Using Social Sciences to Enhance the Realism of Simulation for Complex Urban Environments

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Abstract In this paper we discuss how findings from social sciences research can be injected into a complex urban environment simulator in order to increase the level of realism of the simulated behaviors with respect to the local context. Our team, composed of engineers and social scientists, describe here our approach toward tackling complex simulation problems with embedded human factors. We present some of the results obtained from two different use cases. The rationale and methodology behind those results are further detailed and the limitations and future improvements required are highlighted. This paper shows how simulation should contribute to the improvement of the quality of life of every citizen in a Smart Nation.

1 Introduction

Building a livable and sustainable urban environment is a complex undertaking. Nowadays, architects and engineers turn to simulations to visualize and validate their designs prior to executing their plans. There are many tools for infrastructure and human crowd simulation on the market, some more mature than others, and most of them are engineering focused. However, making assumptions on infrastructure design using simulations based solely on either the engineer's or architect's point of view can lead to a complicated situation at best if not a hazardous one at worst. Traces of such situations can be found in the world around us, e.g. muddy shortcut beside intended sidewalks, bottlenecks at popular passageways, misplaced and/or undersized doors given the evolution of the flows of pedestrians following a

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change of points of interest in the environment. On paper, the design may be sound but the critical human element is missed.

Wetmore in [1] argues that engineering might not have all the tools and techniques to get the job done. He suggests that engineers should borrow tools and techniques from social sciences in order to capture and measure the social implications of their decisions. In other terms, engineers and social scientists should collaborate to design people centric solutions.

Although simulations are enabled through technological means and run on mathematical models, modeling human behavior must inevitably involve the social sciences. In the context of urban simulation, we are particularly interested in human behavior of individuals, groups and crowds. The main disciplines under social sciences that deal with how people behave are Psychology and Sociology. While Psychology studies the intrinsic mechanisms of a human mind, Sociology explores the overall social behaviors of people in their environment. Therefore, our work attempts to connect the outputs of the social sciences as inputs for our engineered behavioral model.

In this paper, we first present in Sect. 2 a brief overview of the related work in the domain of human and crowd simulation. Section 3 then describes our methodology to adapt social sciences approaches to our own crowd simulator SE-Star and vice versa. In Sect. 4 we present some results obtained by our team composed of engineers and social scientists on two use cases. Finally, Sect. 5 discusses these results and the consequences they have for our future works in the domain of simulation, before concluding in Sect. 6.

2 Related Work

To create a high fidelity urban simulation, there are two critical factors to take into account, the human beings (also referred to as “the agents” in simulation) and the infrastructure. To take these two factors into account, it is necessary to model the social behaviors they exhibit.

For the first factor, modeling social behaviors down to the psychological aspect is best achieved through Agent Base Simulation (ABS). As described by Gilbert [2], “agent-based simulation offers the possibility of modeling individual heterogeneity, representing explicitly agents’ decision rules, and situating agents in a geographical or another type of space”. Davidsson [3] positions himself at the intersection of Computer Simulation, Agent-Based Computing and Social Sciences to define the Agent Based Social Simulation (ABSS) approach and how it can help cross-fertilization between the three areas. This approach is further described by Li et al. [4], where the authors identify the underlying social theories for ABSS from both individual agent and multi-agent system perspective.

Regarding the infrastructure, Farenc et al. [5] consider this factor with the notion of "Informed Environment". "Informed Environment" is helpful to create urban infrastructures that provide the virtual humans with knowledge of the environment, improving the human-infrastructure interactions using simple social behavior models. Digging deeper on the social behavior aspect, Musse and Thalmann [6] demonstrated the adoption of sociology to represent several behaviors and represent the visual output for visualization purposes. This approach focuses on the inter-personal interactions in the crowd and how a crowd, composed of individuals moving in various directions with common or different goals, avoids collisions. On individual behavior, Pelechano et al. [7] presented their approach of integrating a psychological model into a crowd simulation system while Chao and Li [8] worked on integrating sociology into the simulator.

In [9], Navarro et al. describe SE-Star, a crowd simulator that has been developed for the past ten years by Thales. "SE-Star is a microscopic multi-agent simulation, which is able to reproduce a large panel of human behaviors via the use of several completely independent processes". SE-Star, a variant of ABSS, is composed of three components, (i) the entities (or agents), (ii) the smart objects and (iii) the environment infrastructure. Each entity is unique and autonomous. A smart object represents an actual system (e.g. ticketing machine, ATM, ticket, signboard, etc.) and offers products and services to the entities in the simulated environment for them to realize actions and satisfy needs. The environment infrastructure is a 3D model of the environment to simulate.

