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Optical implementation of reservoir computing for fast integrative analysis in sensor array processing

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Abstract—Optical reservoir computing (RC) with delayed feedback is expected to realize high-speed data processing. In this scheme, identification and quantification tasks for the mixture of two gases were tested on the basis of 16 channel gas sensor array datasets to realize an electronic nose with comprehensive sensitivity. Both parallel reservoirs with a single-input and a single reservoir with multi-inputs were compared in terms of identification performance and node dynamics. We achieved fast, multi odor information processing by the single reservoir architecture with an optical fiber system implementation.

1. Introduction

Sensing technology plays a significant role in making our lives safer and more convenient in various fields such as environmental monitoring, infrastructure management, medical care, and so on. With recent social attention on IoT-based technology, the importance of sensors has increased, and performance is expanding with the development of machine learning.

Sensing technology has artificially realized the five senses of living things. But among them, olfaction is thought to be the most difficult because odor information involves a wide variety of chemical substances. The olfactory receptors of living things have comprehensive sensitivity, which means wide sensitivity against various chemical substances, but low selectivity. For example, humans have several hundred kinds of comprehensive receptors and can discriminate between more than 1 trillion kinds of odors [1]. In addition, living things, even small insects, process a vast amount of odor information in real time and take immediate action such as avoidance or searching. Although it may be possible to analyze the odor information by using a high performance computer, implementing the processing into a small body or robot will still be challenging with such huge computational resources.

Odor identification algorithms are mainly classified by two methods. One is statistical processing, and the other is neural network analysis [2, 3]. In general, the latter has an advantage in that the identification accuracy is higher in situations where the boundary area is close or unclear. On the other hand, neural networks suffer from a long learning time depending on the amount of processing.

Reservoir computing (RC) is a recurrent neural network that can process time series information [4, 5]. For that reason, RC is expected to be suitable for analyzing odor information with spatiotemporal distribution [6]. RC has an advantage in its ease of learning because an RC algorithm requires adjustment of only readout connections and not the entirety of network connections. In addition, RC can utilize the dynamics of the physical system as a reservoir. Research on exploiting the dynamics of lasers or soft materials is currently being reported [7–9]. In this way, by leaving a part of the calculation process to the physical system, a reduction of computational resources and implementation into a small body or robot are expected.

In this paper, we try to analyze odor information by using a physical RC, particularly with an optical implementation toward fast and large-capacity computation. For system downsizing and simplicity, integration of multiple sensor outputs is applied by just adding a small time delay to each sensor signal, with the expectation of realizing a high speed optical reservoir that can process very large quantities of sensor signals in real-time.

2. Experimental method

2.1. RC with delayed feedback system

We adapted a reservoir model on the basis of the echo state network [5], which has one of the simplest architectures. For optical implementation, it has been demonstrated that delayed feedback systems could accomplish excellent results in complex problems such as nonlinear auto-regressive moving average (NARMA) and speech recognition tasks [8, 10]. In those optical systems, a number of nonlinear nodes and complex connections of traditional neural networks are replaced by a single nonlinear device and a delay line. A high dimensional space of the reservoir is extended into a time space of the delay line. The nonlinear optical devices are already commercially available technologies used for high-speed broadband optical networks, and the continuous technological development should increase the range of photonics applications including optical reservoirs in the future.

2.2. Odor signals

In this analysis, we used a published database [6] for odor signals. The task is component identification and quantification of gas mixtures. The details of an

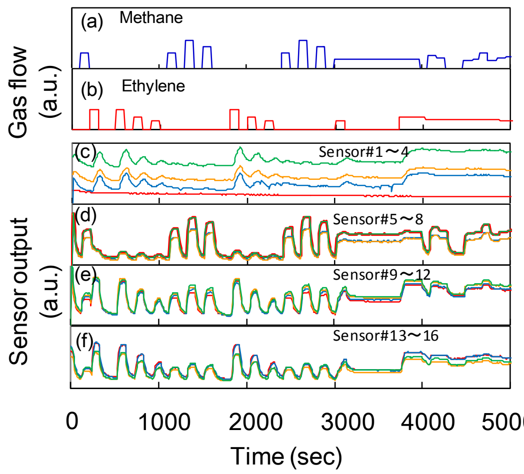

Fig.1 Time profile of (a) Methane, (b) Ethylene gas flow; (c)(d)(e)(f) output signals of four gas sensors [6].

