



Towards a Framework to Model Intelligent Avatars in Immersive Virtual Environments for Studying Human Behavior in Building Fire Emergencies

Jing Lin and Nan Li^(✉)

Department of Construction Management,
Tsinghua University, Beijing 100084, China
lin-jl17@mails.tsinghua.edu.cn, nanli@tsinghua.edu.cn

Abstract. Driven by the fast development of virtual reality (VR) technologies, immersive virtual environments (IVEs) have been frequently used to conduct human behavior experiments for studying human behavior in building fire emergencies. Avatars in these IVEs are usually used to provide social influence and improve the sense of presence experienced by participants. However, limited intelligence of avatars in prior studies significantly lowered the level of sense of presence and reality experienced by participants. Improved intelligent avatars (IAs) are needed for developing high-quality building fire IVEs. A framework for modeling IAs to support the investigation of human behavior in building fire emergencies was proposed in this study. A number of levels of IA intelligence were defined based on the characteristics of avatars in VR for studying human behavior in building fire emergencies. This study also proposed a roadmap to achieve each of these levels of intelligence. A case study was presented to demonstrate how the framework could be used to guide the design of IAs for research purpose. It was concluded that applications of IAs in VR experiments could benefit the investigation of human behaviors, crowd simulation in building fires, and even fire safety design of buildings.

Keywords: Virtual reality · Intelligence · Avatar · Human behavior · Building fire · Evacuation

1 Introduction

Human behavior in building fires, such as occupants' evacuation behavior and fire-fighters' relief behavior, has been studied for decades. Recently, immersive virtual environments (IVEs) have been used to conduct human behavior experiments in many studies [16, 23, 25], driven by the fast development of virtual reality (VR) technologies. These IVE-enabled experiments allow for the collection of rich behavioral data in controlled laboratory environments to support the investigation of human behavior in building fire emergencies [19]. Avatars in these IVEs, such as those used in [14, 19], are usually modeled to have limited, pre-defined behaviors that are arbitrarily set by researchers, without any autonomous responses to or interactions with experiment

participants or other elements in the IVEs. Limited intelligence of avatars significantly lowers the level of sense of presence and reality experienced by participants. As a result, the behavioral data collected in such virtual environments may be less real and valid, compromising their ability to support the investigation of human behavior. Thus, improved intelligent avatars (IAs) are needed for developing high-quality building fire IVEs. This study developed a framework to model IAs, by defining a number of levels of intelligence of IAs, and proposing a roadmap to achieve each of these levels of intelligence.

2 Definition of Intelligent Avatar

Drawing on the concept of artificial intelligence (AI) [21], IAs in IVE-based experiments should think and act like humans or rationally. To simulate the realistic social environment, IAs in IVE-based experiments for studying human behavior in building fire emergencies should act like humans. There are four types of abilities that AIs need to possess in order to perform like humans [21]: (1) communicating ability in human language; (2) memory ability to store information, such as behavioral rules; (3) response ability by using the memory and assessing the results of the responses; and (4) learning ability to adapt to new scenarios and form new memory. Accordingly, behavior target setting (BT), response to the environment (RE), response to avatars' behavior (RAB), response to participants' behavior (RPB), and learning and adaption ability (LAA) are identified as fundamental characteristics of IAs in building fire IVEs in this study, as shown in Table 1. Each of these five characteristics can be further divided into several functional levels, as described in Table 1. A higher level of a given characteristic can be reached by achieving associated new functions, in addition to those already achieved at the lower level, that are described in the rightmost column of the table. It needs to be noted that avatars with none of these characteristics cannot be called IA and are hence not considered in this study.

Table 1. Functional levels of characteristics of IA in building fire IVEs

Characteristics	Descriptions	Levels (Low to high) and associated new functions
Behavioral target (BT)	It could set and modify behavioral targets based on his/her role and perception of the environment	<ul style="list-style-type: none"> • BT1: Have a behavior target that could be fulfilled by its behavior; • BT2: Can choose behavior targets based on its role; • BT3: Can define behavior targets in different priorities; • BT4: Can modify behavior targets based on its perception of the environment

(continued)

Table 1. (continued)

