Prediction based Auto-Pilot Interface for Drone to Object Chasing using Historical TSPI Data

Shinhyoung Jang*, Byeonghwi Park*, Juheon Jeong*,
Jack Mahedy‡, Nebey Gebreslassie‡, Minji Lee†, and Eric T. Matson‡

* Department of Computer Science and Engineering
Chungnam National University, Daejeon, Republic of Korea
† Department of Technology
Purdue University, West Lafayette, IN, USA
‡ Department of Computer and Information Technology
Purdue University, West Lafayette, IN, USA
Email: * {201802151, 201802093, 201802155}@o.cnu.ac.kr,
† lee3450@purdue.edu,
‡ {jmahedy, ngebresl, ematson}@purdue.edu

***Abstract*—Replacing military aircraft with Unmanned Aerial Vehicles (UAV) offers benefits such as the reduction of costs and risks associated with traditional military aircraft. To prevent enemy UAV attacks, research was conducted on various UAV detecting systems, which utilize radar and image processing for identifying drones. However, the misidentification of friendly and hostile drones remains a challenge. This paper proposes a process that uses UAV for reconnaissance. The proposed system includes a chasing algorithm that enables UAV to follow and close in on detected objects, facilitating the identification process. The radar detects the target object's Time Space-Position Information (TSPI) in longitude, latitude, and altitude, which is then utilized to predict the target's trajectory. By using the target's trajectory and the chasing algorithm, the chasing UAV enables the tracking target and closes the distance of the target to identify the object. The result shows that the Ensemble with Linear Regression achieved the highest performance in comparing Machine Learning models. The chasing UAV are programmed to approach the target until they are within 10 meters, providing the user with the opportunity to identify the object, such as by taking a picture or performing other actions as desired.**

***Index Terms*—UAV, DJI, chasing, trajectory prediction**

I. Introduction

UAV have diverse uses including agriculture, security, delivery, and military operations [1]. Using UAV as military aircraft has the advantage of lowering production and maintenance costs and reducing life-threatening risks to military personnel. In the military context, UAVs are capable of performing various tasks, such as intelligence, surveillance, reconnaissance, and cargo and resupply operations. While UAVs have not completely replaced manned aircraft for tasks such as air-to-air combat, strategic bombing, and enemy air defense suppression and destruction, the Department of Defense (DOD) and the analysts believe that these unmanned systems could take on these roles in the future [2], [3]. In the 2022 Russian invasion of Ukraine, Russia operated missions with the HESA Shahed-136 drones avoiding the radar detection of MiG-29 fighter planes. Maneuvering at a low speed and altitude, these small drones were tasked with collapsing the military and civilian power stations [4], [5].

On the other hand, the challenge of mitigating the risk of UAV attacks persists due to the inaccuracy of detecting and difficulties in neutralizing them as shooting them down or causing them to crash. To address this challenge, researchers used several approaches to detect and classify UAV. One of the approaches is using radar, which have been shown to be effective in detecting and classifying drones. For example, the Recurrent Neural Network (RNN)-based Frequency Modulated Continuous Wave (FMCW) radar makes detecting work in real-time. The experiment recorded a false detection rate of 21.1% and a detection accuracy of 96.4% [6], [7]. Another approach is testing with an image processing method to identify the entity with You Only Look Once (YOLO) [8]. With a YOLOv3, the pre-trained machine learning model had an average accuracy of 88.9% when using the unidentified object's image as input [9].

Despite efforts to identify the object, there is a risk of false detection when using partial data to identify an object. More information is required, such as the result from the Thermal Observation Device (TOD) or the shape of the unknown subject, to gain more insight for classification [10], [11]. For example, in December 2022, five North Korean drones entered the Military Demarcation Line (MDL) in South Korea. After determining the subject as a drone from North Korea, the UAV countermeasures operation has executed with the objective of shooting down the drone. However, the mission ended with no results. [12]-[14].

