Target Tracking Using Unmanned Aerial Vehicle

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Abstract: The main aim of this research work is to track a target using unmanned aerial vehicle (UAV). UAV range, bearing and elevation measurements are used to find out the target path. Unscented Kalman filter is explored in this process. The estimated information about range, bearing and elevation is communicated to weapon guidance station by means of personal communication system. Unscented Kalman filter is able to find out the target path with course error $< 3^0$, speed error < 1m/s and elevation error $< 1^0$.

Keywords: Target tracking, Stochastic processing, Statistical signal processing, Unmanned aerial vehicle system, Applied Statistics

1.   INTRODUCTION

Unmanned aerial vehicle (UAV) is the safest airborne warfare system existing in the world today. UAV is a robot like system flying in air mainly used in target tracking. It sends radio waves to track the target parameters like range, bearing and elevation. UAV now-a-days are GPS equipped so that weapon guidance system of UAV will have knowledge about position of UAV [1-3]. Weapon guidance system may be a ship on the surface or an aircraft in air. Data received from UAV is sent to weapon guidance system by means of a personal communication system so that weapon guidance system will be able to know the position and motion of target and releases weapon in that direction. Target tracking is achieved by Unscented Kalman filter (UKF). Target motion parameters particularly at long ranges are nonlinear. So, UKF is considered based on rapidly convergent and unbiased filter problems in Extended Kalman Filter and MGEKF.

Section 2 deals with mathematical modeling and section 3 describes generalized simulator. Section 4 deals about the simulation results and then concluded in section 5.

2.   MATHEMATICAL MODELLING

Consider state vector

$$X_{1S}(k) = [\dot{x}(k)\,\dot{y}(k)\,\dot{z}(k)\,R_x(k)\,R_y(k)\,R_z(k)]^T \tag{1}$$

where $\dot{x}(k)$, $\dot{y}(k)$, $\dot{z}(k)$ (velocity components) and $R_x(k) R_y(k) R_z(k)$ (range components) of target in 3D axes. The state equation becomes[4]

$$X_{1_s}(k+1) = \Gamma w(k) + \emptyset\, X_{1_s}(k) + B(k+1) \tag{2}$$

$\emptyset$ is given by

$$\phi = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ t & 0 & 0 & 1 & 0 & 0 \\ 0 & t & 0 & 0 & 1 & 0 \\ 0 & 0 & t & 0 & 0 & 1 \end{bmatrix} \tag{3}$$

Here t is the measurement interval. $B(k+1)$ is deterministic matrix

$$B(k+1) = \begin{bmatrix} 0 & 0 & 0 & -(-x_0(k)+x_0(k+1)) & -(y_0(k+1)-y_0(k)) & -(-z_0(k))+z_0(k+1) \end{bmatrix} \tag{4}$$

where $x_0\, y_0\, z_0$ are the observer position components.

where $w(k)$ is plant noise

$$w(k) = [w_x\, w_y\, w_z]^T \tag{5}$$

variance of $w(k)$ is

$$E[\, \Gamma(k)\, w(k)\, w^T(k)\, \Gamma^T(k)\,] = S\delta_{ij} \tag{6}$$

here $\delta_{ij} = \sigma_W^2$ (i is equal to j) $\tag{7}$

$\qquad = 0$ othercase

$$S = \begin{bmatrix} ts_1^2 & 0 & ts_1^3/2 & 0 & 0 & 0 \\ 0 & ts_1^2 & 0 & 0 & ts_1^3/2 & 0 \\ 0 & 0 & ts_1^2 & 0 & 0 & ts_1^3/2 \\ ts_1^3/2 & 0 & 0 & ts_1^3/4 & 0 & 0 \\ 0 & ts_1^2/2 & 0 & 0 & ts_1^3/4 & 0 \\ 0 & 0 & ts_1^2/2 & 0 & 0 & ts_1^3/4 \end{bmatrix} \tag{8}$$

$$\Gamma(k) = \begin{bmatrix} t_1 & 0 & 0 \\ 0 & t_1 & 0 \\ 0 & 0 & t_1 \\ t_1^2/2 & 0 & 0 \\ 0 & t_1^2/2 & 0 \\ 0 & 0 & t_1^2/2 \end{bmatrix} \tag{9}$$

Measurement matrix is Z(k) and it is

$$Z(k) = [R_m(k) \; B_m(k) \; E_m(k) \;]^\mathrm{T} \tag{10}$$

here $R_m(k) \; B_m(k)$ and $E_m(k)$ are measured Range Bearing and Elevation

$$R_m(k) = \xi_R(k) + R(k) \tag{11}$$

$$B_m(k) = \xi_B(k) + B(k) \tag{12}$$

$$E_m(k) = \xi_B(k) + E(k) \tag{13}$$

where $R(k)$ is true range and $B(k)$, $E(k)$ are, true bearing and true elevation.

