Localization error reduction for an electric aircraft tractor prototype using Kalman filter

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บทคัดย่อ การใช้งานยานยนต์อัตโนมัติในพื้นที่สนามบินต้องการการระบุตำแหน่งอย่างแม่นยำเพื่อใช้ในการนำทางในเขตการบิน อีกทั้งเพื่อป้องกันการชนกับอากาศยาน อาคาร และ ผู้ปฏิบัติการในพื้นที่ งานวิจัยการทดสอบระบบระบุตำแหน่งบนต้นแบบรถไฟฟ้าขนาดเล็กเพื่อเคลื่อนย้ายอากาศยานนั้นจะใช้ระบบนำร่องด้วยดาวเทียบแบบ global navigation satellite system (GNSS) ที่ง่ายต่อการใช้งานในการระบุตำแหน่งทั้งนี้จะมีการนำข้อมูลไปผสมรวมกับระบบวัดระยะทางผ่านล้อขับเคลื่อนของรถโดยใช้วิธีการผ่านตัวกรองคาลมาน โดยการทดสอบและวัดผลบนต้นแบบรถเคลื่อนย้ายอากาศยาน โดยการติดตั้งระบบนำร่องอัตโนมัตินั้นสามารถเพิ่มความแม่นยำในการผสมรวมกับตัวกรองคาลมานทำให้ค่าผิดผลาดของระบบนำร่องด้วยดาวเทียบลดลงได้อย่างน้อย 32.35% และ เพิ่มขึ้นได้ถึง 56.47% และสามารถชดเชยข้อมูลที่คลาดเคลื่อนของระบบนำร่องด้วยดาวเทียมกับอุปกรณ์วัดความเร่งภายในได้ ซึ่งสามารถแก้ไขปัญหาของสัญญาณที่ผิดปกติและความผันแปรของข้อมูลได้ โดยจากผลการทดลองต้นแบบรถเคลื่อนย้ายอากาศยานสามารถเคลื่อนที่ได้อย่างมีประสิทธิภาพ

***คำสำคัญ* :** ระบบนำร่องด้วยดาวเทียม, อากาศยาน, ตัวกรองคาลมาน, ยานยนต์ไฟฟ้า

Abstract Operating an autonomous vehicle in an airport requires high localization precision to safely navigate the airside and avoid collisions with aircraft, buildings, and personnel. This paper presents an accuracy analysis of the localization system for a small electric aircraft tractor prototype. The system utilizes a Global Navigation Satellite System (GNSS) for positioning and enhances accuracy through data fusion with a wheel odometer using a Kalman Filter. A pilot system was installed on the autonomous small electric aircraft tractor prototype to evaluate performance. Experimental results indicate that the data fusion-based approach reduced GNSS positioning errors by 32.35% in the worst case and up to 56.47% in the best case while also increasing satellite data availability through computational estimation with an Inertial Measurement Unit (IMU). Additionally, the IMU reduces signal error data in certain areas and reduces covariance noise, resulting in more accurate and efficient movement of the electric aircraft tractor.

***Keywords*:** Global Navigation Satellite System, Aircraft, Kalman filter, Electric Vehicles.

1.Introduction

Typically, aircraft can reverse using thrust reversers. However, this method poses a risk of damage to both the aircraft and the airside due to Foreign Object Debris (FOD) from the ground or surrounding structures. To mitigate this risk, aircraft pushback tractors are used to maneuver aircraft on the ground, positioning them for taxiing. These tractors either tow or lift the aircraft by its nose landing gear, requiring them to be both heavy and powerful. Given that the average aircraft weight is approximately 54 tons (119,000 pounds) and requires a pulling force of 334 kN (75,000 pounds), pushback tractors must be designed to handle such loads efficiently.

With the continuous growth of the aviation industry [1], air travel accounts for approximately 54% of tourism-related transportation. Consequently, the need for efficient ground handling operations, including aircraft towing, has become increasingly important. However, traditional pushback tractors are manually operated by human drivers, leading to a high risk of accidents that can result in damage to the aircraft, the tractor, or even personnel [2]. Implementing remote-controlled or autonomous pushback systems could significantly reduce human error-related incidents.

