A Conceptual Generalized Nets Immunological Model for Agent based Exploration of Unknown Environment

Zlatogor Minchev[1*], Dimitar Dimitrov[2]

[1] *Institute for Parallel Processing/Institute of Mathematics & Informatics*
Bulgarian Academy of Sciences
25[A] Acad. G. Bonchev Str., room 116, 1113 Sofia, Bulgaria
E-mail: zlatogor@bas.bg

[2] *Technical University of Sofia, Faculty of Automation*
8 Kl. Ohridski Blvd., Bl. 2, room 2350, 1000 Sofia, Bulgaria
E-mail: dean.fa@tu-sofia.bg

[*] *Corresponding author*

Received: January 15, 2010 **Accepted: March 12, 2010**

Published: April 15, 2010

Abstract: *Exploration of unknown environment in general is a very broad area, which in the current paper is addressed more to the agent based idea and robotics. As far as the agent and its further development – multiagent modus resembles real social systems the interaction between agents could benefit from the natural mechanisms like immune system. The paper presents a conceptual model for exploration of unknown environment, which extends the immune networks' idea with some self-immunization by means of dynamic anti-body generation with application both in mobile and i-mobile robotics (Smart Homes) modeling and control, maintaining practical benefits like energy saving. The model is described in terms of the Generalized Nets Theory, thus providing a convenient and natural environment for agent-based modeling.*

Keywords: *Generalized nets, Artificial immune networks, Agents, Multiagent systems, Exploration, Unknown environment, Smart Homes, Energy saving.*

Introduction

The unknown environment exploration and path-planning tasks have always been interesting for Artificial Intelligence and Robotics [13, 35]. Naturally, the broad meaning of this notion could be rather different, so in the present paper we basically address to mobile agents and hazardous places exploration either on the Earth, or in other planets in the Space where a complete or enough accurate map and GPS navigation is not available or not applicable, so the heuristic solutions are preferable.

Another interesting field for exploration are the i-mobile robots (Smart Homes) where an environment, which is capable to react "intelligently" by predicting and taking autonomous decisions, is presumed. However in Smart Homes the uncertainty is also considered to be important by means of different task decision, including energy saving [10, 16].

Generally, it should be noted that the notion "Smart Homes" supposes an environment, which is capable to react "intelligently" by predicting and taking autonomous decisions. From a computational perspective there is a natural association between such expected functionality and the uncertainty coping.

In Smart Homes the robots could create Building Information Models (BIM) – raster scans of building interiors that include the walls as well as all the building contents. As soon as the BIM are built, mobile robots can drive autonomously in the space and may be used in tasks like: emergency response and architecture verification. Since the robot knows where it is, it can monitor any sensor readings and actions in time and space. For example, robots can scan the interior of a building; take temperature readings and thus facilities the control of energy consumption. The kiosk-style robots can guide visitors during the day, handles security at night etc.

Being on the network, robots can interact with electronic doors, elevators and access control systems. They can also notify the building control system if they encounter conditions that require immediate action. Most of the autonomous robots can perform multiple functions simultaneously.

BIM can also be integrated with Geographical Information Systems (GIS) for providing of local and global information on the performance of facility assets inside and outside of buildings

As far as the solution of these tasks practically requires resources, which could be non-retrievable in some cases, and in other require dynamics specialization, the ideas for self-healing and multiagent based approaches could emerged for applicability [6, 20, 38].

Naturally, these ideas open a vast field for research in the Artificial Intelligence (AI) area during the last several decades and presented ideas like: “artificial life”, “multiagent systems”, “distributed problem solving” and many others [35], which of course are only a mere reflection of the real world but at the same time have given a good model-based approach for research in the area of unknown environment exploration with robots, i.e. a peculiar solution for practical validation and correction of the developed models with real application apart of the “in silico” computer simulations.

The agent based approach for modeling and its hardware projection in robotics for solving the task of unknown or partially known environment exploration, could be investigated from many projections. In fact this approach resembles the natural living creatures’ mechanisms for common existence in: swarms, schools, flocks, packs, colonies and even societies by using organizational approaches like: prominence and negotiations [38].

So the nature of agent and multiagent based modeling could allow a native inclusion of immunology and immune networks [7-9, 11, 12, 14, 15, 17-19, 21, 31, 34, 39, 40] by means of modeling of different mechanisms like: self-healing, self-immunization, natural distribution and internal/external environment communication.

