A MULTIPLE MODEL-BASED SLIDING INNOVATION FILTER

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ABSTRACT

In this brief work, a novel filtering technique that combines the newly developed sliding innovation filter with a multiple model strategy is proposed. Introduced in 2020, the sliding innovation filter is a relatively new filter used for state and parameter estimation. Based on variable structure techniques, it shares the same principles with sliding mode observers. The filter is robust and stable under system modeling uncertainties. The proposed method multiple model-based sliding innovation filter is tested on an electrohydrostatic actuator (EHA) and the results are discussed.

Keywords: sliding innovation filter, multiple models, fault detection, robust estimation

1. INTRODUCTION

The Kalman filter (KF) is the most well-known filter that minimizes state and parameter estimation error. It is applicable on linear, known systems under the presence of white system and measurement noise. In order to make it applicable to nonlinear systems, the KF was extended to several forms including the extended, the unscented (UKF), the cubature (CKF), and the central difference KF (CDKF) [1-11]. However, these filters assume that the system is well-known. If the system changes it structure, the performance of the filter degrades significantly. In order to overcome this, several techniques have been introduced, such as using other type of filters or combining the previous filters with a more robust filter (e.g., sliding mode observer, the smooth variable structure filter, and the sliding innovation filter (SIF) [12-19]). Another approach is to use multiple models and fuse them statistically as in interacting multiple model (IMM) [20-23].

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This very brief paper is organized as follows. The IMM, SIF, and KF are introduced in Section 2. The system under study and the simulation results are summarized in Section 3. The paper is then concluded in Section 4.

2. STRATEGIES IN USE

This section provides a general overview of the IMM strategy along with the UKF and SIF. Figure 1 shows the IMM structure in general. This algorithm is then combined with SIF or UKF. The differences between IMM-SIF and IMM-UKF can be summarized with two main points: the calculation of the a priori (predicted) states and covariance matrix, and calculation of the gain. These can be summarized by Table 1.

The IMM process depends on the mixing probabilities $\mu_{i|j,k|k}$, which is defined as the probability of the system switching from one mode to another mode.

Table 1. IMM-SIF versus IMM-UKF

	calculations of the a priori states and covariance matrix	calculate the gain
SIF	$\hat{x}_{j,k+1\|k} = f_j(\hat{x}_{k\|k}, u_k)$ $P_{j,k+1\|k} = A_j P_{k\|k} A_j^T + Q_k$ $S_{j,k+1\|k} = C_j P_{j,k+1\|k} C_j^T + R_{k+1}$	$K_{k+1} = C^+ diag\left(sat\left(\|e_{1,z,k+1\|k}\|, \psi\right)\right)$
UKF	$X_{i,k\|k} = \hat{x}_{k\|k} \pm \left(\sqrt{(n+\kappa)P_{k\|k}}\right)_i$ $W_i = \frac{1}{2(n)}$ $X_{i,j,k+1\|k} = f_j\left(\mathrm{X}_{i,k\|k}, u_k\right)$ $\hat{x}_{j,k+1\|k} = \sum_{i=0}^{2n} W_i \hat{X}_{i,j,k+1\|k}$ $P_{k+1\|k} = \sum_{i=0}^{2n} W_i\left(\hat{X}_{i,\mathrm{j},k+1\|k} - \hat{x}_{j,k+1\|k}\right)\left(\hat{X}_{i,\mathrm{j},k+1\|k} - \hat{x}_{j,k+1\|k}\right)^T$ $P_{zz,k+1\|k} = \sum_{i=0}^{2n} W_i\left(C\hat{X}_{i,\mathrm{j},k+1\|k} - \mathrm{C}\hat{x}_{j,k+1\|k}\right)\left(C\hat{X}_{i,\mathrm{j},k+1\|k} - \mathrm{C}\hat{x}_{j,k+1\|k}\right)^T$ $P_{xz,k+1\|k} = \sum_{i=0}^{2n} W_i\left(\hat{X}_{i,\mathrm{j},k+1\|k} - \hat{x}_{j,k+1\|k}\right)\left(C\hat{X}_{i,\mathrm{j},k+1\|k} - \mathrm{C}\hat{x}_{j,k+1\|k}\right)^T$	$K_{k+1} = P_{xz,k+1\|k} P_{zz,k+1\|k}^{-1}$

