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Drone Tracking with Drone using Deep Learning

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Abstract—**With the development of technology, studies in fields such as artificial intelligence, computer vision and deep learning are increasing day by day. In line with these developments, object tracking and object detection studies have spread over wide areas. In this article, a study is presented by simulating two different drones, a leader and a follower drone, accompanied by deep learning algorithms. Within the scope of this study, it is aimed to perform a drone tracking with drone in an autonomous way. Two different approaches are developed and tested in the simulator environment within the scope of drone tracking. The first of these approaches is to enable the leader drone to detect the target drone by using object-tracking algorithms. YOLOv5 deep learning algorithm is preferred for object detection. A data set of approximately 2500 images was created for training the YOLOv5 algorithm. The Yolov5 object detection algorithm, which was trained with the created data set, reached a success rate of approximately 93% as a result of the training. As the second approach, the object-tracking algorithm we developed is used. Trainings were carried out in the simulator created in the Matlab environment. The results are presented in detail in the following sections. In this article, some artificial neural networks and some object tracking methods used in the literature are explained.**

*Keywords— **Unmanned Aerial Vehicle, drone tracking, deep learning, yolov5, object detection***

I. INTRODUCTION

With the development of technology and computers taking place in our lives, it has become an important goal to reduce the workload on people and to carry out the work to be done more efficiently. Studies for this purpose have led to the emergence of the concepts of artificial intelligence, deep learning and computer vision. Studies have been carried out to enable computers, which were given the ability to perform numerical and logical operations at the beginning, later on, to gain skills such as decision making, seeing and understanding that are unique to humans. In this context, the concept of artificial intelligence first emerged. Then, the concept of machine learning, which is a sub-field of artificial intelligence, is aimed to give human-specific learning ability to artificial intelligence. Deep learning, which is a sub-branch of machine learning, has recently become a very popular research area. With deep learning, activities such as object tracking, object detection and speech have been brought to machines. Although Unmanned Aerial Vehicles (UAV)[1], which can take off with the effect of aerodynamic forces and have the ability to move autonomously over a certain trajectory or controlled by remote control, are used for military, commercial, recreational or civil purposes, the development of unmanned aerial vehicles, dates back to the years of World War I. Therefore, UAVs were originally used in the military field. Its use has also increased because its cost is less than aircraft and it can be easily controlled in risky missions. Today, drones are now armed and used for reconnaissance and surveillance. Civil use of UAVs has taken time due to military restrictions [2]. In recent years, with the development of technology, the production of drones has increased, and the development and acquisition of professional or personal UAVs have also accelerated. In addition to the use of unmanned aerial vehicles in the military field, their public accessibility has also increased [3]. Cameras and weapons that can be attached to unmanned aerial vehicles in these conditions where access to drones is easier; poses a threat to airspace, property, individual security and privacy. The drone that fell in the garden of the White House in the USA in 2015 and the sighting of drones for a few days around the nuclear power plant in France can be given as examples [3]. Considering all these, autonomous drone detection and tracking are of great importance today. The advantages of Unmanned Aerial Vehicles, especially in the military field, search and rescue activities, and security was taken into account, and the use of UAVs in this field has increased. UAVs that can be controlled remotely or autonomously can follow a certain trajectory and can also detect and track objects thanks to their camera. There are many studies in the literature on drone detection and object detection and tracking using drones. A literature search was conducted for object tracking methods. Which methods were used as a result of this research, procedure times and success rates are given in Table 1.

TABLE I. OBJECT TRACKING METHODS

Object Tracking Method		**Use of**	**Processing Time**	**Success Rate**
Point-Based	Kalman Filter	Kalman Filter Applications	Low-Medium	Middle
	Particle Filter	Recursive Bayesian Filter	Medium -High	Middle
	Multiple Hypothesis Tracking	MHT Algorithm	Low	Low-Medium
Kernel-Based	Basic Template Fitting	Compliance Search Algorithms In Video	Low-Medium	Low

	SVM	Classification Of Pixels In An Image	Middle	Middle
	Fitting Based Classification	Pixel Density In Shape	Middle	Medium-High
Silhouette - Based	Edge Intersecting	Gradient Descent Algorithms	Middle	Medium-High
	Shape Fitting	Hough Transform	High	High

