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FAULT DETECTION AND ISOLATION IN TARGET TRACKING AND CONTROL SYSTEM USING FUZZY CONTROL

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ABSTRACT

One of the important applications of Kalman filter, using its radar systems to detect and estimate the positions of moving objects. For fixed targets, targeting a weapons based on how the projectile in the air. But it is necessary that in addition to moving targets Furthermore, the prophecies also be used. So for anti-aircraft cannon ballistics both the problem and obtain the predictive path review Are. Need to calculate predictive vector estimation of position, velocity and acceleration of the target. In this paper, fuzzy method to analyze factors that Due to an error in estimating the impact point, especially when the target is maneuvering targets are provided.

Keywords: estimating the position of a moving body, maneuvering mode, Kalman filter, fuzzy control.

1. INTRODUCTION

Kalman filter in early 1691 by Mr. Kalman and Basi was introduced. This filter is an optimal observer and quasi algorithm which is capable of intelligent system state variables Dynamic estimate [1]. Due to the nature of objects Described by the dynamic equations of motion today Radar systems widely from the filter to their position estimation is used. In this application if the filter Distance and speed of an object can only estimate (dual-mode) and, if In addition, they also estimate acceleration (three-state) called Is. Compared to some estimation methods in system Radar such as filtering α-β-γ (filter with constant coefficients) Kalman filter has the advantage that the filter depending on the amount of noise Measurement and maneuver the object is not fixed in any period of time to optimally calculate. So the accuracy of this filters moreand less error [3]. Problem tracking goals are In particular maneuver has not been studied in the state space and Different algorithms have been proposed to do this every No one in the face of maneuvers and maneuver of performance of radar targets Are different [4], [5]. Different algorithms for There simulated targets in polar coordinates and Cartesian, the Algorithms are faced with a constant speed without radar targets Maneuver and to implement the objectives of the exercise of estimating filters Relevant are different. If the simulation system.

Not correct track lost property [9]. Ways of There are various simulated exercises purposes, for example, Kalman filtering of various degrees and switch between them, Acceleration estimation during the exercise, in the form of a bunch of information and to Returning to the real-time algorithms and so on. In research acceleration as a random process with autocorrelation View is assumed, the model is able to track targets but its performance with that maneuver when aiming at a constant rate Moving is reduced [5]. Tracking problems often Kalman filters are used in polar coordinates or Cartesian Be. Target tracking algorithm in polar coordinates for Kalman filter using Cartesian coordinates are not easy, because The polar coordinates of non-linear model is a process model But the model output is linear. Since the radar And the target parameters (polar coordinates) estimate, polar model to model noise measurement The objective situation, are more suitable in Cartesian coordinates Although Due to the linearity of the Kalman filter process model simulation and The objective parameters used to estimate the size errors And the decision must be converted from Cartesian to polar coordinates Radar output will result in a non-linear model [7].

One of the other methods and simulation purposes maneuver through The conversion tracking maneuvering targets with standard Bayesian models And Fisher, in fact, this method is based on modeling target The phase space and Kalman filter implementation based augmented And modeling aimed at a location and speed at which the state vector Its acceleration is applied to the system as an unknown input Shall have been scheduled. This method results inWith other methods to lose, especially in the The method, of being biased towards zero tracking error and has no bias in tracking maneuvering targets does not slow down [11].

The main factors that caused the error in the Kalman filter Estimates include [2]:

a. Movable object maneuver to write equations filter the type of motion it is assumed body. But in practice, just as motion we assume no little with the difference that the order of the manor the object is the same.

b. Noise measurements: from radar failure, human error, or Shake radar device that is installed on it.

c. Sampling periods: the period of sampling less radar, the filter response speed of convergence of more and less error will be. in simulations carried out by changing parameters The process noise) caused by the moving body exercises (noise measurement And the sampling period of the radar, the estimation error filter The case is investigated. Finally, a phased approach for the best estimate we have presented a case study.

