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DEVELOPMENT OF AN INTELLIGENT ROBOTIC GRIPPER FOR OBJECT MANIPUTATION USING ADAPTIVE CONTROLLER

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Abstract

This study presents development of an intelligent robot gripper for précised object manipulation using adaptive controller. The aim was to counter the impact of slip and position displacement constraints on object during grabbing, thus making the gripper inefficient. The methodology employed is the experimental and simulation approach. The methods used are experimental investigation of gripper performance developed with Dahl controller, data collection at Robotics and Artificial Intelligence in Nigeria (R.A.I.N) company, development of the gripper position algorithm using the output from proximity sensor, modelling of the adaptive controller using machine learning, development of the intelligent gripper system. The system was implemented with Simulink and tested. The performance of the adaptive controller when examined with Mean Square Error (MSE) was 1.094e-10Mu; the Regression (R) performance was 1. The implication was that the error which occurred during the training of the adaptive controller was tolerable and the controller based on the R values showed it can detect position changes and apply necessary force to hold the object. The step response of the adaptive controller is 10ms as against 45ms in the characterized Dahl controller, thus giving a percentage improvement of 23.33%. The adaptive controller when implemented on the gripper system and evaluated showed that it was able to apply the desired control force necessary for object grabbing and manipulation.

Keywords: Robot; Intelligent Robot Gripper; Adaptive Controller; Dahl Controller; Artificial Intelligence.

1. INTRODUCTION

In the last six decades, robotic technology has revolutionized the industrial sector (Marc et al., 2018) as a redundancy means to help facilitate technical process and maintain standard of production. This is because, robot has the capacity to perform complex and dangerous task repeatedly, execution of multi-functions tirelessly and accurately in faster time at a lower cost compared to humans. Due to this reason, the technology is one of the fastest expanding fields of scientific research with versatility in applications ranging from surveillance, planetary exploration, patrolling, emergency rescue operations, reconnaissance, petrochemical applications, industrial automation, construction, entertainment, museum guides, personal services, intervention in extreme environments, transportation, medical care, and so on, as well as many other industrial and nonindustrial applications. Most of these are already available on the market (Denica et al., 2018).

Flexible robot manipulator arms have been a research area for the last four decades now. This research involves the modelling the dynamics to enhance the behaviour of the robot, vision, navigation, and control performance of the robots respectively. Over the year, various modelling approached have been employed to specify the problem of robot dynamics and provide solution which will enhance it performance, however with extensive consideration of how the distributed parameters and nature of the idealized mechanism can be constructed better (Pavol et al., 2014).

Robot manipulators have limitless applications ranging from industrial to domestic use, however research revealed that despite the domination of robots today in the market and industries, various task meant to be performed by the robot still need human intervention for it to be done properly. In other words, the desired autonomy need for effective operation of robots is yet to be achieved. The requirements for higher speeds and better system performance make it is necessity to consider the dynamic effects of structural flexibility in the design of manipulators.

Today the main issue with this manipulation is in the gripper part. This is the most important part of the robot arm which is used for object manipulation and lots more of other tasks. In the conventional robot, the intelligent is limited to the control of the complete arm degree of freedom and dynamics; however, the gripper requires high level of special control and degree of freedom to manipulate certain task. The human hand for instant is intelligent because, works with relation to the eye and the brain or simultaneous localization and mapping of objects for adaptive manipulation action with precision, however for robot gripper, simultaneous localization and mapping, position adjustment and control force with respect to object displacement are need for précised grabbing and manipulation of objects.

In many cases these parameters must be modelled collectively considering slip for perfect object grab, however this is not the narrative or many robotic gripper and as a result has limited their applications in manufacturing industries furthermore, in other cases the pressure applied to the objects are much, this resulting to damage or negative effect on the object surface and has remained a major problem.

Many solutions have been proposed such as the use of Dahl controller, Proportional integral derivative (PID), fuzzy logic, adaptive control system, etc (Cho, 2012; Pinto and Gupta, 2016; Levine et al., 2016;) have been proposed to solve this problem and the performance of adaptive controller provided better results when compared to the rest, even though solution have not been obtained which considered slip as grabbing constraint. This study therefore, proposes to develop an adaptive control approach which will consider the necessary control parameters and slip to develop control solution using machine learning. This when achieved, will improve the efficiency of robot gripper and hence their industrial applications.

