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On Multi-Agent Systems Intellectics

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Abstract. This paper intends to precisiate the well-known and widespread definitions of both smart and intelligent agent (SA; IA), as well as the smart and intelligent multi-agent system (SS/II_MAS). The use of a unified and standardized agent and multi-agent system description based on definitions of the general systems theory is delivered and proposed as well. The intellectics of multi-agent systems is considered as a kind of an extension of the agent intelligence. Three typical features of human intellectual activities are proposed to be implemented and simulated in an agent/multi-agent system as the basic paradigms for agent and multi-agent system intellectics. As underlined in the paper, operation according to those paradigms (recognition and classification, behavior according to a set of fuzzy rules, and operation according to some prescribed tendency) is solidly mathematically based (correspondingly: mathematical programing, fuzzy logic and stochastic approximation). Finally, results of computerized modeling and simulation are delivered demonstrating the practical vitality and efficiency of the theoretical approach to the realization of the intelligent environment of the Internet of Things and Services (IoT&S) for user‘s comfort in two projects: "Research and Development of Internet Infrastructure for IoT& S in the Smart Environment (IDAPI)" and "Research on Smart Home Environment and Development of Intelligent Technologies (BIATech)".

Keywords: Multi-agent systems; smart agents; intelligent agents; intelligent environment; fuzzy systems.

1. Introduction, Related Work and Motivation

An agent-based approach to various engineering applications, especially to those which involve IT-enabled technologies, is very popular nowadays for two reasons. The first one – the term "agent" itself is very attractive because it appears mysterious and for this reason is suitable for the purpose of advertising new products, and it sounds scientific enough for the researcher circles. The second reason is the fuzziness of agent definitions.

Starting with encyclopaedical fundamentals of the multi-agent systems approach delivered in [1] and [7], researchers can find neither a precise definition on agent nor even a scientific concept to be used for the construction of agent definitions.

So, according to these popular definitions, an agent is an entity, a piece of software or a computer system that functions in an environment in order to meet its design objectives. And if this behavior is autonomous, the agent is called intelligent.

According to the literature [2-6], as well as [8] and [9], an agent is:

- "an entity that senses its environment and acts upon it";
- "an entity that functions continuously and autonomously in an environment in which other processes take place and other agents exist";
- "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".
- "Intelligent agent is a computer system capable of flexible autonomous actions in order to meet its design objectives".
- "Intelligent agents are software entities that carry out some set of operations on behalf of a user or another program, with some degree of independence and autonomy, and in doing so, employ some knowledge or representation of the user's goals or desires".

Such uncertainty in this field of knowledge served as a strong motivation for our research.

We are fully aware that even a mere attempt to precisiate any term is dangerous, but we will take the risk of disclosing the meaning of agent intellectics, or at least put it in a clearly understandable content and attempt to demonstrate its practicability.

Thus, the goal of this paper is threefold: 1) to present our point of view concerning the definition under discussion; 2) to deliver our ideas covering the problem of agent intelligence and 3) to show the intellectics of multi-agent systems as a kind of an extension of the agent intelligence.

Naturally, in a case of several interacting agents present we have a multi-agent system. And it must be emphasized that the intellectics of agent or multi-agent system is hidden in those two mysterious terms: “autonomous” and “design objectives”. We intend to cover those terms by putting some contemporary mathematics and soft computing modeling of three most simple features of human beings widely considered as his/her intellectual activity: 1) recognition and classification (of patterns, processes, situations); 2) behavior according to a set of fuzzy rules and 3) operation according to some prescribed tendency. We emphasize the novelty of such an approach. Roughly speaking, the models of those three activities mentioned above, from a mathematical point of view, are covered by mathematical programming, fuzzy logic and soft computing, and stochastic approximation respectively.

The last part of this paper contains results of simulations demonstrating the features of agent intellectics.

2. Definitions

It is important to note that, for example, the http://scholar.google.lt presents more than 208000 entries according to the item “computerized intelligent agent definition pdf” (2015.01.15). An existence of numerous different agent definitions found in literature suggests the necessity to unify and propose a more precise and systemic one. Here, we deliver our own system of agent definitions based on the properties of its functional organization.

So, an agent (A) is a software/hardware entity which interacts with the environment in a prescribed way and as such - inherits a functional organization based on a deterministic or stochastic (fuzzy) description of its external activity and internal operations. If an agent can act without any programming activity coming from a user, we have a smart or an intelligent agent.

When agent’s external interaction with the environment and its internal operations are based on a crisp algorithmic logic, we have a *smart agent* (SA).

When agent’s external interaction with the environment and its internal operations are based on fuzzy algorithmic logic, we have an *intelligent agent* (IA).

A set of interacting agents is usually considered as a multi-agent system (MAS).

The level of MAS intellectics depends on these types: 1) the type of agents in the MAS and 2) the type of interactions between agents in the MAS. There are four types of MAS formed from possible combinations. These types are presented in Table 1.

Table 1. MAS types

Type of interaction / Type of agent	SMART	INTELLIGENT
SA	SS_MAS	SI_MAS
IA	IS_MAS	II_MAS

Both smart and intelligent agent interaction in the MAS may be performed either in a relatively static or a dynamic way. In the case of a relatively static interaction, the graph of information flow is defined and prescribed in advance; only the timing and the content of the information flow is subjected to smart or intelligent changes. Examples of a relatively static MAS are presented in Fig. 1 and Fig. 2, where interconnected agents A_1-A_6 act upon environmental entities E_1-E_4, and agents A_1-A_{10} act upon entities E_1-E_{10}.

