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Adaptive Fading Kalman Filter with Q-Adaptation for Estimation of AUV Dynamics

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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 any kind of malfunction occurs in the system, KF gives inaccurate results and diverges by time. This study, introduces Adaptive Fading Kalman Filter (AFKF) algorithm with the filter gain correction for the case of system malfunctions. By the use of defined variables named as single and multiple fading factors, the estimations are corrected without affecting the characteristic of the accurate ones.**

I. 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 a fault tolerant filtration algorithm for estimation of AUV dynamics.

Since it was proposed, Kalman filter (KF) has been widely used as the AUV motion dynamics parameters estimation technique [1] and different 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) [2]. In the normal operation conditions of AUV, conventional KF gives sufficiently good estimation results. However, if any kind of malfunction occurs in the system, KF gives inaccurate results and diverges by time. The conventional KF has no capability to adapt itself to the changing conditions of the system. Malfunctions such as actuator failure and increase in the system 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 adaptively.

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. 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 [3]. 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* [4]. Besides, in order to estimate covariance matrices of the measurement and/or system noises based on the innovation or residual vector, number, type and distribution of measurements must be consistent for all epochs within a window.

Another concept is to scale the noise covariance matrix by multiplying it with a time dependent variable. One of the methods for constructing such algorithm is to use a single adaptive factor as a multiplier to the process or measurement noise covariance matrices [3, 5]. 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 [6].

In this study, Adaptive Fading Kalman Filter algorithms with single fading factor (SFF) and multiple fading factor (MFF) are introduced and applied for the motion dynamics parameters estimation process of an AUV. The proposed AFKFs are considerably simpler than the existing and may be preferred, especially for the AUV motion dynamics estimation.

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II. AUTONOMOUS UNDERWATER VEHICLE MATHEMATICAL 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. 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.

The linearised model of REMUS torpedo will be 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.

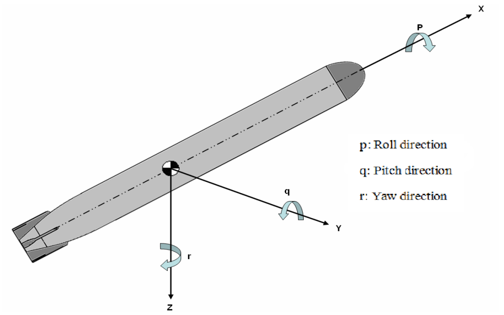

Fig. 1. 6-DOF AUV Angular and Translational Motions

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. Linearized equations of motions in direction of Heave and Pitch angles are given below [7];

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

Equation (1) uses the hydrodynamic which is added linear decrease and deflection of stern surface to define external forces and moments 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;

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

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

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

$$X_D(t) = [w(t); q(t); \theta(t); z(t)] \quad (5)$$

is the state vector.

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

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

where

$$A_D^* = I + \Delta t \times M^{-1} \times A_D ; B_D^* = \Delta t \times M^{-1} \times B_D, \quad (7)$$

$U_D(k)$ is the control input coming from deflection [8].

2.2 *Steering Subsystem of Sample AUV*

Steering subsystem equations are shown below;

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

$$M = \begin{bmatrix} m - Y_{\dot{V}_r} & -Y_r & 0 \\ -N_{\dot{V}_r} & Izz - N_{\dot{r}} & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (9)$$

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

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

2.2.1 Discretization of Steering Subsystem

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

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

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

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.

III. KALMAN FILTER FOR ESTIMATION OF AUV DYNAMICS

A. *Optimum 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,

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

where;

$$\hat{X}(k/k-1) = \Phi(k,k-1)\hat{X}(k-1/k-1) + B(k-1)u(k-1) \tag{18}$$

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

$$K(k) = P(k/k-1)H^T(k)x\left[H(k)P(k/k-1)H^T(k) + R(k)\right]^{-1} \tag{19}$$

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

The covariance matrix of the filtering error is,

$$P(k/k) = \left[I - K(k)H(k)\right]P(k/k-1), \tag{20}$$

The covariance matrix of the extrapolation error is,

$$P(k/k-1) = \Phi(k,k-1)P(k-1/k-1)\Phi^T(k,k-1) + \\ +G(k,k-1)Q(k-1)G^T(k,k-1), \tag{21}$$

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

B. *Adaptive Fading Kalman Filter*

In case of normal operation, where the model for the process noise covariance matches with the real values, regular KF works without any divergence problem if it is tuned correctly for the issued problem. However, when a change occurs in the process noise covariance, the filter fails and the estimation outputs become faulty.

Hence, an adaptive algorithm must be introduced so as an adaptation on process noise covariance (Q-adaptation) is performed and the estimations of the filter are corrected without affecting good estimation characteristic of the remaining process.