Akloufi et al. [4] suggested two different approaches in their study of drone tracking. According to their first approach, deep reinforcement learning was applied to the follower UAV to follow the target UAV. In their second approach, the location of the target UAV in the next frame was estimated using a deep object detector and a search area suggestion (SAP) to track the UAV. In the study [5], in which drone tracking was performed with the millimetric radar system method, success was achieved in short-range detections. Unlu et al. [6] proposed a complete end-to-end autonomous system using a drone with an RGB camera attached. The study presented using the You Only Look Once (YOLO) deep learning algorithm [7], proposes a fighter drone approach to environments where GPS is not available. In the study in which the on-policy deep learning approach was presented in multi-agent training [8], the difference between deep reinforcement learning and deep reinforcement learning was demonstrated. In the study [9] in which the communication problem for swarm drones is examined, a distributed deep reinforcement learning approach is presented to control more than one UAV. In the study, which presents a taxi model for autonomously moving aircraft to reach its customers as soon as possible, [10] eVTOL-based drone taxi method has been developed using a deep reinforcement learning approach. The parameter sharing method is suggested in the training for swarm robots by testing the PPO algorithm in different environments [11]. A new distributed reinforcement learning architecture is presented in many other UAV studies [12]. In this study, the control and optimization of UAVs are aimed. The thesis prepared by Venturini [13], it is aimed to solve the typical difficulties of deep reinforcement learning approaches for swarm drones. Haksar and Schavager [14] used the Distributed deep reinforcement learning approach to detect forest fires and respond as soon as possible. Seejong Park et al. [15] present comprehensive research on systems against drones. A deep reinforcement learning architecture is proposed in the study [16], which observes the movements of drones by simulating a virtual neighborhood. In the study [17] in which deep learning policies were used together with reinforcement learning, the movements of the trained agent were observed.

Studies on autonomous vehicles, such as developing algorithms and testing in the real world, are very costly both in terms of money and time [10]. Simulators such as MATLAB/Simulink, Gazebo, Webots and Microsoft AirSim are used to solve this problem and test new software and new tools faster. This study includes a simulation application based on deep learning and artificial intelligence approaches to autonomously detect and track one UAV (target) using another UAV (tracker). Different approaches for drone detection were examined and an appropriate approach was used for the study. Examined methods are included in the study. MATLAB & Simulink were used for simulation. In addition to the images taken from the internet, images taken from the Microsoft AirSim environment were also used to create the dataset. A drone simulation video created with Microsoft AirSim was used for the test. The detailed content of the application and the results are included in this study.

In the study, object tracking and object detection methods are examined and explained. One of the Deep Learning-based object detection methods; Convolutional Neural Networks (CNN), Regional Based Convolutional Neural Network (R-CNN) and YOLO object detection methods are examined. Methods for object tracking; It has been examined in three categories as Point-Based Object Tracking, Kernel-Based Object Tracking and Silhouette Based Object Tracking.

The aims of this article are given as articles.

- Using deep learning approaches for drone tracking,
- To realize the training stages by creating a simulator environment for object tracking,
- Testing the model in a real environment after successful training

This article continues as follows. In the first part, the deep learning algorithm and object tracking methods used in this study are explained. In the second part, the simulation environment and training parameters are presented. In the third part, the training results are given together with the obtained graphics. In the last section, the article is concluded.

II. Deep Learning Approach To Drone Tracking With Drone

In this section, the deep learning approach and object tracking algorithms used in our study will be explained.

A. Deep Learning Approach for Object Detection

Object detection can be briefly expressed as the classification, identification or interpretation of objects in the image or video. Object detection has been studied for many years. The first algorithm that effectively detects objects used in various fields and applications such as entertainment, agriculture, commerce, health and military is the Viola Jones algorithm, which has entered the literature with the article named "Rapid Object Detection Using A Boosted Cascade of Simple Features" [18]. With the concepts such as deep learning and artificial intelligence, which come into our lives with the ever-changing and developing GPU technology, object detection studies have accelerated and methods with significantly increased accuracy have been developed. When we look at the literature, we see that object detection consists of four stages. These stages are in order; preprocessing, object detection, object classification and object tracking. The object detection stage is of great importance as it will affect the success rate of the next stages. In the continuation of this section, deep learning-based object detection methods are explained.