Since pushback tractors operate over large areas and in proximity to buildings, raw data from Global Positioning System (GPS) or Global Navigation Satellite System (GNSS) must be filtered, as it is often inaccurate due to signal disturbances from cloud cover or reflections from nearby structures [3,4,7]. Data fusion techniques, which integrate GNSS data with Inertial Measurement Unit (IMU) sensors [5] and wheel encoders [6], provide a more accurate localization solution. Typically, pushback tractors tow aircraft by the nose wheel, but precise towing requires trajectory control equations to ensure safe movement. Additionally, multiple ground crew members are usually required to monitor the aircraft during towing, as the driver has limited visibility, increasing the risk of human error due to fatigue or distractions.

This research presents a prototype of a lightweight, all-electric aircraft pushback tractor. The system integrates GNSS with data fusion using an IMU and wheel encoder-based odometer to enhance navigation accuracy. Furthermore, it incorporates an aircraft towing control equation [6] and an electronic differential drive system. The collected data will be evaluated for potential applications in future airport management systems.

2. Material Tools and Methods

2.1 System diagram

The navigation system of the tractor utilizes data from the GNSS, IMU, and wheel encoder. Raw sensor data is processed by a microcontroller to compute acceleration and heading across all axes of the tractor. Subsequently, data fusion with GNSS is performed to enhance localization accuracy. Although GNSS is generally more precise than GPS [8], its data can sometimes be affected by interference and operates at a lower frequency. Additionally, GNSS data must be recalculated, as it is provided in the National Marine Electronics Association (NMEA) 0183 format, specifically the Recommended Minimum Specific GNSS Data (RMC) message, which cannot be used directly. The system diagram is shown in Fig. 1.

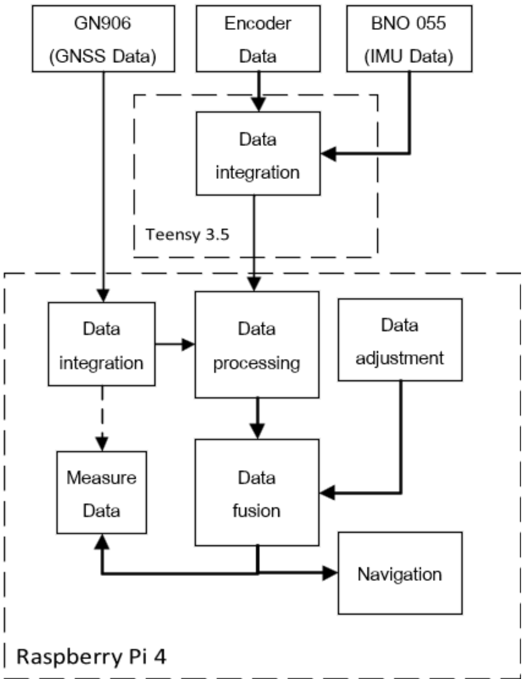

Fig. 1 System diagram

2.2 Data correction

The raw data from the tractor's sensors undergoes correction using three primary sensors. The Inertial Measurement Unit (IMU) provides data along three axes, including acceleration in the X and Y directions (measured in meters per second squared), angular velocity in the X and Y directions (measured in degrees per second), and heading in terms of roll and yaw (measured in degrees). In this research, the BNO055 sensor is used as a low- cost solution for testing.

The GNSS data is obtained from the TOPGNSS GN906 receiver, which provides position and heading information in the Recommended Minimum Specific GNSS Data (RMC) format of the NMEA 0183 standard. Since latitude and longitude are not in metric units, they must first be converted into Mercator projections using Equations (1) and (2).

$$x = R*(\lambda-\lambda_0) \quad (1)$$

$$y = R*\ln(\tan(\frac{\pi}{4}+\frac{\varphi}{2})) \quad (2)$$

Where "x" and "y" represent the tractor's location relative to the reference region, "R" is the radius of the Earth (6,371 km), λ is the longitude, λ_0 is the central meridian, and φ is the latitude [12]. The data from the encoder comes as an electronic signal generated by a magnetic field. As a magnet rotates on a motor shaft, the polarity of the magnet changes, which in turn affects the voltage in the sensor. This voltage variation allows the sensor to determine the strength of the magnetic field and calculate the angle of the shaft in degrees.

