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# Low-Cost IMU and GPS Fusion Strategy for Apron Vehicle Positioning

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***Abstract*—This paper presents a strategy to improve positioning estimation from low-cost Inertia Measurement Unit (IMU) sensor and Global Positioning System (GPS) for apron vehicle localization. IMU sensor provides raw acceleration values and its attitude, while GPS provides geodetic position, velocity, and heading course values. Fusion result from both sensors believed could comply Advanced-Surface Movement Guidance and Control System (A-SMGCS) standard with less economical cost.**

**Within this paper, we propose graded Kalman filter method with several fusion steps. Our method consists of certain process filtering and process update which was associated one to each other. We also introduce a technique to handle the time synchronization and how to determine the low-cost sensor's error tolerance. Our preliminary experiment shows that proposed fusion strategy is able to accommodate both IMU and GPS sensors to provide better position estimation with lesser RMSE value in compared to the ground truth.**

***keyword*—** IMU-GPS, sensor fusion, apron vehicle positioning, A-SMGCS, Kalman filter

## I. Introduction

Surface surveillance and navigation are two essential factors that should be provided in airport surface movement control system. It has to deliver at least surveillance and guidance for ground aircraft and apron vehicles. International Civil Aviation Organization (ICAO) has made standard for surface surveillance system called Advanced Surface Movement Guidance and Control System (A-SMGCS), given through ICAO document number 9830 [1]. In this document, ICAO requires A-SMGCS to cover 4 basic functions which are surveillance, control, planning/routing, and guidance. A-SMGCS system requires robust positioning and localization system. This system is needed to provide prosperous ground aircraft and apron vehicle surveillance to the Air Traffic Controllers (ATC). Basically, the main intention of this surveillance system is to cover safety issues. E.g., collision within the ground aircraft and/or vehicle inside airport area. Common A-SMGCS system adopts GPS and triangulation system for positioning system with total investment reach up to 4.2 M Euro for first and second levels of A-SMGCS at large size airport [2]. Implementation of a low-cost positioning system, such as IMU-GPS positioning system, is expected to reduce those expenses even giving improved system performance.

It cannot be denied that positioning/localization research has been mature and has significant growth for several decades. Some researchers prove that IMU and GPS have the ability to provide robust localization with certain approaches. Current research, Yan et al. [3] introduce dual rate Kalman filter in GPS-INS fusion strategy that consists of high-speed filter and low-speed filter. This method can achieve resolution of 0.1 seconds for each cycle leading to less verdict system. Other studies tries to combine several features on the positioning system, such as wheel encoder [4] and vision data [5]. Nonetheless, these typical sensors are costly compared to regular GPS and IMU sensors. These typical sensors are also hard to install meanwhile IMU-GPS sensor implementation demands less installation procedure and space due to its compact dimension. GPS and Inertia Sensors are also commonly found in a smartphone. Some research, such as [6]–[8] convince that sensors in a smartphone can be used as vehicle positioning device with a promising result. Yet, smartphone is considered as a personal device that unsuitable for dedicated vehicle system.

The goal of this research is to optimize the performance of low-cost IMU and GPS positioning fusion technique by rearranging and using all valuable information from the sensors. This positioning technique is developed to support a low-cost A-SMGCS localization system with robust performance. We also propose a graded Kalman filter method to estimate and make sure that each data, such as velocity and position, is correctly fused and provides better estimated value. Kalman filter is chosen because it has the capability to estimate current values only from the previous value and the covariance of the estimation error.

In the next part, we will present the overview of our system including brief introductions to the sensors and how our fusion strategy works. It is followed by preliminary experiment that we made, then ended with our conclusion and near future work.

## II. System Overview

Our proposed system is based on integrating low-cost IMU and GPS sensors. We begin this section by introducing the working principle of those sensors as well as its fusion strategy.