$$R(k) = \sqrt{R_x^2(k) + R_y^2(k) + R_Z^2(k)} \tag{14}$$

$$B(k) = \tan^{-1}\left(\frac{R_x(k)}{R_y(k)}\right) \tag{15}$$

$$E(k) = \tan^{-1}\left(\frac{R_{xy}(k)}{R_Z(k)}\right) \text{ where } R_{xy} = \sqrt{R_x^2 + R_y^2} \tag{16}$$

Measurement vector is

$$Z(x) = \xi(k) + H(k) \; X_3 \; (k) \tag{17}$$

here H(k) is
$$\begin{bmatrix} 0 & 0 & 0 & \sin(E)\sin(B) & \sin(E)\cos(B) & \cos(E) \\ 0 & 0 & 0 & \dfrac{\cos(B)}{R_{xy}} & \dfrac{-\sin(B)}{R_{xy}} & 0 \\ 0 & 0 & 0 & \dfrac{\cos(E)\sin(B)}{R} & \dfrac{\cos(E)\cos(B)}{R} & \dfrac{-\sin(E)}{R} \end{bmatrix} \tag{18}$$

and
$$\xi(k) = [\xi_R \; \xi_B \; \xi_E]^T \tag{19}$$

The unscented Kalman filter is a combination of classical filter and an unscented transformation, which is made in order to transmit transformation in the model through a non-linear process. UKF gives adequately precise solution.

An easy method is adapted to evaluate the statistical properties of a random variable, enduring a transformation which is not linear is called an unscented transformation. Suppose a random variable x, having an expected value x, covariance P_x and dimension L, imparting through y=g(x). 2L+1 sigma vectors are used to compute statistics of y as follows:

$$\chi_0 = \bar{x}$$

$$\chi_i = \bar{x} + (\sqrt{(L+\lambda)P_x})_i \quad i = 1, 2, 3\ldots\ldots, L$$

$$\chi_i = \bar{x} - (\sqrt{L+\lambda)P_x})_{i-L} \quad i = L+1,\ldots\ldots, 2L$$

$$W_0^{(m)} = \lambda/(L+\lambda)$$

$$W_0^{(c)} = \lambda/(L+\lambda) + (1+\beta-\alpha^2)$$

$$W_i^{(m)} = W_i^{(c)} = 1/\{2(L+\lambda)\} \text{ i=1,2,3……, 2L}$$

where $$\lambda = -L + \alpha^2(L+\kappa) \qquad (20)$$

α is a parameter used for scaling. Here the values of α, κ, β are 0.001,0 and 2 respectively. Using χ_i the following are written.

$$y_i = g(\chi_i) \text{ i} = 1, 2, 3…..,2L \qquad (21)$$

$$\bar{y} \approx \sum_{i=0}^{2L} W_i^{(m)} y_i \qquad (22)$$

$$p_y \approx \sum_{i=0}^{2L} W_i^{(c)} \{y_i - \bar{y}_i\}\{y_i - \bar{y}_i\}^T \qquad (23)$$

UKF implementation is as follows [5-8] Table 1.

UKF algorithm implementation

1. Sigma state vectors are presented as

$$X_1(k) = \left[X_{1s}(k) \quad X_{1s}(k) + \sqrt{(n+\lambda)p(k)} \quad -\sqrt{(n+\lambda)p(k)} + X_{1s}(k)\right] \qquad (24)$$

2. The same are modified with the help of eqn. (2),

3. State vector is anticipated as

$$X_{1s}(k+1|k) = \sum_{i=0}^{2n} W_i^{(m)} X_{1s}(i,k+1|k) \qquad (25)$$

4. The covariance matrix is predicted as

$$P(k+1|k) = \sum_{i=0}^{2n} W_i^{(c)} \left[X_{1s}(i,k+1|k) - X_{1s}(k+1|k)\right]\left[X_{1s}(i,k+1|k) - X_{1s}(k+1|k)\right]^T + S(k) \qquad (26)$$

5. The state vectors are updated as

$$X_1(k+1|k) = \left[X_{1S}(k+1|k) \quad X_{1S}(k+1|k) + \sqrt{(n+\lambda)p(k+1|k)} \quad X_{1S}(k+1|k) - \sqrt{(n+\lambda)p(k+1|k)}\right] \qquad (27)$$

6. Then measurement is anticipated as

$$y(k+1|k) = \sum_{i=0}^{2n} W_i^{(m)} Y(k+1|k) \qquad (28)$$

7. Covariance of innovation is

$$P_{yy} = R(k) + \sum_{i=0}^{2n} W_i^{(c)} \left[Y(i,k+1|k) - y(k+1|k)\right]\left[Y(i,k+1|k) - y(k+1|k)\right]^T \qquad (29)$$

