On-site Autonomous Construction Robots: A review of Research Areas, Technologies, and Suggestions for Advancement

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Abstract –

The use of robotic systems on construction sites can efficiently reduce construction time and increase safety by replacing construction workers in monotonous or dangerous operations. Robots for on-site construction applications are challenging and difficult to implement because of the evolving and unstructured nature of construction sites, the inherent complexity of construction tasks, the uniqueness of products, and labor-intensive modeling and commanding, which require significant human effort and expertise. With the development of data-driven techniques such as machine learning and computer vision, more advanced frameworks and algorithms can be developed to increase the level of adoption in the automation of construction robots. To better understand existing challenges and figure out the best strategies to implement high-level autonomous robotic systems for on-site construction, this study (1) summarizes technologies and algorithms used in construction robots and robotic applications in other industries, (2) discusses potential best usage and development of computer vision and machine learning techniques used in related areas to implement higher-level autonomous construction robotic systems, and (3) suggests a preliminary framework that integrates different technologies, such as vision-based data sensing to collect information, advanced algorithm to detect objects and reconstruct models of the built environment, and reinforcement learning to train robots to self-generate execution plans. This will allow construction robots to navigate and localize on construction sites, recognize and fetch materials, and assemble structures per a simulated plan. The proposed conceptual framework could help with the definition of future research areas utilizing complex robotic systems.

Keywords – Automation; Construction robots; Computer vision; Reinforcement learning

1 Introduction

Construction robots refer to robotic systems designed for construction operations, which typically take place in dynamic environments [1, 2]. Construction automation and robotics have been generating much interest in the construction community for the last decades as a way to improve productivity and reduce injuries or fatalities [3, 4]. Repetitive and labor-intense tasks, such as bricklaying, painting, loading, and bulldozing, are good candidates for automation, and the use of robots can assist in reducing labor force, and create safer work environments. However, compared to the robotic systems used in factories/manufacturing, construction robots have more complicated situations. They are exposed to dynamic and unconstructed environments, which means that predefined actions may not be suitable for all circumstances as construction sites and workspaces are always changing. Therefore, robots need to perceive the environment and understand how to react to the changes [5]. Besides, construction tasks comprise many variables, include different materials [6], and have different sequencing and requirements for assembling. This means that the control of construction robots requires a lot of manual effort to preprogram the motion and trajectory of the robotic system [7]. These challenges make it difficult to implement a high-level autonomous construction robotic system. Considering these challenges, to be able to have an autonomous robotic system to execute specific tasks, other technologies such as data sensing techniques and machine learning can be used to deliver unprecedented levels of data-driven support to substitute human efforts and instructions.

This paper presents an objective review of the use of computer vision techniques (CV) and machine learning (ML) technologies that could be used to achieve a high level of autonomy in robotic construction systems. Based on that, suggestions on a possible framework to implement a high-level autonomous construction robotic system are provided. The rest of this paper is organized as follows. Section 2 summarizes construction robotic applications, discusses challenges currently faced, and provides an overview of CV and ML techniques developed and used in relevant areas that could advance robotic systems applied to construction. Section 3 proposes a possible framework in which CV and ML are used to create an integrated system to achieve autonomous localization, material recognition, and task execution planning. Section 4 summarizes the work presented and provides directions for future research.

2 Application of Construction Robots

In general, construction robots can be classified into four categories: (1) Off-site prefabrication systems, (2) On-site automated robotic systems, (3) Drones and autonomous vehicles (AV), and (4) Exoskeleton wearable devices. For each of these categories, there are several applications. Some examples are summarized in Table 1.

Table 1. Example of construction robot applications

Category	Reference
Off-site prefabrication	[8], [9], [10], [11], [12]
On-site automated and robotic systems	[13], [14], [15], [16], [17]
Drones and AV	[18], [19], [20], [21], [22]
Exoskeletons	[23], [24], [25]

Considering the adoption of each category in the construction industry, off-site prefabrication can significantly help with the advancement of building materials, which follows the same logic and principles of the manufacturing industry. Several building components and structures have already been constructed successfully in this way. Drones and AV applications have already been used widely on construction sites to help with the monitoring process and materials delivery. Exoskeletons pushed the limits of human-robot interaction (HRI). These systems can assist and protect workers performing heavy and dangerous tasks such as lifting heavy loads and are useful to reduce fatigue and facilitate the use of other tools and equipment in awkward positions [26].

