Estimating the Behaviour of a Prismatic-Revolute Robot using a Robust Filtering Strategy

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2023 Advances in Science and Engineering Technology International Conferences (ASET) | 978-1-6654-5474-2/23/$31.00 ©2023 IEEE | DOI: 10.1109/ASET56582.2023.10180589

ABSTRACT– Estimating the states of a manipulator is a challenging task as it consists of sinusoidal functions that cannot be represented by a simple, linear model. In such cases, the well-known extended Kalman filter (EKF) may not yield reliable estimates. The calculation of the Jacobian matrix, as part of the EKF, may not be straightforward and introduces errors in the nonlinear approximations. A relatively new estimation strategy called the sliding innovation filter (SIF) offers an alternative solution to the EKF. The SIF forces the estimates to be within a region of the measurements, with some differences due to system modeling. In this paper, the SIF is used to estimate the states of a robotic arm of type prismatic-revolute (PR). The results are compared with the well-known EKF. A faulty scenario is considered when the robot parameters are poorly defined. The results demonstrate the effectiveness and robustness of the SIF, and offers an alternative estimation strategy for estimating different robot types.

KEYWORDS– Sliding innovation filter, extended Kalman filter, prismatic-revolute, uncertainties, robot system.

1. INTRODUCTION

Sliding innovation filter (SIF) was presented in 2020 as a model based filter that uses the true measurements as hyperplanes and forces the estimates to stay within its zone [1-10]. The filter uses a model that approximate the actual system, and then simulates it using the input [11-20]. SIF belongs to the predictor-corrector filter where the filter refines its prediction by a corrector gain that is derived from Lyapunov theorem. Similar to smooth variable structure filter (SVSF) [21-30] and sliding mode observer (SMO) [31-40], the filter is considered robust and stable against any uncertainty.

SIF is different than the Kalman Filter (KF) and its variances like the Extended KF (EKF), the Unscented KF (UKF), and the Lattice KF (LKF). These filters are known to be optimized filters, that seek to minimize a cost function like least squared error and maximum likehood function [41-50].

In this brief work, the SIF is used to estimate the states of a robotic arm (manipulator). The system consists of two joints: prismatic (P) and revolute (R). The PR system, which will be discussed in the following section, looks similar to the cart-pendulum system. The rest of the paper is organized as follows: Section 2 introduces the robotic arm PR, while Section 3 describes SIF and EKF. The results are illustrated and discussed in Section 4 and concluded in Section 5.

2. PR MODEL

A manipulator robotic arm with two joints; one prismatic and one revolute, is illustrated by the schematic of figure 1. The system moves on x-axis, then the second link rotates around the z-axis. The mechanism is similar to a pendulum on a cart.

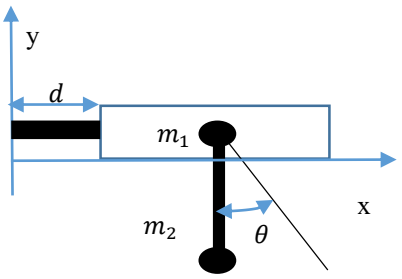


Figure 1. PR robotic arm

To derive the mathematical model for the system, we start with the position of the masses and their velocities.

$$P_{m_1} = [d\ 0\ 0]^T \rightarrow v_1 = \left[\dot{d}\ 0\ 0\right]^T \quad (1)$$

$$P_{m_2} = [d + ls\ \ -lc\ \ 0]^T \rightarrow v_2 = \left[\dot{d} + lc\dot{\theta}\ \ ls\dot{\theta}\ \ 0\right]^T \quad (2)$$

where P_{m_1}, v_1, P_{m_2} and v_2 are the position and velocity of the first mass (m_1), and the position and velocity of the second mass (m_2), respectively. c and s represent the cosine and sine of the angle θ.The angular velocities of the first (ω_1) and second (ω_2) masses are given as:

$$\omega_1 = [0\ 0\ 0]^T \text{ and } \omega_2 = \left[0\ 0\ \dot{\theta}\right]^T \quad (3)$$

Knowing that $g = \left[0\ -g_y\ 0\right]^T$, then the Lagrange function (L) can be formulated as:

$$L = \frac{1}{2}m_1\dot{d}^2 + \frac{1}{2}m_2\left(\dot{d}^2 + 2\dot{d}^2lc\dot{\theta} + l^2\dot{\theta}^2\right) + \frac{1}{2}I_2\dot{\theta}^2 + m_2lcg_y \quad (4)$$

