The Extended Innovation Kalman-Sliding Filter for Nonlinear Estimation

Mohammad AlShabi
Department of Mechanical & Nuclear Engineering, University of Sharjah, UAE
malshabi@sharjah.ac.ae

S. Andrew Gadsden
Department of Mechanical Engineering, McMaster University, Canada
gadsden@mcmaster.ca

ABSTRACT–Predicting and planning a path and extracting the current location are important aspects in the fields of navigation, localization, and autonomous vehicles. This brief paper belongs to these applications with measurement signals that are obtained from linear sensors. The kinematic states of a vehicle, and the maneuvering angle, are extracted by a filter from a noisy environment. Filters are considered to be either accurate or robust, and typically not both (a trade-off exists). In this paper, we introduce a method that combines accuracy with robustness. The well-known extended Kalman filter (EKF) is combined with the relatively new sliding innovation filter (SIF). The proposed algorithm makes use of the EKF gain and structure while utilizing the robustness of the SIF switching-based gain in an effort to provide a good estimate of the states. The result is a suboptimal nonlinear estimation strategy that resists uncertainties and disturbances. The proposed filter is demonstrated on a vehicle in the Cartesian coordinate while maneuvering and performing turns. The results are compared to the classical EKF and SIF.

KEYWORDS–Estimation theory, sliding innovation filter, extended Kalman filter, maneuvering, uncertainties, complex road.

1. INTRODUCTION

Maneuvering and navigation in 2D and 3D environments are known to be tricky, time consuming, and sometimes difficult to achieve. To estimate the vehicle's states including its positions and velocities in Cartesian Coordinates, a filter is required. The filter is an estimation algorithm that tries to recover the hidden information from the direct information that is linked to the measurement signals while reducing the noise effects. For that purpose, some filters use a mathematical model that represents the system and then excites it by the given input. These filters are known as the model-based-filters [1-10]. The pioneer work of Kalman in early 1960s is considered the largest milestone in the field. His filter (KF) finds the optimal solution of well-known and well-modelled linear system, simulated under white Gaussian noise signals. The filter solves the least squared error estimation. For given assumptions, the filter is considered the optimal solution. No other filter may give a better performance. However, once one of the assumptions (at least) is violated, then the filter's performance starts to fall apart [11-14].

To overcome the KF performance's issues, several works have been developed like linearizing the nonlinear model using the Jacobian matrices as in the Extended KF (EKF) [15-17], or using summation of weighted particles as in the Sigma-point KF (SPKF) [18-22]. SPKF includes the pioneer work of Unscented KF (UKF) [19], and the Cubature KF (CKF) [23-24]. These versions of KF make the filter applicable for nonlinear systems. Other works combined the KF or its variants to another stable and robust filter like the Smooth Variable Structure filter (SVSF) [25-28] and Sliding Innovation Filter (SIF) [29-37].

SIF, which was formulated in 2020 as a robust/stable filter, defines a hyperplane from the measurements that represent the true trajectories and forces the estimates to remain on its neighborhood [35]. The filter shares similar principles as the SVSF and Sliding Mode Observer. These filters belong on another category of filtering that target the stability of the filter and making its robust against the uncertainties.

In this brief work, the SIF is combined with the EKF to achieve the benefit of the two filters in term of optimality and robustness/stability. The proposed filter is applied to a nonlinear target tracking application, where a vehicle is maneuvering in a complex road with several turns. However, the new strategy may be applied to any nonlinear estimation problem. The application model is illustrated in Section 2, while the filters and the proposed filter are formulated in Section 3. The results are discussed and concluded in Section 4 and Section 5, respectively.

2. SYSTEM MODEL

A vehicle is assumed to move in a complex road with several turns (up to 10 turns) as shown in Figure 1.