In SE-Star, each entity's brain uses a motivational engine based on the Free-Flow Hierarchy approach that computes the physiological and psychological state of each agent, controlling its motivations and actions based on its traits, perceptions and internal variable as described on Fig. 1.

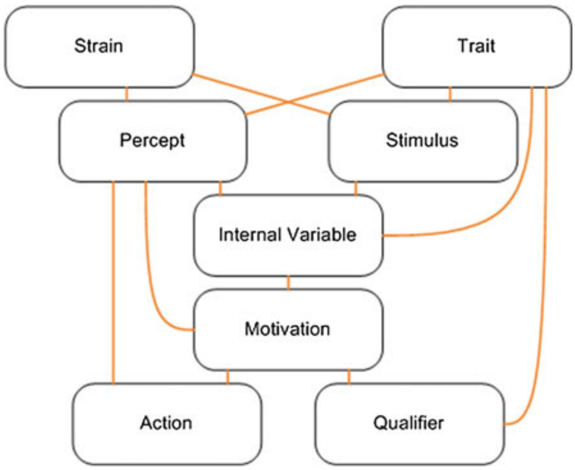

Fig. 1 SE-Star motivational tree

3 Approach

For this study, we chose SE-Star to conduct our simulations. The concepts of entities and smart objects that it encompasses, as well as the motivational engine that it implements for the brain of each agent make this simulator an ideal candidate for our study involving the inputs of social scientists.

3.1 Overview

To construct a realistic model for complex urban simulation, we divided the work into three phases, (i) input (Sect. 3.2), (ii) process (Sect. 3.3) and (iii) output (Sect. 3.4), as described in Fig. 2.

Following Wetmore's recommendations in [1], the team working on the subject includes members from both Engineering and Social Sciences backgrounds.

The first half of the team comprises of four engineers. The senior engineer within the four leads this half of the team to manage the 3D models, define the various simulation systems and help the social scientists with the implementation of the behavior models.

Four social scientists comprise the second half of the team. The psychology specialists model individual behaviors, and the sociology specialists look at social and group behaviors. In addition, a political scientist helps look at the policy implications on individuals, groups and infrastructure. Together, the social

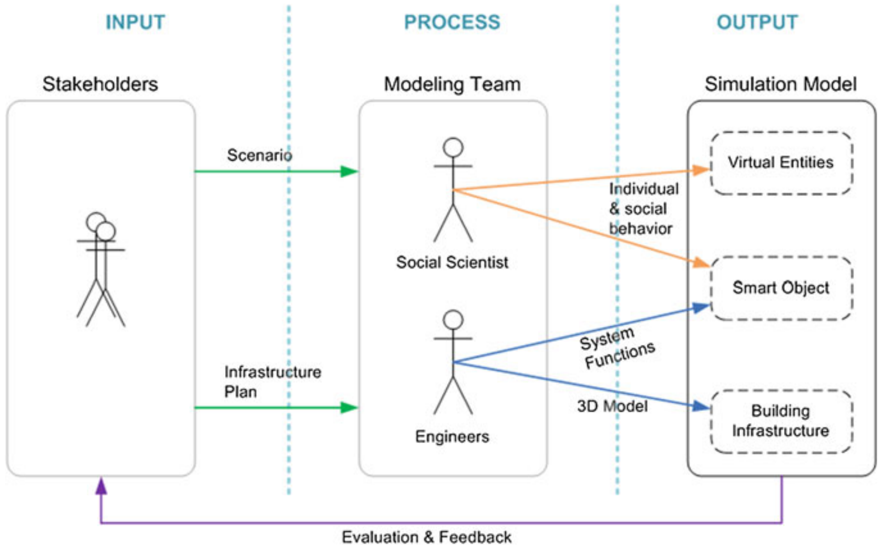

Fig. 2 Workflow for our approach

scientists are responsible for creating the new archetypes of people with distinct behaviors and unique characteristics for each scenario.

3.2 Input Phase

The initial phase of our approach is to identify the various stakeholders related to the environment to be simulated. They provide the context of the simulation as well as the various data and knowledge that they have gathered through experience and observation. Data can range from blueprints of the environment to statistics pertaining to the population to be modeled, while knowledge is more empirical in nature. The stakeholders identified provide feedback and validation on the simulation once the model is developed.

