

Data Optimization on Multi Robot Sensing System with RAM based Neural Network Method

Ahmad Zarkasi¹, Siti Nurmaini²

Robotic Research Laboratory, Computer Engineering Department Faculty of Computer Science, Sriwijaya University
 Jalan Palembang-Prabumulih Km.32, Inderalaya, OI, South Sumatera 30662, Indonesia

¹zarkasi98@gmail.com

²siti_nurmaini@unsri.ac.id

Abstract— Monitoring the environment activities is an attractive thing for development. That is because the human life would affect the surrounding environment. There's a lot of research of environment has been done, one of those is the changes of air quality in urban areas. To measure the level of air quality, the data and information from field measurements and laboratory analysis result was needed. This paper review the research result that focus on sensor data processing in multi robot using RAM based neural network. There are 11 pattern input data were processed by temperature data optimization from 25°C until 35°C, humidity data from 20% until 60% and gas data from 350ppm until 450ppm. The obtained result is from 8 bits and 9 bits become 6 bits in certain level with optimization percentage is 25% and 33,3%. This result effect to the computation load, it's become more simple, the execution time and data communication becomes faster.

Keywords—Air Quality, Multi Robot, RAM based neural network dan data optimization.

I. INTRODUCTION

Monitoring the environment activities is an attractive thing for development. That is because the human life would affect the surrounding environment. There's a lot of research of environment has been done, one of those is the changes of air quality in urban areas [2][3]. To measure the level of air quality, the data and information from field measurements and laboratory analysis result was needed. One of the control and monitoring system is currently being developed is the Intelligent Wireless Mobile Sensor Network (IWMSN).

IWMSN system consist of switching nodes which are individual that able to interact with its environment by sensing, controlling, and communication on the physical parameters. In applications IWMSN system can be made using a combination of static sensor and robotic networks that spread as a base station and mobile station [4][10].

The principle of sensor data processing in application can also be combined with ram-based neural network method. The mechanism is input data amount 2^n will be in group into small group, each data group will processed on certain level and produce the desired output data. For obtained data sensor optimization, ram optimization technique that only process the data on most significant bit (MSB) is one of method approach that best to solve the problem above. Meanwhile the algorithm would help in solving the data processing problem in each data group in certain level [13] [18][20].

For the detection of source simultaneously, using a group of robot (swarm robot) has been developed lately, using a

technology derived from a flock of bird's behavior, fish swarm, a colony of ants or a swarm of bees [9].

II. SYSTEM OVERVIEW

A. RAM Node

Basic architecture of artificial RAM based neural network is single general neural (SGN) or RAM node. SGN was the most primary component, which is comparable to a node of a conventional neural network. A single SGN consists of input vector, memory register, data input register and data output register. Input vector was divide into several parts, each part was connect to the address input of the RAM 1-bit units. SGN hereinafter called RAM node [19][24]. Figure 1 is a RAM node.

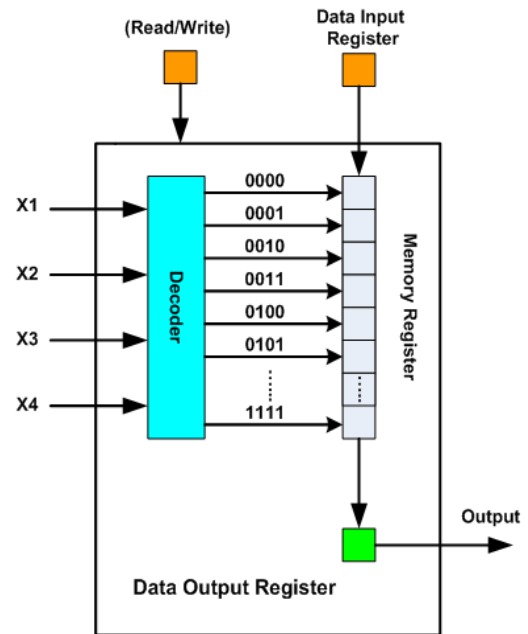


Fig 1. RAM node

B. RAM Discriminator

A RAM-discriminator consists of a set of X bit word RAMs with n inputs and a summing device (Σ). Any such RAM-discriminator can receive a binary pattern of $X.n$ bits as input. The RAM input lines were connecting to the input pattern by a "biunivocal pseudo-random mapping". In order to train the discriminator one has to set all RAM memory locations to 0 logic and choose a training set formed by binary of $X.n$ bits patterns. For each training pattern, a 1 is stored in

the memory location of each RAM addressed by this input pattern. Once the training of patterns is completed, RAM memory contents will be set to a certain number of 0's and 1's. Figure 2 is a RAM discriminator [18].