Simply put, deep learning is training an artificial intelligence using data that exists in the real world. Deep learning, whose popularity and studies are increasing day by day; is based on artificial neural networks (ANN) technology. Artificial Neural Networks have been developed based on the nervous system of humans. ANN consists of artificial nerve cells and layers. These nodal cells can be thought of as neurons in the human brain. Cells are connected by weighted links and layers. These layers are the input layer, the hidden layers, and the output layer, respectively[19]. Fig. 1 shows basic CNN architecture.

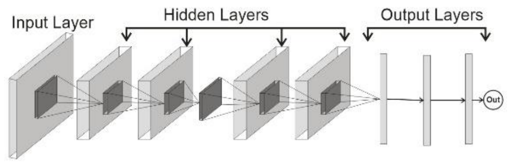

Figure 1. Basic layers of CNN architecture

Convolutional Neural Networks (CNN), with its success in the Large-Scale Visual Recognition (ILSVRC) competition held in 2012, proved itself in the field of image processing and computer vision, making a big impact. Convolutional Neural Networks is a deep learning algorithm that uses images as input. It consists of three layers: convolution, pooling and fully connected [20].

Object detection with Regional-Based Convolutional Neural Networks (R-CNN) is an architecture developed by Ross Girshick et al. in 2014 because it is difficult to detect objects with CNN in images containing multiple objects. It divides the image into regions to find the bounding boxes and runs the detection algorithm to find the objects [21]. The image is divided into 2000 regions and image classification is performed by applying CNN to each region. However, this method is very costly in terms of time. Object detection with R-CNN has different methods such as traditional R-CNN, Fast R-CNN and Faster R-CNN. It is suggested to use Fast R-CNN and Faster R-CNN methods for less time consumption. The comparison of these methods in terms of time is given in Fig. 2.

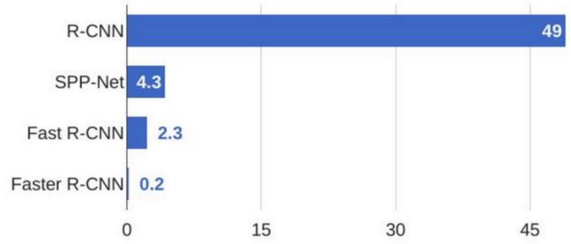

Figure 2. Time –speed comparison of R CNN

B. Object Detection with You Only Look Once

You Only Look Once (YOLO) is an object detection algorithm first described in the article published by Joseph Redmon et al. in 2015 and is also known as YOLOv1 [22]. It is very fast compared to previously developed object detection methods. Because, unlike other object detection methods, it uses a single neural network for the entire image. Fig. 3 shows the Speed Comparisons of Object Detection Methods on Pascal Data Set [23].

	Pascal 2007 mAP	Speed	
DPM v5	33.7	.07 FPS	14 s/img
R-CNN	66.0	.05 FPS	20 s/img
Fast R-CNN	70.0	.5 FPS	2 s/img
Faster R-CNN	73.2	7 FPS	140 s/img
YOLO	63.4	45 FPS	22 s/img

Figure 3. Speed Comparisons of Object Detection Methods on Pascal Dataset

It is a regression-based algorithm that estimates bounding boxes and class probabilities in images at once with a single neural network. It tries to guess the bounding box that determines the position and class of an object. Splits the input image into G x G cells (grid) [24].

YOLOv5 was produced by Ultralytics in June 2020, with the development of the YOLOv4 model on the Pytorch library. YOLOv5 uses the same structures as YOLOv4 in the neck and head. The biggest difference compared to other versions is that it is a Pytorch-based model [25].

C. Object Tracking

Object tracking methods have two main tasks, together with determining the position of the target object to be tracked in the image and establishing the data link relationship between the images of the object whose position has been determined in the successive images. Object tracking methods are divided into three groups such as point-based, kernel-based and silhouette-based. The classification of object tracking methods is shown in Fig. 4.

