Analyzing a Multi-Agent-System Decision Architecture
Aiming to Model the Behavior of Virtual Humans

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Abstract:
In this paper a novel approach on how to model the decision-making of virtual humans in the domain of multi-agent-systems is analyzed. The developed decision architecture embeds strategic behavior for intelligent humanoid agents (Hoogendoorn & Bovy 2004). The aim is to solve the action selection problem in the domain of naturalistic decision-making related to pedestrian movements. Embedding individual, motivational, reactive and proactive dynamic decision-making in virtual humans is the key to fulfill essential characteristics to model high level cognitive behavior of synthetic humanoid agents (de Sevin & Thalmann 2005).

The decision architecture is based on the activation of motivations for the virtual humans and uses Agent-Based Modelling (ABM) and the methodology of System Dynamics (SD). A set of motivations is defined for each virtual human and activation processes are dependent on agent-intrinsic needs modeled as motivational reservoirs and agent-extrinsic multipliers aggregating information coming from the environment. The decision architecture fully distinguishes action selection from navigation and locomotion and fulfills therefore the three-layer architecture originally coming from the area of robotic research (Blumberg & Gal ye an 1995).

The analysis of the developed decision architecture is important for calibration and validation purposes of multi-agent microworlds that enable to conduct risk-free experiments in which realistic virtual human beings – for instance virtual event visitors, virtual airport and train station passengers or virtual parade attendees – need to be embedded. The sophistication of the developed commonly called action selection mechanism (Tyrrell 1993) is done for a case study of a music festival.

Keywords: Multi-Agent System, Agent-Based Modelling, System Dynamics, Decision Architecture, Action Selection Problem, Virtual Humans, Pedestrian Simulation, Risk-Free Microworld

1. INTRODUCTION
The simulation of pedestrian dynamics is an important means for analyzing environments where it is critical to understand how people move and interact. Application scenarios reach from the design of train stations or airports to the layout of music festivals or other public events. The first goal of simulating and analyzing pedestrian dynamics is to reduce the risk of accidents and disasters by realizing an undisturbed flow of people. The second goal is to forecast how much service staff is needed and how to optimize the event layout to minimize waiting times within this context.

Different approaches have been proposed to model pedestrian movement behavior (Schadschneider et al. 2009). They can be roughly classified into macroscopic approaches where the pedestrians’ movements are handled in an accumulated manner (and described as a fluid flow, for example) (Colombo & Goatin 2010), and microscopic approaches where individual persons and their interactions form the basis of the simulation model (Gipps & Marksjö 1985; Helbing & Molnar 1995).

If designed carefully, a microscopic simulation approach is considering three different level of behavior description (Reynolds 1999; Hoogendoorn & Bovy 2004). The locomotion level forms the lowest level and models the actual movement of the humans, i.e. the steps they take and how they react to their immediate environment. The intermediate level, called the tactical level, represents the routing and navigation behavior, and typically is represented by the social force model (Helbing & Molnar 1995) in combination with algorithms operating on a graph network (Kneidl et al. 2012). The highest level is called the strategic level and models the strategic decisions, i.e. it tries to model why people are aiming to reach a certain destination (Hoogendoorn et al. 2011). While both the locomotion and the tactic behavior are quite well understood, the correct modeling of the strategic level is still subject to an intense scientific debate.

A very suitable concept for implementing both the tactic and the strategic level is to apply the well-known approach of multi-agent systems (Ferber 1999). Here, the pedestrians’ behavior is modelled from a strictly egocentric perspective of the individual person by implementing sub-programs (“agents”) that perform actions
only on the basis of their internal states and the knowledge they gain from the surrounding world through well-defined sensors (Hoogendoorn et al. 2011). Any global knowledge is inaccessible for the individual agent. As this concept very closely reflects the real world, it can be seen as the most realistic approach for simulating pedestrian dynamics. A key issue however, is the actual modeling of the decision process of the agent for selecting the actions to perform.

In this paper we present an approach for modeling the action selection processes which is based on System Dynamics (SD) for representing the different motivations of an individual including their dynamic changes over time. The approach is based on findings from cognition science. The suitability of the proposed approach is illustrated by a case study representing an event in an urban environment.

2. CONCEPT
To model the dynamic decision-making of virtual humans that live in a persistent microworld, an advanced concept to computationally model action selection is required. In the following, the decision threshold model that is the key of the concept is discussed first. Secondly, different internal and external sensors that affect the decision threshold of the virtual humans will be described. Thirdly, the concept of the action selection mechanism that aggregates the sensory information and triggers discrete actions is discussed.

