Modeling Human Operator Decision-Making in Manufacturing Systems Using BDI Agent Paradigm

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Abstract

Human operators are imperative to the functioning and success of a manufacturing system. Yet there is a noticeable lack of research in modeling of human operators, especially decision-making aspects. In this paper, the complex task of modeling of human operator decision-making in a manufacturing system is addressed using Belief-Desire-Intention (BDI) agent paradigm. The roles, responsibilities and services of the operator are mapped on to mental models of beliefs, desires and intentions. The dynamic evolution of the mental models is also highlighted. The functioning of the human operator model is illustrated by integrating the model with a shop floor control system.

Keywords
Human operator model, BDI agent, shop floor control system (SFCS)

1. Introduction

Advances in automation technology have caused fundamental changes in the way manufacturing systems work. The functions of human operators have also evolved under the changing manufacturing environment. Human operators are currently performing more information processing, decision-making and control activities than ever before. Hence there is an increasing need to understand and model the decision-making aspects of human operators. On the contrary, there have been only limited research efforts on modeling human decision-making [10]. Modeling of human decision-making in general is extremely difficult, if not impossible, task. However, it becomes much more tractable in the context of a specific situation or activity [8].

An expert system model that mimics the human decision-making to handle potential system failures has been proposed for an automated manufacturing system [1]. Laugery [10] employed discrete-event simulation and task modeling techniques to model human performance. Simulation was chosen due to its ability to describe the dynamic behaviors of the system and the interactions among entities in the system in detail. An Operator Function Model (OFM) [3] has also been proposed to model the human operator’s major functions, such as scheduling and control [4] [8]. In more recent years, agent technology has been increasingly used to model human behavior in a dynamically changing and uncertain environment. Drawing inspiration from Bratman’s [7] philosophical work on practical reasoning, Rao and Goergeff [2] have integrated the theoretical foundations of the BDI agents from both a quantitative decision-theoretical perspective and a symbolic reasoning perspective, and discussed the practical application problems. The BDI paradigm is an acronym for Belief-Desire-Intention, where the system information are stored as beliefs, the goals are represented as desires and the possible plans to reach the goals are modeled as intentions [6]. Lately, the BDI paradigm has become one of the widely used frameworks in agent technology and has been progressively applied to medium to large scale systems.

In this paper, a BDI agent-based human operator model for a manufacturing domain is presented. The advantages of the BDI paradigm include: (1) BDI agent is a relatively mature paradigm, and has been successfully used in large scale systems, (2) several packages, such as AgentSpeak, Jack, and Jadex, exist to support the modeling process, (3) it is based on solid philosophical foundations, and (4) BDI agents can be easily integrated with other agent-based systems and also integrated with any complex systems.

2. The Role of the Human Operator in Manufacturing Systems

In order to construct a formal model a human operator decision-making, the human operator’s role is to be defined. In this research work, we have defined the role of a human operator in a manufacturing system by identifying the operator’s responsibilities and the services required to fulfill those responsibilities (Figure 1). For example, the shop
The role of the human operator in manufacturing systems may include the responsibilities of handling materials, monitoring and controlling the machines, making real-time scheduling decisions. These responsibilities are fulfilled by collecting and processing information, reasoning, executing commands, among others. Thus, the human operator’s role is defined as a set of responsibilities, and a responsibility is a set of services.

**Figure 1. The role of the human operator in manufacturing systems**

### 3. Proposed Human Operator Model

#### 3.1. Overview of the Proposed Human Operator Model

The overview of the proposed human operator model, based on the BDI paradigm, is depicted in Figure 2. The model consists of four major modules: Belief module, Desire module, Decision-making module, and Emotion States. The environment, containing sensors and controllers, is external to the operator model. The Belief module contains the perceptual processor and the beliefs, the Desire module contains the cognitive processor and desires, and the Decision-making module contains the planner, plans (or intentions) and the decision-maker. The beliefs, desires and intentions are also called as mental models and are described in more detail in Section 3.2.

The perceptual processor of the Belief module collects data about the environment through the sensors. The data about the operator itself is also collected. The data from sensors and about the operator are in different formats, such as visual data, auditory data, and vibration data. The perceptual processor transforms these heterogeneous data into a standard format called belief set. In this work, the First Order Predicate Logic (FOPL) is employed as the belief set format. The perceptual processor then filters the data subjectively to obtain information related to its responsibilities and services. As a result, the operator has only partial and possibly biased information about the environment and itself. Hence, it is referred to as beliefs, and not knowledge. In the Desire module, the cognitive processor identifies subjectively the operator’s goals and transforms them into the desires. The desires are also stored as FOPL, which also could be biased. The beliefs and desires are updated as the system evolves.

