Bounded Active Perception

Utku Görkem Ketenci[1,2], Roland Brémond[2], Jean Michel Auberlet[2], and Emmanuelle Grislin - Le Strugeon[1]

[1] Univ. Lille Nord de France, UVHC, LAMIH, F-59313 Valenciennes, France
utku.ketenci@inrets.fr
[2] Université de Paris Est, LEPSiS, UMR INRETS-LCPC

Abstract. There are two kinds of perception: active and passive. This paper is an attempt to take advantage of active perception to improve the agent's perception of relevant information. Through the data filtering capacity, active perception is a useful tool for modeling human-like bounded perception. Using such filters, either the agent or the environment take an active role. We determine several unsolved issues in active perception and do several proposals to implement our concept on the active perception framework. To this end, we benefit from the cognitive science studies. Finally, our proposals are applied to the case of multi-agent traffic simulation.

Keywords: MAS, active perception, situated agent, attention, saliency, traffic simulation.

1 Introduction

The environment plays a significant part in agent definitions. In the well-known definition given in [18], the agent is anything that can be viewed as perceiving its environment through sensors and acting upon this environment through actuators. According to Wooldridge [26], an agent is a computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its design objectives. The environment is also one of the four dimensions when modeling a Multi-Agent System (MAS), together with the agent, the interaction and the organization [3].

The environment plays a significant active and central role specifically in the agent perception modeling. In this paper, we discuss the roles of the environment and of the agent's internal dynamics on the active perception in a MAS, with an application to agent based traffic simulation. Our goal is to reflect the local and contextual perception of humans in such simulated contexts. Moreover, our motivation is to make a realistic model of the driver for the traffic simulation. This paper is a first step in this aim, with a description of a new perception model for the simulated driver, which is not yet validated in real cases but illustrated by a case study.

The remainder of the paper proceeds as follows. First, we define the environment and its active role in a MAS. Then, we define the situated agent, describe the perception modeling and propose a new model for bounded active perception. Finally, our concepts are illustrated by the examples from a traffic simulation.

2 Environment

No common and accurate definition of the environment is provided in the MAS literature. Environment is a general concept and it represents what is external to the agents, including at the same time the physical space, the interaction space, a set of resources, etc. In a simulation context, the environment is made of passive and active objects that the agents can handle or interact with. In [13], a distinction is made between the simulated environment, which is a part of the model, and the simulation environment, which is the software infrastructure or the tool on which the simulation is executed. The present study concerns more specifically the simulated environment, with the aim to improve the interaction model in the representation of human perception.

According to Ferber, the environment collects all the influences coming from the agents [5]. The influences are the attempts to modify a course of events which would have taken place otherwise. The environment returns the reactions resulting of state changes. These reactions are produced by combined influences of all the agents, given its local state and the world laws. The influence-reaction model makes an explicit distinction between what an agent wants to perform, and what actually happens [8]. This distinction shows the environment active role resulting from its evolution laws.

Moreover, Weyns et al. [25] distinguish three environment levels:

- Basic level: the environment at this level is the deployment context. All the deployment tools (database, graph, etc.) belong to this level.
- Abstraction Level: this level hides the low level details of the deployment context. Agents have no direct access to the graph or to the database but they can access them via the abstraction level. As a consequence, any change in the deployment context (e.g. removing one node from the graph or one table from the database) has only low impact on the agents.
- Interaction-Mediation Level: this level supports and controls some interactions between agents (A) and environment (E), with the following actions:
  - Regulation of the access to shared resources (A-E).
    - For example, two agents cannot share the same place in the environment. This kind of constraints is regulated by the environment.
    - The environment is locally observable to the agents. This is typically limited to the current context (spatial, social..) [25].
  - Mediation of interactions between agents (A-E-A).
    - The agents sharing the same environment are governed by the same rules. These rules are imposed by the environment (e.g. physical laws)
    - The environment regulates the perception making some constraints to the agent domain of perception.

These examples present the environment as an active entity in the MAS. In the following, we complete this point with the effects of the environment on the perception behavior of an agent.

3 Situated Agent

Agents are called "situated agents" to emphasize that they operate within an environment, particularly when they are strongly linked or dependent toward this environment [1, 6]. In situated MAS, agent and environment are complementary parts of the multi-agent world: on one hand, the agent attempts to change the actual state of environment according to its internal state (influences); on the other hand, the environment is a data resource which can be invoked by the agent and evolves its actual state depending on the effects of the agents' action and also according to its own dynamics.