2. RESEARCH METHODOLOGY

The research methodology employed is the experimental and simulation method. The software design methodology employed waterfall model. The research method performed an experimental analysis for data collection on a robotic gripper system at the Robotics and Artificial Intelligence in Nigeria (R.A.I.N) company located at Ikeja, Lagos Nigeria, to identify the technical problems with the system, then a solution was modelled which considers position, force and slip using machine learning based adaptive control system with feed forward neural network. This was implemented using Simulink and evaluated.

a. Data Collection

The study collected data through investigation of R.A.I.N robot arm gripper with two fingers. The purpose was to measure the pressure applied on object by the gripper and improve the performance to as to be able to precisely hold slip objects. The experimental process collected sampled objects with the constraints properties (slip) and placed on the object, then the robot arm was configured with the position of the objects via the control unit. The proximity sensor was used for the simultaneous localization and mapping of the robot, then the force sensor was used to measure the amount to pressure which was applied by the finger to grab the object. The setup used for the experiment was presented in the Figure 1;

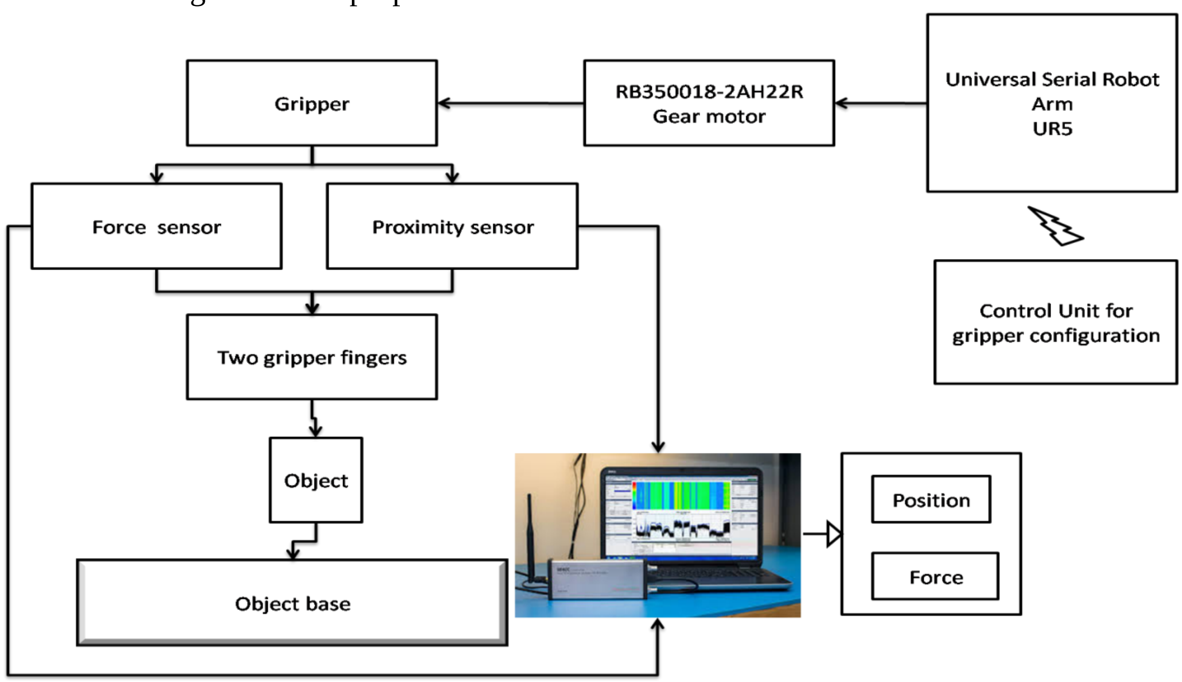

Figure 1: The experimental setup

The Figure 1 presents the block diagram of the experimental setup used for the investigation of the case study robot gripper. From the study, the laptop installed with robot operating system was used to monitor the performance of the gripper. During the test, the object was placed on the object based and the pressure applied by the gripper was measured considering the relationship between the force acting on the surface and the object change in displacement. The result parameters were controlled with Dahl control approach

(Dahl, 1968) and were measured and reported for analysis.

b. Development of gripper system position algorithm

To develop the algorithm, the output of the proximity sensor was used to simultaneously localize and map the position and size of the object placed for manipulation. The positioning was determined using the base dimension as x axis and the height dimension as the y axis. These parameters were used to model the bending angle (θ) of the gripper finger as shown in the Equation1 (Nisha, 2016);

$$\theta = \sum_{i=1}^{n} \theta_i = \frac{6nFdl}{Eq^3p}, \text{ i=1,,,,,n.} \qquad (1)$$

Where E is the young modulus, d is the distance between the connecting links, l is the length, I is the thickness, q is the weight of the object, p is the height of the objects and n is the number of segments the link has to undergoes to grab the object. The pseudocode of the gripping position algorithm was presented as;

