Application of the Sliding Innovation Filter to Unmanned Aerial Systems

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ABSTRACT

The applications of unmanned aerial systems (UASs) have grown in popularity due to their simplicity and availability. The quality of UAS's performance depends usually on adding several sensors and controllers that improve accuracy and flight performance. However, this typically increases the overall cost of the system. In this paper, a technique to enhance the performance while maintaining UAS affordability is proposed. This technique involves the use of an estimation strategy to extract hidden information from only a few sensors while improving the quality of the achieved signal. The simulation results of this method show strong performance, and are compared with another well-known estimation method.

Keywords: Sliding innovation filter, estimation strategies, quadrotor dynamics

1. INTRODUCTION

The sliding innovation filter (SIF) is a newly developed filter that is formulated as a predictor-corrector filter. It is a model-based filter that use two models: one to model the system and another to model the sensor. Its gain was developed using Lyapunov theory and sliding mode concepts [1]. The SIF shares similar principles to the smooth variable structure filter (SVSF) and other sliding mode observers (SMOs) [2-9]. These strategies have different concepts compared with the Kalman filter (KF) and its various forms, which depends on minimizing the state error [10-19]. The sliding mode structures are considered sub-optimal but robust to modeling uncertainties and disturbances [14-19].

Unmanned air vehicles (UAVs) and systems are widely, particularly multirotor vehicles (MV) such as quadcopters. These vehicles use thrust to fly which is produced by propellers turned by electric motors and controlled by electronic speed controllers. The entire dynamic of the vehicle is achieved by changing the speed of the rotors (propeller).

This very brief paper is organized as follows. The SIF is summarized in Section 2. An overview of a common UAV system and model is shown Section 3. Sections 4 and 5 are dedicated to the results of the simulation and concluding remarks, respectively.

Unmanned Systems Technology XXIII, edited by Hoa G. Nguyen, Paul L. Muench,
Brian K. Skibba, Proc. of SPIE Vol. 11758, 117580T · © 2021 SPIE
CCC code: 0277-786X/21/$21 · doi: 10.1117/12.2587346

2. THE SLIDING INNOVATION FILTER

The SIF is an estimation strategy which was derived based on sliding mode principles. It shares the same principles of the SVSF and the SMO, and is formulated as predictor-corrector method. The filter structure is summarized in Table 1.

Table 1. The pseudocode for the SIF code, as per [1].

$k = 0 \rightarrow Initialize\ \hat{\mathbf{x}}_{0|0}\ and\ \mathbf{P}_{0|0}$

Start $k = k + 1$

$\hat{\mathbf{x}}_{i_{k|k-1}} = \hat{\mathbf{f}}(\hat{\mathbf{x}}_{k-1|k-1}, u_{k-1})$

$\hat{\mathbf{z}}_{k|k-1} = \hat{\mathbf{h}}\left(\hat{\mathbf{x}}_{i_{k|k-1}}\right)$

$e_{z_{k|k-1}} = \mathbf{z}_k - \hat{\mathbf{z}}_{k|k-1}, \hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k\left(e_{z_{k|k-1}}\right)$

$\mathbf{K}_k = \mathbf{H}^{+} sat(e_{z_{k|k-1}}, \Psi)$, where $sat\left(e_{z_{k|k-1}}, \Psi\right) = \left\{\begin{matrix} e_{z,1_{k|k-1}}/\Psi_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & e_{z,m_{k|k-1}}/\Psi_m \end{matrix}\right\}$

Go back to Start

3. UAV MODELING

In this work, a special type of UAV is considered, which is the well-known quadcopter. A quadrotor consists of four motors and it is fully controlled by adjusting the speed of the rotors as shown in Fig. 1. This will cause changes in the vehicle location (x, y, z) and orientation (θ, ψ, ϕ). The typical forces on a quadcopter are illustrated by Fig. 3.

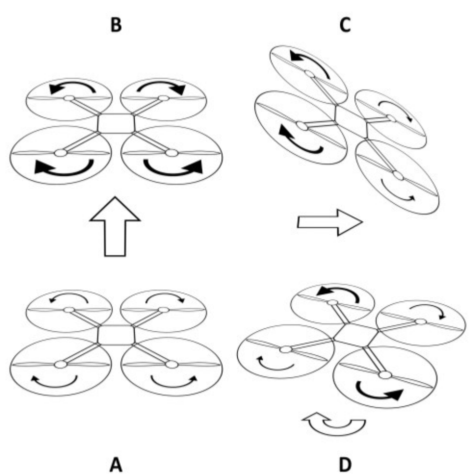

Fig 1. Quadrotor flight: A. Hover, B. Vertical climb, C. Lateral flight, D. Yaw maneuver [20][21]

