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The formulation of the sequential sliding innovation filter and its application to complex road maneuvering

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ABSTRACT

This study presents the development of a new filter, the sequential sliding innovation filter (SSIF), designed for estimating quantities of interest from noisy measurements. The SIF is formulated in a sequential manner, allowing for multiple updates of estimates, making it well-suited for systems with multiple measured states. The filter is applied to an unmanned ground vehicle (UGV) maneuvering in 2-D path in this study, and the results demonstrate that the SSIF outperforms conventional filter and Kalman Filter (KF) in terms of accuracy and efficiency. The SSIF has the potential for use in signal processing, tracking, and surveillance, making it a valuable tool in various fields.

Keywords: UGV, target tracking, SIF, sequential, performance.

1. INTRODUCTION

Estimation techniques are critical in fault and diagnosis applications as they allow for monitoring and assessment of a plant's status using sensor data. These techniques analyze sensor signals to extract comprehensive information, such as hidden states, system parameters, and overall system health, which may not be directly measurable. This extracted information provides valuable insights into the system's condition and enables tracking of its status over time, serving as a basis for identifying deviations from expected behavior that could indicate faults or abnormalities. Timely intervention and mitigation measures can be taken when a fault is detected through raising an alert. Estimation techniques also help improve the accuracy and reliability of system status assessment by considering the limitations and uncertainties associated with sensor measurements [1-10].

One common limitation of sensor data is the presence of noise or disturbances. To mitigate the impact of noise, estimation techniques known as filters are employed. Filters process the sensor signals to eliminate or minimize the effects of noise, enhancing the system response when the estimated information is combined with the controller. By reducing the influence of noise on the estimation process, filters help improve the accuracy and reliability of the system's output, leading to better performance and functionality in fault and diagnosis applications [11-21].

Filtering estimation techniques can be categorized into two main types, with one approach focused on determining the optimal or best solution within certain constraints. An example of such a technique is the Kalman filter (KF), which is widely used in various fields for estimation and tracking purposes. The KF is a mathematical algorithm that provides an optimal estimate of a system's state based on noisy or incomplete measurements. It considers the system's dynamics, measurement data, and statistical properties of noise to estimate the most probable state of the system. The KF is commonly used in navigation, tracking, and control applications where accurate estimation of a system's state is crucial for effective decision-making [22-37].

One of the key strengths of the KF is its ability to handle uncertain and noisy measurements. It uses a recursive algorithm to continually update the estimate of the system's state as new measurements become available, making it well-suited for real-time applications. Additionally, the KF can handle nonlinear systems through extensions such as the Extended Kalman Filter (EKF) [38-43] and the Unscented Kalman Filter (UKF) [44-61], which provide approximate solutions for nonlinear systems. However, it is important to note that the KF has limitations. It relies on assumptions of linearity, Gaussian noise, and accurate knowledge of system dynamics, which may not always hold in practical scenarios. Additionally, the optimum performance of the KF is dependent on the accuracy of the starting state estimate as well as the quality of the measurement data. This is because the KF uses a recursive algorithm.

The second group of filtering estimation methods uses stability functions like Lyapunov functions to make the filter.

