Application of the Sliding Innovation Filter for Fault Detection and Diagnosis of an Electromechanical System

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ABSTRACT

This brief work introduces the use of the relatively new sliding innovation filter in the field of fault detection and diagnosis. This important area is part of signal processing techniques that are widely used in industrial practice, telecommunications, optical systems, and robotics, to name a few. This filter overcomes robustness issues during faults caused by modeling uncertainties. This brief work explores the properties and quality of the filter outputs applied on an electromechanical system. The results are compared with the well-known and studied Kalman Filter.

Keywords: sliding innovation filter, estimation theory, signal processing, fault detection and diagnosis

1. INTRODUCTION

This work includes the relatively new model-based filter that referred to as the sliding innovation filter (SIF). It is a filter that shares the same principles of sliding mode observers and the smooth variable structure filter which was first introduced in 2007 [1-9]. The results are compared to the optimal estimation solution that is known as the Kalman filter (KF) [10-19].

The application under scope in this work is to estimate the states and diagnose the fault when it occurs on an electromechanical system. Quite often an estimation technique is required to accomplish this type of task. Estimation is a mathematical process that is used to predict, estimate, smooth and/or filter noise and other disturbances from a signal while extracting useful information of the system. In this work, a filter is used for fault detection purposes.

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

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2. ESTIMATION THEORIES

Kalman Filter

The KF provides the optimal solution to the estimation problem. The following equations summarize the KF algorithm [20]:

$$\hat{x}_{k+1|k} = A\hat{x}_{k|k} + Bu_k \tag{1}$$

$$P_{k+1|k} = AP_{k|k}A^T + Q_k \tag{2}$$

$$K_{k+1} = P_{k+1|k}C^T\left[CP_{k+1|k}C^T + R_{k+1}\right]^{-1} \tag{3}$$

$$\hat{x}_{k+1|k+1} = \hat{x}_{k+1|k} + K_{k+1}\left[z_{k+1} - C\hat{x}_{k+1|k}\right] \tag{4}$$

$$P_{k+1|k+1} = [I - K_{k+1}C]P_{k+1|k}[I - K_{k+1}C]^T + K_{k+1}R_{k+1}K_{k+1}^T \tag{5}$$

where x, z and u are the state, measurement, and input vectors, respectively. A, B and C are the system, input and measurement matrices, respectively. P, Q and R are the error, and system and measurement noise covariance matrices, respectively.

Sliding Innovation Filter

The SIF is a robust filter that guarantees the stability of a filter during significant modelling uncertainties. The following equations summarize the SIF algorithm [1]:

$$\hat{x}_{k+1|k} = A\hat{x}_{k|k} + Bu_k \tag{6}$$

$$\hat{z}_{k+1|k} = C\hat{x}_{k+1|k} \tag{7}$$

$$K_{k+1} = C_k^+ diag\left[\left|sat\left(z_{k+1} - C\hat{x}_{k+1|k}, \psi\right)\right|\right] \tag{8}$$

$$sat\left(e_{z_{k|k-1}}, \Psi\right) = \begin{Bmatrix} e_{z,1_{k|k-1}}/\Psi_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & e_{z,m_{k|k-1}}/\Psi_m \end{Bmatrix} \tag{9}$$

$$\hat{x}_{k+1|k+1} = \hat{x}_{k+1|k} + K_{k+1}\left[z_{k+1} - C\hat{x}_{k+1|k}\right] \tag{10}$$

3. ELECTROMECHANICAL SYSTEM AND SIMULATION RESULTS

Electromechanical System

In this paper, the electromechanical system in [20] is considered. This system represents an electrohydrostatic actuator (EHA) commonly used to study aerospace flight surface actuators. The system has the following equation for normal operation:

$$x_{k+1} = \begin{bmatrix} 1 & 0.0001 & 0 \\ 0 & 1 & 0.0001 \\ 0 & -41.0258 & 0.6099 \end{bmatrix} x_k + \begin{bmatrix} 0 \\ 0 \\ 0.0135 \end{bmatrix} u_k \tag{11}$$

During the operation, the system suffers from severe friction (between 4 sec to 8 sec) where:

$$x_{k+1} = \begin{bmatrix} 1 & 0.0001 & 0 \\ 0 & 1 & 0.0001 \\ 0 & -51.8627 & 0.2226 \end{bmatrix} x_k + \begin{bmatrix} 0 \\ 0 \\ 0.0135 \end{bmatrix} u_k \tag{12}$$