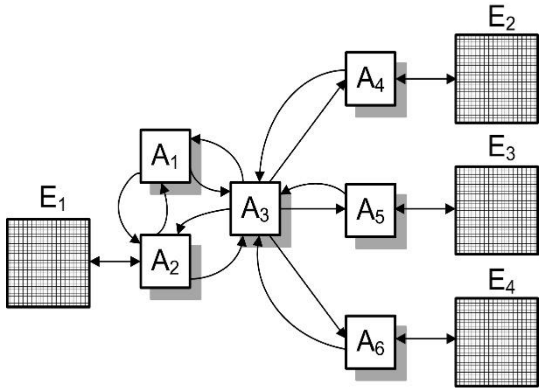

Figure 1. Specialized MAS

Here, the circles correspond to certain zones of agents’ interacting activity. The size of each zone depends on the distance between all possible pairs of agents. Here, the term “distance” is used not in a geometrical or geographical but rather in a physical way, determining the distance between situations in which the agent A_A and the agent A_B function. So, if the situation of agent A_A is described by a set of measurable characteristics a_i, i=1, …, N and the situation of agent A_B – by a set of b_i, i=1, …, N, then the Minkovski distance is

$$D_{AB} = \left(\sum_{i=1}^{N} |a_i - b_i|^p\right)^{\frac{1}{p}} \quad (1)$$

for $p \in R$ (R is a set of real numbers).

Usually, the value of p is determined by practical considerations.

If $D_{AB} > D_0$, where D_0 is a prescribed minimum accepted distance, then A_A or A_B communicates and interacts. It must be emphasized that D_0 changes intelligently according to the MAS and the environmental context.

Such an approach permits us to consider MAS as a smartly or intelligently augmented agent and to use the same general description for both entities.

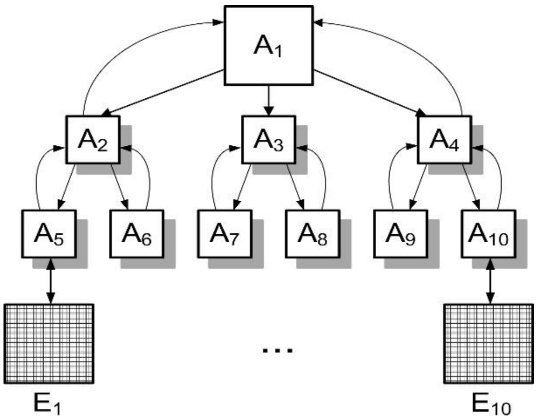

Figure 2. Hierarchical MAS

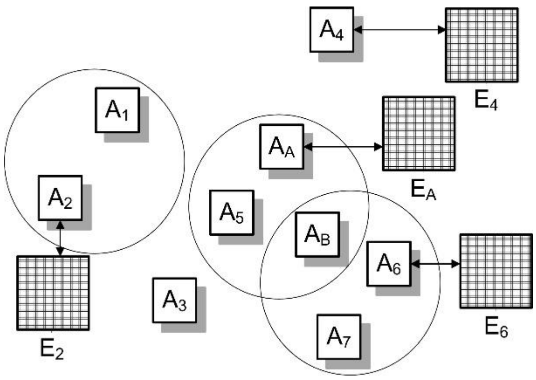

Figure 3. MAS Based On Distance and/or Context Description

3. General Description

The general description of an agent (and/or MAS) must be based on a formalized description of the general system theory. Moreover, when this formalization is performed, the fact that the contemporary agent is a space-time entity must be taken into account.

The best attempt to formalize the description of space – time dependent systems was proposed by prof. Gerhard Wunch from Dresden University in 1975 [10]. Using a similar approach, the agent A is presented by a row consisting of five sets of variables *X, K, Y, R, T* and of two functional transformations Φ, Ψ:

$$A=\{X, K, Y, R, T, \Phi, \Psi\}; \quad (2)$$

Here, X is a set of inputs I, K is a set of agent internal states S, Y is a set of agent outputs O, R is an independent space variable, and T is an independent time variable;

$$\Phi: X\times K\times R\times T\rightarrow K \quad (3)$$

and

$$\Psi: K\times R\times T\rightarrow Y \quad (4)$$

is a transformation of the internal states of the agent and a transformation of agent outputs respectively (see Fig. 4). Here we mean that all dependent variables are functions of the space and time coordinates $X(\rho, t)$ and $Y(\rho, t)$.

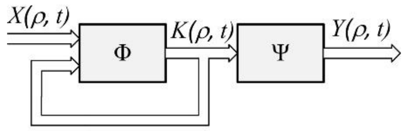

Figure 4. Transformations of Agent's (Or MAS's) Inputs and Internal States into Its Internal States and Outputs

The dimensionality of space usually depends on the problem under investigation. For example, in world financial activity we use two – dimensional space, while problems of environmental and/or marine modeling and simulation are tackled in three – dimensional space.

It must be emphasized that such an agent (or MAS) is able to represent and monitor global, real-life situations adequately only if both transformations (Φ,Ψ) are performed not only crisply but fuzzily, softly and/or using verbal computing mechanisms as well, along with a mixture of real-life variables comprising numerical, crisp, quantitative, deterministic, as well as fuzzy, verbal, qualitative, soft, stochastic, and uncertain (or even erroneous) information.

So, the intellectics of an agent (A) or a multi-agent system (MAS) is determined by the operations of variables and a logic type implemented in the transformations Φ and Ψ.

4. Φ and Ψ Intellectics

As it was mentioned in the introduction, we intend to construct the Φ and Ψ transformations (3) and (4) according to the three most simple features of human beings that are widely considered as his/her intellectual activity: 1) recognition and classification, 2) behavior according to a set of fuzzy rules, and 3) operation according to some prescribed tendency.

