Symbiotic Multi-Path Routing with Attractor Selection

Kenji Leibnitz, Naoki Wakamiya, Masayuki Murata
Osaka University, Graduate School of Information Science and Technology
1-5 Yamadaoka, Suita, Osaka 565-0871, Japan
{leibnitz,wakamiya,murata}@ist.osaka-u.ac.jp

Abstract

In this paper we discuss the effects of symbiosis when using an attractor selection model for multi-path routing in an overlay network. Attractor selection is a biologically inspired approach which is found in E. coli cells to self-adaptively react to changes of a nutrient in the environment. It is driven by noise and we present its application to selecting the paths in an overlay network for the transmission of a packet. This selection is performed with randomization to reduce the selfishness of each flow and to improve the overall performance of the network. Our main focus in this paper lies on showing the symbiotic behavior in the interaction of competing flows.

1 Introduction

Living organisms continuously face a fluctuating environment and adaptation to these changing conditions is essential for the survival of the species. However, due to the high dimensionality of the habitat, each of the upcoming environmental changes rarely repeats itself during the lifetime of an individual organism. Therefore, the development of adaptation rules is not always feasible since learning and evolutionary processes require multiple occurrences of events to which the organisms adapt. Pattern-based learning like in artificial neural networks is only possible, if input patterns and a desired target value exist. When no input patterns are available, the adaptation to new situations is performed in a more self-organized manner. For example, cells can switch from one state to another depending on the availability of a nutrient [7]. These self-adaptive mechanisms are not necessarily optimal from the viewpoint of overall performance, but their main advantage lies in the robustness and the sustainability to external influences. This is a highly important feature for surviving in an unpredictable and fluctuating environment.

In this paper we extend the model of *adaptive response by attractor selection* (ARAS) which was introduced by Kashiwagi et al. [7] and we apply it to multi-path routing. ARAS is originally a model for its host E. coli cells to adapt to changes in the availability of a nutrient for which no molecular machinery is available for signal transduction from the environment to the DNA. We will use this self-adaptive mechanism for determining the packet transmission probabilities over multiple paths in an overlay network.

Each source node of an overlay flow may have several paths to the destination node and splits its traffic over each path depending on the current condition of the network. However, one of the paths is chosen as the *primary path* over which the traffic will be routed with a higher probability, while the *secondary paths* are simply kept alive with a small proportion of the traffic. The reason for using secondary paths is that we require measurements of the quality of all paths to notice a change in the traffic conditions. By considering inline measurements of the input metrics (e.g. round trip delays, available bandwidths) derived from the received acknowledgment packets, we could avoid active measurements to reduce additional measurement overhead. Attractor selection will be used to determine the primary path for a given traffic condition. When the environment conditions, hence link qualities, change such that the active primary path is no longer appropriate, a new primary path is automatically selected. The advantage of our proposal is that there is no explicit routing rule for doing so, but everything is implicitly performed in the differential equations describing the dynamics of the system. Furthermore, we use an inherent noise term to drive the system from one attractor state to another, making the whole system also very stable toward influences from noise.

The remainder of this paper is organized as follows. In Section 2, we discuss related work found on the topic of overlay network routing and selfishness. This is followed in Section 3 by the mathematical model of the attractor selection mechanism and its application to multi-path routing. In Section 4, we show with some simple numerical examples that the system performs well and converges to symbiotic solutions which are best for all involved flows. Finally, this paper is concluded in Section 5 .

2 Related Work

Overlay networks have the appealing feature that their routing can be configured in an application-specific manner without modifying the underlying IP routing scheme. Before we discuss some related work on routing in overlay networks, we will clarify the use of the term multi-path routing. For each traffic flow, we consider multiple paths for distributing the traffic among these paths. By splitting the traffic flow, we introduce path diversity to routing and it becomes more robust to failures of individual links. However, the main advantage of multi-path routing lies on its ability to perform load balancing [3].

The issue of routing in overlay networks has been widely discussed e.g. for *resilient overlay networks* (RON) [2] as an overlay network architecture which is able to improve the loss rate and throughput over conventional BGP routing due to its faster reaction to path outages. End-to-end route selection schemes as employed in overlay routing are however of a highly selfish nature, as they greedily choose paths that offer the highest performance, regardless of the implications on the performance and stability of the whole system. Several publications have investigated selfish routing using a game theoretical approach, cf. [11, 12]. The papers dealing with routing optimization often consider a global view of the network and optimal solutions are computed by linear programming techniques. In our paper we restrict ourselves to the limited scope of information that a node can obtain from measurements of its links. In such a case, Seshadri and Katz [13] provide suggestions to improve the overall stability of the system by imposing some restraints on the degree of selfishness. Using randomization in path selection and a hysteresis for path updates are such possibilities which we will also adopt in our approach.

