Computer Engineering and Applications Vol. 11, No. 2, June 2022

Simulation Design of Artificial Intelligence Controlled Goods Transport Robot

Yurni Oktarina[1,2], Destri Zumar Sastiani[2], Tresna Dewi[2], RD Kusumanto[2]

[1]*Doctoral Program in Engineering Sciences, Universitas Sriwijaya*
[2]*Electrical Engineering Department, Politeknik Negeri Sriwijaya*
**yurni_oktarina@polsri.ac.id*

ABSTRACT

Technological advances enable scientists and researchers to develop more automated systems for life's convenience. Transportation is among those conveniences needed in daily activities, including warehouses. The easy-to-build and straightforward transport robot are desired to ease human workers' working conditions. The application of artificial intelligence (AI), Fuzzy Logic Controller, and Neural Network ensures the robot is able to finish assigned tasks better and faster. This paper shows the concept design of an AI-controlled good transport robot applied in the warehouse. The design is made as fast and straightforward forward possible, and the feasibility of the proposed method is proven by simulation in Scilab FLT and Neuroph.

Keywords: Fuzzy Logic controller, Neural Network, Mobile Robot, Transport Robot.

1. INTRODUCTION

The human need for technology is growing, so technology is proliferating in providing basic needs that have become the subject of the technology itself, such as speed, accuracy, and automation in which a process will occur continuously without human intervention [1]. Technological advancements affect many fields, including the warehousing industry [2]-[4]. The development of technology capable of automatically moving goods will be highly beneficial in the operation of every process in the warehouse [3][4]. A system that can assist humans in moving goods is required to accomplish this. This automated system is expected to assist or even replace the majority of the roles played by human workers in the transportation of goods [5]-[11].

A sensor is one of the components commonly used in designing an automated system, in this study, a mobile robot [12]-[15]. It is connected to a system and serves as an input, where the one applied in this study is the proximity sensor. In mobile robots and claws, proximity sensors are used to detect the distance between the robot and objects. In addition to sensors for input, robots require artificial intelligence (AI) to help them finish the assigned task. Fuzzy Logic Controller (FLC) [16]-[20] and Neural Network (NN) [21]-[26] are mainly used in AI.

This paper presents the Simulation Design of Artificial Intelligence Controlled Goods Transport Robot, in which the design is given in the mechanical and electrical circuits. The robot motion is governed by the rules set in the Fuzzy Logic Controller and Neural Network Controller to smooth the motion. The designed robot is equipped with a claw to grab the goods and transport them from one station to another.

2. METHODS

This research creates a mobile robot used in industry to transport goods. The robot moves using two artificial intelligence methods: the Fuzzy Logic Controller (FLC) and the Neural Network (NN). The application of FLC in the development of control systems enables the design of indirect controls 0 and 1 and the ability to make judgments based on sensor inputs, while the implementation of NN to control robot movement. The proximity sensor was employed in this study. Figure 1 is the diagram block to show the design of the mobile robot for transporting goods in this study.

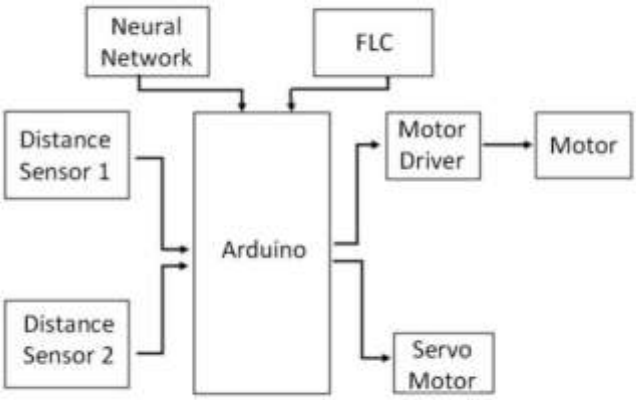


FIGURE 1. Diagram block of FLC and NN application in this study.

