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Research Article

Multi-Sensor Data Fusion for Path Prediction of Escaping from Engagement in Unmanned Aerial Vehicle Scenario

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Abstract

Achieving air superiority is one of the key steps to success in warfare. It is necessary for a combat aircraft to have the survivability it needs in an aggressive combat environment. Unmanned aerial vehicles (UAVs) suffer from maintaining the maneuverability and navigational ability in the event of a disconnection from the control station. In this paper, an escape path prediction algorithm developed by fusing multi-sensor data is presented to facilitate the escape of engagement of UAVs. Data from radars are evaluated in the Extended Kalman Filter and used to make estimations. The estimations made are used in constraint optimization to generate an instantaneous optimal escape route. Since the constraints and objective function are not linear, nonlinear programming is used as a method of constraint optimization. According to the simulation results, the proposed method shows a promising result for escaping from engagement in the selected scenario.

Keywords: Unmanned Aerial Vehicle, Extended Kalman Filter, Nonlinear Programming, Sensor Fusion, Data Fusion, Engagement, Path Prediction.

İnsansız Hava Araçlarında Angajmandan Kaçış Yolu Kestirimi İçin Çok Sensörlü Veri Füzyonu

Öz

Savaşta başarı elde etmenin en önemli koşullarından birisi, hava üstünlüğünü sağlamaktır. Saldırgan muharebe ortamında bulunan bir savaş uçağının, gereken hayatta kalma özelliklerine sahip olması gerekmektedir. İnsansız hava araçlarında (İHA), kontrol istasyonuyla olan bağlantının kesilmesi durumunda, İHA'nın hareket ve seyrüsefer kabiliyetlerini koruması zorlaşır. Bu bildiride, insansız hava araçlarının angajmandan kaçışını sağlamak için çok sensörlü veri füzyonu yöntemiyle geliştirilen bir kaçış yolu kestirimi algoritması sunulmaktadır. Gelen radar verileri, tahmin yapmak üzere Genişletilmiş Kalman Filtresine sokularak değerlendirilir. Yapılan tahminler, doğrusal olmayan programlama yönteminde kullanılır ve anlık optimal kaçış yolu belirlenir. Sahip olunan kısıtlamalar ve amaç fonksiyonu lineer olmadığı için kısıtlı optimizasyon yöntemi olarak doğrusal olmayan programlama kullanılır. Simülasyon sonuçlarına göre, önerilen yöntem seçilen senaryoda angajmandan kaçış için umut verici sonuçlar sunmuştur.

Anahtar Kelimeler: İnsansız Hava Aracı, Genişletilmiş Kalman Filtresi, Doğrusal Olmayan Programlama, Sensör Füzyonu, Veri Füzyonu, Angajman, Kaçış Yolu Kestirimi.

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1. Introduction

One of the most important conditions for success in warfare is to achieve air superiority. It is of great importance for an aircraft to be able to use the survivability features hidden in the aircraft when it is in a man-made hostile environment, in order to provide air dominance. This research is focused on a decision-making algorithm to develop maneuverability of the combat aircraft in engagement conditions. The term "engagement", which is often used in military matters, refers to a combat between two sides. Engagement is initiated by the attacking force to perform a task. Engagement ends when the attacker completes the mission or quits the mission (Dupuy, 1987). For an aircraft to successfully exit the engagement, it is important to make quick decisions based on the aircraft's maneuverability and its opponent's position. This research is based on a dogfight engagement with an attacking aircraft. The aim is to ensure that the attacked aircraft escape from engagement in the most optimized way by making fast and accurate decisions. In this scenario, the attacking party may also be Air-to-Air Missile (AAM) or Surface-to-Air Missile (SAM), rather than a combat aircraft.

This study aims to develop a path planning algorithm for the unmanned aerial vehicle (UAV) to survive the engagement on its own in case the unmanned aerial vehicle (UAV) which is disconnected from the ground control station during an engagement. It is important that the UAV is able to use its autopilot features when disconnected from the control station. These features include optimal escape route estimation to avoid engagement. For these reasons, in this paper, it is aimed to combine data from different sensors by processing them under the influence of noise, and to come up with an optimal escape path prediction estimation algorithm.