experiment for the data collection are described in ref. [6]. The data was generated from a 16 metal-oxide (MOX) sensor array in response to dynamic gas mixtures in a flow chamber. Figure 1 shows the time series of two setting points for the gas-flow controller and 16 sensor outputs. Although all sensors respond to both methane and ethylene, the sensitivity and dynamics are different. For example, sensors #1–4 are sensitive to ethylene, and the response speed is relatively low, whereas sensors #5–-8 show lower sensitivity to methane rather than ethylene. Sensors #9–12 and sensors #13–16 have high sensitivity against ethylene and methane, but these properties are not the same. So these are regarded as artificial olfactories with comprehensive sensitivity.

An integrative analysis of the odor information is examined by using the single node optical reservoir. Output weight connections were tuned in order to minimize the differences between the reservoir outputs and the setting points of gas-flow meters. Calculation results are evaluated with a normalized error as shown in equation (1). L, y, and $\hat{y}$ are the number of calculation points, reservoir outputs, and setting points of gas-flow, respectively. In this experiment, the number of calculation points was limited to around 4000 by the memory size of measuring equipment such as the signal generator and the readout oscilloscope as described in the following section.

$$error = \frac{1}{L}\sum_{1}^{L}\sqrt{(y(t)-\hat{y}(t))^2} \qquad (1)$$

2.2. Optical implementation

The setup of the optical reservoir is shown in Fig. 2, which is similar to those of prior research [10]. The input signal was extended to 100-step pulse signals by using a preprocessing algorithm called a mask process [7]. A telecom Mach-Zehnder (MZ) modulator was used as a nonlinear node. The output optical signal intensity of the MZ modulator varies sinusoidally with the input voltage as shown in equation (2).

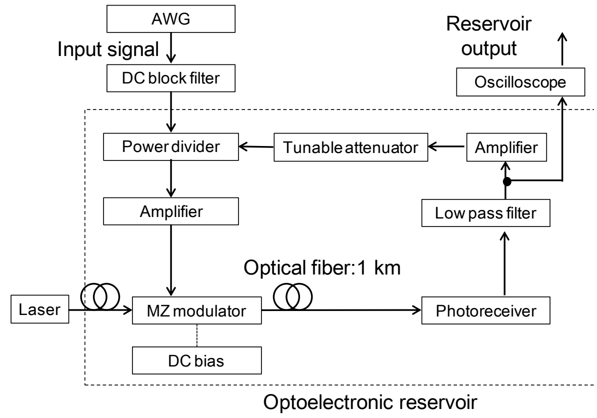

Fig. 2 Optical implementation of reservoir computing with a single nonlinear element subject to delayed feedback.

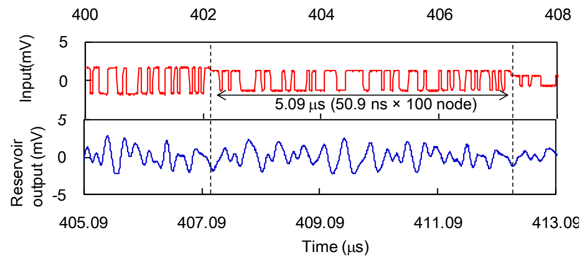

Fig. 3 An example of input and reservoir output time traces.

$$P(V) = 1 + \sin(\omega V + \varphi) \qquad (2)$$

The output optical pulse signals are coupled to the delay line, which is a 1 km-optical fiber and an RF electronic cable. 100 pulse signals with a 50.9 ns-width generated by the mask process are kept in the delay line as virtual nodes. The optical signal streams after propagating the delay fiber are transferred to electrical pulses in the photoreceiver and then divided into two directions. One is the readout port, and the other is the feedback port. The feedback signal intensity is a parameter adjusted by a voltage amplifier and an attenuator. As this feedback system could show bifurcation and chaotic properties because of the feedback signals, the intensity is restricted to be low in order to sustain a non-chaotic state. The readout signal was observed or processed by a control computer, then transferred to the output signal. Fig. 3 shows a part of one scalar input divided by a mask signal and the corresponding reservoir dynamics as an example.