$$\hat{x}_{k|k}, P_{k|k}$$

Calculate the a priori states and covariance matrix

$$e_{1,z,k+1|k} = z_{k+1} - C_1\hat{x}_{1,k+1|k}$$

Calculate $K_{1,k+1}$

$$\hat{x}_{1,k+1|k+1} = \hat{x}_{1,k+1|k} + K_{1,k+1}e_{1,z,k+1|k}$$

$$P_{1,k+1|k+1} = (I - K_{1,k+1}C_1)P_{1,k+1|k}$$

$$e_{1,z,k+1|k+1} = z_{k+1} - C_1\hat{x}_{1,k+1|k+1}$$

$$\Lambda_{1,k+1} = \frac{exp\left(\frac{-\frac{1}{2}e_{1,z,k+1|k}^T e_{1,z,k+1|k}}{S_{1,k+1}}\right)}{\sqrt{|2\pi S_{1,k+1}|}}$$

…

Calculate the a priori states and covariance matrix

$$e_{n,z,k+1|k} = z_{k+1} - C_n\hat{x}_{n,k+1|k}$$

Calculate $K_{n,k+1}$

$$\hat{x}_{n,k+1|k+1} = \hat{x}_{n,k+1|k} + K_{n,k+1}e_{n,z,k+1|k}$$

$$P_{n,k+1|k+1} = (I - K_{n,k+1}C_n)P_{n,k+1|k}$$

$$e_{n,z,k+1|k+1} = z_{k+1} - C_n\hat{x}_{n,k+1|k+1}$$

$$\Lambda_{n,k+1} = \frac{exp\left(\frac{-\frac{1}{2}e_{n,z,k+1|k}^T e_{n,z,k+1|k}}{S_{n,k+1}}\right)}{\sqrt{|2\pi S_{n,k+1}|}}$$

$$c = \sum_{j=1}^{n} \Lambda_{j,k+1} \sum_{i=1}^{n} p_{ij}\, \mu_{i,k}\,, \qquad \mu_{j,k} = \frac{1}{c}\Lambda_{j,k+1}\sum_{i=1}^{r} p_{ij}\,\mu_{i,k}, j = 1, \dots, n$$

$$\hat{x}_{k+1|k+1} = \sum_{j=1}^{r} \mu_{j,k+1}\hat{x}_{j,k+1|k+1}$$

$$P_{k+1|k+1} = \sum_{j=1}^{r} \mu_{j,k+1}\left\{P_{j,k+1|k+1} + (\hat{x}_{j,k+1|k+1} - \hat{x}_{k+1|k+1})(\hat{x}_{j,k+1|k+1} - \hat{x}_{k+1|k+1})^T\right\}$$

Fig. 1 IMM algorithm [24].

3. SYSTEM UNDER SCOPE AND SIMULATION RESULTS

3.1 The Electrohydrostatic Actuator (EHA)

The EHA from [24] is used to test the proposed method IMM-SIF. The system is shown in Fig. 2 and summarized by the following state equation:

$$x_{k+1}=\begin{bmatrix} x_{1,k}+Tx_{2,k} \\ x_{2,k}+Tx_{3,k} \\ \left[1-T\dfrac{a_2V_0+M\beta_eL}{MV_0}\right]x_{3,k}-T\dfrac{(A_E^2+a_2L)\beta_e}{MV_0}x_{2,k} \\ -T\dfrac{2a_1V_0x_{2,k}x_{3,k}+\beta_eL\left(a_1x_{2,k}^2+a_3\right)}{MV_0}sgn\left(x_{2,k}\right)+T\dfrac{A_E\beta_e}{MV_0}u_k \\ \dfrac{1}{A_E}\left(a_2x_{2,k}+\left(a_1{x_{2,k}}^2+a_3\right)sgn\left(x_{2,k}\right)\right) \end{bmatrix} \tag{1}$$

