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ABSTRACT
Greater understanding of how highly skilled operators achieve high machine performance and productivity can inform the development of automation technology for construction machinery. Current human operator models, however, have limited fidelity and may not be useful for machinery automation. In addition, while physical modeling and simulation is widely employed in product development, current operator simulation models may be a limiting factor in assessing the performance envelope of virtual prototypes. A virtual operator modelling approach for construction machinery was developed. Challenges to the development of human operator models include determining what cues and triggers human operators use, how human operators make decisions, and how to account for the diversity of human operator responses. Operator interviews were conducted to understand and build a framework of tasks, strategies, cues, and triggers that operators commonly use while controlling a machine through a repeating work cycle. In particular, a set of operation data were collected during an excavator trenching operation and were analyzed to classify tasks and strategies. A rule base was derived from interview and data analyses. Common nomenclature was defined and is explained. Standard tasks were derived from operator interviews, which led to the development of task classification rules and algorithm. Task transitions were detected with fuzzy transition detection classifiers.

Key words: human operator modeling—construction machinery—excavator trenching—machinery operations

INTRODUCTION
Introducing new product features can impact machine performance goals such as higher productivity or fuel economy. Virtual design, the process by which new features are modeled and tested in a simulation environment, is typically conducted early in the design process where it is less expensive to make changes. While machines have been modeled with a fidelity that enables robust testing, approaches to operator modelling technology are limited, which in-turn limits the ability of engineers to make solid comparisons in the virtual prototyping stage between different design alternatives. Given the tightly coupled, non-linear nature of the sub-system dynamics in off-road vehicles, combined with a strong human-in-the-loop involvement of operators, dynamic simulation of the complete vehicle system must include the operator, environment, and working tasks (Filla et al., 2005).

Expert human operators display several characteristics: humans can adapt quickly to context using prior experience and training; humans have the ability to integrate contextual cues and strategies; and expert operators can often outperform automated functions. As human operators gain experience, their operations progress from a primarily knowledge-based behavior, to rule-based behavior, and finally to skill-based behavior (Rasmussen, 1983). Knowledge-based behavior depends on explicitly formulated goals and plans. With more practice, operators become rule-based, where sequences of action become rules to follow. Eventually, the expert exhibits skill-based behavior, where much of the action takes place without conscious control (Rasmussen, 1983). These human characteristics are quite different from those of automated machine systems.

An automated system can significantly improve consistency of repeated tasks in a stable, controlled environment which does not have much variation. In the research area of autonomous vehicles, optimal operation methods were identified, which were used to control the vehicle autonomously for situations without much variation (Bradley, 1998; Wu, 2003). However,
when the operating environment or conditions change within which an automated system operates, higher-level machine intelligence technologies, beyond closed-loop control, must be in place for the autonomous system to adapt to these changes. Developing these types of behavioral responses for autonomous systems is challenging. A robust automation system with perception of external cues and use of internal goals, may be able to exhibit adaptive behavior. For this behavior, expert human operator behavior and decision making process may have great utility. A virtual operator model aims to capture key behaviors of human operators, enabling autonomous system to adapt to external environment changes.

A virtual operator model is designed explicitly to be independent of the vehicle model. Without this independence, operator models that are highly tuned for particular vehicle models must be retuned when vehicle designs are changed. To avoid the cumbersome nature of this tight dependency, an operator model should adapt to changes in vehicle capabilities such as available power or mechanical linkage constraints.

The objective of this work was to develop an approach to virtual operator modeling (VOM). The VOM is an encapsulated model independent from the machine model with a well-defined interface. The outputs of the VOM are the control inputs to the construction machine model. The VOM should simulate human operators' behavior and decision making to generate appropriate control inputs for vehicle model simulation. The initial phase of this work is described in this paper.

The methodology used to inform the VOM design included expert operator interviews, machine data analysis, and task-based state modelling. The ability to have adaptive VOM will enable enhanced performance analysis including fuel efficiency, productivity, and component loading and strategies for robust automation technology development.

RELATED WORK
Preliminary studies of operator modeling found in autonomous vehicle research helps to develop an understanding of how a virtual operator model can be used to improve autonomous control systems. Data collection, task analysis and human behavior study techniques can be combined to gather, organize, and represent how human operators perform certain operations, supported by their strategies, situation awareness, knowledge, and decision making process.

