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THE PERFORMANCE ANALYSIS OF EXTENDED KALMAN FILTER ON RADAR TARGET TRACKING

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ABSTRACT

In this study, the tracking performance of radar target tracking process by using extended Kalman filter is analyzed. For this purpose, the obtained real radar datasets are used for extraction of the target motion model, observation model, processing noise and measurement noise equations based on experimental study respectively. Extended Kalman filter algorithm is applied to the equations and the results of target tracking are evaluated. The evaluation process is done for some processing and measurement noise level and successful results are obtained.

***Keywords: Radar**, Target tracking, Extended Kalman filter (EKF).*

1. INTRODUCTION

Radar target tracking have become more popular because of developments in computer systems. Target tracking is carried out by using one or more sensor in the same environment [1-5]. These sensors may be radar, sonar or infrared (IR) related to environment. In this paper, target tracking in the experimental environment by using one sensor is studied.

1.1. Radar and Radar's Basic Principles

The word radar is an abbreviation for "Radio Detection And Ranging". In general, radar systems use modulated waveforms and directive antennas to transmit electromagnetic energy into a specific volume in space to search for targets [1], [2], [3], [9]. Objects (targets) within a search volume will reflect portions of this energy (radar returns or echoes) back to the radar. These echoes are then processed by the radar receiver to extract target information such as range, velocity, angular position, and other target identifying characteristics [4].

Radar can be classified as ground based, airbone, spaceborne, or ship based radar systems. They can also be classified into numerous categories based on the specific radar characteristics, such as the frequency band, antenna type, and waveforms utilized. Another classification is concerned with the mission and/or the functionality of the radar. This includes: weather, acquisition and search, tracking, track-while-scan, fire control, early warning, over the horizon, terrain following, and terrain avoidance radars. Phased array radars utilize phased array antennas, and are often called multifunction (multimode) radars. A phased array is a composite antenna formed from two or more basic radiators. Array antennas synthesize narrow directive beams that may be steered mechanically or electronically. Electronic

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steering is achieved by controlling the phase of the electric current feeding the array elements, and thus the name phased arrays are adopted.

Radars are most often classified by the types of waveforms they use, or by their operating frequency. Considering the waveforms first, radars can be Continuous Wave (CW) or Pulsed Radars (PR). CW radars are those that continuously emit electromagnetic energy, and use separate transmit and receive antennas. Unmodulated CW radars can accurately measure target radial velocity (Doppler shift) and angular position. Target range information cannot be extracted without utilizing some form of modulation. The primary use of unmodulated CW radars is in target velocity search and track, and in missile guidance. Pulsed radars use a train of pulsed waveforms (mainly with modulation). In this category, radar systems can be classified on the basis of the Pulse Repetition Frequency (PRF), as low PRF, medium PRF, and high PRF radars. Low PRF radars are primarily used for ranging where target velocity (Doppler shift) is not of interest. High PRF radars are mainly used to measure target velocity. Continuous wave as well as pulsed radars can measure both target range and radial velocity by utilizing different modulation schemes.

1.2. Target Tracking and Target Tracking Techniques

Target tracking can be defined as accurately measuring the target dynamics like position, velocity, acceleration of ship, plane etc. by using sensors such as radar, sonar,… etc.

For state estimate in target tracking systems Kalman filter commonly is used because of Kalman filter evaluations only a former state estimation and new measuring values for new state estimation [3], [4]. According to used target moving models parameters, Kalman filter is separated in two classes. Those parameters may be linear or nonlinear. Those classes are named as standard Kalman filter, extended Kalman filter and adaptation Kalman filter.

First, correct target state model and measure model must be found for achievement correct target tracking [5]. After target with measures was setup correct target state estimates are become current.