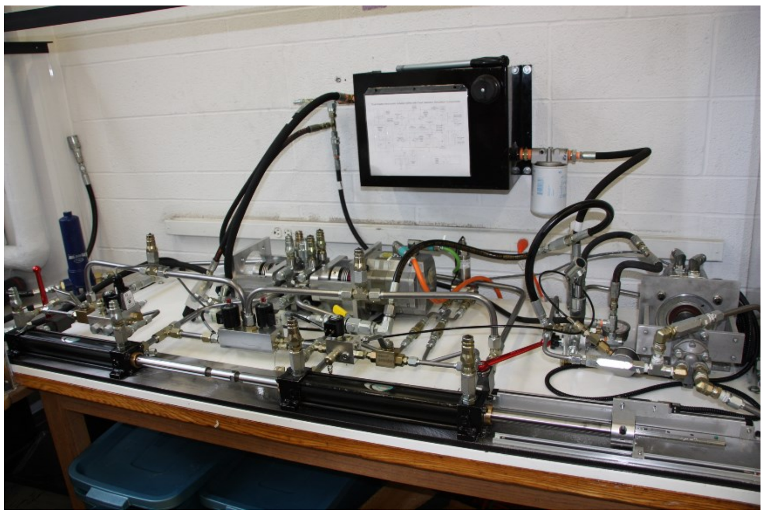

Fig 2. The EHA under study [24].

The system is studied under three different operating modes: normal mode, friction mode, and internal leakage mode. We assume that only the first and the fourth states are measured. The sample rate used in this simulation was $T = 0.1\ ms$. The results of the proposed method are shown in Fig 3. The proposed method was compared to IMM-UKF. The comparisons are shown in Figures 4 and 5, and Tables 2 and 3.

3.2 Results and Discussion

Both the IMM-SIF and IMM-UKF successfully detected the correct operating mode. The IMM-UKF strategy correctly identified the normal operation with a probability level of 70.28% while IMM-SIF had 93.26%. They obtained the leakage operation with the highest probability level of 80.33% for IMM-UKF and 96.27% for IMM-SIF. For the friction mode, the highest probability levels were 93.68% and 93.91% for the IMM-UKF and IMM-SIF, respectively. In this example, the IMM-SIF has better performance in detecting the correct operating mode.