2023 Advances in Science and Engineering Technology International Conferences (ASET) | 978-1-6654-5474-2/23/$31.00 ©2023 IEEE | DOI: 10.1109/ASET56582.2023.10180704

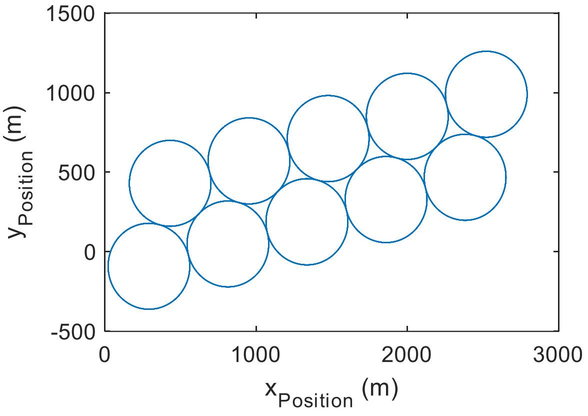


Figure 1. The complex road model.

The equation of the model is derived as follows [37]:

$$\begin{bmatrix} x_{1,k+1} \\ x_{2,k+1} \\ x_{3,k+1} \\ x_{4,k+1} \\ x_{5,k+1} \end{bmatrix} = \begin{bmatrix} x_{1,k} + M_k\, x_{2,k} - N_k\, x_{4,k} \\ c\, x_{2,k} - s\, x_{4,k} \\ x_{3,k} + N_k x_{2,k} - M_k\, x_{4,k} \\ s\, x_{2,k} + c\, x_{4,k} \\ x_{5,k} \end{bmatrix} + \begin{bmatrix} w_{1,k} \\ w_{2,k} \\ w_{3,k} \\ w_{4,k} \\ w_{5,k} \end{bmatrix} \quad (1)$$

where:

$c = cos\left(x_{5,k}T\right)$, $s = sin\left(x_{5,k}T\right)$ $M_k = \frac{sin(x_{5,k}T)}{x_{5,k}}$ and $N_k = \frac{1-cos(x_{5,k}T)}{x_{5,k}}$, $x_{1,k}$ and $x_{3,k}$ are the position in x- and y-axes, respectively, $x_{3,k}$ and $x_{4,k}$ are the velocity in x- and y-axes, respectively, and $x_{5,k}$ is the maneuvering angular speed. w is the system noise and disturbances. T is the sampling time, and the subscript k and $k+1$ represent the time step. The system equation can be simplified as:

$$\rightarrow x_{k+1} = f(x_k) + w_k \quad (2)$$

The measurement signals are defined as:

$$\begin{bmatrix} z_{1,k+1} \\ z_{2,k+1} \\ z_{3,k+1} \\ z_{4,k+1} \\ z_{5,k+1} \end{bmatrix} = \begin{bmatrix} x_{1,k+1} \\ x_{2,k+1} \\ x_{3,k+1} \\ x_{4,k+1} \\ x_{5,k+1} \end{bmatrix} + \begin{bmatrix} v_{1,k+1} \\ v_{2,k+1} \\ v_{3,k+1} \\ v_{4,k+1} \\ v_{5,k+1} \end{bmatrix} \quad (3)$$

where z is the measurement signal and v is the measurement noise and uncertainties. The measurement equation can be simplified as:

$$\rightarrow z_{k+1} = x_{k+1} + v_{k+1} \quad (4)$$

The system is considered to have nonlinear model with linear sensor model. Due to the nonlinearity, the KF cannot be applied and a nonlinear form of the filter is needed. EKF is going to be used in this paper. However, the Jacobian cannot capture the high nonlinearity; therefore, the system noise covariance matrix, Q, will be increased to minimize the error. The Jacobian of the system, F, is defined as the following:

$$F = \frac{\partial f}{\partial x}\Big|_{x=x_k} = \begin{bmatrix} 1 & M_k & 0 & -N_k & F_1 \\ 0 & c & 0 & -s & F_2 \\ 0 & N_k & 1 & -M_k & F_3 \\ 0 & s & 0 & c & F_4 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (5)$$

where:

$$F_1 = \frac{(Tx_{5,k}c-s)x_{2,k}}{x_{5,k}^2} - \frac{x_{4,k}(Tsx_{5,k}-1+c)}{x_{5,k}^2} \quad (6)$$

$$F_2 = -sx_{2,k}T - Tcx_{4,k} \quad (7)$$

$$F_3 = \frac{x_{2,k}(Tsx_{5,k}-1+c)}{x_{5,k}^2} - \frac{(Tx_{5,k}c-s)x_{4,k}}{x_{5,k}^2} \quad (8)$$

$$F_4 = Tcx_{2,k} - Tsx_{4,k} \quad (9)$$

The measurement matrix is already a linear matrix of the form:

