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A Physical Reservoir Computing Processor for ECG-to-PCG Signals Prediction

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Abstract—An electrocardiogram (ECG) is a medical test that records the electrical activity of the heart over a period of time. This non-invasive and painless test makes ECG an essential tool in cardiology for diagnosing and monitoring heart health. Phonocardiogram (PCG) are typically used as an adjunct to the expertise of healthcare professionals rather than as a standalone diagnostic tool. By applying ECG signals to predict the corresponding PCG signals, no additional test for PCG is needed. These predictions can assist doctors in making informed decisions about patient care and treatment plans by merely collecting ECG signals. Physical reservoir computing (RC), as a bio-inspired algorithm, has received growing research interest. Under the term neuromorphic, physical RC processes the raw signals in the analogue domain with in-memory computing, thus reducing massive power consumption. At the same time, RC is a special type of Recurrent Neural Network (RNN) that is suitable for time-dependent signal processing. The ECG/PCG dataset we used here was experimentally collected by 10 people. We applied a recently proposed physical RC architecture called Rotating Neuron Reservoir and achieved an average NRMSE of 0.3690 for prediction, aiming to propose and construct a neuromorphic processing core for the ECG-to-PCG prediction task.

Index Terms—Physical Reservoir Computing, neuromorphic processor, Electrocardiogram, Phonocardiogram

I. INTRODUCTION

The electrocardiogram (ECG) is a skin-surface measurement of the potential changes that result from the electrical polarisation changes of the heart. The magnitude of the signal recorded at a cutaneous level depends on the mass of the activated heart muscle [1]. The recorded waves, therefore, relate to the activation state of the heart. In particular, a normal ECG recording usually contains three distinct features - the QRS complex, and the P and T waves - that arise from different activation states. The P wave indicates the onset of atrial contraction, the QRS complex arises from the activation of the ventricles, and the T wave is produced by the electrical repolarisation of the ventricles.

The phonocardiogram (PCG), on the other hand, is a recording of the sound waves produced by the structural and

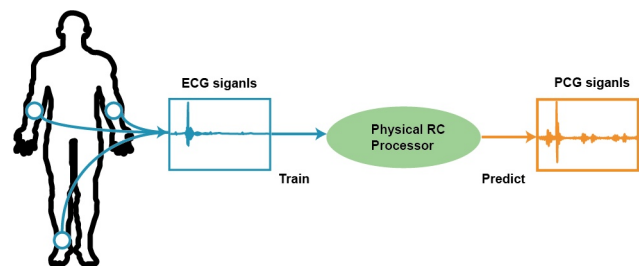


Fig. 1. The conceptual figure of ECG-to-PCG prediction using a physical reservoir processor

hemodynamic changes that consist of a complex of the heart muscle, valves, and blood flow [2]. As the heart repeats its contraction-relaxation (systole-diastole) cycle, pressure waves emanate to the chest wall and this is then set into vibration [3]. Therefore, a PCG recording is mainly produced by those cardio-hemic effects that are energetic enough to travel to the skin surface without dissipating. Normally, the first (S1) and the second (S2) heart sounds are the two most easily recorded. Unsurprisingly, these are related to the most energetic heart muscle movements - the onset of the systole and diastole, respectively.

PCG and ECG are both diagnostic tools used in cardiology, but they provide different types of information about the heart and its functioning. Since ECG provides information about the electrical activity of the heart, it can diagnose arrhythmias [4], ischemia (inadequate blood flow to the heart), and conduction system abnormalities [5]. It's particularly useful for identifying irregular heart rhythms and ischemic events. PCG provides information about the mechanical aspects of the heart's functioning. It is often the first screening for cardiac problems [6] and can help identify abnormalities in heart sounds, such as murmurs or extra heart sounds, which can be indicative of valvular problems [7], chamber abnormalities, or