3.1 Generic Global Model

Weyns proposes a generic model of Situated Agent [23] including four modules: *Perception*, *Memorization*, *Decision* and *Execution*.

- The purpose of the *Perception* module is to make the agent aware of the environmental changes. In a dynamic and complex environment, this is an important task. Its output is a percept which describes the states of environment entities.
- The *Memorization* module records information in order to map the internal state of the agent with the state of environment. The existence of this module is left to the designer's choice (e.g. the reactive agent has no memorization module).
- The *Decision* module is the action selection module. It takes as input the percepts and the current knowledge of the agent. Within this, the agent deliberates and selects appropriate actions to realize.
- The *Execution* module accomplishes the action selected by the *Decision* module.

In agent models, the decision module has been the subject of numerous studies, while the perception module is often reduced to a passive filter. We assume that agent perception may benefit from integrating active perception into the agent's framework.

According to Brooks [1], "mobility, acute vision and the ability to carry out survival related tasks in a dynamic environment provide a necessary basis for the development of true intelligence." For us, "acute" vision includes active perception, that is, the agent's capacity to capture relevant information.

3.2 Active Perception

Perception is not a direct understanding of the current environmental state. It includes a process to interpret raw data. A situated agent perceives its environment through sensors. In a simulation context, the sensors are at the interface between the environment entities and the agent. At first, data about the environment are provided by the entities and the other agents. Then the agent interprets these data according to its representation of the environment.

In the agent basic cycle of perception-decision-action, the perception is generally taken in its passive sense, i.e. as the reception of external stimuli by the agent physical or virtual sensors. In passive perception, the agent acquires as most data as possible during the sensing phase. This approach does not require that the agents deliberate explicitly about their sensing needs [20].

Conversely, active perception is supervised by the current intention or action. Active perception enables the agent to perceive what is necessary for its current goals. This minimizes the useless information, and thus the use of unnecessary resource, and maximizes useful information acquisition. The information need comes from the agent's current state. According to Ferber [6], the active perception system receives simultaneously a) the information from the sensors and b) the expectations and goals from the internal state.

In [22], the active perception is integrated in the situated agent's perception model, based on three submodules (Fig. 1):

1. Sensing: This module takes the picture of the current state of the environment constrained by perceptual laws imposed by environment (Fig. 1) and by foci chosen by the agent's decision module. It produces a representation r. A perceptual law is an expression which constrains the representation according to the requirements of the modeled domain. For instance, it may specify that an area behind an obstacle is out of the scope of a perceiving agent, or add some noise to perception. Weyns et al. [22] stated that "Focus selection enables an agent to direct its perception; it allows the agent to sense the environment for specific types of information." The foci are imposed by the decision module. For example, a *smell* focus allows the agent to express its intention to smell its neighborhood, typically to sense pheromones [24]. In the same context, perceptual law [24] may specify which items an agent is able to "see" in its neighborhood. If e.g. an agent A requests a perception with a focus `see(`A`, 5)` and the general view-range is 4, the law will cut off the perceived area to a range of 4 cells relative to the agent's current location.
2. Interpreting: This module matches the representation r with a percept p. A percept is made of expressions understandable by internal machines through the descriptions. For instance, a set of objects can be interpreted as a group of objects, or as several distinct objects. In a traffic simulation, for instance, a set of following vehicles may be interpreted as one entity.
3. Filtering: This module is the last part of the active perception. Through a set of filters, the agent selects the percepts which match specific selection

criteria, to be used in the Decision module. The Decision module imposes the filters. The outputs are the filtered percepts.

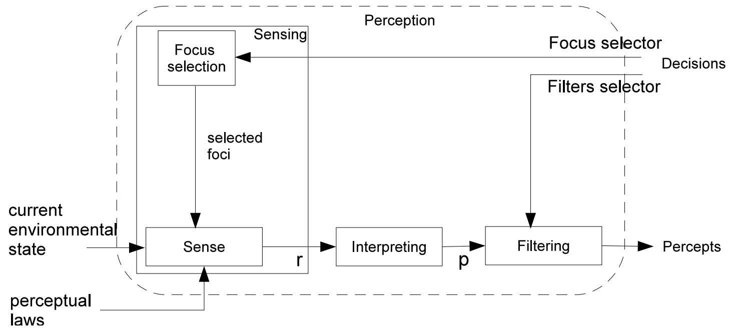

Fig. 1. The model of active perception, after [22]

In [22], Weyns et al. proposed a formal description of their model which is too general for a practical implementation. However this model is detailed enough to represent the capacity to filter irrelevant informations, and thus constitutes the framework for our proposition, which aim is to implement the resource-bounded agents (like human) in an active vision framework.

