Analysis of an Artificial Hormone System

(Extended abstract)

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Abstract:

The increased complexity of modern networks and the increasingly dynamic access patterns in multimedia consumption have led to new challenges for content delivery. Dynamic networks and dynamic access patterns result in a complex system. To deliver content efficiently we introduced an artificial hormone system that is capable of handling the dynamics, is self-organizing, robust and adaptive. The content placement problem is NP complete and is closely related to several hard problems including edge-disjoint path routing, scheduling and the bin packing problem. The evaluation of self-organizing algorithms brings also a real challenge. For a first evaluation we created and ILP model of the problem. It is applied to get the exact optimum that serves as a bound in the evaluation of the solution algorithms. In this paper, we examine the convergence of the algorithm and found that the hormone levels converge to a limit at each node in the typical cases. We form a series of theorems on convergence with different conditions by starting with a specific base case and then we consider more general, practically relevant cases. The theorems can be proved by exploiting the analogy between the Markov chains and the artificial hormone system.

Keywords: self-organizing algorithm, convergence, routing, content delivery

1 Introduction

Artificial hormone systems [1] are bio-inspired self-organizing algorithms that promise a robust and adaptive behavior [2] to cope with the problem of content delivery in dynamic networks [3]. The algorithm

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introduced in [4] is inspired by the endocrine system of higher mammals and provides the possibility of sharing small multimedia units in a self-organizing manner during and after a social event. In case of the artificial hormone algorithm, nodes are glands that create, consume and forward hormones through the network (the blood stream). Hormones indicate interest in a specific content unit. Content units react on hormones, by moving from lower towards higher hormone concentration. Therefore, the algorithm can successfully deliver the units on the requesting node if the hormone level increases strictly monotonically towards the requesting node. The hormone levels at the time of decisions on the directions of forwarding the units are formed after many iterations of the algorithm. We examine the convergence of the hormone levels in order to approximate the hormone levels with their limits. Our main result is that the hormone levels converge to a limit in the general cases. Furthermore, we are interested in whether the hormone distribution is monotonic towards the requesting node.

Our talk gives an overview of our results on the analysis of the content placement problem and the hormone-based algorithm. Section 2 introduces the problem and refers to the NP-completeness results. Section 3 describes the hormone based algorithm and shows some results on the monotonicity of the hormone levels. Section 4 includes theorems on the convergence of the hormone-based algorithms.

2 Optimal Content Placement Problem

Each network node can store and forward content objects and generate requests (hormones) for them. The atomic building element of the content is called content *unit* that cannot be further split and each content unit is routed along a single path. The units may form compositions which include a sequence of units with possible timing constraints. If a unit is requested by several users at the same time, then their delivery paths may share common segments. The problem input includes the network graph, the initial location of the units, the storage capacities of the nodes, the link bandwidths, the unit sizes and the series of the requests. Several requests generated at the same time are processed simultaneously. Queues are formed for each link where the incoming content units can wait before forwarding if the link is busy. The content placement problem is to route all requested content objects simultaneously to the requesting nodes. The problem is a multi-objective optimization problem in the general case. The optimization goals to be minimised include the average delay and the number of units that do not arrive in time (if videos are transmitted, the subsequent video frames have to arrive within a given deadline to provide proper quality).

The problem is computationally hard. If storage capacities are given for the nodes, the Bin Packing problem can be easily reduced to this problem in order to prove the $\mathcal{NP}$-completeness. Even if storage capacities are not considered (i.e., infinite storage is assumed), the problem still remains computationally difficult. In this case, the $\mathcal{NP}$-completeness can be shown with the help of the Edge-Disjoint Path problem. It follows from the proof that the content placement problem remains computationally hard, even if each request demands only one single unit. If compositions are formed from the units, the Time-Path Scheduling Problem that is a special Multiprocessor Scheduling Problem can be reduced to the content placement problem even if only one request is created in the system.

We developed the Integer Linear Program model (ILP) of the problem as well. Our idea was to use ILP for the evaluation of other algorithms [5]. Although ILP offers an inefficient solution in the practice, it produces absolute bounds for the evaluation of practical methods. Based on the ILP model, an optimization tool has been introduced that includes preprocessing, generating ILP model for a problem instance, solving the generated ILP and generating statistics. We applied the tool to evaluate the self-organizing algorithm presented in the next section.