4.1. MAS Intellectics Based On Situation Recognition

The approach to the problem mentioned in the title is based on the theoretical considerations and practical experience delivered in [11].

Let us imagine that our environment, in order to be intellectualized, must perform a certain action p that is adequate to the situation that has arisen in the environment. Moreover, similar situations must trigger the same action. And this is the reason why we call a group of similar situations that require the p-th action as a class of situations (let's say, p-class) generated when they correspond to the p-th pattern. In the case of multiple actions (and multiple environmental situation patterns), we have $p= 1, 2, \ldots, r, \ldots, S$.

Usually, each concrete situation is described by N features numbered as $n =1, 2, \ldots, i, \ldots, N$. In the case of certain feature extraction, measurement and normalization procedures are performed [14], the i-th feature of a situation that belongs to the p-th class (corresponds to the p-th pattern) can be represented by a real number α_{pi} that expresses a degree of intensity of this particular feature. It is convenient to use a vector-row notation to describe the whole situation $\vec{\alpha}_p = (\alpha_{p1}, \alpha_{p2}, \ldots, \alpha_{pi}, \ldots, \alpha_{pN})$. If we have several situations (indexed by $l =1, 2, \ldots, k, \ldots, L$) and know in advance that they are similar according to a certain on and belong to class p (they are originated by the p-th pattern), then we can say that the situations of class p are represented by a set of vectors $\vec{\alpha}{^0}{^l_p}$ ($l =1, 2, \ldots, k, \ldots, L$).

As a rule, better reasoning results are achieved when features of situations are not only normalized but centered as well [12, 13]. It means that the whole situation is represented as a vector

$$\vec{\alpha}{^0}{^l_p} = \left(\vec{\alpha}{^0}{^l_{p1}}, \vec{\alpha}{^0}{^l_{p2}}, \ldots, \vec{\alpha}{^0}{^l_{pi}}, \ldots, \vec{\alpha}{^0}{^l_{pN}}\right) \tag{5}$$

with components calculated according to the following formula:

$$\alpha{^0}{^l_{pi}} = \alpha^l_{pi} - \frac{1}{N}\sum_{j=1}^{N} \alpha^l_{pj} \tag{6}$$

So, all available information about the patterns of situations is hidden in the set of $\vec{\alpha}{^0}{^l_p}$, for $\forall_p$, where $p = 1, 2, \ldots, r, \ldots, S$ and $l = 1, 2, \ldots, k, \ldots, L$. Now, the main task is to determine or extract the significance of the pattern's features of each situation group (let's say, group p) and to present them in a vector form known as the generalized situation's pattern (GSP)

$$\vec{K}_p = (K_{p1}, K_{p2}, \ldots, K_{pi}, \ldots, K_{pN}). \tag{7}$$

The problem can be easily solved if the corresponding linear programming problem (LPP) is formulated in the following way.

Let us select randomly one representative of the situation class p, for example $\vec{\alpha}{^0}{^k_p}$ (we will call it "central" in order to make it easier to understand). Let's say we need to find such K_{pi} for $\forall_i$ so that the measure of degree of certainty $\Phi_p\left(\vec{\alpha}{^0}{^k_p}\right)$ of belonging of the selected situation k to the pattern p would be maximum:

$$\Phi_p\left(\vec{\alpha}{^0}{^k_p}\right) = \sum_{i=1}^{N} \alpha{^0}{^k_{pi}} K_{pi} \to max \tag{8}$$

and it must be reached under the following constraints:

$$\sum_{i=1}^{N} \alpha{^0}{^l_{pi}} K_{pi} \geq \gamma \sum_{i=1}^{N} \alpha{^0}{^k_{pi}} K_{pi}\text{, for } \forall_l \tag{9}$$

and

$$\sum_{i=1}^{N} \alpha{^0}{^l_{ri}} K_{pi} \leq \kappa \sum_{i=1}^{N} \alpha{^0}{^k_{pi}} K_{pi}\text{, for } \forall_{r,\neq p} \text{ and } \forall_l . \tag{10}$$

It is recommended to choose optimal values of real numbers γ and κ from interval [0-1], and γ > κ [12]. Specific values of those coefficients depend on the experts' knowledge or guess concerning the structure (internal connections and dispersion of patterns' features) of the pattern (or class). Physical meaning of (9) is tightly connected with the understanding of "positive similarities" inside the class p. The physical meaning of (10) corresponds to the concept of dissimilarities between certain patterns of situations (in our case – the pattern of class p) and all other classes r (or "negative similarities") for $\forall_{r,\neq p}$. Even a quick overview of the problem described above shows that the problem really belongs to the class of linear programing problems (LPP) where inequalities (9) and (10) need additional constraints:

$$0 \leq \vec{K}_p \leq A \tag{11}$$

where A is any practically convenient real number, serving as maximum degree of importance and informativeness of features that describe the pattern of the p-th class of situations.

Naturally, the solution of the LPP (8)-(11) for the pattern of situations (class) p consists of the obtained value for

$$max\Phi_p(\vec{\alpha}^k_p) = \Phi_{pmax} \tag{12}$$

and the generalized pattern of situations for class p:

$$\vec{K}_p = (K_{p1}, K_{p2}, \ldots, K_{pi}, \ldots, K_{pN}). \tag{13}$$

The procedure must be repeated for all classes of situation patterns ($\forall_p$). In this way, a set of S solutions will be generated. The recognition procedure for the situation must be performed taking into account the need of fulfilling proportionality condition that guarantees the same numerical degree of certainty to the same qualitative evaluation of the situation using verbal definitions of the similarity between situations:

$$\mathrm{c_1\Phi_{1max}} = \cdots = \mathrm{c_p\Phi_{pmax}} = \ldots = \mathrm{c_S\Phi_{Smax}} = \mathrm{B} \tag{14}$$

where B and c_p are real numbers.

