12-1-2000

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Proceedings of the 39th IEEE
Conference on Decision and Control
Sydney, Australia • December, 2000

Statistical-Learning Control of an ABR Explicit Rate Algorithm for ATM Switches

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Abstract

This paper illustrates the application of statistical-learning control results for the design of an Available Bit Rate (ABR) congestion control algorithm. The proposed methodology allows us to take into account the nonlinearities of the model and the uncertainty of the parameters in the design phase. Some simulation results are shown.

1 Introduction

In this paper we illustrate the application of statistical-learning control results to Available Bit Rate (ABR) congestion control algorithms. The ABR service category is used with Asynchronous Transfer Mode (ATM) networks to handle highly bursty and varying data applications. ATM was selected by the International Telecommunication Union (ITU) for Broadband Integrated Service Digital Network (B-ISDN).

ABR traffic sources receive explicit feedback from the ATM switches and adjust their transmission rates in order to match their share of the network resources. ATM networks and specifically their ABR service control has provided a fertile area of applications for control designers as witnessed by the recent flury of papers [1, 3, 4]. Most of these papers however have made simplifying assumptions regarding the model of the network or its connectivity. In this paper, we use the nonlinear model and controller provided in [1] and apply statistical learning methods. The model of [1] is nonlinear although the control designs used are based on linearized methods. The author in [1] described how the new generation of ATM switches provide per virtual connection (VC) queuing and scheduling, resulting in fair sharing of the link bandwidth. This then frees the controller to concentrate on the congestion control problem for each VC. The designs in [1] concentrate on designing linear controller for the linearized version of the buffer dynamics. This however will only provide local design and analysis tools. Here, instead, the design will be based directly on the nonlinear model.

[1]The research of C. T. Abdallah is partially supported by NSF Grant INT-9818312

2 The Model

¿From [1], the local closed-loop dynamics of a VC are described by equation (1b) where R denotes the explicit rate (ER) computed by a switch for a given VC and Q denotes the buffer occupancy of that VC at the switch.

$$Q(n+1) = Sat_B\left\{Q(n) + \sum_{i=0}^{d} l_i(n)R(n+1-i) - \mu(n)\right\} \quad (1a)$$

$$R(n+1) = Sat_C\left\{R(n) - \sum_{j=0}^{J} \alpha_j(Q(n-j) - Q^0) - \sum_{k=0}^{K} \beta_k R(n-k)\right\} \quad (1b)$$

where $\lambda(n)$ is the rate at the ABR switch, $\mu(n)$ is the service rate (considered an external input) at the switch during the interval $[n, n+1]$, l_i are unknown plant parameters, d is the roundtrip delay between switch, source and back to switch (see [3] for a discussion of the importance of knowing d exactly), B is the buffer size, C is the maximum ER, and Q^0 is the desired buffer occupancy. The number of controller parameters J and K along with the parameters themselves α_j and β_k are to be found such that stability and some performance are attained ([2]). Note that the Q equation in (1b) describes the plant (Buffer) dynamics, while the R equation describes the controller structure and that

$$Sat_a(x) = \begin{cases} 0 & \text{if } x < 0, \\ a & \text{if } x > a, \\ x & \text{otherwise} \end{cases}$$

It was shown in [2] that it is sufficient (at least in the case of linearized model) to take $J = 1$ and $K = d$ in order to completely place the poles of the closed-loop system. The approach in [1] consists of removing the saturation functions to linearize the system, and then to use the linearized model to design an LQR controller.

3 Statistical Design

In this paper, we use a different track by designing the controller directly for the nonlinear model (1b) using statistical-learning control. Note that the saturation nonlinearities pose no additional problems for such design methodology. Let $d = 12$; then we denote by $Y \in \mathcal{Y} \subseteq \mathbb{R}^{15}$ the vector of controller coefficients and by $X \in \mathcal{X} \subseteq \mathbb{R}^{13}$ the uncertain plant parameters l_i. The nominal model is recovered by letting $l_i = 0, i = 0, \ldots d-1, l_d = 1$. These controller and plant coefficients are chosen to have uniform distributions in assigned intervals.