### A. Inertia Measurement Unit (IMU)

Modern Inertia Measurement Unit normally utilizes gyroscope, accelerometer, and magnetometer sensor unit. This combination is commonly known as 9 Degree of Freedom (9-DoF), since each sensor represents 3 axis values (normally in X, Y, and Z axes). Lately, an additional sensor is also added such as a barometric sensor to form a 10-DoF sensor. Advanced IMU sensor system that we use for this research is embedded with internal processing unit including filtering capability. Internal IMU process combined 9-DoF sensor resulting absolute orientation in Euler angle (pitch, roll, and yaw) [9]. On the other hand, raw data, such as acceleration values, are still accessible for system calculating purpose. However, those acceleration values are very sensitive to certain noises such as vehicle engine vibration. Hence, some filtering techniques are considered to apply. Several data that are mainly used for our proposed fusion strategy are yaw-IMU data, which represent heading orientation of the vehicle, and acceleration values to calculate velocity and vehicle distance traveled.

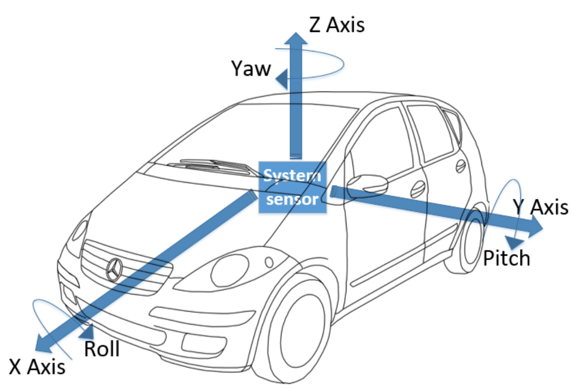


Fig. 1: 3D axis and orientation in Euler angles

### B. Global Positioning System (GPS)

GPS provides several positioning data. The information is delivered in an NMEA 0183 standard format which frequently used in GPS receivers. Normally, position data is given in geographical coordinate system, such as latitude and longitude that represent an earth position. This geographical coordinate system can be calculated to find the distance between two coordinate points by using the Pythagorean theorem. We introduce this distance value as GPS distance in the next discussion. By referring to the result, we believe that Pythagorean method is not the best method to adopt in this system. However, based on our experiences, for a short moving distance, Pythagorean theorem proved to have better performance in calculation efficiency with a respectable result.

$$x_{gps} = V(\triangle \text{lat}) \quad (1)$$

$$y_{gps} = H(\triangle \text{lon}) \cos(\frac{\pi}{360}(\Sigma \text{lat})) \quad (2)$$

$$\delta_{gps} = \sqrt{x_{gps}^2 + y_{gps}^2} \quad (3)$$

where,

| | | |
|---|---|---|
| $x_{gps}$ | : | X axis, GPS position toward north |
| $y_{gps}$ | : | Y axis, GPS position toward east |
| $\delta_{gps}$ | : | Magnitude of GPS vector |
| $H$ | : | 111302.616 ; 1 longitude degree in meters |
| $V$ | : | 110574.610 ; 1 latitude degree in meters |
| $\triangle$lat | : | difference between two latitude value |
| $\triangle$lon | : | difference between two longitude value |
| $\Sigma$lat | : | summation between two latitude value |

The equation above shows how we calculate GPS distance from obtained latitude and longitude values. In the GPS system that we use, GPS not only provides geographical coordinates but also comes up with GPS course and GPS ground velocity value. All of this information will be used as main information sources to update and estimate position in our fusion strategy.

### C. Fusion Strategy

We introduce a fusion strategy called graded Kalman filter to integrate IMU and GPS positioning information, and then estimate current vehicle position (Figure 2). This strategy combines several information parameters such as IMU velocity and distance (obtained from integrating IMU acceleration), yaw-IMU orientation, GPS position, GPS velocity, and GPS heading. In our proposed graded Kalman filter, we use two basic state estimation models representing IMU sensor model and GPS sensor model. IMU state estimation model is used in the fusion method as long as there is no update from GPS sensor. This process calculates current estimated velocity and distance traveled by the system.

