Task Delegation and Architecture for Autonomous Excavators

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***Abstract* — The construction industry is required to deliver safe, productive machines. One method being considered by heavy equipment manufacturers is autonomy. Implementing autonomy to heavy machines is unique, due to the highly skilled nature of a machine's operation meaning that different levels of autonomy may be more suitable for different tasks. Therefore, effective collaboration strategies between human operators and machines are needed. This paper proposes a machine architecture that considers the task delegation between the operator and machine.**

Keywords* — *Autonomy, System design, Task delegation

I. Introduction

Many autonomous achievements can be seen within the automotive industry, with features such as cruise control and emergency braking becoming more common place, guided by SAE J3014 [1]. This has been essential for standardising a roadmap towards full autonomy for the whole sector for safety reasons. A difficulty that is faced by the automotive industry is the clarity of task delegation between SAE J3014 levels 2 and 3, with the end-user being the most notable example. There are several examples, such as Tesla's Autopilot [2], where users assume a higher capability than stated.

The shrinking skilled workforce in the construction industry and task complexity means that task delegation between machines and operators is a challenge that needs to be understood when implementing autonomy. Heavy plant manufacturers face this challenge without a standard framework to follow. Autonomy can be achieved using established strategies like A* [3] and Rapidly-Exploring Random Tree but these struggle with task complexities [3].

Having a standardised architecture will help heavy plant manufacturers implement solutions across several types of machines whilst providing clarity of the machine capability to the construction industry. This paper addresses the issue of task delegation through the development of a novel autonomous excavator architecture and identifies opportunities to use technology such as Building Information Modelling (BIM) and Reinforcement Learning (RL) for a more integrated implementation of heavy plant machinery in the construction site.

II. Existing Literature

One of the first autonomous excavator architectures was in LUCIE [4]. However, this was solely focused on trenches and doesn't seem to have a layered architecture to enable fast and slow reactions. LUCIE also required hard-coding actions, such as when to curl the bucket, which resulted in less flexibility and, potentially, more processing during run-time.

One company that provides autonomy solutions, ASI, proposes a three-stage autonomy system which can be applied to different machines [5]. This doesn't discuss how task delegation was decided for automation tasks nor does it discuss the scenario of driver assist. It also seems more focused on bulk-digging for mining.

Mastalli et al. investigated a control system that used learning and simulation [6] but didn't investigate driver roles. Stentz et al. proposed an autonomous loading system for truck loading [7] but this architecture is complex and task specific. An aspect that these authors focused on was the visual aspect which has advanced significantly. Mastalli et al also discussed the advantages of using RL for working in highly constrained environments without the need for hard-coding.

To date, little work has been done on task delegation for excavators, despite its importance for developing autonomy. Kim investigated task-planning for excavation, which would divide the excavator's project into tasks to be completed [8]. This could have been an opportunity to mention how tasks could be delegated to operators as autonomy developed.

There are several examples in literature of human-machine task delegation in robotics that can be used to address the shortcomings of the automotive sector when applied to heavy plant. Sheridan [9] defined four main application areas of Human-Robot Interaction (HRI), supervisory control and automated vehicles were most applicable to this project. Task delegation is often applied to manufacturing with heavy or repetitive movements allocated to a robot and infrequent dexterous tasks given to a human. Another framework of delegation included Task Specification Trees [10], which used auctions to delegate tasks as actioned by human requests. To delegate, a Delegation Protocol, an extension of a Contract Net Protocol, was used. This relied on an internal manager or subcontractor that auctioned tasks to several agents. These could be based on distance and skillset, depending on the requirements.

One final aspect to consider is the use of turn-taking. With the operator and machine working on the same task, sometimes it is useful for a robot to take the driver's turn when fatigue is noticeable. Turn-taking is also important as it retains driver skill and attention, which makes it a valuable consideration for level 2 and 3 autonomy. Turn-taking was applied to a social machine [11] where good turn-taking was described as having little overlap of the human and minimal time spent between turns.

A crucial consideration is for the machine to know when to take control and how to hand it back, which is a notable problem for semi-autonomous cars [12]. This is critical in cars as the tasks the machine performs are usually at speed, which means that unexpected changes can lead to a clumsy handover. One review paper [13] discussed task allocation in the mining industry, highlighting the importance of human operators due to their judgement. Although this paper was aimed towards mining, meaning trenching isn't considered, there are several transferable concepts that can be applied to construction.

III. Driver Roles

An expert operator performed 15 trenching tasks in different soil conditions at different operating speeds in Mevea [14] to understand driver behaviour and to identify autonomy opportunities. The driver over-corrected when aligning the bucket to the trench, as seen in Figure 1. This was identified as an initial task for a machine to consider when operating alongside an expert operator.

