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MODELING OF INTELLIGENT ROBOTIC GRIPPER FOR PRÉCISED OBJECT MANIPULATION USING ADAPTIVE CONTROL TECHNIQUE

[1]Nwankwo Chinedu V., [2]Eke James

Department of Electrical and Electronic Engineering, Enugu State University of Science and Technology, Enugu State, Nigeria

Corresponding Author Email: valvinco@yahoo.com

Abstract

This paper presents modelling of an intelligent robotic 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 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 Gripper; Adaptive Controller; Artificial Intelligence; Dahl Controller

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 non industrial applications. Most of these are already available in 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 modeling dynamics to enhance the behavior of the robot vision, navigation, and control performance of the robots respectively. Over the years, various modeling approach have been employed to specify the problem of robot dynamics and provide solution which will enhance its performance, however with extensive consideration of how the distributed parameters and nature of the idealized mechanism can be better constructed (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 needed for effective operation of robots is yet to be achieved. The requirements for higher speeds and better system performance make it a 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 are 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 it works with relation to the eyes and the brain, so simultaneous localization and mapping of objects and amount of pressure applied considering the slip surface of the object are easier with precision; however for robot gripper, simultaneous localization and mapping of objects, position adjustment and control force with respect to object displacement are need for précised grabbing and manipulation of objects.

In many cases, this parameter must be modeled collectively considering slip for perfect object grab, however this is not the narrative of many robotic grippers 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 (Pinto and Gupta, 2016; Levine et al., 2016; Cho, 2012) 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 paper 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. LITERATURE REVIEW

Pavol et al, (2014) published research on Advanced Robotic Grasping System Using Deep Learning, where attempts to develop an intelligent robot with the application of mathematical model for a coupled system in which the object properties are known. However, the performance result of this system was not stated in the work, therefore an improved work to enhance this system will be developed.

Xi and Jan (2018) in their research work on Industrial Robot Control with Object Recognition based on Deep Learning. In this work, an industrial robot UR5 which is designed to perceive, locate and interact with different tools such as office supplies and tools. This robot feeds the image data acquired by the camera to a deep learning Faster-RCNN network to recognize and localize the present object. Although this robot performed well but the combination of RNN and CNN algorithms for this robot increased the delay response time of the robot, therefore an improvement is required.

Ricardo and Hermann (2019) presented a research work on Highly Effective Deep Learning based Escape Route Recognition Module for Autonomous Robots in Crisis and Emergency Situations. This system was designed for the assistance and location of escape routes for individuals in a time of crisis and emergency situations. This system is dependent on three blocks of a depth-wise convolutional layers, a max pooling layer, and a batch-wise normalization layer before classification of the image. The performance of this system is recorded to be 96.81% but the delay time of this robot is 92seconds, therefore, an improvement should be made for a smaller delay time.

Huaping et al, (2017) in their research work on Recent Progress on Tactile Object recognition presented a detailed discussion on tactical object recognition. The tactical sensors measure the physical properties of objects and its correlation with the environment. Visual-tactical fusion, exploratory procedure and data sets is also reviewed explicitly in this work to provide a clear view about this technique for an easy adoption and application in future works.

Soren and Kanpur (2014) presented research on Object Recognition Using Deep Neural Networks which presented in details how far the fields of object recognition and deep neural networks have progressed over many years. Then the performances of the recently developed neural network algorithms are presented too and some of the areas of application of deep neural networks was also presented. With the information provided on this research it will assist in a long way in developing efficient object recognition robots and better algorithms.

3. METHODOLOGY

The software design methodology employed waterfall model. The research method performed an experimental analysis on a robotic gripper system at the Robotics and Artificial Intelligence in Nigeria (R.A.I.N) to identify the technical problems, then a solution was modeled which considers position, force and slip using machine learning based adaptive control system. This was implemented using Simulink and evaluated.