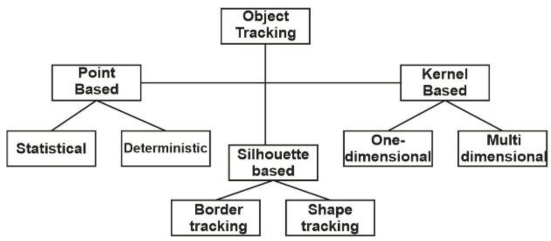

Figure 4. Classification of object tracking methods

1) The point-based object tracking method

In the point-based object tracking method, the object to be tracked is expressed with points. The positions and distance information of these points between successive images are expected to give close results in the next, incoming image. Kalman filtering [26], this method invented by Rudolf Kalman of Hungarian origin, is widely used in real-time object tracking applications due to its simplicity and speed. The particle filtering method [27] is a kind of Monte Carlo method of sequential and Bayesian theory, which is based on the point mass representation of the probability density function applied to any state model [28]. The advantage of the particle filter is that it can prevent sudden changes in the movements of the target object and blockages. The disadvantage of the particle filter is the degradation of particles on the tracked object. Object tracking fails due to corrupted particles.

2) *The kernel-based object tracking method*

The kernel-based object tracking method [29] is in the group of parameterless estimators that do not have a constant function and constant parameter values. Fixed value methods are not used in parameterless systems and all information is taken into account when a prediction will occur. The Mean Shift algorithm is a non-parametric statistical method introduced by Fukunaga in 1975 [30]. The Mean Shift approach is a parameterless approach that is computationally based on the density difference estimation and does not require intensive computation to detect the peak of the probability distribution. The model applied in this study is summarized in Fig. 5.

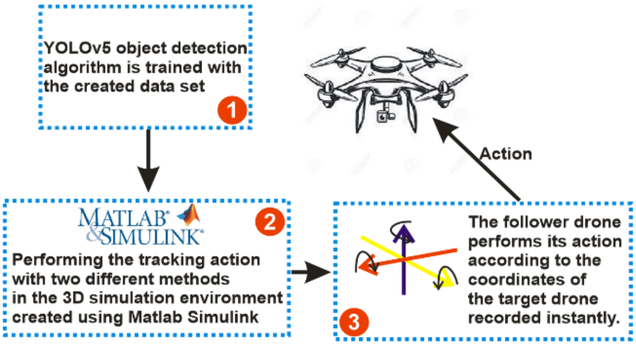

Figure 5. The working diagram of the model developed for this application

3) *The silhouette-based object tracking method*

Shapes of objects may not be definite. For this reason, the recommended method for tracking objects with complex geometric shapes is silhouette-based object tracking. The purpose of silhouette-based object trackers is to detect the object model formed in the current image using the results obtained in previous images [31]. A silhouette template database is used for objects with uncertain shapes. The shape to be selected is the shape that is most similar to the object shapes in the silhouette template database. This method can be examined in two sub-categories as boundary tracking and shape tracking. Border tracking is the process of searching the borderlines of the object determined in the current image and the boundaries of the objects in the next images. In shape tracking, it is assumed that the silhouette of the object to be tracked is transferred to the next image. It performs the search process by calculating the similarity and difference values between the silhouette and model of the object, the silhouette and model of the objects detected in the current image, together with the data collected from the previous images [31].

III. SIMULATION ENVIRONMENT AND TRAINING SETTINGS

Within the scope of this study, "Drone Detection and Tracking Simulation" was developed by using the Matlab/Simulink environment and the YOLOv5 algorithm, consisting of a follower drone and a target drone. In the continuation of the study, there is information about drone detection, development environment, drone tracking and simulation environment.

Quad helicopter was preferred for the drone models created. In order to describe the quadcopter motion in 3D space in terms of equations, 6 degrees of freedom (6 DOF) with Euler angles where the gravitational force is constant (g= 9.81 m/s2) and the center of mass and the center of gravity are assumed to be equal are used. The orientation equation used for 6 DOF body frames is shown in (1).

$$M = I^b \omega_n^b + \omega_n^b x I^b \omega_n^b \tag{1}$$

The rotation equation used for 6 DOF body frames is shown in (2)

$$F = m(v^b + \omega_n^b x v^b) \tag{2}$$

While creating the mathematical model of the quadcopter, Newton's equations of motion were used. In order to define angular movements and rotational movements, the inertia axis, which is defined as the fuselage axis and the fixed axis, is needed on the quadcopter.

