Accuracy Enhancement of Consumer-Grade Global Positioning System (GPS) for Photogrammetric and City Mapping Determinations

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Abstract

This paper address the fluctuation of a low-cost global GPS problem using an open platform of autonomous multi-rotors and particularly applying in location spotting from high accuracy UAV survey data. A city or urban planning requires a large scale of high precision survey data after data gathering using the photogrammetry method to regenerate the orthomosaic map. There was a problem when referring data from the map for access in real locations guided by a normal grade GPS receiver. The problem shows that the normal GPS cannot effectively work with high accuracy data. The aim of this study was to create a map location device using a normal GPS receiver for using high accuracy data from the industrial-grade UAV survey platform. We tested various GPS sensors applied with the Kalman filtering approach compared with the other source of field data then tuned the filter algorithm to improve the performance. The result shows that the Kalman filtering algorithm is presented significant reform to overcome the GPS data fluctuation problem and show a certain direction to perform the next step of a cost-effective map data pointer device.

Keywords: city planning, UAV data, GPS accuracy, mapping location, Kalman

1. Introduction

Urban planning for area management requires a great deal of data called as spatial data or GIS data (Geographic Information System) related to location on the earth's surface. It consisted of point displaying data of the location, for example, school building, sky-rises, and office complexes, line displaying features of line such as road, river, highway, etc., area or polygon displaying features of the area such as administrative areas and building area. To create GIS or Spatial Data mostly required satellite and land surveying. However, there are some limitations of data received from the satellite, for example, ground sampling distance (GSD) that hinders detailed area observation or GPS miscalculation. It results in inland navigation inaccuracy.

Therefore, unmanned aerial vehicle technique has become a key for geographical photography mapping and GIS with Photogrammetry technique result in HD maps. With Real-Time Kinematic (RTK), GPS accuracy increased making a centime-scale map more precise that is sufficiently suitable for navigation and town planning.

From application in the army to analytic system and navigation, until robot and artificial intelligence technology, the evidence mentioned above leads to undeniability that GPS has become a part of people's daily life. With its reliability and variety of applications, GPS is seen as a very beneficial innovation for human. But GPS is still a limited technology, for example, geographic factors and/or inaccurate signals (Open-sky GNSS accuracy with smartphones has often been claimed to be "about 5 meters") that can lead to Software Failure (Diggelen & Enge, 2015). Therefore, innovation requires the accuracy of data, such as, AI or robot, an algorithm is added to prevent inaccurate data that can cause problems. For the processing system of the industry-grade Unmanned Vehicle that can be found in the market, it is necessary to have the ability to process accurate coordinates for navigation to increase reliability and commercial advantage which these devices will have algorithms that can deal with these problems.

However, in robots that require high accuracy of the coordinates, like Unmanned Aerial Vehicle, they can also deal with a variance of GPS. Beck, H (Beck & Couillard, 2016), mentioned algorithm for improving the accuracy of necessary data for taking off and landing of unmanned aerial vehicles called Kalman filter.

After completion of UAV mapping, all coordinates were analyzed on a map to refer to real places requiring highly accurate GPS equipment for real location navigating. Besides, high-quality and accurate tools are expensive and difficult to operate. To improve the proficiency and accuracy of a moderate GPS receiver is another method of problem-solving. The said idea is to install GPS with noise filtering and display a new set of average calculations different from previous GPS data. As a result, it can navigate more effectively and accurately.

2. Background

Using algorithms to increase the effectiveness in the work of Unmanned Aerial Vehicle has been mentioned widely in both the improvement of device control and stating coordinates. The experiment by Hadrien Beck (Beck & Couillard, 2016), points out that using Kalman filter with UAV with Lidar installed can improve effectiveness in controlling the device to be able to take off and land on its own (Beck & Couillard, 2016). Even though Kalman Filter is used widely because of its simplicity, optimality, tractability and robustness, but using it with the non-linear system may cause a minimum mean squared error (MMSE). However, there is an Alternative model of Kalman filter that is used widely to estimate and filter data in the system that is non-linear known as Extended Kalman Filter (EKF) (Julier & Uhlmann, 1997). In the aspect of increasing effectiveness in stating coordinates.