This in fact allows a goal-oriented projection of the real world complexity by means of General System Theory (GST) [5] and a reasonable attempt for usages of natural experience in coping with artificially generated problems/solutions (like AI and robots), imposed back to nature (like unknown environment navigation/exploration). Here it should be noted that GST in its multiagent context could mathematically implement the Non-linear Dynamics [32, 33] but in this case, it is not able to completely explain and in general to control the developed systems’ instability and uncertainty. In fact this approach allows only limited solution for preliminary defined boundary conditions and in the rest of interesting situations refers to statistical methods. This however gives a quite narrow model application, which could be heuristically extended with the help of immune networks inclusion in the agent/multiagent based modeling and Entity-Relationship machine interpretation with Generalized Petri Nets [2] (or just Generalized Nets – GNs), which for more then 25 years have been developed as a theory with a lot of interdisciplinary applications [1, 4] including agent based modeling and robotics [24-29].

The present paper will demonstrate a conceptual GN model for agent-based exploration of unknown environment that implements the multiagent based modeling concept and immune networks inclusion in the agents' behavior and intelligence.

Related work

The unknown environment exploration with agents and robots is discussed in details in [29]. Apart of this mobile and i-mobile robotics (Smart Homes) suppose an environment, which is capable to react "intelligently" under uncertainty [10, 16]. Here it would be briefly noted that generally this process could be realized with many different approaches like: dead-reckoning, GPS, GIS, maps usage and building, referred to SLAM problem solving, Kalman filtering, path-planning algorithms development, grid-worlds studying and even random search. However the most fundamental difference is the information for the environment in itself, i.e. the exploration of the unknown environment under different uncertainty, which practically is the key problem in general. Regarding this the uncertainty in itself could be coped in different ways: fuzzy sets [42], intuitionistic fuzzy sets and other fuzzy sets modifications [3], probabilities and statistics, Non-liner Dynamics and its measures [32], Belief Networks, non-probabilistic and paradoxical reasoning, etc. [35-37]. What however is addressing in detail the current paper are the publications which utilize a reflexive behavior of agents [7, 21, 24, 40].

The new element, which the authors want to note in the present paper, is related to the immune mechanism implemented in their agents. Similar to [40] the present idea is assuming an agent-based approach, which also includes a modified artificial immune networks' approach described in GN terms.

In the next paragraph a few remarks on the artificial immune networks will be given.

Materials and methods

Short remarks on immune networks

According to [34] the role of the immune system for high-order multicellular living organisms is protection from foreign substances such as viruses, bacteria, other parasites and mutated own cells generalized under the notion "antigens". The body identifies invading antigens through two inter-related systems: the innate immune system and the adaptive immune system. A major difference between these two systems is that adaptive cells are more antigen-specific and have greater memory capacity than innate cells. Both systems depend upon the activity of white blood cells where the innate immunity is mediated mainly by phagocytes, and the adaptive immunity is mediated by lymphocytes.

Phagocytes possess the capability of ingesting and digesting several microorganisms and antigenic particles on contact. The adaptive immune system uses lymphocytes that can quickly change in order to destroy antigens that have entered the bloodstream.

Lymphocytes are responsible for the recognition and elimination of the antigens. They usually become active when there is some kind of interaction with an antigenic stimulus leading to the activation and proliferation of the lymphocytes. Two main types of lymphocytes, namely

B-cells and T-cells, play a remarkable role in both immunities. When an antigen (a foreign body) invades the human body, only a few of these immune cells can recognize the invader.

As far as the complete mechanisms of work in the living creatures immune system are much more complicated and probably not completely studied yet, in the present paper we have adopted the idea of "artificial immune systems", [11, 15, 39] which have many interesting applications [12] and is suitable enough for our further considerations.

The idiotypic network hypothesis, assumed here was proposed in [19] and is based on the concept that lymphocytes are not isolated, but communicate with each other through interaction among antibodies. B-lymphocytes have specific chemical structure and produce "Y" shaped antibodies. The antibody recognizes an antigen like a key and lock relationship. According to [18] the structure of the antigen and the antibody could be represented in the way shown on Fig. 1, where the part of the antigen recognized by the antibody is called "epitope", and the part of the antibody that recognizes the corresponding antigen determinant is called "paratope". The antigenic characteristic of the antibody is called "idiotope". Antibodies stimulate and suppress each other by the idiotope-paratope connections and thus form a large-scaled network. The idiotypic network theory is usually modeled with differential equations simulating the dynamics of lymphocytes [14].

