Noise-Assisted Control in Information Networks

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Abstract

In recent years, interesting phenomena were revealed where the inherent noise enhances the adaptability of a system to its changing environment in a resilient manner. The application of such methods can be found in a wide variety of fields, from biology to engineering. In this paper we discuss the application of noise-assisted mechanisms to control and manage information networks. Specifically, we focus on two mechanisms, stochastic resonance and adaptive response by attractor selection, and show how they can be applied in self-adaptive network control to improve the robustness and reliability of the system.

1. Introduction

Nowadays, information networks have become an indispensable social infrastructure. As such, they must be reliable and dependable. However, considering the drastic increase in the number of nodes constituting an information network, their heterogeneity in terms of reliability, availability, and performance, and the wide variety of behavior of users, future information networks are likely to face unexpected events more often than before.

Traditional information systems are designed in such a way that they are capable to adapt to various changes in the environment. However, their degree of adaptation is very limited since adaptive mechanisms are pre-programmed and pre-installed into an information system taking into account possible conditions predicted at the development and deployment phase. The system gives the best performance as far as conditions of the operating environment are within the predicted range. Once an unexpected event happens or operating conditions go out of range, the system may easily collapse. In these cases, until a system administrator manually fixes the problem by modifying the system or changing the environment, the system is unavailable and cannot provide any service, as could be seen in the recent collapses of IP-based phone services. By introducing additional mechanisms to overcome unexpected problems, an information system achieves higher adaptability. However, at the same time, it becomes more complicated and more rigid. This makes the system even more fragile. A requirement for future information networks is therefore that they are capable of operating with moderate performance even under unexpected conditions, where the current networks would fail, see Fig. 1.

If we look at biological systems, they exhibit surprisingly adaptive behavior. Colonies of ants can be found anywhere, on the ground, on walls, sometimes even indoors. Even if the conditions of the surroundings drastically change, a colony still survives. Adaptation mechanisms of biological systems are completely different from that of information systems as they do not have any specific set of rules for adaptation. They are not optimized for any specific environment either, which may continuously fluctuate during the course of their evolution. Therefore, the capability to adapt to such changing conditions is essential for the survival of the biological systems. However, due to the high dimensionality of the environment, each change rarely repeats itself during the lifetime of an individual. As a result, pre-programmed adaptation rules are not always feasible because the learning process requires multiply occurring events before the biological system can adapt.

Moreover, adaptation in biological systems is performed by feedback loops, which can be either *positive* by enforcing positive experiences, or *negative* by "learning from mistakes made in the past". However, it may take a long time for the system to adapt to sudden and drastic changes in the environment. Unlike pre-programmed systems which have no rules for certain events, the biological system would be able to gradually adapt to the new environment after the sudden deterioration of its performance.

An additional characteristic of biological systems is that they are exposed to both internal and external noise. Biological systems are characterized by the existence of an inherent noise term which causes fluctuations and variations in internal conditions and states, such as the concentrations of metabolites and translation rates of mRNA. Observations

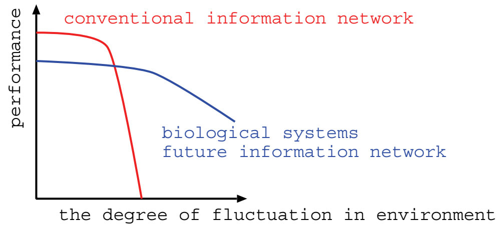

Figure 1. Resilient future networks

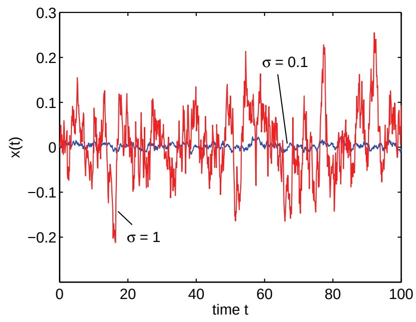

Figure 2. Langevin equation for $\gamma = 1$

of the environment through which a biological system determines its behavior also has much noise and brings a perturbation to a stable system. Such fluctuations are essential to its adaptation process.

In this paper we discuss control mechanisms for information networks which make use of the noise in the system in order to self-adaptively organize and manage these networks. We begin this paper by discussing how noise influences biological systems in Section 2 and then illustrate how to use noise to provide stable and robust control in information networks. Specifically, we consider two fundamental approaches based on *stochastic resonance* (Section 3) and *adaptive response by attractor selection* (Section 4), and describe their possible applications. Finally, this paper is concluded in Section 5.