J. Z. Sasiadek (Sasiadek & Wang, 2003) showed that using Adaptive Fuzzy Kalman Filtering can reduce divergent occurred from Extended Kalman Filter and effectiveness in navigation that was quite accurate. They also said that their method is suitable for UAV that is Low-Cost Realtime Control (Sasiadek & Wang, 2003) similar to using Sigma Kalman Filter that was developed from an Extended Kalman Filter that can calculate a more accurate location to be used with MIU, GPS and Digital Compass on UVA (Zhang & Huynh, 2005). Zhang P (Zhang & Huynh, 2005). explained the Extended Kalman Filter is beneficial in reducing inaccuracies and increasing ability in controlling and satisfyingly stating location in UAV which is a non-linear system. However, it was found that some experiments used Standard Kalman Filter with a Non-linear model to improve the effectiveness of data as well (Schmitz & Elyoussef, 2016).

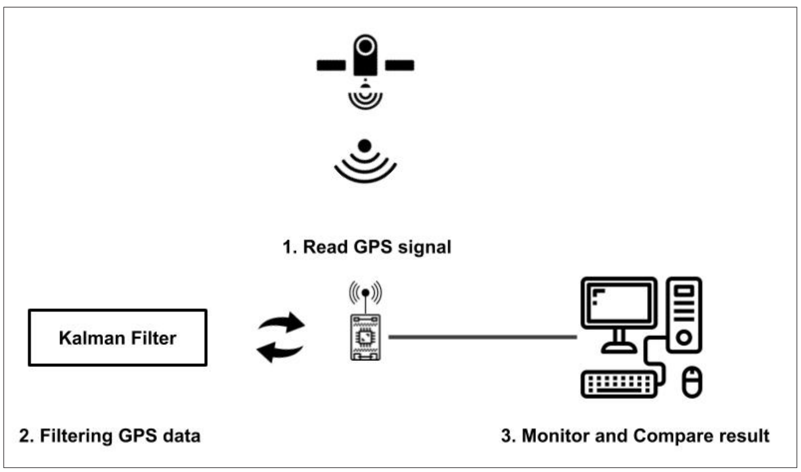
3. Methodology

3.1 Structure

Devices for measurement installed into drones for input and output include microcontroller Arduino Uno R3 and GPS signal receiver Ublox NEO-M8N. This experiment is a model receiving coordinates from GPS Sensor while installing with UAV by keeping coordinates by keeping signals from GPS and processing through Kalman Filter while the device receiving GPS is not moving to compare inaccuracy of coordinates of GPS observed and after filtered through Kalman Filter.

The procedure of the system starts from the Micro-controller ordering GPS signal receiver to read GPS, which information being processed is SkyTraq receiver's NMEA messages called $GNGGA (Langley, 1995 which will show data of Time, position, and fix related data of the receiver. Then, take obtained value to change from String to Double to calculate through KF after receiving and processing. Data of Latitude, Longitude, and Altitude will be compared with the line graph expecting coordinate data from UAV with Implement Kalman Filter that will have less inaccurate value than UAV without Implement Kalman Filter as in figure 1.

Figure 1. System architectural model




```
double Xpe0 ; //  prior estimate
double Xe1 ; // estimate of X at time k
double Xe0 ; // estimate of X at time k-1
double Ppec0 ; // prior error covariance
double P1 ; // error covariance at time k
double P0 ; // error covariance at time k-1
double K ; // kalman gain
double Z ; // observed value at time k
float R ; // measurement noise covariance
float Q ; // process noise covariance
```

Figure 2. Kalman filter variable for C++

```
Z = GetLat() ; // Get observed gps latitude value
Xpe0 = Xe0 ; // prediction step
Ppec0 = P0 + Q ; // prediction step
K = Ppec0 / ( Ppec0 + R ); // compute kalman gain
Xe1 = Xpe0 + K * (Z - Xpe0 ); // Update estimated value
P1 = ( 1 - K ) * Ppe0 ; // update estimated covariance
_Latitude = Xe0 ; // return result
Xe0 = Xe1 ; // update value for future estimation
P0 = P1 ; // update covariance for future estimation
```

Figure 3. Kalman filter equation for C++

3.2 Kalman Filter Approach

Kalman Filter is a device for estimating the value of a linear system by minimizing mean square error which Kalman filter will be the most effective when the signals received are all Gaussian noise (Kleeman).