3.1 Model of the gripper problem formulation

To develop a model of the gripper problem formulation, the idea is to model the torque exerted by the gear and dc motor in grabbing an item. To achieve this, the mass of the object was considered alongside gravitational force acting on the weight of the object as (Nisha, 2016);

$$W = m_o g \quad (1)$$

Where M is the mass of the objects, g is the gravitational acceleration acting on the objects. The frictional force F_f between the gripper fingers required to hold the object was presented as;

$$F_f = \mu N \quad (2)$$

Where μ is the frictional coefficient, N is the normal frictional force required to pick up the object. To determine the actual force required to hold the object, the equation 1 and 2 were used as;

$$F_f = \frac{W}{2} \quad (3)$$

Resolving the force horizontally as;

$$-F_1 \cos(\propto + \beta) - F_2 \cos(\varphi + N) = 0 \quad (4)$$

Whereφ,$\propto$ and β are dependent on the positions of the interconnected links based on the size of the object.

$$T_G = F * r \quad (5)$$

$$F_1 = F\cos\theta \quad (6)$$

Resolving the forces vertically

$$F_1 \sin(\propto + \beta) - F_2 \sin(\theta) = 0 \quad (7)$$

Where r is the radius of the gears, F_1, F_2 and F are the force components acting on the gripper link direction, components of the force direction acting on the second link and the force acting on the respective gear link. According to Nisha (2016) the most vital part of the gripper system is the jaw as it is the part which comes into contact with the object to be grabbed and the required grabbing force is the normal component of frictional force i.e. both frictional force and normal force.

3.2 Development of gripper system position algorithm

To develop the algorithm, the output of the proximity sensor was used to Simultaneously Localize and Map (SLAM) the position and size of the object placed for manipulation. The positioning was determined using the base dimension as the 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 in the equation 8;

$$\theta = \sum_{i=1}^{n} \theta_i = \frac{6nFdl}{Ex^3y}, \text{ i=1,,,,,n.} \quad (8)$$

Where E is the young modulus, d is the distance between the connecting links, l is the length, I is the thickness, x is the weight of the object, y is the height of the objects and n is the number of segments. 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 8*
7. *Adjust gripper angle to equal step 5*
8. *Add tolerance of +0.5mm to step 7*
9. *Position gripping finger*
10. *Connect with the object*
11. *stop*

3.3 Model of the Adaptive controller using machine learning

To develop a model of the adaptive controller, neural network was used and train with experimental data collected R.A.I.N which represented the relative displacement between two constant surfaces (x) as shown in the equation 9 (Dahl, 1968);

$$f(x) = \beta(1 - e^{-\alpha x}) \qquad 9$$

Where f(x) is the frictional force acting between two contact surfaces, while the f(x) at varying pressure was presented as equation 10 (Yuan et al., 2020);

$$F(x) = \begin{Bmatrix} a(p)(1 - e^{-b(p)x}) & 0 \le x \le x_1(p) \\ c(p)x + d\,(p) & x > x_1(p) \end{Bmatrix} \qquad 10$$

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). These data were collected at various pressures as shown in the figure 1 and used to develop the adaptive control system.

