High-accuracy UAV Navigation based on Multi-sensor Fusion

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***Abstract*—Many current navigation systems for unmanned aerial vehicles (UAV) heavily rely on the accuracy of the Global Positioning System (GPS) sensor. The failure of such a GPS sensor or its low-quality data can downgrade flight performance or even lead to the crash of the whole system. This paper proposes a Sensor Fusion method, known as Extended Kalman filter (EKF), that improves relative navigation accuracy and robustness by fusing all available measurements. Using partial derivatives and Taylor series expansion, EKF linearises the predict and update phases for current estimates. Through a series of comparison experiments, the combination of different sensor types (e.g., GPS, IMU, and RADAR sensors) delivers various positioning efficiencies, but all outperform the navigation performance of the GPS alone.**

I. Introduction

A common problem with previous UAV tracking systems is reliance on the measurement data from only a single sensor. The effectiveness and stability of the UAV system can collapse in case of malfunction or damage from a sensor occur. Moreover, almost all tracking sensors mounted on UAVs come with errors and noise because of their hardware limits. Further, they also have the significant disadvantage of only working in specific environments and conditions [1]. Especially, the high-accuracy pose estimation is highly challenging when the UAV flies in cluttered environments with disturbances, for example, wind gusts.

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Many various nonlinear filter solutions have been discussed in the high-accuracy positioning applications, where there are many sources of uncertainty [2]. Despite demonstrating promising performance, neural filters require large amounts of data, sensitive to noise in data, and inapplicable for the dynamic environments. They are, therefore, adopted offline to process an excess of previously collected operational data. Fuzzy systems demand expert experience or instructions in advance [3]. The simpler complementary filter algorithms cannot reject measurements with significant errors.

These call for novel solutions to deal with measurement uncertainties and relax the exact sensor model. The contributions of this paper are: 1)

1) A sensor fusion method based on extended Kalman filter [4] is introduced. This algorithm merges many measurement information to produce a more accurate result than the GPS, compared to only two-sensors fusion of the alternatives.
2) This paper considers many sensor fusion cases to validate the UAV localisation capability and recommend users.

The rest of this paper is organized as follows. In Section 2, a literature review of related work is presented, including existing sensor systems and measurement filters on UAV navigation. The structure and the implementation of extended kalman filter is introduced in Section 3. Our experimental environment, methodology and results are discussed in Section 4. Finally, concluding remarks are presented in Section 5.

II. Related work

A. Existing sensor systems used on UAV navigation

1) Global Positioning System (GPS): Free, accurate, and regularly updated position measurements have made GPS the most popular positioning method in the world. Range and range-rate measurements are provided via GPS. However, this method has several constraints because it transmits and receives signals based on radio signals, making it error-prone. GPS signals can be slow as they pass through the atmosphere, possibly reflected many times before reaching the GPS receiver. In addition, GPS signal is affected by the number of satellites seen by the GPS receiver. As a result, the accuracy of GPS receivers is on average less than 15 meters, which can not meet the demand for high-accuracy UAV navigation [5].

2) Inertial Navigation System (INS): Another sensor that can provide a UAV system with data on position, speed, and inclination angles is the Inertial Measurement Unit (IMU). Components of an IMU are usually a combination of multiple accelerometers, gyroscopes, and magnetometers. This sensor measures the UAV platform's acceleration (a_x, a_y, a_z) and rotation rates (p, q, r), which can than be processed and transformed to provide position (x, y, z), velocity(u, v, w) and attitude (ϕ, θ, ψ). The IMU has a high data update rate, but the errors in the data (Accelerometer bias, gyros drift, temperature and vibrations) are often accumulate, so it is not suitable for long-term positioning. These disadvantages can be solved by incorporating a GPS sensor with error and a low sampling rate but do not drift from the actual position. It can be seen that GPS and IMU can limit each other's weaknesses and interact with each other to produce more accurate results [6].

3) A vision-based sensor: Image-based methods for performing Simultaneous Localization And Mapping (SLAM) are popular because of the camera's affordability, availability, and low weight. The principle of this method is based on the design of algorithms to compare the difference between frames. The downside of this technique, when applied to UAVs, is closely related to the high speed of movement of these platforms or when they navigate in large spaces. Moreover, they do not provide a robust solution for UAVs due to their low reliability in the long run, due to cumulative errors and other factors to the camera, such as lighting [7].

