Autonomous Excavator System with Real-World Deployment

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***Abstract*— Excavators are widely used for material-handling applications in unstructured environments, including mining and construction sites. Workers operating excavators suffer from prolonged working hours and loads, which can result in injuries and fatalities. In this paper, we highlight our recent progress on developing autonomous excavator systems (AES) for material loading tasks. We present an architecture that combines perception, planning and control. We fuse multi-modal perception sensors, including LiDAR and cameras, with advanced image enhancement, material and texture classification, object detection, terrain traversability mapping, motion planning, and terrain navigation algorithms. AES has been successfully deployed in a real-world scenario, where two excavators automatically operate in recycling pipelines and handle hazardous industrial solid waste material. AES can achieve 24 hours of continuous operation for the scenario and has been used by the customer for more than $8,500$ hours.**

I. INTRODUCTION

Excavators are considered the most versatile heavy equipment and are frequently used in different applications corresponding to construction, mining, exploration, environmental restoration, archaeological investigations, emergency rescue, etc. The size of global market for excavators is predicaed to grow to 63.14 billion USD by 2026 [7], and a total of $380,000$ new excavators are projected to be sold in 2024 in China [8].

Currently, excavators are mainly operated by human operators. In addition to facing life-threatening incidents or injuries, human operators may have to operate excavators in extremely abominable working conditions, such as working in remote areas, or even in desert, where conditions include heavy dust and extreme high or low temperatures [1]. Furthermore, workers also suffer from prolonged working hours and loads, which can result in fatigue and injuries [2]. Our work deals with developing an autonomous excavator system (AES) [12]. An unmanned excavation system would vastly reduce the number of casualties or injuries during excavation operations. Moreover, such an excavator could conduct tedious and repetitive tasks for extended hours, thereby increasing the overall throughput.

Efficiency, robustness, and generalizability are the three essential requirements in terms of designing an autonomous excavator [3], [5], [9]. To operate robustly in real world scenarios, the system needs to operate under an extensive range of environmental conditions that vary by the terrain types, weather, lighting conditions etc.

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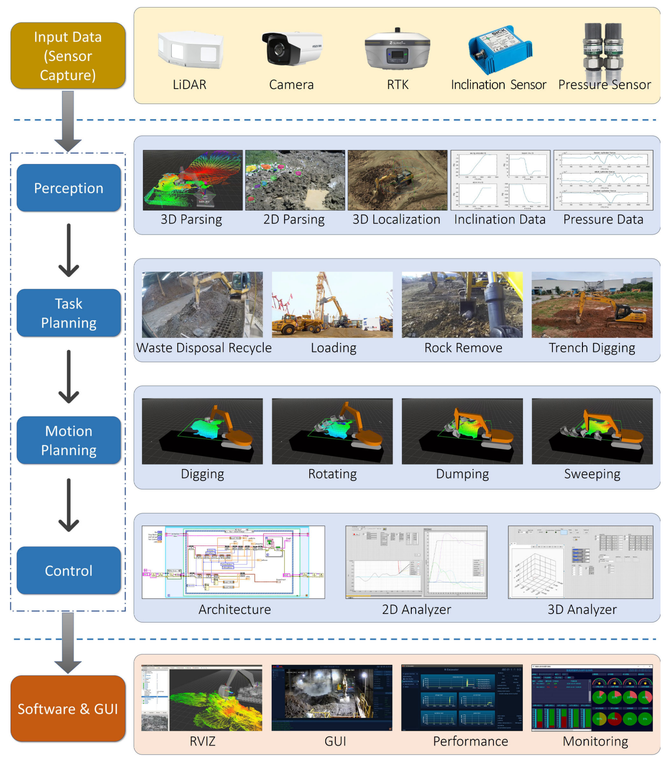

Fig. 1. Overview of Autonomous Excavator System (AES)

Considering these challenges, we develop a set of algorithms and a robust autonomous excavator system (AES) [4], [10], [11], [12], [13]. Our system mainly consists of three main modules: perception, planning, and control together with a HW sensors layer and an application layer. Specifically, we mount LiDAR and cameras on the excavator and employ multi-modal sensor-fusion approaches to perceive the surroundings and the attributes of the target objects, including source material piles, dump trucks, dumping area, impurities, and obstacles. Our perception pipeline follows the "coarse-to-fine" manner, which can not only reduce the overall run-time, but also improve the system performance, enabling prolonged automatic operations without human operator assistance. Based on the perception results, we design a hierarchical planning module composed of a task level planning layer and a motion planning layer for both excavator arm and base movement. For excavator motion control, to overcome the complex non-linearity, large time delay and large disturbances during excavation, we use a hierarchical motion controller.

