Dynamic Homeostasis in Packet Switching Network

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The purpose of this study is to advance the idea of *homeostasis* found in biological systems by developing or simulating artificial systems. The idea of homeostasis was first introduced by W. B. Cannon Cannon (1963) during the cybernetic era and is a mechanism that maintains internal states of a system (e.g., calcium levels in the blood, body temperature, or an immune response). Simply put, this mechanism could be explained by the negative feedback loop within the system. For example, in the case of a healthy human body, if body temperature increases too much, the body tries to lower the temperature by sweating. If calcium levels in the blood are too low, the body tries to generate calcium to maintain a certain percantage of calcium in the blood. However, in some circumstances, it is also possible to maintain the system function by deviating from the steady state. This is system-level homeostasis instead of component-level homeostasis. Some studies have constructed the theoretical background of this concept.

Ashby argued that the brain is an adaptive machine with local or global feedback controls, which he termed the *ultra-stability* (Ashby, 1960; Franchi, 2013). When a system reaches a critical condition, which is measured by the essential variable, it changes its behavior. It suddenly randomly alters its dynamic parameters to update the global behavior until it escapes the critical condition. This random updating of the parameter to restore a functional state is called *ultra-stable control*. Di Paolo studied biological adaptation as a new version of Ashby's ultra-stability. Using the example of a visual field inversion experiment (or equivalently, the upside-down glasses experiment) (Stratton, 1896), he argued that biological adaptation is different from mechanical adjustments that do not have internal dynamics (Paolo, 2000). When glasses are reversed, the vertical and horizontal visual perspectives are completely reversed as well. However, within a week or so, a human can start to restore normal perception. As Di Paolo argued, this outstanding adaptability, called *homeo-adaptation*, is provided by synaptic plasticity (Paolo, 2000). Iizuka and Di Paolo used the same idea to show how a simple mobile agent restores its phototaxis (Iizuka and Paolo, 2007).

The idea of homeostasis is not limited to the biological system of an organism but is also found in the Gaia hypothesis[1] (Lovelock and Margulis, 1974). Its theoretical model is constructed as the Daisyworld and has been studied by many researchers (Harvey, 2004; Ikegami and Suzuki, 2008; Ikegami, 2013). Briefly, in the Daisyworld model, local temperature is regulated by black and white daisies by self-tuning population sizes. Since black and white daisies have different albedos (reflections of light), when the local temperature increases, white daisies will outgrow black ones. Conversely, when the temperature drops, black daisies outgrow white ones. This competition will implicitly regulate the surrounding temperature, which is known as rein control homeostasis. The Gaia hypothesis, which sounded as if life on earth purposely optimizes the earth's environment, resulted in a number of criticisms. Nonetheless, the interactions within a large ecosystem and the resulting self-regulating mechanism is to be investigated further.

The essential mechanism of homeostasis in the above examples is maintaining instability to organize adaptation. Ashby's random updating system parameters or Di Paolo's ignition of synaptic plasticity are such examples. As an example of homeostasis, Ikegami and Suzuki made a mobile robot that places daisies on its surface and showed the robot self-moved as a result of the regulation of surface temperature (Ikegami and Suzuki, 2008). Maintaining instability accommodates change in the environment. This mechanism of organizing inherent instability is the main theme of this paper.

To quantitatively study this notion of homeostasis through the Internet, we examine a packet-switching network (PSN) simulator, called ns-2, and discuss its adaptability and robustness. A PSN is a backbone mechanism of the Internet that provides adaptive dynamics in the system. The Internet is an interesting case for the study of artificial life as it is an open-ended system in which the amount of input from outside changes constantly; it also exhibits autonomous behavior (Ikegami et al., 2011). Given a set of nodes in the

[1]The Gaia hypothesis is introduced by J. Lovelock and considers the entire planet as an individual entity.

network, a PSN makes sure that data, divided into so-called *packets*, are sent safely to the Internet. We argue that a PSN shows adaptation to the system (i.e., the adjustments of packet congestion in the system) via the self-organization of many attractors. If a system is too rigid to change its behavior according to changes in external input, no adaptation is expected. Moreover, if a system is merely enforced by external changes and cannot restore its original behavior, it is still not an adaptive system but the system has a single, stubborn, attracting state. In contrast, the Internet is capable of constantly exchanging packets by adapting to environmental changes. Based on this phenomenon, we consider adaption of a PSN as involving many attractors and the ability to switch from one attractor to another.

The robust behavior of a PSN is controlled by the number of packets each node can send; this is called the congestion window size or *cwnd*. The cwnd of each node changes according to the congestion state on the network. A global congestion state of the entire system indirectly feeds back onto the local cwnd dynamics of each node. The self-organization mechanism of the PSN is the underlying mechanism that enables the system to maintain a certain throughput—the number of packets sent per unit time—thus making the system efficient. By varying the amount of input data to the PSN system, we investigate the possible self-organization of attractors in the optimal temporal dynamics of cwnd and discuss the adaptability of the PSN.

We conducted experiments on PSN using ns-2 on a network consisting of 30 nodes. Figure 1 shows some examples of such self-organization of attractors of cwnd time series. Here time series are divided into windows of a fixed length and each window is converted into a feature vector using principal component analysis. Depending on the node and its congestion state or the amount of input, it shows different self-organization of attractors and the state transits from one attractor to another, which we call *quasi-attractor*. When the amount of input is low, the system jumps around a few number of attractors. On the other hand, when the amount is high, the system starts to create many states and becomes more complex.

We also investigated the cwnd states in relation the throughput rate, in which throughput rate is defined as the sum of the inverse value of each packet 's transmission time. When the amount of input to the system is small, a stable but lower throughput rate is achieved with a set of a few stable quasi-attractors. However, when the input to the system is larger, the number of states starts to negatively correlated with the throughput rate. Yet, interestingly, the total average number of successfully transmitted packets keeps increasing with the increase in the input amount to the system. We would like to call this as an evidence of a new kind of homeostatic control by the organization of attractors. The PSN can maintain its average throughput under the perturbation. In the workshop, we would like to discuss commonalities and differences of homeostasis in biological systems and artificial systems such as Internet.

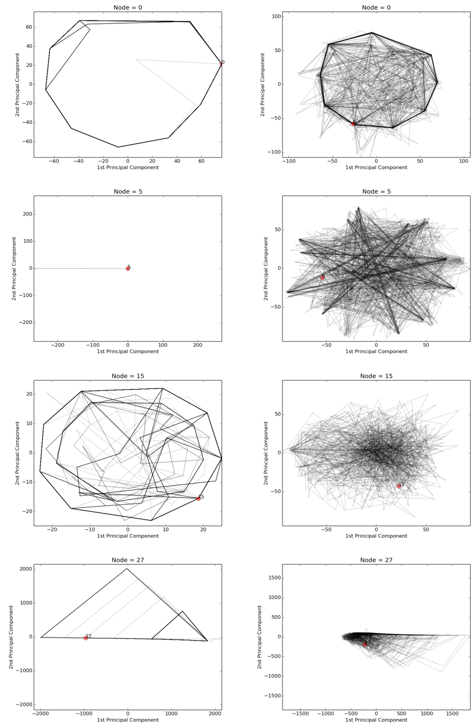

Figure 1: **Example of self-organization of attractors in the time series of nodes.** The x-axis is the first principal component and the y-axis is the second principal component. (Left) Traces of cwnd window feature vectors when the input to the system is low. (Right) Traces of cwnd window feature vectors when the input to the system is high.

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