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Biologically inspired self-organizing networks

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Abstract: Information networks are becoming more and more complex to accommodate a continuously increasing amount of traffic and networked devices, as well as having to cope with a growing diversity of operating environments and applications. Therefore, it is foreseeable that future information networks will frequently face unexpected problems, some of which could lead to the complete collapse of a network. To tackle this problem, recent attempts have been made to design novel network architectures which achieve a high level of scalability, adaptability, and robustness by taking inspiration from self-organizing biological systems. The objective of this paper is to discuss biologically inspired networking technologies.

Keywords: self-organization; biological systems; adaptability; robustness; swarm intelligence; attractor selection

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In our everyday life we are surrounded by a huge number of information processing devices, such as personal computers, mobile phones, video game consoles, television sets, digital video recorders, automatic teller machines, and vending machines, which are directly or indirectly connected to networks and provide us with a variety of networked information services. With the advancement of mobile phone technology and the proliferation of new devices, such as RFID (radio frequency identification), new networked information services are expected to emerge in the very near future and more diverse types of information will be exchanged between these devices.

1 Introduction

To accommodate such large numbers of heterogeneous types of devices and the tremendous amount of traffic they generate, information networks are becoming more complex and sophisticated. Following design methodologies for conventional network architectures, networks are usually optimized for best performance based on an estimation or prediction of the number of users and their behavior, the amount of traffic they will produce, and the expected operational environment. Furthermore, in order to improve their robustness, networks are equipped with failure recovery mechanisms based on predictions of the type, magnitude, and duration of possibly occurring failures, and they are deployed with additional tolerance margins to treat further exceptional cases. Therefore, such conventional networks can operate in a desired way as long as the operational conditions are within the expected range. Unfortunately, they are vulnerable and may easily collapse once an unexpected amount of traffic or unexpected demand is encountered, either due to abuse, attacks, or unexpected failures for which the network was simply not prepared. Furthermore, due to the enormous complexity of such networks, it may take a substantial amount of time to recover from such failures.

Taking into account the diversity and unpredictability of the operational environment, future information networks need to be capable of maintaining a high level of scalability, adaptability, and robustness. Recently, the field of biologically inspired networking has

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been attracting many researchers and developers, since it appears highly promising as a means to establish more scalable, adaptive, and robust information networks. The source of the emergence of scalability, adaptability, and robustness in biological systems is their inherently self-organizing structure. Global and collective behavior of a self-organizing system is reached through local interactions among the entities constituting the system. Each entity operates on a set of simple rules and behaves in accordance with entirely local information that can be obtained through observation of its local surroundings and communication with its neighbors. Bonabeau et al[1] state four principles of self-organization. These principles are: positive feedback to reinforce good control; negative feedback to suppress overshooting and provide stabilization; direct and/or indirect interactions among entities; exploitation of fluctuations to leap from local suboptimal solutions.

A self-organizing system does not have a centralized control unit dominating the whole system; emergence of controllers lies in the nature of self-organization. Owing to this fact, a self-organizing system has high adaptability and robustness; however, this is at the cost of performance. When the operational conditions stay within the expected range, a conventional and optimally designed system on a centralized architecture achieves better performance and is superior to a self-organizing system as intuitively illustrated in Fig. 1.

However, we argue that this lower performance will eventually be compensated for by advancements in network technologies, such as increases in channel capacity and the development of new devices. Instead, we would do better directing our attention to the adaptability and robustness of self-organizing systems rather than to their performance. In fact, self-organizing biological systems are not structured to achieve optimal performance since they must continue to slowly evolve while adapting to a dynamically changing environment. There are always some spare or even idle resources and sometimes even inefficient control can be observed. Such unused resources are the source of adaptability and robustness, and similar strategies of tradeoffs between quantity and quality will also be essential for future network technologies.

