of the construction outcome depends on whether the UAV follows the route correctly (Vasey et al. 2020).

Startup Companies
Construction robot startup companies have contributed significantly toward the development and deployment of construction robots. They intend to improve construction productivity and safety by designing new construction robotics solutions and introducing them to construction sites. Some of the recently commercialized construction robots and construction robot startup companies that have gained traction include TyBot, IronBot, Semi-automated Mason (SAM), Material Unit Lift Enhancer (MULE), Fastbricks Robotics, Williams Robotics, and Rebartz.

TyBot and IronBot are autonomous rebar assembly robots; TyBot ties rebars and IronBot carries and places rebars without human workers’ intervention (Advanced Construction Robotics 2021). Both TyBot and IronBot can be categorized as the Full Autonomy fabrication group.

SAM and MULE are a bricklaying robot and a lift-assisting robot, respectively, for handling and placing material on-site (Construction Robotics 2021). They can be categorized as the Preprogramming assembly robot group.

Fastbricks Robotics is a giant robot arm mounted on a truck for the bricklaying process (FBR 2021). It has dynamic stabilization technology to help stabilize the arm and allow precise positioning in outdoor environments. Fastbricks Robotics can be categorized as the Adaptive Manipulation assembly robot group.

Williams Robotics (2021) developed a panel assembly robot for prefabrication for assembling timber into stud walls. It can be categorized in the Preprogramming assembly robot group.

Finally, Rebartz (2021) developed a prefabrication robot that assembles rebar into cages off-site by robot arms. It is categorized in the Preprogramming assembly robot group.

The second type of construction robot startup companies are involved in additive manufacturing or 3D printing robots. These companies include Cellular Fabrication and Hyperion Robotics. Cellular Fabrication is a large-scale 3D printing robot for prefabrication, combining industrial robotics, algorithms, and a novel “freeform” extrusion technology (Branch Technology 2021). Cellular Fabrication can be categorized in the Full Autonomy additive manufacturing group. Hyperion Robotics (Hyperion Robotics 2021) has also developed a 3D printing robot and can be categorized in the Full Autonomy additive manufacturing group.

The third type of construction robot startup company specializes in robotics earthmoving equipment. Such companies include Built Robotics and Kewazo. Built Robotics (2021) has developed an autonomous dozer, an autonomous excavator, and autonomous compact track loaders (CTL) capable of self-driving and grading tasks. Human workers have to perform the site planning tasks,
and the robots can be categorized as the Improvisatory Control assembly and earthmoving robots group. Kewazo (2021) developed an intelligent robotics elevator on scaffolds to deliver scaffold parts to human workers in time and in place; it can be categorized in the Full Autonomy autonomous excavators group.

The fourth type of construction robot startup company develops site-layout robots. These include Dusty Robotics,Scaled Robotics, and Civ Robotics. Dusty Robotics (2021) is a BIM-driven robotic layout system that draws the construction layout onto sites according to the BIM model; it can be categorized in the Adaptive Manipulation maintenance and cleaning robots group. Scaled Robotics (2021) is a site and construction-project monitoring mobile robot. Human workers use the joystick controller to tele-operate the robot. It can be categorized as part of the Preprogramming maintenance and cleaning robots group. CivDot and CivDrone are mobile and drone robots for laying out points and lines in infrastructure and road construction projects (Civ Robotics 2021). The human workers prepare the site layout plan and monitor the process. It can be categorized in the Preprogramming road and infrastructure construction robots group.

Challenges in Human–Robot Collaboration in Construction

Different construction human–robot collaborative teams have limitations and challenges for particular construction tasks. We have identified three major challenges.

Safety Concerns

Safety is the major concern in construction human–robot collaboration. The robot needs to ensure that it does not collide with human coworkers during the collaboration before being deployed to real construction sites (Salmi et al. 2018; You et al. 2018). Despite numerous research studies that have addressed the issue of whether it is safe enough for the human worker to work alongside robots on unstructured construction sites via computer vision or sensors (Kim et al. 2019a, 2020; Lee and Moon 2014; Liang et al. 2019b), this is still an open research field to investigate.

