MANEUVERING TARGET TRACKING WITHCONSTANT ACCELERATION MOTION MODEL USING HYBRID MAMDANI FUZZY-KALMAN FILTER ALGORITHM

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ABSTRACT

In this paper the Kalman Filter and the Fuzzy Inference System hybrid algorithm has developed to get more accurate estimation result for maneuvering target tracking. Fuzzy Logic has used to adjust the process covariance error and measurement covariance error of the Kalman Filter process in the system model. The state space model used for estimation is a constant acceleration motion model, and the measurement model is a three-dimensional Cartesian coordinatmodel. The measurement result of the sensor containing noise estimated using the Kalman Filter (KF) algorithm. Then, the covariance error resulting from the KF process is used as input to the Fuzzy Inference System (FIS) for correction based on the mismatch between innovation vector and innovation covariance. The result of this correction used to obtain the optimal Kalman gain. The proposed system model leads to improved accuracy in the simulation case.

Keywords: target tracking, mamdani fuzzy inference system, kalman filter.

1. INTRODUCTION

Target tracking is essential in many practical sensor-based applications, such as in radar, sonar, and wireless sensor networks. Tracking a maneuvering target is challenging because the sensor measurement system must be inaccurate (the measurement contains noise), and the sensor does not know the situation of the target environment that affects the motion of the target, so the dynamic nature of the target cannot be adequately modeled.

Based on research [1], the estimation of the target state in which maneuvering using the Kalman filter with a constant velocity motion model produces a target trajectory that shifts from the true trajectory. It is known that the choice of the state space model is important.

Many algorithms about target tracking have been developed, which can be grouped into three types [2]. The first type is based on maneuver dynamics modeling, which is based on the concept of initial-motion uncertainty and uses stochastic process methods, such as the Singer model and the Jerk model [3]. The next type of maneuvering target tracking model is the optimal nonlinear filter, which is based on the initial measurement uncertainty. Several nonlinear filter algorithms have been offered to eliminate errors caused by nonlinearities in the process of tracking maneuvers, such as Extended Kalman Filters (EKF) [4], and Unscented Kalman Filters (UKF) [5, 6]. The third type of algorithm is a learning-based recursive filter and multi-model based methods, such as multilayer perceptron [7], Fuzzy-Neural Network [8], and Multilayer backpropagation [9].

There are times when several algorithms are combined to get more accurate results. In this paper, the Kalman Filter and the Fuzzy Inference System hybrid algorithm are developed to get more accurate estimation results. Fuzzy Inference System is used to adjust the process covariance error and measurement covariance error in the system model. The state space model to estimate the Kalman Filter is a constant acceleration motion model.

2. METHOD

The method in this research is to make a system model and its algorithm, then simulate the model that has been made. Target is simulated with a computer with predetermined target maneuver. Noise on the target measurement is given so that it can describe the real situation. The system model is built, as shown in Figure-1.

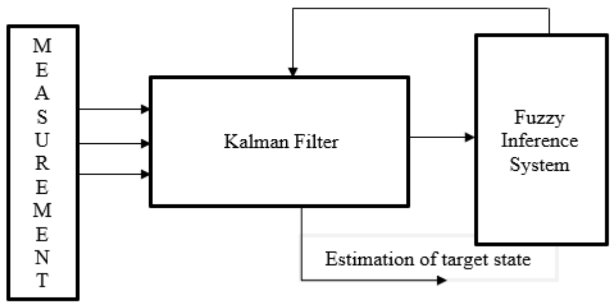

Figure-1. Estimator system model.

The measurement result of the sensor containing noise enters the Kalman Filter (KF) to estimation; the covariance error resulting from the KF estimation stage input into the Fuzzy Inference System (FIS) to adjust. In this research using Mamdani FIS method. Several studies using the Mamdani method can be seen in [10], [11], the results of the FIS adjustment are then feedback to KF. This covariance error value will be used to estimate the target state.

