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Bio-inspired Approaches for Engineering Adaptive Systems

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Abstract

Adaptive systems are composed of different heterogeneous parts or entities that interact and perform actions favouring the emergence of global desired behavior. In this type of systems entities might join or leave without disturbing the collective, and the system should self-organize and continue performing their goals. Furthermore, entities must self-evolve and self-improve by learning from their interactions with the environment. The main challenge for engineering these systems is to design and develop distributed and adaptive algorithms that allow system entities to select the best suitable strategy/action and drive the system to the best suitable behavior according to the current state of the system and environment changes. This paper describes existing work related to the development of adaptive systems and approaches and shed light on how features from natural and biological systems could be exploited for engineering adaptive approaches.

Keywords: Natural and biological systems, Adaptive systems, Bio-inspired approaches, Feedback loops

1. Introduction

During the past few years, research in artificial intelligence, agent-based systems, mobile and autonomous robots, distributed systems, and autonomic systems, has focused on the development of adaptive approaches and systems that modify their own behavior at run-time to address constantly changing environments. Some of these approaches are inspired by features and capabilities seen in natural and biological systems, e.g., human brain, immune systems, ant colony, flocks of birds[1,2,3]. The capabilities of these systems have been exploited in a variety of computation systems and been perceived as an efficient system model for developing adaptive systems and reconfigurable/evolvable

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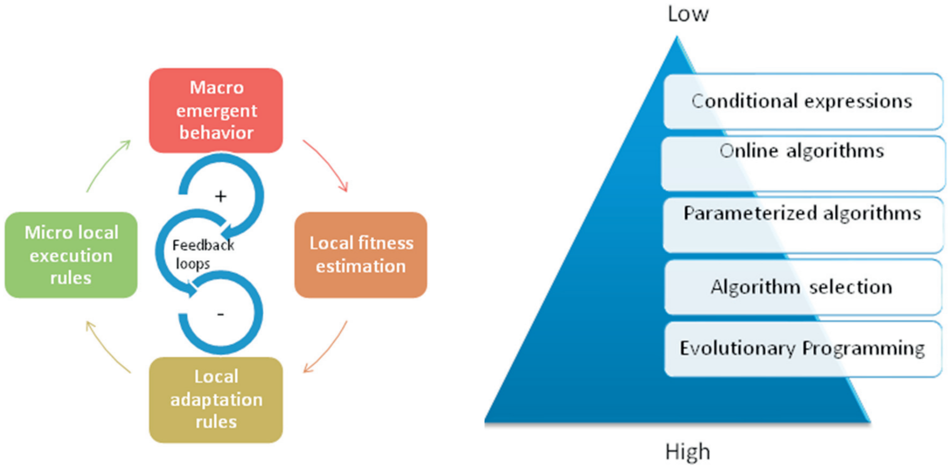
hardware systems[4,5,6,7,8,9,10]. The objective of such research is to develop autonomic systems with self-aware (e.g., self-configuration, -organization, -optimization) properties at component level and strengthen the self-design and fault-tolerance aspect (emergence of self-* [11,12,10]).

Recent studies have emphasized that designing adaptive systems requires a shift from the current top-down design approach to a bottom-up design approach[12,13]. In a bottom-up design approach, local rules allow system components to collaborate in a distributed manner in order to enable the emergence of behaviors at a global level (Fig. 1). However, designing and engineering autonomic/adaptive systems requires answering the following research questions[12,13]: *1)* how to design basic system components in which decisions are distributed and not fully controlled by a single component?, *2)* how to design strategies (at micro level) that allow the system to adapt to environment changes (at macro level) by selecting the best suitable actions/strategies?, *3)* what are the dynamic rules that drive the system to the expected behavior (i.e., reliable, performance and energy efficient)?, *4)* what are techniques and tools for studying the effectiveness of these mechanisms and evaluating the expected functionalities and performance metrics?.

The main goal is to develop run-time mechanisms so that the system autonomously adapts its structure and its behavior during the course of operation. However, several challenges must to be tackled in order to carry out the bottom-up design approach for engineering adaptive systems. For example, the design and development of adaptive mechanisms, called also self-* features[13], following this bottom-up design paradigm have been mainly studied to develop large and self-adaptive distributed systems.

