# Perception and BDI Reasoning Based Agent Model for Human Behavior Simulation in Complex System

Jaekoo Joo

Systems and Management Engineering, Inje University
197 Inje-ro, Gimhae-si 621-749, Republic of Korea
jjoo@inje.ac.kr

**Abstract.** Modeling of human behaviors in systems engineering has been regarded as an extremely complex problem due to the ambiguity and difficulty of representing human decision processes. Unlike modeling of traditional physical systems, from which active humans are assumed to be excluded, HECS has some peculiar characteristics which can be summarized as follows: 1) Environments and human itself are nondeterministic and dynamic that there are many different ways in which they dynamically evolve. 2) Human perceives a set of perceptual information taken locally from surrounding environments and other humans in the environment, which will guide human actions toward his or her goal achievement. In order to overcome the challenges due to the above characteristics, we present an human agent model for mimicking perception-based rational human behaviors in complex systems by combining the ecological concepts of affordance- and the Belief-Desire-Intention (BDI) theory. Illustrative models of fire evacuation simulation are developed to show how the proposed framework can be applied. The proposed agent model is expected to realize their potential and enhance the simulation fidelity in analyzing and predicting human behaviors in HECS.

**Keywords:** Human Behavior, Affordance theory, BDI theory, Agent-based Simulation, Social Interaction.

## 1 Introduction

Both cognitive and rational reasoning aspects of human behaviors must be accommodated in developing common framework for modeling and simulation of Human-Environment Complex System (HECS) due to the critical role of humans in systems operation and dynamics. However, modeling of human behaviors in systems engineering has been regarded as an extremely complex problem due to the ambiguity and difficulty of representing the nondeterministic and dynamic nature of human decision processes, which makes the research difficult and slow. Unlike modeling of traditional physical systems, from which active humans are assumed to be excluded, HECS has some peculiar characteristics which can be summarized into two. First, environments and human him/herself are nondeterministic and dynamic that there are many different ways in which they dynamically evolve. The characteristics mainly

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stem from dynamic properties of environmental information and its using during human decision making processes. The nondeterministic characteristics of human itself means that human can take a number of different actions even though they are located in the same environmental situation. Furthermore, his/her physical and emotional conditions that can be easily changed according to outside situation may affect decision making processes. These nondetermistic aspects make human do not take an action just by following action route predetermined off-line. Second, human perceives a set of perceptual information taken locally from surrounding environments and use it with a series of complex rational reasoning processes, which will guide human actions toward his or her goal achievement. The perceptual information is classified into environs static data, environs dynamic data, and social interaction data with other humans. At any instant of time, there may exist various assigned objectives that the human is asked to accomplish. In order to achieve a goal(s), a human anticipates perceptually-available outcomes and opportunities to take an action using the perceptual information. In order to overcome the challenges due to the above characteristics, we present a generic modeling framework for mimicking perception-based rational human behaviors by combining the ecological concepts of affordance- and the Belief-Desire-Intention (BDI) theory. According to Gibson, the perceived information regarding sets of affordance-effectivity taken from their surrounding environs is used for a human to make decisions to take action [1]. Rao and Georgeff argued the necessity of three attitudes of Belief, Desire and Intention (BDI), representing respectively, the information, motivational, and deliberative states of human agent [2]. While the perceptual property of affordance provides a basic idea of how a perception guides human actions, the mental attitudes of BDI are critical for achieving adequate or optimal performance when deliberation is subject to resource bounds [3]. In our previous work, we developed and verified an agent-based formal simulation framework of affordance-based human behaviors in emergency evacuation situations [4]. In the work, however, our perspective on human behavior was limited to individual decision making with only human perceptions rather than more complex problem domains involving rational reasoning and human interactions. In this paper, we will extend the framework by accommodating the rational reasoning aspects of human behavior in HECS. To this end, the perceptual information is firstly classified to clarify their influence on human action decisions in the context of the developed framework. Second, the functionalities and processes of perception and BDI reasoning of human agent are discussed. Finally, an exemplary scenario is developed and illustrative models of fire evacuation simulation are developed to show how the proposed framework can be applied. The proposed human behavioral modeling framework is expected to enhance the modeling fidelity and simulation credibility for human-included complex systems.