However, applications for on-site construction robots have many limitations when compared to other categories. Current on-site construction robots mostly rely on preprogrammed processes to perform single repetitive tasks, such as bricklaying, steel-truss assembly, steel welding, façade installation, wall painting, concrete laying, etc., which do not involve multi-task or multi-robot construction. Current on-site robotic systems assist the construction work but could not take the place of workers and need supervision or assistance from an operator. Having the possibility of on-site construction robots being able to adapt to construction environments and perform multiple tasks without humans' hardcoding or programmed orders is not trivial, and further research is needed to create a high level autonomous on-site construction robot to unleash the great potential and opportunities of such systems. The focus of this paper is in that area.

2.1 Data-driven techniques

The advancement of data-driven techniques such as computer vision and machining learning has dramatically improved the efficiency and accuracy of robotic systems in multiple areas. Different applications in manufacturing, surgery, self-driving vehicles, structure inspection, and maintenance, have benefited from this and experienced improved productivity and accuracy.

Considering how a construction robot should work on a construction site, previous researches focused on the following elements to fulfill the automation of construction robot: (1) localization of the robot, (2) materials (i.e., workpiece) recognition and selection, (3) optimized control and task execution, and (4) monitor and maintenance, the following subsections provide a review of the technologies that could be used in each step (Tables 2 and Table 3).

2.2 Localization

Construction sites are characterized by being unstructured and dynamic. This creates extraordinary challenges for robots to localize and navigate in such environments. On-site robots should be able to avoid obstacles to reach a specific location to execute a given task. That requires extra sensing strategies or modalities to help robots perform work adaptively.

Table 2. CV techniques used in construction robots

Step	Computer Vision Techniques		
Localization	GPS	Camera markers	SLAM (mapping and reconstruction)
Material recognition	Point clouds segmentation	Stereo image (reconstruction)	Edge detection
Task plan execution		VR models simulation	VR, HRI
Monitor control	Point cloud	SLAM	VR

An excellent way to make sure robots find the right position while guaranteeing accuracy is by using cameras and markers. For example, [5] showed that a robot could use a camera and fiducial markers to find the position to execute a construction activity. While that provided reliable position reference for the robot to navigate, it did not consider obstacles. Robots cannot react to the dynamic changes of the construction site, and the position of the markers needs to be manually modified, which requires a lot of manual efforts.

Table 3. ML techniques used in construction robots

Step	Machine Learning
Localization	Reinforcement learning for path planning and tracking (A*, LQR)
Material recognition	Deep learning or machine learning for Object Detection
Task plan execution	Reinforcement learning for simple task simulation such as bricklaying.

Currently, the most effective way to solve this problem is by using Simultaneous Localization and Mapping (SLAM). For example, [27] used V-SLAM with RGBD camera on an autonomous Unmanned Aerial Vehicle (UAV) platform for asset tracking in an outdoor construction site. [28] proposed a mobile indoor robotic monitoring and data collection framework using RGB sensors and fiducial markers. [29] proposed an autonomous robot equipped with different sensors to collect data used to conduct an automatic assessment of the state of construction. Autonomous navigation was achieved using an Adaptive Monte Carlo Localization (AMCL) algorithm. SLAM provides mapping and localization in an unknown environment and gives feedback for robots to understand the environment as well as estimating their current pose. Other applications based on SLAM include research focused on the modeling and reconstruction of the built environment using point cloud segmentation. For example, [30] proposed an integrated system that automatically provides detailed as-is semantic 3D models of buildings through raw data of point clouds. This system can better deliver environment information into digital models, provide a more reliable platform for robotic execution planning and simulation.

Based on this, reinforcement learning (RL) and optimal control could be used to provide a more robust trajectory planning result to deal with complex and dynamic problems. [31] utilized an A* algorithm to find an optimal sequence of biped robots' feet and hand contacts to cross a complicated terrain. [32] presented a quadrotor controller using iterative linear-quadratic regulator (LQR) algorithm to pass a window with slung load without the need for manual manipulation of the system dynamics, heuristic simplifications, or manual trajectory generation. RL can easily apply the navigation and collision avoidance mechanisms by learning from scratch, via a continuous, self-supervised learning process with less human effort involved and provide much more reliable simulation for more complicated non-linear dynamic systems. RL allows for further advancement of the mobility functionalities of robots.

