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ESTIMATION OF UAV DYNAMICS WITH THE COMPARISON OF KALMAN FILTER AND ROBUST KALMAN FILTER

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Abstract:

In this paper generally focused on application of Robust Kalman Filter (RKF) algorithm to the estimation of high speed of an underwater autonomous vehicle (UAV) dynamics. In this normal operation conditions of UAV, conventional Kalman filter gives sufficiently good estimation results. Actually, Kalman filter gives inaccurate results and also diverges by time when the measurements are not reliable. Later it was appendix to Robust Kalman Filter algorithm with the filter gain correction for the malfunctions which are raised by the measurements of this filter. Finally, it was addition to Optimized Kalman Filter (OKF) with the improvement of Fuzzy logic controller and also it was linearized by improved less noise and also low time diverges with in the shot span of period. This method was implemented in MATLAB R2020a w.r.to. the results.

Keywords: *UAV, Optimized Kalman Filter, Fuzzy logic, Filter gain.*

1. INTRODUCTION:

The research on underwater systems has gained an interest during the last decades with applications taken place in various fields. The significant number of Underwater Autonomous Vehicles (UAVs) has been developed. UAVs require a precise navigation system for localization, positioning, guidance, path tracking and control during long period of duty cycle. In order to develop an accurate and robust navigation and control system for an UAV and it is to derive fault tolerant filtration algorithms for estimation of UAV dynamics. Kalman filter has been already implemented widely used as UAV motion dynamics parameters estimation technique and also different Kalman filter types have been developed. Using KF it is possible to estimate motion dynamics parameters of an UAV, which has a typical navigation sensor such asa compass, pressure depth sensor and also inertial navigation systems (INS).

In the normal operation conditions of UAV, conventional Kalman filter gives sufficiently good estimation results. KF gives inaccurate results and diverges by time and when the measurements are not reliable because of any kind of malfunction is found in estimation systems. KF can be adaptive [2] and insensitive to the priori measurements or system uncertainties by using various different techniques. Residual Based adaptive Estimation (RAE), Innovation Based Adaptive Estimation (IAE) and Multiple Model Based Adaptive Estimation (MMAE) are three basic approaches to the adaptive Kalman filtering [4].

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In IAE or RAE methods, adaption is applied directly to the covariance matrices of the measurement system. In the state estimation performance of the unscented Kalman filter (UKF) has been improved by proper tuning of both the unscented transform parameters and the process and measurement noise covariance matrices of the dynamic system model. If there is a malfunction in the measurement system, then Robust Kalman Filter (RKF) algorithm can be utilized and by the use of a measurement noise scale factor (MNSF) as multiplier on the measurement noise covariance matrix. In this article, Robust Kalman Filter algorithm with single measurement noise scale factor is introduced and also is applied for the motion dynamics parameters estimation process of an UAV.

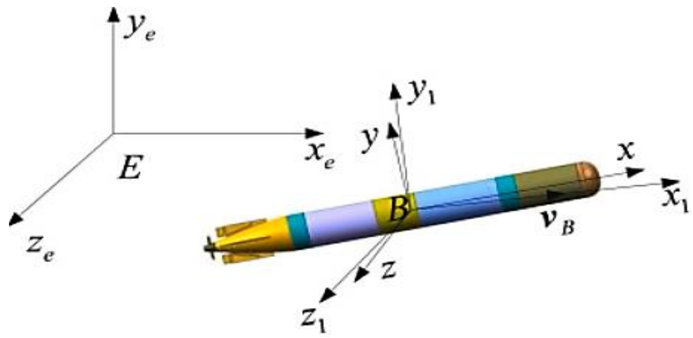


Fig.1. Underwater vehicle dynamics

2. UNDERWATER AUTONOMOUS VEHICLE MODEL DESCRIPTION:

UAV modelling is fairly complicated, and an exact analysis is only possible by including the surrounding fluid (sea water). While this can be done using partial differential equations along with ordinary differential equations. UAV move in 6 degrees of freedom (6DOF) since six independent coordinates are necessary to determine the position and orientation of a rigid body [6]. The first three coordinates and their time derivatives are of translational motion along x, y and z-axes while the last three coordinates (ϕ, θ, ψ) and time derivatives are used to describe orientation and rotational motion.

