Analysis of Reservoir Computing Using Oscillator Circuit

Kazuki Yasufuku, Yoko Uwate and Yoshifumi Nishio

†Dept. of Electrical and Electronic Engineering, Tokushima University
2-1 Minami-Josanjima, Tokushima, Japan
Email: {yasufuku, uwate, nishio}@ ee.tokushima-u.ac.jp

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***Abstract*— This paper presents an investigation into networked reservoir computing using interconnected oscillators. Specifically, the Bonhoeffer-van der Pol (BVP) oscillator is used as the basis for the reservoir, and its performance is evaluated in speech recognition tasks. The results reveal that the BVP reservoir exhibits enhanced fidelity to input waveforms and improved accuracy in speech recognition compared to the van der Pol (VDP) reservoir. Furthermore, the impact of reservoir configuration on accuracy is examined by varying the number of oscillators, the connection probability, and the coupling strength. The results indicate that accuracy improves as the parameters are increased. These results emphasize the importance of carefully selecting and setting the dynamics of the physical system and parameters of the reservoir to achieve optimal performance.**

***Keywords*— oscillator, reservoir computing, synchronization**

I. INTRODUCTION

Recent advancements in AI (Artificial Intelligence), particularly deep learning, recurrent networks, and large-scale language modeling, have led to profound breakthroughs across various applications such as speech recognition, image classification, and natural language processing [1]-[5]. However, these conventional AI models face challenges due to parameter tuning intricacies, learning costs, and electricity consumption [6]. These demands pose limitations on deploying AI systems in environments constrained by resources or on edge devices with restricted power and computational capacities.

Surprisingly, nature offers impressive examples of efficient computational systems. For instance, insects, despite their small brains, demonstrate the ability to navigate intricate environments, process sensory information, and display intelligent behaviors using limited computational resources [7]. This raises the question of whether there are alternative computational paradigms that can achieve high performance while being energy-efficient and resource-friendly.

Reservoir computing (RC) is one such paradigm. It is a method attracting significant attention in the AI domain, promising efficient and precise computations while reducing traditional AI models' energy and computational needs. RC has its origins in echo-state networks, a special model of recurrent neural networks [8], [9] and liquid-state machines based on neuroscientific findings [10]. Unlike conventional neural networks, which require extensive parameter tuning, it mainly requires only learning of the readout layer due to its inherent dynamics of nonlinear projection of inputs into a high-dimensional space. This unique feature echo-state simplifies learning while still delivering effective performance. More interestingly, RC is not limited to neural networks, but has been implemented using a variety of physical systems, including water systems, optoelectronic devices, and photonic systems, and has attracted much attention in recent years [11]-[13]. While RC has exhibited promising results, our understanding of its potential and the optimal architectures for maximizing computational accuracy still have gaps. Future research should focus on exploring innovative reservoir designs, enhancing training algorithms, and investigating the fusion of reservoir computing with other AI techniques.

This study delves into networked reservoir computing using oscillators as computational elements. Coupled oscillator models are not only engineering but also fundamental in modeling and analyzing the synchronization behavior of systems with rhythmic behavior, including systems in ecology, and neuroscience [14]-[17]. Among these, the synchronization phenomena of van der Pol oscillators, simple yet versatile coupled systems of nonlinear oscillators, have garnered considerable attention. This system can approximate various natural phenomena, enhancing its utility. FitzHugh and Nagumo in 1962 derived the BVP model as a simplified version of the Hodgkin-Huxley equation. The BVP equation, considered a reasonable extension of the VDP equation, can be realized in a circuit with simple passive elements and a single nonlinear conductor. Its simplicity often positions it as a fundamental oscillation unit to explain the behavior of the nervous system and circadian rhythms [18]-[20].

Interestingly, compared to VDP, BVP exhibit a wide array of nonlinear phenomena, including limit cycles, equilibrium bifurcations, and hard oscillations. Therefore, we leverage the unique dynamics of oscillators for computational tasks and employ their synchronization properties for information processing. This study contrasts two different circuit configurations, VDP and BVP, as reservoirs to verify their performance in achieving superior calculation accuracy.