3 Hormone-based algorithm

The hormone-based algorithm is a self-organizing algorithm introduced in [4]. The algorithm creates an artificial hormone system where requests for units are mapped to hormones. The hormone level can be represented by a real number and it may vary on the different nodes of the network. Since there are

several paths on which hormones can spread, an evaporation mechanism is introduced. The hormones can be created by the network nodes and diffused over the network. Since there are several paths on which hormones can spread, an evaporation mechanism is introduced. The hormone-based algorithm includes search for the requested unit and then the delivery of the units to the requesting clients. In the search phase, the hormone is spreading in the network. If the hormone reaches a node storing the requested unit then the increasing hormone levels attract the required unit and guide it on an appropriate path to the requester.

3.1 The steps of the algorithm

The main steps of the hormone-based algorithm are as follows: handling incoming requests, diffusing hormones, moving units, evaporating known hormones. These steps are continuously repeated in each node of the distributed content delivery system.

In the algorithmic step of handling incoming requests, the requesting node starts the presentation of the unit if the requested unit is present on it. Otherwise, it generates hormones in order to indicate the demand for the unit. In the step of diffusing hormones, a part of the hormone on the node is distributed among the neighbors according to their provided link quality. If the hormone reaches a node storing the requested unit then the unit is forwarded from the storing node to its neighbor with the highest hormone level in the step of moving units and the unit gets towards the place of the request. The evaporation reduces the hormones by a constant value and then deletes the hormone if its value is below a specified threshold. This step ensures that the hormones on alternative paths will disappear from the system after delivering the unit at the destination. The changes in the hormone level for a whole iteration can be formulated as follows:

$$\overline{\mathbf{h}}(t+1) = (\overline{\mathbf{h}}(t) + \overline{\mathbf{b}}(t+1))\mathbf{A}$$

Where

- $\overline{\mathbf{h}}(t) = (h_1(t), h_2(t), ..., h_n(t))$: the vector containing the hormone levels on each node at iteration t
- $\mathbf{A}$: The diffusion matrix. Matrix item a_{ij} gives how much of the hormone on node i is forwarded to node j in the step of diffusion (or preserved if $i = j$). Network edges with better quality get more hormones and the corresponding matrix element becomes larger.
- $\overline{\mathbf{b}}(t) = (b_1(t), b_2(t), ..., b_n(t))$: the vector containing the additive terms for each node at iteration t. $b_i(t)$ may be negative as well and vary in each iteration.

3.2 Some definitions

The elements of $\mathbf{A}$ are all non-negative, less than or equal to one and the sum of the elements for each row is equal to one. Therefore, the elements can be the transition probabilities between the states of a Markov chain and $\mathbf{A}$ corresponds to a transition probability matrix. Therefore, we introduced the regularity for the hormone update function, which is one of the basic terms of the Markov chains. We call a hormone system *regular* if some power of the diffusion matrix has only positive elements. A necessary condition for the regularity is that the network is strongly connected. The connectivity is sufficient as well if there are loop edges at each node which is typical in case of the hormone-based algorithm and therefore the results on regular Markov chains can be applied to the hormone update in most cases.

For simplicity, $\mathbf{A}$ is assumed to be constant, i.e., independent from the time. In reality, the elements of the matrix may vary depending on the changes in the load of the corresponding links. Copying/moving units in the network causes also changes in the diffusion. However, the duration of forwarding a unit takes typically much longer time than updating the hormone levels, therefore, the matrix is assumed to be constant during the hormone-update process. Let us call the diffusion *time-homogeneous* if both the diffusion matrix and the location of the units are the same after each iteration.

The *normalised fixed vector* $\overline{\mathbf{w}}$ of the diffusion matrix has the property $\overline{\mathbf{w}}\mathbf{A} = \overline{\mathbf{w}}$ and the sum of its components is 1. The normalized fixed vector is unique for a regular hormone system similarly to the fixed probability vector for the regular Markov chains.

Some nodes may delete the hormone (e.g., at evaporation if the hormone level is low). Let us call the nodes deleting the hormone *deleting nodes*. The other nodes that do not delete hormones are called *preserving nodes*. For deleting nodes, the additive term depends on the current hormone level ($b_i(t) = -h_i(t)$). The deleting nodes receive hormones but do not forward them to any neighbors.

