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Estimation of LOS Rates for Target Tracking Problems using EKF and UKF Algorithms- A Comparative Study

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A B S T R A C T

One of the most important problems in target tracking is Line of Sight (LOS) rate estimation for using from PN (proportional navigation) guidance law. This paper deals with estimation of position and LOS rates of target with respect to the pursuer from available noisy RF seeker and tracker measurements. Due to importance of exact estimation on tracking problems most target position and LOS rates have been estimated with least error rather than actual values. In this paper, extended Kalman filter (EKF) and unscented Kalman filter (UKF) algorithms are used for estimation of target position in three-dimensional (3-D) and LOS rates in elevation and azimuth for seekers and trackers. For comparison of algorithms, model of the system was simulated using MATLAB and many tests were carried out. Simulation experiments showed that the efficiency of EKF due to least RMSE had better performance. However, the performance of EKF algorithm dramatically decreased when initializations (initial state assumption) were not near to real values, which in this condition UKF method provided a more accurate approximation. Numerical results from simulations show that the UKF is robust against uncertainties and has better state estimation accuracy. Therefore, UKF algorithm is appropriate, and it can run on target tracking systems.

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1. INTRODUCTION

Tracking problems can be used in, radar, sonar and IR-based tracking systems. Civil applications include sonar-based robotic navigation and TV camera-based people and object tracking [1, 2]. Line of Sight (LOS) rate estimation is one of the most important problems that used in modern homing missiles with PN (proportional navigation) guidance law. RF seeker is generally used in the pursuer as sensor to measure relative range, range rate, LOS angles and rates between pursuer and target as shown in Figure1. The equipment is typically mounted on a movable platform (such as aircraft, missile's seeker, and airborne tracking systems) [3]. When the sensor is controlled to point toward the target, more or less direct approaches can be used to estimate the LOS rates [4]. These measured signals are contaminated by high degree of noise due to eclipsing, glint, radar cross section (RCS) fluctuation and thermal noise [5]. In 1960, R.E. Kalman designed the filter for prediction, estimation problems that now arepopularly known as the Kalman filter[6]. A Kalman filter can be defined as an optimal recursive data processing algorithm. Kalman filter is characterized by accurate estimation of state variables under noisy condition, which makes it suitable for drives, robotic manipulators and other industrial applications. The algorithm is formulated in two steps, which involve; prediction and updating. Most tracking problems of nonlinear models that used extended Kalman filter (EKF) [7]and unscented Kalman filter (UKF) [8] can be solved in two dimensions[9]. Nonlinear estimators includingEKF and UKF algorithms have beenused for only 2D tracking problems[10]. Early research on the bearing-only filtering problem in 2D, used the easy-to-implement discrete-time EKF with relative Cartesian coordinates. In some work [11], the EKF was implemented using a discretized linear approximation for both the predicted state estimate and covariance. All the approaches mentioned use of a two dimension state estimation. Inanother study [12], tracking problems in three

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dimensions were solved using extended Kalman filter (EKF), unscented Kalman filter (UKF), and particle filter (PF). In some study [5], pursuer target relative position and velocity components along with target acceleration in the inertial frame have been estimated using EKF from available seeker measurements. In another work [13], comparison of estimation states for seeker system of a missile using Sliding Mode Observer and extended Kalman filter approaches was presented. Interacting multiple model (IMM) based AEKF seeker filter has been designed to operate in the close loop homing guidance to track highly manoeuvring Air Breating Targets[14]. In the literature [15], the problems of state estimation, tracking control and shape control in a micro-cantilever beam with nonlinear electrostatic actuation were investigated using extended Kalman filter algorithm. An interacting multiple model unscented Gauss-Helmert filter (IMM-UGHF) is presented in the literature [16]. Also, Gaussian-sum cubature Kalman filter and original algorithm of CKF have been compared for the bearings only tracking problems[17].