2.1 The decision threshold
Decision-making is the central cognitive function of the brain. The brain can be interpreted as a complex information processing system (Ullman & Poggio 2010) and is responsible for weighing up different alternatives, to select actions and to interact with the world around us. How humans make decisions is an extensive research topic and many scientific disciplines such as neuroscience, biology, psychology, sociology, cybernetics, economics, computer science and especially artificial intelligence research aim to clear the fog in this area. Hence, the research topic is quite interdisciplinary and models that aim to explain certain aspects combine knowledge of different disciplines. One model that is widely applied is the model of a decision threshold. A decision threshold “ultimately determines the decision process by balancing evidence accumulation and deliberation in order to appropriately select an action” (Green 2012). In other words, in the decision threshold model a decision criterion accumulates decision evidence over time until a boundary in form of a decision threshold is crossed and an action is triggered.

In the area of two-alternative forced-choice (TAFC) tasks a row of different models were proposed to model the accumulation of decision evidence. In the drift-diffusion model (Smith 2000) accumulation is due to a random walk process (see Figure 1), where noisy sensory information corresponds to the accumulation of decision evidence and thus is a matter of a stochastic process, rather than a deterministic one. Other models in the area of stochastic evidence diffusion are the Ornstein-Uhlenbeck model (Ricciardi & Sacerdote 1979), the race model (Pike 1966), the mutual inhibition model (Usher & McClelland 2001), the feedforward inhibition model (Shadlen & Newsome 1996) and the pooled inhibition model (Wang 2002). Tasks where these models perform very well, are tasks with reaction times, as some empirical studies substantiate (Platt & Glimcher 1999).

Figure 1: Example of six evidence accumulation sequences from an unbiased (100% noise) source. The dotted lines indicate the thresholds for decision-making for each of the two alternatives.

In this paper, the basic idea of the stochastic drift-diffusion model is apprehended, but the modification is very fundamental. The diffusion is not modeled as a stochastic process, but rather based on first-order differential equations resulting in deterministic accumulation patterns. To do so, the System Dynamics (SD) methodology is used. This approach is seen as very suitable to model diffusion processes (Ford 1999) and thus decision evidence accumulation. This method results into a deterministic decision evidence accumulation framework, rather than a
stochastic one. With this framework different motivations that emerge over time can be modelled. The three basic assumptions of this framework are partly in contrast to the assumptions of stochastic decision evidence accumulation models (Bogacz et al. 2006): a) preferences are integrated over time, b) the decision process is not a subject to random fluctuations and c) actions are triggered when sufficient decision evidence has accumulated.

2.2 Action selection by aggregating internal and external sensory information

The basic idea of a decision threshold is quite straightforward, but the difficulty is to aggregate different internal and external sensory information of the synthetic agents as the decision evidence criteria that affect the decision-making of the agents (see Figure 2). In this context, internal states function as memory reservoirs of agent-intrinsic motivations that are modified by nonlinear diffusion processes. External sensors of the agents capture information from the environment and modify the agent-intrinsic motivations in form of multiplier functions.

![Diagram](https://via.placeholder.com/150)

Figure 2: The schematic principle of the action selection mechanism. Internal stimuli are caused by internal states within the agents. External stimuli are dependent on sensory information the agent receives from the environment. All stimuli are aggregated in the action selection mechanism to describe the nonlinear decision evidence accumulation processes.

The consideration of agent-intrinsic and agent-extrinsic stimuli in the described way enables to fulfill the key requirements for the aim to incorporate autonomy within the decision-making entities. According to (de Sevin & Thalmann 2005), autonomous agents should exhibit individual, motivational, reactive and proactive behavior and additionally, opportunities and demands that spontaneously come from the environment should not be ignored. On the one hand, internal states of the agents (hunger, thirst, resting need, etc.) that can ascertain by internal sensors ensure to incorporate the individual, motivational and proactive behavior component into the agent. On the other hand, the retrieval of external information enables to create reactive agents and to incorporate behavior that takes into account opportunities and demands that come from the environment. Hence, both types of sensory information should be considered and are part of the developed action selection mechanism respectively multi-agent-system decision architecture.

3. IMPLEMENTATION AND RESULTS

To test the developed decision evidence accumulation framework, a case study in the domain of an urban event was conducted. Hence, the decision architecture aims to model the action selection of virtual event visitors. After the introduction of the case study in the next section, the implementation of the decision architecture is presented and simulation results are discussed.