Once GPS data are available, current estimated velocity is then updated with GPS velocity value. The update process is using Kalman filter based on GPS state estimation model. As a result, new estimated velocity value is obtained. Furthermore, new estimated velocity value is then integrated by time to achieve estimated distance traveled value. This value is then again updated by Kalman filter process with GPS distance value as an update input. As explained in the previous subsection, GPS distance value is calculated with Pythagorean technique.

*1) Distance Traveled Calculation:* It was already mentioned that IMU sensor provides acceleration values in a 3-dimensional axes. However, in our proposed method, we use 2-dimensional axes which are X and Y axes. Our method started by calculating the magnitude between 2 acceleration axes. This value represents total acceleration experienced by the system. We calculate this magnitude because, in our proposed method, we will fuse the total velocity experienced by the

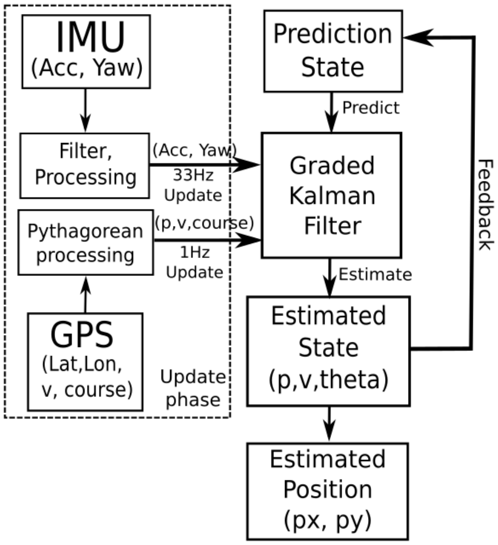


Fig. 2: Fusion strategy

IMU with ground GPS velocity. As a note, since we focus on distance travel value measured by the accelerometer, we keep the movement acceleration sign (positive/negative) as an indicator of accelerate or decelerate movement in the main axis. The function is given as follows:

$$|a| = \sqrt{a_x^2 + a_y^2} \tag{4}$$

Assume that acceleration direction is in X axis ($a_x$),

$$a = \begin{cases} |a| & \text{if } a_x \geq 0; \\ -|a| & \text{if } a_x < 0. \end{cases}$$

The IMU state prediction itself is given by a transfer function described below:

$$\begin{aligned} \mathbf{x}_k &= F\mathbf{x}_{k-1} + Bu \\ &= \begin{bmatrix} 1 & \triangle t \\ 0 & 1 \end{bmatrix} \mathbf{x}_{k-1} + \begin{bmatrix} \frac{\triangle t^2}{2} \\ \triangle t \end{bmatrix} u \end{aligned} \tag{5}$$

where,

$$\mathbf{x}_k = \begin{bmatrix} p_k \\ v_k \end{bmatrix} \quad \text{and} \quad u = [a]$$

$p_k$ : distance-travel prediction
$v_k$ : velocity prediction
$a$ : magnitude of acceleration

This IMU state estimation model is used to estimate position and velocity value as long as there is no GPS update from the sensor. When there is an update from GPS, graded Kalman filter will use GPS estimation model described below:

Fuse with GPS velocity,

$$(U_k, Q_k) = (v_{gps}, \Sigma_{vgps})$$

$$\begin{aligned} K &= \hat{\mathbf{P}}_{v|k-1}(\hat{\mathbf{P}}_{v|k-1} + Q_k)^{-1} & (6) \\ \hat{v_k} &= \hat{v}_{k-1} + K(U_k - \hat{v}_{k-1}) & (7) \\ \hat{\mathbf{P}}_{v|k} &= Q_k - KQ_k & (8) \end{aligned}$$

where,

$v_{gps}$ : velocity from GPS
$\Sigma_{vgps}$ : GPS velocity covariance error
$K$ : Kalman gain
$\hat{v_k}$ : estimated velocity
$\hat{\mathbf{P}}_{v|k}$ : estimated velocity error covariance