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (10)$$

The system and noise measurement vectors are Gaussian with zero mean and the following covariance matrices:

$$Q = 3.3 \times \begin{bmatrix} 10^{-5} & 0 & 0 & 0 & 0 \\ 0 & 10^{-7} & 0 & 0 & 0 \\ 0 & 0 & 10^{-5} & 0 & 0 \\ 0 & 0 & 0 & 10^{-7} & 0 \\ 0 & 0 & 0 & 0 & 10^{-9} \end{bmatrix} \quad (11)$$

And

$$R = 3.3 \times \begin{bmatrix} 10^{-3} & 0 & 0 & 0 & 0 \\ 0 & 10^{-7} & 0 & 0 & 0 \\ 0 & 0 & 10^{-3} & 0 & 0 \\ 0 & 0 & 0 & 10^{-7} & 0 \\ 0 & 0 & 0 & 0 & 10^{-9} \end{bmatrix} \quad (12)$$

The initial condition for the state is:

$$x_0 = [100\ 10\ 100\ 10\ 0.1]^T \quad (13)$$

The system will have a constant value for $x_{5,k}$ unless there is a turn, and the filter needs to estimate it.

3. METHODOLOGY

3.1 SIF algorithm

The SIF estimate an unrefined estimate during a stage referee to as the prediction stage. The estimate is called the a priori estimate ($\hat{\mathbf{x}}_{k|k-1}$). Then the filter refine the estimate to the a posteriori estimate ($\hat{\mathbf{x}}_{k|k}$) during the update stage. These steps are summarized as follows:

1- **Prediction Stage**,

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

$$\hat{\mathbf{z}}_{k|k-1} = \hat{\mathbf{x}}_{k|k-1} \qquad (14)$$

2- **Update Stage**,

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

$$\hat{\mathbf{z}}_{k|k} = \hat{\mathbf{x}}_{k|k} \qquad (15)$$

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

$$S_{i,k} = \begin{cases} \frac{\left|\mathbf{z}_{i,k} - \hat{\mathbf{z}}_{i,k|k-1}\right|}{\psi_{i,k}} & \left|\mathbf{z}_{i,k} - \hat{\mathbf{z}}_{i,k|k-1}\right| < \psi_{i,k} \\ 1 & \left|\mathbf{z}_{i,k} - \hat{\mathbf{z}}_{i,k|k-1}\right| \geq \psi_{i,k} \end{cases} \qquad (16)$$

where $\psi_{i,k}$ is the boundary layer for the i^{th} measurement.

3.2 EKF algorithm

The EKF is also a predictor and corrector filter. However, the further calculation is required to obtain the error covariance matrix in it's a priori and a posteriori forms. These will be later used to calculate the correction gain as summarized here:

1- **Prediction Stage**,

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

$$\hat{\mathbf{z}}_{k|k-1} = \hat{\mathbf{x}}_{k|k-1} \qquad (17)$$

2- **Update Stage**,

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

$$\hat{\mathbf{z}}_{k|k} = \hat{\mathbf{x}}_{k|k} \qquad (18)$$

where:

$$\mathbf{K}_k = \mathbf{P}_{k|k-1}\left(\mathbf{P}_{k|k-1} + \mathbf{R}_k\right)^{-1} \qquad (19)$$

and

$$\mathbf{P}_{k|k-1} = \mathbf{F}_{k-1}\mathbf{P}_{k-1|k-1}\mathbf{F}_{k-1}^{T} + \mathbf{Q}_{k-1} \qquad (20)$$