The remainder of this paper is structured as follow. Section 2 presents existing research directions in developing adaptive systems. Section 3 highlight features from natural and biological systems and how they can be used for engineering adaptive approaches. In Section 4, we briefly describe some results from past and ongoing work for developing bio-inspired approaches. Conclusions and perspectives are given in Section 5.



(a) Design paradigm for autonomic/adaptive systems (b) Adaptation rules and techniques

Fig. 1. Design paradigm for autonomic/adaptive systems and Adaptation rules and technique[12,13,14]

2. Related work

Recently, researchers from the software engineering community have clearly stated that building self-adaptive systems is a major challenge and put emphasis on the effectiveness of using theories from control engineering, with well-established mathematical modeling tools for performance evaluation and stability study, and natural systems[15]. They have highlighted that *feedback loops* are core design elements and should be made explicit in modeling, design, implementation, and validation approaches[16]. Autonomic computing communities have indirectly exploited feedback loops to develop systems that manage themselves according to an administrator's goals. In fact, the IBM concept of MAPE-K (monitor, analyze, plan, execute over a knowledge base) can be also seen as a feedback loop[17].

It's worth noting that in the control engineering field, research has focused on the design and development of complex adaptive systems by emphasizing positive and negative feedback loops also seen in natural and biological systems. Complex systems are *complex* because of the multiple *feedbacks/interactions* among the various components of the system. In other words, actions taken on an element in a system might result in changes in the state of the element and these, in turn, might bring about changes in other linked elements. The effects may trail back to the first element, this is called feedback that can be positive or negative. Positive or self-reinforcing feedback amplifies the current change in the system. Negative or self-correcting feedback seeks balance and provides equilibrium by opposing the changes taking place in the system. The two types of feedback should be combined to insure the stability of the system[18,19,20,21]; positive feedback alone pushes the system beyond its limits and, eventually out of control, while negative feedback alone prevents the system from reaching its optimal behavior. These feedback loops are essential to design and develop Antifragile systems[22] in which entities must evolve and self-improve by learning from their interactions with the environment.

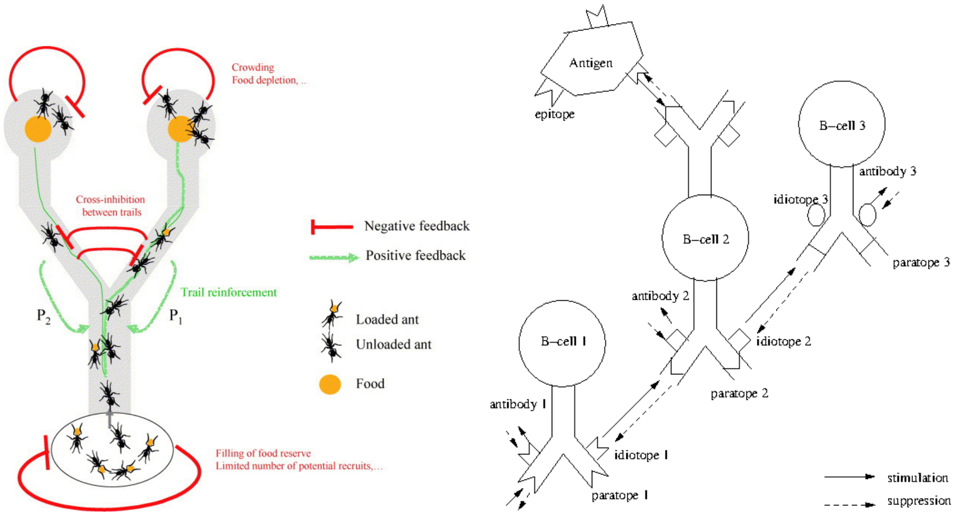
Previous studies clearly show the potential of using the principle of *feedback control* for designing adaptive systems. However, despite the variety of existing models, there is still no general methodology for designing local adaptation rules. Thus, modeling and studying these self-* mechanisms for adaptive systems, while in parallel developing tools required to understand and evaluate them[23], remains an important and open challenge that needs to be addressed. From algorithms perspectives, several techniques could be used to develop algorithms with increasing level of adaptiveness as illustrated in (Fig. 1[14]). The most common techniques use *if/switch statements* to evaluate the local function or expression to select a suitable action. Online parametrized techniques are used to select an action based on inputs and parameters that can evolve over time. The algorithm selection technique chooses the most effective algorithm among a fixed set of available algorithms based on given properties, for a specific task or environment state. The AI-based learning and evolutionary programming provide techniques to select suitable actions and generate new actions. For example, a mechanism inspired by the immune system is proposed in[24,25] for intelligent selection of actions by a mobile robot; it was adapted from a model proposed in[26], in which the authors describe a nonlinear dynamical model using differential equations for the immune system based on the immune idiotypic network hypothesis proposed in[27]. The use of linear equations formulation and iterative methods, which is preferred to a nonlinear system or coupled differential equations that can have multiple attractors, to model adaptive behaviors was proposed in[5]. Action selection algorithms for adaptive behavior emergence can be then modeled by a simple linear system solving[5]. The immune system model has been used in several artificial intelligence approaches[28,29,5].