1. *Start*
2. *Insert object for manipulation*
3. *Identify proximity sensor output*
4. ***SLAM object and get the dimension with step 3***
5. ***Read x and y dimension of the object***
6. ***Apply Equation 1***
7. ***Adjust gripper angle to equal object dimension***
8. ***Add tolerance of +0.5mm to step 7***
9. ***Position gripping finger***
10. ***Connect with the object***
11. ***stop***

2.1 Model of the Adaptive controller using machine learning

To develop a model of the adaptive controller, neural network was used and trained with live data collected from R.A.I.N which represented the relative displacement between two constant surfaces (x) as shown in the Equation2 (Dahl, 1968);

$$f(x) = \beta(1 - e^{-\alpha x}) \qquad (2)$$

Where f(x) is the frictional force acting between two contact surfaces, while the F(x) at varying pressure was presented as Equation 3 (Yuan et al., 2020);

$$F(x) = \begin{Bmatrix} a(p)(1 - e^{-b(p)x}) & 0 \le x \le x_1(p) \\ c(p)x + d\,(p) & x > x_1(p) \end{Bmatrix} \qquad (3)$$

Where $x_1(p)$ is the turning point from transition slip phase, a,b,c,d are the coefficient of the piece wise function (Dahl, 1968)at various pressures and used to develop the adaptive control system.

3. THE MACHINE LEARNING CONTROL ALGORITHM

The machine learning control algorithm employed for the development of the adaptive controller is Dynamic Neural Network (DNN) adopted from (Palnitkar and Cannady, 2004). A DNN is a type of neural network characterized with the ability to adapt online and solve control problem in dynamic environment. The reason this was employed in this system was to develop a gripper which can be controlled to grab various objects irrespective of the dynamic surface property.

To develop a DNN, a Multi-Layered Neural Network (MLNN) was reconfigured using gradient descent based back-propagation algorithm to adjust the displacement between the object and the force acting between the two contact surfaces of the gripper finger. To develop the adaptive controller, the data collected were fed to the

DNN model for training as shown in the Figure 2 to generate the adaptive controller;

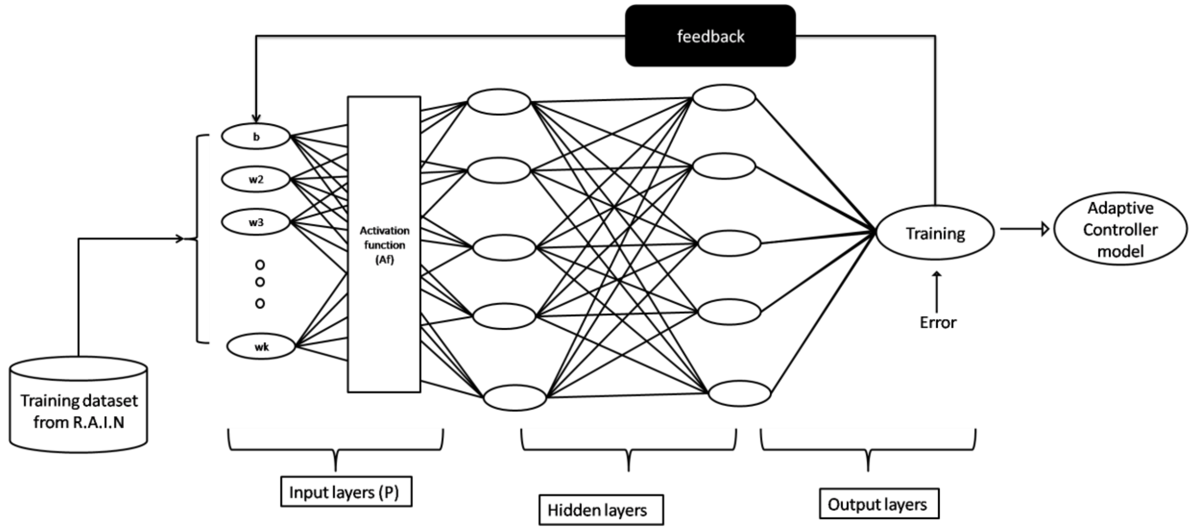

Figure 2: Model of the training DNN

The Figure 2 presented the system identification and training of the DNN model. Data of the gripper performance were fed to the DNN for training using gradient descent training algorithm (Alexander, 2020). Before the training process, the data were divided into test, training and validation sets by the DNN training tool and then trained. During the training, the neurons were tested and the disturbances were fed back to the input layer until the least mean square error was achieved and then the adaptive controller model generated which when extended to Simulink generated the simulation version of the adaptive controller. The flowchart of the adaptive control process was presented in the Figure 3;