The remainder of the paper is organized as follows. First, the system model for the three-dimensional tracking problem, which is of interest in this paper, is described. Then, existing and improved algorithms including extended Kalman filter (EKF), unscented Kalman filter (UKF) proposed for estimating position and LOS rates are outlined. Section 4 discusses the performance metrics used when comparing the different algorithms. In this section, system is simulated using MATLAB, and tested for many scenarios. The details of the simulations done and the comparisons of the performances of the algorithms are given in Section 4. Finally, concluding remarks are highlighted.

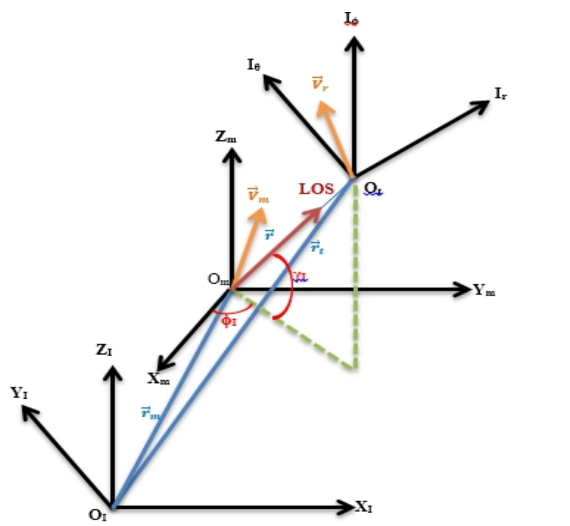


Figure 1. Schematic diagram of pursuer and target engagement

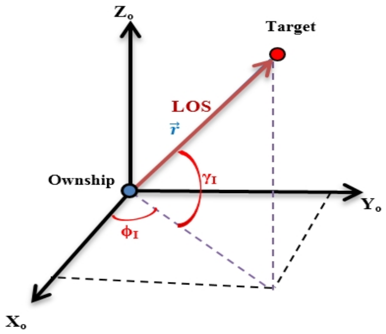


Figure 2. Definition of tracker coordinate frame bearing and elevation angle[12]

2. MATHEMATICAL MODEL

For modeling of tracking problem,the dynamics of the target is modeled as a state space model. There is a one moving target in the scene and two angular sensors for tracking it [18]. The Cartesian states of the target and ownship (tracker) are defined [12].

$$X^t = [x^t y^t\ z^t \dot{x}^t \dot{y}^t \dot{z}^t]' \quad (1)$$

and

$$X^o = [x^o y^o\ z^o \dot{x}^o \dot{y}^o \dot{z}^o]' \quad (2)$$

The relative state vector is defined by[18]:

$$X = X^t - X^o \quad (3)$$

Thus, the state vector can be expressed as[18]:

$$X_k = [x\ \ y\ \ z\ \ \dot{x}\dot{y}\dot{z}] \quad (4)$$

The dynamics of the target is modeled as a linear, discretized Wiener velocity model [19]:

$$X_k^t = F_{k-1} X_{k-1}^t + w_{k-1} \quad (5)$$

whereF_{k-1} and $w_{k-1}$are the state transition matrix and integrated process noise, respectively, for the time interval $[t_{k-1}\ ,\ t_k]$:

$$\Delta t = t_{k-1} - t_k \quad (6)$$

$$F_{k-1} = \begin{bmatrix} 1 & 0 & 0 & \Delta t & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta t & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta t \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (7)$$

where$w_{k-1} \sim N(0, Q_{k-1})$ is Gaussian process noise with zero mean and covarianceQ_{k-1} that must be discretized with power spectral density Qc[18]:

$$Qc = diag(0,0,0,q1,q2,q3) \quad (8)$$

The process noise meaning that the dynamic system cannot be modeled entirely deterministically.