2. Noise in Biological Systems

All entities in nature are never perfect or deterministic and fluctuations can be found on every level of biological systems. For example, if we consider cells of the same type, the values of the quantities describing them will vary from cell to cell and for a single cell, these values will also fluctuate over time [4]. Furthermore, when we consider mutations in the natural selection process, biological systems adapt over many generations to be able to better survive in a dynamically changing habitat. Influences from mutation introduce diversity and adaptability to new challenges.

The basic principle of fluctuation in biological systems can be observed by the *Brownian motion* of particles immersed in a fluid. This is a continuous-time stochastic process and can be modeled by the general *Langevin equation*.

$$\frac{dx(t)}{dt} = -\gamma\, x(t) + \eta(t) \qquad (1)$$

Equation (1) describes the dynamics of the velocity $x(t)$ of the Brownian particle, γ is the friction coefficient of the underlying fluid, and $\eta(t)$ is the random noise term. Solution of (1) can be done by the Fokker-Planck equation to obtain the probability density function of the position and velocity of the particle. Figure 2 shows the dynamics of (1) for $\gamma = 1$ and different values of the standard deviation σ. Obviously, this system has a stable point at 0 to which it returns regardless of the strength of oscillation σ. In a similar way, the diffusion coefficient γ expresses the adaptation strength of the system, so the larger it is, the faster the system will approach the stable point.

The relationship between fluctuation and its response is discussed in [16]. The authors describe a measurable quantity in a biological system as a variable x which is influenced by a parameter a. Let $\langle x \rangle_a$ be the average of x under the influence of a. Then, it is shown in [16] show that if an external force is applied such that this parameter a becomes $a + \Delta a$, then the change in the average value of x is proportional to its variance at the initial parameter value a.

$$\frac{\langle x \rangle_{a+\Delta a} - \langle x \rangle_a}{\Delta a} \propto \left\langle (\delta x)^2 \right\rangle \qquad (2)$$

The underlying assumption is that the distribution of x is approximately Gaussian. The result in (2) is similar to the *fluctuation-dissipation theorem* in thermodynamics, however, with the difference that it is also valid for non-thermodynamic quantities and in cases where the fluctuation-dissipation theorem in physics is not applicable at all. The fluctuation-response relationship can be considered as the basic model which explains how the existence of noise enhances the adaptability of a system, see Section 4.

3. Information Networks Adaptive to Noisy Environment

Stochastic resonance is the phenomenon where the correlation among a weak source signal and an output signal of a non-linear system is enhanced by the existence of additional noise. With stochastic resonance, a biological system can detect a weak signal or slight perturbations hidden in the noisy environment through unreliable and inaccurate biological sensors. An information network is also exposed to a fluctuating and noisy environment from physical layer, where electromagnetic signals suffer from the influence of dynamically changing magnetic fields, to the

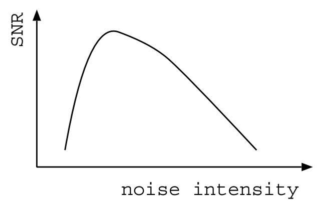

Figure 3. Noise-assisted signal detection

application layer, where the quality of communication considerably changes due to influences by other sessions competing for shared communication resources. In this section, we consider stochastic resonance to make an information network adaptive to a fluctuating operating environment.

3.1. Stochastic Resonance

A biological system observes its environment by biological sensors and takes actions suited to the conditions of the surroundings. Due to many dynamic and unavoidable factors, such as wind, sound, light, heat, or the existence/movement of other biological systems, signals that are meaningful or even fatal to a biological system are hidden within the noisy input signals. Furthermore, biological sensors themselves are not accurate or precise. They are inherently noisy. Nevertheless, a biological system can recognize a weak signal hidden in a noisy and unclear input.

From an engineering point of view, noise is nothing but disturbance and much effort has been devoted into developing techniques to enhance and improve the *signal-to-noise ratio* (SNR) by using, for example, a higher signal power, a noise-resilient codec, or a noise filter. On the contrary, in a biological system, phenomena where the existence of noise enhances SNR are often observed. A crawfish can notice approaching fish with the help of strong noise in the dynamic water flow, although the fish makes only small and inconspicuous changes. The phenomenon is called *stochastic resonance* [3, 10, 17, 19]. In Fig. 3, a typical bell-shaped curve of stochastic resonance with a peak at a certain level of noise intensity is illustrated for SNR vs. noise intensity.