Estimate travel distance,

$$\hat{p_k} = \hat{p}_{k-1} + \hat{v}_k \triangle t \tag{9}$$

Fuse with GPS distance value,

$$(V_k, S_k) = (p_{gps}, \Sigma_{pgps})$$

$$\begin{aligned} K &= \hat{\mathbf{P}}_{p|k-1}(\hat{\mathbf{P}}_{p|k-1} + S_k)^{-1} & (10) \\ \hat{p_k} &= \hat{p_k} + K(V_k - \hat{p_k}) & (11) \\ \hat{\mathbf{P}}_{p|k} &= S_k - KS_k & (12) \end{aligned}$$

where,

$p_{gps}$ : Distance-traveled value from GPS
$\Sigma_{pgps}$ : GPS distance-traveled covariance error
$K$ : Kalman gain
$\hat{p_k}$ : estimated distance-traveled
$\hat{\mathbf{P}}_{p|k}$ : estimated distance-traveled error covariance

Graded Kalman filter follows natural Kalman filter steps on its calculation process as described below [10]:

$$\begin{aligned} \mathbf{x}_k &= F\mathbf{x}_{k-1} + Bu \quad \text{; Step 1} \\ \mathbf{P}_k &= F\mathbf{P}_{k-1}F^T + Q_k \quad \text{; Step 2} \\ \mathbf{y}_k &= \mathbf{Z}_k - \mathbf{H}\mathbf{x}_{k-1} \quad \text{; Step 3} \\ S_k &= H\mathbf{P}_k H^T + R_k \quad \text{; Step 4} \\ \mathbf{K}_k &= \mathbf{P}_{k-1}H^T S_k^{-1} \quad \text{; Step 5} \\ \hat{\mathbf{x}_k} &= \mathbf{x}_{\hat{k-1}} + K_k(\mathbf{y}_k) \quad \text{; Step 6} \\ \hat{\mathbf{P}_k} &= (I - \mathbf{K}_k H)\mathbf{P}_{k-1} \quad \text{; Step 7} \end{aligned}$$

*2) System Orientation:* Orientation is also predicted by using Kalman filter. These orientation data are delivered in form of degrees (0 - 360 degree) based on the earth northward. Since the IMU sensor update resolution (33 Hz) is higher than GPS (1 Hz), Yaw-IMU value is used as the basic estimation for the orientation Kalman filter system. Once GPS course is updated, GPS data will update the current estimation value in Kalman filter approach.

Given IMU Orientation function:

$$(W_k, T_k) = (\theta_0, \Sigma_0)$$

$$K = \hat{\mathbf{P}}_{k-1}(\hat{\mathbf{P}}_{k-1} + T_k)^{-1} \quad (13)$$
$$\hat{\theta}_k = \hat{\theta}_{k-1} + K(W_k - \hat{\theta}_{k-1}) \quad (14)$$
$$\hat{\mathbf{P}}_k = T_k - KT_k \quad (15)$$

When there is update from GPS orientation,

$$(Z_k, R_k) = (\theta_1, \Sigma_1)$$

$$K = \hat{\mathbf{P}}_{k-1}(\hat{\mathbf{P}}_{k-1} + R_k)^{-1} \quad (16)$$
$$\hat{\theta}_k = \hat{\theta}_{k-1} + K(Z_k - \hat{\theta}_{k-1}) \quad (17)$$
$$\hat{\mathbf{P}}_k = R_k - KR_k \quad (18)$$

where,

$\theta_0$ : orientation value from IMU
$\Sigma_0$ : IMU orientation covariance error
$\theta_1$ : orientation value from GPS
$\Sigma_1$ : GPS orientation covariance error
$K$ : Kalman gain
$\hat{\theta}_k$ : estimated orientation
$\hat{\mathbf{P}}_k$ : estimated orientation error covariance