Finally, a severe leakage coefficient (between 8 sec to 10 sec) where:

$$x_{k+1} = \begin{bmatrix} 1 & 0.0001 & 0 \\ 0 & 1 & 0.0001 \\ 0 & -73.5364 & 0.6015 \end{bmatrix} x_k + \begin{bmatrix} 0 \\ 0 \\ 0.0135 \end{bmatrix} u_k \tag{13}$$

In this study, the simulation is conducted under the following conditions:

1. Assuming all states are measured.
2. Assuming only the position is measured.

Estimation and Fault Detection Results

The simulation results are summarized by Table 1 and Figures 1 through 3. The results revealed that both the SIF and KF perform on the same level when all states are measured. In this case, the KF yields better estimation performance. However, when the number of measurements were reduced, the SIF provided better results. The root mean squared error (RMSE) of the SIF was increased by almost 5% between the two cases. The RMSE of the KF was increased by almost million times (for the acceleration state) indicating a failed result.

Table 1. RMSE results for Case 1 and Case 2.

	RMSE			
	Case1		Case 2	
	KF	SIF	KF	SIF
$\boldsymbol{x}$	5.3×10^{-6}	3.2×10^{-6}	3.8×10^{-9}	7.4×10^{-6}
$\boldsymbol{V_x}$	7.3×10^{-9}	7.2×10^{-9}	3.6×10^{-2}	7.7×10^{-9}
$\boldsymbol{A_x}$	7.2×10^{-7}	7.2×10^{-7}	1.6×10^{-1}	7.4×10^{-7}

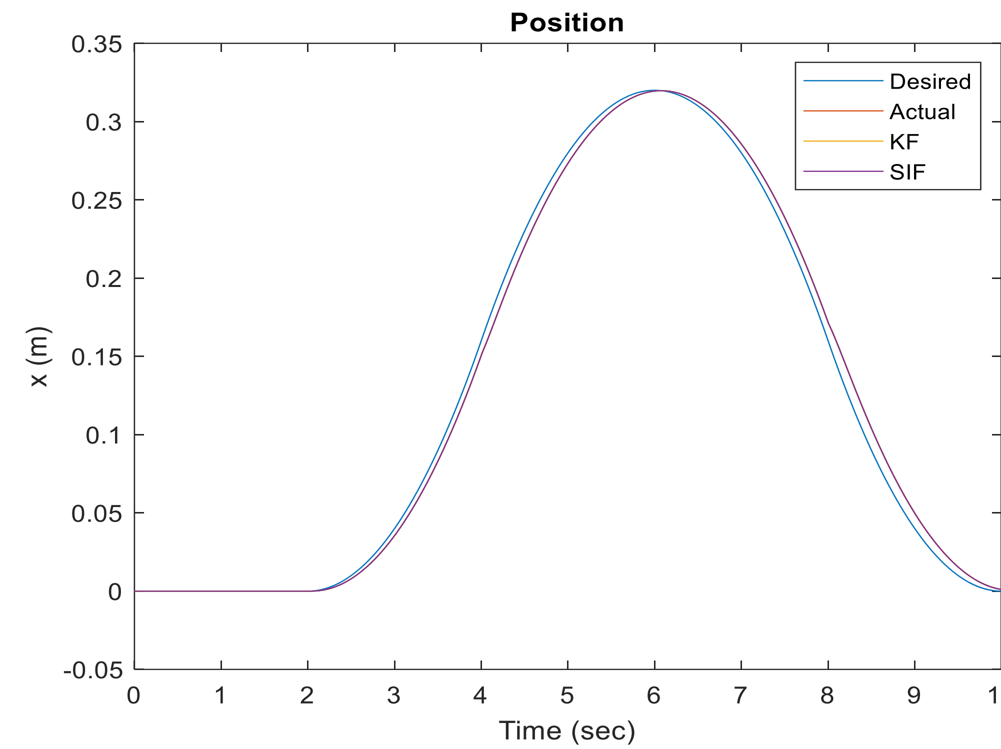

Figure 1. Estimated position trajectory using the KF and SIF strategies for Case 2.