There are other studies with various approaches on this subject. Capello et al. (2015), proposed a Particle Filter based navigation and guidance system based on Remotely Piloted Aircraft Systems (RPAS). López & Żbikowski (2018), proposed an autonomous decision-making algorithm for unmanned combat aircraft (UCAV) with 14 different maneuvering options. Each decision is evaluated based on a score equation considering external constraints (López & Żbikowski, 2018).

In this paper, a UAV guidance and navigation method based on Extended Kalman Filter and Nonlinear Programming is presented. In the first step, to estimate the enemy aircraft, position the multiple-sensor values are fused using the Extended Kalman Filter. Two sensors are used: One of them is the range sensor and the other is the angle sensor. After the prediction of the enemy aircraft position and direction a constraint optimization was made with the help of nonlinear programming. In this step, the constraints are defined according to the coordinate axes of the escaping UAV. Hence, UAV maneuverability can change according to the pitch, the roll, and the yaw axes of the UAV. Thus, the nonlinear programing is applied on the coordinate axes of the escaping UAV. After the obtaining the solution according to the coordinate axes of the escaping UAV, the solution is converted to the original coordinate axes. In briefly, based on these two methods, an escape path prediction algorithm has been developed.

The rest of the paper is outlined as follows: In the next section, the background information about the Extended Kalman Filter and nonlinear programing is briefly explained. In Section 3, the proposed method is introduced. The simulation results of the proposed method are demonstrated in Section 4. Finally, in the last section conclusion remarks are put forward.

2. Related Works

2.1. The Extended Kalman Filter

The Kalman filter method was proposed by Rudolf E. Kalman in 1960. The Kalman filter is an algorithm which takes continuous measurements as inputs in order to estimate desired unknown variables. Some of the main areas where the Kalman filter is used are; tracking, navigation and guidance in aviation, vehicle control, position estimation applications with inertial measurement unit, statistics, and economics (Meinhold & Singpurwalla, 1983). Kalman filter is also very important in multi sensor data fusion.

Kalman filters are used to predict new states of the system, taking into account of previous states of the system and current noise. The transition from the k-1 state to the k state is defined as:

$$x_k = Fx_{k-1} + B\mathrm{u}_{k-1} + \mathrm{w}_{k-1} \qquad \text{(Eq. 1)}$$

In the [Eq. 1], the state vector is denoted by x, the state transition matrix is denoted by F, control matrix of the input u is denoted by B and the zero mean Gaussian process noise is denoted by w (Kim & Bang, 2019). However, real-world problems are mostly nonlinear, including the problem in this paper. When a Gaussian distribution is applied to a nonlinear function, the output does not have a Gaussian distribution (Riberio, 2004). Thus, Extended Kalman Filter (EKF) is used when predicting nonlinear functions. In Extended Kalman Filter, system model is linearized around the estimation of the last state. This locally linearized model is used to give an approximation of the optimal prediction (Riberio, 2004).

State transition and measurement models for EKF are:

$$x_k = f(x_{k-1}, \mathrm{u}_{k-1}) + \mathrm{w}_{k-1} \qquad \text{(Eq. 2)}$$

$$z_k = h(x_k) + v_k \qquad \text{(Eq. 3)}$$

Where f provides the current state x_{k-1} and is the function of x_{k-1} and u_{k-1}. The measurement function is denoted by h, z_k is the measurement and v_k is the measurement noise. In the Extended Kalman Filter, there are two stages. The names of these stages are prediction and update. The output of the previous update stage becomes the input to the prediction state. With the outputs of the prediction stage, Kalman gain, and updated state estimates are calculated in the update stage. Prediction stage is modeled as:

$$\hat{x}_k^- = f(\hat{x}_{k-1}^+, u_{k-1}) \qquad \text{(Eq. 4)}$$

$$P_k^- = F_{k-1}P_{k-1}^+F_{k-1}^T + Q \qquad \text{(Eq. 5)}$$

Where the hat operator '^' means the estimate, '+' signifies prior, '-' signifies posterior, $\hat{x}_k^-$ is predicted state estimate and P_k^- is predicted error covariance (Kim & Bang, 2019). Update stage is modeled as:

$$y_k = z_k - h(\hat{x}_k^-) \qquad \text{(Eq. 6)}$$

$$K_k = P_k^-H_k^T(R + H_kP_k^-H_k^T)^{-1} \qquad \text{(Eq. 7)}$$

$$\hat{x}_k^+ = \hat{x}_k^- + K_k y \quad \text{(Eq. 8)}$$

$$P_k^+ = (I - K_k H_k)P_k^- \quad \text{(Eq. 9)}$$

Where y_k is measurement residual, K_k is Kalman gain, $\hat{x}_k^+$ is updated state estimate and P_k^+ is updated error covariance (Kim & Bang, 2019). F and H are Jacobian matrices of f and h. The covariance matrix of process noise is represented by Q, and the covariance matrix of measurement noise is represented by R. In order to obtain detailed information about this topic, (Kim & Bang, 2019) can be studied.

2.2. Nonlinear Programming

Nonlinear Programming is an optimization problem solving method. It is used when constraints or objective function are nonlinear. In a nonlinear optimization problem, minimization or maximization of an objective function is made depending on a set of constraints, where these constraints can be equality or inequality constraints. The formulation for nonlinear programming used in this paper is defined as:

$$\min_X f(X) \quad \text{(Eq. 10)}$$

$$LB \leq X \leq UB \quad \text{(Eq. 11)}$$

$$A_{eq} * X = b_{eq} \quad \text{(Eq. 12)}$$

$$A * X \leq b \quad \text{(Eq. 13)}$$

$$C_{eq}(X) = 0 \quad \text{(Eq. 14)}$$

$$C(X) \leq 0 \quad \text{(Eq. 15)}$$

In [Eq. 10], $f(X)$ is the objective function. In [Eq. 11], terms LB and UB, denotes the lower and upper boundaries of the input X. In [Eq. 12], A_{eq} and b_{eq} are linear equality constraints. In [Eq. 13], A and b are linear inequality constraints. In [Eq. 14], $C_{eq}(X)$ is nonlinear equality function. In [Eq. 15], $C(X)$ is nonlinear inequality function (MathWorks, 2021).

3. The Proposed Method

In this proposed method, The Extended Kalman Filter and nonlinear programming method are used together to develop the escape path estimation algorithm. MATLAB program (MathWorks, 2021) is used to develop this proposed algorithm and make the necessary simulations. A simple architecture of the proposed method is shown in the Figure 1 below:

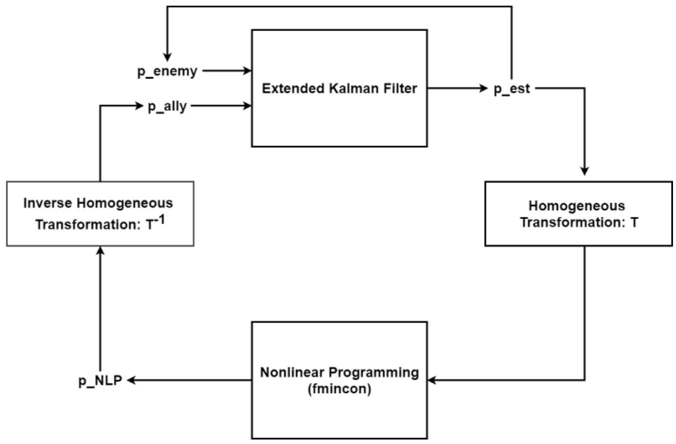

Figure 1: Overview of the proposed method

Where p_ally represents the position data of the friendly aircraft, which the escape path prediction algorithm is applied on. The position data of the attacking enemy aircraft that has been evaded is represented by p_enemy. The system calculates p_est and p_NLP for each time point, working in a loop for each time interval. "p_est" is the prediction value of the p_enemy position data obtained from The Extended Kalman Filter. This p_est prediction value is given as an input to the fmincon function (MATLAB fmincon, 2021). Fmincon is a built-in MATLAB function for nonlinear constraint optimization. Fmincon outputs the optimal escape vector p_NLP. Adding p_NLP to the value p_ally had in the previous time interval gives the new value of p_ally at the current time. Thus, an optimal escape position for a time interval is assigned to the friendly aircraft based on the estimated position of the attacking aircraft. The coordinate axis of the ally UAV changes at each time step, as the ally UAV performs different maneuvers. For this reason, at each time step, the nonlinear programming constraints and solution must be relative to the ally UAV's coordinate system. The relative distance between the ally UAV and the attacking UAV undergoes a homogeneous transformation from the original coordinate system to the coordinate system of the ally UAV before entering the nonlinear programming method fmincon. Once an optimal solution is found, it must go through an inverse homogeneous transformation to be converted back to the original coordinate system.

