

# Investigation of the Control Enhancement of Three Drones Under a Dynamic Environment Using Deep Reinforcement Learning Algorithm

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**Abstract**— An Enhanced Control Approach for navigating three drones under dynamic environment using Deep Reinforcement Learning Technique. DRL approach was used in this research work to enhance the control of three drones and overcome collisions of drones under dynamic environment. The aim of this research work focused on enhancing the control angles of the three drones and collision avoidance. To do this, characterization of the already existing drone and the environment in which the drone will operate was first determined. This was done by implementation of simultaneous localization and mapping. Next was to develop a quad-copter model in SIMULINK, which was achieved by developing a mathematical model of a quad-copter using Newton Euler angle method in SIMULINK in order to enhance the control variables of the rotational and translational movement of the quad-copter. After this, the development of control system for multiple quad-copter in SIMULINK was done by comparing the control of three drones when PID and is implemented and when it was not implemented. Then after, was the implementation of Deep Reinforcement Learning Algorithms, model and NNQL training respectively. This was realized by integrating the two already designed models for the enhancement and control of the multiple drones in terms of changes in velocity and time when PID&DRL is implemented in the system and when it is not implemented. All the above were performed by simulation using Python and MATLAB, the results show the three drones with deep RL and PID controllers showed better enhanced control, collision and obstacles avoidance with 95.1% success over the multiple drones without deep RL which have only 4.89% success when compared to other researcher. Hence, the proposed DRL techniques proved to work well in simulation and real Life Application even under dynamic environment (indoor).

**Keywords**— ROS –Robotics Operating System, DRL- Deep reinforcement learning, NNQL –Neural Network Q-learning, PID-Proportional Integral Derivative.

## I. INTRODUCTION

In a global world, enhancing the control of more than one directional remotely operated navigation equipment (drone), under dynamic environment has been one of the complex problems for autonomous groups of drones. Some popular approaches to autonomous navigation used combination of different intelligent navigation techniques and algorithms to autonomously navigate drones in both static and dynamic environment. However, real time navigation still holds challenges for drone navigation in complex crowded environment. The problem of controlling three drones under dynamic environment includes the search for a path which a drone has to follow in an environment. The navigation problems

emerging alongside community over the last decade stated that navigation is a serious challenge for autonomous system in an unstructured and complex environment due to irregular shape of the environment and this required real-time planning. In order to improve the planning of three drones, system models that can provide solutions to localization, map building planning and control strategy should to be developed. The three questions that need to be answered in any autonomous system are, “where am I?” “Where do I go?” and “How do I get there?”. The solution to these questions gives rise to the tasks of self-localization, map building, path planning and collision free route. In this present research, deep reinforcement learning (DRL) will be used to perform the work of the controller as described in the foregoing presentation. With its capabilities, DRL is expected to enhance the control of three drones as these responsibilities are carried out. New researchers are adopting already existing technique and aiming at improving on them. This research work would attempt to enhance the control system of drones with four rotors mechanism in order to use this technique DRL thus requiring more challenging and efficient algorithms. Controlling three dynamic and remotely operated navigation equipment under dynamic environment has been identified as a crucial problem in the operation of drones and the field of robotics in general. Among the identified problems are determination of collision free route, shortest path, low run time and modeling of the dynamic environment where the drone is expected to operate. The situation is made more complex when the control of multiple drones is involved. Studies have shown that local and global path-planning lacks robustness due to environmental uncertainty especially when drones are operated on environments different from the one in which the drone has been configured. It has also been established that in drone operation as in the field of robotics, to navigate an unknown environment without a preexisting map and without any knowledge of the environment poses a complex problem. The consequences of the identified problems include crashing collision of drones, loss of human lives, destruction of buildings and other structures due to crash of drones, extended time of operation, failure to actualize assigned operation as well as financial losses. Based on the problems and associated consequences as stated, deep reinforcing learning is proposed in this research to make the learning agent which is the drone to be able to learn the best navigable approach to use in order to

accumulate the most positive results overtime. This will make the drone to learn how to navigate through the best path from the starting point to the destination without having prior knowledge of the environment. To achieved the aim stated above, the following specific objectives are proposed. (1) Characterization of an already existing drone system (2) the dynamic environment in which the drone operates. (3) Development of a Simulink model of a quad copter.