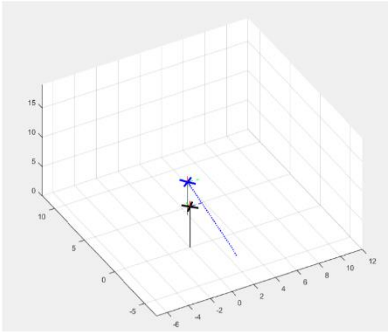

Figure 6. Created simulation environment

As seen in Fig. 6, in the simulation environment; There is a blue tracker drone and a black lead, target drone. The starting positions for both drones have been determined. Coordinates lines in blue, red and green colors are determined for the follower and the target drone. The blue axis of the follower drone is also the camera axis.

A. *Quadcopter Drone Modeling*

Quadcopters are unmanned aerial vehicles with four propellers, vertical take-off and landing capability, and six degrees of freedom. The thrust forces of the propellers, whose mobility consists of rotors, are used. The quadcopter, which has a cross-frame, has four engines: front, rear, left and right. The motors provide movement by creating a lifting force in the direction of the rotation axis of the propellers. Quadcopters move with roll (ψ), yaw (ϕ) and pitch (θ) angles [1]. The right and left propellers rotate clockwise, while the rear and front propellers rotate counterclockwise. This situation, together with the rotation of the propellers of the quadcopter at equal speed, ensures that the torque in the center is balanced and the orientation angle remains constant, as well as the upward movement. The difference in speed between the right and left propellers changes the roll angle of the quadcopter. The speed difference between the front and rear propellers changes the pitch attitude [31]. Fig. 7 shows the quadcopter's parameters.

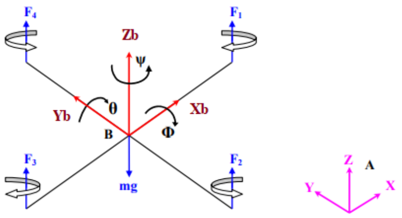

Figure 7. Quadcopter's Lift Forces and Coordinate System

Within the scope of the study, real-time drone detection was carried out using YOLOv5. Some of the data set used was taken from the internet, and some of it was created by us using Microsoft AirSim. The YOLOv5 algorithm was run on Google Colaboratory. Although the number of datasets consisting of images taken from drones is large, the number of datasets consisting of drone images is limited. The data set we use, some of which is taken over the internet, consists of approximately 2500 drone images, together with the images we have taken from the drone simulation we have created in the AirSim environment. 80% of the images are divided into two folders, for training and 20% for testing. LabelImg program was used to create label files in YOLO format for images. In the training phase, 640x640 input images were trained on the ANN with batch=16 and epochs=1000 values. Results from test images on videos are shown in Fig.8.

Figure 8. Result from test images on videos

B. Data Set

Although the number of datasets consisting of images taken from drones is large, the number of datasets consisting of drone images is limited. In addition to the pictures on the internet, the pictures created by using the AirSim simulation environment were brought together and the data set of our project was created.

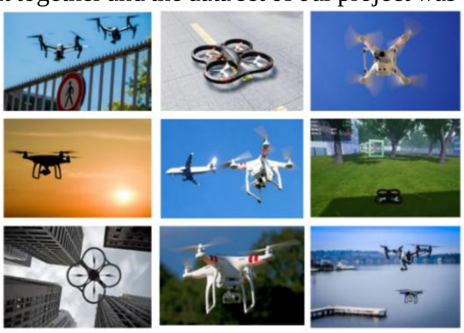

Figure 9. Sample images from the dataset

The dataset consists of approximately 2500 different drone images. 80% of these pictures are reserved for training and 20% for testing. Finally, the label files of these images in YOLO format were made ready for education using the LabelImg program. Some pictures in the data set are shown in Fig. 9.