In the field of AI and especially in robotics a dynamic decentralized behavior arbitration mechanism based on immune networks was developed for collision-free goal following behavior and a garbage-collecting problem [17, 40, 41].

In this approach the "intelligence" is expected to emerge from interactions among agents (competence modules) and between the agent (robot) and its environment.

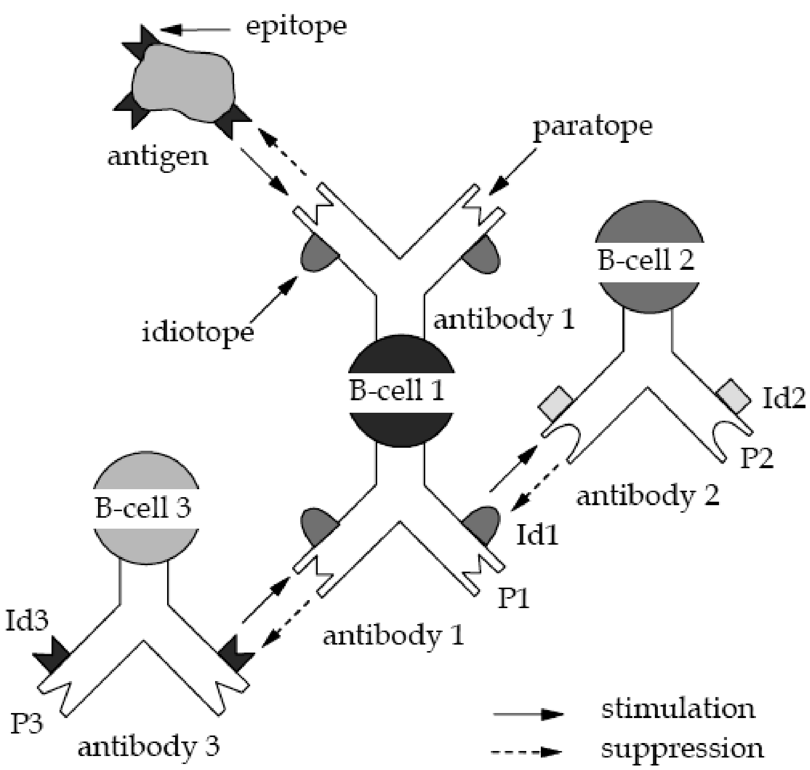

Fig. 1 Structure of an artificial immune network after [18]

Some examples of artificial immune systems applications are, e.g. the dynamic antibody selection mechanisms and the artificial immune navigation and system identification [9, 39-41].

Both applications however suffer from generalization because of the differential equations mathematical model usage in determining of the antibodies concentration dynamics. The proposed solution in the present paper is more general, but heuristic and assumes a logical process modeling with Generalized Nets Theory.

In the next paragraph, short remarks on GNs Theory will be given.

Short remarks on Generalized Nets theory

Generalized Petri Nets Theory (or just Generalized Nets Theory), has been developed and tested for more then 25 years. GNs are flexible and convenient tool for description, modeling and simulation of different areas of our everyday life, including Artificial Intelligence [1, 2, 4, 13, 35]. Compared to Petri Nets, GNs offer more suitable modeling environment by means of deadlock situation break and knowledge representation power. The key reason for this is the Entity-Relationship (E-R) paradigm used in GNs knowledge representation, which strongly contrasts with the Petri Nets hierarchical organization.

The basic building elements of GNs are: transitions, places, tokens and predicate matrices. The full family of symbols and signatures utilized in GNs could be found in [2]. In this paper we have selected the reduced GNs, so the model uses three main symbolic notations: the Latin letter Z (denotes a transition) followed by an Arabic number, that indexes this transition, (e.g. Z_1 or $Z_{1,i}$, for the first or for the $i^{\text{-th}}$ transition in the GN, where: i is a natural number, i.e. $i \in \mathbf{N}$), the Latin letter l (denotes an input or output place in accordance with its position: left – input place, right – output place), also followed by an index (e.g. l_i, for the the $i^{\text{-th}}$ place in the GN, $i \in$ N) and the indexed Latin letter r (e.g. r_i for the $i^{\text{-th}}$ matrix in the GN, $i \in \mathbf{N}$), which denotes the predicate matrix of a transition. The links between the transitions are based on the notion that input places of one transition could be output places of another or vice versa. The main idea of GNs work is to move virtual tokens among the net (from input to output places or sometimes vice versa), satisfying the conditions of the predicate matrices of the included in the net transitions and keeping track of the obtained tokens' characteristics.

