A Framework for Modeling and Analysis of Ambient Agent Systems: Application to an Emergency Case

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Abstract It is recognized in Ambient Intelligence that ambient devices should be modeled as intelligent autonomous components rather than passive information sources. The agent paradigm suits well for representation of both intelligent ambient devices and humans. However, modeling complex cognitive dynamics from which intelligent behavior of agents emerges is not trivial. In this paper a formal framework is proposed for declarative modeling of cognitive processes and behavior of agents in an ambient intelligence system. Models obtained by the framework are executable and can be used directly for simulation and analysis. The framework provides rich analysis possibilities of qualitative and quantitative properties, specified at local (agent) and global (system) levels. An application of the framework in the context of a subway evacuation case is described in the paper.

1 Introduction

It is often argued in Ambient Intelligence that ambient devices should be modeled as intelligent autonomous components rather than passive information sources (cf [9]). The agent paradigm suits well for representation of intelligent ambient devices [5]. Agents are autonomous entities able to make decisions and interact with the environment by communication, observation and actions. Externally observable behavior of intelligent agents emerges from their complex cognitive dynamics. The cognitive dynamics comprises cognitive processes which, as widely recognized in the literature [6], influence intelligent agents' decision making: e.g., belief revision, learning, dynamics of trust, generation and development of emotions.

In general, modeling of ambient agent systems is a challenging task. Models of such systems should account for complexity of human behavior, heterogeneity and autonomous behavior of technical systems, and interaction among all system ac-

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tors. Both quantitative and qualitative system properties are required to be modeled. Furthermore, relations between diverse processes and states of different aggregation levels of a system should be defined explicitly. In this paper we propose a formal framework, which addresses all these modeling requirements and provides means for performing various simulation experiments with ambient intelligence systems. In contrast to other existing approaches and tools for modeling and analysis of ambient intelligence systems (cf [7]), the framework allows declarative modeling of cognitive processes of agents including belief revision, trust and emotion development, and decision making. Furthermore, the framework enables modeling externally observable behavior of agents such as communication between agents and physical actions of agents in the environment (e.g., movement). The structure and dynamics of the environment can be modeled as well. Specifications of systems created using the framework can be simulated directly. The framework proposes rich means for analysis of simulation results, based on the technique described in [1]. An application of the framework in the context of a subway evacuation case is described in the paper. In particular, results are presented of the analysis how the penetration rate of ambient devices and the quality of knowledge of human and ambient agents influence the evacuation dynamics. The paper is organized as follows. The evacuation case is introduced briefly in Section 2. Then, the modeling approach is presented in Section 3 with a particular focus on decision making of agents. After that the analysis results for the case are described in Section 4. Section 5 concludes the paper.

2 Case Study

In this section a subway evacuation case is described investigated in the frames of the SOCIONICAL project.

An explosion occurred in a train situated in an underground tunnel between two stations. The explosion was followed by fire and smoke, which have been spreading throughout the tunnel. Because of the blast some doors are damaged, so people are able to escape outside of the train through the formed openings. In other carriages all doors are closed and could not be opened manually. People from the first and last carriages have a possibility to escape through the driver's and back doors. Also, people from other carriages can get out of the train through one of the available exits using buffers between carriages. Some people believe that tracks might still be alive and prefer to stay in the train. The train driver puts much effort to release and guide people to exits of the tunnels. As the driver acts confidently and in a knowledgeable way, many evacuees have a high trust towards him.

Two types of ambient devices are distinguished in the case: centralized devices installed in tunnels (e.g., LCD screens and loudspeakers) and personal ambient devices carried by human agents (e.g., PDA's, cell phones). It is assumed that any device can contact another device within its covering radius. Furthermore, a human agent possessing a personal device is able to exchange information with it. Also, centralized devices provide information to human agents in their neighborhood.

Both types of devices provide two types of information used in decision making by agents: (1) information about currently possible options to move (i.e., paths to exits on the subway map) and (2) information that can be used by agents to evaluate their options: (a) the availability (i.e., possibility to cross) of locations along different paths, and (b) the degree of danger based on the fire and smoke concentration at a location.

The train driver has a personal device which is able to communicate with the Network Control Center and to gain the most recent information from there. Some percentage of the passengers in each carriage possess personal ambient devices. Every carriage is equipped with wireless communication points, through which devices of the driver and passengers can communicate with each other. Some communication points are broken.