2.1 MECHANICAL DESIGN

The mechanical design of the mobile robot applied in this study is given in Figure 2. The body is made of acrylic with the features of easy to work with, strong, and not easy to crack.

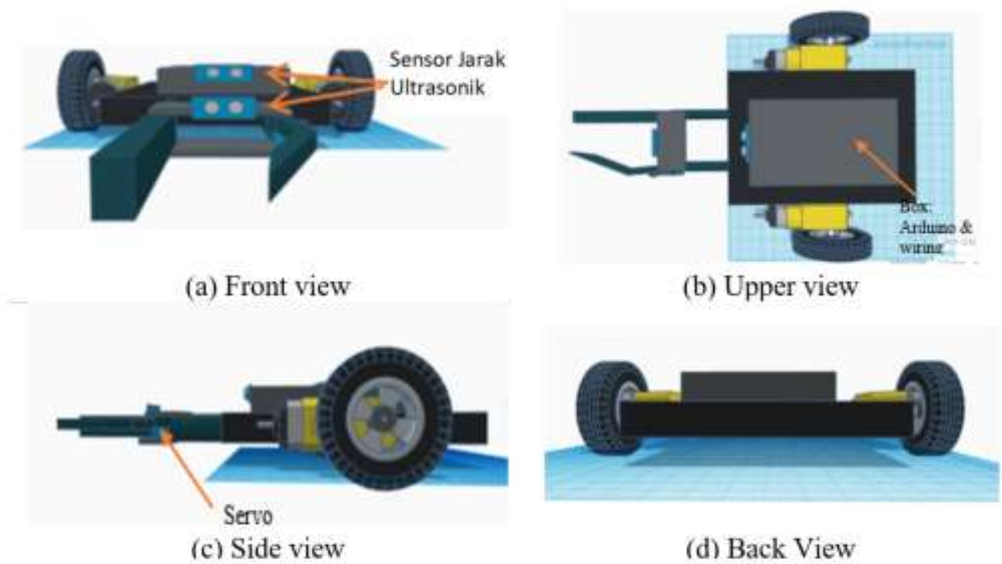


FIGURE 2. The mechanical design of goods transport mobile robot

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

The mechanical design in Figure 2 shows that the mobile robot is equipped with claws installed in from the robot to grab and place goods and move them to a predetermined place.

2.2 ELECTRICAL DESIGN

Figure 3 presents the mobile robot's electrical design or circuit schematic for transporting goods.

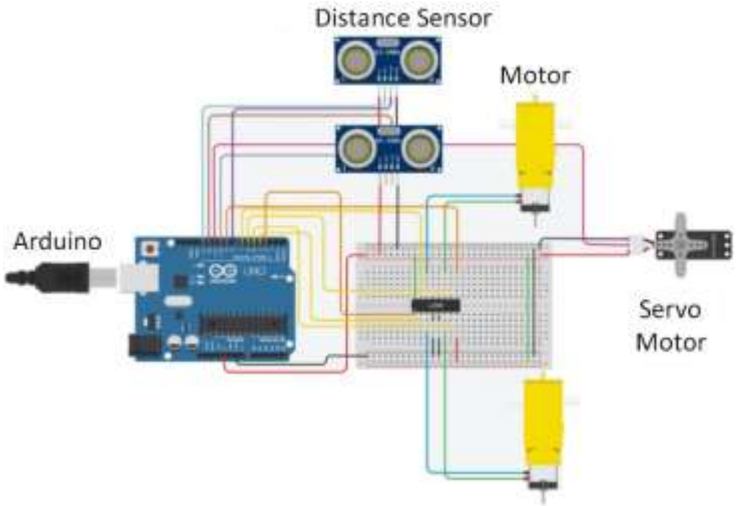


FIGURE 3. Diagram block of FLC and NN application in this study.