When the unknown situation $\vec{x}^0$ is under consideration, its degree of belonging to the pattern p can be evaluated by

$$\Phi_\mathrm{p}(\vec{\mathrm{x}}^0) = \sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{x}^0_\mathrm{i} \mathrm{K_{pi}} \text{ for } \forall_\mathrm{p} . \tag{15}$$

The maximum value can be considered as an argument for the environment's action.

A complex of such procedures enables us to construct a situation recognition instrument capable of assigning any unknown but properly described situation $\vec{x}$ to one of the possible patterns (or classes) and perform the corresponding environmental action 1, 2, …, r, …, S.

Descriptions of real situations, as well as descriptions collected from different environmental models, standards or user's requirements are usually collected in a certain data base (DB in Fig. 5(a)) and used to evaluate $\vec{K}_p = (K_{p1}, K_{p2}, \ldots, K_{pi}, \ldots, K_{pN})$ – the significance of each parameter in the description of a situation.

Evaluation is performed according to the LPP procedure described above. Obtained results are used in the structure of a generalized description of the MAS (see Fig. 4) to perform the transformation of inputs (situation's description) into agent (or MAS) internal states, as well as the transformation of its internal states into outputs that determine environment's actions (Fig. 5(b)).

4.2. MAS Intellectics Based On the Fuzzy Rules Approach

The approach to the problem mentioned in the title is based on the theoretical considerations and practical experience delivered in [13-15]. As it was stated in the previous subsection, the environment to be intellectualized will have to perform a certain action *p* which is adequate to the situation that has arisen in the environment. And as before, similar situations must trigger the same action. This similarity must be described fuzzily and the action must be performed by the MAS behaving as a certain fuzzy system.

The inference of ordinary fuzzy systems is usually based on: 1) derivation of verbal (linguistic) or parametric consequents by preprocessing lists of fuzzy rules that contain verbal or parametric antecedents connected by certain fuzzy logic operations and 2) a defuzzification process based on some compositional rule or formula.

Types of rules can be presented as follows:

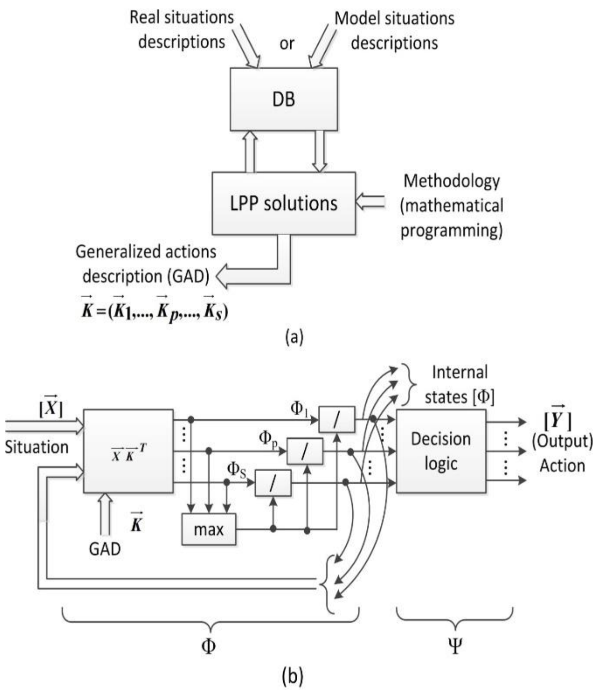

Figure 5. Functional Organization of the MAS Corresponding to the Type 1 Agents

IF x is *A* AND *y* is *B THEN z* is *C* (for Mamdani fuzzy models),

IF x is *A* AND *y* is *B THEN z=F*(*x,y*) (for Takagi-Sugeno fuzzy models).

Defuzzification procedures for the two cases mentioned above can be described as reasoning based on a set of consequents *C* using the CoG (center of gravity) or MoM (mean of maximum) methods for Mamdani type systems [14, 15], and MF (fuzzy mean) method as reasoning by evaluation of all results *z* included and processed according to the formula *F*(*x,y*) for Takagi-Sugeno systems.

A block-diagram of an ordinary fuzzy system corresponding to both cases is presented in Fig. 6.

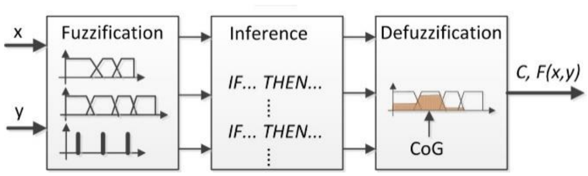

Figure 6. Ordinary Fuzzy System

As a matter of fact, the task of recognizing action's pattern, as it is noted in the introduction, belongs to the class of fuzzily described problems and requires a defuzzified answer.

Functional organization of an agent (or MAS) based on the fuzzy rules approach is delivered in Fig. 7(a) and 7(b).