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Examples of these types of filters are the sliding mode observer (SMO) [62-86], the smooth variable structure (SVSF) [87-103], and the sliding innovation (SIF) filters [104-112]. The drawbacks of the first category are mitigated to some degree by filters of the SMO, SVSF, and SIF varieties. They make an effort to provide stability and robustness in the estimate, both of which may be lacking in the first category. The use of stability factors such as Lyapunov functions guarantees that these filters will maintain the consistency of the estimating process despite the presence of disturbances and uncertainties. The second category of filters may not offer a perfect solution, but they do provide resilience and stability, which may be of critical importance in circumstances in which dependability and robustness are more essential than optimality. The performance of the system might be improved, and its limitations eliminated by combining filters from both groups. If at least two filters, one from each category, are included into the estimation process, the result may be one that is more reliable and accurate. While the second group does not give an ideal solution, the first group suffers from a lack of resilience and stability and is susceptible to a number of limitations (as their names imply). One technique to increase performance while simultaneously minimizing the number of constraints that are imposed is to combine at least two filters, one from each category [113-123]. Using many models and combining them into a single model via a process known as interactive multiple modeling (IMM) [124-135] is another technique to accomplish this goal. Moreover, Several works have explored various aspects of estimation and control, including quadrature Kalman filters for robotic manipulators, fuzzy image processing for text detection and character recognition, hybrid estimation-based techniques for partial discharge localization, space cooling using geothermal single-effect water/lithium bromide absorption chiller, estimation strategies for the condition monitoring of a battery system in a hybrid electric vehicle, a systematic review of grid-connected photovoltaic and photovoltaic/thermal systems, and unmanned aerial vehicles parameter estimation using artificial neural networks and iterative bi-section shooting method [136-142]. Recent research has explored various adaptive Kalman filters and other estimation methods to improve the accuracy of state estimation for a diverse range of applications, such as battery management, motion control, vehicle running states, symmetry recognition, UAV flight trajectory tracking, smart grids, nanosatellite attitude estimation, and generator parameter estimation. The purpose of this study work is to explore the use of the sliding innovation (SIF) filter in conjunction with the sequential approach that was introduced in [171].

2. METHODOLOGY

2.1. System under study

In this article, a complicated maneuvering system that involves a vehicle moving in the x-y plane at varying velocities and in a variety of forms is analyzed and discussed. On this system, several filters, including KF, SIF, and SSIF, are evaluated, and the results are afterwards compared. The maneuvering model is regarded as a nonlinear system due to the fact that the interactions between variables are not linear and that it incorporates sinusoidal signals. The system comprises five states, including the locations on the x- and y-axes, respectively denoted by x_1 and x_3, the velocities on both axes, respectively denoted by x_2 and x_4, and the maneuvering rotational angle, denoted by x_5. It is presumed that measurements have been taken in all of the states. The discrete version of the model is specified further down by the use of (1) to (2).

$$\begin{bmatrix} x_{1,k+1} \\ x_{2,k+1} \\ x_{3,k+1} \\ x_{4,k+1} \\ x_{5,k+1} \end{bmatrix} = \begin{bmatrix} x_{1,k} + \frac{sin(x_{5,k}T)}{x_{5,k}}\ x_{2,k} - \frac{1-cos(x_{5,k}T)}{x_{5,k}}\ x_{4,k} \\ cos(x_{5,k}T)\ x_{2,k} - sin(x_{5,k}T)\ x_{4,k} \\ x_{3,k} + \frac{1-cos(x_{5,k}T)}{x_{5,k}} x_{2,k} - \frac{sin(x_{5,k}T)}{x_{5,k}}\ x_{4,k} \\ sin(x_{5,k}T)\ x_{2,k} + cos(x_{5,k}T)\ x_{4,k} \\ x_{5,k} \end{bmatrix} + \begin{bmatrix} w_{1,k} \\ w_{2,k} \\ w_{3,k} \\ w_{4,k} \\ w_{5,k} \end{bmatrix}, \begin{bmatrix} z_{1,k+1} \\ z_{2,k+1} \\ z_{3,k+1} \\ z_{4,k+1} \\ z_{5,k+1} \end{bmatrix} = \begin{bmatrix} x_{1,k+1} \\ x_{2,k+1} \\ x_{3,k+1} \\ x_{4,k+1} \\ x_{5,k+1} \end{bmatrix} + \begin{bmatrix} v_{1,k+1} \\ v_{2,k+1} \\ v_{3,k+1} \\ v_{4,k+1} \\ v_{5,k+1} \end{bmatrix} \quad (1)$$

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

2.2. The Sequential SIF

The sequential approach was combined with KF in [136] for systems with multiple measured states. In this approach, the a posteriori states and covariance matrix are updated using one measurement signal at a time. This helps overcoming the issues of computational time, existence, and complexity associated with matrix inversions. In this work, the SIF is reformulated using the sequential approach, and the algorithm is summarized by fig. 1, where m is the number of measurement signals, ψ is the boundary layer, and sat is the saturated function. In this work, we assume that the first state is measured twice with two different sensors. This can be adapted easily by the SSIF compared to the SIF and KF.