3. RESULTS AND DISCUSSION

3.1. Architecture for multiple signal analysis

At first, for integrative analysis of 16 sensor signals, we tested two types of reservoir architectures. One is a parallel nodes system [11], and the other is a single node system with overlapped input signals. The parallel system just uses multiple 16 reservoirs with the delayed feedback as shown in Fig. 4 (a). On the other hand, in the case of the single node system, 16 sensor signals were overlapped

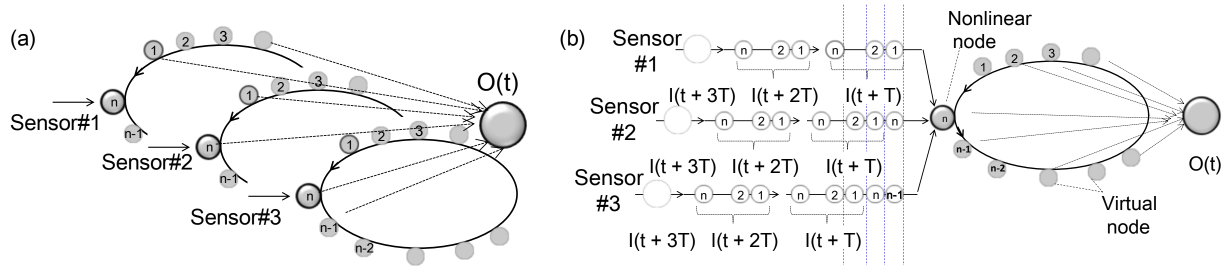

Fig.4 Schematic of (a) parallel multi reservoir [11], (b) single node reservoir with pre-process of multi-input signals by small time shift.

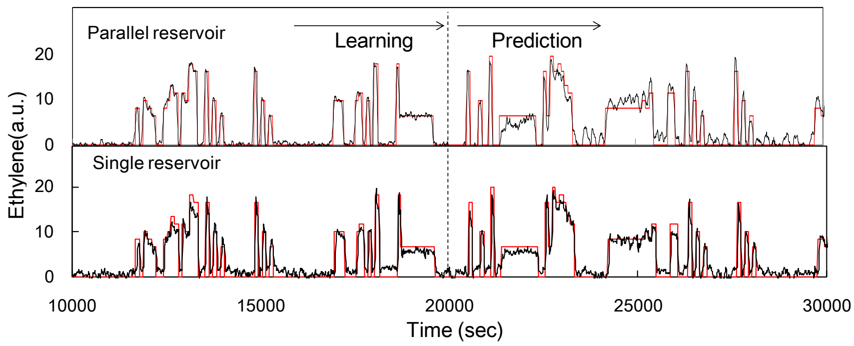

Fig. 5 Learning and identification results of ethylene gas obtained by parallel and single optical reservoir.

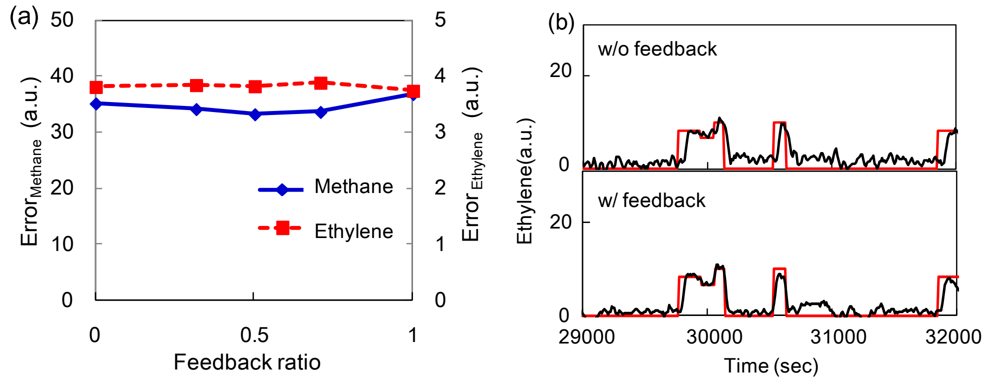

Fig. 6 (a) Identification results depending on feedback coefficient, (b) time series identification results of ethylene gas.

after adding a different small time delay (a mask pulse width delay between each signal) as shown in Fig. 4 (b), with the expectation of system downsizing and simplicity.

Figure 5 shows a comparison of leaning and identification results of ethylene gas for two systems. The output weights were trained during the first half of 20000 seconds, and identification tests were performed in the latter half. At the prediction phase, there is no significant difference in the appearance and error value between the parallel reservoirs and the single reservoir systems.