2. MODELS UNCERTAINTY

Two basic models for the simulation of uncertainty, Bayesian model And Fisher. These models are two known processes the state-space structures are white. In many Articles simulation models in state-space aims

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mentioned. Bayesian model is one of the most important and most common models by uncertainty. Bayesian model uncertainty Figure distributed random variables and stochastic processes Probabilistic clear or certain moments of the first and second Modeled. Assuming that the target in a two-dimensional coordinates in a moving screen and with respect to the three-dimensional Assuming the target in each dimension of the problem and is independent of the dimension the other, in the form of state-space model (1) and (2) to express the aim of the exercise is to be considered.

$$X(n+1) = F(n)X(n) + G(n)w(n) \quad (1)$$

$$Z(n) = H(n)X(n) + v(n) \quad (2)$$

X(n) state
Z(n) observation
V(n) white observation uncertainty
W(n) white system driving uncertainty
X(0) initial condition

$$E\{v(n_1)v(n_2)^T\} = \begin{cases} R(n_1) n_1 = n_2 \\ 0 \quad else \end{cases}$$
$$E\{w(n_1)w(n_2)^T\} = \begin{cases} Q(n_1) n_1 = n_2 \\ 0 \quad else \end{cases}$$
$$E\{x(0)x(0)^T\} = \varphi$$

In many applications, *w* can be quite uncertain Then the model will come in the form of Fisher's model, in some of the Fisher model as a Bayesian model when the limit states The Q (0) =I will be considered. It should be noted that the two models are very different conceptually they [7].

2.1 Bayesian filtering model

Bayesian model for the uncertainties of probabilistic models Something used and w (n), v (n), X (0) as Random variable with mean zero are white. Matrices G (n), F (n), H (n) in equation (1) as According to the observations turned out functions should be assumed until the z (1) ... z (n2), n2 vector X (n1) estimated that the formulas Kalman filter common form of equation (3) leads to:

$$\hat{X} = (N+1|N) = F(N)\hat{X}(N) + K(N+1)[z(N+1) - H(N+1)F(N)\hat{X}(N|N)]$$
$$K(N+1) = \sum(N+1|N)H^T(N+1)R^{-1}(N+1)$$

$$\sum(N+1|N+1) = \sum(N+1|N) - \sum(N+1|N)\,H^T(N+1)[R(N+1)H(N+1)\sum(N+1|N)H^T(N+1)]H(N+1)\sum(N+1)\sum(N+1|N) = F(N)\sum(N|N)F^T(N) + G(N)Q(N)G^T(N)$$

$\sum(N|N)$is the error variance and $\sum(N+1|N)$isError covariance matrix is a step forward.

2.2. Tracking algorithm

In many articles simulation methods aimed at Mentioned state space. The state space model.Figure1for the express purpose without maneuvering considered In which:

$$X = [x(n)v_x(n)\ \ y(n)v_y(n)\ \ z(n)z_z(n)]$$

White noise w, noise matrix G, transfer matrix Fvariance σ 2 system the target position. z and y and x, w The G and F matrices of discrete equations of state The intervals between the samples T (T: Continuous sampling time Is (and using Newton's laws of motion to They are as follows:

$$F = \begin{bmatrix} 1 & T & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & T & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & T \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$G = \begin{bmatrix} \frac{T^2}{2} & 0 & 0 \\ T & 0 & 0 \\ 0 & \frac{T^2}{2} & 0 \\ 0 & T & 0 \\ 0 & 0 & \frac{T^2}{2} \\ 0 & 0 & T \end{bmatrix}$$

Measurement noise radar that v (n),) the) 2R is considered as Gaussian and the error covariance matrix and the measurement matrix H is as follows.