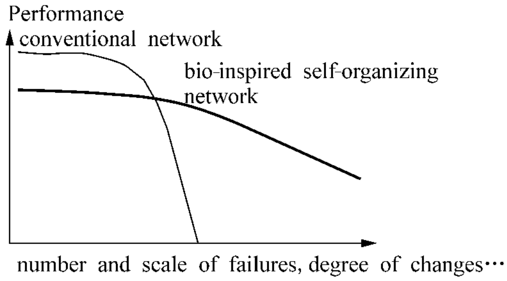

Fig. 1 Comparison of self-organizing networks and conventional networks. Self-organizing networks should be inferior in performance to conventional networks under ideal conditions, but show greater resilience under unexpected conditions.

Although it is also possible for a conventional system to improve its adaptability and robustness by introducing additional and redundant network resources and more sophisticated recovery mechanisms, this would only result in a slight shifting of the critical point to the right in Fig. 1, remaining far below the range of adaptability and tolerance that a self-organizing system possesses.

2 Lessons from biological dynamics

Biological systems are highly dynamical systems. They control, regulate, and adapt themselves according to observations of their dynamically changing surroundings, their internal condition, and their interaction with neighboring organisms, e. g., individuals or cells.

2.1 Self-organizing network control inspired by swarm intelligence

Swarm intelligence is organized collective behavior emerging from local interactions among simple agents in a colony of social insects such as ants or bees[1].

One of the well-known examples of swarm intelligence is the foraging behavior of ants, which find the shortest path from their nest to a food source through indirect interaction among each other mediated by pheromone trails (see Fig. 2). The underlying theoretic model, called ant colony optimization (ACO)[2], is known as a heuristic for the travelling salesman problem (TSP) and has been successfully applied in routing protocols, for example, AntNet[3].

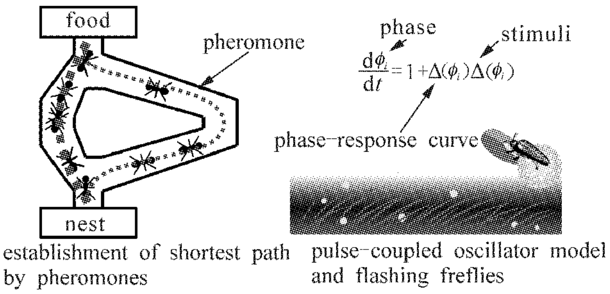

Fig. 2　Examples of swarm intelligence: foraging ants and synchronously flashing fireflies

Another similar example shown in Fig. 2 can be found in the interactions of groups of fireflies or crickets[4]. Some species of fireflies exhibit synchronized behavior in flashing. A firefly periodically flashes according to its intrinsic timer when it is not interacting with other fireflies. However, when fireflies form a group, a flash of one firefly stimulates others in its vicinity. Stimulated fireflies advance the phase of their own timer by a small amount. In this way some advance their timer just enough to flash concurrently. By stimulating each other repeatedly, they eventually begin to flash simultaneously and at the same regular interval. Pulse coupled-oscillator (PCO) is a mathematical model which explains the emergence of synchronization in a group of fireflies[5].

Since synchronization and scheduling is indispensable for effective and efficient network operation, several control mechanisms have been developed based on the PCO model. For example, by adopting the PCO model, wireless sensor nodes can schedule message emissions so that they will not cause collisions among each other on the wireless channel. Additionally, effective sleep scheduling based on synchronization leads to higher throughput, smaller delays, and longer lifetimes in a wireless sensor network[6].

In the case of swarms of bees, they efficiently share roles within their colony, such as foraging and nesting, based on needs without any centralized control. In the response threshold model, each individual has a threshold which expresses their willingness or hesitation to perform a given task[1]. When demand for a task exceeds this threshold, there is a high probability an individual will become engaged in the task. In addition, there is a reinforcement mechanism which generates specialists for a certain task[7]. Once an individual has performed a task for a period of time, it lowers its threshold for that task and becomes more likely to perform the task in the future. This method of division of labor gives the colony high resilience. When individuals performing a certain task are eliminated, others dedicated to another task eventually begin taking over this task and as a result the appropriate balance of role sharing is maintained. As an example, we can consider the task of caching in a content sharing network. The amount of cached content in the network can be balanced, eventually resulting in excessively redundant content being discarded and a smaller cache being maintained[8].

