A Survey on Bio-inspired Networking

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Abstract

The developments in the communication and networking technologies have yielded many existing and envisioned information network architectures such as cognitive radio networks, sensor and actor networks, quantum communication networks, terrestrial next generation Internet, and InterPlaNetary Internet. However, there exist many common significant challenges to be addressed for the practical realization of these current and envisioned networking paradigms such as the increased complexity with large scale networks, their dynamic nature, resource constraints, heterogeneous architectures, absence or impracticality of centralized control and infrastructure, need for survivability, and unattended resolution of potential failures. These challenges have been successfully dealt with by Nature, which, as a result of millions of years of evolution, have yielded many biological systems and processes with intrinsic appealing characteristics such as adaptivity to varying environmental conditions, inherent resiliency to failures and damages, successful and collaborative operation on the basis of a limited set of rules and with global intelligence which is larger than superposition of individuals, self-organization, survivability, and evolvability. Inspired by these characteristics, many researchers are currently engaged in developing innovative design paradigms to address the networking challenges of existing and envisioned information systems. In this paper, the current state-of-the-art in bio-inspired networking is captured. The existing bio-inspired networking and communication protocols and algorithms devised by looking at biology as a source of inspiration, and by mimicking the laws and dynamics governing these systems are presented along with open research issues for the bio-inspired networking. Furthermore, the domain of bio-inspired networking is linked to the emerging research domain of nanonetworks, which bring a set of unique challenges. The objective of this survey is to provide better understanding of the potentials for bio-inspired networking which is currently far from being fully recognized, and to motivate the research community to further explore this timely and exciting topic.

1. Introduction

The last few decades have witnessed striking developments in communication and networking technologies which have yielded many information network architectures. One prominent product of this evolution, the Internet, is itself an unprecedented success story which has shown the enormous potential of information networks in terms of impact on society, economy and quality of life. While this potential is, in the Internet case, still only partially exploited as it continues to diffuse into every aspect of our daily lives in many different forms; the next generation of information systems with salient offsprings ranging from quantum communication networks [1] to InterPlaNetary Internet [2] is beginning to make its way, posing phenomenal challenges to researchers and engineers.

These next generation information networks are envisioned to be characterized by an invisible and ubiquitous halo of information and communication services, which should be easily accessible by users in a transparent, location-independent, and seamless fashion [3]. Therefore, the result will be a pervasive and, in fact, living network extending the current Internet capabilities. This ubiquitous networking space will include, in addition to the traditional Internet-connected devices, networked entities which are in much closer interaction with us such as wearable networks [4], in-body molecular communication networks [5], unattended ground, air, and underwater sensor networks [6], self-organizing sensor and actor networks [7, 8] and locally intelligent and self-cognitive devices exploiting the communication resources with the help of cognitive capabilities, e.g., cognitive radio networks [9]. Clearly, this vision implies that almost every object will be able to effectively and collaboratively communicate, thus becoming, to some extent, a node of the future pervasive Internet-like global network.

The evolution in communication and networking technologies brings many such potential advantages to our daily lives. At the same time, the complexity of the existing and envisioned networked information systems has already gone far beyond what conventional networking paradigms can do in order to deploy, manage, and keep them functioning correctly and in an expected manner. Self-organization techniques are demanded to overcome current technical limitations [10]. In fact, there exist many

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common significant challenges that need to be addressed for practical realization of these existing and next generation networking architectures, such as increased complexity with large scale networks, their dynamic nature, resource constraints, heterogeneous architectures, absence or impracticality of centralized control and infrastructure, need for survivability, and unattended resolution of potential failures.

Clearly, most of the existing and next generation communication systems cannot be handled according to the conventional networking paradigms, which are not able to accommodate the scale, heterogeneity and complexity of such scenarios. Novel paradigms are needed for designing, engineering and managing these communication systems.

While the challenges outlined above such as scalability, heterogeneity and complexity are somehow new by-products of the evolution in the communication technologies in the last few decades, they have been successfully dealt with by Nature for quite some time. Unlike the evolution in the communication technologies which have brought these challenges about, the evolution in Nature have yielded artifacts which are actually the solution approaches that can handle many of these challenges with an elegance and efficiency still far beyond current techniques.

In fact, when we look carefully into nature, it is clearly observed that the dynamics of many biological systems and laws governing them are based on a surprisingly small number of simple generic rules which yield collaborative yet effective patterns for resource management and task allocation, social differentiation, synchronization (or de-synchronization) without the need for any externally controlling entity. For example, by means of these capabilities, billions of blood cells which constitute the immune system can protect the organism from the pathogens without the any central control of the brain [11]. Similarly, an entire organism is autonomously maintained in a relatively stable equilibrium state via a major functionality, i.e., homeostasis, for the operation of vital functions without any need for a central biological controller [12]. The task allocation process in the insect colonies is collaboratively decided and performed according to the willingness of an individual such that the overall task is optimized with a global intelligence comprised of simple individual responses [13].

These examples and, in general, as a result of millions of years of evolution, biological systems and processes have intrinsic appealing characteristics. Among others, they are

- adaptive to the varying environmental circumstances,
- robust and resilient to the failures caused by internal or external factors,
- able to achieve complex behaviors on the basis of a usually limited set of basic rules,
- able to learn and evolve itself when new conditions are applied,
- effective management of constrained resources with an apparently global intelligence larger than the superposition of individuals,
- able to self-organize in a fully distributed fashion, collaboratively achieving efficient equilibrium,
- survivable despite harsh environmental conditions due to its inherent and sufficient redundancy.

These characteristics lead to different levels of inspiration from biological systems towards the derivation of different approaches and algorithm designs at each of the networking layers for efficient, robust and resilient communication and information networks. Therefore, in order to keep pace with the evolution in networking technologies, many researchers, members of this very young research community, are currently engaged in developing innovative design paradigms inspired by biology in order to address the networking challenges of existing and envisioned information systems. The common rational behind this effort is to capture the governing dynamics and understand the fundamentals of biological systems in order to devise new methodologies and tools for designing and managing communication systems and information networks that are inherently adaptive to dynamic environments, heterogeneous, scalable, self-organizing, and evolvable.

Besides bio-inspired networking solutions, communication on the nano-scale is being investigated with two important but conceptually different goals. On the one hand, bio-inspired nano machinery is investigated in order to build machines on the nano level using communication and actuation capabilities derived from biological counterparts. More specifically, the most promising communication mechanism between nano-machines forming nano-scale networks is currently envisioned to be molecular communication, i.e., coding and transfer of information in terms of molecules, which is also mainly inspired by the cellular signaling networks observed in living organisms. On the other hand, such nano-machines can also be used in the main field of molecular biology to study biological systems. Thus, we aim to link both bio-inspired research and nano-communication by looking at state-of-the-art solutions in both domains.

In this paper, we present a survey of the bio-inspired networking and communication protocols and algorithms devised by looking at biology as a source of inspiration, and by mimicking the laws and dynamics governing these systems. It should be also noted that we leave the existing and quite comprehensive literature on the communication and computing algorithms based on evolutionary techniques, e.g., genetic algorithm, out of our scope, and mainly focus on the networking paradigms and solution approaches inspired by the biological systems and processes and their governing dynamics. Furthermore, in spite of the many successful applications of bio-inspired research, we emphasize that the main challenge is neither the inspiration nor the application, but is understanding the biological system and its behavior, the modeling of the system, and the conceptual derivation of technical solutions. Therefore, our objective is to provide better understanding of the current state-of-the-art and the research issues in the broad field of bio-inspired networking and help the research community to find appealing hints for future explorative activities on this timely and exciting topic.

The remainder of the paper is organized as follows. In Section 2, we summarize the most challenging questions in networking and provide pointers to biological similarities and solutions. We explore the proposed biological systems and processes whose models can be exploited towards the design of novel networking paradigms in Section 3. In Section 4, we investigate the current and proposed protocols and algorithms based on and inspired by biological systems for a diverse set of networking architectures. This includes a summary of activities in the field of bio-inspired networking. After that, we connect the bio-inspired networking domain to the upcoming field of nanonetworks in Section 5, which also focuses on establishing communication networks within biological systems. Finally, we state the concluding remarks in Section 6.

2. Challenges in Networking

Clearly, there exist many challenges for the realization of the existing and the envisioned next generation network architectures. At the same time, similar problems and their naturally evolved biological solution approaches also exist for these networking paradigms. In this section, we review the most challenging fundamental issues for networking and highlight the analogies with their counterparts and corresponding solution approaches which already exist in biological systems. Most of the listed challenges relate to problems in wireless networks such as mobile ad hoc networks or sensor networks. With the increasing use of ubiquitous computing, many of the most important networking issues relate to such networks. At the same time, due to a vast amount of research efforts over wireless and mobile networking domains, the existing examples of bio-inspired solutions addressing these common major challenges are, hence, observed in the current literature of these research areas as well.

Furthermore, some challenges explored here, e.g., large-scale networking, heterogeneous architectures, also stand as important barriers for the realization of future Internet architectures including the Internet of things [14]. Moreover, some security aspects such as the spreading of Internet worms is covered by the examples discussed in Section 4. It needs to be noted that this section cannot be seen as a full reference of challenges in networking, but as a list that can finally be addressed by bio-inspired solutions.

Here, instead of exploring networking problems in terms of functionalities and algorithms in each layer of communication protocol stacks for diverse set of network architectures,[1] we overview the main common challenges of the existing and the next generation networks brought about by the evolution in communication technologies and the increasing demand posed upon them.

2.1. Large scale networking

One of the main challenges is related to the sheer size exhibited by the networking systems, which connect huge numbers of users and devices in a single, omni-comprehensive, preferably always-on network. The size of this omni-comprehensive network, in terms of both number of constituent nodes and running services, is expected to exceed by several orders of magnitude that of the current Internet.

For example, Wireless Sensor Networks (WSNs) having a broad range of current and future applications are generally envisioned to be composed of a large number, e.g., in numbers ranging between few hundreds to several hundred thousands, of low-end sensor nodes [15]. The first direct consequence of such large scales is the huge amount of traffic load to be incurred over the network. This could easily exceed the network capacity, and hence, hamper the communication reliability due to packet losses by both collisions in the local wireless channel as well as congestion along the path from the event field towards the sink [17]. Consequently, the difficulty level for the selection of the appropriate set and number of nodes and their reporting frequency for reliable yet efficient communication also increases with the network size [18].

Similarly, it becomes more important to find the optimal routes, if possible, in order to keep the communication overhead at acceptable levels during the dissemination of a large amount of information over a large scale network. As the network scale expands, the number of possible paths, and hence, the search space for the optimal route in terms of a preset criteria, also drastically enlarges. The number of routing tables to maintain, and, regardless of a specific routing mechanism, the amount of traffic for table updates experience the same increase as the network scales up.

Clearly, the deployment, effective communication, and management in large scale networks, e.g., sensor networks and mobile ad hoc networks, cannot be manually realized. Hence, networking mechanisms must be scalable and adaptive to variations in the network size. Fortunately, there exist many biological systems that inspire the design of effective communication solutions for large scale networks. For example, as discussed in Section 4.1.1 in detail, based on optimizing global behavior in solving complex tasks through individual local means, Ant Colony Optimization (ACO) techniques [19] provide efficient routing mechanisms for large-scale mobile ad hoc networks [20]. In addition, information dissemination over large scales can be handled with the help of epidemic spreading [21, 22, 23], which is the main transmission mechanism of viruses over

[1] Exhaustive surveys of network and communication challenges for some of these architectures can be found in [6, 7, 9, 15, 16].

the large and scale-free organism populations. Similar examples, as presented in Section 4, clearly show that the potential adverse effects of large scale networking may be handled with bio-inspired mechanisms.

2.2. Dynamic nature

Unlike the early communication systems composed of a transmitter / receiver pair and communication channel, which are all static, the existing and the envisioned networking architectures are highly dynamic in terms of node behaviors, traffic and bandwidth demand patterns, channel and network conditions.