2.3 Small electric aircraft tractor prototype

The design of small electric aircraft tractor prototype has two electronic system to use to control and navigate tractor first power system it uses microcontroller to control motors with encoder and calculate wheel odometer that have power source from 8 cell 24v Lithium Iron phosphate (LiFePo4) and 3 cell 12v Lithium polymer (Lipo) for use to separated noise from power system with sensor show in Fig.2 and Fig.3.

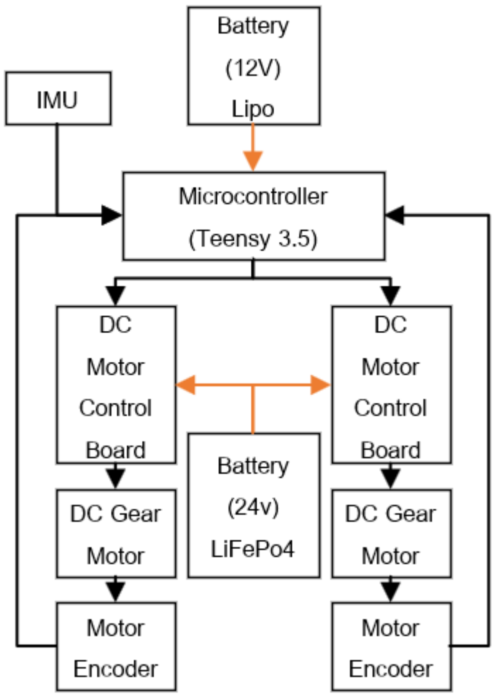

Fig. 2 Power system

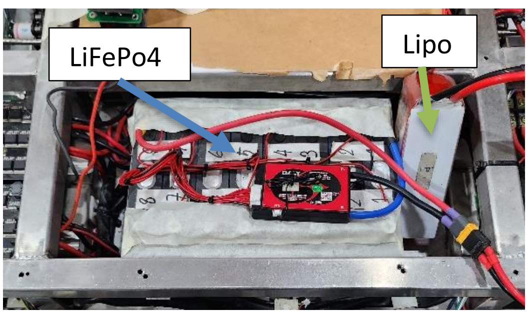

Fig. 3 Battey system

The second process system is used to run navigation system and calculate Kalman with all of sensors and send back to control laptop in Fig.4 – 6.

