

Waveform Classification by Two-Layer Reservoir Computing with van der Pol Oscillators

Yasufumi Kajino, Yoko Uwate, and Yoshifumi Nishio
Dept. of Science and Technology for Innovation, Tokushima University, Japan
Email : {kajino, uwate, nishio}@ee.tokushima-u.ac.jp

Abstract— In this research, one van der Pol oscillator is considered as one node, and the oscillators are interconnected using resistors to form a reservoir layer. A networked reservoir computing model which has two layers is proposed (two-layer reservoir). A waveform classification is performed, and the accuracy is compared with a single-layer reservoir. The results show that changing the nature of the oscillator for each layer improves the classification accuracy. This result suggests that using the two-layer reservoir increases design flexibility and improves accuracy.

Keywords; coupled oscillators, reservoir computing, two layers

I. INTRODUCTION

A Deep learning is a machine learning technique based on artificial neural networks. It has excellent performance in image and speech recognition and natural language processing [1]–[3]. However, it requires a lot of calculation time and computational resources to train large models, making it difficult to predict learning time. Therefore, machine learning models with low computational complexity and high performance are important. A reservoir computing is a highly accurate method that requires less energy and computation than traditional AI models. Unlike traditional neural networks, a reservoir computing requires only operations primarily in the readout layer. It also has its own unique dynamics, which is a nonlinear projection of the input onto a higher dimensional space.

This study focuses on a network reservoir computing, which uses oscillators as computational elements. Coupled oscillator models are the basis for modeling and analyzing rhythmic behavior in neuroscience and engineering [4], [5]. van der Pol oscillators are particularly simple and versatile coupled systems. In our study, increasing the number of reservoir layer to two improves the efficiency and accuracy of reservoir computing systems. Our research contributes to the development of energy-efficient, high-performance systems suitable for resource-limited environments.

II. PROPOSED METHOD

A. Proposed reservoir model

In this study, a two-layer reservoir using interconnected oscillators is proposed. The oscillators are coupled alternately through resistors. Fig. 1 shows an overview of the structure of the proposed two-layer reservoir computing model.

The circuit equation is shown below. N is the number of oscillators.

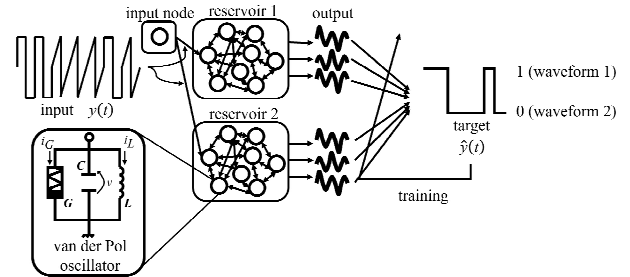


Figure 1. Proposed reservoir computing model (two-layer reservoir).

$$\begin{cases} C \frac{dv_n}{dt} = -i_L - i_G - \sum_{n,k=1}^N \frac{1}{R_{nk}} (v_k - v_n) \\ L \frac{di_n}{dt} = v_n \end{cases} \quad (1)$$

A van der Pol oscillator includes nonlinear resistors exhibiting third-order characteristics. The current-voltage characteristic of the nonlinear resistor is shown below.

$$\begin{aligned} i_g &= -g_1 v + g_3 v^3 \\ g_1, g_3 &> 0 \end{aligned} \quad (2)$$

The circuit equation is normalized using the normalization parameters. The normalization parameters and the normalization equations are shown in (3) and (4).

$$\begin{cases} v - \frac{g_1 C}{\sqrt{g_3}} x, i - \frac{g_1 C}{\sqrt{g_3} L} y, t - \sqrt{LC} \tau \\ v - g_1 \sqrt{\frac{L}{C}} \gamma - \frac{1}{R} \sqrt{\frac{L}{C}} \end{cases} \quad (3)$$

$$\begin{cases} \frac{dx_n}{d\tau} = \gamma x_n (1 - x_n^2) - y_n - \sum_{n,k=1}^N K_{nk} (x_k - x_n) \\ \frac{dy_n}{d\tau} = x_n \end{cases} \quad (4)$$

K is the coupling strength and represented by (5).

$$K_{nk} = E_{nk} \gamma_{nk} \quad (5)$$

Here, E represents the adjacency matrix of the network. It indicates whether the k th oscillator is coupled to the n th oscillator. If $E = 1$, it means they are connected, $E = 0$ indicates that they are not coupled.

B. Simulation method

For the input signal waveform, a data set of 20,000 mixed waveform of square and sawtooth wave with amplitudes ranging from -1 to 1 was used. Each data point was input at 1τ intervals according to the Runge-Kutta method. The first 10,000 data sets were used for training and remaining 10,000 data sets were used for test. Each period of the square and sawtooth waves is generated from 80 data sets, and each waveform period is repeated a minimum of two times and a maximum of four times, and then mixed randomly. The Runge-Kutta method was used to simulate the oscillators by solving the normalized equations of the van der Pol oscillator. A moving average of the oscillator voltage and a moving average of the current in the reservoir layer were taken. These were the outputs of the reservoir layer. The target function is time series of one-hot vectors in which the sawtooth wave part is 0 and the square wave part is 1 in the input waveform. Ridge regression is performed using the data of reservoir layer output and the target function.