However, interaction with the stakeholders can also bias the behavioral models toward particular use cases, preventing a good generalization of these behavioral models. In this case a Systematic Framework, with reusable behavioral models based on established studies in Social Sciences, should be created. Such a framework not only reduces the effort when defining behaviors for new use cases by reusing models from contextually similar use cases, but also improves the quality of the simulation, unleashing the human-like innovative spirit in our simulation model.

In this Input phase, the engineering part of the team shall focus on the environmental infrastructure and system part of the problem while the social scientists shall gather from the stakeholders as much information as possible regarding the social behaviors and processes that they observe in their environment.

3.3 Process Phase

The Process phase is where the stakeholder's inputs are analyzed and transformed into a highly realistic simulation model. The environment to be simulated is virtualized into a 3D model, typically based on building or city plans provided by the stakeholders. The equipment and systems, known as smart objects, are analyzed and modeled. Smart objects' characteristics, the possible actions and reactions of the human beings populating the environment and observed by the stakeholders, are crucial details needed in the modeling process.

Furthermore, to complete the panel of data and knowledge provided by the stakeholders, psychological and sociological studies can be conducted on-site by the social scientists of the team. The result of this phase is one or more models enabling a realistic simulation of the environment.

The working experience between engineers and social scientists has to be managed delicately due to the inherent differences in terms of perspectives and skill sets between these two backgrounds. For instance, an engineer sees an Automated Teller Machine (ATM) as a machine dispensing money while a sociologist might see the correlations with age, socio-economic class, etc. Social scientists might find it hard to understand the computer language used to code the simulation models, whereas engineers from the same team could assist to overcome this weakness. Hence, the team's dynamics plays a significant role in getting the social scientists and engineers to understand and respect each other's points of view in generating a representative simulation model.

3.4 Output Phase

In the output phase, the team implements the model(s) derived during the previous phase into the three components of SE-Star. These are identified as the entities, the smart objects and the environment infrastructure. The links between the components are also established and simulations can be run to assess the validity of the models derived. Validation of the output is conducted together with the stakeholders. It includes the testing of various scenarios, the generation of 'What if…?' scenarios, and the tweaking of different variables the client is concerned about. The observations are then compiled into a report delivered to the client.

4 Results

In this Section, we present two case studies that have been successfully implemented using our approach and SE-Star. The first case study (Sect. 4.1) describes the different behaviors existing for the evacuation of a building when a fire drill is occurring versus during an actual fire. The second case study (Sect. 4.2) aims at describing the arrival of passengers in an airport and how they decide on their mean of transportation to leave the airport after collecting their luggage.

The work performed on these case studies has enabled us to test the limits and capabilities of SE-Star as well as to learn from these limitations and to suggest future improvements. More importantly, we were able to analyze the fit between social sciences data and a computer engineered framework, and therefore to confirm the possibility for these two domains to complement each other.

Hence, the objective of this paper is to create awareness on the benefit of coupling social sciences with complex systems. This statement may seem obvious but is in fact a challenging feat to implement. Few simulators available on the market incorporate social sciences insights and real data, and thus a gap remains between reality and simulation. It is hoped that the case studies mentioned in this paper, though descriptive, present some ways to overcome these gaps.

4.1 Case Study 1: Fire Evacuation

In this case study, we simulate a very familiar environment, namely our office building, and trigger a fire evacuation of this building in two different circumstances, (i) a fire drill and (ii) a real fire. The intention of this simulation is to contrast the situations and behaviors during the evacuation when it is a drill versus when it is a real emergency.

4.1.1 Input

Before going for an emergency situation (whether drill or real), the normal situation has to be modeled and simulated. For that, our social scientists have observed the behaviors of our fellow employees, their integration within the environment and their use of the various facilities on a typical working day. Our engineers came up with a 3D model of the building and the various facilities available. For the fire drill situation, our team relied on video surveillance footages as well as feedbacks from the team in charge of the security of the premises. On the other hand, for the real emergency evacuation it is quite impossible to observe how people act as there were no prior incidents. Therefore, two evacuation theories were used for that model, (i) the Emergent Norm Theory described by Kuligowski [11] and (ii) the Familiarity Model of Mawson [12].

4.1.2 Process

For the drill evacuation, based on what is observed, a simple broadcast of the PA system increases the virtual entities' motivation to evacuate. All staffs leave through the main entrance and gather at the assembly point outside of the premise.

Regarding the real emergency situation, we rely on (i) the Emergent Norm Theory [11] and (ii) the Familiarity Model [12]. To emulate these two theories, we modify smart objects to induce certain behaviors.