# 2 Background

## 2.1 Affordance Theory and Perception-Based Action

The perception-based action was initiated by Gibson who regarded a human action as a consequence of direct perception of affordance (action opportunity provided by the environment) and effectivity (an individual's ability to take a specific action) [1]. Thereafter, Turvey defines affordance as a real property of the animal-environment system (AES) that is perceived directly toward the execution of a potential action [5]. Turvey bases the definition of affordance in terms of properties that represent a potential state and are not currently realized (called dispositional properties or dispositions). Dispositions occur in pairs in which a property of the environment (i.e., walk on – ability for the person) is complemented by a property of the animal's capability known as an effectivity (i.e., to walk on the stairs' surface). So the terms of affordance and effectivity can be combined together so that they incur a different property (i.e., climb the stairs) to be activated. For example, in case of a person-climbing-stairs system ($W$), a person ($Z$) can walk ($q$), stairs ($X$) can support something ($p$), and they together yield climbing property ($r$). This formal definition of affordance, effectivity, and juxtaposition function can be mapped to the precondition set of state transition function and provides a foundation that the concept of an affordance can be combined with software engineering and systems theory. Kim et al. have suggested an affordance-based descriptive formalism for complex human-involved systems using finite state automata [6]. In their work, an environmental system is defined as a set of nodes and arcs that describe discrete states of the system and the transitions between states, respectively.

## 2.2 BDI Theory and BDI Agents

Rao and Georgeff argued the necessity of three attitudes of Belief, Desire and Intention (BDI) [2]. The core concepts of the BDI paradigm allow use of a programming language to describe human reasoning and actions in everyday life. Because of this straightforward representation, the BDI paradigm can map extracted human knowledge into its framework relatively easily. Raubal suggests a perceptual way-finding model that integrates simulated environmental states and agent beliefs within a "Sense-Plan-Act" framework [7]. Shendarkar et al. propose the use of an agent-based simulation modeling paradigm to construct a crowd simulation [8]. However, they do not use the concept of direct perception, which produces immediate human actions with reference to dynamic environments.

## 2.3 Human Behavior Modeling and Simulation

Traditionally human agents in a system had been modeled as a part of physical resources and assumed to be passive elements taking actions and making decisions based upon pre-programed/rule-based logics in modeling and simulation problems. However, complex cognitive processes corresponding to human decision behaviors cannot be easily inferred using a logical rule-based model, a statistical model, or an analytical predictive model. In agent-based modeling, a flexible set of attributes is assigned to each person, so that an intelligent agent mimics the abstract characteristics of a human. Evacuation models such as Egress, Building Exodus, Simulex, Exit, and Wayout can be used to simulate the evacuation efficiency of buildings [9]. Building Exodus and Simulex, widely used as commercial software for evacuation simulations, assume the presence of a rational agent able to assess the optimal escape route and avoid static physical obstructions [10-11]. However, none of them is grounded on both the ecological concept of affordance and a formal system that enables individual decision making based on human perceptions of dynamic environmental elements and rational reasoning for the simulation.

# 3 Agent-Based Simulation of Human-Environment Complex System

In this section, we briefly explain overall framework of our approach to agent-based simulation of human behaviors. In software engineering, an agent is defined as a computer system situated in an environment and capable of autonomous action to meet system objectives [12]. An agent in a simulation model implies a nature for each entity and expresses the complex interactions with other agents in the environment so that the simple agent rule can generate complex system behaviors. For an agent-based simulation of human behaviors, there should be two kinds of agent model: human agent model and environmental agent model. While a human agent model is represented by goals, perception abilities, a decision making algorithm, and action capabilities, an environmental agent model maps the dynamics of environmental elements onto the system model. Several attributes and characteristics of each agent are defined to reflect the diversity of the humans and environmental elements in the system.