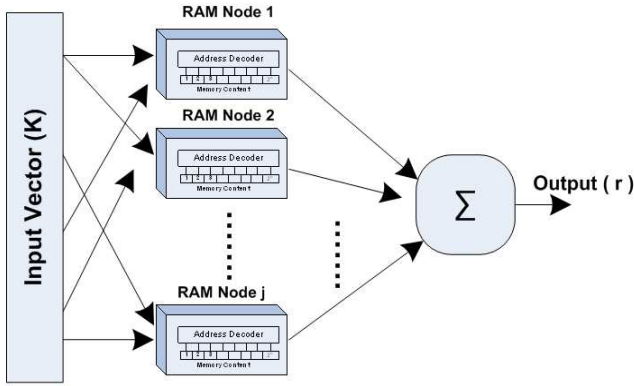


Fig 2. RAM discriminator

C. Multi Robot

Multi robot has a simple physical structure but powerful, each robot has a common behavior so able to cooperate, communicate, and coordinate [19]. There are some intelligence algorithm of swarm commonly used in optimization problem, one of that is particle swarm algorithm. Particle swarm optimization (PSO) Algorithm was first introduced by Dr. Eberhart and Dr. Kennedy in 1995 at neural network conference in Perth, Australia. PSO Algorithm is a stochastic-based optimization technique inspired by social behavior of a flock of birds and fish swarm [11].

Compared to the single robot approaches, multi robot-solution potentially provide the superiority in term of resistance to failure, accelerating the completion of a task because it work in paralel way or increase in accuracy due to the exchange of sensory information [22].

D. Temperature and Humidity Quality

: The temperature show the degre of heat object, the higher temperature of an object, the more heat that object. Microscopically, temperature shows the energy of an object. Each atom in each object is moving, whether it in displacement or movement in vibration place. The higher atoms energy that making up the object, the higher the temperature of that object [23].

According to Block and Richardson (2001), relative humidity of a mixtuer of water-air defined as a partial pressure of water vapor (e) in the mixture to saturated vapor pressure (e_s) at that temperature. Humidity relative using the unit percent and calculated this following way

$$RH = \frac{P(H_2O)}{P^*(H_2O)} \times 100\% \dots(1)$$

where:

RH is a relative mixture humidity

$P(H_2O)$ is partial pressure of water vapor and

$P^*(H_2O)$ is mixture to the saturated vapor pressure

E. Environmental Quality

In its development, the various research about environment localization using autonomous robot have been carried out to obtain the variety of alternative solutions, such as localization signal sources including the voice [16], light [3], the leaks in pressurized systems [7], the danger of aerosols from spilled nuclead/ chemical [17][8]. The fire's source in forest fires [20], Sea hydrothermal [21], hazardous chemical discharge in water body [6], and the spills of an oil [1]. But the research about simultaneously localization for various target has still rarely did [2].

III. HARDWARE IMPLEMENTATION

A. Single Robot

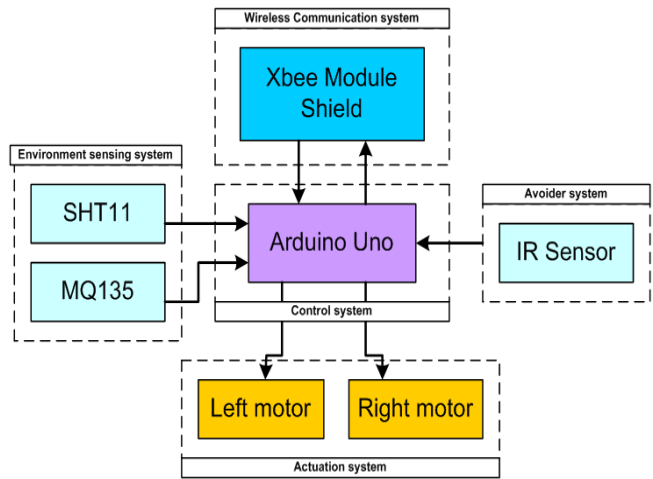


Fig 3. Single robot architecture

Figure 3 is a single robotic achitecture The purpose of designing single robot is to find out the characteristic, data retrieval and data processing individually. The environmental data such as temperature, relative humidity, and air quality.

B. Multi Robot

The purpose of designing the swarm robot is to find out the characteristic, data acquisition and data processing collectively. That environmental data such as temperature, relative humidity, and air quality have been first optimized using RAM-based neural network method. Figure 4 is a multi robot scheme.