Using the Euler-Lagrange method, the system is:

$$u = M\ddot{\Phi} + V(\Phi, \dot{\Phi}) + G(\Phi) \quad (5)$$

Where u is the input and $M = \begin{bmatrix} (m_1 + m_2) & m_2 lc \\ m_2 lc & (m_2 l^2 + I_2) \end{bmatrix}$, $V(\Phi, \dot{\Phi}) = \begin{bmatrix} -m_2 ls\dot{\theta}^2 \\ 0 \end{bmatrix}$ and $G(\Phi) = \begin{bmatrix} 0 \; m_2 lsg_y \end{bmatrix}^T$. Φ is the system variables and it is equal to $[d \; \theta]^T$.

The discrete representative of the is defined for the states:

$$\mathbf{x} = [x_1 \; x_2 \; x_3 \; x_4]^T = \begin{bmatrix} d \; \theta \; \dot{d} \; \dot{\theta} \end{bmatrix}^T \quad (6)$$

As follows:

$$\mathbf{x}_{k+1} = \mathbf{x}_k + T_s \begin{bmatrix} x_3 \\ x_4 \\ M^{-1}\left(u - V(\Phi, \dot{\Phi}) - G(\Phi)\right) \end{bmatrix}_k \quad (7)$$

For simplicity, the system is rewritten as:

$$\mathbf{x}_k = f(\mathbf{x}_{k-1}, \mathbf{u}_{k-1}) + \mathbf{w}_{k-1}, \mathbf{z}_k = \mathbf{H}_k \mathbf{x}_k + \mathbf{v}_k \quad (8)$$

where T_s is the sampling time and it has a value of $1msec$, and the system noise and measurement noise vectors are $\mathbf{w}_{k-1}$ and $\mathbf{v}_k$, respectively.

3. METHODOLOGY

3.1 SIF algorithm

The SIF has a prediction and a correction stages. In the first stage, an unrefined estimates called the a priori estimate ($\hat{\mathbf{x}}_{k|k-1}$) is obtained using the system model. Later, in the second stage, the filter corrects the estimate to a refined version called the a posteriori estimate ($\hat{\mathbf{x}}_{k|k}$). These steps are as follows:

1- <u>Prediction Stage</u>,

$$\hat{\mathbf{x}}_{k|k-1} = \hat{f}\left(\hat{\mathbf{x}}_{k-1|k-1}, \mathbf{u}_{k-1}\right), \hat{\mathbf{z}}_{k|k-1} = \mathbf{H}_k \hat{\mathbf{x}}_{k|k-1} \quad (9)$$

2- <u>Update Stage</u>,

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \left[S_k\left(\mathbf{z}_k - \hat{\mathbf{z}}_{k|k-1}\right)\right], \hat{\mathbf{z}}_{k|k} = \mathbf{H}_k \hat{\mathbf{x}}_{k|k} \quad (10)$$

where Sat_k is a square diagonal matrix with elements defined as:

$$S_{i,k} = \mathbf{H}_k^+ \begin{cases} \frac{|\mathbf{z}_{i,k} - \hat{\mathbf{z}}_{i,k|k-1}|}{\psi_{i,k}} & \left|\mathbf{z}_{i,k} - \hat{\mathbf{z}}_{i,k|k-1}\right| < \psi_{i,k} \\ 1 & \left|\mathbf{z}_{i,k} - \hat{\mathbf{z}}_{i,k|k-1}\right| \geq \psi_{i,k} \end{cases} \quad (12)$$

where $\psi_{i,k}$ is the boundary layer for the i^{th} measurement and $\mathbf{H}_k^+$ is the pseudoinverse of the measurement matrix.

