Navigating the Uncharted: Exploring Indoor Localization with IMU-based Systems using Kalman Filters (KF, EKF, UKF) with Code

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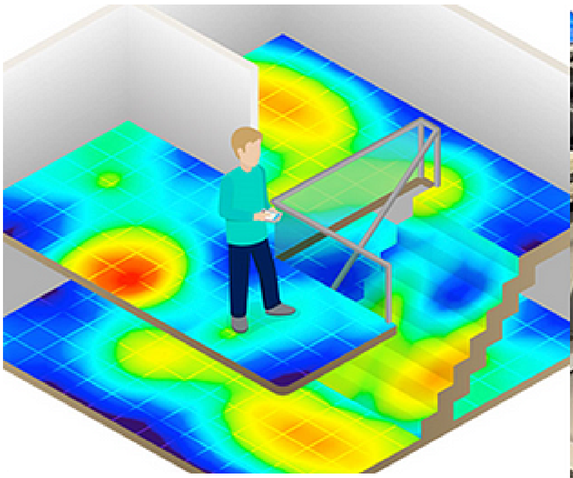
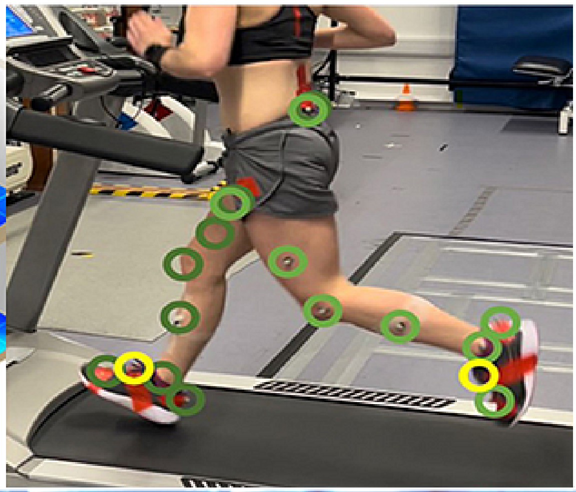
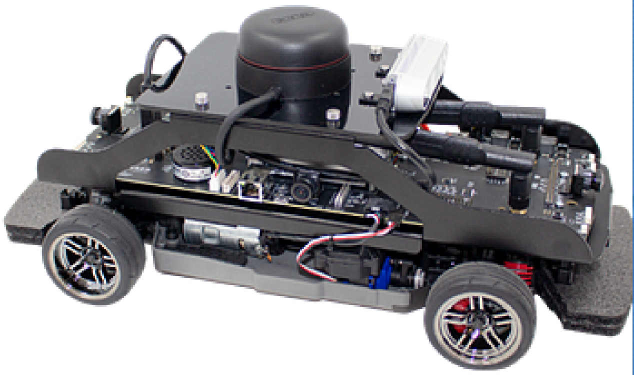
Top highlight

GPS has long been the go-to solution for finding our way in navigation. However, alternative approaches are necessary for GPS-denied environments like tunnels and caves. Enter IMU-based systems, leveraging gyroscopes and accelerometers to tackle the challenges of indoor localization. In this blog post, we dive into an intriguing project that explores the potential of IMU-based systems, specifically focusing on the implementation of Kalman Filter (KF), Extended Kalman Filter (EKF), and Unscented Kalman Filter (UKF) for enhanced indoor navigation.

