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ABSTRACT

Estimating the position of a unmanned ground vehicle (UGV) that is navigating a complex road is a challenging task. Numerous algorithms have been developed to estimate the maneuvering status of the UGV. In this study, a newly developed filtering technique called the sliding innovation filter (SIF) is combined with multiple model technique to improve the estimation accuracy. The SIF uses the measured states as a discontinuous hyperplane to constrain the estimates to stay close to it. By combining the benefits of both methods, the proposed filter minimizes chatter during position estimation when the UGV is maneuvering. The effectiveness of the proposed method is evaluated on a UGV navigating an S-shaped road, and the results are compared to those obtained using the standard SIF.

Keywords: sliding innovation filter, multiple models, complex road, robust estimation

1. INTRODUCTION

In fault and diagnostic applications, estimation methods are crucial because they provide monitoring and evaluation of a plant's state based on data obtained through sensors. The goal of the estimating process is to analyze the signals received from the sensors in order to derive information that may not be clearly observable, such as hidden states that describe the dynamic behavior of the system, system parameters, and overall system health. Extracting this data allows for in-depth analysis of the system's health and monitoring of its evolution over time. As such, it may be used as a foundation for spotting out-of-the-ordinary occurrences that may point to systemic issues. An alarm may be triggered whenever a problem is found, allowing for rapid response and corrective action. Since estimating approaches account for the constraints and uncertainties associated with sensor readings, the state assessment of the system is both more accurate and reliable. Reduce the influence of noise or disturbances in the sensor data using an estimation approach, such as a filter, to improve the quality of the estimated information and provide more reliable problem and diagnostic findings [1-10]. Because sensors are inherently limited, their output is often noisy. Estimation methods using filters are used to lessen the significance of such disruptions or noise. When processing sensor data, filters are employed to get rid of or significantly reduce the impact of any background noise. When the approximated data is used in conjunction with the controller, the system's reaction is improved. Filters can enhance efficiency and functionality in fault and diagnostic applications by minimizing the impact of noise on the estimation process [11-21]. When it comes to filtering estimating methods, there are two primary schools of thought. One emphasizes finding the best possible answer given a set of restrictions, while the other emphasizes finding the optimum solution. One such method is the Kalman filter (KF), which has found use in many different areas for estimate and tracking [22-37].

The KF is a mathematical procedure that gives the best possible estimation of the state of a system using only imperfect or noisy data. Using the dynamics of the system, the measured data, and the statistical features of noise, it calculates a likely state for the system. Accurate prediction of a system's status is vital for efficient decision making, making the KF popular in applications including navigation, tracking, and control. The capacity of the KF to deal with uncertain and noisy readings is one of its main strengths. Because it employs a recursive method to update the estimate of the system's status in real time as new measurements become available, it is particularly useful in such situations. Additional extensions of the KF, such as the Extended Kalman Filter (EKF) [38-43] and the Unscented Kalman Filter (UKF) [44-61], give approximate solutions for nonlinear systems. While the KF is useful, it does have certain restrictions. Some situations may not satisfy its underlying assumptions of practical applicability, such as linearity, Gaussian noise, and complete understanding of system dynamics.

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The KF's optimum performance also is dependent on the precision of the starting state estimate and the precision of the measurement data. Filtering estimating methods that employ stability functions like Lyapunov functions fall under the second class of methods. Sliding mode observers (SMOs) [62–86], smooth variable structure filters (SVSFs) [87–103], and sliding innovation filters (SIFs) [104–112] are only a few examples. Some of the drawbacks of the first group are mitigated by SMO, SVSF, and SIF filters. The second group aims to provide the first group with the robustness and stability in estimate that it lacks. In spite of disturbances and uncertainties, these filters will maintain a stable estimation process thanks to stability factors like Lyapunov functions. The second set of filters is less likely to provide a perfect answer, but they do guarantee consistency and durability, which might be crucial in certain circumstances. It is possible that the performance and limitations of each set of filters might be improved by combining them. To improve the estimation process, it is recommended to combine at least two filters, one from each class. Both groups suffer from the problems implied by their names: the first lacks resilience and stability and is susceptible to a variety of limitations, while the second fails to give an ideal solution. Increasing performance while decreasing the overall number of constraints may be achieved by combining at least two filters, one from each category [113-123]. It may also be accomplished by the use of many models that are fused together, as in an interacting multiple model (IMM) [124-135].
The research paper aims to investigate the application of the sliding innovation filter (SIF) and the interacting multiple model (IMM) strategy in aeronautical actuator systems. Overall, the research paper aims to provide a comprehensive analysis of the application of the SIF-IMM approach in aeronautical actuator systems, including its architecture, performance, and potential implications for practical use. It may contribute to the existing literature on estimation techniques for aeronautical systems and serve as a reference for future research and applications in this area.