The Figure 3 presented how the adaptive controller was developed with the MLNN and data collected from the training set. The parameters of the gripper behaviour modelled in Equation2 and 3 were loaded to the DNN and identified by the neurons for training using the gradient descent training algorithm which allows the neurons to adjust to the data at every iterative step defined by the epoch values in Table 1until the control algorithm were generated. During the training process, the Mean Square Error (MSE) was evaluated and when not equal or approximately zero, the neurons were adjusted until the least MSE was achieved in five iterative steps consecutively (i.e validation). This was equally applied with regression model and when the accepted result was obtained which implied that the DNN have learnt the desired pressure needed to be applied to an object, and then the adaptive controller model was generated. The block diagram of the new system was presented in Figure 4;

To develop the model of the intelligent robotic gripper arm, the gripper positioning algorithm and then model of the adaptive controller were used to develop the flow chart as shown in Figure 5;

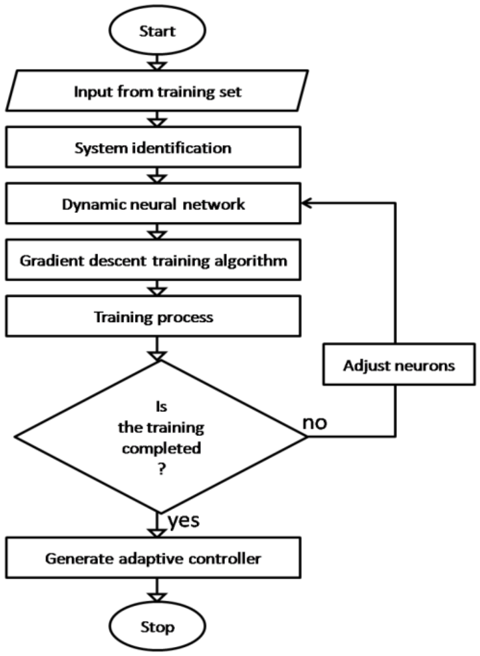

Figure 3: Adaptive controller system

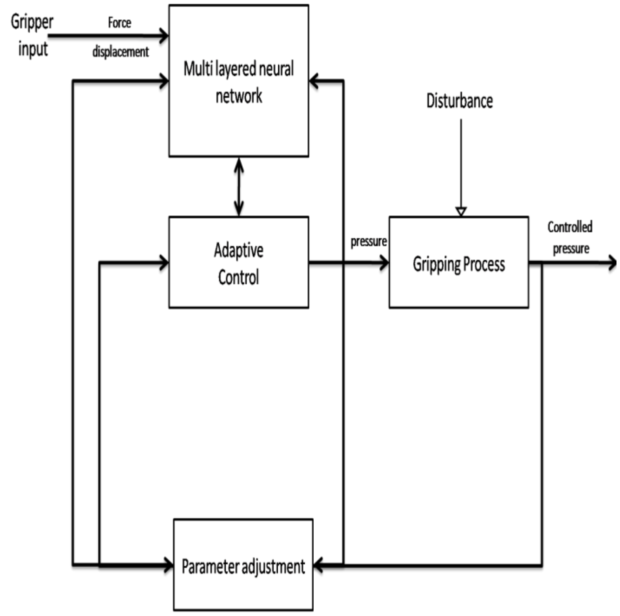

Figure 4: Block diagram of the adaptive controller

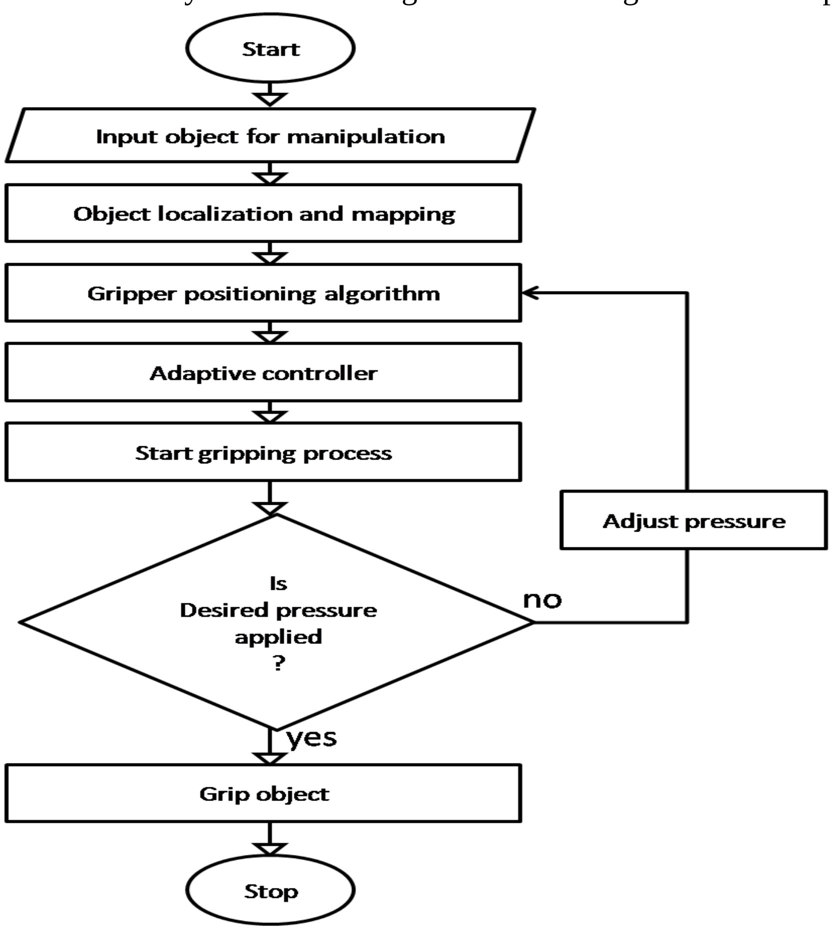

Figure 5: flow chart of the intelligent robot gripper arm

a. Model of the intelligent robotic gripper arm