2.3 Workpiece recognition and selection

The robot needs to go to its workpiece instead of having the workpiece brought to it, which produces a reversed spatial conveyance between the robot and the product [33]. Construction materials (i.e., workpiece) tend to exhibit considerable geometric variation. Due to their substantial size and properties, materials are often susceptible to large deflections and geometric irregularities [34]. Thus, the methods used to sense and identify the material on specific parts of the structure would be crucial for the robot to navigate around the site and find the right place to start the construction work. Previous research has investigated the ability of construction robots to adapt to the actual pose and geometry of their workpiece to perform their work. The following subsections address some of the key elements required.

2.3.1 Model registration techniques

Some approaches in manufacturing register complete 3D CAD models to determine the relative pose of the workpiece to be carried out [35]. However, such approaches are not expected to work well for construction tasks because the geometry of an individual workpiece can deviate substantially from its as-designed shape [36]. Previous studies utilized model registration techniques by matching the corresponding data and information of the workpiece with the registered models to figure out the relative pose between the as-designed object and the actual object. [7] proposed a framework to sense the data of complicated and irregular materials by producing a correlation score between the sensor data and the model to conduct dexterous tasks. These tasks require acquiring enormous and high-quality information from the environment, which requests an advanced integrated sensing system to describe the real world. Besides, the matching process also relies on human efforts or advanced algorithms to provide quick and reliable feedback. There is still great potential for the advancement of techniques and integrated frameworks to generate reliable feedback to on-site robotic systems.

2.3.2 Vision-based techniques

To get precise information and sensor data of the pose and the geometry of the workpiece, many studies used vision-based techniques such as fiducial markers to target desired objects for on-site construction robots. [37] proposed a framework using fiducial markers for robots to set specific waypoints to navigate around the building to gather information. However, the approach required the environment to be fitted with fiducial markers, which may not be ideal for real-world construction applications.

Other computer vision techniques (e.g., stereo images, edge detection, and laser scanning) have been used to find the best algorithm and strategy to identify the workpiece. Some examples are summarized next.

1. *Stereo images*

[38] showed the rudimentary ability of a robot to identify and pick up tiles using stereo cameras and a suction gripper in a robotic tile installation operation. Stereo images can help with the 3D reconstruction of specific objects; however, the efficiency and accuracy of the learning algorithm significantly limited the shape and categories of the materials.

2. *Edge detection*

[39] and [40] used edge detection to identify simple shape wires; however, their applications might not work well for a wide range of object geometries. The edge detection approach and algorithm are widely developed and greatly used in related areas, such as self-driving vehicles using supervised learning, or a weakly supervised learning framework. For example, [41] proposed a segmentation-detection collaborative network (SDCN) for more precise object detection under weak supervision with less dataset required. With these advancements in object detection techniques, on-site construction robotic system could be further developed to recognize more complicated and specific materials.

3. *Laser scanning*

Another method to get the geometry and pose of the objects is using laser scanning techniques to get the point-cloud data of the object and then clarify the object into different classes. [42] demonstrated that a robotic excavator could use laser rangefinders to adapt its plan to the topology of nearby soil and the pose of a nearby truck for a digging and dumping operation. Similarly, [43] showed that a robot could construct a dry block wall in an adaptive manner by sensing the wall's top course with a 2D laser rangefinder and modifying the installation poses of subsequent blocks accordingly. However, point clouds are massive and do not have specific classifications.

2.4 Task execution and planning

Once the materials are prepared, the next stage is to generate the execution plan. Instead of manually hardcoding the plan and trajectory to execute specific tasks, machine learning techniques can be used to train the robot so that the best trajectories and motions can be autonomously generated. Among multiple varieties of machine learning technologies, RL is the most relevant techniques to the robotic motion and control. RL is a subfield of machine learning where an agent learns by interacting with its environment, observing the results of these interactions, and receiving a reward accordingly [44]. RL enables a robot to autonomously discover an optimal behavior through trial-and-error interactions with its environment.