Stochastic resonance was first introduced to explain the periodicity of the glacial age. The variation of the total volume of ice sheets on the earth in an order of million years shows much fluctuation. We cannot see any specific pattern there. However, once we consider the power spectrum of the time series, there are strong peaks at certain cycles. The highest is at 0.1 million years, which corresponds to the eccentricity of the earth's orbit, but the variation in the orbit and that in the amount of insolation as its result are too small as a cause of the periodicity of the glacial age, i.e., the drastic changes in the global climate. It implies that a weak signal, i.e., the variation in the orbit, is amplified with the help of strong noise such as the geothermal heat, which has more direct influences on the global climate.

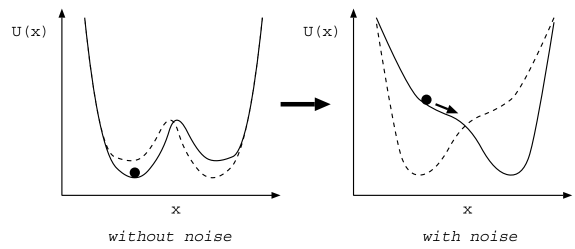

Figure 4. Bistable SR model

In the case of biological sensing systems, stochastic resonance was found in the mechanoreceptor cells on the tail fan of the crayfish *Procambarus clarkii*, for example. These cells are used to detect an approaching predator, which causes a small perturbation in water flow around the victim. Lab experiments on the hair cells obtained the similar bell-shaped curve as in Fig. 3 [20]. Other examples of stochastic resonance in biological systems can be found in [19].

3.2. Mathematical Model

An intuitive explanation of stochastic resonance is as follows. Imagine a bistable potential, in which a particle exists (Fig. 4). With a weak periodic or aperiodic signal, the potential changes between states indicated by solid and dashed lines. Since the signal is too weak to make a basin shallow enough, the particle cannot hop over the barrier and stays at the bottom of one basin. Now, we introduce noise as the source of perturbation in the potential. If the noise is too small, the particle remains stuck in one basin. If the noise is strong enough, the bottom of the basin with the particle may rise above the barrier and the particle moves to the other basin. With the appropriate level of noise intensity, the probability that the particle moves among basins is highest when the weak source signal is strongest. However, if the noise is too large, the movement of the particle becomes completely independent of the weak source signal. It means that the correlation, or SNR, among particle movement and weak source signal has a peak at a certain noise intensity (Fig. 3).

This dynamics is formulated by the first order Langevin equation as,

$$\frac{dx(t)}{dt} = -\frac{dU(x(t))}{dx} + \epsilon \sin \omega t + \eta(t), \tag{3}$$

where $x(t)$ is the position of the particle at time t, function $U(x)$ defines the base potential, $\epsilon \sin \omega t$ corresponds to a weak source signal, and $\eta(t)$ is the white Gaussian noise. An example of $U(x)$ is $-\alpha x^2 + \beta x^4$, where $\alpha = 1/2$ and

$\beta = 1/4$. In the case of the bistable potential model, an output signal has only two different ranges of values, i.e., the left and right basins, and we obtain an on-off or high-low type of output signal by placing a threshold at the center of the distribution. The transition between the two states is well synchronized with the source signal at the doubled frequency when the noise intensity is at the appropriate level.

A network of multiple threshold devices also shows the stochastic resonance phenomenon even for suprathreshold signals, whereas stochastic resonance is only observed for subthreshold signals with a single threshold [10, 17]. For the input signal $x(t)$ containing noise, the output signal $y(t)$ of a multi-threshold network is defined as

$$y(t) = \sum_{i=1}^{N} y_i(t), \quad (4)$$

where N is the number of threshold devices and

$$y_i(t) = \begin{cases} 1, \text{if } x(t) + \eta_i(t) > \theta_i \\ 0, \text{otherwise} \end{cases}, \quad (5)$$

where $\eta_i(t)$ gives the local noise at threshold device i and θ_i is the threshold of the device. The network behaves as a quantizer.

3.3. SR-based Network Control

There have been several papers adopting stochastic resonance to control of information systems [11, 13, 14]. For example in [11], they show that the quality of image damaged by noise can be enhanced by a bistable system. In [13, 14], they consider a scenario where sensor data obtained at distributed wireless sensor nodes are collected at a fusion center with a non-linear fusion function.

In this section, we take a wireless sensor network as an example of information systems which suffer from environmental noise. For example, the received signal strength indicator (RSSI) is often used as the quality index of the wireless link between neighboring nodes. In localizing a node by triangulation positioning, RSSI is mapped to the geographic distance by a function sometimes obtained by fitting a curve to a set of experimental results on RSSI and distance [9]. However, RSSI considerably fluctuates due to instability of the wireless communication medium and characteristics of circuits of node devices [9, 15].