3. Natural and biological systems

Biological and natural systems, such as Immune systems, honey Bee, and Ant colonies, have several features and organizing principles (e.g., feedback loops as depicted in Fig. 2) that can be exploited in designing and developing adaptive systems. More precisely, these superorganisms often use self-organizing behaviors and feedback loops that allow the system achieve reliable and robust solutions using information gathered from entities[30]. As also stated by Kholodenko in[31], positive and negative feedback loops are key elements of information processing in all biological systems. These feedback loops allow improving information flow and decision making at multiple levels, without centralized control.

For example, in honey bees, the waggle dance could be seen as a positive feedback to attract the attention of other entities about foraging at a specific location. The biological immune system can be seen as a *massively distributed architecture* with a diverse set of cells distributed throughout the body but *communicating* using chemical signals. There is *no central control* (i.e. distributed); the multitude of independent cells work together resulting in the *emergent behavior* of the immune system. The immune system *evolves to adapt* and improve the overall system performance (e.g. organizational memory). Examples of combinations of such feedbacks include positive and negative selections and stimulation/suppression in the immune system and the pheromone evaporation and deposit by Ants[27,26,32,25] (Fig.2).

These systems can be seen as complex collective systems in which the behaviour emerges from the the product of interactions between individual entities. These entities followed a simple set of rules (i.e., not via top-down mechanism) and react only to their local environment. These features and principles (e.g., bottom-up mechanisms, feedback loops) could be used for designing a scalable, adaptive and efficient framework to bring answers to some of the research questions mentioned above.



(a) Ants (b) B-cells

Fig. 2. Examples of feedback loops between Ants and between B-cells of the human immune system [32,25,27].

4. Illustrative Examples

In this section, we highlight specific aspects being investigated and concern the development of adaptive approaches and follow the *bottom-up design paradigm* in order to shed more light on the usefulness of *natural and biological system* principles for developing adaptive approaches.