2. IMM-SIF

2.1 SIF

The sliding innovation filter, which was developed by 2020 and documented in reference [110], is a unique approach that utilizes the true state as a hyperplane for reference during the estimation process. The estimated state is constrained to remain within a certain neighborhood of this hyperplane in order to ensure stability. The filter operates in two distinct steps, which are further explained below.

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

The a priori estimate, $\hat{\mathbf{x}}_{k+1|k}$, and its measurement, $\hat{\mathbf{z}}_{k+1|k}$, are calculated as:

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

$$\hat{z}_{k|k-1} = \hat{x}_{k|k-1} \tag{2}$$

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

The a posteriori estimate, $\hat{\mathbf{x}}_{k|k}$, and its measurements, $\hat{\mathbf{z}}_{k|k}$, are calculated as:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + \left[\left(z_k - \hat{z}_{k|k-1}\right)\right]^{\circ} sat\left(\left|z_k - \hat{z}_{k|k-1}\right|, \Psi_k\right) \tag{3}$$

$$\hat{z}_{k|k} = \hat{x}_{k|k} \tag{4}$$

Where Ψ_k is the designed boundary layer, $A^{\circ}B$ is schur product, and sat is the saturated function.

2.2 IMM-SIF

The proposed filter, which is the interacting multiple model sliding innovation filter (IMM-SIF), is based on [106] and is summarized here. The filter consists of three stages:

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

The a priori estimate, $\hat{x}_{j,k|k-1}$, and its covariance matrix, $P_{j,k|k-1}$, for model j, are calculated as:

$$\hat{x}_{j,k|k-1} = A_j\hat{x}_{k-1|k-1} \tag{5}$$

$$P_{j,k|k-1} = A_j P_{k-1|k-1} A_j^T + Q_{k-1} \tag{6}$$

Where Q_{k-1} is the system covariance matrix. Then we calculate the innovation covariance matrix, $S_{j,k|k-1}$, with the use of measurement's noise covariance matrix, R_k, as follows:

$$S_{j,k|k-1} = H_k P_{j,k|k-1} H_k^{\mathrm{T}} + R_k \tag{7}$$

2- <u>Correction Stage</u>:

The a posteriori estimate, $\hat{x}_{j,k|k}$, its covariance matrix, $P_{j,k|k}$, and likehood function, $\Lambda_{j,k+1}$, for model j, are calculated as:

$$K_k = diag\left(sat\left(\left|z_k - H_k \hat{x}_{j,k|k-1}\right|, \Psi_k\right)\right) \tag{8}$$

$$\hat{x}_{j,k|k} = \hat{x}_{j,k|k-1} + K_{j,k}\left(z_k - H_k \hat{x}_{j,k|k-1}\right) \tag{9}$$

$$P_{j,k|k} = \left(I - K_{j,k}\right) P_{j,k|k-1} \tag{10}$$

$$\Lambda_{j,k} = \frac{exp\left(\frac{-\frac{1}{2}\left(z_k - H_k \hat{x}_{j,k|k-1}\right)\left(z_k - H_k \hat{x}_{j,k|k-1}\right)^T}{S_{j,k|k-1}}\right)}{\sqrt{\left|2\pi S_{j,k|k-1}\right|}} \tag{11}$$

3- <u>Fusion Stage</u>:

We update mode probability for model j, $\mu_{j,k}$, using the mixing probabilities, p_{ij}, and the likehood function as follows:

$$\mu_{j,k} = \frac{1}{\sum_{j=1}^{n} \Lambda_{j,k+1} \sum_{i=1}^{n} p_{ij} \mu_{i,k}} \Lambda_{j,k+1} \sum_{i=1}^{r} p_{ij}\, \mu_{i,k}, j = 1, \dots, n \tag{12}$$