## 3.1 System Architecture for Agent-Based Simulation of Human-Environment Complex System

By accommodating and reflecting the above characteristics of agent-based simulation of human behaviors, system architecture of the agent-based human behavior simulator is developed as depicted in Figure 1. The simulation model is composed of three major parts: 1) Human agent, 2) Environmental agent, and 3) FSA-based state transition map. Human agent represents each human in the system. It perceives environs data which is classified dynamic environs data from environmental agent and static environs data from other static elements in the environment such as building structure and sign information. Human agent interacts with other human agents in the system and receives social interaction data as a result of the interaction. Both with the perceived environmental and social information, human agent makes action decisions by a series of cognitive and rational reasoning processes using a series of algorithms. Environmental agent maps the dynamics of environmental elements in the system such as fire, smoke, and flood onto the simulation model. It acts according to its peculiar physical law of state transition dynamics. It should be noted that only fire is considered as environmental agent in this paper. FSA-based state transition map is a formal automata model of HECS describing the whole state map including a goal state, which can be transited by human actions and environmental dynamics in the system. The FSA model provides dynamic (temporal and spatial) situations and the preconditions of possible transitions for agents in the system. While the FSA-based state transition map itself is a descriptive model for representing a system, the agent models generate each event to drive the FSA model according to the dynamically changing situation.

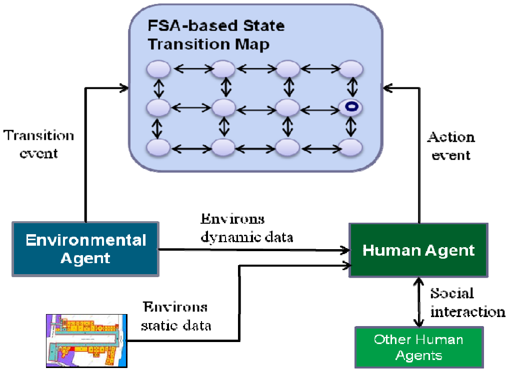


**Fig. 1.** System architecture of the proposed agent-based simulator

## 4 Perception and BDI Reasoning-Based Human Agent Model

In this section, we explore the logical cognition and reasoning processes of human action from the point of environmental perception to decision making and execution in order to design a human agent model for the simulation as illustrated in figure 2. The human agent model is designed to generate an action decision through three phases: perception, reasoning and cognition, action decision making. Each of the phases is illustrated below.

### 4.1 Perception Phase

When human is placed in a situation forcing to make urgent action decisions like emergent evacuation, he/she will try to grasp the situation by sensing current information on outside environment. If there are other humans who are close enough to interact with in the system, the human may consider the social interaction data in making action decisions. Furthermore, human should check his/her internal physical and psychological states such as emotion and cultural tendency on the current system before taking an action. The external perceptual data obtained from outside affect the outcome of internal perception.

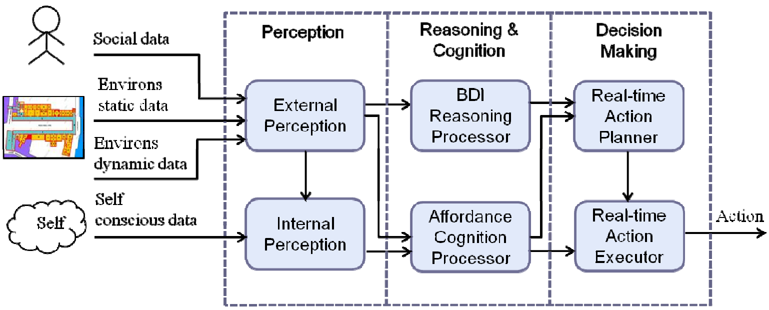


**Fig. 2.** Functional structure of perception and BDI reasoning-based human agent model

### 4.2 Reasoning and Cognition Phase

As soon as receiving the external and internal perceptual information, human starts to process them through complex mental processes of reasoning and cognition to make a series of action decisions which is believed to be able to lead to his/her goal achievement. In this paper, while perception is defined as a mental process of receiving external and internal information, reasoning and cognition is defined as some sorts of mental processes of computation (including screening) and fabrication of the information. There are two different modules in this phase: BDI reasoning processor and Affordance cognition processor. The outputs of these reasoning and cognition processors are used for next decision making phase.

