Autonomous Excavator System for Construction Automation

Ruitao Song, Samuel Ong, Liuwang Kang, Shiyu Jin
Yuan-Chih Peng, Zhenpeng He, Lingfeng Qian, Liangjun Zhang*

Robotics and Autonomous Driving Lab (RAL), Baidu Research

***Abstract*—Construction automation plays a pivotal role in enhancing efficiency, reducing costs, and ensuring safety within the construction industry. This paper highlights our latest advancements in the realm of autonomous excavator systems (AES) specifically designed for earth moving operations at construction sites. Our proposed architecture integrates cutting-edge technologies such as LiDAR and cameras based multi-modal perception, state-of-the-art localization and mapping, object detection, terrain traversability mapping, motion planning, and navigation algorithms. Currently, our AES demonstrates proficiency in executing three construction earth moving tasks: truck loading, trenching, and unstructured terrain navigation. To showcase its performance, we conducted a live demonstration (Fig. 1) where all three tasks were seamlessly completed consecutively without human intervention, highlighting its exceptional effectiveness and robustness. Furthermore, we have incorporated an emergency stop feature to enhance safety during navigation, automatically halting the excavator upon detecting obstacles along its future path. To the best of our knowledge, this represents the first autonomous excavator system with the capability to seamlessly perform multiple construction earth moving tasks. Experiment video is available at https://www.youtube.com/watch?v=mMPLjP5OVNk.**

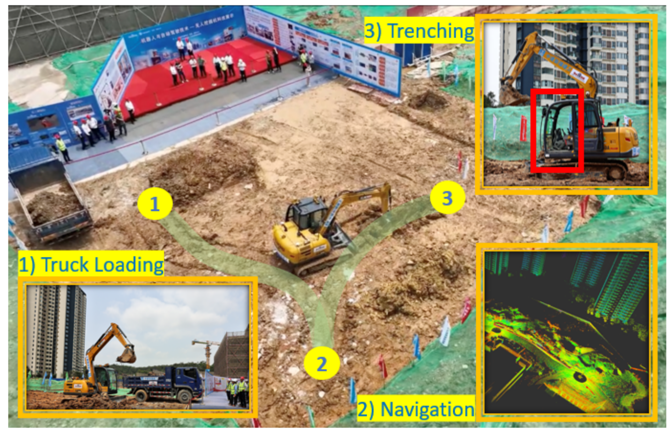

Fig. 1: A live demonstration highlighting our autonomous excavator system's performance together with a leading construction cooperator in Guangzhou, China, April 2023. The autonomous excavator is able to seamlessly complete three tasks including truck loading, navigation, and trenching in construction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

I. INTRODUCTION

The construction industry heavily relies on earth moving for constructing essential infrastructures like roads, bridges, and skyscrapers [1, 2, 6, 7, 9, 11, 12]. As automation technologies advance, there is increasing demand for automation in earth moving within the construction industry. Earth moving automation enhances productivity by automating machinery, particularly excavators, resulting in more efficient completion of construction projects with reduced errors and manual labor. Furthermore, automation improves operational safety in construction sites known for their hazards, including heavy machinery, unpredictable terrain, and tight deadlines. Integrating automated earth-moving equipment, such as excavators, minimizes human errors, mitigates injury risks, and creates a safer working environment for construction workers.

In this research paper, we present an expansion of our previous work on the Autonomous Excavator System (AES) [3, 5, 10, 13, 14] designed specifically for construction earth moving tasks. In April 2023, we successfully conducted a live demonstration (Fig. 1) in collaboration with a prominent construction partner in Guangzhou, China. The demonstration showcased various earth moving activities including truck loading, terrain navigation, and trenching. Notably, our autonomous excavator performed these tasks seamlessly without human intervention, demonstrating the system's efficacy in earth moving operations. It's worth mentioning that the demonstration took place in a controlled working area without other vehicles or workers, as the system was not actively monitoring obstacles during navigation. To enhance the system's reliability and safety, we recently implemented an emergency stop feature that continuously monitors potential obstacles along the planned trajectory and initiates a stop command when necessary.

*Corresponding author: liangjunzhang@baidu.com

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

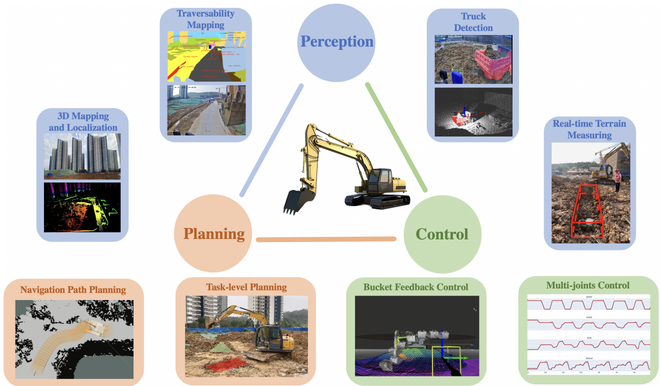

Fig. 2: The key modules and their main functions in the core algorithms of our autonomous excavator system.

