Biologically Inspired Adaptive Multi-Path Routing in Overlay Networks

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***Abstract*— In this paper we propose a multi-path routing scheme based on a biologically inspired attractor selection model. The advantage of this approach is that it is highly noise-tolerant and capable to operate in a very robust manner under varying environmental conditions. Furthermore, the route selection is performed in accordance to the recommendations given in [1] to reduce the selfishness in favor of an improved overall system performance.**

***Index Terms*— attractor selection, multi-path routing, selfish routing, dynamic system**

I. Introduction

Biologically inspired algorithms are known to be extremely robust and able to adapt well to different environment conditions. Imitating biological mechanisms has often inspired researchers to conceive algorithms that perform well in uncertain environments. One example is the application of *swarm intelligence* [2] in telecommunication networks, cf. [3], [4]. Highly distributed individuals operate toward a common goal through *stigmergy* where they interact indirectly by modifying the environment.

In this paper we propose a "no-rule" multi-path routing scheme which is based on a biological attractor selection model. The purpose of our model is to provide a self-adaptive path selection scheme for multi-path overlay networks that operates in a robust manner. We consider application level routing in overlay networks as most promising application for our model, as this allows greater flexibility in controlling the routing task without modifying the underlying IP routing scheme. This issue has been discussed e.g. for RON [5] as an overlay architecture which is able to improve the loss rate and throughput over conventional BGP routing due to its faster reaction to path outages.

However, end-to-end route selection schemes as employed in overlay routing are 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. [6], [7], [8]. In [1], suggestions are made to improve the overall stability of the system by imposing some restraints on the degree of selfishness.

Unlike [9], [10] [11], we will consider in this paper a generic multi-path network and our intention is to provide a basic mechanism to improve the robustness of overlay routing. Since our method uses the noise inherent in the network to drive the path selection decision, it is highly resilient to external noise influences. Furthermore, the routing decisions follow the guidelines given in [1] to reduce the selfishness of each individual flow, in order to obtain a better and more stable system-wide performance.

The remainder of this paper is as follows. We will discuss our assumption on the network architecture and multi-path routing in Section II. Section III describes the underlying theoretical model. In Section IV we show how we use this model in the framework of multi-path routing and give some examples with numerical results. Finally, the paper is concluded with an outlook on future work.

II. Outline of the Multi-Path Routing Approach

In this section we will discuss the key issues in our adaptive multi-path routing approach. In the systems we are considering, no centralized control takes place, i.e., path selection is performed entirely based on locally available information. Furthermore, our method requires no knowledge of the network topology. The goal is to distribute the total traffic flow from source to destination over M routes with transmission rates m_i as shown in Fig. 1. The flow is split up such that the major part is routed at a high bitrate R_H over the *primary path*, while the remaining parts are equally distributed on *secondary paths* with lower bitrate R_L.

The algorithm we propose in this paper operates in the following way. When a new flow between source

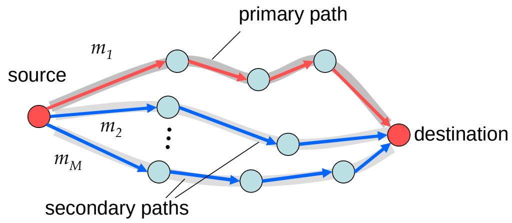


Fig. 1. Primary and secondary paths

and destination arrives, the paths are established. Since we have no knowledge about the topology, the source must send probing packets which are forwarded to the destination. This happens with RREQ and RREP packets similarly to AODV [12]. However, not only a single route is determined in this way, but the M best feasible paths are stored. Once the first path is found, the transmission can begin over it. Subsequently adding and removing paths imposes no problem to the mechanism as we will show later it can operate seamlessly when the number of paths is changed. However, the number of paths should be kept within certain limits M_{min} (not less than 3) and M_{max}. Once the number of current paths M reaches M_{min}, the discovery of additional paths is again activated.

