Improving bearings-only target state estimation tracking problem by using adaptive and nonlinear kalman algorithms

Tammam Khadour, Michel Al Saba, Louay Saleh

Department of Electro-Mechanical Engineering, Higher Institute for Applied Sciences and Technology, Syria

Article Info	ABSTRACT
	Finding the best estimate of the process state from noisy data is the main problem in tracking systems, many efforts and researches have been done to remove this noise. More useful information about the target's state can be extracted from observations by using a more appropriate model for the target's motion or using additional sensors. In this paper, we will introduce two methods to improve the estimation of bearing-only target tracking problem in two dimensions (2D). The first method is by adding a third sensor and making a good alignment of those sensors, and at the same time an extended Kalman filter (EKF), unscented Kalman filter (UKF) and cubature Kalman filter (CKF) are implemented. The second method is by applying an adaptive nonlinear Kalman filter (ANKF) for two sensors to solve the problem of measurement variance uncertainty. *Copyright © 2019 Institute of Advanced Engineering and Science.* **

Corresponding Author:

Tammam Khadour,
Department of Electro-Mechanical Engineering,
Higher Institute for Applied Sciences and Technology,
Damascus, Syria- BP 31983.
Email: tammam.khaddour@hiast.edu.sy

1. INTRODUCTION

Different types of vehicles like cars, ships, planes perform different types of maneuvers from simple to complex. A single model does not represent all such maneuvers and particular multiple models are constructed to accurately describe and aid in predicting the trajectory according to the application [1].

Many specific dynamic models of target motion have been developed for maneuvering target tracking. The simplest model for a maneuvering target are the white-noise acceleration model [2]. Many target tracking algorithms are proposed based on so many different filters, such as alpha-beta filter, Gaussian sum filter. nonlinear Kalman filter and adaptive Kalman filter as in [3-4]. The Kalman filter is used for state estimation of some linear dynamic system [5-6], which can estimate the future state of the signal based on the signal statistical characteristic, the algorithm is formulated in two steps: prediction and updating. More common methods for dealing with a nonlinear model is to use the extended Kalman filter (EKF) [7].

Results of implementing non-linear Kalman filter for 2D tracking problems using two sensors showed that there are problems when the target is near the straight line which is between the two sensors [8]. The UKF algorithm is based on the Unscented Transform (UT) for computing the mean and covariance matrix of a variable, it is far easier to implement than the EKF [9]. For system model with a good linear and quadratic approximations the EKF works well but if the system is more nonlinear the UKF is often superior over EKF, the CKF algorithm is used in many applications like simultaneous localization and mapping [10], and in improving the tracking performance [11]. A Gaussian-sum cubature Kalman filter with improved

robustness demonstrated good accuracy and efficiency for the bearings-only tracking problem compared to the original algorithm of CKF [12]. In adaptive Kalman filter (AKF) the filter adjusts its knowledge about the mean and covariance matrix values according to the gap between the predicted estimations and the current measurements. A new methodology is proposed based on the use of weighted least squares methodology instead of traditional least square approach [13]. The estimation of parameter and state of nonlinear high-speed objects by adaptive unscented Kalman filter is proposed in [14]. The navigation system depends on sensors output, where the navigation output must be accurate and robust with erroneous measurements which caused from noise, that makes the noise process very important for sensors and control process in mobile robot [15]. Using a mobile robot for following sound sources in real time depending on an active virtual impedance algorithm for obstacle avoidance where the new algorithm changes the impedance dynamically in two cases: one distance sensor and two distance sensors, using more ultrasonic sensors for future research [16]. Implemented binary motion sensors for the problem of automated position estimation, using Passive Infrared (PIR) motion sensors with the suggested estimator, develop the detection system by different sensor models and arrangements is a future work [17]. A very important Kalman Filter use is to reduce the noise on the accelerometer and gyroscope sensors for quadrotor navigation system, where the bias and zero velocity compensations are able to improve the position estimation of the quadrotor by reducing the effects of drift due to integration [18].