Xie et al. [15] propose a routing scheme which takes into account the user-optimal routing and network-optimal routing, where the former converges to the Wardrop equilibria and the latter to the minimum latency solutions. In [14] an analytical model is constructed for multi-path routing which leads to an optimal number of links over which dynamic multi-path routing should be conducted. Su and de Veciana [14] propose a policy of routing the traffic to a set of links with loads within a factor of the least loaded and show that this is especially suitable for high speed networks carrying bursty traffic flows. An adaptive multi-path routing algorithm is proposed by Gojmerac et al. [5] that operates with simple data structures and is independent of the underlying network layer routing protocol. This is achieved by local signaling and load balancing resulting in the reduction of signaling overhead. A further measurement based multi-path routing scheme is proposed by Güven et al. [6].

Another well known, biologically-inspired method that is efficient for routing is AntNet [4], which uses mobile agents that mimic the behavior of ant colonies. It operates by sending forward ants to probe routes and backward ants to update the routing tables at each intermediate node. Traffic is then routed along the paths with certain probabilities. The problem considered in our paper differs from that approach, in that it focuses on the adaptive selection of already determined paths.

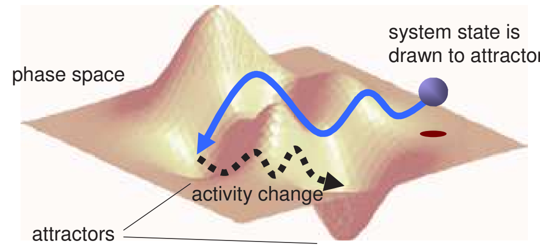


Figure 1. General attractor selection concept

3 Mathematical Model of ARAS

Attractors are a key issue in chaos theory and are often used in mathematical models found in physics and bioinformatics. Basically, we can outline the attractor selection method as follows. We describe the dynamics of an M-dimensional system by a set of differential equations as in Eqn. (1) for $i = 1, \ldots, M$.

$$\frac{dm_i}{dt} = \frac{syn(\alpha)}{1 + m_{max}^2 - m_i^2} - deg(\alpha)\, m_i + \eta_i \qquad (1)$$

In the original model in [7], the functions $syn(\alpha)$ and $deg(\alpha)$ are the rate coefficients of mRNA synthesis and degradation, respectively, and with m_{max} we denote the maximum value of all m_i. Each differential equation has a stochastic influence from an inherent Gaussian noise term η_i. The system solution converges to an attractor which is an equilibrium point in the M-dimensional state space. The attractors are completely defined by the terms in Eqn. (1). Additionally, the dynamic behavior of the system is influenced by the cell activity or vigor α. In the normal operation case, α does not have an effect on the convergence to one of the attractors. On the other hand, when the environment conditions change by lack of a certain nutrient, α changes its value and the random noise term dominates the system evolution. This essentially causes a random walk which is relaxed once a suitable solution is found and convergence to the attractor representing that solution is achieved, see Fig. 1. The random walk phase can therefore be viewed as a random search for a new solution state. This behavior is similar to the well known simulated annealing [1] method, with the main difference that the temperature is not only cooled down, but dynamically adapted by the activity term whenever the environment changes. For this reason, the activity α is defined over another differential equation which takes into account the input values (nutrients) and is adapted based on how appropriate the current system state is with respect to these input values, see Section 3.2.

3.1 Equilibrium Points

The equilibrium points of Eqn. (1) can be easily computed and have the condition

$$\frac{dm_i}{dt} = 0 \qquad \forall i = 1, \ldots, M.$$

Let us assume without restriction of generality that m_i is maximal for an index $i = k$. Inserting this into Eqn. (1) we obtain M resulting vectors of the type

$$\mathbf{x}^{(k)} = \left[x_1^{(k)}, \ldots, x_M^{(k)}\right]^T \qquad k = 1, \ldots, M$$

with component values

$$x_i^{(k)} = \begin{cases} \varphi(\alpha) & i = k \\ \frac{1}{2}\left[\sqrt{4 + \varphi(\alpha)^2} - \varphi(\alpha)\right] & i \neq k \end{cases} \tag{2}$$