4) Light detection and ranging (Lidar): LiDAR is another sensor alternative for creating location solutions based on point clouds. Lidar has many advantages such as ample and accurate data supply, can be used in complex terrains, is not affected by day and night and harsh environmental conditions. Their limitations arise when integrating such approaches into UAVs, which, due to the intense vibrations and fast movements of the UAV, can create drift that renders the system unsustainable for long periods. Also, The large size and computational resources for data analysis make it difficult to apply for UAV real-time applications [8].

5) Radio Detection And Ranging (radar): Finally, a sensor used to measure distance accurately is Radar. This detection system uses radio waves to determine the distance (range), azimuth, or velocity of one or more objects. It has been widely used in the military, aviation, marine to detect the distance to how the object is measured. By knowing the wave speed and the time it takes for the wave to return, it is possible to know the distance from the transmitter to the target. Radar is able to work well in all types of weather, is unaffected by the environment, and has high accuracy. Radar sensors can be used as an alternative to GPS in environments where radio signals are blocked and turbulent.

6) Summary: The selection of sensors used on the UAV system is suitable for high accuracy, low cost, and operating costs, can be suitable for many different types of environments, and the amount of computation to operate in real-time is very important. To meet the topic's requirements, the sensors selected are GPS, IMU, and RADAR. Below is a comparison table comparing the advantages and disadvantages of different types of sensors:

B. Measument filters

1) Kalman filter: The most popular algorithm for the current Sensor Fusion method is the Kalman Filter (KF), which is a method based on recursive Bayesian filtering where the noise in your system is assumed Gaussian. In Bayesian filtering, the al-

Criteria	GPS	IMU	RADAR	LIDAR	CAM
Resolution	●○○	●●●	●○○	●●○	●●●
Accuracy	●○○	●●○	●●●	●●○	●●●
Affected by environment	●○○	●●●	●●●	●●○	●●○
Radio signal reliance	●○○	●●●	●●●	●●●	●●●
Affected by velocity	●●○	●●○	●●●	●○○	●○○
Size	●●●	●●●	●●●	●○○	●●●
Cost	●●●	●●●	●●○	●○○	●●●

TABLE I

EXISTING SENSOR SYSTEMS COMPARISON. ONE BLACK DOTS REPRESENTS 'BAD', WHILE TWO AND THREE BLACK DOTS INDICATE 'OK' AND 'GOOD', RESPECTIVELY

gorithm alternates between prediction (estimate of current state) and update (observation of sensors). Basically, the algorithm will make the prediction and correct it according to the estimated update value, following these two steps until the desired accuracy is reached. Here are basic equations of two steps:

In prediction step, state estimate $x_{k|k-1}$ and covariance estimate $P_{k|k-1}$ are calculated:

$$x_{k|k-1} = F_k x_{k-1|k-1} + B_k u_k \tag{1}$$

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k \tag{2}$$

Where F is the state transition matrix used to predict the value of the next $x_{k|k-1}$ and $P_{k|k-1}$; Q_k is the process noise covariance matrix and u_k is control effort.

The system outputs are in update step. The difference between the predicted measurement $x_{k|k-1}$ and actual measurement z_k is defined as:

$$y_k = z_k - H_k x_{k|k-1} \tag{3}$$

Where H_k is the extraction matrix used to extract the theoretical sensor readings. The estimate and measured value are now fused linearly using equation:

$$x_{k|k} = x_{k|k-1} + K_k y_k \tag{4}$$

where $x_{k|k}$ is the new updated estimate, The degree of inaccuracy between the measured value and the best guess is determined by kalman gain K_k, which is a weighted number and has the ability to change value over time. Finally looking at the error covariance of this new updated estimate, we get the following equation:

$$P_{k|k} = (I - K_k H_k) P_{k|k-1} \tag{5}$$

2) Extended kalman filter: Although the Kalman filter is capable of providing real-time vehicle position updates, it is based on linear system models. In this case, and extended version of Kalman filter called Extened Kalman Filter (EKF) is used, where by extending the Taylor series the nonlinear system is linearized and approximated around each current state estimate. The linear Kalman filter is then applied to generate the next state estimate. Thus, we can use the EKF algorithm to apply to nonlinear sensor data. A distinguishing feature of KF and EKF filters is that they do not require a large amount of computation and are easy to apply in real time. This makes them well-suited to the UAV systems of this topic.

Compare to Kalman filter, the system model in equation (1) and measurement model in equation (3) of EKF are fixed and shown below:

$$x_{k|k-1} = f(x_{k-1|k-1}, u_k) \tag{6}$$

$$y_k = z_k - h(x_{k|k-1}) \tag{7}$$

Where the nonlinear system and measurement models are represented by f and h respectively. The functions must be linearized in order to use nonlinear functions f and h.