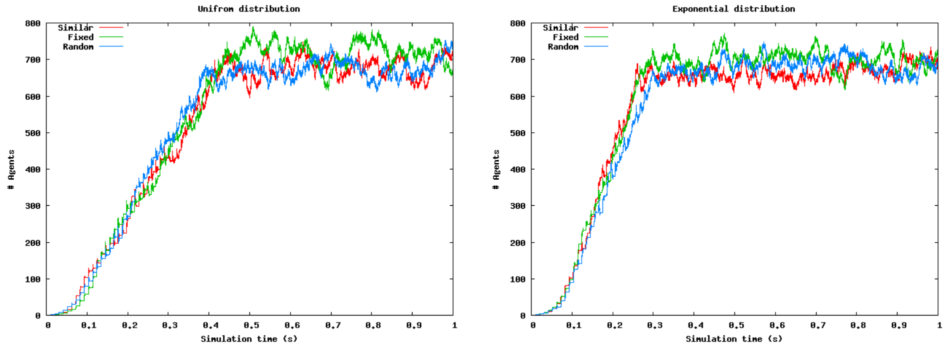
4.1. Biological system-based approaches

A resource discovery approach based on mobile agent paradigm and inspired by the human immune system has been proposed to dynamically regulate the population size of mobile agents that can clone themselves in large distributed environments without any centralized control or global information gathering. Each agent is equipped by a controller equivalent to the immune idiotypic network. An antigen corresponds to the inter-arrival time of agents to a node and provokes an adaptive immune response. Mobile agent behaviors (i.e., actions) are *death* or *kill*, *move* and *clone* and are linked with a stimulation/suppression feedback loop [29,33]. For example, the action *clone* inhibits the action *move* (i.e., migration), while the action *kill* inhibits the *clone* action. The action *clone* is stimulated by both actions *kill* and *move*. Formally x_c, x_m and x_k can be considered as the concentrations associated respectively with the *clone*, *move* and *kill* behaviors (i.e., B-cells). Their variations can be expressed for example as follows [34,5]:

$$\dot{x}_c = (x_c + x_k - x_m + m_c - K_c)x_c$$
$$\dot{x}_m = (x_m + x_c - x_k + m_m - K_m)x_m$$
$$\dot{x}_k = (x_k + x_m - x_c + m_k - K_k)x_k$$

where the values K_c, K_m, and K_k are constants and denote the dissipation factor representing the antibody's natural death of the behavior *clone*, *move* and *kill* respectively. Variables m_c, m_m, and m_k correspond to the affinity of the antigen with the three respective behaviors (i.e., B-cells). Figure 3 shows the evolution of dynamic agent population size during the simulation when the Uniform and Exponential distributions are applied.

Another approach that allows organizing resources into communities by creating dynamic affinity relationships with feedback loops to represent services in the network. In this approach, peers (i.e., servers) are organized into communities by the creation of affinity relationships, like the idiotypic network [27] created by human immune cells (i.e., services/resources) against foreign antigens (i.e., user requests), as illustrated in Fig. 2-b. A reinforcement learning mechanism, in the form of *feedback loops*, is used as a *gradient ascent/descent*, to adjust and dynamically



(a) Uniform (b) Exponential

Fig. 3. The evolution of mobile agents' population [29,33]

reinforce relationship affinity values according to delivered responses (i.e., user reward/penalty). Inside communities, affinity relationships are adjusted as follows:

$$m_{ij}^{(s)}(k+1) = m_{ij}^{(s)}(k) + \mu(LocalSat_{ij}^{(s)} - f(m_{ij}^{(s)}(k)))$$

where $m_{ij}^{(s)}$ is the value of the affinity between a resource of the server i and a resource of a server j for a particular service s. f is the logistic equation $f(m_{ij}) = \frac{1}{1+\exp(-m_{ij})}$, μ is a positive value between 0 and 1. $LocalSat_{ij}^{(s)}$ is equal to 0 or 1 based on local reward/penalty for a particular service s. When all required resources are discovered, the path computed between an end point in the community and the initial entry point will be further reinforced globally by secondary affinity adjustments. The affinity variation for a particular request between a server s_i and a server s_j is determined as follows:

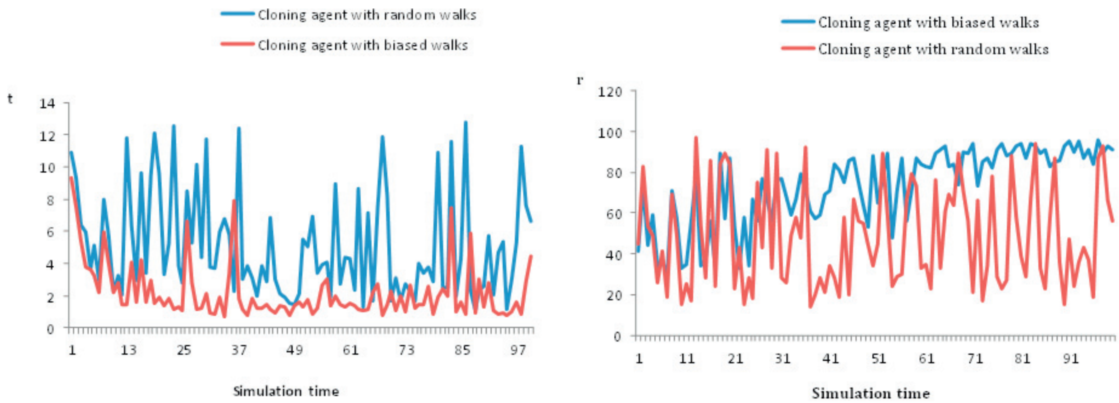
$$\Delta m_{ij}^{(s)}(k) = \mu(GlobalSat_{\varphi}^{(s)} - f(m_{ij}^{(s)}(k)))$$

