Neural Extended Kalman Filter Based Angle-Only Target Tracking with Different Observer Maneuver Types

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Abstract - *The main issue in the angle only target tracking problem is to estimate the states of a target by using noise corrupted measurement of elevation and azimuth. The states consist of relative position and velocity between the target and the platform. In this study the tracking platform (observer) is a sea skimming anti-ship missile (SS-ASM) with an active radar seeker. Normally, an active radar seeker gives the information of relative range and closing velocity to the target together with line of sight (LOS) and LOS rate of elevation and azimuth. However, when a missile jammed, the missile cannot give the information of relative range between itself and the target yet can measure LOS angles and LOS rates. In the jammed environment, to estimate the range from the LOS and LOS rate measurements, the missile has to maneuver to ensure the observability for range estimation. Two different maneuver types are examined: classic sinusoidal motion and motion with Modified Proportional Navigation Guidance (MPNG). Since sea skimming anti-ship missiles keep constant altitude during the flight, which is almost below 10 or 5 meters, elevation channel is not included through the estimation and it is assumed that the missile moves only in horizontal plane. Two different approaches for range estimation are investigated and compared on simulated data: the standard Extended Kalman Filter (EKF) and the Neural Extended Kalman Filter (NEKF). The system model for estimation is formulated in terms of Modified Spherical Coordinate (MSC) for 2D horizontal missile-target geometry. Moreover, enhancement of the NEKF based estimation algorithm is introduced.*

Key Words: Target state estimation, Range estimation, Neural Extended Kalman Filter, Anti-Ship missiles, Modified Proportional Navigation Guidance, Modified Spherical Coordinate, Weaving maneuver.

1. INTRODUCTION

Relative range information between a missile and a target can be used in terminal phase of the flight in order to increase the guidance performance of the missile [1]. Active radar seeker can give the range information but when it encounters with a jammer then it cannot sense relative range anymore. However, seeker still measures the LOS angles and LOS rates. With the measured angles and angle rates, the range can be estimated if the missile maintains appropriate maneuvers to guarantee the observability.

The estimation of target position and velocity based on angle measurements is called angle-only target tracking, passive ranging or bearing-only-tracking. The problem of angle-only target tracking is well studied in literature. The fundamental of target tracking that is given in [2]. [3] covers most aspects of tracking and has one chapter which explains only target tracking problem. [4] shows and compares different types of tracking methods.

Since the angle-only target tracking problem has nonlinear nature, nonlinear filtering techniques are required for the tracking solution. Due to the fact that Cartesian coordinate are simple to implement, it is used extensively for target tracking with EKF. In Cartesian coordinate, system model is linear and measurement model is highly nonlinear. However, it is revealed that the filter with Cartesian coordinate shows unstable behaviour characteristics [5]. In [6], the system is formulated in MSC which is well suited for angle-only target tracking. This coordinate system decouples the observable and unobservable components of the state vector.

Observability is the other issue in target tracking problem. Observability requirements are investigated for only the constant velocity trajectory case in two [7] and three dimensions [8]. Detailed works on observability can be found also in [9], [10], [11], and [12]. Implementation of pseudo linear filter for bearing-only target motion analysis can be found in [13] with observability analysis. In MSC, if there is no observer maneuver (no acceleration), reciprocal of range becomes unobservable even if the target is stationary or moving with constant velocity. However, in [14] it is stated that as long as there is LOS rate in the system, the range can be estimated even there is no observer maneuver for stationary targets. Thus, for the stationary target cases, system equations given in [6] should be modified so that range could be estimated when the observer has no maneuver.

In this study, to obtain observability for the target tracking problem two different maneuver types are investigated. First one is the sinusoidal trajectory of the observer known as weaving maneuver. This maneuver is also used at terminal phase of the SS-ASM to escape target ships defence systems. Another maneuver is obtained by using modified proportional navigation guidance (MPNG) as guidance law at terminal phase of the observer. MPNG law is used for short-range air-to-air intercept scenarios for missiles which have IR seeker so far. Detailed studies can be found in [15], [16], and [17].

Even if the full observability is obtained through the target state estimation problem, true states cannot be estimated exactly with standard EKF and there will remain gaps between the true states and the estimated states. At this point, Neural Extended Kalman Filter (NEKF) can be used to fill these gaps. NEKF is introduced first in [18]. Main idea of the NEKF is to reduce effects of unmodeled dynamics, mismodeling, extreme nonlinearities and linearization in the standard EKF [19]. Obtained improvement by using NEKF instead of EKF in the system model provides more accurate state estimate. Weights in the NEKF are coupled with EKF states and the weights are trained by Kalman gains [20].

There are several areas of usage of NEKF. For instance, errors in sensor measurements may emerge from different sources such as noise and sensor limitations which may result in biases. In these cases calibration for the sensor model can be achieved by NEKF [21], [22]. Another area of usage is the tracking problems with interacting multiple models (IMM). The NEKF algorithm is used to improve motion model prediction during the target maneuver [23], [24], [25], [26], [27]. Moreover, NEKF is used for the missile intercept time calculation [28], [29].

Extended Kalman filter, neural extended Kalman filter and required maneuver types to obtain observability in target tracking problem with modified spherical coordinates are studied in this study. The necessary analyses are conducted and obtained results are presented.