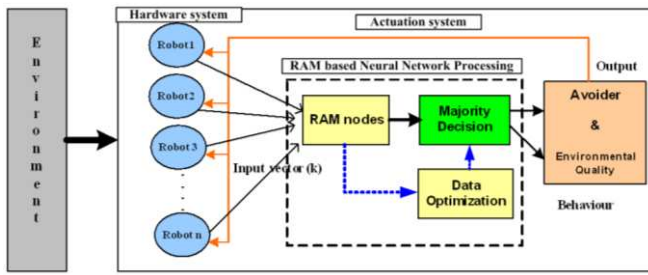


Fig 4. Multi robot scheme

C. RAM Node Data Optimization

The used strategy in this sensor data optimization is in its node RAM. Each RAM node will store 6 bits of input data that is 6 bits of MSB data. The processed data is temperature sensor data, humidity and gas sources with total 18 bits data. This is intended to make the input pattern becomes more optimal because there are only 3 pattern that is invisible, so the computational process become more simple. Design of RAM node can be seen in Figure 5.

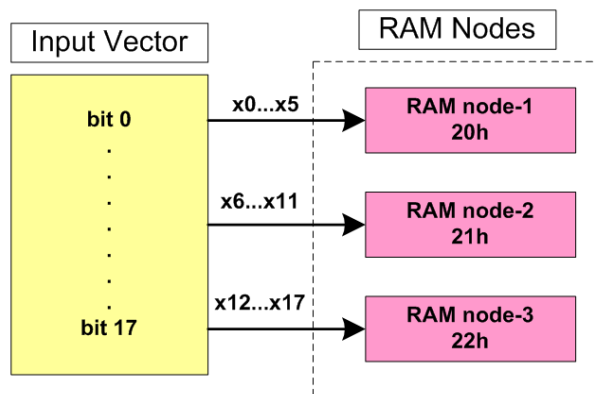


Fig 5. RAM node

In the design of RA node devide into 3 group of input data pattern, that is RAM node-1 for the temperature data, RAM node-2 for the humidity days, and RAM node-3 for the gas data. Sequentially, its data is 011001 until 011101, 001100 until 100110 and 01011001 until 1110011. All of the input data pattern has been optimized.

D. Discriminator Data Optimization

RAM discrimanator has 2 RAM nodes, each node has 6 bits word ($X=6$), with a total input vector 8 bits ($n=8$) so each RAM discriminator can receive 48 binary input patterns. In the design, there are 2 RAM discriminator. Discriminator_A is a temperature data and humidity, while Discriminator_B is the gas source data. The output of each discriminator will determine the winner of class winner. For the design block of RAM discriminator can be seen in Figure 6.

E. Training Process at Neural Network

Temperature sensor data, humidity and gas respectively stored at address 20h, 21h and 22h. This addresses is RAM

node address for each nerve. Temperature sensor reading range devided into two reading parameter group, that is **Medium** and **Warm**, with the data 011001 until 011011 and 011100 until 011101. While for humidity **Normal** and **Medium** with the data 001100 until 100011 and 100110 until 100111. For gas parameter is **Good** and **Bad**, with the data 1011001 until 1110011 and 1000000. The values of parameter above is a threshold value for the neural network. If the sensor value doesn't match the threshold, so the activation function indicates the input is o (0000b).

The class of neural that grouped in RAM discriminator, consist of 2 class. That is discriminator_A and discriminator_B, with consecutive addresses 30h and 32h. RAM discriminator receive the maximum data 10000b and minimal data 00100b. RAM discriminator_A and discriminator_B can determine the final result (output) directly (class winner).

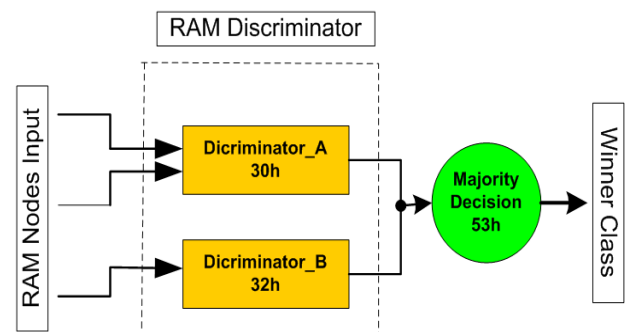


Fig.6 RAM discriminator

IV. EXPERIMENTAL EVALUATION

A. Input Pattern Data

Input data is the actual data being used as a reference data in data process to the neural network. Pattern input consist of 3 data group which is each temperature, humidity, and gas. Temperature data pattern is the data taken from temperature 25°C until 35°C, while the humidity data is 20% until 60%. For the gas data from 350pp, until 450ppm. Table I represents the data input pattern.