The working format of the Kalman filter will include three steps which are initialization, Prediction, and Update. From the equation below, the Initialization of some studies called a state definition, checking the system to determine significant variables to estimate the value. Prediction step (1)(2) and Update step(3) (4)(5) are important steps for recursive coordinations by using the obtained value to calculate to predict the outcome. Aside from covariance, Kalman gain is another significant variable to determine the weight of possible value by measuring prior value.

$$\hat{x}_{\bar{k}} = \emptyset \hat{x}_{k-1} + Bu \qquad \text{(Eq.1)}$$

$$P_k^- = \emptyset . P_{k-1} \emptyset^T + Q_k \qquad \text{(Eq.2)}$$

$$K_k = P_k^- H^T (H P_k^- H^T + R)^{-1} \qquad \text{(Eq.3)}$$

$$\hat{x}_k = \hat{x}_k^- + K_k (z_k - H \hat{x}_k^-) \qquad \text{(Eq.4)}$$

$$P_k = (1 - K_k H) P_k^- \qquad \text{(Eq.5)}$$

From the equation above, it can be written in C++ with variables as in figure 2 and the equation in figure 3 that the equation is divided into three sets of Altitude, Latitude, and Longitude.

In this experiment, data that will be processed include Latitude, Longitude, and Altitude which are separated into two groups of indoor and outdoor data. Data collection by turning on GPS signal was receiver through Micro-controller Arduino Uno R3 and keeping both coordinate and height value. Before and after implementing the Kalman filter, the GPS module was set to not moving for 20 minutes in under mostly cloudy atmosphere conditions before statistically evaluating the data.

4. Results

The result of the experiment is separated into 2 cases. The fist is an indoor experiment, it aimed to understand GPS behavior with a very weak signal. The indoor test shows how the raw data will fluctuates and expecting high error when performing the test. Second is the outdoor experiment, this study focused on better data set due to there more GPS signal, but it will show some fluctuation.

The first group of the result will compare with data after applying the filter and display the enhance accuracy by examining the distance accuracy from before, and after through the method.

4.1 Indoor measurement before filter process

In approximately 20 minutes, there are 1527 sets of data measured from GPS located indoor in the mostly cloudy atmosphere as in figure 4 (Veness) showing distance between the points that have the highest and lowest coordinates of approximately 11.49 meters.

Figure 4. A distance between the highest and lowest coordinate value without Kalman filter and measured in indoor condition

Table 1. The statistical value of an observed GPS data without Kalman filter in indoor condition

Observed GPS Coordination (Indoor)

	Longitude	Latitude	Altitude
Mean	98.981786	18.501896	302.4519
Med	98.981788	18.501897	302
SD	1.5831E-05	1.7522E-05	2.6685
Var	2.5061E-10	3.0701E-10	7.1209
Mod	98.981788	18.501905	301.2
Max	98.981819	18.501932	307.6
Min	98.98175	18.501852	296.3

Figure 5. Distance between the highest and lowest coordinate value with filter measured in indoor condition

Table 2. Statistical value of an observed GPS data in indoor condition after implemented the filter

GPS Coordination with Kalman Filter (Indoor)

	Longitude	Latitude	Altitude
Mean	98.981786	18.501896	302.52
Med	98.9817847	18.5018968	302.31
SD	1.3443E-05	1.6357E-5	2.4505
Var	1.8072E-10	2.6757E-10	6.0051
Mod	98.981781	18.50188	304.50
Max	98.9818130	18.5019295	307.16
Min	98.9817558	18.5018595	297.63

Table 1 has shown statistical data from measured data including Mean, Median, Standard Deviation, Variance, Mode, Maximum value, and Minimum value

4.2 Indoor measurement after the filter process

Figure 5 shows the distance between the GPS coordinates that has the highest and lowest value measured indoor after being through Kalman Algorithm, in which the distance was approximately 9.85 meters and had statistical data as shown in Table 2.

4.3 Outdoor measurement before Implementing Kalman Filter

Figure 6 is a distance between the highest and lowest coordinates measured from GPS Signal Receiver outdoor in the mostly cloudy atmosphere by collecting 1527 sets of data for 20 minutes which the distance was approximately 3.21 meters with statistical data as shown on Table 3.