Emergent Norm Theory

This theory is based on norms. Norms generally are the rules and regulations that groups live by. Individuals go through day-to-day activities so often that they have become routines. However, disasters disrupt the normal routine of individuals. Faced with the unknown, individuals are required to make a concerted effort to create new meaning out of new and unfamiliar situations. This is done through the perception of environmental and social cues. The type of action chosen depends on the perceived characteristics of the threat. Hence, inhabitants will usually take some time to evacuate even after the fire alarm, or any other warning system, has activated.

In the simulation, the first stage is therefore to have the entities not evacuate immediately when the alarm sounds, but rather after the danger is confirmed by an individual. The fire will activate an invisible smart object near a workspace. The entity at this workspace will perceive the broadcast of the invisible smart object and he will have the motivation to search for the source of danger. He will venture out the door and perceive the fire. This will cause him to display the message “Fire!” The fire broadcast decreases the ‘search motivation’ and increases the entity ‘inform motivation’ which drives the entity to interact with 4 invisible smart objects in the office. The ‘inform motivation’ causes the ‘inform qualifier’ to activate. Others will perceive this qualifier and have their ‘evacuation motivation’ increased. Since the informing entity is going around the office interacting with invisible smart objects, it is as if he is trying to tell everyone of the danger because at every interaction he will display the “Fire!” message. At the final invisible smart object, he will have his ‘inform need’ reduced and ‘evacuate need’ increased, and thereafter will evacuate with the rest of the entities.

Familiarity Model
Rather than flight or flee, this model suggests that the typical response to danger is affiliation. People tend to turn to and protect loved ones even in the face of threats. Because of this, when people are forced to evacuate, they tend to do so in a group thereby maintaining proximity and close contact with familiar people.

During the simulation, as the entities perceive the ‘inform qualifier’, their ‘evacuation need’ increases. However, this is the first phase of the evacuation, named ‘evacuation1 need’, that will make the entities gather at the corridor. There, two invisible smart objects give off broadcasts. One of these invisible smart objects reduces ‘evacuation1 need’ while the other will increase ‘evacuation2 need’. This takes a few moments so it is as if they are stopping to wait for their peers. Subsequently, ‘evacuation2 need’ makes them gather at the assembly point.

4.1.3 Output

The fire evacuation simulation was benchmarked against video surveillance footages and verification from staff members. In a simulation without social behavior, the entities will start evacuating as soon as the fire alarm is triggered and they will strictly follow the predefined process flow. The entities enriched with social sciences cues exhibit behaviors as suggested in [11, 12].

The results demonstrate that social behavior theories can be translated into our simulator to simulate drills of emergency situations and real emergencies. Such models should be of interest to design drills that are more realistic but also to assess the quality of the results of the drill versus how people would have performed should the situation have been a real emergency.

4.2 Case Study 2: Transportation Choice

This case study models a busy airport where arriving passengers are faced with a decision to take connecting transport to the city. We intend to create the generic model passengers archetype and simulation model. This model can then be used to study the impact of environmental changes on passengers' behaviors, e.g. how the closure of certain areas due to renovations is affecting passengers' decision to take a particular mode of transport.

4.2.1 Input

Our engineers started by constructing the 3D model of an airport and modeled the smart objects in this airport arrival hall. With limited stakeholders input, the social sciences team worked on sourcing for data related to people's perceptions of different transport systems in Singapore. The team decided to use publicly accessible data such as [13–16]. These data enable us to understand peoples' considerations when making a decision on their choice of transport and how different groups of people evaluate the different modes of transport differently.

4.2.2 Process

The process phase went through two steps, to (i) determine the various personality traits and social characteristics each entity will exhibit influencing its final decision and (ii) identify the archetypes of entities and how each predetermined traits and characteristics will vary in these archetypes.

Personality Traits and Social Characteristics
Human behaviors are often quite complex in the sense that they have many determinants. Some of these determinants might involve acquired and innate physiological factors (learned or inherited behavioral predispositions), or they could include environmental causes and situational exigencies. Thus, the first step to predict the behavior of a group or individual is to identify and learn its determinants. In the context of travelers deciding on the mode of transport to take from an airport, what influences the decision to take a taxi, the MRT, or a bus is very much related to one's consumption pattern, shaped by one's socio-economic class, thriftiness and association with materialistic values.

The diagram presented on Fig. 3 is a simplified version of SE-Star's motivational tree developed by our team specifically for this use case. It illustrates the decision processes and the inter-connectivity of various factors in the entities' brain, starting from traits and strains at the top, leading to their final action to take a taxi (in this example) at the bottom.