The following components are used in the electrical design shown in Figure 3: Arduino (with power supply), distance sensor, servo motor, motor driver (IC 1293D), and DC motor. When the distance sensor installed on the mobile robot detects the assigned good, the motors stop and activate the clam. As the clam approaches the goods, the distance sensor installed on the clam senses its proximity to the good. The distance sensor is necessary to ensure no crush on goods and obstacles; hence, the mobile robot can finish its assigned task well.

3. RESULT AND DISCUSSION

3.1 FLC DESIGN

Figure 3 presents the mobile robot's electrical design or circuit schematic for transporting goods. The Mamdani method with Triangular curves is used to design Fuzzy Logic Controller (FLC) in this system, and the Scilab FIS application is used in the simulation. The rule based is given in Table 1 by considering inputs from distance sensors and the outputs to move 2 DC motors and a servo motor.

TABLE 1.
Rules base for FLC design

No	Input		Output	
	Dist1	Dist2	Robot Motion	Claw
1	Near	Near	Stop	Open
2	Medium	Near	Slow	Open
3	Far	Near	Fast	Open
4	Near	Medium	Stop	Close
5	Medium	Medium	Slow	Close
6	Far	Medium	Fast	Close
7	Near	Far	Stop	Close
8	Medium	Far	Slow	Close
9	Far	Far	Fast	Close

The ultrasonic proximity sensor in this system has three linguistic variables with fuzzy sets; Near (0 – 50 cm), Medium (25 – 75 cm), and Far (50 – 100 cm) shown as the membership function in Figure 4.

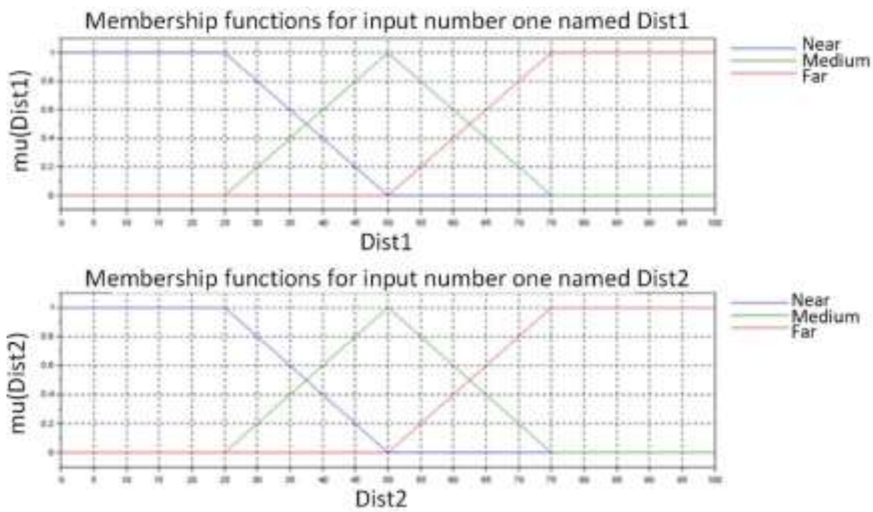


FIGURE 4. Input membership function considered in this study

DC motors considered in this study have three linguistic variables with fuzzy sets; Stop (0 – 125 rpm), Slow (50 – 175 rpm), and Fast (125 – 255 rpm). At the same time, the servo motor has two linguistic variables with fuzzy sets, namely Close (0 – 60o) and Open (30 – 90o). The output in this study is given as the output membership function in Figure 5.