Operator Modeling Approaches
Two virtual operator modeling approaches, task-oriented and reference-oriented, for construction equipment, were found in the literature. Task-oriented approaches simulated machine operations that go through a repeated sequence of tasks to accomplish a high-level goal. Operation modelling was based on a finite state machine and combination of a finite state machine and controllers for generating machine control inputs for each task making up the operation (Filla, 2005; Elezaby, 2011). Generally, a decision making module and a command conditioning module are needed for virtual operator modeling. The decision-making module perceives and classifies information. The command conditioning module generates appropriate control inputs. Validation was limited to the comparison of simulated paths with experimental paths for different vehicle components (Filla, 2005). By contrast, a reference-oriented approach simulates machines navigating along predefined paths to accomplish some type of operational goal. For example, a steering controller was developed for vehicles by compensating path tracking errors (Norris, 2003).
Operator modeling attempts can be also found in research investigating approaches to enabling the autonomous operation of construction equipment. Operator strategies and behavior were studied and used to develop the control module for autonomous trenching activities. For example, adaptation to different obstacles was realized by using different strategies from discovered through operator behavior studies. It was determine, for example, that human operators penetrate and drag the bucket for dense soil, while they penetrate and rotate the bucket for loose soil (Bradley, 1998). Additionally Wu (2003) developed an approach to automatic adaptation to different materials for a wheel loader dig cycle by using neural network and fuzzy logic approaches.

Task Modeling Approaches

Data collection and task analysis are human factors methods, which are commonly used for human subject-related research. Data collection is normally the first step to start the project, which collects specific information about the tasks, the system, and operation information of human operators including communication and controls. Common data collection methods include interviews, questionnaires, and observations (Stanton & Walker, 2005). Task analysis methods result in hierarchical task analysis, which decomposes the higher level task into subtasks with detailed information needed to perform the task. In general, task analysis can be classified as knowledge-based and entity-relationship-based analysis: knowledge-based analysis focuses on the knowledge in term of objects to the task; entity-relationship-based analysis focuses on finding the connection between actions and objects (Dix, Finley, Abowd & Beale, 2004).

Autonomous Control

Autonomy in semi-controlled environments like those associated with construction or agricultural application requires specification and generation of human-like behavior. Han et al. (2015) presented a multi-layered design framework for behavior-based autonomous or intelligent systems. Intelligent systems have the ability to perceive cues from the environment and machine and plan processes for adapting to different situations. Blackmore et al. (2007) proposed a behavior-based approach to agricultural field robotics with the capability to perform operations in unknown field conditions, which includes integrated human-like adaptation ability with intelligence for perception, and decision making in robotics.

MODELING METHODS

For this project, the excavator trenching operation was selected as the target construction machine operation for virtual operator development. Excavator trenching is a very common construction operation, which contains multiple tasks and deals with multiple situations. During the operation, an operator needs to make a trench at a predetermined location and orientation with defined dimensions, and dump the material either in a defined area or into a truck. Operators tend to work at their maximum ability to finish trenching as soon as possible. To automate the trenching operation, an autonomous system must mimic human operator behavior to adapt to different situations or disturbances during the operation.

To develop a virtual operator model that replicates human operator behavior, operator interviews were first conducted to understand the approach of operators and to collect information about their behavior. The modeling structure described in Figure 1 describes the elements of the VOM.
The virtual operator model interacts with the vehicle model through a well-defined interface.

The vehicle model provides machine signals like cylinder extension length and velocity. Vehicle data can be translated into the absolute position and orientation of machine implement elements such as buckets and booms through a kinematic model of the machine. These dynamic variables are closely related to the visual cues that the human operator uses for decision making during the work cycle. The signal flow in this operator model and vehicle model structure forms a closed loop for simulation.