3.2 EKF algorithm

The EKF is similar to the SIF as it is a predictor-corrector filter. However, it needs to calculate the error covariance matrix ($\mathbf{P}$) using the Jacobian matrix of the system model ($\mathbf{A}$) and the system and measurement covariance matrices, $\mathbf{Q}$ and $\mathbf{R}$, respectively. The algorithm is summarized as follows:

1- <u>Prediction Stage</u>,

$$\hat{\mathbf{x}}_{k|k-1} = \hat{f}\left(\hat{\mathbf{x}}_{k-1|k-1}, \mathbf{u}_{k-1}\right), \hat{\mathbf{z}}_{k|k-1} = \mathbf{H}_k \hat{\mathbf{x}}_{k|k-1} \quad (13)$$

2- <u>Update Stage</u>,

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + K_k\left(\mathbf{z}_k - \hat{\mathbf{z}}_{k|k-1}\right), \hat{\mathbf{z}}_{k|k} = \mathbf{H}_k \hat{\mathbf{x}}_{k|k} \quad (14)$$

Where

$$\mathbf{K}_k = \mathbf{P}_{k|k-1}\mathbf{H}_k^T\left(\mathbf{H}_k \mathbf{P}_{k|k-1}\mathbf{H}_k^T + \mathbf{R}_k\right)^{-1} \quad (16)$$

and

$$\mathbf{P}_{k|k-1} = \mathbf{A}_{k-1}\mathbf{P}_{k-1|k-1}\mathbf{A}_{k-1}^T + \mathbf{Q}_{k-1} \quad (17)$$

4. SIMULATION RESULTS

The EKF and SIF are applied to the nonlinear system PR robotic arm derived in Section 2. The algorithms are simulated 1000 times as Monte Carlo simulation for each case of the two cases, without (case 1) and with (case 2)

Table 1. Simulation parameters for system and filters

Parameter	Actual System	Filter with no uncertainties	Filter with uncertainties
m_1	$1\ kg$	$1\ kg$	$0.01\ kg$
m_2	$0.1\ kg$	$0.1\ kg$	$0.01\ kg$
I_2	$0.0037\ kg.m^2$	$0.0037\ kg.m^2$	$0.0\ kg.m^2$
l	$0.3\ m$	$0.3\ m$	$0.1\ m$
ψ_k for SIF		$[0.1\ 0.1\ 0.3\ 0.5]^T$	
$Q = R$ for EKF		$diag([3.33 \times 10^{-5}\ \ 3.33 \times 10^{-5}\ \ 3.33 \times 10^{-3}\ \ 3.33 \times 10^{-3}])$	
P_0 for EKF		$diag([3.33 \times 10^{-4}\ \ 3.33 \times 10^{-4}\ \ 3.33 \times 10^{-2}\ \ 3.33 \times 10^{-2}])$	

modeling uncertainties. The parameters of the two cases are summarized in table 1. Each simulation has different noise amplitudes. For each run, the root mean squared error (RMSE) and the maximum absolute error (MAE) are calculated as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{ns}\left(x_{Actual,i}-x_{Prediction,i}\right)^2}{ns}} \quad (18)$$

$$MAE = \max(|x_{Actual} - x_{Prediction}|) \quad (19)$$

Figure 2 shows the Monte Carlo Simulation results for case 1 and case 2, while Figures 3 and 4 show the error of the states for case 1 and case 2, respectively. The results are grouped for RMSE in (a) and (c), and MAE in (b) and (d). The results are found for the best solution for both filter in both cases and they are tabulated in Table 2 for case 1 and Table 3 for case 2. The results show similar behavior during Monte Carlo simulation. Moreover, they show a superior performance of SIF compared to EKF for both cases. Moreover, they show that the SIF's RMSE and MAE are reduced up to 25% compared to the EKF performance for case 1, and up to 50% for RMSE and 90% for MAE for case 2.