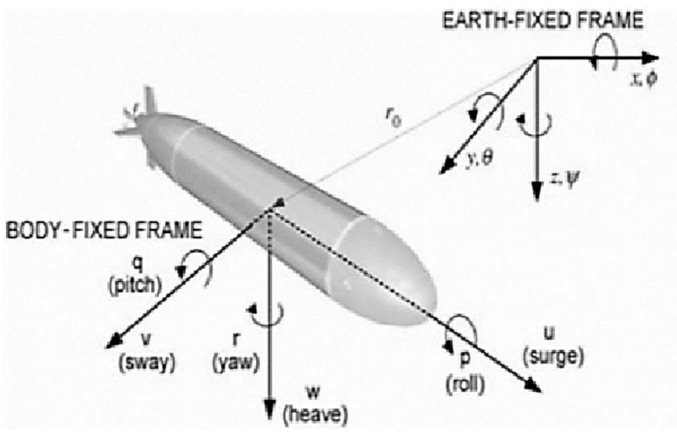


Fig. 2. UAV Dynamics along with angular and linear velocities

The model of REMUS torpedo is used instead of sample UAV in calculations [7]. 6 different motion variables help to determine position and orientation. The first three coordinates (x, y,z) are used to determine the position. The time derivatives of three coordinates (u,v,w) define transitions along x, y and z. Euler angles show the orientation. The time derivatives of Euler angles are (p,q,r) express the rotational motion.

3. SUBSYSTEM MODEL OF SAMPLE DIVING UAV:

Generally diving subsystem model includes heave velocity w, angular velocity q in pitch direction, pitch angle θ, depth z and bending of stern surface deflection δ_s. The diving subsystem neglects sway velocity v, roll rate of rotation r, heading angle Ψ, roration mode (p, φ) and initial horizontal movements of X and Y. Let us assumed a vehicle is to move with constant velocity u_0 with respect to water and pitch angle 0.

4. FINITE -DIFFERENCE FOR DIVING SUBSYSTEM:

Diving subsystem equations are given below:

The mathematical model of the diving subsystem can be written in the matrix form as,

$\dot{X}_D(t) = M^{-1}A_D X_D(t) + M^{-1}B_D\delta s_{(t)},$

Where,

$X_D(t) = [w(t); q(t); \theta\ (t); z(t)]$ is the state vector.

After finite difference we obtain the diving subsystem model in the following terms:

$X_D(k+1) = \hat{A}_D \ x\ X_D\ (k) + \hat{B}_D\ x\ U_D(k),$

Where,

$\hat{A}_D = 1 + \Delta t\ x\ M^{-1}\ x\ A_D;$

$\hat{B}_D = \Delta t\ x\ M^{-1}\ x\ B_D;$

$U_D(k)$ is the control input coming from deflection.

5. ESTIMATION OF UAV DYNAMICS FOR KALMAN FILTER:

Consider the following linear discrete dynamic system:

$X(k+1) = \phi(k+1, k)\ X(k) + B(k)u(k) + G(k + 1, k), W(k).$

$Z(k) = H(k)\ X(k) + v(k)$

Where X(k) is the m-dimensional state vector of the system at time t_k, $\phi(k+1,k)$ is the m x m transition matrix of the system, u(k) is the p x 1control vector, B(k) is the m x p control distribution matrix, W9k) is the r-dimensional random gaussian noise vector (system noise) with zero mean and known covariance structure. G(k+1,k) is the m x r transition matrix of the system noise, z(k) is the s-dimensional measurement vector at time t_k, v(k) is the s-dimensional measurement noise vector with zero mean and known covariance structure, H(k) is the S x m dimensional measurement matrix of the system. There is no correlation between the system noise W(k) and the measurement noise v(k).

$\hat{X}\ (k/k) = \hat{X}\ (k/k-1) + K(k) \left[z(k - H(k)\hat{X}(k/k-1)\right]$

Where

$\hat{X}\ (k/k-1) = \varphi\ (k, k-1)\ \hat{X}(k-1/k-1) + B(k-1)u(k-1)$

Is the extrapolation value, K(k) is the gain matrix of the optimum linear Kalman filter:

$K(k) = P(k/k\text{-}1)\, H^T (k) x\, [\, H(k)\, P(k/k\text{-}1)\, H^T (k) + R(k)]^{-1}$

R(k) = covariance matrix of measurement noise.

The covariance matrix of the filtering error is

$P(k/k) = [\, I - K(k)H(k)\,]\, P(k/k\text{-}1),$

Where I= Identity matrix

6. ROBUST KALMAN FILTER ALGORITHM WITH KALMAN FILTER GAIN CORRECTION:

Generally, Kalman filter is directly sensitive to any measurement noise like abnormal measurements, instantaneous shifts in measurement channel and decrease in device accuracy, background noise etc. When the mathematical model used in filter to measure the noise the changes in decrease the accuracy of estimation significantly. In this case, Robust Kalman filter can be used to prevent noise from malfunction measurement channel.