2. COORDINATE SYSTEMS

2.1 Cartesian Coordinate System

A general choice of coordinate system in the angle-only target tracking problem is to use Cartesian coordinates illustrated in Fig-1. The x-axis points through the east, the y-axis points through the north.
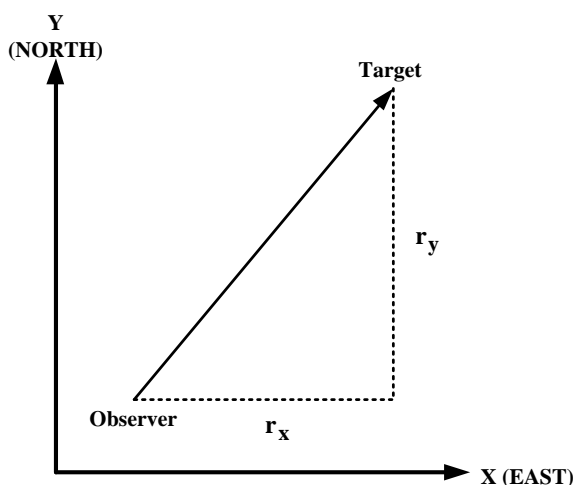

Fig- 1: 2D Cartesian Coordinate System

The state vector in Cartesian Coordinate System is denoted by x_{car} and is given by:

$$x_{car} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} x \\ y \\ \dot{x} \\ \dot{y} \end{bmatrix} \tag{1}$$

2.2 Modified Spherical Coordinate System

Another coordinate system alternative to the Cartesian coordinate is Modified Spherical Coordinate System. The state vector in MSC is:

$$y_{msc} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} \dfrac{1}{r} \\ \lambda \\ \dfrac{\dot{r}}{r} \\ \dot{\lambda} \end{bmatrix} \tag{2}$$

The first state is the reciprocal of range, the second state is bearing angle (λ), the third state is range rate divided by range and the fourth state is bearing rate $(\dot{\lambda})$.

In Fig-2, r denotes the range between target and observer. λ is the line of sight angle (LOS) and it is measured in Cartesian Coordinate System of which Y-axis is along the initial LOS to the target so that $\lambda(0) = 0$.

Cartesian Coordinate System based EKF reveals unstable behavior and biased estimates through the angle only target tracking problem [6]. Thus, MSC is used to deal with instability and biased estimation. One of the most important reasons to use MSC as coordinate system in the angle only
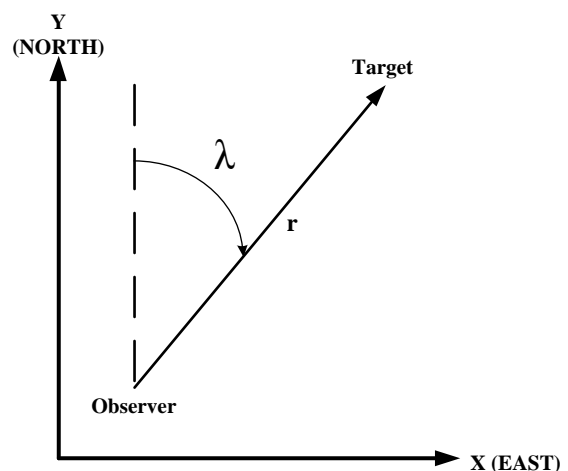

Fig- 2 2D Modified Spherical Coordinate System

target tracking is because MSC decouples observable and unobservable components of the state vector. Even if filter is not fully observable, estimation performance of observable states do not affected from the unobservable states.

2.3 State Equations in Coordinate Systems

The constant velocity discrete time state equations for system modelled in Cartesian Coordinate System is described as:

$$x_{k+1}^{car} = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & T & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} x_k^{car} + \begin{bmatrix} \frac{T^2}{2} & 0 \\ 0 & \frac{T^2}{2} \\ T & 0 \\ 0 & T \end{bmatrix} w_k \quad (3)$$

Bearing angle (LOS angle)and bearing rate are measurement of the system and they are written as:

$$z_k^{car} = \begin{bmatrix} \lambda \\ \dot{\lambda} \end{bmatrix} = \begin{bmatrix} \arctan\left(\dfrac{x}{y}\right) \\ \dfrac{\dot{x}y - x\dot{y}}{x^2 + y^2} \end{bmatrix} \quad (4)$$

In Cartesian Coordinate, the state equations are linear and time invariant. However, measurement equations are highly nonlinear. In MSC, the continuous state equation of motion can be written as [6]:

$$\begin{aligned} \dot{y}_1 &= -y_3 y_1 \\ \dot{y}_2 &= y_4 \\ \dot{y}_3 &= y_4{}^2 - y_3{}^2 + y_1 \left[a_x \sin(y_2) + a_y \cos(y_2) \right] \\ \dot{y}_4 &= -2y_4 y_3 + y_1 \left[a_x \cos(y_2) - a_y \sin(y_2) \right] \end{aligned} \quad (5)$$

where a_x and a_y are the Cartesian components of relative acceleration through the north and east directions. In (5), under the condition of neither target nor observer maneuvers, the last three states are decoupled from the first (inverse of relative range) state. Therefore, in the absence of acceleration all states except the first is theoretically observable using angle only information [32]. The measurement equation in MSC is:

$$z_k^{msc} = C \cdot \begin{bmatrix} \lambda \\ \dot{\lambda} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} \lambda \\ \dot{\lambda} \end{bmatrix} \quad (6)$$

3. OBSERVABILITY ISSUE

3.1 Observability Analysis

Without any maneuver of the observer (nonzero relative acceleration) y_1 is not observable in the filter whether the target is stationary or moving with constant velocity. However, it is stated that in [30] and [14] in the case of

nonzero LOS rate, relative range can be estimated for stationary target even if there is no observer maneuver. Thus, for stationary target estimation, proposed filter in [6] should be modified in such a way that system becomes observable for stationary target without any observer maneuver.