4.4 Outdoor measurement after Implementing Kalman Filter

After estimating the value of coordinates and height observed from GPS through Kalman Filter. The algorithm provided the distance between two coordinates with the highest and lowest value of approximately 2.63 meters (figure7) and the statistical value measured is as shown in table 4.

5. Result of Analysis

From the experiment, it showed that Kalman Filter could deal with data measured from GPS both outdoor and indoor to be more stable compared with data that were not filtered through Kalman Filter significantly, meaning number of Standard deviation and Variance measured after being through Kalman Filter and had a lower value which means the dispersion of data decreased. It can be observed from figure 4-5, and figure 6-7 that the radius of data dispersion was 1.64 meters narrower (from 11.49 meters to 9.85 meters) indoor and 0.58 (from 3.21 meters to 2.63 meters) outdoor.

Figure 6. A distance between the highest and lowest coordinate value without Kalman filter and measured in outdoor condition

Table 3. The statistical value of an observed GPS data without Kalman filter in outdoor condition

Observed GPS Coordination (Outdoor)

	Longitude	Latitude	Altitude
Mean	98.951015	18.805784	335.993971
Med	98.951019	18.805784	336.1
SD	6.6869E-06	2.9142E-06	6.8221E-01
Var	4.4715E-11	8.4924E-12	4.6541E-01
Mod	98.951019	18.805786	336.1
Max	98.951019	18.805791	337.8

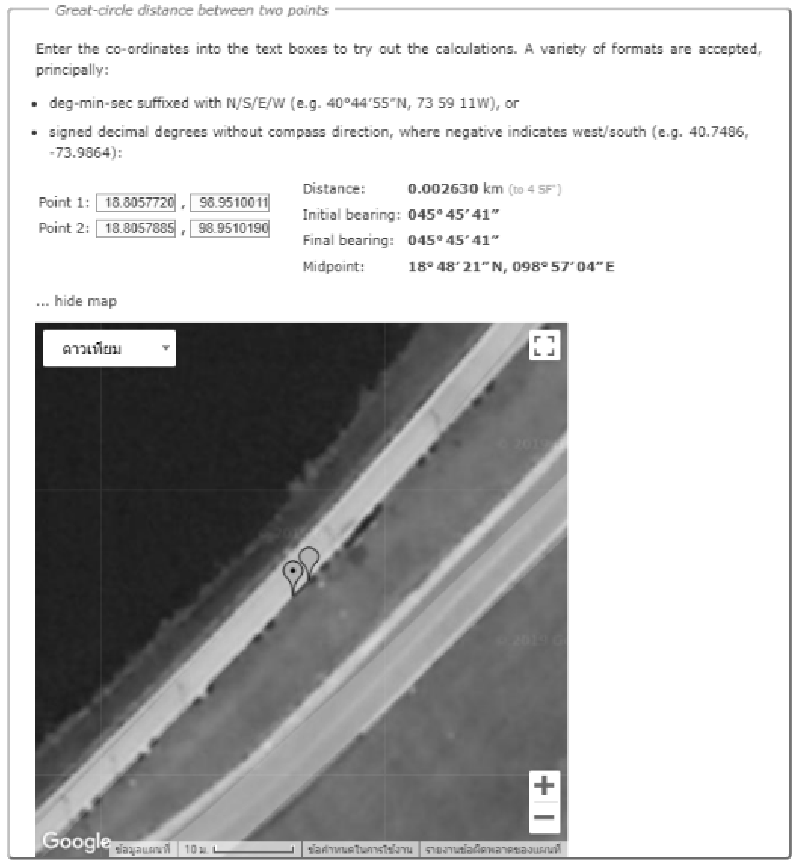


Figure 7. Distance between the highest and lowest coordinate value with Kalman filter measured in outdoor condition

Table 4. The statistical value of an observed GPS data in outdoor condition after implemented Kalman filter

GPS Coordination with Kalman Filter (Outdoor)

	Longitude	Latitude	Altitude
Mean	98.951015	18.805784	336.02
Med	98.9510190	18.8057847	336.03
SD	5.7866E-06	2.4951E-06	5.8351E-01
Var	3.3484E-11	6.2253E-12	3.4049E-01
Mod	98.951019	18.805772	337.70
Max	98.9510190	18.8057885	337.73
Min	98.9510011	18.8057720	334.63

Furthermore, the result also showed that the dispersion of coordinates and height measured from GPS outdoor had less inaccuracy than data measured from GPS indoor.