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

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In this regard in models with maneuverability, acceleration in the form of an additional term in the equation (1) Will be applied in the form of equation (5) becomes:

$$X(n+1) = F(n)X(n) + B(n)u(n) + G(n)w(n)$$

$$B = \begin{bmatrix} \frac{T^2}{2} & 0 & 0 \\ T & 0 & 0 \\ 0 & \frac{T^2}{2} & 0 \\ 0 & T & 0 \\ 0 & 0 & \frac{T^2}{2} \\ 0 & 0 & T \end{bmatrix}$$

It is worth noting that although the target acceleration and acceleration u the purpose of this acceleration track is quite uncertain but limited.

3. SIMULATION RESULTS

To achieve the desired results Tuesday a software program respectively. The first program Kalman filter function, and the second movement Body, taking into account the effect of process noise and measurement noise, and the third program without measurement noise is simulated motion Them. Simulation time is 411 seconds. In Scenario the first target is moving with constant acceleration in a two-dimensional space the sudden acceleration is altered so that the direction it completely changes. In Figure-1 estimation result the position of a moving body in three dimensions provided by the Kalman filter is. Radar 1-second sampling time is considered.

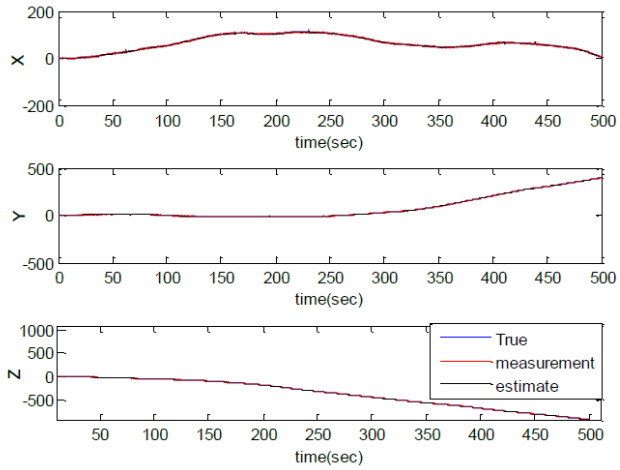

Figure-1. The position of a moving body in three-dimensional coordinates.

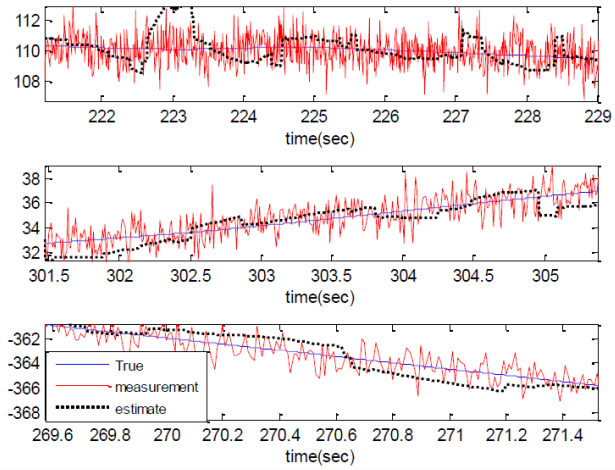

Figure-2. Moving object positions from up close.

Now to examine the effects of measurement noise in estimating Kalman filter described above. In this stage, strong noise The Kalman filter to react in the face of this noise studywe were created equal form be noisy in other words the size of 21 has set up the initial state effects (3) then the noise as much as 1We will look low noise (Figure-5). To investigate the effect of reducing At this stage only a sampling period of the sampling period Radar Changes.

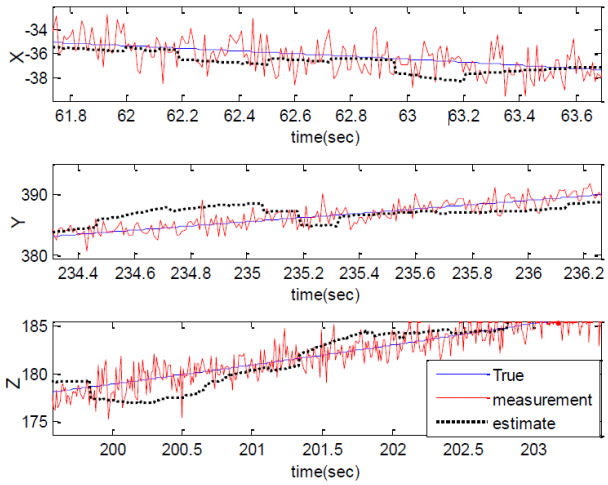

Figure-3. Strong noise effects in estimating the position of a moving object.