3.3 Monotonicity in time

The series of the hormone levels in subsequent iterations on the same node have some nice monotonic features. For simplicity, we assume that only one request is generated in the first iteration. If the hormone levels are increasing in an iteration then the hormone update steps provide almost always greater or equal hormone levels for the next iteration. Based on the monotonic features of the algorithmic steps, we proved that if the hormone level monotonically increases with time at each node in iteration $t_0(t_0 > 1)$, then it does in each later iteration as well. The condition on monotonicity for each node seems to be restrictive, but we found the following simple condition for it: If the hormone level increases at the requesting node in the second iteration then the hormone level at each node monotonically increases in each iteration. A simple corollary is that if a hormone level is larger than 0 on a node in iteration $t_0(t_0 > 1)$ and the hormone level monotonically increases with time at each node in the same iteration then the hormone level remains always positive on the node. As a consequence, the set of preserving nodes is monotone increasing in each iteration $t \geq t_0$.

4 Convergence results

The hormone update function is iterated for several times before the decision is made on the direction of forwarding the units based on the current hormone levels. The time scale of copying a unit is much longer than the one of the hormone update because the size of the content unit is much larger than the one of the messages containing the hormones. Since the number of iterations between the decisions is usually large, the hormone levels at the decisions can be approximated with their limits. We examine the convergence of the algorithm on a series of cases by starting with a basic, restrictive condition and then we consider more common, practically relevant conditions. We give formulas for the limits of the hormone values in each case. The results are based on the analogy of the artificial hormone system with the Markov-chains. All of our results refer to regular systems and time-homogeneous diffusion.

4.1 Zero additive term

We found that if the additive term $\overline{\mathbf{b}}(t)$ is zero for iterations $t > 1$ then the hormone level converges at each node. The limit of the hormone level vector is $\eta_0\overline{\mathbf{w}}$, where $\overline{\mathbf{w}}$ is the normalised fixed vector of the diffusion matrix and η_0 is the hormone level generated by the requesting node in the first iteration. For this reason, the relative values of the hormone in the network depends only on the normalised fixed vector ($\overline{\mathbf{w}}$) of the diffusion matrix and is independent from the algorithm parameters and the location of the requesting node. In these systems, the units are forwarded always to the same direction independently where the requesting node is located. This result is not surprising if we think on the analogy with Markov chains. The regular Markov chains converge to the stationary distribution (also called as equilibrium distribution) independently from the starting distribution.

4.2 Constant additive term

If the additive term is constant for iterations $t > 1$ and $\sum_{i=1}^{n} b_i > 0$ (b_i is the ith component of $\overline{\mathbf{b}}$) then the hormone levels are asymptotically equivalent with the linear function $t \cdot (\sum_{i=1}^{n} b_i) \cdot \overline{\mathbf{w}}$ where $\overline{\mathbf{w}}$ is the normalised fixed vector of the diffusion matrix. According to this, the hormone levels diverge and are

unbounded. However, if the algorithm is stopped after a specific time, the hormone levels can be well approximated by a linear function. Similarly to the case of the zero additive term, the relative values of the hormone levels also depend on the fixed vector ($\overline{\mathbf{w}}$) of the diffusion matrix. Therefore, the requested unit would be always guided to the same node independently from the location of the requesting node.

4.3 Fixed set of deleting nodes

The condition on the constant additive term is not typical because the network usually contains deleting nodes for which the additive term varies in time. The deleting nodes correspond to the absorbing states of the Markov chains while the preserving nodes correspond to the transient states if the network is connected. The elements of $\mathbf{Q}$ denoting the diffusion matrix restricted to the columns and rows of preserving nodes correspond to the transition probabilities between the transient states of an absorbing Markov chain. For this reason, we can apply the theorems on the absorbing Markov chains to prove the convergence of the hormone system with deleting nodes. If the set of preserving (or deleting) nodes is fixed and nonempty, the convergence results can be reformulated as follows: if the additive term is zero for the preserving nodes for iterations $t > 1$ then the hormone levels converge to zero at each node. Furthermore, if the additive term is constant nonzero for the preserving nodes, then the hormone levels converge at each node. According to this, the convergence of the hormone levels has changed and the algorithm becomes convergent in the case of the constant additive term.

4.4 General regular system

Now, let us turn to the general case and drop the condition of the fixed set of preserving nodes. If the hormone system monotonically increases with time, there is a maximal set of preserving nodes that never decreases (see Subsection 3.3). The convergence results on the fixed set of preserving nodes can be applied to the maximal set and we get that the hormone levels converge at each node in the general case as well.

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