The contributions of this study are the development in bearings-only target state estimation tracking problem by using many Kalman Filter algorithms (EKF, UKF, CKF) to reduce the noise on the sensor, improving the accuracy of estimation by adding a third sensor as hardware solution, which avoid the target movement on the straight line between two sensors, and change the alignment of those three sensors to have an accurate estimation. Another solution is software depending on [19] which is based on the innovation-based adaptive estimation (IAE) approach and the adaptive fading Kalman filter (AFKF) approach. This method was used to solve measurement variance uncertainty with two sensors in linear states. In this paper we will use the algorithms presented in [19] but we will change the flow chart of the (IAE, AFKF) algorithms to be suitable for nonlinear measurement as adaptive nonlinear Kalman filter (ANKF) for two sensors. Results will then be compared.

The structure of this paper is as follows: Section two presents the bearing-only tracking model. Section three describes nonlinear Kalman filters (EKF, UKF, and CKF). Section four concerns proposed method using Adaptive Kalman filter implementation. In section five simulation results are compared (EKF, UKF, and CKF) in two sensors case, three sensors case and using proposed ANKF with two sensors case. Finaly conclusion will be presented in section six.

2. BEARING-ONLY TRACKING MODEL

Target motion and sensor measurement models in the two dimensional (2D) case are considered. In cartesian coordinates, the target state e_k with position (x_k, y_k) and velocity $(\dot{x}_k, \dot{y}_k)$ at time k is expressed as [8]:

$$e_k = (x_k \quad y_k \quad \dot{x}_k \quad \dot{y}_k)^T \tag{1}$$

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

$$e_k = \begin{pmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} e_{k-1} + v_{k-1} \tag{2}$$

Where v_{k-1} is Gaussian process noise with zero mean and covariance:

$$Q_{k-1} = \begin{pmatrix} \frac{1}{3}T^3 & 0 & \frac{1}{2}T^2 & 0 \\ 0 & \frac{1}{3}T^3 & 0 & \frac{1}{2}T^2 \\ \frac{1}{2}T^2 & 0 & T & 0 \\ 0 & \frac{1}{2}T^2 & 0 & T \end{pmatrix} \sigma_v^2 \tag{3}$$

Where T is the sampling time and σ_v^2 is the spectral density of the noise. The measurement model for sensor i is defined as:

$$z_k = h(e_k, k) = \begin{pmatrix} \theta_k^1 \\ \theta_k^2 \end{pmatrix} + w_k \tag{4}$$

Where $\theta_k^i = \arctan(\dfrac{y_k - s_y^i}{x_k - s_x^i}) + w_k^i$ and (s_x^i, s_y^i) is the position of sensor i and $w_k^i \sim N(0, \sigma_w^2)$.

3. NONLINEAR KALMAN FILTER
3.1. Extended Kalman Filter (EKF)

The extended Kalman is the nonlinear version of the Kalman filter which linearizes about an estimate of the current mean and covariance. First order extended Kalman filters are presented. The EKF model is [4], [8]:

$$\begin{cases} e_k = f(e_{k-1}, k-1) + v_{k-1} \\ z_k = h(e_k, k) + w_k \end{cases} \tag{5}$$

Where the processing and measurement noise are white Gaussian with:

$$\begin{cases} v_{k-1} \sim N(0, Q_{k-1}) \\ w_k \sim N(0, R_k) \end{cases} \tag{6}$$

The EKF algorithm:
a. Prediction

$$\begin{cases} m_k^- = f(m_{k-1}, k-1) \\ P_k^- = F_e(m_{k-1}, k-1)P_{k-1}F_e^T + Q_{k-1} \\ \left[F_e(m, k-1)\right]_{j,i} = \dfrac{\partial f_j(e, k-1)}{\partial x_i}\Bigg|_{e=m} \end{cases} \tag{7}$$