**BDI Reasoning Processor**

The BDI reasoning processor generates a set of reasoning information including beliefs, desires, and intention by receiving external perceptual information. Its functional structure is illustrated in figure 3. Beliefs are not just perceptual information simply given from environments, but information the agent has about the environmental world through some computation and reasoning processes as a result of receiving perceptual data. They are synthesized information showing action alternatives and their results that a human agent could currently choose. Therefore, they represent the structure of possible action alternatives within his/her PB or partial map of the environmental world (Belief-accessible possible worlds). They are stored at long-term memory. Beliefs generator in figure 3 transforms the environs and social data into beliefs. Beliefs are lately used not only for desire generation and deliberation, but for real-time action planning. Desires are state of affairs that the agent would wish to bring about. They contain the information about the objectives to be accomplished, the priorities and payoffs associated with the various objectives. Based on the beliefs and initial intentions, the human agent decides desires via Desire generator. For example, if there are several exits or intermediate positions to escape from fires in a building and a human agent select some of them as goals of its evacuation movement, they can be decided as desires in the simulation. Intentions means desires the agent has committed to achieve. The human agent filters the desires and selects some of them to commit via Deliberator. They play a critical role in practical reasoning by reducing options during action decision making processes.

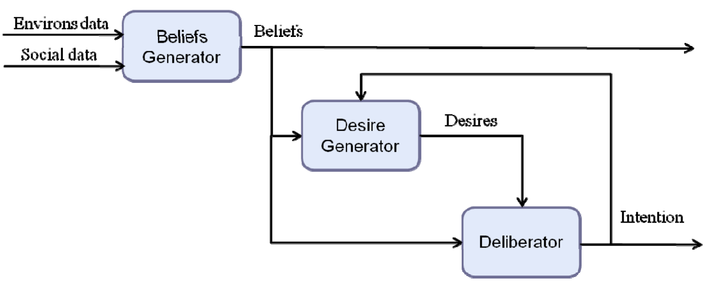


**Fig. 3.** Functional structure of BDI reasoning processor

**Affordance Cognition Processor**

Based on not only the perceived external information taken from surrounding environs, but self conscious data obtained from internal perception of human, Affordance cognition processor judges whether there exists any affordance-effectivity sets which satisfying the action possibilities to achieve the selected intentions. While beliefs are stored at long-term memory and obtained through computation or reasoning processes, affordance (a perceptual property of the environment that provides an action opportunity offered to human) is a quick response as a result of receiving perceptual information without any reasoning processes and it is stored at short-term memory. Affordance and effectivity (an individual's ability to take a specific action) can be mapped to the precondition of specific action which is triggered by a juxtaposition function [7]. Affordance is lately used not only for real-time planning, but for action decision executing.

## 4.3 Decision Making Phase

**Real-Time Action Planner**

The real-time action planner generates a feasible sequence of actions reaching from the current toward the goal state for a human agent. In order to do that, the planner refers to not only beliefs and intentions generated by BDI reasoning processor, but also sets of affordances and effectivities produced by the affordance cognition processor. Intention is used as goal state. Beliefs provide the planner a set of important information (for example, the layout of an environmental space) to determine an optimal route from the current to goal state among possible alternative routes. The dynamic data of affordance and effectivities is used to screen the possible alternative routes out by eliminating the alternative routes which do not satisfy the action condition of affordance-effectivities. If an unexpected or undesired situation occurs in the system while it makes transitions from one state to another on the state map of the FSA-based state transition map. it causes a transition that leads to deviation from the active plan. If it happens, the planner immediately recalculates the plan in order to cope with the dynamic change of the environment.

**Action Decision Executor**

Action decision executor, an event generator dedicated for human agent, generates each action event according to pre-defined human action plans by receiving perceived affordances and effectivities from human agents. Since the affordance-based FSA model is just a descriptive model for representing a system, there should be an event generator to drive it according to the dynamically changing situation. Action events are generated based on the following four steps: 1) An external state transition triggers the action decision generator to reschedule future events for the simulation. 2) The Action decision executor takes a plan to consider human's willingness and preference, and evaluate the chance of the next action that is planned. 3) As soon as the condition of affordance and effectivity for actualizing the next action on the plan is met, the action decision executor generates event to make a transition to the next state. 4) Finally, the events are generated based on the plan, which will make a transition to the next state as a result.