The Figure 4 presented the block diagram of the adaptive controller. In the figure, the gripper input was feed to the MLNN to develop the adaptive control system which was used to apply the necessary pressure on the object, during this process, the displacement between the force applied and the position of the object due to slip was modelled in Equation3 were feedback and the control parameter adjusted until the desired pressure was applied to hold the object. From the flow chart in Figure 5, when the object was placed, the position and dimension was localized by the proximity sensor and then the output used to dimension the bending angle of the gripper as in Equation1 to develop the positioning gripper positioning algorithm. The tolerance of 0.05mm (to create the air gap between the object and the gripper before gripping) was used to ensure that the gripper perfectly embraced the object, then the adaptive controller was used to control the pressure applied on the object and then grab it.

4. SYSTEM IMPLEMENTATION

To implement the system, the models and algorithm developed was used to configure the robotic gripper in Simulink platform. The adaptive algorithm was implemented with neural network toolbox and then used to develop the intelligent robot gripper system as shown in Figure 6;

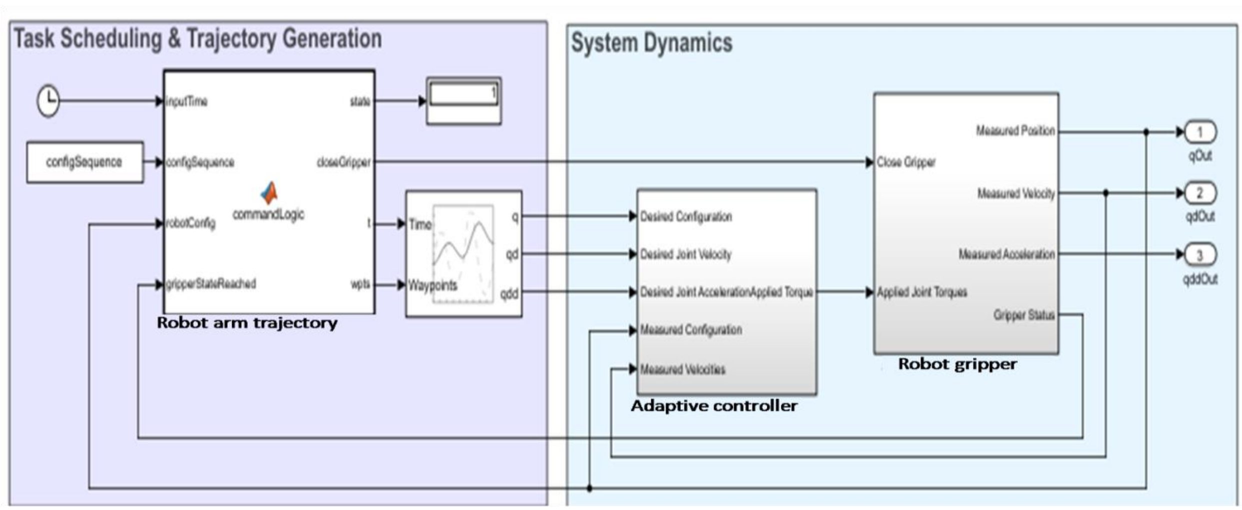

Figure 6: Model of the intelligent robot controller

The Figure 6 presented the implemented robotic gripper system developed. The system was made of three major sections which are the trajectory tracking robot arm, the adaptive controller which is responsible for the application of controlled pressure on the robot gripper. The Simulink model was simulated using parameters in Table 1whose values were informed from the investigating the gripper and the results presented in the next section.