B. RAM Node Data Optimization

The result of RAM node can be seen in Table II, which is sensor data before and after optimization. The data that processed in RAM node only the data that has been optimization, that is 4 bits MSB data. There are 5 RAM nodes representing 5 of input patterns. The percentage of memory allocation optimization is 50% for each RAM node.

RAM node-1 data and RAM node-2 data were optimized in percentage is 25% and RAM node-3 data percentage is 33,3%.

C. Discriminator Data Optimization

Discriminator data grouped in discrimintaor_A thas has the maximal data 100110 and minimal data 001100. This data is the result from RAM node-1 and RAM node_2 process. Discriminator_B has the maximal data 111001 and minimal

data 101100. This data is the result from RAM node_3. For the detail can be seen in Table III.

TABLE I
INPUT PATTERN DATA

Input (Reference data)					
Temperature		Humidity (nonlinier)		Gas	
⁰ C	result	RH%	result	(ppm)	result
5	0100 0110	5	0000 1101	50	00 0011 0011
10	0100 1110	10	0001 1010	100	00 0110 0110
15	0101 0101	15	0010 0110	150	00 1001 1001
20	0101 1101	20	0011 0011	200	00 1100 1101
25	0110 0101	25	0100 0000	250	01 0000 0000
30	0110 1101	30	0100 1101	300	01 0011 0011
35	0111 0100	35	0101 1001	350	01 0110 0110
40	0111 1100	40	0110 0110	400	01 1001 1001
45	1000 0100	45	0111 0011	450	01 1100 1100
50	1000 1011	50	1000 0000	500	10 0000 0000
55	1001 0011	55	1000 1100	550	10 0011 0011
60	1001 1011	60	1001 1001	600	10 0110 0110
65	1010 0011	65	1010 0110	650	10 1001 1001
70	1010 1011	70	1011 0011	700	10 1100 1100
75	1011 0010	75	1011 1111	750	10 1111 1111
80	1011 1010	80	1100 1100	800	11 0011 0010
85	1100 0010	85	1101 1001	850	11 0110 0110
90	1100 1010	90	1110 0110	900	11 1001 1001
95	1101 0001	95	1111 0010	950	11 1100 1100
100	1101 1001	100	1111 1111	1000	11 1111 1111
105	1110 0001				
110	1110 1001				
115	1111 0000				
120	1111 1000				
125	1111 1111				

TABLE II
DATA OPTIMIZATION

Data Optimization				
RAM Node	Data 8 bits		Data 6 bits	
	Max	Min	Max	Min
RAM Node-1	0111 0011	0110 0010	0111 00	0110 00
RAM Node-2	1001 1001	0011 0011	1001 10	0011 00
RAM Node-3	1110 0110	1011 0011	1110 01	1011 00

TABLE III
DISCRIMINATOR DATA

Discriminator Data Optimization		
Discriminator	Data 6 bits	
	Max	Min
Discriminator_A	1001 10	0011 00
Discriminator_B	1110 01	1011 00

D.. Output Pattern Data

Table IV is output pattern table. The greatest pattern value is the best pattern value, which is produces output pattern system (winner class). In table above, output pattern produced was parameter environmental quality 9temperature, humidity, and gas). Each input pattern has 2 different input pattern This is cause by each pola has common data but the position from each neural is different.

TABLE IV
OUTPUT PATTERN

Input Pattern	Output Pattern		Explanation
0110 01	0101 1001	Medium	Temperature
0110 11	0101 10 11		
0111 00	0101 1100		
0111 01	0101 1101	Warm	
0011 00	1000 1100	normal	Humidity
1000 11	1010 0011		
1001 10	1010 0110		
1001 11	1010 0111	Medium	
1011 001	1110 1100	Good	Gas
1110 011	1111 0011		
1000 000	1100 0000		

V. CONCLUSION

The obtained result from the research are as follows, the taken sample data is the temperature data from temperature 25⁰C until 35⁰C, humidity data from 20% until 60% and gas data from 350ppm until 450ppm. The optimized data is done on 8 bits and 9 bits become 6 bits data in certai level, with optimization percentage 25% and 33%. This result is affect to the computation load to be more simple, the excecution time and data communication become faster.

Out of 11 input pattern will be selected the best input pattern to determine the output pattern (winner class) which is its quality environmental quality parameters (temperature, humidity, and gas).

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