$GlobalSat_{\varphi}^{(s)}$ is the global reward/penalty value regarding the provided service s. Fig. 4 compares a random walk technique with a biased walk technique using the reinforcement learning mechanism. The results show that without reinforcement learning, each peer has no knowledge of the distributed resources provided by other peers and, consequently, the request resolution time is high. Using the reinforcement learning mechanisms, as more simulator time elapses, peers learn from delivered responses leading to an improved performance in request resolution. Furthermore, the biased walk using reinforcement learning provides better results in terms of found resources than the random walk technique.

4.2. Natural system-based approaches

The general context is to develop adaptive broadcasting approaches for ad hoc networks (e.g., MANETs, VANETs). In such dynamic environments, an increasing the number of redundant broadcast messages will increase resource utilization indirectly affecting network performance (called broadcast storm problem in [36]). More precisely, as rebroadcasting causes trade-off between reachability and efficiency, the core problem is finding a way to minimize the number of redundantly received messages in order to save transmission energy while, at the same time, maintaining good latency and reachability. Therefore, the selection of relay nodes is a major design consideration in broadcasting algorithms. In this direction, a decentralized and adaptive approach for information dissemination (AID) in dynamic networks is presented in [37,38]. Each node, based on the number of received messages, decides whether or not to rebroadcasting a message without the aid of a central controller.

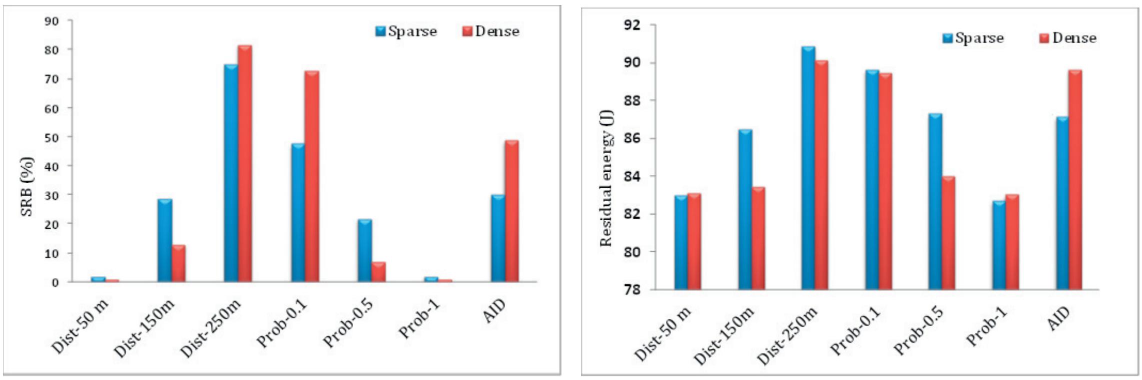
Fig. 5 shows the SRB (Saved ReBroadcast) and energy consumption in the context of MANETs. As expected, rebroadcasting causes a tradeoff between energy efficiency and SRB [38]. As more rebroadcast sent, more energy is consumed. For example, when the distance threshold is fixed to 50m, more messages are submitted, and then more energy



(a) Resolution time (b) Discovered resources

Fig. 4. Request resolution time t in ms and the percentage r of resources found using agent cloning in the case with random walks and biased walks [35]

is consumed, but higher reachability is achieved. When the distance threshold is higher (250m), fewer messages are sent and reachability dropped to lower levels, but less energy is consumed. The AID scheme was also evaluated in the context of VANETs. The AID scheme is a more efficient alternative protocol since it increases the number of SRB and the network becomes less congested, resulting in shorter end to end message delays.