*3) Positioning Calculation:* Final estimated position can be obtained from both estimated travel distance and estimated orientation. Estimated travel distance value presents how far the object moves forward within a certain time frame, meanwhile estimated orientation shows the direction of the object moves toward the north. From these two data, we can calculate the coordinate position of X and Y axes with the Pythagorean equation as follows:

$$\begin{bmatrix} p_x \\ p_y \end{bmatrix} = \begin{bmatrix} p_{x-1} \\ p_{y-1} \end{bmatrix} + \begin{bmatrix} \sin(\hat{\theta}) \\ \cos(\hat{\theta}) \end{bmatrix} (\hat{p}_k - \hat{p}_{k-1}) \quad (19)$$

where,

$p_x$ : position in X axis
$p_y$ : position in Y axis

*4) System Covariance Error:* System covariance error is calculated to update the prediction of priori estimate covariance in step 2 of Kalman filter. Some are also used in step 4 which is the calculation of innovation/residual covariance. In our proposed algorithm, covariance error from the accelerometer is used to predict a priori estimate covariance of $p$ and $v$ (step 2), meanwhile, when there is GPS update, GPS $p$ and $v$ covariance error are used to calculate residual covariance (step 4). This residual is essentially used to calculate the optimal Kalman gain of the system. Basically, covariance errors declared in Kalman filter are described as a Gaussian distribution with mean zero as follows.

$$\Sigma_k \sim N(0, Q_k)$$

$Q_k$ is a process noise covariance matrix which is calculated by analysing the sensor behaviour in steady condition. For example, in accelerometer, we keep the sensor steady in one position for a certain time, then we calculate the covariance error from fluctuation data measured for each acceleration axes. In IMU and GPS orientations, covariance errors are calculated based on GPS and IMU orientation results in our preliminary experiment (straight track with fix direction). Further, GPS velocity and distance-travelled covariance error are developed based on the GPS chipset datasheet [11]. We take the maximum accuracy error mentioned which is 3 meters for position accuracy and 0.1 m/s for velocity accuracy as references.

## III. On Going Experiment

### A. Experimental System Development

We developed our experimental system based on Arduino Mega 2560 as a control unit, BNO055 IMU absolute orientation sensor, and MTK3339 for GPS sensor. BNO055 is equipped with 3 main internal sensors (accelerometer, gyroscope, and magnetometer) and an internal processing unit to calculate absolute orientation in term of 3 axes Euler angles (pitch, yaw, and roll). Based on the datasheet [9], BNO055 adopts quaternion filter to provide these orientation values. On the other hand, MTK3339 is a GPS module which provides all the information in NMEA 183 data format. The resolution of this GPS module is adjustable and can be set up to 10 Hz [12]. However, for our experiment, we set the resolution of 1Hz for GPS receiver updates and 33Hz for the IMU sensor.

Figure 3 shows the designed experimental system. The host processor (Arduino Mega 2560) collects and controls all the distribution data from the sensors through several serial communication protocols. The data themselves are collected in offline mode for several testing scenarios then saved into a data storage module. Afterward, the data are processed using mathematical processing tool.

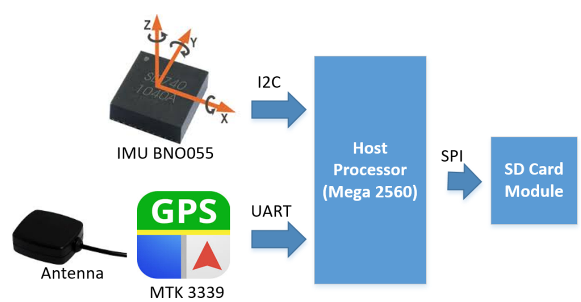


Fig. 3: Designed experimental system

### B. Preliminary Experimental Scenario

For the experimental purpose, we have done a preliminary experiment using a car with several testing criteria. We fixed the sensor in the front-left passenger dashboard (Figure 1) and placed the GPS antenna on the top of the testing vehicle. Figure 4 shows our dedicated track for the experiment. A straight route with 100-meter distance was set up inside our campus, heading to the east with 88 degrees direction from northward. As shown below, the red line represents our initial track (ground truth) and the yellow line displays GPS positions (in latitude and longitude) obtained from our preliminary experiment.