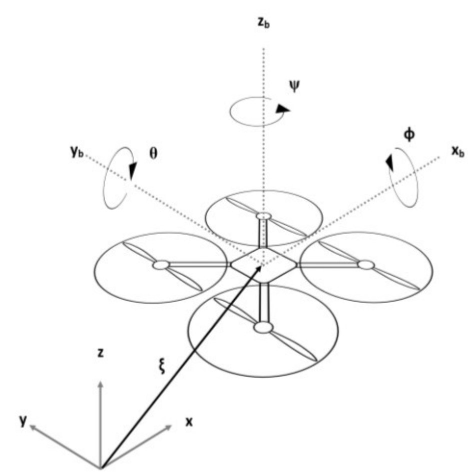

Fig 2. Basic coordinate system for a quadrotor [20][21].

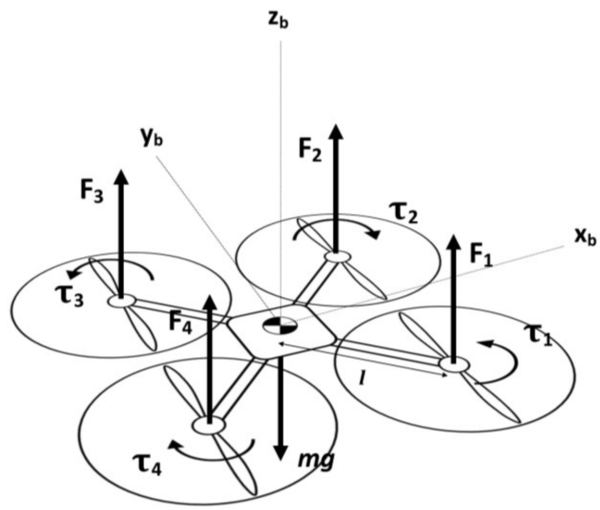

Figure 3. Force and moment balance applied on a quadrotor [20, 21].

The equations of movement are derived in [20, 21] and are summarized as follows, after ignoring the drag forces:

$$\begin{gathered}
\ddot{x} = \frac{(\sum_{n=1}^{4} F_n)(\sin\psi \sin\phi + \cos\psi \cos\phi \sin\theta)}{m} \\
\ddot{y} = \frac{(\sum_{n=1}^{4} F_n)(\cos\phi \sin\psi \sin\theta - \cos\psi \sin\phi)}{m} \\
\ddot{z} = \frac{(\sum_{n=1}^{4} F_n)(\cos\theta \cos\phi) - mg}{m} \\
\ddot{\theta} = l(-F_1 - F_2 + F_3 + F_4)/J_1 \\
\ddot{\phi} = l(-F_1 + F_2 + F_3 - F_4)/J_2 \\
\ddot{\psi} = C(F_1 - F_2 + F_3 - F_4)/J_3
\end{gathered} \tag{1}$$

where the parameters are defined by Table 2. We considered a simple case where all the states are measured.

Table 2. Model parameters used in the simulation [21].

Parameter	**Value (Units)**
J_1, J_2	$0.05\ kg\ m^2$
J_3	$0.10\ kg\ m^2$
m	$4\ kg$
l	$0.315\ m$
C	$1\ m$
g	$9.18\ m/s^2$
T_s	$0.001\ sec$

4. SIMULATION RESULTS

The system in Section 3 was simulated using MATLAB. Both the EKF and SIF are used to estimate the states assuming all the states are measured. The system has twelve states: the previously mentioned states, and their derivatives. The forces are assumed to be random forces that varies between -10 to 10 N. The noise vectors are assumed white and less than 5% of the state's values. Two case scenarios are evaluated:

1. Case 1: No modeling uncertainties.
2. Case 2: With modeling uncertainties.

The root mean squared error (RMSE) results are summarized in Table 3, and Figures 4 and 5. The results revealed that the EKF has better performance than the SIF for Case 1 where the RMSE was almost 20% lower. On the other hand, when modelling uncertainties are present (Case 2), the SIF yields a better performance as the EKF started to give poor results which reached more than 600 times the RMSE that was obtained by the SIF. After taking a closer look at the SIF, it appeared that the RMSE was raised with less than 2% when modelling uncertainties were present. This further demonstrates the robustness and stability of the SIF.

Table 3. RMSE for Case 1 and Case 2.