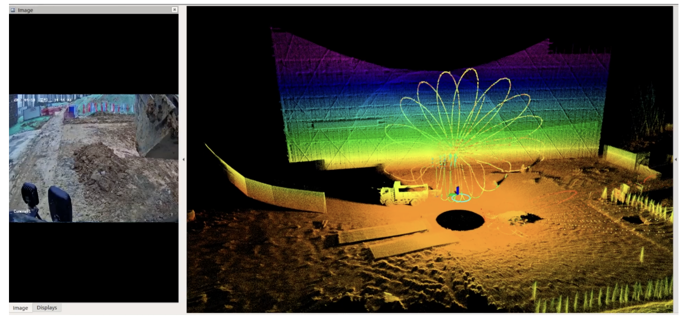

Fig. 3: A 360-degree scanning is initially performed to obtain the excavator location and the surrounding environment. The scanning result is mapped to the saved global map to determine the location of the excavator.

produces hardware control commands based on the planning module's output, which are relayed to the excavator to track the desired motions. Moreover, the application layer in our system continually 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, and measuring the terrain.

To enhance localization accuracy and excavator control, we utilize a saved global point cloud map to match LiDAR scanning data, enabling the excavator to estimate its position and assess terrain for navigation and excavation (Fig. 3). For rapid truck detection, we employ a customized object detection module using RGB camera images. The identified truck's 3D point cloud data from LiDAR is used for pose estimation, crucial for determining the appropriate dumping location. Additionally, LiDAR data generates an elevation map, allowing effective digging strategy planning based on sensor feedback and operator-defined task regions.

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 for completing the sub-region excavation efficiently and accurately, and Base Move Sub-tasks planner for planning the trajectory of the excavator to move to the desired locations. Finally, the motion primitive layer generates feasible excavator arm and base motion. Please refer to [13] for more details.

D. Terrain Traversability based Navigation

We use an efficient semantic-geometric fusion method [3] to extract a traversability map representation, which leverages the physical and computational constraints of the robot, including maximum climbing degree, width of the body, runtime computational budget, etc. In our approach, The terrain is represented as an elevation grid map and is updated in real-time based on incoming point clouds and RGB images. Internally, each grid cell in the map stores the average height value of the latest points within this cell, as well as overall information about those points like update time, slope, step height, and their semantic information. We first define critical ranges based on the excavator's capability of surmounting tough terrains. Whenever the geometry of the terrain is out of that range, we would assign bad traversability score on that region. When the terrain score is in a reasonable range, we fine-tune the weight for geometry and semantic of the terrain such that the final traversability map is useful for trajectory planning.

A trajectory is planned based on the traversability map, and the control system ensures the trajectory is followed in real-world scenarios. The planner also limits the trajectory's curvature with hybrid A^* algorithm to prevent the excavator from becoming stuck in soft terrain.

E. Emergency Stop

When the AES is following the trajectory during terrain navigation tasks, the planner does not monitor the surrounding obstacles or re-plan the trajectory to avoid potential collisions. Therefore, we recently added another safety layer to our system by implementing a stand-alone emergency stop module which immediately terminates the navigation planner and controller if an obstacle is detected near the path of the excavator.

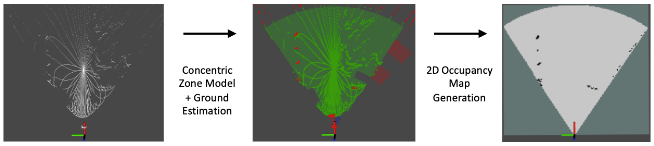

Fig. 4: Overview of Local Obstacle Map Generation

The emergency stop module replies on a local occupancy map around the excavator developed based on the idea found in [8] which bins the points in each scan into different sectors and determine the ground plane for each sector. From the ground plane in each sector, we can segment the non-ground points through a threshold height, and determine them to be either a positive or negative obstacle.

These ground and non-ground points are then converted to a 2D occupancy map with the Octomap library [4]. With the generated local map (Fig. 4) of the front of the excavator, we constantly check the path of the excavator and raise a stop command if an obstacle large enough intersects with the path.

III. Experiments

We conducted a live demonstration showcasing autonomous truck loading, terrain navigation, and autonomous trenching (Fig. 1). These tasks were seamlessly executed without human intervention, as shown in snapshots (Fig. 7). Additionally, we validated our semantic-geometric traversability mapping module and emergency stop feature at a separate test site. For the demonstration, we used a 7.5-ton hydraulic excavator with a drive-by-wire system, controlled by software via a CAN bus interface. The platform's sensing capabilities were enhanced with multiple sensors, including real-time kinematic (RTK) GPS, inclinometers, LiDAR, and RGB cameras. The traversability mapping module and emergency stop feature were tested on another 20-ton hydraulic excavator sharing the same sensor setup.

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. 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. 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 [13].

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 $0.020 \pm 0.101m$.

Fig. 7: Snapshots of the experiments. (1) Autonomous truck loading; (2) Terrain navigation; (3) Autonomous trenching.

