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Robust Kalman Filter Based Estimation of AUV Dynamics in the Presence Of Sensor Faults

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Abstract: This article is basically focused on application of the Robust Kalman Filter (RKF) algorithm to the estimation of high speed an autonomous underwater vehicle (AUV) dynamics. In the normal operation conditions of AUV, conventional Kalman filter gives sufficiently good estimation results. However, if the measurements are not reliable because of any kind of malfunction in the estimation system, Kalman Filter (KF) gives inaccurate results and diverges by time. This study, introduces Robust Kalman Filter algorithm with the filter gain correction for the case of measurement malfunctions. By the use of defined variables named as measurement noise scale factor, the faulty measurements are taken into the consideration with a small weight and the estimations are corrected without affecting the characteristic of the accurate ones. In the presented RUKF, the filter gain correction is performed only in the case of malfunctions in the measurement system and in all other cases procedure is run optimally with regular KF.

1. INTRODUCTION

The research on underwater systems has gained an immense interest during the last decades with applications taken place in many fields. Therefore, the significant number of autonomous underwater vehicles (AUVs) has been developed for the solving of wide spectrum of scientific and applied tasks of sea research and development in the world.

AUVs require a precise navigation system for localization, positioning, path tracking, guidance, and control during long period of duty cycle. In order to develop an accurate and robust navigation and control system for an AUV, it is needed to derive fault tolerant filtration algorithms for estimation of AUV dynamics.

Since it was proposed, Kalman filter has been widely used as the AUV motion dynamics parameters estimation technique (Lammas *et al.,* 2010) and different Kalman filter (KF) types have been developed with that purpose. By using KF, it is possible to estimate motion dynamics parameters of an AUV, which has a typical navigation sensor outfit such as compass, pressure depth sensor, and some class of inertial navigation system (INS).

In the normal operation conditions of AUV, conventional Kalman filter gives sufficiently good estimation results. However, if the measurements are not reliable because of any kind of malfunction in the estimation system, KF gives inaccurate results and diverges by time. The conventional KF has no capability to adapt itself to the changing conditions of the measurement system. Malfunctions such as abnormal measurements, increase in the background noise etc. affects instantaneous filter outputs and process may result with the failure of the filter. In order to avoid from such condition, the filter must be operated robustly.

KF can be made adaptive and hence insensitive to the priori measurements or system uncertainties by using various different techniques. Multiple Model Based Adaptive Estimation (MMAE), Innovation Based Adaptive Estimation (IAE) and Residual Based Adaptive Estimation (RAE) are three of basic approaches to the adaptive Kalman filtering (Mohamed and Schwarz, 1999). In the first approach, more than one filters run parallel under different models for satisfying filter's true statistical information. However, that can be only achieved if the sensor/actuator faults are known. Also, this approach requires several parallel Kalman filters to run and the processing time may increase in such condition (Hide et al., 2004). In IAE or RAE methods, adaptation is applied directly to the covariance matrices of the measurement and/or system noises in accordance with the differentiation of the residual or innovation sequence. To realize these methods, the innovation or residual vectors must be known for *m* epoch and that causes an increment in the storage burden, as well as the requirement to know the width of the "moving window". Besides, in order to estimate covariance matrix of the measurement noise based on the innovation or residual vector, number, type and distribution of measurements must be consistent for all epochs within a window.

In (Scardua and daCruz, 2017) 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. The tuning problem is solved by a stochastic search algorithm and by a standard model-based optimizer.

Another concept is to scale the noise covariance matrix by multiplying it with a time dependent variable. One of the

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methods for constructing such algorithm is to use a single adaptive factor as a multiplier to the process or measurement noise covariance matrices (Hide *et al.*, 2004; Hu *et al.,* 2003). This algorithm, which may be named as Adaptive Fading Kalman Filter (AFKF), can be both used when the information about the dynamic process or the priori measurements is absent. However, when the point at issue is the recent measurements, another technique to scale measurement noise covariance matrix and make filter robust (insensitive to recent measurement faults) should be used. Therefore, if there is a malfunction in the measurement system, Robust Kalman Filter (RKF) algorithm can be utilized and by the use of a measurement noise scale factor (MNSF) as a multiplier on the measurement noise covariance matrix insensitiveness of the filter to the current measurement faults can be satisfied (Hajiyev and Soken, 2014; Kang et al., 2014; Soken and Hajiyev, 2014; Cilden-Guler et al., 2017). As a consequence, via a correction applied to the filter gain, good estimation behaviour of the filter will be secured without being affected from faulty current measurements.