	RMSE			
	Case1		Case 2	
	SIF	EKF	SIF	EKF
x	0.0565	0.0451	0.0579	7.3470
V_x	0.0562	0.0454	0.0576	2.3041
y	0.0562	0.0448	0.0579	8.7617
V_y	0.0566	0.0451	0.0579	2.2811
z	0.0567	0.0452	0.0579	26.1833
V_z	0.0563	0.0459	0.0578	6.6621
θ	0.0568	0.0459	0.0575	8.3496
$d\theta/dt$	0.0564	0.0452	0.0574	2.0356
ϕ	0.0565	0.0455	0.0573	2.1490
$d\phi/dt$	0.0566	0.0456	0.0578	0.7340
ψ	0.0567	0.0461	0.0575	5.7745
$d\psi/dt$	0.0557	0.0449	0.0573	1.6427

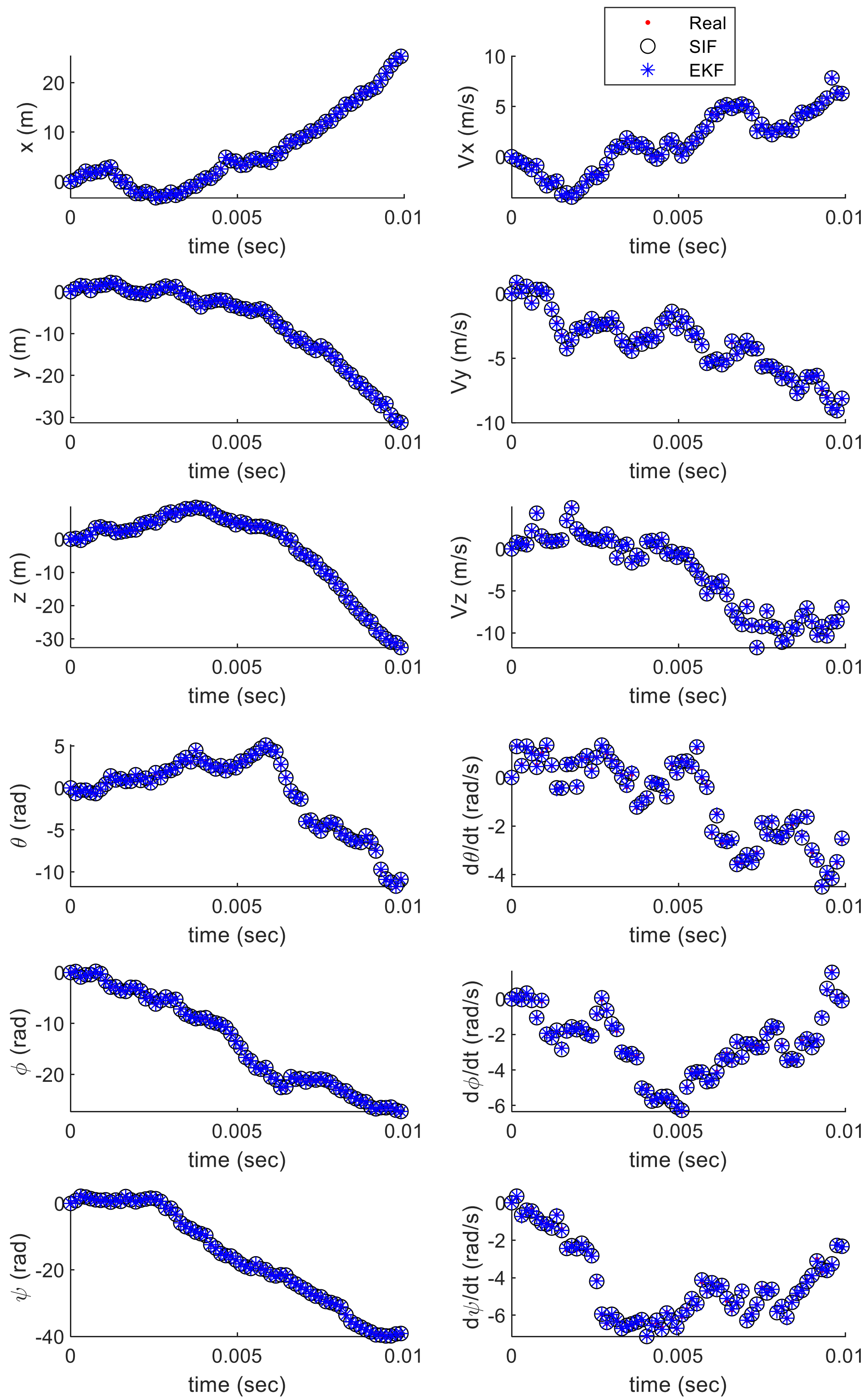

Figure 4. Positions and heading angle for case 1.