However, Standard Kalman Filter still could not provide effective data stabilization as expected even data dispersion decreased, height and coordinates of GPS filtered through Kalman still could not be used to predict the obvious location, even during the situation that sensor does not move both indoor and outdoor, referring to graph on figure 8-17.

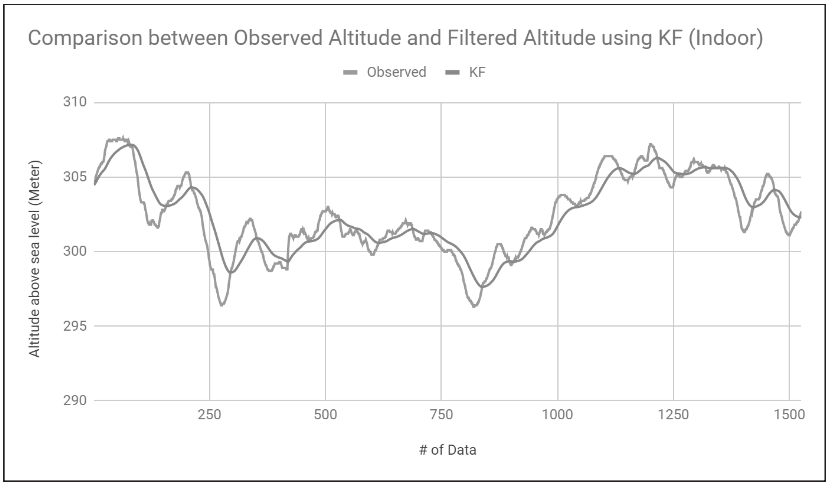


Figure 8. Comparison between an observed altitude above sea level (blue) and altitude above sea level filtered by Kalman filter (red) in indoor condition

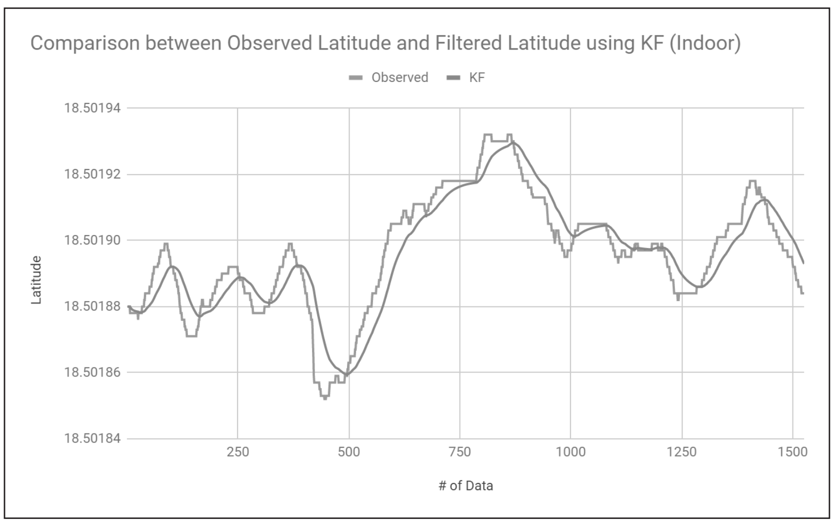


Figure 9. Comparison between an observed latitude (blue) and latitude filtered by Kalman filter (red) in indoor conditio