2.4.1 RL applications

Many studies have contributed to the applications of RL in robotics, included locomotion [45], manipulation [46], and autonomous vehicle control [47]. However, there are very few reinforcement learning-based applications for construction robots. Most of them are in the areas of simple tasks such as grasping objects, in-hand object manipulation, door opening, and simple structures construction. For example, [48] described an iterative decentralized planning and learning method, to generate construction and motion strategies to build different types of three-dimensional structures using multiple quadrotors. [49] presented a framework using an actor-critic algorithm consisting of small autonomous mobile robots and block sources, which allows robots to gather blocks from the sources to build a user-specified structure.

2.4.2 From Single-Agent to Multi-Agent

In early 2016, [50] proposed a novel multi-agent framework along with deep reinforcement learning to learn a single-agent policy.

For large-scale control systems and communication networks, multi-agent reinforcement learning allows collaboration among different agents. The system's behavior is influenced by the whole team of simultaneously and independently acting agents in a common environment. For example, [51, 52] investigated a network which optimally divides the tasks for indoor building environment navigation among a group of robots to determine optimal routes to visit multiple locations. This is crucial for large-scale work, especially construction activities, which allows multiple robots to work simultaneously and can either give feedback to other agents or speed up construction work.

3 Discussion and proposed system

Construction robots have the potential to conduct specific construction tasks autonomously. A possible direction for the evolution of on-site robots is to train them to construct like human beings without humans' hardcoding or preprogrammed orders. This means that after getting the models and instructions from the engineers and designers, robotic systems can automatically make their own decisions and select different materials among various parts of the structure to accomplish complicated tasks. With that in mind, we proposed a high-level (conceptual) on-site autonomous construction robotic framework that combines CV and ML techniques (Figure 1).

3.1 Localization

We propose to fulfill the autonomous localization function by using SLAM algorithms, such as V-SLAM (RGB-sensor, Inertial Measurement Unit), and Laser-SLAM (Kinect) and point cloud segmentation to map and reconstruct the dynamic environment into virtual models. This allows to set up the position of execution by using augmented markers or manual selection.

For path planning in real-world on-site construction, robots should be able to work on large construction sites to fulfill different functionalities such as climbing, getting across holes, and balancing on uneven surfaces. The controllers for that involve complex analytical manipulation of the dynamics, which requires lots of extra effort to program. Reinforcement algorithms seem to be a good fit for more complex robotic applications that allow real-time environment feedback with less error while providing robust control for localization.

3.2 Workpiece recognition and selection

The proposed framework uses a combination of model registration techniques and sensing techniques to find the right materials to use and the installation position of the workpiece. BIM and CAD models are used by previous research to conduct the matching between a pre-designed plan to the material in use. With relation to the virtual models created in the localization subsection, the reconstructed VR models of the environment can also help with the matching of the real-world materials with desired models and provide feedback on the construction process. In general, the next step to recognize and select materials is set up manually with much effort of commanding. In the conceptual framework, with a predefined dataset of materials to use in the designed structure (i.e., stereo images, edge detection, laser scanning), the robots could automatically recognize the materials required through deep neural networks. Even though they are in different shapes or different locations, the robots could tell them apart in different classes. The matching process can provide state and action feedback for robots to generate the execution plan in order to get the required materials when constructing a complicated structure composed of different materials.