We have deployed AES in real-world scenarios, where two excavators automatically operate in recycling pipelines and handle hazardous industrial solid waste material produced by various industrial activities. We demonstrate that our system can be seamlessly integrated within the pipelines for loading and dumping industrial waste, which are hazardous for human operators. We have extensively tested AES in different scenarios. AES can achieve 24 hours of continuous operation for this waste material loading scenario and has been used by the customer for more than $8,500$ hours.

II. AES Overview

A. Hardware System

The robot platform is a hydraulic excavator equipped with the drive-by-wire system. Currently, we have developed and tested multiple different sizes of excavators, including 6.5-ton and 7.5-ton compact excavators, 33.5-ton standard excavators, and 49-ton large excavators. These excavation platforms offer enormous output power to conduct various excavation tasks successfully. A control interface through a CAN bus is used so that the entire unit can be controlled by software. To ensure safety, a fallback human control mechanism is implemented in case of an emergency.

To sense the excavator locations and motions, multiple sensors are installed for AES. We use a real-time kinematic (RTK) positioning device to provide the location of the excavator. Inclinometers are used to measure the angles of different joints of the excavator. A combination of light detection and ranging (LiDAR) sensors and RGB cameras collect the environmental information for the perception module to fuse, process, and analyze the surroundings.

B. Software Architecture

There are three software modules in our system. The perception module is designed for sensing various obstacles, modeling the terrain, classifying the material, and locating the dump truck. Based on the perception results, the planning module optimizes the motion trajectories for the excavator arms and base. Then the control module transfers the planning results to the hardware control commands, which are sent to the excavator to track the desired motion. In addition, the application layer of the software adjusts the other modules based on the application.

All modules run simultaneously as nodes under the ROS framework. In the following, we provide more details on the perception and planning modules, which are the key components that enable our system to be deployed in real-world scenarios.

III. Coarse-to-Fine Perception System

Our perception module focuses on parsing and understanding the surroundings and identifying the target objects in the unstructured working zones. In specific, to handle various challenging scenarios, we perform coarse-to-fine 2D/3D perception for LiDAR point clouds and camera RGB inputs, including:

1) Recognizing the texture of the material and modeling the shape of the material pile to perform the loading operation;
2) Detecting the impenetrable portion of the material to avoid direct contact between it and the excavator's arm;
3) Identifying the blocking obstacles that need to be removed;
4) Determining the pose of the trucks for material dumping;
5) Constructing the terrain traversability mapping of the environments for the excavator to navigate;
6) Enhancing the images through computer vision methods, such as dedusting, which aims to remove the influence of dust in image capturing, thus improving the performance of obstacle identification and texture recognition.

Our perception module works in a "coarse-to-fine" manner and exploits state-of-the art algorithms like semantic segmentation, instance segmentation, texture and material recognition, object detection and dedusting. Taking a stone detection and segmentation task as an example, an image enhancement algorithm is first used. Then a texture and material recognition algorithm is exploited to identify the stone/puddle/pipe area from the whole image. Next, a 2D detection and segmentation algorithm is utilized to segment these objects accurately. Finally, the 2D segmentation and LiDAR's depth information are combined to fit the 3D bounding box for each detected obstacle.

During the excavation operation, especially for handling stone and soil, dusts often exist in the working area. The dust can considerably affect the recognition of obstacles, such as rocks and trucks. To solve this problem, we propose a deep neural network based dedusting method [10] to generate clean images from dusty input images in closed-loop manner. Taking dust image as input, an encoder and three decoders are used to recover atmospheric light, clean image and transmission map, simultaneously. The encoder is used to extract features, where Dense Feature Fusion strategy and Residual Group are utilized in the encoder process to obtain better feature representation. In the decoder process, deconvolutional layers are used to up-sample the features, then SOS Boosted strategy is employed to enhance the obtained features. Clean loss and reconstruction loss are utilized so that the proposed network can converge well during the training.