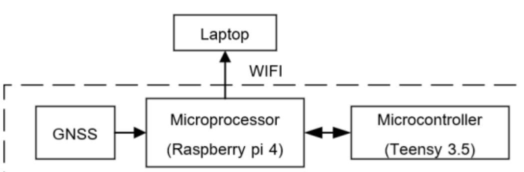

Fig. 4 Data process system

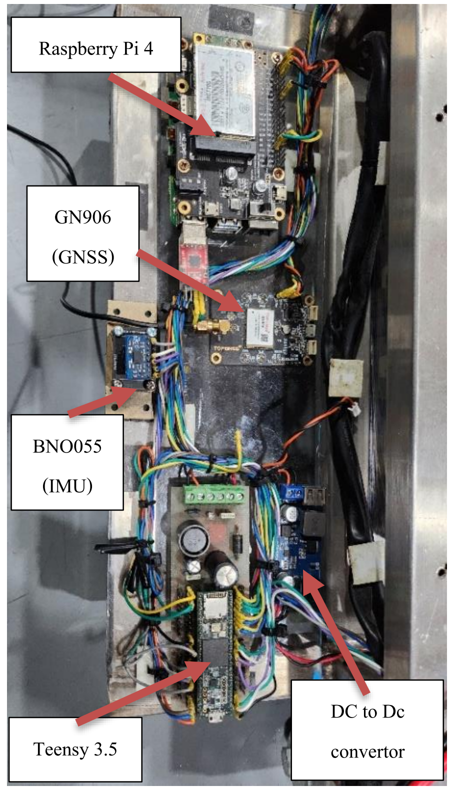

Fig. 5 Electronic part of data process system

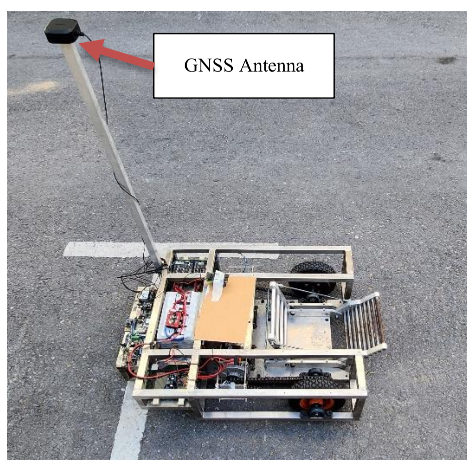

Fig. 6 Small electric aircraft tractor prototype

2.4 Mathematical model of aircraft pushback tractor

The tractor uses 2 wheels in the back to move and rotate is a type of driving system called the nonholonomic [8] shown in Figure 2 by x_P, y_P is start point of the tractor, x'_P, y'_P is a next position of the tractor in x and y axis, θ_P is the heading of the tractor in start point, θ'_P heading of the tractor in next position, V_P is velocity of tractor, V_L is edge velocity in the left wheel, V_R is edge velocity in the right wheel that can build a basic Eq. (3) to use in wheel odometer that use encode from motor follow Fig. 7.

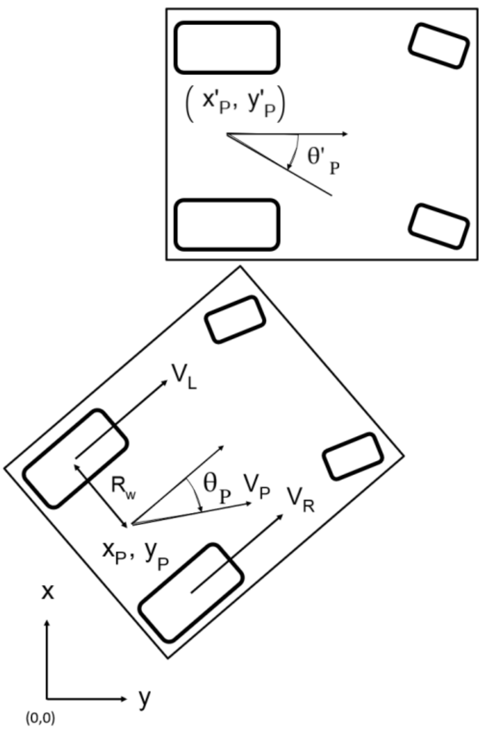

Fig. 7 Variables for creating equations of motion for tractor

$$\begin{bmatrix} x'_P = V_P\cos\theta_P \\ y'_P = V_P\sin\theta_P \\ \theta'_P = \omega \end{bmatrix} = \begin{bmatrix} \cos(\theta) & -\sin(\theta) & 0 \\ \sin(\theta) & \cos(\theta) & 0 \\ 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} V_P \\ 0 \\ \omega \end{bmatrix} \quad (3)$$

2.5 Data fusion

Data fusion uses other data to predict lost and non-accurate data more precisely [9,10], Date fusion works in two stages that is prediction data stage and the update data stage, as shown in Fig. 8.

The prediction stage uses two models: the state transition model and the observation model, as shown in Equations (4) and (5). In these equations, x_k represents the state vector at the current time, x_{k-1} represents the state vector at the previous time step, A is the state transition matrix, B is the control matrix, u_k is the control input vector, w_k is the process noise vector, y_k is the measurement vector, H is the observation matrix, and v_k is the measurement noise vector.