According to the mobility patterns of the nodes, network dimensions, and radio ranges; communication links may frequently be established and become obsolete in mobile ad hoc networks [24]. Furthermore, due to mobility of the nodes, and environmental variations as a result of movement, the channel conditions and hence link qualities may be highly dynamic. Similarly, in the target tracking applications of sensor networks, based on the target behaviors and the area to be monitored, the amount of traffic created by the sensor nodes may drastically increase at the time of detection and may decay with time. This imposes varying load on the network which may result in inefficient capacity utilization if static approaches are employed.

Dynamic spectrum access and its management in cognitive radio networks is another important case where the dynamic nature of the user behaviors, channel requests and application-specific bandwidth demands pose significant challenges on the network design [9]. The objective of cognitive radio networks itself is to leverage the dynamic usage of spectrum resources in order to maximize the overall spectrum utilization.

The list of examples could be expanded, which, however, would only further reinforce the fact that communication techniques need to be adaptive to the dynamics of the specific networking environment. To this end, the biological systems and processes are known to be capable of adapting themselves to varying circumstances towards the survival. For example, Artificial Immune System (AIS), inspired by the principles and processes of the mammalian immune system [25], efficiently detects variations in the dynamic environment or deviations from the expected system patterns. Similarly, activator-inhibitor systems and the analysis of reaction-diffusion mechanisms in biological systems [26] also capture dynamics of the highly interacting systems through differential equations. As will be explored in Section 4, many biologically inspired approaches, e.g., activator-inhibitor mechanisms [27], AIS [28], can be exploited to develop communication techniques which can adapt to varying environmental conditions.

2.3. Resource constraints

As the communication technologies evolve, demands posed upon the networks also drastically increase in terms of the set of available services, service quality including required bandwidth capacity, and network lifetime. For example, the current Internet can no longer respond to every demand as its capacity is almost exceeded by the total traffic created, which lays a basis for the development of next generation Internet [29].

At the same time, with the increased demand from wireless networking, fixed spectrum assignment-based traditional wireless communications has become insufficient in accommodating a wide range of radio communication requests. Consequently, cognitive radio networks with dynamic spectrum management and access has been proposed and is currently being designed in order to improve utilization of spectrum resources [9].

On the other hand, some next generation networking architectures, e.g., InterPlaNetary Internet [2], intrinsically possess resource constraints due to their physical and structural limitations. More specifically, for the networks composed of nodes that are inherently constrained in terms of energy and communication resources, e.g., WSNs [15], Mobile Ad Hoc Networks (MANETs) [24], nano-scale and molecular communication networks [5], these limitations directly bound their performance and mandate for intelligent resource allocation mechanisms.

The biological systems yet again help researchers by providing pointers for mechanisms and solution approaches which address the trade-off between the high demand and limited supply of resources. For example, in the foraging process [30], ants use their individual limited resources towards optimizing the global behavior of colonies in order to find food source in a cost-effective way. As explained in Section 4.1.1, the behavior of ant colonies in the foraging process inspire many resource-efficient networking techniques. Furthermore, cellular signaling networks, and their artificial counterpart, represent and capture the dynamics of interactions contributing to the main function of a living cell. Hence, they might also enlighten important avenues to obtain efficient communication techniques for resource constrained nano-scale and molecular communication networks.

2.4. Need for infrastructure-less and autonomous operation

With significant increase in network dimensions both spatially and in the number of nodes, centralized control of communication becomes unpractical. On the other hand, some networks are by definition free from infrastructure such as wireless ad hoc networks [24], Delay Tolerant Networks (DTNs) [2], WSNs [15], and some have a heterogeneous, mostly distributed and non-unified system architecture such as cognitive radio networks [9], wireless mesh networks and WiMAX [16]. These networking environments mandate for distributed communication and networking algorithms which can effectively function without any help from a centralized unit.

At the same time, communication networks are subject to failure either by device malfunction, e.g., nodes in a certain area may run out of battery in sensor networks, or misuse of their capacity, e.g., overloading the network may cause heavy congestion blocking the connections. In most cases, networks are expected to continue their operation without any interruption due to these potential failures. Considering the dynamic nature, lack of infrastructure, and impracticality of centralized communication control, it is clear that networks must be capable of re-organizing and healing themselves to be able to resume their operation. Hence, the existing and next generation information networks must have the capabilities of self-organization, self-evolution and survivability.

In order to address all these needs, networks must be equipped with similar set of intelligent algorithms and processes as largely observed in biological systems. In fact, inherent features of many biological systems stand as promising solutions for these challenges.

For example, an epidemic spreading mechanism could be modified for efficient information dissemination in highly partitioned networks and for opportunistic routing in delay tolerant networking environments [23]. Ant colonies, and in general insect colonies, which perform global tasks without the control of any centralized entity, could also inspire the design of communication techniques for infrastructureless networking environments [31]. Furthermore, synchronization principles of fireflies [32] could be applied to the design of time synchronization protocols as well as communication protocols requiring precise time synchronization. Activator-inhibitor systems may be exploited for distributed control of sensing periods and duty cycle of target tracking sensor networks [33, 34]. The autonomous behavior of artificial immune systems may be a good model for the design of effective algorithms for unattended and autonomous communication in sensor networks [28]. Thus, as discussed in Section 4 in detail, the potential handicaps of lack of infrastructure and autonomous communication requirements in various networking environments could be addressed through careful exploration of biological systems.

2.5. Heterogeneous architectures

The other critical aspect of many of the existing and envisioned communication networks is linked to their heterogeneity and its resultant extremely complex global behavior, emerging from the diverse range of network elements and large number of possible interactions among them. Next generation communication systems are generally envisioned to be composed of a vast class of communicating devices differing in their communication / storage / processing capabilities, ranging from Radio Frequency Identification (RFID) devices and simple sensors to mobile vehicles equipped with broadband wireless access devices.

For example, as one of the emerging and challenging future networking architectures, the *Internet of things* (IoT) is defined as a vision of network of objects which extends the Internet capabilities into our daily lives transforming our immediate environment into a large-scale wireless networks of uniquely identifiable objects. One of the main research problems for the realization of the vision of IoT is that it will exhibit high degrees of heterogeneity in terms of node types, e.g., ranging from smart household appliances to even consumer goods such as a yogurt can identified with RFID tags [14].

Similarly, cognitive radio networks involve the design of new communication techniques to realize the co-existence of different wireless systems communicating on overlapping spectrum bands with an ultimate objective of maximizing the spectrum utilization. Wireless mesh networks and WiMAX are also expected to be composed of heterogeneous communication devices and algorithms [16].

Sensor and Actor Networks (SANETs) architecturally incorporate both heterogeneous low-end sensor nodes and highly capable actor nodes [7, 10]; and Vehicular Ad Hoc Networks (VANETs) [35] exhibit significant levels of heterogeneity in terms of wireless communication technologies in use and mobility patterns of ad hoc vehicles.

Such heterogeneity and asymmetry in terms of capabilities, communication devices and techniques need to be understood, modeled and effectively managed, in order to allow the realization of heterogeneous novel communication networks. Different levels of heterogeneity are also observed in biological systems. For example, in many biological organisms, despite external disturbances, a stable internal state is maintained through collaborative effort of heterogeneous set of subsystems and mechanisms, e.g., nervous system, endocrine system, immune system. This functionality is called "homeostasis", and the collective homeostatic behavior [36] can be applied towards designing communication techniques for networks with heterogeneous architectures. On the other hand, insect colonies are composed of individuals with different capabilities and abilities to respond to a certain environmental stimuli. Despite this inherent heterogeneity, colonies can globally optimize the task allocation and selection processes via their collective intelligence [13]. Similar approaches can be adopted to address task assignment and selection in SANETs [37, 38], for spectrum sharing in heterogeneous cognitive radio networks [31], as well as multi-path routing in overlay networks [39, 40].

2.6. Communication on the micro level

With the advances in micro- and nano-technologies, electro-mechanical devices have been downscaled to micro and nano levels. Consequently, there exist many micro- (MEMS) and nano-electro-mechanical systems (NEMS), and devices with a large spectrum of applications. Clearly, capabilities for communication and networking at micro even at nano scales become imperative in order to enable micro and nano devices to cooperate and hence collaboratively realize certain common complex task which cannot be handled individually. In this regard, "nanonetworks" could be defined as a network composed of nano-scale machines, i.e., nano-machines, cooperatively communicating with each other and sharing information in order to fulfill a common objective [41].

While the communication and networking requirements at these scales might be similar from the functional perspective, there exist significant differences between the communication at the traditional and micro / nano scales. The dimensions of nano-machines render conventional communication technologies such as electromagnetic waves, acoustic, inapplicable at these scales due to antenna size and channel limitations. Furthermore, the communication medium and channel characteristics also show important deviations from the traditional cases due to the rules of physics governing these scales.

The main idea of nano-machines and nano-scale communications and networks have also been motivated and inspired by the biological systems and processes. Hence, it is conceivable that the solutions for the challenges in communication and networking at micro and nano-scales could also be developed through inspiration from the existing biological structures and communication mechanisms.

In fact, many biological entities in organisms have similar structures with nano-machines. For example, every living cell has the capability of sensing the environment, receiving external signals, performing certain tasks at nanoscales. More importantly, based on transmission and reception of molecules, cells in a biological organism may establish cellular signaling networks [42], through which they can communicate in order to realize more complex and vital tasks, e.g., immune system responses. Therefore, as will be explored in Section 5 in details, the inspiration from cellular signaling networks, and hence, molecular communication [43], provide important research directions and promising design approaches for communication and networking solutions at micro- and nano-scales.

3. Biological Models Inspiring Communication Network Design(er)s

The main intention of this survey is to introduce and to overview the emerging area of bio-inspired networking. Therefore, the scope of this section is first to introduce the general approach to bio-inspired networking by discussing the identification of biological structures and techniques relevant to communication networks, modeling the systems and system properties, and finally deriving optimized technical solutions. Secondly, we try to classify the field of biologically inspired approaches to networking – selected examples are presented in more detail in Section 4. Bio-inspired algorithms can effectively be used for optimization problems, exploration and mapping, and pattern recognition. Based on a number of selected examples, we will see that bio-inspired approaches have some outstanding capabilities that motivate their application in a great number of problem spaces.

As this paper focuses on recent approaches to bio-inspired networking, we explicitly exclude the broad field of evolutionary algorithms, which are successfully applied to optimization problems in many areas of computer science and engineering. As a further remark, it should be noted that self-organization of (massively) distributed systems is also not in our scope – whereas many of the discussed biological examples also provide solutions to this problem [10].

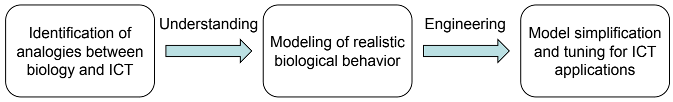

Figure 1: Necessary steps to adapt biological mechanisms to technical solutions

3.1. Modeling approaches

Before introducing the specific biological models that have been exploited towards the development and realization of bio-inspired networking solutions, we need to briefly study the general modeling approach. First modeling approaches date back to the early 1970ies [44, 45]. Since that time, quite a number of technical solutions mimicking biological counterparts have been developed and published. Typical bio-networking architectures showing the complete modeling approach are described in [46, 47]. This bio-networking architecture can be seen as a catalyzer or promoter for many other investigations in the last decade. A more recent work of this architecture shows that there is still room for further improvements [48].

Looking at many papers and proposals that have been derived in recent years, some of this can be understood as attempts to present (engineering) technical solutions with some similarities to biological counterparts without really investigating the key advantages or objectives of the biological systems. Obviously, many methods and techniques are really bio-inspired as they follow principles that have been studied in nature and that promise positive effects if applied to technical systems. Three steps can be identified that are always necessary for developing bio-inspired methods that have a remarkable impact in the domain under investigation:

1. *Identification of analogies* – which structures and methods seem to be similar,
2. *Understanding* – detailed modeling of realistic biological behavior,
3. *Engineering* – model simplification and tuning for technical applications.