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

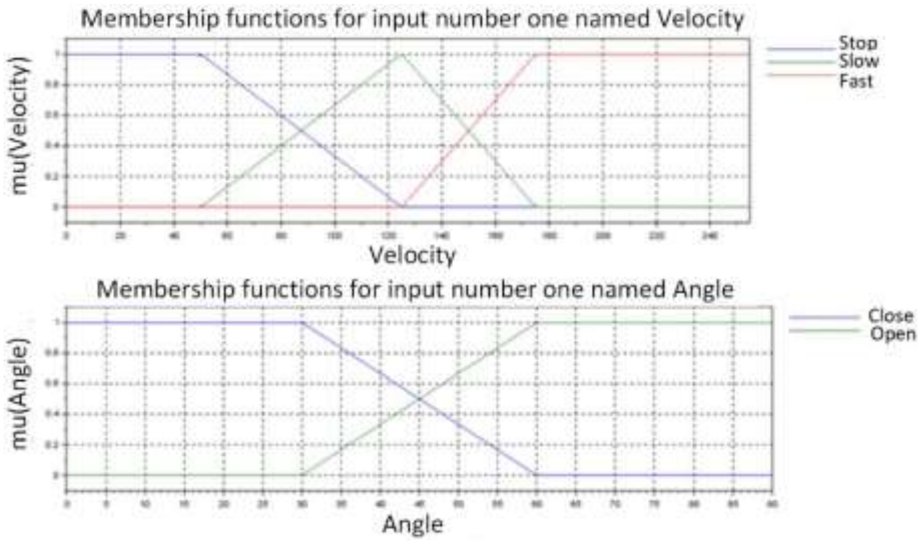


FIGURE 5. Output membership function considered in this study

The fuzzy sets continued into a process called fuzzification, which is the process of crisp mapping input from the controlled system into a functional fuzzy set [4]. Eqs show the fuzzification process, followed by inference which reasoning uses fuzzy input and predetermined fuzzy rules to produce the fuzzy output [5]. The inference of distance sensor is given by Eq. 1, motor velocity in Eq. 2, and servo motor angle in Eq. 3.

$$\mu_D[x] = \begin{cases} 0, \; x \geq 50 \\ \frac{50-x}{50-25}, \; 25 \leq x \leq 50, \\ 1, \; x \leq 25 \end{cases}$$

$$\mu_S[x] = \begin{cases} 0, \; x \leq 25; \; x \geq 75 \\ \frac{x-25}{50-25}, \; 25 \leq x \leq 50 \\ \frac{75-x}{75-50}, \; 50 \leq x \leq 75 \end{cases} ,$$

$$\mu_J[x] = \begin{cases} 0, \; x \leq 50 \\ \frac{x-50}{75-50}, \; 50 \leq x \leq 75. \\ 1, \; x \geq 75 \end{cases} \tag{1}$$

$$\mu_B[x] = \begin{cases} 0, \; x \geq 125 \\ \frac{125-x}{125-50}, \; 50 \leq x \leq 125, \\ 1, \; x \leq 50 \end{cases}$$

$$\mu_L[x] = \begin{cases} 0, \; x \leq 50; \; x \geq 175 \\ \frac{x-50}{125-50}, \; 50 \leq x \leq 125 \\ \frac{175-x}{175-125}, \; 125 \leq x \leq 175 \end{cases} , \tag{2}$$

$$\mu_C[x] = \begin{cases} 0, \; x \leq 125 \\ \frac{x-125}{175-125}, \; 125 \leq x \leq 175. \\ 1, \; x \geq 175 \end{cases}$$

$$\mu_T[x] = \begin{cases} 0, \; x \geq 60 \\ \frac{60-x}{60-30}, \; 30 \leq x \leq 60, \\ 1, \; x \leq 30 \end{cases}$$

$$\mu_B[x] = \begin{cases} 0, \; x \leq 30 \\ \frac{x-30}{60-30}, \; 30 \leq x \leq 60. \\ 1, \; x \geq 60 \end{cases}$$

(3)

The fuzzy sets continued into a process called fuzzification, which is the process of crisp mapping input from the controlled system into a functional fuzzy set [4]. Eqs show the fuzzification process, followed by inference which reasoning uses fuzzy input and predetermined fuzzy rules to produce the fuzzy output [5]. The final process in fuzzy logic is defuzzification, which aims to convert each result from the inference engine expressed as a fuzzy set to a real number [6]. The following steps depict the process