The transmission rates m_i are automatically selected by our method according to measured values of the path metric ℓ_i of each path i. In order to reduce the overhead of the routing method itself, we suggest to use an inline measurement approach for obtaining these values, e.g. round trip times of packets. These measurements are updated at regular intervals which we denote as measurement window T_M. Based on the received metric values a new best solution is obtained and selected every T_R intervals.

III. Adaptive Response by Attractor Selection

We now consider the biological model for *Adaptive Response by Attractor Selection* (ARAS) presented in [13]. ARAS is 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. The appealing feature of this mechanism is that it is highly noise-tolerant and can even be stimulated by noise. Therefore, in this paper we will use ARAS as a robust, noise-tolerant algorithm for multi-path routing in communication networks.

A. Sketch of the Basic Idea

The basic idea of ARAS is that attractors form solutions for the optimal assignment of output values m_i to certain input values ℓ_i at which the system is stable. The locations of these attractors in the phase space are entirely determined by the differential equation system describing the dynamics of the output values m_i. Furthermore, the differential equations of m_i are stochastic since they contain an influence from a Gaussian random term. The selection of the appropriate attractor (i.e. solution) of the system is performed based on the current input values ℓ_i and changes are triggered by an *activity* term $0 \leq \alpha \leq 1$. The activity α tunes the degree of randomness controlling the dynamic system. If $\alpha = 0$, the system performs a random walk, whereas for $\alpha > 0$, the noise influence is reduced and the system converges to one of the attractors, which appears as the best solution.

The basic principle of attractor selection is shown in an example in Fig. 2. Until time $t = 500$ the system is stable with no particular reaction toward any input value. When $500 < t \leq 1000$ we introduce some external influence by modifying the input vectors. This causes that activity α drops to 0 and a random walk is performed for the output values m_i. After $t > 1000$ a new stable condition is found with $m_2 > m_1$ and it is maintained until another external influence occurs. This is reflected by an activity term $0 < \alpha < 1$.

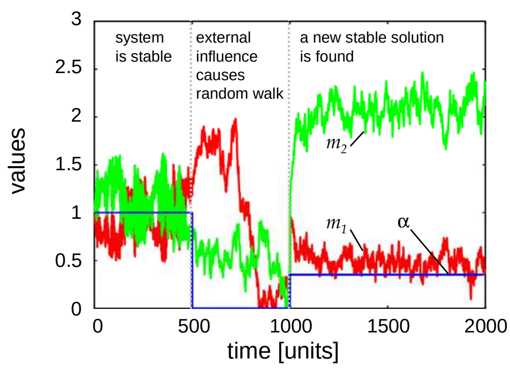


Fig. 2. Basic principle of attractor selection

B. Features of the Biological Model

The original attractor selection model for a biological system was introduced in [13]. The biological model describes two mutually inhibitory operons where m_1 and m_2 are the concentrations of the mRNA that react to certain changes of nutrient in a cell. The basic functional behavior is described by the following differential equation system.

$$\begin{aligned}\frac{dm_1}{dt} &= \frac{syn(\alpha)}{1+m_2^2} - deg(\alpha)\, m_1 + \eta_1 \\ \frac{dm_2}{dt} &= \frac{syn(\alpha)}{1+m_1^2} - deg(\alpha)\, m_2 + \eta_2\end{aligned} \tag{1}$$

The functions $syn(\alpha)$ and $deg(\alpha)$ are the rate coefficients of mRNA synthesis and degradation, respectively. They are both functions of α, which represents cell activity or vigor. The terms η_i are independent white noise inherent in gene expression.

The dynamic behavior of the activity α is given as:

$$\frac{d\alpha}{dt} = \frac{pro}{\prod_{i=1}^{M} \left[\left(\frac{nutr\_thread_i}{m_i + nutrient_i} \right)^{n_i} + 1 \right]} - cons\, \alpha, \qquad (2)$$

where pro and $cons$ are the rate coefficients of the production and consumption of α. The term $nutrient_i$ represents the external supplementation of nutrient i and $nutr\_thread_i$ and n_i are the threshold of the nutrient to the production of α and the sensitivity of nutrient i, respectively.