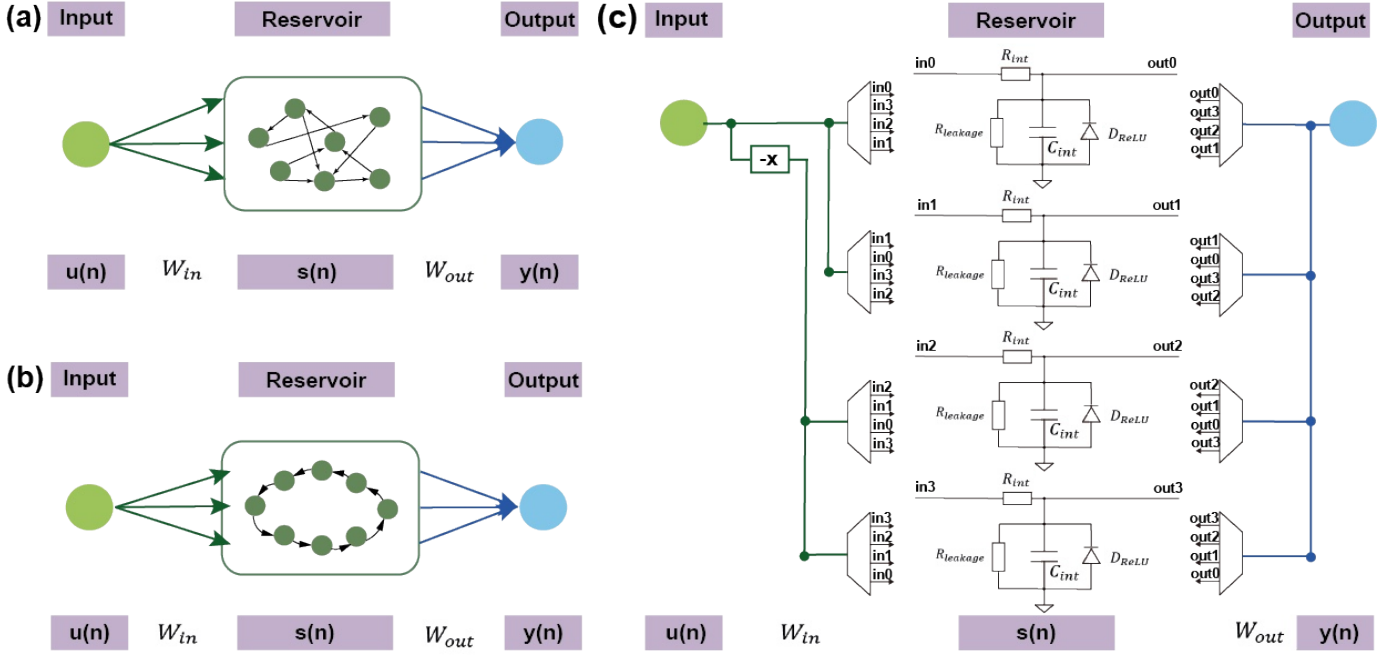


Fig. 2. The description for reservoir architecture. It contains three different topologies. The first two are software-based structures. The third one is a physical RC architecture implemented by an electronic circuit. (a) An example of a classical reservoir. The connections among the neurons are random. (b) An example of a simple cyclic reservoir (SCR). The topology of the connections among the neurons is simplified and reflects a ring structure. (c) An example of a 4-neurons electronic rotating neuron reservoir. In this topology, the connections of the input-to-reservoir layer and reservoir-to-output layer are shifted at each time step, controlled by analogue multiplexers.

other structural heart issues.

From a clinical standpoint, obtaining ECG measurements is more convenient for healthcare professionals because the traditional medical stethoscope cannot deliver PCG data in a digital format. Therefore, the ability to predict PCG information from recorded ECG signals is highly valuable, particularly considering that these two signals offer distinct insights into the heart's operation. Machine learning algorithms can be applied to predict the PCG based on collected ECG signals.