b. Update

$$\begin{cases} \dfrac{\partial h^i(e_k)}{\partial x_k} = \dfrac{-(y_k - s_y^i)}{(x_k - s_x^i)^2 + (y_k - s_y^i)^2} \\ \dfrac{\partial h^i(e_k)}{\partial y_k} = \dfrac{-(x_k - s_x^i)}{(x_k - s_x^i)^2 + (y_k - s_y^i)^2} \\ \dfrac{\partial h^i(e_k)}{\partial \dot{x}_k} = 0 . \qquad \dfrac{\partial h^i(e_k)}{\partial \dot{y}_k} = 0 \end{cases} \tag{8}$$

$$\begin{cases} u_k = z_k - h(m_k^-, k) \\ S_k = H_e(m_k^-, k)P_k^- H_e^T(m_k^-, k) + R_k \\ K_k = P_k^- H_e^T(m_k^-, k)S_k^{-1} \\ m_k = m_k^- + K_k u_k \\ P_k = P_k^- - K_k S_k K_k^T \\ \left[H_e(m, k)\right]_{j,i} = \dfrac{\partial h_j(e, k)}{\partial x_i}\Bigg|_{e=m} \end{cases} \tag{9}$$

The m_k^- and P_k^- are the predicted mean and covariance of the state.

3.2. Unscented Kalman Filter (UKF)

In models with high non-linear predict and update functions (*f, h*) EKF gives particularly poor performance because the covariance is propagated through linearization of the underlying non-linear model. The unscented Kalman filter (UKF) is a sampling method uses a deterministic sampling technique known as the unscented transform (UT) to pick a minimal set of (2n+1) sample points called (sigma points) around the mean of the n-dimensional distribution of the covariance matrix, where computational efficiency is the advantage of the (UT). The UKF algorithm [4], [8], [9]:

a) Sigma point

The *n*-dimensional e_k with mean $\hat{e}_{k/k}$ and covariance $P_{k/k}$ is approximated by $2n+1$ weighted samples named *sigma points* selected using the following algorithm:

$$\begin{cases} \chi^0_{k/k} = \hat{e}_{k/k}, \quad W_0 = \kappa/(n+\kappa) \\ \chi^i_{k/k} = \hat{e}_{k/k} + \left(\sqrt{(n+\kappa)P_{k/k}}\right)_i, \quad W_i = 1/2(n+\kappa) \\ \chi^{i+n}_{k/k} = \hat{e}_{k/k} - \left(\sqrt{(n+\kappa)P_{k/k}}\right)_i, \quad W_{i+n} = 1/2(n+\kappa) \end{cases}$$

(10)

where κ is a tuning parameter of the filter which is recommended to be chosen such that $\kappa + n = 3$, $\left(\sqrt{(n+\kappa)P_{k/k}}\right)_i$, $i = 1, \cdots, n$, is the ith row or column of the matrix square root of $(n+\kappa)P_{k/k}$, and W_i is the weight associated with the ith point.

b) Prediction

$$\begin{cases} \chi^i_{k+1/k} = f(\chi^i_{k/k}, k) \\ \hat{e}_{k+1/k} = \sum_{i=0}^{2n} W_i \chi^i_{k+1/k} \\ P_{k+1/k} = Q_k + \sum_{i=0}^{2n} W_i \left(\chi^i_{k+1/k} - \hat{e}_{k+1/k}\right)\left(\chi^i_{k+1/k} - \hat{e}_{k+1/k}\right)^T \end{cases}$$

(11)

c) Update

$$\begin{cases} Z^i_{k+1} = h(\chi^i_{k+1}) \\ \hat{z}_{k+1} = \sum_{i=0}^{2n} W_i Z^i_{k+1} \\ \hat{e}_{k+1/k+1} = \hat{e}_{k+1/k} + K_{k+1}(z_{k+1} - \hat{z}_{k+1}) \\ P_{k+1/k+1} = P_{k+1/k} - K_{k+1} P^{vv}_{k+1} K^T_{k+1} \end{cases}$$