3. MEASUREMENT MODELS

Outputs or measurement model for the range(r_k), range rate($\dot{r}_k$), LOS angles in elevation and azimuth(ϕ_k,γ_k) and LOS rates ($\dot{\phi}_k,\dot{\gamma}_k$)using the relative Cartesian state vector $X_k$is [12]:

$$z_k = h(X_k) + r_k \tag{9}$$

where:

$$h(X_k) = \begin{bmatrix} r_k \\ \dot{r}_k \\ \phi_k \\ \dot{\phi}_k \\ \gamma_k \\ \dot{\gamma}_k \end{bmatrix} \tag{10}$$

$$\begin{aligned} r_k &= \sqrt{x_k{}^2 + y_k{}^2 + z_k{}^2} \\ \dot{r}_k &= \frac{x_k\dot{x}_k + y_k\dot{y}_k + z_k\dot{z}_k}{\sqrt{x_k{}^2+y_k{}^2+z_k{}^2}} \\ \phi_k &= \tan^{-1}\frac{y_k}{x_k} \\ \dot{\phi}_k &= \frac{(x_k\dot{y}_k - y_k\dot{x}_k)}{(x_k{}^2+y_k{}^2)} \\ \gamma_k &= \tan^{-1}\frac{z_k}{\sqrt{x_k{}^2+y_k{}^2}} \\ \dot{\gamma}_k &= \frac{z_k(x_k{}^2+y_k{}^2) - z_k(x_k\dot{x}_k+y_k\dot{y}_k)}{(x_k{}^2+y_k{}^2+z_k{}^2)(\sqrt{x_k{}^2+y_k{}^2})} \end{aligned} \tag{11}$$

wherer_k is a zero mean white Gaussian measurement noise with covariance R[18]. This noise means that there is a certain degree of uncertainty in them.

$$r_k^i \sim N(0, \mathrm{R}) \tag{12}$$

$$R = diag\left(\sigma_r^2, \sigma_{\dot{r}}^2, \sigma_\phi^2, \sigma_{\dot{\phi}}^2, \sigma_\gamma^2, \sigma_{\dot{\gamma}}^2\right) \tag{13}$$

4. NONLINEAR FILTERING ALGORITHMS

4. 1. Extended Kalman Filter

In estimation theory, the EKF is the nonlinear version of the Kalman filter which linearizes about an estimate of the current mean and covariance.Due to the linearization step, the EKF is sub-optimal [20]. The steps for the first-order EKF algorithm computationis as follows [10]:

The steps for the first order EKF algorithm[18]

Prediction:

$m_k^- = f(m_{k-1}, k-1)$

$P_k^- = F_x(m_{k-1}, k-1)\, P_{k-1} F_x^T + Q_{k-1}$

Update:

$v_k = y_k - h(m_k^-, k)$

$S_k = H_x(m_k^-, k) P_k^- H_x^T(m_k^-, k) + R_k$

$K_k = P_k^- H_x^T(m_k^-, k) S_k^{-1}$

$m_k = m_k^- + K_k v_k$

$P_k = P_k^- - K_k S_k K_k^T$

Prediction and update steps for EKF algorithms have listed in table above,where $m_k^-$and$P_k^-$are the predicted mean and covariance of the state, respectively, on the time step k before seeing the measurement. m_k and P_k are the estimated mean and covariance of the state, respectively, on time step k after seeing the measurement. v_k is the innovation or the measurement residual on time step k. S_k is the measurement prediction covariance on the time step k. K_k is the filter gain, which tells how much the predictions should be corrected on time step k. The matrices $F_x(m, k-1)$ and $H_x(m, k)$ are the Jacobians of f and h, with elements [18]:

$$[F_x(m, k-1)]_{j,j'} = \frac{\partial f_j(x, k-1)}{\partial x_{j'}}|_{x=m} \tag{14}$$

$$[H_x(m, k)]_{j,j'} = \frac{\partial h_j(x, k)}{\partial x_{j'}}|_{x=m} \tag{15}$$