These primary principles of investigating and exploiting biological inspirations are depicted in Figure 1. First, analogies between biological and technical systems such as computing and networking systems must be identified. It is especially necessary that all the biological principles are understood properly, which is often not yet the case in biology. Secondly, models must be created for the biological behavior. These models will later be used to develop the technical solution. The translation from biological models to the model describing bio-inspired technical systems is a pure engineering step. Finally, the model must be simplified and tuned for the technical application. As a remark,

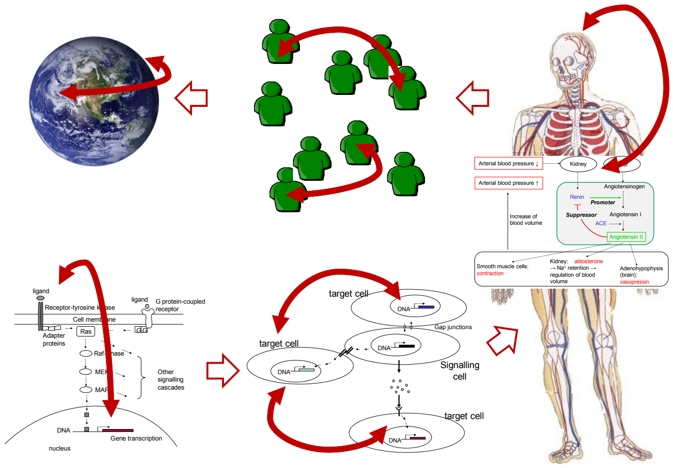

Figure 2: Communication and coordination on micro and macro level. Depicted is the information exchange within a cell, between cells, within the human body, among people, and around the globe

it should be mentioned that biologists already started looking at bio-inspired systems to learn more about the behavioral pattern in nature [49]. Thus, the loop closes from technical applications to biological systems.

3.2. Classification and categorization

Basically, the following application domains of bio-inspired solutions to problems related to computing and communications can be distinguished:

- *Bio-inspired computing* represents a class of algorithms focusing on efficient computing, e.g. for optimization processes and pattern recognition.
- *Bio-inspired systems* constitute a class of system architectures for massively distributed and collaborative systems, e.g. for distributed sensing and exploration.
- *Bio-inspired networking* is a class of strategies for efficient and scalable networking under uncertain conditions, e.g. for autonomic organization in massively distributed systems.

Looking from biological principles, several application domains in networking can be distinguished. Table 1 summarizes the biological domains that are, together with specific examples of successful application to networking, detailed in Section 4.

Besides these specific algorithms that are mimicking biological mechanisms and behavior, the general organization of biological systems, i.e. the structure of bodies down to organs and cells, can be used as an inspiration to develop scalable and self-organizing technical systems, in particular computer networks. Respective control frameworks and complete bio-networking architectures have been investigated [46, 48].

Figure 2 depicts another interesting property of many biological communication and coordination mechanisms. If studying those techniques on the micro level, i.e. on a cellular basis or the signaling pathways between cells, similar mechanisms can be identified compared to studies of the macro level, i.e. the coordination among people in a group or even around the globe. In summary, many models are similar on the micro and macro level – basically exploiting similar communication and coordination mechanisms.

This degree of similarity has advantages. First of all, the precise modeling of specific communication aspects can frequently be done using existing models for other domains. For example, the diffusion of proteins to neighboring cells can be described with a similar communication model like the epidemic spreading of viruses between different people. Mathematical models are often the same. On the other hand, such similarity requires especial care when selecting the right biological model as source for inspiration to solve a technical problem. If the models do not perfectly match, the technical solution may be limited in its functionality or effectiveness.

Further summaries in this field can be found in form of book chapters in [93] and in [94]. Additionally, the book "Advances in Biologically Inspired Information Systems - Models, Methods, and Tools" can be recommended as a source of general bio-inspired solutions to technical systems [95].

4. Approaches to Bio-inspired Networking

In this section, we introduce the current state-of-the-art in bio-inspired networking based on examples for the various networking paradigms. The following list is not meant to be comprehensive and to completely represent all approaches in the domain of bio-inspired networking. However, we selected a number of techniques and methods for more detailed presentation that clearly show advantages in fields of communication networks. In the discussion, we try to highlight the necessary modeling of biological phenomena or principles and their application in networking.

4.1. Swarm Intelligence and Social Insects

Coordination principles studied in the fields of swarm intelligence [13] and especially those related to social insects give insights into principles of distributed coordination in Nature. In many cases, direct communication among individual insects is exploited, e.g., in the case of dancing bees [51]. However, especially the stigmergic communication via changes in the environment is as fascinating as helpful to coordinate massively distributed systems. For example, Ma and Krings studied the chemosensory communication systems in many of the moth, ant and beetle populations [50]. The difference between the "wireless" network of an insect population and an engineered wireless sensor network is that insects encode messages with semiochemicals (also known as infochemicals) rather than

Biological principle	Application fields in networking	Selected references
Swarm Intelligence and Social Insects	distributed search and optimization; routing in computer networks, especially in MANETs, WSNs, and overlay networks; task and resource allocation	[50, 51, 13, 52, 19, 30, 53, 20, 54, 39, 40, 37, 38, 55, 56]
Firefly Synchronization	robust and fully distributed clock synchronization	[32, 57, 58, 59, 60, 61, 62]
Activator-Inhibitor Systems	(self-) organization of autonomous systems; distributed coordination; continuous adaptation of system parameters in highly dynamic environments	[63, 26, 64, 27, 65, 33, 34]
Artificial Immune System	network security; anomaly and misbehavior detection	[66, 25, 67, 68, 69, 18, 70, 11, 36]
Epidemic Spreading	content distribution in computer networks (e.g. in DTNs); overlay networks; analysis of worm and virus spreading in the Internet	[21, 23, 71, 72, 73, 74, 75, 76, 77, 78, 22, 79, 80, 72, 81, 71]
Cellular Signaling Networks	coordination and control in massively distributed systems; programming of network-centric operating sensor and actor networks	[82, 42, 83, 84, 85, 86, 87, 88, 34, 89, 90, 91, 92]

Table 1: Categorization of biological phenomena and networking algorithms mimicking these concepts

with radio frequencies. Application examples of the bees' dance range from routing to intruder detection [51]. Another typical example is the communication between ants for collaborative foraging. We discuss the ACO and its application for routing, task allocation, and search in peer-to-peer networks in the following.

4.1.1. Ant Colony Optimization

Ant Colony Optimization (ACO) is perhaps the best analyzed branch of swarm intelligence based algorithms. In general, swarm intelligence is based on the observation of the collective behavior of decentralized and self-organized systems such as ant colonies, flocks of fishes, or swarms of bees or birds [13]. Such systems are typically made up of a population of simple agents interacting locally with one another and with their environment.

In most cases, swarm intelligence based algorithms are inspired by the behavior of foraging ants [13]. Ants are able to solve complex tasks by simple local means. There is only indirect interaction between individuals through modifications of the environment, e.g. pheromone trails are used for efficient foraging. Ants are "grand masters" in search and exploration.

ACO is based on the principles of the foraging process of ants.[2] Ants perform a random search (random walk) for food. The way back to the nest is marked with a pheromone trail. If successful, the ants return to the nest (following their own trail). While returning, an extensive pheromone trail is produced pointing towards the food source. Further ants are recruited that follow the trail on the shortest path towards the food. The ants therefore communicate based on environmental changes (pheromone trail), i.e. they use stigmergic communication techniques for communication and collaboration.

The complete ACO algorithm is described in [19, 30]. The most important aspect in this algorithm is the *transition probability* p_{ij} for an ant k to move from i to j. This probability represents the routing information for the exploring process

$$p_{ij}^k = \begin{cases} \dfrac{[\tau_{ij}(t)]^\alpha \times [\eta_{ij}]^\beta}{\sum\limits_{l \in J_i^k} [\tau_{il}(t)]^\alpha \times [\eta_{il}]^\beta} & \text{if } j \in J_i^k \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Each move depends on the following parameters:

- J_i^k is the *tabu list* of not yet visited nodes, i.e. by exploiting J_i^k, an ant k can avoid visiting a node i more than once.
- η_{ij} is the visibility of j when standing at i, i.e. the inverse of the distance.
- τ_{ij} is the pheromone level of edge (i, j), i.e. the learned desirability of choosing node j and currently at node i.
- α and β are adjustable parameters that control the relative weight of the trail intensity τ_{ij} and the visibility η_{ij}, respectively.

After completing a tour, each ant k lays a quantity of pheromone $\Delta\tau_{ij}^k(t)$ on each edge (i, j) according to the following rule, where $T^k(t)$ is the tour done by ant k at iteration t, $L^k(t)$ is its length, and Q is a parameter (which only weakly influences the final result)

$$\Delta\tau_{ij}^k(t) = \begin{cases} Q/L^k(t) & \text{if } (i,j) \in T^k(t) \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

Dynamics in the environment are explicitly considered by the ant foraging scheme. The pheromone slowly evaporates. Thus, if foraging ants are no longer successful, the pheromone trail will dissolve and the ants continue with their search process. Additionally, randomness is also a strong factor during successful foraging. A number of ants will continue the random search for food. This adaptive behavior leads to an optimal search and exploration strategy.

[2] Other foraging methods, e.g. *E.coli* bacteria have also been used as inspiration for efficient communication in ad hoc networks, e.g. for data harvesting in vehicular networks [52].

This effect is provided by the pheromone update rule, where $\Delta\tau_{ij}(t) = \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t)$. The decay is implemented in form of a coefficient ρ with $0 \leq \rho < 1$.

$$\tau_{ij}(t) \leftarrow (1-\rho) \times \tau_{ij}(t) + \Delta\tau_{ij}(t) \tag{3}$$

According to [19], the total number of ants m is an important parameter of the algorithm. Too many ants would quickly reinforce suboptimal tracks and lead to early convergence to bad solutions, whereas too few ants would not produce enough decaying pheromone to achieve the desired cooperative behavior. Thus, the decay rate needs to be carefully controlled.

In the following, selected applications in networking are discussed that are based on the main concepts of ACO.

4.1.2. Routing

Perhaps the best known examples of ACO in networking are the AntNet [53] and AntHocNet [20] routing protocols. Both protocols follow the concepts of ant routing. In particular, so called agents are used to concurrently explore the network and exchange collected information in the same way as ants explore the environment. The communication among the agents is indirect, following the stigmergy approach, and mediated by the network itself.

AntNet provides a proactive routing approach that relies on the idea to periodically launch mobile agents towards randomly selected destination nodes. The key objective for these explorer agents is to find a minimum cost path, i.e. a shortest path, between the source and the destination, and to update the path-related routing entries in the network. Following the ACO algorithm, so called *forward ants* randomly search for the destination using a greedy stochastic policy. After locating the destination, the agents turn into *backward ants* and travel home on the same path used for exploration. In this way, all routing tables of traversed nodes are updated with the most current information about the destination node. In order to avoid congestion, AntNet maintains a probability p_d for creating explorer agents according to the current traffic conditions.

The routing tables as used by AntNet and AntHocNet are represented by $\mathcal{T}_k$, which defines the probabilistic routing policy currently adopted for node k. For each destination d and for each neighbor n, $\mathcal{T}_k$ stores a probabilistic value P_{nd} expressing the quality (desirability) of choosing n as a next hop towards destination d. The outgoing probabilities are constrained by $\sum_{n \in \mathcal{N}_k} P_{nd} = 1$.

Similar to AntNet, AntHocNet [20] is based on the ACO algorithm used in the context of ad hoc networks. AntHocNet sets up paths when they are needed at the start of a session. Thus, AntHocNet represents a reactive routing approach. Improved scalability compared to AntHocNet has been achieved by HOPNET [54], an algorithm based on ants hopping between so called zones. It consists of local proactive route discovery within a node's neighborhood and reactive communication between the neighborhoods.

Another work to be named in the domain of routing is the self-adaptive multi-path routing in overlay networks [39, 40]. Again, randomness is exploited to find optimal solutions in selecting network paths. Even though this approach is namely focusing on adaptive responses from attractors, the attractors can be compared to the explorer ants and the probabilistic routing decisions.