1) Adaptive fading KF with single fading factor:

When there is an actuator fault in the system that results with changes in the control distribution matrix, a similar approach for Q adaptation can be followed.

$$P_\Delta(k) = H(k)P(k/k-1)H^T(k) + R(k) = \\ H(k)\left[\Phi(k/k-1)P(k-1/k-1)\Phi^T(k/k-1)\right]H^T(k) \\ +H(k)\left[\Lambda(k)G(k-1)Q(k-1)G^T(k-1)\right]H^T(k) + R(k) \tag{22}$$

in which adaptive factor (weight coefficient) $\Lambda(k)$ is calculated from the innovation sequence

$$\Delta\left(k\right)=z\left(k\right)-H\left(k\right)\hat{X}\left(k/k-1\right) \tag{23}$$

analysis results.

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

$$\begin{aligned}&tr\left\{\Delta(k)\Delta^T(k)\right\}\geq tr\left\{E\left[\Delta(k)\Delta^T(k)\right]\right\}\\&=tr\left\{E\left[H(k)\left(X(k)-\hat{X}(k/k-1\right)+v(k)\right]\times\left[H(k)\left(X(k)-\hat{X}(k)\right)+v(k)\right]^T\right\}\\&=tr\left\{H(k)P(k/k-1)H^T(k)+R(k)\right\}\end{aligned} \tag{24}$$

When a significant change in the conditions of operation of the measurement system occurs, the prediction of observations $H\left(k\right)\hat{X}\left(k/k-1\right)$ will considerably differ from the observation results $z(k)$ .Consequently, the sum of the discrepancy squares on the left side of (24) 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 (24) 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 (24) in this case the following expression can be obtained;

$$\begin{aligned}&tr(\Delta(k)\Delta^T(k))=\\&tr(H(k)\left[\Phi(k/k-1)P(k-1/k-1)\Phi^T(k/k-1)\right]H^T(k))\\&+tr(H(k)\left[\Lambda(k)G(k-1)Q(k-1)G^T(k-1)\right]H^T(k))+tr(R(k))\end{aligned} \tag{25}$$

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

$$\Lambda(k)=\frac{\Delta^T(k)\Delta(k)-tr\left(H(k)\left[\Phi(k/k-1)P(k-1/k-1)\Phi^T(k/k-1)\right]H^T(k)\right)-tr(R(k)}{tr(H(k)\left[G(k-1)Q(k-1)G^T(k-1)\right]H^T(k))} \tag{26}$$

Apart from that point, if there is a fault in the system, $\Lambda(k)$ must be put into process as,

$$\begin{aligned}&P(k/k-1)=\Phi\left(k/k-1\right)P\left(k-1/k-1\right)\Phi^{\mathrm{T}}\left(\mathrm{k},\mathrm{k}-1\right)\\&+\Lambda(k)G\left(\mathrm{k}-1\right)Q\left(\mathrm{k}-1\right)G^{\mathrm{T}}\left(\mathrm{k}-1\right)\end{aligned} \tag{27}$$

If the left side of the expression (24) is greater than the right side, the fading factor value $\Lambda(k)$ will increase. This corresponds to the beginning of adaptation of filter. Consequently the covariance matrix of innovation sequence $P_\Delta(k)$ (22) increases, and the filter gain matrix $K(k)$ increases too, 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 $\Lambda(k)$, weakening of the corrective influence of innovation sequence, etc. The final expressions of the proposed adaptive (Q-adaptation) filtration algorithm with the single fading factor can be presented via the formulas (17), (18), (19), (20), (26) and (27).

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 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 $\Lambda(k)$. 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.

2) Adaptive fading KF with multpile fading factor

In this case again, reel and theoretical values of the innovation covariance matrix must be compared. When there is an actuator fault, the real error will exceed the theoretical one. Hence, if a fading matrix Λ_k, built of fading factors, is added in to the algorithm as,

$$\begin{aligned}&\frac{1}{\mu}\sum_{j=k-\mu+1}^{k}\tilde{\Delta}(k)\tilde{\Delta}^T(k)=H(k)[\Phi\left(k/k-1\right)P\left(k-1/k-1\right)\Phi^{\mathrm{T}}\left(\mathrm{k},\mathrm{k}-1\right)\\&+\Lambda(k)G\left(\mathrm{k}-1\right)Q\left(\mathrm{k}-1\right)G^{\mathrm{T}}\left(\mathrm{k}-1\right)]H^T(k)+R(k)\end{aligned} \tag{28}$$