A crucial issue is the definition of the proper $syn(\alpha)$ and $deg(\alpha)$ functions. In our case, the ratio between $syn(\alpha)$ and $deg(\alpha)$ must be greater than 2 to have two different solutions of Eqn. (1) when there is a lack of one of the nutrients. When it is equal to 2, there is only a single solution for $m_1 = m_2 = 1$. The functions are defined in [13] as given in Eqn. (3).

$$syn(\alpha) = \frac{6\,\alpha}{2+\alpha} \qquad\qquad deg(\alpha) = \alpha \qquad (3)$$

The system reacts to changes in the environment in such a way that when it lacks a certain nutrient i, it compensates for this loss by increasing the corresponding m_i value. This is done by modifying the influence of the random term η_i through α, see Fig. 3. When α is near one, the equation system operates in a deterministic fashion. However, when α approaches 0, the system is dominated by the random terms η_i and it performs a random walk.

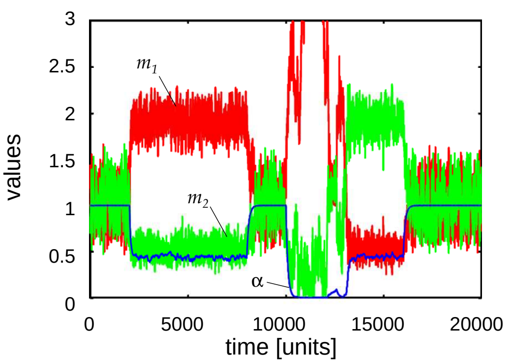


Fig. 3. Biological attractor selection model

In Fig. 3 we can recognize the following behavior. When both m_i values are equal, the activity is highest and equal to 1. As soon as there is a lack of the first nutrient ($2000 \le t < 8000$), m_1 compensates this by increasing its level. When both nutrient terms are fully available again ($8000 < t \le 10000$), activity α becomes 1 again. An interesting feature can be observed after $t = 10000$. Here, the random walk causes the system to search for a new solution, however, it first follows a wrong direction until about $t = 12000$, causing α to become nearly 0. As soon as the system approaches the direction toward the correct solution again, α recovers and the system gets stable again.

C. Extension of the Mathematical Model

The basic biological model from [13] is not directly applicable as it only considers a two-dimensional system, whereas the multi-path problem is of a higher dimension. Let $M > 2$ denote the number of paths among which we split up the traffic from the source to destination. Let us define the following notation.

$$\overline{m} = [m_1, \ldots, m_M]^T \qquad\qquad \tilde{m} = \max_j\ m_j$$

Here, $\overline{m}$ is the vector over all m_i and $\tilde{m}$ is their maximum value. The dynamic behavior of each m_i is determined by the following system of M equations, cf. Eqn. (4).

$$\frac{dm_i}{dt} = \frac{syn(\alpha)}{1 + \tilde{m}^2 - m_i^2} - deg(\alpha)\, m_i + (\gamma - \alpha)^{\nu}\, \eta_i \quad (4)$$

Beside the inclusion of the maximum of m_i in (4), it differs from the original equations by controlling the activity α with the parameters γ and ν. Furthermore, for the sake of simplicity we define

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

Solving equation system (4) for its equilibrium, i.e. $\frac{dm_i}{dt} = 0$, yields results of the type

$$\overline{x}^{(k)} = \left[x_1^{(k)}, \ldots, x_M^{(k)} \right]^T$$

with $k = 1, \ldots, M$ and the components of the vector are

$$x_i^{(k)} = \begin{cases} \frac{1}{2}\left(\sqrt{4 + \varphi(\alpha)^2} - \varphi(\alpha) \right) & \text{if } i = k, \\ \varphi(\alpha) & \text{otherwise.} \end{cases}$$

Since the transmission rate m_k for a certain path k is higher than the other rates $m_i, i \neq k$, we distinguish the paths into *primary* and *secondary paths*.