4.1.3. Task Allocation

Based on the same concepts, integrated task allocation and routing in SANETs has been investigated [37, 38]. The proposed architecture is completely based on probabilistic decisions. During the lifetime of the SANET, all nodes maintain and adapt a probability $P(i)$ to execute a task out i of a given set. Reinforcement strategies are exploited to optimize the overall system behavior. It needs to be mentioned that the integrated task allocation and routing approach represents a typical cross-layer solution. Application layer and network layer are both responsible for operating the entire SANET.

Task selection is performed by the nodes according to a probabilistic scheme. It is assumed that all the agents know *a priori* a list of tasks $T_{agent} = \{T_1, T_2, \ldots, T_n\}$ that they can perform. Each agent k associates a task $i \in T_{agent}$ to a real number τ_i^k, which is representing the pheromone level. Heterogeneity is inherently supported. Therefore, the task lists of different agents will be different. The probability to chose a task $P(i)$ can now be calculated as (with $\beta_{task} \geq 1$ used for improved exploitation of good solutions):

$$P(i) = \frac{(\tau_i^k)^{\beta_{task}}}{\sum\limits_{j \in T_{agent}} (\tau_j)^{\beta}_{task}} \tag{4}$$

All agents initialize their pheromone level $\tau_i^k = \tau_{init}$. Afterwards, this level is updated according to the achieved task:

$$\tau_i^k = \begin{cases} \min(\tau_{max}, \tau_i^k + \Delta\tau) & \text{if task } i \text{ was successful} \\ \max(\tau_{min}, \tau_i^k - \Delta\tau) & \text{otherwise} \end{cases} \tag{5}$$

The routing is performed similar to the techniques proposed in AntNet and AntHocNet except for one major difference. In order to support the task specific communication, the routing table is extended to cover different forwarding probabilities for the defined tasks, i.e. a class parameter c is added for each routing entry for destination d. Accordingly, the forwarding probability is denoted as ${}_c\mathbf{R}_{nd}$. This allows the exploitation of task specific communication paths. Basically, this technique can be also used for supporting different message priorities in the routing process.

4.1.4. Search in Peer-2-Peer Networks

Search in Peer-2-Peer (P2P) networks is usually provided by centralized or decentralized lookup tables. However, the effort to find data in unstructured decentralized

P2P networks can easily become the dominating factor. The use of ant-based approaches in this domain is expected to solve some of the typical problems.

A self-organized approach for search in P2P networks has been proposed in [55]. The resulting algorithm is a typical ant-based approach to query routing in P2P networks. It is based on results from addressing the exploitation-exploration dilemma, i.e. the question when to exploit available information and when to explicitly explore the network. In particular, it exploits the best results known so far for path selection, or it can explore a path that is not currently known as the best one in order to possibly find an improved solution to the problem. If it succeeds, this will enhance the performance of the system.

Similarly, Antares, which is also an ant-inspired P2P information system for a self-structured grid [56], maintains information in a distributed system. Antares uses agents to manage the storage and replication of data. These agents follow again the concepts of ACO by computing optimized pick and drop probabilities.

4.2. Firefly Synchronization

Precise synchronization in massively distributed systems is a complex issue and hard to achieve. Recently, new models for clock synchronization have been proposed based on the synchronization principles of fireflies. In this context, early biological experiments have been conducted by Richmond who also discovered the underlying mathematical synchronization model [32].

Basically, the firefly synchronization is based on pulse-coupled oscillators [57]. The simple model for synchronous firing of biological oscillators consists of a population of identical integrate-and-fire oscillators. A local variable x_i is integrated from zero to one and the oscillator fires when $x_i = 1$. Then, the x_i jumps back to zero.

$$\frac{dx_i}{dt} = S_0 - \gamma x_i \tag{6}$$

Multiple oscillators are assumed to interact in form of simple pulse coupling: when a given oscillator fires, it pulls the others up by a fixed amount ϵ, or brings them to the firing threshold, whichever is less.

$$x_i(t) = 1 \Rightarrow \forall j \neq i : x_j(t^+) = min(1, x_j(t) + \epsilon) \tag{7}$$

As a result, for almost all initial conditions the population evolves to a state in which all the oscillators are firing synchronously.

The presented concept of self-organized clock synchronization has been successfully applied to synchronization in ad hoc networks [58, 59]. Using a linearly incrementing phase function ϕ_i, the local pulse of a node is controlled: when ϕ_i reaches a threshold ϕ_{th}, the local oscillator fires. For a period of T, this can be described as follows:

$$\frac{d\phi_i(t)}{dt} = \frac{\phi_{th}}{T} \tag{8}$$

When coupling identical oscillators, the phase can be controlled according to Equation 7. Additional effort is needed to compensate the transmission delays in ad hoc and sensor networks. This can be done by selecting appropriate values for ϵ. In particular, the phase shift is dynamically updated according to the estimated transmission delay.

The general application of this clock synchronization technique for wireless networks is discussed in [60]. The main result is the identification of the so called "deafness problem", i.e. the problem that nodes cannot receive and transmit simultaneously. This can be solved by dividing the synchronization cycle into two parts, one for listening to other firing nodes and one for local phase update and pulse firing. This can easily be achieved by doubling the original period T to $2T$.

Furthermore, synchronization-based data gathering in sensor networks has been presented in [61]. The idea is to optimize the energy efficiency for periodic data gathering in WSNs. In the described approach, a base station centric sensor network is consisting of concentrically placed sensors. Then, the firefly based synchronization is used to distribute stimuli for the sensors to measure data and to transmit the results to the base station. Thus, fully self-organized coordinated sensing can be achieved.

A similar synchronization scheme has been proposed for application in overlay networks [62]. In order to address the synchronization issue in P2P networks as a result of network dynamics, failures, and scale, firefly based clock synchronization has been applied as a robust and scalable heartbeat synchronization.

4.3. Activator-Inhibitor Systems

The basis for exploiting the characteristics of activator-inhibitor systems in technical systems is the analysis of reaction-diffusion mechanisms. In the 1950ies, the chemical basis of morphogenesis has been analyzed [63]. The underlying reaction and diffusion in a ring of cells has been successfully described in form of differential equations. Assuming that for concentrations of X and Y chemical reactions are tending to increase X at the rate $f(X,Y)$ and Y at the rate of $g(X,Y)$, the changes of X and Y due to diffusion also take into account the behavior of the entire system, i.e. all the neighboring N cells. Thus, the rate of such chemical reactions can be described by the $2N$ differential equations [63] (where $r = 1, \ldots, N$, μ is the diffusion constant for X and ν is the diffusion constant for Y):

$$\begin{aligned} \frac{dX_r}{dt} &= f(X_r, Y_r) + \mu(X_{r+1} - 2X_r + X_{r-1}) \\ \frac{dY_r}{dt} &= g(X_r, Y_r) + \nu(X_{r+1} - 2X_r + X_{r-1}) \end{aligned} \tag{9}$$

For general application (independent of the shape of the generated pattern or the structure of interacting systems), this set of differential equations can be written as (with F and G being nonlinear functions for (chemical) reactions, D_u and D_v describe the diffusion rates of activator and inhibitor, and ∇^2 is the Laplacian operator):

$$\frac{du}{dt} = F(u,v) - D_u \nabla^2 u$$
$$\frac{dv}{dt} = G(u,v) - D_v \nabla^2 v \quad (10)$$

A direct application of Turing's formula is described in [26]. In this approach, reaction-diffusion pattern formation is used to support high-level tasks in smart sensor networks. In particular, on-off patterns in large-scale deployments for forest fire scenarios have been investigated. As a key result, different shapes have been detected such as stripes, spots, and ring patterns, that can be exploited for high-level activities such as navigating robots to the source of the fire.

Further experiments and considerations on reaction-diffusion based pattern generation in sensor networks are described in [64]. Again, reaction-diffusion based control mechanisms have been investigated. Similarly, cooperative control can be achieved based on a reaction-diffusion equation for surveillance system [27].

As can be seen from the mentioned approaches, sensor coordination is one of the primary application fields for employing activator-inhibitor mechanisms. In the following, two further solutions are depicted that coordinate sensing activities in WSNs to achieve improved energy performance, i.e. to maximize the *network lifetime* [96].

In [65], pattern formation models are used to coordinate the on-off cycles of sensor nodes. In particular, sensors are allowed to control their sensory and their radio transceiver while, at the same time, the network needs to be able to transmit sensor data over a multi-hop network to one or more data sinks. In order to achieve this objective, the sensor field operates as a discrete approximation, in space and in time, of equation system 10. Each sensor stores its own activator and inhibitor values and broadcasts them every τ seconds. Using the received data, the neighboring nodes re-evaluate the reaction-diffusion equations. Sensors with a activator value exceeding some (given) threshold become active by turning on their sensing circuitry. As shown in [65], the performance of the system achieves astonishingly good results.

Similarly, the distributed control of processing periods is investigated in [33, 34]. Using the programming system Rule-based Sensor Network (RSN) [87], a sensor network is configured for target tracking. In this example, the duty cycle is controlled by a promoter / inhibitor system that takes into account the efficiency of the local observations and the results from neighboring nodes. By exploiting the information transmitted towards a sink node, each node can estimate the need for further local measurements and adequately update the local sampling period.

4.4. Artificial Immune System

The term Artificial Immune System (AIS) refers to a terminology that refers to adaptive systems inspired by theoretical and experimental immunology with the goal of problem solving [66]. The primary goal of an AIS, which is inspired by the principles and processes of the mammalian immune system [25], is to efficiently detect changes in the environment or deviations from the normal system behavior in complex problems domains.

The role of the mammalian immune system can be summarized as follows: It protects the body from infections by continuously scanning for invading pathogens, e.g. exogenous (non-self) proteins. AIS based algorithms typically exploit the immune system's characteristics of self-learning and memorization. The immune system is, in its simplest form, a cascade of detection and adaptation, culminating in a system that is remarkably effective. In nature, two immune responses were identified. The primary one is to launch a response to invading pathogens leading to an unspecific response (using Leucoytes). In contrast, the secondary immune response remembers past encounters, i.e. it represents the immunologic memory. It allows a faster response the second time around showing a very specific response (using B-cells and T-cells).

An AIS basically consists of three parts, which have to be worked out in the immune engineering process [66]:

- *Representations* of the system components, i.e. the mapping of technical components to antigens and antibodies.
- *Affinity measures*, i.e. mechanisms to evaluate interactions (e.g., stimulation pattern and fitness functions) and the matching of antigens and antibodies.
- *Adaptation procedures* to incorporate the system's dynamics, i.e. genetic selection.

A first AIS has been developed by Kephart [67], and early approaches showing the successful application of such AISs in computer and communication systems have been presented in [25, 68]. Meanwhile, a number of frameworks are available. Focusing on the design phase of an AIS, de Castro and Timmis [66] proposed an immune engineering framework. A similar conceptual frameworks for Artificial Immune Systems for generic application in networking has been presented in [69]. Again, three steps for designing the framework have been emphasized: representation, selection of appropriate affinity measures, and development of immune algorithms. In this framework, Markov chains are used to describe the system's dynamics.

Data analysis and anomaly detection represent typical application domains [66]. The complete scope of AISs is widespread. Sample applications have been developed for fault and anomaly detection, data mining (e.g., machine learning, pattern recognition), agent based systems, control, and robotics. Pioneering work by Timmis and co-workers needs to be mentioned who conceptually analyzed the AIS and applied it to several problem domains [69, 11, 36].

An application of an immune system based distributed node and rate selection in sensor networks has been proposed in [18]. Sensor networks and their capabilities, in particular their transmission rate, are modeled as antigens and antibodies. The distributed node and rate selection (DNRS) algorithm for event monitoring and reporting is achieved by B-cell stimulation, i.e. appropriate node selection.. This stimulation depends on the following influences: (1) the affinity between the sensor node (B-cell) and event source (pathogen), (2) the affinity between the sensor node and its uncorrelated neighbor nodes (stimulating B-cells), and (3) the affinity between the sensor node and its correlated neighbor nodes (suppressing B-cells). Thus, this algorithm exploits also an activator-inhibitor scheme for optimizing the affinity measure in an AIS.