One strategy to obtain the shape of an object is through close-range imaging. This method provides more information such as whether it is armed [15]. Two approaches to achieve this: using a camera that has the ability to zoom in at any distance or employing our drone to chase and make a physical distance closer. When the distance becomes shorter, it's possible to capture a clear image or neutralize the target. Predicting the next location of the object is important to accomplish the chasing. To predict, data which includes latitude, longitude, altitude and vector is utilized to forecast the future location. In general, RAdio Detection And Ranging (RADAR) locates a target object in the sky and determines the vector by subtracting 2 locations [16]. When using time series data with location, it involves speed and heading while using location with latitude, longitude and altitude. The sequential data works as an input of ML models and the output is the next movement of the object. The latency of receiving commands from a computer to a drone is considered a hyperparameter to control.

This paper focuses on predicting DJI's drones' future location as well as pursuing the UD. As DJI, the Chinese company whose market share to 76 percent in 2021, its aircraft become more of a threat [17]-[19]. Location data which includes latitude, longitude, and altitude from the drone is exported from the interface with the implementation of the DJI Mobile Software Development Kit (SDK). Due to the challenge of determining the communication latency between devices, the ML models use estimated figures to predict the drone's next location. The performance of ML models is measured with the error rate of the next location at *k* sec. The chasing algorithm works with the autopilot method. The distance between the target position and UAV is constantly monitored in order to make changes in direction and speed in a 3-dimensional space. The derived separate vector value from the monitor worked as $pitch$, $roll$, and $throttle$ variables to move the drone every 200ms [20].

II. Related Work

Forecasting the next location of target is a critical component of the system. In order to create a mathematical model, it is necessary to predict the trajectory of the aircraft. This section provides an overview of previous research on this topic.

Ziyu Zhao *et al.* focused on aircraft trajectory prediction using deep learning with Trajectory Change Point (TCP) [21]. TCP is created by using a trajectory clustering algorithm and analyzing the relationship between meteorological information such as the average geopotential height (meter), average temperature (Celsius), wind direction (square degree), and past data including longitude, latitude, altitude, and velocity [22]. TCP is used to determine the aircraft's heading direction, which may change depending on the weather [23]-[26]. They utilized mixture density Long Short-Term Memory (LSTM) to apply to the probability distribution to reflect factors of uncertainty such as airspace environment and pilot's ability [25]-[27]. As a result of performance evaluation like European distance Error (EE), trajectory prediction in this paper was more accurate than in previous studies. Although the paper was based on aircraft, it is worth to apply on UAV since aviation industries include them.

Xie Lei *et al.* presented a paper under the theme of Unmanned Combat Aerial Vehicle (UCAV) maneuvering trajectory prediction in Particle Swarm Optimization-Convolution Neural Network (PSO-CNN) [28]. They used three control variables such as throttle, angle of attack, and roll angle. The spatial coordinates information like longitude, attitude, and altitude can be derived by using an equation including control variables. They proposed trajectory prediction with a suitable Convolution Neural Network (CNN) model. CNN has an input layer, hidden layers, and an output layer. Each of the layers embodies a weight value. When the weight value is updated by backpropagation, the problem called vanishing gradient has a possibility to occur [29]. However, PSO-CNN is likely going to avoid this problem as it uses a heuristic optimization algorithm to transform the weight update into an optimization problem. The proposed PSO-CNN method outperformed other methods such as LSTM, Adaboost-BackPropagation (BP), and CNN, achieving superior performance.

Another paper conducted by Peng Shu *et al.* mentioned the trajectory prediction of UAV based on LSTM [30]. They utilized 3-dimensional past data such as longitude, latitude, and altitude in UAV trajectory time series data. These data were used as input values by Stacked Bidirectional and Unidirectional LSTM (SBULSTM). SBULSTM is composed of unidirectional LSTM layers, Bidirectional LSTM (BLSTM) layers, a full connection layer, and a dropout layer. By using BLSTM, not only related past data but also related future data is considered [31]-[33]. They made the model using SBULSTM and got high accuracy in trajectory prediction.

Although previous research has demonstrated that deep learning models have been shown to effectively predict trajectories using TSPI data, they have limitations in terms of computational speed and resource utilization. As a result, other machine learning models are being explored to overcome these limitations. This study proposes a comparison of the performance of various machine learning models to identify the optimal trajectory prediction model.

III. Methodology

Fig. 1 shows the mechanism of the entire system, which functions in the following manner: (1) A Radar or Light Detection and Ranging (LiDAR) system detects the coordinates of an unidentified object at t seconds; (2) Radar or LiDAR system sends TSPI to computer; (3) To ensure compatibility with the Machine Learning models, the computer preprocesses and applies them to predict the drone's future location at time ($t = t + k$); (4) transmit data to our drone and move to predicted position.