4. 2. Unscented Kalman Filter

Unscented Kalman filter (UKF) is nonlinear Kalman filter which shows promise as an improvement over the EKF [21]. In the UKF, the probability density is approximated by a deterministic sampling of points, which represent the underlying distribution as a Gaussian. UKF uses the unscented transformation (UT) to approximate the moments [8]. In UT, deterministically we choose a fixed number of sigma points, which capture the desiredmoments (at least mean and covariance) of the original distribution of **x** exactly.After that wepropagate the sigma points through the non-linear functionand estimate the moments of the transformed variable from them.The steps for the UKF algorithm computationis as follows [10]:

The steps for the UKF algorithm [18]

Prediction:

$X_{k-1} = [\, m_{k-1} \dots m_{k-1}] + \sqrt{c}[0 \ \sqrt{p_{k-1}} - \sqrt{p_{k-1}}]$

$\hat{X}_{k-1} = f(X_{k-1}, k-1)$

$m_k^- = \hat{X}_k\, w_m$

$P_k^- = \hat{X}_k W [\hat{X}_k]^T + Q_{k-1}$

Update:

$X_k^- = [m_k^- \dots m_k^-] + \sqrt{c}[0 \ \sqrt{P_k^-} - \sqrt{P_k^-}]$

$Y_k^- = h(X_k^-, k)$

$\mu_k = Y_k^- w_m$

$S_k = Y_k^- W [Y_k^-]^T + R_k$

$C_k = X_k^- W [Y_k^-]^T$

$K_k = C_k S_k^{-1}$

$m_k = m_k^- + K_k [\, y_k - \mu_k]$

$P_k = P_k^- - K_k S_k K_k^T$

Prediction and update steps for UKF algorithms have been listed in table above,where $and\ C_k$ are predicted mean of the measurement, and cross-covariance of the state and measurement, respectively, on the time step k [18].

5. SIMULATION AND RESULTS

For using Kalman filter algorithms, firstly,the continuous-time dynamic equation must be written in discrete form.The states of the target at time step (t) consist of the position in three-dimensional Cartesian coordinates x, y *and* z and the velocity toward those coordinatesaxes $\mathrm{V_x}, \mathrm{V_y}$ *and* $\mathrm{V_z}$. Thus, the dynamics of the target is modeled as the state space model (5).In Table 1 the value of parameters for simulationare listed.Table 2 summarizes three tested scenarios in desired initialize for EKF and UKF algorithms (Scenario 1) and in undesired initialize (Scenario 2) and (Scenario 3) over 500 Monte Carlo runs.

Figure 3 shows the real trajectory of target and estimation of position with EKF and UKF algorithms. The averages of position RMSE per run are summarized in Table 3. The RMSE computation was performed by the two algorithms. It can be seen that the UKF significantly outperforms the other algorithm in 2 and 3 test scenarios due to least RMSE. Root mean square error (RMSE) for each running simulationis given by [23]:

$$RMSE(t) = \sqrt{\frac{1}{N_{MC}}\sum_{j=1}^{N_{MC}}\left\|x_t^{True} - x_t^{€(j)}\right\|_2^2} \quad (16)$$

where$N_{MC} = 500$ is Monte Carlo runs number, $x_t^{€(j)}$is estimation for j Monte Carlo runs on (t) time and x_t^{True} is the true value.

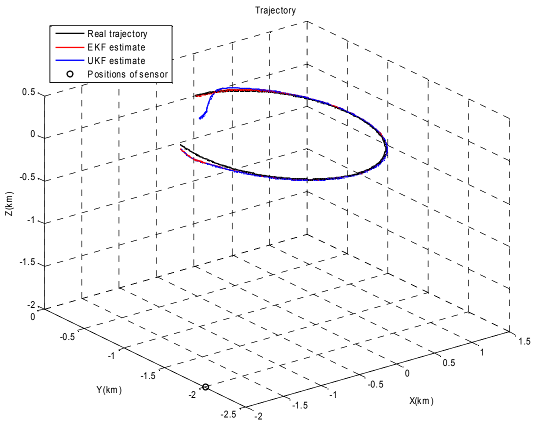
In Table 3 the root mean square errors are listed. RMSE (mean of position errors) of three tested methods in desired initialize for EKF and UKF (Scenario 1) and in undesired initialize (Scenario 2) and (Scenario 3) over 500 Monte Carlo runs.