IV. Hierarchical Planning and Control System

We develop a hierarchical planner architecture for general excavation applications [11]. As shown in Fig. 2, there are two levels of task planners plus one level of motion primitives. From top to bottom, they are 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 excavation operation and the moving of the base to the desired position. Based on this

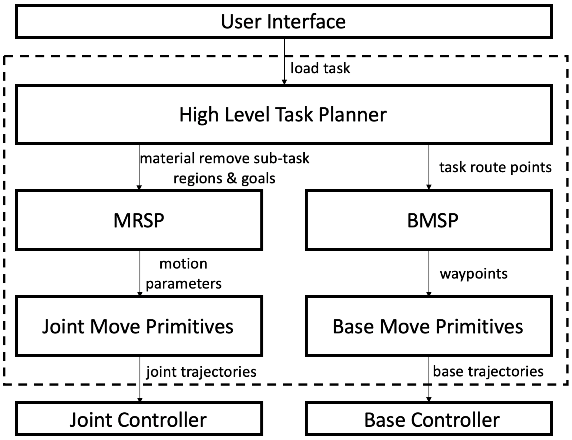

Fig. 2. AES Planning Architecture.

characteristic, our planner currently separates the arm movement and base movement into two planning pipelines. The high-level task planner plays the role of determining which location the excavator needs to move to and which region of material the excavator needs to dig. The sub-tasks planners deals with these types of sub-tasks, namely material removal sub-tasks (MRSP) for completing the sub-region excavation efficiently and accurately, and base move sub-tasks (BMSP) for planning the waypoints for the excavator to move to the desired locations. Finally, the motion primitive layer uses advanced motion planning approaches for generating feasible excavator arm and base motion. Overall, our hierarchical planning system is closely related to the perception module, as shown in Fig. 3. The system can account for the terrain shape as well as the location of obstacles, trucks and other machinery, explicitly. The system architecture and planner algorithms are able to generate effective task and motion plans, which are suitable for various excavation tasks.

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 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.

V. Terrain Traversability based Navigation

To enable the excavator navigating on complex terrain environment, we present a terrain traversability mapping and navigation system for traversability prediction and autonomous navigation. Traversability [6] refers to the capability of a ground vehicle to reside over a terrain region under an admissible state wherein it is able to enter given its current state. Based on the coarse-to-fine perception system, we use an efficient semantic-geometric fusion method to extract a traversability map representation, which leverages the physical and computational constraints of the robot, including maximum climbing degree, width of the body, run-time computational budget, etc. A trajectory is planned

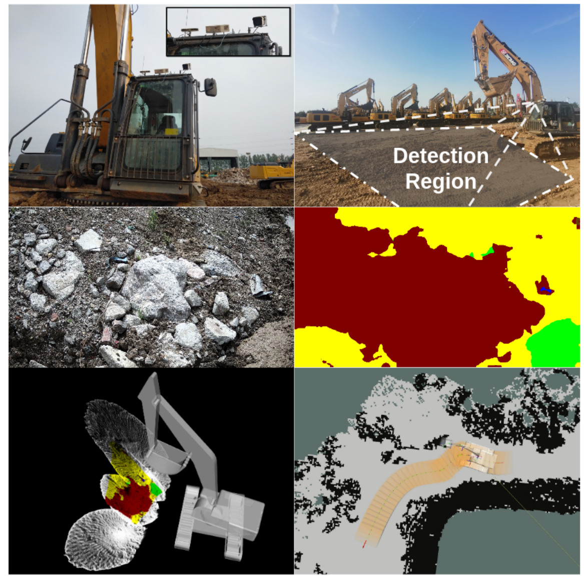

Fig. 3. Terrain Traversability Mapping and Navigation System.

based on this map representation, and the control system ensures that the trajectory is followed in the real-world. In our approach, we first define critical ranges based on the maximum climbing degree of the excavator. 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.

VI. Experimental Results

Our autonomous excavation system has been evaluated under multiple controlled, real-world testing scenarios. To thoroughly test the system capability, we set up scenarios in a closed test field, mimicking common real-world use cases for an excavator. Based on the successful test results in these scenarios, we also evaluated the efficiency and robustness of the system in one of our deployment sites, a waste disposal factory.