The conceptual Generalized Nets immunological model for agent-based exploration of unknown environment

In this section the conceptual Generalized Nets immunological model for agent-based exploration of unknown environment (or briefly – conceptual immune GN model) will be described in GNs' terms. The model is depicted in Fig. 2.

Model idea

As it is clear from Fig. 2 the conceptual immune GN model consists of several transitions denoted as follows: $Z_{1,i}$ (i = 1, 2, …, n, $n \in \mathbf{N}$), that represent the preliminary available agent's antibodies, according to the idiotypic network model [19], however the transition Z_2 makes the difference in our model, representing a immune brain stem module, which is capable to gather information from the antibodies in accordance with their reaction to the external antigens (which in the present case are simple external environment characteristics like: light, radiation, temperature, humidity, other detectable objects' proximity, etc.)

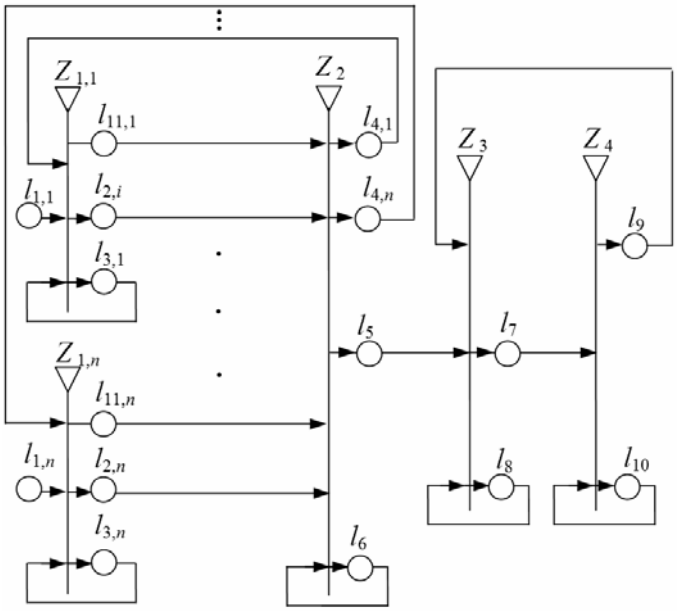

Fig. 2 The conceptual Generalized Net immunological model for agent-based exploration of unknown environment

This immune brain stem is responsible for antibodies $Z_{1,i}$ information history, update and further delivering to the agent's controller (Z_3) and effectors (Z_4) elements. Here it should be noted that there is a key difference in our model from the idiotypic network ones, because the present one is providing dynamics for both information fusion and antibodies evolution emerging into a hybrid combination of initial phagocytes based innate immune system and an adaptive immune system realized on the basis of multiagent based antibodies controlled with prominence from a immune brain stem module, which is able to self-immunize the model from new unknown external antigens.

Model elements

Transition $Z_{1,i}$ ($i = 1, 2, ..., n$, $n \in \mathbf{N}$) has the following structure:

$$Z_{1,i} = \langle \{l_{1,i}, l_{4,i}, l_{3,i}\}, \{l_{2,i}, l_{3,i}, l_{11,i}\}, r_{1,i}, \wedge (l_{1,i}, l_{3,i})\rangle,$$

where

$$r_{1,i} = \begin{array}{c|ccc} & l_{2,i} & l_{3,i} & l_{11,i} \\ \hline l_{1,i} & false & W_{1,i,3,i} & false \\ l_{4,i} & false & W_{4,i,3,i} & false \\ l_{3,i} & W_{3,i,2,i} & true & W_{3,i,11,i} \end{array}$$

and

$W_{1,i,3,i}$ = "there is an external antigen influence to the agent";
$W_{3,i,2,i}$ = "$X_1^{\alpha_{1,i}} = X_0^{\alpha_{2,i}}$";
$W_{3,i,11,i} = \neg W_{3,i,2,i}$;
$W_{4,i,3,i}$ = "tokens $\alpha_{1,i}$ are in places $l_{4,i}$";
$W_{6,4,i}$ = "antibody $Z_{1,i}$ code supplement is available".