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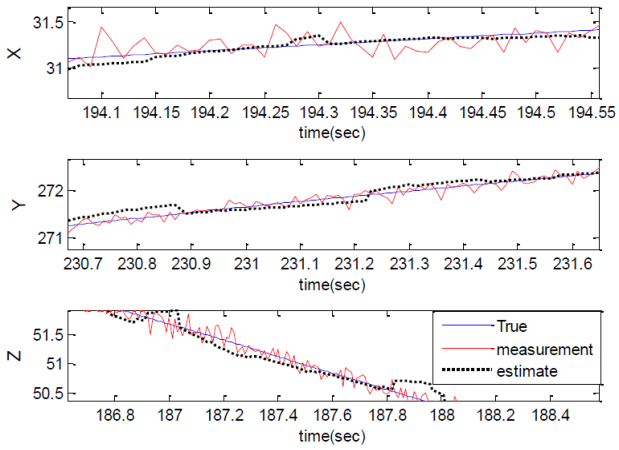

Figure-4. The effect of low noise in estimating the position of a moving body.

According to the Figures, (3) and (4) we find that the Kalman filter And by increasing its sensitivity to measurement noise Filter error increases sharply. In Figure-4 times the sampling period, consider we estimate that a 1 / very low noise then against 119 (resulted.

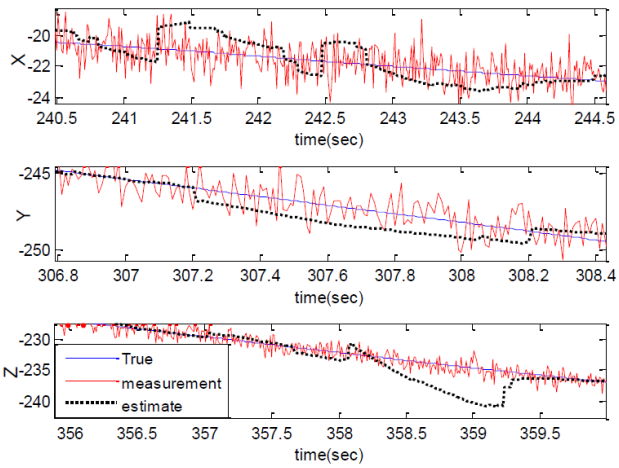

Figure-5. The effect of sampling period T=100.

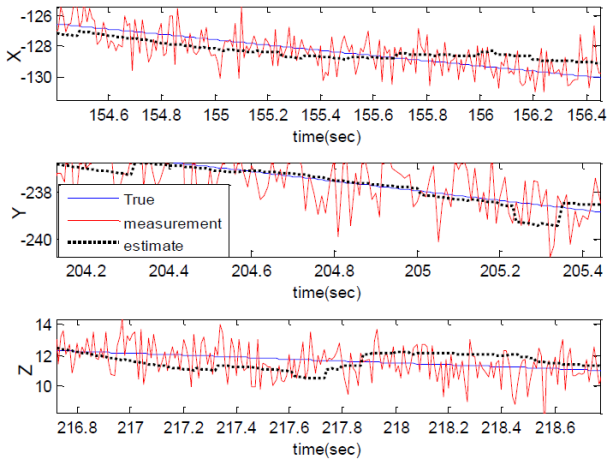

Figure-6. The effect of sampling period T=0.01.

