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Self-Organization Based Network Architecture for New Generation Networks

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SUMMARY A new generation network is requested to accommodate an enormous number of heterogeneous nodes and a wide variety of traffic and applications. To achieve higher scalability, adaptability, and robustness than ever before, in this paper we present new network architecture composed of self-organizing entities. The architecture consists of the physical network layer, service overlay network layer, and common network layer mediating them. All network entities, i.e. nodes and networks, behave in a self-organizing manner, where the global behavior emerges through their operation on local information and direct and/or indirect mutual interaction. The center of the architecture is so-called self-organization engines, which implement nonlinear self-organizing dynamics originating in biology, physics, and mathematics. In this paper, we also show some examples of self-organization engines.

key words: *new generation network, network architecture, self-organization, nonlinear dynamic model*

1. Introduction

To satisfy a wide range of requirements and desire of people and to support our daily life in many aspects, a variety of fixed devices such as PCs, servers, home electric appliances, mobile devices and small and embedded devices, e.g. tags and sensors, will be distributed in the environment and connected with each other to organize networks. Those devices generate a great variety of traffic in accordance with a type of device, application, service, and context. Furthermore, the number and location of devices, condition of communication environment, and traffic characteristics dynamically and considerably change every moment.

In such environment, a network would often face unexpected or unpredictable user behavior and traffic pattern, which are beyond the assumption made in designing and building the network. As a result, the performance considerably deteriorates or at worst the network completely collapses. Therefore, the conventional design methodology, where structures, functionalities, algorithms, and parameters are optimized to accomplish the best performance assuming certain operating environment, and fault detection, avoidance, and recovery mechanisms are prepared and preprogrammed for expected failure, is no longer feasible [1].

Taking into account requirements for a new generation network stated above, in this paper we present new network architecture which is more scalable to the number of nodes and scale of network, more adaptive to traffic patterns and their dynamic change, and more robust to expected and unexpected failure independently of size and duration, than ever before. Our basic idea is to organize and control the whole network system in a self-organizing manner, where the global conrol emerges from localized behavior of entities and their interaction.

Our architecture has three layers; physical network, service overlay network, and common network mediating inter and intra layer interaction. All entities constituting a network system, i.e. node, network, and layer, behave in a self-organizing manner. A node self-organizes MAC, scheduling, routing, congestion control, and other control by using nonlinear functional modules called *self-organization engines*. SO engines operate based on local information obtained through environmental observation and information exchange with neighbors. Networks interact with each other directly by exchanging messages and/or indirectly by changing operating environment shared among them to self-organize the whole network system.

In the following sections, we first introduce the basic concept of our architecture. Then examples of SO engines and their application scenarios are shown. Finally, we conclude the paper by indicating future issues.

2. Self-Organization Based Architecture

2.1 Basic Concept

A new generation network system should keep providing network services to users and applications independently of the size of system and condition of operating environment, the degree of their diversity and dynamic change, and the scale and duration of failure. In our self-organization based network system, a node consists of autonomous and simple control mechanisms, mutual and local interaction among nodes organizes a network, and inter and intra layer interaction among networks organizes the whole network system.

A self-organization based system does not require any centralized control, which becomes the main cause of fragility and introduces nonnegligible control and maintenance overhead. Self-organization is also different from so-called distributed centralized control or centralized control distributed over entities, where all entities share the same view of the system and perform the same calculations as in link-state routing. A self-organized network system can avoid letting a single and local failure, e.g. link disconnec-

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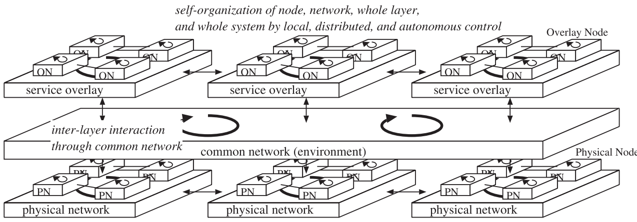

Fig. 1 Self-organization based network architecture.

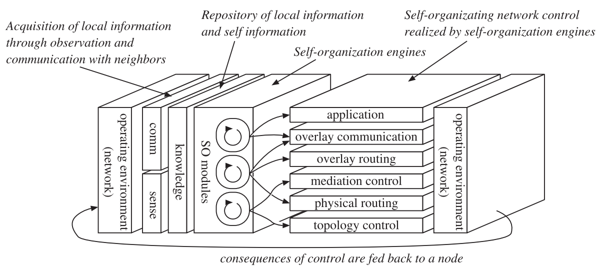

Fig. 2 Node architecture.

tion, involve the whole system by propagating the failure information to all other nodes. This contributes to the higher robustness and scalability of the system.

Our network architecture has three layers (Fig. 1). They are the physical network layer consisting of wireless and wired access networks and optical core networks, the service overlay network layer consisting of service or application-oriented overlay networks, and the common network layer mediating the two layers. These layers are self-organized through inter and intra-layer mutual interaction among networks.