The eigenvalues of the Jacobian matrix of (4) at the solutions $\overline{x}^{(k)}$ always reveal negative values, thus, leading to stable attractors [14]. Note that at $\varphi^* = 1/\sqrt{2}$ we have a special point, as the solutions $\overline{x}^{(k)}$ are only defined when $\varphi(\alpha) \ge \varphi^*$. For $\varphi(\alpha) = \varphi^*$ we obtain a single solution $\overline{x}$ with the same entries $\forall_{i=1}^{M}\ x_i = \varphi(\alpha)$.

To fully define the model, we need to give the basic dynamic behavior of the activity α and the functions $syn(\alpha)$ and $deg(\alpha)$. Based on the above mentioned constraints, the quotient $\varphi(\alpha)$ should be a decreasing function with $\varphi(1) = \varphi^*$.

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

The parameter β in Eqn. (5) is used to scale the output values to a given co-domain.

The function α maps the input values ℓ_i to the activity and is the driving function for the whole routing operation as it controls the influence of randomness on the Eqn. (4). To characterize α, we map it to three discrete values α^* based on certain conditions. If all paths should be treated equally, we set $\alpha^* = 1$. However, if the current primary path is not the best path anymore, we choose a fixed value smaller than 1, e.g. $\alpha^* = 0.85$. Otherwise, no suitable solution has been found and the search for a more appropriate solution is performed with a random walk, i.e. $\alpha^* = 0$. The dynamic behavior of function α simply follows

$$\frac{\mathrm{d}\alpha}{\mathrm{d}t} = \sigma\left(\alpha^* - \alpha\right) \tag{6}$$

with the adaptation rate of σ. In our experiments we use a value of $\sigma = 0.5$.

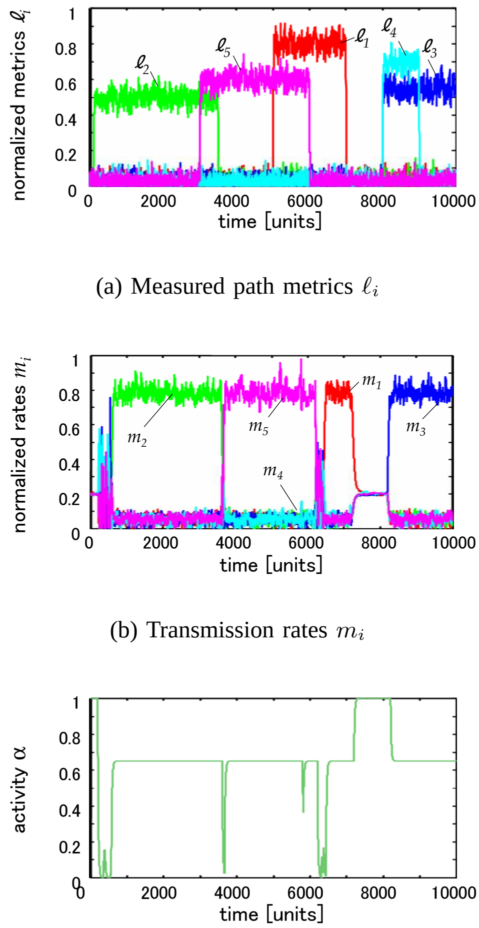
IV. Application of Attractor Selection to Multi-Path Routing

In this section we adapt the activity function α to the specific case of multi-path routing. The m_i values represent the (normalized) transmission data rates for each path i. If each m_i is chosen entirely selfishly, it leads to a significant decrease in the overall system-wide performance. For this reason, [1] suggests three restraints on this greedy behavior: (*i*) randomization in the route selections, (*ii*) route changes performed with a hysteresis threshold, and (*iii*) increase of the time interval between route changes.