In this paper, Robust Kalman Filter algorithm with single measurement noise scale factor is introduced and applied for the motion dynamics parameters estimation process of an AUV. The proposed RKF for measurement noise scaling are considerably simpler than the existing and may be preferred, especially for the AUV motion dynamics estimation.

2. AUTONOMOUS UNDERWATER VEHICLE MODEL

AUV modelling is fairly complicated, and an exact analysis is only possible by including the underlying infinite dimensional dynamics of the surrounding fluid (sea water). While this can be done using partial differential equations in Computational Fluid Dynamics (CFD) computer tools, it still involves a formidable computational burden, infeasible for most practical applications.

AUVs move in 6 degrees of freedom (6DOF) since six independent coordinates are necessary to determine the position and orientation of a rigid body (See Fig.1). The first three coordinates and their time derivatives are of translational motion along the x, y and z-axes, while the last three coordinates (ϕ, θ, ψ) and time derivatives are used to describe orientation and rotational motion.

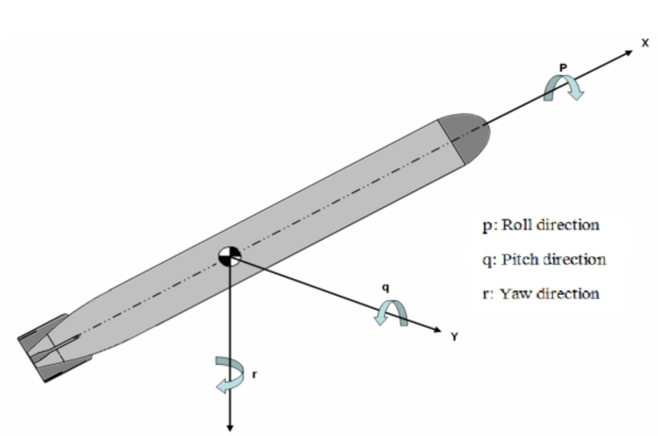

Fig. 1. 6-DOF AUV Angular and Translational Motions

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

2.1 Diving Subsystem of Sample AUV Model

Basically, diving subsystem includes heave velocity w, angular velocity q in pitch direction, pitch angle θ, depth z and bending of stern surface (deflection) δ_s. Diving subsystem neglects sway velocity v, roll rate of rotation r, heading angle ψ , rotation mode (p, φ) and initial horizontal movements of X and Y. Vehicle is assumed to move with constant u_0 velocity with respect to water and 0 pitch angle. Linearised equations of motions in direction of Heave and Pitch angles are given below (Lynn and Fodrea, 2002);

$$\begin{bmatrix} m - Z_{\dot{w}} & m x_G - Z\dot{q} & 0 & 0 \\ m x_G - M_{\dot{w}} & I_y - M\dot{q} & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \dot{w} \\ \dot{q} \\ \dot{\theta} \\ \dot{z} \end{bmatrix} = \begin{bmatrix} Z_w & Z_q - mu & 0 & 0 \\ M_w & M_q - m x_G u_0 & -\overline{BG_Z W} & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & -u_0 & 1 \end{bmatrix} \begin{bmatrix} w \\ q \\ \theta \\ z \end{bmatrix} + \begin{bmatrix} Z_\delta \\ M_\delta \\ 0 \\ 0 \end{bmatrix} \delta_s, \quad (1)$$

Equation (1) uses the hydrodynamic which is added linear decrease and deflection of stern surface to define external forces and moment. In addition, vertical distance between mass center z_G and buoyancy center z_B model the moment from $\overline{BG_z}$.