The first step is to build a target state space model used in the Kalman Filter algorithm. In this study, the motion of a target is modeled as follows:

$$x_{k+1} = F_k x_k + G_k w_k, \quad (1)$$

where F_k is the state transition matrix, and G_k is the noise excitation matrix.

w_k is zero mean, white Gaussian process with the assumption that the covariance Q_k is known. $[w_k \sim N(0, Q_k)]$

The measurement vector z_k from true state x_k is modeled by the equation,

$$z_k = H_k x_k + v_k, \tag{2}$$

where H_k is an observation model that maps true state space into an observation space.

v_k is zero mean, white Gaussian measurement with the assumption that the covariance R_k is known. $[v_k \sim N(0, R_k)]$

The state space model is a constant acceleration motion model. The state transition matrix F_k that describes the system dynamics in the constant acceleration model is given as follows:

$$\mathbf{F_k} = \begin{bmatrix} 1 & \Delta t & \Delta t^2/2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & \Delta t & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & \Delta t & \Delta t^2/2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & \Delta t & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & \Delta t & \Delta t^2/2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & \Delta t \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{3}$$

where Δt is the sampling interval, and the sampling time when measurement data is received is uniform.

The excitation matrix $\boldsymbol{G_k}$ is given by,

$$G_k = \begin{bmatrix} \Delta t^2/2 & 0 & 0 \\ \Delta t & 0 & 0 \\ 1 & 0 & 0 \\ 0 & \Delta t^2/2 & 0 \\ 0 & \Delta t & 0 \\ 0 & 1 & 0 \\ 0 & 0 & \Delta t^2/2 \\ 0 & 0 & \Delta t \\ 0 & 0 & 1 \end{bmatrix} \tag{4}$$

The process noise covariance matrix Q_k is given by,

$$Q_k = \begin{bmatrix} \sigma_x^2 & 0 & 0 \\ 0 & \sigma_y^2 & 0 \\ 0 & 0 & \sigma_z^2 \end{bmatrix} \tag{5}$$

Measurement matrix $\boldsymbol{H_k}$ is given by,

$$H_k = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}, \tag{6}$$

The measurement noise covariance matrix R_k, assuming that all measurement noise is uncorrelated, given by,

$$R_k = \begin{bmatrix} \sigma_{xm}^2 & 0 & 0 \\ 0 & \sigma_{ym}^2 & 0 \\ 0 & 0 & \sigma_{zm}^2 \end{bmatrix} \tag{7}$$

The state vector x_k represents position and velocity of the target in Cartesian coordinates *x, y,* and *z,* that is $x_k = [x\ \dot{x}\ \ddot{x}\ y\ \dot{y}\ddot{y}\ z\ \dot{z}\ \ddot{z}]^T$.

Using this state space model, then the target state estimate using the Kalman Filter. The equation of the Kalman Filter algorithm is given as follows:

- Predict

State predicted determine based on the following equation:

$$\hat{x}_{k|k-1} = F_k \hat{x}_{k-1|k-1} \tag{8}$$

Predicted estimate covariance:

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + G_k Q_k G_k^T \tag{9}$$

- Correct

Innovation: $e_k = z_k - H_k \hat{x}_{k|k-1}$ (10)

Innovation covariance: $S_k = H_k P_{k|k-1} H_k^T + R_k$ (11)

Optimal Kalman gain: $K_k = P_{k|k-1} H_k^T S_k^{-1}$ (12)

Updated state estimate:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k e_k \tag{13}$$

Updated estimate covariance:

$$P_{k|k} = (1 - K_k H_k) P_{k|k-1} \tag{14}$$

Initial condition: $\hat{x}_{0|0} = x_0 = H_k z_0,\ P_{0|0} = \varepsilon I$

In each stage of the target estimation process, the fuzzy inference system is used to adjust the values of R_k and Q_k. Fuzzy logic adjust the noise covariance process Q_k and the error covariance measurement R_k based on the equation,

$$Q_k = q_k Q_0 \tag{15}$$

$$R_k = r_k R_0 \tag{16}$$

where q_k and r_k are scaling factors, Q_0 and R_0 are the initial values of Q_k and R_k .

The scaling factors q_k and r_k are based on the correction innovation vector in equation (10) and the innovation covariance in equation (11) [10], [11]. The mismatch between innovation vectors and innovation covariance is defined as follows:

$$E_k = e_k e_k^T \tag{17}$$

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$$S_k = H_k P_{k|k-1} H_k^T + R_k \quad (18)$$

$$\alpha_k = \frac{1}{n}\sum_{i=1}^{n} \frac{E_{k(i,i)}}{S_{k(i,i)}} \quad (19)$$

where n is the dimension of the matrix and α_k is the average of the diagonal element.

Fuzzy Inference System is used to minimize the discrepancies given in equation (19).