We can see that better underestimated the effect of the sampling period the result has seen fewer errors. So we can conclude that reducing the sampling period, particularly radar once the object has a long leash is more important Position (T) PPT. They may be in time Body, great changes, but these changes are filtered Stay away. Using fuzzy logic capability of logical information And new are created, the Kalman filter due to the restriction Math can use them to perform usage tracking slow. Therefore, the use of fuzzy logic as a system that the ability to use human knowledge is absolutely necessary and reasonable it seems [11]. For this purpose, can be fuzzy logic to the effect of increasing the estimation error Kalman filter used. As the results of the sampling period and the effect of noise size Showed a reduction or increase of these factors in estimation error Kalman filters are very effective, especially when the object We are moving maneuver. Linguistic variables within A set of fuzzy rules include: Maneuver and (T) sampling period, Manuverment (moving body) these laws Tables (1) and (2) and) 3). V (n) measurement noise Come. The first rule means that: if the sampling period and measurement noise is low, whereas low maneuver motion The Kalman filter estimation error is very small. So this Fuzzy system has three inputs and one output.

Table-1. Fuzzy rules of maneuvering moving is small.

s.p / n.m	low	medium	high
low	very low	low	medium
medium	low	medium	medium
high	medium	medium	high
low maneuverability moving object			

Table-2. Fuzzy rules of maneuvering moving is medium.

s.p / n.m	low	medium	high
low	low	medium	medium
medium	medium	medium	high
high	medium	high	high
mediummaneuverability moving object			

Table-3. Fuzzy rules of maneuvering moving is high.

s.p / n.m	low	medium	high
low	medium	medium	high
medium	high	high	very high
high	high	very high	very high
high maneuverability moving object			

note: s.p is Sampling period and n.m is Noise measurements.

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In fuzzy systems, input and determine the Join them to each of the fuzzy sets through functions. Membership, which is in the form of function (9) and (10) and (11) it can be seen:

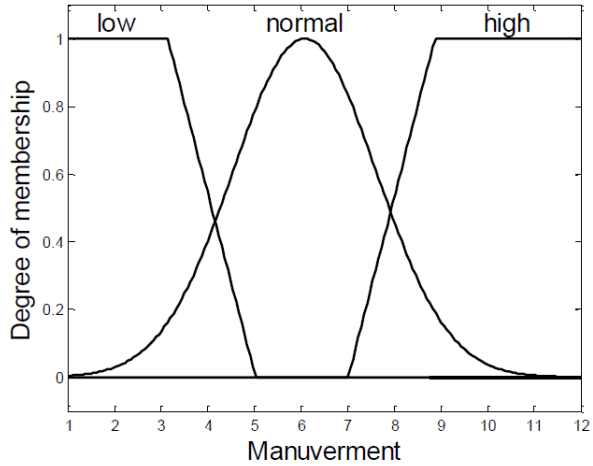

Figure-7. Input membership functions maneuver motion.

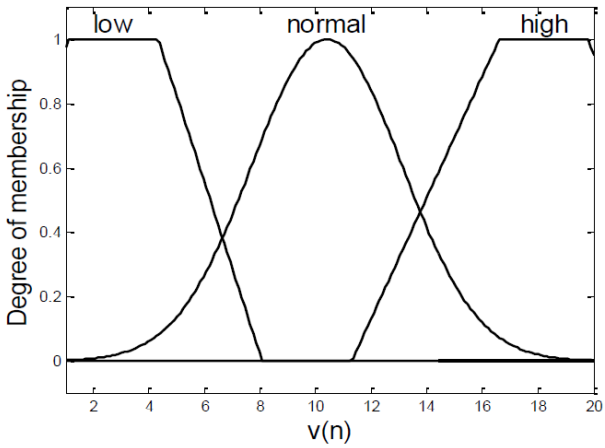

Figure-8. The membership functions for input measurement noise.