Transition Z_2 has the following structure:

$$Z_2 = \langle \{l_{2,i}, l_{11,i}, l_6\}, \{l_{4,i}, l_5, l_6\}, r_2, \vee (l_{2,i}, l_{11,i}, l_6) \rangle,$$

where

$$r_2 = \begin{array}{c|ccc} & l_{4,i} & l_5 & l_6 \\ \hline l_{2,i} & false & false & W_{2,i,6} \\ l_{11,i} & false & false & W_{11,i,6} \\ l_6 & W_{6,4,i} & W_{6,5} & true \end{array}$$

and

$W_{2,i,6}$ = "tokens $\alpha_{1,i}$ are in place $l_{2,i}$";
$W_{11,i,6} = \neg W_{2,i,6}$;
$W_{6,4,i}$ = "antibody $Z_{1,i}$ code supplement is available";
$W_{6,5} = \neg W_{6,4,i}$.

Transition Z_3 has the following structure:

$$Z_3 = \langle \{l_5, l_8, l_9\}, \{l_7, l_8\}, r_3, \vee (l_5, l_8) \rangle,$$

where

$$r_3 = \begin{array}{c|cc} & l_7 & l_8 \\ \hline l_5 & false & W_{5,8} \\ l_8 & W_{8,7} & true \\ l_9 & false & W_{9,8} \end{array}$$

and

$W_{5,8}$ = "token α_3 is in place l_5";
$W_{8,7}$ = "token δ_1 is in place l_8";
$W_{9,8}$ = "token δ_1 is in place l_9".

Transition Z_4 has the following structure:

$$Z_4 = \langle \{l_7, l_{10}\}, \{l_9, l_{10}\}, r_4, \vee (l_7, l_{10}) \rangle,$$

where

$$r_4 = \begin{array}{c|cc} & l_9 & l_{10} \\ \hline l_7 & false & W_{7,10} \\ l_{10} & W_{10,9} & true \end{array}$$

and

$W_{7,10} = W_{7,10}$ = "$X_0^{\varepsilon} \neq X_0^{\delta_1}$";
$W_{10,9}$ = "$X_1^{\varepsilon} \neq X_0^{\delta_1}$".

Model work

The presented conceptual Generalized Nets immunological model for agent-based exploration of unknown environment work is demonstrated into six steps (defining one loop from the model work), reiterating this steps after the end of Step 6, again from Step 1 and assuming that during the new iteration, tokens which are entering the model are united with the existing ones from the previous loop and keeping the loop history in the new tokens characteristics.

Step 1: Tokens $\alpha_{1,i}$ enter places $l_{1,i}$ (i = 1, 2, …, n, $n \in \mathbf{N}$) with initial characteristics $X_0^{\alpha_{1,i}}$ = "external antigen code"; tokens $\alpha_{2,i}$ enter places $l_{3,i}$ with initial characteristics $X_0^{\alpha_{2,i}}$ = "antibody $Z_{1,i}$ code"; token β enters place l_6 with initial characteristic X_0^{β} = "agent's known antibodies codes"; token δ enters place l_8 with initial characteristic X_0^{δ} = "agent's controller initial status" and token ε enter place l_{10} with initial characteristic X_0^{ε} = "agent's effectors initial status".

Step 2: Tokens $\alpha_{1,i}$ enter places $l_{3,i}$ if $W_{1,i,3,i}$ = "there is an external antigen influence to the agent" is true, $X_1^{\alpha_{1,i}} = X_0^{\alpha_{1,i}}$; token δ is divided into two tokens: δ (stays at place l_8) and δ_1, enters place l_7 with new characteristic $X_0^{\delta_1}$ = "agent's effectors desired status" if $W_{8,7}$ = "token δ_1 is in place l_8" is true.

Step 3: Tokens $\alpha_{1,i}$ enter places $l_{2,i}$ if $W_{3,i,2,i}$ = "$X_1^{\alpha_{1,i}} = X_0^{\alpha_{2,i}}$" is true otherwise they enter places $l_{11,i}$ if $W_{3,i,11,i} = \neg W_{3,i,2,i}$; token δ_1 enters place l_{10} if $W_{7,10}$ = "$X_0^{\varepsilon} \neq X_0^{\delta_1}$" is true; X_1^{ε} = "agent's effectors current status".