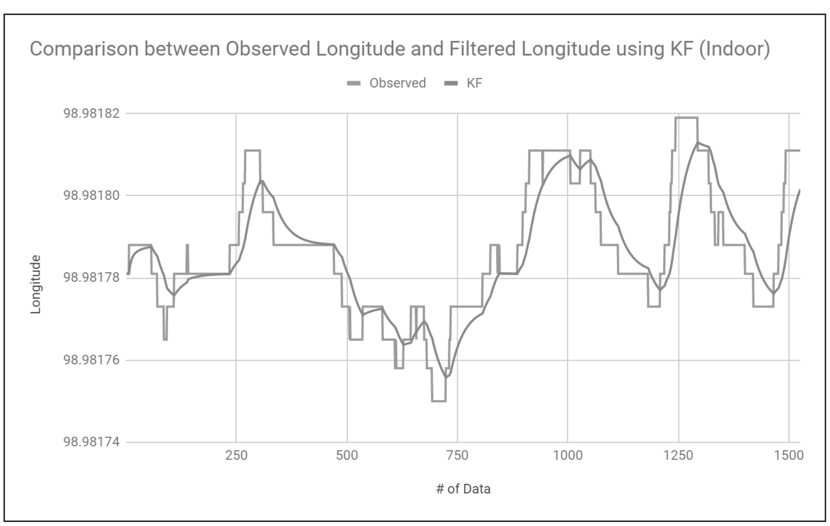


Figure 10. Comparison between an observed longitude (blue) and longitude filtered by Kalman filter (red) in indoor condition

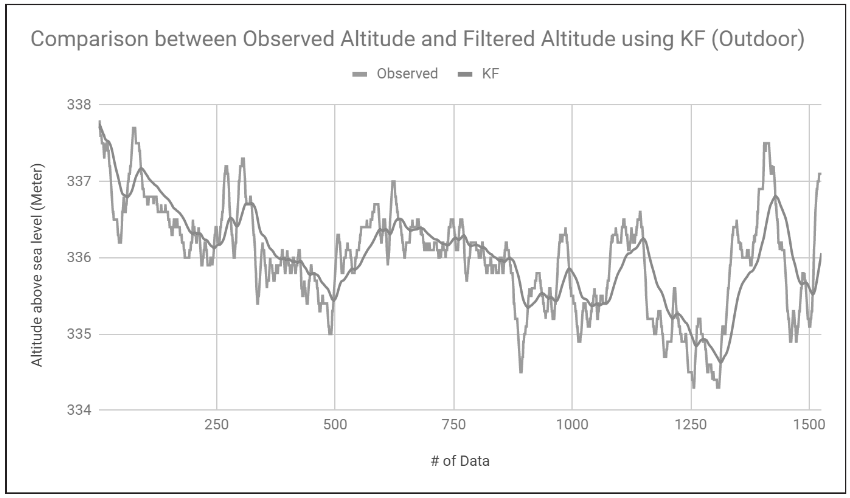


Figure 11. Comparison between an observed altitude above sea level (blue) and altitude above sea level filtered by Kalman filter (red) in outdoor condition

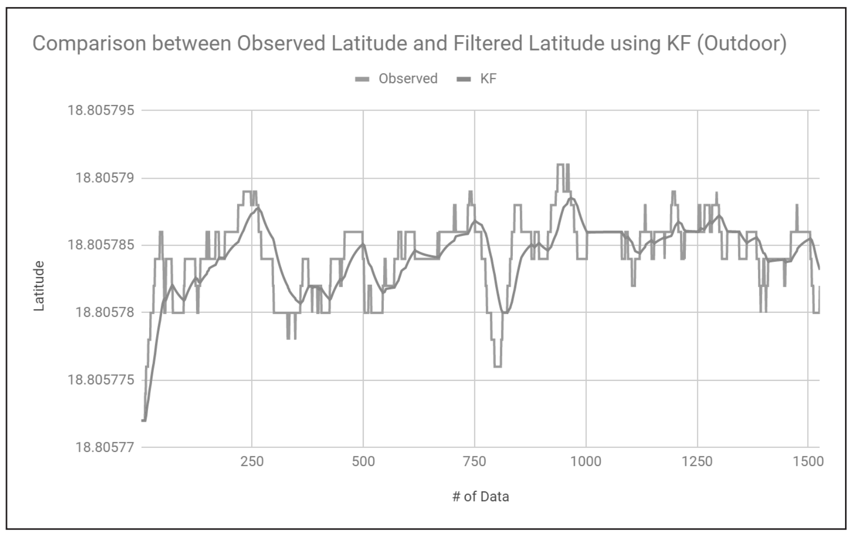


Figure 12. Comparison between an observed latitude (blue) and latitude filtered by Kalman filter (red) in outdoor condition