Two particular research questions are addressed in this case study: (I) How does the penetration rate of ambient devices in the population of agents influence the evacuation speed? (II) How does the completeness and correctness of knowledge of agents influence the evacuation effectiveness? To answer these questions simulation has been performed, which will be considered in Section 4.

3 Modeling approach

To specify dynamic properties of a system, the order-sorted predicate logic-based language called LEADSTO is used [2]. Dynamics in LEADSTO is represented as evolution of states over time. A state is characterized by a set of properties that do or do not hold at a certain point in time. To specify state properties for system components, ontologies are used which are defined by a number of sorts, sorted constants, variables, functions and predicates.

LEADSTO enables modeling of direct temporal dependencies between two state properties in successive states, also called dynamic properties. A specification of dynamic properties in LEADSTO is executable and can be depicted graphically. The format is defined as follows. Let α and β be state properties of the form conjunction of atoms or negations of atoms, and e, f, g, h non-negative real numbers. In the LEADSTO language the notation $\alpha \twoheadrightarrow_{e,f,g,h} \beta$ means: if state property α holds for a certain time interval with duration g, then after some delay (between e and f) state property β will hold for a certain time interval of length h. For example, the property 'if agent A observes fire during 1 time unit, then after that A will run away from the fire during 1 time unit' is formalized as:

$$observation\_result(fire) \twoheadrightarrow_{0,0,1,1} performed(runs\_away\_from\_fire)$$

From the external perspective the behavior of an agent is specified by dynamic relations between agent's input and output states, corresponding to interaction with other agents and with the environment in a multi-agent system. An agent perceives information by observation and communication and generates output in the form of communication or actions.

From the internal perspective the behavior of an agent is characterized by causal relations between internal states of the agent, based on which externally observable behavioral patterns are generated. The externally observable behavior of an agent is determined largely by the agent’s decision making. The process of decision making in a highly dynamic environment (e.g., during an evacuation) is influenced greatly by information provided to the agent by diverse information sources. The higher the agent’s trust in an information source the more the agent is apt to accept information from this source and to adapt its beliefs using this information. Due to the space limitations only an informal description of the cognitive model is provided. For a complete formal description we refer to [3].

Beliefs of an agent are time-labeled internal representations created based on communication and observation results received by the agent. Beliefs are specified using the function $belief(p : STATPROP, v : VALUE, t : TIME)$, here p is the content of the belief and v is the degree of confidence of the agent that the belief is true from the interval $[0,1]$ at time point t.

Trust is an attitude of an agent towards an information source (e.g., another human agent, an ambient device) that determines the extent to which information received by the agent from the source influences agent’s belief(s). The trust to a source builds up over time based on the agent’s experience with the source. In particular, when the agent has a positive (negative) experience with the source, the agent’s trust to the source increases (decreases). For more details on modeling beliefs, trust and interaction between them we refer to [3].

It is often claimed that most beliefs of a human agent are emotionally loaded (see e.g., [6]); also trust of an agent to a source and decision making are influenced by emotions. In the proposed framework emotional influences on cognitive state (such as beliefs, trust and decision making states) are modeled by *body loops* (see [4]) over these cognitive states:
cognitive state → *preparation for the induced bodily response* → *induced bodily response* → *sensing the bodily response* → *sensory representation of the bodily response* → *induced feeling*

For more details on modeling of emotions we refer to [3].

Agents act according to the adopted plans. A *plan* is a (partially) ordered set of actions, required to be done to satisfy agent’s goals. Plans are represented as beliefs and can be communicated between agents. For example, a part of plan $P1$ that specifies for an agent the sequence of locations l1, l2, l3 is formalized as $belief(follows\_after\_in(go\_to\_location\_from(l3,l2), go\_to\_location\_from(l2,l1), P1),1)$. Plan descriptions vary in the degree of specificity. Abstract (or partial) plans contain high level actions that can be further refined into more specific actions. Furthermore, alternative ways of refinement of high level actions can be specified. In the evacuation scenario an agent may have several plans how to reach possible exits. These plans may be partial and contain movement actions between significant locations only (such as junction points, locations with elevators, stairs). There could be different paths between two significant positions.

An agent evaluates an option using the following criteria:

(1) *Desirability of an option*: to which extent the option brings to the satisfaction of the current desire(s). In the evacuation scenario the desirability of an option depends on the agent's beliefs about how close the agent's state will be to the state of being evacuated after the execution of the option.