- Motor speed = 165 → 20% Slow and 80 % Fast. Fast = (2 x 125 + 8 x 175) / 10 = 165
- Servo motor angle = 50 → 33,3% Close and 66,6% Open. Open = (3,3 x 30 + 6,7 x 60) / 10 = 50,1

3.2 NN DESIGN

This system is designed using a Neural Network (NN) in addition to FLC. The type of NN used in this study is Single Layer Perceptrons (SLP). A single layer perceptron (SLP) is an artificial neural network with only one processing layer[7]. The input data is routed directly to the output neuron through weights, and the sum of all dot products in each neuron connects the input variable and the 'weight.'

Perceptron can be trained simply by using the delta rule, which calculates the error generated by the output layer against the actual value, which is then used to correct the 'weight' weighting. The single-layer perceptron can only be used for linear separable problems, which means that the output boundaries are clearly defined and only have two possibilities [8].

The workings of a single layer where the input layer from the source node is projected directly to the neuron's (computing node's) output layer, but not vice versa. This modeling is a type of feedforward network, but what is meant by a single layer is the network's output. In contrast, the input has no effect because the computational process does not occur when inputting is absent [9]. This study used the Neuroph studio application for the Neural Network experiment. A truth table is required before the simulation can begin. The conversion value to binary is obtained using the rule base in Table 1 and presented in Table 2. The truth data in Table 2 is used for the NN training process.

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

TABLE 2.
Rules base conversion to binary table for NN Simulation

No	Input		Output	
	Dist1	Dist2	Robot Motion	Claw
1	0	0	0	1
2	1	0	1	1
3	1	0	1	1
4	0	1	0	0
5	1	1	1	0
6	1	1	1	0
7	0	1	0	0
8	1	1	1	0
9	1	1	1	0

The single-layer perceptrons used in this study given in Figure 6 have two input layers (In 1 and In 2) coming from two distance sensor input (front and claw sensor) and two neurons in the output layer (Out 1, Out 2) that represent the DC motor and servo motor.

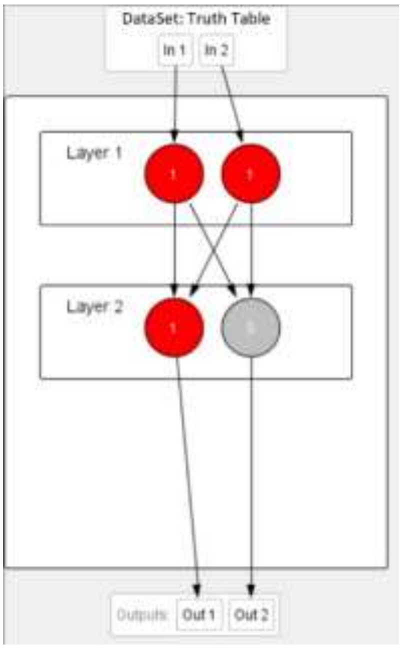
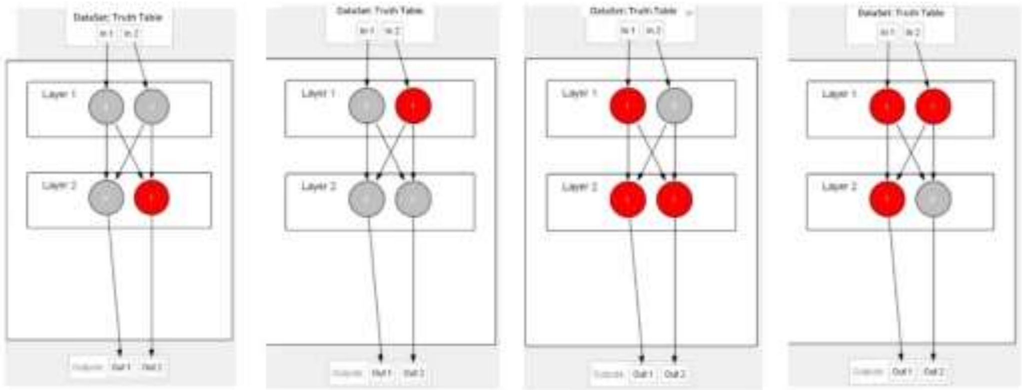