TABLE 1. Value of parameters

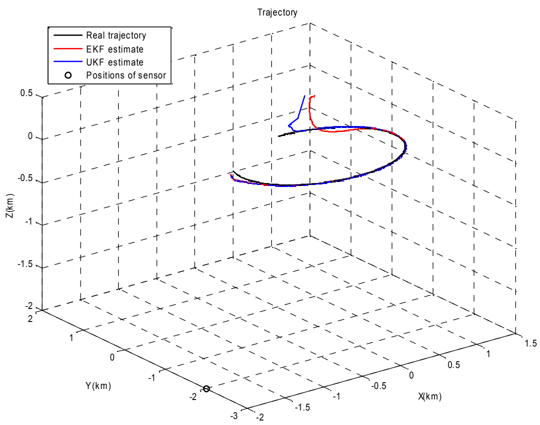
Parameters	Value
Start point of target	$\mathrm{X}(0) = [0\ 0\ 0\ 1\ 0\ 0]^T$
Position of sensor	$X_o = (-2, -2, -2)$
Power spectral density	$R = diag(0.05^2, 0.05^2, 0.05^2, 0.05^2, 0.05^2, 0.05^2)$
Covariance of measurement noise	$\mathrm{P_0} = diag(0.75, 0.75, 0.75, 10, 10, 10)$
Covariance of the stateon the initial time	$dt = 0.01$
Time interval	$N_{MC} = 500$
Monte Carlo runs number	

TABLE 2. Tests scenarios

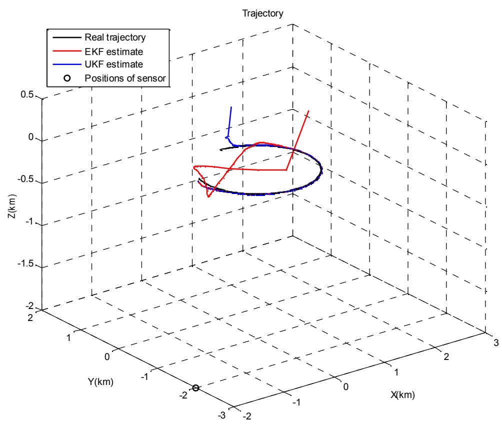
Parameter	Scenarios	Value
Mean of the stateon the initial time ($\mathrm{M_0}$)	S1	$\mathrm{M_0} = [2\ 2\ 2\ 1\ 1\ 0]^T$
	S2	$\mathrm{M_0} = [3.2\ 1.2\ 2.1\ 1.2\ 2.2\ 0.1]^T$
	S3	$\mathrm{M_0} = [-0.5 - 0.5\ 2.1\ 2.5\ 2.5\ 0.1]^T$



(a) Scenario 1



(b) Scenario 2

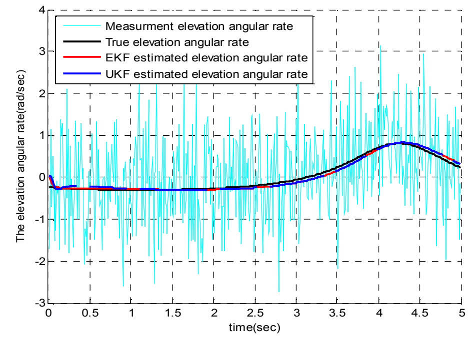


(c) Scenario 3

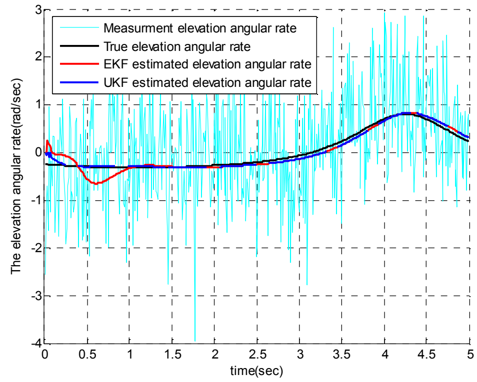
Figure 3. Comparison of EKF and UKF algorithms for position estimation