(a) SRB-save broadcast (b) Remaining energy

Fig. 5. Evaluation of AID with probabilistic and distance based algorithms [37]

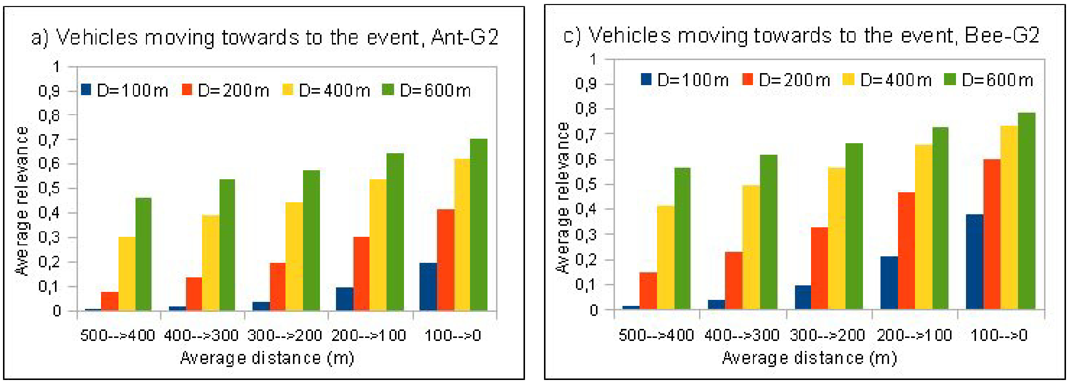
Other swarm based distributed broadcasting approaches inspired by Ants and Bees direct and indirect communication principles for VANETs are proposed in [39]. For example, when an abnormal environmental event is noticed on the road surface, a safety message is created to inform other vehicles and roadside units along its way. This is similar to Ant/Bee behaviour, i.e. when an Ant/Bee observes a food source it creates pheromone/dance to convey indirectly to other Ants/Bees about route information of that food source. Similarly, when a vehicle v_i observes an event p_j that needs to be disseminated to other vehicles, it will generate a safety message m_{p_j} and will report to RSU (Road Side Unit). This message includes a timestamp t_0, the location information, and an initial relevance value $R^0_{v_i,p_j}(t_0)$ and is disseminated periodically up to a time T, which represents the maximum timespan required to handle the event.

When a node v_k receives a message from another node v_ℓ, we can differentiate between two strategies, G1 and G2. By the strategy G1, information in the header, which is generated by the source node, will not be changed by receivers. Using G2, the receiver node uses the relevance value of intermediate (sender/forwarder) nodes instead of the initial (original) relevance generated by the source node. For example, using G2, a node v_k calculate the new relevance value using node's v_ℓ information as follows:

$$R_{v_k,p_j}(t+\tau) = \frac{2 * R_{v_\ell,p_j}(t)}{1+\exp(\frac{d+\lambda\tau s}{D})}$$

where d is the distance between the current location of receiver vehicle v_k and the location where the event is appeared (source). s is the current speed of v_k. The quantity of $\lambda\tau s$ represents the influence of distance variation during the assessment delay τ. λ is a sign, representing direction of the vehicle: -1 (resp. +1) if it moving toward (resp. opposite direction) the accident location. It is worth noting that the value of λ equal 1 will cause positive output for R_{v_k,p_j}, which ensures a monotonic increasing function while the value of λ equal -1 implies a negative output for R_{v_k,p_j} and a monotonic decreasing function[40].

Fig. 6 depict relevance values obtained by centralized and distributed approaches. The centralized approach is inspired by bee colony principles, in which communications are indirect via RSUs. The distributed approach is inspired by ants, in which communications and relevance values updating is influenced by intermediate nodes.



(a) Distributed approach (Ants based)

(b) Centralized approach (Bees based)

Fig. 6. average relevance value behavior according to different selected geographical area D, using strategy G2[39]

5. Conclusions and future work

This paper highlighted that natural and biological systems principles, together with the bottom-up design rules, are useful for designing algorithms and mechanisms for adaptive systems. The illustrative examples provide some insight on how to design local and appropriate methods that allow system components to select the best suitable strategy/action and drive the system to provide the best suitable behavior according to the current system state and environment changes. However, developing models to evaluate self-* mechanisms requires knowledge insight in existing feedback control systems and system dynamics methods. Especially, insight in mechanisms based on the principle of feedback control and in designing local adaptation rules and mathematical models to evaluate these mechanisms.