(2) *Possibility to realize*: indicates the agent's confidence that the option can be realized. In the evacuation scenario it is calculated based on the confidence values of the agent's beliefs about the accessibility of locations in the plan and the degree of danger of each of these locations (e.g., amount of smoke and fire). These beliefs take into account the agent's representation of the environmental dynamics (e.g., about smoke spreading) and the agent's average speed.

(3) *The amount of effort*: how much effort needs to be invested to realize the option; depends on the skills, knowledge, physical and other characteristics available to the agent. In the emergency scenario the amount of effort is calculated based on the agent's beliefs about the distance to the exit.

To model an emotional influence on the process of evaluation of options, the value $eval_p$ for option p, calculated based on (1), (2) and (3) is provided as input for a body loop (for more details see [3]):
$preparation\_state(b, v1)\ \&\ body\_state\_for(b, option(p))\ \&\ belief(eval(p, v2), 1, t)$
$\&\ feeling(b, v3))\ \&\ present\_time(t)$
$\twoheadrightarrow_{0,0,1,1}\ preparation\_state(b, v1 + \gamma 1 \cdot (g(v2, v3, v4, \beta 1, \beta 8(t, t2), \beta 9, \beta 10) - v3)),$
where $g(v2, v3, \beta 1, \beta 2, \omega 1, \omega 2) = 1/(1 + e^{-\beta 1 \cdot (\omega 1 \cdot v2 + \omega 2 \cdot v3 - \beta 2)})$

After all available plan options have been evaluated, the agent chooses and commits to the one with the highest feeling value. After the agent has committed to a plan, it evaluates all possible refinements of the first action of the plan along the same evaluation criteria as for plans and chooses the one with the highest feeling. Note that the agent re-evaluates the available plan options continuously and can retract from its plan commitment at any time point.

4 Simulation and Analysis Results

To answer the research questions for the evacuation case posed in Section 2, simulation of a number of scenario variants described in the upper part of Table 1 was performed. In the simulation the following setup was used: The train comprises 4 coaches. An explosion occurred in the last coach, which is close to Exit A. Exit B is further away from the train, however the path to that exit is free of smoke at the beginning of each simulation. The train is populated in random manner with 20 heterogeneous human agents (5 per coach) of different types represented equally in the agent population: conservative extrovert/introvert, neutral, flexible extrovert/extrovert, neurotic flexible extrovert (for more details see [3]). In the scenario's with ambient devices a centralized ambient device is located in the tunnel on the way to Exit B. It is assumed that human agents do not know each other; initially the trust relations between human agents are neutral (0.5). An exception is the train driver agent, who is initially highly trusted (0.9) by other agents. Initially human agents have average trust in their personal ambient devices (0.6). The simulation time is 24 minutes. The obtained simulation traces describing the evacuation of agents over time are visualized in Figure 1.

Table 1 An overview of simulation trials 1-10 and the quality of knowledge of the evacuated agents in these trials; three categories of quality are distinguished: High: $d \in [0, 0.3)$, Average: $d \in [0.3, 0.7]$, and Low: $d \in (0.7, 1]$

Simulation trial / Characteristic	1	2	3	4	5	6	7	8
Penetration rate	0	10	50	100	0	10	50	100
% agents with correct beliefs	10	10	10	10	50	50	50	50
% agents with incorrect beliefs	0	0	0	0	50	50	50	50
# agents with *High* knowledge	1	6	7	7	7	13	8	11
# agents with *Average* knowledge	13	9	10	8	3	3	5	4
# agents with *Low* knowledge	2	5	3	5	0	4	4	4

Following [1], the dynamics of a simulation model can be studied by specifying dynamic statements in terms of temporal logical expressions, and automatically verifying these statements against simulation traces. For formalize such temporal statements the Temporal Trace Language (TTL) [8] is used, of which LEADSTO is a sublanguage.

To investigate how the penetration rate of ambient devices influences the evacuation speed two properties were verified on the simulation traces:

P6 - Evacuation Time t

There is a time point $t1$ in trace γ on which all agents are evacuated
and all other time points $t2$ on which agents are evacuated are later than $t1$
and the time that passed between the start of the simulation and $t1$ is t.