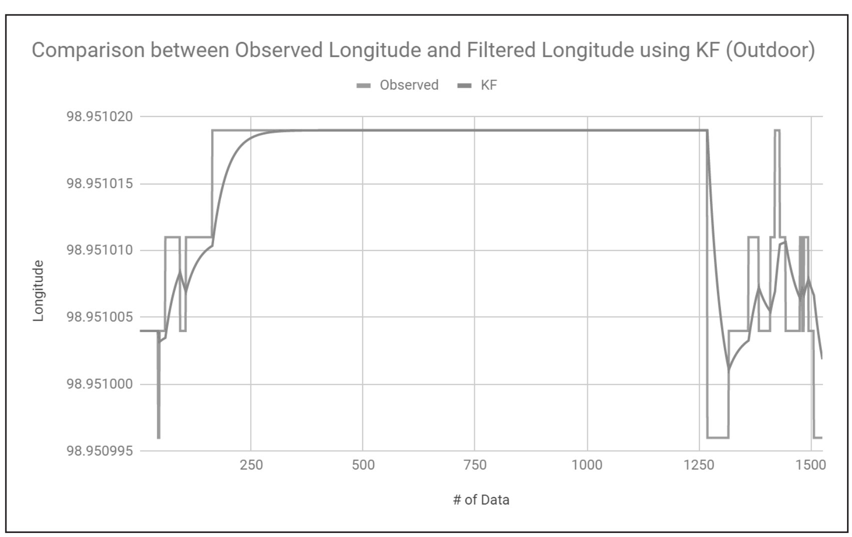


Figure 13. Comparison between an observed longitude (blue) and longitude filtered by Kalman filter (red) in indoor condition

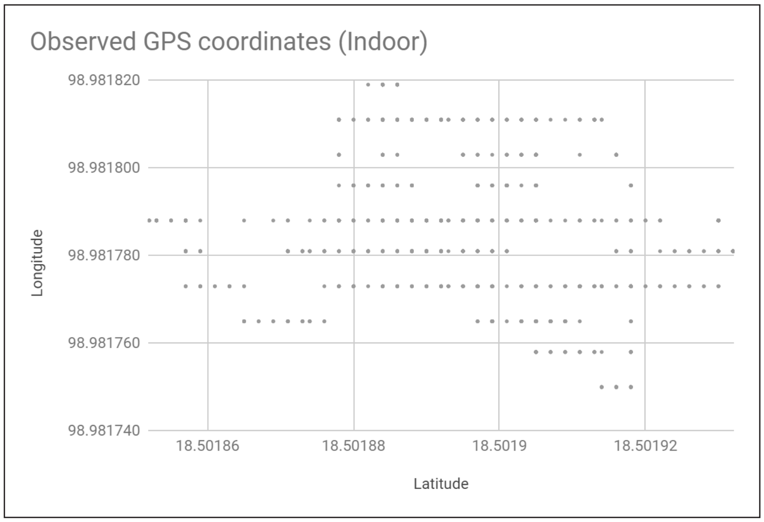


Figure 14. Observed GPS Coordinates in indoor condition without implementing a Kalman filter

