MODELLING AGGREGATE HETEROGENEOUS ATM SOURCES USING NEURAL NETWORKS

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ABSTRACT

In this paper it is proved that artificial neural networks are adequate tools to obtain superposition models of multiplexed ATM traffic sources. It is shown how complex mathematical models can be replaced by a modular, adaptive and parallel architecture, capable of developing complicated algorithms. In particular, we approximate a superposition of individual ATM sources by a two-state Markov Modulated Poisson Process (MMPP). This approximation is performed by a neural system, matching four statistics of the aggregate traffic to those of the MMPP. The approach is evaluated by numerical examples, showing that it is adequate for estimating delay attributes and cell-level congestion.

INTRODUCTION

The main problems of the future Broadband Integrated Service Digital Network (B-ISDN), based on Asynchronous Traffic Mode (ATM), are due to the need of supporting multimedia services. One of these problems is modelling of ATM traffic. ATM networks have to transmit information belonging to a wide variety of services, with different nature and requirements of quality of service. This flexibility implies a great difficulty in finding a simple, efficient and universal model that can simulate any type of traffic.

One of the easiest ways to approximate a simple ATM traffic source is via an On-Off model, a renewal process with two states. The main advantages of this model are its simplicity and easy mathematical tractability. However, ordinary ATM traffic is not only the stream of a simple source but the result of multiplexing many multimedia sources. So, it is necessary to carry out models that can also approximate arbitrary aggregate ATM traffic. The proposed solutions usually imply Markov chains [1] [2] [3]. One of the most referenced models is the Markov Modulated Poisson Process (MMPP) of two states. The MMPP is a doubly stochastic process where the cell rate follows a Poisson distribution determined by the state of a continuous Markov chain. The principal drawback, when using this model, is the complexity of the mathematical tools that it involves if we need to handle high order statistical moments or queuing parameters.

In this paper we show how complex algorithms can be replaced by artificial neural networks to achieve superposition models. In particular, we focus our study on a neural indirect control scheme [4] proving that feedforward multilayer perceptrons can model any aggregate traffic, only knowing its statistical descriptor. In our case, this statistical descriptor will depend on the number of connected sources of two different traffic classes.

NEURAL SYSTEM DESCRIPTION AND ANALYSIS

Heffes and Lucantoni [1] have shown that the MMPP model can approximate correctly a traffic superposition if it is defined in such a way that four of its statistical characteristics match those of the aggregate traffic. These statistics are: the mean cell arrival rate (m), the short term variance-to-mean ratio (v_1) of the number of cell arrivals in the interval $(0, t_1)$, the long term variance-to-mean ratio (v_2) of the number of arrivals, and the skewness index (s) in t_2 , defined as the third central moment-to-mean ratio of the number of cell arrivals in $(0, t_2)$.

A MMPP model is defined by four parameters: the mean sojourn times r_1^{-1} and r_2^{-1} in states 1 and 2, respectively, and the cell rates λ_1 and λ_2 of the Poisson Process for each state.

The values of this descriptor $p = \{m, v_1, v_2, s\}$ are determined in [1] in terms of the model parameters r_1^{-1} , r_2^{-1} , λ_1 , λ_2 . Solving the equations in [1] we could obtain the parameters of a MMPP model that matches the statistical descriptor of a given traffic superposition. To avoid this analytical solution, which even involves iterating calculations, we propose the indirect neural controller depicted in figure 1. The system consists of four modules: the S module is a simulated ATM node where all the individual sources are multiplexed. In this module, we can measure the statistical descriptor of the traffic superposition $\mathbf{p}^{[S]} = \{m^{[S]}, v_1^{[S]}, v_2^{[S]}, s^{[S]}\}$. The input traffic is described by the vector $\mathbf{n} = \{n_1, n_2, \dots, n_N\}$ where n_i is the number of

connected sources of the class i ($i=1,2, \dots, N$). The C module is the network controller, which estimates the parameters of the superposition model $\mathbf{k}=\{r_1^{-1}, r_1^{-2}, \lambda_1, \lambda_2\}$ as a function of the input traffic. This module calculates the vector $\mathbf{k}=\mathbf{F}(\mathbf{n}, \mathbf{W})$, being $\mathbf{W}$ the weight matrix of the multilayer perceptron. Unfortunately, it is not possible to supervise the learning phase of this neural network as long as we do not know the right components of the vector $\mathbf{k}$ and, consequently, cannot generate learning patterns to train the network directly. To overcome this difficulty, we propose an indirect control scheme, which requires two new modules (K and E). The K module analytically calculates the statistics $\mathbf{p}^{[K]}=\{m^{[K]}, v_1^{[K]}, v_2^{[K]}, s^{[K]}\}$ of the MMPP models, using the equations in [1]. The E module is the network emulator. It is another multilayer perceptron and yields at its outputs the statistical parameters $\mathbf{p}^{[E]}=\{m^{[E]}, v_1^{[E]}, v_2^{[E]}, s^{[E]}\}$ of the MMPP model. Unlike the C module, the learning of this E network can be supervised, as we can backpropagate the error: $e^{(E)} = 1/2 (p^{(K)} - p^{(E)})(p^{(K)} - p^{(E)})^T$, using the gradient $\partial e^{(E)} / \partial \mathbf{V}$, where $\mathbf{V}$ is the weight matrix of the network emulator.