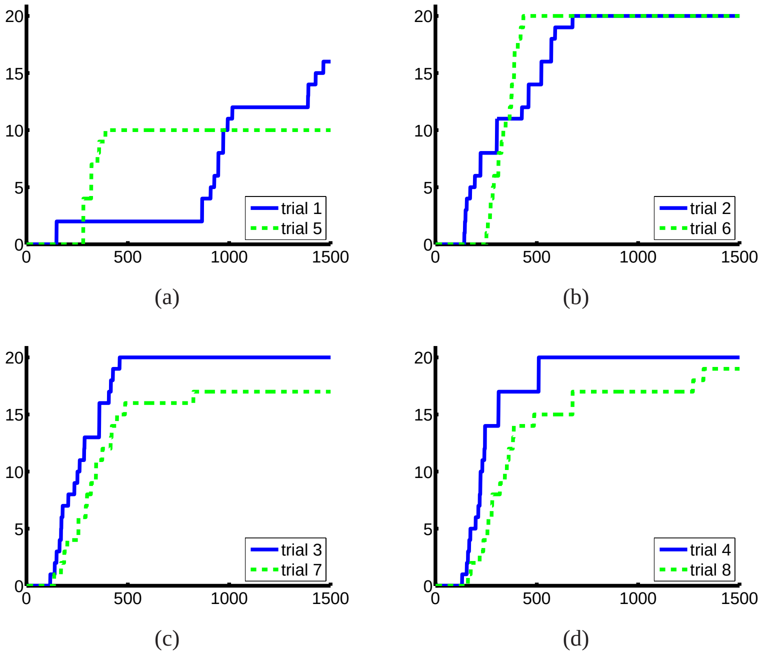
P7 - Quicker Evacuation Time

If in trace $\gamma1$ there are $x1$% correct agents, $y1$% incorrect agents, and $z1$% AmI devices,
and in trace $\gamma2$ there are $x2$% correct agents, $y2$% incorrect agents, and $z2$% AmI devices,
then the total evacuation time in $\gamma1$ is quicker than in $\gamma2$.

The verification showed that P6(trial 1, 1500), P6(trial 4, 1500), P6(trial 5, 1500), P6(trial 7, 1500), P6(trial 8, 1500) are not satisfied.

Based on the verification of property P7 on all simulation traces the following conclusions were made:

Conclusion 1: In all simulation scenario's adding ambient devices accelerates the evacuation process (in comparison with the scenario's without ambient devices).



(a) (b) (c) (d)

Fig. 1 The dynamics of evacuation in the simulation trials 1-8; the horizontal axis is time in seconds and the vertical axis is the number of evacuated human agents

Conclusion 2: In the scenario's, in which the percentages of agents with incorrect knowledge and with correct knowledge are both small ($\leq$ 10%) in comparison with the number of agents with no knowledge (simulation trials 1-4), adding a small number of ambient devices (10%) is sufficient to accelerate the evacuation process significantly.

Conclusion 3: For the scenario's, in which the numbers of agents with correct knowledge and with incorrect knowledge are both high (simulation trials 5-8), exists a penetration rate threshold; below this threshold the speed of the evacuation is improved significantly in comparison with the scenario's without ambient devices, and above the threshold the evacuation slows down.

By the following property we investigated the relation between the quality of knowledge of agents and the evacuation effectiveness:

P9 - Knowledge Distance for Agent a

If in trace γ at time t
agent a has belief i_1 with strength x_1 and ... and a has belief i_n with strength x_n
and i_1 in the world has strength y_1 and ... and i_n in the world has strength y_n
then the knowledge distance for agent a is $\sqrt{\sum_{i=1}^{n}(x_i - y_i)^2/n}$.

The results of verification of this property for the evacuated agents are provided in the lower part of Table 1. As one can see from the table, almost in every simulation trial agents with low quality of knowledge were evacuated. Partially this result can be attributed to the structure of the world used in the simulation. Partially this is because some agents found their way to an exit by following other agents.

Note that the results presented are based completely on the obtained simulation traces and still require validation.

5 Conclusions

In this paper a novel, agent-based framework is proposed for declarative modeling and analysis of ambient intelligence systems. An important advantage of the framework is that it allows modeling cognitive processes from which intelligent behavior of agents emerges. The automated analysis means provided by the framework allows detailed qualitative and quantitative investigation of the system behavior in different scenarios and contexts. In the future more sophisticated types of agents will be considered, which realize diverse Theory of Mind aspects (e.g., adaptation of an ambient agent to a human). Also, more elaborated types of support by ambient agents will be included in the framework.

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