II. METHODOLOGY

The type of drone that was characterized was called quad-copter which is the type of drone with four rotors. The reason for the study was to evaluate quad-copter performance. This objective was achieved by examining the operational characteristics of a quad-copter. The characterization of the dynamic environment was done by translating the 2D point cloud map of the drone’s environment into a 3D map. This was done using sensor fusion of the data obtained from the laser scanners, encoder and gyroscope that is from the three drones operating on a known and unknown environment which was used to know its correct position relative to its co-ordinates frames in order to know how to get to the target location. This was achieved by developing a mathematical model using or adopting Newton Euler method. After that, was the implementation of the mathematical model develops in Simulink using Simulink blocks to represent those control variables and equations. When the mathematical develop model was Simulated the results with respect to velocity versus time of reaction. Quad-copter uses two sets of identical fixed pitched propellers; two clockwise CW and two counter clockwise CCW, which use revolutions per minute RPM to control lift and torque. Control of vehicle motion was achieved by altering the rotation rate of one or more rotor discs, thereby changing its torque load and thrust/lift characteristics. Newton Euler method was adopted because this method is based on Newton’s second law on the rigid body. Angular orientation approach, this approach uses Newton Euler techniques to develop one of the quad-copter famous model equation for the 6- DOF. Force moment approach was also based on Newton Euler techniques this approach uses relationship between force and moment balance to develop the helicopter equation of motors.

III. EQUATIONS

were  $I_x, I_y & I_z$  are helicopter modeling moment of inertia with respect to

$X_B, J_B$  and  $Z_B$  axes respectively. Were the following X, Y and Z axis’s represented below:

$$I_{xx} = \text{rotational inertia along } x - \text{axis} \dots \dots (1)$$

$$I_{yy} = \text{rtational inertia along } Y - \text{axis} \dots \dots (2)$$

$$I_{zz} = \text{rtational inertia along } z - \text{axis} \dots \dots (3)$$

Newton Euler method which was used to develop quad-copter mathematical model in MATLAB and Simulink. The equations and control variables generated from developed mathematical model was used to design a control system for the three drones. Where PID was implemented and designed using Simulink blocks. PID control algorithm was also implemented in the system which is known as motor-mixing algorithm. Then after the control system was simulated the behavior in relation

velocity and time graph for the operation was observed and there coded result gave rise to the data. Then after the development of the six angles for quad-copter model, next was developing the motor model in which the motor uses brushless DC motors for quad-copter modeling. Where the effect of the dead-zone was incorporated in the rotor modeling the dead-zone means a region of operation in brushless DC motors and the motor generates no rotational motor and torque after receiving signal for rotation. This research is spherically apt considering the use of drones in many spheres of human endeavor in particular and the numerous advances in the use and application of artificial intelligence in the highly technological world of today. Enhancing the control of more than one directional remotely operated navigation equipment (drone), under the dynamic environment has been one of the complex problems for autonomous groups of drones. . The major interest in drones navigation under dynamic environment is to find a collision free path from a given start position to a predefined target point in the work space. While the drone is accomplishing its desired takes under control, it needs to do that at a fast speed, collect information about the dynamics environment including its current position and should be able to make decision to safely avoid static and dynamic obstacles in order to reach the goal within the prescribe time. The problem of controlling three drones under dynamic environment includes the search for a path which a drone has to follow in an environment. Deep Reinforcement Learning was able to demonstrate reliable and robust performance in autonomous navigation of three drones under dynamic Environment. During the simulation of the DRL algorithm, DRL was able to gain good independent navigational confidence. The DRL approach provided the three drones with strong learning ability to perform autonomous navigation.