It is mentioned before that in order to obtain full observability, the observer needs to execute a maneuver. When both the observer velocity and target velocity are constant, the a_x and a_y terms are equal to zero, the y_1 term drops off the $\dot{y}_3$ and $\dot{y}_4$ functions. Therefore y_1 (the reciprocal of range) is not observable when neither the observer nor the target has any acceleration.

3.2 Observability with Sinusoidal Motion

To get observability through the target tracking estimation problem the observer needs to execute maneuver. First maneuver type analyzed in this study is sinusoidal motion. Sinusoidal motion can be obtained from open loop ± acceleration command series or from sinusoidal position command to the observer.
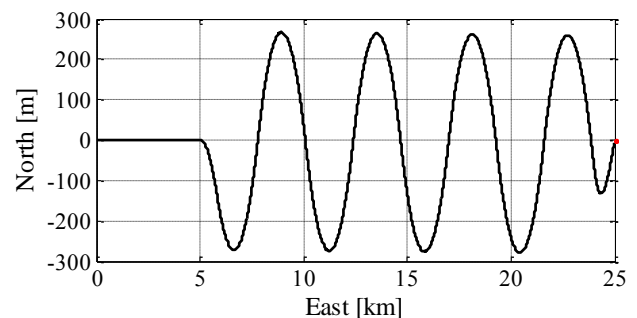

Fig- 3 Sinusoidal motion of the observer

3.3 Observability with Modified Proportional Navigation Guidance

Standard proportional navigation guidance law (PNG) does not provide observability for MSC based target state estimation. Another way to obtain observability for target tracking problem is to use modified proportional navigation (MPNG) as guidance law [15], [17], [33]. The missile acceleration command a_c perpendicular to the current LOS generated by MPNG can be expressed for 2D intercept scenarios

$$a_c = NV_c \dot{\lambda} + k\left(\lambda_{current} - \lambda_0\right) \quad (7)$$

where N is navigation constant, V_c is closing velocity (V_c can be replaced with negative of missile velocity since ship targets are quite slow compared the ASMs) and k is a positive constant and should be chosen with consideration of observer maneuver capability. λ_0 is the initial Los angle where maneuver starts and $\lambda_{current}$ is the current LOS angle

measured by the seeker. In the second term of (7), by subtracting λ_0 from current λ, oscillatory motion is obtained around the initial LOS vector.
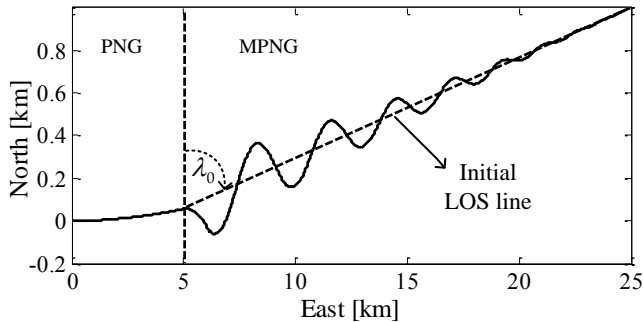

Fig- 4 Missile flight path with MPNG

In Fig-4, the observer is at $(0, 0)$ km and stationary target is at $(1, 25)$ km at the beginning of terminal flight. The observer is guided by PNG at first and then guided by MPNG from 5 km east to the end of flight. For large LOS angles, the second term of (7) dominates the acceleration command and provides oscillatory motion (helps to increase observability) and then through the end of the oscillatory motion second term of guidance law goes to zero. Thus, through the end of the flight MPNG becomes PNG and it is preserved target-hit efficiency.

4. EKF AND NEKF ALGORITHMS

4.1 EKF

If the dynamic target model, relative states of the system and the measurements are taken into account, total system model for angle-only target tracking can be written as:

$$\begin{aligned} \mathrm{x}_{k+1} &= f(\mathrm{x}_k, \mathrm{u}_k, \mathrm{w}_k) \\ \mathrm{y}_k &= c(\mathrm{x}_k, \mathrm{v}_k) \end{aligned} \tag{8}$$

where y is measurement vector, x is the state vector and u is the input vector. w and v represent the process and measurement noise respectively and they are assumed to be uncorrelated zero mean Gaussian noises with covariance matrices Qk and Rk respectively.

$$\begin{aligned} \mathrm{w}_k &\sim N\left(0, \mathrm{Q}_k\right) \\ \mathrm{v}_k &\sim N\left(0, \mathrm{R}_k\right) \end{aligned} \tag{9}$$

One cycle of EKF algorithm is given as:

$$\left.\begin{aligned} \hat{x}_{k|k-1} &= f(\hat{x}_k, \mathrm{u}_k, \mathrm{w}_k) \\ \hat{P}_{k|k-1} &= J_f \hat{P}_{k-1|k-1} J_f^T + Q_k \\ K &= \hat{P}_{k|k-1} J_c^T \left[J_c \hat{P}_{k|k-1} J_c^T + R \right]^{-1} \\ \hat{x}_{k|k} &= \hat{x}_{k|k-1} + K \left[y_k - c(\hat{x}_{k|k-1}) \right] \\ \hat{P}_{k|k} &= \hat{P}_{k|k-1} - K J_c \hat{P}_{k|k-1} \end{aligned}\right\} \tag{10}$$

where J_f and J_c are the Jacobeans of the functions f and c respectively.

4.2 NEKF

The NEKF is an estimation procedure that can be used in target tracking systems due to its adaptive nature [26]. When highly nonlinear systems are linearized and discretized or due to mismodeling of the system, the plant model may not be totally known [19]. When such conditions occur, estimation of the target states can become insufficient. The NEKF is used to compensate the unmodelled dynamics of the plant basically. As mentioned in [20], a neural network can be trained online with Kalman filter gains because the neural network weights are coupled to the standard EKF with the neural network terms.