8. The cross covariance is

$$P_{xy} = \sum_{i=0}^{2n} W_i^{(c)} \left[X(i,k+1|k) - X(k+1|k)\right]\left[Y(i,k+1|k) - y(k+1|k)\right]^T \qquad (30)$$

9. Kalman gain is

$$G(k+1) = P_{xy} inv(P_{yy})$$ (31)

10. The state is estimated as

$$X(k+1|k+1) = X(k+1|k) + G(k+1)(y(k+1|k+1) - y(k+1|k))$$ (32)

11. Covariance is represented by

$$P(k+1|k+1) = P(k+1|k) - G(k+1)P_{yy}G(k+1)^T$$ (33)

Initial target state vector, target velocity components are computed using first and second measurement sets of range bearing and elevation measurements. The detailed processing of Kalman filter is shown in Figure 1.
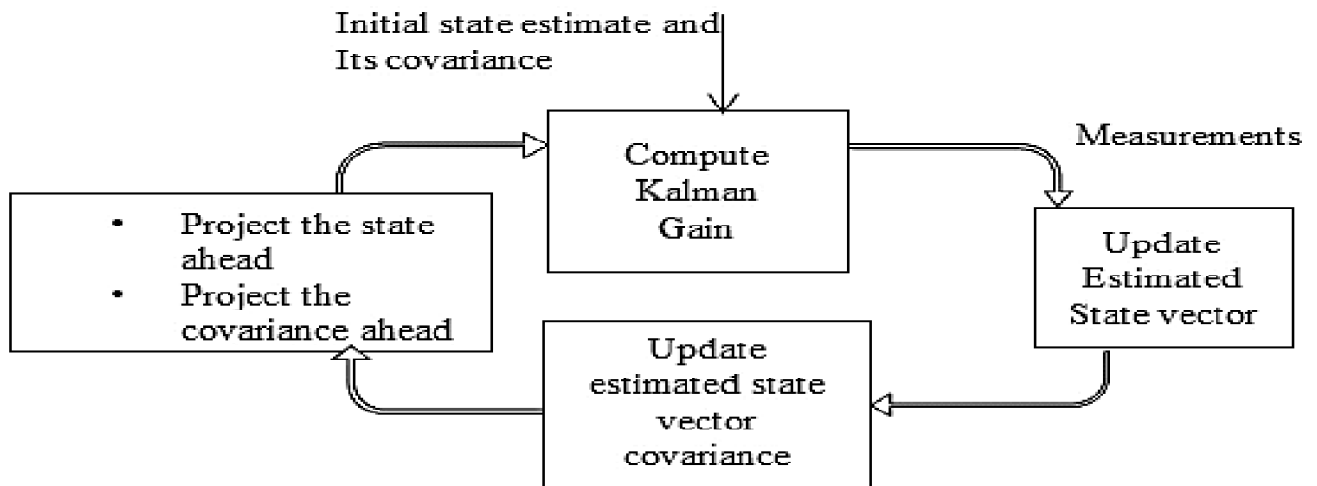

Figure 1: Unscented Kalman filter process

3. GENERALIZED SIMULATOR

Let initial position of the target be (x_t, y_t, z_t) and the target moves with velocity v_t. After time t seconds, observer position changes and the change in the observer position is given by

$$dx_0 = v_0 * \sin(ocr) * \sin(oph) * t$$ (34)

$$dy_0 = v_0 * \cos(ocr) * \sin(oph) * t$$ (35)

$$dz_0 = v_0 * \cos(oph) * t$$ (36)

where ocr and oph are observer course and pitch respectively.Now the new observer position becomes

$$x_0 = x_0 + dx_0$$ (37)

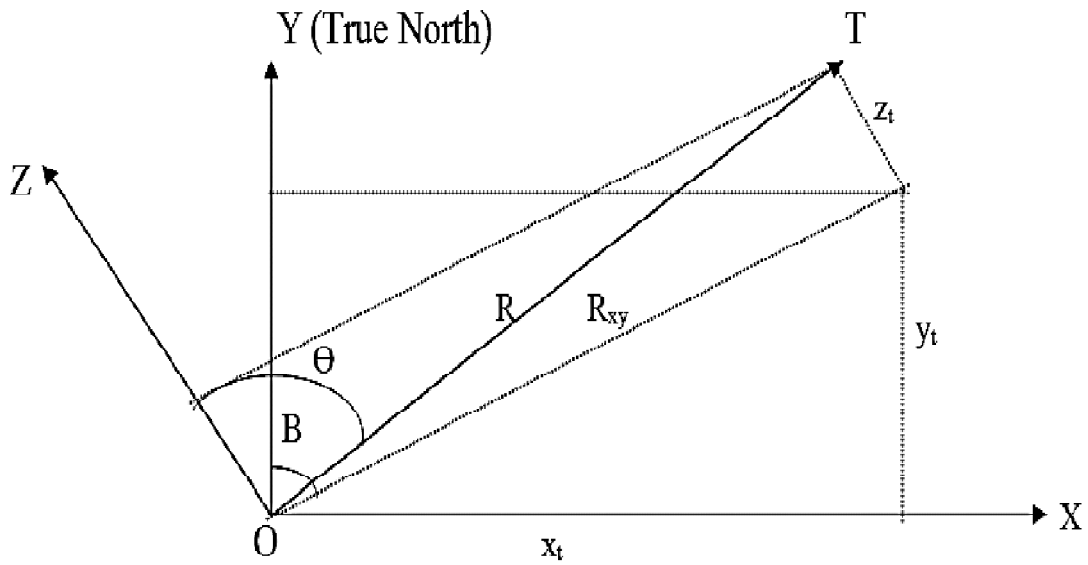$$y_0 = y_0 + dy_0$$ (38)