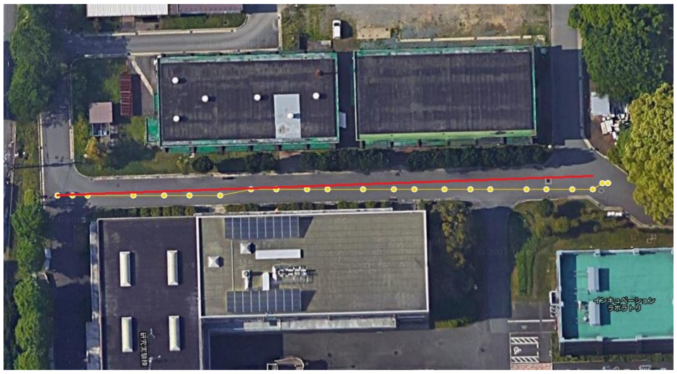

Fig. 4: Ground truth (red) and GPS position (yellow) obtained on 100 meter straight track

Several main objectives of this preliminary experiment are to analyse the IMU and GPS sensors output characteristic and define an initial setup condition. To validate the proposed fusion strategy with the real collected sensor data. Further, to use the analysis results as references for the next development.

### C. Experimental Results and Analysis

All the information gathered from the preliminary experiment scenario is simulated and analysed with our proposed graded Kalman filter. Our simulation is done with Matlab 2016 student version, afterwards, we analyse the results for our future research development. Preliminary experiment results show that the proposed method able to compensate GPS and IMU positioning errors as shown in Figure 5. In this figure, calculated GPS positions (yellow line) are plotted for each second the information was received. IMU positioning is also calculated and then results are presented with the green line. General comparison with the ground truth (red line) shows that both sensors are experiencing some positioning errors especially GPS sensor. Error in GPS position could reach up to 1 meter meanwhile IMU sensor experience less error. Main visible error for IMU sensor is that it overvalues the total distance traveled up to 102.8 meters.

We calculate the error using RMSE method to get an exact number on how much error generated from each sensor compared to the benchmark. We have done this by comparing positioning results from IMU, GPS, and fused position with the ground truth.

RMSE formula is given as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

where,

$y$ : benchmark value, and $\hat{y}$ : sensor/estimated value

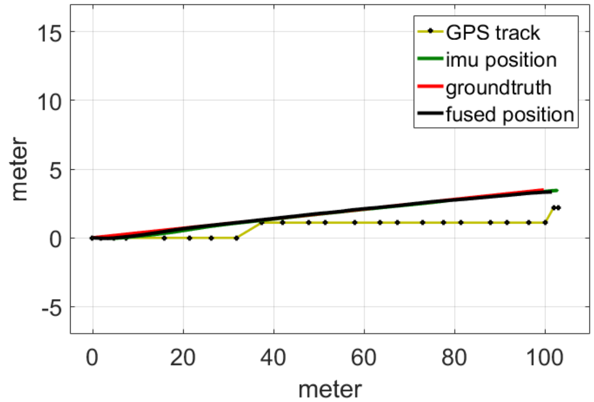


Fig. 5: Comparison between ground truth, GPS track, IMU position, and fused position

TABLE I: RMSE result comparison

| RMSE | X Axis RMSE | Y Axis RMSE | Total Dist. RMSE |
|---|---|---|---|
| GPS | 11.9735 | 0.8805 | 3.3090 |
| IMU | 7.9335 | 0.2916 | 2.4613 |
| G-KF | 7.0126 | 0.2903 | 1.6273 |

Table I represents the RMSE comparison between GPS, IMU, and our proposed method. It shows that comparing with the results in X and Y axes position, graded Kalman filter surpasses the GPS performance. It also has slight better RMSE compared to IMU sensor positioning outcome. X axes tends to have bigger RMSE value than Y axes, since the object movements are mainly on the X axes. In total distance traveled calculation, our method also outperforms both IMU and GPS sensors results with RMSE value 1.6273. This value is roughly half than GPS RMSE (3.3090) and 0.834 lesser then IMU RMSE value.