General rules of adaptive Q_k dan R_k determined as follows,

1. If $\alpha_k = 1$ (this mean $\boldsymbol{E_k}$ and $\boldsymbol{S_k}$ is equal) then Q_k and R_k unchanged.
2. If $\alpha_k > 1$ (this mean $\boldsymbol{E_k}$ is greater than $\boldsymbol{S_k}$) then increase Q_k dan R_k.
3. If $\alpha_k < 1$ (this mean $\boldsymbol{E_k}$ is smallerthan $\boldsymbol{S_k}$) then decrease Q_k dan R_k.

3. RESULTS AND DISCUSSIONS

In conducting simulations to test the system model, the target is maneuvering. Targets are given an additional zero-mean Gaussian noise. Measurements were produced for 100 measurements, with an interval of each measurement is1second (Δt = 1 second). The following are the target motions to be estimated. The initial velocity and position of the target are as follows: [20.45 km -112.5 m/s 11.25 km -62.5 m/s 2 km 2.5 m/s]. In the beginning, the target moves at a constant velocity. At 48 seconds to 92 seconds, the target maneuvering with the acceleration of 12.5 m/s^2 in the y-axis direction. Then after 92 seconds, the target maneuvering with the acceleration of -5 m/s^2 in the x-axis direction and -5 m /s^2 in the y-axis direction. The true target trajectory and the measurement target trajectory (true target + noise) are shown in Figure-2.

To evaluate the performance of the system model will use the criteria of Root Mean Square Error (RMSE),

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(\boldsymbol{x}_k - \hat{\boldsymbol{x}}_k)^T(\boldsymbol{x}_k - \hat{\boldsymbol{x}}_k)} \quad (20)$$

x_k is the true target position dan $\hat{x}_k$ is the estimated target position.

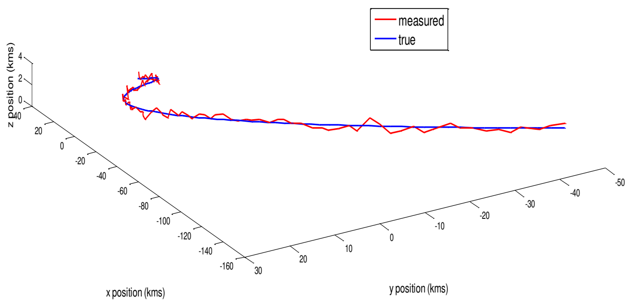

Figure-2. True target and measurement trajectory.

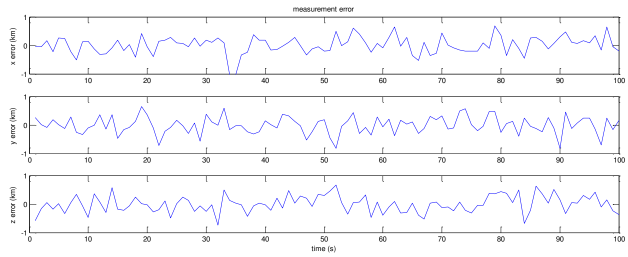

Figure-3. Graph of measurement error.

The graph of measurement error of the target is shown in Figure-3, with RMSE value is 0.08965.

The Kalman filter algorithm is used to estimate the target state.

The covariance matrix of the process Q_k is assumed to be small, and is determined as follows:

$$\boldsymbol{Q_k} = \begin{bmatrix} 0{,}005 & 0 & 0 \\ 0 & 0{,}005 & 0 \\ 0 & 0 & 0{,}005 \end{bmatrix} \quad (21)$$

The noise covariance matrix R_k following values are taken,

$$R_k = \begin{bmatrix} 3 & 0 & 0 \\ 0 & 3 & 0 \\ 0 & 0 & 3 \end{bmatrix} \quad (22)$$

Value of $\hat{x}_{0|0}$ dan $P_{0|0}$ determined as follows,

$$\hat{\boldsymbol{x}}_{0|0} = \boldsymbol{z}_0 \quad \text{dan} \quad P_{0|0} = 0.01 I_9 \quad (23)$$

Estimation results using the Kalman filter are shown in Figure-4.