3) Intelligent filters: Some other algorithms can be mentioned to apply to nonlinear data systems such as Particle Filter or Intelligent filters(Fuzzy filter, Neural Networks, Deep learning), but they have in common that the computational volume is very large and can cause delay when processing data. The comparison among filters is shown below:

Filter	KF	EKF	Partile filter	Intelligent filter
Model	linear	nonlinear	nonlinear	nonlinear
Assumed distribution	Gaussian	Gaussian	non-Gaussian	non-Gaussian
Computational cost	low	low	high	high
Need of reference	no	no	no	yes

TABLE II

MEASUREMENT FILTERS COMPARISON

III. UAV LOCALISATION USING ETENDED KALMAN FILTER

In the flowchart above, pose estimation is estimated by assigning weights (kalman gain K) to the prediction and the measurements. EKF alo requires the application of linearisation of the non-linear models from IMU and RADAR sensors.

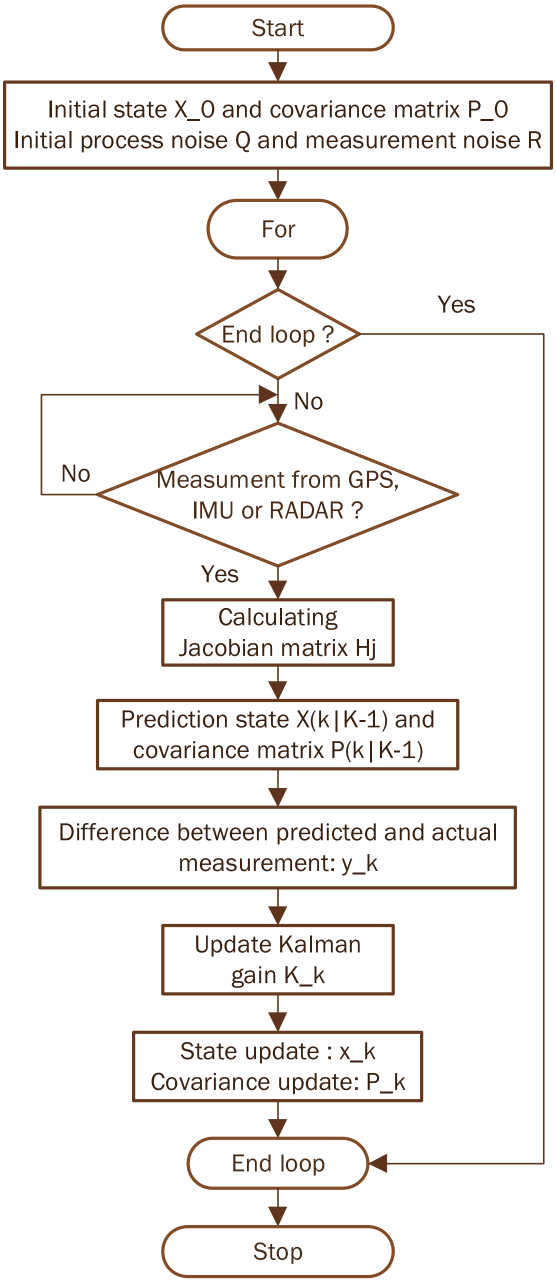

Fig. 1. EKF flow chart for pose estimate

A. GPS and IMU integration

Acceleration and angular velocity of our UAV are assumed to be constant. The motion model is define as follow:

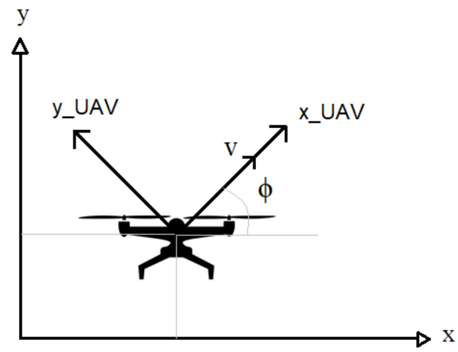

Fig. 2. UAV model

$$f(x_{k-1}, u_k) = \begin{bmatrix} x_k \\ y_k \\ \phi_k \\ \omega_k \\ v_k \\ a_k \end{bmatrix} = \begin{bmatrix} x_{k-1} + v_{k-1}\Delta t \cos\phi_{k-1} \\ y_{k-1} + v_{k-1}\Delta t \sin\phi_{k-1} \\ \phi_{k-1} + \omega_{k-1}\Delta t \\ \omega_{k-1} \\ v_{k-1} + a_{k-1}\Delta t \\ a_{k-1} \end{bmatrix} \tag{8}$$

Where x_k and y_k are the present position of UAV. ϕ_k, ω_k are yaw angle and angular rate, while v and a are velocity and acceleration respectively. Δt is time step.