The Extended Kalman Filter model used in this paper is a suitable model for the scenario in the paper. In this model, there are two sensors on the friendly aircraft: the range sensor and the angle sensor. The position of the attacking aircraft is estimated with the help of Extended Kalman Filter, using the distance and angle data detected from these sensors on the friendly aircraft under noise (Kim & Bang, 2019). Standard deviation of process noise (w_(k-1)) and standard deviation of measurement noise (v_k) are given to the Extended Kalman Filter as inputs. Thus, the EKF could be tested under different noise conditions as desired. A detailed diagram of the Extended Kalman Filter is shown in Figure 2.

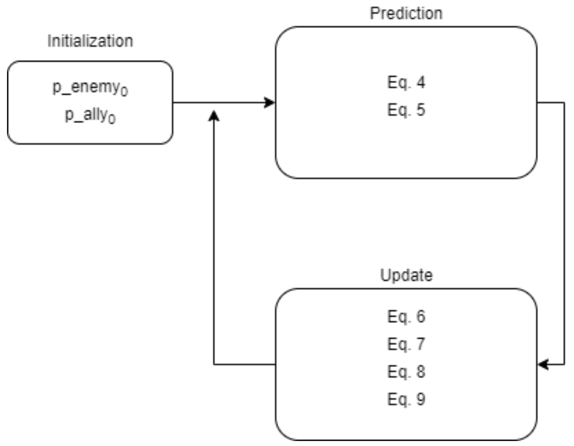

Figure 2: Extended Kalman Filter Model

Initial points of the friendly and enemy aircrafts are given in the initialization stage. In the prediction stage, predictions of state estimate and the error covariance are made as in equations 4 & 5. In the update stage, measurement residual and Kalman gain are calculated [Eq. 6] & [Eq. 7]. State estimate and the error covariance are also updated [Eq. 8] & [Eq. 9].

In this paper, the built-in MATLAB function fmincon is used as a nonlinear programming method. Fmincon finds the minimum of a multivariable function with constraints. The constraints of the mentioned function and the objective function are specified for fmincon as stated in equations 10, 11, 12, 13, 14 and 15. Fmincon starts from a starting point x0 and tries to reach the value x that will bring the function with defined constraints to its minimum value (MathWorks, 2021). The purpose of fmincon is to find a minimizer x value. The objective function used in this proposed method is an essential score function used in aviation to evaluate the relative distance and collision between two aircrafts (Burgin & Owens, 1975), (McGrew et al, 2010). The objective score function is defined as (López & Żbikowski, 2018):

$$Sc = \left(1 - \frac{|\epsilon + \lambda|}{\pi}\right)\left(e^{-\frac{d - d_{opt}}{K\pi}}\right) \qquad \text{(Eq. 16)}$$

In [Eq. 16], Sc denotes score resulting from the positions and angles of the two aircrafts relative to each other. The ϵ & λ represents the angles formed between the movement vectors of two aircraft and the LOS (Line of Sight) line. The relative ϵ & λ angles of the two aircrafts are shown in Figure 3. The distance between two aircrafts is denoted by d. Desired optimal distance is denoted by d_opt. Finally, the constant K is used to create a proportional adjustment between the angle and the distance. In this proposed method, d_opt value is 700 and K value of 600 is used based on an effective K value used in relative study (López & Żbikowski, 2018).