To include such conditions in our model, we propose the following activity function. Let k be the index of the currently chosen primary path and ℓ_{max} and ℓ_{min} be the maximum and minimum of all link metric values $\ell_i \in [0, 1]$, respectively. We consider normalized metric values, with higher values being preferred for choosing a path, e.g. available bandwidth. We perform these routing updates after an interval of T_R and measurements are taken during the measurement window T_M. The updates of the target α^* are only performed after every T_R or if the system has not yet converged.

$$\alpha^* = \begin{cases} 1 & \ell_{max} - \ell_{min} < \Delta \\ 0.85 & \ell_k + H \geq \ell_{max} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

When all ℓ_i lie within a margin Δ, i.e., $\ell_{max} - \ell_{min} < \Delta$, we set $\alpha^* = 1$ and have no special preference for a path. On the other hand, when $\ell_k + H \geq \ell_{max}$ the current solution is still valid and $\alpha^* = 0.85$, otherwise $\alpha^* = 0$. Here, H is the hysteresis threshold. The randomization of the paths implicitly takes place, as the system sometimes converges to a suboptimal solution.



(a) Measured path metrics ℓ_i

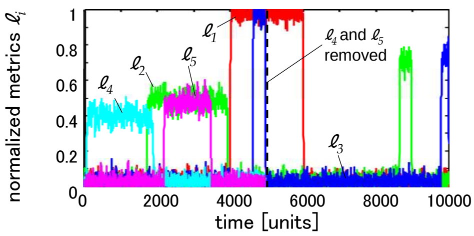
(b) Transmission rates m_i

(c) Activity α

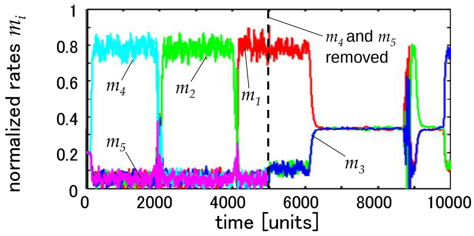
Fig. 4. Example scenario with $M = 5$ paths

An example scenario is depicted in Fig. 4. In this example we selected $\Delta = 0.1$ and $H = 0.2$, $T_R = 200$, and $\gamma = 1.5$. We varied the normalized link metrics ℓ_i such that they have high values during certain periods shown in Fig. 4(a) and low (zero) values else. The resulting normalized transmission rates are depicted in

Fig. 4(b). It can be seen that whenever the environment changes due to better available paths, the system adapts in an appropriate way. Note that sometimes a short time is required until the system converges to a new solution.



(a) Measured path metrics ℓ_i



(b) Transmission rates m_i

Fig. 5. Removal of paths 4 and 5 at $t = 5000$

An example for the robustness of the method is shown in Fig. 5. Here we artificially caused paths 4 and 5 to be removed due to outage conditions at $t = 5000$. The mechanism, however, continues in its usual operation and the primary and remaining secondary paths are nearly unaffected by this influence. The only evidence pointing to the removal of paths is that the level for the secondary paths R_L is slightly raised.

V. Conclusion and Outlook

In this paper we introduced a new biologically inspired method for multi-path routing based on adaptive response by attractor selection. This method takes measurements of the path metrics, e.g. available bandwidth, and automatically selects the appropriate bandwidths for each path. The selection of the paths is done with no explicit rules, but only by letting the system converge to an attractor solution. Since it uses random variables to find the optimal solutions, it is highly tolerant to noise and capable to operate in a very robust manner under varying environmental conditions. Outages and temporal loss of paths can be easily compensated.

The attractor selection method is a self-organizing scheme, which is driven by the formulation of the activity function. While we have introduced a method for the implementation as path selection scheme in this paper, a lot of research issues remain open. We concentrated in this paper on the mathematical formulation of the attractor selection method itself and only briefly outlined the path set-up phase. A more detailed discussion of mechanism to search for new paths and the evaluation of the overall network stability are required. Furthermore, the investigation of mappings based on different input values and their combinations, as well as the application of this scheme in an ad-hoc/sensor network environment is subject to future work.

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