(13)

$$\begin{cases} P^{vv}_{k+1} = \sum_{i=0}^{2n} W_i \left(Z^i_{k+1} - \hat{z}_{k+1}\right)\left(Z^i_{k+1} - \hat{z}_{k+1}\right)^T + R_{k+1} \\ P^{xv}_{k+1} = \sum_{i=0}^{2n} W_i \left(\chi^i_{k+1/k} - \hat{e}_{k+1}\right)\left(\chi^i_{k+1/k} - \hat{e}_{k+1}\right)^T \\ K_{k+1} = P^{xv}_{k+1}(P^{vv}_{k+1})^{-1} \end{cases}$$

(12)

3.3. Cubature Kalman Filter (CKF)

The CKF is a Kalman-filter-based algorithm that uses the third-degree spherical-radial rule to generate cubature points with normalized weights to numerically approximate the multidimensional integrals involved in Bayesian filtering [8], [10], [11], [12]:

a) Prediction

- Calculate the cubature points from the intersection of n-dimension unit sphere and the Cartesian axes c_i:

$$\xi_i = \begin{cases} \sqrt{n}c_i & i = 1,...,n \\ -\sqrt{n}c_{i-n} & i = n+1,...,2n \end{cases}$$

(14)

- Propagate the cubature points:

$$X_{i,k-1/k-1} = \sqrt{P_{k-1/k-1}}\,\xi_i + m_{k-1/k-1} \tag{15}$$

- Evaluate the cubature points with the dynamic model function:

$$X^*_{i,k-1/k-1} = f(X_{i,k-1/k-1}) \tag{16}$$

- Estimate the predicted state mean:

$$m_{k/k-1} = \frac{1}{2n}\sum_{i=1}^{p^n} X^*_{i,k-1/k-1} \tag{17}$$

- Estimate the predicted error covariance:

$$P_{k/k-1} = \frac{1}{2n}\sum_{i=1}^{p^n} X^*_{i,k-1/k-1} X^{*T}_{i,k-1/k-1}$$
$$- m_{k/k-1}m_{k/k-1}^{T} + Q_{k-1} \tag{18}$$

b) Update
- Calculate the cubature points from the intersection of n-dimension unit sphere and the Cartesian.
- Propagate the cubature points:

$$X_{i,k/k-1} = \sqrt{P_{k/k-1}}\,\xi_i + m_{k/k-1} \tag{19}$$

- Evaluate the cubature points with the measurement model function:

$$Z^*_{i,k/k-1} = f(X_{i,k/k-1}) \tag{20}$$

- Estimate the predicted measurement:

$$\hat{z}_{k/k-1} = \frac{1}{2n}\sum_{i=1}^{p^n} Z^*_{i,k/k-1} \tag{21}$$

- Estimate the innovation covariance matrix:

$$S_{k/k-1} = \frac{1}{2n}\sum_{i=1}^{p^n} Z^*_{i,k/k-1} Z^{*T}_{i,k/k-1}$$
$$- \hat{z}_{k/k-1}\hat{z}_{k/k-1}^{T} + R_k \tag{22}$$

- Estimate the cross-covariance matrix:

$$P_{xy,k/k-1} = \frac{1}{2n}\sum_{i=1}^{p^n} X^*_{i,k-1/k-1} Z^{*T}_{i,k/k-1}$$
$$- m_{k/k-1}\hat{z}_{k/k-1}^{T} \tag{23}$$

- Calculate the Kalman gain term and the smoothed state mean and covariance:

$$\begin{cases} K_k = P_{xy,k/k-1}S_{k/k-1}^{-1} \\ m_{k/k} = m_{k/k-1} + K_k(z_k - \hat{z}_{k/k-1}) \\ P_{k/k} = P_{k/k-1} - K_k P_{yy,k/k-1} K_k^{T} \end{cases} \tag{24}$$