2.1.1 Discretization for Diving Subsystem

Diving subsystem matrices are given below;

$$M = \begin{bmatrix} m - Z_{\dot{w}} & m x_G - Z\dot{q} & 0 & 0 \\ m x_G - M_{\dot{w}} & I_y - M\dot{q} & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad (2)$$

$$A_D = \begin{bmatrix} Z_w & Z_q - mu & 0 & 0 \\ M_w & M_q - m x_G u_0 & -\overline{BG_Z W} & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & -u_0 & 1 \end{bmatrix}, \quad B_D = \begin{bmatrix} Z_\delta \\ M_\delta \\ 0 \\ 0 \end{bmatrix}, \quad (3)$$

The mathematical model of the diving subsystem can be rewritten in the matrix form as;

$$\dot{X}_D(t) = M^{-1} A_D X_D(t) + M^{-1} B_D \delta_s(t), \quad (4)$$

where

$$X_D(t) = [w(t); q(t); \theta(t); z(t)] \tag{5}$$

is the state vector.

After discretization we obtain the diving subsystem model in the following form:

$$X_D(k+1) = A_D^* \times X_D(k) + B_D^* \times U_D(k), \tag{6}$$

where

$$A_D^* = I + \Delta t \times M^{-1} \times A_D ; B_D^* = \Delta t \times M^{-1} \times B_D \tag{7}$$

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

2.2 Steering Subsystem of Sample AUV

Steering subsystem equations are shown below;

$$\begin{bmatrix} m-Y_{\dot{V}_r} & -Y_{\dot{r}} & 0 \\ -N_{\dot{V}_r} & Iz-N_{\dot{r}} & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \dot{v}_r \\ \dot{r} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} Y_{V_r} & Y_r - mU_0 & 0 \\ N_{V_r} & N_r & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} v_r \\ r \\ \psi \end{bmatrix} + \begin{bmatrix} Y_\delta \\ N_\delta \\ 0 \end{bmatrix} \delta_r(t), \tag{8}$$

$$M = \begin{bmatrix} m-Y_{\dot{V}_r} & -Y_{\dot{r}} & 0 \\ -N_{\dot{V}_r} & Iz-N_{\dot{r}} & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{9}$$

If the inverse of M matrix in (9) is calculated and multiplied both sides with M^{-1} in (8), equation transforms to;

$$\begin{bmatrix} \dot{v}_r \\ \dot{r} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} m-Y_{\dot{V}_r} & -Y_{\dot{r}} & 0 \\ -N_{\dot{V}_r} & Iz-N_{\dot{r}} & 0 \\ 0 & 0 & 1 \end{bmatrix}^{-1} \begin{bmatrix} Y_{V_r} & Y_r - mU_0 & 0 \\ N_{V_r} & N_r & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} v_r \\ r \\ \psi \end{bmatrix} + \begin{bmatrix} m-Y_{\dot{V}_r} & -Y_{\dot{r}} & 0 \\ -N_{\dot{V}_r} & Iz-N_{\dot{r}} & 0 \\ 0 & 0 & 1 \end{bmatrix}^{-1} \begin{bmatrix} Y_\delta \\ N_\delta \\ 0 \end{bmatrix} \delta_r(t), \tag{10}$$

2.2.1 Discretization of Steering Subsystem

A and B matrix are defined as below in equation (10):

$$A_S = \begin{bmatrix} m-Y_{\dot{V}_r} & -Y_{\dot{r}} & 0 \\ -N_{\dot{V}_r} & Iz-N_{\dot{r}} & 0 \\ 0 & 0 & 1 \end{bmatrix}^{-1} \begin{bmatrix} Y_{V_r} & Y_r - mU_0 & 0 \\ N_{V_r} & N_r & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{11}$$

$$B_S = \begin{bmatrix} m-Y_{\dot{V}_r} & -Y_{\dot{r}} & 0 \\ -N_{\dot{V}_r} & Iz-N_{\dot{r}} & 0 \\ 0 & 0 & 1 \end{bmatrix}^{-1} \begin{bmatrix} Y_\delta \\ N_\delta \\ 0 \end{bmatrix}, \tag{12}$$

If A_S and B_S matrices are defined as (11) and (12), A_S^* and B_S^* matrices are also defined for discretization as below;

$$A_S^* = I + \Delta t \times A_S ; B_S^* = \Delta t \times B_S , \tag{13}$$

Let us define the state vector as $X_S = \begin{bmatrix} v_r & r & \psi \end{bmatrix}^T$. Then the mathematical model of the steering subsystem can be written in the discrete form as:

$$X_S(k+1) = A_S^* \times X_S(k) + B_S^* \times U_S(k), \tag{14}$$

Here, $U_S(k)$ is control input by rudders. Discretized model (14) will be used for Kalman applications.