FIGURE 6. The simplified NN simulation

Before beginning the NN simulation, several other parameters must be set, including: max error = 0.01, learning rate = 0.5, Momentum = 0.0, learning algorithm = back propagation, input bias = 1, and connection weights = randomly assigned. The NN will generate wheel movement to move the robot to the right or left.



(a) Input 0 0 (b) Input 0 1 (c) Input 1 0 (d) Input 11

FIGURE 7. Single layer NN simulation considered in this study

Input: 0; 0; Output: 0; 1; Desired output: 0; 1; Error: 0; 0;
Input: 0; 1; Output: 0; 0; Desired output: 0; 0; Error: 0; 0;
Input: 1; 0; Output: 1; 1; Desired output: 1; 1; Error: 0; 0;
Input: 1; 1; Output: 1; 0; Desired output: 1; 0; Error: 0; 0;
Total Mean Square Error: 0.0

FIGURE 8. Data simulation result

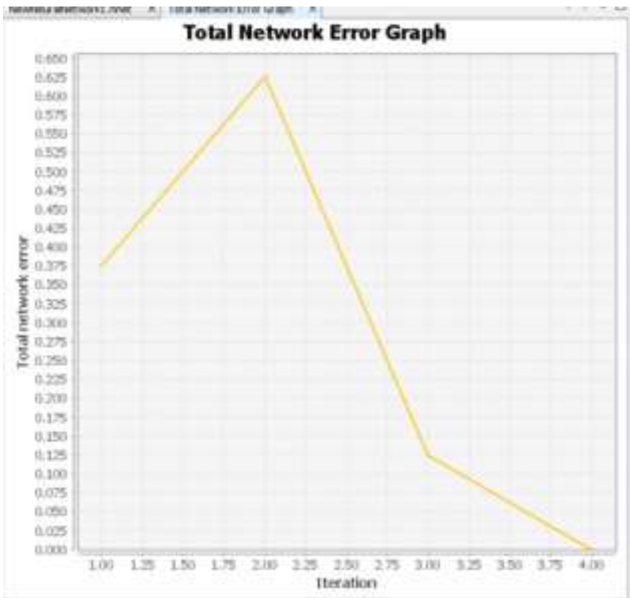


FIGURE 9. NN simulation result

After completing the Neural Network training, a test is performed to determine the total error and all individual errors. Figure 8 give the training results, showing the total error and all individual errors that occurred. The total mean square error is 0.0. The total mean square error is used to calculate the robot's motion error results in reaching the target. These results are promising, indicating that an effective method was used as a learning parameter. Figure 9 depicts the total network error graph, which shows an increasing and then decreasing graph.

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

4. CONCLUSION

This paper presents the design of AI controlled goods transport robot. The mechanical and electrical design are given to show the possibility of realizing the proposed method. The AIs presented here are FLC and NN. The proposed method effectiveness is proven by simulation in Scilab FLT for FLC and Neuroph for NN. The simulation results show that the AI controlled goods transport robot can be realized and simple to be implemented in warehouse or factory.

REFERENCES

[1] R. R. Shamshiri,C. Weltzien, I. A. Hameed, I. J. Yule, T. E. Grift, S. K. Balasundram, L. Pitonakova, D. Ahmad, and G. Chowdhary, "Research and Development in Agricultural Robotics: A Perspective of Digital Farming," Int. J. Agric & Biol Eng., Vol. 11, No. 4, pp. 1-14, 2018.

