The simulated waveforms are shown in Fig. 2, while the corresponding experimentally observed waveforms are shown in Fig. 3a-c. The quality of the experimental synchronisation can be appreciated looking at Fig. 3b that shows the variable $x_2$ against the variable $x_3$, each one corresponding to the other in the master and slave systems. Finally, Fig. 3c shows the observed phase portrait in the $x_4-x_5$ plane when the forcing signal is applied. In Fig. 3c, the presence of a small ripple superimposed onto the decoded signal can be observed. This could lead to the wrong conclusion that the two circuits are not exactly synchronised; however, Fig. 3b excludes this case. The correct explanation of this fact is immediately obtained by measuring the actual current fed by the block $B_3$. In fact, this current is slightly corrupted by the master itself due to the nonideal features of the realised current source generator. Apart from the triangular wave, other different waveforms have also been taken into account (e.g. sine waves, square waves, speech and musical signals, and so on), with successful results.

Finally, it has been noted that the above cited ripple is always present independently from the nature of the considered transmitted signals. Therefore it could be significantly reduced by using a better current source or by filtering the decoded signal by means of a lowpass filter.

Conclusions: In this Letter it has been shown how two SC-CNN-based circuits, generating the dynamics of the Chua oscillator, are used successfully for signal transmission. The SC-CNN approach for generating complex dynamics is quite general; in fact, simply changing the templates of a fixed structure system, it is possible to choose a different chaotic attractor. Alternatively, the architecture can be easily augmented by adding new cells in order to generate higher order dynamics [6]. Even if, in the reported case, the inverse system method has been considered, the modularity of the SC-CNN approach allows an easy implementation of other synchronisation methods [1, 2]. In this way, we stress the concept that the SC-CNN framework represents a suitable platform for chaotic system synchronisation with potential applications in secure communication systems.

References


statistical characteristics match those of the aggregate traffic. These statistics are: the mean cell arrival rate \( \lambda_0 \), the short term variance to mean ratio \( \lambda_1 \) of the number of cell arrivals in the interval \((0, t_1)\), the long term variance to mean ratio \( \lambda_2 \) of the number of arrivals, and the skewness index \( \lambda_3 \) defined as the third central moment to mean ratio of the number of cell arrivals in \((0, t)\).

A MMPP model is defined by four parameters: the mean sojourn times \( r_1 \) and \( r_2 \) in states 1 and 2, respectively, and the cell rates \( \lambda_1 \) and \( \lambda_2 \) of the Poisson Process for each state.

The values of this descriptor \( p = (m, n, r_1, r_2) \) are determined in [1] in terms of the model parameters \( r_1 \), \( r_2 \), \( \lambda_1 \), \( \lambda_2 \). Solving the equations in [1] we could obtain the parameters of a MMPP model which 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 Fig. 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 \( p = (m, n, r_1, r_2) \). The input traffic is described by the vector \( n = (n_1, n_2, ..., n_n) \) where \( n_i \) is the number of connected sources of the class \( i \) \((i = 1, 2, ..., N) \). The \( C \) module is the network controller, which estimates the parameters of the superposition model \( k = (r_1, r_2, \lambda_1, \lambda_2) \) as a function of the input traffic. This module calculates the vector \( k = P(n, W) \), with \( W \) being 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 \( k \) 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 \( p = (m, n, r_1, r_2) \) 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 \( p = (m, n, r_1, r_2) \) of the MMPP model.

Unlike the \( C \) module, the learning of this \( E \) network can be supervised, as we can backpropagate the error: \( e^0 = 1/2(p^0 - p_0)^2 \), using the gradient

\[
\frac{\partial e^0}{\partial W} = -(p^0 - p_0) \frac{\partial p^0}{\partial W} = -(p^0 - p_0) \frac{\partial p^0}{\partial S} \frac{\partial S}{\partial W}
\]

where \( \partial p^0/\partial W \) is replaced by \( \partial p_0^0/\partial W \), as \( p^0 \) tends asymptotically to \( p_0 \). Thus, the \( C \) module will adjust its weights to minimise 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 the \( C \) module will be able to calculate a superposition model (vector \( k \)), as a function of the number of active sources (vector \( n \)). These MMPP models will approximate the statistical characteristics of the aggregate traffic as accurately as the error has been reduced on both neural networks.

### Table 1: Characteristics of individual ATM sources for classes 1 and 2

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Peak rate</th>
<th>Average duration of on-state</th>
<th>Average duration of off-state</th>
<th>Burstiness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 1</td>
<td>Mbytes</td>
<td>ms</td>
<td>ms</td>
<td>2</td>
</tr>
<tr>
<td>Class 2</td>
<td>10</td>
<td>0.5</td>
<td>2.0</td>
<td>5</td>
</tr>
</tbody>
</table>