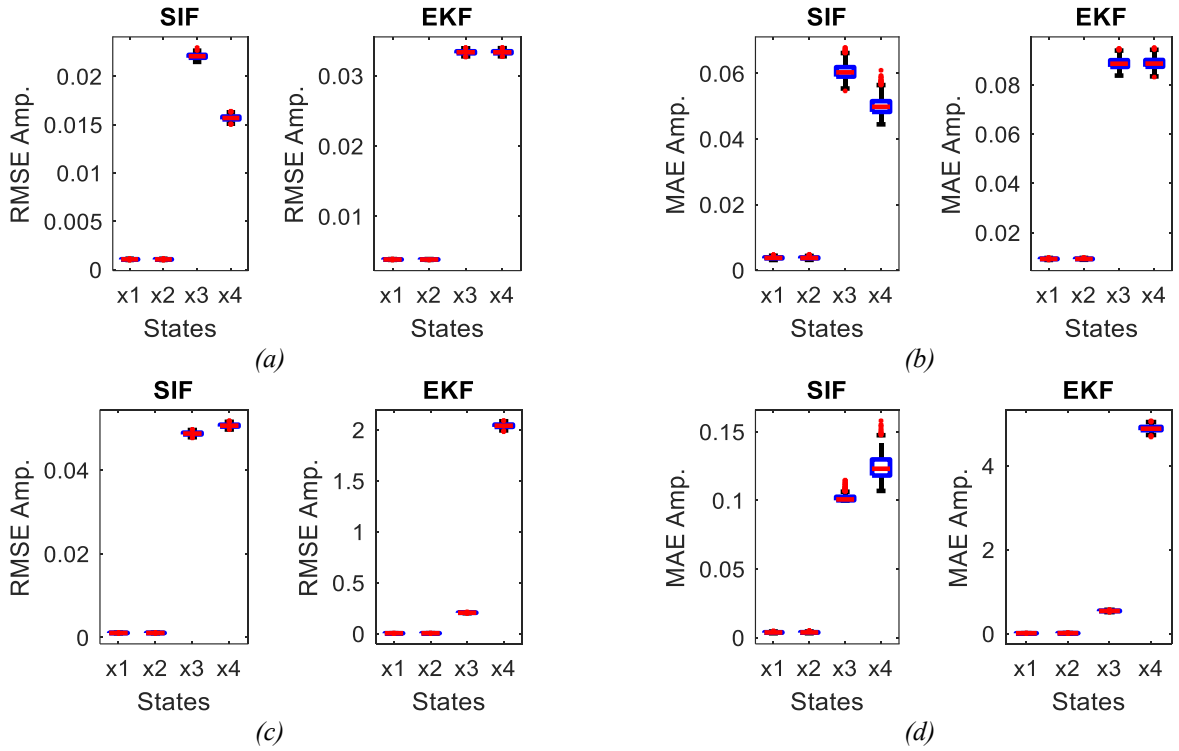
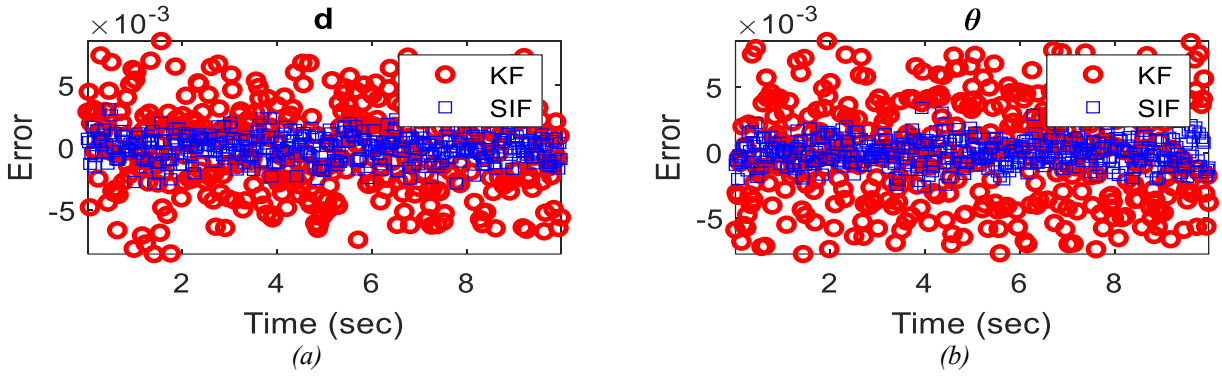
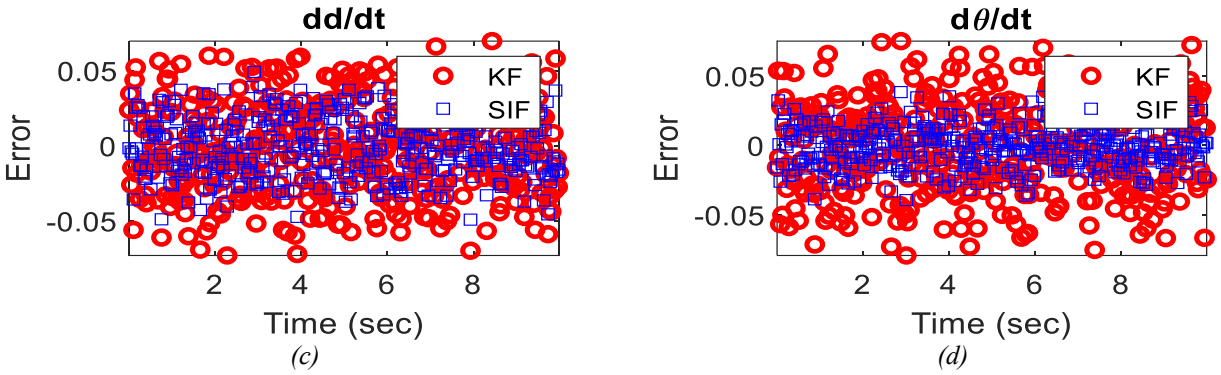


