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Nonlinear thermo-acoustic phase modulator for physical reservoir computing

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5 **Nonlinear thermo-acoustic phase modulator**

6 **for physical reservoir computing**

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19 This study proposes a nonlinear thermo-acoustic phase modulator for application in

20 physical reservoir computing. We designed and fabricated the modulator, and then

21 investigated the properties such as insertion loss and modulation effects. Finally, we

22 constructed a physical reservoir system with the proposed modulator and demonstrated

23 benchmark tasks. The modulator makes use of surface acoustic waves, which contributes to

24 fast processing and low power consumption. The modulator has a waveguide which also acts

25 as a microheater. The modulation principle is a wave-velocity reduction caused by heating

26 the surface of the substrate with the microheater, which provides nonlinearity and short-term

27 memory required for the reservoir system. We confirmed these characteristics in the

28 measurements of the modulator, and we verified the effectiveness of the modulator in the

29 reservoir system with 2.3 of memory capacity in STM task and 0.066 of NMSE in NARMA2

30 task.

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1. Introduction

Machine learning is an essential technology for modern life, and the demand continues to increase exponentially. Accordingly, the amount of processed information has been getting larger. This situation causes processing delays or an increase in power consumption.¹⁾ One of the solutions is physical reservoir computing (PRC), which is a machine learning algorithm utilizing nonlinear physical systems as computational resources. Reservoir computing (RC) is an architecture having a recurrent neural network that consists of three layers, input, reservoir, and output layer. The conceptual diagram is shown in Fig. 1(a). The structure is recurrent neural networks that have randomized weights W_{in} and W , and trained output weights W_{out} , which contributes to a reduction in the total number of weights optimized during the training phase.²⁾ As shown in Fig. 1(b), in the PRC scheme, physical systems are applied to the reservoir layer, then the dynamics process information instead of other processing units such as CPUs or GPUs, which leads to more reduction in power consumption. It is known that there are three requirements for physical systems applied to PRC, nonlinearity, short-term memory, and high dimensionality.³⁾ High dimensionality refers to the network having a wide variety of internal states and configurations that can be used for computation. For non-physical networks, this is provided by the interconnection of multiple neurons. A time-multiplexing system is a common method to realize high dimensionality in physical neural networks.⁴⁾ This method enables the PRC system, with a single physical element and only one output channel, to serve multiple nodes, which provides a compact system. Recently, PRC has been attracting much attention, and it has been researched in various communities.^{3),5)} For instance, optical systems,⁵⁾⁻⁹⁾ spintronic systems,¹¹⁾⁻¹³⁾ electromechanical systems,¹⁴⁾⁻¹⁷⁾ and in-materia reservoir¹⁸⁾⁻²⁰⁾ were applied.

In this research, we propose to exploit a surface acoustic wave (SAW) for application to PRC. A SAW is an elastic wave traveling on a solid surface. SAW devices are one of its applications^{21),22)} Generally, the wave is generated by applying an AC voltage to IDTs (interdigital transducers) on a piezoelectric material surface. SAW devices operate at high frequencies ranging from several MHz to GHz and offer a wide bandwidth, enabling high-speed information processing. Additionally, SAWs exhibit low propagation loss, which contributes to reduced required power. These characteristics make SAW devices highly suitable for constructing a PRC system with fast processing capabilities and low power consumption.

However, conventional SAW devices exhibit highly linear responses, which hinder their use as nonlinear activators in PRC systems.²³⁾ In our previous report, a PRC system with a

SAW resonator was proposed, and the concept was demonstrated through benchmarks²⁴. Nevertheless, the resonator's responses were essentially linear, which put a strict limitation on further applications.

We introduce a thermo-acoustic phase modulator to address the problem of linearity. Two-port SAW phase modulators have been demonstrated in prior research^{25),26)}. The modulation principle is a deformation of the device substrate by applying heat or electrical field to the wave's path. We extend this methodology by integrating the waveguide and heater elements. Our design makes the device structure simple, and in addition, it realizes more efficient modulation. In this paper, we propose a new design of a SAW phase modulator, and we investigate the properties of the fabricated modulator. Then two benchmark tasks are conducted to evaluate a PRC system containing the modulator.

