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Optimizing dynamical states for high-speed photonic computing

Michael J. Wishon[†‡], Alexandre Locquet [†‡], C.Y. Chang[†*], Daeyoung Choi[†‡], and D.S. Citrin[†‡]

†UMI 2958 Georgia Tech-CNRS, Georgia Tech Lorraine
2 Rue Marconi, 57070, Metz, France
‡School of Electrical and Computer Engineering, Georgia Institute of Technology
777 Atlantic Drive NW, 30332-0250, Atlanta, Georgia, USA
∗ School of Physics, Georgia Institute of Technology
837 State St NW, 30332-0250, Atlanta, Georgia, USA
Email: mwishon@gatech.edu, alocquet@georgiatech-metz.fr

Abstract—Photonic neuromorphic computing is the intersection of sub nanosecond fluctuations with the performance and energy efficiency of the human brain. These systems operate based on a nonlinear transformation of input streams, and by fully understanding the attractor dynamics of the transformation it is possible to optimize these dynamics for a computing task. By optimizing the dynamical state of our neural net, we are able to process over 70 million digits per second.

1. Introduction

We exploit the fast, sub-nanosecond dynamics of semiconductor lasers to realize a photonic implementation of a neural network. Currently, a major focus of photonic computing is based on a subset of recurrent neural networks known as reservoir computing (RC). In RC, nonlinear, interconnected neurons are excited by input streams. Characteristics about the neuron's response to the input stream are extracted in order to gain information about the input stream. Using the extracted information and a set of training weights (linear multipliers), it is possible to determine the input to the reservoir. Thus, one can do separation tasks involving speech or image recognition, for example, based on the nonlinear response of such systems.

The set of weights are calculated (trained) in standard neural networks by a recurrent method of guess and check where inputs drive the system and the weights are incrementally adjusted in order to garner the desired response. This process can be difficult and further only converge to a local minimum. Thus, a method of fast, global training was desired, and RC emerged as a solution to the quandary. In RC, the neural network known as the reservoir forms the basis of a nonlinear response. The response itself is not trained as in standard recurrent neural networks. Instead, the reservoir is sampled at a set rate (θ) and an output is generated. The output is then subjected to a set of weights which are calculated using a simple linear regression[1, 2]. These systems were experimentally demonstrated in opto-electronic systems [3, 4, 5, 6, 7], and have demonstrated state-of-the-art performance in chaotic time-series prediction [3] and in spoken-digit recognition [4].

The parameters with the largest effect on the quality of the photonic computer are external cavity length, modulation rate, bias current, and feedback level (η). In this study, we focus on the most profound of these, the feedback level. As feedback is varied in laser systems, many different dynamic regimes are accessed, including quasi-periodicities, limit cycles, double periodicities, and deterministic chaos. These vastly different regimes have a crucial impact into how the system's nonlinear transformation affects inputs and thus deserve attention.

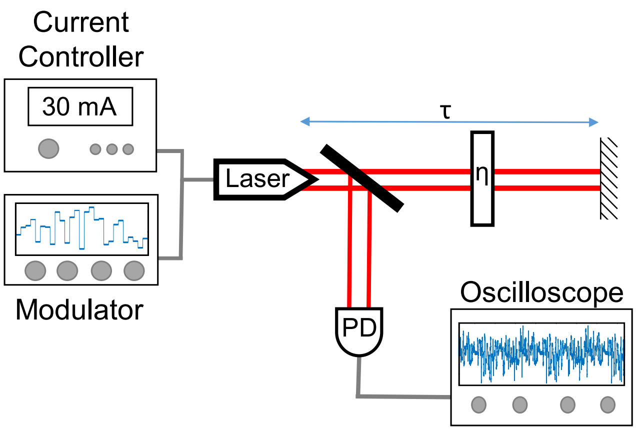

Figure 1: The laser is biased near threshold (30 mA), and a modulation (0.5 V) is combined with the bias current in order to electrically inject the input streams into the reservoir. Feedback is controlled by rotating a quarter-wave plate relative to a fixed linear polarizer. A beam splitter, fiber coupler, fast photodiode, and oscilloscope are used in tandem to make the measurement.

We utilize a free-space laser subjected to external optical feedback (210 cm) from a highly reflective mirror. We modulate the input stream onto the laser at high data rates (1 GS/s) through a bias-tee (20 GHz) and RF probe (25 GHz). The resulting output is measured in the time domain utilizing a fast photodiode (12 GHz) and oscilliscope (40 GS/s and 12 GHz). The experimental setup is represented in Fig. 1.

2. Spoken digit recognition

We demonstrate the speed and effectiveness of our system using spoken-digit recognition. Specifically, we use the NIST TI-46 corpus [8]; the corpus is a set of spoken digits by five female speakers who utter ten times the ten digits in English for a total of 500 spoken digits. The unprocessed audio signal for each digit is split into 130 time slices of equal duration. The resulting time slices are processed using a cochlear ear model [9]. The number of modulations per delay is given by the number of channels utilized in the model. Each channel corresponds to a frequency component; therefore, the model emulates the ear by calculating a Fourier transform of the input signal. After the cochlear model, the value of each channel from each of the different slices are summed into single values and held for a duration equal to the inverse of the modulation rate (θ). The resulting bit stream is multiplied by a a binary mask consisting of the values ± 1. The value that each duration is multiplied is chosen at random. The resulting signal is the input stream that we modulate across the laser.