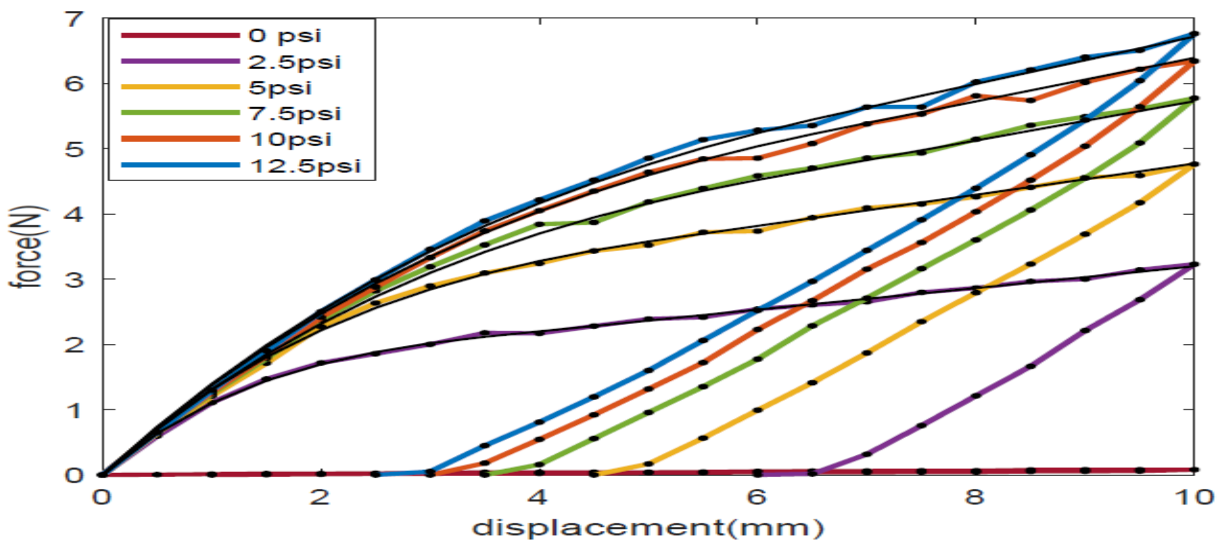

Figure 1: Model of the training data

4. SYSTEM MODELLING

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 adaptive 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 back propagation algorithm to adjust the displacement between the object and the force acting between the two contact surfaces of the gripper finger. The model of the DNN was presented as shown in the figure 2. Where P is the input neurons, w is the weight of the neurons, b is the bias function, AF is the activation function. To develop the adaptive controller, the data collected were feed to the DNN model for training as shown in the figure 3 to generate the adaptive controller;

