ISSN 2350-1022

International Journal of Recent Research in Mathematics Computer Science and Information Technology
Vol. 1, Issue 2, pp: (36-43), Month: October 2014 – March 2015, Available at: www.paperpublications.org

Learning Process Interaction Aided by an Adapter Agent

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Abstract: **Computational models have played an important role in the discovery and understanding of the complexities during the learning process. One complexity is the distraction factor on educator-learner interaction affecting the quality of the learning process.**

We model an adaptive system model able to dynamically adapt considering user's performance, simulating the learner as a museum user and the educator as an exhibition module using BDI agents; we adapt the BDI architecture using Type-2 fuzzy inference system to add perceptual human-like capability on agents in order to describe the interaction on user's experience. The resulting model allows content adaptation by creating a personalized interaction environment.

Keywords: **Learning Process, Adaptive System, Interaction, BDI Agents, Type-2 Fuzzy System.**

I. INTRODUCTION

We are living in the information revolution where technology facilitates tasks and activities of people making them productive, moreover, is important to evaluate in terms of technology truly helps people. How the technology can help educators and learners during the learning process? This research present a novel approach to improve the capacity of offer adapted content, and information considering the learner's performance in order to increase educator-learner interaction.

1.1 Learning Process

The learning process is a relatively constant change on individual's behaviour (knowledge, attitude and skill) that can occur at any place or time consciously or unconsciously. The success of the learning process depends on collaboration among educators and learners.

1.1.1 Distraction Factor on Learning Process

Is important to consider the distraction factor in the learning process. Distractions are manifestations in the real-world context where there are often involved multiple tasks that are happening in parallel to the educator- learner interaction. The distraction concept is a complex process, and researching human distraction could be difficult.

1.2 Agent Model Representation

In order to simulate the learner and educator into the adaptive system model, we use BDI agents; the User BDI Agent (UA) represents "Learner", the Exhibition-module Adapter BDI Agent (AA) represents "Educator" and the Content Domain BDI Agent (DA) represents "Information and content". The UA simulates the learner's performance caused by various factors (interaction level and distance).

The AA monitors the learner's performance using type-2 fuzzy logic to develop fuzzy perception to deliver adapted content type avoiding distractions and keeping the learner's interest in the learning process interaction.

II. RELATED WORK

In situational perceptions research, fuzzy logic has been playing an important role, there is an interesting research on the reduction of distraction factors on HCI, [1] introduces a fuzzy perception model for BDI agents, to support the simulation of the decision-making processes in environments with imperfect information;

2.1 Computational intelligence

Computational Intelligence involves adaptive mechanisms to perceive and learn intelligent behaviours presented in complex and chaotic environments also possess attributes of abstraction, discovery and association [2].

Nowadays, CI has attracted more attention over the traditional artificial intelligence because the CI is tolerant of imprecise information, partial truth and uncertainty [3].

2.1.1 Adaptive system

An adaptive system is knowledge-based; it can alter functionality and interaction aspects automatically in order to achieve adequately different preferences and requirements of different users. The adaptive system must be able to adapt dynamically considering user's needs based on three elements: user, domain and adapter [4].

2.2 Fuzzy Inference Systems

The Computing using inference based on fuzzy logic is a popular method of computing. The Fuzzy Inference System (FIS) represents the primary unit of a logic system. The FIS can formulate adequate rules upon the rules the decision is made. Exists FL type-1 [5] with certain values and FL type-2 [6] with subjective values.

2.3 Agent-Based Modelling

The ABM considers behaviours that emerge from interactions of numerous autonomous agents [7]. The ABM has capabilities to address the uncertainty of the real world actions using fuzzy logic techniques [8].

2.3.1 BDI agent architecture

BDI model is an abstraction of human deliberation based on rational actions theory in the human cognition process [9]. In the BDI paradigm, agent's states are represented through three types of components: Beliefs, Desires and Intentions.

III. CHILDREN'S MUSEUM CASE STUDY

We validate our agent's model by analysing and observing in order to identify the involved elements during the learning process among learner (museum user) and educator (exhibition-module); the case study was carried out modelling scenes on interactive environments.

The Children's Museum "El Trompo" located in Tijuana, Mexico, is an excellent place for our case study, it is an interactive educational museum dedicated to children, and its primary goal is to be a place to interact and play while learning. We analysed the behaviour, actions, performance, distraction factors, interaction distance and interaction level of 500 users from 6 to 12 years old; we also analysed the interactive content type, information or services provided by the exhibitions, all this in order to create a model with agents as close to a real environment.