Characteristics	Descriptions	Levels (Low to high) and associated new functions
Response to environment (RE)	It could respond to perceived environment by text, voice or other reactions	<ul style="list-style-type: none"> • RE1: Can respond one-time to a pre-defined situation, such as an occurrence of a fire; • RE2: Can respond consecutively to multiple pre-defined situations; • RE3: Can interact with perceived environment by text, voice or other reactions
Response to avatars' behavior (RAB)	It could perceive and respond to other avatars' behavior by text, voice or other reactions	<ul style="list-style-type: none"> • RAB1: Can respond one-time to a certain avatar's pre-defined behavior, such as calling for help; • RAB2: Can respond to a specific pre-defined behavior of any avatar; • RAB3: Can respond consecutively to multiple pre-defined behaviors of any avatar; • RAB4: Can interact with avatars by text, voice or other reactions
Response to participants' behavior (RPB)	It could respond to perceived participants' behavior by text, voice or other reactions	<ul style="list-style-type: none"> • RPB1: Can respond one-time to a specific pre-defined behavior of a single participant, such as his/her proximity; • RPB2: Can respond to a specific pre-defined behavior of multiple participants; • RPB3: Can respond consecutively to multiple pre-defined behaviors of a single participant; • RPB4: Can interact with participants by text, voice or other reactions
Learning and adaption ability (LAA)	It could adapt to any unexpected situations by learning from experiences	<ul style="list-style-type: none"> • LAA1: Can adapt to unexpected situations by trying random choices of pre-defined responses; • LAA2: Can adapt to unexpected situations by learning from its experiences; • LAA3: Can adapt to unexpected situations by observing and learning from other avatars' experiences; • LAA4: Can adapt to unexpected situations by observing and learning from participants' experiences

3 Avatars in Building Fire IVEs

Avatars in building fire IVEs that have been modeled and used in previous studies are reviewed and assessed based on the above characteristics, to summarize the state of the art of and identify the gaps in modeling IAs. A total of twelve relevant studies were found through keyword searching in *Web of Knowledge*, *Scopus*, and *Google Scholar*. These studies were published between 2008 and 2018 in nine international journals and three international conferences. A detailed review of these publications found that avatars reported in eight of them did not qualify as IAs based on the aforementioned criterion. For avatars in the remaining four studies, only two characteristics were partially achieved. Specifically, RE2 was achieved, as some avatars could avoid obstacles during evacuation wayfinding [20]. Some avatars achieved RPB1 since they could respond to the proximity of a participant with onscreen text or voice [2, 7, 9]. Avatars in prior studies did not exhibit other characteristics of IAs.

In general, the avatars in prior studies had relatively low levels of intelligence. However, it is important to note that the research objectives vary in different studies, such as studying the impact of signage [24] or social influence [12] on human behavior in building fire emergencies. Considering that modeling ideal IAs may come at considerable costs, avatars do not always have to be the most intelligent. Rather, the level of intelligence of avatars should be tailored to the needs of specific studies. Thus, this study proposed a framework that provided definitions of different levels of intelligence of avatars, which could be used to fulfill different needs in studying human behavior in building fire emergencies, as well as a roadmap that ultimately led to the development of the most intelligent IAs.

4 Framework for Developing IAs in Building Fire IVEs

Achieving higher levels of intelligence relies heavily on the advancement of various VR and AI technologies, such as graphical processing hardware capabilities, rendering and visualization algorithms, and cognitive and behavioral models. To pave the way for more intelligent avatars, this study classifies the intelligence of avatars in building fire IVEs at five different levels, each of which is defined based on the aforementioned five characteristics of IAs. These definitions are summarized in Table 2. IAs at every intelligence level either inherit the same characteristics of the lower level AIs, or are more advanced with regard to certain characteristics as suggested in Table 2.

Based on the proposed framework, a simple character (Level I) can respond to a specific change in the environment or from one specific avatar or participant for only once [2, 7, 9]. For instance, when a participant was near a simple character acting like a victim, another simple character acting as medical service worker would speak to the participant “*I’m taking care of him; you go to the exit*” [9]. An intelligent character (Level II) can continuously respond to a specific pre-defined behavior of multiple avatars and participants [20]. Both simple and intelligent characters would not be able to respond to scenarios that are not pre-defined. Agents, on the other hand, can respond to unexpected situations. There are simple agents, intelligent agents, and human agents, which are differentiated mainly by their different levels of learning ability. A simple