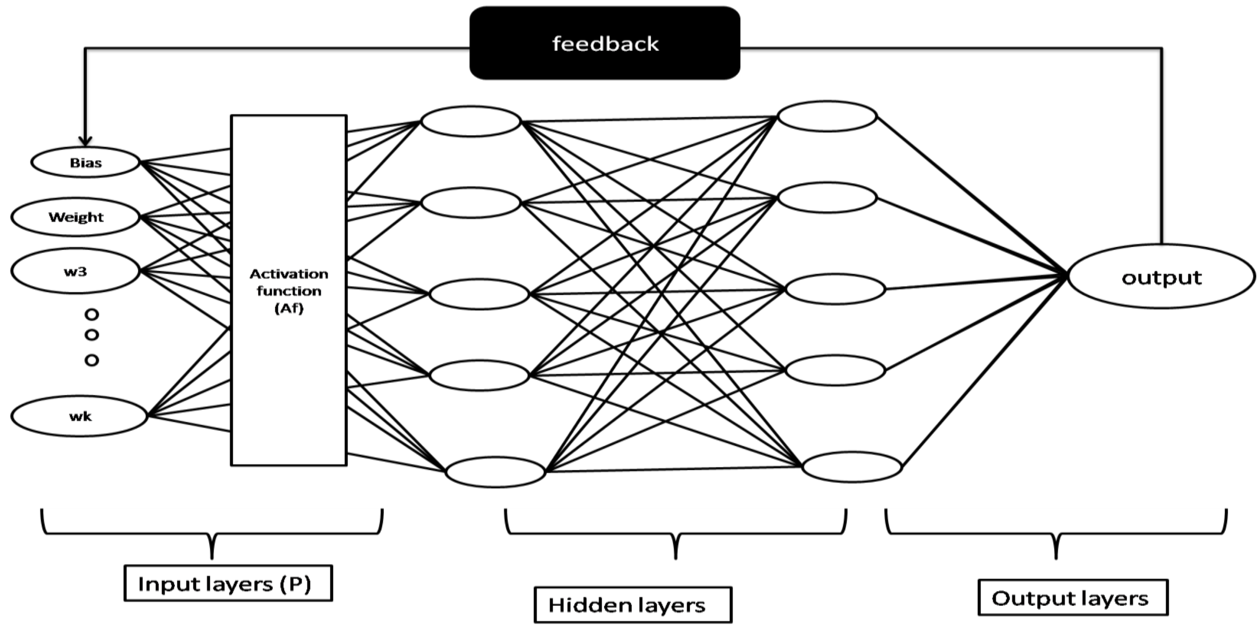

Figure 2: Model of the DNN

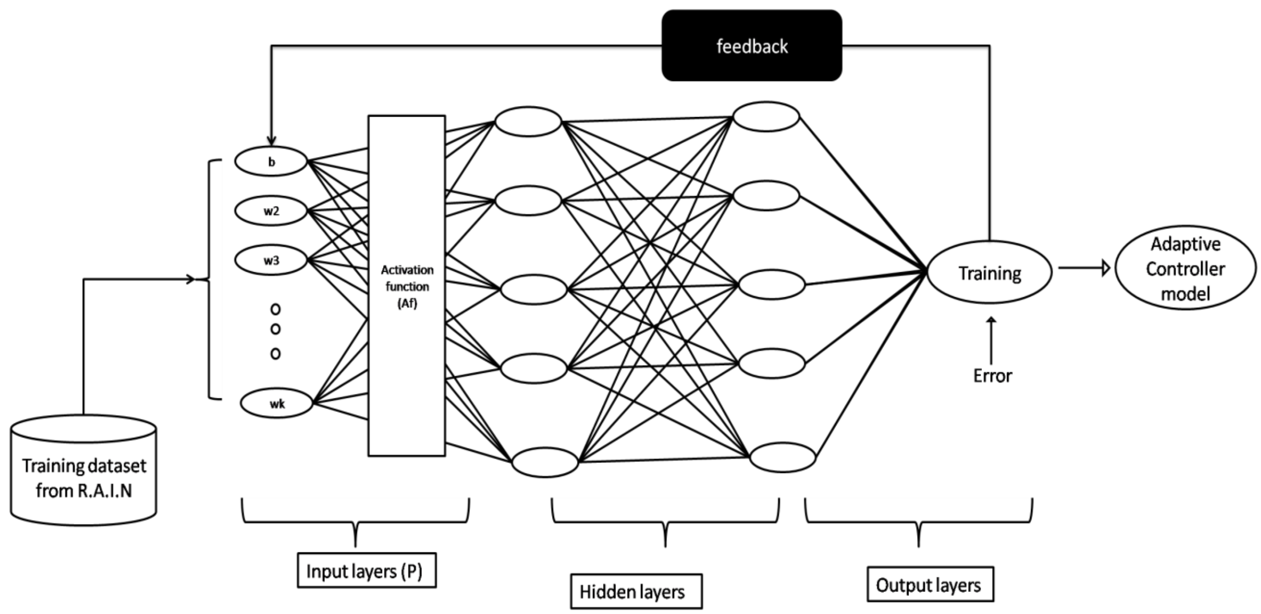

Figure 3: Model of the training DNN

The figure 3 presented the system identification and training of the DNN model. Data of the gripper performance was feed 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 feed back to the input layer until the least mean square error was achieved and then the adaptive controller generated. The flowchart of the adaptive control process was presented in the figure 4;