Transiton matrix H_j need to be linearized using jacobian matrix:

$$H_j = \frac{\partial f}{\partial x} = \begin{bmatrix} 1 & 0 & -\sin\phi_{k-1} v_{k-1}\Delta t & 0 & cos\phi_{k-1}\Delta t & \\ 0 & 1 & \cos\phi_{k-1} v_{k-1}\Delta t & 0 & sin\phi_{k-1}\Delta t & \\ 0 & 0 & 1 & \Delta t & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & \Delta t \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{9}$$

B. GPS and Radar integration

A radar sensor can measure speed within its line of sight $\rho^{\cdot}$ using something called a doppler effect. It can also measure distance of nearby objects that can easily be converted to polar coordinates (ρ, φ)

Similarly, we also have motion model and jacobian matrix H_j as follow:

$$\begin{bmatrix} x_k \\ y_k \\ vx_k \\ vy_k \end{bmatrix} = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_{k-1} \\ y_{k-1} \\ vx_{k-1} \\ vy_{k-1} \end{bmatrix} \tag{10}$$

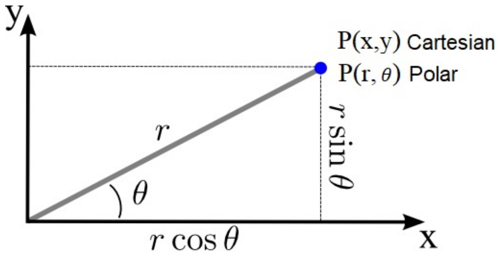

Fig. 3. Radar coordinate

$$H_j = \begin{bmatrix} \frac{\rho}{x_k} & \frac{\rho}{y_k} & \frac{\rho}{vx_k} & \frac{\rho}{vy_k} \\ \frac{\varphi}{x_k} & \frac{\varphi}{y_k} & \frac{\varphi}{vx_k} & \frac{\varphi}{vy_k} \\ \frac{\dot{\rho}}{x_k} & \frac{\dot{\rho}}{y_k} & \frac{\dot{\rho}}{vx_k} & \frac{\dot{\rho}}{vy_k} \end{bmatrix}$$

$$= \begin{bmatrix} \frac{x_k}{\sqrt{x_k^2+y_k^2}} & \frac{y_k}{\sqrt{x_k^2+y_k^2}} & 0 & 0 \\ \frac{-y_k}{x_k^2+y_k^2} & \frac{x_k}{x_k^2+y_k^2} & 0 & 0 \\ \frac{y_k(vx_k y_k - vy_k x_k)}{(x_k^2+y_k^2)^{1.5}} & \frac{x_k(vy_k x_k - vx_k y_k)}{(x_k^2+y_k^2)^{1.5}} & \frac{x_k}{\sqrt{x_k^2+y_k^2}} & \frac{y_k}{\sqrt{x_k^2+y_k^2}} \end{bmatrix} \quad (11)$$

IV. Experimental Setup and Results

We use Matlab function *generateCircularTrajSensorData()* to produce our UAV measurement data based on an 8-shaped trajectory. The results for each case are below.

It is observed that more sensors measurements are fused, more accurate pose estimate is obtained. As shown in Fig. 9, the GPS sensor alone produce a root mean square error (RMSE) of only 0.51 while that of the GPS+IMU+RADAR sensors case is only 0.11. Moreover, the GPS+RADAR generates a significantly lower RSME than the GPS+IMU, namely, 0.33 compared to 0.41. This result means that the GPS and RADAR combination produces more accuracy navigation than the GPS and IMU under the EKF filter.

Especially, in case failure of RADAR sensor shown in Fig. 10, RADAR is eliminated for a short period of time and the EKF estimation accuracy is decreased but then follow closely to the truth trajectory of the UAV .