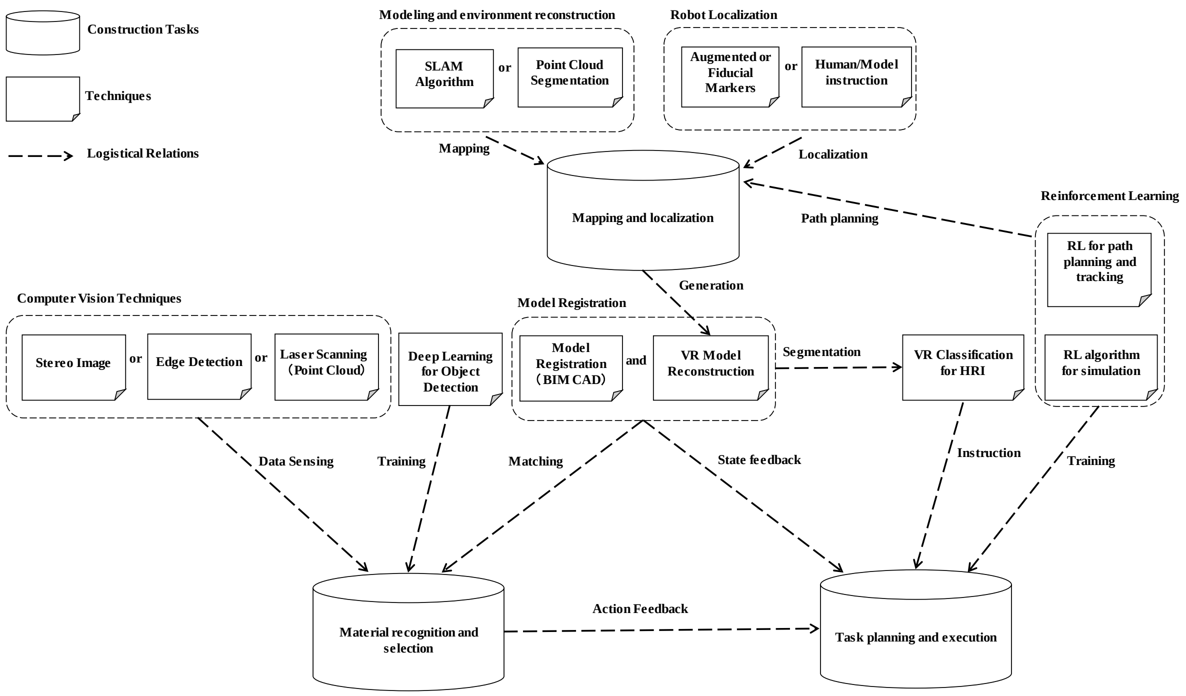

Figure 1. Conceptual on-site autonomous construction robotic system

3.3 Task execution and planning

For the autonomous execution and planning of tasks, there is no doubt that a combination of robotics and reinforcement learning will be very relevant. Some simple tasks (e.g., laying bricks, tying rebar, installing doors), could be done by current computation capacity and frameworks developed. With the information of the environment extracted from the previous step of mapping and information of material, we can describe the state of the robot and task. Then algorithms can be developed with a predefined reward policy to tell the robot what the demanded motion or execution is. Commonly used is the deep neural network-reinforcement learning framework or inversed reinforcement learning, which can teach the robot to search for the right policy when the environment and state evolve. This can greatly decrease the human interaction with the robot(s) during construction. Besides, the proposed framework allows for the advancement of multiple robots to do the construction at the same time on the same tasks with future development.

4 Conclusions and outlook

Robotic systems have the potential to provide numerous advantages to the construction industry. This paper summarizes and discusses some of the techniques and algorithms that could be used to develop autonomous on-site construction robots further. Based on that, we propose a generic conceptual framework that can fulfill the whole construction process with minimal human interaction. We suggest using computer vision techniques and point clouds with an advanced algorithm to detect, identify, and reconstruct components in the construction environment. The framework aims to train the robot to understand the environment and identify the task and allocated materials in construction sites. Besides, the framework involves virtual reality models to extract and deliver information to robots for simulation and training, which not only guarantees the best solution for construction tasks but also allows the monitoring and controlling process to ensure that the motion and execution of the robots are executed as planned. At the same time, we propose reinforcement learning to train robots to learn like humans so that they can learn from previous errors and the results from previous iterations conducted during the simulation.

However, there are still some big challenges in the implementation of the proposed framework. First, the complexity of the construction site could produce noise to the robotic system, which will greatly influence the efficiency and accuracy. Second, the calculation capacity of the algorithm is not advanced enough to finish a complicated task. Techniques and algorithms are still in development and require extra effort to test and improve. Third, the implementation from the virtual world to the real environment could result in unexpected differences. To solve this problem, more advanced sensing techniques and more accurate models need to be generated in order to make sure the accuracy of the simulation process.

Future work includes testing the efficiency of the proposed framework using a robotic arm to build-up specific applications with computer vision techniques and reinforcement learning algorithms. We will develop and test schemes on mapping and reconstruction of real-world construction environments into virtual models. Tests will be conducted on construction materials from simple shape to irregular shape, as well as from single category to multi-categories. Based on this, we will train the robot to generate its own execution plan, from a single task to complex works that involve multiple tasks. To account for scalability, a multi-agent-based framework that allows several robots to collaborate will be considered.

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