The 500 spoken digits are split into 450 for training and 50 for testing and 20-fold cross validation is performed for statistical significance. Using the reservoir's response and a target function ($\hat{y}(l)$), k weights (W_l) are calculated by minimizing the mean square error (MSE),

$$\text{MSE} = \frac{1}{k}\sum_{l=1}^{k}(\hat{y}(l) - y(l))^2. \tag{1}$$

Future output's are subjected to the calculated weights and whichever is closest to the target function is the reservoir's guess.

2.1. Experimental Results

We study here the word error rate (WER) as a function of feedback for our system. The WER is simply the number of words wrong over the number of words attempted. In our case, a word is simply the computer's guess at the digit. In Fig. 2, we can see that for low feedback levels we have low error. From the zoom-in, the error is low $\sim 2\%$ for no feedback, but the error decreases until a minimum error of $\sim 0.001\%$ at a feedback of $\sim 16\%$.

At minimum feedback, the laser is dynamically characterized by stable continuous-wave emission. With an increase in feedback, an undamping of the characteristic relaxation oscillation frequency occurs and limit cycles emerge. The dynamics of this stable limit cycle is where the optimum operating condition is found. After this point, we see an increase in the error rate. The increase is due to a regime known as intermittency. Intermittency is characterized by a constant switching between several different stable trajectories in phase space [10]. After intermittency, the laser enters into chaos. When chaos is reached at a feedback $> 40\%$ the error drastically increases.

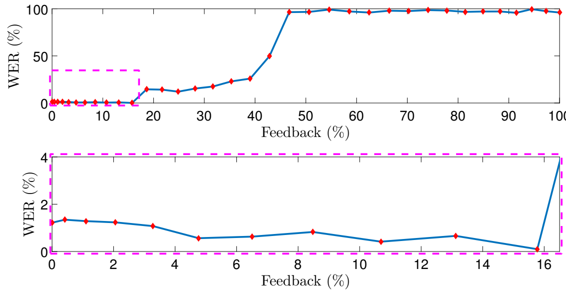

Figure 2: Word error rate (WER) as a function of feedback strength (η). For low feedbacks, low error rates are observed. A minimum in the error ($\sim 0.001\%$) is observed with a feedback rate $\sim 16\%$.

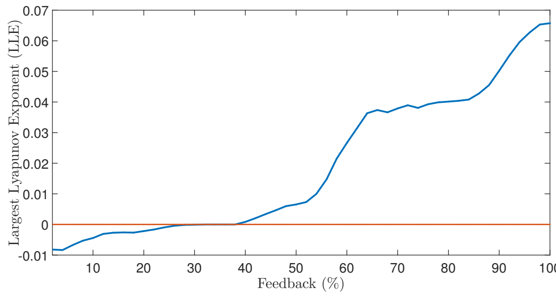

Figure 3: The largest Lyapunov exponent (LLE) as a function of feedback is plotted for our dynamical system. When the LLE is greater than zero chaotic behavior is observed.

We can further explain the dynamics of the system using the largest Lyapunov exponent (LLE). The LLE is a measure of the fastest expanding dimension in a dynamical system, and when it is greater than zero the system has chaotic behavior. We previously measured the LLE for this laser in [11] and again for the system parameters here in Fig. 3. By comparing Figs. 2 and 3, we can understand how the rate of expansion and attractor dynamics play a role in photonic computing. But first some context: it was proposed by Legenstein and Maass that the LLE was a way to characterize the performance of a dynamical system for RC [12]. It was stated that the reservoir should be operated at the edge of chaos, or maximum expansion rates without sensitive dependence on intial conditions (chaos). Further, they showed that the LLE is a similar measure to the Jacobian of the weight matrix in neural networks being equal to 1 for stability and optimal performance.

Since the quality of the nonlinear transform is predicated on the attractor dynamics and for low values of LLE the rate of expansion is very low the error rate is not optimal. This occurs because different input streams are not mapped to vastly different places in phase space and thus the computer can not as effectively identify the bits. As the LLE increases we see an increase in the quality of the computer's ability (decrease in WER). Which corresponds to a faster rate of expansion in the attractor's dynamics, thus, leading to current modulation patterns that are separated further apart and more easily distinguished with the machine learning techniques.

After the optimum, we see an increase in the error during intermittency. This intuitively makes sense because we train on one set of dynamics but are testing on another. This is related to the idea of consistency, and has been shown to be important for reservoir systems [13]. Further, when chaotic dynamics are reached there is a sensitive dependence on initial conditions further exacerbating the problem and leading to even greater errors and experimentally confirming [12, 13].

3. Discussion

From our experiment it is clear that the dynamics of the computer's attractor plays a major role in its performance. It was found experimentally that we should operate dynamically as close to chaos as possible while avoiding intermittency and chaos. The purpose being to maximize the LLE or the divergence of trajectories in phase space. Thus allowing the computer to more easily identify different temporal input patterns (digits), but avoiding conditions where the dynamics are changing rapidly or sensitive to initial conditions.

Finally, our RC demonstrated excellent performance in spoken digit recognition in optimal conditions with a WER of $\sim$ 0.001%, and the free-space reservoir system, to the best of our knowledge, demonstrates state of the art performance in terms of speed by classifying over 70 million digits per second [14] due to its short delay and the optimization of the attractor dynamics.

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