3.1 Case Study

The observed real-world event has the name *Back to the Woods and* took place in July 2014 and 2015 in Garching, Germany with approximately 5000 visitors both times. A description about this event can be found in (Biedermann et al. 2015). The aim is to map this event to a microworld to be able to test the decision architecture and to conduct risk-free experiments within this artificial world. Included are all these kind of possible explicit decisions that lead inevitably to a position change of the virtual event visitors. Actions that result from the decision architecture are for instance: *buy food, buy drinks, go to the toilette, go dancing, go resting and leave the event.*

Anylogic as multi-method simulation software, enabling to model and simulate within the discrete event, agent-based and system dynamics modelling and simulation paradigm (Borschchev 2013), is used as software tool. Anylogic enables to fully separate action selection of the agents from navigation and locomotion and fulfill therefore the three layer architecture (Blumberg & Galyean 1995) coming from the field of robotic research. Figure 3 shows a screenshot of the simulation environment with the main simulation area containing all modeled markup elements for the simulated event.
3.2 Decision architecture and decision evidence accumulation

The whole software architecture of the simulation is quite complex and cannot be fully documented here (see Handel 2016 for more details). Highlighted are the parts relevant for the decision architecture. The simulation is mainly organized in two classes. The main class contains beside many other elements the major iteration loop that governs the decision-making requests of the autonomous virtual event visitors. But the actual action selection mechanism is embedded in the visitor agent class and thus in each instance of the virtual event visitor population. As provided with Figure 2, the action selection mechanism is based on agent-intrinsic internal states and agent-extrinsic environmental sensory information. The nonlinear decision evidence accumulation of the internal states is provided with the System Dynamics building block elements: stocks, flows and auxiliary variables.

In Figure 4, the dependencies of three different internal states are shown: hunger, thirst and need for toilette. These states are modeled as stocks respectively reservoir variables and are regulated by corresponding in- and outflows that are in turn depended on different auxiliary variables. This approach allows incorporating essential causal interdependencies in the decision logic. The inflow rates of the hunger and thirst stock are dependent on the current activity the agent is conducting. For instance, if the agent is performing a physically demanding activity, the accumulation of decision evidence for the associated go eating and go drinking activities increase.
At some point in the simulation, enough decision evidence for these activities has accumulated to exceed the defined decision threshold and the mentioned activities are triggered resulting in a complete emptying of decision evidence in the corresponding stocks. The triggered actions buy food or buy drink result in turn in a delayed inflow of the need for toilette stock. Different delay times (DTfood and DTliquid) pointing at the corresponding inflow together with the delay marks indicate the first order delay within the inflow variable. At some point enough decision evidence for the toilette visit activity has accumulated that the go to toilette action is triggered.

The stock and flow approach enables to regulate the accumulation of decision evidence that affect the internal motivations of the virtual event visitors. The other mentioned activities are modeled also with this framework of nonlinear motivation evolution. A full documentation can be found in Handel 2016. The next step is to consider the external stimuli in the decision-making mechanism. The incorporation of two different environmental circumstances, namely the length of waiting queues in the simulation and the distance to the place of activity satisfaction, are explicitly documented here. Different program functions, such as getQueueLength( ) or getDistanceTot(), enables to collect the sensory information individually for each entity. The numeric return parameters of these functions are normalized and affect as multiplier functions the amount of accumulated decision evidence for each motivation. In other words, sensory information is collected by the agents themselves and is used to antedate or to delay activities of the agents and thus to embed reactivity in decision logic and to recognize opportunities and demands coming from the simulated microworld.

3.3 Simulation results

In Figure 5, the nonlinear motivation evolution of one embedded virtual event visitor in the simulation is shown. The accumulation of decision evidence (the fill level in the stock variables) for the six explicitly modelled motivations is plotted over time. The initial values are generated based on a distribution function of empirical data in respect of all event visitors. The figure indicates that after the decision evidence of one motivation exceeds a defined threshold, an action is triggered and the corresponding volume of decision evidence in the internal state stock is emptied affecting the inflow rate of other internal states stocks. Hence, fundamental causal interdependencies between different conducted activities can be indicated within the graphs.

Figure 5: The chart visualizes the action selection mechanism in action. The six different motivations vary over time – as a result of firstly the stock and flow dynamics that change the internal states (internal stimuli) and secondly the multipliers processing the information from the environment (external stimuli).