3.3 EKF/SIF algorithm

The proposed filter combines the EKF with the SIF as follows:

1- **Prediction Stage**,

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

$$\hat{\mathbf{z}}_{k|k-1} = \hat{\mathbf{x}}_{k|k-1} \qquad (21)$$

2- **Update Stage**,

If $\left|\mathbf{z}_{i,k} - \hat{\mathbf{z}}_{i,k|k-1}\right| > \gamma_i$ (22)

Then

$use\ (15)\ and\ (16)$

$reset\ the\ value\ of\ the\ \mathbf{P}_{0|0}$

Else

$use\ (18) - (20)$

Where $\mathbf{P}_{0|0}$ is 10 times the identity matrix, $\psi = [29\ 0.01\ 29\ 0.01\ 0.1]^T \times 10^{-2}$ and $\gamma = [16\ \ 1.6\ 16\ 1.6\ 16]^T \times 10^{-2}$.

4. SIMULATION RESULTS

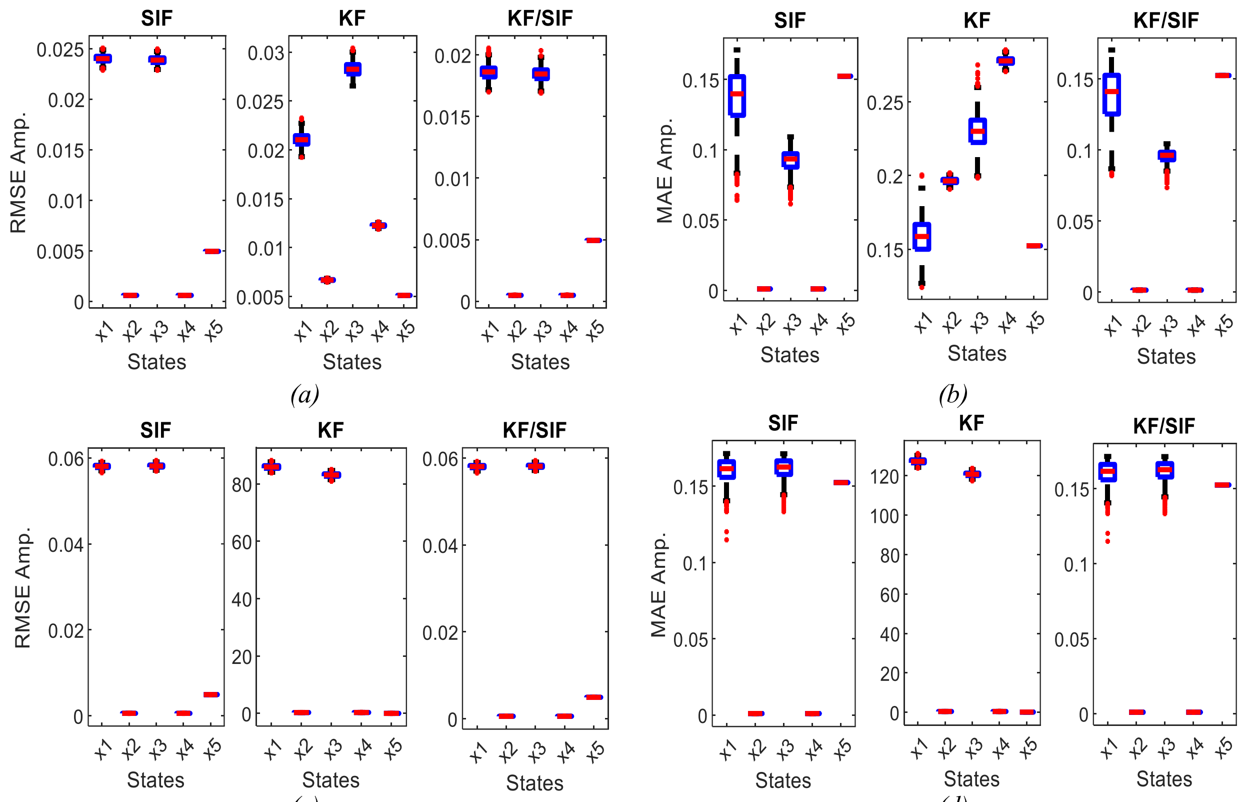
The EKF, SIF and EKF/SIF are applied to the system in Section (2). Monte Carlo Simulation are conducted with repeated simulation up to 1000 times. Two cases were considered, case 1 for the model of (1) and case (2) by assuming $x_{5,k}$ is very small to make the system linear. The sampling time is 1 sec. Each simulation has a different noise generation. Bothe the root mean squared error (RMSE) and the maximum absolute error (MAE) are calculated using (23) and (24), respectively, and where recorded for case 1 and case 2 in Table 1 and 2, respectively.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{ns}\left(x_{Actual,i} - x_{Prediction,i}\right)^2}{ns}} \qquad (23)$$