Step 4: Tokens $\alpha_{1,i}$ from place $l_{2,i}$ enter place l_6 if $W_{2,i,6}$ = "tokens $\alpha_{1,i}$ are in place $l_{2,i}$" is true, otherwise, on this step, tokens $\alpha_{1,i}$ from $l_{11,i}$ enter place l_6 if $W_{11,i,6} = \neg W_{2,i,6}$ and token β obtains the new characteristic X_1^{β} = "updated agent's known antibodies codes"; token δ_1 enters place l_9 if $W_{10,9}$ = "$X_1^{\varepsilon} \neq X_0^{\delta_1}$" is true; $X_1^{\delta_1}$ = "agent's effectors current/desired status difference".

Step 5: Tokens $\alpha_{1,i}$ enter place $l_{4,i}$ if $W_{6,4,i}$ = "antibody $Z_{1,i}$ code supplement is available" is true, otherwise they unite into token α_3 and enter place l_5 if $W_{6,5} = \neg W_{6,4,i}$ is true, $X_0^{\alpha_3}$ = "agent's controller new status"; token δ_1 enters place l_8 if $W_{9,8}$ = "token δ_1 is in place l_9" is true, $X_1^{\delta_1}$ = "agent's effectors current status".

Step 6: Token α_3 enters place l_8 if $W_{5,8}$ = "token α_3 is in place l_5", $X_1^{\alpha_3}$ = "agent's controller new status"; tokens $\alpha_{1,i}$ enters places $l_{3,i}$ where they unite with tokens $\alpha_{2,i}$, giving them new characteristic $X_1^{\alpha_{2,i}}$ = "antibody $Z_{1,i}$ updated code" if $W_{4,i,3,i}$ = "tokens $\alpha_{1,i}$ are in places $l_{4,i}$" is true.

Discussion

The revealed in the present paper "Conceptual Generalized Nets Immunological Model for Agent based Exploration of Unknown Environment" is an ad-hoc principal approach for exploration of unknown environment, which extends the immune network idea with some self-immunization by means of dynamic anti-body generation based on centralized multiagents concepts for control.

As far as the predicates used in the present model are coping with uncertainty by means of measuring differences between antigens, antibodies and effector states an implementation of fuzzy sets and intuitionistic fuzzy sets is also applicable by means of their evaluation [2, 3]. Additionally, the flexiblily of GNs allows easy model modifications via operators [2] and the inclusion of already existing GN models (see e.g. [24-29]) for augmenting the present model capabilities and utilization of the miultiagent based approach, which in fact, combined with the uncertainty coping (see e.g. [22, 23, 30]) produce a powerful heuristic modeling environment based on GNs and nature immunology principles [34].

The authors' future plans for development are related to practical implementations in both mobile and i-mobile robotics (Smart Homes) GN models for resources control (like energy, water, light, etc.), uncertainty coping and immune networks.

Acknowledgements

The study was supported by National Science Fund – Bulgarian Ministry of Education, Youth and Science – Project DTK 02/1,2009. We also express our gratitude to Dr. Tsvetana Nikolova, MD from Medical Center "Dr. I. S. Greenberg" for the valuable immunological consultations provided during the present paper preparation.

References

1. Alexieva J., E. Choy, E. Koycheva (2007). Review & Bibliography on Generalized Nets Theory & Applications, In: A Survey of Generalized Nets (E. Y. H. Choy, M. Krawczak, A. Shannon, E. Szmidt, (Eds.)), Raffles KvB Monograph № 10, Sydney, Australia.
2. Atanassov K. (2007). On Generalized Nets Theory, Bulgarian Academic Monographs (11), Sofia, Academic Publishing House "Prof. Marin Drinov".
3. Atanassov K. (1999). Intuitionistic Fuzzy Sets – Theory and Applications, Springer-Verlag.
4. Atanassov K., H. Aladjov (2000). Generalized Nets and Machine Learning, Sofia, Academic Publishing House "Prof. Marin Drinov".
5. Bertalanffy L. (1968). General System Theory: Foundations, Development, Applications, New York.
6. Bonabeau E., M. Dorigo, G. Theraulaz (1999). Swarm Intelligence: From Natural to Artificial Systems, New York, Oxford University Press.
7. Canhan R., A. Jackson, A. Tyrrell (2003). Robot Error Detection using an Artificial Immune System, Proceedings of the 2003 NASA/DOD Conference on Evolvable Hardware, July 9-11, 199-207.
8. Castro L., F. Zuben (2000). Artificial Immune Systems – A Survey of Applications, TR DCA-RT 02 February.
9. Chen P. (2009). Using Immune Network in Nonlinear System Identification for a 3D Parallel Robot, Information Technology Journal, 8(6), 895-902.
10. Christiansson P. (2000). Knowledge Representation and Information Flow in the Intelligent Building, Proceedings of the Eighth International Conference on Computing in Civil and Building Engineering, ICCCBE-VIII 2000, Stanford University (R. Fruchter,