2. THE KALMAN FILTER

The Kalman filter is linear estimator that minimizes the mean squared error as long as the target dynamics are modeled accurately [1], [4], [5], [6], [7], [8]. All other recursive filters, such as the $\alpha\beta\gamma$ and the Benedict-Bordner filters, are special cases of the general solution provided by Kalman filter for the mean squared estimation problem. Additionally, the Kalman filter has the following advantages:

1. The gain coefficients are computed dynamically. This means that the same filter can be used for a variety maneuvering target environments.
2. The Kalman filter gain computation adapts to varying detection histories, including missed detections.
3. The Kalman filter provides an accurate measure of the covariance matrix. This allows for better implementation of the gating and association processes.
4. The Kalman filter makes it possible to partially compensate for the effects of miss-correlation and miss-association.

3. THE EXTENDED KALMAN FILTER (EKF)

In view of the very limited feasibility of the implementation of the optimal filter, which consists of a functional recursion, suboptimal algorithms are of interest. The recursive calculation of the sufficient statistic consisting of the conditional mean and variance in the linear-Gaussian case is the simplest possible state estimation filter. As indicated earlier, in the case of a linear system with nonGuassian random variables the same simple recursion yields an approximate mean and variance.

A framework similar to the one from linear systems is desirable for a nonlinear system. Such an estimator, called the extended Kalman filter (EKF), can be obtained by a series expansion of the nonlinear dynamics and measurement equations.

If our system model and measurement model are nonlinear, we should use extended Kalman filter for correct state estimate [2], [3], [7]. There is main different between the extended Kalman filter and standard Kalman filter. This different is to be obtained from radar polar coordinate measurement of target dynamics are used directly in extended Kalman filter. Those polar coordinate measurements shouldn't be transformed to cartesian coordinate, but it isn't in standard Kalman filter. Nonlinear target dynamics on polar coordinate certainly should be transformed to cartesian coordinate for using standard Kalman filter.

Measurement error on the vertical moving to radial direct is the most important drawback of extended Kalman filter. This error origins from nonlinear effects (Those effects be can't ignored). Although target dynamics are commonly represented on cartesian coordinate, radar measurements are obtained on polar coordinate. Those radar measurements are expressed big nonlinear relation. For solving this problem:

1. After polar measurements are transformed to cartesian, standard Kalman filter is used or
2. Polar observations are used by extended Kalman filter.

Although both of methods give good results, great errors may appear by using first method [10].

When extended Kalman filter is used for state estimate, measurement vector contains radial distance, azimuth angle and Doppler velocity (radial velocity) on polar coordinates. State vector on the cartesian coordinates is given as below:

$$X(k)=\begin{bmatrix} x \\ \dot{x} \\ y \\ \dot{y} \end{bmatrix} \tag{1}$$

$$Z(k)=\begin{bmatrix} r \\ \theta \end{bmatrix} \tag{2}$$

system model and measurement model respectively:

$$X(k+1)=FX(k)+Gw(k) \tag{3}$$

$$Z(k)=HX(k)+v(k) \tag{4}$$

Nonlinear measurement relation for Z(k) Cartesian coordinates is written as below:

$$Z(k)=h(x(k))+v(k)= \begin{bmatrix} \sqrt{x(k)^2+y(k)^2} \\ tan^{-1}(y(k)/x(k)) \end{bmatrix} + \begin{bmatrix} v_r \\ v_\theta \end{bmatrix} \tag{5}$$

Measurement noises v_r ve v_θ, have zero mean white Gauss distribution. Those noises variance are σ_r^2 and σ_θ^2. In state of the there isn't correlation between the σ_r^2 and σ_θ^2, measurement noise covariance matrix is $R(k)=diag\{\sigma_r^2,\sigma_\theta^2\}$.