A. *Perception Results*

Fig. 4 demonstrates an excavator's process for digging and then loading truck, which is captured in a real-world mining operation scenario. As shown in Fig. 4 (Input dust image), the digging and truck loading process suffer from heavy dust, and camera images for the working areas and the excavator are blurry. In such a process, it is difficult for human eyes to perceive the surrounding and detect objects due to the existed dust. It could be even harder for computer vision technologies to perceive. For instance, the rock areas are difficult to localize even for humans. Therefore, the dust heavily impedes the automation of this process. As shown in Fig. 4 (Results), our approach can remove the influence of dust effectively, and the excavator and rocks areas can be easily detected after the dedusting process.

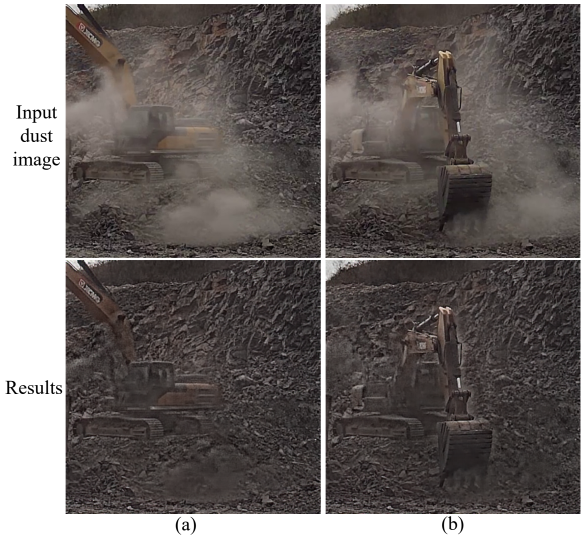

Fig. 4. Dedusting results of real-world captured dust images.

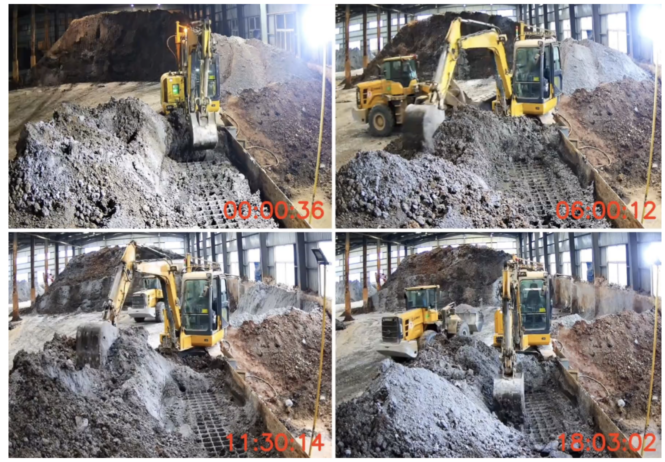

Fig. 5. Robust and non-stop operation of AES in a real-world waste disposal scenario.

B. *Terrain Navigation*

Our system is deployed on a actual worksite larger than 200 m^2. Our robust mapping and navigation system ensures that the excavator is able to reach the given goal in all trials, and maintains the average error under 9 cm overall.

C. *AES Deployment for Real-World Scenarios*

We have successfully deployed AES to a real-world scenario, where AES can run continuously for 24 hours without any human intervention as shown in Fig. 5. For the waste disposal and recycling applications, the excavator is assigned to load industrial waste material into a designated area. Afterward, the material is transferred and recycled. The material may consist of excessive dust, which is toxic to human beings. The material pile is not stable and could collapse, which is another threat to human operators. The speed of material loading by the excavator must coordinate with the belt conveyor's speed and material processing rate. Hence, there is a high-efficiency requirement for our autonomous excavator. In addition to satisfying the efficiency requirement, our autonomous excavator system can handle both dry and wet material. AES can also function at night. In this scenario, AES can operate a whole 24-hour day without any human intervention. The 7.5-ton excavator can handle as much as 67.1 m^3 material per hour, which is closely equivalent to a human operator's performance. Furthermore, AES performs consistently over time, while the performance of human operators may vary. Since the deployment, AES system has been used by the customer for more than $8,500$ hours.

VII. Conclusion

In conclusion, we highlight our recent progress on developing autonomous excavator system and deploying AES to real-world. In future, we plan to extend the system to handling more diverse scenarios, such as excavating fragmented rocks and operating in challenging weather conditions. We also would like to develop approaches for sensing and modeling material physical properties and excavation resistance force for autonomous excavation.

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