F. Pena-Mora, K. Roddis, (Eds.)), American Society of Civil Engineers, Reston, Virginia, USA.
11. Dasgupta D., N. Attoh-Okine (1997). Immunity-based Systems: A Survey, Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics, Orlando, Florida, October 12-15, 363-374.
12. Dasgupta D. (2007). Artificial Immune Systems: A Bibliography, Computer Science Department, University of Memphis, USA, CS TR № CS-07-004, ver. 5.8.
13. Dimitrov D., D. Nikovski (1999). Artificial Intelligence, Technical University – Sofia Publishing House Complex (in Bulgarian).
14. Farmer J., N. Packard, A. Perelson (1986). The Immune System Adaptation, and Machine Learning, Physica D, 22,184-204.
15. Garrett S. (2005). How do We Evaluate Artificial Immune Systems?, Evolutionary Computation, 13(2), 145-178.
16. Hong X., C. Nugenta, M. Mulvenna, S. McClean, B. Scotney, S. Devlin (2009). Evidential Fusion of Sensor Data for Activity Recognition in Smart Homes, Pervasive and Mobile Computing, 5, 236-252.
17. Ishiguro A., T. Kondo, Y. Watanabe, Y. Uchikawa (1995). Dynamic Behavior Arbitration of Autonomous Mobile Robots using Immune Networks, Proceedings of ICEC'95, 722-727.
18. Ishiguro A., Y. Watanabe, Y. Uchikawa (1995). An Immunological Approach to Dynamic Behavior Control for Autonomous Mobile Robots, Proceedings of IROS'95, 1, 495-500.
19. Jerne N. (1974). Towards a Network Theory of the Immune System, Annals of Immunology, 125C, 373-389.
20. Liu Y., K. Passino (2000). Swarm Intelligence: Literature Overview, http://www.ece.osu.edu/~passino/swarms.pdf
21. Luh G., W. Liu (2008). An Immunological Approach to Mobile Robot Reactive Navigation, Applied Soft Computing, 8, 30-45.
22. Minchev Z. (2004). An Intuitionistic Fuzzy Sets Application in Infrared Object-reflecting Sensors of a Mobile Robot, Notes on Intuitionistic Fuzzy Sets, June 20-21, 10(4), 82-85.
23. Minchev Z., O. Manolov, S. Noykov, U. Witkowski, U. Rükert (2004). Fuzzy Logic Based Intelligent Motion Control of Robot Swarm Simulated by Khepera Robots, Proceedings of the 2004 Second International IEEE Symposium "Intelligent Systems", Varna, Bulgaria, June 22-24, 1, 305-310.
24. Minchev Z. (2004). Generalized Nets Model for Control of Mobile Robot, Proceedings of BioPS'04, Sofia, Bulgaria, December 6-8, III.42-III.45.
25. Minchev Z. (2005). Biologically Inspired Object Localization for a Modular Mobile Robotic System, International Journal Bioautomation, 3, 43-56.
26. Minchev Z., K. Atanassov (2005). On the Possibility for Generalized Nets Modeling of Modular Robotic Systems, Advanced Studies on Contemporary Mathematics, Kyungshang 10(2), 169-174.
27. Minchev Z. (2005). Generalized Nets Representation of Biological Inspired Multi-agent Based Modelling, Proceedings of BioPS'05, Sofia, Bulgaria, October 25-26, III.81-III.94.
28. Minchev Z. (2005). Generalized Nets Modelling and Control of Modular Mobile Robotic System, Proceeding of the Sixth International Workshop on Generalized Nets, Sofia, 34-42.
29. Minchev Z. (2006). Generalized Nets Models and Intuitionistic Fuzzy Sets Algorithms for Modelling and Control of Mobile Robots in Unknown Environment, Ph.D. Thesis, Sofia, Bulgaria (in Bulgarian).