$$z_0 = z_0 + dz_0$$ (39)

Figure 2: Target and observer positions

From Figure 2.

$$x_t = R_{xy} * sin\ (B) \tag{40}$$

$$y_t = R_{xy} * cos\ (B) \tag{41}$$

$$sin(\theta) = R_{xy}\ /\ R \tag{42}$$

Substituting equations (40) in (41) and (42)

$$x_t = R * sin\ (\theta) * sin\ (B) \tag{43}$$

$$y_t = R * sin\ (\theta) * cos\ (B) \tag{43}$$

$$z_t = R * cos\ (\theta) \tag{44}$$
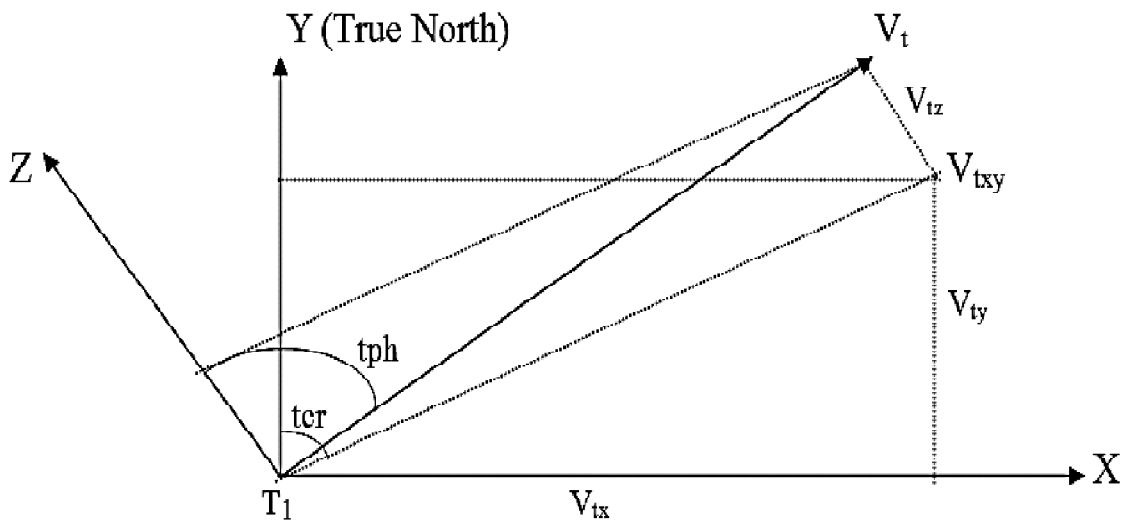
Figure 3: Target and observer velocities

When the target is in motion with velocity v$_t$, change in target position after t seconds, from Figure 3.

$$dx_t = v_t * \sin(tcr) * \sin(tph) * t \tag{45}$$

$$dy_t = v_t * \cos(tcr) * \sin(tph) * t \tag{46}$$

$$dz_t = v_t * \cos(tph) * t \tag{47}$$

where tcr and tph are target course and pitch respectively.

Now the new target position is

$$x_t = x_t + dx_t \tag{48}$$
$$y_t = y_t + dy_t \tag{49}$$
$$z_t = z_t + dz_t \tag{50}$$