Table 1: Simulation parameters

Parameters	Values
Torque of dc motor	1.66Nm
Voltage output of the robot	12V
Angular speed	$0.1337rad/sec^{-1}$
Gripper finger max velocity	$0.195ms^{-1}$
Frictional coefficient between finger and object	2
Maximum gripping force	26.5N
Number of gripper finger	2

5. ADAPTIVE CONTROLLER RESULT

The performance of the adaptive controller developed was evaluated using MSE and regression. The MSE was used to evaluate the training performance, while the Regression (R) was used to test the ability of the controller to detect slip and apply controlled force to counter it. The MSE performance was presented in the Figure 7;

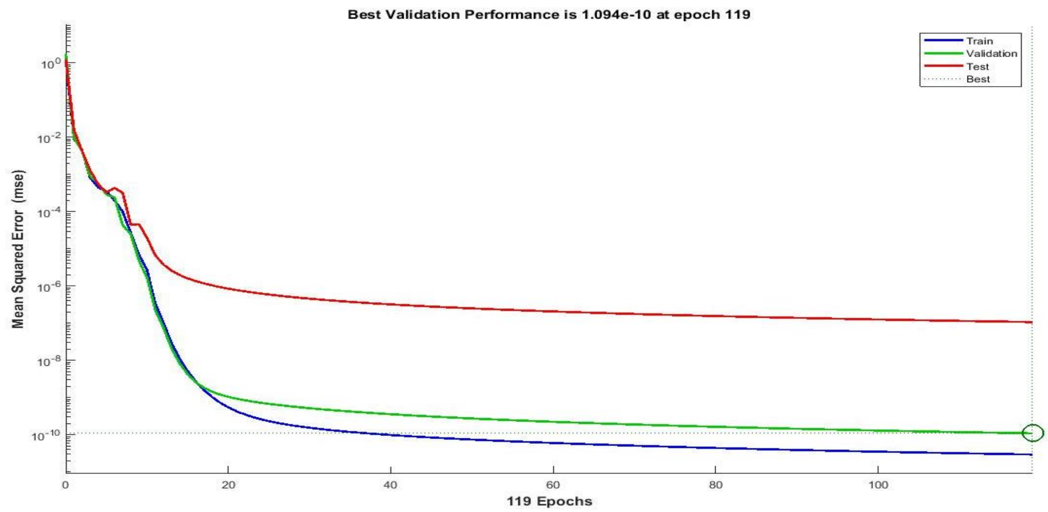

Figure 7: MSE result of the adaptive controller

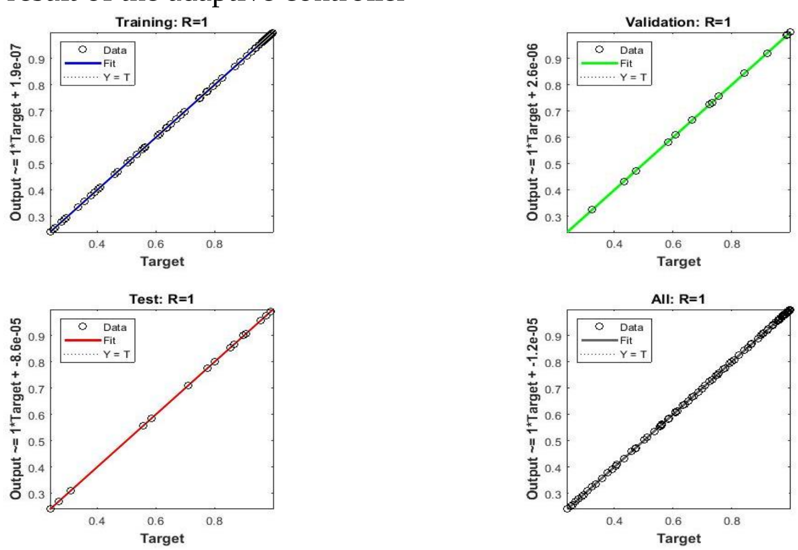

Figure 8: The regression result of the adaptive controller

The MSE was used to investigate the training performance of the DNN to generate the adaptive controller. The result showed that the validated MSE achieved is 1.094e-10Mu at epoch 119. This result implied that the error which occurred with the DNN training was tolerable as it is close to the ideal error value of zero, thus indicating good training performance and also implied that over-fitting does not occur during the training process. The next result evaluated the ability of the controller to detect displacement due to slip surface and apply desired force for counter. This was evaluated with regression analyser as in Figure 8.

The Figure 8 presented the regression performance of the adaptive controller developed. The result showed that the average R performance achieved is 1. This implied that the controller correctly identified the displacement on the objects and applied the desired force for control. Having evaluated the performance of the adaptive controller and validate the result using MSE and R, the adaptive controller was used to develop the intelligent robot gripper system.