C. Terrain Navigation

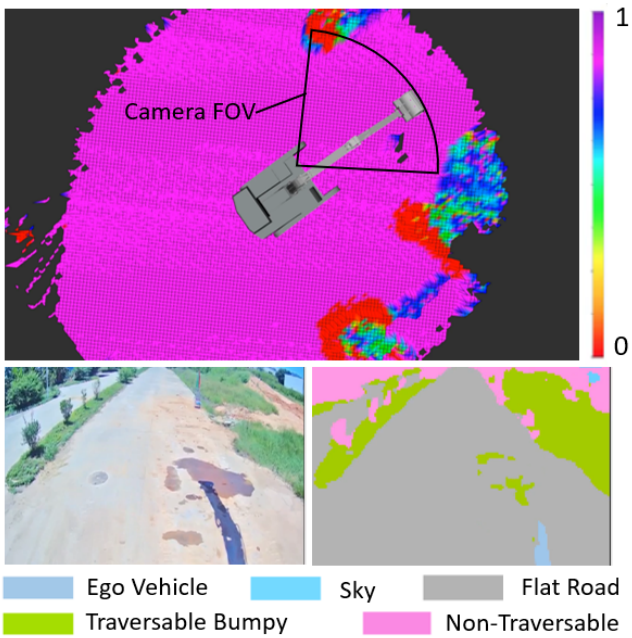

Fig. 8: Traversability mapping for navigation. Bottom-Left: camera image; Bottom-Right: segmentation result is shown by color; Top: accumulated traversability map, purple (1) means traversable, red (0) means non-traversable.

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. Fig. 8 shows the semantic-geometric based traversability map obtained by moving the excavator within the work site. The segmentation result is shown in the lower-left image with the final accumulated traversability map in the right plot. The final traversability score is calculated based on the algorithms in [3]

During the live demonstration, 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 and 7.

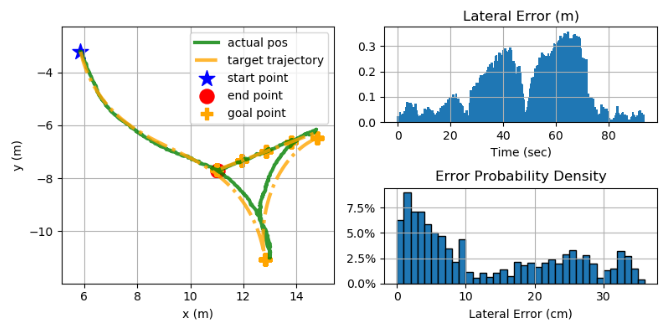

Fig. 9: Navigation from the truck loading position to the trench position, then reversing 4 times during trenching: The green line is the excavator's actual position. The orange line is the planned trajectory. The orange crosses indicate the intermediate goals where the excavator needs to stop.

The trajectory tracking results of the live demonstration are presented in Fig. 9. The lateral tracking error is defined as the distance between the excavator's current position and its closest point on the desired trajectory. The maximum tracking error is less than $0.35m$ and occurs when the excavator is turning sharp turns on the soft terrain. The tracking error is less than $0.3m$ during about 90% of the time and less than $0.1m$ during 50% of the time.

D. Emergency Stop

Emergency stop plays a vital role in safe navigation on complex and changing terrain. To validate the functionality of the emergency stop system during navigation, we set up a scenario where the excavator path passes through an obstacle. The obstacle, a stationary wheel loader seen in Figure 10, was stationed between the excavator starting point and the goal point. During navigation, the local map generated showed the obstacle moving towards excavator as the excavator drives forward. For reference, the origin of the local map is defined as the center of the excavator, which has a track length of $4m$ and a minimum front swing radius of $3m$. The obstacle, on entering the preset safety zone - defined as a $6m$ by $4m$ rectangle in front of the excavator (green area seen in Figure 10), resulted in a *stop* command being issued by the emergency stop system to the controller. The excavator stopped immediately during the test with a distance of approximately $2m$ between the from to the excavator and the obstacle. The emergency stop tests were repeated successfully with objects of various sizes, down to a footprint of $0.5m$ in diameter.

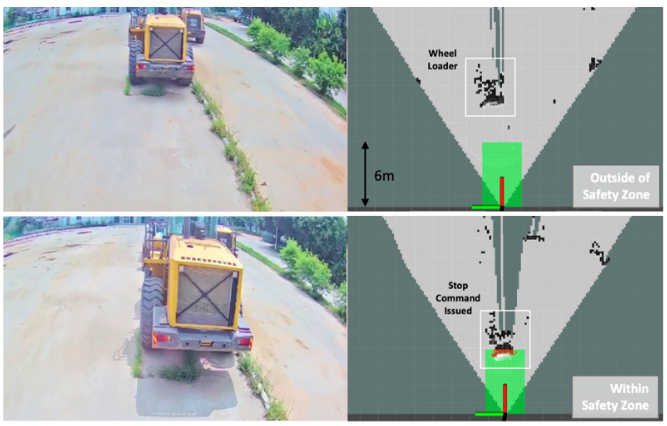

Fig. 10: Excavator Emergency Stop Demonstration

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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