$$MAE = \max\left(\left|x_{Actual} - x_{Prediction}\right|\right) \qquad (24)$$

The Monte Carlo performance of the filters is plotted in Figure 2, and the error performances are plotted in Figure 3 for case 1and Figure 4 for case 2.

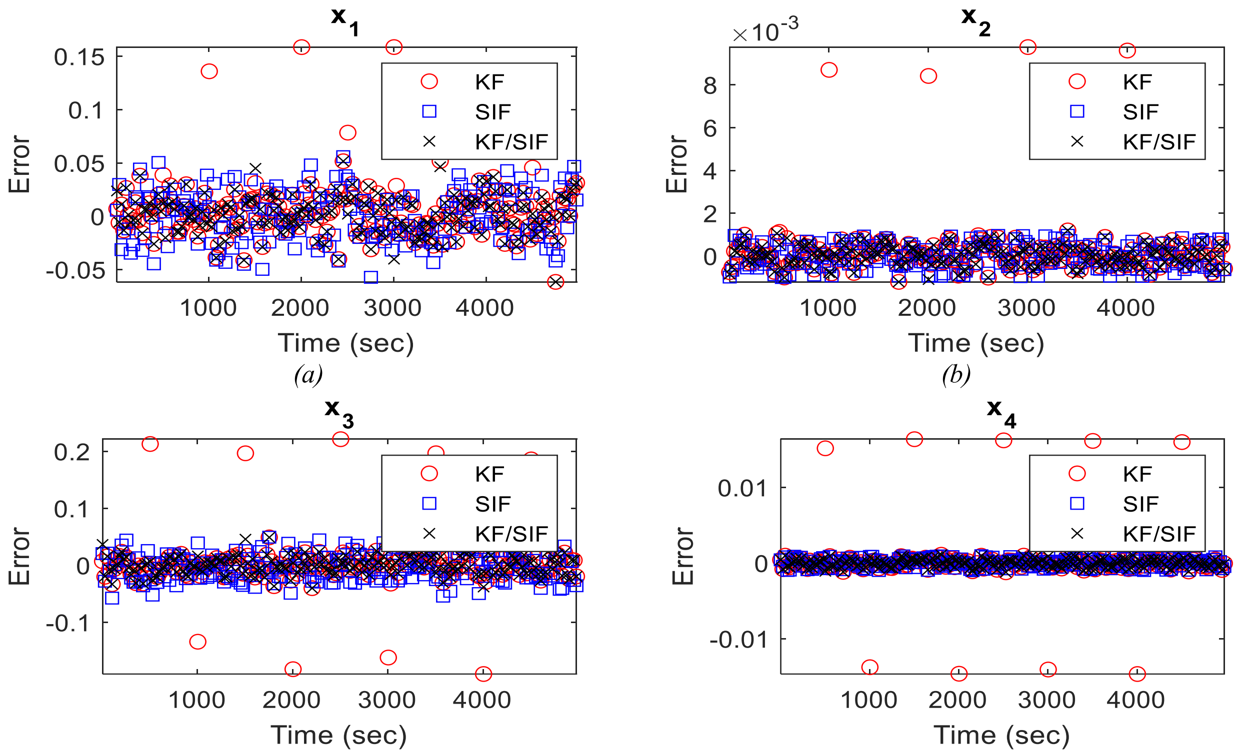
The results show a superior performance for the proposed method compared to the EKF and SIF. Due to the nonlinearity in the system, the SIF performed better then EKF in both cases. This is due to the fact that the Jacobian method does not approximate the high nonlinearity in the system.



