Autonomous Excavator System for Construction Earth Moving

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***Abstract*— Construction automation is vital for increasing efficiency, reducing costs, and enhancing safety in the industry. In this paper, we present our latest advancements in autonomous excavator systems (AES) specifically designed for earth moving operations in construction sites. Our proposed architecture integrates perception, planning, and control by merging multi-modal perception sensors like LiDAR and cameras with state-of-the-art localization and mapping, object detection, terrain traversability mapping, motion planning, and navigation algorithms. To showcase the performance, we successfully conducted a live demonstration (Fig. 1) for construction earth moving with multiple tasks including trucking loading, unstructured terrain navigation, and trenching. The AES is able to seamlessly complete all three tasks without any human operator intervention, highlighting its advanced level of effectiveness and robustness. To the best of our knowledge, this is the first autonomous excavator system capable of seamlessly performing multiple construction earth moving tasks. Experiment video is available at https://www.youtube.com/watch?v=mMPLjP5OVNk.**

I. INTRODUCTION

Earth moving plays a vital role in the construction industry when developing infrastructures such as roads, bridges, and skyscrapers [1], [2], [3], [4], [5], [6], [7]. With the development of automation technologies, there is an increasing demand for earth moving automation in the construction industry. One key reason why earth moving automation is crucial lies in its ability to optimize productivity. By automating machinery, such as excavators, construction projects can be completed more rapidly, with fewer errors, and with a reduced need for manual labor. Besides, construction earth moving automation helps to improve operation safety. Construction sites are widely recognized as hazardous environments due to the presence of heavy machinery, unpredictable terrain, and tight deadlines that can lead to accidents. However, the use of automated earth-moving equipment, such as excavators, has the potential to minimize human error and decrease the risk of injury, ultimately creating a safer working environment for construction workers.

Despite the above mentioned benefits, there are several technical challenges that must be addressed for earth moving automation to reach its full potential. The first challenge is developing advanced systems capable of handling complex tasks in dynamic environments. These systems must be able to adapt to changing conditions and make informed decisions based on real-time data, such as terrain and surrounding changes. Another technical challenge is the integration of the autonomous excavator system. This is challenging due to the presence of numerous hardware and software modules with unique requirements. The interaction between different modules must be carefully orchestrated to ensure seamless and efficient operation. Extensive effort in tuning and testing the software modules is required to optimize system performance.

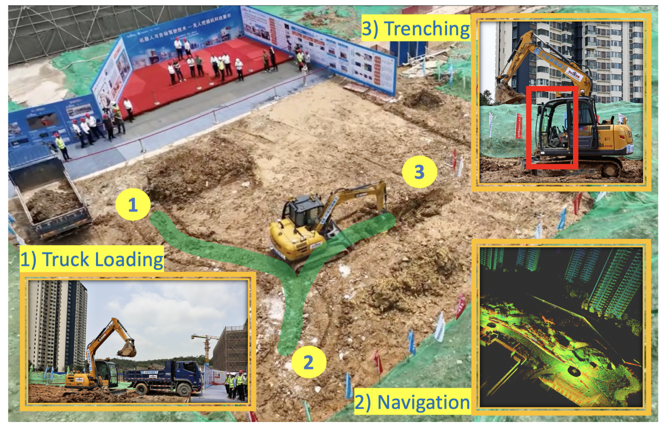

Fig. 1: A live demonstration highlighting our autonomous excavator system's performance together with a leading construction cooperator in Guangzhou, China, April 2023. The autonomous excavator is able to seamlessly complete three tasks including truck loading, navigation, and trenching in construction scenarios. No human operator is in the excavator, as shown in the red bounding box.

In this paper, we extend our previous work on Autonomous Excavator System (AES) [8], [9], [10], [11], [12] to the application of construction earth moving tasks. Our system primarily comprises three core modules—perception, planning, and control—along with a hardware sensors layer and an application layer. Specifically, we equip the excavator with LiDAR and cameras, utilizing multi-modal sensor-fusion techniques to perceive the environment and target object attributes. Based on the perception results, we have designed a hierarchical planning module consisting of a task-level planning layer and a motion planning layer for both the excavator arm and the base movement. To address the complex non-linearity, significant time delay, and large disturbances during excavation, we employ a hierarchical motion controller for excavator motion control. This comprehensive approach ensures the effective functioning of our autonomous excavator system.

To showcase the effectiveness and robustness of our au-

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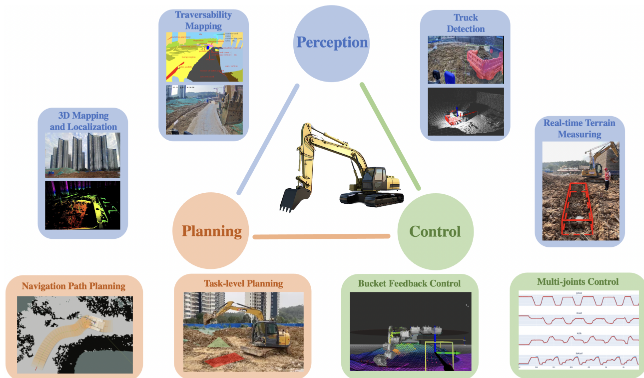

Fig. 2: The key modules and their main functions in the core algorithms of our autonomous excavator system.

tonomous excavator system for earth moving in construction scenarios, we successfully conducted a live demonstration (Fig. 1) together with a leading construction cooperator in Guangzhou, China, in April 2023. During the demonstration, we performed typical earth moving tasks on construction sites, such as trucking loading, terrain navigation, and trenching. Our autonomous excavator was able to seamlessly complete these tasks without human intervention, demonstrating the effectiveness of the system in autonomous earth moving. To the best of our knowledge, this is the first autonomous excavator system capable of seamlessly performing multiple construction earth moving tasks.

