Implementation of Electronic Nose in Omni-directional Robot

Harianto, Mohammad Rivai, Djoko Purwanto

Department of Electrical Engineering, Institute Teknologi Sepuluh Nopember (ITS)

Article Info	ABSTRACT
<i>Article history:</i> Received Jan 12 th , 2013 Revised Feb 20 th , 2013 Accepted Mar 26 th , 2013	Electronic nose (E-nose) is a device detecting odors which is designed to resemble the ability of the human nose. E-nose can identifying chemical elements that contained in the odors. E-nose is made of arrays of gas sensor, each of it could detect certain chemical element. When detects gases, each sensor will generate a specific pattern for each gas. These patterns could be classified using neural network algorithm.
<i>Keyword:</i> Electronic nose Multi layer perceptron Gas sensor	Neural network is a computational method based on mathematical models which has the structure and operation of neural networks which imitate the human brain. Neural network consists of a group of neurons conected to each other with a connection named weight. The weights will determine wether neural networks could compute given inputs to produce a specified output. To generate the appropriate weight, the neural network needs to be trained using a number of gasoline and alcohol samples. The training process to generate appropriate weights is done by using back propagation algorithm on a personal computer. The appropriate weight then transferred to omni-directional robot equipped with e-nose. The result shows that the robot could identify the trained gas.
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Corresponding Author:

First Author, Department of Computer Engineering, STIKOM Surabaya, Raya Kedung Baruk 98, Surabaya 60298, Indonesia. Email: hari@stikom.edu

1. INTRODUCTION

Nowadays, gas sensor has developed vastly, it begins for detection gas in our surrounding environment such us carbon dioxide, carbon monoxide, ethanol, methane and oxygen. This invention of gas sensor has lead to many researchers to explore and do experiment in several fields such as in medical, industry and military. Nowadays several gas sensors with certain specification were combined as an array sensor so that it could be identify some certain scent containing gasses that specified with the gas sensors. Green et al project to discriminating bacteria in suspension based on the scent has been done using electronic nose method [7].

The gas sensor usually is attached in a mobile robot and designed like human nose and it is called electronic nose. This project, which is to recognize object that has certain smell, have been done by Lilienthal et al [10], [11] in 2001 and Loutfi et al in 2005 [12], since then, application and research based on electronic nose attached to mobile robot become popular.

Lilienthal et al in the research has successed to mapping gas concentration in building using mobile robot [9]. Zang et al designed mechanical electronic nose with the sensor arrays inside [16]. This research has problem that gas sensor can not detect similar gas which has similarity chemical characteristics. This problem can be solved using neural network algorithm.

The previous works about mobile robot with electronic nose that using neural network have been done by Duckett et al [5], Farah et al [6], and Ishida et al. But their objective were to locate the odour source using learning algorithm to guide the robot direction.

In this research, neural network is used to detect several different gasses with has similarity chemical characteristics. However, processing neural network algorithm training stage on a robot will burden the processing unit in the robot. So, the training process will be done on the computer. When the appropriate weights are generated, those weights will be transferred to the robot. The robot's processing unit will only need to compute a feed forward neural network.

a. Neural Network

Neural Network (NN) can be used to solve non linear and complex function. When it is used to design Multi-Input Single-Output (MISO) systems, NN mapp n-dimension input to single dimension output [1]. In field control, input usually comes from error which is difference from real outputs and set point. In this paper, NN has function a pattern recognition of electronic nose to identify certain gas.

Neuron in artificial intelligent acts as a biology nerve. Several input (x) will multiply with each appropriate weight (w).

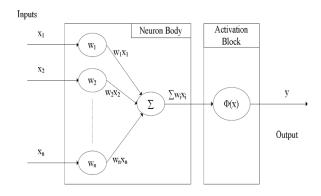


Figure 1. Neuron Model

Then add all the result of multiplication with output from inside activation function to take single degree output F(x,w) [2], this process can be seen in Figure 1.

$$in_i = \sum_j W_{ji} * a_j \tag{1}$$

To activate each neuron in NN network need activation function such as hiperbolic function, step, impulse and sigmoid. Sigmoid function, like shown in Figure 2, amongs the other activation function, is closer with the real function of brain, so it's often used in many research.

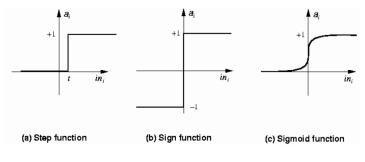


Figure 2. Activation Function

Set of neuron can become a network which has function as computation equipment to solve problem. The amount of neuron and network architecture for each problem has different solution. NN architecture for generall can be seen in Figure 3.

From the Figure 3, two inputs (v1 and v2) are connected to hidden layer with weight w1 until w6. Output from hidden layer is connected to hidden layer with weight w11 until w21.