II. RESERVOIR COMPUTING WITH OSCILLATOR CIRCUIT

In this study, we present a novel approach for reservoir computing utilizing a networked configuration of interconnected oscillators. The proposed methodology harnesses the unique dynamics of oscillators to enable efficient and accurate computations. Fig. 1 provides an overview of the structure of the networked reservoir computing system.

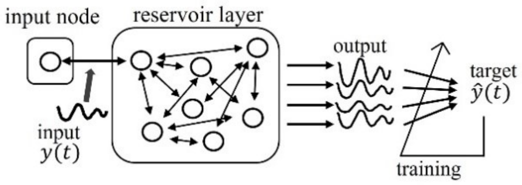

Fig.1. Configuration of the proposed oscillator reservoir.

To enable effective information processing, input signals are introduced into the oscillator network and propagated through the interconnections between the oscillators. The resulting output signals are obtained from multiple output terminals positioned within the network. Input signals are input by adjusting the strength of the connection between the input node and the reservoir layer. Data input to the oscillator network is mapped to a high-dimensional feature space to facilitate pattern recognition in readout. The oscillator network used in this study exhibits key properties that make it well-suited for reservoir computing. Firstly, it possesses nonlinear characteristics, enabling the network to capture and process complex input patterns. Additionally, the network operates in a high-dimensional space, enhancing its computational capacity and enabling the representation of intricate relationships within the data. Lastly, the network demonstrates short-term memory properties, enabling it to retain and utilize past information to inform current computations. It is important to note that the coupling strength within the reservoir layer is fixed throughout the computations. We also conducted a comparative analysis to evaluate the impact of coupling strength on the network's performance. Details of this analysis will be discussed later in the paper. The output signals of the network are obtained by measuring the voltage differences between each oscillator and a reference oscillator.

Two different circuit configurations were utilized to assess the effectiveness of the proposed networked reservoir computing approach. The circuit models used in this study are shown below in Fig. 2.

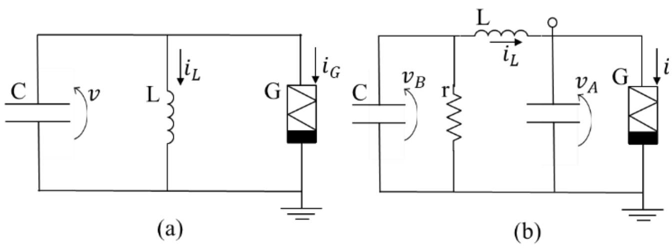

Fig.2. Circuit model (a)VDP. (b)BVP.

First, the circuit equation for the VDP circuit is shown in Equation (1).

$$\begin{cases} C\dfrac{dv_n}{dt} = i_L - i_G - \displaystyle\sum_{k=1}^{N} \frac{1}{R}(v_k - v_n) \\ L\dfrac{di_n}{dt} = v_n \end{cases} \tag{1}$$

R represents the resistance value connecting the circuits.

Normalize the circuit equations using the normalization parameters. The normalization parameters and the normalized circuit equations are shown in Eqs. (2), (3).

$$\begin{cases} v = \sqrt{\dfrac{g_1}{g_3}}x \ , \quad i = \sqrt{\dfrac{g_1 C}{g_3 L}}y \ , \ t = \sqrt{LC}\tau \\ \varepsilon = g_1\sqrt{\dfrac{L}{C}} \ , \ \ \gamma = \dfrac{1}{R}\sqrt{\dfrac{L}{C}} \end{cases} \tag{2}$$

$$\begin{cases} \dfrac{dx_n}{d\tau} = \varepsilon x_n(1 - {x_n}^2) - y_n - \displaystyle\sum_{k=1}^{N} K(x_k - x_n) \\ \dfrac{dy_n}{d\tau} = x_n \end{cases} \tag{3}$$

In the computer simulations, we assume that the voltage and current characteristics of the nonlinear resistor in each oscillator are given as follows.

$$i_g = -g_1 v + g_3 v^3 \tag{4}$$
$$(g_1, \ g_3 > 0).$$

The circuit equation for the BVP circuit is shown in Eq. (5).

$$\begin{cases} C\dfrac{dv_{A_n}}{dt} = -i_L - i_G - \displaystyle\sum_{k=1}^{N} \frac{1}{R}(v_{A_n} - v_{A_k}) \\ C\dfrac{dv_{B_n}}{dt} = i_L - \dfrac{1}{r}v_B \\ C\dfrac{d_{i_{L_n}}}{dt} = v_A - v_B \end{cases} \tag{5}$$

R represents the resistance value connecting the circuits.