$$x_k = Ax_{k-1} + Bu_k + w_k \quad (4)$$

$$y_k = Hx_k + v_k \quad (5)$$

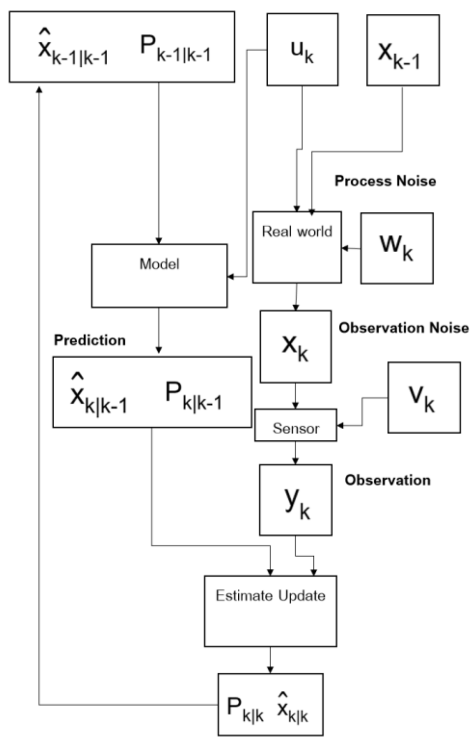

Fig. 8 Data fusion operation

Where w_k is process noise in vector, y_k is measured data from the sensor at current in vector unit, H is observation model in the matrix, v_k is observation noise in the matrix.

The update data stage is used to calculate new data for prediction in the future by using the past data, which can be described into two stages: prediction from controlled variables and update data.

The prediction from controlled variables involves two equations: the prediction from controlled variables and the stage error estimation or covariance, which are represented in Eq. (6) and (7). The current variables originate from the previous stage. The $\hat{x}_{k|k-1}$ is prediction variables from previous stage, $P_{k|k-1}$ is estimation covariance at current from the previous stage, $P_{k-1|k-1}$ is estimation covariance from the previous stage, Q_k is process noise covariance.

$$\hat{x}_{k|k-1} = A\hat{x}_{k-1|k-1} + Bu_k \tag{6}$$

$$P_{k|k-1} = AP_{k-1|k-1}A^T + Q_k \tag{7}$$

Update data is a stage to update new data by integrating the sensor to improve and give weight to data to find estimation variables has three main stages observation stage update stage and update error covariance. Observation stages the equation shown in Eq. (8), and (9)

$$\hat{y}_{k|k-1} = H\hat{x}_{k|k-1} \tag{8}$$

$$z_k = y_k - \hat{y}_{k|k-1} \tag{9}$$

where H is the observation model in the matrix, z_k is difference variables from previous and current data.
Update stage the equation shown in Eq. (10)

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k z_k \tag{10}$$

Where K_k is Kalman gain in the matrix Update error covariance can be calculated following
Eq. (11).

$$P_{k|k} = (I-K_kH) \cdot (x_k-\hat{x}_{k|k-1}) \\ (IK_kH)^T + K_k var(v_k) K_k^T \tag{11}$$

To find process noise covariance (Q_k) and process noise (w_k) to tune Kalman by find normal error of sensor by static test by parking the tractor for 5 minutes.

Fig. 9 shows error of wheel odometer and GNSS while tractor park that wheel odometer have maximum error from stop point is maximum error is 0.176 m by noise of control to hold tractor to keep in static position and GNSS have maximum error is 2.378 m that mean GNSS have a lot of noise to localize itself by this two data we can use to tune Kalman by Q_k and put error of two sensor in w_k that made Kalman to have maximum error reference with wheel odometer 1.19 m from 2.35 m and RMSE is 0.62 m from 1.25 m or error have been reduce by 50% and 50.4% that mean Kalman can help to reduce error of GNSS

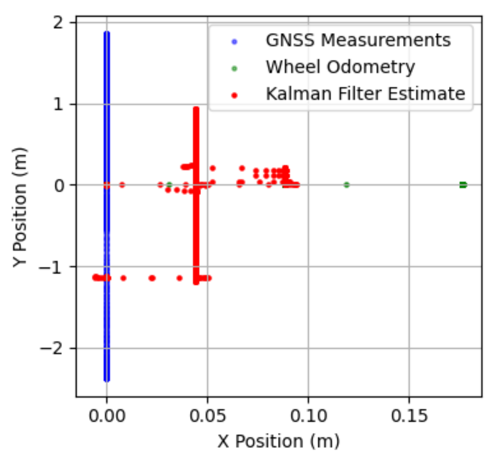

Fig. 9 Static test

Table 1 Process noise covariance error in percent

Process noise covariance	Before use Kalman (m)	After use Kalman (m)	Reduce (%)
1	1.25	0.63	49.60
0.5	1.25	0.63	49.60
0.25	1.25	0.63	49.60
0.15	1.25	0.62	50.40
0.05	1.25	0.62	50.40

Table 1 shown effect of noise covariance error (Q_k) on the Kalman filter. By fine-tuning the covariance values, the maximum error reduction was achieved, as indicated by the decrease in root mean square error (RMSE) from 0.63 m to 0.62 m. This result demonstrates that Q_k influences the mean error and effectively reduces GNSS noise.