2. Experimental methods

2.1 Thermo-acoustic phase modulator

The conceptual illustration of the proposed modulator is shown in Fig. 2. A gold layer is deposited on a 128°Y-X black lithium niobate wafer to fabricate two IDTs and a waveguide. The waveguide also acts as the microheater to heat the wave path by Joule heating. The IDTs and the waveguide are simultaneously fabricated using gold, and the thickness is 100 nm. The IDTs are designed to have the center frequency of 300 MHz and have an impedance of 50 Ω , such that they are impedance matched to the cabling and signal source.²¹⁾ The IDTs have 50 pairs of electrodes, each with a length and width of 130 μm and 3.13 μm respectively. The type of waveguide used in our design is called an overlay-type waveguide.^{27),28)} The wave propagation velocity is slower in the guide than that of the free surface because of mass loading effect. That creates a difference between the refractive indexes of each region. Thus, the propagating SAW is confined inside the waveguide. The taper angle, α , is 2.7° to minimize the loss²⁸⁾. The confinement of the SAWs inside the waveguide is important for fast modulation provided by local heating. The length and width of the microheater are 5 mm and 10 μm , respectively.

The phase shift $\Delta\Phi$ is proportional to temperature rise ΔT on the substrate surface, as expressed with the following equation²⁸⁾,

$$\Delta\Phi = \frac{2\pi L}{\lambda} \frac{dn}{dT} \Delta T \quad (1)$$

where L is the length of the microheater, λ is the wavelength, dn/dT is the velocity temperature coefficient of the substrate. The velocity temperature coefficient of 128°Y-X

lithium niobate is -71.3 ppm/K^{28}). Considering the temperature rise is proportional to the square of the voltage applied to the microheater (heater voltage), Eq. 1 is expressed as Eq. 2,

$$\Delta\Phi = AV^2 \quad (2)$$

where A is a constant value, and V is the heater voltage. We make use of the nonlinear relationship between the heater voltage and phase shift as a nonlinear activation in PRC systems.

2.2 Device fabrication

After cleaning with acetone, isopropyl alcohol, and deionized water, a 128°Y-X black lithium niobate substrate (Yamaju Ceramics) was dehydrated on a hotplate at 120°C for 10 minutes. An image reversal photoresist (AZ5214E, MicroChemicals) was applied using a spin coater. The substrate was pre-baked on the hotplate at 90°C for 2 minutes. The wafer was exposed at 10.5 mJ/cm^2 using a double-sided mask aligner (SUSS, MA6 BSA, Suss MicroTech), followed by an image reversal bake at 110°C for 2 minutes. Flood exposure was then conducted at 365 mJ/cm^2 without a photomask. The resist was developed using a 2.38% tetramethylammonium hydroxide solution (NMD-3, Tokyo Ohka) for 30 seconds. A gold layer of 100 nm thickness was deposited using a custom-made electron-beam evaporator. The lift-off process was conducted in N-methyl-2-pyrrolidone at 80°C for 2 hours. The wafer was diced into chips using a dicing saw (DAD322, Disco). Finally, the chip was mounted on a custom-made PCB and connected by wire bonding.

2.3 Measurement of device characteristics

The measurement configurations with a vector network analyzer (PicoVNA 106, Pico Technology) and a reconfigurable multi-instrument platform (Moku:Pro, Liquid Instruments). are described in Fig. 3. The instrument provides functions of a lock-in amplifier, an arbitrary waveform generator, and an oscilloscope in this setup. The ac driving voltage applied to the input IDT was set at $0.7 V_{\text{rms}}$, which represents the root mean square (RMS) value of the applied voltage. On the dc response test, the input voltage to the microheater was up to 5 V. On the ac response test, a triangle wave with an amplitude ranging from 0 V to 5V and a frequency ranging from 0.5 kHz to 50 kHz was used.