On the one hand, a formal safety standard for human–robot collaboration in the construction industry should be developed to normalize the design of construction robots, collaborative workspaces, and human–robot interaction mechanisms. While an ISO standard for collaborative robots has already been developed, it mainly focuses on industrial robot systems and cannot be fully generalized to robots and work environments in the construction industry (ISO 2016). On the other hand, promising advancements in topics such as multi-robot safety (Liang et al. 2018), worker activities identification (Liu et al. 2016; Zhang et al. 2018a), or real-time tracking of construction robot and coworkers (Wu et al. 2010) can be made to promote the deployment of collaborative robots for on-site construction.

Loose Tolerances

Loose tolerances is one of the major issues in the construction industry (Milberg 2006). Similar to the fault-tolerance paradigm in the industrial cobot system (Crestani et al. 2015; Hentout et al. 2019), the discrepancy between the design model and the actual workplace needs to be identified by construction robots. Work-plan adaption and replanning methods are necessary to overcome the discrepancy (Lundeen et al. 2019). Even though the loose tolerance issue of the construction robot has led to several studies (Nahangi et al. 2015; Nahangi and Haas 2016; Rausch et al. 2017), there is still a research effort needed on the general approach of integrating discrepancy control into construction human–robot collaboration.

Industry Adoption

Based on the work reviewed, construction robots have become an important technology to advance the construction industry. However, real construction site adoption is still limited (Saidi et al. 2018). The bricklaying robot (Construction Robotics 2019) and UAV (Liu et al. 2014) are two well-known on-site applications due to their affordability and relatively low complexity. Pan and Pan (2020) surveyed stakeholders to find the determinants of construction robot adoption from the perspectives of building contractors. High costs and compatibility are two significant determinants that hinder construction robot adoption. Construction is a low-profit and high-risk industry, and the major clients of construction companies—e.g., public owners—typically follow the lowest bid price method to procure constructed facilities; this generally inhibits the adoption of new technologies (Davila Delgado et al. 2019).

In addition, human workers’ psychological states should be considered for the adoption of construction robots on-site. A proper level of trust should be established for human workers to effectively and safely collaborate with robots. Too much trust can result in automation bias and safety issues, while lack of trust can lead to human workers’ underuse of reliable automation and efficiency reduction (Wickens et al. 2015). HRC design should also take into consideration human operators’ mental stress and wellbeing during collaboration. You et al. (2018) found that separated workspace can promote human workers’ trust in robots and, as a result, increase their perceived safety and reduce their worry and fear. However, more research effort on human workers’ psychological aspects is expected to promote the adoption of HRC in the construction industry.

Recommendations for Future Research

We have identified two major future research directions in the construction human–robot collaborative-teams area. These are discussed in the following sections.

Robot Learning from Demonstration

Robot LfD, Imitation Learning, or programming by demonstration methods (Argall et al. 2009; Billard et al. 2008; Hussein et al. 2017) open avenues to new research areas of teaching robots complicated construction tasks (Liang et al. 2019a), which are typically difficult to preprogram as trajectories for the robot or to define as optimization problems. Instead, skilled human workers can complete those tasks intuitively. By using robot LfD methods, human workers can transition their work profiles to that of demonstrators and supervisors and can continue to serve essential roles in the performance of construction work. The advantage of such human–robot collaboration is knowledge transfer, whereby robots can directly absorb knowledge and experience from skilled human workers and perform the tasks under human workers’ guidance.

