A Spiking Neural Network for Time-Efficient Gas Concentration Level Estimation in Resistor-Type Gas Sensors

*Donghee Kim, Jiseong Im, Seongbin Hong, Yujeong Jeong, Gyuweon Jung, Wonjun Shin, Jinwoo Park, and Jong-Ho Lee

Department of Electrical and Computer Engineering and Inter-University Semiconductor Research Center (ISRC)
Seoul National University, Seoul 08826, Republic of Korea
E-mail: *michaelking@snu.ac.kr, jhl@snu.ac.kr

Abstract

Artificial intelligence is being applied to various fields, and related research is actively underway. In this paper, transient gas responses obtained from a metal-oxide-based resistor-type gas sensor are used as datasets for a spiking neural network-based approach to estimate the gas concentration level. The effects of various input gas response ranges on testing accuracy are investigated. Training the network with limited input data ranging from t = 100 s to t = 280 s showed the highest accuracy of 90.35%.

I. Introduction

Nowadays, the importance of gas detection in the atmospheric environment is increasing with the growing interest in healthcare [1]. Hydrogen sulfide (H_2S) is one of the toxic gases that cause fatal damage to the human respiratory system. Numerous types of gas sensors such as electrochemical, optical, and semiconductor-type gas sensors have been continuously developed to detect the H_2S gas [2-3]. Among semiconductor-type gas sensors, a resistor-type sensor is a typical gas sensor with a simple structure. Since chemical reaction with H_2S and oxygen molecules changes the resistivity of the sensing material, target gases are detected by measuring the change in resistance of the sensor.

Recently, there have been increasing attempts to analyze gas sensor data using artificial intelligence [4-5]. However, only a few reports have been conducted by applying spiking neural networks (SNNs). SNNs imitate the structure of the human nervous system as a network of neurons and synapses. SNN-based neuromorphic computing has advantages in limited power resource situations because of its low power operation [6].

In this study, we investigate the possibility of using SNN and STDP (spike-timing-dependent plasticity) for gas concentration level estimation for the first time of our knowledge. A limited range of transient gas responses to various H_2S concentrations is used as datasets. Transient responses are obtained by a resistor-type gas sensor with an Indium-Oxide (In_2O_3) sensing layer.

Various time ranges of the response data are applied for network training and testing. Experimental results showed that the accuracy when using only the front part of the response data was higher than that when using the entire response data. Our experiment showed that SNN can serve as a tool for gas estimation work.

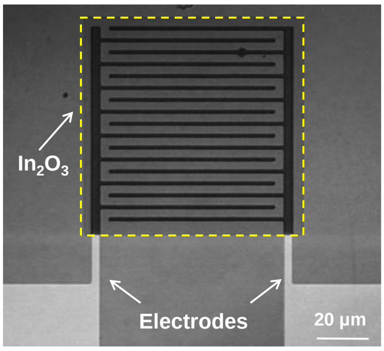

Fig. 1. SEM image of the fabricated resistor-type gas sensor.

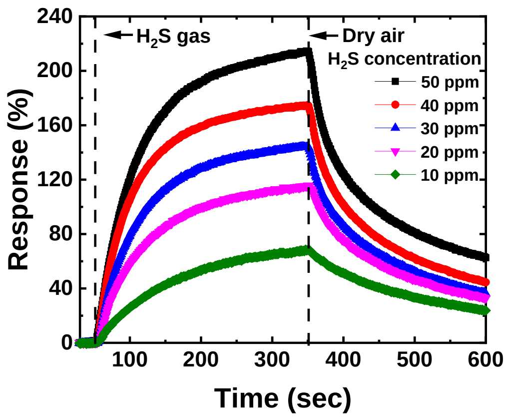

Fig. 2. Transient responses of the gas sensor as a parameter of H_2S concentration at 180 °C. Gas responses reach the maximum response value at t = 360 s. The recovery of the sensor lasts up to 800 s.