# 5 Illustration: Warehouse Fire Evacuation Problem

## 5.1 Scenario

To verify the applicability of the perception and BDI reasoning-based agent model for human behavior simulation, the Warehouse Fire Evacuation (WFE) problem [5] is applied. In this considered WFE Problem, a fire breaks out in a warehouse in which two human operators are working. The warehouse area is equally divided in a rectangular grid of 0.8   0.8 m2 which is used for either storage or passageway. In this storage area, goods are stacked up so high that operators cannot observe what happens over the storing lots. Fires are firstly broken out at three different locations in the warehouse and are fast propagated to neighboring lots in a certain amount of speed. As soon as an operator perceives the fire, he/she shall have to find a possible and safe route to an exit along passageway by considering perceived surrounding situations in order to escape from the fires. When he/she tries to move to a next passageway lot, if the lot is already occupied with a fire, he/she cannot access to the lot and have to find another passageway that offers an affordance to move.

## 5.2 Model Description

The human behaviors in this evacuation problem can be interpreted as a typical example of the perception and BDI reasoning-based human agent model of human behavior simulation. Dynamics of the warehouse can be implemented by the floor layout of the warehouse and a dynamic interaction between human agents and propagating fire agents in the warehouse. In most cases of evacuation problems, human obtains environs data and social interaction data from perception. Furthermore, human behaviors are greatly affected by physical states due to injury or psychological states such as normal or panic. In case of the WFE example, the external perceptual information includes positions of fire and goods and their distance from current position. The social interaction data include the positions of other workers in the floor. There are two kinds of internal human data: physical and psychological. Human action abilities can be leveled according to physical states such as severely wounded, wounded, and normal. These kinds of perceptual information are used to generate beliefs, desires, and intentions. In case of WFE problem, beliefs contain location and distance of each cell from current position of human agent. Beliefs are made by using not only his or her prior knowledge about the floor layout in the warehouse, but perceived information on surrounding situations within the PB. Since the beliefs are determined through dynamic perception of the floor according to movement of each human agent, they have relativistic values. Beliefs are used as a basis for generating plans to the way to the exits. The goal of each evacuee is to get out of the warehouse via one of the exits while avoiding a spreading fire. Based on the beliefs on exits or intermediate position to the exits, BDI reasoning processor determines desires and then filters them to generate intentions. Cells occupied by goods or fires are assigned with very high values to ensure that there is no affordance of move-ability to an evacuee and he or she will never attempt to occupy them.

To perform this behavior, each human agent perceives whether its adjacent lots within PB provide it with the affordance, “is-move-able” for the human agent, or not. In this warehouse evacuation problem, the affordance is “move-ability for an evacuee to an adjacent lot,” and the accompanying effectivity for a human agent is “capability to move to an adjacent lot.” Based on the beliefs, intentions, and affordance-effectivity pairs, each evacuee will make a plan for his or her movements along passageways to the exit. The affordance-effectivity pairs are also used as trigger for generating action event by human decision executor.

# 6 Conclusion

In this research, a modeling framework for designing human agents that is able to mimic perception-based rational human behaviors in human-environmental complex systems is proposed by combining the ecological concepts of affordance- and the Belief-Desire-Intention (BDI) theory. The proposed modeling framework deal with not only perceptual aspects of human behaviors, but can accommodate more complex problem domains involving rational reasoning and human interactions and communications. The perceptual information is firstly classified in order to clarify its influence on human action decisions. The functionalities and processes of the proposed human agent are discussed in detail. An exemplary scenario is developed and illustrative models of fire evacuation simulation are developed to show how the proposed framework can be applied. However, the aspects of emotion and culture are not deeply explored how they will affect reasoning and decision making process of human behaviors. While social factors such as interactions and communications within and between groups of people are groundings of the simulation models, they will be considered (e.g. social psychology, emotions, cultures, and knowledge levels) in the future in order to enhance swarm intelligence and behaviors into account. The proposed framework is expected to realize their potential and enhance the simulation fidelity in analyzing and predicting human behaviors in HECS. Also, implementation and validation of the simulation will should be followed via human experiments in a suitable task environment (e.g. virtual reality).

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