GPS/INS integration during GPS outages using machine learning augmented with Kalman filter

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Abstract: Nowadays a tremendous progress has been witnessed in Global Positioning System (GPS) and Inertial Navigation System (INS). The Global Positioning System provides information as long as there is an unobstructed line of sight and it suffers from multipath effect. To enhance the performance of an integrated Global Positioning System and Inertial Navigation System (GPS/INS) during GPS outages, a novel hybrid fusion algorithm is proposed to provide a pseudo position information to assist the integrated navigation system. A new model that directly relates the velocity, angular rate and specific force of INS to the increments of the GPS position is established. Combined with a Kalman filter the hybrid system is able to predict and estimate a pseud GPS position when GPS signal is unavailable. Field test data are collected to experimentally evaluate the proposed model. In this paper, the obtained GPS/INS datasets are pre-processed and semi-supervised machine learning technique has been used. These datasets are then passed into Kalman filtering for the estimation/prediction of GPS positions which were lost due to GPS outages. Hence, to bridge out the gaps of GPS outages Kalman Filter plays a major role in prediction. The comparative results of Kaman filter and extended Kalman filter are computed. The simulation results show that the GPS positions have been predicted taking into account some factors/measurements of a vehicle, the trajectory of the vehicle, the entire simulation was done using Anaconda (Jupyter Notebook).

Keywords: GPS, Kalman filter, Semi-supervised learning, INS, Navigation, Global Positioning System

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1. Introduction

Of late there has been a wide use of Global Positioning System (GPS) which has been very popular among a wide range of applications. Global Positioning System provides an outright positioning and navigation information at any time around the globe. GPS provides calibrated information about the accurate position of the devices/vehicles. GPS/INS integrated navigation system finds its dominance in navigational solutions due to its low-cost and miniaturization [1][2]. An inertial navigation system (INS) yields comparatively low noise second to second. An INS provides information regarding navigation only when GPS failures occur. Inertial navigation systems are used as dead-reckoning systems commonly. Inertial Navigation System an independent navigation framework that doesn't depend on any peripheral data regardless of the characteristics of the area screw up with time, making it difficult to work unreservedly for a long time [1][2][3]. Despite, the qualities of the location blunder collect with time, making it hard to work freely for quite a while, Global Positioning System (GPS) can gauge three-dimensional position and velocity precisely. However, the burden is susceptible to noise and control. INS is an autonomous navigation system that does not rely upon any external data. The integration of GPS/INS can overcome many challenges of the individual systems [7]. Since the early ’90s, INS/GPS integrated navigation has been an incredible accomplishment at home and abroad, and it has formed into a specific innovation. INS/GPS coordinated navigation system functions as follows:

When a GPS signal is acceptable, the system chooses the integrated navigation mode. The exactness of incorporated navigation fundamentally relies upon GPS accuracy, and the inertial estimation unit (IMU) blunders can be assessed and repaid on the web. At this point when GPS signal is lost or blocked, the system consequently moves into inertial navigation mode. This loss of GPS signals is known as GPS outages which causes the navigation system to deteriorate completely without compensation. To bridge out such gaps Kalman Filter plays a vital role in efficient prediction. Kalman filter (KF) is widely used as a prediction-correction filter for measuring the unmeasured state of the system. An extended Kalman filter[6] is used to find a relation between the various measurements and to conclude which gives accurate smoothing results. The Kalman filter is used for the estimation of variables of interest when the variables cannot be measured directly. It also estimates the state of the system (ex: the position of a car, the velocity with which the car is moving) even in the presence of noise. Here, it is used for the prediction of positions that get lost due to outages [3][7][8]. Therefore, the Global positioning system and Inertial navigation system together provide a wide range of applications such as military, satellites, land vehicle applications, marine applications, etc. Some relevant studies can be found in [9] and [10]

2. Kalman filtering

Kalman Filter essentially utilizes i) mathematical models of the dynamic system, described by difference or differential equations (in the state space form), ii) actual, and invariably noisy measurements of the system, and iii) the weighted sum of predicted state and measured data (→ residuals) to generate optimal estimates of the states [10]. Here, only equations for the discrete time KF are given. The state space model of a dynamic system in discrete domain is expressed by

$$x(k+1) = \varphi x(k) + Gw(k) \tag{2.1}$$

$$z(k) = Hx(k) + v(k) \tag{2.2}$$

In (2.1), x is the state of the system, and w is a white Gaussian process noise sequence with zero mean and covariance matrix Q; and in (2.2), z is the observation vector, and v is a white Gaussian measurement[11] [12] noise sequence with zero mean and covariance matrix R; ϕ is the state transition matrix, and H is the measurement model. Using the known model of the dynamic system, statistics Q and R of the noise processes, and noisy measurements z(.), properly tuned KF obtains the optimal estimates of the system states x. The discrete KF equations are given as