2.2　Network control inspired by biological mechanisms

Biological systems are organized in a hierarchical structure: ecosystem, group, individual, organ system, organ, tissue, and cells. Each level or layer is self-organized within the biological system. A higher layer entity is controlled and organized by interaction and cooperation among lower layer entities.

The immune system is a complex system to protect vertebrates from infection by pathogens. It distinguishes self, such as cells from its own body, from non-self, such as pathogens. It then attacks and eliminates the non-self. In contrast to primary immunity, such as skin and gastric acid, secondary immunity has a mechanism to learn and remember new pathogens and reinforce itself. A model of the biological immune system called an artificial immune system (AIS)[9] has been applied to detection and protection from denial-of-service (DoS) attacks[10]. In this system, each node in a network cooperates with other nodes to learn to distinguish between self and non-self, and to detect and block non-self, or suspicious traffic. Security mechanisms based on AIS are simple and easy to implement. By placing many detectors in a network high adaptability and robustness can be attained.

Living organisms such as animals and fishes have a periodic pattern on their surface or coat. Certain patterns are specific to a species and similar patterns are generated independently of changes to the size or figure of an individual. Even if a part of the pattern is lost due to injury, it is eventually regenerated. Pattern generation is also a result of self-organizing morphogenesis, i. e., the chemical interaction of morphogens among cells. A reaction-diffusion model explains the process of pattern generation. In this model, two hypothetical chemical substances, called an activator and an inhibitor, are synthesized, decomposed, and diffused [11]. Through chemical reactions and diffusion of the hypothetical morphogens, a heterogeneous spatial distribution of morphogen concentrations emerges and a pattern is generated. Depending on the functions and parameters of the model, a variety of patterns such as mazes, spots, and stripes can be generated as shown in Fig. 3.

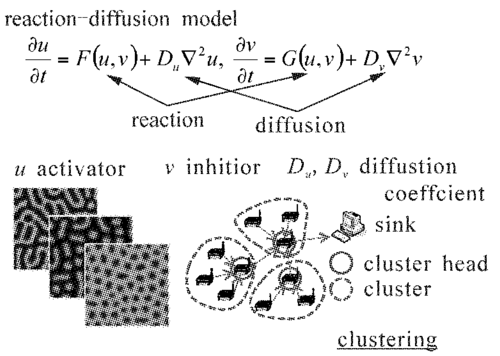

Fig. 3 Reaction-diffusion based clustering in a wireless sensor network. The distribution of clusters in a wireless sensor network resembles a spot pattern self-organized by the reaction-diffusion model

Taking inspiration from self-organized pattern generation, several applications to network control have been proposed such as spatial time division multiple access (S-TDMA) scheduling[12], routing, and content distribution. In the case of clustering of wireless sensor networks, a spot pattern is most suitable[13]. For saving energy consumed in long distance transmission of wireless signals and for efficient use of wireless channel capacity, neighboring nodes form a group, called a cluster. One representative node among them, called a cluster head, takes responsibility for collecting sensor data from the other nodes in the cluster, called cluster members, and sends the collected data to a sink. To balance the energy consumption, cluster heads should be uniformly distributed within the monitored region. Therefore, a spatial distribution of cluster heads resembling the spot pattern of morphogen concentrations is most appropriate. Since the role of cluster heads should be rotated among the nodes, it is best to determine the initial morphogen concentrations depending on the amount of residual energy of each node. After a spot pattern emerges, the node with the highest morphogen concentration becomes a cluster head in that spot, or cluster. Forwarding data from cluster members to a cluster head can be accomplished by simply following the gradient of the morphogen concentration. A node sends data to the neighboring node with the highest morphogen concentration. Eventually, all data reaches the node with the highest morphogen concentration in the cluster-the cluster head.