2.2 Node Architecture

Each of physical and overlay nodes consists of communication and sensing module, knowledge database module, and SO engines, and network control functions (see Fig. 2). The knowledge database maintains local information obtained by the communication and sensing modules and the status information of node itself. An SO engine, that is, a basic component for self-organization, operates on information in the knowledge database and reacts to its changes. By using SO engines, a node performs a variety of network control.

2.3 Self-Organization Engines

A self-organization engine implements a nonlinear mathematical model in the form of temporal differential equation. Examples of nonlinear models include a pulse-coupled oscillator model [2], a reaction-diffusion model [3], and an attractor selection model [4], and so on. These models are mainly derived from self-organizing behavior of biological systems which are inherently fully-distributed, autonomous, and self-organizing. In these models, globally organized patterns, e.g. synchronization, spatial pattern, and global adaptation, emerge from mutual interaction among entities operating on the same equations. To achieve the higher scalability, adaptability, and robustness, the complexity of control for new generation networks should not depend on the number of nodes or the size of network and the protocol to implement should be easy, simple, and lightweight. Furthermore, each node must be able to control itself based on locally available information and we should not allow a single node to dominate and control the whole network system. By adopting models mentioned above, each node only needs to calculate a set of differential equations to determine its behavior without need for global information or central control unit. Sample applications of these models to network control will be shown in 3.

2.4 Intra-Layer Interaction

Nodes interact with neighbors by directly exchanging messages. In addition, they indirectly interact with each other through environmental change. The autonomous behavior of node would change the environment, by consuming the bandwidth for example. In reaction to such environmental changes, other nodes would change their behavior accordingly. Such indirect interaction or implicit communication induced by environmental change is called *Stigmergy* [5] and it is one of important principles of self-organization.

Physical and service overlay networks also interact with each other within each dedicated layer. Interaction among networks is accomplished by direct message exchanges or mediation of the common network layer, which implements an information sharing mechanism like P4P [6] and i3 [7]. Examples of cooperative networking can be found in some literatures [8], [9], where networks are dynamically connected and even merged into one to achieve higher efficiency and performance.

2.5 Inter-Layer Interaction

In the self-organizing network architecture, the common network layer helps entities belonging to different layers to interact with each other in exchanging and sharing information, getting feedback, and even controling entities of the other layer. We should note here that inter-layer interaction should be kept loose, because unnecessarily strong interdependency makes a system fragile and causes unintended consequences.

In the network architecture, small-scale perturbation such as local congestion, link disconnection, and node failure is handled by localized and prompt reaction of surrounding nodes. On the contrary, a network system adapts to large-scale variation, such as spatial and simultaneous failure, by a series of reactions induced by mutual interaction among entities and spreading over the whole network, layer, and network system. Furthermore, from an inter-layer control viewpoint, influence of small-scale physical failure is absorbed in the physical network layer and hidden from the service overlay network layer. On the other hand, against large-scale physical failure, the physical network layer tries to avoid affecting the upper layer, while service overlay networks gradually adapts to changes in physical network. As a result of such cooperative and self-organizing behavior, the system-level adaptability, stability, and robustness can be accomplished.

3. Examples of Self-Organizing Control

A pulse-coupled oscillator model explains synchronized behavior observed in a group of flashing fireflies [2]. In a pulse-coupled oscillator model, an oscillator, i.e. firefly, maintains a timer. It fires when the phase of timer ϕ reaches one, stimulates coupled oscillators to advance their phase, and then initializes the phase to zero. The dynamics of phase ϕ is formulated as,

$$\frac{d\phi_i}{dt} = \frac{1}{T_i} + \frac{\Delta(\phi_i)}{|\{j|j \in \mathcal{N}_i, \phi_j = 1\}|} \sum_{j \in \mathcal{N}_i} \delta(1 - \phi_j). \tag{1}$$

In (1), T_i stands for the intrinsic interval of oscillator i's timer and $\mathcal{N}_i$ is a set of oscillators coupled with oscillator i. $\Delta(\phi_i)$ is a monotonically increasing nonlinear function which determines the amount of stimulus. The global synchronization, where all oscillators fire simultaneously, can be accomplished without all-to-all coupling. Depending on parameters and functions, so-called phase-lock condition, where oscillators fire alternately with the constant phase difference, can also be accomplished and a traveling wave appears. The model has been applied to self-organized scheduling [10], [11].

Next a reaction-diffusion model describes emergence of periodic patterns on the surface of animal coat through chemical interaction among cells [3]. In a reaction-diffusion model, two hypothetical morphogens, i.e. activator and inhibitor, are considered. The dynamics of morphogen concentrations is formulated as,

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

where u and v are concentrations of activator and inhibitor, respectively. The first term of right-hand side is called a reaction term and expresses chemical reactions, i.e. activation and inhibition among morphogens. The second term called a diffusion term is for interaction among neighboring cells. To generate a pattern, the condition $D_u < D_v$, i.e. the speed of diffusion of inhibitor is faster than that of activator, must be satisfied. Autonomously generated patterns can be used in several network controls where a pattern appears, such as routing, clustering, and placement. For example, a spot pattern generated by the reaction-diffusion model resembles to the clustered structure of a wireless sensor network [12] and spatial TDMA MAC schedule [13].