5.1 Result of the intelligent robot gripper in Simscape

The result of the intelligent gripper presented a simulation version of the robot developed with the adaptive controller and the position algorithm. The position algorithm was used to control the bending angle of the gripper as modelled in the Equation1, while the adaptive controller was used to regulate the force required to grab an object at varying displacement. The Figure 9 presented a test object used to evaluate the performance of the gripper, while the Figure 10 presented the application of the position algorithm.

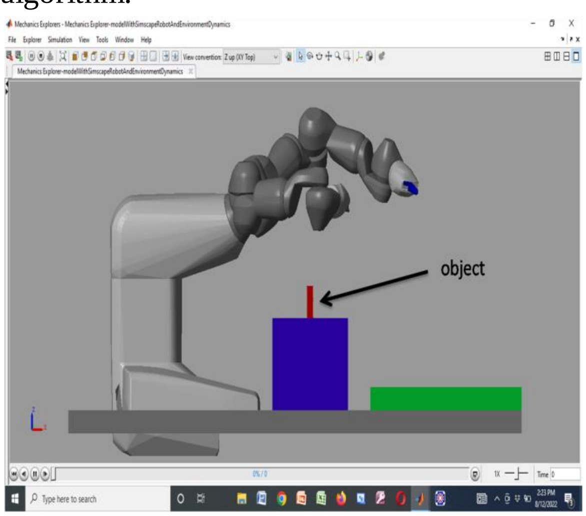

Figure 9: Result of the gripper and test object

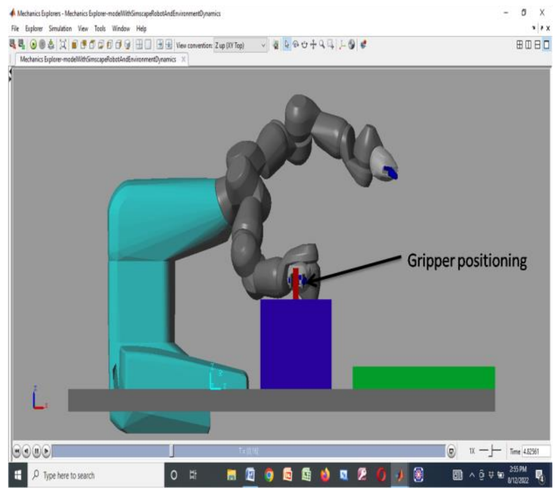

Figure 10: Positioning performance of the gripper

The Figure 10presented the performance of the positioning algorithm developed to control the bending angle of the gripper. The data collected of the object from the proximity sensor was used to position the gripper and embrace the object for grabbing. The position control algorithm used the size of the object to dimension the opening of the gripper so as to grab the object for manipulation. To achieve this grab process, controlled force was applied to the object according to the friction force model via the adaptive controller and then grab the object as shown in Figure 11;

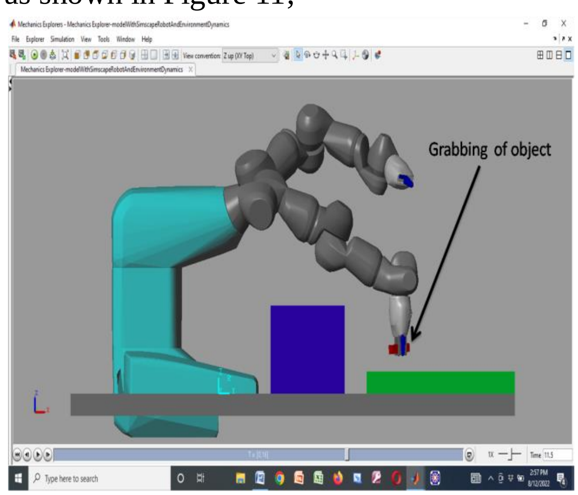

Figure 11: The grabbing result of the gripper

The Figure 11 showed how the gripper was able to successfully manipulate the object from one position to another and then placed on the desired point as shown in the Figure 12;