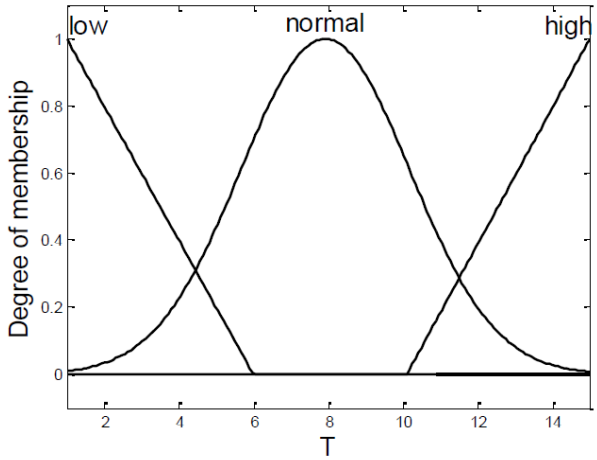

Figure-9. Membership functions input sampling period.

As a result of fuzzy rules between the input and output functions, the diagrams in Figures (12) and (13) and (14) is reached. The Benefits According to these figures, corrects functions easier Join inputs and outputs and, if necessary, amend the rules is fuzzy. See, they cushioned behavior shows.

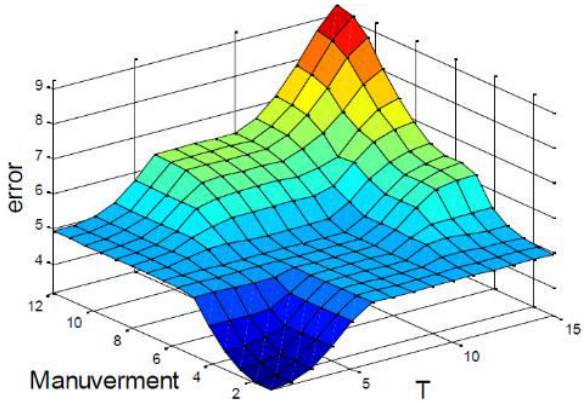

Figure-10. Three-dimensional level T and Manuvermentinputs.

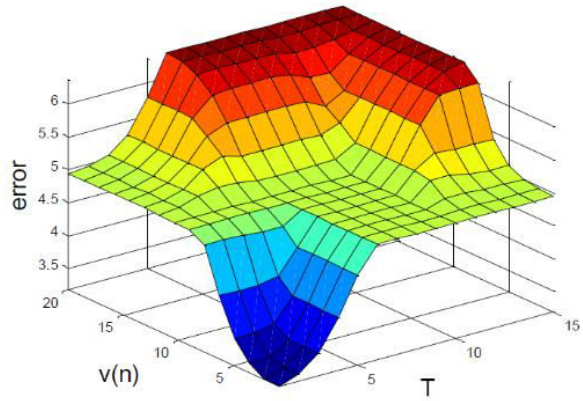

Figure-11. Three-dimensional level T and V(n)inputs.

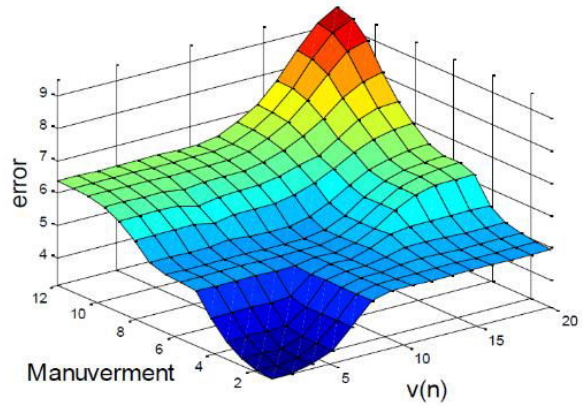

Figure-12. Three-dimensional level V(n) and Manuverment inputs

4. CONCLUSIONS

During convergence, data filter response Kalman was invalid and should not be used. Thereby reducing this time is very important. Proper selection period Sampling and increase the number of state variables measured By radar systems, play a crucial role in accelerating Convergence and error estimates are reduced. Kalman filter Sensitive to measurement noise caused by error Radar and size measuring equipment is there. Thereby reducing important role in reducing measurement noise variance filter error Will Kalman.

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