We fuse the outputs from each model together using

$$\hat{x}_{k|k} = \sum_{j=1}^{r} \mu_{j,k} \hat{x}_{j,k|k} \tag{13}$$

$$P_{k|k} = \sum_{j=1}^{r} \mu_{j,k} \left\{P_{j,k|k} + \left(\hat{x}_{j,k|k} - \hat{x}_{k|k}\right)\left(\hat{x}_{j,k|k} - \hat{x}_{k|k}\right)^T\right\} \tag{14}$$

3. SYSTEM UNDER SCOPE

This paper examines a sophisticated maneuvering system that involves a UGV moving in the x-y plane at varying velocities and shapes. The maneuvering model is considered to be nonlinear due to the non-linear relationships to the maneuvering angle and sinusoidal signals involved. The model comprises of five states, which are the positions on the x- and y-axes (x_1 and x_3, respectively), the velocities on both axes (x_2 and x_4, respectively), and the maneuvering rotational angle (x_5). It is assumed that all the states can be measured. However, in this paper, the model can be reduced to 4 states, as state five is omitted. The matrix hence become linear but variable with time. The discrete form of the model is defined by equations (15) to (16), which include the sensor equations.

$$\begin{bmatrix} x_{1,k+1} \\ x_{2,k+1} \\ x_{3,k+1} \\ x_{4,k+1} \end{bmatrix} = \begin{bmatrix} 1 & \frac{sin(\omega T)}{\omega} & 0 & -\frac{1-cos(\omega T)}{\omega} \\ 0 & cos(\omega T) & 0 & -sin(\omega T) \\ 0 & \frac{1-cos(\omega T)}{\omega} & 1 & -\frac{sin(\omega T)}{\omega} \\ 0 & sin(\omega T) & 0 & cos(\omega T) \end{bmatrix} \begin{bmatrix} x_{1,k} \\ x_{2,k} \\ x_{3,k} \\ x_{4,k} \end{bmatrix} + \begin{bmatrix} w_{1,k} \\ w_{2,k} \\ w_{3,k} \\ w_{4,k} \end{bmatrix} \rightarrow x_{k+1} = A_k(x_k) + w_k \tag{15}$$

$$z_{k+1} = x_{k+1} + v_{k+1} \tag{16}$$

A_k is measured at three operational time, $0^o, 3^o$ and -3^o, to be as follows:

$$A_1 = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & -1 \\ 0 & 0 & 0 & 1 \end{bmatrix}, A_2 = \begin{bmatrix} 1 & 0.995 & 0 & -0.0262 \\ 0 & 0.9986 & 0 & -0.0523 \\ 0 & 0.0262 & 1 & -0.995 \\ 0 & 0.0523 & 0 & 0.9986 \end{bmatrix}, \text{and } A_3 = \begin{bmatrix} 1 & 0.995 & 0 & -0.0262 \\ 0 & 0.9986 & 0 & 0.0523 \\ 0 & 0.0262 & 1 & -0.995 \\ 0 & -0.0523 & 0 & 0.9986 \end{bmatrix}, \text{respectively.}$$

4. RESULTS AND DISCUSSION

In this paper, the IMM-SIF is applied to system in section 3, which represent an unmanned ground vehicle's (UGV) movement in the path of Fig 1. The results are summarized by Fig 2, which represents the real and estimated trajectories, Fig 3., which represents the real and estimate maneuvering of the UGV, Table 1, which represents the root mean squared error (RMSE), and Table 2, which represents the accuracy in retrieving the rotational mode.