The virtual operator model consists of three modules: the human perception module, the task model module, and the control model module. The human perception module is responsible for acquiring the vehicle model measurements and transforming them into information at the human perception level that human operators use for decision making. The vehicle model produces measurements such as cylinder displacements. However, humans perceive the vehicle in terms of position and location, such as bucket height. A kinematic model translates raw vehicle data into human-level perceptual cues. The human perception model triggers transitions between tasks by interpreting these visual cues and sounds to trigger transitions between tasks. The task model module uses the results from the human perception module to determine the sequence and status of tasks. The control model module uses task goals, modified by external conditions like soil condition, environmental condition, to generate control inputs for the vehicle model.

Three steps were followed to develop a modeling approach for virtual operator modeling. The first step was to interview operators, observe the operation, and acquire machine data. Secondly, the operation was analyzed to define the tasks and relate machine data to those tasks. The third step developed the transition detection classifier to identify transitions between tasks, which led to a state sequence model.

**Data Collection**

Operator interviews were conducted to gain a deeper understanding of the information needed and operator behaviors during the trenching operation. An interview protocol was developed to determine an operator's operating experience, behavior, strategies, and possible problems.
during operation. Three participants with different backgrounds and skill levels participated in the interviews. With experience from a wide range of different machines, the interviews provided general information about the trenching operation in general and was not limited to specific types of machines. The interview protocol was used to guide the interviews, and written notes as well as audio records were collected from the interviews. In addition, operators reviewed recorded videos of themselves operating the machinery. They reviewed their operation and walked through the video in a think-aloud technique (Lewis, 1982; Ericsson & Simon, 1993) with verbal identification of tasks, needs, goals, strategies, and behavior. This work collected both descriptive data as well as quantitative data, which enabled a combination of knowledge based and entity relationship based analysis for accurate task analysis.

Machine data recorded during predefined excavator trenching operations were used for analysis of operator’s operational behavior. An excavator was equipped with cameras inside the cab and outside the cab, which captured both video and audio, an eye tracking sensor to record and track the real-time view field of the operators, and sensors were used to log data produced from the machinery itself. Machine operation data were collected during the operation with signal channels of operator inputs, cylinder positions, and relative speed and direction.

Task and Data Analysis
Task analysis was used to represent the trenching operation and to support a detailed understanding of trenching. Tasks were identified and described based on operator interviews and operation observations. Perception of cues, selection of strategies, and subtasks was summarized in detail.

Machine data were analyzed and related to the task analysis, which described the tasks identified for trenching and specified control input information related to each task. Data analysis was performed on the machine data to identify different tasks defined from task analysis, which represents the actual operation information about the sequence, timing information, and control inputs of the tasks.

Task and data analysis resulted in a qualitative task analysis and a quantitative data-based task classification, which provided an accurate description of the trenching operation. A task model was established to represent the trenching operation with detailed information about human operator behavior, strategies, and control input for each task.

Fuzzy Transition Detection Classifiers
By classifying numerical signals into human perceivable information used for reasoning, fuzzy transition detection classifiers were developed for successful detection of transitions between tasks. Transition detection classifiers predicted the transitions between tasks, which can inform the virtual operator model when to generate control inputs for the next task. Based on machine data, the dynamic state of excavator implement elements were determined through a kinematic model, which can be translated to human perceivable descriptive information using fuzzy transition detection classifiers. Fuzzy transition detection classifiers were used to identify the transition between tasks based on some of these common cues and triggers that operators use. To develop the fuzzy transition detection classifier, membership functions were determined to describe each of signals required for rules, which were classified into different levels with descriptive language similar to how human operators perceive the signals. A set of rules were derived based on the classified human perceivable signals to identify transitions between tasks, which serve as reasoning statements in the fuzzy transition detection classifiers. The outputs
from the fuzzy transition detection classifiers represent the transitions between the tasks. By successfully identifying the transitions between tasks, the state model was completed, which represents the current state of the operation and the start of the next state.

MODELING RESULTS

Task and Data Analysis Results

The tasks and sub-tasks of the trenching operation were identified from the operator interviews and are summarized in a nominal task timeline (see Figure 2). Five main tasks were identified within the trenching operation: bucket filling, bucket lifting, swing to dump, dumping, and swing back to trench. The timing of the start and end of each task was estimated through review and analysis of video of a trenching operation for one of the participants. It was noted in both interviews and video analysis that the tasks overlap. Task overlap was a consistent theme among all participants – one participant said that the more expert the operator, the more he or she can overlap tasks to increase efficiency and reduce cycle time. While the video analysis of timing provided a qualitative estimation of task overlap, vehicle data analysis (described later in this section) was used to obtain more precise estimates of task timing.