where for the sake of simplicity we have defined

$$\varphi(\alpha) = \frac{syn(\alpha)}{deg(\alpha)}. \tag{3}$$

The resulting equilibrium points all have the structure

$$\mathbf{x}^{(k)} = [L, \ldots, L, H, L, \ldots, L] \tag{4}$$

with a single high value H at the k-th entry and all others are low values L. Note that at $\varphi^* = \frac{1}{\sqrt{2}}$ we have a special point, as the solutions $\mathbf{x}^{(k)}$ are only defined when $\varphi(\alpha) \geq \varphi^*$. For $\varphi(\alpha) = \varphi^*$ we obtain a single solution $\mathbf{x}$ with $H = L$.

The eigenvalues of the Jacobian matrix at the solutions $\mathbf{x}^{(k)}$ always reveal negative values, leading to stable attractors [9]. To fully define the model, we will describe in the following section the basic dynamic behavior of the activity α and the functions $syn(\alpha)$ and $deg(\alpha)$.

3.2 Determination of the Activity Dynamics

The structure of solution vectors is extremely useful to indicate that the k-th path is chosen as primary path from the possible M paths or there is no specific primary path and the traffic is equally split among all paths. In our model, the latter case will only be used in a transitional phase during the search for solutions as in Eqn. (4). Therefore, we use for $\varphi(\alpha)$ an increasing function in the interval [1,2] with $\varphi(1) = \varphi^*$ given in (5) by the functions $syn(\alpha)$ and $deg(\alpha)$.

$$syn(\alpha) = \alpha\left[\sqrt{\alpha - 1} + \varphi^*\right] \qquad deg(\alpha) = \alpha \tag{5}$$

Let us now discuss the desired behavior of α. In order to specify its behavior, we must define what should be represented by activity. In this paper, we consider a generic path metric for routing which is obtained by the load on each path. We measure the current load condition of each link and derive the path metric from it. In the following numerical examples, we use a very simple load balancing case where the initial load of each link is equal and the load of the path is defined as the maximum load of each link it contains, so a "better" path is characterized by a smaller value of its metric value l_i.

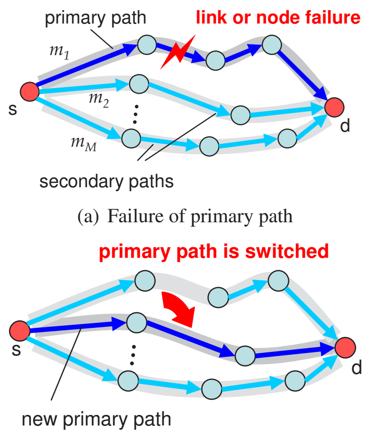
The output values m_i are the normalized to probabilities for selecting path i and should reflect the l_i values by preferably choosing their minimum values. Hence, when $l_{min} = l_k$ is the minimum of all input values, we wish that the system obtains m_k maximally. Furthermore, we introduce with Δ a hysteresis threshold in order to limit unnecessary switching between paths to increase the stability of the system. The use of such a hysteresis beside randomization of path selection was reported in [13] to reduce the selfishness and help improve the overall system performance.

$$\frac{d\alpha}{dt} = \delta\left(\prod_{i=1}^{M}\left[\left(\frac{m_i}{m_{max}}\frac{l_{min}}{l_i + \Delta}\right)^n + 1\right] - \alpha\right) \tag{6}$$

The formulation of the dynamic behavior of α is given in Eqn. (6). The factor δ is the rate of adaptation and can also be used to modify the sensitivity of the algorithm and n is simply a scaling factor.

3.3 Application to Multi-Path Routing

We use the attractor selection model to self-adaptively determine the path for each packet with a certain probability, which is obtained from m_i by normalization. The main problem is that for a source-destination pair, exactly one path is chosen as primary path based on the current environment condition. When the situation changes and the current primary path is no longer the best choice, the scheme adapts to selecting a different primary path which is better suited. The desired behavior is shown in Fig. 2. There are M paths from source s to destination d and one of these is the primary path over which the traffic is transported. If a link or node fails on this path, the primary path is automatically switched to the best secondary path. The switching of paths should not only occur in such drastic conditions as link failures, but also of course when due to changed load conditions one of the secondary paths seems more appropriate as primary path.