2.4 SAW-PRC system

A schematic diagram of the SAW-PRC system with the proposed modulator is shown in

Fig. 4. In the system, high dimensionality was realized by a time-multiplexed system to create virtual nodes.^{9),16)} In this approach, the input signal was held during the constant interval τ , then the signal was sampled with a certain interval to define the virtual nodes N in the time domain. We defined the number N and the time interval θ of nodes, thus we obtained the following equation,

$$\tau = N\theta \quad (3)$$

An arbitrary waveform generator of the Moku:Pro was used to generate input signals and a mask function for the input layer, then the input signal and the mask function were multiplied using the cloud compile function of Moku:Pro. The multiplexed input was injected into the microheater of the phase modulator. In the reservoir layer, a waveform generator of the Moku:Pro was configured to generate a SAW at the input IDT. The modulated signal from the output IDT was amplified, and it was demodulated by the lock-in amplifier to detect the phase modulation. The phase change was recorded by an external oscilloscope (Picoscope 5244D-MSO, Pico technology). The recorded time-series data were sent to a PC to conduct the training and testing of machine-learning tasks using Python. The ridge regression was used to optimize the output weights in the training.

2.5 Reservoir computing benchmarks

Short-term memory (STM) task and NARMA2 task are conducted to demonstrate the SAW-PRC system, since the former task is a fundamental and commonly-used one and the latter one is a time-series prediction task, this is used to evaluate both short-term memory and nonlinearity of PRC systems.^{13),17),29)}

2.5.1 Short-term memory task

STM task tests the memory capacity of PRC systems. The random binary input $u(t)$ is applied to the reservoir. On the k -step STM task, the output network is optimized to recall the input $u(t-k)$, in which k is the delay timestep. The reservoir output $y(t)$ is compared with the target $u(t-k)$, then we evaluate the agreement $r^2(k)$ by the following equation,

$$r^2(k) = \frac{\text{Cov}^2(u(t-k), y(t))}{\text{Var}(u(t-k)) \times \text{Var}(y(t))} \quad (4)$$

where $\text{Cov}()$ and $\text{Var}()$ are the covariance and variance, respectively. $r^2(k)$ ranges from 0 to 1. If it equals 1, the system can recall perfectly the input k steps before. We evaluated the performance by the memory capacity (MC) calculated by the following equation,

$$MC = \sum_{k=1}^{\infty} r^2(k) \quad (5)$$

We can interpret MC as the number of past inputs that the system can memorize. For example, when $MC = 1$, the system can memorize only the previous input. Ideally the summation process is infinite, but in this report, the calculation of MC was terminated at $k = 5$ due to computational time.

2.5.2 NARMA2 task

In the NARMA2 task, a random input $u(t)$ in the range from 0 to 0.5 is input to the reservoir layer. NARMA2 model is a second-order nonlinear model and the next reservoir output $y(t+1)$ is defined as

$$y(t+1) = 0.4y(t) + 0.4y(t)y(t-1) + 0.6u^3(t) + 0.1 \quad (6)$$

The next output is generated by the current and previous output and the random input. The weights to the output layer are optimized for one-step-ahead prediction. We examined the performance by the normalized mean square error (NMSE) defined by,

$$NMSE = \frac{1}{M} \times \sum_{t=1}^M \left(\frac{y(t) - \hat{y}(t)}{\sigma^2(y(t))} \right)^2 \quad (7)$$

where $\hat{y}(t)$ is the predicted output, σ is standard deviation, and M is the number of samples.

To verify if the modulator works as a reservoir, we also conducted this task with the system without the modulator, which means the input signals are not transformed at all with the reservoir layer.

2.5.3 Measurement condition for benchmarks

We conducted these benchmarks with $N = 15$ virtual nodes. The amplitudes of the mask function were random binary values 0 and 1. The amplitudes of the masked signals were scaled between 0.1 V and 5.0 V. In these measurements, we changed the driving frequency f and input interval θ . The driving frequency f ranged from 280 MHz to 300 MHz. The input interval θ ranged from 0.1 μ s to 100 μ s.

For the benchmark tasks, the total input numbers were 500 and 800, both the first 400 inputs were used for training, and the remaining 100 and 400 inputs were used for testing in STM and NARMA2 tasks, respectively.

3. Results

3.1 Device characteristics

The overall view and partial view of the fabricated modulator are shown in Fig. 5, and the linear transmission characteristics of the modulator are plotted in Fig. 6. The minimum insertion loss of 21.6 dB was observed at 296.16 MHz. The center frequency shifted by $\sim 3\%$ from the designed value due to mass loading. Figure 7(a) describes the phase shift against the dc heater voltage. The maximum shift was -321.28° at 5 V. We confirmed the nonlinear relationship between the phase shift and the heater voltage.