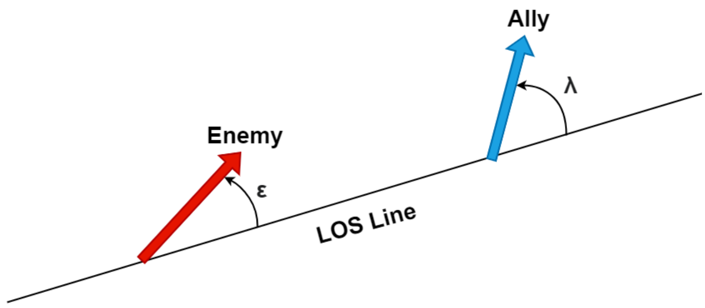

Figure 3: Relative angles of the two aircrafts (adapted from (López & Żbikowski, 2018))

After the prediction of the enemy aircraft position and direction, a constraint optimization was made. The constraints must be defined according to the coordinate axes of the escaping UAV. Since, UAV maneuverability can change according to the pitch, the roll, and the yaw axes of the UAV. Therefore, the nonlinear programing is applied on the coordinate axes of the escaping UAV. On the other hand, each time step the UAV can make a different maneuver, so the coordinate axes of the escaping UAV are changed for each time step. The coordinate axes of the escaping UAV and the original coordinate axes can be managed in the algorithm in carefully. Therefore, the solution UAV position and direction found in nonlinear programing according to the coordinate axes of the escaping UAV must be translated and rotated with respect to the original coordinate axes. To achieve this coordinate axes translation, a similar approach like the one given in (Neff, 2021) is used in this paper.

To find the direction of the UAV, the flight mechanism must be determined. In this paper, the following approach is used for UAV maneuverability. The UAV has 3 axes: the pitch, the roll and the yaw. To change the altitude (the pitch control) the elevator is used. After the coming the desired altitude position, the UAV is updated its position as the flat position according to the ground. Thus, z axis in the UAV coordinate axes and z axis in the original coordinate axes are the same all nonlinear solution process. On the other hand, to arrive some points in 3-dimensional space, in addition to z axis movement, x and y axes movements are needed. It is assumed that the UAV has a high maneuverability capacity, and thus, to turn left or right the following the flight mechanism is used: Instead of the use of rudder for yaw control, the firstly the roll control is used by ailerons or flaperons and then using elevator the desired direction is aligned with the nose of the UAV. After the coming the desired direction position in x-y plane, the UAV is updated its position as the flat position according to the ground.

To further explain this mechanism, one scenario is explained. Let's the UAV only changes its direction to the left side according to the nose in x-y plane without changing the altitude position. In this case, the 1st command is the right aileron up and the left aileron down. The 2nd command is the right aileron flat and the left aileron flat. The 3rd command is the elevator up. The 4th command is the elevator flat. The 5th command is the right aileron down and the left aileron up. The 6th command is the right aileron flat and left aileron flat. At the end of these commands, the UAV is flat position according to the ground and the direction of the UAV is changed an angle in x-y plane.

After the obtaining the solution according to the coordinate axes of the escaping UAV, the solution is converted to the original coordinate axes. In briefly, based on these two methods, an escape path prediction algorithm has been developed.

4. The Experimental Results

The simulation results are realized using MATLAB (MathWorks website, 2021). It has been assisted from Introduction to Kalman Filter and Its Applications website (2021) in the implementation of extended Kalman Filter for the selected scenario.

The selected scenarios are defined as follows: In the selected scenario, there are two UAVs traveling in open space, one ally and one hostile enemy. The Enemy UAV's starting point is assumed to be the point (0,0,0) in meters and moves at 1000km/h in the x-axis only. The initial point of the ally UAV is the point (500,0,0) in meters. Main input of the ally UAV for the target tracking is a radar system with range and angle measurements. The standard deviation of the process noise used in the Extended Kalman Filter is 0.5m/s for velocity in all three axes. Since we have the target position data of the hostile enemy UAV when this escape path prediction system is activated on the UAV, the EKF's initial guess of target position is the measured position of the enemy UAV. Simulations were made for a period of 30 seconds. In nonlinear programming, the lower and upper boundaries for input X are given as follows for x, y, and z: LB = [-69.4445, -69.4445, -69.4445], UB = [277.7778, 69.4445, 69.4445] in meters. These values are the maximum and minimum meters the solution of the fmincon can be for each second. LB and UB were determined based on the mobility of the ally UAV and were obtained by converting 1000 km/h and 250 km/h to m/s. There are no linear equality or inequality constraints. The nonlinear inequality function $C(X)$ is the maximum resultant value that fmincon's solution in x, y and z combined. $C(X)$ is equal to the expression in [Eq. 17] where 1000 is the maximum value of velocity in km/h and 0.277778 is the constant value to convert km/h to m/s.