As a result of this learning, the network emulator will adjust its weights and it will tend to identify the K module. But the actual aim of this module is to enable the learning of C Network by backpropagating the error $e^{(C)} = 1/2 (p^{(S)} - p^{(K)})(p^{(S)} - p^{(K)})^T$, by means of the gradient:

$$\frac{\partial e^{(C)}}{\partial \mathbf{W}} = -(p^{(S)} - p^{(K)}) \frac{\partial p^{(K)}}{\partial \mathbf{W}} = -(p^{(S)} - p^{(K)}) \frac{\partial p^{(E)}}{\partial \mathbf{W}}$$

where $\partial p^{(K)} / \partial \mathbf{W}$ is replaced by $\partial p^{(E)} / \partial \mathbf{W}$ as $p^{[K]}$ tends asymptotically to $p^{[E]}$. Thus, C module will adjust its weights to minimize the error of the statistics corresponding to its outputs (the parameters of the desired MMPP model). The final result, at the end of the learning phase, is that C module will be able to calculate a superposition model (vector $\mathbf{k}$), as a function of the number of active sources (vector $\mathbf{n}$). These MMPP models will approximate the statistics of the superposition as accurately as the error has been reduced on both neural networks.

SIMULATION AND NUMERICAL RESULTS

To evaluate the performance of the proposed scheme we considered an ATM multiplexer loaded with two different types of traffic (class 1 and class 2). Each individual source was modelled via an ON-OFF model, whose characteristics are shown in Table I. These characteristics were selected to cover a wide range of services. So classes 1 sources could correspond to a narrowband service whereas classes 2 sources would represent a broadband service with a more bursty behaviour. The transfer rate of the link is 150 Mbits/s and the ATM cell length 53 bytes. Therefore, the service time (slot) for a cell is 2.83×10^{-6} s ($53 \times 8 / 150$ Mbits/s). Times t_1 and t_2 were chosen to get a good fit over the whole range of curves v and s . We obtained 75 training patterns of statistics introducing 75 different $\mathbf{n}$ vectors into the module S. These $\mathbf{n}$ vectors are random combinations of n_1 class 1 sources and n_2 class 2 sources, with $n_1=\{0,1, \dots, 75\}$ and $n_2=\{1,2, \dots, 40\}$. This range was established to avoid the saturation of the ATM link. Once the patterns are generated, the learning phase of the neural network is performed. The Network Controller module was designed with 2, 25 and 4 neurons in its input, hidden, and output layers, respectively. The dimension of the Network Emulator module was 4-15-4. A backpropagation algorithm was used and, after training, the

mean quadratic errors, normalizing between 0 and 1, were lower than 3×10^{-6} . The trained neural system was tested with several sets of patterns, different from those of the learning phase. In all the cases the test error was acceptable, lower than 6×10^{-6} and in the same range of that of the learning phase.

The MMPP models obtained by the above procedure are checked to know their accuracy. Their behaviour in a queue is compared with that of the superposition of individual sources. So the model will be as accurate as it can approximate some parameters that normally determine the quality of an ATM communication. These parameters are: **the cell delay** (average waiting time of a cell in the queue, considering infinite queue size) and **the cell loss probability**. This comparison is depicted in figures 2 and 3, with a simulation of 20×10^6 cells for each sample. Figure 2 shows how the MMPP approximates quite well the average delay. Cell loss probability is depicted in figure 3. The behaviour of the MMPP is closer to the aggregate traffic results as the traffic load condition increases. However, for light traffic condition, MMPP model miscalculates the actual aggregate traffic losses. These results are similar to those in [3]. It is also proved the difficulty of characterizing a bursty traffic. Hence, the error of the MMPP models grows when the influence of class 2 sources, whose burstiness is 5, is greater than that of class 1 sources, with burstiness equal to 2. Furthermore, these estimations even get worse if we consider longer queue sizes since MMPP represents cell level better than burst level [2].

CONCLUSIONS

We have achieved through multilayer perceptrons a procedure to generate models for superposition of ATM traffic sources. With this procedure, any multiplexed traffic of superposed heterogeneous sources can be approximated by a superposition model, just knowing its statistical descriptor and avoiding complex equations and algorithms.

In this paper, we have analysed the behaviour of the MMPP model that our neural system generates by approximating four statistical characteristics of the ATM aggregate traffic. But our system is neither limited to these statistics nor to the MMPP model. Using the modularity and the adaptive learning of neural networks, we could evaluate any set of statistics or any other superposition model, just changing the dimension of the networks and simulating new traffic patterns. Thus, we could obtain more accurate models by increasing the number of statistics to match, or proposing processes with higher complexity than MMPP.

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