Although the machine learning algorithms today especially the deep neural networks (DNNs) can handle various complex tasks, ranging from image processing to natural language processing, the power consumed for training the networks is massive. The end of Moore's law and the bottleneck of Von Neumann architecture are the two leading elements that hinder the further development of neural networks. Neuromorphic Computing, inspired by neurobiology, is expected to solve the challenges by mimicking how the human brain functions with analog and in-memory computing, aiming at power-efficient computation [8], [9]. Reservoir Computing (RC), under the term neuromorphic, is a special type of recurrent neural network (RNN) that can efficiently handle temporal signal processing [10]. The concept comes from mapping the input sequential data to a high-dimensional dynamical state space and performing a regression at the output layer. The physical realization of RC has become a heated topic owing to its simplified architectures to realize efficient machine learning tasks [11], [12]. Rotating Neuron Reservoir (RNR) is a recently proposed physical RC paradigm that evolved

from a Simple Cyclic Reservoir (SCR) topology [13]. In this work, we applied RNR to perform the ECG-to-PCG prediction task for 10 subjects. The average normalized root mean square error (NRMES) for the prediction of the 10 subjects is 0.3690. In our work, both the ECG dataset and PCG dataset were experimentally collected.

This paper is organized as follows: Section II introduces the description of the RNR network and Section III introduces the methodology of the ECG/PCG prediction and the performance evaluation. The conclusion will be presented in Section IV.

II. DESCRIPTION OF NETWORK

Reservoir Computing (RC) is a special type of recurrent neural network (RNN), where the current network responses are dependent not only on the current inputs but also on the historical inputs. The network can be sensitive to small changes in the time series, which endows it with an excellent ability to process time-dependent sequences. Some also think of RC as an analogy to support vector machine (SVM) and consider the reservoir as a temporal kernel [14]. Both techniques apply a trick to map the input to a high-dimensional feature space to allow for linear separation. The difference is that RC has a recurrent nature owing to its structure which will be discussed in detail in the following section.

A. Reservoir computing topologies

A reservoir network contains three layers: an input layer, a reservoir layer, and an output layer. The injected input $u(n)$ is multiplied by an input weight matrix W_{in} , then this product

goes to the reservoir layer. The reservoir generates transient responses $s(n)$ for the input injection. The process can be represented by the state update equation as shown below.

$$s(n) = f(W_{in}u(n) + Ws(n-1)) \quad (1)$$

W is the reservoir coefficients matrix, and f is the nonlinear activation function, it could be sigmoid, tanh or ReLU. The responses, also known as the states of the reservoir, are collected for training. In our work, we choose to use a simple linear regression called ridge regression for the prediction task. The output weight matrix W_{out} is calculated by the equation shown below:

$$W_{out} = Y^{target} S^T (SS^T + \beta I)^{-1} \quad (2)$$

Finally, at the output layer, the prediction at time n is achieved by the multiplication of the output weight matrix W_{out} and the state $s(n)$ generated for the input at time n .

$$y^{pred}(n) = W_{out}s(n) \quad (3)$$

In a classical reservoir topology, the connections among the neurons are randomly connected, leading it hard to implement by hardware. Simple cyclic reservoir (SCR) topology was proposed to reduce the complexity of the reservoir without degradation to performance [15]. The connections among the neurons are fixed. The major difference between the two topologies lies mathematically in the reservoir coefficients matrix W . The coefficients reflect the connections among neurons. In a classical reservoir, the coefficients are randomly generated numbers from the uniform distribution $[-1,1]$. Therefore, the connections among neurons are random as shown in Figure 2(a). Whilst in SCR, the coefficients weight matrix can be replaced by the following structure:

$$\begin{bmatrix} 0 & 0 & \dots & 0 & 0 & 1 \\ 1 & 0 & \ddots & 0 & 0 & 0 \\ 0 & 1 & \ddots & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & \ddots & 1 & 0 & 0 \\ 0 & 0 & \ddots & 0 & 1 & 0 \end{bmatrix} \quad (4)$$

Therefore, the connections among neurons are fixed and reflect a ring structure as illustrated in Figure 2(b). The fixed structure allows it to be implemented by hardware components. Correspondingly, the hardware implementation of the SCR topology, Rotating Neuron Reservoir is shown in Figure 2(c), they have been proven to be mathematically equivalent in [13]. The weights in the input matrix are randomly chosen -1 and 1, and are realized by a randomly chosen positive or negative signal source. Analogue multiplexers are used to shift the connections between input-to-reservoir and reservoir-to-output and delivered the masked input at each time step. The dynamic neurons are modelled by Leaky-Integrate circuits,

with a diode to act as the ReLU activation function. The dynamic responses of each neuron at the whole training phase are collected for training by linear regression. Predictions are made similarly by simply multiplying the collected response and the output weight matrix as demonstrated in equation (2) and (3).