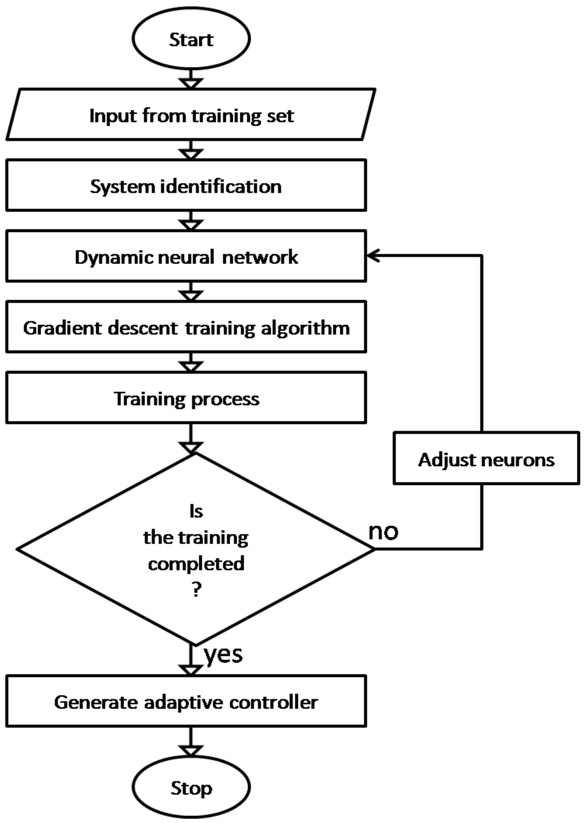

Figure 4: Flowchart of the adaptive controller system

The figure 4 presented how the adaptive controller was developed with the MLNN and data collected from the training set. The parameters of the gripper behavior modeled in equation 9 and 10 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 until the control algorithm were generated. During the training process, the Mean Square Error (MSE) were 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, then the adaptive controller was generated. The block diagram of the new system was presented in figure 5;

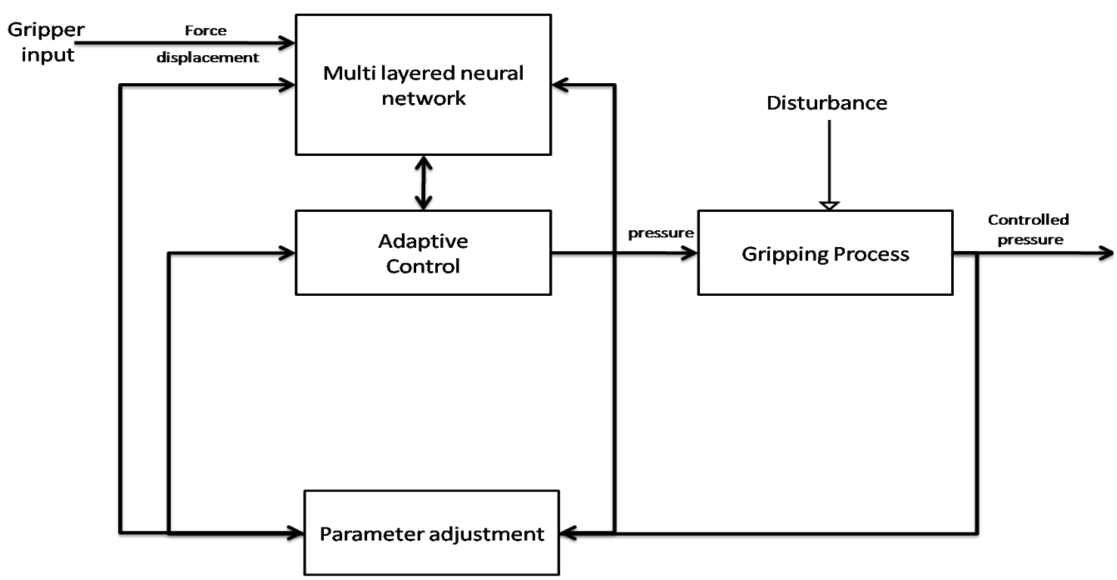

Figure 5: Block diagram of the adaptive controller

The figure 5 presented the block diagram of the adaptive controller. In the figure, the gripper input was fed 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 modeled in equation 10 were feedback and the control parameter adjusted until the desired pressure was applied to hold the object.

4.1 Model of intelligent robotic gripper arm

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 model as shown in figure 6;