The true system model is written as:

$$x_{k+1} = f\left(x_k, u_k\right) \tag{11}$$

and the estimator system model is:

$$\hat{x}_{k+1} = \hat{f}\left(\hat{x}_k, u_k\right) \tag{12}$$

The error between true and the estimated system $\varepsilon = f - \hat{f}$ can be estimated by artificial neural network (ANN). Multi-layer perceptron (MLP) structure is used as ANN model. MLP consists of three or more layers (an input and an output layer with one or more hidden layers). A MLP with a single hidden layer scheme is given in Fig-5.
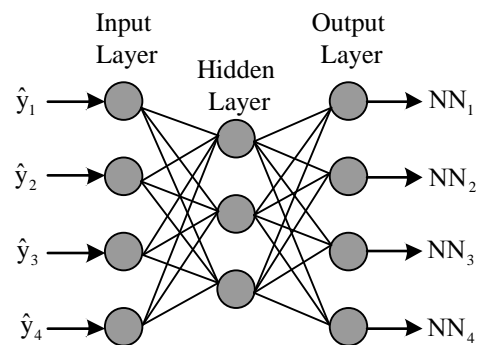

Fig- 5 ANN scheme for MLP

There are 4 neurons in the input and the output layer (one neuron for each state of the tracking filter). Also there are 3 neurons in the hidden layer. $\hat{y}_1, \hat{y}_2, \hat{y}_3$ and $\hat{y}_4$ are the estimated states of the tracking filter. After ANN modification, system becomes:

$$f = \hat{f} + NN \tag{13}$$

In the hidden layer of neural network, a large variety of functions can be used. The function usually used in NEKF is given in (14) and it can squeeze the large magnitude values

between -1 and +1. It is used as squashing function and shown in Fig-6.

$$g(y) = \frac{1 - e^{-y}}{1 + e^{-y}} \qquad (14)$$

Each output of the ANN can be written as:

$$NN_{k=1:4}(x, w, \beta) = \sum_{j=1}^{3} \beta_{jk} g\left(\sum_{i=1}^{4} w_{ij} x_i \right) \qquad (15)$$

where x_i's are the input signals to the neural network, in this case estimated states, the function 'g' is defined as activation function before, w and β are the input and the output weights of the neural network respectively. 'i' is the number of neurons in the input layer (4 for this case), 'j' is the number of neurons in the hidden layer (3 for this case), 'k' is the number of neurons in the output layer (4 for this case).

The NEKF is a combination of the EKF and neural network weights and so the NEKF state vector is:

$$\overline{x}_k = \begin{bmatrix} x_k & w_k & \beta_k \end{bmatrix}^T \qquad (16)$$

There are 4 states for the target tracking, 12 states for the input weights and 12 states for the output weights in the NEKF algorithm for this case and there are 28 states totally. After including ANN terms to the angle only target tracking system, NEKF becomes:

$$f(x_k, u_k) = \hat{f}(\hat{x}_k, u_k) + NN(\hat{x}_k, w_k, \beta_k) \qquad (17)$$

The associated Jacobian of the NEKF for the target tracking would be:

$$\overline{J}_f = \frac{\partial f(\overline{x}_k)}{\partial \overline{x}_k} = \begin{bmatrix} J_{11} & J_{12} \\ \scriptstyle 4x4 & \scriptstyle 4x24 \\ J_{21} & J_{22} \\ \scriptstyle 24x4 & \scriptstyle 24x24 \end{bmatrix}_{28x28} \qquad (18)$$

where

$$J_{11} = \left[\underbrace{\overline{A} + \frac{\partial NN(x_k, w_k, \beta_k)}{\partial x_k}}_{4x4} \right] \qquad (19)$$
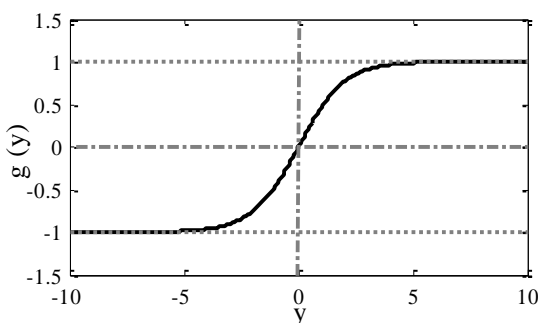

Fig- 6 Sigmoid squashing function

$$J_{12} = \begin{bmatrix} \underbrace{\frac{\partial NN(x_k, w_k, \beta_k)}{\partial w_k}}_{4x12} & \underbrace{\frac{\partial NN(x_k, w_k, \beta_k)}{\partial \beta_k}}_{4x12} \end{bmatrix} \qquad (20)$$

$$J_{21} = \begin{bmatrix} 0 \\ \scriptstyle 24x4 \end{bmatrix} \qquad (21)$$

$$J_{22} = \begin{bmatrix} I \\ \scriptstyle 24x24 \end{bmatrix} \qquad (22)$$

and $\overline{A}$ is the Jacobian of the continuous state equation of motion defined in (3). Finally, NEKF algorithm becomes:

$$\left. \begin{array}{c} \hat{\overline{x}}_{k|k-1} = \begin{bmatrix} f(\hat{x}_{k-1|k-1}) + NN(\hat{x}_{k-1|k-1}, \hat{w}_{k-1|k-1}, \hat{\beta}_{k-1|k-1}) \\ \hat{w}_{k-1|k-1} \\ \hat{\beta}_{k-1|k-1} \end{bmatrix} \\ \hat{P}_{k|k-1} = \overline{J}_f \hat{P}_{k-1|k-1} \overline{J}_f^T + Q_k \\ K = \hat{P}_{k|k-1} C^T \left[C \hat{P}_{k|k-1} C^T + R \right]^{-1} \\ \hat{\overline{x}}_{k|k} = \begin{bmatrix} \hat{x}_{k|k} \\ \hat{w}_{k|k} \\ \hat{\beta}_{k|k} \end{bmatrix} = \hat{\overline{x}}_{k|k-1} + K \left[y_k - C \hat{\overline{x}}_{k|k-1} \right] \\ \hat{P}_{k|k} = \hat{P}_{k|k-1} - K C \hat{P}_{k|k-1} \end{array} \right\} \quad (23)$$

and for MSC target tracking problem, due to dimensionality measurement matrix (LOS and LOS rate are the measurements) in the above equation becomes:

$$C = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \; 0_{2x24} \qquad (24)$$

4.2 Process Noise Q and Measurement Noise R

The uncertainty in the state estimation due to random target dynamics or mismodeling of the target dynamics is typically represented by the process noise covariance matrix Q [27]. T is the sampling interval and σ_q is the target maneuver standard deviation. The choice of σ_q can be considered as tuning process for simulation results. Q is formulated in the Cartesian coordinates but the tracking filter is completed in MSC. To express process noise in MSC, necessary transformation of Q from the Cartesian to MSC can be found in [28]. For the states $\begin{bmatrix} x & y & \dot{x} & \dot{y} \end{bmatrix}^T$ process noise covariance matrix becomes in the Cartesian coordinates:

$$Q = \begin{bmatrix} \dfrac{T^3}{3} & 0 & \dfrac{T^2}{2} & 0 \\ 0 & \dfrac{T^3}{3} & 0 & \dfrac{T^2}{2} \\ \dfrac{T^2}{2} & 0 & T & 0 \\ 0 & \dfrac{T^2}{2} & 0 & T \end{bmatrix} \sigma_q^2 \qquad (25)$$

The measurement noise in LOS and LOS rate is assumed to be independent. R is a diagonal matrix given below. σ_λ and $\sigma_{\dot\lambda}$ are the standard deviation of measurement noise.

$$R = diag\left(\sigma_\lambda^2 \quad \sigma_{\dot\lambda}^2 \right) \qquad (26)$$

5. ESTIMATION WITH EKF AND NEKF

Results of EKF and NEKF based angle-only target tracking simulation performed against constant velocity targets are given in this section. Before presenting the results, parameters should be set to initialize the filter. The first parameter is the initial range and taken as 24 km. Speed of the missile and the target is taken as 272 m/s and 30 m/s respectively. Standard deviation of the LOS angle measurement noise is 0.6 degree and 0.015 degree/s for the LOS rate measurement noise. Initial estimate of the range standard deviation is 2 km and standard deviation for the target speed is taken as 10 m/s. Sampling rate T is 0.01 s and σ_q is 0.01 m/s2. For the NEKF, initial values of the weights are taken as 0.0001 and standard deviations of the weights are $10^{-10} I$.

The flight paths of the missile-target and the corresponding interception geometry are demonstrated in Fig-7. In this scenario, at the beginning the missile is at (0, 0) and the target is at (25, 0) km. Also the missile has initial 4 degrees heading angle from the east. The target has constant 20 m/s velocity components through the east and the north. The missile is guided by proportional navigation guidance (PNG) until the relative range decreases up to 20 km. Then the missile starts sinusoidal motion by open-loop acceleration commands and estimation starts with sinusoidal motion and ends with it. When the estimated relative range is less than 2 km, sinusoidal motion of the missile stops and missile is guided by PNG again at last 2 km. In the evaluation, N=400 Monte Carlo simulations were performed with the same scenario but with different measurement noise characteristics. The performance is evaluated using the root mean square error for each time.

$$RMSE(t) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(x_i^{true} - \hat{x}_{t,i} \right)^2} \qquad (27)$$

In (27), $\hat{x}_{t,i}$ denotes the estimate at time t, for Monte Carlo simulation i. Simulation results are given in Fig-8 to 11.
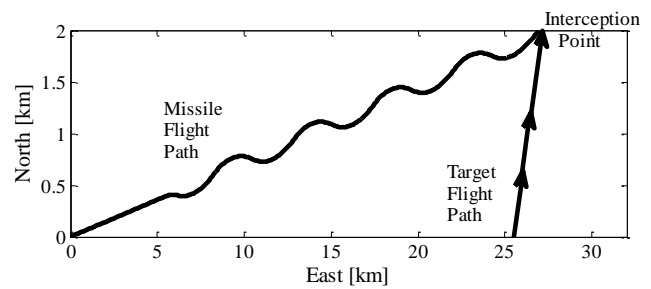