There isn't correlation between process noise and measuring noise. If all system matrixes and noise covariance Q(k) and R(k) are known to give optimum result in linear systems. If one of the system dynamic with measurement relation or both of them aren't linear, the relation is expansioned to tailor series. The second term and more high degrees terms of this Tailor series are dropped. Thus the Tailor series is made linear. This process is called extended Kalman filter together this process and Kalman filter process. This process is given as bellow. There, H_k is Jacobean matrix of h(.) measurement function at X(k/k-1) [2], [3], [7], [11].

$$h(x(k)) \approx h(X(k/k-1))+ H_k(X(k)-X(k/k-1)) \tag{6}$$

$$H_k=\frac{\partial h(x)}{\partial x}\bigg|_{x=X(k/k-1)}= \begin{bmatrix} x/r & y/r \\ -y/r^2 & x/r^2 \end{bmatrix}_{X(k/k-1)} \tag{7}$$

range estimate and derivative of range parameter are $\bar{r}_k$ and r' respectively.

$$\bar{r}_k=(x(k/k-1)^2+y(k/k-1)^2)^{\frac{1}{2}} \tag{8}$$

In this state, Filter relations are ordered again for extended Kalman filter,
State estimate:

$$X(k+1/k)=FX(k/k) \tag{9}$$

Calculate of innovation:

$$inn(k+1) = Z(k+1) - h[X(k/k-1)] \quad (10)$$

Covariance of state error:

$$P(k+1/k) = FP(k/k)F^T + GQG^T \quad (11)$$

Covariance of innovation:

$$S(k+1) = H_k P(k+1/k) H_k^T + R \quad (12)$$

Gain of the filter:

$$K(k+1) = P(k+1/k) H_k^T S(k+1)^{-1} \quad (13)$$

Estimate of covariance:

$$\begin{aligned} &P(k+1/k+1) = \\ &[I - K(k+1)H_k]P(k+1/k) \end{aligned} \quad (14)$$

Again state estimate:

$$\begin{aligned} &X(k+1/k+1) = \\ &X(k+1/k) + K(k+1)inn(k+1) \end{aligned} \quad (15)$$

4. FEATURES OF USED EXPERIMENT SET IN APPLICATION STUDY

The experiment application was carried out on Lab-Volt radar experiment set. This set has education purpose and multi functions. Pulsed radar transmitted was adjusted to 9.4 Ghz. This frequency is oscillator frequency of Radio Frequency (RF). A metal square plaque was used by being target. This metal square plaque has 20 cm x 20 cm dimensions.

This target was moved by variable velocity on target table and the used model of target move in the experiment application was obtained there.

5. THE REALIZED TARGET TRACKING APPLICATION BY USING EXTENDED KALMAN FILTER

As stated in Section 3, we use two important relations for solving of target tracking problem. Those relations are system model and measurement model respectively. If those relations contain nonlinear term, The Extended Kalman Filter (EKF) is commonly used for target tracking [3], [12].

Since relations and algorithm of the extended Kalman filter and main different among the extended Kalman filter with the standard Kalman filter were given in Section 3. In this section, only used target tracking equations and obtained graphics of result will be given for realized target tracking application by using extended Kalman filter.

In this realized application study, to have obtained models of target moving from experiment set were used. Technical features of this experiment set were given in section 4. The state matrix contains target position, target velocity and target acceleration knowledge. Therefore the state matrix has three dimensions. The acceleration moving model was selected for used target in this application.

The target moving model and used relations the extended Kalman filter were obtained by discrete Markov process [2], [3], [11], [12]. Future states in the discrete Markov process are determined by certain present states.