Figure 2. Task timeline based on human operator interviews. Task start and end times were calculated based on analysis of videos of trenching operations.

The durations of specific tasks were overlaid on traces of the machine cylinder extension lengths, swing speed, and operator inputs (see Figure 3). The topmost graph of Figure 3 shows the cylinder extension positions for the Boom, Arm, and Bucket. The remaining graphs show operator control inputs for Swing, Boom, Arm, and Bucket. All these signals were used to identify the five tasks: Bucket Filling, Bucket Lifting, Swing to Dump, Dumping, and Swing to Trench within two work cycles. Rectangular bars with different colors were used to show the start time point and end time point of tasks with task names on them. Timing information of tasks could be directly read from the diagram.
Transition Detection

Task transition identification aims to predict when the operator transitions attention from one task to another based on vehicle state. Measured vehicle signals were classified into human perceivable descriptive information, which enabled human-like reasoning rules. For example, by comparing the bucket height to the ground surface, three levels were defined for states BelowSurface, NearSurface, and AboveSurface.

Table 1 contains the example of rules used in the fuzzy transition detection classifiers to detect the transition between Swing to Trench and Bucket Filling.

With this information, the operator model transitions through the task model and provides correct reference inputs to the controller and task model. Figure 1 represents the transition identification result between Swing back to Trench and Bucket Filling. The green line represents the fuzzy classification result for the transition detection. The blue line represents the ground truth task for Bucket Filling, which describes when Bucket Filling starts and ends. By comparison of the traces, the correct detection happens when the green line starts to rise slightly ahead of blue line, since the goal of the classifier is to predict a transition between tasks. If the green line raises later than the blue line, the transition is detected late.
Table 1. Transition Rules to detect the transition between the Swing and Bucket Filling tasks.

**From Swing to Trench to Bucket Filling:**

1. If (BucketHeight is BelowSurface) and (SwingAngle is NearTrench) and (ExtensionDistance is Extended) then (BucketFillTransition is BucketFill)
2. If (BucketHeight is BelowSurface) and (SwingAngle is NearTrench) and (ExtensionDistance is MidRange) then (BucketFillTransition is BucketFill)
3. If (BucketHeight is BelowSurface) and (SwingAngle is NearTrench) and (ExtensionDistance is Retracted) then (BucketFillTransition is BucketFill)
4. If (BucketHeight is AboveSurface) then (BucketFillTransition is Swing2Dig)
5. If (BucketHeight is NearSurface) and (SwingAngle is NearTrench) and (ExtensionDistance is Extended) then (BucketFillTransition is Swing2Dig)

Figure 4. Transition Detection Results between Swing back to Trench and Bucket Filling
By combining all identified transitions within the trenching operation, the sequence of tasks and current state of the operation can be represented. Figure 5 visualizes the sequence of the tasks with information about when each task starts, which can be considered as a state sequence model. An accurate task sequence is important timing and state information for control signal generation.

**Figure 5. State Sequence derived from Fuzzy Transition Detection Classifiers to Represent the Transition Time to each Task**

**DISCUSSION AND CONCLUSION**

Virtual operator modelling based on studies of human operator perception, decision making, and behaviors can be used to improve development of autonomous and robotics systems and improve evaluation methods in virtual environments. It has a direct benefit for automating construction activities. Initial work focused on construction vehicle operation; future work will expand the application area to agricultural operations, using similar approaches. The main challenges of developing virtual operator models are understanding the ability of human operators to adapt, modeling operator perception, and modeling operator decision making. This paper introduced methods used to collect data and identify information needed to start modelling. A fuzzy logic task transition model has shown promising performance in correctly identifying transitions between tasks. Expert behavior has in part been identified as the ability of operators to overlap tasks within an operation. Future work will include developing methods for identifying overlapping tasks, modeling overlap, and generating control inputs.

**ACKNOWLEDGEMENTS**

This work was funded by Deere & Company. The opinions expressed herein are those of the authors and do not necessarily reflect the views of Deere & Company.
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