Table 2. Definitions of different levels of avatar intelligence based on levels of IAs' characteristics

Levels of avatar intelligence	Associated levels of IAs characteristics				
	BT	RE	RAB	RPB	LAA
I - Simple character	BT 1	RE 1	RAB 1	RPB 1	
II - Intelligent character			RAB 2	RPB 2	
III - Simple agent	BT 2	RE 2	RAB 3	RPB 3	LAA 1
IV - Intelligent agent	BT 3	RE 3	RAB 4	RPB 4	LAA 2&3
V - Human agent	BT 4				LAA 4

agent (Level III) can choose behavioral targets based on its role, and respond to environments, avatars, and participants continuously as pre-defined. Since human behavior in building fire emergencies has a characteristic of randomness [17], a simple agent responds to unexpected situations by randomly selecting a behavior that it can perform. An intelligent agent (Level IV) can further prioritize behavioral targets, interact with environments, avatars and participants in different ways, and learn from how it responded to the scenarios in the past and how other IAs respond to diverse scenarios. Lastly, a human agent (Level V) can modify behavioral targets and adjust behaviors to adapt to surrounding environment by pre-defined rules, and learning from its own, other IAs' or participants' experiences.

In previous studies, simple characters, intelligent characters, and simple agents have been used [2, 7, 9, 20]. Ideally, IAs should be developed in a way that they both satisfy the requirements of research and minimize time and cost for modeling. Therefore, based on a holistic review of prior research, different levels of IAs are suggested for different aims for research, as outlined in Fig. 1, which is also a roadmap that highlights the technical bottlenecks for achieving every level of IAs and demonstrates how the most intelligent IAs can be ultimately achieved.

Some of the bottlenecks highlighted in Fig. 1 need technological breakthroughs. For instance, although voice recognition has been widely used in speeches [10] and smart home systems [1], how to recognize the voice of participants and present reasonable voice feedback to participants would require advanced voice recognition technologies in building fire emergencies. What would be more challenging is to train IAs to learn, not only from its own behavior, but also from other avatars and participants. This learning process includes perception and recognition of others' expression, voice, behavior and surrounding environment, and evaluation of consequences of others' responses.

As the most intelligent IA, a human agent should perceive the changeable environment, think like humans, and behave like humans to fulfill their behavioral targets in building fire emergencies. Based on the existing literature on human behavioral response in building fires [4, 6, 11, 13, 22], the cognitive process of behavioral decision-making in response to fire emergencies is identified, based on which a conceptual model of a human agent is developed in this study (Fig. 2).