The sample time interval of the radar is $dt = t_k - t_{k-1}$ [11]. The used three degree state equation, target moving model, process noise, measurement noise and relations of the extended in this application study are given at bellow respectively:

According to this, system relations and measurement relations are given as bellow respectively:
State matrix:

$$X(k) = \begin{bmatrix} 10 \\ -6 \\ 2 \end{bmatrix} \quad (16)$$

Initial state estimate:

$$X_{hat}(k) = \begin{bmatrix} 11 \\ -6.51 \\ 2.5 \end{bmatrix} \quad (17)$$

Observation (measurement) matrix:

$$H = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \quad (18)$$

Initial state estimate error covariance matrix:

$$P = \begin{bmatrix} 0.5 & 0 & 0 \\ 0 & 20 & 0 \\ 0 & 0 & 25 \end{bmatrix} \quad (19)$$

State transition matrix:

$$F = \begin{bmatrix} 0 & 1 & 0 \\ -0.0011 & -0.0063 & -0.0096 \\ 0 & 0 & 0 \end{bmatrix} \quad (20)$$

After the experiment set which was given in Section 4 was taken reference for to obtain target moving model, model of the target moving dynamic, measurement vector, process noise, EKF relations and measurement noise were used at the automatic target tracking application by EKF on MATLAB. To have obtained results in this application study was showed in figure 1-6. Those results contain target position estimate error of the EKF, the real target position and estimated target position by the EKF, target velocity estimate error of the EKF, the real target velocity and estimated target velocity by the EKF, target acceleration knowledge estimate error of the EKF, the real target acceleration knowledge and estimated target acceleration knowledge by the EKF respectively.

6. CONCLUSIONS

Nowadays, The Kalman filter is commonly used in target tracking algorithm [13], [14], [15], [16]. Because the Kalman filter can certainly represent to target moving model and estimate last state. This estimate is realized under various measurement noises and process noises by the Kalman filter. The extended Kalman filter is a Kalman filter type. In this study, to be realized target tracking application of the extended Kalman filter by using Lab-Volt radar education set was presented.

The extended Kalman filter was proofed to be a good state estimator under various process noise and measurement noise by using to have been obtained target real moving model, measurement model, process noise model and measurement noise model. The extended Kalman filter estimate results were given in figure 1-6.

In real applications concern this study, Multi target tracking applications may examination by taking reference multi target moving models instead of a nonlinear target moving model.

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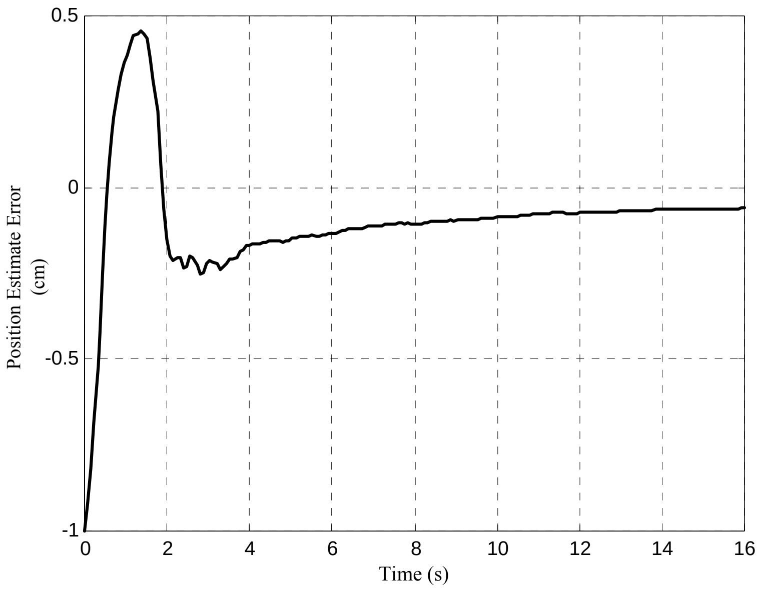