(a) Failure of primary path

(b) Switching to secondary path

Figure 2. Desired behavior of routing method

Let us assume an overlay network where each node has no exact knowledge of the topology. The routing algorithm consists of two major steps: (*i*) route setup phase and (*ii*) the route maintenance phase. In the *route setup phase* we use a decentralized method similarly like in AODV routing [10]. The route setup phase is initiated when the transmission request to an unknown node arrives at the source. Probe packets are broadcast to the neighbors who in turn forward these packets to their neighbors until a path to the destination is found. As soon as the first path is set up, transmission over this route will start. In such a way up to M routes are gradually collected and the route maintenance phase with the attractor selection algorithm will proceed with these M paths. After the setup phase, the *route maintenance phase* is entered, in which the scheme will mostly operate using the previously described attractor selection method. However, in the case that paths are lost in the course of that phase and a minimum threshold of M_{min} is reached, route setup for additional paths is invoked again.

4 Numerical Results

The layout of the considered network for our simulation studies is shown in Fig. 3. Let us consider two flows with sources s_1 and s_2 and their respective destinations are d_1 and d_2. Each link is numbered in this example and the paths for flow 1 are highlighted in Fig. 3. The paths for each flow are summarized in Tab. 1 and we denote them with $p_{i,j}$, where i is the flow number and j is the number of the path.

Thus, there are two links, 2 and 5, which are shared among the flows. Initially all links are equally loaded. In order to investigate the resilience of our proposed method, we assume that at time $t = 5000$, link 8 has a sudden drastic increase in its load caused by some external influence. Then, in the case that flow 2 is using the path which contains link 8 as its primary path, it will switch to the path $p_{2,1}$, see Fig. 4(b). If flow 2 had initially chosen path $p_{2,1}$ as its primary path, it would maintain it and there would be no change. The path change of flow 2 increases the load at link 5. Since this link was also used by path $p_{1,2}$ of flow 1, see Fig. 4(a), it reacts to this change by moving its primary path to path $p_{1,1}$.

The system returns to a stable condition and we again introduce an external influence which causes link 3 to increase its load at $t = 7500$. Since the main objective is to choose the path with the lowest link metric, the system reacts again by making flow 1 switch back to path $p_{1,2}$. As this path change involves again that link 5 is shared for the primary paths of flow 1 and 2. This is a solution which is accepted rather “reluctantly” which is indicated by the lower probabilities. The result, however, is a symbiotic solution which is best for both interacting flows.

Note that in this example the affected links are still available after the described events, however, with a drastically higher load. If they were to fail instead, the proposed approach would also react to it, by simply removing the failed path from the computation. In this simple example with two flows and two paths each, it is a trivial case, so we don't consider it here. Further discussions on the resilience in the presence of link failures can also be found in [8].

5 Conclusion

In this paper we presented an application of adaptive response by attractor selection to multi-path routing in overlay networks. It is based on a biologically-inspired method and is robust to sudden changes in the environment. The method converges to attractor solutions in the phase space and the selection of the appropriate attractor is driven by the activity term α. We have seen that by adequately defining

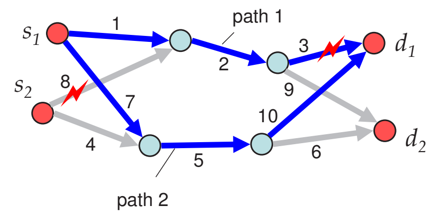
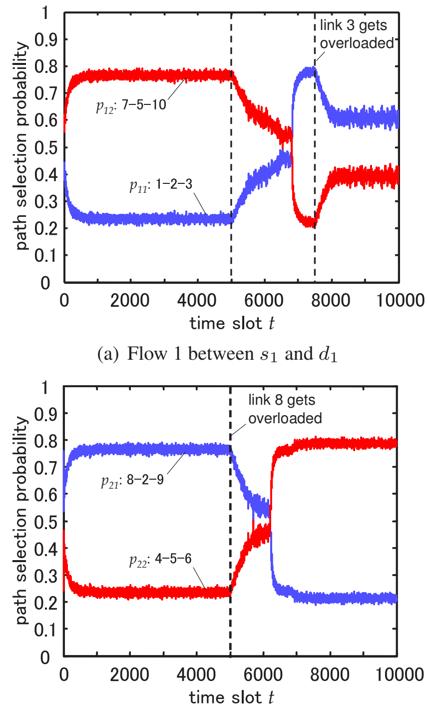


Figure 3. Considered network topology

Table 1. Paths in considered layout

	path 1	path 2
flow 1	$p_{1,1}$: $1 \rightarrow 2 \rightarrow 3$	$p_{1,2}$: $7 \rightarrow 5 \rightarrow 10$
flow 2	$p_{2,1}$: $8 \rightarrow 2 \rightarrow 9$	$p_{2,2}$: $4 \rightarrow 5 \rightarrow 6$



(a) Flow 1 between s_1 and d_1

(b) Flow 2 between s_2 and d_2

Figure 4. Path transmission probabilities for flows 1 and 2

the dynamic behavior of α, we are able to map the input metric to the selection probability of a primary path in a self-adaptive way. Additionally, we use randomization and a hysteresis for path changes to reduce the selfishness of individual flows and improve the overall system performance.