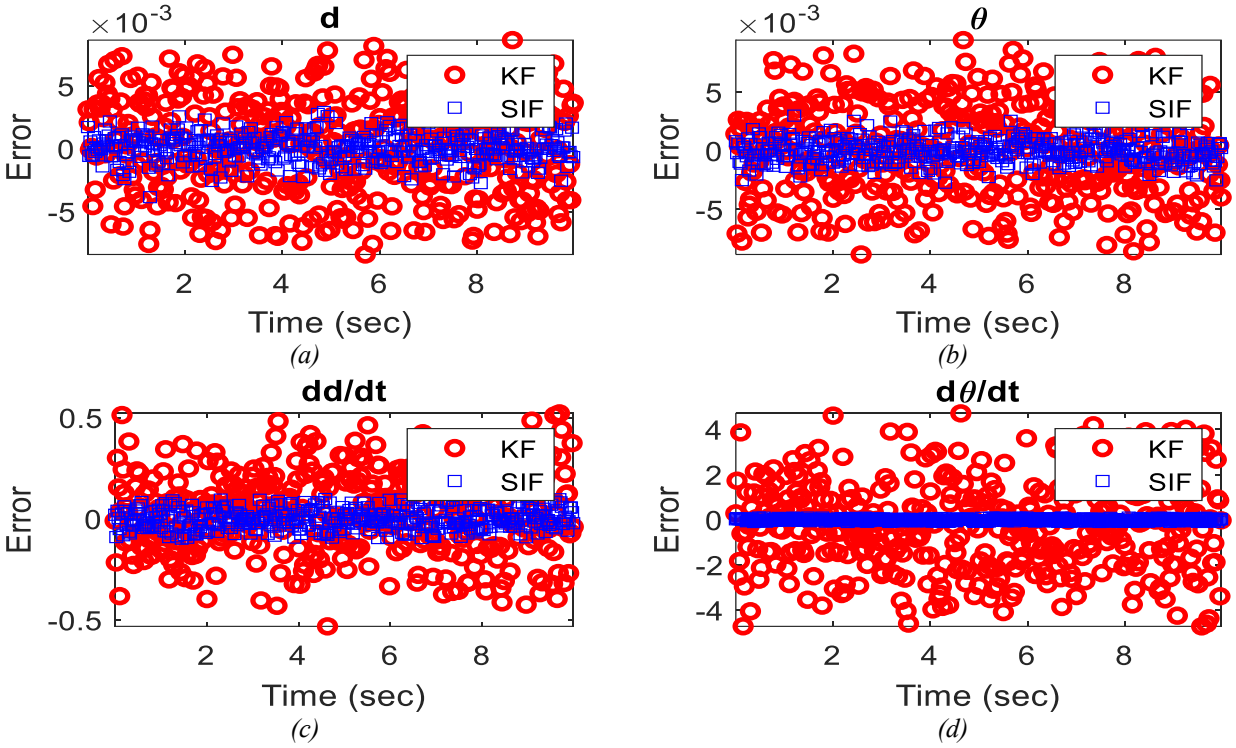
Figure 2. The Monte Carlo Simulation results for (a) RMSE and (b) MAE for case 1, and for (c) RMSE and (d) MAE for case 2.





(c) (d)

Figure 3. The performance of the filters for (a) first, (b) second, (c) third and (d) fourth states for case 1.



(a) (b) (c) (d)

Figure 4. The performance of the filters for (a) first, (b) second, (c) third and (d) fourth states for case 1.