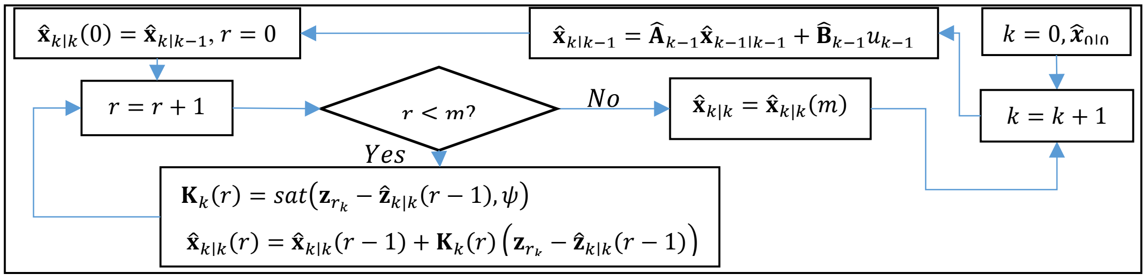

Fig. 1: The Sequential SIF Algorithm, [136]

3. RESULTS AND DISCUSSION

In this study, the SIF, KF and SSIF are utilized for the maneuvering system as described in Section 2.1. The results are presented in Figures 2, 3, and 4, which depict the vehicle positions, velocities, and maneuvering rotational angle, respectively. A comparison of the results is conducted based on the Root Mean Squared Error (RMSE), which is summarized by Table 1. The results demonstrate that all filters exhibit accurate state estimation performance. Furthermore, the SSIF outperforms the SIF, showing lower RMSE by up to 30%. Moreover, one advantage of SSIF is that it uses one measurement at a time, which reduces the inverse computation, and gives capability of adopting systems with number of measurement larger than the number of states. Additionally, SSIF and SIF have simple structures and require fewer computations compared to other filters such as KF.

