AntNet combined to Stochastic Estimator Learning Automata (SELA) for QoS routing in ATM networks

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Abstract

In this work we combine two different but complementary approaches to implement a novel multi-agent based system for Quality-of-Service (QoS) routing in ATM networks. Mobile ant agents from the AntNet routing system (Di Caro & Dorigo, 1998) are slightly modified and adapted to improve and enrich the capabilities of SELA-routing (Atlasis, Saltouros & Vasilakos, 1998), a system of (static) distributed stochastic estimator learning automata (SELA) agents for QoS routing in ATM networks. The properties of the new routing system, integrating static and mobile learning agents, are discussed and, simulation results are reported for different topologies and audio-video traffic streams in ATM-like networks.

1 Introduction

The transmission capacity of current network technology allows to support multiple classes of network services associated to different quality-of-service (QoS) requirements[1] . In this way, new data and multimedia applications with specific requirements (for example in terms of end-to-end delay and bandwidth) can properly be transmitted over the network. QoS routing is the first, essential step toward achieving QoS guarantees. It identifies and selects a path that meets the QoS constraints while providing an efficient utilization of the network resources. When a new application arrives and requires some specific network resources, the local connection admission control (CAC) component make use of the routing table information to decide if the QoS requirements can be met and the connection accepted.

The problem of building and using node routing tables (for both QoS and/or best-effort requirements) can be described as a distributed multi-agent reinforcement learning (RL) [8] problem in a continually changing environment. At every node an RL agent make use of local, evaluative information, to build in an adaptive way the local routing table. The criterion that the set of RL agents must collectively optimize is the number of accepted connections over an (hypothetically) infinite time horizon while respecting all the associated QoS constraints.

In this work we use two sets of non-homogeneous RL agents to adaptively learn routing tables in QoS ATM networks with variable bit rate (VBR) traffic. We combine a system of mobile agents derived from the routing algorithm AntNet [2, 3] together with SELA-routing [1], a system of distributed stochastic estimator learning automata (SELA [9]). The AntNet's agents

[1] There is an extensive literature on QoS, considered the central role it will play in integrated service network systems. A good introduction and discussion of current hot topics in QoS can be found in [7] and [6]

(or ants) are mobile distributed agents that collect online information to support the operations of the SELA's agents, statically connected to the network nodes and directly responsible for routing/admission decisions.

2 Using modified AntNet agents to enrich SELA functionalities

AntNet is an instance of the ACO meta-heuristic, inspired by the shortest path finding behavior of real ant colonies [4, 5]. Ants move over the network collecting information about traffic distribution, time distances and, trying to discover uncongested paths. The collected information is read/written from/to the node routing tables, containing [0,1] real-valued entries P_{nd}. These P_{nd} values express the desirability of choosing a specific next-hop node n for every possible final destination d. In order to give the system an explorative component P_{nd} are used as probabilities when a local routing decision is taken by a moving ant. Such a system of agents can be seen as an online monte carlo sampling of the current, distributed, network status. The collected statistical information is used to iteratively modify the estimate of the values P, and, therefore, of the local routing decision policy. This system has been applied to adaptive routing in best-effort networks and in extensive simulations showed performance superior to several other routing algorithms representing the state-of-the-art of routing algorithms.

In this work the behavior and the scheduling of AntNet agents is slightly modified in order to support and enrich the functionalities of SELA-routing agents. SELA-routing is a system of distributed stochastic estimator learning automata (SELA) modified to learn routing tables. SELA-routing showed very good performance in simulation experiments for QoS routing in ATM networks. In SELA-routing (SELA for short, in the following), at each network node a stochastic learning automaton tries to learn the optimal decision policy for source routing. Once a connection request is issued the information local to the node is used by the automaton to decide if there is a path that can actually meet the connection's QoS requirements. All the possible paths meeting the QoS constraints are considered. If a minimum hop path is found it is selected, otherwise the SELA agent looks for a path optimizing some network utilization criterion. If a feasible path is estimated to exist the connection setup process is activated over the nodes of the selected path, otherwise the connection is refused. The action of selection of a path triggers a feedback signal from the "environment". This signal is used for the continual learning of a vector of probability values that scores the goodness of every QoS-feasible path. The signal from the environment is generated through the application of a mathematical model (based on a fluid-like approximation) of the traffic and of the network utilization. The application of the model relies on the, somehow unrealistic, assumption that every connection can provide an almost complete description of its characteristics.