References

1. Caro, G.D., Dorigo, M.. Antnet: Distributed stigmergetic control for communications networks. *Journal of Artificial Intelligence Research* 1998;**9**:317–365.
2. Cohen, I.R.. Real and artificial immune systems: computing the state of the body. *Nature Reviews, Immunology* 2007;**7**:569–574.
3. Bakhouya, M., Gaber, J.. Approaches for ubiquitous computing. *Wireless Ad hoc and Sensor Networks, Eds H Labiod, ISTE Publishing Knowledge/John Wiley and Sons Inc ISBN 978190520986* 2008;:111–142.
4. Gordon, G.W.T., Bently, P.J.. On evolvable hardware. *In Ovaska, S and Sztandera, L (Ed) Soft Computing in Industrial Electronics* 2002;:279–323.
5. Gaber, J.. Action selection algorithms for autonomous system in pervasive environment: A computational approach. *TAAS* 2011;**6**(1):10.
6. Gaber, J., Bakhouya, M.. An affinity-driven clustering approach for service discovery and composition for pervasive computing. *Proceedings of IEEE ICPS'06* 2006;:277–280.

7. Babaoglu, O., Canright, G., Deutsch, A., Caro, G.A.D., Ducatelle, F., Gambardella, L.M., et al. Design patterns from biology for distributed computing. *ACM Transactions on Autonomous and Adaptive Systems (TAAS)* 2006;**1**(1):26–66.
8. Upegui, A., Thoma, Y., Sanchez, E., Perez-Uribe, A., Moreno, J., Madrenas, J.. The perplexus bio-inspired reconfigurable circuit. *Second NASA/ESA Conference on Adaptive Hardware and Systems (AHS)* 2007;:600–605.
9. Moore, M., Suda, T.. A decentralized and self-organizing discovery mechanism. *Proc of the First Annual Symposium on Autonomous Intelligent Networks and Systems* May 2002;.
10. Bakhouya, M.. A bio-inspired architecture for autonomic network-on-chip. *Autonomic Networking-on-Chip: Bio-inspired Specification, Development, and Verification Part of the Embedded Multi-core Systems (EMS) Book Series Edited by:Phan Cong-Vinh Taylor and Francis/CRC Press* 2012;:1–19.
11. Babaoglu, O., Jelasity, M., Montresor, A., Fetzer, C., Leonardi, S., Moorsel, A.V., et al. The self-star vision. *Selfstar Properties in Complex Information Systems, LNCS* 2005;**3460**:1–20.
12. Miorandi, D., Pellegrini, F.D., Mayora, O., Giaffreda, R.. Collective adaptive systems: Scenarios, approaches and challenges. *ftp://ftpcordiseuropaeu/pub/fp7/ict/docs/fet-proactive/shapefetip- cas10 enpdf* 2010;.
13. Kernbach, S., Schmick, T., Timmis, J.. Collective adaptive systems: Challenges beyond evolvability. *http://arxivorg/abs/11085643* 2011;.
14. Heinzemann, C.. Modeling behavior of self-adaptive systems. *http://ebookbrowsecom/modeling-behavior-of-self-adaptive-systems5-ppt-d217019628* 2012;.
15. Cheng, B.H.C., de Lemos, R., Giese, H., Inverardi, P., Magee, J.. Software engineering for self-adaptive systems: A research roadmap. *LNCS* 2009;**5525**:1–26.
16. Brun, Y., Serugendo, G.D.M., Gacek, C., Giese, H., H. Kienle, M.L., Muller, H., et al. Engineering self-adaptive systems through feedback loops. *Software Engineering for Self-Adaptive Systems, LNCS Hot Topics* 2009;**5525**:48–70.
17. Kephart, J.O., Chess, D.M.. The vision of autonomic computing. *Computer* 2003;**36**(1):41–50.
18. Estrin, D., Govindan, R., Heidemann, J., Kumar, S.. Next century challenges: Scalable coordination in sensor networks. *Proceedings of ACM/IEEE MobiCom* 1999;:263–270.
19. Borshchev, A., Filippov, A.. From system dynamics and discrete event to practical agent based modeling: Reasons, techniques, tools. *The 22nd International Conference of the System Dynamics Society* 2004;:1–23.