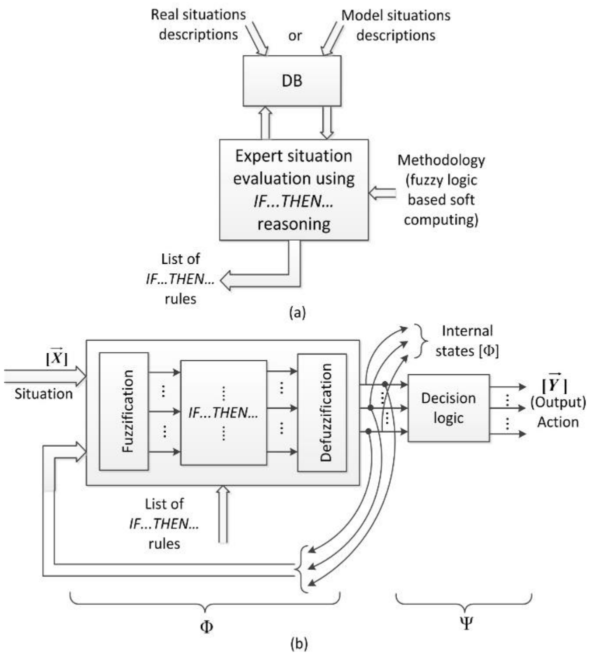

Figure 7. Functional Organization of the MAS Corresponding to the Type 2 Agents

Here, data from a DB are used to construct a list of fuzzy rules that serve as an inference engine for the transformation of inputs (situation's description) into internal states, as well as the transformation of its internal states into outputs that determine environment's actions according to the generalized description of the agent or MAS (see Fig. 4).

4.3. MAS Intellectics Based On Prescribed Behavioral Tendencies

According to our approach, MAS is able to organize a successful intellectual behavior of the environment while possessing information only on a general tendency prescribed by experts or possible users. In such case, a decentralized adaptive control process aimed at intellectualizing our environment is involved [16, 17]. The backbone of this approach is seen in a space-time extension of the well-known stochastic approximation procedure combined with computerized fuzzy verbal and perceptual reasoning [18]. The idea of extending and using the stochastic approximation procedure is evoked by the fact that each system acts according to its inherent internal potential function V(*K*,*X*). Sometimes, this function itself cannot be determined explicitly in terms of classic mathematics. Instead, we are able to measure or evaluate some decisively important characteristics of behavior $Q(K,X)$ depending on the situation that occurs in the environment. Usually, the situation requires to minimize or maximize the averages of those characteristics $\mathcal{M}\{Q(K,X)\}$ (here $\mathcal{M}$ stands for mathematical expectation). When substituting unknown potential ***V***-function for the available set of characteristics Q, it is convenient to use a certain additive or multiplicative function $\Re\{*\}$ that permits to form only one function $\Re\{Q(K,X)\}$, for example- to be minimized stochastically around a local minimum:

$$\Re\{\mathcal{M}\{\mathrm{Q(K,X)}\} \to \min. \tag{16}$$

The convergence of *K* towards a desirable state KC that can determine the environment's action as its reaction to the current situation during the process of stochastic approximation can be performed according to the gradient procedure:

$$\frac{\mathrm{dK}(\rho,\mathrm{t})}{\mathrm{d}\rho} = \Gamma_\rho(\rho,\mathrm{t})\mathrm{grad}\,\Re\{\mathrm{Q(K,X)}\} \tag{17}$$

$$\frac{\mathrm{dK}(\rho,\mathrm{t})}{\mathrm{dt}} = \Gamma_\mathrm{t}(\rho,\mathrm{t})\mathrm{grad}\,\Re\{\mathrm{Q(K,X)}\}. \tag{18}$$

This procedure can be performed by the algorithm shown in Figure 8.

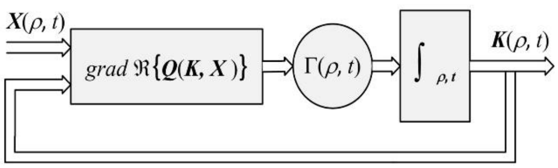

Figure 8. The Stochastic Approximation Performed According to the Space-Time Gradient Procedure

Actual implementation of all the operations of this algorithm is based on space-time integration procedures discussed and elaborated in [10, 12, 19].

It is well known [14, 18] that such a procedure converges only probabilistically:

$$P\left\{\lim_{\rho,t\to\infty}[K(\rho,t) - K_C] = 0\right\} = 1 \tag{19}$$

This convergence is shown in Fig. 9.

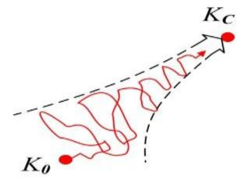

Figure 9. Probabilistic Convergence Process

The probabilistic convergence of the procedure is guaranteed under sufficient (but not necessary) requirements imposed on the functions of characteristics $Q(K,X)$ and sequences of coefficients of proportionality $\Gamma(\rho,t)$ [16, 17]: Q must vary slower than quadratic parabola, and coefficients Γ must decrease approximately according to the law Γ/n, where n is a number of iteration.

So, using these assumptions and procedures, MAS is able to adapt itself to the prescribed tendency of environment's behavior, and do so in an online fashion.

Corresponding functional organization of the agent (or MAS) based on the behavioral tendency prescription is shown in Fig. 10(a) and 10(b).

It is important to emphasize that the whole procedure of agent (or MAS) behavior converging towards a proper environmental action is realized in the online regime.

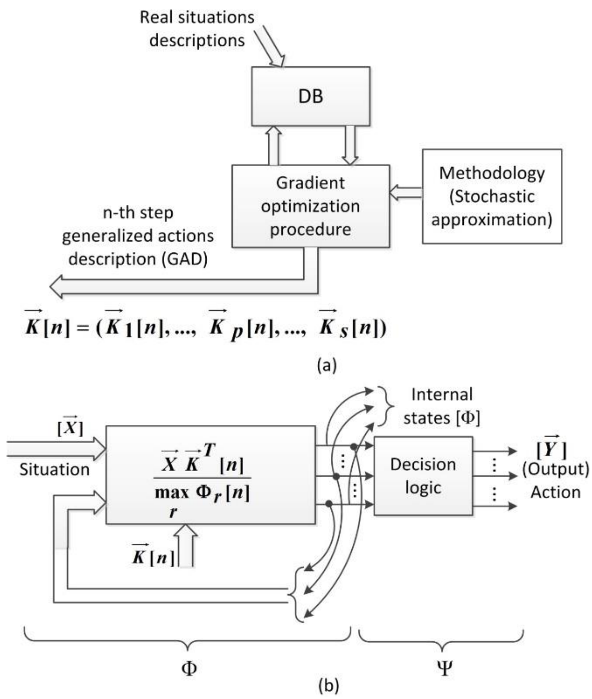

Figure 10. Functional Organization of MAS Corresponding to the Type 3 Agents

5. On Preliminary Application

This research was performed under the methodological philosophy developed according to the results of COST Action IC0702 “Combining Soft Computing Techniques and Statistical Methods to Improve Data Analysis Solutions (SOFTSTAT)”.