$tr\{\Delta(k)\, \Delta^T (k)\} \geq tr\{E[\Delta(k)\Delta^T (k)]\} = tr\, \{H(k)\, P(k/k\text{-}1)\, H^T (k) + R(k)\}$

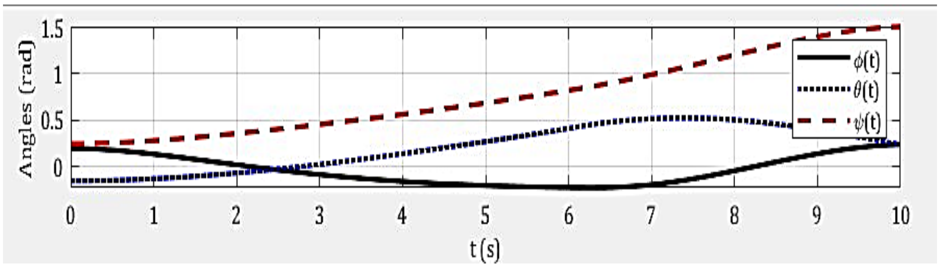
Hence taking the expression tr{Δ(k) Δ^T (k)} = Δ^T (k)Δ(k) into consideration, the following formula for the adaptive factor S(k) is obtained.

$$S(k) = \frac{\Delta^T(k)\Delta(k) - tr\left\{H(k)P(k/k-1)H^T(k)\right\}}{tr\left\{R(k)\right\}}$$

The optimal estimation algorithm gives the possibility to accomplish an adaption of filter to the change of measurement system operation conditions. Where P(k) increases, and the filter gain matrix K(k) decreases. This will lead to the decrease of innovation sequence Δ(k0 and adapitve factor S(k), weakening of the corrective influence of innovation sequence etc.

7. SIMULATION RESULTS:

The simulation results are comparision between kalman filter and robust kalman filter with respect to measurement noise factor and also towards the kalman values converges the actual values. Kalman filter has the v_r, r, ψ parameters in noraml conditions. All the simulation results are programmed with MATLAB R2020. In the figures, red line refers to RKF estimated green line refers to actual filter, blue line referes to measured error.



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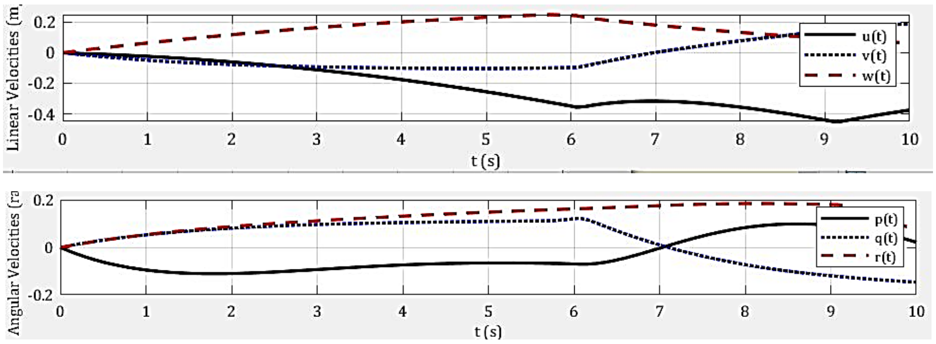

Fig. 3. Kalman filter results for angular velocities and linear velocities

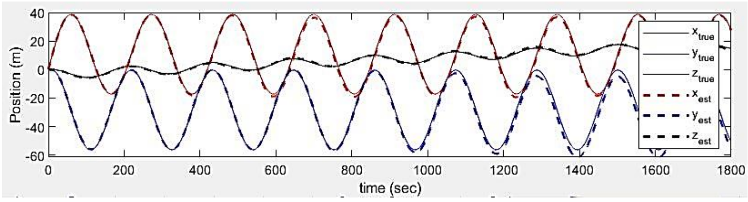

Fig.4. Position of kalman filter for true and estimation errrors

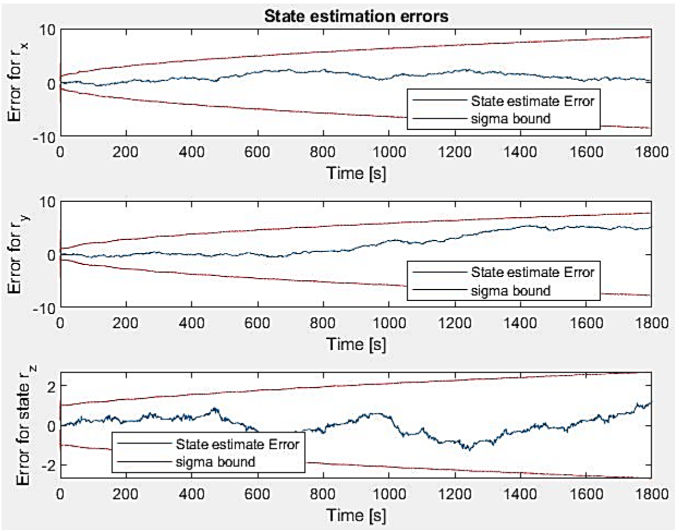

Fig.5. State estimation errors for r_x,r_y, r_z angles

8. CONCLUSION:

In this estmation system, Robust kalman filter with filter gain corection coefficient is presented. Due to be changed of coefficients of gain matrix by the results of every observation in response to optimal functions. Finally in this article, the kalman filter and robust kalman filter comparisons of noise factor and also some measurement variances are determined.

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