Tracking a Manoeuvring Target with Radar Measurements using Extended Kalman Filter

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Abstract:

In this paper, a maneuvering target is tracked in three-dimensional space using Aerial Unmanned Vehicle with the use of bearing angle, range and elevation angle measurements. The altered measurements are processing by using the extended Kalman filtering algorithm. The proposed design is used for detection of any maneuver in target uses in chi-square algorithm. The communication arrangement is provided with the estimated target parameters with the help of global positioning system. The implementation of the target and observer paths and outcomes are presented with mathematical modeling for simulation of the proposed work.

Keywords: Extended Kalman Filter, Motion Analysis of Maneuvering Target, Aerial unmanned vehicle.

1 Introduction

Aerial unmanned vehicle (AUV) is a in effective inflight war car found in latest times. AUV is an automaton device soaring in air usually used for tracing a goal. Parameters which can be used to song the goal, like bearing, variety and elevation are detected through sending radio waves. AUV in recent times are provided with worldwide positioning structures in order that armament management device of AUV maintains song of it. Armament management device can be an plane in air or a deliver at the surface. Data determined from AUV is directed to armament management device with the assist of worldwide positioning device in order that armament management device gets to recognize the goal's region and route and to launch armament in that way. The maximum not unusual place Extended Kalman clear out (EKF) set of rules is used for monitoring the goal. Parameters representing goal motion, at extended levels are usually nonlinear. Consequently, EKF is notion primarily based totally on balancing and quickly converging clear out problems springing up in Kalman clear out [1-2].

Target tracing is performed utilizing EKF [3-7]. In this research, the fundamental involvement is tracing a goal this is maneuvering in direction, as recommended in [4, 5]. Observing residual plot of bearing goal on my own cannot visualize. So, goal maneuver is detected through the residuals received from a random collection with 0 suggest the use of chi-rectangular distribution in gliding window. An innovation this is rectangular and normalized is applied to stumble on if goal is below maneuver or not. For acquiring the best end result for the duration of goal maneuver, adequate amount of plant noise is tallied to the plant noise covariance matrix. Once the maneuver is concluded, plant noise is dropped back.

The relation of goal kingdom factors is non-linear to the observations i.e., bearing and elevation, that makes the manner greater non-linear in nature. So, the Kalman clear out that's greatest for linear manner isn't always relevant for 3–D monitoring of the goal. For minimalism of the complexity in method, the goal shifting with constant velocity and maneuvering handiest in its direction perspective is presumed. The device noise measured is white Gaussian noise added due to ruckus with inside the goal's velocity.

2 Mathematical Modeling

2.1 System Model

Contemplate the state vector as follows:

$$X_S(\kappa t)=[\dot{x}(\kappa t) \quad \dot{y}(\kappa t) \quad \dot{z}(\kappa t) \quad R_x(\kappa t) \quad R_y(\kappa t) \quad R_z(\kappa t)]^T. \qquad (1)$$

Here $\dot{x}(\kappa t)$, $\dot{y}(\kappa t)$, $\dot{z}(\kappa t)$ denotes the speed components of target and $R_x(\kappa t)$, $R_y(\kappa t)$, $R_z(\kappa t)$ denotes its range components in x, y and z directions correspondingly. The state vector for subsequent time is calculated using the following equation.

$$X_s(\kappa t+1) = \emptyset X_s(\kappa t) + b(\kappa t+1) + \Gamma w(\kappa t). \quad (2)$$

Ø is given by

$$\emptyset = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ t & 0 & 0 & 1 & 0 & 0 \\ 0 & t & 0 & 0 & 1 & 0 \\ 0 & 0 & t & 0 & 0 & 1 \end{bmatrix}. \quad (3)$$

Here t is time frame at which observation is acquired. $b(\kappa t+1)$ is deterministic control matrix and is provided by

$$b(\kappa t+1) = \begin{bmatrix} 0 \\ 0 \\ 0 \\ -\left(x_0(\kappa t+1) + x_0\,(\kappa t)\right) \\ -\left(y_0(\kappa t+1) + y_0\,(\kappa t)\right) \\ -\left(z_0(\kappa t+1) + z_0\,(\kappa t)\right) \end{bmatrix}^T. \quad (4)$$

Here $x_0\,, y_0\,, z_0$ denotes the observer location in x, y and z directions. In order to lessen the mathematical complication, Y–axis is considered as reference for computing all the bearing angles and Z- axis for computing elevation angles. Let $w(\kappa t)$ represent gaussian process noise.

$$w(\kappa t) = [w_x \quad w_y \quad w_z]^T. \quad (5)$$

Variance of $w(\kappa t)$ is given by

$$E[\,\Gamma(\kappa t) w(\kappa t) w^T(\kappa t) \Gamma^T(\kappa t)] = Q\delta_{ij}. \quad (6)$$