3.1 Exhibition module selection

After analysing different exhibition modules, we chose an interesting one with features that allow us to get the majority of the parameters to analyse in the research; the exhibition module's name is "move domain". The exhibition module simulates a virtual world to use different means of transport. The interface exhibition consists of four sub-modules: joystick sub-module to handle the plane, steering wheel and pedals sub-module to drive a car, handlebars sub-module to ride a bike and a rope sub-module to fly a balloon. Fig. 1 depicts the analysed exhibition module.

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Fig. 1: Analysed Interactive Exhibition Module

IV. MODELLING INTERACTION ON CHILDREN'S MUSEUM

We model our case study as an adaptive system, efficient and adequate to support human interaction in order to avoid distraction factors. The learner as a museum user is surrounded and helped by a context-aware environment. The model aspects are referred to operations associated to contextual sensing, contextual adaptation, contextual resources, controlling information and services considered in an automatic museum user's performance, in order to deliver adapted interactive content. Our Adaptive System Model (ASM) is composed by three different models: User Model (UM), Domain Model (DM) and Adapter Model (AM).

- User Model (UM). The UM allows the Adaptive System Model the ability to represent and distinguish between different users and act accordingly to this identification. The UM provides an effective experience interaction related to the user's context. In UM, the user's profiles are based on its interactions. The UM is composed by the User Agent (UA); this agent contains information about the user's preferences, performances, context, communication and interaction type. The UA allows user's identification relating it directly to its profile, the profile is managed and controlled considering the different user's interactions building and updating the user's profile, getting a record of user's behaviour and performance. The UA is constituted by descriptions that are considered relevant to the user, providing information (to Adapter Agent) in order to suit the environment for each user individually.

- Domain Model (DM). The DM has all information, resources and contents of the entities that compose interaction's environment. The DM allows interaction scenes among different entities as users with its context. The DM uses data of the user and aided by AA to offer content and services according to user's profiles and user's performance. The DM is composed by the Domain Agent (DA); the DA has contents, descriptions, interaction time-line, interaction type, interaction media of all the entities involved on the interaction environment. The DA is directly related with environment's resources. The DA is responsible for managing all resources and content that a user needs, result of interactions. The DA has the ability, aided by the AA, to offer multiple resources with adapted content according to the user's performance.

- Adapter Model (AM). The AM runs, adapts and controls services and contents of the interaction environment, the AM permits context awareness in different situations based on user's performance. AM is composed by Adapter Agent (AA); this entity is able to collaborate, interchange information and services with other agents (DA, UA) solving complex interactions. The AA is directly related to interaction process, and is responsible for processing all applications for users, processes services and contents based on user performance, the results of this relationship are adapted processes, offering to users all adapted processes based on the user's profile and performance. The AA applies fuzzy logic inferring rules, in order to compare situational requirements with user's properties. The AA has fuzzy perceptions in order to analyse user's performance offering the adapted data avoiding the distraction factor. Fig. 2 depict in details the adaptive model.