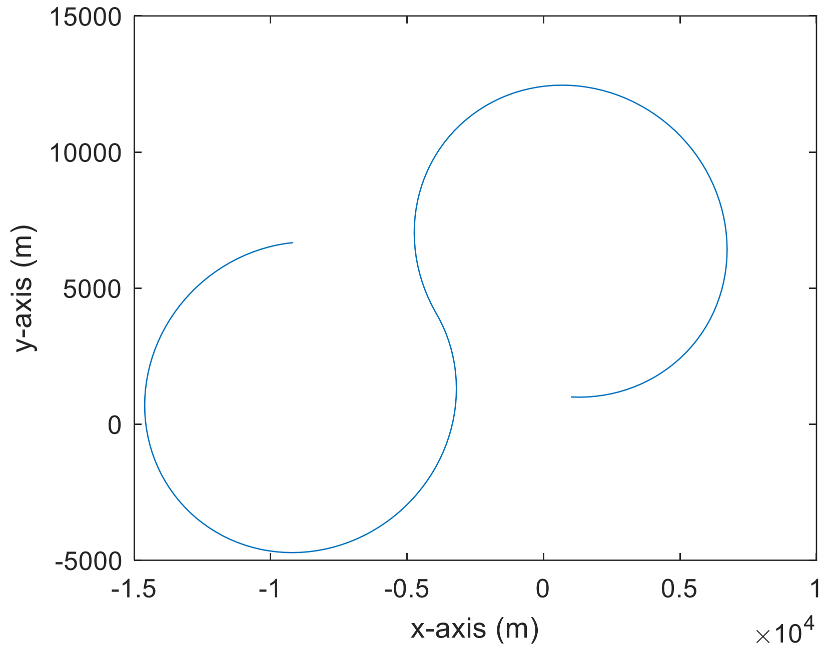

Fig 1. UGV path in 2-D environment

From Fig 2, the results show a good match between the estimated and actual trajectories. Table 1 also agrees with the results as the RMSE of the positions are 0.3547 and 2.633 m in a system that moves in km. The velocities have small RMSEs as well with magnitude less than 0.024 m/s while the actual speed could reach 300 m/s. The confusion matrix of Table 2 and Fig 3 show that the proposed algorithm can detected the turning mode with accuracy above 99%.

Table 1. RMSE of the simulated results

	MAE in			
	$x_1\ (m)$	$x_2 (m/s)$	$x_3\ (m)$	$x_4 (m/s)$
$\mathrm{IMM-SIF}$	0.3547	0.0231	2.6330	0.0238

Table 2. IMM-SIF Mode Probability Results (Confusion Matrix)