[2] Dewi T., Risma P., Oktarina Y., and Kusumanto RD., 2019, Motion Control Analysis of a Spherical Robot as a Surveillance Robot, Journal of Physics: Conference Series, 1167(1), 012004.

[3] Oktarina Y., Dewi T., and Risma T., 2020, The Concept of Automatic Transport System Utilizing Weight Sensor, *Computer Engineering and Application Journal*, 9(2), pp. 155-163. doi:10.18495/COMENGAPP.V0I0.339

[4] Dewi T., Risma P., Taqwa A., Rusdianasari, and Renaldi H., 2020, Experimental analysis on solar powered mobile robot as the prototype for environmentally friendly automated transportation, *Proc. iCAST on Engineering Science*, 24-25 Oct 2019, Bali: Indonesia, doi:10.1088/1742-6596/1450/1/012034.

[5] B.K. Patle, Alok Jha, Anish Pandey, N. Gudadhe, S.K. Kashyap, The Optimized Path For A Mobile Robot Using Fuzzy Decision Function, Materials Today: Proceedings, Vol 18, No 7, pp 3575-3581, 2019. https://doi.org/10.1016/j.matpr.2019.07.288.

[6] Dewi T., Risma P., Oktarina Y., and Muslimin S., 2018, Visual Servoing Design and Control for Agriculture Robot; a Review, pp. 57-62, *Proc. 2019 ICECOS*, 2-4 Oct. 2018, Pangkal Pinang: Indonesia. doi: 10.1109/ICECOS.2018.8605209.

[7] Dewi T., Risma P., and Oktarina Y., 2020, Fruit Sorting Robot based on Color and Size for an Agricultural Product Packaging System, *Bulletin of Electrical Engineering, and Informatics (BEEI)*, 9(4), pp. 1438-1445. doi: 10.11591/eei.v9i4.2353.

[8] Dewi T., Mulya Z., Risma P., and Oktarina Y., 2021, BLOB Analysis of an Automatic Vision Guided System for a Fruit Picking and Placing Robot, International Journal of Computational Vision and Robotics, 11(3), pp. 315-326. https://doi.org/10.1504/IJCVR.2021.115161.

[9] Dewi T., Anggraini C., Risma P., Oktarina Y., and Muslikhin, 2021, Motion Control Analysis of Two Collaborative Arm Robots in Fruit Packaging System, SINERGI, 25(2), pp. 217-226. http://doi.org/10.22441/sinergi.2021.2.013

[10] Oktarina Y., Dewi T., Risma P., and Nawawi M., 2020, Tomato Harvesting Arm Robot Manipulator; a Pilot Project, *Journal of Physics: Conference Series*, 1500, p 012003, *Proc. 3rd FIRST*, Palembang: Indonesia.

[11] Al Yahmedi A.S., and Fatmi M.A., 2016. Fuzzy Logic Based Navigation of Mobile Robots," Intech, 6, pp. 111-133.

[12] Dewi T., Uchiyama N., Sano S., and Takahashi H., 2014, Swarm Robot Control for Human Services and Moving Rehabilitation by Sensor Fusion, *Journal of Robotics*, 2014(278659), 11 pages. https://doi.org/10.1155/2014/278659.

[13] Dewi T., Amperawan, Risma P., Oktarina Y., and Yudha D. A., 2020, Finger Cue for Mobile Robot Motion Control, *Computer Engineering and Application Journal*, 9(1), pp. 39-48. doi: 10.18495/COMENGAPP.V9I1.319.

[14] Dewi T., Oktarina Y., Risma P., and Kartini S., 2019, Desain Robot Pengikut Manusia Sederhana dengan Fuzzy Logic Controller, Proc. Annual Research Seminar (ARS), 5(1), pp. 12-16, 16 Nov 2019, Palembang: Indonesia.