All bio-inspired network control mechanisms introduced in this section are based on the four previously mentioned principles of self-organization. For example, in a reaction-diffusion based clustering mechanism, nodes interact with each other through diffusion of morphogens. This results in positive and negative feedback in the chemical reactions of the morphogens, resulting in activation and inhibition, and the pattern fluctuates due to dynamically changing residual energy so that the pattern generated does not always remain the same.

However, there is still a lot of room for further investigation in this field. For example, nesting of insects, schooling of fish, flocking of birds, heat shock responses, cell differentiation and biological symbiosis can also provide basic models for self-organizing network control mechanisms.

3 Noise-assisted adaptation

Biological systems are inherently noisy and within a group of biological organisms there are no absolutely identical individuals. Cells constituting a tissue are different from each other in terms of the amount of substances, even if they all play the same role. Furthermore, biological systems continuously keep changing and even the level of diversity within the population does not stay the same. As stated in Section 1, noise or fluctuation is one of the main principles for self-organization. It helps a system to leap from local minima and adapt to new environments.

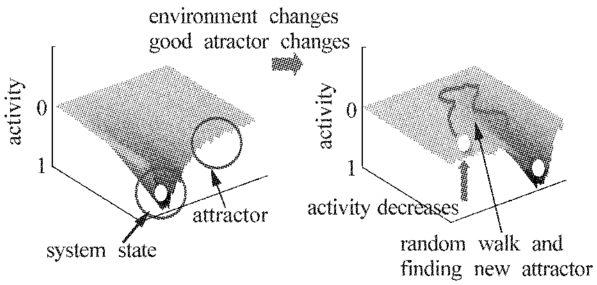

Fig. 4 Attractor selection model. The system is driven by fluctuations to find a new good attractor.

The attractor selection scheme is a model of the adaptation mechanism in the genetic expression of E. coli cells as they respond to environmental changes in nutrient concentration[14]. Although a cell may not have signal transduction pathways for adapting to all possible events occurring outside, it can automatically adjust its state of gene expression in order to increase its activity or growth rate when facing an environment with very low nutrient levels. The stochastic Langevin-type of differential equation shown below describes how the dynamics of the messenger RNA (mRNA) concentration X in an E. coli cell is composed of a deterministic control function and a term reflecting the inherent noise in gene expression.

$$\frac{\mathrm{d}X}{\mathrm{d}t} = f(X) \times \alpha + \eta.$$

The deterministic control function f is multiplied with a parameter , called activity, which corresponds to the growth rate of the cell. When an appropriate attractor, i. e., a stable gene expression state for the current nutrient condition is reached, the activity becomes high and as a result the deterministic control dominates the dynamics of X so that its state remains at this attractor in spite of existing fluctuations. However, once the nutrient conditions change and the chosen attractor becomes no longer suitable, activity decreases and the noise term is dominating. The system begins to look for a new good attractor by randomly searching in the phase space. When it eventually approaches a suitable attractor, the activity begins to increase again and the deterministic control driving the gene expression X towards the good attractor is reinforced, see Fig. 4 and 5.

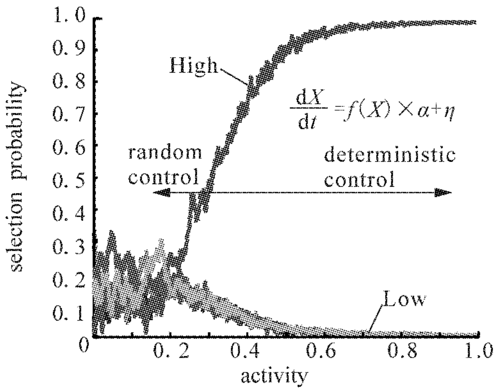

Fig. 5 Attractor selection-based multipath routing. As the activity becomes high, one appropriate path is preferably chosen with a higher selection probability

Future information networks will often face unexpected, unpredicted, and irresolvable conditions due to the number of connected users and devices, the diversity in usage, behavior, and traffic patterns, as well as their temporal variations. Therefore, a conventional design methodology, which prepares for recovery and adaptation of predictable failures and changes, is no longer valid. The attractor selection model is a powerful means of making a network adaptive and robust in such environments, since it does not require any preconfigured recovery and adaptation mechanisms. It has been applied to routing and topology control[15], for example, an attractor selection-based routing mechanism outperformed other conventional routing mechanisms in unreliable and unstable wireless network scenarios.