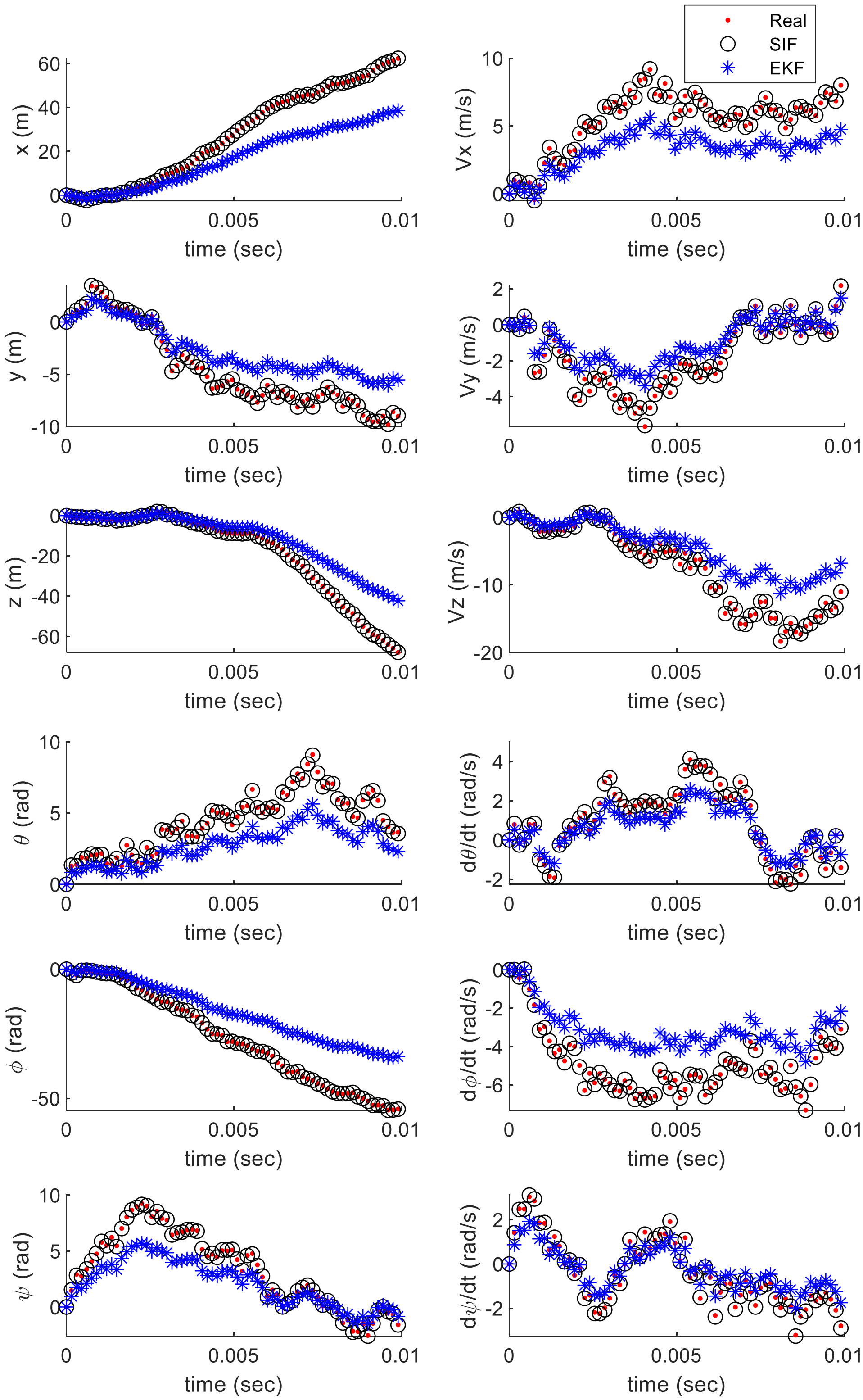

Figure 5. Positions and heading angle for case 2.

5. CONCLUSIONS AND FUTURE WORK

In this brief paper, the SIF was used to estimate the states of a simulated quadcopter system. For completeness of the work, the results were compared to the well-studied EKF. The results demonstrated that EKF yielded the best solution when modelling uncertainties and disturbances were absent. However, the SIF provided the best performance under unknown environments. In future work, an experimental setup will be used to verify the simulated results, and a fewer number of sensors will be considered to check the efficiency of the proposed method.

6. APPENDIX

The following table summarizes the main nomenclature used in this paper.

Table 4. List of nomenclature.

$^{-1}$ ^{T}	Inverse, and transpose, respectively.	$\mathbf{K}_X$	The correction gain of the filter X.
$\mathbf{e_m}$	The estimation error vectors in $\mathbf{m}$.	m, n	Number of measurements and states, respectively.
$\mathbf{f}(.)$	The system's model function.	T_s	Sampling time, and is equal to 0.001 $sec.$
$\mathbf{h}(.)$	The sensor's model function.	$\mathbf{x}$	The state's vector.
i, j	Subscripts used to identify elements.	$\mathbf{z}$	The output's vector.
k	Time step value.	x, y, and z	Location coordinates
$k\|k-1$	The a priori value at time k.	θ, ϕ, and ψ	Orientation
$k\|k$	The a posteriori value at time k.	J	Polar moment of inertia

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