This section describes suggested systems in this paper. These are the use of Radar and LiDAR systems in detecting an object and specific mathematical technologies with ML models such as Linear Regression, Non-Linear SVM Regression, and Ensemble method.

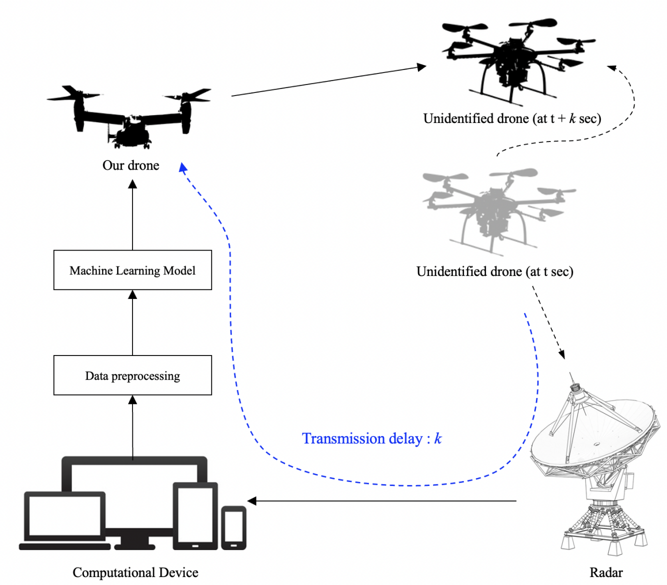

Fig. 1. System Mechanism

A. Detecting System

- The Radar system sends out high-powered data signals and receives reflected waves from the objects. The reflected radio waves are amplified through a conversion process. Only valid signals are selected by the Low Noise Amplifier (LNA) and converted to a lower frequency. These signals are demodulated to digital and fed into the processor [16]. The result from the processor includes the object's bearing, distance, altitude, and velocity. Since the data from the Radar is relative, it needs to be converted to absolute data.
  The Cartesian coordinate system has a feature that regards 3-dimensional objects' coordinates as 2-dimensional elements, even though the earth is not a perfect sphere. Equation (1) is combined with the local angle (θ) and distance (d) of the Radar, and absolute coordinates (g) of the Radar.

$$\begin{bmatrix} x_{g,t} \\ y_{g,t} \\ z_{g,t} \end{bmatrix} = \begin{bmatrix} x_{l,t} \\ y_{l,t} \\ z_{l,t} \end{bmatrix} + d_t \begin{bmatrix} cos\theta_t \\ sin\theta_t \\ 0 \end{bmatrix} \tag{1}$$

- Seungwoon Kim and Hoseok Jang proposed using LiDAR to detect UAV [34]. LiDAR determines the distance to an object by emitting a laser beam toward the target and measuring the time it takes for the reflected light to return to the sensor. They gained higher accuracy by using LiDAR rather than the existing Radar system. LiDAR detects drones with its feature that gives the 3D shape of the target object. However, it has two fatal drawbacks such as overpriced cost and dependence on weather conditions for quality performance.

B. Machine Learning Models

The Kalman Filter algorithm, which uses TSPI to forecast the next position, shows that there is a relation between velocity, heading, location of previous data, and future positions. The UAV trajectory, which consists of sequential previous data, is applicable to the Kalman Filter [35].

Following the algorithm, the air route is correlated with mathematical formulas or ML models with each TSPI. However, paradoxically, the Deep Learning model needs more computation time and resources than Machine Learning, this paper focuses on the ML model [36]. Also, 3-dimensional data consists of the vector, any velocity, and heading are no needed for the models.