At the learning phase, however, the parallel reservoirs show an over-fitting tendency, which might be derived from small training data with too many fitting parameters.

In such conditions, nonlinear node dynamics were not necessary for achieving successful processing. On the other hand, the single node system requires nonlinear dynamic properties as described in Section 3.3. In the following analysis, we adapted the single node reservoir system with a delayed and overlapped signal.

3.2. Feedback signal effect

Figure 6 (a) shows the calculation error depending on the feedback signal ratio against the input signal at the prediction phase, in the total long time span as expressed by equation (1). There is no significant difference in error with respect to the feedback ratio. On the other hand, Fig. 6 (b) shows an enlarged illustration of the predicted results with and without feedback signals. The output signal without signal feedback shows a large delay (700 ~ 800 sec) compared to the target value because of the response delay of the gas sensors as shown in Fig. 1. With signal feedback, the delay of the output signal was reduced to around 200 sec. This is a slow-response compensation effect [6] of reservoir computing, which calculates the signal change of the short duration in the

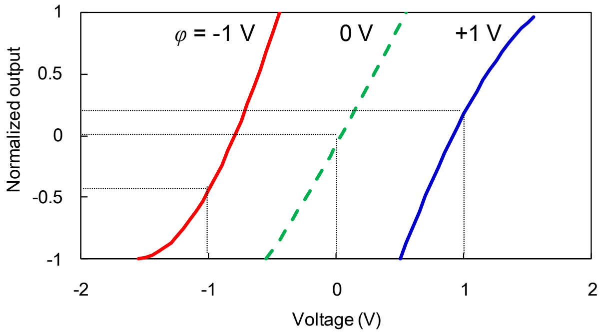

Fig. 7 Normalized electrical/Optical transform function of MZ modulator at various bias voltages.

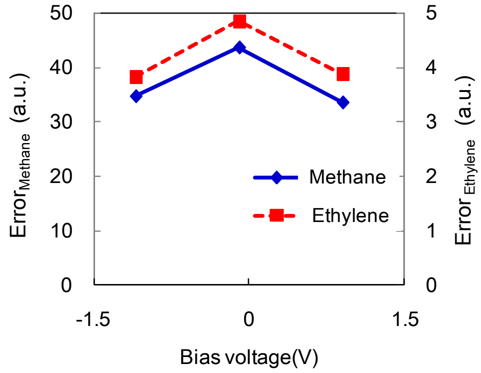

Fig. 8 Identification errors depending on feedback coefficient.

recurrent network. Real time, sequential analysis including time compensation will be powerful tools for fast detection of a moving odor source and quick escape from dangerous gas.

3.3. Nonlinearity

Identification performance dependence on nonlinearity of the node was investigated. The nonlinear properties of the MZ modulator are tuned by changing the operation voltage. In this section, bias voltage φ in equation (2) was shifted as shown in Fig. 7. The input signal amplitude was fixed to $V_{pp} = 1.1$ V (± 0.55 V) in each instance. The electrical-to-optical conversion property of the MZ modulator is almost linear at a bias voltage of 0 V. On the other hand, at a bias voltage of -1 V (+1 V), the lower (higher) voltage side of the conversion characteristics acts as nonlinear conversion processing on the input signal.

Figure 8 shows the calculation error depending on the bias voltage. At a bias of 0 V, values for the error are higher than those with other bias conditions. These results indicate that the nonlinear conversion property of the single node reservoir with delayed feedback is an important factor for highly accurate odor analysis from multiple sensor arrays with comprehensive sensitivity. The nonlinearity should improve the identification outputs because it increases the diversity of the 100 virtual node conditions. In other words, the diversity of the 100 basis functions is enhanced because of the nonlinearity of the activation function for getting the reservoir output O(t) with an weighted linear combination. As a result, accurate emulation is expected to be improved. This should reduce the identification errors with a MZ modulator bias condition of ± 1 V.

4. CONCLUSION

We demonstrated that the single optical reservoir successfully identified the time series mixed gas composition by analyzing odor signals generated from 16 sensor outputs and determined that the identification accuracy depends on the nonlinearity of the optical modulator. In addition, these results show that the feedback loop of the reservoir realizes predictive gas identification, meaning high sensitive detection by compensating for the slow-response of the gas sensors.

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