(a) (b)

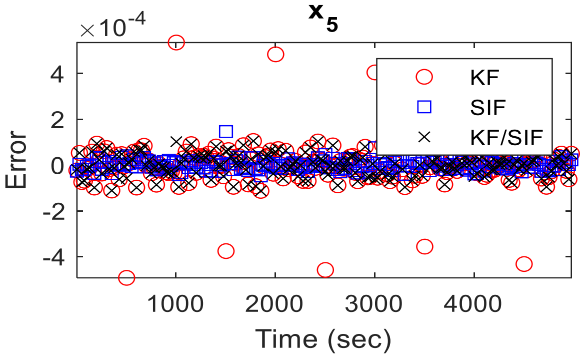
(c) (d)

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.



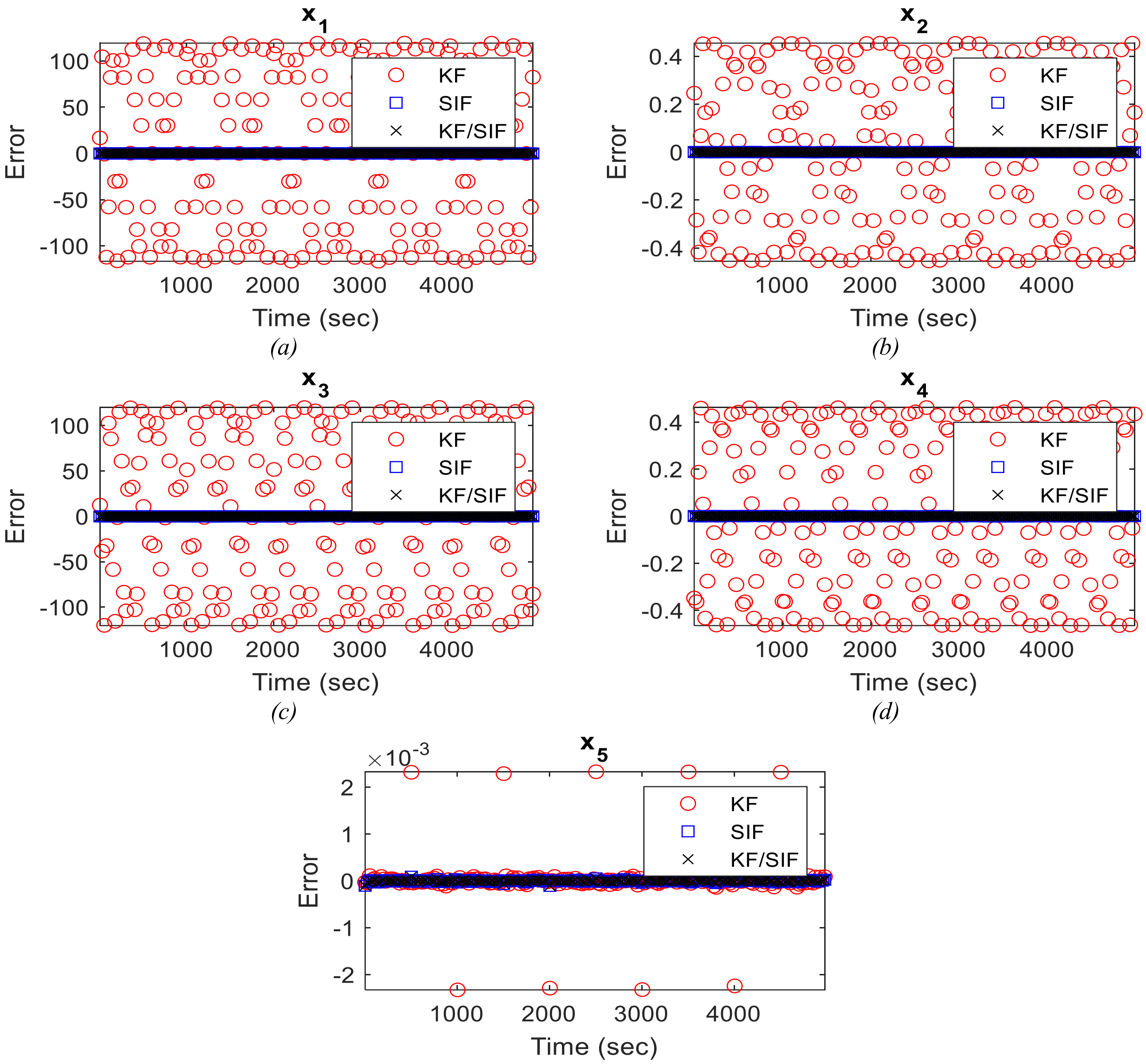
(a) (b)