Normalize the circuit equations using the normalization parameters as in VDP. The normalization parameters and the normalized circuit equations are shown in Eqs. (6), (7).

$$\begin{cases} v_A = \sqrt{\dfrac{g_1}{g_3}}x \ , \quad v_B = \sqrt{\dfrac{g_1}{g_3}}y \ , \quad i_L = \sqrt{\dfrac{g_1 C}{g_3 L}}z \ , \\ \varepsilon = g_1\sqrt{\dfrac{L}{C}} \ , \ \ K = \dfrac{1}{R}\sqrt{\dfrac{L}{C}} \ , \quad \sigma = \dfrac{1}{r}\sqrt{\dfrac{L}{C}} \ , \ t = \sqrt{LC}\tau \end{cases} \tag{6}$$

$$\begin{cases} \dfrac{dx_n}{d\tau} = \varepsilon x_n(1 - {x_n}^2) - z_n + \displaystyle\sum_{k=1}^{N} K(x_k - x_n) \\ \dfrac{dy_n}{d\tau} = z_n - \sigma y_n \\ \dfrac{dz_n}{d\tau} = x_n - y_n \end{cases} \tag{7}$$

N is the number of oscillators to be connected to. Also, K is coupling strength.

The tasks conducted in this study encompassed speech recognition. Detailed procedures for these tasks will be presented in the Results section.

Simulation Method:

For simulation purposes, the Runge-Kutta method was used, enabling accurate and efficient computation of the system dynamics.

Learning Method:

Ridge regression was used for the learning process. The aim was to determine the optimal output weights to achieve desired performance. The output weights were determined using the equation:

$$\hat{W}_{out} = DX^T(XX^T + \beta I)^{-1} \quad (8)$$

Here, $\hat{W}_{out}$ refers to the output weights, D represents the teacher signal matrix, X is the output matrix of the reservoir, and $X^{\dagger} = X^T(XX^T)^{-1}$ denotes the pseudo-inverse of X. The parameter $\beta > 0$ is the regularization parameter, and I denotes the unit matrix. By including β in the linear regression, overlearning is prevented.

For the evaluation of the speech recognition task, the Word Error Rate (WER) metric was used. WER is a measure that quantifies the percentage of misclassifications in the recognized speech output compared to the ground truth. A lower WER indicates a higher level of accuracy in the speech recognition task.

III. Simulation Results

A. Speech Recognition Task

In the subsequent step, a speech recognition task was conducted. An overview diagram is shown in Fig. 3.

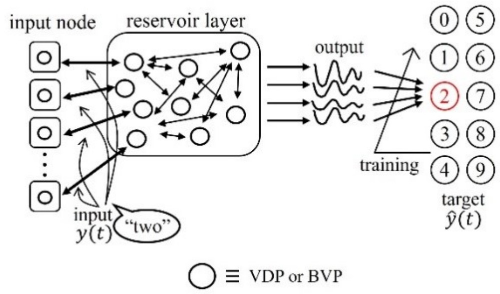

Fig.3. Speech Recognition Overview.

For the input dataset, a total of 500 data samples were utilized, consisting of recordings from five different speakers enunciating each of the numbers from zero to nine, repeated 10 times. The input data used in this study is adapted from Lyon's auditory model. After removing the silent parts, the speech signal is transformed into a cochleargram representation. This conversion results in time series data with dimensions corresponding to different frequency channels. In our case, the cochleargram data is characterized by 77 dimensions, reflecting the spectral characteristics of the speech signal. The dataset was divided such that half of the data, encompassing five pronunciations of each number spoken by each of the five speakers, was allocated for training purposes, while the remaining data was reserved for testing [21]. Similar to the input waveform generation task, the initial transient response of 10,000τ was disregarded in this task as well. Since the available data was limited, no data was fed into the reservoir during the initial 10,000τ period, and the training and test data were introduced from 10,001τ onwards. The training process involved observing the output of the VDP and BVP reservoirs, as shown in Fig. 4, respectively.