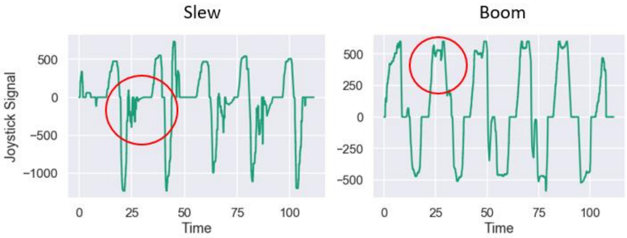

Fig. 1. Slew and boom during trenching, with hesitations circled

IV. Proposed Design

A. Architecture

To accompany the task delegation, a three-layered architecture made up of planning, control and hardware layers has been developed, see Figure 2. The control layer has also been designed with human and machine operation in mind with a task delegation module (Delegator). The operator and controller work together on a task, based on the user needs, exchanging information as instructions or feedback.

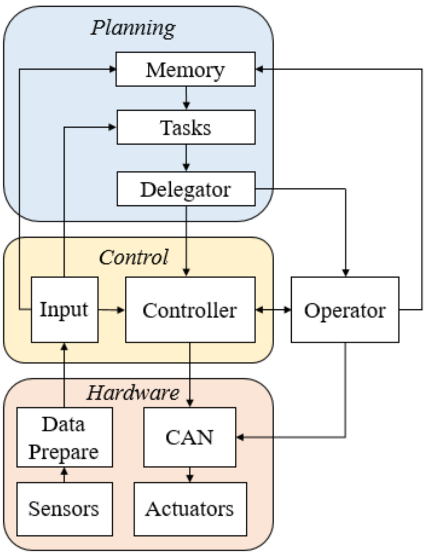

Fig. 2. Autonomous Excavator Architecture

The planning layer is where long-term plans and delegation occur. By using turn-taking, control alternates between the operator and the controller. Memory contains the excavation plans and can be the link-up to BIM, reducing site setting-out and providing managers with work information. These are divided into tasks that are then delegated to the machine and operator.

In the control layer, designers have the option of implementing their own control system and determining their own inputs. This split allows the introduction of machine-learning algorithms, such as RL, to be easily implemented. The operator can interrupt the controller and the controller informs the operator on its progress as well as identifying if it is uncertain for a decision. Training can be done with an excavator digital twin, using software like Mevea [14] before testing on a real-world machine. This improves the level of testing and simulations that can be done in advance.

The hardware layer is where control commands enter the CAN bus and control the requested actuators. Sensors receive data which then undergo any necessary preparation prior to being inputted into the controller. This modular approach can then be applied to other machines, reducing costs and providing a standard architecture. This is where safety features must also be included to ensure a reactive response.

B. Task Delegation

Performance is not the only factor to consider with autonomy; autonomous features could lead to operator mind wandering, leading to accidents [15]. The transition between tasks is also important [12] as there is an adjustment period.

A turn-taking system addresses operator mind wandering, with both the machine and operator given tasks, based on the job and autonomy level. Additionally, the machine can ask to takeover a task, repeating the task five times and returning to position, based on the performance drop of the operator. By taking turns, the machine can help to guide a novice and help alleviate the workload of an expert operator without diminishing expert skills. The actuations that an excavator can perform depend on autonomy level, with slew and boom identified as the initial tasks. The proposed structure for analysing performance is based on actor-critic methods to review both the driver and RL's performance. The turn-taking module is shown in Figure 3 along with example operator and learning algorithm behaviour.

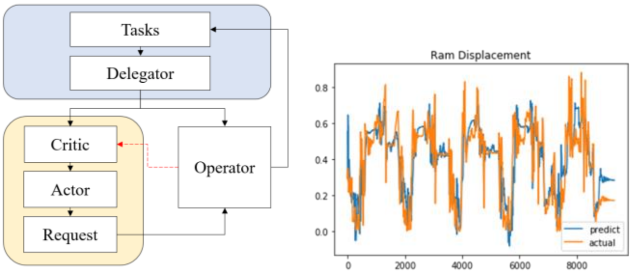

Fig. 3. Turn-taking policy (left) and learner predicting with operator (right)

V. Conclusions

A standardised architecture for autonomous excavation that considers task-delegation has been proposed within this paper, which is simple to implement and flexible for different applications. One of the most promising control strategies is RL, as it has been applied to several robotics tasks [16]. Therefore, it is the focal point for future work because of its operator-like behaviour. It also has the potential of being flexible enough to be applied to new machines outside of excavators and the construction industry.

The next stage in this research is to implement the architecture into real-world machines to confirm transferability. Although future work is focused on investigating the feasibility of RL, it is also important to consider how it can be implemented. Task delegation will also include the further investigation of human factors such as mind wandering to ensure safety and well-being.

VI. Acknowledgements

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