The accuracy of signal detection with stochastic resonance depends on the distribution of the source signal, the distribution of external noise, and the setting of control parameters such as thresholds and the number of threshold devices. Since the distribution of external noise and in some cases even the distribution of the source signal cannot be precisely predicted in reality, it is impossible to determine the optimal control parameters in advance. Therefore, to tackle the problem of uncertainity, we need to use techniques such as the one proposed in [1] or feedback-based adaptation [12, 18].

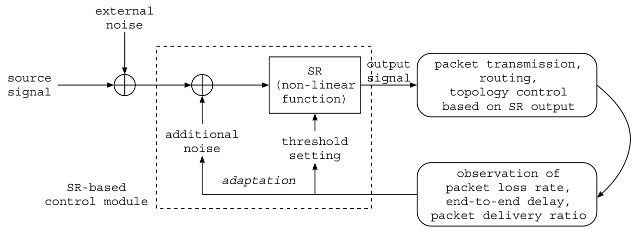

Figure 5. SR-based control for WSNs

We should note here that the accuracy of stochastic resonance can never exceed that of the optimal detection system. However, to build the optimal system, the full knowledge about distributions of signals and noise is required. If actual distributions differ from the assumption, the accuracy of signal detection considerably deteriorates. In addition, on-line adjustment of the optimal system is often difficult. On the other hand, stochastic resonance-based systems are less sensitive to signal and noise distributions and setting of control parameters [1]. Thus, stochastic resonance-based systems are useful under unpredictable environments.

In Fig. 5, we illustrate stochastic resonance-based control for wireless sensor networks. A source signal, such as RSSI and sensor data, and other observations, is first exposed to environmental noise. Then, the noisy signal is input to a SR-based control module. In the module, artificial noise is added to the input signal to shift the operating point on the x-axis in Fig. 3. It means that the accuracy of detection of stochastic resonance can be enhanced through adjusting noise [12] and thresholds. An output signal extracted from a noisy input signal by a non-linear system is then used for network-related control such as packet transmission, routing, and topology control. Consequent results of control are obtained as network-oriented performance metrics, such as packet loss rate, end-to-end delay, and packet delivery ratio. It implies that the accuracy of detection cannot be directly evaluated by comparing input and output signals. Instead, the accuracy should be conjectured from the appropriateness of control which is performed based on output signals. From network-oriented performance, additional noise and/or thresholds are adjusted.

4. Activity-Based Adaptation in Information Networks

In this section we will focus on the concept of *adaptive response by attractor selection* (ARAS). ARAS is a biologically inspired method for adaptively selecting one solution among several candidates which best reflects the

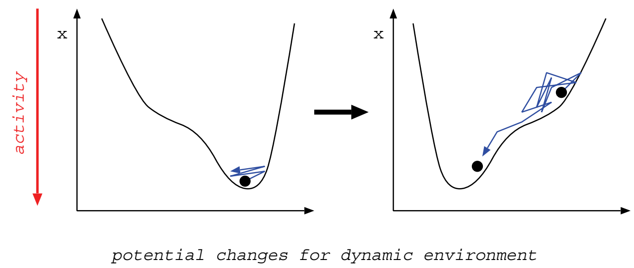

Figure 6. General concept of ARAS

current situation in a dynamic environment. The original model describes that a gene network composed of mutually inhibitory operons allows its host *Escherichia coli* cells to adapt to changes in the availability of a nutrient for which no molecular machinery is available for signal transduction [5]. The selection of the attractor is determined by a *cell activity* or vigor leading to an alternative expression of the operon that produces the enzyme adaptively to the designated nutrient availability.

4.1. Attractor Selection Model

In ARAS, we make use of the interaction between the inherent system fluctuation and its response as described in Section 2. The multiple states of gene expression utilize the concept of attractors. An *attractor* is the stable point or region to which the orbit of a dynamical system recurrently returns regardless of the initial conditions [4]. Even if a state is perturbed by fluctuations, the system state will be drawn over time to an attractor. For example, the Langevin equation (1) is drawn to the attractor at $x = 0$.

In a mathematical formulation, ARAS can be given by a stochastic differential equation system that can be regarded as a specialized form of the Langevin equation in (1).

$$\frac{d\boldsymbol{x}(t)}{dt} = f\left(\boldsymbol{x}(t)\right) \times \alpha(t) + \boldsymbol{\eta}(t) \tag{6}$$

The terms $\boldsymbol{x}(t)$ and $\boldsymbol{\eta}(t)$ in (6) are M dimensional vectors, while $\alpha(t)$ represents activity which is directly influenced by the environment. If this value approaches 0, indicating that the current attractor is unsuitable for the environment, the dynamics of (6) is entirely determined by the random term $\boldsymbol{\eta}(t)$. On the other hand, when $\alpha(t) \gg 0$, the influence of the random perturbation becomes negligible and the system converges to an attractor solution in a deterministic way (Fig. 6). These attractors are defined by the function f.