$$X(1)^2 + X(2)^2 + X(3)^2 - (1000 * 0.2777778\,)^2 \qquad \text{(Eq. 17)}$$

First, the scenario where the user input of standard deviation of measurement noise is given [0.5, 0.5, 10] for two angles and distance respectively is run on MATLAB. The measurement covariance matrix is constructed by the same noise characteristic [0.5, 0.5, 10]. The xy-axis trajectories of enemy and Ally UAVs are shown in Figure 4. Figure 5 shows the trajectories of UAVs in three dimensions. The values on the axes in the figures are in meters. As can be seen in Figure 4 and Figure 5, the ally UAV made its escape by making deviations in the y and z axes in the escape route. As the enemy UAV's position estimation sways in the z axis over time, the Ally UAV slopes to the z direction and escapes.

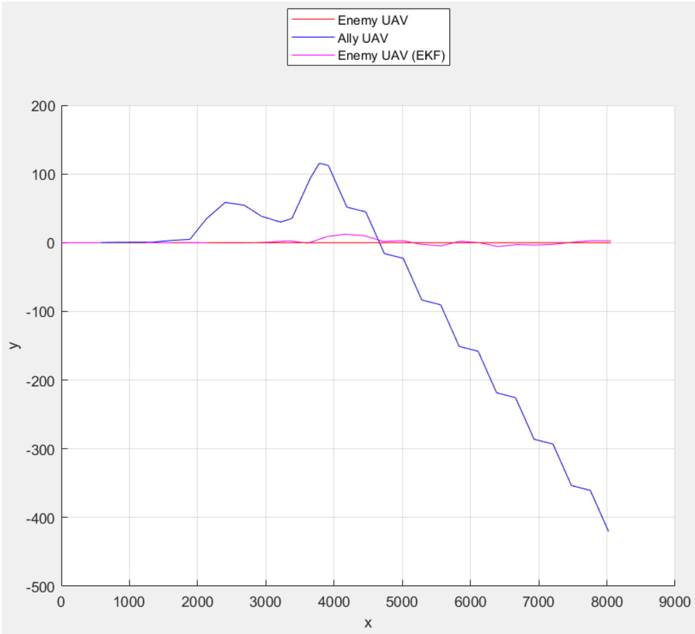

Figure 4: xy-axis trajectory of the UAVs in the first scenario

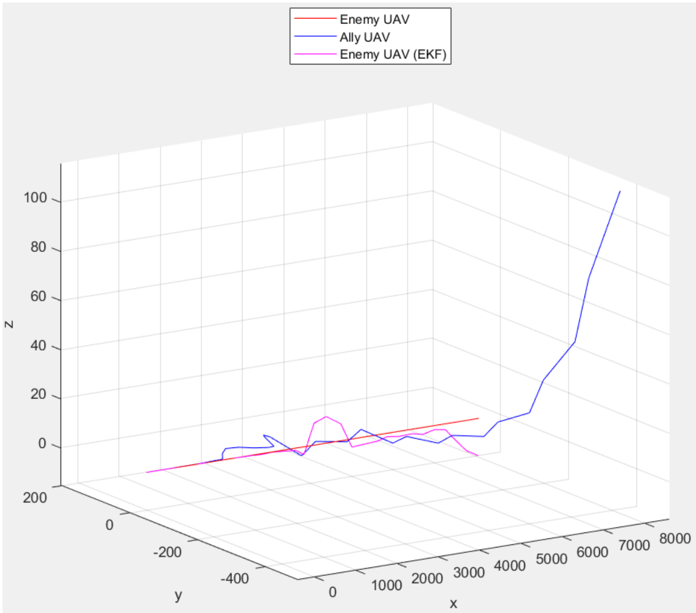

Figure 5: 3D trajectory of the UAVs in the first scenario

After the first scenario, the scenario where the user input of standard deviation of measurement noise is given [2, 2, 50] for two angles and distance respectively is run on MATLAB. The measurement covariance matrix is constructed by the previous scenario noise characteristic [0.5, 0.5, 10]. Figure 6 and