IV. Simulation And Test Results

Within the scope of the project, training was carried out in the MATLAB & Simulink simulation environment by using our tracking algorithm for drone tracking. The project consists of two phases. In the first stage, a model was created by training the YOLOv5 object detection algorithm with the determined parameters. In the second stage, our object tracking algorithm is presented in four different options and results are obtained. In the continuation of the section, these four different options are presented with simulation environments. These; normal tracking mode for complex track, frame tracking mode for complex track, normal tracking mode for surround tracking mode, and frame tracking mode for surround tracking mode. Normal

A. Tracking Mode for Drone Tracking.

If the normal tracking mode is desired to be selected, the angular velocity of the model (depending on the surrounding rate) cannot be included in the process and its value is selected as 0 (zero). By deactivating the surround feature, the follower drone is prevented from surrounding the target drone. Fig. 10 and Fig.11 show the simulation of two different paths presented for the normal follow mode.

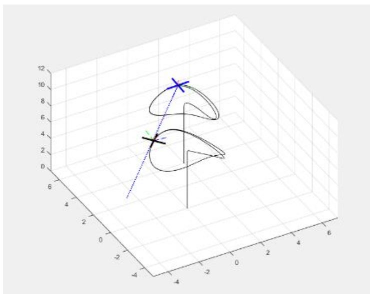

Figure 10. Normal tracking mode for complex path

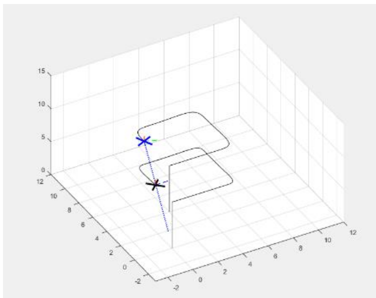

Figure 11. Normal tracking mode for square path

B. Surrounding Tracking Mode for Drone Tracking with Drone

The surrounding velocity is determined by the angular velocity. By selecting the angular velocity of the model 0.5, the surrounding mode is activated. The follower drone also surrounds the target drone while following it. Fig. 12 and fig. 13 show the simulation results for two different paths of the surround tracking mode.

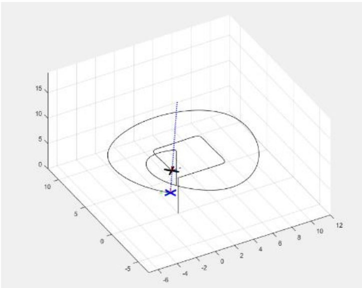

Figure 12. Surrounding track mode for square path

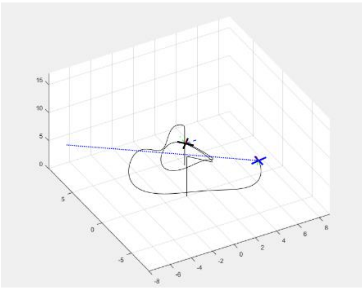

Figure 13. Surrounding track mode for complex path

C. Test Results

The resulting graph for the complex path with the normal tracking mode is given in Fig. 14. The top graphic shows the change of coordinate information of the tracker drone over time. The bottom graph shows the time-varying coordinate information of the tracked (lead, target) drone. The resulting graph for the square path when the normal viewing mode is selected is given in Fig. 15. The top graph shows the change of coordinate information of the tracking drone over time. The bottom graph shows the time-varying coordinate information of the tracked (lead, target) drone. When the graphs are compared, the distance between the two drones is subtracted. On the path determined as a square, both drones move steadily when the z-axis reaches a certain height. The resulting plot for the complex path with the selected surrounding tracking mode is given in Fig. 16. The top graph shows the change of coordinate information of the tracking drone over time. The bottom graph shows the time-varying coordinate information of the tracked (lead, target) drone. The resulting graph for the square path with the selected perimeter monitoring mode is given in Fig. 17. The top graph shows the change of coordinate information of the tracking drone over time. The bottom graph shows the time-varying coordinate information of the tracked (lead, target) drone. As can be seen from all three graphs, the distance between the two drones was calculated during graph drawing. It can be said that the X and Y values, they come to the same position at the same time.