The two approaches, AntNet and SELA appears to be quite complementary. In AntNet, agents: (i) perform online monte carlo sampling of the network status to collect useful information in an unbiased, model-free way, (ii) collectively build probabilistic distance-vector-like routing tables for multi-path routing. In SELA, agents: (i) individually and locally learn routing tables using local models, (ii) manage single-path source-routing decisions, (ii) they do not carry out explicit network exploration. In this work we leave unmodified the basic functionalities of AntNet and SELA agents while we add characteristics to AntNet agents to provide the SELA system with new/enriched functionalities. In this way the essential components that made AntNet and SELA very successful are conserved into the new routing system and are combined together in order to overcome some of the weaknesses of both systems. The way the ant behavior and scheduling are modified are summarized below:

- Ants are used to collect information for the online estimation and validation of the model SELA uses for the feedback from the environment. The model is made simpler (a weighted fair share queuing discipline is used) and it is no longer required to the connection to specify most of all of its characteristics. Ants move making use of their usual routing tables, kept separated from the source-routing tables used by SELA agents. In this way network exploration and routing of data traffic follow different dynamics and the risk of unoptimized/wrong routing decisions is kept low, while the level of exploration can be defined and tuned in an independent way.

- Ants are used to monitor the traffic over established paths. If the network load becomes heavily unbalanced and/or new resources are made available, the connection can be re-routed over a new, more convenient path or split over a multi-path.

- At the connections' setup time SELA agents keep applying their source routing strategies to identify feasible paths. If more than one QoS-feasible paths are found, ants are launched throughout all the candidate paths and temporary reserve, if possible, the path resources. Every ant reports to the SELA CAC/routing agent the characteristics of the probed path and the best path (in terms of the required QoS and network utilization) is then selected, while other reserved resources are released. If more than one path can satisfy the requirements (and the path superposition is very low), the additional path is selected too and the connection is split over a multi-path.

3 Discussion and results

The new routing system arising from the above combination of ant agents and SELA agents is a RL multi-agent system showing many interesting hybrid features:

- Source and non-source routing are combined together: at setup time ants are used to probe the candidate paths selected by the SELA agent at the source node.

- Per-connection multi-path routing can be used. Data can be split (deterministically or probabilistically) in a way proportional to the estimated goodness and utilization of each path.

- Online sampling and mathematical models of the existing traffic and network utilization are used together, allowing for more robust estimates.

- Ants act concurrently with the SELA and the data traffic actions. The system is organized as two communicating but independent sets of learning agents. The behavior of the ant agents is completely fault tolerant and it is aimed at improve/enrich SELA's learning and adaptivity capabilities.

- The learning rates and exploration components can be set independently at the ant and/or SELA level, giving the system many degrees of freedom and control.

With respect to the original AntNet, ants of AntNet+SELA have additional characteristics and their schedule is such that they collect general information about the whole network, as in AntNet, but also very specific connection-related information (at setup time and for re-routing in case of congestion). AntNet+SELA ants communicate in the same stigmergic way as AntNet ants: the presence of SELA agents does not directly affect the ants' behavior. It affects it only in term of routing decisions for data traffic, that make use of routing tables built through a two-steps dynamics: (i) ants make use of their private routing tables to collect network information, (ii) this information is used used by SELA to update the routing tables used by data traffic.

The system has been tested by simulation on some arbitrary and real network topologies. New connections arrive according to Poisson and log-normal distributions of audio and video traffic streams. QoS constraints are expressed in terms of end-to-end delay, delay jitter and required bandwidth (maximum Cell Transfer Delay, Cell Delay Variation and Cell Loss Ratio using ATM terminology).

We report simulation results and comparisons with other algorithms for QoS under light and heavy, evenly and unevenly traffic conditions, to show the effectiveness of the AntNet+SELA approach using the rate of accepted connections as the evalution metric.

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