Table 2. RMSE and MAE for case 1

	RMSE in		*MAE* in	
	SIF	*EKF*	*SIF*	*EKF*
$x_1\ (m)$	1.1×10^{-03}	3.8×10^{-03}	3.9×10^{-03}	9.4×10^{-03}
$x_2(rad)$	1.0×10^{-03}	3.8×10^{-03}	3.4×10^{-03}	9.3×10^{-03}
$x_3(m/s)$	2.2×10^{-02}	3.3×10^{-02}	5.8×10^{-02}	8.6×10^{-02}
$x_4(rad/s)$	1.5×10^{-02}	3.3×10^{-02}	4.7×10^{-02}	8.9×10^{-02}

Table 3. RMSE and MAE for case 2

	$RMSE$ in		MAE in	
	SIF	*EKF*	*SIF*	*EKF*
$x_1\ (m)$	1.1×10^{-03}	3.9×10^{-03}	3.9×10^{-03}	9.3×10^{-03}
$x_2(rad)$	1.0×10^{-03}	4.0×10^{-03}	3.4×10^{-03}	1.1×10^{-02}
$x_3(m/s)$	4.8×10^{-02}	2.0×10^{-01}	1.0×10^{-01}	5.4×10^{-01}
$x_4(rad/s)$	5.0×10^{-02}	2.0×10^{00}	1.1×10^{-01}	4.8×10^{00}

5. CONCLUSION

In this short paper, the relatively new SIF was applied to a highly nonlinear robotic system of type PR. The SIF was applied under two cases, without and with uncertainties. The performance was compared to the EKF. The results demonstrated a strong performance for the SIF as compared to the EKF, with the largest RMSE of 0.05 and MAE of 0.11. In the future, additional investigations will be conducted for higher-order systems with fewer number of measurements than states.

REFERENCES

[1]. Lee, A.S., Gadsden, S.A., Al-Shabi, M. 2021. An Adaptive Formulation of the Sliding Innovation Filter. IEEE Signal Processing Letters, 28, art. no. 9457191, pp. 1295-1299.

[2]. Al Shabi, M., Gadsden, A., El Haj Assad, M., Khuwaileh, B., Wilkerson, S. 2021. Application of the sliding innovation filter to unmanned aerial systems. Proceedings of SPIE - The International Society for Optical Engineering, 11758, art. No 117580T.

[3]. Al Shabi, M., Gadsden, S.A., El Haj Assad, M., Khuwaileh, B. 2021 A multiple model-based sliding innovation filter. Proceedings of SPIE - The International Society for Optical Engineering, 11756, art. no. 1175608.

[4]. Al Shabi, M., Gadsden, S.A., El Haj Assad, M., Khuwaileh, B. 2021. The two-pass sliding innovation smoother. Proceedings of SPIE - The International Society for Optical Engineering, 11756, art. no. 1175609.

[5]. Al Shabi, M., Gadsden, S.A., El Haj Assad, M., Khuwaileh, B. 2021. Application of the sliding innovation filter for fault detection and diagnosis of an electromechanical system. Proceedings of SPIE - The International Society for Optical Engineering, 11756, art. no. 1175607.

[6]. Gadsden, S.A., Al-Shabi, M., Wilkerson, S.A. (2021) Development of a second-order sliding innovation filter for an aerospace system. Proceedings of SPIE - The International Society for Optical Engineering, 11755, art. no. 117550T.

[7]. Gadsden, S. A., Al-Shabi, M. 2020. The Sliding Innovation Filter. IEEE Access, 8, art. no. 9096294, pp. 96129-96138.

[8]. Bustos, R., Gadsden, S.A., Malysz, P., Al-Shabi, M., Mahmud, S. 2022. Health Monitoring of Lithium-Ion Batteries Using Dual Filters. Energies, 15 (6), art. no. 2230.

[9]. Alsadi, N., Hilal, W., Surucu, O., Giuliano, A., Gadsden, S., Yawney, J., AlShabi, M. 2022. Neural network training loss optimization utilizing the sliding innovation filter. Proceedings Volume 12113, Artificial Intelligence and Machine Learning for Multi-Domain Operations Applications IV; 121131Z.

[10]. Spotts, I., Brodie, C., Gadsden, A., AlShabi, M., Collier, C. 2021. A comparison of nonlinear filtering methods for blackbody radiation applications in photonics. Proceedings Volume 11841, Optics and Photonics for Information Processing XV; 118410O.

[11]. Kailath, T. 1974. A View Of Three Decades Of Linear Filtering Theory. IEEE Transactions on Information Theory IT-20 (Issue 2): 146-181.