Fig. 1. Position estimate error of the EKF

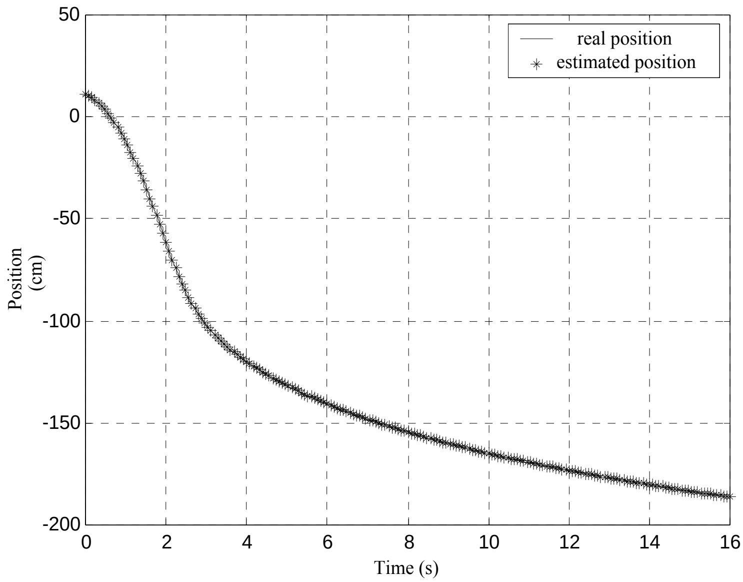

Fig. 2. The real target position and estimated target position by the EKF

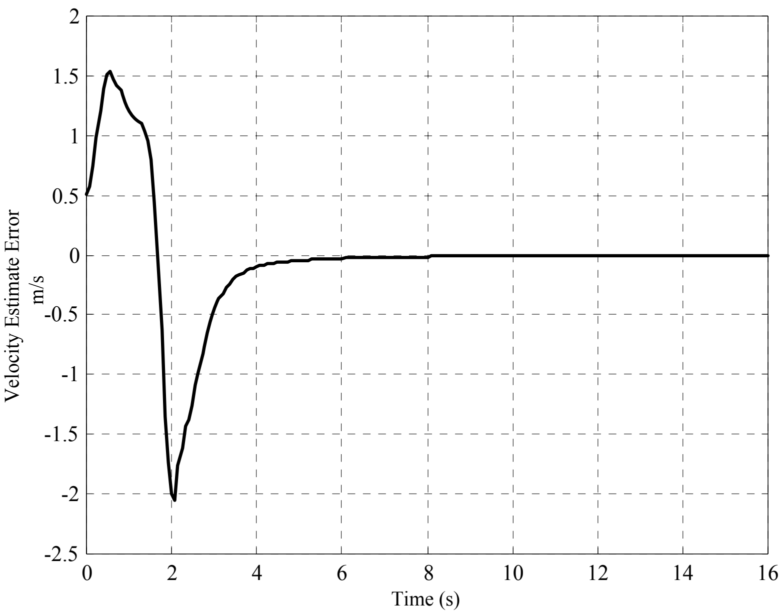

Fig. 3. Target velocity estimate error of the EKF

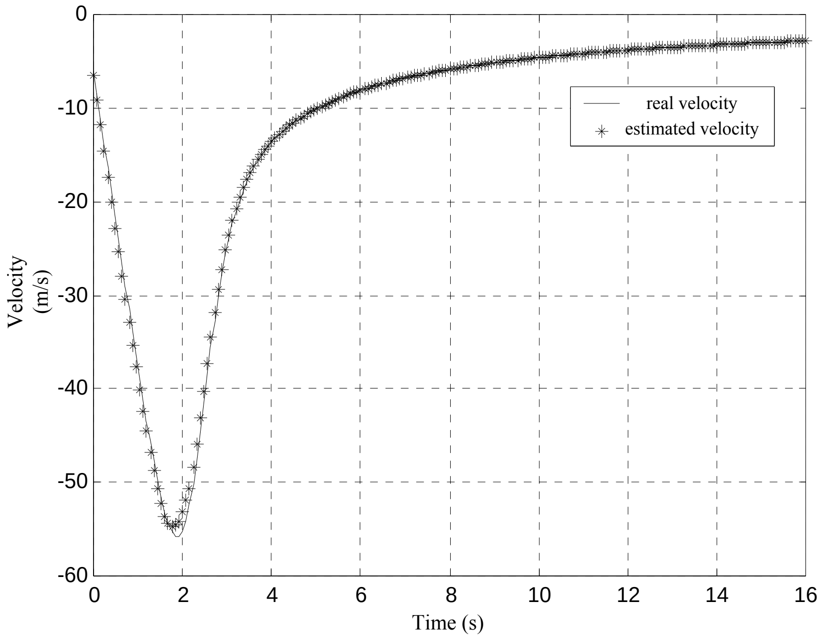