- The Linear Regression reveals the relation (β) between input (X) and output (y) with the distribution of train data. The β indicates the feature's weight, which specifies how much the input data affects the output, in the regression model, shown in Equations (2), (3). If the estimate of the weight matrix is called $\hat{\beta}$, the error of this equation forms as $y - \hat{\beta}X$. When matrix X has the possibility of the determinant of 0 and different column and row lengths, an error occurs when applying the inverse matrix. Equation (4), the Least Square Method (LSM), helps to reduce the error rate [37]. The regressed value $\hat{y}$ is derived by applying test-set X and the $\hat{\beta}$ on Equation (2) [37]-[38].

$$y = \beta X \tag{2}$$

$$y = \beta_0 x_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n, (x_0 = 1) \tag{3}$$

$$\hat{\beta} = (X^T X)^{-1} X^T y \tag{4}$$

- If the number of features increases, the complexity and overfit probability are induced in the ML model. The Ridge Regression, which matches the scales within elements in $\hat{\beta}$, is suggested to reduce these problems by using hyperparameter λ, which measures complexity. Equation (5) result is the feature that is appropriate to the model; Equation (6) is the error formula of the Ridge Regressor [39].

$$\hat{\beta}_{ridge} = (X^T X + \lambda I_p)^{-1} X^T Y \tag{5}$$

$$E(w) = \sum_{i=1}^{n} (y_i - \sum_{j=1}^{p} x_{ij}\beta_j)^2 + \lambda \sum_{j=1}^{p} {\beta_j}^2 \tag{6}$$

- The Non-Linear Soft Vector Machine (Non-linear SVM) unveils the k features relation in k-dimension. When the variable data is non-separable, this approach assumes that the proper mapping function φ that makes data separate in a higher dimension exists. Based on the fact w is treated as Equation (7) in this model, the Equation (8) is derived. As the decision function equation (8), also known as the φ method, uses the inner product of the data variables $x_1 x_2$, ${x_1}^2$, and so on [40].

$$w = \sum_{i=1}^{N} \alpha_i y_i \varphi(x_i) \tag{7}$$

$$f(x) = w^T \varphi(x) + b = \sum_{i} \alpha_i y_i \varphi(x_i)^T \varphi(x) + b \tag{8}$$

Equation (9) is the method Kernel trick substituting the inner product in Equation (7). This approach focuses on how to explain the similarity of $\varphi(x_i)^T \varphi(x_j)$. The Kernel trick gives various formulas to describe relativity. Table 1 shows Kernel functions [40].

$$f(\phi(x)) = \sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b \tag{9}$$

TABLE I
KERNEL FORMULAS

Kernel	***Formulation***	***Hyperparameter***
Linear Kernel	$K(x_i, x_j) = X_i{}^T X_j$	None
Polynomial Kernel	$K(x_i, x_j) = (X_i{}^T X_j + r)^d$	r, d
RBF Kernel	$exp(\frac{-\|\|x_i - x_j\|\|^2}{\sigma^2})$	σ
Hyper-tangent Kernel	$K(x_i, x_j) = tanh(kx_i{}^T x_j + \theta)$	k, θ

- Ensemble Regression, based on the idea that models obtained a different perspective on the problem, gives the output using the base learners' result. There are several ways to provide different perspectives on the models by varying the number of training data, or by changing the ratio of the training set to the total [40].
- The Bagging method, one of the Ensemble methods, uses low bias and high variance base learners [41]. It utilizes full trees that use random subsets of features that are provided to the overfitted model. Each tree of the mechanism has a different number of data that is applied as a distinct view. Using majority voting, also known as 'high variance cutting', all predicted results from base learners are combined into one by calculating the mean. Fig. 2 shows Bagging Method's concept.

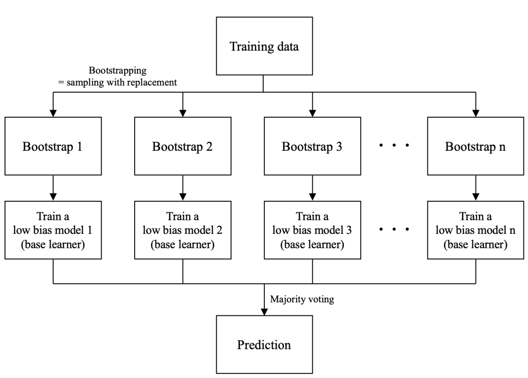

Fig. 2. Bagging Ensemble

IV. EXPERIMENT

A. System Architecture

The system architecture for controlling a drone consists of a computer, an android device, a remote controller and a DJI Air 2S [42]. The computer contains the ML model to predict the next location of the target object. The minimum android device SDK version is 21 and the DJI android SDK is 4.16.1. The connections between the devices are shown in Fig. 3.