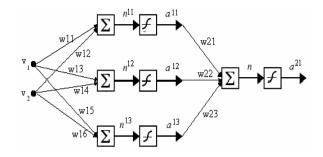


Figure 3. Architecture Neural Network

b. Gas Sensor

Four gas sensors from Figaro Engineering Inc [17] were used in this research. They are TGS 2600, TGS 2610, TGS 2611, and TGS 2612. Main part of TGS is a semiconductor metal oxide. TGS sensor has a resistance sensor that is dependent to oxygen concentration contacting directly with semiconductor metal oxide. The changes of potential barrier intergrain from tin oxide gas sensor can be seen in Figure 4. Figure 4 (a) shows the changes without any chemical gas, while Figure 4 (b) shows movement when there is any chemical gas. Oxygen increases barrier potential level. This causes increase resistance of sensor material. If there is any chemical substance detected by the sensor, oxide intensity would be reduced by the concentration of oxygen. This situation leads the reduction of the barrier potential intergain as it is seen in Figure 4(b) and reduce the resistance of resistor.

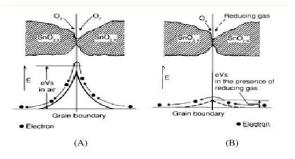


Figure 4. Intergrain Potential Barrier

Relation between sensor resistant and gas concentration can be seen in Equation 2.

 $R = A [C]^{-\alpha}$

(2)

Which R is resistant sensor metal-oxide, C is gas concentratrion, A is coefficient response for some gases, and α is sensitivity. A and α depend on material type of sensor and temperature sensor.

Sensor TGS has two main parts; first part is tin oxide (SnO2) as sensor material. This material is connected to pin 2 and 3. Second part is the heater for heating sensor material. This heater is connected to pin 1 and 4. Figure 5 show the structur of gas sensor TGS 26XX.

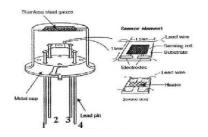


Figure 5. TGS Sensor Structure

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Schematic for Sensor TGS can be seen in Figure 6. Sensor TGS needs supply circuit (Vc) and also heater which has input power (VH) respectively in pin 1 and pin 4. A load is connected to pin 2. This load will be used as concentration measurement of gas which is in.

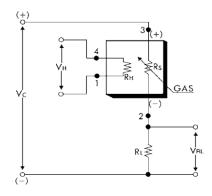


Figure 6. TGS Schematic

c. Omni-directional Robot

Omni-directional robot is a robot with a steering system which could move in all direction. This steering system is using omni directional poly roller wheel (omni-wheel). Figure 7 shows that robot with omni-wheel could perform a complex movements to reach a specific position. This steering system enables the robot to moving in x and y axis, so it has two degree of freedom (DoF). Usually, there are omni-directional robot's that using 3 or 4 omni-wheels. The configuration of these omni-wheels position on the robot will affect robot's movements significantly. The farther the distance of front and rear wheels, the faster the robot could rotate.

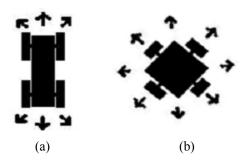


Figure 7. Difference between the (a) standard and (b) omni-directional wheel's movement

Since research done by Dickerson et al [4] in 1991 about omni-directional robot using mecanum wheels, there have been many research group that developing an omni-directional robot like Mori et al [14] that are studying about the mechanism and the running modes of the omni-directional robot.



Figure 8. Omni-directional robot

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In this research, we use a modular omni-directional robot from FESTO called Robotino® the same like the one used by Treesatayapun [15]. The robot could be equipped with various device. The features that are used in this research are 4 pins analog input, 4 I/O pins with 0-10V voltage level, webcam, and wireless connection to controlling the robot from computer. Figure 8 shows the omni-directional robot that is used.

2. RESEARCH METHOD

Previous research about methanol and ethanol has been done by Marques [13]. Marques used only one gas sensor as robot navigation tool to locate gas location. In our research, we used an array gas sensor that will be used as electronic nose to identify combustible gasses such as gasoline and alcohol. In this research, four kind of gas sensors were used to process the input. They are TGS 2600, TGS 2610, TGS 2611, and TGS 2612. Three procedures is used in this project. Firstly, taking sample array sensor data form different gases, for instance gasoline, alcohol, and other gasses such as general odor and methane. This step is done with the modified electronic nose practical diagram from Daqi's research [3]. Secondly, those data Were trained in computer using back propagation algorithm. The result of this process are appropriate weight weight and bias for each neuron. Finally the last procedure, this weight and bias implemented in robot using the same network when it was trained. The program controlled the robot actually run from the computer that connected with robot using wireless communication. Figure 9 shows the block diagram of the system.

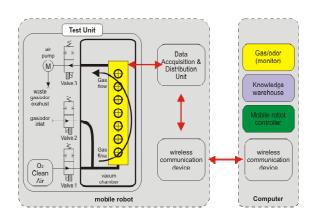


Figure 9. Block diagram of the system

Figure 10. Perceptron architecture for electronic nose

(3)

$$f(y) = \frac{1}{1 + e^{-\alpha y}}$$

Figure 10 shows the neural network architecture used in this research. Figure 10 revealed that input analog (x) comes from array sensor and bias then multiply with weight (w). The result is output neuron that has summing function from multiplication (x) and (w) and then the neuron activated using sigmoid function.