[12]. Anderson, B.D.O., and J.B. Moore. 1979. Optimal Filtering. Prentice-Hall.

[13]. Maybeck, P. 1979. Stochastic Models, Estimation, And Control. (Academic Press, Inc).

[14]. Bar-Shalom, Y., and X. Li. 1993. Estimation and Tracking: Principles, Techniques and Software. Norwood, MA: 1993 ARTECH HOUSE, INC.

[15]. Barakat, M. 2005. Signal Detection And Estimation. Norwood :Artech House.

[16]. Bar-Shalom, T., X. Li, and T. Kirubarajan. 2001. Estimation With Applications To Tracking And Navigation – Theory, Algorithm And Software. John Wiley & Sons, Inc.

[17]. Spotts, I., Brodie, C.H., Gadsden, S.A., Al-Shabi, M., Collier, C.M. 2001. A comparison of nonlinear filtering methods for blackbody radiation applications in photonics. Proceedings of SPIE - The International Society for Optical Engineering, 11841, art. no. 118410O.

[18]. Jilkovand, V., and X. Li. 2002. On The Generalized Input Estimation. Information & Security 9: 90-96.

[19]. Sadati, N., and A. Ghaffarkhah. 2007. Polyfilter; A New State Estimation Filter For Nonlinear Systems. International Conference on Control, Automation and Systems. 2643-2647.

[20]. Zheng, J., Y. Feng, and X. Yu. 2008. Hybrid Terminal Sliding Mode Observer Design Method for Permanent Magnet Synchronous Motor Control System. 2008 International Workshop on Variable Structure Systems (VSS 2008) (IEEE) 106 - 111.