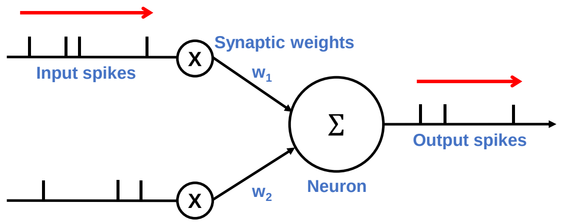

Fig. 3. Neuron and synapses of SNN (LIF model).

II. Methods

A. Device Structure and Transient Response

Fig. 1 shows the SEM image of the fabricated resistor-type gas sensor. The resistor-type sensor consists of two interdigitated electrodes and a sensing layer covering them on top. The sensor is fabricated on a 6-inch *p*-type silicon wafer by using CMOS process technology. Thanks to its simple structure, the fabrication process is relatively simple.

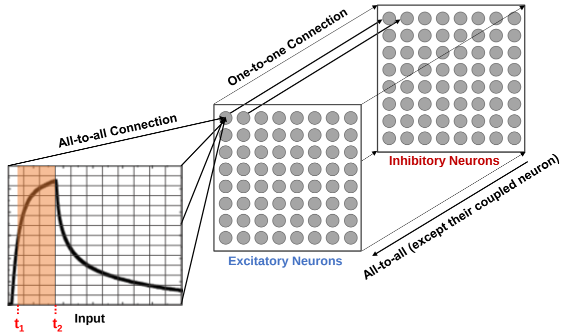

Fig. 4. Network architecture. The red shaded area in the input layer represents the time range of the data used for training and testing. The intensity values of the samples not in the shaded area are processed as zero.

Fig. 2 shows the transient gas response of the sensor as a parameter of H_2S concentration at 180 °C. The sensor starts to react with the injected target gas (@ t = 50 s), reacts for 300 s, and then starts to recover after injecting dry air into the test chamber (@ t = 350 s). The response is obtained using the following equation,

$$Response\ (\%) = \left(\frac{I_{gas}}{I_{air}} - 1\right) \times 100 \tag{1}$$

where I_{gas} and I_{air} are the currents when exposed to the target gas and dry air, respectively. As the H_2S gas concentration increases from 10 ppm to 50 ppm, the max response value (@ t = 360 s) gradually increases (68%, 115%, 144%, 174%, and 214%).

B. Network Architecture

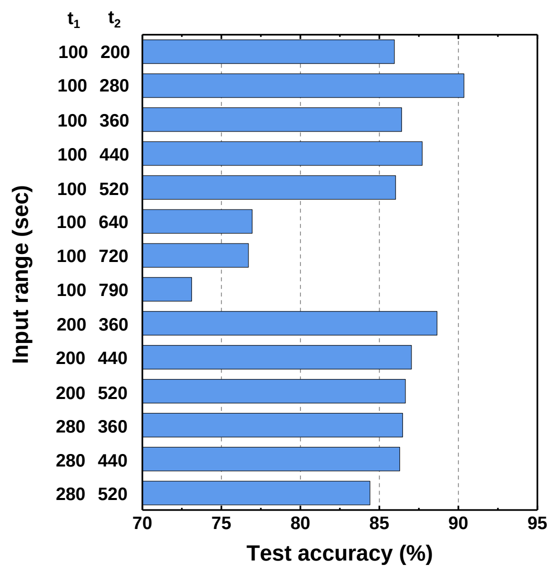

Fig. 5. Test accuracy with respect to a various time range (from t_1 to t_2) of transient gas response data. Note that the gas reaction starts at t = 50 s and reaches the maximum response value at t = 360 s (Fig. 2).