TABLE 3. RMSEs of estimating the position in kilometers

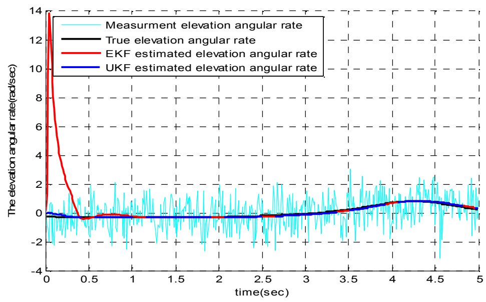
Algorithm	RMSE scenario 1	RMSE scenario 2	RMSE scenario 3
EKF	0.1066	0.1912	0.7993
UKF	0.1687	0.1076	0.5644



(a) Scenario1

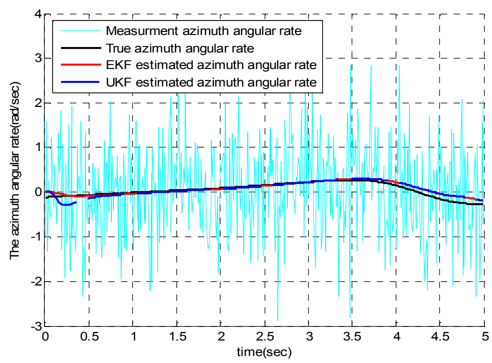


(b) Scenario 2

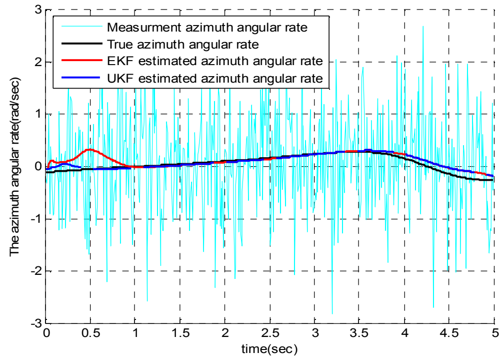


(c) Scenario 3

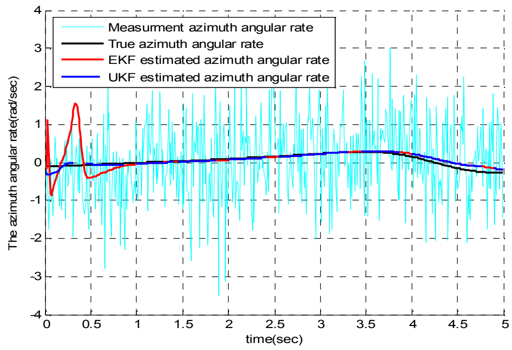
Figure 4. Comparison of EKF and UKF algorithms for elevation angular rate ($\dot{\phi}_k$) estimation



(a) Scenario 1



(b) Scenario 2



(c) Scenario 3

Figure 5. Comparison of EKF and UKF algorithms for azimuth angular rate ($\dot{\gamma}_k$) estimation

TABLE 4. RMSEs of estimatingmeasurements

Measurement	Scenario 1		Scenario 2		Scenario 3	
	EKF	**UKF**	**EKF**	**UKF**	**EKF**	**UKF**
$\dot{\phi}_k$(rad/s)	0.0540	0.0599	0.1169	0.0585	1.5730	0.0631
$\dot{\gamma}_k$(rad/s)	0.0576	0.0721	0.1130	0.0607	0.2516	0.0636

Figures 4 and 5 shows the comparison of EKF and UKF algorithms for estimation of LOS ratesin elevation and azimuth($\dot{\phi}_k,\dot{\gamma}_k$), respectively.