20. Ogata, K.. System dynamics 2004;(ISBN 0-13-142462-9).
21. Caulfield, C.W., Maj, S.P.. A case for systems thinking and system dynamics. *IEEE International Conference on Systems, Man and Cybernetics* 2001;:2793–2798.
22. Florio, V.D.. Antifragility = elasticity + resilience + machine learning: Models and algorithms for open system fidelity. *http://arxivorg/abs/14014862* 2014;:1–7.
23. Florio, V.D., Coronato, A., Bakhouya, M., Serugendo, G.D.M.. Service-oriented communities: Models and concepts towards fractal social organizations. *SITIS 2012* 2012;.
24. Ishiguro, A., Watanabe, Y., Kondo, T., Uchikawa, Y.. Proposal of decentralized consensus-making mechanisms based on immune system-application to a behavior arbitration of an autonomous mobile robot. *AProc of AROB* 1996;:122–127.
25. Y. Watanabe A. Ishiguro, Y.S., Uchikawa, Y.. Emergent construction of behavior arbitration mechanism based on the immune system. *Advanced Robotics* 1998;**12**(3):227–242.
26. Farmer, J.D., Packard, N.H., Perelson, A.. The immune system, adaptation and machine learning. *Physica* 1986;**22D**:72–81.
27. Jerne, N.K.. Towards a network theory of the immune system. *Ann Immunol (InstPasteur) 125C* 1974;:373–389.
28. Suzuki, J., Yamamoto, Y.. Building an artificial immune network for decentralized policy negotiation in a communication endsystem : Openwebserver/inexus study. *Proceedings of The 4th World Multiconference on Systemics, Cybernetics and Informatics* 2000;.
29. Bakhouya, M., Gaber, J.. Adaptive approach for the regulation of a mobile agent population in a distributed network. *5th International Symposium on Parallel and Distributed Computing* 2006;:360–366.
30. Nieh, J.C.. A negative feedback signal that is triggered by peril curbs honey bee recruitment. *Current Biology* 2010;(20):310C315.
31. Kholodenko, B.N.. Cell-signalling dynamics in time and space. *Rev Mol Cell Biol* 2006;(7):165C176.
32. Detrain, C., Deneubourg, J.L.. Self-organized structures in a superorganism: do ants behave like molecules. *Physics of Life Reviews* 2006; **3**(3):162–187.
33. Bakhouya, M.. An adaptive approach based on mobile agents and inspired by immune system for service discovery in large scale networks. *PhD Thesis, Universite de Technologie de Belfort-Montbeliard, N 34* 2005;:1–156.
34. Bakhouya, M., Gaber, J.. Distributed self-regulation approach of a mobile agent population in a network. *Research Report RR-02, UTBM* 2002;:1–14.
35. Bakhouya, M., Gaber, J.. A query routing approach based on users' satisfaction for resource discovery in service-oriented networks. *World Wide Web* 2010;**13**(1-2):61–73.
36. Ni, S., Y.Tseng, , Chen, Y., Sheu, J.P.. The broadcast storm problem in a mobile ad hoc network. *International Conference on Mobile Computing and Networking* 1999;:151–162.
37. Bakhouya, M., Gaber, J., Lorenz, P.. An adaptive approach for information dissemination in vehicular ad hoc networks. *Journal of Network and Computer Applications* 2011;**34**(6):1971–1978.
38. Medetov, S., Bakhouya, M., Gaber, J., Wack, M.. Evaluation of an energy-efficient broadcast protocol in mobile ad hoc networks. *The 20th International Conference on Telecommunications* 2013;.
39. Medetov, S., Bakhouya, M., Gaber, J., Zinedine, K., Wack, M.. A bee-inspired approach for information dissemination in vanets. *ICMCS* 2014;:1–6.
40. Gaber, J.. Spontaneous emergence model for pervasive environments. *Globecom Workshops* 2007;:1–6.