Different aspects of a concrete implementation and application of intellectics of the multi-agent systems (MAS) were used in two projects under support of the EU Structural Funds: 1) “Research and Development of Internet Infrastructure for IoT& S in the Smart Environment (IDAPI)“ (project VP1-3.1-ŠMM-08-K-01-018) and 2) “Research on Smart Home Environment and Development of Intelligent Technologies (BIATech)” (project VP1-3.1-ŠMM-10-V-02-020). Both projects are supervised by the Ministry of Education and Science (MES) of the Republic of Lithuania.

The main research task specified in the framework of those projects is to develop an infrastructure, its functional organization, technologies and design methodology suitable for the implementation of the Internet of Things and Services (IoT&S) environment based on MAS intellectics for the comfort of users.

In both projects, the models of functional organization of MAS were developed according to the three approaches delivered and investigated in Sections 2-4 of this paper.

Computer simulation of the modeled environment actions was performed following the approach based on MAS intellectics. Said approach is delivered in Subsections 4.1-4.3. Simplified illustrative examples to help better understand the movement actions activated by intelligent agents in the smart home environment are delivered in this Section. A virtual environment was created to test the agent decision-making. It consists of a plane made of blocks. Dimensions of the plane are 30 × 30 blocks (Fig. 11).

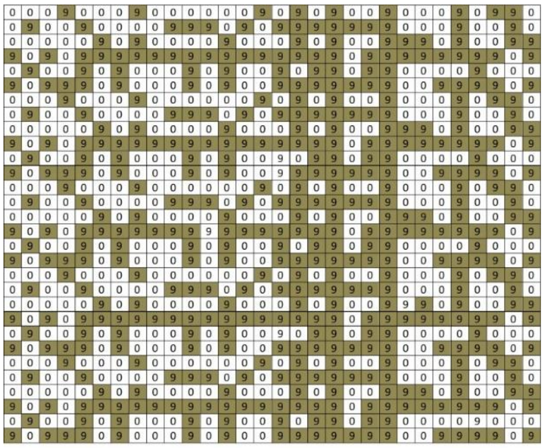

Figure 11. Generated Initial Plane

Each block has a property that we called a repulsion value. It ranges from 0 to 9. Block repulsion pattern was generated from the initial set of 20 block groups sized 3 x 3 (Fig. 12).

The initial plane can be altered with noise. The noise has a uniform distribution in the interval [0-9]. At each given moment, the agent could sense the repulsion of N = 9 blocks (square) with the agent in the center (circle) (Fig. 13). The higher the repulsion of the block, the more the agent “does not like” that block.

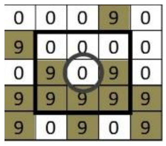

Figure 13. Environment of the Agent

There are S = 4 actions the agent can make to affect the environment: it can walk by one block to the chosen direction (left, up, right, down). Agent decision-making process was performed in three phases:

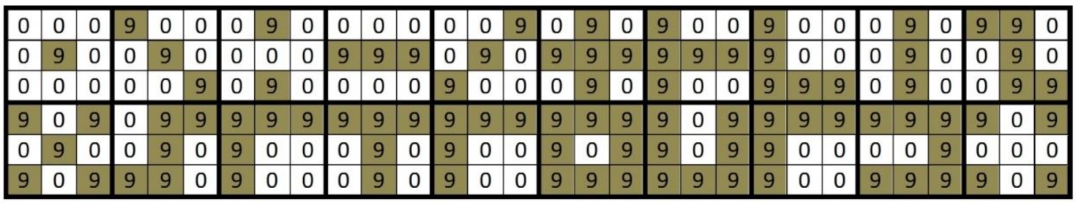

Figure 12. Initial Set of Twenty 3×3 Blocks

Table 2. LPP solutions

p	K_{p1}	K_{p2}	K_{p3}	K_{p4}	K_{p5}	K_{p6}	K_{p7}	K_{p8}	K_{p9}	Φ_{pmax}
1	9.00	6.80	2.20	0	5.30	9.00	0	4.50	7.10	50.62
2	0	0	1.00	4.00	2.00	7.00	9.00	9.00	4.00	90.00
3	9.00	5.50	0	9.00	1.20	0	7.40	3.10	0	123.26
4	6.90	7.30	7.60	9.00	3.10	9.00	0	0	3.8	109.04

1. Agent forms an opinion about the situation (Φ transformation according to (3) is performed). The result of this phase is an opinion about each direction he could go to.
2. Agent forms intentions based on its opinion. In this phase, the agent considers if it has reached the border in order to eliminate the possibility of stepping over it. The result of this phase is a list of actions the agent wants to perform.
3. Agent makes a decision based on his intentions by following these rules:

– If agent wants to perform one action – it decides to perform it;

– If agent wants to perform two or three actions (if these are to move left and right or up and down at the same time), it performs a summarized action (even a diagonal movement) and so on. The second and the third phases together form a Ψ transformation according to (4).

Finally, after deciding what to do, the agent performs an action or actions and then arrives at a new situation. Then, the process is repeated.