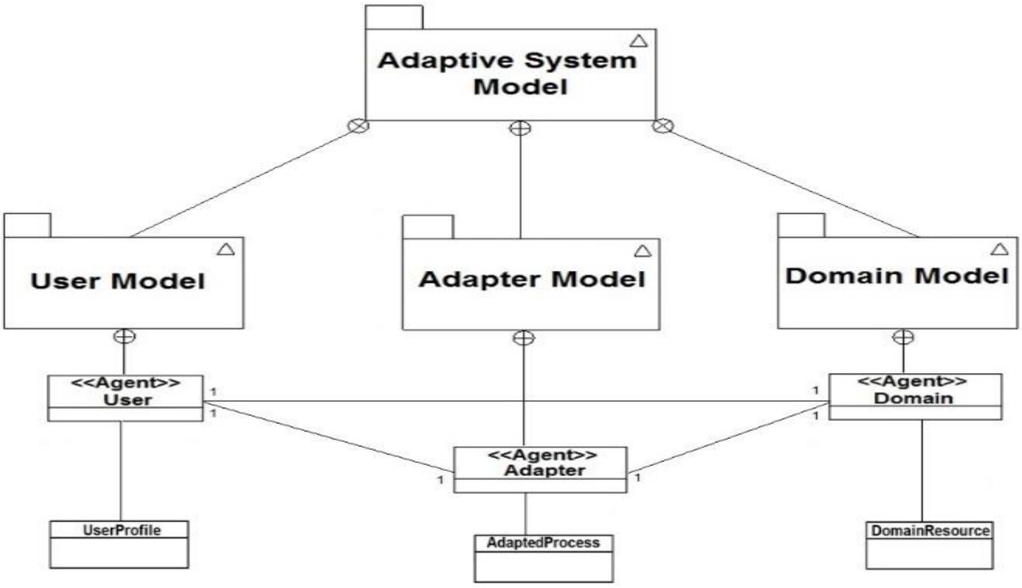

Fig. 2: Adaptive System Model

4.1 Agents Modelling

One of the reasons that motivate agent's use is because the agents are seen as entities that emulate or simulate mental processes rational behaviour, like personal assistants, where agents are entities that help users accomplish a task such as finding ways to improve the interaction through an interactive museum. The agents represent systems that interact with their environment cognitively.

In our research, we define the agents based by interactive museum elements; composed by three principal actors: museum user as User Agent (UA) “Learner”, Exhibition-module Adapter Agent (AA) “Educator” and Content Domain Agent (DA) “Information and content”.

The User Agent (UA) representing the user’s performance (distance and interaction level) is evaluated by fuzzy perceptions of Exhibition-module Adapter (AA) obtaining the adapted interactive content type, keeping the user’s interest by avoiding distraction; these agents have direct communication all the time, requesting and receiving information. Fig. 3 represents the three agents involved in learning process interaction.

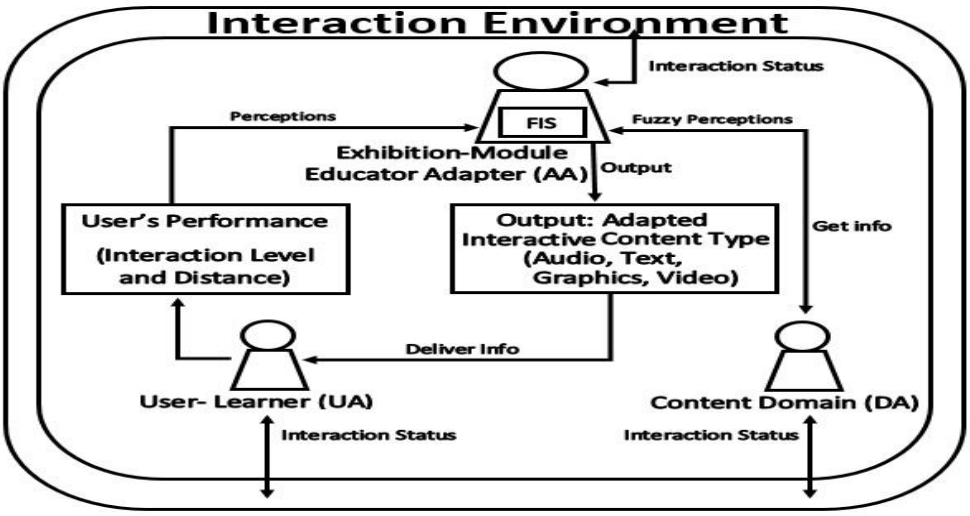

Fig. 3: Involved agents on learning process interaction

ISSN 2350-1022

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4.1.1 Formalization of BDI Agent

Formal methods are frequently used in computer science in order to verify the correctness and attended properties of the model. There are different approaches i.e., formal methods as internal specification languages to be used by the agent to reason and act and the formal methods as external meta-languages to be used by the designer to specify, design, and verify certain properties of agents.

The formalism should be used for both of these purposes; the properties of agency, an agent architecture, requires a computationally efficient internal language, while the variety of complex behaviours that an agent can exhibit, demands the language to be more expressive. In this research, we followed the BDI logic a mix of internal and external meta-language to axiomatising properties of agents, particularly in the interactions among user agent (UA) and exhibition module agent (AA).

Our formalization based in [10], this research offers an alternative, and a restricted, first order characterization of BDI agents. Firstly we defined an important element of the agent, the κ is a predicate symbol, and (τ 1 ,τ 2 ,...τ n) are terms then κ (τ 1 ,τ 2 ,...τ n) or κ(τ) or -κ(τ) are belief atoms. A belief atom and its negation are described as belief literal. A ground belief atom is named a base belief atom. For example, an user's library simulation, where there are three book stands adjacent, here the user can be in any stand, then available books appear on any book stand, and the user can choose any to take it to his study table and read it. While doing this, the user must not be in the same bookstand as the librarian because the librarian is arranging the books.