Physical RC has been widely applied in temporal signal processing, ranging from spoken digits recognition to biomedical signal classification like ECG and EMG [16]–[18]. In our work, we applied the RNR topology for the ECG to PCG prediction. The methodology can results will be presented in the following section.

III. METHODOLOGY AND RESULTS

A. Dataset collection

ECG and PCG data were simultaneously gathered in an office setting at the University of Glasgow, as depicted in Figure 3. The ECG data was acquired using the 'Attys' device, a creation of the University of Glasgow. This ECG device is linked with three identical electrodes for recording electrical signals from the left and right elbow, as well as the inner side of the ankle. Subsequently, the collected data is transmitted to a laptop via a Bluetooth connection. As for the PCG data, it was obtained using an optical stethoscope, positioned approximately 1 meter in front of the test subject. This optical stethoscope comprises a 532nm laser diode and a high-speed industrial camera. The laser diode emits a beam towards the subject's neck area, while the camera captures the reflected speckle pattern from the neck. Due to that the laser speckle movement is highly correlated with the blood flow movement in the neck blood vessel, a Farneback optical flow algorithm [19], [20] is then utilized to transform the laser speckle vibrations into the audio PCG signal.

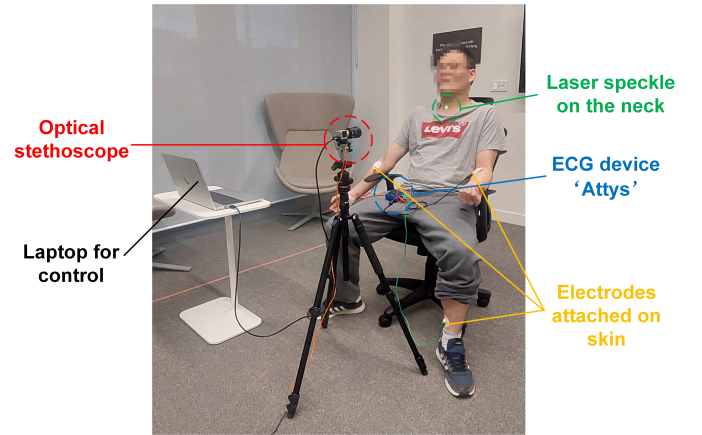


Fig. 3. Experimental setup of ECG and PCG measurement.

B. Data preprocessing

The ECG and PCG signals were downsampled from 500 Hz and 1470 Hz to 150 Hz respectively owing to the limitation of memory capacity in RC [21]. The length of the signals was shortened to be remembered by the network more easily. After

TABLE I
EXPERIMENTAL RESULTS FOR EACH SUBJECT

Subject No.	1	2	3	4	5	6	7	8	9	10	Average
NRMSE	0.6927	0.6006	0.4704	0.1676	0.1604	0.2120	0.2023	0.5719	0.0647	0.5478	0.3690

the downsampling, the signals are injected into the network directly without any segmentation and feature extraction, which is one of the merits of RC.

C. Results of prediction

Included in the dataset, there are 9 repetitions for each of the 10 subjects. 6 of them were used for training and the remaining were used for testing. It was simulated in MATLAB with an electronic circuit built by Simulink. In the simulation, there are 400 neurons in total and other parameters are kept in accordance to the empirical value as proposed in [13]. The prediction error was quantified by NRMSE. An example of the prediction results for subject 8 is shown in Figure 3. The NRMSE for subject 5 is 0.1604 and the network is able to predict the reconstructed PCG from the input ECG data in an excellent way.