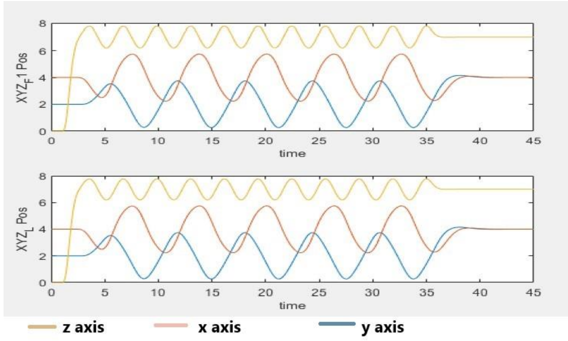

Figure 14. Result plot for complex path with normal tracking mode selected

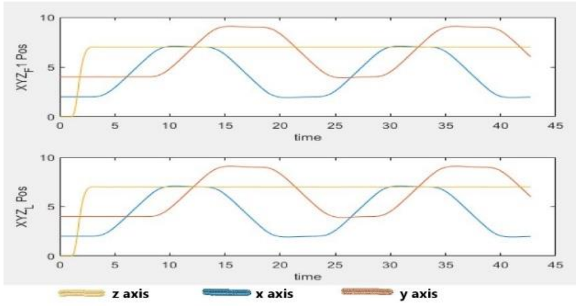

Figure 15. Result plot for square path with normal tracking mode selected

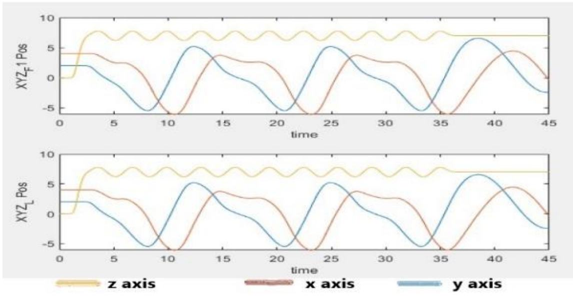

Figure 16. Result plot for complex path with surrounding follow mode

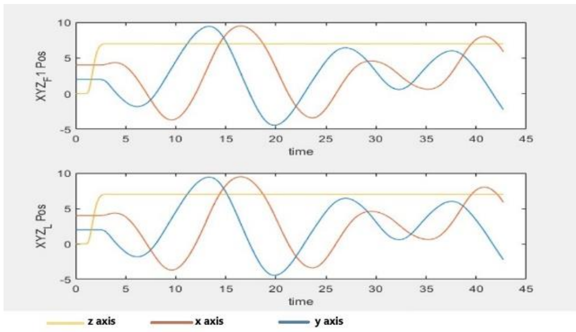

Figure 17. Graph of axes with time for square path and surrounding track mode

In Fig. 18, the precision and recall graph that emerged as a result of the training with the drone data set is shown. As mentioned before, precision and recall values close to 1 are directly proportional to success level of the training. As can be seen in the graph, the performance value is 0.934, which is quite a high value. From this, we can deduce that the detection study achieved 93% success.

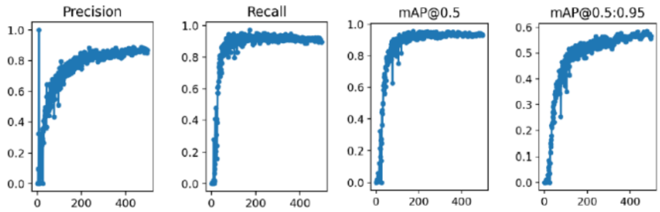

Figure 18. Precision and recall graph that emerged as a result of the training

V. CONCLUSION

In the study, the concepts of object detection methods, object tracking methods and Unmanned Aerial Vehicles are mentioned. As the result of this work; a Drone tracking simulation with a drone was developed in Matlab & Simulink environment, using the YOLOv5 algorithm and the tracking algorithm are developed. The purpose of the study, its operation and the methods used are mentioned. The success rate after the training with the data set consisting of approximately 2500 data for drone detection was approximately 93%. According to this result, it can be deduced that higher success rates can be obtained when training is performed with a larger data set. Based on the graphics and figures for drone tracking, we can deduce that the tracking algorithm has a high accuracy rate.

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