3. Results and Discussion

The experiment evaluates the accuracy of the GNSS, wheel odometer, and data fusion by comparing errors from GNSS data processed with a Kalman filter, using the wheel odometer as a reference. The analysis considers both maximum error and root mean square error (RMSE). The testing is conducted in four different scenarios.

The first test is a linear test. The tractor moves forward 5 meters and stops to assess the Kalman filter's performance in a straight-line motion.

The second test is the square test. The tractor follows a 4 × 4-meter square path to evaluate the Kalman filter's effectiveness in both the X and Y axes.

The third test is a circular test. The tractor moves along a circular path with a 2-meter radius to analyze how the Kalman filter handles simultaneous X and Y- axis corrections.

The fourth test is a linear and curved turn. The tractor moves forward 5 meters before making a turn with a 4- meter radius, simulating the typical towing path of an aircraft.

In Fig. 10, show the error of GNSS and Kalman by reference with wheel odometer to drive the tractor 5 m and stop. From that Maximum error between GNSS with wheel odometer is 1.23 m and RMSE is 0.91 m, Kalman with wheel odometer is 0.61 m and 0.46 m, or 50.4% and 49.45%.

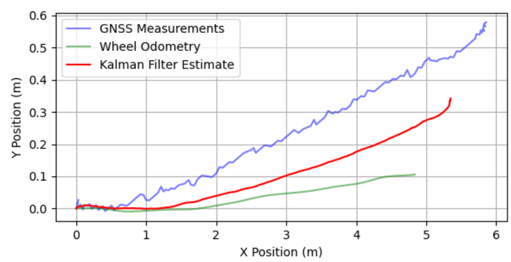

Fig. 10 Linear test

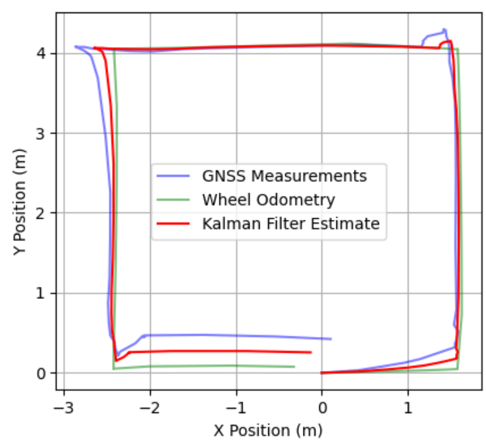

Fig. 11 Square test

In Fig. 11, show error of GNSS and Kalman by reference with wheel odometer to drive in square shape that have 4 by 4 m. to test how accuracy of Kalman to handle in X and Y axis and 90 degrees turn that have Maximum error between GNSS with wheel odometer is 0.85 m and RMSE is 0.44 m and Kalman with wheel odometer is 0.37 m and 0.2 m.

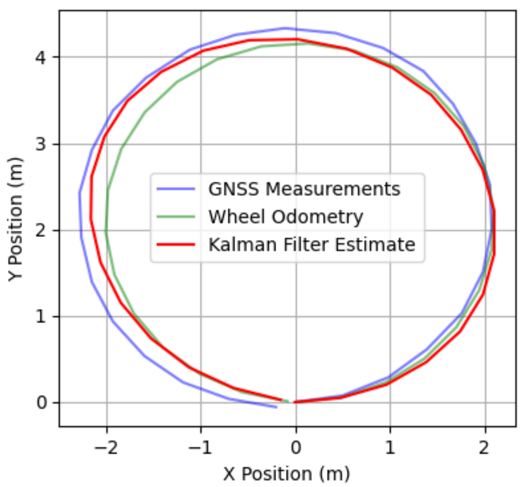

Fig. 12 Circle test

In Fig. 12, show error of GNSS and Kalman by reference with wheel odometer to drive in circle shape with 2 m radius to see how accurate of Kalman to help with X and Y axis in same time that have Maximum error between GNSS with wheel odometer is 0.34 m and RMSE is 0.24 m and Kalman with wheel odometer is 0.23 m and 0.13 m