In Table 4 the root mean square errors have been listed. RMSE of measurements estimate, LOS rates in elevation and azimuth ($\dot{\phi}_k,\dot{\gamma}_k$), respectively. In three tested scenarios (desired initialize for EKF and UKF (Scenario 1) and in undesired initialize (Scenario 2) and (Scenario 3)) over 500 Monte Carlo runs were conducted. Therefore, based on these observations, Figures 4 and 5 show that the efficiency of EKF due to least RMSE has better performance (Scenario 1) for estimation of LOS rates in elevation and azimuth ($\dot{\phi}_k,\dot{\gamma}_k$).

However, the performance of EKF algorithm dramatically decreased when initialization (initial state assumption) is not good(Scenario 2 and 3), which in this condition UKF method provides a more accurate approximation.The results (Table 4) show that the efficiency of UKF against uncertainties due to least RMSE has better performance. In this respect, the UKF has the same appeal as linearization for the EKF, but unlike linearization the UKF provides sufficient accuracy to be applied in many highly nonlinear filtering and control applications.Thus UKF algorithm has significant accuracy improvement over EKF algorithm.

6. CONCLUSION

In this paper, EKF and UKF algorithms were compared for state estimation in target tracking problems. Firstly, mathematical modelsof system were obtained. Then, LOS rates in elevation and azimuth were estimated using both EKF and UKFtechniques. The state estimation for tracking system created in MATLAB has been tested using both EKF and UKF techniques. The results obtained showed that the efficiency of EKF due to least RMSE has better performance. However, the performance of EKF algorithm dramatically decreased when initializationsarenotnear real values.Numerical results from simulations show that the UKF is robust against uncertainties and has better state estimation accuracy. Thus, UKF method is interested for using in target tracking systems.In the future, it can extend the UKF to multi-sensor tracking problems.

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Unscented Kalman Filter

چکیده

یکی از مهمترین مسائل در تعقیب هدف، تخمین نرخ خط دید برای استفاده در قانون هدایت ناوبری تناسبی می‌باشد. این مقاله بر روی تخمین موقعیت یک هدف متحرک و نرخ‌های خط دید مابین ردیاب و هدف بر اساس اندازه‌گیری‌های همراه با نویز در جستجوگرهای فرکانس رادیوییوردیاب‌ها تمرکز نموده است. بعلت اهیمت فراوان تخمین دقیق در مسائل ردیابی می‌بایست موقعیت و نرخ‌های خط دید هدف با خطای کمتری نسبت به مقادیر واقعی تخمین زده شوند. در این مقاله الگوریتم‌های فیلتر کالمن توسعه یافته (EKF) و فیلتر کالمن خنثی (UKF) برای تخمین موقعیت هدف در سه بعد ونرخ‌های خط دید در سمت و فراز برای جستجوگرها و ردیاب‌ها استفاده شده است. برای مقایسه الگوریتم‌ها، مدل سیستم با استفاده از نرم‌افزار MATLAB شبیه سازی شده و تعدادی سناریو اجرا گردیده است. نتایج آزمایش‌های شبیه‌سازی نشان می‌دهد کهدر ابتدا، کارایی EKF به علت خطای مربع میانگین ریشه (RMSE) کمتر،عملکرد بهتری داشته اما زمانی که مقادیر اولیه (فرض حالت اولیه) به مقدار واقعی نزدیک نباشد عملکرد EKF بصورت فزاینده‌ای کاهش می‌یابد که در این شرایط، روش UKFدقت تخمین حالت بهتری دارد. نتایج عددی از شبیه‌سازی‌هانشان می‌دهد که UKF از دقت بهتری برخوردار بوده و در برابر نامعینی‌ها مقاوم‌تر است. بنابراین الگوریتم UKFمناسب بوده و می‌تواند در سیستم‌های ردیابی هدف بکار گرفته شود.

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