3. KALMAN FILTER FOR ESTIMATION OF AUV DYNAMICS

3.1 Optimum Linear Kalman Filter Equations

Consider the following linear discrete dynamic system:

$$X(k+1) = \phi(k+1,k)X(k) + B(k)u(k) + G(k+1,k)W(k), \tag{15}$$

$$z(k) = H(k)X(k) + v(k), \tag{16}$$

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

Apparently, the optimum linear Kalman filter that estimates the state vector of the system (15) is expressed with the following recursive equations system:

Equation of the estimation value,

$$\hat{X}(k/k) = \hat{X}(k/k\text{-}1) + K(k)\left[z(k) - H(k)\hat{X}(k/k\text{-}1)\right], \tag{17}$$

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:

$$K(k) = P(k/k-1)H^T(k)x\left[H(k)P(k/k-1)H^T(k) + R(k)\right]^{-1} \tag{18}$$

$R(k)$ is the covariance matrix of measurement noise.

The covariance matrix of the filtering error is,

$$P(k/k) = \left[I - K(k)H(k)\right]P(k/k-1), \tag{19}$$

where I is the identity matrix.

The covariance matrix of the extrapolation error is,

$$P(k/k-1) = \phi(k,k-1)P(k-1/k-1)\phi^T(k,k-1) + +G(k,k-1)Q(k-1)G^T(k,k-1), \quad (20)$$

where $Q(k-1)$ is the covariance matrix of system noise.

3.2 Robust Filter Algorithm with Kalman Gain Correction

Kalman Filter is definitely sensitive to any measurement noise (abnormal measurements, instantaneous shifts in measurement channel and decrease in device accuracy, background noise etc.) If, the state of the process of measurement system is not correspond to mathematical model used in filter, the changes caused by normal malfunctions in measurement channel, decrease the accuracy of estimation significiantly. In this case, Robust Kalman Filters can be used to prevent from noise.

The state space model of system is explained by (15)-(16).
In case of normal operation of the measurement system, the filter works according to the conventional algorithms. But if the condition of operation of the measurement system do not correspond to the models used in the synthesis of filter, then the gain matrix of Kalman filter automatically changes due to a change in the covariance matrix of the innovation sequence according to the following rule;

$$P_\Delta(k) = H(k)P(k/k-1)H^T(k) + S(k)R(k), \quad (21)$$

in which adaptive factor (weight coefficient) $S(k)$ is calculated from the innovation sequence $\Delta(k) = Z(k) - H(k)\hat{X}(k/k-1)$ analysis results, where $P(k/k-1)$ is the covariance matrix of extrapolation errors, $R(k)$ is the covariance matrix of measurement noise, $\hat{X}(k/k-1)$ is the extrapolation (prediction) value. The filter gain matrix in this case can be written in the following form

$$K(k) = P(k/k-1)H^T(k) \left[H(k)P(k/k-1)H^T(k) + S(k)R(k)\right]^{-1}, \quad (22)$$

According to the proposed approach the gain matrix is changed when the following condition is valid

$$tr\left\{\Delta(k)\Delta^T(k)\right\} \geq tr\left\{E\left[\Delta(k)\Delta^T(k)\right]\right\} = tr\left\{\begin{matrix} E\left[H(k)\left(X(k)-\hat{X}(k/k-1)\right)+V(k)\right]\times \\ \left[H(k)\left(X(k)-\hat{X}(k)\right)+V(k)\right]^T \end{matrix}\right\} = tr\left\{H(k)P(k/k-1)H^T(k)+R(k)\right\}, \quad (23)$$