Three types of agents were implemented for each approach proposed in Section 4. First of all, the LPP approach was used to form the intellect. There were S = 4 situation classes, one for each action. 12 situations from the initial movement plane were selected randomly as representatives for these classes: 3 for each of the classes, one being picked as "central" (k) as it is stated in subsection 4.1. LPPs were constructed ((8) – (11) for each p) with $\gamma = 0.8$ and $\kappa = 0.2$.

Obtained solutions are shown in Table 2. The values of generalized patterns $\vec{K}_p$ and Φ_{pmax} were used for the type 1 agent.

Fuzzy rules according to Subsection 4.2 were used to form the intellectics of the type 2 agent. jFuzzyLogic library was used [20, 21]. First of all, linguistic variables were defined for input and output variables. There were 9 input variables for each block the agent sensed, and 4 output variables for each action.

Fuzzy rules were created to evaluate the situation. Because jFuzzyLogic library was used, the rules were defined by FCL [22]. The list of those 11 rules is presented below:

```
RULEBLOCK blockUp
      AND : MIN;
        ACT : MIN;
        ACCU : MAX;
        RULE 0 : IF x0 IS low AND x3 IS low AND x6 IS low THEN LEFT IS high;
        RULE 1 : IF (x0 IS low AND x3 IS low AND x6 IS high) OR (x0 IS low AND x3 IS high AND x6
IS low) OR (x0 IS high AND x3 IS low AND x6 IS low) THEN LEFT IS mid;
        RULE 2 : IF (x0 IS low AND x3 IS high AND x6 IS high) OR (x0 IS high AND x3 IS low AND x6
IS high) OR (x0 IS high AND x3 IS high AND x6 IS low) THEN LEFT IS low;
        RULE 3 : IF x0 IS low AND x1 IS low AND x2 IS low THEN UP IS high;
        RULE 4 : IF (x0 IS low AND x1 IS low AND x2 IS high) OR (x0 IS low AND x1 IS high AND x2
IS low) OR (x0 IS high AND x1 IS low AND x2 IS low) THEN UP IS mid;
        RULE 5 : IF (x0 IS low AND x1 IS high AND x2 IS high) OR (x0 IS high AND x1 IS low AND x2
IS high) OR (x0 IS high AND x1 IS high AND x2 IS low) THEN UP IS low;
        RULE 6 : IF x2 IS low AND x5 IS low AND x8 IS low THEN RIGHT IS high;
        RULE 7 : IF (x2 IS low AND x5 IS low AND x8 IS high) OR (x2 IS low AND x5 IS high AND x8
IS low) OR (x2 IS high AND x5 IS low AND x8 IS low) THEN RIGHT IS mid;
        RULE 8 : IF (x2 IS low AND x5 IS high AND x8 IS high) OR (x2 IS high AND x5 IS low AND x8
IS high) OR (x2 IS high AND x5 IS high AND x8 IS low) THEN RIGHT IS low;
        RULE 9 : IF x6 IS low AND x7 IS low AND x8 IS low THEN DOWN IS high;
        RULE 10 : IF (x6 IS low AND x7 IS low AND x8 IS high) OR (x6 IS low AND x7 IS high AND x8
IS low) OR (x6 IS high AND x7 IS low AND x8 IS low) THEN DOWN IS mid;
        RULE 11 : IF (x6 IS low AND x7 IS high AND x8 IS high) OR (x6 IS high AND x7 IS low AND x8
IS high) OR (x6 IS high AND x7 IS high AND x8 IS low) THEN DOWN IS low;
        END_RULEBLOCK
```

A method capable of achieving a prescribed behavioral tendency proposed in Subsection 4.3 and based on the stochastic approximation approach was used to form the intellectics of the type 3 agent. The behavioral tendency was constructed in the following form:

$$\Re\{-\mathcal{M}_1\{Q_1(K,X)\} + \mathcal{M}_2\{Q_2(K,X)\} - \mathcal{M}_3\{Q_3(K,X)\} - \mathcal{M}_4\{Q_4(K,X)\}\} \to \min. \quad (20)$$

It means that four partial behavior types were constructed for each action. Important characteristics for each partial behavior were selected from the area that the agent sensed (Table 3):

Since agent learning (or self-training) is performed online, two implementations of opinion phase logic were made for the agent of this type. One was for learning, and the other was for an already known internal state K that has been formed when learning online.

All implemented agents (agents of three types) were put to different tests. Agents of the first and second type were tested by going through the following steps:

Table 3. Description of Partial Actions

Behavior	Mathematical representation	Visual presentation
Left	$Q_1(\vec{K},\vec{X}) = x_0k_0 + x_3k_3 + x_6k_6$	0 9 0 9 9 0 9 0 0
Up	$Q_2(\vec{K},\vec{X}) = x_0k_0 + x_1k_1 + x_2k_2$	0 9 0 9 9 0 9 0 0
Right	$Q_3(\vec{K},\vec{X}) = x_2k_2 + x_5k_5 + x_8k_8$	0 9 0 9 9 0 9 0 0
Down	$Q_4(\vec{K},\vec{X}) = x_6k_6 + x_7k_7 + x_8k_8$	0 9 0 9 9 0 9 0 0

1. Agent was forced to perform an action sequence containing 100 actions in the initial environment. These action sequences were recorded.
2. Noise was applied and the agent performed another action sequence of the same length. This was repeated for every noise level. Each sequence was recorded.
2. Performance was evaluated by comparing the action sequence with the initial one in a noisy environment. The comparison of these actions has shown the reliability of agent training; it means that to some degree the agent is noise -proof.
4. First three steps were performed 10,000 times, with a random starting position of the agent each time. Performance results were summed up and divided by the run count. In this way, the average agent performance was calculated.