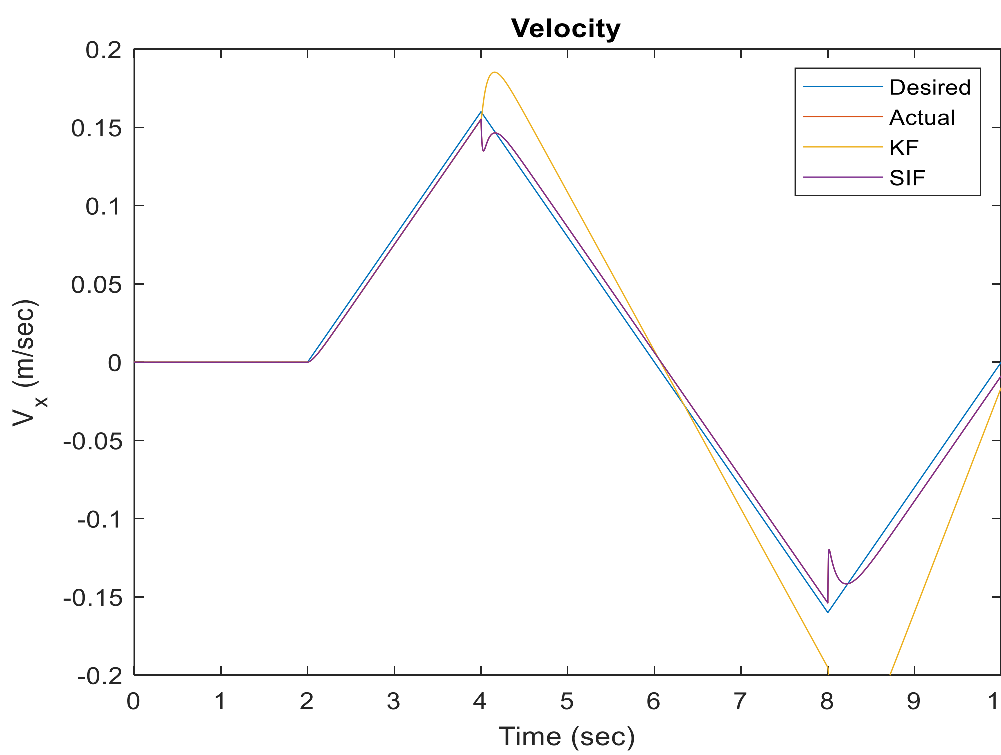

Figure 2. Estimated velocity trajectory using the KF and SIF strategies for Case 2.

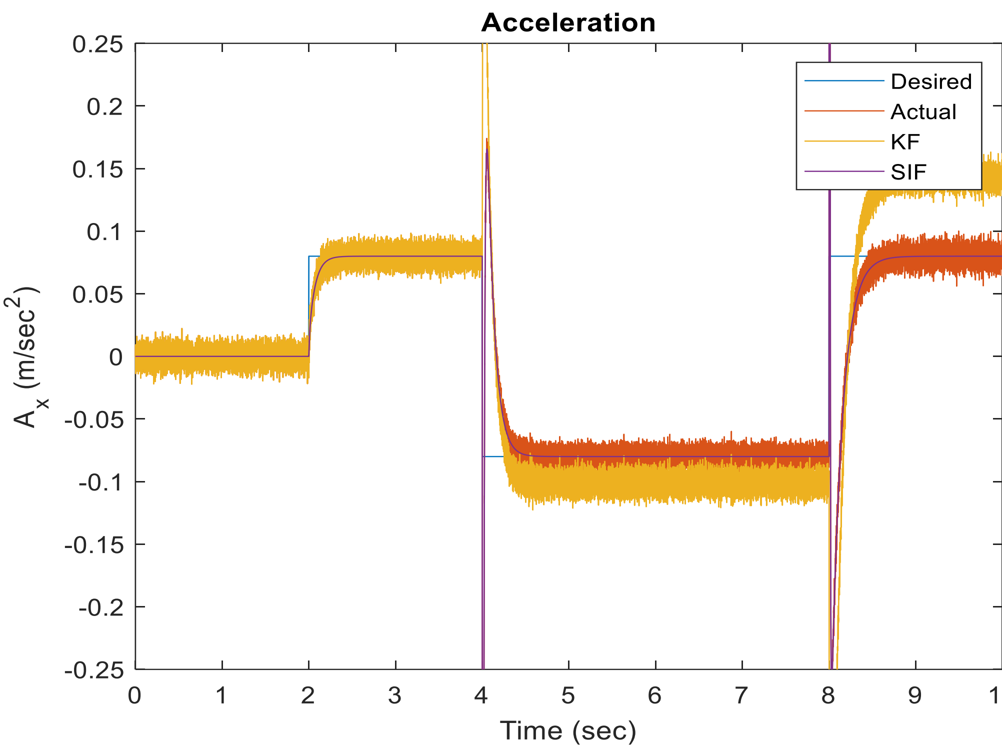

Figure 3. Estimated acceleration trajectory using the KF and SIF strategies for Case 2.

4. CONCLUSIONS

In this very brief paper, the SIF and KF were used to estimate the states during faulty conditions of an EHA. The results showed that SIF was robust during the fault condition and resisted the negative effects of modelling uncertainties compared with the KF. This was clearly observed when the number of measured states was reduced. For future work, an experimental setup will be used to verify the results and a more comprehensive study and comparison will be completed.

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