The planner of the Decision-making module generates alternative plans of action based on the beliefs and guided by the desires. The generated plans are then stored in the plan set (plans or intentions). A plan is defined as a sequence of actions that the operator needs to perform to achieve its goals. The reasoning procedure of the planner is discussed in detail in Section 3.2. The decision maker selects an optimal/satisfactory plan and executes it through the controllers in the environment. The decision maker’s strategy to select a plan can be modeled either as an optimization algorithm, decision-models, or game theoretic models. The Emotion States impacts the Belief, Desire and Decision-making modules. Explicit modeling of the emotion states and its impact on other parts are beyond the
3.2. Three Mental State Models of Human Operator
In the proposed model, the human operator agent is completely specified based on the events that it can perceive, the actions it may perform, the beliefs it may hold, the goals it may adopt, and the plans that give rise to its intentions. These are captured by the beliefs within the Belief module, desires within the Desire module and plans (intentions) within the Decision-making module.

A belief model (or set) describes information about the environment, internal states that a human operator may hold, and the operational rules it can apply in the reasoning process. The belief set is updated as the system evolves. In this work, we employ First Order Predicate Logic (FOPL) to represent the beliefs. A predicate is an expression representing a function from a domain to the set \{true, false\} (i.e., a Boolean function). Predicate logic is a mathematical model for reasoning with predicates, and the FOPL is a relatively mature method and its reasoning mechanisms can be modeled as programs. The belief state of an operator agent is denoted by a 3-tuple: \(<\text{Itself, Environment, Rules}>\). The hierarchy of a human operator’s beliefs is shown in Figure 3, and an exemplary belief set of a human operator is shown in Table 1.

![Figure 2. Overview of the proposed human decision-making model](image-url)

![Figure 3. An exemplary hierarchical structure of operator's belief set](image-url)
Table 1. An exemplary belief set in terms of FOPL form

<table>
<thead>
<tr>
<th>symbols</th>
<th>meanings</th>
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<tbody>
<tr>
<td>Belief {operator}</td>
<td>the belief set of the operator</td>
</tr>
<tr>
<td>Belief_operator (self, environment, operators)</td>
<td>The three classes of operator’s belief about itself, its environment, and operation rules.</td>
</tr>
<tr>
<td>Belief_operator_part1 (current-state, process-plan)</td>
<td>The operator’s belief about part 1, including its current state and process plan.</td>
</tr>
<tr>
<td>Belief_operator_part1_currentstate (part1 (machine1, finished), part1(machin2, finished), part1(machine3, unprocessed))</td>
<td>The operator’s belief about part 1. Part 1 has finished its processing in machine 1 and machine 2, and not processed on machine 3 yet.</td>
</tr>
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A desire model constitutes the goal-oriented analogue of an activity specification, consisting of a hierarchical collection of goals. Furthermore, the agent is capable of multi-tasking and can address multiple goals in parallel. The desire state is denoted by a 3-tuple: \(<\text{Current}, \text{Local}, \text{Global}>\). The desire model can be represented hierarchically in FOPL form similar to the belief model.

The planner is responsible for the reasoning ability of a human operator for it to make decisions about its actions. By applying operational rules, the agent generates plans that will lead it from its current state to its goal state. The generated alternative plans will be stored in a plan set for decision-making. In this work, we employ STRIP style structure [9] for representing the operational rules. Each operational rule consists of three STRIPS-style operator elements. First, the ADD list contains new predicates that the operational rule causes to become true. Second, the DELETE list contains old predicates that the operational rule causes to become false. Finally, the PRECONDITION list contains those predicates that must be true for the operational rule to be applied. An exemplary STRIPS-style planning and the reasoning procedure are depicted in Figure 4. In step 1, the agent compares the current state (current beliefs) with the goal state (desires). In step 2, the agent applies one of the operational rules such that its precondition list is satisfied by the agent’s current beliefs. After a specific operational rule is applied, the operator’s belief is updated (Step 3). The predicates in the rule’s DELETE list are deleted from the beliefs, and the predicates in the ADD list are added into the beliefs. This procedure continues until the goal state is reached.