II. Autonomous Excavator System

A. System Overview

As illustrated in Fig. 2, our core algorithms primarily consist of three essential modules: perception, planning, and control. The perception module is designed to sense various obstacles, model the terrain, classify materials, and locate the dump truck. Utilizing data from the perception module, the planning module generates optimal motion trajectories for the excavator's arms and base. Subsequently, the control module produces hardware control commands based on the planning module's output, which are relayed to the excavator to track the desired motions. Moreover, an application layer adjusts other modules based on specific applications to ensure smooth operation. In the following sections, we delve deeper into the perception, planning, and navigation modules, which are the critical components that enable our system to be implemented in real-world scenarios.

B. Perception System

The perception system, which comprises a 3D LiDAR sensor and a 2D RGB camera, enables us to comprehend the work environment while precisely guides the excavator to pinpoint the task areas. As shown in Fig. 2, the major functions of the perception system includes: Localizing the excavator, constructing the terrain traversal mapping, estimating the truck pose, detecting human operators, and measuring the terrain.

To enhance the robustness of the localization from GPS RTK, we use a previously saved global point cloud map

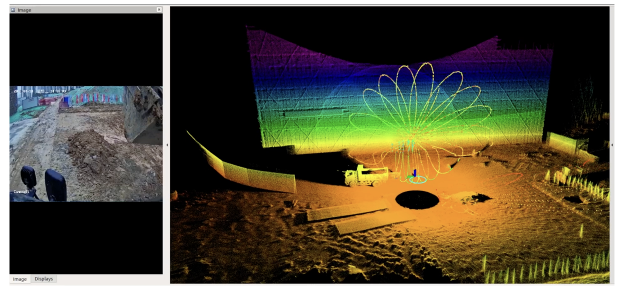

Fig. 3: A 360-degree scanning is initially performed to obtain the excavator location and the surrounding environment. The scanning result is mapped to the saved global map to determine the location of the excavator.

of the workspace to match the scanning data from the LiDAR, allowing the excavator to accurately estimate its current location and the surrounding terrain for navigation and excavation, as shown in Fig. 3. Both the LiDAR and the camera are calibrated using the excavator arm in hand-eye calibration [13]. Compared to the LiDAR-based SLAM algorithm, our method incorporating a global map enables us to achieve a higher level of localization accuracy.

The 2D images from the RGB cameras are utilized for fast human and truck detection. When a human operator is detected, a safety measure is triggered. The detected truck is further processed with its corresponding 3D point cloud data from the LiDAR to estimate both the position and orientation of the truck, which is used to determine the dumping location in the truck loading task.

In addition, the LiDAR point cloud data is used to obtain the elevation map of the workspace. The operator can specify the desired task region, and our algorithm plans out the digging strategy based on the sensor feedback. As discussed in [14], obtaining a valid map is challenging due to disturbances caused by dust, excavator motion, and sometimes rain and wind. Hence, we developed a nonlinear minimum filter over a sensing time to obtain reliable data.

C. Hierarchical Planning and Control System

We develop a hierarchical planner architecture for general excavation applications. The planner includes high-level task planner layer, sub-task planners layer, and motion primitives layer. In most scenarios, the excavator alternates between the motion of its arm to perform the excavation operation and the moving of the base to the desired position. The high-level task planner determines the locations where the excavator needs to navigate to and the regions to be excavated. The sub-tasks planners deal with sub-tasks, namely Material Removal Sub-tasks planner (MRSP) for completing the sub-region excavation efficiently and accurately, and Base Move Sub-tasks planner (BMSP) for planning the trajectory of the excavator with hybrid A^* to move to the desired locations. Finally, the motion primitive layer generates feasible excavator arm and base motion.

Excavator motion control can be challenging because the hydraulic excavator is a complex non-linear system with a large time delay and is subject to large disturbances during

(1)
(2)
(3)


Fig. 4: Snapshots of the experiments. (1) Autonomous truck loading; (2) Terrain navigation; (3) Autonomous trenching.

excavation. We use a hierarchical motion controller, which consists of a bucket end-effector following controller, an excavator base controller, and low-level machine-specific look-up tables, which map the command velocity to the hydraulic valve command. The details of the planning and control system can be found in [9].