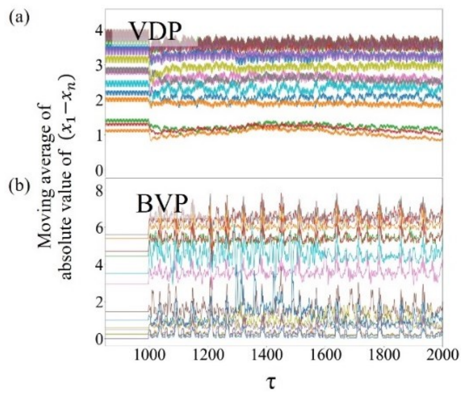

Fig.4. Output during training of the reservoir. (a) VDP. (b) BVP. The reservoir consists of N = 100, with a connection probability of 1.0 (indicating perfect coupling) in the reservoir layer. As parameter values, ε=0.1 and K=0.03 were used for the reservoir layer. Only 15 responses are listed for visibility.

The ridge regularization parameter β was set to 1.0 for verification purposes. The outcomes of the speech recognition task are presented in Figs. 5 and 6. Also, the respective training and test errors (WER) are also shown in TABLE Ⅰ.

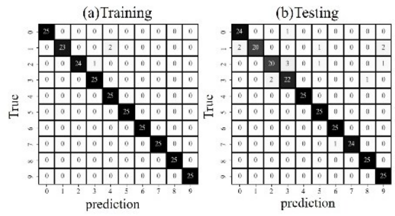

Fig. 5. Confusion Matrix for Speech Recognition using VDP Reservoir (a) Training Prediction (b) Test Prediction.

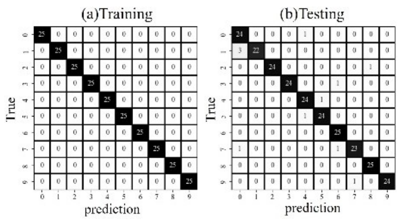

Fig. 6. Confusion Matrix for Speech Recognition using BVP Reservoir (a) Training Prediction (b) Test Prediction

TABLE I. Error Evaluation of Speech Recognition Task VDP and BVP (WER)

	without reservoir	VDP	BVD
train	0.7280	0.000	0.012
test	0.7320	0.044	0.06

Figure 4 demonstrates the input of the speech waveform at the 10000τ stage, and a comparison is made between the reservoir outputs of the VDP and BVP circuits. It is observed that the reservoir output of the VDP circuit does not fully reflect the input waveform, while the BVP circuit exhibits a better correspondence between the reservoir output and the input waveform. This difference in waveform representation is believed to have a direct impact on the accuracy of speech recognition. This has also been confirmed in reservoirs using spin torque oscillators, and it has been confirmed that microwave application provides a quick response (fast relaxation) and improves reservoir performance [22]. Furthermore, Figs. 5, 6 and TABLE Ⅰ provide clear evidence of the disparity in speech recognition results. Despite the similarity in experimental conditions, except for the differences in circuit configurations, a significant discrepancy in accuracy is observed. This indicates that the choice of the circuit has a profound influence on the overall performance and accuracy of the speech recognition task. These findings emphasize the importance of selecting the appropriate circuit architecture for specific applications, as different circuit configurations can lead to substantial variations in the accuracy and performance of cognitive tasks. Further investigation and analysis are necessary to understand the underlying factors contributing to these differences and optimize circuit designs for specific computational tasks. While the flexibility in material selection for reservoir computing holds great appeal, our results highlight the importance of meticulous material selection tailored to the specific task. This strategic selection of suitable materials in reservoir computing has the potential to significantly improve accuracy and overall performance in applications.