4. PROPOSED ALGORITHM - (ANKF)

One of the KF problems occurs when the noise statistics Q and R are unknown, to solve this problem the adaptive Kalman filter is used. In this article we will use two algorithms which are presented in [19] while changing some steps according to nonlinear problem. The innovation-based adaptive estimation (IAE) approach and the adaptive fading Kalman filter (AFKF) approach for Linear Kalman filter are used in [19], where Figures 1 and 2, show those two algorithms. We changed the Block A by Block B and C which are the EKF algorithm for nonlinear problem.
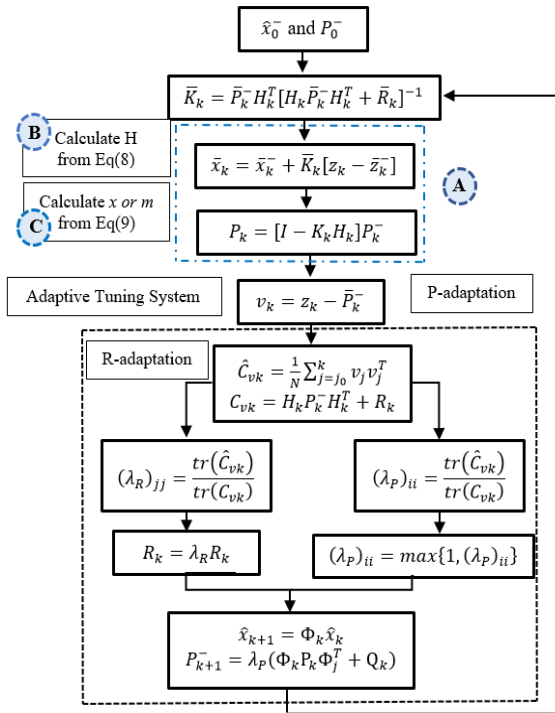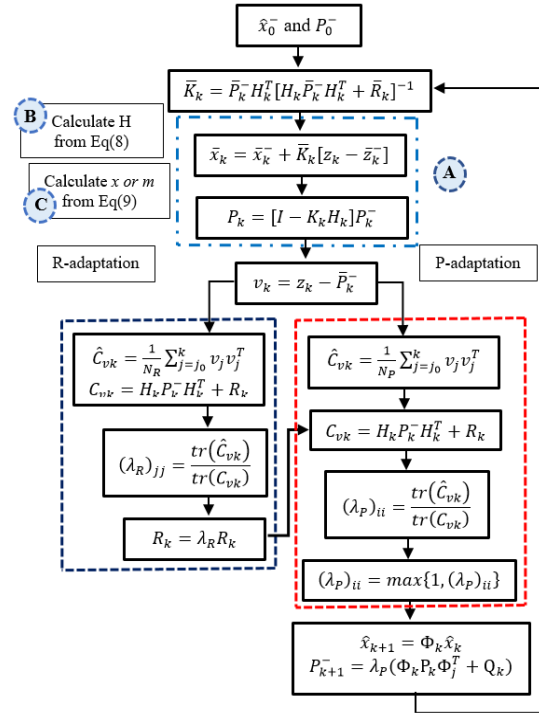

Figure 1. Flow chart of the proposed ANKF1 method   Figure 2. Flow chart of the proposeANKF2 method

Where:

a. $\lambda_P = diag[\lambda_1. \lambda_2 \dots . \lambda_m]$ is a factor to option the new $\bar{P}_k^-$

b. The algorithms of various adaptive fading are depending on λ_i values:

$$\begin{cases} \lambda_i \leq 1 \; steady \; state \; processing \\ \lambda_i > 1 \; unstable \; filtring \\ \lambda_i = 1 \; change \; to \; KF \end{cases}$$

c. $\bar{C}_{vk}$: is calculated for deviation due to the changes of covariance and measurement noise.

d. The optimum fading factors are: $\lambda_i = (\lambda_P)_{ii} = max\left\{1. \frac{tr(C_{vk})}{tr(C_{vk})}\right\}; i = 1.2 \dots . m$

The covariance matrices can be defined as:

Single factor: $\lambda_j = (\lambda_R)_{jj} = \frac{tr(\hat{C}_{vk})}{tr(C_{vk})}; j = 1.2 \dots . n$

Multiple factors: $\lambda_j = (\lambda_R)_{jj} = \frac{tr(\hat{C}_{vk})_{jj}}{tr(C_{vk})_{jj}}; j = 1.2 \dots . n$

The adaptation measurement is: $\bar{R}_k = \lambda_R R_k$

5.   SIMULATION RESULTS
The EKF, UKF and CKF were applied to estimate the position of a target following two scenarios:
- Scenario1: two sensors.
- Scenario2: three sensors.