D. Terrain Traversability based Navigation

To enable the excavator to navigate complex terrain environments, we introduce a terrain traversability mapping and navigation system for traversability prediction and autonomous navigation. Traversability [15] refers to a ground vehicle's ability to traverse a terrain region while maintaining an admissible state, taking into account its current state. In our system, we employ an efficient geometric method to extract a traversability map representation, considering the robot's physical and computational constraints such as maximum climbing degree, body width, and real-time computational budget [10]. A trajectory is planned based on this map representation, and the control system ensures the trajectory is followed in real-world scenarios. The planner also limits the trajectory's curvature to prevent the excavator from becoming stuck in soft terrain.

In our approach, we first define critical ranges based on the excavator's maximum climbing degree. If the terrain geometry falls outside of this range, we assign a poor traversability score to that region. When the terrain score is within a reasonable range, we fine-tune the weight for geometry and semantics of the terrain, optimizing the final traversability map for trajectory planning.

III. Experiments

The robot platform is a 7.5-ton hydraulic excavator equipped with a drive-by-wire system, which is controlled by software via a CAN bus interface. Multiple sensors, such as real-time kinematic (RTK), inclinometers, LiDAR, and RGB cameras are installed to enhance the platform's sensing capabilities.

To showcase our AES capabilities, we demonstrate in the following construction scenario, including autonomous truck loading, terrain navigation, and autonomous trench, as illustrated in Fig. 1. The three tasks are executed seamlessly without human interruption. Snapshots of the experiments are shown in Fig. 4.

A. Autonomous Truck Loading

Fig. 5: Autonomous truck loading. During the operation, the 3D truck pose is estimated as shown in the upper-right window, and the task area is designated as a red box as shown in the lower-right window.

Autonomous truck loading is a highly desirable feature in construction due to its repetitive and time-consuming nature. The objective of this task is to accurately identify the designated digging area and the truck pose for dumping by utilizing the perception system introduced in Sec.II-B, as illustrated in Fig. 5.

In this task, a $2m \times 3m \times 1m$ box is defined at a 45-degree angle by the excavator for digging, employing the same dig-and-dump strategy as in MRSP. The key difference is that the dumping area is determined by the 3D truck pose. Our planning also takes the truck geometry into account to avoid possible collisions.

The root-mean-square tracking errors of the excavator bucket are (0.167, 0.135, 0.282) m in the x-, y-, and z-axes, respectively. These errors primarily stem from the coupling effects between hydraulic joints. While these errors are acceptable for task completion, there is potential for improving our controller design to achieve higher accuracy.

Our AES demonstrates consistent performance over time, unlike the potentially variable performance of human operators. These results emphasize the potential of AES in enhancing efficiency and reducing the workload for human operators.

B. Terrain Navigation

With terrain traversability evaluation, our navigation system allows the excavator to move autonomously and safely through rugged terrain while avoiding obstacles, detecting changes in the environment, and accurately positioning itself for digging or other tasks. The traversability map of the work site for navigation is obtained by calculating the geometric information using the global LiDAR point cloud map.

As described in Sec. II-C, the human operator defines the target location of the excavator according to the construction task and inputs the coordinate to the system through the user interface. For this specific construction work, the excavator is required to move from the truck loading point 1 to the trench start point 3 automatically after the truck loading task is completed, as shown in Fig. 1.

C. Autonomous Trenching

Excavator trenching has a wide range of applications in construction and civil engineering projects, including the installation of underground utilities, excavation for drainage systems, landscaping, and road construction. In the autonomous trenching task, we demonstrate the ability to excavate a trench (Fig. 6). The objective of the task is to remove soil within a cuboid-shaped area. This can be accomplished by dividing the trench task into multiple sub-tasks along the length with the high-level task planner. The excavator then autonomously selects the dig points within each sub-task area based on the elevation map generated by the perception system. The soil is excavated through a series of 'dig-and-dump' loop until the predetermined height criteria is met. The excavator moves on to the next sub-task once a sub-task is completed, until the entire trench task is finished. Further details on the trench task and the excavation process can be found in [9].

Fig. 6: Autonomous trenching. The goal is to excavate a $1m \times 1m \times 6m$ area as shown in the red cuboid.

Fig. 6 displays the result of excavating a $1m \times 1m \times 6m$ area, with each sub-task being $1m \times 1m \times 2m$. The trench task is divided into 5 sub-tasks, with an $1m$ overlap between adjacent sub-tasks. On average, it takes 5 'dig-and-dump' loops to complete a sub-task, and each 'dig-and-dump' loop has an execution time of 24.2 seconds. The entire trench task, including the base movement, is completed in 11.78 minutes. The average depth error in the trench is $0.020 \pm 0.101m$.

IV. Conclusion

In this paper, we present our recent progress in developing an autonomous excavator system for construction earth moving. Our system integrates advanced perceptions, planning, and control algorithms that are specifically tailored to construction earth moving tasks. The system's effectiveness and robustness were demonstrated through a successful live demonstration of its capabilities in truck loading, navigation, and trenching.

In the future, we plan to further enhance the system's capabilities to handle a broader range of scenarios, including excavating fragmented rocks and operating in challenging weather conditions. We also aim to optimize the system's robustness and reliability and deploy it in real construction projects.

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