An Artificial Immune System approach to misbehavior detection in MANETs is described in [70]. In particular, an AIS has been designed to detect misbehavior in Dynamic Source Routing (DSR), a typical reactive MANET protocol. For the representation of routing events, letters from the alphabet are used, e.g. "A=RREQ sent" or "E=RREQ received". Antibodies are represented as received sequences of such routing events. Then, a matching function can be defined using sequences of those letters, e.g. "Gene 1=#E in sequence" (refer to [70] for more details). Then, the AIS is used to identify a node as "suspicious" if a corresponding antigen is matching any antibody. Furthermore, a node is classified as "misbehaving" if the probability that the node is suspicious, estimated over a sufficiently large number of data sets, is above a threshold.

4.5. Epidemic Spreading

Epidemic spreading is frequently used as an analogy to understand the information dissemination in wireless ad hoc networks. Information dissemination in this context can refer to the distribution of information particles (as usually provided by ad hoc routing techniques) [21, 23] or to the spread of viruses in the Internet [71, 72] or on mobile devices [73]. Biological models of virus transmission provide means for assessing such emerging threats and to understand epidemics as a general purpose communication mechanism.

A number of mathematical models of the different networks have been investigated that lie at various points on a broad conceptual spectrum. At one end are network models that reflect strong spatial effects, with nodes at fixed positions in two dimensions, each connected to a small number of other nodes a short distance away. At the other end are scale-free networks, which are essentially unconstrained by physical proximity, and in which the number of contacts per node are widely spread. The main difference is in the epidemic spread. In scale-free networks, epidemics can persist at arbitrarily low levels, whereas in simple two-dimensional models a minimum level of virulence is needed to prevent them from dying out quickly [73].

The system model for epidemic communication relies on a population, i.e. a number of nodes that represent the network. Information entities are exchanges among the nodes using a diffusion algorithm. All transmissions are usually assumed to be atomic, i.e. there will be no split during diffusion. Then, all the nodes can be distinguished into two groups: susceptible nodes, $S(t)$ describes this set at a certain time t, and infective nodes $I(t)$ [74]. The diffusion algorithm is then a process that converts susceptible nodes into infective nodes with a rate $\alpha = \frac{\beta x}{N} I(t)$, where β is the probability of information transmission, i.e. the infection probability, x describes the number of contacts among susceptible nodes, and N is the total number of nodes. The infection rate can then be described as:

$$\frac{dI}{dt} = \alpha \times S(t) = \frac{\beta x}{N} I(t) \times S(t) \tag{11}$$

A measure for the connectedness of the nodes is termed *eigenvector centrality*. Let us consider a graph model of the network topology and denote by A the corresponding adjacency matrix. The eigenvector centrality of a node i is defined being proportional to the sum of the eigenvector centralities of i's neighbors, where e represents the vector of nodes' centrality scores. Otherwise stated, e is the eigenvector of A relative to the eigenvalue λ:

$$e_i = \frac{A \times e}{\lambda} \tag{12}$$

Depending on the particular application scenario, the healing rate, i.e. the non-negative rate of converting infective nodes, also needs to be considered in this equation.

There is a wide application range for epidemic communication in computer networks. Primarily, the focus is on routing in mobile ad hoc networks with growing interest in opportunistic routing [75], in which messages are passed between devices that come into physical proximity, with the goal of eventually reaching a specified recipient.

For example, the understanding of the spread of epidemics in highly partitioned mobile networks has been studied in [23]. The main application field in this work was the use of epidemic communication in DTNs. As a conclusion, the paper outlines the possibility to roughly measure the importance of a node to the process of epidemic spreading by the node's eigenvector centrality. Regions, as defined by the steepest-ascent rule, are clusters of the network in which spreading is expected to be relatively rapid and predictable. Furthermore, nodes whose links connect distinct regions play an important role in the (less rapid, and less predictable) spreading from one region to another.

The characteristics of epidemic information dissemination have been carefully modeled to investigate the inherent characteristics [76]. For example, the buffer management plays and important role and a stepwise probabilistic buffering has been proposed as a solution [77].

Detailed models have been built to study the performance impact of epidemic spreading [78] Whereas Markov models lead to quite accurate performance predictions, the numerical solution becomes impractical if the number of nodes is large. In [78], an unified framework based on ordinary differential equations is presented that provides appropriate scaling as the number of nodes increases. This approach allows the derivation of closed-form formulas for the performance metrics while obtaining matching results compared to the Markov models.

In this view, the power of epidemics for robust communication in large-scale networks has been investigated by quite a number of approaches [21, 22, 79]. The interesting result is that the network topology plays an important role whether epidemics can be applied for improved robustness and efficiency. In particular, the scale-free property must be ensured in order to overcome possible problems with transmissions that quickly die out.

A slightly different problem (and solution) has been addressed in [80]. The targeted question is that the problem of determining the right information collection infrastructure can be viewed as a variation of the network design problem – including additional constraints such as energy efficiency and redundancy. As the general problem is NP-hard, the authors propose a heuristic based on the mammalian circulatory system, which results in a better solution to the design problem than the state-of-the-art alternatives. The resulting circulatory system approach for wireless sensor networks is quite similar to the epidemics approach even though only the communication within an organism is used as an analogy.

Besides efficient routing solutions, the application to network security is probably the most important aspect of epidemic models. The spread of Internet worms has been studied recently with astonishing results [72, 81, 71].

4.6. Cellular Signaling Networks

Basically, the term signaling describes the interactions between single signaling molecules [82]. Such communication, also known as signaling pathways [42, 83], is an example for very efficient and specific communication. Cellular signaling occurs at multiple levels and in many shapes.

Briefly, cellular interactions can be viewed as processing in two steps. Initially, an extracellular molecule binds to a specific receptor on a target cell, converting the dormant receptor to an active state. Subsequently, the receptor stimulates intracellular biochemical pathways leading to a cellular response [83]. In general, the following two cellular signaling techniques can be distinguished [84].

Intracellular signaling – The signal from the extracellular source is transferred through the cell membrane. Inside of the target cell, complex signaling cascades are involved in the information transfer (signal transduction), which finally result in gene expression or an alteration in enzyme activity and, therefore, define the cellular response.

Intercellular signaling – Cells can communicate via cell surface molecules. In this process, a surface molecule of one cell or even a soluble molecule, which is released by one cell, directly binds to a specific receptor molecule on another cell. Soluble molecules such as hormones can also be transported via the blood to remote locations.

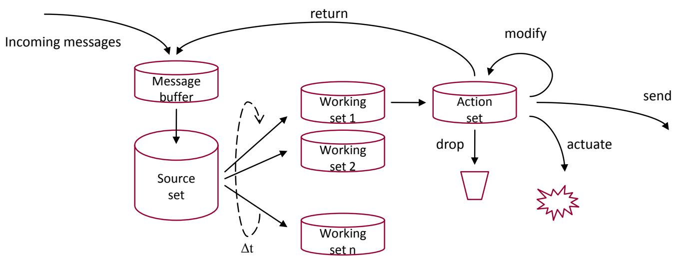

Figure 3: The working behavior of a single RSN node. Received messages are stored in a buffer. After Δt, they are selected to a working set according to specific criteria, and finally processed, i.e. forwarded, dropped, etc.

A key challenge for biology is to understand the structure and the dynamics of the complex web of interactions that contribute to the structure and function of a living cell. In order to uncover the structural design principles of such signaling networks, network motifs have been defined as patterns of interconnections occurring in complex networks at numbers that are significantly higher than those in randomized networks [85].

A couple of approaches have been discussed using artificial signaling networks. Most of this work is targeting programming schemes for massively distributed systems such as sensor networks. In the following, two of the most successful approaches will be introduced: RSN and Fraglets. Another approach is on parallel execution of IF-THEN constructs using artificial cell signaling networks with molecular classifier systems [86].

4.6.1. Rule-based Sensor Network

Rule-based Sensor Network (RSN) is a light-weight programming scheme for SANETs [87, 88]. It is based on an architecture for data-centric message forwarding, aggregation, and processing, i.e. using self-describing messages instead of network-wide unique address identifiers. It has been shown that RSN can outperform other SANET protocols for distributed sensing and network-centric data pre-processing in two dimensions: (a) reactivity of the network, i.e. the response times for network-controlled actuation can be reduced, and (b) communication overhead, i.e. the bandwidth utilization on the wireless transmission channels was improved.

Figure 3 depicts the working behavior of a single RSN node. After receiving a message, it is stored in a message buffer. The rule interpreter is either started periodically (after a fixed Δt) or after the reception of a new message. An extensible and flexible rule system is used to evaluate received messages and to provide the basis for the node programming scheme. The specific reaction on received data is achieved by means of predicate-action sequences of the form `if PREDICATE then { ACTION }`.

Op	Input	Output
Transformation rules		
nul	$[nul : tail]$	- (fraglet is removed)
dup	$[dup : t : u : tail]$	$[t : u : u : tail]$
split	$[split : t : \ldots : * : tail]$	$[t : \ldots], [tail]$
send	$_A[send : B : tail]$	$_B[tail]$
Reaction rules		
match (merge)	$[match : s : tail_1]$, $[s : tail_2]$	$[tail_1 : tail_2]$
matchP (persist)	$[matchP : s : tail_1]$, $[s : tail_2]$	$[tail_1 : tail_2]$ $[matchP : s : tail_1]$

Table 2: Typical fraglet transformation and reaction rules [89], where $*$ is a position marker for splitting fraglets and $_X[\ldots]$ specifies the place where a fraglet is stored

First, all messages matching the predicate are stored in so called working sets. Finally, the specified action is executed on all the messages in the set. Using such rule-sets, complex and dynamic behavior can be modeled. Examples are event monitoring applications in sensor networks or target tracking under energy constraints. In biological systems such behavior can be modeled (or studied) using signaling networks and repetitive patterns, or motifs.

The period of RSN execution Δt has been identified as a key parameter for controlling the reactivity vs. energy performance of the entire RSN-based network. Basically, the duration of messages stored in the local node introduces an artificial per-hop delay. The optimal value for Δt affects the aggregation quality vs. real-time message processing. A promoter-inhibitor system has successfully been applied to solve this issue [34] (see Section 4.3).

4.6.2. Fraglets

A metabolistic execution model for communication protocols was named Fraglets [89]. Similar to RSN, this model is also based on the concept of data-centric communication. Furthermore, the execution relies on the unification of code and data, featuring a single unit called "fraglets" that are operands as well as operators. Fraglets have surprising strong ties to formal methods as well as to molecular biology. At the theory level, fraglets belong to string rewriting systems. In particular, fraglets are symbol strings $[s_1 : s_2 : \ldots tail]$ that represent data and/or logic, where *tail* is a (possibly empty) sequence of symbols. Each node in the network has a fraglet store to which incoming fraglets are added. The node continuously examines the fraglet store and identifies which fraglets need to be processed. Simple actions lead to transformations of a single fraglet. More complex actions combine two fraglets. If several actions are possible at a time, the system randomly picks one action, atomically removes the involved fraglets from the store, processes them, and puts potential results back into the store [89].

Table 2 lists some typical (selected) rules for fraglet transformation and reaction on events.

Using the fraglet system, network-centric operations can be specified to be executed by participating nodes after reception of a specific fraglet. A simple example of a fraglet program is the following confirmed-delivery protocol (CDP) that transfers received $[cdp : data]$ fraglets from A to B, with per packet acknowledgments [89]:

$$_A[matchP : cdp : send : B : deliver]$$
$$_B[matchP : deliver : split : send : A : ack : *]$$

Further research on fragets has been conducted w.r.t. resilience and robustness [90],self-modifying and self-replicating programs using fraglets [91], and the extensibility of the fraglet system, e.g. cryptographic primitives have been added to provide security measures for the fraglets system [92].

5. Nano-scale and Molecular Communication

Incredible improvements in the field of nano-technologies have enabled nano-scale machines that promise new solutions for several applications in biomedical, industry and military fields. Some of these applications require or might exploit the potential advantages of communication and hence cooperative behavior of these nano-scale machines to achieve a common and challenging objective that exceeds the capabilities of a single device. At this point, the term "nanonetworks" is defined as a set of nano-scale devices, i.e., nano-machines, communicating with each other and sharing information to realize a common objective. Nanonetworks allow nano-machines to cooperatively communicate and share any kind of information such as odor, flavor, light, or any chemical state in order to achieve specific tasks required by wide range of applications including biomedical engineering, nuclear, biological, and chemical defense technologies, environmental monitoring.