where tr (.) is the trace of matrix. When a significant change in the conditions of operation of the measurement system occurs, the prediction of observations $H(k)\hat{X}(k/k-1)$ will considerably differ from the observation results $z(k)$. Consequently, the sum of the discrepancy squares on the left side of (23) will characterize the real filtration error, while the right side determines the theoretical accuracy of the innovation sequence, obtained on the basis of a priori information. If condition (23) is met, then the real filtration error exceeds the theoretical error. Therefore, it is necessary to correct the filter gain matrix beginning from this moment. Substituting (21) in (23) in this case the following expression can be obtained;

$$tr\left\{\Delta(k)\Delta^T(k)\right\} = tr\left\{H(k)P(k/k-1)H^T(k)\right\} + S(k)tr\left\{R(k)\right\}, \quad (24)$$

Hence taking the expression $tr\left\{\Delta(k)\Delta^T(k)\right\} = \Delta^T(k)\Delta(k)$ into consideration, the following formula for the adaptive factor $S(k)$ is obtained:

$$S(k) = \frac{\Delta^T(k)\Delta(k) - tr\left\{H(k)P(k/k-1)H^T(k)\right\}}{tr\left\{R(k)\right\}}, \quad (25)$$

Using (21), (22) and (25) in the optimal estimation algorithm gives the possibility to accomplish an adaptation of filter to the change of measurement system operation conditions. If the left side of the expression (23) is greater than the right side, the adaptive factor value $S(k)$ will increase. This corresponds to the beginning of adaptation of filter. Consequently the covariance matrix of innovation sequence $P_\Delta(k)$ (21) increases, and the filter gain matrix $K(k)$ (22) decreases, which will cause strengthening of the corrective influence of innovation sequence in the estimation algorithm and approach the estimation value $\hat{X}(k/k)$ to the actual value $X(k)$. This will lead to the decrease of innovation sequence $\Delta(k)$ and adaptive factor $S(k)$, weakening of the corrective influence of innovation sequence, etc.

The final expressions of the proposed adaptive filtration algorithm with the filter gain correction can be written in the following form:

Equation of the estimation value;

$$\hat{X}(k/k) = \hat{X}(k/k-1) + K(k)\Delta(k), \quad (26)$$

Equation of the extrapolation value,

$$\Delta(k) = z(k) - H(k)\hat{X}(k/k-1), \quad (28)$$

The gain matrix of Kalman filter,

$$K(k) = P(k/k-1)H^T(k)P_\Delta^{-1}(k), \quad (29)$$

The covariance matrix of the innovation sequence,

$$P_\Delta(k) = H(k)P(k/k-1)H^T(k) + S(k)R(k), \quad (30)$$

The adaptive factor ,

$$S(k) = \frac{\Delta^T(k)\Delta(k) - tr\left\{H(k)P(k/k-1)H^T(k)\right\}}{tr\left\{R(k)\right\}}, \quad (31)$$

The covariance matrix of estimation errors.

$$P(k/k) = \left[I - K(k)H(k)\right]P(k/k-1), \quad (32)$$

The covariance matrix of extrapolation errors,

$$P(k/k-1) = \phi(k,k-1)P(k-1/k-1)\phi^T(k,k-1) + G(k,k-1)Q(k-1)G^T(k,k-1), \quad (33)$$

where $Q(k-1)$ is the covariance matrix of system noise.

In contrast to the standard optimal filtration algorithm, in which the filter gain $K(k)$ is changed by program, current measurements in the proposed algorithm have larger weight, since the coefficients of matrix $K(k)$ are corrected by the results of each observation. This algorithm is adapted to the measurement system operation conditions by the approximation of theoretical covariance matrix $P_\Delta(k)$ to the real covariance matrix of innovation sequence, according to changing adaptive factor $S(k)$. The mentioned change is accomplished because of regarding the matrix $\Delta(k)\Delta^T(k)$, which characterizes the real filtration error. Proposed adaptive KF will ensure the guaranteed adaptation of the filter to the change of the measurement system operation conditions.