Our fusion method is also able to interpolate position resolution. Compared to GPS which is only capable of giving positioning value for each second, our proposed method is apt to provide more precise position resolution of approximately 30 milliseconds. This could be done due to the fusion strategy which integrates information that we got from IMU sensor to GPS positioning sensor. Figure 6 shows how fused position (black line) has interpolation position, represented by dotted mark, results in higher positioning resolution. As shown in this figure, estimated position experienced some position estimation gap (e.g., 24 meters and 29 meters). This phenomenon happens as a result of our fusion method while fusing latest estimated IMU position with current GPS position. In this case, latest prediction position from IMU is delayed for some length then updated by the GPS.

## IV. Related Work

Our research focuses on developing vehicle positioning strategy, particularly for apron vehicle localization. We developed our technique by calculating the distance traveled by the system, heading estimation, then the position in X and Y axes.

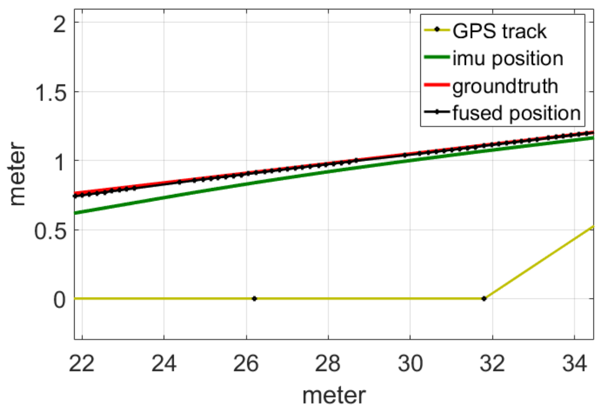


Fig. 6: Position interpolation in fused position results

Those are done by using low-cost IMU and GPS sensors which are widely available in the market. Many researchers work to improve IMU orientation performances where basically they works are related to pedestrian dead reckoning (PDR). Those works are important to deliver sturdy movement orientation which also needed in our research. Madgwick et al. [13] introduced quaternion method with magnetic angular rate and gravity (MARG) to provide robust orientation from IMU sensor. Zhou et al. [14] introduced $A^3$ as a method, which has same quaternion basis, to handle accelerator and gyroscope sensors in smartphones to provide an instant phone attitude. This quaternion method is also used in BNO055 IMU sensor as a basic fusion technique to calculate orientation in Euler angle. However, without the basic understanding of IMU sensor fusion technique, robust positioning system will be difficult to realize.

In vehicle positioning research, Yan et al. [3] introduced dual rate Kalman filter to improve accuracy in the navigation system. Kim et al. [15] used GPS and dead reckoning method (velocity measurement and vehicle steering angle) to get stable position data. In addition, some other research also tried to add additional sensors such as odometer sensor [4], [5] and vision sensor [5]. From those papers, we would consider adopting some additional sensors in our future system. By the rapid development of sensors and the integrated system in it, several methods can be developed to accommodate various sensor outputs. Graded Kalman filter could become one of the example that accommodates those changes.

## V. Conclusion and Future Work

We conclude that our proposed fusion strategy can fulfill our target criteria in the apron vehicle positioning system. Working progress shows that this strategy is able to accommodate all the information needed from IMU and GPS sensors that we use. However, some experiments are still needed to conduct for several scenarios such as turning track and gravel road. We also need to encounter several practical errors which could emerge in experiment process. Some challenges we faced so far were that the IMU BNO055 sensor orientation is immensely sensitive to the local magnetic environment and requires such initialization phase. Moreover, engine vibrations from the vehicle could increase the covariance error value in our graded Kalman filter system, resulting in poor estimation results. Digital filters are considered to apply to handle noisy acceleration signal. System linearity will also be our main focus in our future work to improve estimation accuracy. Some sensor fusion approaches can be adopted to handle non-linear systems such as extended Kalman filter, unscented Kalman filter, or Particle filter. An additional consideration for our future work is to add extra valuable positioning information to our proposed method such as odometer sensor and map matching technique implementation.

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