Despite the similarity between communication and network functional requirements of traditional and nano-scale networks, nanonetworks bring a set of unique challenges. In general, nano-machines can be categorized into two types: one type mimics the existing electro-mechanical machines and the other type mimics nature-made nanomachins, e.g., molecular motors and receptors. In both types, the dimensions of nano-machines render conventional communication technologies such as electromagnetic wave, acoustic, inapplicable at these scales due to antenna size and channel limitations. In addition, the available memory and processing capabilities are extremely limited, which makes the use of complex communication algorithms and protocols impractical in the nano regime.

Furthermore, the communication medium and the channel characteristics also show important deviations from the traditional cases due to the rules of physics governing these scales. For example, due to size and capabilities of nano-machines, traditional wireless communication with radio waves cannot be used to communicate between nano-machines that may constitute of just several moles of atoms or molecules and scale on the orders of a few nanometers. Hence, these unique challenges need to be addressed in order to effectively realize the nano-scale communication and nanonetworks in many applications from nano-scale body area networks to nano-scale molecular computers.

The motivation behind nano-machines and nano-scale communications and networks have also originated and been inspired by the biological systems and processes. In fact, nanonetworks are significant and novel artifacts of bio-inspiration in terms of both their architectural elements, e.g., nano-machines, and their principle communication mechanism, i.e., molecular communication. Indeed, many biological entities in organisms have similar structures with nano-machines, i.e., cells, and similar interaction mechanism and vital processes, cellular signaling [42], with nanonetworks. Within cells of living organisms, nano-machines called molecular motors, such as dynein, myosin [97], realize intracellular communication through chemical energy transformation. Similarly, as already explained in Section 4.6, within a tissue, cells communicate with each other through the release over the surface and the diffusion of certain soluble molecules, and its reception as it binds to a specific receptor molecule on another cell [84].

Apparently, cellular signaling networks are the fundamental source of inspiration for the design of nanonetworks. Therefore, the solution approaches for the communication and networking problems in nanonetworks may also be inspired by the similar biological processes. The main communication mechanism of cellular signaling is based on transmission and reception of certain type of molecules, i.e., molecular communication, which is, indeed, the most promising and explored communication mechanism for nanonetworks.

In nature, molecular communication between biological entities takes place according to the ligand receptor binding mechanism. Ligand molecules are emitted by one biological phenomenon; then, the emitted ligand molecules diffuse in the environment and bind the receptors of another biological phenomenon. This binding enables the biological phenomenon to receive the bound molecules by means of the diffusion on cell membrane. The received ligand molecules allow the biological phenomenon to understand the biological information. For example, in a biological endocrine system, gland cells emit hormones to intercellular environment; then, hormone molecules diffuse and are received by corresponding cells. According to the type of emitted hormone, the corresponding cells convert the hormone molecule to biologically meaningful information. This natural mechanism provides the molecular communication for almost all biological phenomena.

Following the main principles of this mechanism, a number of studies have been performed on the design of nano-scale communication. Molecular communication and some design approaches are introduced [98],and its fundamental research challenges are first manifested in [99]. Different mechanisms are proposed for molecular communication including a molecular motor communication system [100], intercellular calcium signaling networks [43], an autonomous molecular propagation system to transport information molecules using DNA hybridization and bio-molecular linear motors. An information theoretical analysis of a single molecular communication channel is performed in [5]. An adaptive error compensation mechanism is devised for improving molecular communication channel capacity in [101]. In [102], molecular multiple-access, relay and broadcast channels are modeled and analyzed in terms of capacity limits and the effects of molecular kinetics and environment on the communication performance are investigated. Based on the use of vesicles embedded with channel forming proteins, a communication interface mechanism is introduced for molecular communication in [103, 104]. In addition, a wide range of application domains of molecular communication based nanonetworks are introduced from nano-robotics to future health-care systems [105].

Clearly, inspired by biological systems, molecular communication, which enables nano-machines to communicate with each other using molecules as information carrier, stands as the most promising communication paradigm for nanonetworks.[3] While some research efforts and initial set of results exist in the literature, many open research issues remain to be addressed for the realization of nanonetworks.

Among these, first is the thorough exploration of biological systems, communications and processes, in order to identify different efficient and practical communication techniques to be inspired by and exploited towards innovative nanonetwork designs. The clear set of challenges for networked communication in nano-scale environments must be precisely determined for these different potential bio-inspired solution avenues. Applicability of the traditional definitions, performance metrics and well-known basic techniques, e.g., Time Division Multiple Access (TDMA), random access, minimum cost routing, retransmission, error control, congestion, must be studied. Furthermore, potential problems for the fundamental functionalities of nanonetworks, such as modulation, channel coding, medium access control, routing, congestion control, reliability, must be investigated without losing the sight of the bio-inspired perspective in order to develop efficient, practical and reliable nanonetwork communication techniques through inspiration from the existing biological structures and communication mechanisms.

6. Conclusion

The realization of most of the existing and the next generation networks, e.g., cognitive radio networks, sensor and actor networks, quantum communication networks, vehicular communication networks, terrestrial next generation Internet, and InterPlaNetary Internet, have many

[3] A comprehensive survey of nanonetworks with molecular communication can be found in [41].

common significant barriers such as the increased complexity with large scale networks, dynamic nature, resource constraints, heterogeneous architectures, absence or impracticality of centralized control and infrastructure, need for survivability and unattended resolution of potential failures. At the same time, there exist many biological systems and processes with intrinsic appealing characteristics such as adaptivity to varying environmental conditions, inherent resiliency to failures and damages, successful and collaborative yet practical and simple operation, self-organization, survivability, and evolvability.

In this paper, the common fundamental networking challenges, the current status of research efforts to address them from the perspective of bio-inspired networking is captured. Researchers have started to realize the significance and potentials of bridging the gap between the these two distinct domains under the cross-disciplinary field of bio-inspired networking. Through the existing research results, it has been shown that the inspiration from biology is, indeed, a powerful source of innovative network design.

A list of current active related research projects and dissemination tools for the related research results are provided in Table 3 and 4, respectively. Inevitably, these lists cannot cover all projects and activities related to bio-inspired networking. Furthermore, some of the major conferences and workshops as well as journals and special issues specifically devoted to the field are listed in Table 4. As the topic of bio-inspired networking is meanwhile listed in the scopes and programs of most networking conferences, the list aims to emphasize the events that have been specifically established by the bio-inspired research community.

Despite the considerable amount of ongoing research in this direction, the bio-inspired networking research community is quite young, and there still remain significantly challenging tasks for the research community to address fundamental challenges for the realization of many existing and most of the emerging networking architectures. In this regard, a vast space of biological systems, which still remains unexplored, needs to be thoroughly investigated in order to discover their artifacts to be used towards accelerating the evolution in the information and communication technologies domain. We anticipate that this survey will provide better understanding of the potential for bio-inspired networking, which is currently far from being fully utilized, and to motivate the research community to further explore this timely and exciting topic.

References

[1] J. I. Cirac, S. J. van Enk, P. Zoller, H. J. Kimble, H. Mabuchi, Quantum Communication in a Quantum Network, Physica Scripta T76 (1998) 223–232.

[2] I. F. Akyildiz, O. B. Akan, C. Chen, J. Fang, W. Su, The state of the art in interplanetary Internet, IEEE Communications Magazine 42 (7) (2004) 108–118.

[3] S. Dobson, S. Denazis, A. Fernandez, D. Gaiti, E. Gelenbe, F. Massacci, P. Nixon, F. Saffre, N. Schmidt, F. Zambonelli, A Survey of Autonomic Communications, ACM Transactions on Autonomous and Adaptive Systems (TAAS) 1 (2) (2006) 223–259.

[4] R. L. Ashok, D. P. Agrawal, Next-Generation Wearable Networks, IEEE Computer 36 (11) (2003) 31–39.

[5] B. Atakan, O. B. Akan, An Information Theoretical Approach for Molecular Communication, in: 2nd IEEE/ACM International Conference on Bio-Inspired Models of Network, Information and Computing Systems (IEEE/ACM BIONETICS 2007), Budapest, Hungary, 2007.

[6] I. F. Akyildiz, D. Pompili, T. Melodia, Underwater acoustic sensor networks: research challenges, Elsevier Ad Hoc Networks 3 (3) (2005) 257–279.

[7] I. F. Akyildiz, I. H. Kasimoglu, Wireless Sensor and Actor Networks: Research Challenges, Elsevier Ad Hoc Networks 2 (2004) 351–367.

[8] F. Dressler, A Study of Self-Organization Mechanisms in Ad Hoc and Sensor Networks, Elsevier Computer Communications 31 (13) (2008) 3018–3029.

[9] I. F. Akyildiz, W.-Y. Lee, M. C. Vuran, S. Mohanty, NeXt generation/dynamic spectrum access/cognitive radio wireless networks: a survey, Elsevier Computer Networks 50 (13) (2006) 2127–2159.

[10] F. Dressler, Self-Organization in Sensor and Actor Networks, John Wiley & Sons, 2007.

[11] J. Timmis, M. Neal, J. Hunt, An Artificial Immune System for Data Analysis, Biosystems 55 (2000) 143–150.

[12] S. Camazine, J.-L. Deneubourg, N. R. Franks, J. Sneyd, G. Theraula, E. Bonabeau, Self-Organization in Biological Systems, Princeton University Press, 2003.

[13] E. Bonabeau, M. Dorigo, G. Theraulaz, Swarm Intelligence: From Natural to Artificial Systems, Oxford University Press, 1999.

[14] E. Welbourne, L. Battle, G. Cole, K. Gould, K. Rector, S. Raymer, M. Balazinska, G. Borriello, Building the Internet of Things Using RFID, IEEE Internet Computing 33 (3) (2009) 48–55.

[15] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, E. Cayirci, Wireless sensor networks: a survey, Elsevier Computer Networks 38 (2002) 393–422.

[16] I. F. Akyildiz, X. Wang, W. Wang, Wireless mesh networks: a survey, Elsevier Computer Networks 47 (4) (2005) 445–487.

[17] Ö. B. Akan, I. F. Akyildiz, Event-to-Sink Reliable Transport in Wireless Sensor Networks, IEEE/ACM Transactions on Networking (TON) 13 (5) (2005) 1003–1016.

[18] B. Atakan, O. B. Akan, Immune System Based Distributed Node and Rate Selection in Wireless Sensor Networks, in: 1st IEEE/ACM International Conference on Bio-Inspired Models of Network, Information and Computing Systems (IEEE/ACM BIONETICS 2006), IEEE, Cavalese, Italy, 2006.

[19] M. Dorigo, V. Maniezzo, A. Colorni, The Ant System: Optimization by a colony of cooperating agents, IEEE Transactions on Systems, Man, and Cybernetics 26 (1) (1996) 1–13.

[20] G. Di Caro, F. Ducatelle, L. M. Gambardella, AntHocNet: An adaptive nature-inspired algorithm for routing in mobile ad hoc networks, European Transactions on Telecommunications, Special Issue on Self-organization in Mobile Networking 16 (2005) 443–455.

[21] W. Vogels, R. van Renesse, K. Briman, The Power of Epidemics: Robust Communication for Large-Scale Distributed Systems, ACM SIGCOMM Computer Communication Review 33 (1) (2003) 131–135.

[22] T. Tsuchiya, T. Kikuno, An Adaptive Mechanism for Epidemic Communication, in: 1st International Workshop on Biologically Inspired Approaches to Advanced Information Technology (Bio-ADIT2004), Vol. LNCS 3141, Springer, Lausanne, Switzerland, 2004.