(c) (d)



(e)

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



(a) *(b)* *(c)* *(d)* *(e)*

Figure 4. The performance of the filters for (a) first, (b) second, (c) third (d) fourth and (e) fifth states for case 2.

Table 1. RMSE and MAE for case 1

	$RMSE$ in			MAE in		
	SIF	*EKF*	*EKF/SIF*	*SIF*	*EKF*	*EKF/SIF*
$x_1\ (m)$	2.4×10^{-02}	2.0×10^{-02}	1.8×10^{-02}	1.8×10^{-01}	1.6×10^{-01}	1.7×10^{-01}
$x_2(m/s)$	6.0×10^{-04}	6.7×10^{-03}	5.0×10^{-04}	1.0×10^{-03}	2.0×10^{-01}	1.5×10^{-03}
$x_3(m)$	2.4×10^{-02}	2.7×10^{-02}	1.7×10^{-02}	1.7×10^{-02}	2.2×10^{-01}	9.2×10^{-02}
$x_4(m/s)$	6.0×10^{-04}	1.2×10^{-02}	5.0×10^{-04}	1.0×10^{-03}	2.8×10^{-01}	1.3×10^{-03}
$x_5(rad/s)$	4.9×10^{-03}	5.1×10^{-03}	4.9×10^{-03}	1.5×10^{-01}	1.5×10^{-01}	1.5×10^{-01}

Table 2. RMSE and MAE for case 2

	$RMSE$ in			MAE in		
	SIF	*EKF*	*EKF/SIF*	*SIF*	*EKF*	*EKF/SIF*
$x_1\ (m)$	5.7×10^{-02}	8.4×10^{01}	5.7×10^{-02}	1.7×10^{-01}	1.2×10^{03}	1.7×10^{-01}
$x_2(m/s)$	6.0×10^{-04}	3.1×10^{-01}	6.0×10^{-04}	1.0×10^{-03}	4.6×10^{-01}	1.0×10^{-03}
$x_3(m)$	5.8×10^{-02}	8.4×10^{-02}	5.8×10^{-02}	1.6×10^{-02}	1.2×10^{02}	1.6×10^{-02}
$x_4(m/s)$	6.0×10^{-04}	3.3×10^{-01}	6.0×10^{-04}	1.0×10^{-03}	4.7×10^{-01}	1.0×10^{-03}
$x_5(rad/s)$	4.9×10^{-03}	5.1×10^{-03}	4.9×10^{-03}	1.5×10^{-01}	1.5×10^{-01}	1.5×10^{-01}

5. CONCLUSION

In this brief paper, a new method that combines the EKF with the SIF is proposed. The resulting filter was tested by estimating a vehicle's position and velocity on a very complex road. The results were compared to both classical strategies (the EKF and the SIF). The results demonstrate a strong performance of the proposed EKF/SIF over the standard filters, even when modeling uncertainties were present. In future work, the algorithm will be tested on higher-order systems with hidden states that have been built for experimentation.