Tareget true bearing, range and elevation are

$$true\,bearning = \tan^{-1}\left(\frac{x_t - x_0}{y_t - y_0}\right) \tag{51}$$

$$true\,range = \sqrt{(diff\,(x_t, x_0)^2 + (diff\,(y_t, y_0)^2 + (diff\,(z_t, z_0)^2} \tag{52}$$

$$true\,elevation = \tan^{-1}\left(\frac{R_{xy}}{z_t - z_0}\right) \tag{53}$$
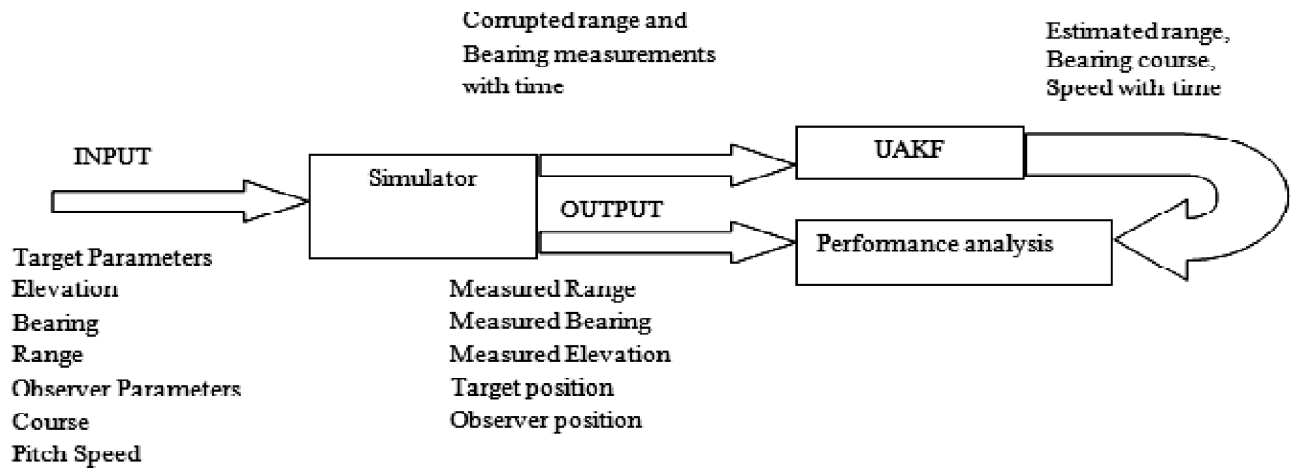

Figure 4: Block diagram of TMA in simulation mode

Block diagram of target motion analysis in simulation mode is shown in Figure 4. Corrupted measurements are applied to estimate target motion parameters (TMP) using EKF. Estimated TMP are compared with that of true values.

4. SIMULATION RESULTS

It is assumed that the experiment is conducted in favorable conditions. This simulation is carried out on a personal computer using Matlab. The scenario chosen for evaluation of algorithm is shown in Table 2. For example, scenario 1 describes a target moving at an initial range of 3000m with bearing and elevations of 45⁰. Its

initial course is 255^0 moving with a speed of 10m/s. The range, bearing and elevation measurements are corrupted with 10m (1σ), 0.33^0(1σ) and 0.33^0(1σ) respectively.

In simulation mode, estimated and actual values are available and hence the validity of the solution is based on certain acceptance criterion is possible. The following acceptance criterion is chosen based on weapon control (this topic is not discussed here) requirement. The solution is converged when error in course $<= 3^0$, error in speed estimate $<= 1$m/s and error in elevation estimate $<= 1^0$.

The estimates and true paths of target are shown in Figure 5 and Figure 9 for scenario1 and 2 respectively. For clarity of the concepts, estimated speed, course and elevation errors for scenario1 are presented in Figure 6, 7 and 8 respectively. For scenario 2 errors in speed, course and elevation are presented in Figure 10, 11 and 12 respectively. The solution is converged when the course, speed elevation are converged. The convergence time (seconds) for the scenarios is given in Table 3. In simulation, it is observed that the solution is converged at 28th sample for course, 26th sample for speed and 3rd sample for elevation respectively for scenario1. So, for scenario 1, the total solution is obtained at 28 samples. Similarly for the other scenario the convergence time is shown in Table. Similarly for scenario 2, it is observed that the estimated course, speed and elevation are converged at 13th, 25th and 3rd samples respectively. So the convergence time for scenario 2 is obtained at 25th sample.

Table 2
Input scenarios chosen for the algorithm

Scenario	Target range (m)	Target bearing (deg)	Target Course (deg)	Target speed (m/s)	Target Elevation (deg)	Noise in bearing (1σ)(deg)	Noise in Range (1σ)(m)	Noise in bearing measurements (1 σ)(deg)
1	3000	45	255	10	45	0.33	10m	0.33
2	3000	135	315	8.5	135	0.33	10m	0.33