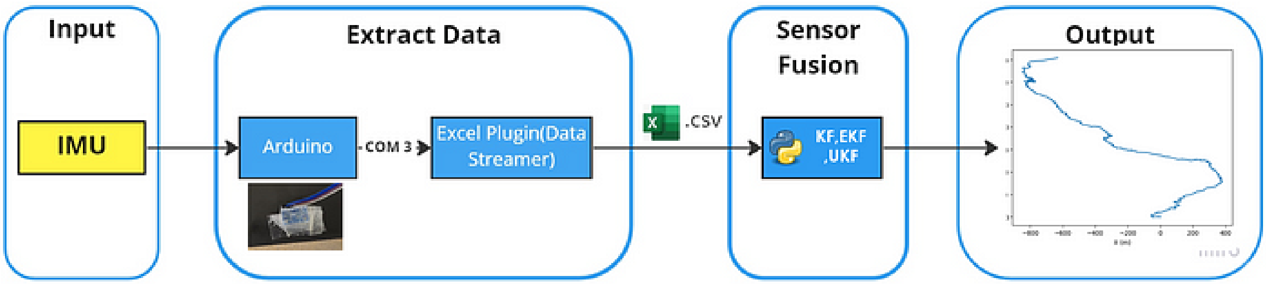
IMU Application: Indoor field navigation using IMU sensors is a versatile technique employed in diverse applications like robotics, virtual reality, and human motion analysis. One notable application is in fitness tracking, where IMU sensors accurately monitor body movement metrics such as steps taken, distance traveled, and calories burned during exercise. Additionally, in the realm of virtual reality, IMU sensors enable seamless tracking of the user's head and hand movements, facilitating immersive experiences and natural interaction with the virtual environment.





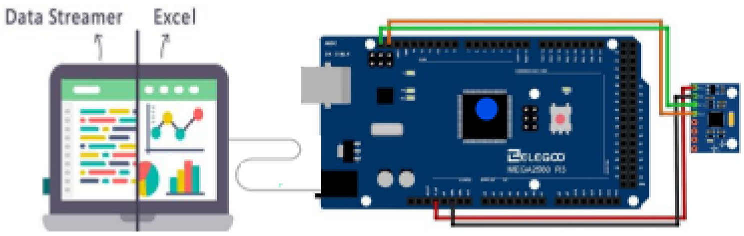


Methodology: The first phase of the project involved capturing raw data using suitable software. We then plotted the raw data to gain insights into the data. Next, we implemented three Kalman filters: Kalman Filter, Extended Kalman Filter, and Unscented Kalman Filter to correct the data. Additionally, we tuned the parameters of the filters by changing the Q noise covariance or R measurement error covariance to optimize the system's performance.