Figure 4. An example of STRIP style planning (reasoning) procedure
4. Integration of BDI Model with Automated Control System

An automated shop floor control system has been implemented in the Computer Integrated Manufacturing Laboratory of The University of Arizona. Although considerable coordination and automation logic is built into the current control system, one limitation is its inability to handle unexpected situations, such as, collision between a robot and a machine, failure to insert a part into the chuck, or communication errors among controllers. When such anomalies occur, the entire system needs to be reset and restarted. To overcome this limitation, we propose to integrate the proposed human operator model with the automated control system. In the integrated system, the operator model monitors, detects and resolves conflicts to ensure the continued operation of the shop floor. The architecture of the integrated shop floor control system is depicted in Figure 5. There are three major components in the architecture, (1) human operator model, (2) shop floor control system, and (3) the physical shop floor.

In the automated shop floor control system (Figure 5), the ERP system sends orders to the task generator, which then generates the sequences of tasks required to produce the orders. The task generator sends the tasks to the manufacturing execution system (MES), and the MES controls the equipment controllers in the physical shop floor to execute these tasks. When a task is completed, the MES sends an ‘ok’ message to the task generator and the system continues. In the proposed integrated system, the task generator sends a task command to both the MES and the human operator (denoted by A in Figure 5). Now, whenever the state of the physical shop floor changes, the perceptual processor transforms the updated information into FOPL and updates the belief set (denoted by B in Figure 5). The planner compares the beliefs with desires. If the belief set (updated shop floor status) confirms with the goals in desires, an ‘ok’ message is sent to the MES (denotes by C and D in Figure 5), and the shop floor system continues (monitoring mode). If the belief is different from the goal (occurrence of an error), the planner will further generate new plans that will force the system reach the target state (denoted by E in Figure 5). Then the decision-making engine selects one of the optimal/satisfactory plans and executes it in the equipment controllers (denoted by F in Figure 5). The operator then controls the physical shop floor system until the target state is reached (control mode).

As an example, consider that the task generator generates a series of tasks for a robot to pick up a part from the buffer and put it into the chuck of a turning machine. This procedure can be represented graphically in Message-based Part State Graph (MPSG) based on Deterministic Finite Automata (DFA) model [5] (Figure 6). The circles in MPSG represent states, and the arrows represent the messages.

![Figure 5. Automated control architecture integrated with BDI](image)

![Figure 6. An exemplary MPSG of the robot](image)
It is supposed that the robot collides with the turning center before it puts the part into the chuck. The sensors in the system perceive the accident and the robot automatically stops. The whole subsystem (the robot and the turning machine) cannot recover themselves and suspends their operations. Now, the current shop floor state information (collision) is sensed by the operator’s beliefs. Since the task generator has sent the ‘put’ message to the operator’s desires before the collision has occurred, the planner in the agent can detect the conflict between the goal (desire) and current belief (collision). The planner then generates the alternative plans for the system to recover and reach the goal state (similar to the planning procedure illustrated in Section 3.2). As shown in Figure 7, after applying rule_1 and rule_2, the robot will again attempt to put the part into the chuck of the turning machine. If the part is properly put at this time, the sensor will sense the status and send it to beliefs. Then the planner compares it with the desires, and an ok message is sent to the MES to resume the control of shop.

<table>
<thead>
<tr>
<th>Beliefs:</th>
<th>collision (robot,machine(turning))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Desires:</td>
<td>put_ok_bs</td>
</tr>
</tbody>
</table>

**Rule_1:**
- ADD list: collision_clear
- DELETE list: collision(robot, machine(x))
- PRECONDITION list: collision(robot, machine(x))

**Rule_2:**
- ADD list: reput(robot, machine(x), y)
- DELETE list: robot_adjust
- PRECONDITION list: robot_adjust

Figure 7. An exemplary procedure to recover from an error

**5. Conclusion and Future Work**
In this work, a new human operator model for manufacturing systems has been proposed. BDI agent paradigm is employed to model the human operator from both the external and internal perspectives. From the external perspective, the operator agent’s role was defined, and from internal perspective, the agent’s mental models were modeled as belief, desire and intention. A proof of concept was successfully demonstrated by integrating the proposed operator model with an automated shop floor control system. Currently, work is being carried out to model of the emotional state and its impact on the dynamic evolution of three mental models.

**References**