In order to use the randomized algorithm methodology, this problem has been reformulated in the following way. Let us fix the following design requirements: *i)* the buffer occupancy should converge to Q^0 in less than 400 ms; *ii)* the overshoot in the buffer should not exceed 40%. Now define a cost function

$$\Psi(Y) = \max\{\psi_1(Y), \psi_2(Y)\} \quad (2)$$

where

$$\psi_1(Y) = \begin{cases} 0 & \text{if all requirements on the nominal plant are met} \\ 1 & \text{otherwise} \end{cases}$$

and $\psi_2(Y) = E(\zeta(X,Y))$, where E indicates the *expected value* with respect to X, and

$$\zeta(X,Y) = \begin{cases} 0 & \text{if all requirements on the nominal plant are met} \\ 1 & \text{otherwise} \end{cases}$$

Our aim is to minimize the cost function (2) over $\mathcal{Y}$. using the following algorithm [5]:

Algorithm 1 *Given:*

- *Sets $\mathcal{X}$ of plant parameters and $\mathcal{Y}$ of controller parameters,*
- *Probability measures P on $\mathcal{X}$ and Q on $\mathcal{Y}$,*
- *An accuracy parameter $\varepsilon \in (0,1)$, a level parameter $\alpha \in (0,1)$, and a confidence parameter $\delta \in (0,1)$.*

Let $R_P(\zeta(\cdot)) = \mathbb{E}_P[\zeta(X,\cdot)]$ *and* $R_{P_n}(\cdot) = \frac{1}{n}\sum_{j=1}^{n} \zeta(X_j,\cdot)$. *Then,*

1. *Choose m controller parameters Y_i with random entries according to the distribution Q where* $m \geq \frac{\log(2/\delta)}{\log[1/(1-\alpha)]}$
2. *Choose n plant parameters X_j with random entries according to the distribution P, where* $n = \lfloor \frac{20}{\varepsilon^2} \log\left(\frac{8}{\delta}\right) \rfloor + 1$
3. *Evaluate the stopping variable* $\gamma = \max_{1 \leq i \leq m} \left| \frac{1}{n} \sum_{j=1}^{n} r_j \zeta(X_j, Y_i) \right|$ *where r_j are Rademacher random variables, i.e. independent identically distributed random variables (also independent of the plant sample) taking values $+1$ and -1 with probability $1/2$ each. If $\gamma > \frac{\varepsilon}{K_1}$, add n more independent plants with parameters having distribution P to the plant samples, set $n := 2n$ and repeat step 3*
4. *Choose the controller which minimizes the cost function R_{P_n}.*

α_0	α_1	β_0	β_1	β_2
0.1983	-0.1936	0.0827	0.0175	0.0161
β_3	β_4	β_5	β_6	β_7
0.0013	0.0039	0.0001	0.0001	0.0068
β_8	β_9	β_{10}	β_{11}	β_{12}
0.0177	0.0082	0.0104	0.0109	-0.1758

Table 1: The parameters of the designed controller.

In this case the algorithm needed 736 controller samples and 50,753 plant samples. The parameters of the *suboptimal* controller are shown in Table 1. In Figure 1 we show the performance of the designed controller for the nominal plant in the case $Q^0 = 100$, $\mu = 50$, $B = 250$, $C = 100$.

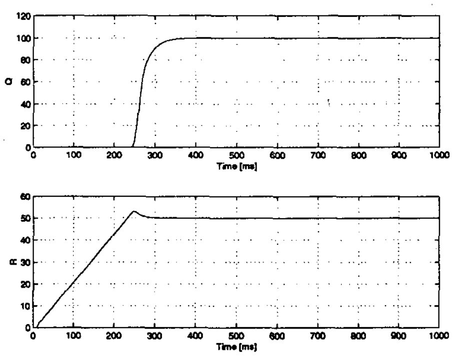

Figure 1: The performance of the designed controller in the nominal case

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