An example of one run of the type 1 agent is shown in Fig. 14(a).

Performance results show that even though the choices an agent makes degrade with higher noise level, it still makes similar choices in 30% of cases:

Noise	1	2	3	4	5	6	7	8	9
Result	38.7	35.6	32.0	31.0	30.4	30.0	29.6	29.2	27.8

Examples of the movement paths for one run taken by the type 2 agent, show that it constantly gets stuck in a movement loop between a few tiles of the environment (Fig. 14 (b)). This, however, does not mean that the agent is acting wrong. Its actions are merely consequences of a situation he got himself into, and for him they are always the right thing to do.

The performance of the type 2 agent is more or less the same as of the first one:

Noise	1	2	3	4	5	6	7	8	9
Result	35.3	34.2	34.9	32.5	30.6	29.8	26.3	28.0	28.2

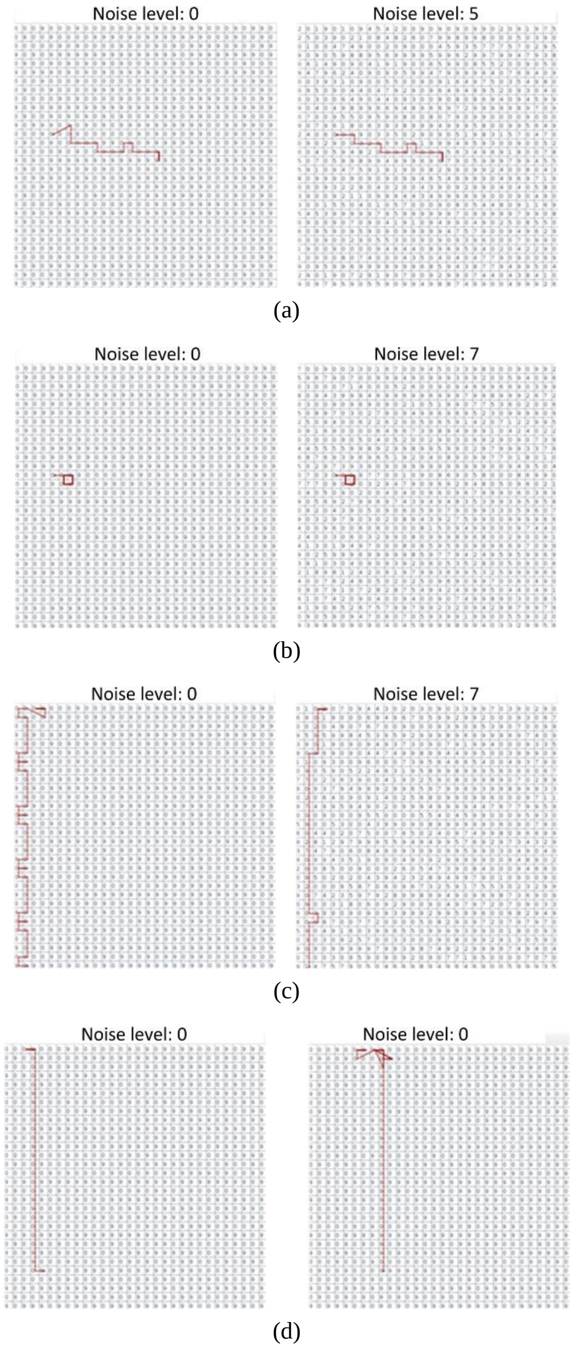

Figure 14. Examples of testing runs performed by agents of the type 1, 2 and 3 subjected to different noise level

A comparison of the performance of agents in a graphical form is presented in Fig. 15.

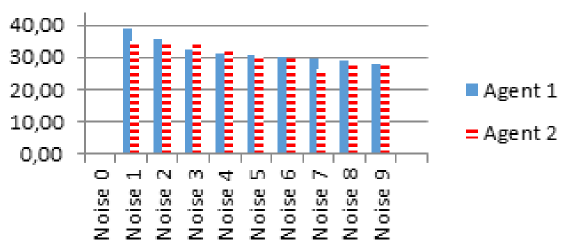

Figure 15. Performance comparison of the Agents

For the type 3 agent, the tendency to "move up" was formulated. The movement paths of the third agent (Fig. 14 (c)) show that it develops a tendency to move up successfully, but, after reaching the top, often gets stuck in two blocks.

5. After the online self-training was performed, the type 3 agent, now possessing a newly-gained knowledge, was put in random places on the initial field. The examples of its behavior after the self-training process (Fig. 14 (d)) show relatively good (or even excellent) performance results.

6. Final Remarks

After summarizing the theoretical and experimental research results, we can state that:

- the well-known and widely spread definitions of the smart and intelligent agent (SA; IA), as well as the smart and intelligent multi-agent system (SS/II_MAS) were precisiated;
- the use of a unified and standardized agent/multi-agent system description based on the definitions of the general systems theory was delivered;
- three typical features of human intellectual activities were proposed to be implemented and simulated in the agent/multi-agent system as basic paradigms for the intellectics of agent and multi-agent systems; it must be underlined that operation according to those paradigms (recognition and classification, behavior according to a set of fuzzy rules, and operation according to some prescribed tendency) is solidly mathematically based (correspondingly: mathematical programing, fuzzy logic and stochastic approximation);
- results of computerized modeling and simulation have demonstrated the practical vitality and efficiency of the theoretical approach for the realization of an intelligent environment of IoT&S for user's comfort;
- a lot of technical and social problems still remain and need to be solved in order to successfully implement a user-friendly environment based on the intellectics of multi-agent systems; some of them are still being researched and will serve as authors' investments in further publications

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