When the human worker demonstrates a task to the robot, additional interaction methods such as voice or gesture are necessary (Chai et al. 2018) to control or to indicate intent to the robot. For example, when the robot has picked up a tile and is preparing it for installation, the human worker can directly point at the target location or say “place at the first location,” with predefined locations in the BIM model to guide the robot. Moreover, some construction tasks require multiple demonstration methods in order to fully understand human workers’ actions. For instance, in the ceiling tile or drywall installation process, components fit close to each other, without significant gap, and the human worker has to apply a fair amount of force to overcome the friction and to push the component into the correct location. Such processes require force or
tactile demonstration to track the physical interaction between the human worker and components. Michalos et al. (2014) proposed the enhancement of LfD by using voice and natural language to command robots and the use of visual recognition methods and force sensors to demonstrate the tasks. The sensor fusion methods are also required to obtain a reliable LfD result by combining different types of demonstration data (Ge 2013).

Finally, when the robot performs the construction task learned by the LfD method on-site, human workers will improve the process if the robot cannot complete the task or the component is not snug; this is the HRC research in the Improvisatory Control category. Further research can be conducted to enable construction robots to learn the improvisation process from human workers (Hamzeh et al. 2018), and the robot can provide the improvisation suggestion or can directly perform the improvised process with a human worker’s consent.

**Human and Multi-Robot Collaboration**

Most of the current human–robot construction collaboration methods are one-to-one collaborations with heavy payload robots. The ability of a human worker to collaborate with multiple robots to complete the construction task can improve efficiency and enhance accuracy. An example includes the application of UAVs to provide additional information on the construction site to on-site mobile robots (Kim et al. 2019c) or the use of multiple robotic arms to manipulate heavy and large components, such as drywall or curtain panels, for installation at desired locations with a human worker’s guidance. Swarm robotics is one of the collaborative methods that aims to coordinate a team of numerous robots (Brambilla et al. 2013; Kayser et al. 2018). Instead of one expensive heavy payload robot, swarm robotics provides a potentially affordable and flexible solution to the construction industry.

Applying multiple robots on construction sites and collaborating with human workers highlights the need for ensuring safety and human–robot trust (You et al. 2018). During the collaboration, human workers and robots have to know where they are in the workspace and the subsequent actions they are going to take. One research direction to ensure the mutual understanding between humans and robots is the application of pose estimation systems to identify locations of humans and robots (Liang et al. 2019b; Newell et al. 2016) and information systems to communicate with each other, such as Digital Twins (Liang et al. 2020b). The other research direction is from the management perspective. For example, when deploying multiple robots on construction sites, the number of robots can be optimized based on the types of tasks and the workspace to reduce redundancy. The robot deployment optimization can also reduce the unnecessary interaction between humans and robots and cost.

**Conclusion**

In this paper, a taxonomy for construction human–robot collaborative work was proposed based on the level of robot autonomy and human effort. Five categories were proposed in the taxonomy, namely Preprogramming, Adaptive Manipulation, Imitation Learning, Improvisatory Control, and Full Autonomy. The state of the art in construction robotics research and practice were reviewed and categorized into the five groups of the taxonomy. Three major challenges of the construction robots were identified and two future research directions in this area were proposed.

With the proposed taxonomy, researchers and scholars in the area of construction robotics can clearly anchor their ongoing and future work within the context of the prior and current state of the art. It provides a framework for the conception of future research work in this area and can potentially promote the next-generation collaborative human–robot construction to move toward higher autonomy levels.

The proposed taxonomy has three limitations and can be improved in the future. First, the proposed taxonomy was built and modified based on the LoRA taxonomy (Beer et al. 2014). If a new form of human–robot collaboration is developed and not included in the LoRA, the taxonomy will need to be modified to accommodate the new human–robot collaboration method. Second, the existing articles are categorized based on how robots interact with human workers. Some of the articles have overlap between two categories and need further clarification. Third, the proposed taxonomy only includes HRC applications in construction. In addition, other aspects of HRC research, such as psychological factors, social impacts, or ethics, are not considered in the taxonomy.

**Data Availability Statement**

All data, models, and code generated or used during the study appear in the published article.

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