Task Delegation and Architecture for Autonomous Excavators

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1. Purpose and Background

There is a need for an autonomous architecture that integrates collaboration with a human operator for excavation. Current standards, like SAE J3014 [1], provide little guidance for human-machine collaboration. One opportunity to develop an operator-like machine is to integrate reinforcement learning into the architecture, alongside a turn-taking policy that improves safety.

2. Autonomy and Task Delegation Literature

One of the first autonomous excavator architectures was in LUCIE [3]. Mastalli et al investigated a control system that used learning and simulation [4] but didn't investigate driver roles. Stentz et al proposed an autonomous loading system for truck loading [5] but this architecture is complex and task specific. Sheridan [6] defined four application areas of Human-Robot Interaction (HRI) where supervisory control and automated vehicles are most applicable to this project.

Another aspect to consider was the use of turn-taking. Turn-taking was applied to a social machine [7] where examples of good turn-taking were described as having little overlap of the human and minimal time spent between turns. Zhou et al also used physical human cues to determine when the machine would need to switch roles, using these to predict intentions. One consideration needed is the handover, which is a concern in automotive autonomy [8].

3. Digital Twins

Digital twins provide a safe and repeatable environment for analyzing driver performance and developing intelligent machines, helping them overcome real-world limitations. Mevea [2] is used for this project as it has excellent fidelity and a Controller Area Network (CAN) module. For this project, the driver was in a test-rig that contained joysticks. Figure 1 shows the Mevea trenching task used for driver data collection.

Fig.1 – Mevea Task

4. Driver Analysis

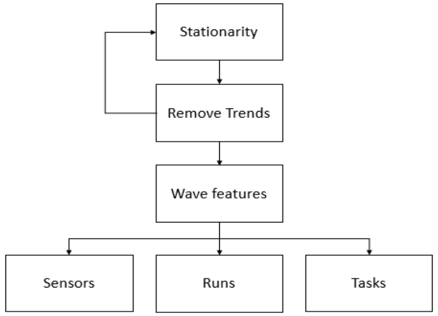

Fig.2 – Methodology

Driver data was collected across 15 task runs (for bulk dig, grading and trenching) in 3 soils at 3 speeds. Next, the data was checked for stationarity and prepared for correlation tasks by detrending. Wave features were extracted to review the noise of the driver inputs. The driver inputs were then analysed against sensors (via correlation), between runs (with cross-correlation) and then against different tasks using peak-to-peak analysis. This was to identify the differences between tasks and opportunities for autonomy. Figure 2 shows the overall methodology.

Figure 3 shows the collected driver data from Mevea. As circled in red, slewing and boom are susceptible to hesitation due to the driver requiring alignment to the trench. This data helped to develop a turn-taking architecture to improve efficiency by giving the machine control.

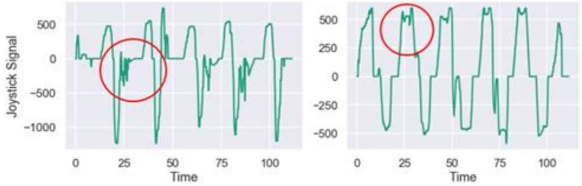

Fig.3 – Over-correction in Slew (left) and Boom (right) for trenching

5. Proposed Architecture

Operator and machine collaborate on a task in this architecture designed for excavation with reinforcement learning implemented, specifically actor-critic methods. Modularity helps to transfer to new machines. Figure 4 shows the architecture

- The planning layer is where long-term plans, such as trench locations, and task delegation occur. These are divided into tasks that are then delegated to the machine and operator. Reactive actions occur in the control layer.
- The control layer allows the introduction of reinforcement learning. 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. The controller contains a module for requesting control of driver tasks.
- The hardware layer is where commands enter the CAN bus and control specific actuators. Sensors send data for preparation before being inputted into the controller. The operator interrupts actions directly in CAN.

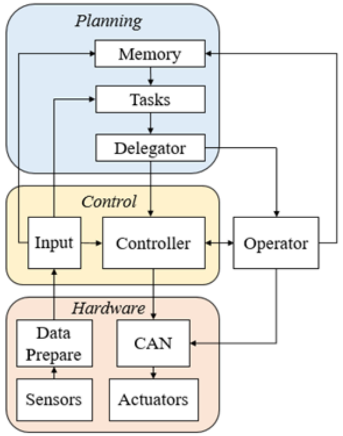

Fig.4 – Overall architecture

6. Turn-Taking Policy

The turn-taking policy proposal utilises the reinforcement learner, specifically actor-critic systems which use two neural networks: one for selecting an action and one for analysing how good an action was. The learner compares its predicted actions to the actual outcome and can suggest an intervention if the operator's performance begins decreasing. This can be done by looking at the difference between what the learner proposed against what was actually done and is shown in Figure 5.

Delegation begins when the learner requests to take over an action. This was chosen over intervening as it can lead to delegation mix-up. It is recommended that Level 2 autonomy is used for controlling slewing during trenching (to ensure smooth repositioning) whilst Level 3 autonomy alternates with the operator to perform one trench dig [1].

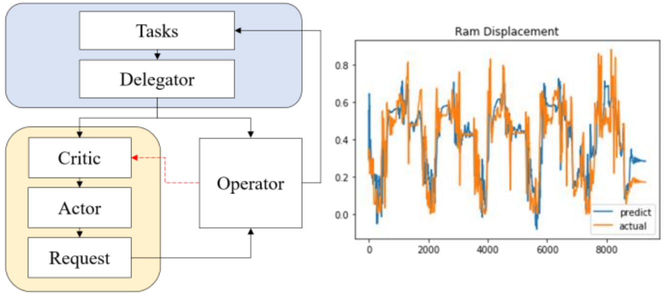

Fig.5 – Turn-taking architecture (left) and learner predicting driver (right)

7. Next Steps and Conclusions

The next stage in this research is to implement the architecture into real-world machines to confirm transferability. Task delegation and turn-taking will also include the further investigation of human factors such as mind-wandering to ensure safety and well-being.

Furthermore, an investigation into the effect of long-term excavation to the driver is needed, which can be done by analysing the drift from optimal performance as time progresses. By determining when the maximum drift occurs, an autonomous function can be deployed.

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