The proposed method ANKF was applied for Scenario3 with two sensors. Table 1 shows the values of parameters for the three scenarios.

Table 1. Value of Simulations Parameters

Parameters	Value
σ_v^2	0.1
$\acute{\sigma}_v^2$ (uncertainly) for adaptive	0.01
σ_w	0.05
Target start state	[0 0 0 0]
Covariance of the state on the initial time	P_0= diag [0.1, 0.1,10,10]
T	0.01s
Monte Carlo runs number	100

5.1.   Scenario 1:
S1(position)= [1-2]; S2(position)= [1-2]. Figure 3 shows the trajectory and the estimated trajectories. Figure 4 shows a zooming to the Figure 3 because results are so close. Table 2. shows the comparison between methods depending on Root Mean Square (RMS) error.
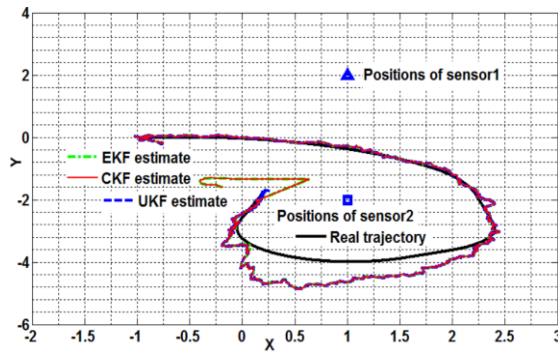

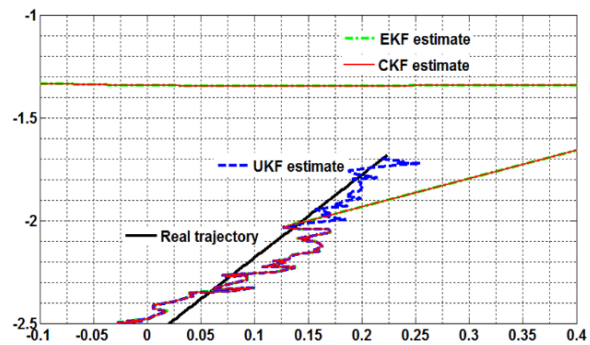Figure 3. The trajectory of scenario 1

Figure 4. Zooming at the trajectory

Table 2. Comparison between the Methods (Scenario1)

Method	RMS error
EKF	0.2547
UKF	0.2243
CKF	0.2579

5.2.   Scenario 2:
S1(position)= [1-2]; S2(position)= [1-2]; S3 (position)= [1-(2/tan(30)), 0] (we select the position of sensor3 to make equilateral triangle).

Figure 5 shows the real trajectory and the estimated trajectories. Figure 6 shows zooming at Figure 5 because the results are so close Table 3 shows the comparison between methods depending on RMS error.

Table 3. Comparison between the Methods (Scenario2):

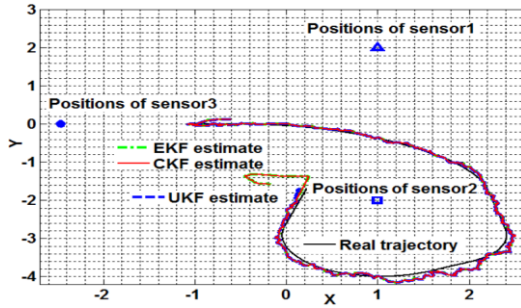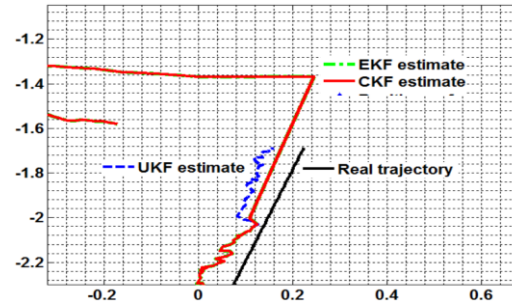| Method	RMS error
EKF	0.13748
UKF	0.06294
CKF	0.13768

Figure 5. The trajectory of scenario 2

Figure 6. Zooming at the trajectory

As expected, adding a third sensor decreased RMS for all algorithms and the UKF algorithm provides the best results.