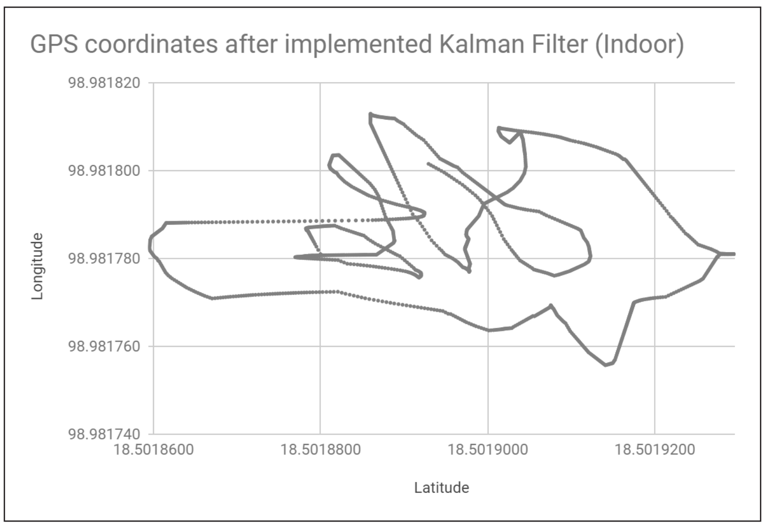


Figure 15. GPS coordinates in indoor condition after implemented Kalman filter

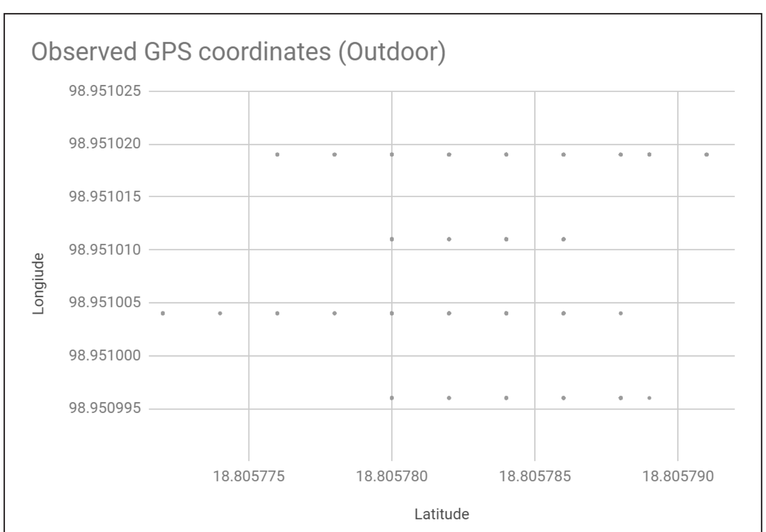


Figure 16. Observed GPS coordinates in outdoor condition without implementing a Kalman filter

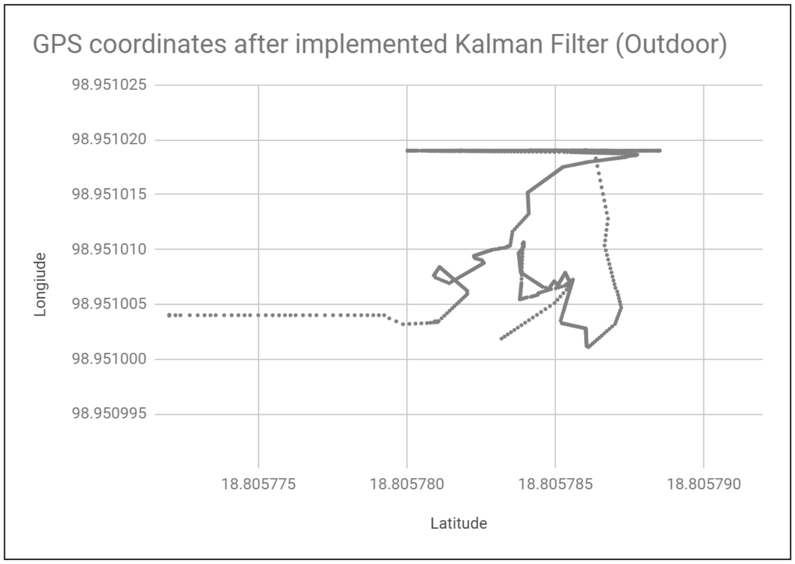


Figure 17. GPS coordinates in outdoor condition after implemented Kalman filter

6. Conclusions

This experiment can be concluded that a standard Kalman filter can deal with the variance of GPS in the Ublox NEO-M8N module at a level both indoor and outdoor. The results show accuracy improvement on low-cost GPS receiver, from this method, is enable us to implement GPS base station receiver or install in any nonmoving device. However, analyzing data of Figures 16 and 17 found that the standard Kalman filter is still not effective enough to be used effectively on unmanned aerial vehicles as it cannot state precise location even when the GPS sensor does not move. And height with the least variance observed from statistical data on Figure 11 still has a data variance radius of approximately 1.5 meters, which is relatively too high for the advanced project.

Compare to the other methods, the Standard Kalman Filter is still not the most suitable choice to filter data in a linear system but can provide a greater benefit for maximize data efficiency from low-cost sensor grade. Despite all that, alternative filters, such as, Extended Kalman Filter, Unscented Kalman Filter, Complementary Filter were developed from Standard Kalman filter algorithm with higher ability to solve problems for nonlinear system and they are interesting for future experiments with a hope of being able to work more effectively than Kalman filter algorithm in this experiment for UAV and GPS handheld device for navigating and location to the specific urban map.

Additionally, the study discovered that the output data could be able to do the further improvement for use the numeric output form to implement with the other receiver module to combine multiple outpudata as an enhanced coordinate result.

7. References

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