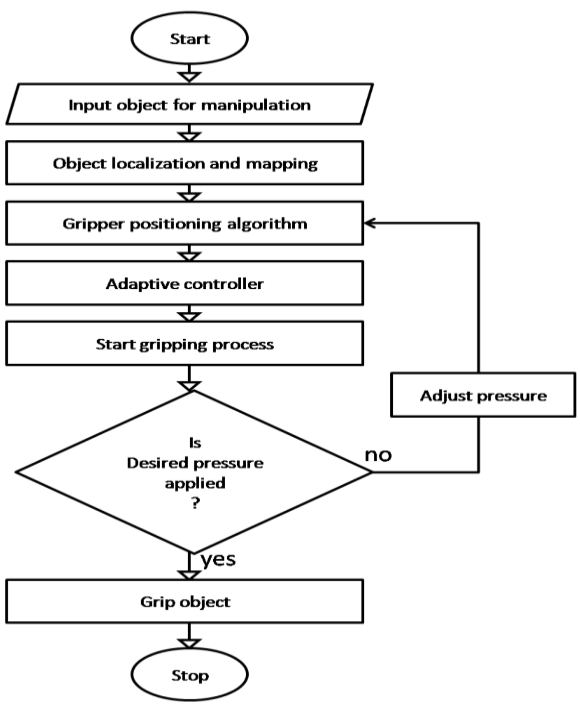

Figure 6: flow chart of the intelligent robot gripper arm

From the flow chart in figure 6, 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 equation 8 to develop the gripper positioning algorithm. The tolerance of 0.05mm 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.

5. 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 7;

The figure 7 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 table 1 and the results presented in the next section.

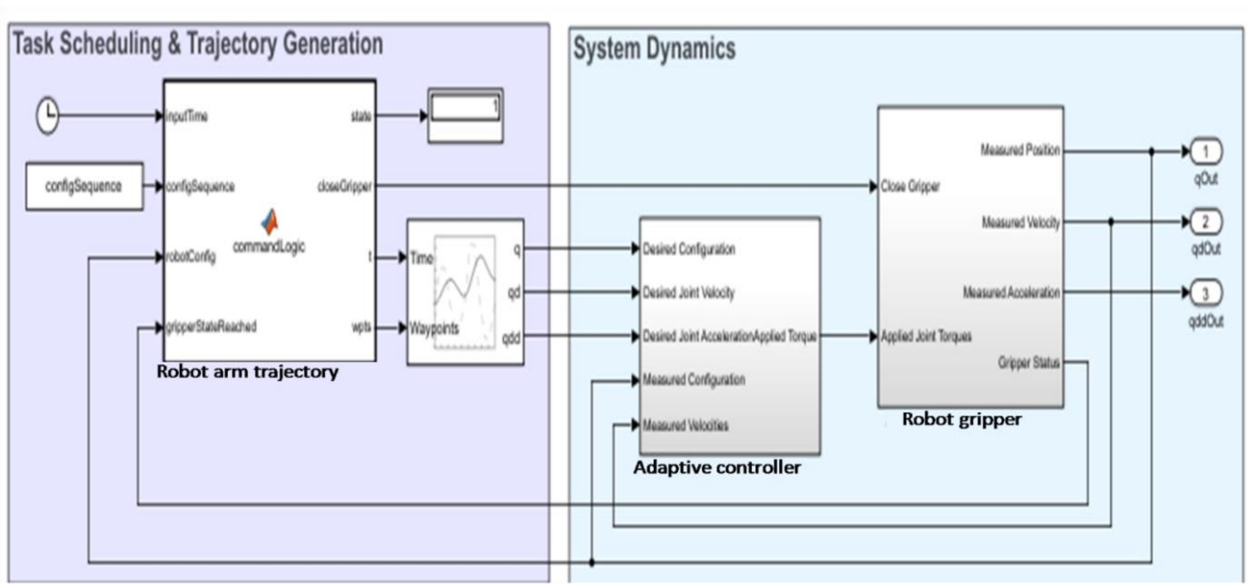

Figure 7: Model of the intelligent robot controller

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

6. RESULTS

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 modeled in the equation 8, while the adaptive controller was used to regulate the force required to grab an object at varying displacement. The figure 7 presented a test object used to evaluate the performance of the gripper, while the figure 8 presented the application of the position algorithm.