30. Minchev Z., D. Dimitrov (2008). Intuitionistic Fuzzy Concept for Navigation of Mobile Agents in Unknown Environment, Proceedings of 9th WSEAS International Conference on Fuzzy Systems (FS'08), Sofia, Bulgaria, May 2-4, 49-53.
31. Parisi G. (1990). A Simple Model for the Immune Network, Proc. Natl. Acad. Sci., Immunulogy, USA, 87, 429-433.
32. Panchev S. (2001). Theory of Chaos (with Examples and Applications), 2nd Edition, Sofia, Academic Publishing House "Prof. Marin Drinov" (in Bulgarian).
33. Parunak H. (1999). From Chaos to Commerce: Practical Issues and Research Opportunities in the Nonlinear Dynamics of Decentralized Manufacturing Systems, Proceedings of Second International Workshop on Intelligent Manufacturing Systems, K. U. Leuven, Belgium, 15-25.
34. Roitt I., J. Brostoff, D. Male (1998). Immunology, 5th edition, Mosby International Ltd.
35. Russell S., P. Norvig (2009). Artificial Intelligence: A Modern Approach, 3rd Edition, Prentice Hall.
36. Semerdjiev Ts., E. Djerassi, L. Bojilov, P. Konstantinova (2006). Sensor Data Processing for Target Tracking. Algorithms and Applications, Softtrade Publishing House, Sofia (in Bulgarian).
37. Smarandache F., J. Dezert (Eds.) (2009). Advances and Applications of DSmT for Information Fusion, Collected Works, American Research Press.
38. Sycara K. (1998). Multiagent Systems, AI Magazine, 19(2).
39. Timmis J., P. Andrews, N. Owens, E. Clark (2008). An Interdisciplinary Perspective on Artificial Immune Systems, Evol. Intel., 1, 5-26.
40. Tsankova D. (2008). Emotional Intervention on Stigmergy Based Foraging Behaviour of Immune Network Driven Mobile Robots, In: Frontiers in Evolutionary Robotics, Hitoshi Iba, (Ed.), I-Tech Education and Publishing, Vienna, Austria, 517-540.
41. Watanabe Y., A. Ishiguro, Y. Uchikawa (1999). Decentralized Behavior Arbitration Mechanism for Autonomous Mobile Robots using Immune Network. In: Artificial Immune Systems and their Applications, Dasgupta D., (Ed.), Springer-Verlag, Berlin, 187-209.
42. Zadeh L. (1965). Fuzzy Sets, Information and Control, 8, 338-353.

Assist. Prof. Zlatogor B. Minchev, Ph.D.
E-mail: zlatogor@bas.bg

Zlatogor Minchev received B.Sc. degree on Informatics (2001) from Veliko Turnovo University "St. St. Cyril & Methodius" and Ph.D. degree in Cybernetics & Robotics (2007) from Technical University of Sofia. Over the last three years he is a director of the Joint Training Simulation & Analysis Center at the Institute for Parallel Processing, Bulgarian Academy of Sciences, executive head of Information & Security Department and an Assistant Professor at the Institute of Mathematics and Informatics, OR Department. Awarded for his professional and team work in the area of ICT by: the President and the Prime Minister of the Republic of Bulgaria, NATO Research & Technology Agency (2007), Bulgarian Association of Information Technologies (2008) and NATO C3 Agency (2010).

Assoc. Prof. Dimitar P. Dimitrov, Ph.D.
E-mail: dean.fa@tu-sofia.bg

Dimitar Dimitrov received M.Sc. degree (1971) and Ph.D. degree (1974) in industrial automation from the Technical University of Warsaw, Poland. In 1974 he joined the Bionics department at Research Institute of Technical Cybernetics, Bulgarian Academy of Sciences. Since 1979 he is a research scientist at Research Center of Robotics, Technical University of Sofia, where from 1994 to 1998 he is a lecturer in Artificial Intelligence and Robotics and chief of Robotics Department. Over the last six years he is a dean of Faculty of Automation, Technical University of Sofia.