[21]. Gadsden, S. A., Al-Shabi, M. 2020. A study of variable structure and sliding mode filters for robust estimation of mechatronic systems. IEMTRONICS 2020 - International IOT, Electronics and Mechatronics Conference, Proceedings, art. no. 9216381.
[22]. Habibi, S. 2005. Performance Measures of the Variable Structure Filter. Transactions of the Canadian Society for Mechanical Engineering 29 (2): 267 - 295.
[23]. Al-Shabi, M., Saleem, A., Tutunji, T.A. 2011. Smooth Variable Structure Filter for pneumatic system identification. 2011 IEEE Jordan Conference on Applied Electrical Engineering and Computing Technologies, AEECT 2011, 2011, 6132500
[24]. Habibi, S. 2007. The Smooth Variable Structure Filter. Proceedings of the IEEE 95 (5): 1026 - 1059.
[25]. Gadsden, S.A., Al-Shabi, M., Kirubarajan, T. 2015. Square-root formulation of the SVSF with applications to nonlinear target tracking problems. Proceedings of SPIE - The International Society for Optical Engineering, 9474, 947408
[26]. Gadsden, S.A., Al-Shabi, M., Kirubarajan, T. 2015. Two-pass smoother based on the SVSF estimation strategy. Proceedings of SPIE - The International Society for Optical Engineering, 9474, 947409
[27]. Al-Shabi, M., Habibi, S. 2011. Iterative smooth variable structure filter for parameter estimation. ISRN Signal Processing, 2011 (1), art. no. 725108.
[28]. Al-Shabi, M., Saleem, A., Tutunji, T.A. 2011. Smooth Variable Structure Filter for pneumatic system identification. 2011 IEEE Jordan Conference on Applied Electrical Engineering and Computing Technologies, AEECT 2011, art. no. 6132500
[29]. Gadsden, S.A., Al-Shabi, M.A., Habibi, S.R. 2013. A fuzzy-smooth variable structure filtering strategy: For state and parameter estimation. 2013 IEEE Jordan Conference on Applied Electrical Engineering and Computing Technologies, AEECT 2013, art. no. 6716481
[30]. Avzayesh, M., Abdel-Hafez, M., AlShabi, M., Gadsden, S.A. 2021. The smooth variable structure filter: A comprehensive review. Digital Signal Processing: A Review Journal, 110, art. no. 102912
[31]. Zheng, J., Y. Feng, and X. Yu. 2008. Hybrid Terminal Sliding Mode Observer Design Method for Permanent Magnet Synchronous Motor Control System. 2008 International Workshop on Variable Structure Systems (VSS 2008) (IEEE) 106 - 111.
[32]. Madani, T., and A. Benallegue. 2007. Sliding Mode Observer and Backstepping Control for a Quadrotor Unmanned Aerial Vehicle. Proceedings of the 2007 American Control Conference. New York City, USA: IEEE. 5887 - 5892.
[33]. Zheng, J., Y. Feng, and X. Yu. 2008. Hybrid Terminal Sliding Mode Observer Design Method for Permanent Magnet Synchronous Motor Control System. 2008 International Workshop on Variable Structure Systems (VSS 2008) (IEEE) 106 - 111.
[34]. Aurora, C., A. Ferrara, and A. Levant. 2001. Speed Regulation of Induction Motors: A Sliding Mode Observer-Differentiator Based Control Scheme. Proceedings of the 40th IEEE Conference on Decision and Control. Florida, USA: IEEE. 2651 - 2656.
[35]. Aurora, C., and A. Ferrara. 2007. A Sliding Mode Observer for Sensorless Induction Motor Sped Regulation. International Journal of Systems Science (Taylor and Francis Group) 38 (11): 913 - 929.
[36]. Bandyopadhyay, B., P. Gandhi, and S. Kurode. 2009. Sliding Mode Observer Based Sliding Mode Controller for Slosh-Free Motion Through PID Scheme. IEEE Transactions on Industrial Electronics 56 (9): 3432 - 3442.
[37]. Barbot, J., T. Boukhobza, and M. Djemai. 1996. Sliding Mode Observer for Triangular Input Form. Proceedings of the 35th Conference on Decision and Control. Kobe, Japan: IEEE. 1489 - 1490.
[38]. Zhao, L., Z. Liu, and H. Chen. 2009. Sliding Mode Observer for Vehicle Velocity Estimation With Road Grade and Bank Angles Adaption. 2009 IEEE Intelligent Vehicles Symposium. Xi'an, China. 701 - 706.
[39]. Bartolini, G., A. Levant, E. Usai, and A. Pisano. 1999. 2-Sliding Mode with Adaptation. Proceedings of the 7th Mediterranean Conference on Control and Automation (MED99). Haifa, Israel. 2421 - 2429.
[40]. Chaal, H., M. Jovanovic, and K. Busawon. 2009. Sliding Mode Observer Based Direct Torque Control of a Brushless Doubly-Fed Reluctance Machine. 2009 IEEE Symposium on Industrial Electronics and Applications, ISIEA 2009 - Proceedings. Kuala Lumpur, Malaysia: IEEE. 866 - 871.
[41]. Chen, Z. 2003. Bayesian Filtering: From Kalman Filters To Particles And Beyond.
[42]. Barker, A., D. Brown, and W. Martin. 1995. Bayesian estimation and the Kalman Filter. Department of Computer Science, Virginia University 30 (10): 55-77.
[43]. Sorenson, H. 1970. Least-Squares Estimation: From Gauss To Kalman. IEEE Spectrum 7 (7): 63-68.
[44]. Chan, Y., A. Hu, and J. Plant. 1979. A Kalman Filter Based Tracking Scheme With Input Estimation. IEEE Transactions On Aerospace and Electronic Systems AES-15: 237-244.
[45]. Grewal, M., and A. Andrews. 2001. Kalman Filtering – Theory And Practice Using MATLAB. John Wiley & Sons, Inc.
[46]. Rahimnejad, A., Gadsden, S.A., Al-Shabi, M. 2021. Lattice Kalman Filters. IEEE Signal Processing Letters, 28, pp. 1355–1359, 9457157
[47]. Tang, X., X. Zhao, and X. Zhang. 2008. The Square-Root Spherical Simplex Unscented Kalman Filter For State And Parameter Estimation. International Conference on Signal Processing Proceedings. 260-263.
[48]. Sun, P., and K. Marko. 1998. The Square Root Kalman Filter Training Of Recurrent Neural Networks. IEEE International Conference on Systems.
[49]. Hyland, J. 2002. An Iterated-Extended Kalman Filter Algorithm For Tracking Surface And Sub-Surface Targets. Oceans 2002 Conference and Exhibition. Conference Proceedings. 1283-1290.
[50]. Lary, D., and H. Mussa. 2004. Using an Extended Kalman Filter Learning Algorithm For Feed-Forward Neural Networks To Describe Tracer Correlations. Atmospheric Chemistry And Physics Discussion 3653-3667.