The beliefs such an agent represents the configuration of the book stand, the location of the user, the location of the librarian, book, and the study table. (i.e., adjacent (X, Y), location (user, X), location (librarian, Y), etc.).

The agent's base beliefs are instances of belief atoms (adjacent (a,b), location (user,a), location (librarian,b), etc.).

One of the activities of the agents is to be aware of the environment, and based on its observation execute some actions. The actions represent changes of the state of the environment i.e., if move is an action, the user moving from a book stand A to book stand B, written as move (A,B) this represent an action, resulting, in an environmental state where the user is in the book stand B and is no longer in book stand A.

The following is a formalism, which is defined by a representation for BDI agent.

A BDI agent is a tuple of 8 elements:

$$\Pi = < \Omega, \Gamma, \Upsilon, \Sigma, \Delta, \Phi\varepsilon, \Phi o, \Phi\iota > \quad (1)$$

where:

1. Ω is the finite set of base beliefs. Each belief is a tuple of belief atoms κ (τ1 , τ2 , … τ n).

$$\Omega i = \kappa(\tau 1, \tau 2, \ldots \tau n) \; \forall \, i = 1, 2, .. m \quad (2)$$

2. Γ is the finite set of base desires;

3. Y is the finite set of intentions. Each intention is a stack of plans to execute where ρ1 is the bottom of the stack; ρn is the top of the stack.

$$\Upsilon = < \rho 1, \rho 2, \ldots \rho n > \quad (3)$$

4. Σ is the finite set of Event, each event is a tuple $<\in, \Upsilon>$, where ∈ is a triggering event and Y is an intention. Each event can be external or internal.

5. Δ is the finite set of Actions to be executed in the environment.

$$\Delta = < \alpha 1, \alpha 2, \ldots \alpha n > \quad (4)$$

These actions may change the state of the environment.

6. Φε is the finite set of selection function, selects an event to process from the set of Σ . The event is removed from the Σ stack; if exists a relevant unifier Ξ unifies triggering events and plans to execute $< \rho 1, \rho 2, \ldots \rho n >$ and the plans are call applicable plans or options $< \rho\Lambda 1, \rho\Lambda 2, \ldots \rho\Lambda n >$

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7. Φo is the finite set of selection function, selects an option or an applicable plan, from a set of applicable plans $< \rho\Lambda 1, \rho\Lambda 2, \ldots \rho\Lambda n >$.

8. Φι is the finite set of selection function, selects an intention to execute from the set Y .

When the exhibition agent executes an intention, it executes the first goal or action of the top of the stack intention.

4.2 Fuzzy perceptions in BDI Agents

The idea to use in museum elements the paradigm BDI and fuzzy logic is to help treat uncertainty information in order to present adapted interactive content. Some utility programs have specific modules to facilitate the accomplishment of this task and provide necessary tools to conduct effective fuzzification, such as, utility JT2FIS [11], used in this research.

4.2.1 Fuzzy perceptions process

The fuzzy perceptions process impacts all museum elements, the interaction environment aided by an exhibition-module adapter agent (AA) obtains fuzzy perceptions from user's performance, this general process begins with the perceiver (χ) observation of changes in the surrounding environment; this changes can be represented as a set of indicators (ζ), every indicator can be described by set membership function values (π), the indicators (ζ) can be perceived by perceivers χ, these perceivers can sense these values and consider as inputs (interaction level and distance) of the FIS, the FIS through its inference generate the output (interactive content type), the fuzzy value resulting will be considered a belief atom κ(τ) where κ(τ) ε Ω belief set. Fig. 4 depicts in details the fuzzy perception process of exhibition-module adapter agent (AA), representing the educator in the learning process.