In the following we will consider the same type of formulation as used in [2] for the protein concentrations of a gene expression network of a cell. We use the sigmoidal regulation function $f(z) = \left(1 + e^{-\mu z}\right)^{-1}$ and the dynamics of each value $x_i(t)$ is then described as in (7) for $i = 1, \ldots, M$, where $w_{ij} \in \{-1, 0, 1\}$ are weights indicating if protein i is inhibited, indifferent, or activated by protein j. The threshold θ regulates the activation for synthesis and μ is the gain parameter of the sigmoid function.

$$\frac{dx_i(t)}{dt} = \left[f\left(\sum_{j=1}^{M} w_{ij} x_j(t) - \theta \right) - x_i(t) \right] \times \alpha(t) + \eta_i(t) \tag{7}$$

The quantities $x_i(t)$ which are originally the protein concentrations can be interpreted as transmission rates or probabilities when we consider a network environment and $\alpha(t)$ would be a function mapping the desired quality of the current network configuration to a scalar. In the following section, we will describe some possible applications of ARAS to self-adaptive control in information networks and explain the different mappings of activity.

4.2. ARAS-Based Network Control

The application of ARAS as simple, yet robust routing path selection method for multi-path overlay networks was presented in [6, 7]. The differential equation system formulating the attractors differs slightly from that described in Section 4.1, but leads only to attractor solutions where one of the M is at a high level and the others are at a low value. ARAS is performed in the route maintenance phase at the source node and the attractor solution with the high value determines the primary path over which the most part of the traffic is routed. Each path is chosen randomly for each packet with a probability proportional to $x_i(t)$, which means that secondary paths deliver packets less frequently.

Activity is mapped in [7] in the following way. Let l_i be the measured latency of packets received over path i. Then, the dynamic behavior of the activity $\alpha(t)$ can be defined as

$$\frac{d\alpha(t)}{dt} = \delta \left[\left(\prod_{i=1}^{M} \left[\left(\frac{x_i(t)}{\max_j x_j(t)} \, \frac{\min_j l_j}{l_i + \Delta} \right)^n + 1 \right] \right)^\beta - \alpha(t) \right].$$

The terms β and δ are parameters which influence the speed at which activity is adapted and Δ is a hysteresis threshold to avoid *path flapping*, i.e., alternating between two or more paths with nearly equal performance. An example result in Fig. 7 shows that when path 2 fails at time step 6000, a new primary path is instantly found.

Since this path selection method can only be applied after routes have been found, it still relies on a separate mechanism for finding these routes. Therefore in [8], ARAS is applied to each node along the path for selecting the next hop node in a mobile ad-hoc network environment. In this case activity is determined at the destination node by evaluating the received packets. Since the objectives are now different from the previous overlay network scenario, the

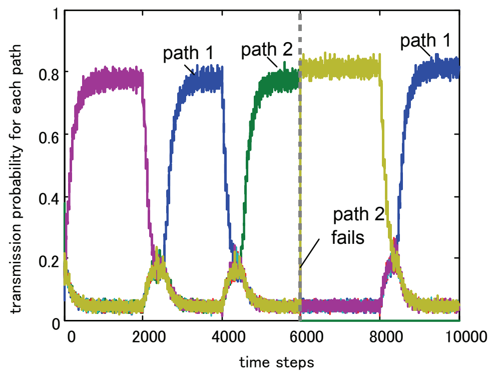

Figure 7. Overlay path selection probabilities

activity function takes into account the path length and the number of hops. On the other hand, depending on the application other quantities, such as measuring the packet delivery ratio or combining several different metrics, are also feasible.

5. Conclusion

In this paper we discussed biologically-inspired models which are assisted by internal or external noise and their application to information networks. Noise is inherent to all biological systems and often these perturbations are the driving factor for adaptation. The application of noise-assisted methods to information networks seems like a promising approach, especially when no centralized control entity is applicable.

However, the methods we discussed in this paper also do have some certain limitations. Due to the time dynamic formulation of the models, they react to the environment and adapt to the system not in an entirely directed way, but also in a noisy manner. This means that the described approaches require some time to react when the environment changes. In addition, even if the system is rather static or not likely to experience any drastic changes, e.g. small-scale corporate networks, the noise-assisted methods are unlikely to perform as well as pre-programmed or centrally controlled systems. Their benefits are most clearly seen in large-scale environments that are unknown and unstable such as wireless sensor networks.

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