B. *Effect of Reservoir Configuration*

This section presents a comprehensive investigation into the accuracy of oscillator reservoirs, with a particular focus on their structural configurations. The reservoir utilized in this study adopts a network-type structure, offering distinct advantages compared to other types such as medium-based reservoirs (e.g., water [11]) or soft material reservoirs (e.g., octopus' legs [23]). Specifically, the network structure allows for more precise design control over the reservoir layer. Building upon the BVP used in the previous chapter, we subjected the reservoir to a speech recognition task.

The primary objective of this investigation was to assess how variations in the reservoir configuration impact accuracy. To achieve this, we examined the accuracy of speech recognition while manipulating key parameters such as the number of oscillators N, coupling strength K, and coupling probability P within the reservoir layer. The following section presents the results obtained from these experiments, shedding light on the relationship between reservoir configuration and accuracy.

The results obtained from the experiments reveal important insights into the relationship between reservoir configuration and accuracy. Fig. 7 (a) shows that as N increases, the accuracy of the reservoir improves. This trend is particularly evident, showing significant enhancements in accuracy up to a certain point, approximately N=125. Additionally, Fig. 8 (b) highlights the influence of connection probability on accuracy during both the learning and verification stages. It demonstrates that a higher connection probability leads to improved accuracy in the reservoir's performance. Furthermore, Fig. 7 (c) demonstrates that increasing K also contributes to enhanced accuracy, albeit to a lesser extent compared to the impact of N and P. These findings underscore the significance of reservoir configuration in achieving optimal accuracy levels for the speech recognition task.

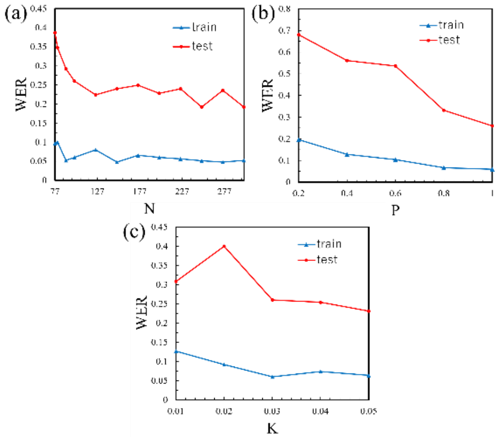

Fig. 7. Accuracy of the speech recognition task in BVP reservoirs with different configurations. We take the average of the three times WERs. (a) Variation of the number of oscillators N, (b) Variation of the coupling probability P, (c) variation of the coupling strength K.

C. *Overall Assessment of Results*

Using BVP instead of VDP improved accuracy in the task. We consider there are two reasons for this. One reason, as mentioned earlier, is that BVP exhibits a fast response and adequately reproduces the input wave during output.

Another reason is attributed to obtaining responses at the edge of chaos. BVP exhibits both periodic and chaotic solutions depending on the parameters. This condition aligns well with the desirable properties of a reservoir that performs better at the edge of chaos. The results, where accuracy improved when varying the parameters shown in Fig. 8, suggest that the circuit's response has approached closer to the edge of chaos.

IV. CONCLUSIONS

We have investigated the accuracy and performance of networked reservoirs using interconnected oscillators. The proposed approach offers advantages in terms of flexible reservoir layer design compared to other types of reservoirs. Specifically, we focused on the BVP oscillator as the physical system and conducted the task of speech recognition. Increasing the number of oscillators (N) and the coupling probability (P) led to improved accuracy in the speech recognition task. Although the effect of varying the coupling strength (K) on accuracy was less pronounced compared to N and P, it still contributed to improved performance. These findings highlight the importance of careful selection and configuration of parameters for achieving higher accuracy in reservoir computing tasks. The flexibility in designing the reservoir structure offers potential for further advancements in the field. Furthermore, the results from our study emphasize the significance of considering the structural characteristics of the reservoir when designing efficient and accurate reservoir computing systems.

Overall, our research contributes to the understanding of networked reservoirs and their applications in artificial intelligence. The insights gained from this study can inform the development of more efficient and high-performing computing systems, paving the way for advancements in cognitive computing and machine learning.

REFERENCES

[1] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, pp. 436-444, 2015.

[2] Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. Retrieved from arXiv:1810.04805.

[3] Li, Jinyu. "Recent advances in end-to-end automatic speech recognition." APSIPA Transactions on Signal and Information Processing 11.1, 2022.