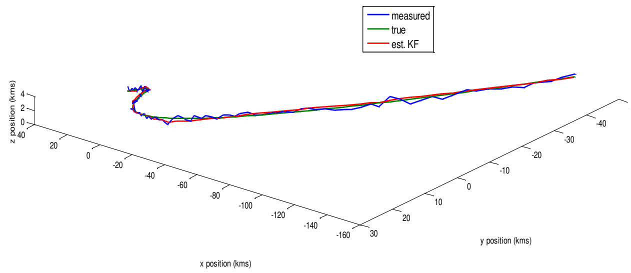

Figure-4. Estimation result using Kalman filter.

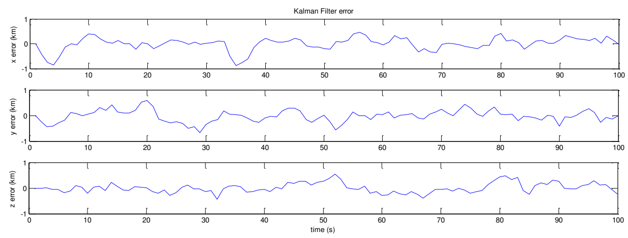

Figure-5. Graph of estimation error.

The graph of the estimation error of the Kalman Filter estimation is shown in Figure-5., with an RMSE

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value of 0.02677. Estimation results have increased accuracy by 70.22% with respect to measurement values.

Fuzzy inference system Mamdani method is used to improve the accuracy of estimation.

Fuzzy Inference System built a system with one input and two outputs. The fuzzy membership functions of input α_k consists of Near to Zero (NZ), Small (S), Medium (M), and Large (L). The fuzzy membership functions of input appear in Figure-6. The membership functions of outputs q_k and r_k consists of Near to Zero (NZ), Near to 1 (N1), Little Larger than 1 (LL1), and Large (L). Figure-7 is a membership function of q_k output and Figure-8 is a membership function for r_k output.

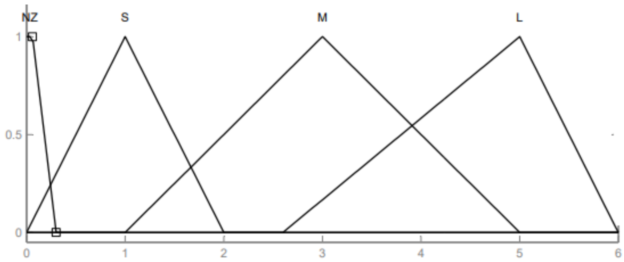

Figure-6. Graph of input membership functions.

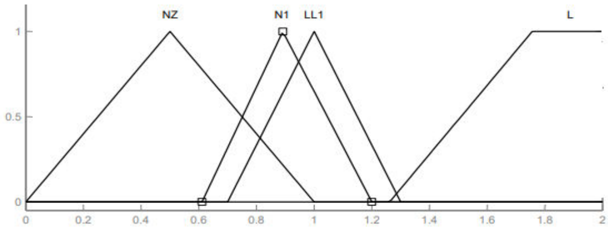

Figure-7. Graph of q output membership functions.

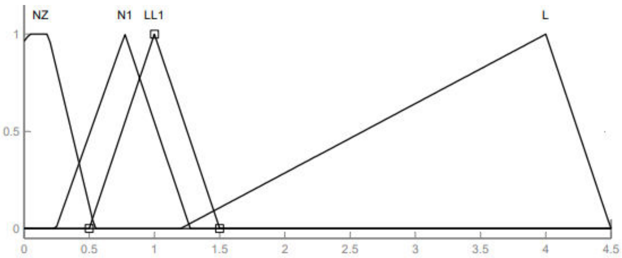

Figure-8. Graph of r output membership functions.

Fuzzy rules are follows:

1. If α is NZ then r is NZ and q is NZ.
2. If α is S then r is N1 and q is N1.
3. If α is M then r is LL1 and q is LL1.
4. If α is L then r is L and q is L.

Defuzzification uses the centroid method.

The estimation results using the Fuzzy-Kalman filter are shown in Figure-9.

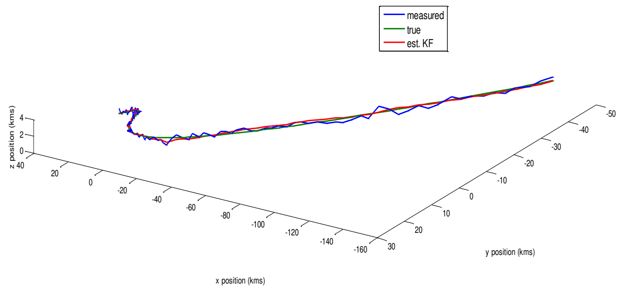

Figure-9. Estimation results using the Fuzzy-Kalman filter.