3. RESULTS AND ANALYSIS

3.1. Response gas sensor

Data which are received from gas sensor are used as data training to determine the weight and bias. Gas sensors (TGS 2600, TGS 2610, TGS 2611, and TGS 2612) were tested with gasoline and alcohol. Output signal from gas sensors can be presented in Figure 11.

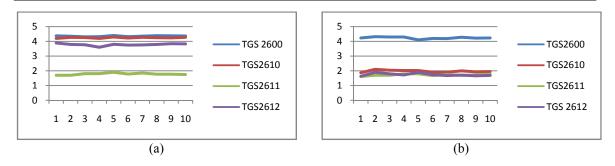


Figure 11. Output of Gas Sensors (a) gasoline (b) alcohol

3.2. Neural network training

The target output of neural network was able to recognize the gasses tested. The target of the neural network can be seen in Table 1.

Table 1. Neural network target				
Jenis Gas	Target			
Jeins Gas	\mathbf{n}_1	n_2	n ₃	
Gasoline	1	0	0	
Alcohol	0	1	0	
Other	0	0	1	

All the 30 data from gas sensor were used to search weight (w) and bias (b). Weight and bias were obtained by entering data training and target in training program, the process to get the weights and bias was shown in Figure 12. The training process parameters used were learning rate (μ) = 0.1, least error = 0.0001 (10⁻⁴), and max iteration = 1,000,000,000 (10⁹). The training process was convergence at 781,338,964 iteration with error (SSE) value = 9.99989696745863E-05. The weight and bias trained then were tested using data trained and new data.

MLP-Pattern Recognition		_				
PENGENALAN	N POLA	GAS PADA	ELECTR	ONIC NO	DSE	
Network Setting		Entry Data Le				
Input Neuron	4		Input Data			
Number of Hidden Layer	2	TGS 2600	TGS 2610	TGS 2611	TGS 2612	
Hidden Layer 1 Neuron 💌	20	1	Output	Target		
Output Neuron	3	Bensin	Alke	ohol	Other	
Reset Network Set N	etwork	5	5		10	
Learning Parameter Setting —	Data Entered	20	20 Input from File			
Learning Rate 0,1	- Testing-					
Least SSE 10E-5	TGS 26	500 TGS 2610	TGS 2611	TGS 2612	:	
Max Iteration 10E+8						
Start Learning	Alkohol -			lest		
	Other					
Continue Learning	other					
Iteration					_	
781338964	Input Ne	uron				
SSE	Number	of Hidden Layer				
9,99989696745863E-05		Hidden Layer 1 Neuron 👻		Load Weight	۲II	
Convergent Out		tput Neuron				

Figure 12. Training weight and bias process

3.3. Identification result

The identification results shown in Table 2. It shows that the success percentage for defined gas, gasoline in experiments 1 - 10 and alcohol ini experimetns 11-20, is 100% each, but when it is tested with other odor gasses, such as air, smoke, methan, etc., like in experiments 21-30, the percentage success rate is down to 70%. So the global success rate is 90% for the trained gasses.

			Т	able 2. Iden	tification Resu	ılt		
No	Tested Gas	Gas Identified	No	Tested Gas	Gas Identified	No	Tested Gas	Gas Identified
1	Gasoline	Gasoline	11	Alcohol	Alcohol	21	Other	Alcohol
2	Gasoline	Gasoline	12	Alcohol	Alcohol	22	Other	Other
3	Gasoline	Gasoline	13	Alcohol	Alcohol	23	Other	Alcohol
4	Gasoline	Gasoline	14	Alcohol	Alcohol	24	Other	Gasoline
5	Gasoline	Gasoline	15	Alcohol	Alcohol	25	Other	Other
6	Gasoline	Gasoline	16	Alcohol	Alcohol	26	Other	Other
7	Gasoline	Gasoline	17	Alcohol	Alcohol	27	Other	Other
8	Gasoline	Gasoline	18	Alcohol	Alcohol	28	Other	Other
9	Gasoline	Gasoline	19	Alcohol	Alcohol	29	Other	Other
10	Gasoline	Gasoline	20	Alcohol	Alcohol	30	Other	Other

4. CONCLUSION

The neural network implemented on omni-directional robot is successfully identify determined gasses such as gasoline and alcohol with success rate 100%, but when it is tested with other gasses which is not trained, the success rate is down to 70%. It might be because there were no sample to those other gas that is failed to tested, so the neural network is being confused to determine which class is those gasses.

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BIBLIOGRAPHY OF AUTHORS

Harianto received BE degree from STIKOM Surabaya in 2002, ME degree from Gadjah Mada University in 2010. He is currently a lecturer at Computer Engineering Department, STIKOM Surabaya, Indonesia. His research interest is in intelligence control system.
Muhammad Rivai received BE degree from Institute of Technology Sepuluh Nopember in 1993, ME degree from University of Indonesia in 1997, PhD degree from University of Airlangga in 2006. He is currently a lecturer at Electrical Engineering Department, Institute of Technology Sepuluh Nopember, Surabaya, Indonesia. His research interest includes odor sensors, electronic circuits, and neural network applications.
Djoko Purwanto received Master and Phd from Keio University Japan. His research interest is in Industrial Robot and Robot Vision.