IV. RESULTS AND DISCUSSION

The system characterization and data collection was based on SLAM- operation with the three drones was achieved as expected. After executing the command-line given below `ros. Launch gribot. twodifferent windows` was opened. The first window was the Rviz a 3D visualization application. It was used to observe and view all the perceived data that the drone was able to get from the environment. The area of the environment by which the drone would operate was taken into consideration in this case, the length and width of the environment in which the drone operate was measured, and this enables the three drones to be trained within its operational environments. From the SLAM software that was installed by using a variety of sensors which includes IMU, GPS, laser scanner, camera etc. before this approach was carried out the following was observed such as

A pre-existing map of a given environment is first built after which the device such as the drone, The drone was made to operate within the existing map by programming it, A variation of this map is then made as the drone moves within the environment, Finally a range of algorithms are used.

After the initialization of the sensors, follows the running the modes which were the SLAM algorithm was Written in python programming language, then the Data visualization script

(RViz) was implemented to run in order to display the obtained map of the perceived data for the data collection action for the four drones was remotely moved round the dynamic environment to collect the dataset. The python program written was used continuously to check if the multiple drone was closer to each other or not. If the drone was still closer, measurement and logging of the sensory data continues if not, the generated map will be saved in a file.

The simulation results of conventional three drones control without DRL algorithm. The results gave some very interesting data which forms the basis for the evaluation of future objectives for the validation and justification of the research.

TABLE 1: Results of Simulation of Conventional three Drones Control with and without DRL

Velocity (ms <sup>-1</sup> ) V1	Velocity (ms <sup>-1</sup> ) V2	Time (ms)
0	0	0
0	0	5
0.00037	0.00039	10
0.00062	0.00092	15
0.00098	0.00188	20
0.00147	0.00294	25
0.00189	0.0039	30
0.0028	0.00595	40
0.00375	0.00798	50
0.0047	0.0099	60

Comparison Graph of the Conventional Drone with and Without Deep Reinforcement Learning.

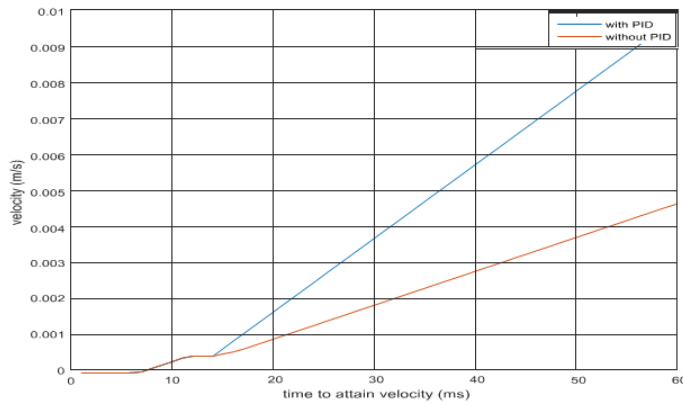


Figure 1: Comparison graph of the conventional drone with and without deep reinforcement learning.

Their velocities are such that even though they started building up at the same time which is after 5ms of starting operation, the two sets of drones changed in velocities thereafter. After about 15ms from the time both set started operation, the velocity of the set with DRL and operating using deep reinforcement learning started moving with increased velocity while the set without DRL was moving with reduced velocity. These differences in their velocities are obviously reflected in their maneuver abilities considering the computations carried out. It was established that the average velocities for conventional and DRL operated drones are 0.001658ms<sup>-1</sup> and 0.3386ms<sup>-1</sup> respectively. This results to an operational ratio of conventional drones with deep RL drones with the values of 0.0489:0.9510. This is a ratio of 4.89%:95.1%

in terms of each set of drones to maneuver an obstacle or avoid an impending collision. Thus put clearly, conventional drones have 4.89% obstacles and collision avoidance capability; drones using deep reinforcement learning have similar capability to the tune of 95.1%. This is a justification for the use of deep reinforcement learning implemented as the intelligent agent in this research. This also validates the research.