One of the main advantages of the proposed method is that it does not use any explicit rules for the selection of the paths, but contains the relationship between input and output parameters in the dynamic behavior of the activity α. By modifying this dynamic behavior, other performance metrics can be taken into account as well. Suitable choices for the input values in an overlay network could be taken from measurements of the end-to-end delays of packets or available bandwidths of the paths. On the other hand, in a wireless ad-hoc network we could consider also RF signal strength or interference levels. Finding suitable relationships between measured input values and the activity are an important issue that we will investigate in the future. The simple network structure in this paper only served to show the general behavior of our approach. Large scale simulation studies with more complex network topologies still need to be conducted to fully demonstrate the benefits of our approach.

Acknowledgment

This research has been supported by the 21st Century COE Program of The Ministry of Education, Culture, Sports, Science and Technology, Japan, under the title *"New Information Technologies for Building a Networked Symbiosis Environment"* and a Grant-in-Aid for Scientific Research (A)(2) 16200003.

References

[1] E. Aarts and J. Korst. *Simulated Annealing and Boltzmann Machines*. Wiley, New York, 1989.

[2] D. Andersen, H. Balakrishnan, M. Kaashoek, and R. Morris. Resilient overlay networks. In *ACM Symposium on Operating Systems Principles (SOSP)*, Banff, Canada, Oct. 2001.

[3] D. Andersen, A. Snoeren, and H. Balakrishnan. Best-path vs. multi-path overlay routing. In *Internet Measurement Conference (IMC)*, Miami Beach, FL, Oct. 2003.

[4] G. Di Caro and M. Dorigo. AntNet: distributed stigmergetic control for communication networks. *Journal of Artificial Intelligence Research*, 9:317–365, 1998.

[5] I. Gojmerac, T. Ziegler, F. Ricciato, and P. Reichl. Adaptive multipath routing for dynamic traffic engineering. In *IEEE GLOBECOM*, San Francisco, CA, Dec. 2003.

[6] T. Güven, C. Kommareddy, R. J. La, M. A. Shayman, and B. Bhattacharjee. Measurement based optimal multi-path routing. In *IEEE INFOCOM*, Hong Kong, March 2004.

[7] A. Kashiwagi, I. Urabe, K. Kaneko, and T. Yomo. Adaptive response of a gene network to environmental changes by attractor selection. submitted as letter to Science.

[8] K. Leibnitz, N. Wakamiya, and M. Murata. Biologically inspired adaptive multi-path routing in overlay networks. In *International Workshop on Self-Managed Systems & Services (SELFMAN 2005)*, Nice, France, May 2005.

[9] J. Murray. *Mathematical Biology, I: An introduction*. Springer, 2002.

[10] C. Perkins and E. Royer. Ad hoc on-demand distance vector routing. In *2nd IEEE Workshop on Mobile Computing System and Applications*, New Orleans, LA, Feb. 1999.

[11] L. Qiu, Y. Yang, Y. Zhang, and S. Shenker. On selfish routing in internet-like environments. In *ACM SIGCOMM*, Karlsruhe, Germany, Aug. 2003.

[12] T. Roughgarden and E. Tardos. How bad is selfish routing? *Journal of the ACM*, 49(2):236–259, Mar. 2002.

[13] M. Seshadri and R. Katz. Dynamics of simultaneous overlay network routing. Technical Report UCB//CSD-03-1291, University of California, Berkeley, CA, Nov. 2003.

[14] X. Su and G. de Veciana. Dynamic multipath routing: asymptotic approximation and simulations. In *ACM SIGMETRICS*, pages 25–36, Cambridge, MA, June 2001.

[15] H. Xie, L. Qiu, Y. R. Yang, and Y. Zhang. On self adaptive routing in dynamic environments – an evaluation and design using a simple, probabilistic scheme. In *International Conference on Network Protocols (ICNP)*, Berlin, Germany, November 2004.