4. SIMULATION RESULTS AND COMMENTS

Simulation results are presented in Figures 2-6. Figures are outputs of programmes with MATLAB codes. In the figures, green line refers to actual value, red line refers to measurement value and blue line refers to Kalman value. The outputs of the programmes written for steering and diving systems are in the figures. In the regular case of system optimum Kalman filter results for steering and diving systems are given in Figures 2-3. From the figures, it can be be seen that the Kalman values converges the actual values.

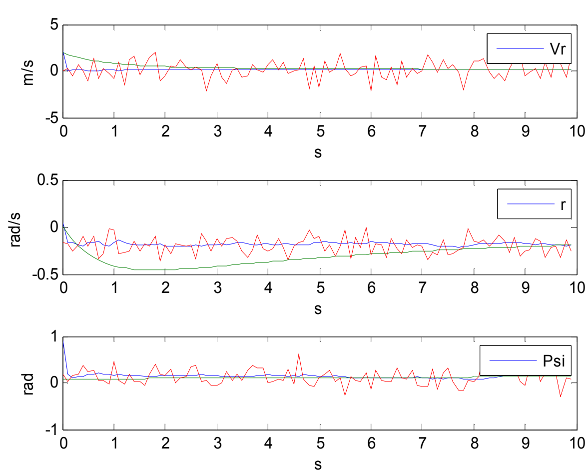

Fig. 2. Kalman filter results for v_r, r, ψ parameters in case of normal conditions.

In measurement channel of r parameter, continuous bias is simulated after the 6th second via the help of the formula distributed:

$$Z_r(k) = r(k) + 0.3 + \sigma_r randn$$

In case of malfunctions, the estimation of state variables of steering system autonomous underwater vehicle by conventional KF is shown in Figures 4. As seen from Fig. 4, the estimation values of r parameter diverge from the actual values after the 6th second. Consequently, it can be said that the regular KF provides bad results in case of malfunctions in measurement channel.

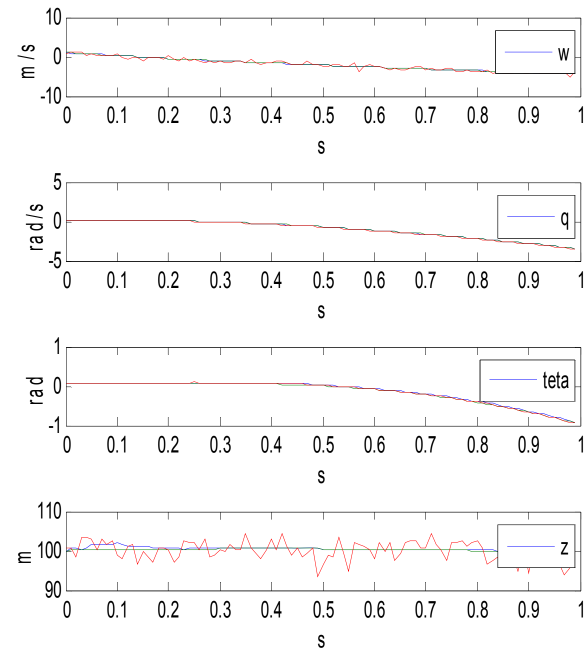

Fig. 3. Conventional KF results for w, q, θ, z parameters in case of normal conditions.

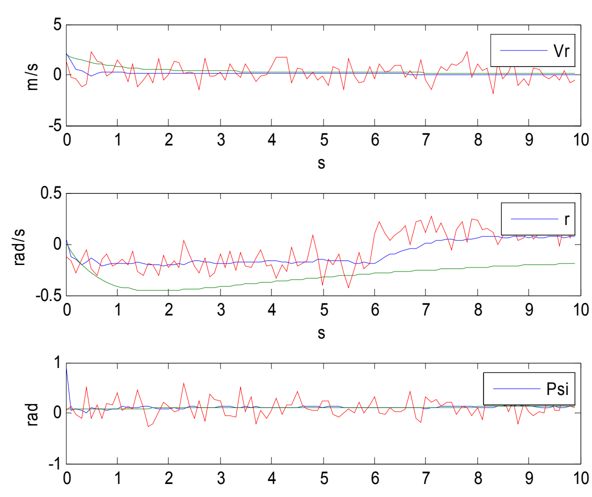

Fig. 4. Conventional KF results for v_r, r, ψ parameters in case of continuous bias in measurement channel of parameter r (after 6th second).