Fig. 4. The real target velocity and estimated target velocity by the EKF

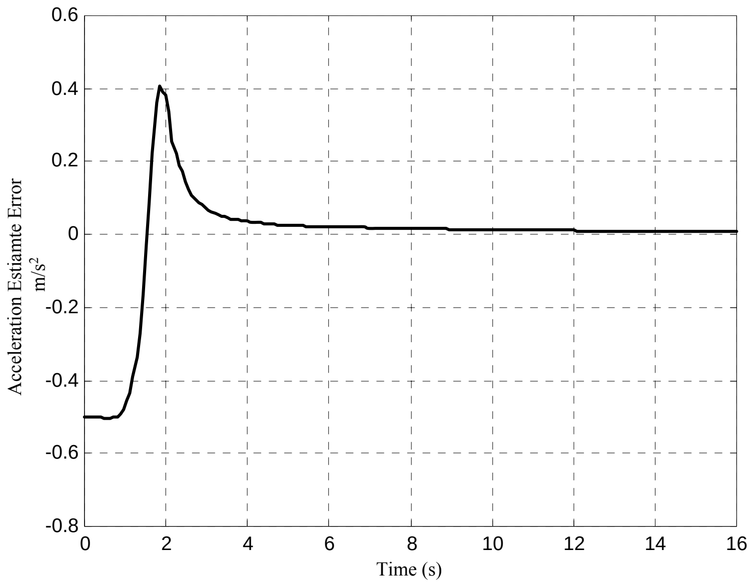

Fig. 5. Target acceleration knowledge estimate error of the EKF

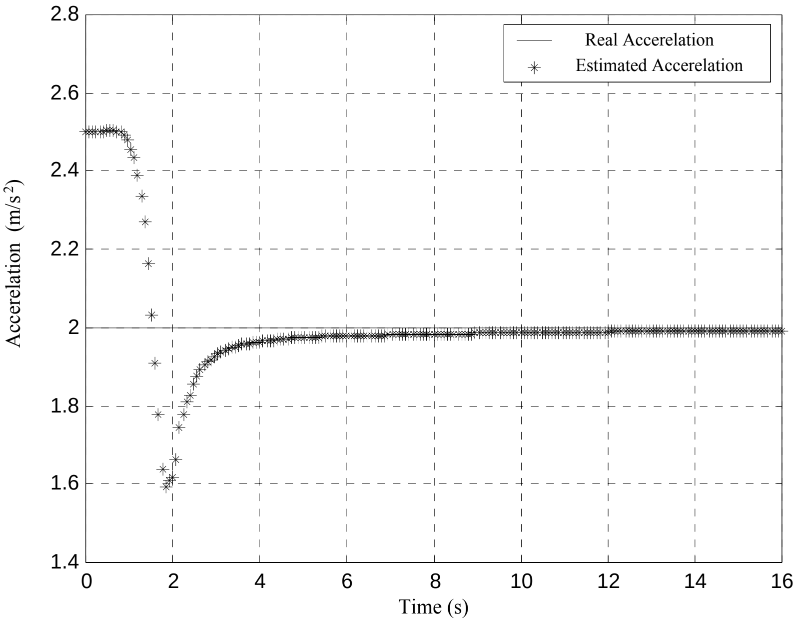

Fig. 6. The real target acceleration knowledge and estimated target acceleration knowledge by the EKF