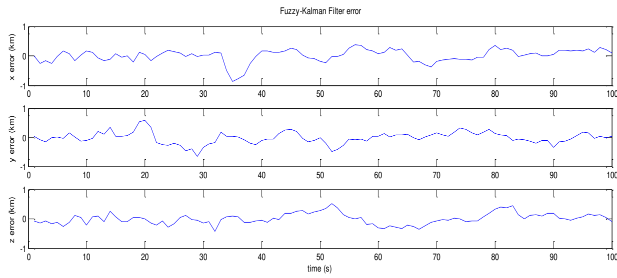

Figure-10. Graph of estimation error using Fuzzy-Kalman Filter.

The RMSE of the estimation result is 0.01737. The estimation result increases accuracy by 72.28% with respect to measurement or increases accuracy by 35.11% with respect to the Kalman Filter estimation.

The scaling factor graph of Q_k can be seen in Figure-11, and the scaling factor graph of R_k can be seen in Figure-12.

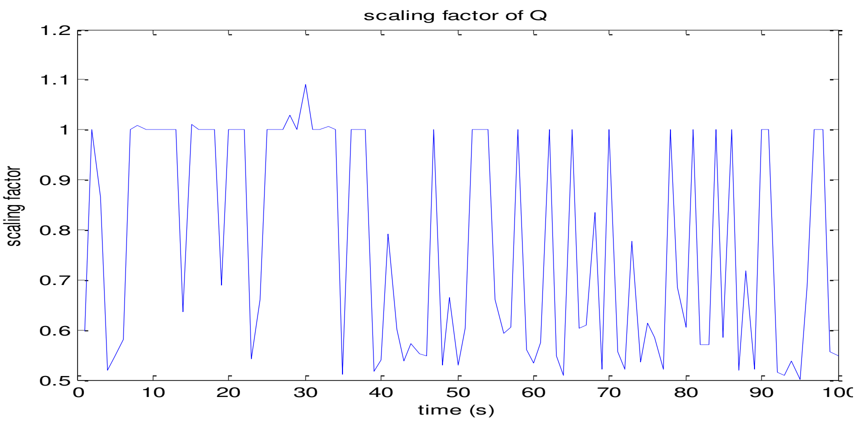

Figure-11. Graph of Q_k scaling factor.

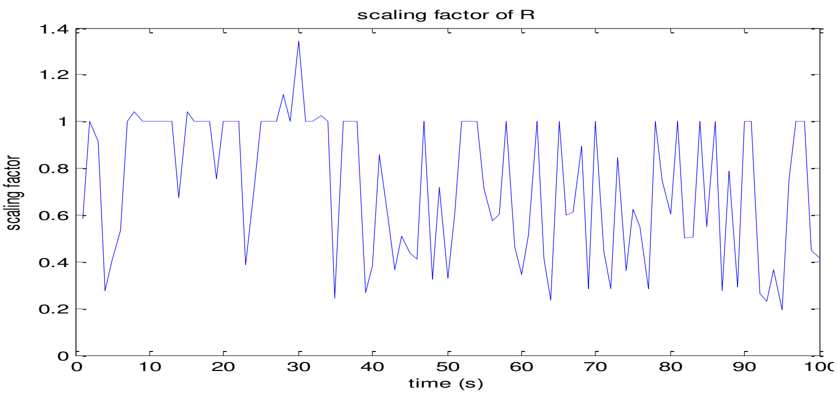

Figure-12. Graph of R_k scaling factor.

4. CONCLUSIONS

In this research, a system has been built to estimate the target state that maneuvering based on the Mamdani Fuzzy Inference System and Kalman Filter. Fuzzy Inference System is used to adjust the values of $\boldsymbol{Q_k}$ and $\boldsymbol{R_k}$ based on the mismatch between innovation vector and innovation covariance. The result of this correction used to obtain the optimal Kalman gain.

Result of the simulation case show that the estimation of the target state using the Kalman Filter produces an increase of accuracy by 40.09% with respect to measurement results, while the estimation result using the Mamdani Fuzzy Inference-Kalman Filter produces an increase in accuracy of 72.28% with respect to the measurement results. This means an increase in accuracy of 35.11% with respect to the estimation results using the Kalman Filter only.

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