ACKNOWLEDGMENT

First and foremost, I give thanks and praises to Almighty God, the most merciful, the most gracious, the giver of wisdom, knowledge and success for giving me the strength, grace, blessing and guidance to complete this work. This journal would not have been possible without the valuable guidance of several people who assisted me in the completion of my research. In particular, I am indebted to my mentor and supervisor, Engr. Prof. Innocent I. Eneh and Engr. Dr. Princewill Eneh for their encouragement, advice, guidance in the completion of my research work.

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APPENDIX 1

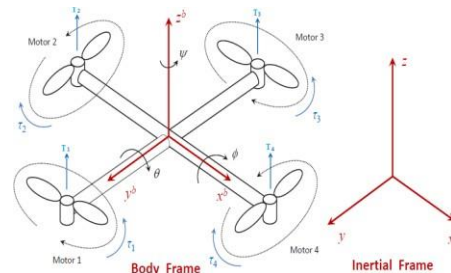


Figure 2: Quad copter structure model in hovering condition

APPENDIX 2

Symbol	Parameters	Value	Units
M	Quad copter total mass	0.65	kg
l	Length of quadcopter	0.19	m
l <sub>xx</sub>	Rotational inertia along x-axis	0.0075	kgm <sup>2</sup>
l <sub>yy</sub>	Rotational inertia along y-axis	0.0075	kgm <sup>2</sup>
l <sub>zz</sub>	Rotational inertia along z-axis	0.013	kgm <sup>2</sup>
R <sub>p</sub>	rotor blade length	0.16	M
l	Rotor blade figure of merit	0.5	
l <sub>r</sub>	Rotors inertia	6.0e-5	kgm <sup>2</sup>
R	Motors resistance	0.6	Ohm

$K_e$	Rotors speedConstant	0.0015	volts $s \text{ rad}^{-1}$
$K_q$	Rotors speedConstant	0.0056	$N. m A^{-1}$
$\eta$	Rotor efficiency	0.75	%
$k_i$	Torque Constant	0.01	$N. s^3$
G	Acceleration dueto gravity	0.81	$m. s^3$
D	Drag coefficient	7.50e-7	
P	Air density	1.1	$kgm^2$

APPENDIX 3

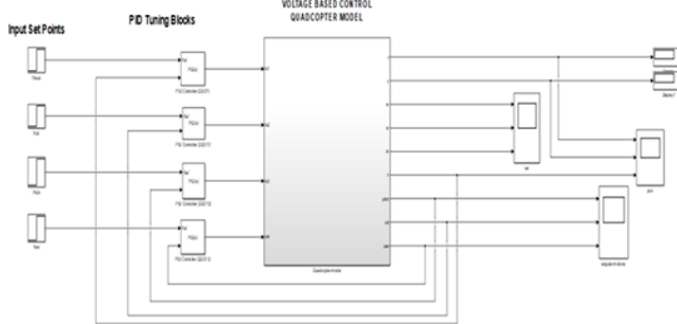
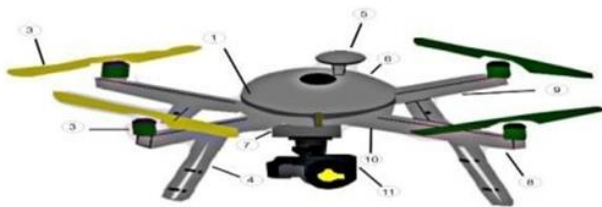


Figure 3: A PID Control System for Multiple Drones



- |                       |                          |
|-----------------------|--------------------------|
| 1. Canopy             | 5. GPS Antenna           |
| 2. Black (Propellers) | 6. Control Board         |
| 3. Brushless Motors   | 7. LI-PO Battery         |
| 4. Landing Skid       | 8. Frame                 |
|                       | 9. LED Light (Front)     |
|                       | 10. LED Light (Back)     |
|                       | 11. Camera with lens Cap |

Figure 4. A Detailed Structure of a Quad Copter Drone with Four Rotors.