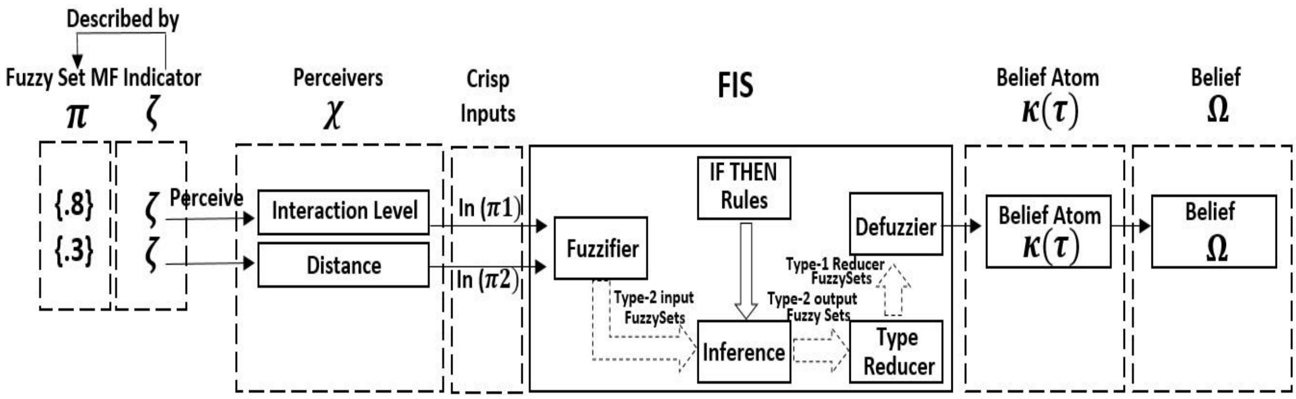

Fig. 4: Fuzzy perception process.

4.2.2 Formalization of BDI agent with fuzzy perceptions

This research seeks to advance modelling interaction on pervasive environments using fuzzy perceptions in BDI agents. The exhibition-module adapter agent (AA) has a fuzzy perception mechanism suitable to the environment. This mechanism requires fuzzy perceptions to define a fuzzy evaluation module in order to evaluate the values generated by the user. This evaluation module or fuzzy perception mechanisms must be adapted to consider the method of Mamdani fuzzy inference [12] and Jason agent-speak [13] to enable the generation of fuzzy belief relative to interaction level and distance. Otherwise, we developed a fuzzy perception for the agent based in the concept of the perception as the ability to collect data that describe a fact with some degree of truth. Then the data can be evaluated and transformed on some belief.

We developed agents for real application that often operate in complex, dynamic, and non-determinism environments. Complex environments make it hard for an agent to build or maintain a faithful model environment. The dynamic nature of environments does not allow an agent to fully control the changes in the environment, since changes can occur as a result of the actions of other agents, and exogenous influences make it impossible to predict with certainty the result of actions and future situations. Agent systems for real application using fuzzy perception thus need the capability to work in worlds with exogenous events, with other agents, and uncertain effects.

The following is a formalism, which is, defined a representation for BDI agent with fuzzy perceptions.

A BDI agent with fuzzy perceptions is a tuple of 3 elements:

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$$\Psi = < \chi, \zeta, \pi > \tag{5}$$

Where:

1. χ is the finite set of sensor from every set of sensors ($\chi \, \varepsilon \, \mathcal{F}$) can perceive ($\zeta$) signals.

2. ζ is the finite set of signals where every signals can be described as set of fuzzy membership functions (π)

3. π is the finite set of fuzzy membership functions. therefore:

$$\mathcal{F} = \{\chi 1, \chi 2, \ldots \chi n\} \tag{6}$$

$$\chi = \{\zeta 1, \zeta 2, \ldots \zeta n\} \tag{7}$$

$$\zeta = \pi = \{\nu 1, \nu 2, \ldots \nu n\} \tag{8}$$

The formalizations described helps us define the agent's base in our environment; therefore, our fuzzy perceptions are given by the following formalism.

$$\pi \rightarrow \zeta \rightarrow \chi \rightarrow \kappa(\tau) \rightarrow \Omega \tag{9}$$

Using these formalisms our agents (user and exhibition-domain), can be represented in an appropriate way, in order to be ready to work in such complex, unpredictable and no deterministic environment is to regard agent as reactive systems.

V. RESULTS

We present results from the sample of 500 museum's users analysed and observed during the learning process interaction represented by the museum users (learner) and exhibition modules (educator). The users were evaluated and processed using a custom fuzzy c-means method of data mining named Data Mined Type-2 (DMT2F) [14] included in the AA. The model's FIS is configured with 2 inputs (interaction level and distance), these inputs are composed with exact parameters considering the 500 users' performance, also is configured with 1 output (Interactive Content Type), this output is very important because it delivers the adapted interactive content type in order to avoid distractions. The table 1 depicts in details analysed users.

