A Study of Changes in Prediction Performance Influenced by Attractor State in Oscillator Reservoir Computing

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Abstract— AI technologies have proven their capabilities in solving complex problems, but they often require significant computational resources and power. This study proposes a reservoir computing (RC) model utilizing Bonhoeffer-van der Pol (BVP) oscillators, leveraging their chaotic dynamics to generate complex, high-dimensional internal states. The paper investigates the impact of the attractor states of these oscillators on the prediction performance of a speech recognition task. Results indicated that the asymmetric attractors led to lower Word Error Rates (WER) compared to periodic ones, suggesting that the diversity of circuit responses is beneficial for RC performance.

Keywords; oscillator, reservoir computing, synchronization, chaos

I. INTRODUCTION

In recent years, artificial intelligence technologies such as deep learning and recurrent neural networks have rapidly developed and demonstrated their capabilities in various domains. These techniques excel particularly in their ability to provide highly accurate solutions to complex problems such as image recognition, natural language processing, and financial forecasting. However, these algorithms are challenged by the large amount of computational resources required and the associated increase in power consumption [1]. One approach to overcome this challenge is reservoir computing (RC), a type of RNN whose internal state is randomly initialized and fixed during the training process [2]. This allows for fast learning by optimizing only some parameters, which is expected to reduce power consumption. We specifically proposed RC with the Bonhoeffer-Van der Pol (BVP) oscillator, which we considered to represent a high-dimensional and complex state space by using the chaotic dynamics of the BVP to generate internal states, resulting in high prediction performance [3]. In this study, we investigate the attractor states of these chaotic dynamics in RC with BVP and the accuracy of speech recognition using them.

A. Reservoir configuration

Figure 1 shows a networked reservoir using the proposed oscillation circuit.

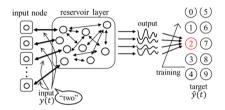


Figure 1. Configuration of the proposed oscillator reservoir.

The oscillation circuit used a BVP. The circuit equation is shown below.

$$\begin{cases} C \frac{dA_n}{dt} = -i_L - i_G - \sum_{k=1}^{N} \frac{1}{R} (v_{A_n} - v_{A_k}) \\ C \frac{dB_n}{dt} = i_L - \frac{1}{R} v_B \\ C \frac{d_i L_n}{dt} = v_A - v_B \end{cases}$$
(1)

The normalized circuit equations are described as follows.

$$\begin{cases} \frac{dx_n}{d\tau} = \varepsilon x_n (1 - x_n^2) - z_n + \sum_{k=1}^N K(x_k - x_n) \\ \frac{dy_n}{d\tau} = z_n - \sigma \\ \frac{dz_n}{d\tau} = z_n - y_n \end{cases}$$
(2)

B. Simulation Methods

This study evaluated speech recognition using oscillator reservoirs. A total of 500 data samples consisting of recordings of five different speakers pronouncing each of the numbers 0 through 9, repeated 10 times, were used for the input data set. The input data used in this study was based on an application of Lyon's auditory model. After removing the silent parts, the speech signal is converted to a cochlear-type speech signal. This transformation yields time series data with dimensions corresponding to different frequency channels. In this study, the cochleagram data is characterized by 77 dimensions that reflect the spectral characteristics of the speech signal. Half of the dataset, containing five pronunciations of each number spoken by five speakers, was allocated for training and the remaining data for testing [4]. The initial transient response of 10,000 to was

ignored. The simulation was performed using the Runge-Kutta method. Signals were input by varying the coupling strength between the input node and the reservoir layer over time. The voltage difference between each oscillator and the reference oscillator was used as the output, which was trained by linear learning. The Word Error Rate (WER) was used to evaluate the accuracy of speech recognition.

II. SIMULATION RESULTS

In this section, we check the accuracy of speech recognition and the oscillator's attractor at that time. The results were checked when the coupling probability P was varied and when the coupling strength K was varied, respectively.

A. When the connection probability P is varied

When P is varied, the error in speech recognition varies as shown in Figs. 2 and 3. The attractors of the oscillators at this time are shown below, with the attractor of one circuit out of 100 placed as representative.

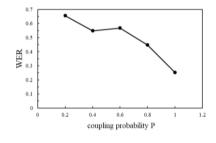


Figure 2. WER when P is varied.

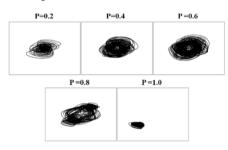


Figure 3. Attractor when P is varied.

B. When the connection strength K is varied

The attractors of the oscillator as K is varied are shown in Figs. 4 and 5, one attractor out of 100 circuits is placed as a representative.

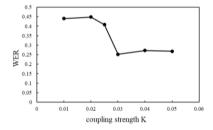


Figure 4. WER when K is varied.

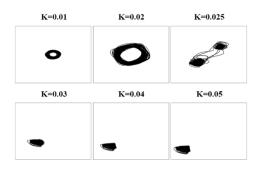


Figure 5. Attractor when *K* is varied.

Figures 2, 3 and 4, 5 show that WER is lower when the attractor is asymmetric rather than periodic. This is thought to be a good physical property for reservoirs as the response of the circuit is more diverse.

III. CONCLUSION

This study proposed and evaluated the use of a reservoir computing (RC) model based on Bonhoeffer-van der Pol (BVP) oscillators for speech recognition tasks. The study utilized the inherent chaotic dynamics of BVP oscillators to generate complex, high-dimensional internal states within the reservoir, aiming to improve prediction performance. The results indicated that the oscillators' attractor states significantly influence the speech recognition accuracy. Specifically, it was found that asymmetric attractors resulted in lower Word Error Rates (WER) as compared to periodic ones. This outcome suggests that asymmetric attractors lead to greater diversity in the circuit response, enhancing the RC's performance in processing and predicting complex, non-linear data such as speech signals. This research offers promising insights into the design of more efficient and powerful RC models. Investigating other types of oscillators and their attractor states might also be beneficial. Additionally, the impacts of varying other parameters could be examined more closely. This could lead to a more nuanced understanding of the dynamics of RCs, potentially informing the design of more effective and energy-efficient RC models for complex tasks like speech recognition and beyond.

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