Finally, an attractor selection model duplicates non-rule adaptation of *E. coli* cells to environmental changes [4]. A mutant *E. coli* cell has a metabolic network consisting of two mutually inhibitory operons, each of which synthesizes different nutrient. When a cell is in a neutral nutrient condition, the concentrations of mRNAs are at a similar level. Once one nutrient becomes insufficient, the level of gene expression for the missing nutrient eventually increases so that a cell can live in the new environment. However, there is no signal transduction, i.e. embedded rule-based mechanism, to switch between two operons. A general form of dynamics of mRNA concentrations is formulated as,

$$\frac{d\vec{x}}{dt} = f(\vec{x}) \cdot \alpha + \vec{\eta}, \tag{3}$$

where $\vec{x}$ corresponds to the concentrations of mRNA. $f(\vec{x})$ represents the metabolic network. α means the cellular activity such as growth rate and expresses the goodness of current behavior, i.e. gene expression. Finally, $\vec{\eta}$ expresses internal and external noise.

A new generation network would often face environmental changes and unexpected condition and thus adaptation is one of fundamental functionalities. In applying to network control, $\vec{x}$ represents control parameters or policy. When the control is appropriate, activity α becomes high and the deterministic control $f(\vec{x})$ dominates the system. Once the environment changes and the control becomes inappropriate, activity α decreases and relative influence of the noise term $\vec{\eta}$ becomes dominant. The system looks for new appropriate control, i.e. a good attractor, by being driven by random and stochastic control. Eventually the system finds and reaches a new good attractor. An attractor selection model has been applied to adaptive routing in in overlay networks [14] and mobile ad-hoc networks [15].

Since those models take the form of nonlinear temporal differential equations, a system operating on SO engines always adapts to temporal changes in the environment. In addition, no global information is required and each entity can determine its behavior by itself and in relation to neighbors.

As an example of inter-layer interaction, we consider a layered sensor-overlay network. Assume that heterogeneous sensor nodes with different operational frequency are deployed in the region. For the sake of energy saving, they adopt sleep control and organize independent networks. Therefore, a node has to wait a receiving node to wake up to send a message if they belong to different WSNs. Now, an overlay network for mission-oriented data gathering is built on WSNs. A possible way that it can do for delay reduction without knowledge of underlying WSNs is to adapt and find the overlay topology leading to smaller delay. On the other hand, if a node operates on frequency of other network, delay can be reduced at the sacrifice of additional energy consumption. However, it does not know the overlay topology. Such cooperative adaptation can be modeled by the attractor selection as,

$$\frac{d\vec{x}_o}{dt} = f(\vec{x}_o) \cdot \alpha + \vec{\eta}_o, \frac{d\vec{x}_w}{dt} = f(\vec{x}_w) \cdot \alpha + \vec{\eta}_w, \tag{4}$$

where $\vec{x}_o$ and $\vec{x}_w$ corresponds to selection of overlay topology and operational frequency, respectively. Overlay and sensor networks share the same information, i.e. activity α, which is defined by the data gathering delay. The both networks behave in an adaptive manner to minimize the data gathering delay as a whole.

We can also combine self-organizing control for multi-objective optimization. In a case of WSNs, for example, two contradicting goals, i.e. small delay and energy efficiency, must be satisfied at the same time. By using the attractor selection model, on one hand, the activity is defined as the energy balance among nodes in cluster head selection in clustering-based communication. On the other hand, the next-hop node can be appropriately chosen in inter-cluster routing by setting the activity by the transmission delay. By running the both attractor selection together, we can expect energy-efficient and small delay transmission in WSNs.

4. Discussion and Future Issues

In this paper, we present the self-organization based network architecture where a network system is self-organized through intra and inter-layer mutual interaction among network entities.

We should mention two major drawbacks of self-organization based control, whereas many results indicate the superiority of our control to conventional ones. Since the global control emerges from local and mutual interaction among entities, in some class of self-organization, it takes time for a system to converge and become stable. We can accelerate convergence, but there is a tradeoff between convergence speed and stability. Another drawback is that it would be difficult to maintain and control the whole system, since there is no central control unit which collects up-to-date global information. Of course it is possible to make all entities report their status to a center, but it only wastes bandwidth and energy. The adaptiveness and stability of system can be guaranteed theoretically based on mathematical discussion to some extent.

In addition to verification of the above perspective based on specific application scenarios, we plan to investigate consequence of intra and inter-layer interaction among self-organizing behaviors and establish the design methodology of self-organizing network system.

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