[23] I. Carreras, D. Miorandi, G. S. Canright, K. Engo-Monsen, Understanding the Spread of Epidemics in Highly Mobile Networks, in: 1st IEEE/ACM International Conference on Bio-Inspired Models of Network, Information and Computing Sys-

Table 3: Current research projects on bio-inspired networking

Project name	Funding	Research area	URL
ANA	EU FET	Autonomic network architecture and principles	http://www.ana-project.org/
BioNet	NSF, DARPA	Bio-networking architecture for design and implementation of scalable, adaptive, survivable/available network applications	http://netresearch.ics.uci.edu/bionet/
BIONETS	EU FET	Bio-inspired service evolution for the pervasive age	http://www.bionets.eu/
CASCADAS	EU FET	Autonomic and situation-aware communications, and dynamically adaptable services	http://www.cascadas-project.org/
ECAgents	EU FET	Embodied and communicating agents interacting directly with the physical world	http://ecagents.istc.cnr.it/
Haggle	EU FET	Situated and autonomic communications	http://www.haggleproject.org/
MC	NSF, DARPA	Molecular communication as a solution for communication between nanomachines	http://netresearch.ics.uci.edu/mc/
Swarmanoid	EU FET	Design, implementation and control of a novel distributed robotic system	http://www.swarmanoid.org/
Swarm-bots	EU FET	Design and implementation of self-organizing and self-assembling artifacts	http://www.swarm-bots.org/
WASP	EU IP	Self-organization of nodes and services in WSNs	http://www.wasp-project.org/

tems (IEEE/ACM BIONETICS 2006), IEEE, Cavalese, Italy, 2006.

[24] I. Chlamtac, M. Conti, J. J. Liu, Mobile ad hoc networking: imperatives and challenges, Elsevier Ad Hoc Networks 1 (1) (2003) 13–64.

[25] S. A. Hofmeyr, S. Forrest, Architecture for an Artificial Immune System, Evolutionary Computation 8 (4) (2000) 443–473.

[26] T. C. Henderson, R. Venkataraman, G. Choikim, G. Choikim, Reaction-Diffusion Patterns in Smart Sensor Networks, in: IEEE International Conference on Robotics and Automation (ICRA 2004), IEEE, New Orleans, LA, 2004, pp. 654–658.

[27] A. Yoshida, K. Aoki, S. Araki, Cooperative control based on reaction-diffusion equation for surveillance system, in: 9th International Conference on Knowledge-Based & Intelligent Information & Engineering Systems (KES 2005), Vol. LNCS 3684, Melbourne, Australia, 2005.

[28] B. Atakan, Ö. B. Akan, Immune System-based Energy Efficient and Reliable Communication inWireless Sensor Networks, in: F. Dressler, I. Carreras (Eds.), Advances in Biologically Inspired Information Systems - Models, Methods, and Tools, Vol. 69 of Studies in Computational Intelligence (SCI), Springer, Berlin, Heidelberg, New York, 2007, pp. 187–208.

[29] B. Metcalfe, The next-generation Internet, IEEE Internet Computing 4 (1) (2000) 58–59.

[30] M. Dorigo, G. Di Caro, L. M. Gambardella, Ant Algorithms for Discrete Optimization, Artificial Life 5 (2) (1999) 137–172.

[31] B. Atakan, O. B. Akan, Biologically-inspired Spectrum Sharing in Cognitive Radio Networks, in: IEEE Wireless Communications and Networking Conference (IEEE WCNC 2007), Hong Kong, China, 2007.

[32] C. A. Richmond, Fireflies Flashing in Unison, Science 71 (1847) (1930) 537–538.

[33] F. Dressler, Self-Organized Event Detection in Sensor Networks using Bio-inspired Promoters and Inhibitors, in: 3rd ACM/ICST International Conference on Bio-Inspired Models of Network, Information and Computing Systems (Bionetics 2008), ACM, Hyogo, Japan, 2008.

[34] F. Dressler, Bio-inspired Feedback Loops for Self-Organized Event Detection in SANETs, in: K. A. Hummel, J. Sterbenz (Eds.), 3rd IEEE/IFIP International Workshop on Self-Organizing Systems (IWSOS 2008), Vol. LNCS 5343, Springer, Vienna, Austria, 2008, pp. 256–261.

[35] A. Boukerche, H. Oliveira, E. Nakamura, A. Loureiro, Vehicular Ad Hoc Networks: A New Challenge for Localization-Based Systems, Elsevier Computer Communications 31 (12) (2008) 2838–2849.

[36] M. Neal, J. Timmis, Once More Unto the Breach: Towards Artificial Homeostasis?, in: L. N. De Castro, F. J. Von Zuben (Eds.), Recent Developments in Biologically Inspired Computing, Idea Group, 2005, pp. 340–365.

[37] T. H. Labella, M. Dorigo, J.-L. Deneubourg, Self-Organised Task Allocation in a Group of Robots, in: 7th International Symposium on Distributed Autonomous Robotic Systems (DARS04), Toulouse, France, 2004.

[38] T. H. Labella, F. Dressler, A Bio-Inspired Architecture for Division of Labour in SANETs, in: F. Dressler, I. Carreras (Eds.), Advances in Biologically Inspired Information Systems - Models, Methods, and Tools, Vol. 69 of Studies in Computational Intelligence (SCI), Springer, Berlin, Heidelberg, New York, 2007, pp. 209–228.

[39] K. Leibnitz, N. Wakamiya, M. Murata, Resilient Multi-Path Routing Based on a Biological Attractor Selection Scheme, in: 2nd International Workshop on Biologically Inspired Approaches to Advanced Information Technology (Bio-ADIT 2006), Vol. LNCS 3853, Springer, Osaka, Japan, 2006, pp. 48–63.

[40] K. Leibnitz, N. Wakamiya, M. Murata, Biologically-Inspired Self-Adaptive Multi-Path Routing in Overlay Networks, Communications of the ACM, Special Issue on Self-Managed Systems and Services 49 (3) (2006) 63–67.

[41] I. F. Akyildiz, F. Brunetti, C. Blázquez, Nanonetworks: A New Communication Paradigm, Elsevier Computer Networks 52 (2008) 2260–2279.

[42] B. Alberts, D. Bray, J. Lewis, M. Raff, K. Roberts, J. D. Watson, Molecular Biology of the Cell, 3rd Edition, Garland Publishing, Inc., 1994.

[43] T. Nakano, T. Suda, M. Moore, R. Egashira, A. Enomoto,

Table 4: Conferences, workshops, journals and special issues on bio-inspired networking

	Name of the event	**URL**
	Conferences and workshops	
Bionetics	International Conference on Bio inspired Models of Network, Information and Computing Systems	`http://www.bionetics.org/`
Biowire	Workshop on Bio-inspired Design of Wireless Networks and Self-Organising Networks	`http://www.usukita.org/?q=node/225`
EvoCOMNET	European Workshop on Nature-inspired Techniques for Telecommunications and other Parallel and Distributed Systems	`http://www.evostar.org/`
Bionetworks	Workshop on Socially and Biologically Inspired Wired and Wireless Networks (colocated with IEEE MASS 2007)	`http://san.ee.ic.ac.uk/bionets07/`
BLISS	The 2008 ECSIS Symposium on Bio-inspired, Learning, and Intelligent Systems for Security	`http://www.see.ed.ac.uk/bliss08/`
BADS	International Workshop on Bio-Inspired Algorithms for Distributed Systems (colocated with IEEE ICAC 2009)	`http://bads.icar.cnr.it/`
	Journals and special issues	
ICST Transactions on Bio-Engineering and Bio-inspired Systems		`http://www.icst.org/`
Journal of Bio-Inspired Computation Research (JBICR)		`http://www.ripublication.com/jbicr.htm`
Inderscience International Journal of Bio-Inspired Computation (IJBIC)		`http://www.inderscience.com/ijbic`
Elsevier Ad Hoc Networks	Special Issue on Bio-inspired Computing and Communication in Wireless Ad Hoc and Sensor Networks	`http://www.elsevier.com/locate/adhoc`
IEEE Journal on Selected Areas in Communications (JSAC)	Special Issue on Bio-inspired Networking	`http://www.jsac.ucsd.edu/`
Springer Transactions on Computational Systems Biology (TCSB)	Special Issue on Biosciences and Bio-inspired Information Technologies	`http://www.springer.com/series/7322`
Springer Soft Computing	Special Issue on Distributed Bio-inspired Algorithms	`http://www.springer.com/engineering/journal/500`
Springer Swarm Intelligence	Special Issue Swarm Intelligence for Telecommunications Networks	`http://www.springer.com/computer/artificial/journal/11721`
Inderscience International Journal of Autonomous and Adaptive Communications Systems (IJAACS)	Special Issue on Bio-inspired Wireless Networks	`http://www.inderscience.com/ijaacs`

K. Arima, Molecular Communication for Nanomachines Using Intercellular Calcium Signaling, in: 5th IEEE Conference on Nanotechnology (IEEE NANO 2005), Nagoya, Japan, 2005, pp. 478–481.

[44] M. Eigen, P. Schuster, The Hypercycle: A Principle of Natural Self Organization, Springer, 1979.

[45] W. R. Ashby, Principles of the Self-Organizing System, in: H. von Foerster, G. W. Zopf (Eds.), Principles of Self-Organization, Pergamon Press, 1962, pp. 255–278.

[46] M. Wang, T. Suda, The Bio-Networking Architecture: A Biologically Inspired Approach to the Design of Scalable, Adaptive, and Survivable/Available Network Applications, in: 1st IEEE Symposium on Applications and the Internet (SAINT), San Diego, CA, 2001.

[47] J. Suzuki, T. Suda, Adaptive Behavior Selection of Autonomous Objects in the Bio-Networking Architecture, in: 1st Annual Symposium on Autonomous Intelligent Networks and Systems, Los Angeles, CA, 2002.

[48] C. Lee, H. Wada, J. Suzuki, Towards a Biologically-inspired Architecture for Self-Regulatory and Evolvable Network Applications, in: F. Dressler, I. Carreras (Eds.), Advances in Biologically Inspired Information Systems - Models, Methods, and Tools, Vol. 69 of Studies in Computational Intelligence (SCI), Springer, Berlin, Heidelberg, New York, 2007, pp. 21–46.

[49] B. Webb, What does robotics offer animal behaviour?, Animal Behavior 60 (5) (2000) 545–558.

[50] Z. S. Ma, A. W. Krings, Insect Sensory Systems Inspired Computing and Communications, Elseview Ad Hoc Networks 7 (4) (2009) 742–755.

[51] M. Farooq, Bee-Inspired Protocol Engineering: From Nature to Networks, Natural Computing, Springer, 2009.

[52] U. Lee, E. Magistretti, M. Gerla, P. Bellavista, P. Lió, K.-W. Lee, Bio-inspired Multi-Agent Data Harvesting in a Proactive Urban Monitoring Environment, Elsevier Ad Hoc NetworksAvailable online: 10.1016/j.adhoc.2008.03.009.

[53] G. Di Caro, M. Dorigo, AntNet: Distributed Stigmergetic Control for Communication Networks, Journal of Artificial Intelligence Research 9 (1998) 317–365.

[54] J. Wang, E. Osagie, P. Thulasiraman, R. K. Thulasiram, HOPNET: A Hybrid ant colony OPtimization routing algorithm for Mobile ad hoc NETwork, Elsevier Ad Hoc NetworksAvailable online: 10.1016/j.adhoc.2008.06.001.

[55] E. Michlmayr, Self-Organization for Search in Peer-to-Peer Networks, in: F. Dressler, I. Carreras (Eds.), Advances in Biologically Inspired Information Systems - Models, Methods, and Tools, Vol. 69 of Studies in Computational Intelligence (SCI), Springer, Berlin, Heidelberg, New York, 2007, pp. 247–266.

[56] A. Forestiero, C. Mastroianni, G. Spezzano, Antares: an Ant-Inspired P2P Information System for a Self-Structured Grid, in: 2nd IEEE/ACM International Conference on Bio-Inspired Models of Network, Information and Computing Systems (IEEE/ACM BIONETICS 2007), Budapest, Hungary, 2007.

[57] R. E. Mirollo, S. H. Strogatz, Synchronization of Pulse-Coupled Biological Oscillators, SIAM Journal on Applied Mathematics 50 (6) (1990) 1645–1662.