The output phase shift as a function of the ac voltage amplitude to the microheater is plotted in Fig. 7(b). The differences between the maximum and minimum phase for each input frequency were 84.6° at 0.5 kHz, 34.6° at 5.0 kHz, and 5.4° at 50 kHz. Using Eq. 1 and the phase values from Fig. 7(b), we estimated the temperature rise of the microheater to be 8.3 K, 3.4 K, and 0.53 K, respectively. The hysteresis in the heater voltage and the phase was observed, which indicates that the past inputs influenced the current output. In other words, the system has short-term memory properties. In addition, the hysteresis curves changed as a function of different input frequencies, which indicates nonlinearity.

3.2 Short-term memory task

Figures 8(a) and 8(b) show the results of STM task. We attained the maximum MC of 2.3. The performance heatmap indicates that the MC increased as the input interval θ became larger, and the MC was degraded at specific frequencies f around 280, 285, and 292 MHz. We investigated the $r^2(k)$ for each delay with a result showing MC of 2. Fig. 8(b) indicates that the system could recall the input delayed by 1 or 2 steps. On the contrary, it was not possible to remember the inputs from more than 2 steps earlier.

3.3 NARMA2 task

Figure 8(c) provides the result of NARMA2 task. We obtained the best NMSE of 0.066. The trend of the performance heatmap was similar to the STM task. Typical target and predicted signals are plotted in Fig. 8(d). The predicted signal tracked well the target. The SAW-PRC system can process the task which requires the nonlinearity and short-term memory.

Figure 8(e) illustrates the comparison between the results of NARMA2 task with the SAW-PRC system or the system without the modulator. The NMSE without the modulator was 0.551. The NMSE of the SAW-PRC system overtook it at an input interval of approximately $2\ \mu\text{s}$, which indicates better performance for input intervals of over $2\ \mu\text{s}$.

4. Discussion

The proposed thermo-acoustic phase modulator exhibited its nonlinearity and short-term memory, indispensable characteristics of a physical reservoir. The fact was also confirmed by the benchmark tasks. The maximum MC of 2.3 in the STM task is comparable to the previous research on PRC systems without a time-delayed feedback loop.^{14),18),19)} The nonlinearity was derived from the quadratic relationship between the heater voltage and the phase, as shown in Fig. 7(b). The nonlinearity is small, but it was adequate to process the NARMA2 task. The lowest NMSE of 0.066 is close to that of previous reports.^{11),18),29)} The heatmaps in Figs. 8(a) and 8(c) exhibit a similar trend in performance. That is because both the STM task and the NARMA2 task require short-term memory of the SAW-PRC system.

In this report, we changed only the driving frequency f and the input interval θ among the hyperparameters including the device's dimension and material properties to investigate the effects on the performance, so there is room for improving the performance by optimization of the other hyperparameters and device characteristics. Especially, the response time of the modulation is a crucial factor, taking Figs. 8(a) and 8(c) into account. When the input interval θ was sufficiently long, the system demonstrated better learning performance. That is because the reservoir state changed sufficiently with a long input interval θ . In Fig. 7(b), lower input frequency caused a larger change in the phase. Considering the input frequency in Fig. 7(b) is corresponding to the reciprocal of the input interval θ in Figs. 8(a) and 8(c), the input interval θ should be long enough to change the phase in the SAW-PRC system. Thus, it is expected that we can make the processing time shorter by enhancing the response time. This may enhance the nonlinearity or short-term memory.

The insertion loss is a dominant factor for the performance. In Figs. 8(a) and 8(c), the region where the insertion loss was bigger than 50 dB shows poor performances in each task. When the insertion loss is large, the information input to the reservoir layer is dissipated before it comes out from the output IDT. Furthermore, in the SAW-PRC system, we amplified the output signal from the modulator by the pre-amplifier. This has the risk of degrading stability and also makes the whole system more complex. Therefore, we will work on reducing the insertion loss to improve the performance of the simple SAW-PRC system. One approach to reducing the loss is a SPUDT (single phase unidirectional transducer), which is beneficial to decrease the loss because the generated SAW travels in a unidirectional manner.³⁰⁾

The time-delayed feedback loop is a promising means to enhance the short-term memory of SAW-PRC systems. This method is often used in optical reservoir systems^{6),8),9)}, and the feedback function is implemented by an optical fiber delay line. These studies show that the

feedback strength and the delay time affect the performance of the PRC systems. We have demonstrated the SAW devices with couplers and delay lines²⁴⁾, and there are a lot of strategies for the waveguide which has a bent structure or ring structure.^{28),31)} By applying them, the time-delayed feedback loop can be implemented in the SAW-PRC system. We wish to integrate the feedback system with the thermo-acoustic phase modulator on a single chip.