REFERENCES

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

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

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

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

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

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

[7]. 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.

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

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

[10]. 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

[11]. Chen, Z. 2003. Bayesian Filtering: From Kalman Filters To Particles And Beyond.

[12]. Barker, A., D. Brown, and W. Martin. 1995. Bayesian estimation and the Kalman Filter. Department of Computer Science, Virginia University 30 (10): 55-77.

[13]. Sorenson, H. 1970. Least-Squares Estimation: From Gauss To Kalman. IEEE Spectrum 7 (7): 63-68.

[14]. 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.

[15]. Grewal, M., and A. Andrews. 2001. Kalman Filtering – Theory And Practice Using MATLAB. John Wiley & Sons, Inc.

[16]. 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.

[17]. 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.

[18]. Al-Shabi, M., Cataford, A., Gadsden, S.A. Quadrature Kalman filters with applications to robotic manipulators. (2018) Proceedings - 2017 IEEE 5th International Symposium on Robotics and Intelligent Sensors, IRIS 2017, 2018-January, pp. 117-124.

[19]. Al-Shabi, M., Hatamleh, K., Al Shaer, S., Salameh, I., Gadsden, S.A. A comprehensive comparison of sigma-point Kalman filters applied on a complex maneuvering road. (2016) Proceedings of SPIE - The International Society for Optical Engineering, 9842, art. no. 98421I.

[20]. Julier, S. 2003. The Spherical Simplex Unscented Transformation. Proceedings of the American Control Conference. 2430-2434.

[21]. Kim, J., and D. Shin. 2005. Joint Estimation Of Time Delay And Channel Amplitude By Simplex Unscented Filter Without Assisted Pilot In CDMA Systems. The 7th International Conference on Advanced Communication Technology. 233-240.

[22]. Wang, L., L. Wang, C. Liao, and J. Liu. 2009. Sigma-Point Kalman Filter Application On Estimating Battery SOC. 5th IEEE Vehicle Power and Propulsion Conference 1592-1595.

[23]. Al-Shabi, M., Gadsden, S.A., Wilkerson, S.A. The cubature smooth variable structure filter estimation strategy applied to a quadrotor controller. (2015) Proceedings of SPIE - The International Society for Optical Engineering, 9474, art. no. 94741I.

[24]. Gadsden, S.A., Al-Shabi, M., Arasaratnam, I., Habibi, S.R. Combined cubature Kalman and smooth variable structure filtering: A robust nonlinear estimation strategy. (2014) Signal Processing, 96 (PART B), pp. 290-299.

[25]. Al-Shabi, M. Sigma-point Smooth Variable Structure Filters applications into robotic arm. (2017) 2017 7th International Conference on Modeling, Simulation, and Applied Optimization, ICMSAO 2017, art. no. 7934865.

[26]. Al-Shabi, M., Bani-Yonis, M., Hatamleh, K.S.The sigma-point central difference smooth variable structure filter application into a robotic arm. (2015) 12th International Multi-Conference on Systems, Signals and Devices, SSD 2015, art. no. 7348201

[27]. Al-Shabi, M., Hatamleh, K.S. The unscented smooth variable structure filter application into a robotic arm. (2014) ASME International Mechanical Engineering Congress and Exposition, Proceedings (IMECE), 4B.

[28]. Gadsden, S.A., Al-Shabi, M., Arasaratnam, I., Habibi, S.R. Combined cubature Kalman and smooth variable structure filtering: A robust nonlinear estimation strategy. (2014) Signal Processing, 96 (PART B), pp. 290-299.

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

[30]. 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.

[31]. 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.

[32]. 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.

[33]. 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.

[34]. 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.

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

[36]. 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.

[37]. AlShabi, M., Gadsden, A. Application of the sliding innovation filter to complex road. 2022. Proc. SPIE

12122, Signal Processing, Sensor/Information Fusion, and Target Recognition XXXI, 121220A.