[58] A. Tyrrell, G. Auer, C. Bettstetter, Fireflies as Role Models for Sychronization in Ad Hoc Networks, in: 1st IEEE/ACM International Conference on Bio-Inspired Models of Network, Information and Computing Systems (IEEE/ACM BIONETICS 2006), IEEE, Cavalese, Italy, 2006.

[59] A. Tyrrell, G. Auer, C. Bettstetter, Biologically Inspired Synchronization for Wireless Networks, in: F. Dressler, I. Carreras (Eds.), Advances in Biologically Inspired Information Systems - Models, Methods, and Tools, Vol. 69 of Studies in Computational Intelligence (SCI), Springer, Berlin, Heidelberg, New York, 2007, pp. 47–62.

[60] A. Tyrrell, G. Auer, Imposing a Reference Timing onto Firefly Synchronization in Wireless Networks, in: 65th IEEE Vehicular Technology Conference (VTC2007-Spring), IEEE, Dublin, Ireland, 2007, pp. 222–226.

[61] N. Wakamiya, M. Murata, Synchronization-Based Data Gathering Scheme for Sensor Networks, IEICE Transactions on Communications, Special Issue on Ubiquitous Networks E88-B (3) (2005) 873–881.

[62] O. Babaoglu, T. Binci, M. Jelasity, A. Montresor, Firefly-inspired Heartbeat Synchronization in Overlay Networks, in: 1st IEEE International Conference on Self-Adaptive and Self-Organizing Systems (SASO 2007), IEEE, Boston, MA, 2007, pp. 77–86.

[63] A. M. Turing, The Chemical Basis for Morphogenesis, Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences 237 (641) (1952) 37–72.

[64] K. Hyodo, N. Wakamiya, E. Nakaguchi, M. Murata, Y. Kubo, K. Yanagihara, Experiments and Considerations on Reaction-Diffusion based Pattern Generation in a Wireless Sensor Network, in: IEEE International Symposium on a World of Wireless, Mobile and Multimedia Networks (IEEE WoWMoM 2007), IEEE, Helsinki, Finland, 2007, pp. 1–6.

[65] G. Neglia, G. Reina, Evaluating Activator-Inhibitor Mechanisms for Sensors Coordination, in: 2nd IEEE/ACM International Conference on Bio-Inspired Models of Network, Information and Computing Systems (IEEE/ACM BIONETICS 2007), Budapest, Hungary, 2007.

[66] L. N. de Castro, J. Timmis, Artificial Immune Systems: A New Computational Intelligence Approach, Springer, 2002.

[67] J. O. Kephart, A Biologically Inspired Immune System for Computers, in: 4th International Workshop on Synthesis and Simulation of Living Systems, MIT Press, Cambridge, MA, 1994, pp. 130–139.

[68] S. A. Hofmeyr, An Immunological Model of Distributed Detection and Its Application to Computer Security, Ph.d thesis, University of New Mexico (1999).

[69] S. Stepney, R. E. Smith, J. Timmis, A. M. Tyrrell, M. J. Neal, A. N. W. Hone, Conceptual Frameworks for Artificial Immune Systems, International Journal of Unconventional Computing 1 (3) (2005) 315–338.

[70] J.-Y. Le Boudec, S. Sarafijanovic, An Artificial Immune System Approach to Misbehavior Detection in Mobile Ad-Hoc Networks, in: 1st International Workshop on Biologically Inspired Approaches to Advanced Information Technology (Bio-ADIT2004), Vol. LNCS 3141, Springer, Lausanne, Switzerland, 2004, pp. 96–111.

[71] C. C. Zou, W. Gong, D. Towsley, L. Gao, The Monitoring and Early Detection of Internet Worms, IEEE/ACM Transactions on Networking (TON) 13 (5) (2005) 961–974.

[72] M. Vojnovic, A. J. Ganesh, On the Race of Worms, Alerts, and Patches, IEEE/ACM Transactions on Networking (TON) 16 (5) (2008) 1066–1079.

[73] J. Kleinberg, Computing: The wireless epidemic, Nature 449 (2007) 287–288.

[74] A. Khelil, C. Becker, J. Tian, K. Rothermel, An Epidemic Model for Information Diffusion in MANETs, in: 5th ACM International Symposium on Modeling, Analysis and Simulation of Wireless and Mobile Systems (ACM MSWiM 2002), ACM, Atlanta, GA, 2002, pp. 54–60.

[75] R. C. Shah, S. Wiethölter, A. Wolisz, When does opportunistic routing make sense?, in: 1st International Workshop on Sensor Networks and Systems for Pervasive Computing (PerSeNS 2005), Kauai Island, HI, 2005.

[76] H. Hayashi, T. Hara, S. Nishio, On Updated Data Dissemination Exploiting an Epidemic Model in Ad Hoc Networks, in: 2nd International Workshop on Biologically Inspired Approaches to Advanced Information Technology (Bio-ADIT 2006), Vol. LNCS 3853, Springer, Osaka, Japan, 2006, pp. 306–321.

[77] E. Ahi, M. Caglar, Ö. Özkasap, Stepwise Probabilistic Buffering for Epidemic Information Dissemination, in: 1st IEEE/ACM International Conference on Bio-Inspired Models of Network, Information and Computing Systems (IEEE/ACM BIONETICS 2006), IEEE, Cavalese, Italy, 2006.

[78] X. Zhang, G. Neglia, J. Kurose, D. Towsley, Performance

Modeling of Epidemic Routing, Elsevier Computer Networks 51 (10) (2007) 2867–2891.
[79] T. Okuyama, T. Tsuchiya, T. Kikuno, Improving the Robustness of Epidemic Communication in Scale-Free Networks, in: 2nd International Workshop on Biologically Inspired Approaches to Advanced Information Technology (Bio-ADIT 2006), Vol. LNCS 3853, Springer, Osaka, Japan, 2006, pp. 294–305.
[80] V. Pappas, D. Verma, B.-J. Ko, A. Swami, A Circulatory System Approach for Wireless Sensor Networks, Elsevier Ad Hoc NetworksAvailable online: 10.1016/j.adhoc.2008.04.009.
[81] G. Kesidis, I. Hamadeh, Y. Jin, S. Jiwasurat, M. Vojnovic, A Model of the Spread of Randomly Scanning Internet Worms that Saturate Access Links, ACM Transactions on Modeling and Computer Simulation (TOMACS) 18 (2) (2008) 1–14.
[82] G. Weng, U. S. Bhalla, R. Iyengar, Complexity in Biological Signaling Systems, Science 284 (5411) (1999) 92–96.
[83] T. Pawson, Protein modules and signalling networks, Nature 373 (6515) (1995) 573–80.
[84] B. Krüger, F. Dressler, Molecular Processes as a Basis for Autonomous Networking, IPSI Transactions on Advances Research: Issues in Computer Science and Engineering 1 (1) (2005) 43–50.
[85] R. Milo, S. Shen-Orr, S. Itzkovitz, N. Kashtan, D. Chklovskii, U. Alon, Network Motifs: Simple Building Blocks of Complex Networks, Nature 298 (2002) 824–827.
[86] J. Decraene, G. Mitchell, B. McMullin, Evolving Artificial Cell Signaling Networks using Molecular Classifier Systems, in: 1st IEEE/ACM International Conference on Bio-Inspired Models of Network, Information and Computing Systems (IEEE/ACM BIONETICS 2006), IEEE, Cavalese, Italy, 2006.
[87] F. Dressler, I. Dietrich, R. German, B. Krüger, Efficient Operation in Sensor and Actor Networks Inspired by Cellular Signaling Cascades, in: 1st ACM/ICST International Conference on Autonomic Computing and Communication Systems (Autonomics 2007), ACM, Rome, Italy, 2007.
[88] F. Dressler, I. Dietrich, R. German, B. Krüger, A Rule-based System for Programming Self-Organized Sensor and Actor Networks, Elsevier Computer Networks 53 (10) (2009) 1737–1750.
[89] C. Tschudin, Fraglets - a Metabolistic Execution Model for Communication Protocols, in: 2nd Symposium on Autonomous Intelligent Networks and Systems (AINS), Menlo Park, CA, 2003.
[90] C. Tschudin, L. Yamamoto, A Metabolic Approach to Protocol Resilience, in: 1st IFIP International Workshop on Autonomic Communication (WAC 2004), Vol. LNCS 3457, Springer, Berlin, Germany, 2004, pp. 191–206.
[91] L. Yamamoto, D. Schreckling, T. Meyer, Self-Replicating and Self-Modifying Programs in Fraglets, in: 2nd IEEE/ACM International Conference on Bio-Inspired Models of Network, Information and Computing Systems (IEEE/ACM BIONETICS 2007), Budapest, Hungary, 2007.
[92] M. Petrocchi, Crypto-fraglets: networking, biology and security, in: 1st IEEE/ACM International Conference on Bio-Inspired Models of Network, Information and Computing Systems (IEEE/ACM BIONETICS 2006), IEEE, Cavalese, Italy, 2006.
[93] F. Dressler, Bio-Inspired Networking - Self-organizing Networked Embedded Systems, in: R. P. Würtz (Ed.), Organic Computing, Springer, Berlin, Heidelberg, New York, 2008, pp. 285–302.
[94] K. Leibnitz, N. Wakamiya, M. Murata, Biologically Inspired Networking, in: Q. Mahmoud (Ed.), Cognitive Networks: Towards Self-Aware Networks, John Wiley & Sons, 2007, pp. 1–21.
[95] F. Dressler, I. Carreras (Eds.), Advances in Biologically Inspired Information Systems - Models, Methods, and Tools, Vol. 69 of Studies in Computational Intelligence (SCI), Springer, 2007.
[96] I. Dietrich, F. Dressler, On the Lifetime of Wireless Sensor Networks, ACM Transactions on Sensor Networks (TOSN) 5 (1) (2009) 1–39.
[97] C. Bustamante, Y. Chelma, N. Forde, D. Izhaky, Mechanical processes in biochemistry, Annual Review of Biochemistry 73 (2004) 705–748.
[98] T. Suda, M. Moore, T. Nakano, R. Egashira, A. Enomoto, Exploratory Research on Molecular Communication between Nanomachines, in: Conference on Genetic and Evolutionary Computation (GECCO 2005), ACM, 2005.
[99] S. Hiyama, Y. Moritani, T. Suda, R. Egashira, A. Enomoto, M. Moore, T. Nakano, Molecular Communication, in: NSTI Nanotech 2005, NSTI, 2005.
[100] M. Moore, A. Enomoto, T. Nakano, R. Egashira, T. Suda, A. Kayasuga, H. Kojima, H. Sakakibara, K. Oiwa, A Design of a Molecular Communication System for Nanomachines Using Molecular Motors, in: 4th IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOMW'06), IEEE, Washington, DC, 2006, p. 554.
[101] B. Atakan, O. B. Akan, On Channel Capacity and Error Compensation in Molecular Communication, Springer Transactions on Computational Systems Biology (TCSB) LNBI 5410 (2008) 59–80.
[102] B. Atakan, O. B. Akan, On Molecular Multiple-Access, Broadcast, and Relay Channel in Nanonetworks, in: 3rd ACM/ICST International Conference on Bio-Inspired Models of Network, Information and Computing Systems (Bionetics 2008), ACM, Hyogo, Japan, 2008.
[103] Y. Moritani, S. Hiyama, T. Suda, R. Egashira, A. Enomoto, M. Moore, T. Nakano, Molecular Communications between Nanomachines, in: 24th IEEE Conference on Computer Communications (IEEE INFOCOM 2005), Miami, FL, 2005.
[104] Y. Moritani, S. Hiyama, S. Nomura, K. Akiyoshi, T. Suda, A Communication interface using vesicles embedded with channel forming proteins in molecular communication, in: 2nd IEEE/ACM International Conference on Bio-Inspired Models of Network, Information and Computing Systems (IEEE/ACM BIONETICS 2007), Budapest, Hungary, 2007, pp. 147–149.
[105] Y. Moritani, S. x. S. Hiyama, T. Suda, Molecular Communication for Health Care Applications, in: 4th IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOMW'06), IEEE, Washington, DC, 2006, p. 549.