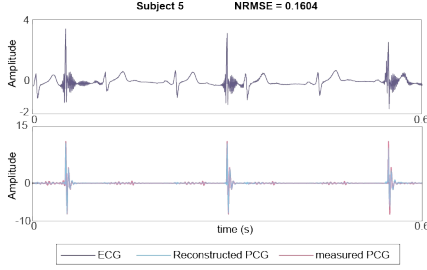


Fig. 4. An example of prediction results. (Top) The input ECG for a time duration of 6s. (Bottom) The measured PCG and the reconstructed PCG data

A histogram illustrating the distribution of NRMSE for each subject is shown in Fig. 4. The NRMSE for half of the subjects lies in the interval $[0, 0.3]$ and the other half distributes in $[0.4, 0.7]$. This could be a result of the collection of the dataset. The difference among the NRMSE for different subjects occurs because of the recording of the dataset was not recorded under the exact same conditions. In the future, the impact of varying data recording conditions for different subjects can be studied to eliminate the inter-subject variability. Overall, the network can predict spikes of PCG signals accurately for each subject. The NRMSE for each subject varies, the highest NRMSE is 0.6927 for subject 1, and the lowest NRMSE is 0.0647 for subject 9, and their average is 0.3690. The experimental results for each subject are listed in Table I.

IV. CONCLUSION

This paper proposes a physical reservoir computing-based method to realize an ECG-to-PCG prediction task. The physical RC architecture used here is an electronic RNR. The performance of the prediction was evaluated by NRMSE and

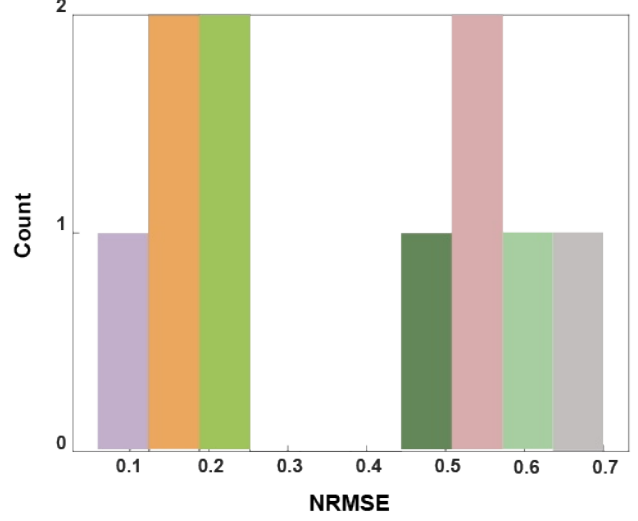


Fig. 5. Histogram for the distribution of NRMSE for each subject.

the lowest NRMSE, highest NRMSE and average NRMSE for a 10-subjects dataset is 0.0647, 0.6927 and 0.3690 respectively. This result is satisfactory and reflects the ability of RNR in prediction tasks. This work exhibits the feasibility of a fully hardware-based RC processor for ECG-to-PCG prediction which can be potentially applied in the medical area in the future work.

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REFERENCES

- [1] N. Herring, and D. J. Paterson, *Levick's introduction to cardiovascular physiology*, CRC Press, 2018.
- [2] S. Dornbush, and A. E. Turnquest, *Physiology, Heart Sounds*, Jan 2023. Available at: <https://www.ncbi.nlm.nih.gov/books/NBK541010/> (Accessed: 13 October 2023)
- [3] A. Leatham, "Phonocardiography," *Br. Med. Bull.*, vol. 8 no. 4, pp.333–342, 1952.
- [4] E. Hoefman, P. J. Bindels, H. C. van Weert, "Efficacy of diagnostic tools for detecting cardiac arrhythmias: systematic literature search," *Neth. Heart J.*, vol. 18 no. 11, pp. 543–551, Nov 2010.
- [5] M. Jastrzębski, "ECG and Pacing Criteria for Differentiating Conduction System Pacing from Myocardial Pacing," *Arrhythm Electrophysiol Rev.*, vol. 10 no. 3, pp. 172–180, Oct 2021.
- [6] I. Bank, H. W. Vliegen and A. V. Bruschke, "The 200th anniversary of the stethoscope: Can this low-tech device survive in the high-tech 21st century?" *Eur. Heart J.*, vol. 37 no. 47, pp. 3536–3543, 2016