[15] Uchiyama N., Dewi T., and Sano S., 2014, Collision Avoidance Control for a Human-Operated Four Wheeled Mobile Robot, *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, 228(13), pp. 2278-2284. https://doi.org/10.1177/0954406213518523.

[16] Oktarina Y., Septiarini F., Dewi T., Risma P., and Nawawi M., 2019, Fuzzy-PID Controller Design of 4 DOF Industrial Arm Robot Manipulator, Computer Engineering and Application Journal, 8(2), pp. 123-136. doi: 10.18495/COMENGAPP.V8I2.300.

[17] Nurmaini S., Tutuko B., Dewi K., Yuliza V., and Dewi T., 2017, Improving Posture Accuracy of Non-holonomic Mobile Robot system with Variable Universe of Discourse, *TELKOMNIKA*, 15(3). Pp. 1265-1279. doi: 10.12928/TELKOMNIKA.v15i3.6078.

[18] Dewi T., Wijanarko Y., Risma P., and Oktarina Y., 2018, Fuzzy Logic Controller Design for Leader-Follower Robot Navigation, *5th Proc. EECSI*, 5(1), pp. 298-303. 16-18 Oct 2018, Malang : Indonesia. doi:10.1109/EECSI.2018.8752696.

[19] Dewi T., Risma P., and Oktarina Y., 2018, Fuzzy Logic Simulation as a Teaching-learning Media for Artificial Intelligence Class, Journal of Automation Mobile Robotics and Intelligent Systems, 12(3), pp. 3-9, 2018, DOI: 10.14313/JAMRIS_3-2018/13

[20] Dewi T., Sitompul C., Risma P., Oktarina Y., Jelista R., Mulyati M., 2019, Simulation Analysis of Formation Control Design of Leader-Follower Robot Using Fuzzy Logic Controller, Proc 2019 ICECOS, 2-3 Oct. 2019, Batam Island: Indonesia. doi:10.1109/ICECOS47637.2019.8984433.

[21] Farooq U., Amar M., Asad M.U., Hanif A., and Saleh S.O., 2014. Design and Implementation of Neural Network of Based Controller for Mobile Robot Navigation in Unknown Environment. *International Journal of Computer and Electrical Engineering*, 6(2), pp. 83-89. doi:10.7763/IJCEE.2014.V6.799

[22] Yudha H. M., Dewi T., Hasana N., Risma P., Oktarina, Y. Kartini S., 2019, Performance Comparison of Fuzzy Logic and Neural Network Design for Mobile Robot Navigation, *Proc. 2019 ICECOS*, 2-3 Oct. 2019, Batam Island: Indonesia. doi:10.1109/ICECOS47637.2019.8984577

[23] Larasati N., Dewi T., and Oktarina Y., 2017. Object Following Design for a Mobile Robot using Neural Network. *Computer Engineering and Application Journal*, 6(1), pp. 5-14. doi:10.18495/COMENGAPP.V6I1.189.

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

[24] Dewi T., Risma P., Oktarina Y., and Roseno M.T., 2017. Neural Network Design for a Mobile Robot Navigation a Case Study. *4th Proc. EECSI*. 23-24 Sep. 2017. Yogyakarta: Indonesia. doi:10.1109/EECSI.2017.8239168.

[25] Dewi T., Risma P., Oktarina Y., and Nawawi M., 2017. Neural Network Simulation for Obstacle Avoidance and Wall Follower Robot as a Helping Tool for Teaching-Learning Process in Classroom. *1st Proc. ICEAT*, 29-30 November 2017, Mataram: Indonesia. doi:10.1088/1757-899X/403/1/012043

[26] Risma P., Dewi T., Oktarina Y., and Wijanarko Y., 2019. Neural Network Controller Application on a Visual based Object Tracking and Following Robot. *Computer Engineering and Application Journal*, 8(1). doi: 10.18495/COMENGAPP.V8I1.280.