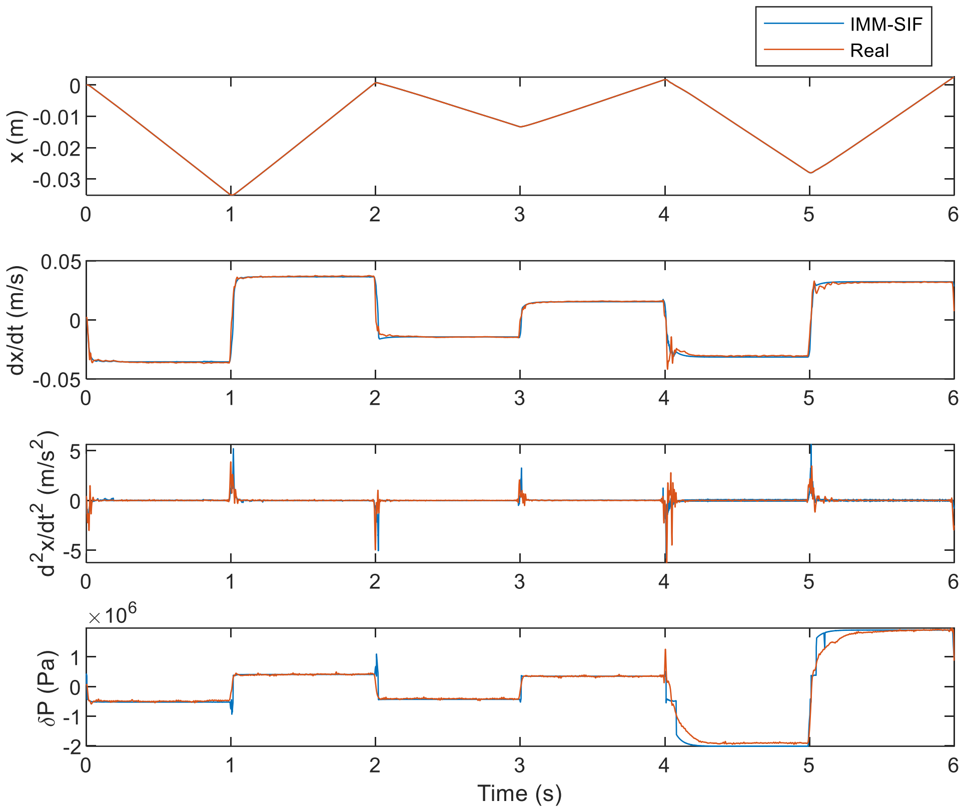

Figure 3. The experimental EHA states with time.

Table 2. IMM-UKF Mode Probability Results (Confusion Matrix)

		Actual Condition		
		Normal	Leakage	Friction
Predicted Condition	Normal	70.28 %	16.67 %	2.72 %
	Leakage	29.63 %	80.33 %	3.60 %
	Friction	0.09 %	3.00 %	93.68 %

Table 3. IMM-SIF Mode Probability Results (Confusion Matrix)

		Actual Condition		
		Normal	Leakage	Friction
Predicted Condition	Normal	93.26 %	3.06 %	2.80 %
	Leakage	6.16 %	96.27 %	3.29 %
	Friction	0.458%	0.66 %	93.91 %

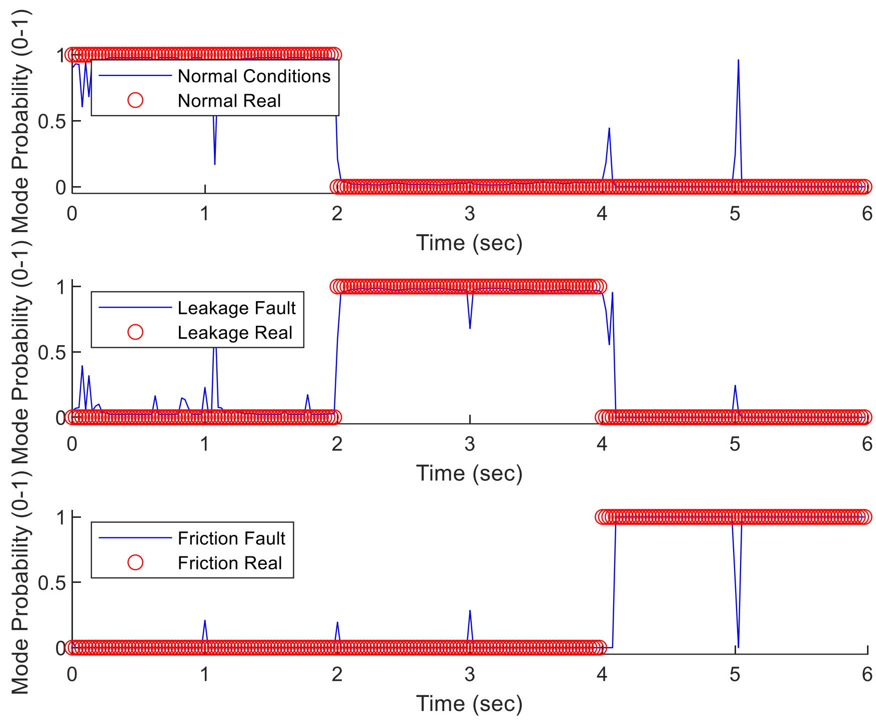

Fig 4. Calculated mode probabilities over time for the EHA using IMM-SIF.