5. Conclusions

In this study, we successfully fabricated the thermo-acoustic phase modulator having the non-linearity and short-term memory required for PRC systems. The modulation principle, based on Joule heating, contributes to the essential properties of the modulator. It was verified that the modulator functions as a nonlinear element in the SAW-PRC system using the two benchmarks. In the results, there was a maximum MC of 2.3 in STM task and a minimum NMSE of 0.066 in NARMA2 task.

In the future, we are going to add other PRC components such as couplers and/or delay lines not only to improve the performance but also to realize an on-chip integrated SAW-PRC system

Acknowledgments

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Figure Captions

Fig. 1. Conceptual diagram of (a) reservoir computing, and (b) physical reservoir computing, in which the multiple inputs are created by time-multiplexing with a mask function.

Fig. 2. Schematic illustration of thermo-acoustic phase modulator with two IDTs and waveguide which works as microheater to heat wave path for phase modulation.

Fig. 3. Measurement setup for (a) linear transmission, and (b) phase-modulation effect. The modulation is performed by applying a voltage to the microheater.

Fig. 4. Diagram of SAW-PRC system with the thermo-acoustic phase modulator. Heater voltage and phase detected at lock-in amplifier are defined as input and output of reservoir, respectively.

Fig. 5. Fabricated modulator. (a) overall view (a part of the microheater is truncated), and (b) partial view.

Fig. 6. Insertion loss of thermo-acoustic phase modulator.

Fig. 7. Phase shift as functions of (a) dc heater voltage, and (b) ac heater voltage (triangular wave).

Fig. 8. Result of benchmark tasks. (a) Trend of performance in STM task with spectrum of insertion loss in upper window. (b) $r^2(k)$ plot for each delay in STM task ($f = 296.32$ MHz, $\theta = 49.4$ μ s). (c) Trend of performance in NARMA2 task. (d) Target (Black) and predicted (Red) signal at testing phase in NARMA2 task ($f = 297.55$ MHz, $\theta = 16.0$ μ s). (e) Comparison of NMSE performed by SAW-PRC system (Red) and system without the modulator (Blue). The shaded areas mean the standard deviation.

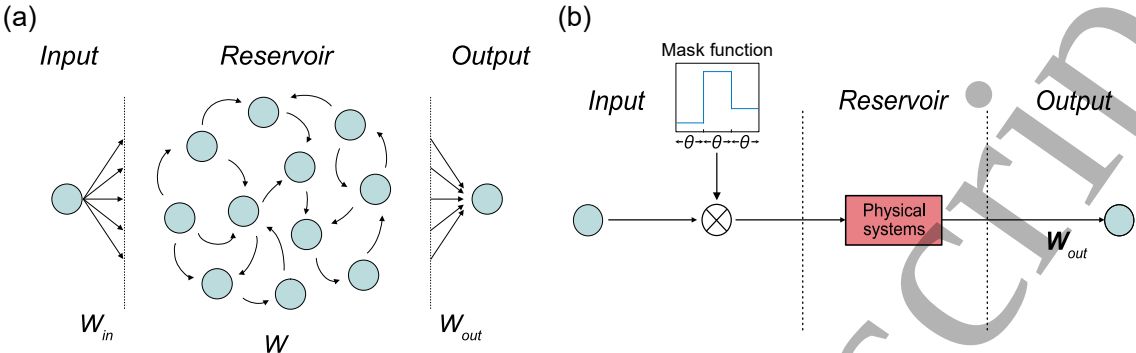


Fig.1.