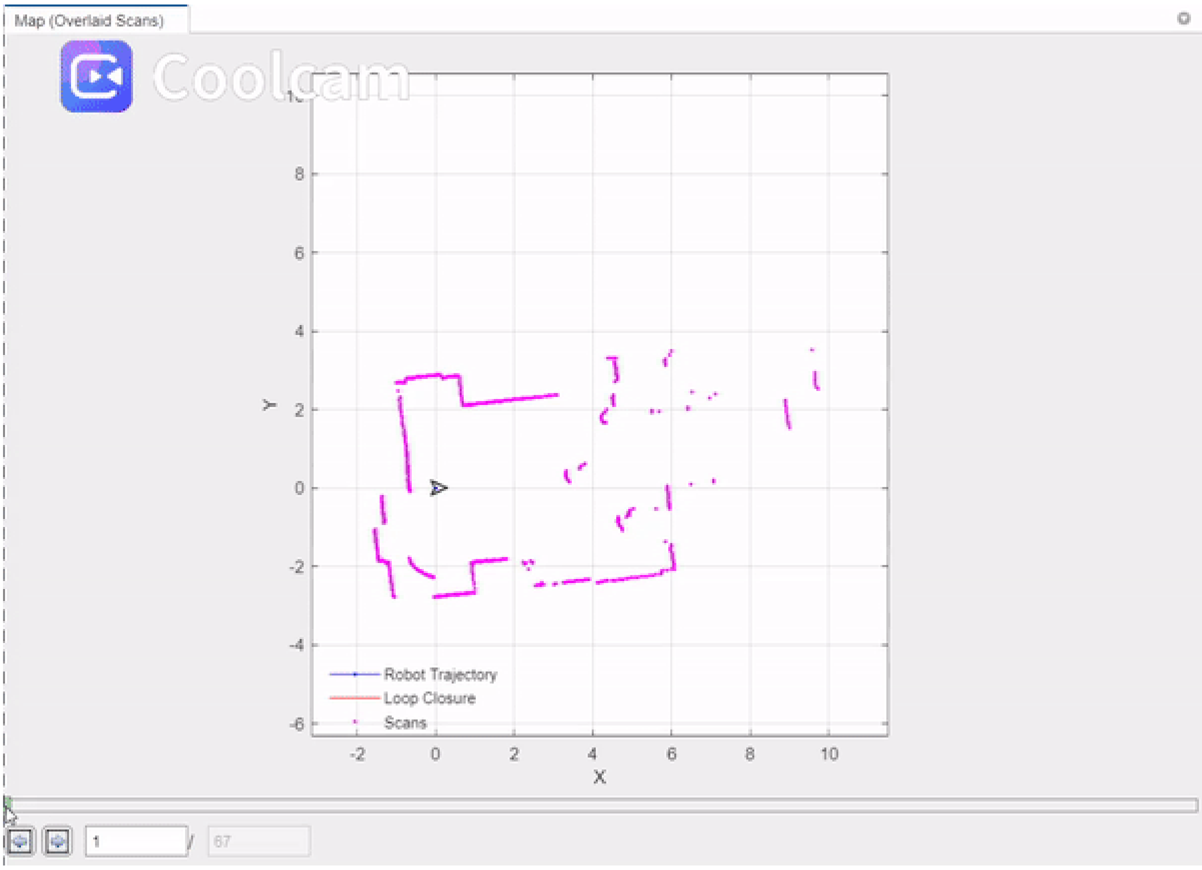
Process Flow

Extract Data: The IMU sensor is connected to an Arduino board, and the raw data is stored in CSV format using the MS Excel Plugin (Data Streamer). This plugin enables the IMU sensor to send or receive data from a computer through a COM port, increasing the processing speed and eliminating the need for external storage, such as a Micro SD card.



Taken from ELEGOO starter Kit Tutorial & Microsoft support

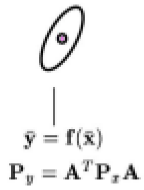
Sensor Fusion: Sensor fusion is the process of fusing or combining multiple data from multiple sensors to improve accuracy. The gyroscope provides the angular velocity measurement which provides the change the orientation and accelerometers provide linear acceleration which gives the change in velocity estimated. Combing these two data to improve accuracy is called sensor fusion by implementing KF, EKF, and UKF.

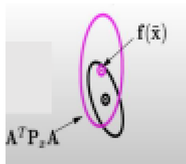


Kalman Filter (KF): The Kalman filter has two main steps: the prediction step and the update step. In the prediction step, the filter estimates the previous state of the system and models its dynamic system using a covariance matrix to account for uncertainties in the state estimate and the system dynamics. In the update step, the filter corrects the state estimate by incorporating sensor measurements and updates the covariance matrix accordingly. The Kalman filter is a recursive process and continues to iterate until the last step is reached.

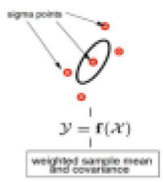
Extended Kalman Filter (EKF): The Extended Kalman Filter (EKF) is an extension of the Kalman filter used in nonlinear systems. In the Kalman filter, we assume that the system is linearized. In contrast, the EKF uses a linearized estimate of the system state in the prediction step and a nonlinear model in the update step to correct and update itself recursively until it reaches its final state.

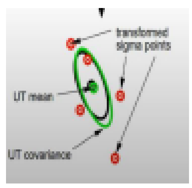
Unscented Kalman Filter (UKF): The Unscented Kalman Filter (UKF) is similar to the EKF, but it uses a deterministic sampling technique for approximation using a set of sigma points. It implements non-linear transformations on these sigma points and recomputes the Gaussian distribution. The UKF uses three parameters, namely, **K, α,** and **λ,** to control the spread of the sigma points from the mean. The higher the values of these parameters, the more the sigma points spread from the mean.