The evaluation method will be explained. First, the output of the model is binarized by setting the threshold to 0.5. Next, in one period of the input waveform, the most frequently occurring labels are arranged as representative values to obtain a binary label sequence. Finally, the percentage of agreement between the binary label sequence obtained earlier and the target is evaluated using the accuracy rate (ACC). Compare the accuracy rate when the reservoir layer is a single-layer and when the reservoir layer is a two-layer.

III. SIMULATION RESULTS

When the reservoir layer is a single-layer, the simulation was performed in a fully coupled state with 100 nodes and a coupling strength of 0.05. When the reservoir layer is a two-layer, the simulation was performed in a fully coupled state with 50 nodes in each layer and a coupling strength of 0.05 in each layer. In this simulation, the parameter ε which represents the nonlinearity of the van der Pol oscillator and p which represents the coupling probability of oscillators are changed, and the results is compared. Tab. I shows the results of ACC. The accuracy is the average over 10 trials.

TABLE I. RESULTS OF THE SIMULATION

Reservoir type	single-layer				two-layer	
					reservoir1	reservoir2
ε	0.1	0.1	0.5	0.5	0.1	0.5
p	1	0.01	1	0.01	0.1	0.01
ACC	0.975	0.947	0.970	0.883	0.978	

In the two-layer reservoir, when ε and p changed for each layer, the ACC is higher than when the single-layer reservoir has the highest ACC.

Figure. 2 shows the input waveform and teacher waveform ($\tau = 0 \sim 800$). Fig. 3 shows the output of the two-layer reservoir model. The blue line is the output of the training phase, and the red line is the output of the validation phase. The green line shows the teacher waveform.

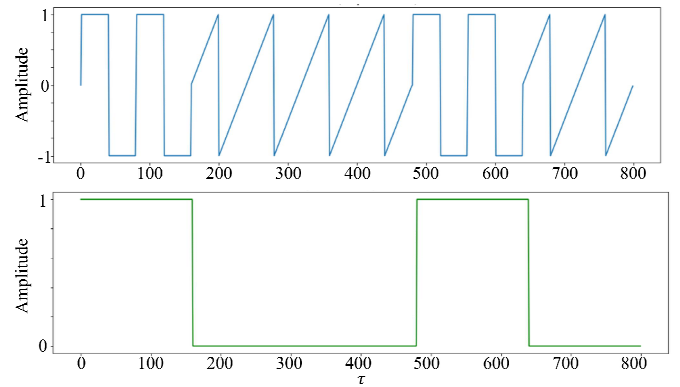


Figure 2. input waveform (top) and teacher waveform(bottom).

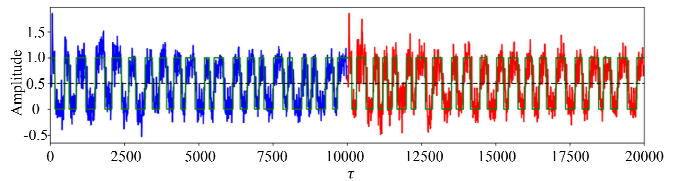


Figure 3. Output of proposed reservoir model.

From Fig. 3, it can be confirmed that the output of the model follows the target function.

IV. CONCLUSION

In this study, a two-layer reservoir computing model using a van der Pol oscillator was proposed and evaluated its classification accuracy. Increasing the number of reservoir layers to two allows for even more flexible reservoir layer design. By changing the values of ε and p for each layer, the ACC was improved compared to the single-layer reservoir. It can be inferred that by increasing the output patterns of the reservoir layer and effectively increasing the dimensionality, it has become possible to map to even higher dimensional spaces.

REFERENCES

- [1] K. Radha, M. Bansal, "Speech and speaker recognition using raw waveform modeling for adult and children's speech: A comprehensive review," *Engineering Applications of Artificial Intelligence*, vol.131, 107661, 2024.
- [2] B. A. Kumar, N. K. Misra, "Masked face age gender identification using CAFFE-modified MobileNetV2 on photo and real-time video images by transfer learning and deep learning techniques," *Expert Systems With Applications*, vol.426, 123179, 2024.
- [3] J. S. Chou, P. L. Chong, C. Y. Liu, "Deep learning-based chatbot by natural language processing for supportive risk management in river dredging projects," *Engineering Applications of Artificial Intelligence*, vol.131, 107744, 2024.
- [4] L. L. Bonilla, C. J. Vicente, R. Spigler, "Time-periodic phases in populations of nonlinearly coupled oscillators with bimodal frequency distributions," *Physica D*, vol.113, pp79-97, 1998.
- [5] T. Yamane, Y. Katayama, R. Nakane, G. Tanaka, D. Nakano, "Wave-based reservoir computing by synchronization of coupled oscillators," *International Conference on Neural Information Processing*, vol.9491, pp.198-205, 2015.