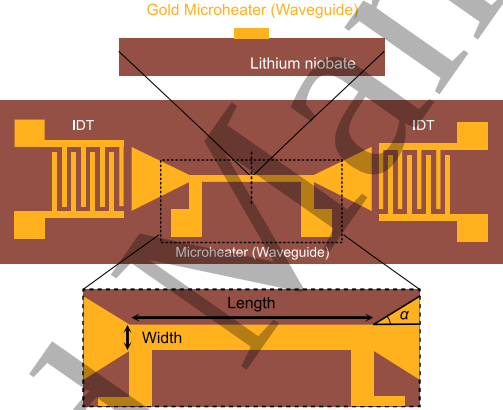


Fig.2.

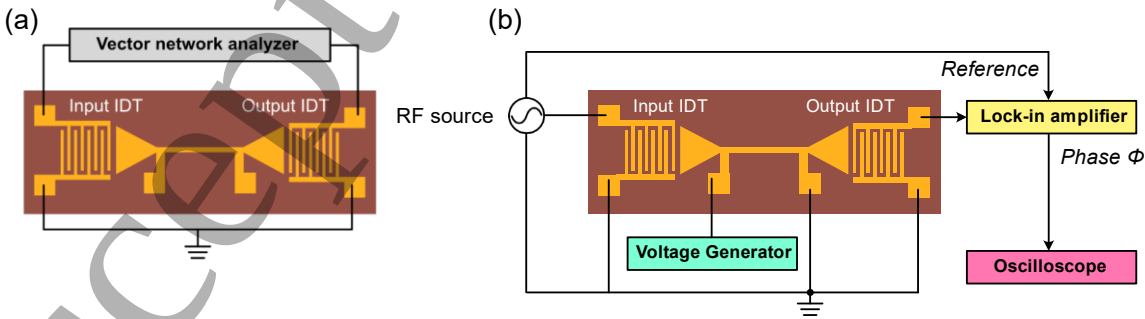


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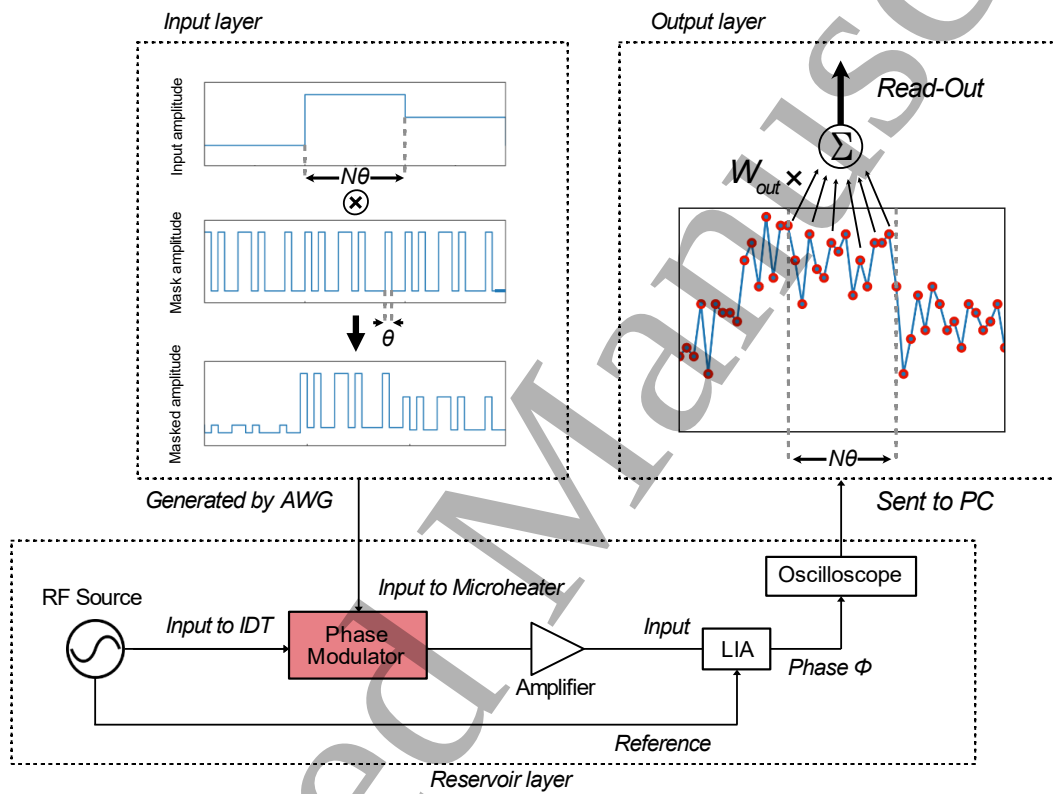