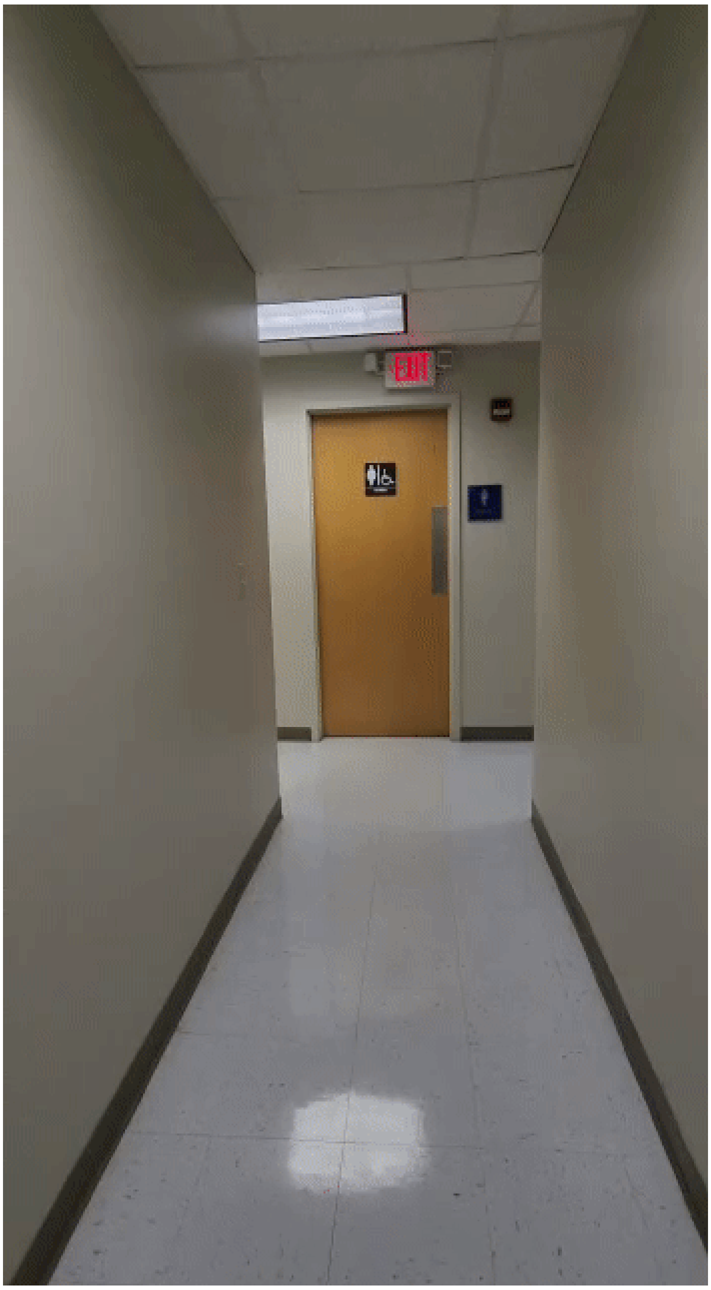




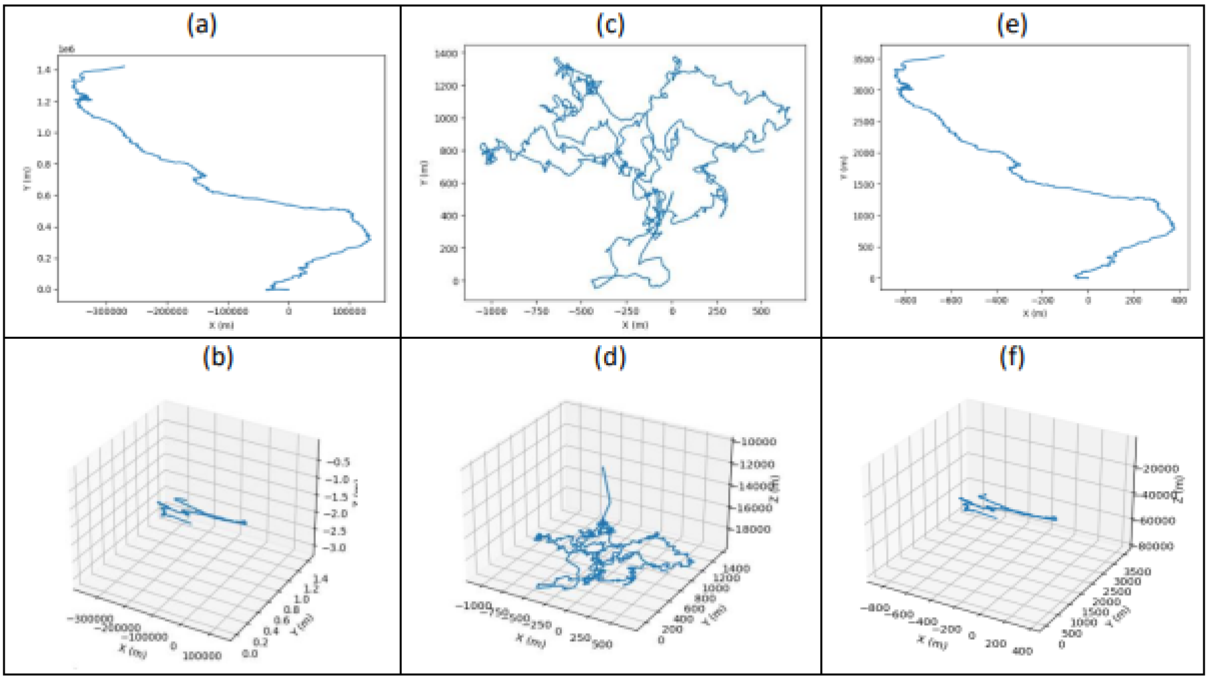
For the experiment, we choose two different areas took on the normal walking steps, and record the data the first.