		Actual Condition	
		CCW	CW
Predicted Condition	CCW	1%	100%
	CW	99%	0%

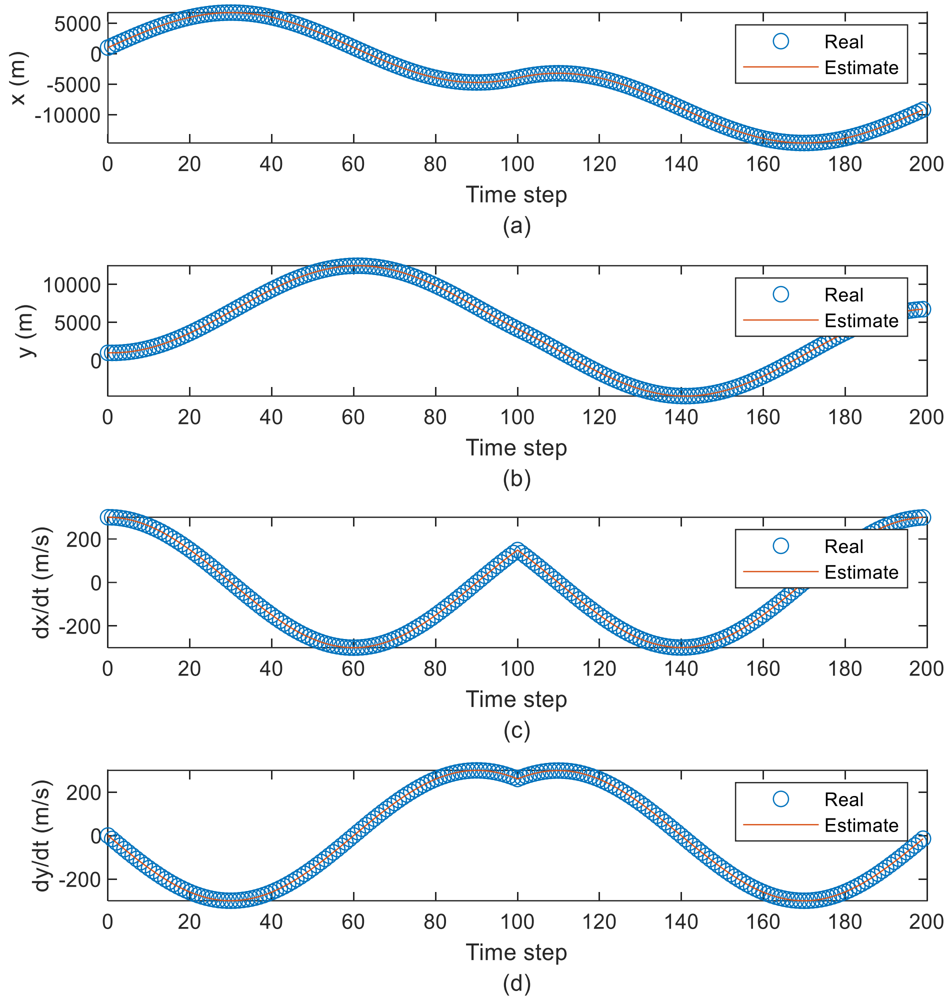

Fig 2. The trajectories of the real system and the proposed method estimation including (a) x-position, (b) y-position, (c) x-velocity and (d) y-velocity

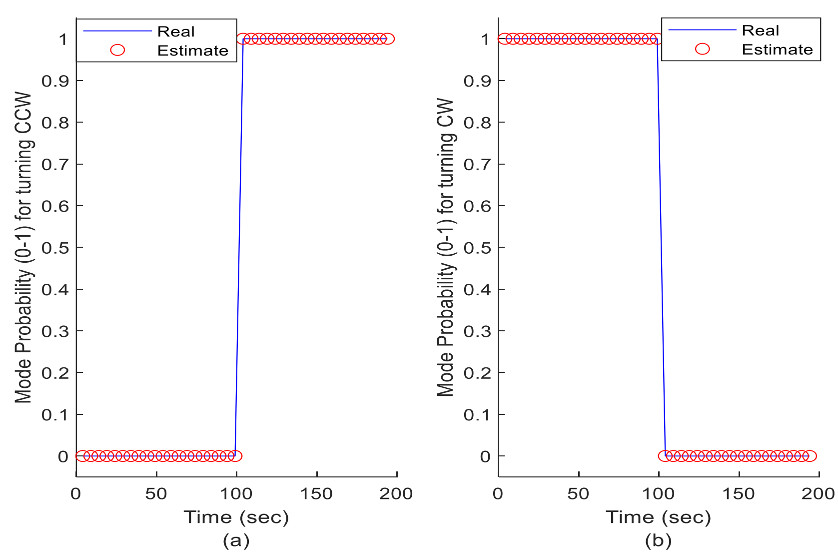

Fig 3. Operation Mode for the real system and the proposed method estimation

5. CONCLUSIONS

In this concise study, the combined approach of IMM-SIF was employed to estimate the UGV's trajectories in 2-D path S-Shape path. The findings revealed that the IMM-SIF approach yielded estimates with maximum RMSE of 2.633 which is less than 1% of the magnitude. Additionally, the IMM-SIF approach demonstrated a high accuracy rate of at least 99% in predicting the operation mode. Moreover, the study highlights the importance of estimation methods in fault and diagnostic applications, as they provide monitoring and evaluation of a plant's state based on data obtained through sensors. The proposed filtering technique can be used as a foundation for spotting out-of-the-ordinary occurrences that may point to systemic issues. Furthermore, the study suggests that combining at least two filters, one from each class, can improve the estimation process by increasing performance while decreasing the overall number of constraints. Overall, this study provides valuable insights into the development of more effective filtering techniques for autonomous UGV navigation and has potential implications for various other fields that rely on estimation methods.

In addition to the promising results obtained in this study, there are several avenues for further exploration and expansion of the IMM-SIF approach in the field of fault detection. Additionally, comparative studies could be carried out to benchmark the IMM-SIF approach against other estimation techniques, such as KF or other sliding mode observer methods. This would provide insights into the relative advantages and limitations of the IMM-SIF approach compared to other existing methods, and contribute to the body of knowledge in the field of fault and diagnosis applications.

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