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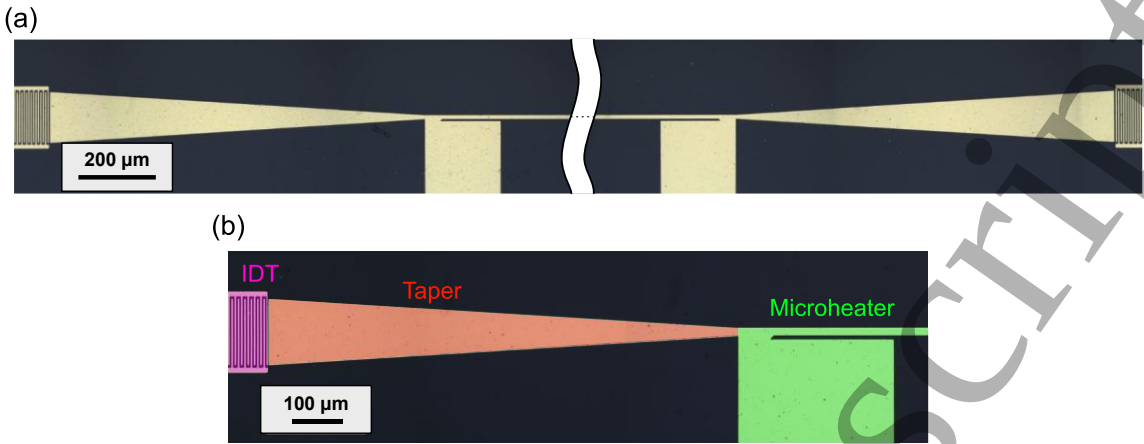


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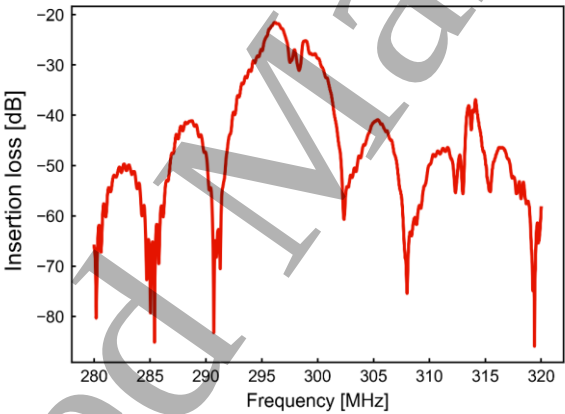


Fig.6.

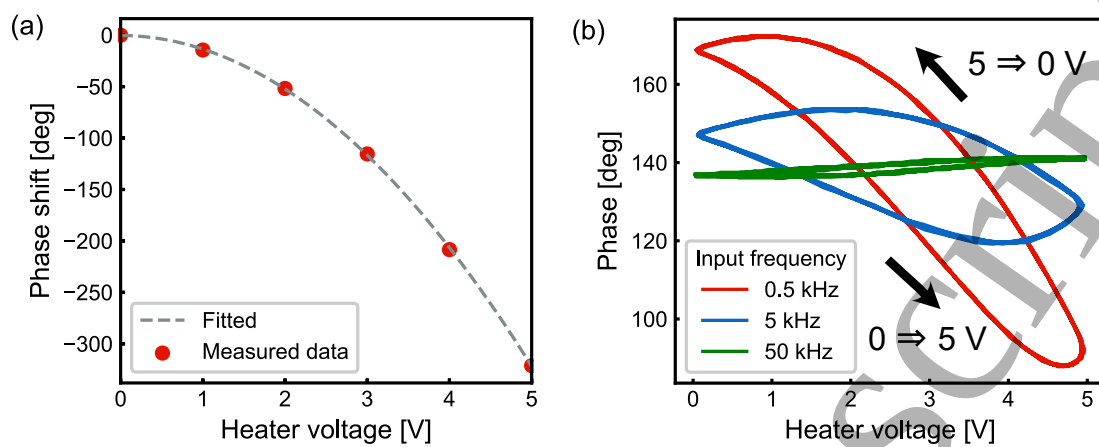


Fig.7.