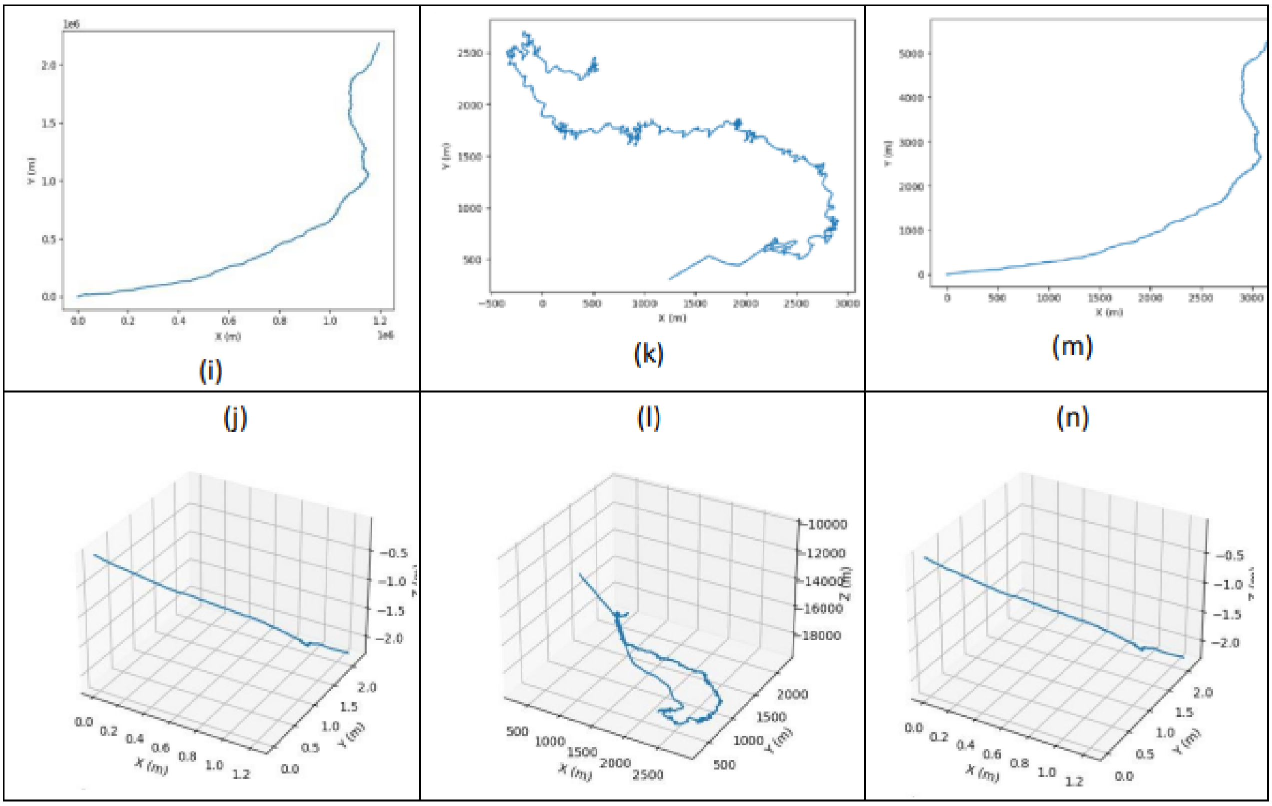


Indoor Tracking



(a) KF with Q=0.01, **(b)** 3D plot using KF, **(c)** EKF with Q=0.01, **(d)** 3D plot using EKF, **(e)** UKF with Q=0.01, **(f)** 3D plot using UKF

Outdoor Tracking



(i) KF with Q=0.01, (j) 3D plot using KF, **(k)** EKF with Q=0.01, **(l)** 3D plot using EKF, **(m)** UKF with Q=0.01, **(n)** 3D plot using UKF

The plot above illustrates that to achieve optimal accuracy, the filters need to be tuned by adjusting the **noise covariance (Q)** and **measurement error covariance**. It is evident that **EKF** is highly sensitive to Q. In EKF, the nonlinear model is linearized around the current estimated state, and the linearized model is used for prediction. Even a slightly inaccurate linearized model can significantly impact the filter's performance by changing the covariance matrix.

Conclusion: In conclusion, this project aimed to develop an IMU-based indoor localization system using the GY-521 module and implement three filters, namely the Kalman Filter, Extended Kalman Filter, and Unscented Kalman Filter, to improve the accuracy of the localization. The raw data was captured and plotted to get insights about the data. The filters were implemented and tuned by changing the noise covariance and measurement error covariance to get better results. The results showed that EKF is highly sensitive to Q, and a slightly inaccurate linearized model can significantly impact the model by changing the covariance matrix. By tuning the parameters, we were able to improve the accuracy of the localization system. Overall, this project provides insights into the importance of sensor fusion and the use of different filters to improve accuracy in indoor localization systems.

For code:

References:

1. Michael Wrona’s Blog “Designing a Quaternion-Based EKF for Accelerometer, Gyroscope, & Magnetometer Fusion”.
2. 2. Implements a linear Kalman filter using Python “KalmanFilter”.
3. 3. Filtering of IMU Data Using Kalman Filter by Naveen Prabu Palanisamy.
4. 4. ENAE 788M: Hands-On Autonomous Aerial Robotics: Extended Kalman Filter and Unscented Kalman Filters
5. 5. FilterPy — Kalman filters and other optimal and non-optimal estimation filters in Python.

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