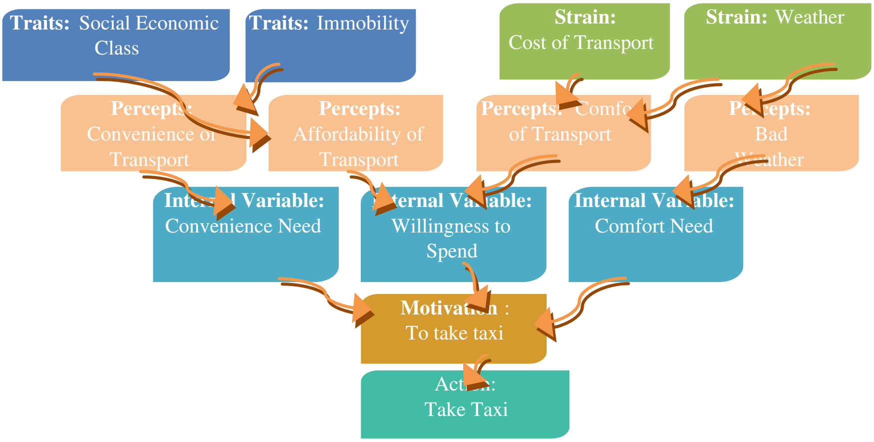

Fig. 3 SE-Star's motivational tree leading to the action to take a taxi

Table 1 The different profiles of entities and the variations of some traits and strains

	Locals	Tourists	Business travelers
Socio-economic class	Varies	Varies	Varies
Convenience need	High	High	High
Willingness to spend	Low	High	High
Number of luggage	High	Low	Low

Profiles of Entities Archetypes

The simulation features three main archetypes of passengers, (i) Locals, (ii) Tourists and (iii) Business Travelers that depict the crowd in the airport arrival hall on a typical day. The archetypes are based on the three most common passengers defined by the stakeholders. Sub-archetypes variants can be derived based on the main archetypes. The Table 1 presents a generalization of different profiles of entities coupled with an excerpt of the traits and strains.

4.2.3 Output

We have modeled a generic airport terminal with localized social behaviors. We observed expected and unexpected behaviors that were not predetermined such as the swarming behavior toward the luggage carousel when the first pieces of luggage appear, lost tourists looking for information due to the lack of local knowledge and the formation of queues at taxi stands and bus stops.

During our fieldwork we also observed behaviors that are not reproduced by our simulator such as impatient passengers who tend to cut queues, families who tend to cluster around a point in the queue, couples who tend to be side by side in a queue.

All these group characteristics and behaviors are still lacking in our current model, an area identified for our future research.

Using the same behavioral models, it will be possible to test at a site or township level the transportation capacity in various scenarios such as passenger increase (*e.g.* due to an event), infrastructure works or a breakdown. This approach could be scaled up to the level of the entire city transportation system.

5 Future Work

Having involved social sciences in our simulation modeling, we have uncovered valuable insights into the strength and weaknesses of our simulator SE-Star. We shall look into improving Group Behavior modeling. The notion of Group Brain and Group Objective where two or more individuals having the same goals share a "common brain" and inter-entities communication could be further explored. At a macro level, simulations should consider social structures and implication of culture influencing the desires, beliefs and values.

Regarding social sciences itself as contributor to SE-Star, we find out that much as psychology easily finds its place into the study, sociology's angle of attack to contribute appears less obvious. This direction of study needs to be further researched, through further field researches, modification of the simulation engine or how the smart objects are apprehended by the virtual entities.

6 Conclusion

In this paper, we presented our integrated team composed of both engineers and social scientists and its approach to enhance the realism of a simulator for complex urban environments. We also presented some results of simulations produced by that team, using our crowd simulator SE-Star.

The newly formed multi-disciplinary team has proven to be very effective in tackling complex problems, introducing new social behaviors into our virtual entities, and thus enhancing the simulation fidelity. Members were able to contribute in their respective domains of expertise, helping to analyze and integrate the stakeholders' requirements into those new models. From our case studies we uncovered that some social sciences theories can indeed be implemented in SE-Star, in particular those pertaining to psychology, while some others, related to sociology, would require some modifications of our engine.

For future work we intend to further improve group behavior and inter-entity communication in SE-Star. We shall further take into consideration the impact of social sciences to improve our current approach, focusing in particular on strengthening the contributions of psychology and improving the weight of sociology.

We believe the approach we have described could be used as a reference to build more "humanistic" simulation models. Those models should enable engineers to simulate the social implications of their work, thus minimize the mismatch of expectation between the intended design and the desires of the citizens, effectively contributing to the improvement of the quality of life.

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