Fig- 7 Missile-target interception geometry

Both the EKF and the NEKF give same results between the 20th and the 70th seconds for all states of the estimation. After the 70th second, the NEKF gives better result than the EKF. This situation stems from the fact that the LOS angle starts to grow through the end of the flight and this growth results with the linearization error in the Jacobian matrices due to small angle assumption and the neural terms of the NEKF tries to decrease the error in linearization. Basically, the NEKF improves the LOS angle filtering performance and this enhancement also improves the estimation of the other states. On the other hand, without the observability of the target, the NEKF cannot train its weights and weights are coupled to the estimation states so that the NEKF will diverge faster than the EKF. When designing the neural network based Kalman filter, the observability issue should be considered carefully.
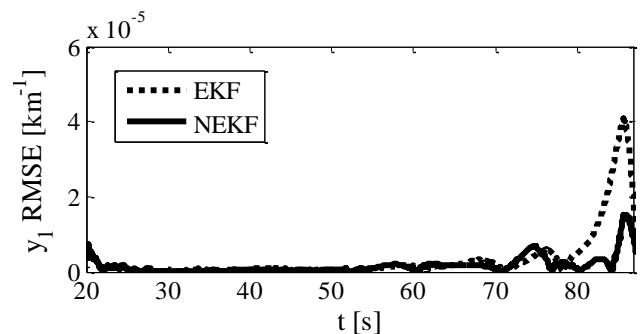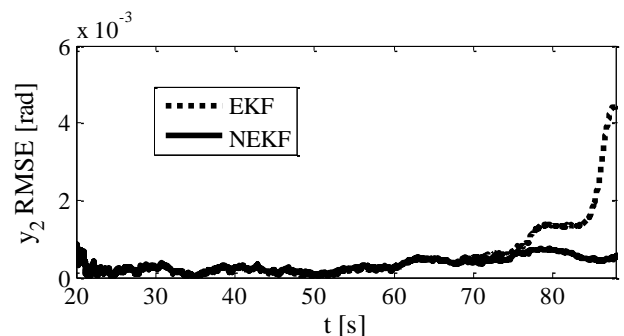

Fig- 8 RMSE in state y_1
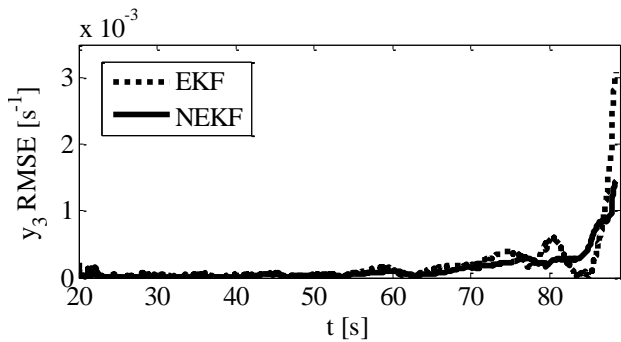

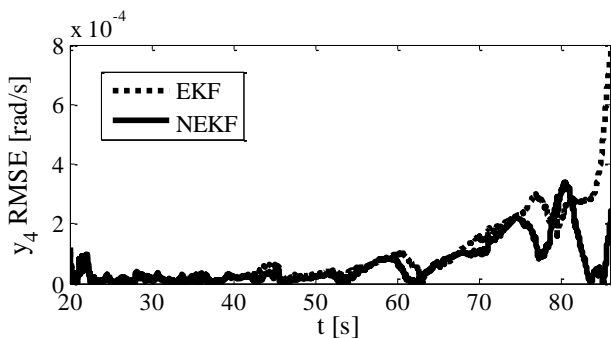**Fig- 9** RMSE in state y_2

Fig- 10 RMSE in state y_3

Fig- 11 RMSE in state y_4

6. ESTIMATION WITH DIFFERENT OBSERVER MANUVER TYPES

Previously the state estimation of a target with sinusoidal motion was implemented. Sinusoidal motion is sufficient for observability but through the end of the flight LOS angle starts to increase and this increase causes erroring the LOS angle filtering and affects the performance of range estimation. Instead of using standard EKF, NEKF structure is introduced to overcome this problem.

Another maneuver to get the observability for the range estimation is obtained by using modified proportional navigation as guidance law. MPNG is composed of two terms. The first term is the standard proportional navigation guidance and the second term includes LOS angle multiplied with a constant. This second term of the MPNG is the source of the oscillatory motion. With the oscillatory motion system becomes observable and through the end of the flight MPNG becomes standard PNG which guarantees the target hit.

There is not LOS angle increase for the maneuver obtained by MPNG. Instead of LOS angle increase, there is reduction in the amplitude of oscillation and this reduction causes LOS angle reduction too. As a result the system becomes unobservable for the estimation and estimation of the range starts to diverge. In this part the main issue is to analyze the maneuver types for the range estimation. That's why for both maneuvers with MPNG and sinusoidal motion, estimation is performed when the system is fully observable.
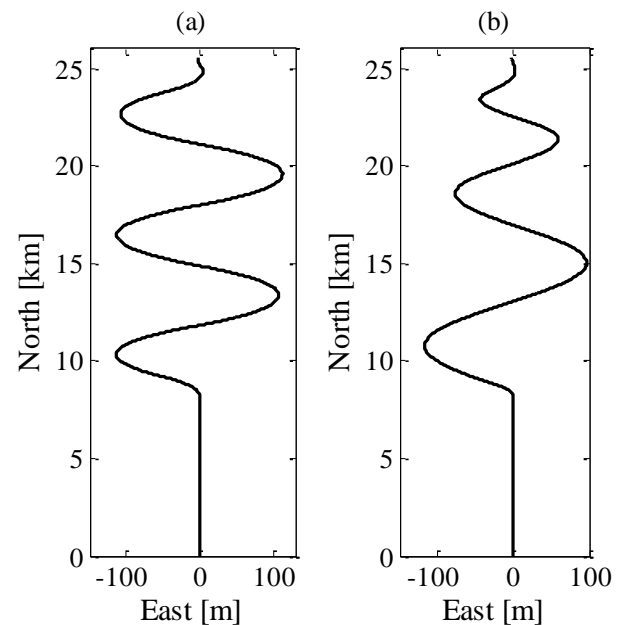

Fig- 12 Flight path of the missile for stationary target, (a) is for sinusoidal motion and (b) is for MPNG

To analyze the effect of maneuver type on estimation performance, two simulation scenarios are generated. In Fig-12, the missile flight paths are shown. In part (a), maneuver by sinusoidal motion and in part (b) maneuver by MPNG are demonstrated. All conditions for both of the scenarios are the same other than the maneuver types. Both of the scenario maneuvers are started at 5 km from the missile initial position and ends at 3 km before the stationary target. In this way the divergency due to observability loss for the maneuver obtained by MPNG is prevented.