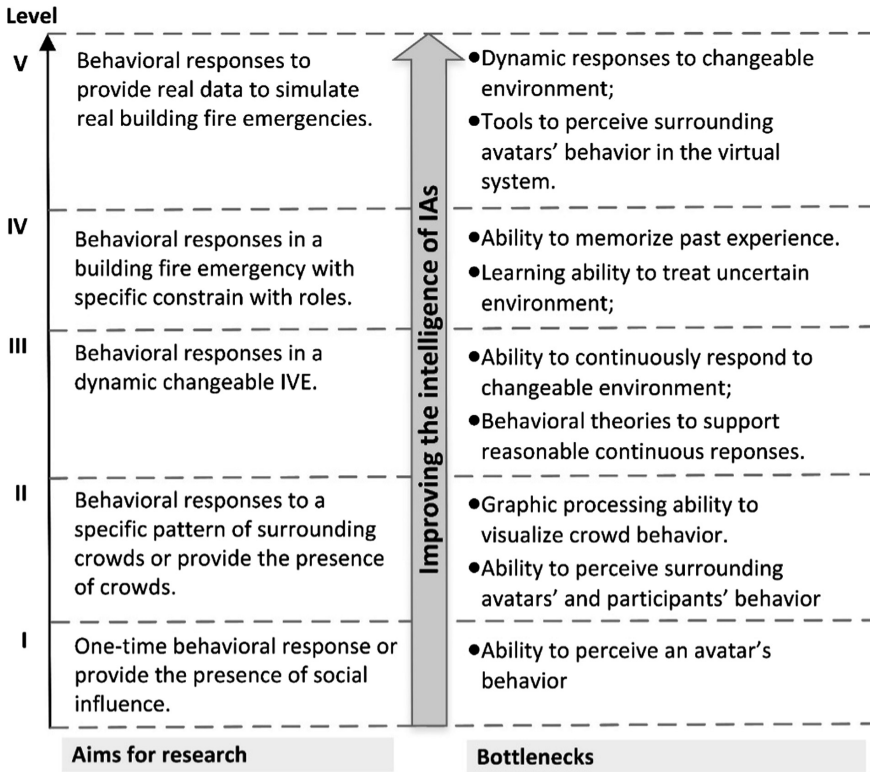


Fig. 1. Roadmap to develop different levels of IAs

A human agent should have one or more achievable behavioral targets based on its role in a building fire [18]. For instance, a ‘patient’ agent should investigate whether a fire exists and set a target of successful evacuation from the hospital, whereas a ‘nurse’ agent should have an additional target of helping patients to evacuate. Different behavioral targets should be assigned different priorities [3, 5, 15]. Human agents would keep perceiving the surrounding environments [8], including physical environment, other human agents and experiment participants, and take actions accordingly. In the proposed model, there are two different decision-making processes for human agents’ behaviors. The first one is to follow pre-defined rules for pre-defined scenarios, such as the avatars modeled in [2, 7, 9, 20]. The pre-defined scenarios and rules are usually based on existing knowledge of human behavior in building fire emergencies. If the perceived environment is different than all pre-defined scenarios, human agents would set their primary target and take actions based on learning outcomes about others’ behavior and their own past experiences in similar scenarios [15]. During their evacuation process, human agents would continuously perceive environments, take actions, fulfill all targets based on priorities, until all behavioral targets are fulfilled.

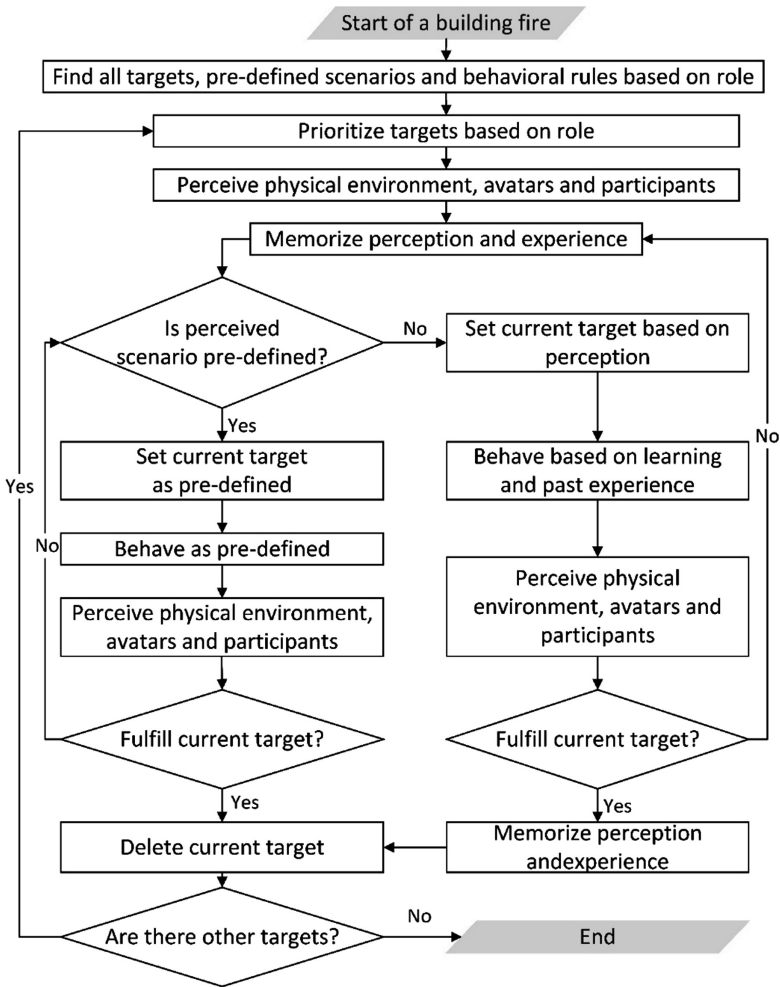


Fig. 2. A conceptual behavioral model of a human agent

5 Case Study

This paper presents a case study which used IAs in VR-based experiments for studying the effects of crowd dynamics, design visibility and residential location on people's evacuation wayfinding in building fires.