Table 3
Convergence time in samples for the chosen scenarios

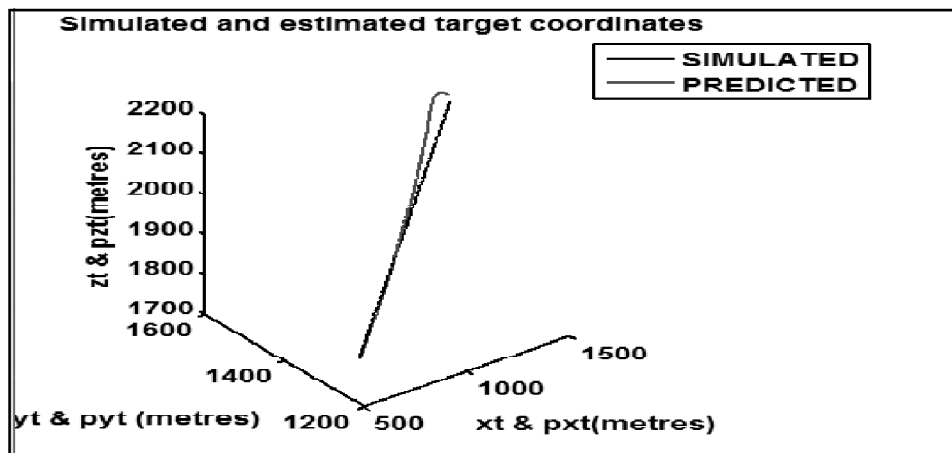| Scenario1	Course	Speed	Elevation	Total solution
1	28	25	3	28
2	13	25	3	25

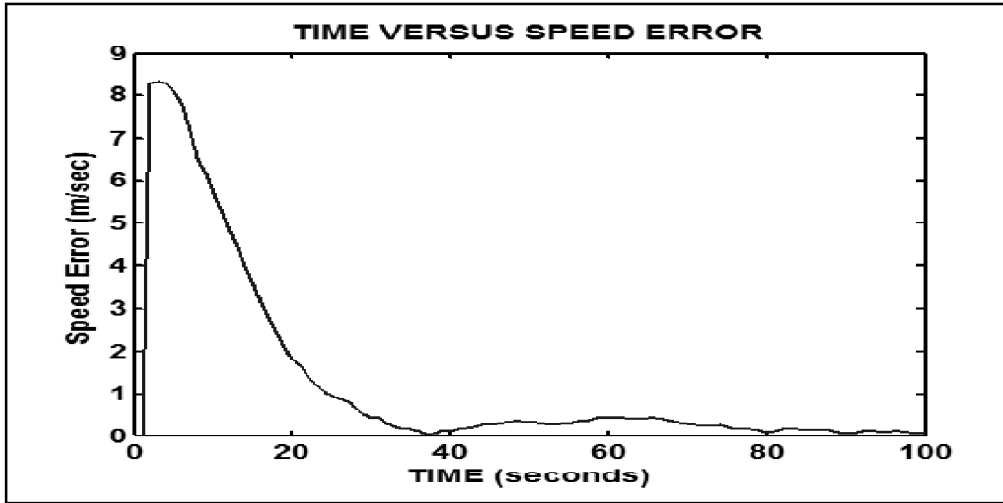**Figure 5: Simulated and estimated target paths**
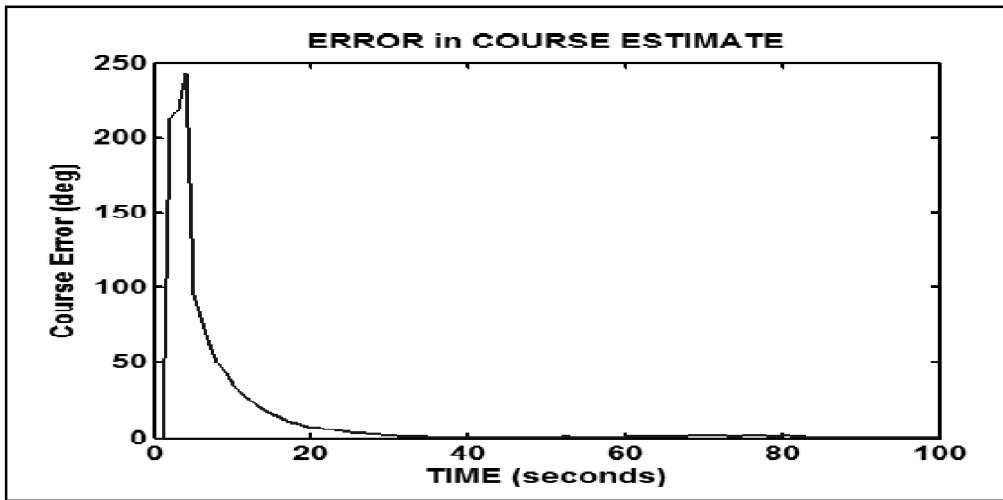
Figure 6: Error in speed estimate