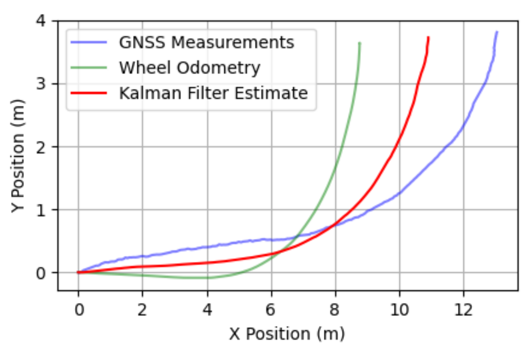

Fig. 13 Linear and curve turn

In Fig. 13, show error of GNSS and Kalman by reference with wheel odometer to drive straight 5 m and turn with radius 4 m and stop that same as towing path of light aircraft use that have Maximum error between GNSS with wheel odometer is 4.28 m and RMSE is 2.50 m. That means error has been increased by complex paths that have a lot of changing data, but Kalman can help to reduce error to 2.14 m and 1.26 m, or 50% and 49.6%; on the other hand, Kalman filter can help to reduce covariance noise in GNSS data.

Table 2 Comparison in term of maximum error

Type of test	**Before Use Kalman (m)**	**After Use Kalman (m)**	**Reduce (%)**
Static	2.38	1.19	50.00
Linear	1.23	0.61	50.41
Square	0.85	0.37	56.47
Circle	0.34	0.23	32.35
Linear and curve turn	4.28	2.14	50.00

Table 2 shown compare of Maximum error to all test in percent that have maximum reduced error is 56.47% in square shape and minimum error reduced is 32.35% in circle shape and average error of all test is 48.91% and maximum error distant is 2.14 m in linear and curve turn, from Square and Circle shape accuracy of sensor that change error to under 1 meter because weather and area of test field that have a lot of signals reflection or reduce efficiency of signals by building cloud tree and etc. that higher than tractor can reduce signal from GNSS.

Table 3 Comparison in term of Root mean square error

Type of test	Before Use Kalman (m)	After Use Kalman (m)	Reduce (%)
Static	1.25	0.62	50.40
Linear	0.91	0.46	49.45
Square	0.44	0.2	54.55
Circle	0.24	0.13	45.83
Linear and curve turn	2.5	1.26	49.60

Table 3 shown compare of RMSE to all test in percent that have maximum reduced RMSE is 54.55% or from 0.44 m to 0.2 m and minimum is 45.83% or 0.24 m to 0.13 m that mean Kalman can reduce covariance noise of navigation system

4. Conclusion

The accuracy analysis of the localization system for a small electric aircraft tractor prototype demonstrates improved GNSS data for airside operations through data fusion with an Inertial Measurement Unit (IMU). This approach increased tractor positioning accuracy by 32.35% in the worst case and up to 56.47% in the best case in terms of maximum error. However, while the root mean square error (RMSE) can be reduced, the Kalman Filter being a linear filter has limitations when applied to inherently non-linear GNSS data.

Experimental results show that accuracy improves in linear motion scenarios, but in cases involving linear and curved turns, the Kalman Filter alone is insufficient to correct distance errors effectively. To enhance accuracy, adopting a non-linear filtering approach such as an Extended Kalman Filter (EKF), integrating a high-accuracy IMU, or utilizing Real-Time Kinematic (RTK) positioning could provide significant improvements.

Nevertheless, the observed maximum error of 2.14 meters remains too high for safe aircraft towing. According to the Federal Aviation Administration (FAA), the acceptable towing path misalignment should be within 0.3 to 0.5 meters [11]. To meet this standard, integrating additional localization methods, such as LiDAR sensor fusion at the front of the tractor, should be considered. Furthermore, recalibrating process noise to mitigate sensor errors caused by environmental factors and adopting a non-linear filtering approach could further improve localization accuracy.

5. Acknowledge

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