4 Bounded Active Perception

Before make our propositions to improve active perception with psychological notions, we must define these notions. In cognitive science, attention is an important research topic [10, 14]. There are two cognitive processes characterizing attention: top-down and bottom-up process.

- The top-down information process is goal-driven: Humans (or agents) pay attention to some environmental elements in order to achieve their goal (or intention). Thus, the current goal determines the relevance of the collected information. We see that the active perception approach is an appropriate tool to implement this top-down information process.
- The bottom-up information process is data-driven: Salient data attracts the agents attention. Non-salient items are not (or weakly) perceived; the implementation of this principle needs some ideas about the object's saliency, in a way which only depends on environmental properties.

Perception is then a balance between these two information processes. It may happen that the top-down information process prevents the acquisition of bottom-up salient data.

Furthermore, the humans have *limited capacity.* They can process simultaneously a limited amount of data. If the current goal needs an amount of data above the agent's capacity, it should select most relevant percepts.

Our proposition is to integrate bounded active perception to the agent model, on the basis of current cognitive psychology knowledge. In the remainder of this section, we present how these concepts can be used in relation with the simulation of the agent's resource-bounded perception.

4.1 Focus Selection

The foci selection is needed in both the bottom-up and the top-down processes. This concept is interesting here because we can separate, in the selection of relevant percepts, top-down focus, which depends on the current intention, and bottom-up saliency focus, which only depends on the entity's properties (color, size...etc.) and relative location (apparent size angle, etc.).

Top-down Focus : The top-down foci can be imposed by the Decision module (see "Focus Selector" Fig. 2): a focus can be understood as a domain of interest in the spatial sense. For example, some parts of the spatial domain are scanned in order to achieve the current intention. The explored spatial domain is constrained to the domain of interest by the top-down focus.

Bottom-up Saliency Focus : Bottom-up saliency is a key notion used to model selective attention [9, 15]. The idea is that early visual features, such as colour, intensity, orientation and movement compete for the selection of visual attention. A bottom-up focus should allow to sense salient data (see "Saliency Focus" Fig. 2). This kind of foci is permanent and compute saliency of the entities in the environment, from the agent's point of view. The entities with high saliency become a part of the agent's representation even if they are out of the top-down foci.

4.2 Filtering

After the interpretation stage, the sensed information through the foci is sent to the filtering module. We propose to use the filters not only as a data selector that matches a specific selection criterion, but also as a workload limiting process modeling the resource-bounded capacity of the agent, and as a sorting tool based on the percept's relevance. We use these filters to implement these two concepts.

Sorting Percepts with respect to Relevance: The relevance of a percept depends on the agent's current intention. To achieve its goals, a rational agent makes a plan, composed of ordered tasks. The effective realization of a task depends on the state of specific objects in the environment. Because of the situation changes in dynamic environments, these states must be checked to make sure the current intention is still relevant before applying the planned tasks. For example, a collector agent must be sure of the availability of a collecting object. The agent must emphasize the current task and the inputs needed for this task. If a percept is related to the current intention, its relevance is higher than the relevance of the other percepts. The filters undertake the responsability of sorting the percepts (see "Percept sorting Filters" in Fig. 2) according to the current task. Thus, a top-down process may contribute to direct sensing toward relevant objects.

Resource-Bounded Perception: In the aim of achieving a realistic simulation of human perception, the limits due to the workload must be taken into account. As a first approximation, the most relevant seven percepts [17] are considered as a default limit (see "Resource-bounded Filter" in Fig. 2). The complexity of the current tasks, i.e. the cognitive workload, can modify this limit. This is discussed further in the paper (section 6).

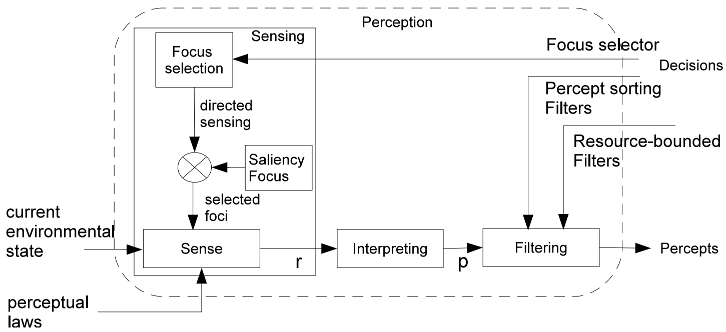

Fig. 2. The extended model of active perception

5 Application to Traffic Simulation

5.1 Traffic Model

The microscopic traffic simulation presents a distributed and complex context that is well-adapted for agent-based modelling. In agent-based traffic simulation, the driver is an autonomous social agent, sharing a common environment with other similar agents.