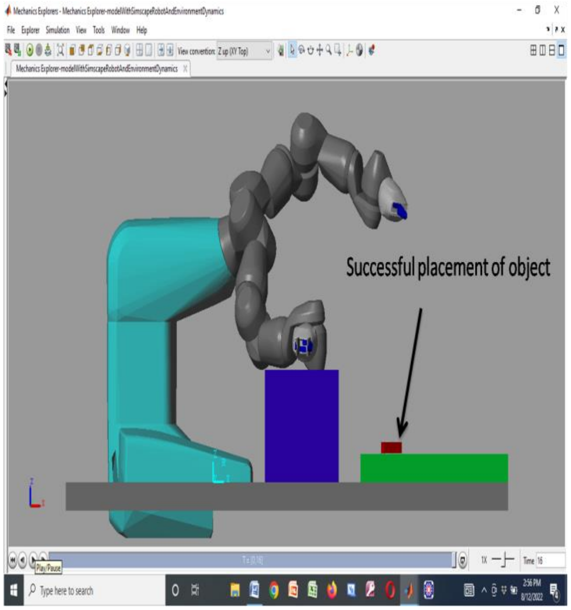

Figure 12: Result of the successful object placement

From the Figure 10 to 12, the performance of the intelligent gripper was presented and discussed. The results showed how the gripper position algorithm was able to assign appropriate bending angle to the gripper finger, then the adaptive controller was used to apply the desired force needed for the grabbing and manipulation of objects.

a. Result of System Integration

Having developed the adaptive control system, simulated as an intelligent robotic gripper and analysed, the adaptive controller was integrated at the R.A.I.N robotic gripper control system and tested using a blocked shaped object that is slippery like in the experimental analysis conducted earlier, prior to the development of the new system, and the result was presented in the Table 2;

Table 2: Result of the Gripper with Adaptive controller

Displacement (mm)	Force (N)
1	0.03581
2	0.37283
3	0.39491
4	0.45333
5	0.50807
6	0.54924
7	0.61617
8	0.90965
9	1.85794
10	3.19332
11	3.68667
12	3.73865
13	3.94519
14	4.47235
15	4.58068

The Table 2 presented the controlled force acting on the object when tested with the adaptive controller developed with DNN.

6. CONCLUSION

This research presents the development of an intelligent robotic gripper system using adaptive control system. The approach employed developed adaptive control system and gripper position algorithm to implement intelligent gripper system which can grab and manipulate objects correctly. The system when tested showed that the MSE of the adaptive controller training is 1.094e-10Mu, Regression is 1. The adaptive controller when implemented on the gripper system and evaluated showed that it was able to apply the desired control force necessary for object grabbing and manipulation. When comparative tested, the average force exerted on the object with adaptive controller is 2.60N as against

11.36N which was applied by the Dahl controller. The percentage control success achieved with the adaptive control system over the Dahl counterpart is 77.11%.

7. REFERENCES

Alexander, A. (2020). Introduction to deep learning. MIT 6.S191.

Cho, S. I., Chang, S. J., Kim, Y. Y., & An, K. J. (2012). Development of a three-degrees-of-freedom robot for harvesting lettuce using machine vision and fuzzy logic control. Biosystems Engineering, 82, 143–149.

Dahl, P. R. (1968). A solid friction model. Technical Report TOR-0158(3107-18)-1, Aerospace Corp El Segundo CA, 4(2), 301-317.

Danica K., Joakim G., Hakan K., Patric J., & Robert K. (2018). Interactive, collaborative robots: Challenges and opportunities. In Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence (IJCAI-18), Robotics, Perception and Learning Lab, KTH Royal Institute of Technology, Stockholm, Sweden (Vol. 4(1), pp. 49-60).

Gao, Y., Huang, X., Mann, I. S., & Su, H.-J. (2020). A novel variable stiffness compliant robotic gripper based on layer jamming. Journal of Mechanisms and Robotics, 4(1), 102-118. Retrieved from https://www.researchgate.net/publication/341280784

Levine, S., Pastor, P., Krizhevsky, A., & Quillen, D. (2016). Learning hand-eye coordination for robotic grasping with deep learning and large-scale data collection. In 2016 International Symposium on Experimental Robotics (ISER) (pp. 60-74).

Marc T., Jonathan T., Lea B., Ludwig-Dehm, P. M., & Wägner, S. (2018). Industrial robotics: Insights into the sector's future growth dynamics. Advanced Industries, Visual Media Europe, 4, 72-89.

Nisha, B. (2016). Design of a two-fingered friction gripper for a wheel mobile robot. In Advanced Computing and Communication Technologies, Advances in Intelligent Systems and Computing (Vol. 452, pp. 195-203).

Palnitkar, R., & Cannady, J. (2004). A review of adaptive neural network. In IEEE Southeast Conference, Proceedings (pp. 26-29).

Pavol B., Pavol B., & Nikitin, Y. (2014). Advanced robotic grasping system using deep learning. Procedia Engineering, 96, 10–20. https://doi.org/10.1016/j.proeng.2014.12.092

Pinto, L., & Gupta, A. (2016). Supersizing self-supervision: Learning to grasp from 50k tries and 700 robot hours. In 2016 IEEE International Conference on Robotics and Automation (ICRA) (pp. 3406–3413).