Where $\delta_{ij} = \sigma_w^2 \quad (i = \kappa t)$ (7)

$= 0$ otherwise.

$$Q = \begin{bmatrix} ts^2 & 0 & 0 & ts^3/2 & 0 & 0 \\ 0 & ts^2 & 0 & 0 & ts^3/2 & 0 \\ 0 & 0 & ts^2 & 0 & 0 & ts^3/2 \\ ts^3/2 & 0 & 0 & ts^3/4 & 0 & 0 \\ 0 & ts^2/2 & 0 & 0 & ts^3/4 & 0 \\ 0 & 0 & ts^2/2 & 0 & 0 & ts^3/4 \end{bmatrix} \quad (8)$$

$$\Gamma(\kappa t) = \begin{bmatrix} t & 0 & 0 \\ 0 & t & 0 \\ 0 & 0 & t \\ t^2/2 & 0 & 0 \\ 0 & t^2/2 & 0 \\ 0 & 0 & t^2/2 \end{bmatrix} \quad (9)$$

$Z(\kappa t)$ denotes the matrix of all observations and is represented as:

$$Z(\kappa t) = [R_m(\kappa t) \quad B_m(\kappa t) \quad \Theta_m(\kappa t)]^T\,. \quad (10)$$

Here $R_m(\kappa t), B_m(\kappa t)$and $\Theta_m(\kappa t)$ are measured range, bearing and elevation.

$$R_m(\kappa t) = R(\kappa t) + \xi_R(\kappa t)\ . \quad \textbf{(11)}$$

$$B_m(\kappa t) = B(\kappa t) + \xi_B(\kappa t)\ . \quad \textbf{(12)}$$

$$Z(\kappa t) = [R_m(\kappa t) \quad B_m(\kappa t) \quad \Theta_m(\kappa t)]^T\ . \quad \textbf{(13)}$$

where $R(\kappa t)$, $B(\kappa t)$ and $\Theta(\kappa t)$ are simulated true values of range, bearing angle and elevation angle respectively.

$$R(\kappa t) = \sqrt{R_x^2(\kappa t) + R_y^2(\kappa t) + R_Z^2(\kappa t).} \quad \textbf{(14)}$$

$$B(\kappa t) = tan^{-1}\big(R_x(\kappa t)/R_y(\kappa t)\big). \quad \textbf{(15)}$$

$$\Theta(\kappa t) = tan^{-1}\big(R_{xy}(\kappa t)/R_Z(\kappa t)\big)\ . \quad \textbf{(16)}$$

$$\text{Where } R_{xy} = \sqrt{R_x^2 + R_y^2} \quad \textbf{(17)}$$

Measurement vector is given by

$$Z(\kappa t) = H(\kappa t)X_s(\kappa t) + \xi(\kappa t). \quad \textbf{(18)}$$

$$H(\kappa t) = \begin{bmatrix} 0 & 0 & 0 & \sin(B)\sin(\Theta) & \sin(\Theta)\cos(B) & \cos(\Theta) \\ 0 & 0 & 0 & \frac{\cos(B)}{R_{xy}} & \frac{-\sin(B)}{R_{xy}} & 0 \\ 0 & 0 & 0 & \frac{\sin(B)\cos(\Theta)}{R} & \frac{\cos(\Theta)\cos(B)}{R} & \frac{-\sin(\Theta)}{R} \end{bmatrix}. \quad \textbf{(19)}$$

$$\text{And } \xi(\kappa t) = [\ \xi_R \quad \xi_B \quad \xi_\Theta\ ]^T. \quad \textbf{(20)}$$

2.2 EKF Algorithm

All EKF implementation is as follows.

i). The initial state vector's estimate and its covariance matrix estimate be taken as $X(0|0)$ and $P(0|0)$ respectively.

ii). For the subsequent time, the state vector is calculated as $X_s(\kappa t + 1)$:

$$X_s(\kappa t + 1) = \emptyset(\kappa t + 1|\kappa t)X_{\kappa t}(\kappa t) + b(\kappa t + 1) + \omega(\kappa t). \quad \textbf{(21)}$$

iii). State vector's covariance matrix for the subsequent time is given as follows.