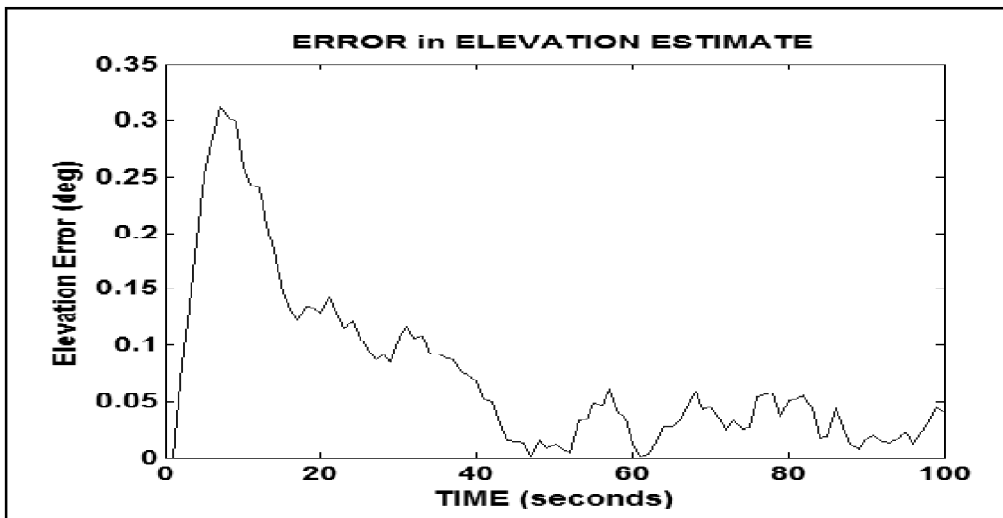**Figure 7: Error in course estimate**

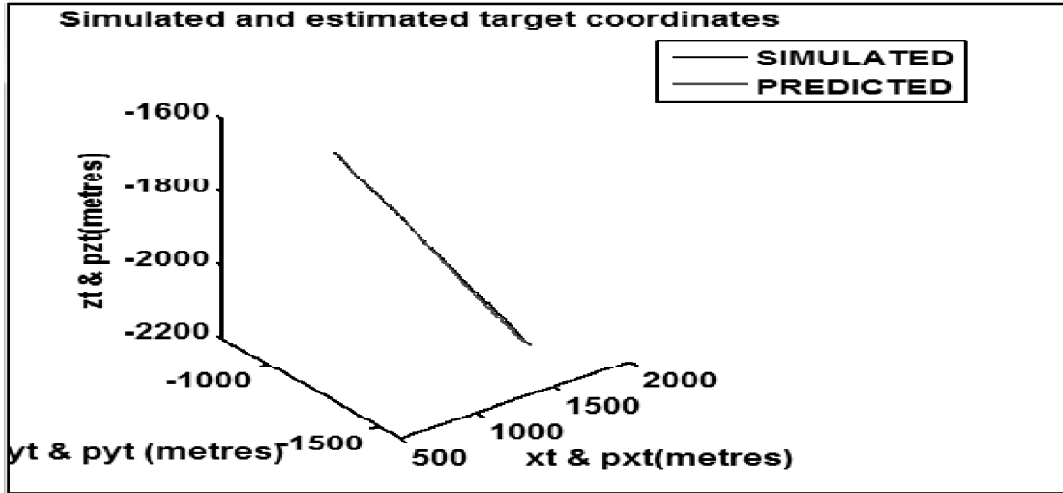**Figure 8: Error in elevation estimate**