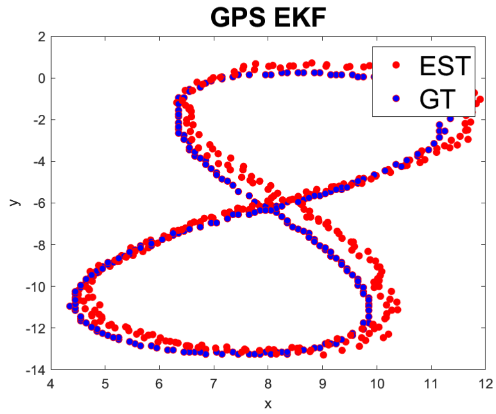

Fig. 4. GPS EKF

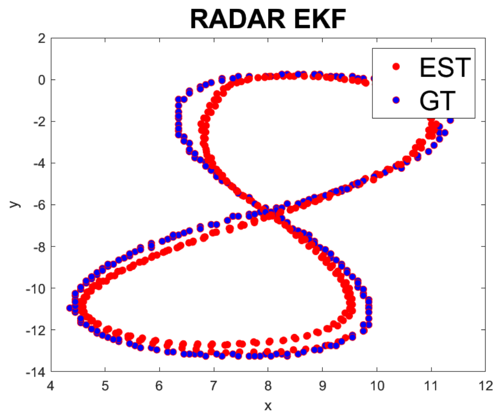

Fig. 5. RADAR EKF

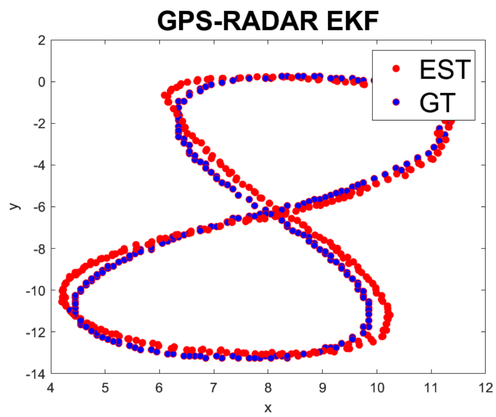

Fig. 6. GPS+RADAR EKF

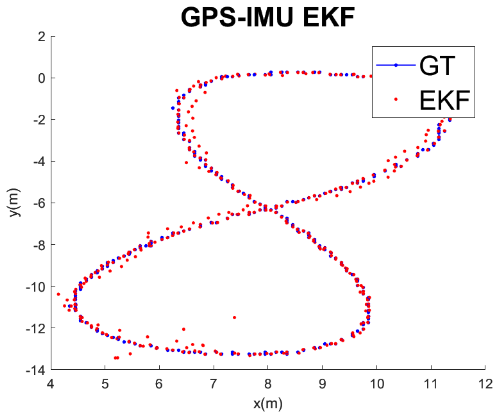

Fig. 7. GPS+IMU EKF

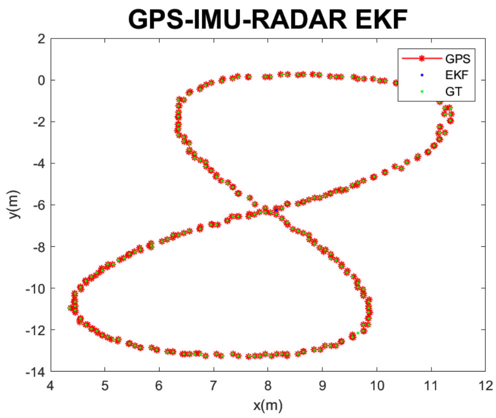

Fig. 8. GPS+IMU+RADAR EKF

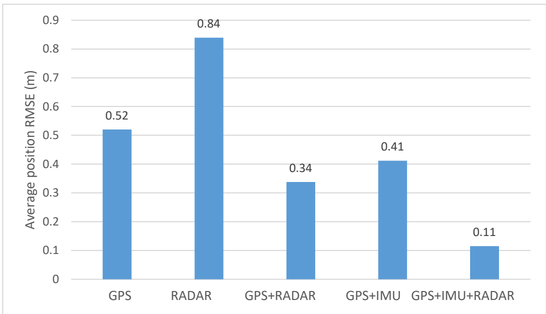

Fig. 9. EKF results comparison

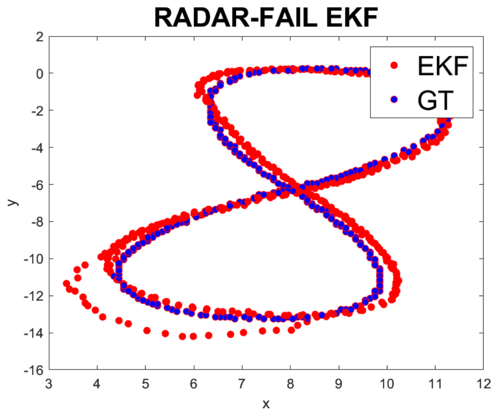

Fig. 10. EKF results comparison

V. Conclusion

This paper has made a comparison for the combination of many types of sensors on the uav navigation system. Our key conclusions are:

1) Compare to GPS-ony navigation, all cases of sensor combination give greater results, especially when combine there sensor GPS, IMU and RADAR
2) This paper recommended users which sensors should be combine together.

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