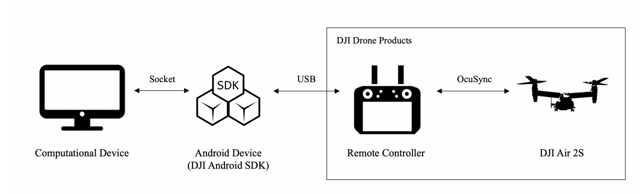

Fig. 3. System Architecture

Fig. 4 shows more detail about the data flow of our system: (1) Radar or LiDAR obtains unidentified object's coordinates. The location detected serves as input data for the ML model; (2) append data into queue; (3) if the queue's length is lower than k, the threshold that determines a sufficient number of features gathered, keep repeating (1) until the length is equal to k, then predict the next location of k with the ML models, such as Linear Regression, SVM Regression and Ensemble method; (4) transmit result from the ML models to the good drone to chase and go back to step (1) to repeat the process. This process keeps running until the distance between the good drone and chased target object is closer than the threshold.

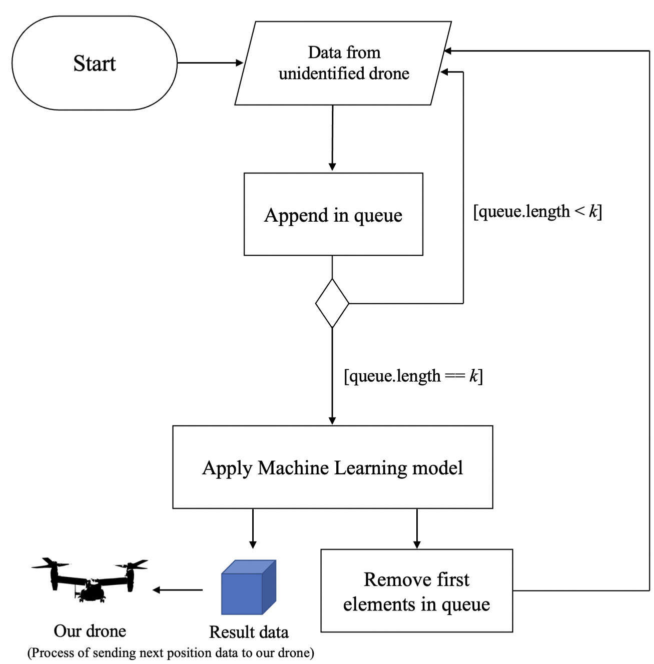

Fig. 4. Data Flow in System

This flow has three important points: data communication latency, the drone movement method, and the process of data collection for UD's coordinates to verify the ML model. The data network connections include the android device to the computer and the android device via the remote controller to the DJI AIR 2S. The network connection latency assumed as more than one second to make it general. The UAV moved with the auto-pilot function which was implemented with the support of the DJI Android SDK. Regarding dataset collection, the drone simulator performs as well as Radar or LiDAR for locating the target's latitude, longitude, and altitude.

B. Auto-Pilot Method

DJI's product contains a waypoint mission feature that defines the flight path of the drone without the user's manual control. The waypoint mission method was referenced to implement the auto-pilot method [43]. The variables to move DJI AIR 2S as latitude, longitude, and altitude are $pitch$, $roll$ and, $throttle$, which contain velocity and direction.

Fig. 5 indicates the quadrant which is related to the $pitch$, $roll$ and, $throttle$. The angle between the drone and the target, calculated with cosine and sine, gives an initial value of pitch and roll. In the DJI Android SDK, the values of pitch and roll are approximately $\pm 15m/s$. The feature throttle is converted to a scalar using the tangent function. The proportions used to calculate tangent are the difference of height (Δt), distance (Δd) between chased and chasing drone, and the maximum value of the 2-dimensional vector scalar which is the result of $pitch$ and $roll$. In the DJI Android SDK, the value of the throttle is restricted to $\pm 4m/s$. Since this value derives from the tangent function, an overflow handling method that restricts the range of speed needs to be implemented [44]-[45].