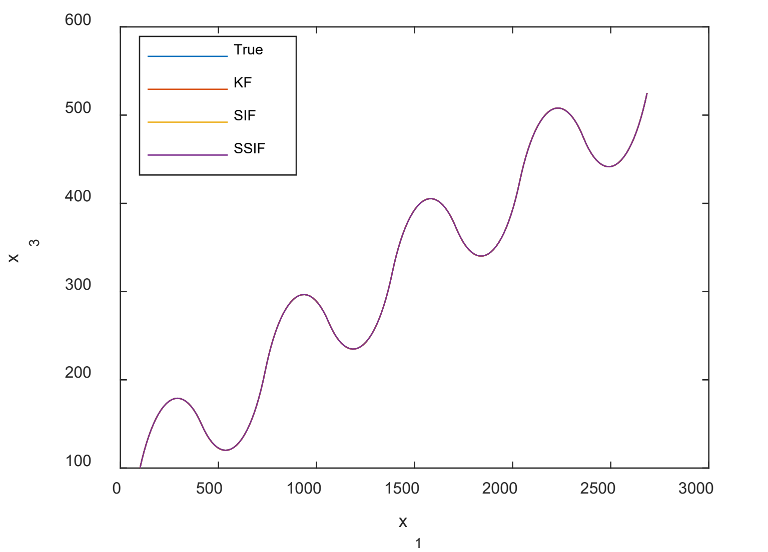

Fig. 2. The estimation of the position in x-y plane for KF, SIF and SSIF

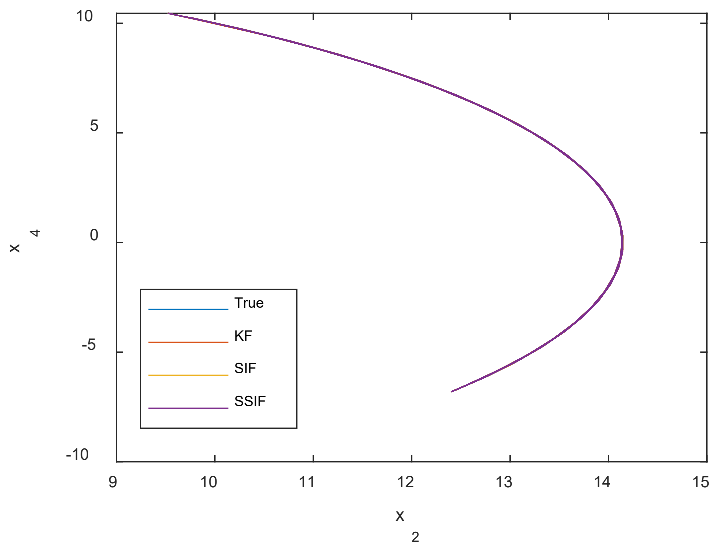

Fig. 3. The estimation of the velocity in x-y plane for KF, SIF and SSIF

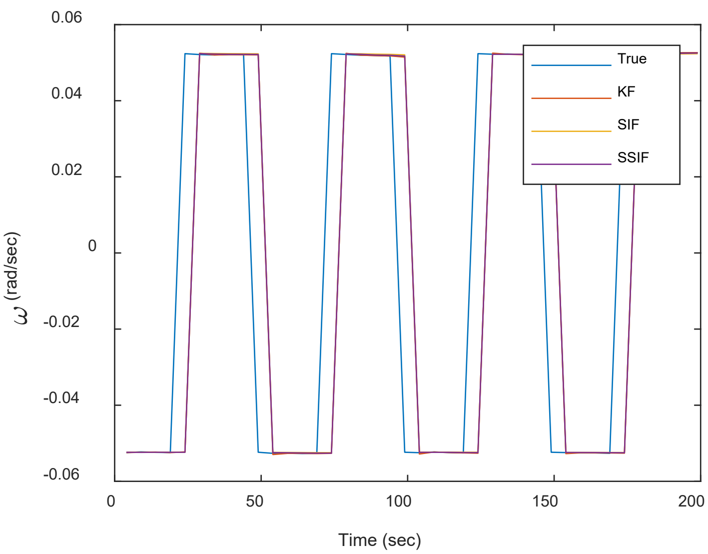

Fig. 4. Estimation of the fifth state for KF, SIF and SSIF

Table 1. RMSE of the simulated results

	$RMSE$ in				
	$x_1\ (cm)$	$x_2(cm/s)$	$x_3(cm)$	$x_4(cm/s)$	$x_5(rad/s)$
SSIF	8.0×10^{-3}	5.7×10^{-4}	2.4×10^{-2}	5.4×10^{-4}	2.0×10^{-2}
SIF	2.9×10^{-2}	6.0×10^{-4}	2.8×10^{-2}	6.9×10^{-4}	2.0×10^{-2}
KF	6.5×10^{-2}	3.3×10^{-2}	8.8×10^{-2}	4.6×10^{-2}	2.0×10^{-2}

4. CONCLUSION

In this study, the SIF, KF and SSIF are used to estimate vehicle trajectories, velocities and maneuvering rotational speed. The results show that all filters perform well on the system with superior performance to the SSIF, where the results are improved up to 30% in term RMSE. In conclusion, this study presents a comprehensive study of the SIF and its sequential form. The proposed sequential SIF updates estimates several times and uses only one measured state at each update stage, making it suitable for systems with multiple measured states. Overall, this study contributes to advancing the field of estimation theory by introducing a new filter that can improve system performance in various applications. Future research can explore further optimization of the sequential SIF parameters for specific applications and investigate its applicability to other systems beyond maneuvering applications.

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