Figure 7 show the trajectories of UAVs in the xy-axis and three-dimensional axis. If we compare the two scenarios, the standard deviation of measurement noise values in the second scenario are higher than the values in the first scenario. Therefore, in the second scenario, the estimation of the location of the enemy UAV with the EKF is more deviated. Thus, a greater deviation in the z direction is seen in the trajectory of the ally UAV.

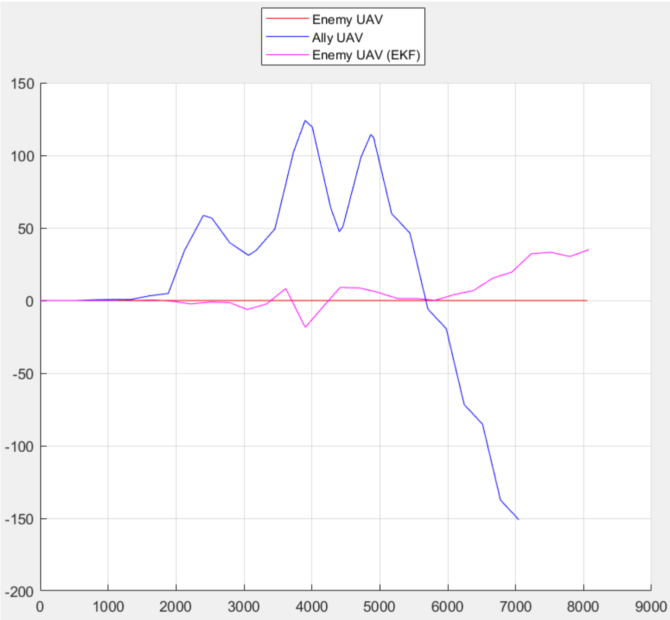

Figure 6: xy-axis trajectory of the UAVs in the second scenario

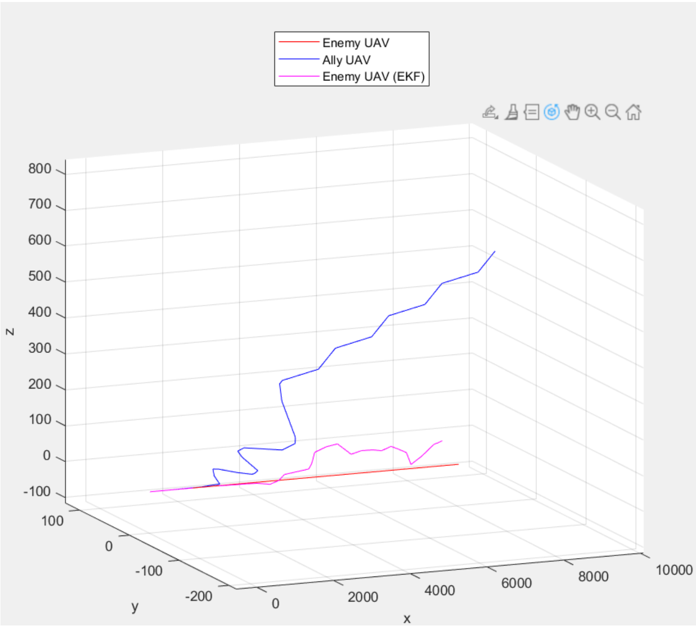

Figure 7: 3D trajectory of the UAVs in the second scenario

5. Conclusions

In this study, an escape path prediction algorithm that combines Extended Kalman Filter and Nonlinear Programming is presented. The algorithm was implemented on MATLAB and the simulations of the scenarios were made on MATLAB. As a result of the simulations, it has been observed that different standard deviation of measurement noise values cause different results in EKF and accordingly nonlinear programming finds different solutions. Thus, the quality of radars in aircrafts can be an important factor for an artificial intelligence based algorithms like the given in thispaper.

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