In the simulated microworld complex macro behavior emerges from the agent-specific micro motives in form of the described decision architecture of the virtual event visitors. To visualize the simulated microworld, the 3D-postvisualization software PedVis (Handel et al. 2015) is used. Figure 6 shows screenshots of the visualized Back to the Woods case study. The left side of the figure shows the entrance area of the event. Due to modelled queuing situation in respect of ticket and security checks a queue forms in the simulation, as in the real-world event (tiny picture at the bottom of the figure), because the inflow exceeded the outflow. The right picture shows a bird’s eye perspective on the simulated microworld with the included 3D-object of the simulation.
4. ANALYSIS AND VALIDATION ATTEMPTS

After the implementation of the decision architecture is described in principle, the simulation results are analyzed and discussed in this section. For validation attempts it is necessary to compare the simulation results with real-world data. For this purpose, empirical data was collected at the Back to the Woods event in 2014 and 2015. Beside the post-evaluation of video recordings, documented in Biedermann et al. 2015, 278 event visitors were interviewed with semi-structured questionnaires at different times of the event in respect of their current needs (hunger, thirst, etc.). While the video recordings allow counting – for instance – the amount of people in front of vendor stands, the questionnaires allow statistical assessments of the internal states and motivations on an individual and on an aggregate basis over time.

Figure 7: The left side of the figure shows the aggregation of the interviewed event visitors’ needs over time in form of fourth-order polynomial trend lines. The right side of the figure shows the mean values for the six different explicitly modelled decisions as mean values over the whole virtual event visitor population.

In Figure 7, a comparison of the data from the questionnaires (left side) and data from the simulation in form of a plot of the aggregated internal states – the mean values of the virtual event visitor population (right side) – is shown. The graphs plotting the empirical data resulted as follows: Several event visitors were asked with the questionnaires about their current needs (hunger, thirst, etc.) based on 5-point Likert scale at different moments of time. Each point on the Likert scale was transformed into a numerical value so that all values could be plotted in one single diagram with the need manifestation respectively decision evidence as y-axis-value and the point of time of the data assessment as x-axis-value. The aggregation of all data points was made with a mathematical fourth-order polynomial trend line resulting in the graphs depicted in the figure. The graphs on the right side resulted from the simulation incorporating the decision evidence accumulation framework that was described in the last section. These graphs resulted from calculating the mean values of the amount of decision evidence respectively the numerical values within the stocks variables in respect of the whole agent population over time. Without providing here statistical data about data match or going into deeper discussion about curve fitting, it can be stated that the principle shape of the graphs are quite similar. Hence, the validity of the decision structure affecting the behavior of each agent – the micro motives – is increased and solidified with this data evaluation.
In Figure 8, a comparison of the emergence of waiting queues that are quantified based on the amount of queuing persons is assessed. The left diagram shows the amount of persons queuing in front of vendor stands and other facilities at the real-world event over time. This data was collected based on post-evaluation of the mentioned video recordings. Every five minutes within the hour-long video material the amount of persons queuing in front of the event facilities was counted. The video material was furthermore used to measure the length of service times for the vendor stands respectively duration of use of the mobile toilets to incorporate the necessary input data of the delay times for the service with lines markup elements within the simulation. More about this data collection and the importance of accurate service times as calibration parameters can be found in (Handel & Borrmann 2015). The graphs on the right result from these calibration values and the macro behavior in form of the amount of queuing agents as a consequence of the collective dynamic decision-making of the virtual event visitors. In summary, the shape and characteristic of the graphs are very much alike and even the peak values fit quite well. Therefore it can be stated that the decision architecture is very suitable to deliver valuable benchmarks to a potential event planner using the decision architecture for the assessment of needed service staff and event facilitates.

5. CONCLUSIONS

In this paper, we have presented a novel approach for modeling the decision-making process of virtual agents in the context of pedestrian dynamics. The approach is based on the decision-threshold assumption grounded in cognitive science. In contrast to existing approaches that model the dynamic changes in motivations through a stochastic drift-diffusion model, we make use of first-order differential equations resulting in deterministic accumulation patterns. The System Dynamics methodology is applied for modeling the dynamic diffusion processes. By means of the presented case study of an urban music festival, we were able to prove the general suitability of the developed approach and present first validation results which show a very good match between simulation results and reality. Our future research will focus on extending the internal states of the agents, and applying the concept in different contexts of pedestrian dynamics in order to prove its general applicability. Gathering real-world data for validating the simulation’s results will continue to be a key aspect of our research.

6. ACKNOWLEDGMENTS

This research was funded by the German Federal Ministry of Education and Research as part of the program Research for Civil Protection (disclosure Urban Safety).

7. REFERENCES