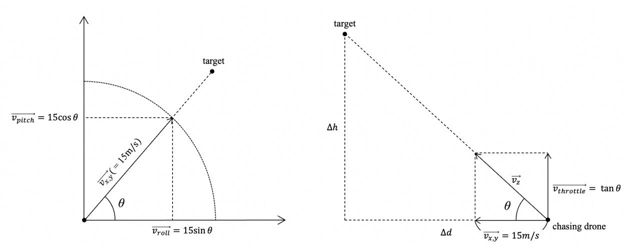

Fig. 5. Calculate Velocities of Drone

C. Data Collection

The data produced in the real world has various variables that don't remain constant (wind, clouds, sunset, etc). To ensure uniformness of conditions, the DJI-supported simulator was used to create the UAV data. The simulator for DJI AIR 2S, DJI Assistant 2 (Consumer Drones Series), has some changeable values which are the home location of latitude, and longitude, wind speed for three directions x, y, and z [46]. The drone interface uses the home location of the simulator as the starting point of the saved trajectory log of UAV.

Once the simulated UAV takes off, it moves every 200ms by the auto-pilot method. The thread functions with logging the location every 500ms. To make a pinpoint (marker), there are two ways: touching the map by hand and drawing with a method. The first way allows users to build a customized flight path instantly. By forcing the user to focus on the drone's movement, it allows the user to alter the trajectory at any given time. The second method follows the initialized baseline of the air route and reflects the user's instruction instantly. Since the latitude and longitude of all locations on the route are compiled when the application is installed, the user doesn't need to focus on changing every heading of the drone.

Fig. 6 describes how to collect the dataset by using the thread that draws markers at interval 40 seconds. When drawing the pinpoint on a map, UAV fly to the marker by using the Auto-Pilot method. It moves until distance between the chased and chasing drone is less than 10m. Before running the process, the air route of the drone (letter z shape, number 8 shape, etc) has to be initialized as an array.

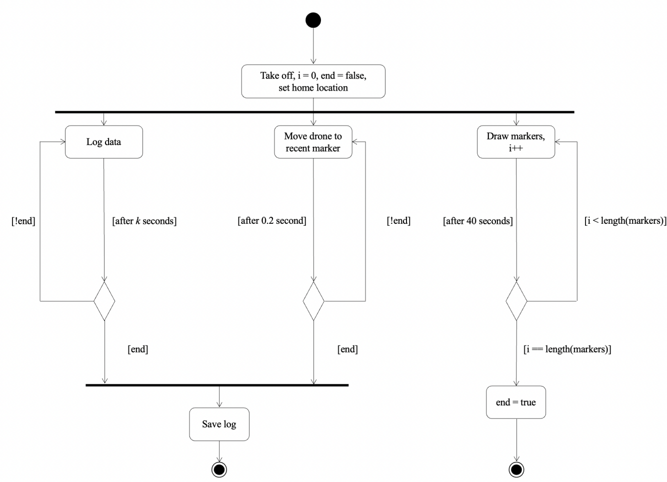

Fig. 6. Data Collection Flow

D. Verify Machine Learning Models

During target object prediction and pursuit, latency needs to be considered when calculating the result. The feature considers as the hyperparameter owing to the environment where the system is used makes the feature inconsistent. Preprocessing the raw data to find the trajectory includes setting the data set period as the hyperparameter t seconds and concatenating the k separate location data which includes latitude, longitude, and altitude. The drone's velocity and heading also affect the next movement of the object. These features are explainable as the location data is used.

ML models Linear Regression, Non-linear SVM, and the Ensemble model are the target to verify. The Linear Regression model utilizes the idea that all data are on a k-dimension plane. The Non-linear SVM model, which uses RBF kernel, predicts trajectory with the reason that the data is on the non-linear structure. The ensemble method which uses the Bagging algorithm forecasts future locations by combining the results from each linear model into one.

Fig. 7-9 illustrates the trajectory between real and predicted from each model in a 3-dimensional space. Since the risk of overfitting in Linear Regression exists, Ridge Regression is essential. As hyperparameters, such as the training ratio, the number of estimators, λ, γ, and the number of the estimation model, affect the performance, the research considers each condition of Machine Learning. To choose these for ML models, the gridSearchCV method, which finds the best hyperparameters set, is suggested in this research and produces the result such as Table 2. The dataset obtained from the DJI AIR 2S trajectory has been divided into a 10:1 ratio of train and test sets for use in machine learning models.