Fig. 3 shows the schematic diagram of the neurons and synapses of the SNN. The leaky integrate and fire (LIF) model is used to model the neuron dynamics. The membrane potential V is described by

$$\tau \frac{dV}{dt} = (E_{\mathrm{rest}} - V) + g_{\mathrm{e}}(E_{\mathrm{exc}} - V) + g_{\mathrm{i}}(E_{\mathrm{inh}} - V) \tag{2}$$

where τ is the time constant, E_{rest} is the resting membrane potential, g_{e} and g_{i} are the conductances of the excitatory and inhibitory synapses, and E_{exc} and E_{inh} are the equilibrium potentials of the excitatory and inhibitory synapses, respectively. The input spikes are multiplied by the weight of each synapse and this result is added up in the neuron. If the membrane potential exceeds the threshold voltage, an output spike is generated, sent to the next neuron, and the membrane potential is initialized.

The SNN architecture used in this study is shown in Fig. 4, which is based on the work of [7]. The network has a multi-layer architecture (784-100-100) including an input layer, an excitatory layer, and an inhibitory layer. The first layer is the input layer, containing a 28×28 two-dimension array of neurons, and the second and third layer is the excitatory and inhibitory layer, respectively (100 neurons each). The samples of the transient gas response curve are taken and reconstructed as an array of 28×28 values. The intensity value (0 or 126) of each sample is converted into a Poisson-spike train and fed to an input neuron. Input neurons are linked to the excitatory neurons in the form of an all-to-all connection. Excitatory neurons are connected to inhibitory neurons via a one-to-one connection. Also, each of the inhibitory neurons is connected to all excitatory neurons, except for its coupled neuron. For further details on the model structure and its operation, see [7].

Spike timing-dependent plasticity (STDP) method is used to train the SNN. The method updates the synaptic weights through the temporal relationship between the pre-synaptic spikes and the post-synaptic spikes, as shown in eq. (3)

$$\Delta w_{\mathrm{ij}} = \sum_{\mathrm{pre}} \sum_{\mathrm{post}} W(w_{\mathrm{ij}}, \Delta t) \tag{3}$$

where W is the learning function of STDP and Δt is the time difference between the pre-synaptic spike and the post-synaptic spike. If the Δt is positive, the weight is increased, and this process is called long-term potentiation (LTP). But if the Δt is negative, the weight is decreased, and this process is called long-term depression (LTD).

III. Results and Discussion

The SNN network described above was implemented using an SNN library [8]. The network was trained with 5,000 examples (1,000 gas response curves for each H_2S gas concentration from 10 ppm to 50 ppm) prepared by adding random noise to the original curves. The training was repeated twice and then afterward, 1,000 examples were used to test the trained neural network. The accuracy of the gas concentration level estimation is averaged over the 1,000 test sets.

We have chosen fourteen different time ranges and compared the results after training the network with the data within the chosen time ranges. The testing accuracy results are shown in Fig. 5. Training the network with the data within a time range of t_1 = 100 s to t_2 = 280 s showed the highest accuracy of 90.35%. The accuracy tends to decrease when t_2 is greater than 360 s at a fixed t_1 = 100 s. In particular, when t_2 is greater than 640 s, the accuracy drops below 76.95%. Note that the gas response reaches the maximum value at t = 360 s (Fig. 2). The accuracies when t_2 = 360 s, 440 s, and 520 s (86.41%, 87.71%, and 86.03%) at a fixed t_1 = 100 s have no significant difference from the accuracies when t_1 = 200 s (88.65%, 87.03%, and 86.65%) or t_1 = 280 s (86.47%, 86.29%, and 84.01%) together with the same t_2.

IV. Conclusions

In this work, we have designed a spiking neural network and trained it with transient gas response data within various limited time ranges. Transient responses at five different H_2S concentrations for our experiment were obtained from the resistor-type gas sensor having In_2O_3 as a sensing material. The effects of various time ranges of the input data on testing accuracy were investigated. Training and testing the network with the front part of the input data (from t = 100 s to t = 280 s) showed the highest accuracy of 90.35%. It is quite interesting that this range does not include the time when the maximum response value appears (t = 360 s). Considering that it takes about 800 s for the gas sensor to fully recover, time-efficient estimation of gas concentration level is possible by training the spiking neural network in the way studied in this paper.

Acknowledgements

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