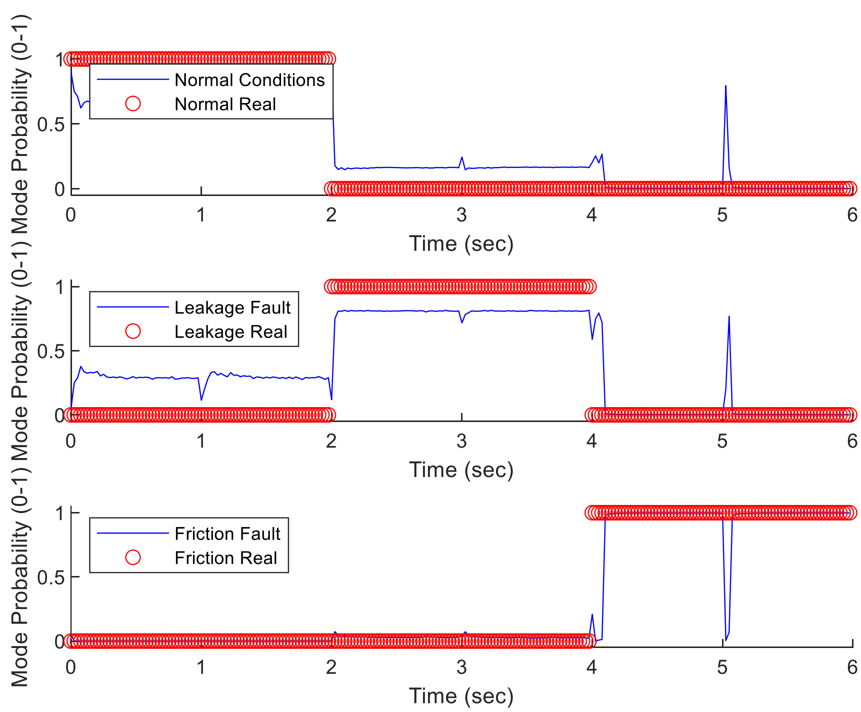

Fig 5. Calculated mode probabilities over time for the EHA using IMM-UKF.

4. CONCLUSIONS

In this very brief work, both the SIF and KF were combined with the IMM technique. The methods were used to estimate the states during faulty conditions of an electrohydrostatic actuator. The results demonstrated that the IMM-SIF was robust during fault conditions and predicted the correct operating mode with a higher probability compared with the IMM-UKF. For future work, an experimental setup will be used to verify the results and a more comprehensive study and comparison will be completed.

Appendix

Table 6. List of Nomenclature and Corresponding Definition

$\boldsymbol{f}$	Nonlinear system	$\boldsymbol{e_z}$	Innovation vector
$\boldsymbol{x}$	State vector	$\boldsymbol{\psi}$	SIF smoothing boundary layer width
$\boldsymbol{z}$	Measurement vector	$\boldsymbol{\mu_j}$	Mode probabilities
$\boldsymbol{A}$	linearized system matrix	$\boldsymbol{\mu_{i\|j}}$	Mixing probabilities
$\boldsymbol{C}$	Measurement matrix	$\boldsymbol{\Lambda_j}$	Likelihood function
$\boldsymbol{K}$	Filter gain matrix	$\boldsymbol{diag}[\boldsymbol{a}]$	Diagonal of some value **a**
$\boldsymbol{P}$	State error covariance matrix	$\boldsymbol{sat}()$	Saturation function
$\boldsymbol{P_{xz}}$	Cross-covariance matrix	$\|\boldsymbol{a}\|$	Absolute value of **a**
$\boldsymbol{P_{zz}}$	Innovation covariance matrix	$\boldsymbol{T}$	Sample rate
$\boldsymbol{Q}$	System noise covariance matrix	+	Pseudoinverse of a non-square matrix
$\boldsymbol{R}$	Measurement noise covariance matrix	~	Error or difference of some value
$\boldsymbol{S}$	Innovation covariance matrix	^	Estimated values

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