$$P(\kappa t + 1|\kappa t) = \emptyset(\kappa t + 1|\kappa t)P(\kappa t)\emptyset^T(\kappa t + 1|\kappa t) + Q(\kappa t + 1) \quad \textbf{(22)}$$

iv). Gain of the EKF is considered as follows:

$$G(\kappa t + 1) = P(\kappa t + 1|\kappa t)\emptyset^T(\kappa t + 1|\kappa t)[H(\kappa t + 1)P(\kappa t + 1|\kappa t)\ H^T(\kappa t + 1) + R]^{-1} \quad \textbf{(23)}$$

v). The state estimation and its error covariance:

$$X_s(\kappa t + 1|(\kappa t + 1) = X_s\ (\kappa t + 1|\kappa t) + G(\kappa t + 1)\ [Z(\kappa t + 1) - \hat{Z}(\kappa t + 1)] \quad \textbf{(24)}$$

$$P(\kappa t + 1|\kappa t + 1) = [1 - G(\kappa t + 1)H(\kappa t + 1)P(\kappa t + 1|\kappa t)] \quad \textbf{(25)}$$

vi). For next iteration

$$X_s(\kappa t|\kappa t) = X(\kappa t + 1|\kappa t + 1) \quad \textbf{(26)}$$

$$P(\kappa t|\kappa t) = P(\kappa t+1|\kappa t+1) \quad (\mathbf{27})$$

2.3 Target Maneuver Detection

At the time of target's movement at constant speed and course, the plant noise is a smaller amount. But, as the target starts its maneuver, the plant noise is gradually risen [10, 11]. In order to increase the plant noise, the plant covariance matrix is increased by multiplying it with a fledge factor of 10 till the target executes maneuvering. When the target maneuver is completed i.e., it attains the required course, the plant noise is brought back to its reduced value. The regulated squared innovation, $\gamma_\varphi(\kappa t)$, is calculated as follows.

$$\gamma_\varphi(\kappa t) = \varphi^T(\kappa t)S^{-1}(\kappa t+1)\varphi(\kappa t+1) \quad (\mathbf{28})$$

Where $\varphi(\kappa+1)$ is

$$\varphi(\kappa t+1) = Z(\kappa t+1) - h(\kappa t+1, X(\kappa t+1/\kappa t)) \quad (\mathbf{29})$$

Let $S(\kappa t)$is

$$S(\kappa t+1) = H(\kappa t+1)P(\kappa t+1/\kappa t)H^T(\kappa t+1) + \sigma^2 \quad (\mathbf{30})$$

Let

$$d(\xi) = \gamma^T S^{-1}\gamma \geq c \quad (\mathbf{31})$$

where S is $diag\{S(\kappa t)\}$ and

γ=φ1 φ2……$\varphi\kappa t T$ $\gamma = [\varphi(1) \;\; \varphi(2) \ldots\ldots \varphi(\kappa t)]^T$ (**32**)

Here c is threshold with constant value and d is statistical value of the chi-square distribution. This gliding window of size 5 samples is chosen for this application.

3 Simulation and Results

Assuming that studies is instructed at first-class ecological circumstances, simulation is performed on a pc the use of Matlab. The trajectories which are observed through goal and observer are as selected in Table 1, for overall performance validation of the process. For instance, state of affairs 1 defines a goal at a gap distance of 2km far from the spectator, shifting with an preliminary path attitude and pace of 170o and 300m/s correspondingly. The initial bearing found is 0o. The observations, bearing attitude and distance are assumed to be tarnished having a popular deviation in mistakes of 0.33o (1σ) and 0.01km (1σ) correspondingly. From 300s onwards, goal begins off evolved its maneuver in path converting to 295o with a rotating frequency of 3o for each second. The goal's preliminary elevation attitude is 0o for ease. The observer is presumed to transport with chronic tempo of 25m/s and with 90o path.

The countless accessibility of observations for on every occasion pattern is presumed. The actual values of the goal role and observer role are generated the use of Matlab software. Hence, the expected parameters are authenticated primarily based totally at the actual modeled parameter values constructed on unique suitable standards. The reputation degree is desired on the idea of armament manage necessity. The answer is mentioned or believed to be received while inaccuracy in expected path is much less than or same to 30 and inaccuracy in expected pace of goal is much less than or same to 1m/s.

For state of affairs 2, the approximations and actual tracks of goal together with that of observer trajectory are proven in Fig.1. For precision of the notions, Fig. 2 and Fig. three indicates the real and expected path attitude and pace of the goal for state of affairs 2 correspondingly. Likewise, goal's real and expected elevation attitude for the equal state of affairs is depicted in Fig.4. The end result is mentioned or encountered if the inaccuracies in expected path and expected pace of the goal are with inside the indoors of the receiving conditions. Table.2 presents the answer convergence time samples in seconds for the conditions furnished as in Table.1.

Let us do not forget state of affairs 2 to assess the algorithm, wherein the goal is maneuvering in its path. The convergence time of results inside reputation standards for the expected path as soon as the goal completes maneuver, is at 460th time pattern and at 67th time pattern earlier than goal maneuvers. As pace of goal is unchanged, there may be best one convergence time, i.e., forty three seconds, earlier than and after goal maneuver.