[4] Wu, Zifeng, Chunhua Shen, and Anton Van Den Hengel. "Wider or deeper: Revisiting the resnet model for visual recognition." Pattern Recognition 90 pp. 119-133, 2019.

[5] Chowdhary, KR1442, and K. R. Chowdhary. "Natural language processing." Fundamentals of artificial intelligence pp.603-649, 2020.

[6] Strubell, E., Ganesh, A., & McCallum, A, Energy and Policy Considerations for Deep Learning in NLP. arXiv preprint arXiv:1906.02243, 2019.

[7] Burrows, Malcolm. "The neurobiology of an insect brain." , 1996.

[8] Jaeger, H, The "echo state" approach to analyzing and training recurrent neural networks. In Proceedings of the German Workshop on Artificial Intelligence pp. 10-19, 2001.

[9] Jaeger, H., & Haas, H, Harnessing Nonlinearity: Predicting Chaotic Systems and Saving Energy in Wireless Communication. Science, 304(5667), 78-80, 2004.

[10] Maass, W., Natschläger, T., & Markram, H, "Real-Time Computing Without Stable States: A New Framework for Neural Computation Based on Perturbations. Neural Computation" , 14(11), 2531-2560, 2002.

[11] Fernando, C., & Sojakka, S, "Pattern Recognition in a Bucket" . In W. Banzhaf, J. Ziegler, T. Christaller, P. Dittrich, & J.T. Kim (Eds.), Advances in Artificial Life. ECAL 2003 Vol. 2801. Springer, Berlin, Heidelberg, 2003.

[12] Vandoorne, K., Dambre, J., Verstraeten, D., Schrauwen, B., & Bienstman, P, "Parallel Reservoir Computing Using Optical Amplifiers" . IEEE Transactions on Neural Networks, 22(9), 1469-1481, 2011.

[13] Coulombe, J. C., York, M. C. A., & Sylvestre, J, "Computing with networks of nonlinear mechanical oscillators" . PLoS ONE, 12(6), 2017.

[14] Bonilla, L. L., Pérez Vicente, C. J., & Spigler, R, Time-periodic phases in populations of nonlinearly coupled oscillators with bimodal frequency distributions. Physica D: Nonlinear Phenomena, 113(1), 79-97, 1998.

[15] Hoppensteadt, F. C., & Izhikevich, E. M, Weakly Connected Neural Networks (Vol. 126). Springer Science & Business Media, 2012.

[16] Debbouche, N., Ouannas, A., Momani, S., et al, Fractional-order biological system: chaos, multistability and coexisting attractors. The European Physical Journal Special Topics, 231, 1061-1070, 2022.

[17] Ahn, S., & Rubchinsky, L. L, Temporal patterns of dispersal-induced synchronization in population dynamics. Journal of Theoretical Biology, 490, 110159, 2020.

[18] Nishiuchi, Y., Ueta, T., Kawakami, H., Classification of Bifurcations and Oscillations in Coupled BVP Oscillators. Journal of Signal Processing, 18(1), 39-48, 2014.

[19] Ueta, K., Uwate, Y., & Nishio, Y, Analysis of Frustration by Coupled Ring and Star of BVP-VDP Oscillator. IEEE Workshop on Nonlinear Circuit Networks (pp.72-75), 2017.

[20] Ueta, T., Miyazaki, H., Kousaka, T., & Kawakami, H, Bifurcation and chaos in coupled BVP oscillators. International Journal of Bifurcation and Chaos, 14(04), 1305-1324, 2004.

[21] Tanaka, G., Nakane, R., & Hirose, A., Reservoir Computing. Morikita shuppan, 2022.

[22] Tsunegi, S., Taniguchi, T., Nakajima, K., Miwa, S., Yakushiji, K., Fukushima, A., Yuasa, S., & Kubota, H., Physical reservoir computing based on spin torque oscillator with forced synchronization. Applied Physics Letters, 114(16), 164101, 2019.

[23] Nakajima, K., Hauser, H., Li, T., et al, Information processing via physical soft body. Scientific Reports, 5, 10487, 2015.