Robust Kalman filter estimation results in case of constant bias in r parameter's measurement channel (after 6th second) are presented in Figure 5. As seen from Figure 5, although there is a malfunction in measurement channel, the estimation values provided by RKF converges to the actual values. In this case, filter works robust against measurement malfunction.

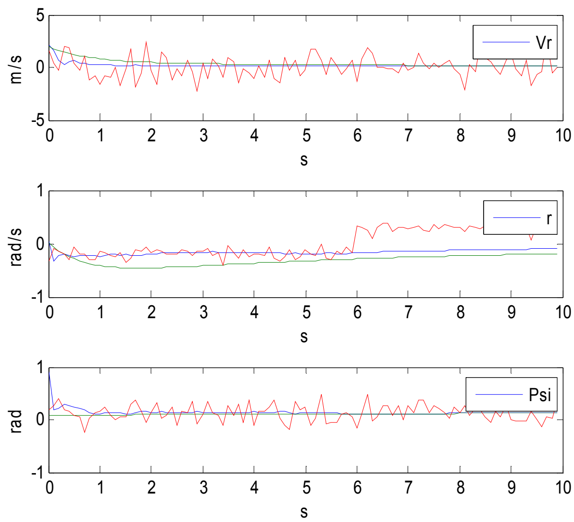

Fig. 5. RKF estimation results for v_r, r, ψ parameters in case of continuous bias in measurement channel of parameter r (after 6th second) .

The change of adaptive factor S is shown in Figure 6. Until the 6th second (when the malfunction appears), S=1. After malfunction appears, adaptive factor increases and changes the filter gain matrix to prevent from the effect of malfunction. In conclusion, the effect of measurements with malfunction to estimation values is decreased and RKF provides estimation values converging to actual values.

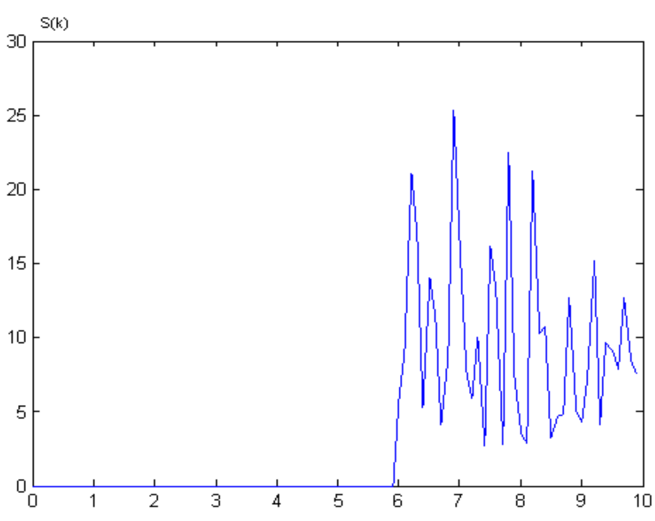

Fig. 6. The change of adaptive factor S.

5. CONCLUSION

In case of malfunctions in estimation system, Robust Kalman Filter with filter gain coefficient correction is presented. Due to be changed of coefficients of gain matrix by the results of every observation in response to optimal filter algorithm which filter gain is changed by programme, current measurements have more importance in proposed algorithm. In this algorithm, by the way of change of adaptive factor, theoretic covariance matrix can be made adaptive to measurement system operation conditions by converging to actual covariance matrix of innovation series. Proposed filter algorithm supplies the adaptation to change in operation conditions of filter's measurement system. Consequently, error's of estimation system can be corrected without affecting the good estimation behaviour.

Application of the proposed RKF algorithm to autonomous underwater vehicle dynamic model shows that it provides the adaptation to changes in operation conditions of measurement system and provides correct results for both of the regular and failure conditions. Simulation results show that the application of proposed algorithm to AUV fault tolerant steering and diving control system is beneficial.

This approach does not require the statistical feature of premise fault and past time data. Moreover, computational demands are not high.

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