4 Conclusion

Information networks that have been designed, built, and operated based on self-organizing biological models achieve a high level of scalability, adaptability, and robustness. Some biological mechanisms introduced in this paper are modeled by nonlinear temporal differential equations. The formalism available through these equations permits a mathematical and theoretical treatment and analysis of the stability and convergence properties of bio-inspired networks. Furthermore, we should design and build network control mechanisms by extending models from mathematical biology, exploiting well established theories from physics and mathematics, not merely mimicking or imitating the behavior of actual biological systems.

However, we should also note that the self-organization mechanisms mentioned in this paper are, on their own, not fully sufficient to establish scalable, adaptive, and robust information networks, which provide users and applications with network services appropriate for levels of demand and environmental conditions. We also need to develop, for example, self-configuration mechanisms which recognize current system conditions and cause the network to reconfigure itself. Furthermore, it is necessary to consider how interaction among different self-organizing entities may detrimentally affect each other and bring instability. Currently, we are further investigating such mechanisms, as discussed in this paper, within the scope of the research projects "Special Coordination Funds for Promoting Science and Technology: Yuragi Project" and "Global COE (centers of excellence) Program for Founding Ambient Information Society Infrastructure" of the Ministry of Education, Culture, Sports, Science and Technology, Japan.

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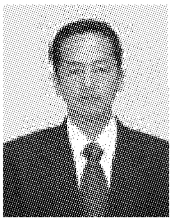

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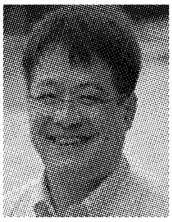

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智能科学新著介绍——《人工情感》

王志良教授编著的《人工情感》一书,已于 2009 年由机械工业出版社出版. 该书作为“人工心理与数字人技术丛书”之一,写作目的继续以人为本,以人与自然的和谐相处为研究目标,多学科交叉结合为研究手段,以人工科学为主要研究领域,主要面向研究生和重点高校高年级学生.

情感能力是人类智能的重要标志,是人类智能的一个不可分割的部分,它在人的感知、推理、决策、计划、创造以及社交等诸多活动中起着不可或缺的作用. 人工情感是指以人类学、心理学、脑科学、认知科学、信息科学、人工智能等学科为理论基础,利用信息科学的手段对人类情感过程进行模拟、识别和理解,使机器能够产生类人感情,并与人类进行自然和谐的人机交互. 随着智能科学、心理学、脑科学、信息科学的蓬勃发展,越来越多的科研工作者投入到情感计算、人工情感、人工大脑、机器人、虚拟现实等多学科交叉合作研究的领域. 王志良教授在多年研究的基础上,整理编写了这本书,详细地介绍了人工情感的相关理论和算法,总结了他所在课题组的研究成果,给出了人工情感的情感建模及应用实例.

全书共有 9 章. 第 1 章主要介绍人类情绪的相关理论以及研究发展历程;第 2 章叙述了情绪数量化描述的基本方法及情绪的维度理论;第 3 章介绍了情感建模的发展状况及前沿研究;第 4 章主要介绍了人工情感数字化建模的研究新进展及应用实例;第 5 章介绍了情感在数字化教学系统中的应用;第 6 章给出了人脸识别系统的设计范例;第 7 章详细介绍了表情识别系统的设计;第 8 章阐述了人工情感技术在游戏设计中的应用;第 9 章介绍了人工情感在智能机器人中的应用.

本书适宜从事计算机、自动化、电子信息、模式识别、智能科学、人机交互技术的科研人员阅读,也可以作为高等院校相关专业学生、研究生的教学参考书.

(王志良 郑思仪)