Estimated states of NEKF based target tracking results are given in Fig-13 to16. These figures indicate estimation performance for both maneuver types are almost the same since the estimation is stopped before the system becomes unobservable for the MPNG-maneuver and linearization error becomes dominant for the sinusoidal motion.
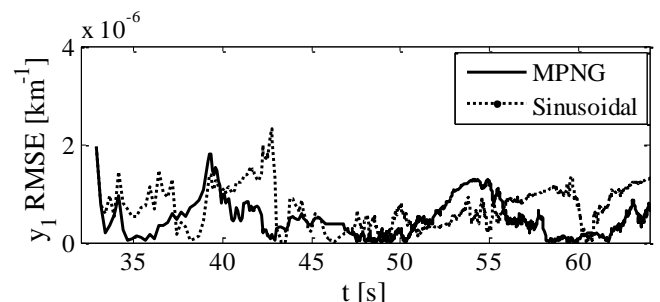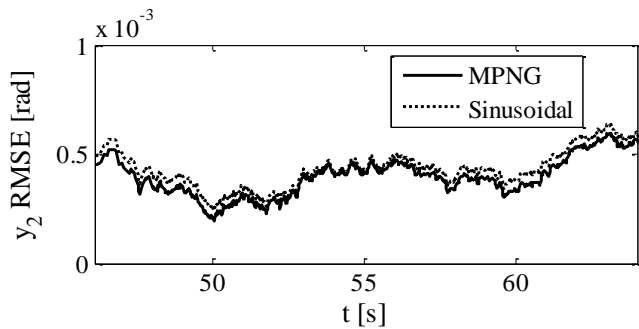

Fig- 13 RMSE in state y_1
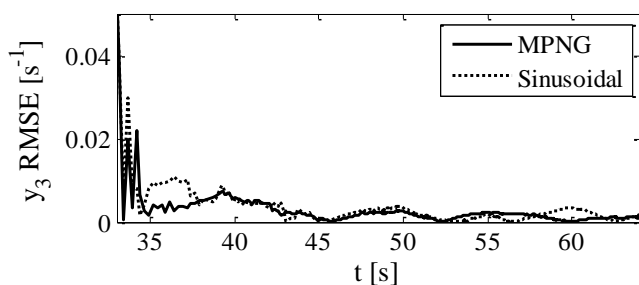
Fig- 14 RMSE in state y_2
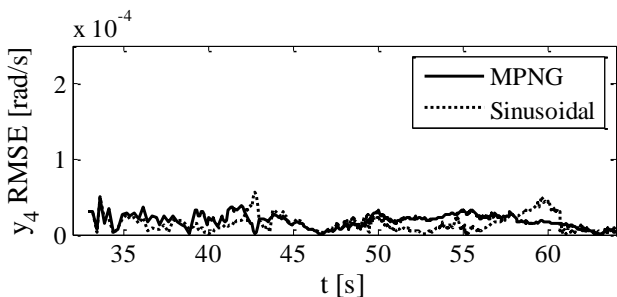

Fig- 15 RMSE in state y_3

Fig- 16 RMSE in state y_4

From this time forth, effects of maneuver types on target state estimation are analyzed with acceleration command history, side slip angle (beta), mach, angle of attack (alpha) and Euler angles.
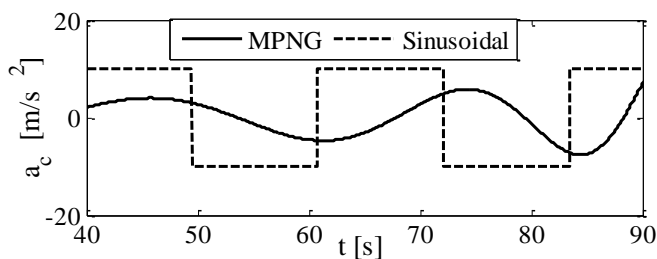

Fig- 17 Acceleration command history for different maneuver types

Fig-17 demonstrates the acceleration command history which shows less effort is needed for MPNG. Therefore, less force is applied to missile wings.

Flight paths for both maneuvers are given in Fig-12 before. Maneuver with MPNG has less amplitude than the sinusoidal motion at the east axis due to its oscillatory nature. Decrease in maneuver amplitude results with less side slip angle and the results for the side slip angles are given inFig-18. While side slip angle for MPNG varies between [-1.5 +1.5] degrees, it is [-3 +3] degrees for the sinusoidal motion. This causes less drag force for the missile in MPNG case.
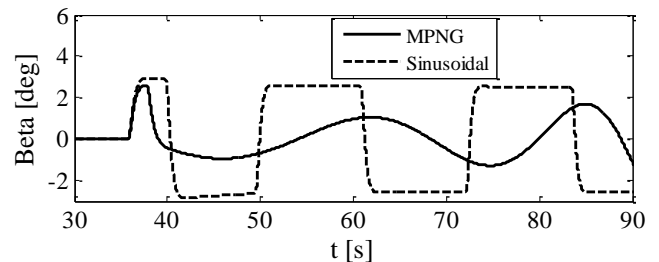