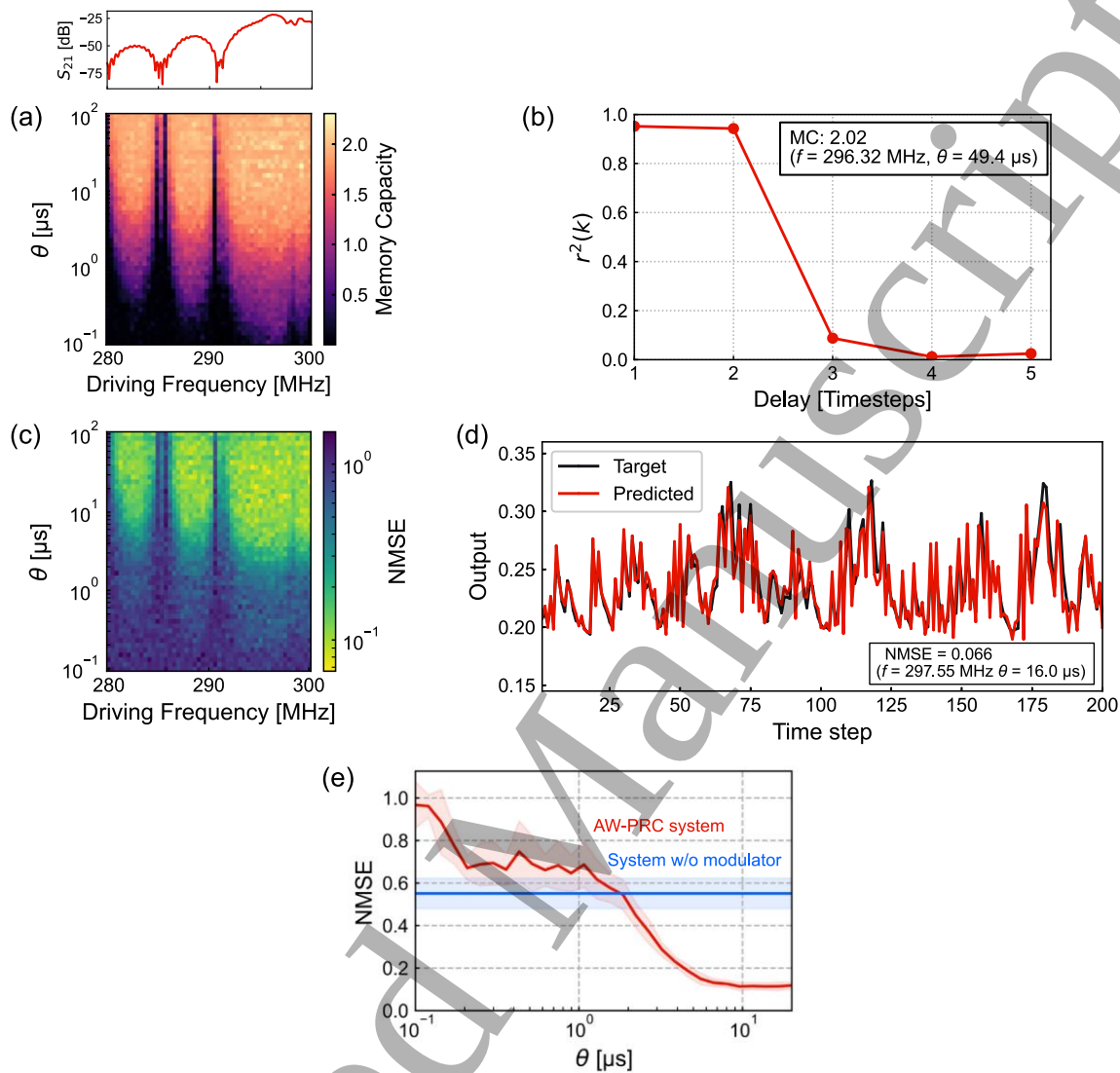


Fig.8.