Simulation and numerical results: To evaluate the performance of the proposed scheme we considered an ATM multiplexor loaded with two different types of traffic (class 1 and 2). Each individual source was modelled via an on-off model, whose characteristics are shown in Table 1. These characteristics were selected to cover a wide range of services. So the sources of class 1 could correspond to a narrowband service whereas the sources of class 2 would represent a broadband service with a more bursty behaviour. The transfer rate of the link is 150Mbit/s and the ATM cell length is 53 bytes. Therefore, the service time (slot) for a cell is 2.83 \( \times 10^{-6} \) s \((53 \times 8/150 \text{Mbit/s})\). Times \( t_1 \) and \( t_2 \) were chosen to get a good fit over the whole range of curves \( r \) and \( s \). We obtained 75 training patterns of statistics introducing 75 different \( n \) vectors into the module \( S \). These \( n \) vectors are random combinations of \( n_1 \) class 1 sources and \( n_2 \) class 2 sources, with \( n_i = (0, 1, ..., 75) \) and \( n_2 = (0, 1, 2, ..., 40) \). 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, normalising between 0 and 1, were lower than 3 \( \times 10^{-6} \). 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 \( \times 10^{-6} \) and in the same range of that of the learning phase.

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**Fig. 1** Block diagram of system

**Fig. 2** Average cell delay for MMPP model and aggregate traffic

× MMPP model
○ aggregate traffic

**Fig. 3** Cell loss probability for MMPP model and aggregate traffic, considering a queue size of 25

× MMPP model
○ aggregate traffic
The MMPP models obtained by the above procedure were checked to ascertain 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 Figs. 2 and 3, with a simulation of $20 \times 10^6$ cells for each sample. Fig. 2 shows how the MMPP approximates the average delay quite well. Cell loss probability is depicted in Fig. 3. The behaviour of the MMPP is closer to the aggregate traffic results as the traffic load condition increases. However, for light traffic conditions, the MMPP model miscalculates the actual aggregate traffic losses. These results are similar to those in [3]. It is also proved the difficulty of characterising 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 a procedure for generating models for the superposition of ATM traffic sources using multilayer perceptrons. With this procedure, any multiplexed traffic of superposed heterogeneous sources can be approximated using a superposition model, just knowing its statistical descriptor and avoiding complex equations and algorithms.

In this Letter, we have analysed the behaviour of the MMPP model generated by our neural system approximating four statistical characteristics of the ATM aggregate traffic. Our system is neither limited to these statistics nor to the MMPP model though. Using the modularity and the adaptive learning of neural networks, we could evaluate any set of statistics or any other superposition model, just knowing its statistical descriptor and avoiding complex equations and algorithms.

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References


2.4Gbit/s all-optical pulse discrimination experiment using a high-speed saturable absorber optical gate

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Indexing terms: Signal processing, Optical switches, Optical repeaters

3ps, 2.4Gbit/s all-optical pulse discrimination is achieved with an optical discriminator (ODSC) using a high-speed saturable absorber optical gate. 3ps pulses generated using a monolithically integrated mode-locked laser diode (MLDL) are used to reduce the switching energy of an optical gate.

Introduction: In the future, all-optical signal regeneration using high-speed optical devices will be essential to a large capacity optical transmission network. So far, a Sagnac mirror has been used to demonstrate all-optical signal regeneration [1 – 3]; however, it suffers from excessive signal delay and a severe limitation on operating wavelength between the signal and the control lights. We proposed an all-optical regenerator [4] employing a high-speed saturable absorber optical gate [5], which regenerates and reshapes a degraded optical signal. The optical gate has the advantages of compactness, a fast response time (subpicosecond to picosecond range), a wide operating wavelength range and threshold characteristics; therefore, it is more suitable for an ODSC.

This Letter demonstrates all-optical discrimination for a 2.4 Gbit/s 23-stage pseudorandom bit stream (PRBS) signal degraded by ASE noise. Using 3ps pump pulses instead of 10ps pulses, the bit rate of the ODSC is improved from 600Mbit/s [4] to 2.4Gbit/s.

Device structure and short pulse operation: A high-speed saturable absorber optical gate comprises an InGaAsP/InP DBR mirror layer, a Be-doped low-temperature-grown InGaAs/InAlAs multiple quantum well (MQW) layer (saturable absorber), an InAlAs/InP phase control layer, a Au mirror layer and an InP substrate. For highly repetitive operation, it is necessary to reduce power consumption in an optical gate because excessive heat degrades device performance. One solution to this problem is using an optical pulse whose width is shorter than the carrier relaxation time of MQWs. We have estimated the effect of pulswidth on the peak transmission of a saturable absorber. The response of the saturable absorber is approximated by the following rate equation.

$$\frac{dN}{dt} = -a(N - N_0)s - \frac{N}{t_{rel}}$$

where $a$ is the differential absorption coefficient, $N$ is the carrier density, $N_0$ is the carrier density for transparency, $s$ is the photon density and $t_{rel}$ is the carrier relaxation time. The parameter values are assumed to be $a = 2 \times 10^8$ cm$^{-1}$, $N_0 = 5 \times 10^{18}$ cm$^{-3}$, $t_{rel} = 5$ ps, the spot area is 9 $\mu$m, the thickness of the saturable absorber is 10 $\mu$m, and the refractive index is 3.3. The calculated results are shown in Fig. 1. These indicate that the required energy for the same peak transmittance is effectively reduced when a shorter...