Table I: Results of Interactive Content Type Using the Dmt2f

Subject	Interaction Level	Distance	DMT2F Interactive Content Type
1	1.6738	0.4168	0.5553 (audio)
2	2.0087	0.3130	0.0.5451 (audio)
3	3.0073	0.6225	0.5921 (graphics)
4	4.1161	0.8769	0.7665 (video)
5	4.3935	0.3055	0.7370 (video)
6	3.8101	0.3505	0.7166 (text)
…	…	……	
500	4.3870	0.6969	0.7679 (video)

The sample results obtained were the 20% of users content type video was delivered, the 21% of users was content type audio, the 32% of users was content type text, and the 27% of users was content type graphics. We consider that audio content requires low interaction, graphics content requires medium interaction, text content requires high interaction and video content requires extremely high interaction. We conclude with this results that interactive content type text is the most adapted to interact in this kind of interactive environment, helping to avoid possible distractions factors originated by inadequate content.

VI. DISCUSSION

The user's low performance is a consequence by distraction factors during interaction, taking time to recover from it, affecting in a full distraction of interaction or abandonment by the user in the interaction. When a user is interrupted it is necessary to recall a progress made before the interrupt occurrence, but if we recall this progress with the adapted content the distraction's recovery is faster, otherwise the distraction's recovery can be slower.

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VII. CONCLUSIONS

In this research, we model and simulate with agents the learner (UA) – Educator (AA) interaction; both agents are provided with BDI approach that permits build BDI allowing mental states for reasoning. The AA uses a fuzzy logic approach to have fuzzy perception of user's performance improving interaction and avoiding distractions. We have demonstrated that we offer the adapted content type; we can complete the interaction inclusive with some distractions.

This research can be an alternative, in order to approach successful interaction during learning process representing an option to minimize or avoid distraction factors during interactions.

ACKNOWLEDGEMENT

We would like to thank to the National Council for Science and Technology of Mexico, the Autonomous University of Baja California and the Interactive Museum "El Trompo" A.C. for the support granted for this research.

REFERENCES

[1] Farias, G., Dimuro, G., & Costa, A. (2010). Bdi agents with fuzzy perception for simulating decision making in environments with imperfect information. Proceedings of the Multi-Agent Logics, Languages, and Organisations Federated Workshops, 627, 23-41.

[2] Hassaniena A, Al-Shammari E and Ghali N. Computational intelligence techniques in bioinformatics In: Computational Biology and Chemistry. Elsevier Journal, 2013, 47: 37-47

[3] Andina D, and Pham D. Computational intelligence for engineering and manufacturing. In: Springer-Verlag, eds. Berlin Heidelberg, Germany, 2007.

[4] Benyon D. Accommodating individual differences through an adaptive user interface. Presented by Alison Nichols, October 21, 1997.

[5] Zadeh L. Fuzzy sets. In: Information and Control, 1965, 8: 338--353

[6] Zadeh L. The concept of a linguistic variable and its application to approximate reasoning. In: Information Science, 1975, 8: 199--249

[7] Sokolowski J, Banks C. Principles of Modeling and Simulation: A Multidisciplinary Approach. In: John Wiley and Sons, eds, New Jersey, 2009

[8] Ramos C, Augusto J, Shapiro D. Ambient intelligence-the next step for artificial intelligence. In: IEEE Intelligent Systems, 2008, 23: 15--18

[9] Bratman M E. Intentions, Plans, and Practical Reason. In: Harvard University, eds. Cambridge, MA, 1987

[10] Rao A, George M. AgentSpeak(L): BDI agents speak out in a logical computable language. In: Walter Van de Velde and John Perram, eds. In: Proceedings of the Seventh Workshop on Modelling Autonomous Agents in a Multi-Agent World, 1996, 1038:42-55

[11] Castanon-Puga M, Castro J, Flores-Parra J, et al. JT2FIS A Java Type-2 Fuzzy Inference Systems Class Library for Building Object-Oriented Intelligent Applications. In: Advances in Soft Computing and Its Applications. Lecture Notes in Computer Science, 2013, 8266: 204-215

[12] Barros L, Bassanezi R. Topicos de Logica Fuzzy e Biomatematica. In: Universidad de Estadual de Campinas(Unicamp): IMECC, Campinas, Brazil, 2006

[13] Bordini R, Bazzan A, Jannone R, et al. Agentspeak: efficient intention selection in bdi agents via decision–theoretic task scheduling. In: New York ACM, eds. Proceedings of the first international joint conference on autonomous agents and multi–agent systems, Bologna, Italy, 2002.1294–1302

[14] Rosales R, Flores D, Palafox L et al. Representation of interaction levels using data mining and type-2 fuzzy inference system. In: Science China, 2014, under review.