Table. 1. Scenarios of target and observer positions

Parameters	Scenarios 1	Scenarios 2
Opening Range of target (m)	2000	3000
Opening bearing of target (deg)	0	0
Opening course of target (deg)	135	170
Course of target after 300s (deg)	235	295
Speed of target (m/s)	300	400
Elevation of target (deg)	0	0
Speed of observer (m/s)	25	20
Course of observer (deg)	90	90
Bearing angle noise (1σ) (deg)	0.33	0.33
Range noise (1σ) (m)	10	10
Elevation angle noise (1 σ) (deg)	0.33	0.33

Table. 2. Convergence time sample of solution in seconds

Parameter converged		Scenarios 1	Scenarios 2
Earlier to target maneuver	Course	54	67
	Speed	84	43
	Elevation	8	2
	Solution Convergence	84	67
Post target maneuver	Course	385	460
	Speed	84	43
	Elevation	8	2
	Solution Convergence	385	460

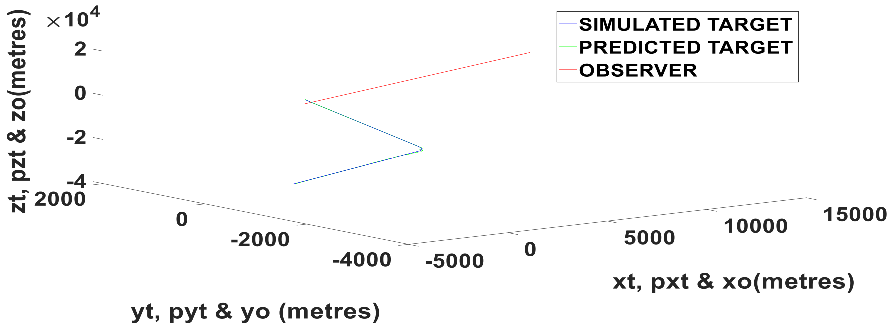

Fig.1 Simulated and true trajectories of target and observer of scenario 2

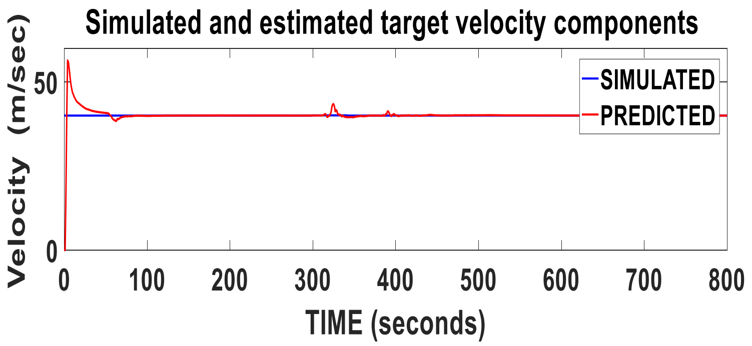

Fig.2 Factual velocity vs projected velocity of target for scenario 2

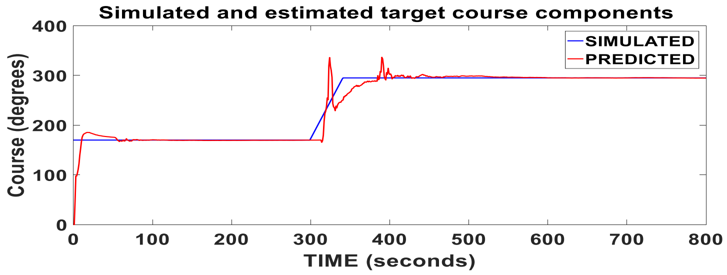

Fig.3 Factual course vs projected course of target for scenario 2

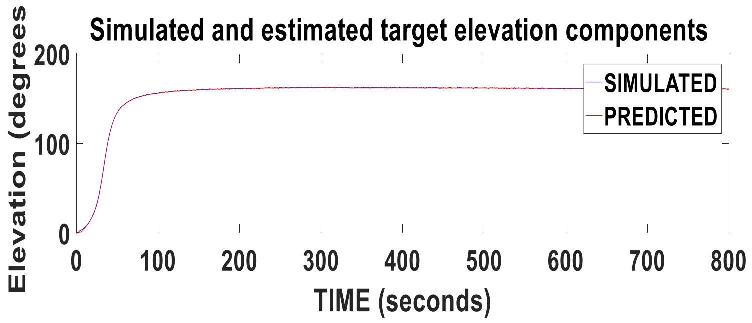

Fig.4 Factual elevation vs projected elevation of target for scenario 2

4 Conclusion

In this paper, extended kalman filter algorithm is used to track the maneuvering target in the three-dimensional plane. The development of the simulation is made by EKF is suggested for approximate target parameters in AUV systems.

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