TABLE II
HYPERPARAMETER IN MACHINE LEARNING MODELS

Models	*Latitude*	*Longitude*	*Altitude*
Ridge	$\lambda : 1$	$\lambda : 1$	$\lambda : 1$
SVM	$C : 100, \gamma : 10^{-4}$	$C : 100, \gamma : 10^{-4}$	$C : 100, \gamma : 10^{-6}$
Bagging	$estimators : 30$	$estimators : 30$	$estimators : 30$

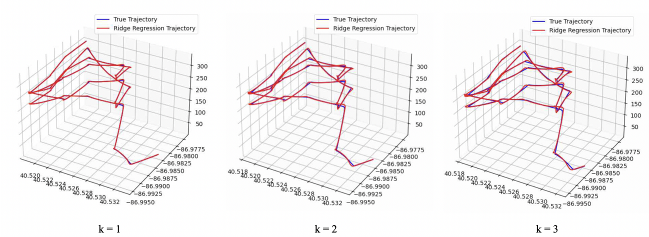

Fig. 7. Ridge Regression

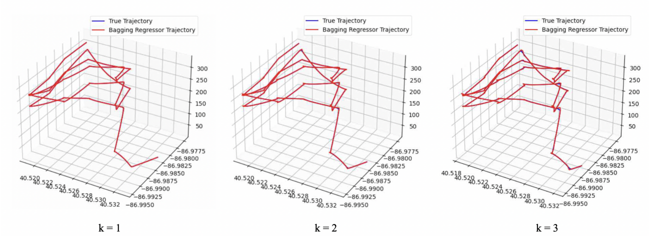

Fig. 8. Bagging Regression

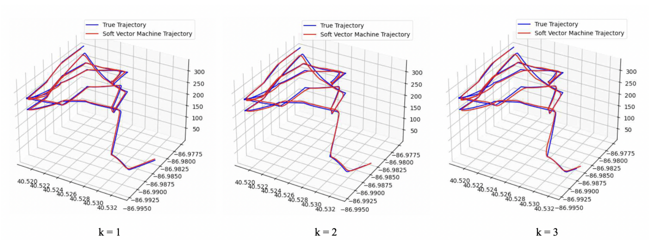

Fig. 9. SVM Regression

Fig. 10 shows a comparison of the MAPE of each model, which was calculated with Equation (10) based on the transmission delay (k) [47]. MAPE presents a ratio of how different the predicted and real data are in absolute value. The Ensemble Regression is the best prediction model based on MAPE. The trajectory data of UAV, a value between Linear Regression and Non-Linear SVM, contains linearity that can be predicted in mathematics. The different view of data makes more information about predicting.

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \frac{|y_i - \hat{y}_i|}{y_i} \tag{10}$$

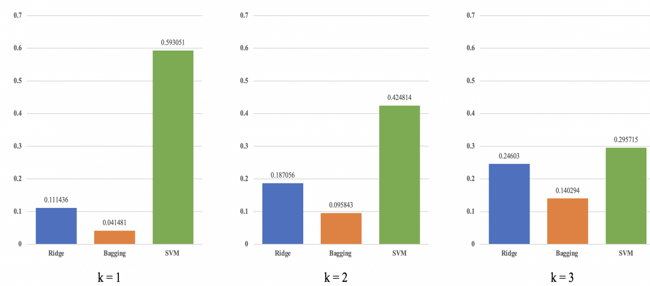

Fig. 10. Performance Evaluation of Machine Learning

V. CONCLUSION

This paper proposes a process for detecting object, predicting the trajectory, and lastly chasing the object. The experiment concentrates on verifying the forecast of the next move and implementing the autopilot method. When the ML model gives the result, which is calculated with the assumption of transmission latency with the devices, the chasing drone moves to the target pinpoint until the distance between objects is shorter than the threshold or a new pinpoint has been drawn. To check the linearity of TSPI data, the MAPE calculated from Linear Regression and Non-linear SVM has been compared. From the MAPE of the ML models, Ensemble with linear regression gives the best result.

Although this paper conducted a limited experiment with DJI drones and omit how to detect the object, the process can be generalized with detecting, predicting and chasing. Future research should investigate latency calculation in different environments.

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