- [7] A. Vahanian, O. Alfieri, F. Andreotti, M. J. Antunes, et al., "Guidelines on the management of valvular heart disease (version 2012): The Joint Task Force on the Management of Valvular Heart Disease of the European Society of Cardiology (ESC) and the European Association for Cardio-Thoracic Surgery (EACTS)," *Eur. Heart J.*, vol. 33 no. 19, pp. 2451—2496, Oct 2012.
- [8] J. D. Kendall and S. Kumar, "The building blocks of a brain-inspired computer," *Applied Physics Reviews*, vol. 7, no. 1, 2020, doi: 10.1063/1.5129306.
- [9] T. E. P. Catherine D. Schuman, Robert M. Patton, J. Douglas Birdwell, Mark E. Dean, Garrett S. Rose, James S. Plank, "A Survey of Neuromorphic Computing and Neural Networks in Hardware," *arXiv*, 2017, doi: 10.48550/arxiv.1705.06963.
- [10] H. Jaeger, "The "echo state" approach to analysing and training recurrent neural networks—with an erratum note," *German National Research Center for Information Technology*, Bonn, Germany, 2001, vol. 148.
- [11] G. Tanaka et al., "Recent advances in physical reservoir computing: A review," *Neural Netw.*, vol. 115, pp. 100-123, Jul 2019, doi: 10.1016/j.neunet.2019.03.005.
- [12] G. Tanaka et al., "Recent advances in physical reservoir computing: A review," *Neural Netw.*, vol. 115, pp. 100-123, Jul 2019, doi: 10.1016/j.neunet.2019.03.005.
- [13] X. Liang and Y. Zhong, "Rotating neurons for all-analog implementation of cyclic reservoir computing," *Nat Commun*, 2022, doi: 10.1038/s41467-022-29260-1.
- [14] M. Lukoševičius and H. Jaeger, "Reservoir computing approaches to recurrent neural network training," *Computer Science Review*, vol. 3, no. 3, pp. 127-149, 2009, doi: 10.1016/j.cosrev.2009.03.005.
- [15] A. Rodan and P. Tino, "Minimum complexity echo state network," *IEEE Trans Neural Netw.*, vol. 22, no. 1, pp. 131-44, Jan 2011, doi: 10.1109/TNN.2010.2089641.
- [16] Y. Ding, X. Liang, T. Middelmann, J. Marquetand, and H. Heidari, "MMG/EMG Mapping with Reservoir Computing," in *IEEE International Conference on Electronics, Circuits and Systems (ICECS)*, 2022: IEEE, doi: 10.1109/icecs202256217.2022.9971109.
- [17] X. Liang, J. Mercer, H. Heidari, "A Delay Based Neuromorphic Processor for Arrhythmias Detection," *IEEE International Symposium on Circuits and Systems (ISCAS)*, pp. 1-5, 2020, doi: 10.1109/ISCAS45731.2020.9181032.
- [18] X. Liang, H. Li, A. Vuckovic, J. R. Mercer, and H. Heidari, "A Neuromorphic Model with Delay-based Reservoir for Continuous Ventricular Heartbeat Detection," *IEEE Trans Biomed Eng.*, vol. PP, Nov 19 2021, doi: 10.1109/TBME.2021.3129306.
- [19] Farneback, G. "Two-Frame Motion Estimation Based on Polynomial Expansion," in *Proceedings of the 13th Scandinavian Conference on Image Analysis*, pp. 363-370, Halmstad, Sweden, 2003.
- [20] N. Wu and S. Haruyama, "Real-time audio detection and regeneration of moving sound source based on optical flow algorithm of laser speckle images," *Opt. Express*, vol. 28, pp. 4475-4488, 2020.
- [21] H. Jaeger, "Short term memory in echo state networks," *German National Research Center for Information Technology, GMD Report 152*, 2002.

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