Based on the roadmap illustrated in Fig. 1, studies aiming at understanding people's behavioral responses to the wayfinding pattern of surrounding crowds should involve avatars of intelligent character (level II). Thus, the case study should model the avatars in its IVEs who could respond to a specific pre-defined behavior of any other avatars and the experiment participants.

The IVE used in the case study was based on a metro station in Beijing, China. The script of the fire scenario in the IVE was designed based on a fire accident in a metro station in Hong Kong: fire occurred in a metro train in a metro section; passengers (avatars) were initially onboard the train or waiting at the platform (Fig. 3); the burning metro train approached platform in the station (Fig. 4); and passengers (avatars) had to evacuate from the station. The participant acted as a passenger initially positioned at the platform.



Fig. 3. Intelligent characters waiting for metro train at platform in the case study



Fig. 4. Burning metro train approaching platform in metro station in the case study

There were 53 IAs in the IVE that varied in age and gender. Each IA had a visual access with a range of 270° based on its head orientation. When the burning metro train emerged within 15 m of the IAs' view, the IA would perceive the signal of a fire

emergency and start to evacuate. Based on literature review, three patterns of crowd dynamics during evacuation wayfinding were modeled in the IVE: even distribution (50% vs. 50%), uneven distribution (80% vs. 20%), and binomial distribution (100% vs. 0%, as shown in Fig. 5) at each intersection. The behavioral target of every avatar was set as running through its pre-defined path that led to one of the exits of the station. To improve the realism of the crowd dynamics, avatars were modeled to be able to respond to collisions with other avatars and participants by scuttling away from collided avatars and participants. Specifically, the tactile sensor of IAs would continuously work to detect the distance from other objects, IAs, and participants. Once the distance was within 0.1 m, IAs would slightly adjust their orientation to avoid collisions.



Fig. 5. Intelligent characters evacuating from metro station in the case study

While the results of the case study are still being analyzed and prepared for a separate publication, there are two lessons learned from the use of avatars in the case study that are noteworthy. Firstly, the maximum number of IAs that could be modeled in the IVE was largely constrained by the capability of mainstream graphics processors (GTX 1080 was used in the study). Overloaded graphics processors could cause discontinuous or delayed display of the IVE shown to participants. This prevented the possibility of modeling a high-density crowd that would block certain points in the evacuation paths in the IVE, as it would happen in reality. Future research should consider the tradeoff between the need for more intelligence and finer-grained rendering in IAs, and the need for simply more IAs. Secondly, avatars' responses to the proximity of both virtual elements and participants were relatively easy to model. However, their abilities to respond to gestures of avatars and participants, and to learn from past experiences were still challenging to achieve. Future research requiring IAs with these characteristics would need novel solutions to address these needs.

6 Conclusion

Avatars could improve IVEs used in the investigation of human behavior in building fire emergencies. However, the intelligence of avatars used in prior studies was not always sufficient to provide a high sense of presence and social influence. This study firstly defined what an IA is and what important characteristics an IA should possess. Secondly, the IAs used in prior research on human behavior in building fire emergencies was reviewed. By identifying the state of the art in IAs development and the existing gaps, a framework for modeling IAs to better support the investigation of human behavior in building fire emergencies was proposed in this study. Different levels of avatar intelligence in building fire IVEs were defined in this framework for satisfying different research needs. Moreover, the framework includes a roadmap to achieve high intelligence in IAs, which also identifies the bottlenecks in achieving each of the five levels of IAs. While the highest level of IAs, human agent, is yet to be achieved at the moment due to technological and methodological constraints, the proposed framework provides a conceptual behavioral model of a human agent. Future research, by benefiting from the advancement of knowledge about mechanisms of human behavior in building fire emergencies as well as the development of VR and AI technologies, could improve the intelligence of avatars based on the roadmap and the conceptual behavioral model.

A case study was presented, which guided by the proposed framework utilized intelligent characters in the investigation of people's wayfinding behavior in building fire emergencies. Lessons learned from the case study were reported. As the authors envisioned and the case study demonstrated, applications of IAs in VR experiments could largely improve VR-based human evacuation behavior studies, and ultimately enable more fine-grained crowd simulation in building fires, and support reliable evaluation of fire safety design of buildings as well as various other applications.

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