Then the fading matrix can be determined as,

$$\begin{aligned}&\Lambda(k)=\left[\frac{1}{\mu}\sum_{j=k-\mu+1}^{k}\Delta(k)\Delta^T(k)-H(k)\Phi\left(k/k-1\right)P\left(k-1/k-1\right)\Phi^{\mathrm{T}}\left(\mathrm{k},\mathrm{k}-1\right)H^T(k)-R(k)\right]\\&\times\left[H(k)G\left(\mathrm{k}-1\right)Q\left(\mathrm{k}-1\right)G^{\mathrm{T}}\left(\mathrm{k}-1\right)H^T(k)\right]^{-1}\end{aligned} \tag{29}$$

The gained fading matrix should be diagonalized since the Q matrix must be a diagonal, positive definite matrix.

$$\Lambda^*=diag\left(\lambda_1^*,\lambda_2^*,...,\lambda_n^*\right), \tag{30}$$

where,

$$\lambda_i^*=\max\left\{1,\Lambda_{ii}\right\} \qquad i=1,n\,. \tag{31}$$

Here, Λ_{ii} represents the i^th^ diagonal element of the matrix Λ. Apart from that point, if there is a fault in the system, Λ_k^* must be put into process as,

$$P(k/k-1)=\Phi(k/k-1)P(k-1/k-1)\Phi^{T}(k,k-1)$$
$$+\Lambda^{*}(k)G(k-1)Q(k-1)G^{T}(k-1) \qquad (32)$$

Remark that, due to the scale matrix or fading matrix the covariance of the estimation error of AFKF increases in comparison with OKF. Therefore, adaptive algorithm is operated only when the there is a fault and in all other cases procedure is run optimally with regular Kalman filter. Process is controlled by the use of a kind of statistical information. At that point, following two hypotheses may be introduced: γ_0 - the system is normally operating; γ_1 - there is a malfunction in the estimation system. To detect failures a statistical function may be defined as [9],

$$\beta(k)=\Delta^{T}(k)\left[HP(k/k-1)H^{T}+R\right]^{-1}\Delta(k) \qquad (39)$$

This statistical function has χ^2 distribution with s degree of freedom where s is the dimension of innovation vector.

If the level of significance, α , is selected as,

$$P\left\{\chi^2>\chi^2_{\alpha,s}\right\}=\alpha; \qquad 0<\alpha<1, \qquad (40)$$

the threshold value, $\chi^2_{\alpha,s}$ can be found. Hence, when the hypothesis γ_1 is correct, the statistical value of $\beta(k)$ will be greater than the threshold value $\chi^2_{\alpha,s}$, i.e.:

$$\gamma_0:\beta(k)\le\chi^2_{\alpha,s} \quad \forall k$$
$$\gamma_1:\beta(k)>\chi^2_{\alpha,s} \quad \exists k \qquad (41)$$

IV. SIMULATION RESULTS

A. OKF Results

Steering subsystem model is used to simulate the actuator malfunction case. It is shown that with OKF the mentioned statistical tests can be used to detect the actuator faults in the system. The control distribution matrix of the system is changed to simulate the actuator fault case. The results when fault is present in actuator channel are given in the Figs 2-3.

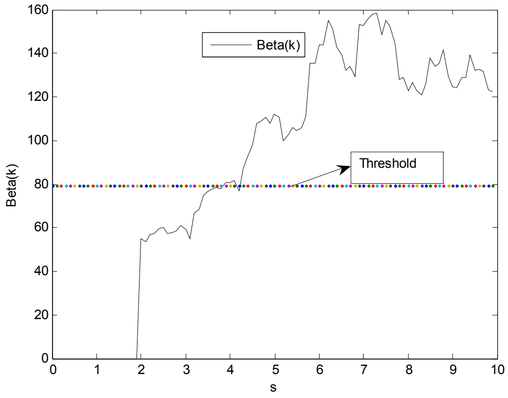

Fig.2. Actuator fault detection results when OKF is used

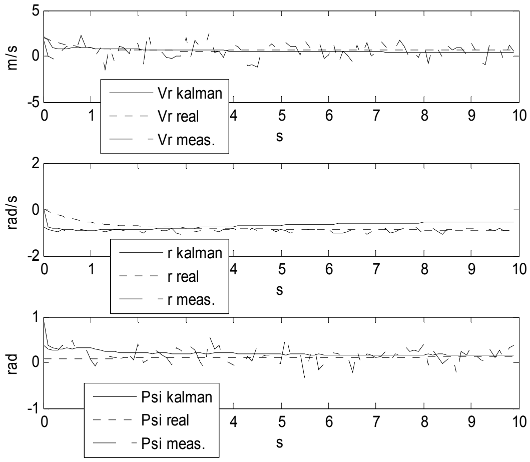

Fig.3. OKF estimation results in the case of actuator failure

The statistical tests using the values determined in OKF can detect the actuator faults as we can observe. Figs. 2-3 show that the OKF is affected from actuator fault and diverges by time.

B. AFKF with SFF Simulation Results

The control distribution matrix B is changed and a simulation is made using AFKF with SFF. As seen from Figs.4-5, AFKF with SFF is insensitive to actuator faults. It is observed that the adaptive filter gives better results compared to that of the OKF.