We have implemented a demonstration of the limited resource effect with our microscopic traffic simulation in a previous work [12]. In that work, the agent behavior follows one of two behavioral rules, one for straight lanes, one for road crossing. On straight sections, the agent's speed tends to reach the desired speed, unless other drivers prevent him to do so. The interaction between two consecutive agents is described in the road traffic literature as a "car following task". We have implemented this classical task as a speed regulation behavior according to what is described in [11].

One tough issue in agent-based traffic models is the "road crossing", which may explain that most agent-based traffic simulations avoid urban situations. The key problem is the complexity of the agents' interactions, and the number of agents involved in the road crossing at the same time.

Recently, Mandiau et al. [16] proposed an algorithm derived from the game theory, where a driver selects a number of players when approaching a road crossing, and decides at each time step to GO or to STOP depending on his evaluation of the relative priorities with the other players selected in the game. The GO/STOP decision is then translated into an acceleration for the driver's vehicle, and the process is iterated at each time step. Based on this approach, we have implemented an active bounded perception for the selection of the players, which now depends on the traffic context and more specifically on how this context is perceived by the agent.

5.2 Application of Active Perception

Feeding a multi-agent model with a psychological model of the driver is an alternative strategy compared to usual microscopic traffic simulations [2]. We consider that perception is the weak part of current MAS-based traffic simulation models. With active perception, we have tried to make more realistic the perception of a driver-agent, and thus the emerging behavior.

The agent in our model has two modes: "car following" and "road crossing". Each mode corresponds to a distinct intention and to different expected information. The needed information are the distance from the previous car and its speed in the "car following" mode. In the "crossroad mode", these are the identification of the vehicles, their trajectory, location, acceleration and speed in potential conflict at the crossroad. Each task can require a different amount of cognitive resource. Hence, the cognitive load created by the road crossing mode is assumed to be higher than in the car following mode because of the number of the processed information and the complexity of the operation.

The application of our active bounded perception model in this simulation context is illustrated by two examples in two different modes.

Car following Focus selection in the context of car following is straightforward because of the simplicity of car following which does not divide attention by many foci. The driver tries to perceive the first vehicle in front of him. One focus is the spatial area towards the followed vehicle, with a parametric range. If there is a pedestrian crossing, another focus is over the pedestrian crossing. The environment constrains these foci in order to establish a realistic perception (e.g. the area behind the obstacles are not visible). The interpreting step creates a percept with the coordinates and the speed of the perceived vehicles. Filtering takes all the percept and sorts them with respect to their relevance related to the current intention. Then, it returns the most relevant percepts to the Decision module, which follows the car following law [11]. In addition, the decision module checks whether the driver is in a car following mode, and changes the behavioral mode (or intention) if needed.

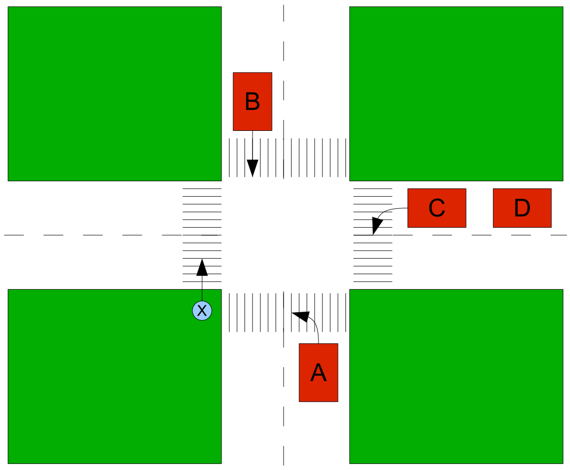

Fig. 3. Simulation of a road crossing (4 vehicles, named A to D, and 1 pedestrian X .

Road Crossing In the road crossing mode (See Fig. 3), the agent should pay attention to all forthcoming vehicles.