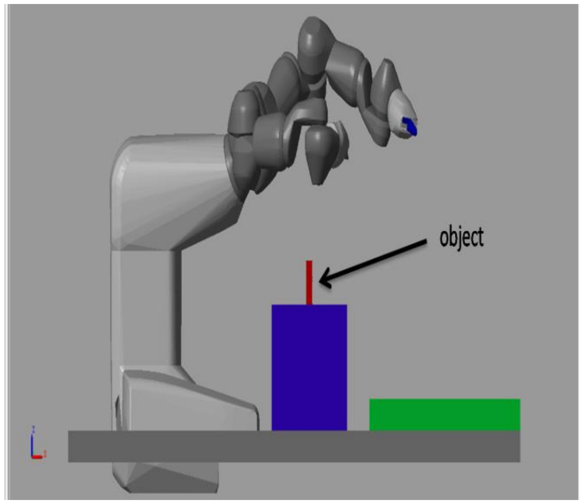

Figure 8: Result of the gripper and test object

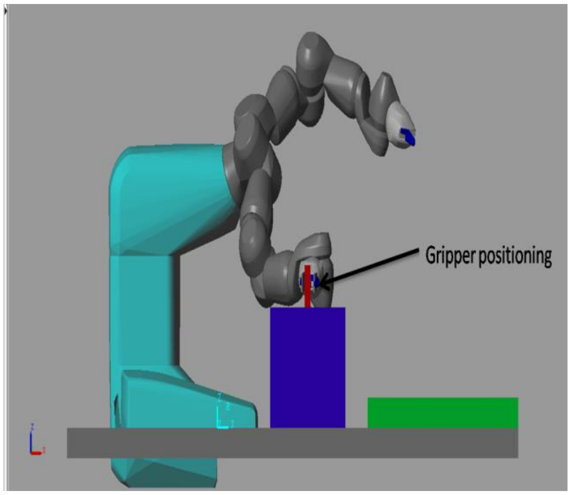

Figure 9: Positioning performance of the gripper

The figure 9 presented 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 figure10;

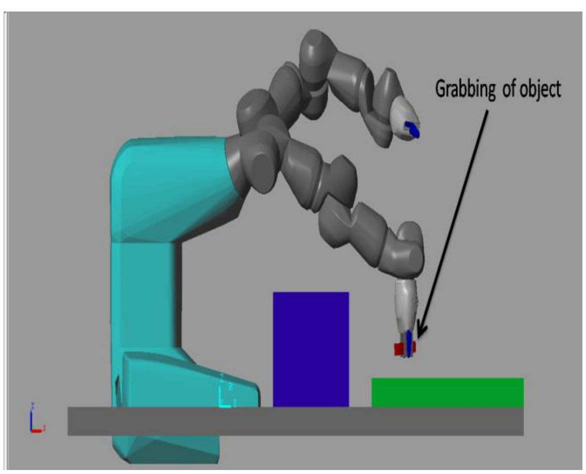

Figure 10: The grabbing result of the gripper

The figure 10 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 11;

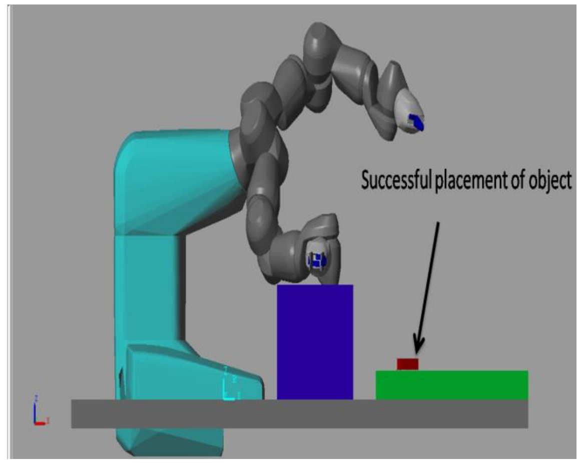

Figure 11: Result of the successful object placement

From the figure 8 to 11, 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.

7. CONCLUSION

This paper presents the modeling of an intelligent robotic gripper system using adaptive control system. The approach employed developed adaptive control system and gripper position algorithm to develop an intelligent gripper which can grab and manipulate objects correctly. The system when tested giving a percentage improvement of 77.11%. 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, thus implying that the new gripper with adaptive controller is very reliable to grab object and not damage it.

7.1 RECOMMENDATION

Having developed, tested and validated the adaptive controller-based gripper system developed; the following were recommended for further studies. The adaptive algorithm can be used to improve other industrial robot arm for better object gripping performance. The study was also recommended for the optimization of other mobile robots developed at R.A.I.N used for domestic and industrial applications.

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