5.3. Scenario 3:
In this scenario we used the adaptive Kalman filter with nonlinear measurement matrix from [4]:

$$h(x_k. k) = \begin{pmatrix} \theta_y \\ \psi_z \end{pmatrix} = \begin{bmatrix} tan^{-1}(y_k/x_k) \\ tan^{-1}(z_k/\sqrt{x_k{}^2 + y_k{}^2}) \end{bmatrix} \tag{25}$$

The two proposed adaptive Kalman filters algorithms are used, and compared with the most used algorithm EKF. Results are shown on Figures 7 and 8:
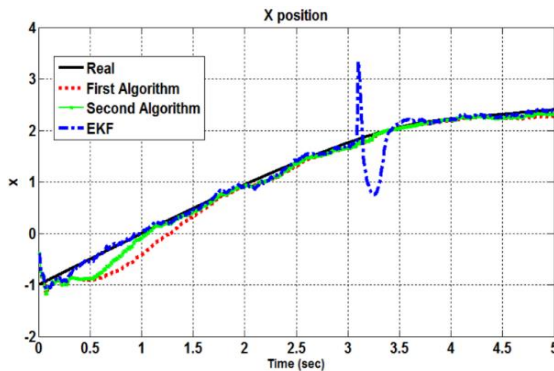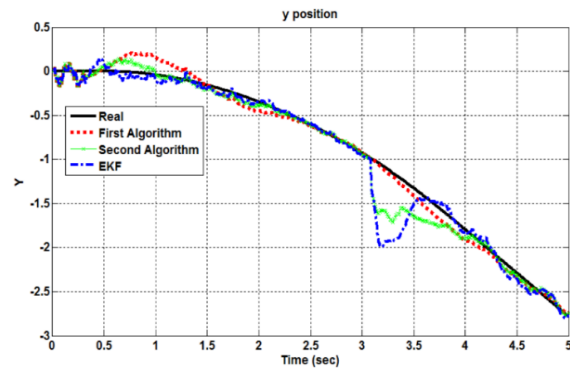

Figure 7. The trajectory of scenario 3

Figure 8. Zooming at the trajectory

We can see from Table 4 that the RMS error decreased by using adaptive Kalman filter with nonlinear measurement matrix comparing with Extended Kalman Filter (EKF). The ANKF2 algorithm provides the best result in estimation better than EKF and ANKF1 with ratio of about 50%.

Table 4. Comparison between the Methods (ANKF, EKF):

Method	RMS error
EKF	0.5652
ANKF1	0.5112
ANKF2	0.2730

6.   CONCLUSION
In this paper, we proposed nonlinear Kalman filter algorithms (EKF, UKF, and CKF) to improve and find the best estimate of the process state from noisy data, in bearings-only target state estimation tracking problem in three scenarios. In the first scenario we applied the past three algorithms with two sensors case, where the UKF gave the best RMS error by Monte Carlo 100 runs number. In the second

scenario we applied the algorithms and added a third sensor making equilateral triangle, the results showed that the RMS error with UKF is decreased with ratio about 50%. Surely, adding the third sensor in a good alignment will give better results but in some problems like mobile robot adding a third sensor is meaningless. This means the solution is software by developing algorithms.

We used adaptive Kalman filter which is based on (IAE) and (AFKF) to solve measurement variance uncertainty with two sensors in linear states, and changed the flow chart of the algorithm by applying an adaptive nonlinear Kalman filter (ANKF), the results of ANKF1 and ANKF2 were better than EKF in view of RMS error, and the ANKF2 was the best. The following future work is to estimate the angular and angular rate for highly maneuvering targets in pitch and yaw with the nonlinear ANKF algorithms.

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