The three main components of the Perception Module are detailed below:

- Sensing: The agent senses the entities in the perception domain constrained by the physical laws and foci. The agent's top-down focus covers the incoming ways towards the road crossing; this limits the perception. The environment is in charge of the physical laws. Due to its location in the environment, each agent has a different representation. The sensing may detect salient data by means of a saliency focus. For instance, the pedestrian X (See Fig 3) can be seen by vehicle A due to his color, contrast and movement. The saliency is computed by the agent by taking into account angular size.
- Interpreting: In a virtual environment, this is the simplest part of the active perception. Agent creates a percept from the entity and other agents representations.
- Filtering: The first step of the top-down filtering is the relevance ranking. The agent ranks the percepts with respect to their relevance for the current task. In Fig. 3, agent A sees B, C and D. However, D is irrelevant for A to

achieve its road crossing intention (because of the existence of C). The filter ranks D in the third position. Because the potential conflict with C is earlier than with B, agent C is ranked as more relevant than B. After this sorting process, agent A takes the most relevant percepts and sends them to the Decision module. If the number of percepts is higher than 7, the bounding filter filters the less relevants.

6 Discussion and Perspectives

Active perception was handled in many scientific papers. However, a model of the realistic human behavior is still in progress. For example, [20, 21] integrate the generic model of Weyns with the Situation Awareness [4].

Our work is an attempt to enhance the perception for a situated agent used in human behavior simulations. We have proposed four main idea in the context of active perception: bounded perception, top-down ranking filter, bottom-up saliency and top-down focus selection.

We see also that not only the agent but also the environment plays an active role in modeling perception. The agent's Decision module chooses foci and filters while the environment imposes the physical laws. We use both bottom-up saliency and the filters as a limiting system and the focus to select a domain of interest.

Our improvement will enable the agent to sense salient entity and to take into account if this entity has a relation with current intention. Otherwise, the top-down filters filtre the percept related to this entity. In this model, the salient entity is not a distractor. It means that a salient but irrelevant entity does not prevent the acquisition of a relevant information. In real world, the human's attention is so attracted by the saliency that he/she misses some relevant information. In order to modelize a human like perception model, we must improve this part of the model using a gradient of saliency around the selected focus. We must propose also a criteria to rank the salient and relevant information.

Moreover, the humans have to make decisions under temporal pressure, in a continuously changing world. Therefore, sometimes, they decide an action despite the lack of information because of their resource-bounded capacity. Solutions exist to limit the amount of percepts to acquire. For instance, an agent must know *when* to sense [20]. Instead of interpreting and sorting the percepts at each time step, an agent should sense the changes between previous and actual situation. If a change is detected, the agent interprets the current representation and applies the filters on the percepts for selection and use in the Decision module. Otherwise, they use the previous version of the information. Furthermore, So and Sonenberg state that the deliberation yields little benefit if there is only small changes in the agent's beliefs since the last perception [21]. In this situation, the agent can bypass deliberation and execute directly the next action. It avoids an unnecessary deliberation and saves cognitive resource.

An agent may execute several tasks at the same time, but a human cannot without losing performance due to divided attention. However, some two or three tasks can be done together and completed without performance loss. Experience has an important role about the realisation of several tasks at the same time. Through the experience, human can execute the familiar task in a "routine" manner so the familiar task does not reduce the performance of another task: a veteran and novice must be tackled separately. Futur work can include taking into account the agent's learning capabilities. In perception, experience is a capacity of searching the most relevant percepts in the right place. So, the experienced driver does not waste his limited resource for searching irrelevant data, or sensing places where there is probably nothing that concerns the task. This idea implies a learning mechanism applied to the relevance probability and is linked to expected utility. Expected utility of a goal (e.g. the goal to perceive a specific data) has two dimensions: Goal Value (utility of perceiving) and Belief Strength (probability to find relevant percept in a place) [19]. These two kinds of knowledge can be improved through the experience. Another approach is given in [7], where the expected utility is examined in the context of information relevance.