Fig- 18 Side slip angle for two maneuver types

Fig-19 shows the mach profile for both the MPNG and the sinusoidal motion. From the 30th second to 50th second missile tries to increase the velocity to the commanded mach of 0.8 and MPNG allows reaching to the commanded Mach number faster than the maneuver by sinusoidal motion. Moreover, the maneuver obtained by using MPNG results in less undesired descends in Mach number.
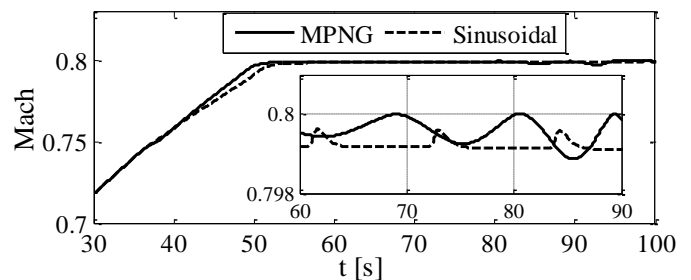

Fig- 19 Mach profile for two maneuver types
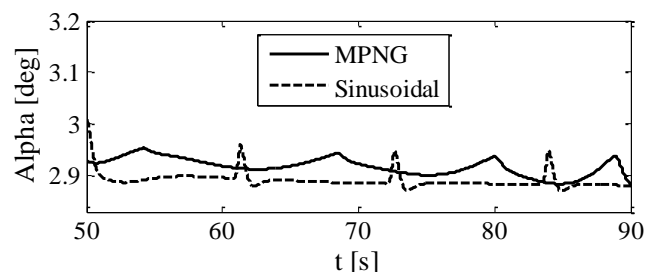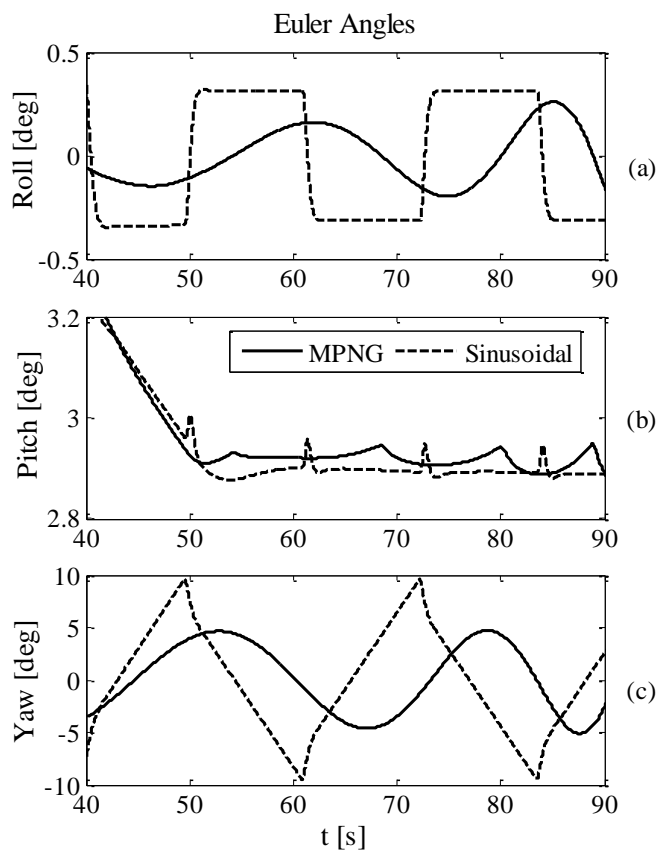

Fig- 20 Alpha for two maneuver types

Fig-20 shows the alpha profile for two types of maneuver. Since the analyzed missile is a sea skimming missile, motion

in elevation channel is not included to the estimation filters and so it is not expected to observe different alpha values for two types of maneuver. The alpha vs. time graph supports this argument because alpha profile is almost the same for two maneuver types.

Fig-21 demonstrates the Euler angles for both maneuvers generated by the MPNG and by the sinusoidal motion. While the missile maneuvers in yaw channel, due to the coupled dynamics of the missile, a small roll angle is induced in the system and it is bigger for the sinusoidal motion than the MPNG case. Moreover, in Fig-21 part (c), the maneuver obtained by the MPNG causes smaller yaw angle and less drag force.

Fig- 21 Euler angles for two maneuver types

7. CONCLUSION

Estimation of the relative range between a target and the missile is studied. The estimation is performed by using the measurements obtained from a RF seeker and missile acceleration information obtained from IMU. The tracking missile is assumed to be a sea skimming anti-ship missile.

The main problem for the angle-only target tracking is the observability. If the tracking filter is not observable then the filter starts to diverge. To ensure the observability through the estimation the missile has to maneuver. Two different maneuver types are studied; the sinusoidal motion and the oscillatory flight path generation for the missile by using the

modified proportional navigation guidance law. It is mentioned that the linearization error in covariance update of the filter becomes apparent through the end of the flight for the sinusoidal motion and it brings about observability problem for the oscillatory motion. In order to evaluate the both maneuver types equally, the estimation is stopped before linearization and the observability problems are emerged. After setting the same conditions for the analyzed maneuvers, the MPNG shows advantages over the sinusoidal motion. First, the sinusoidal motion is executed by open-loop acceleration commands but the oscillatory motion has closed-loop nature. This feature is quite important for the target hitting efficiency. Another advantage of the oscillatory motion includes the aerodynamic efficiency. While the amplitude of the maneuver decreasing, the missile is exposed to less beta angle which helps to reduce the aerodynamic drag force applied on the missile. Reduction in the aerodynamic drag force results with less fuel consumption which is more desired.

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