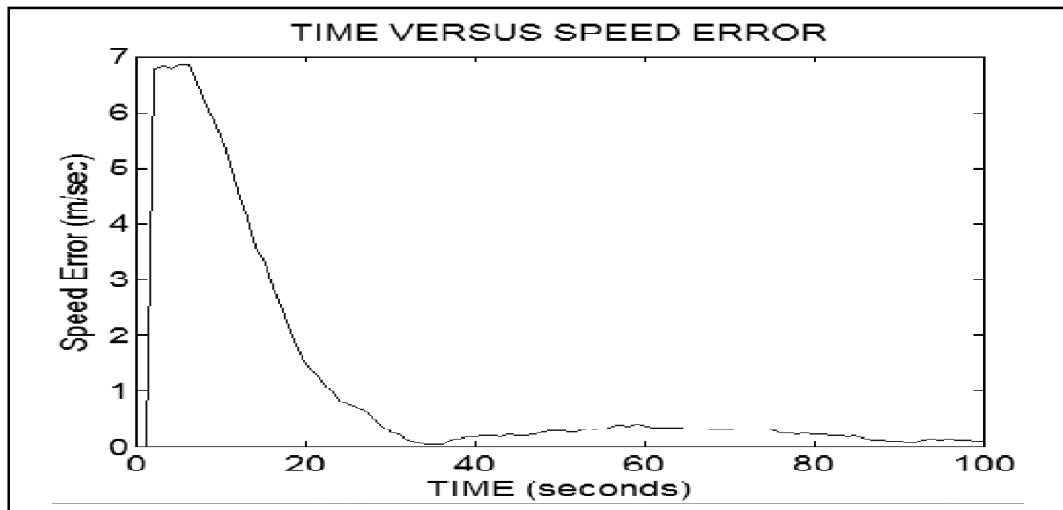**Figure 9: Simulated and estimated target paths**
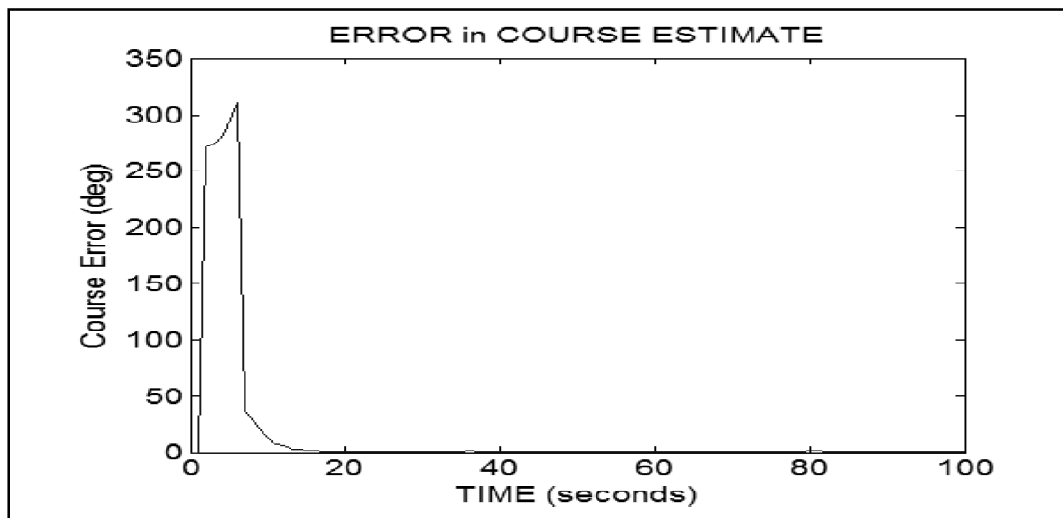

Figure 10: Error in speed estimate

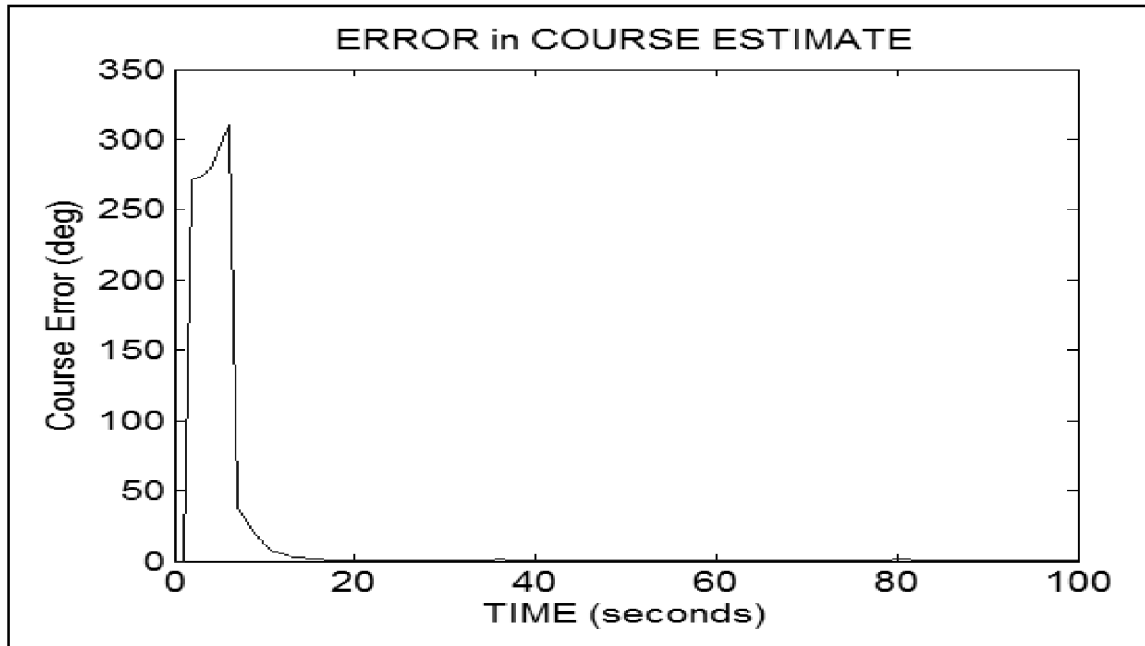**Figure 11: Error in course estimate**

Figure 12: Error in course estimate

5. CONCLUSION

Based on the results obtained in simulation, Unscented Kalman filter is recommended to estimate target course, speed in active target tracking from UAV systems.

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