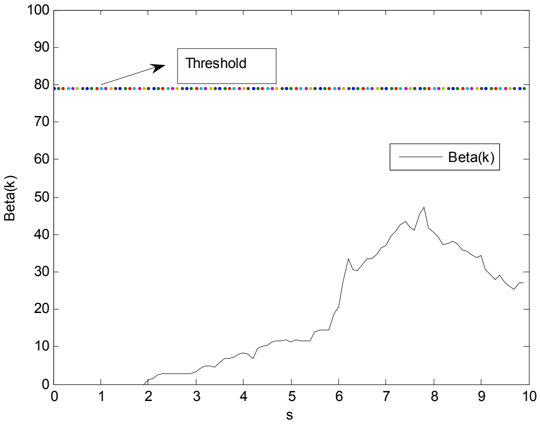

Fig.4. Actuator fault detection results when AFKF with SFF is used

C. AFKF with MFF Simulation Results

AFKF with MFF is also simulated in the case of actuator failure. As seen from Fig.6, AFKF with MFF is insensitive to actuator faults. Fig.7 shows that, the results of the adaptive filter with multiple factor are also better from that of the OKF.

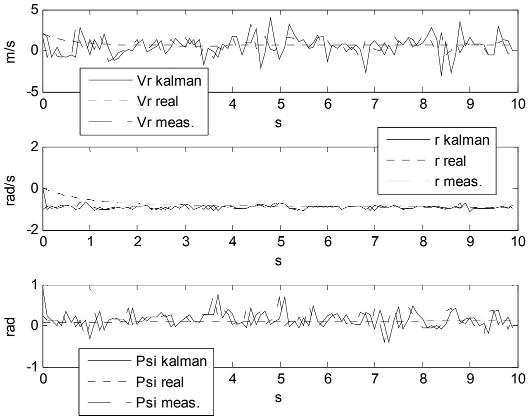

Fig.5. AFKF with SFF estimation results in the case of actuator failure

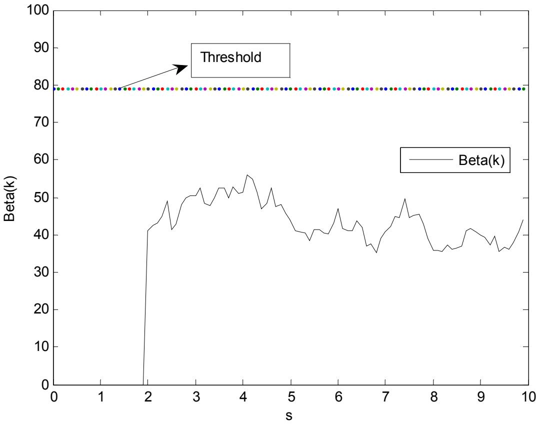

Fig.6. Actuator fault detection results when AFKF with MFF is used

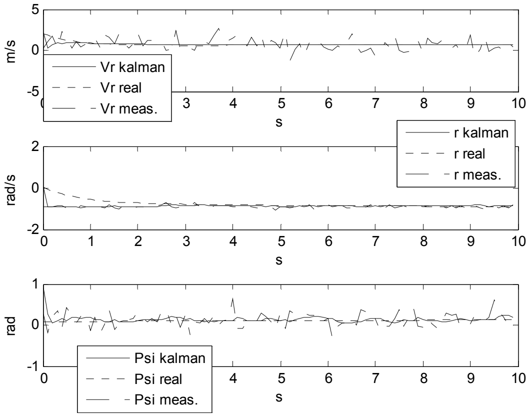

Fig.7. AFKF with MFF estimation results in the case of actuator failure

As we can observe AFKF with MFF gives accurate results. The results of both the single and multiple fading factors filters are better than the results of the OKF. The adaptive filter estimation values converge to the real values and fault detection algorithm results stay under the threshold values. We can also conclude that the results obtained from AFKF with MFF are better than the AFKF with SFF results.

V. CONCLUSION

In case of malfunctions in system, Adaptive Fading Kalman Filters with single and multiple fading factors are proposed. Due to the change of coefficients of gain matrix by the results of every observation in response to optimal filter algorithm which filter gain is changed by program, current measurements have more importance in proposed algorithms. In this algorithm, by changing the adaptive factor, theoretical covariance matrix can be made adaptive to system operation conditions by converging to actual covariance matrix of innovation series. Proposed filters supply the adaptation to change in operation conditions of system. Consequently, estimation system errors can be corrected without affecting the good estimation behavior.

Application of the proposed adaptive filters to autonomous underwater vehicle dynamic model shows that it provides the adaptation to changes in operation conditions of system and provides correct results for both of the regular and system 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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