References

1. Brooks R. A.: Intelligence without representation, Artificial Intelligence 47, 139-159 (1991)
2. Champion A., Espié S., Auberlet J.M.: Behavioral traffic simulation with ARCHISIM. In: Proceedings of the 2001 Summer Computer Simulation Conference (SCSC), pp. 359-364, Orlando, Florida, USA (2001)
3. Demazeau Y.. From interactions to collective behaviour in agent-based systems. In: First European Conference on Cognitive Sciences (ECCS'95), pp. 117-132, Saint Malo, France (1995)
4. Endsley, M.R.: Toward a theory of situation awareness in dynamic systems, Human Factors 37(1), 3264 (1995)
5. Ferber J. and Gutknecht O.: A meta-model for the analysis and design of organizations in multi-agent systems. In: Proceedings of Third International Conference on Multi- Agent Systems (ICMAS'98), pp. 128-135, IEEE Computer Society (1998)
6. Ferber J.: Multi-Agent Systems: An Introduction to Artificial Intelligence, Addison-Wesley (1999)
7. Gehrke J.D.: Evaluating Situation Awareness of Autonomous Systems. In: in Performance Metrics for Intelligent Systems Workshop, pp. 206213. NIST, (2008).
8. Helleboogh, A., Holvoet, T., Berbers, Y.: Simulating actions in dynamic environments. In: Conceptual Modeling and Simulation Conference,pp. 123129, LSIS, Universite Paul Cezanne Aix Marseille III (2005)
9. Itti L., Koch C.: Computational Modeling of Visual Attention. Nature Reviews Neuroscience 2, pp. 194-203 (2001)
10. Itti L., Rees G., Tsotsos J.(eds): Neurobiology of attention. New York: Academic Press (2005)
11. Kesting A., Treiber M., Helbing D.: Agents for traffic simulation. In Multi-Agents sytems: Simulations and Applications, pp. 325356. Taylor and Francis (2009)
12. Ketenci U-G., Auberlet J-M., Brémond R., Grislin-Le Strugeon E.: Impact of attentional factors in a multi-agent traffic simulation. In: Proc. of the 23rd Annual Conference on Computer Animation and Social Agents, Saint-Malo, France (2010)

13. Klügl, F., Fehler, M., and Herrler, R.: About the role of the environment in multi-agent simulations. In: Weyns, Danny and Parunak, H. Van Dyke and Michel, Fabien (eds.) Environments for multi-agent systems. LNCS, vol. 3374, pp. 127149, Springer-Verlag (2005)
14. Knudsen, E. I.: Fundamental components of attention. Annu. Rev. Neurosci. 30, 57-78 (2007)
15. Koch C. and Ullman S.: Shifts in Selective Visual Attention: Towards the Underlying Neural Circuitry. Human Neurobiology 4, 219227 (1985)
16. Mandiau R., Champion A., Auberlet J.-M., Espie S., and Kolski C.: Behaviour based on decision matrices for a coordination between agents in a urban traffic simulation. Applied Intelligence 28(2), 121138 (2008)
17. Miller G.: The magical number seven +- two, some limits on our capacity for processing information. Psych Review, 8197 (1956)
18. Russell S. and Norvig P.: Intelligent Agents. In: "Artificial Intelligence: A Modern Approach", Chapter 2, pp. 33-58. Prentice Hall (1995)
19. Piunti, M., Goncalves, J., Martinho, C.: Modeling expectations for affective agents. In: Proceedings of the ACII-07 Doctoral Consortium (2007)
20. So R., Sonenberg L.: The Roles of Active Perception in Intelligent Agent Sytems. In: Proceedings of the Eighth Pacific Rim International Workshop on Multi-Agents (PRIMA'05), pp. 161-174, Kuala Lumpur, Malaysia (2005)
21. So R., Sonenberg L.: Situation Awareness as a Form of Meta-level Control. In: Proceedings of the First International Workshop on Metareasoning in Agent-Based Systems at the Sixth International Joint Conference on Autonomous Agents and Multiagent Systems, Honolulu, Hawaii (2007)
22. Weyns D., Steegmans E., Holvoet T.: Towards active perception in situated multi-agent systems, Applied artificial intelligence 18 (9-10), 867-883 (2004)
23. Weyns, D., Holvoet, T.: A Formal Model for Situated Multi-agent Systems. Formal Approaches for Multi-Agent Systems, Special Issue of Fundamenta Informaticae 63(2) (2004)
24. Weyns, D., Helleboogh, A., Holvoet, T.: The Packet-World: a Test Bed for Investigating Situated Multi-Agent Systems. Software Agent-Based Applications, Platforms and Development Kits, Whitestein Series in Software Agent Technology. (2005)
25. Weyns D., Omicini A., Odell J.: Environment as a first-class abstraction in multiagent systems. International Journal on Autonomous Agents and Multi-Agent Systems 14 (1), 5-30 (2007)
26. Wooldridge M. and Jennings N. R.: Intelligent agents: Theory and practice. The Knowledge Engineering Review 10(2), 115-152 (1995)