Time propagation

State estimate : $\tilde{x}(k+1) = \phi\,\hat{x}(k)$ (2.3)

Covariance (a priori):
$$\tilde{P}(k+1) = \phi\hat{P}(k)\phi^T + GQG^T \tag{2.4}$$

Data update

Residual/innovations:
$$e(k+1) = z(k+1) - H\ \tilde{x}(k+1) \tag{2.5}$$

Kalman Gain: $K = \tilde{P}H^T(H\tilde{P}H^T + R)^{-1}$ (2.6)

Filtered estimate: $\hat{x}(k+1) = \tilde{x}(k+1) + K\ e(k+1)$ (2.7)

Covariance (a posteriori): $\hat{P} = (I - KH)\tilde{P}$ (2.8)

Kalman gain function/matrix can be also written as

$$K = \tilde{P}H^T S^{-1} \; ; \; S = H\tilde{P}H^T + R \quad (2.9)$$

In (2.9), S is the theoretical/predicted covariance matrix of the residuals. The actual residuals can be computed from the measurement data update cycle by using (2.5), and their standard deviations (or absolute values) can be compared with the standard deviations obtained by taking the square roots of the diagonal elements of S, i.e. from (2.9). Any mismatch between these two quantities indicates that the performance of the KF is not satisfactory, since the filter is not tuned properly.

3. Methodology

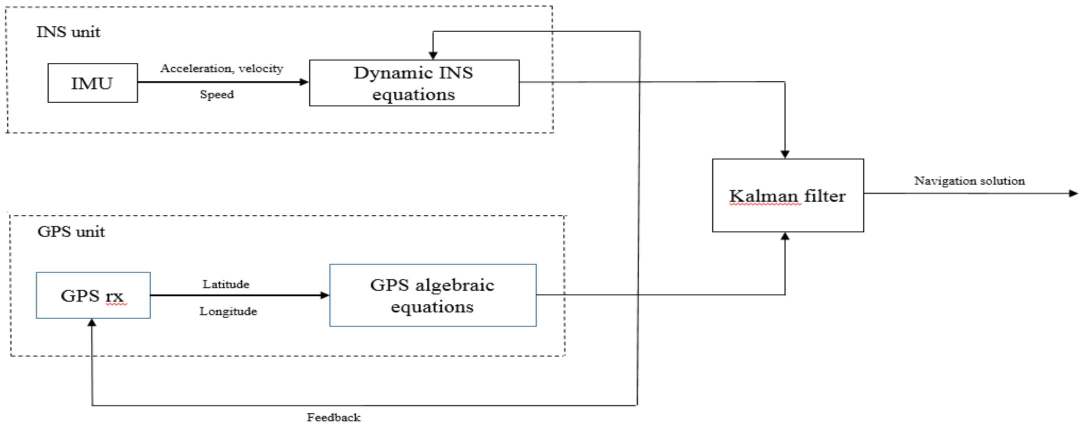

Figure 1: System Model

The system is designed as shown in Figure 1 to provide a complete solution of navigation information without any compensation. The obtained GPS/INS datasets have to be pre-processed as the datasets will be raw in format. To, make the datasets into readable format we have to pre-process them. Here, pre-processing is converting the datasets into a readable format which is understood by the system. In many systems, the data will be trained by an artificial intelligence module. In this paper we have used a semi-supervised machine learning technique which is less time consuming than the individual training of datasets as it allows the data to self-train itself. In semi-supervised learning[4][5],a large amount of unlabeled dataset is combined with a very small amount of named /labeled dataset during training. When enough datasets are not available to produce a precise model and when we don't have the necessary resources to get more data, a semi-supervised machine learning technique is used to increase data size. This learning helps the data to self-train without the use of an artificial intelligence module. Once the datasets are pre-processed, the loading, re-organizing, and reading of datasets take place. It is then sent into the filtering process, where Kalman filter comes into the picture which provides us GPS positions based on several factors considered. The datasets will not be equally based on time leading to variations. Such variations will be rounded off to the next nearest value. During rounding off the datasets will sometime be missed and when this happens the datasets will be automatically assigned as NA (not assigned) as shown in Table:1. When a graph is plotted based on these rounded off values we can get to know the places where GPS data is missing. The next step is the Kalman filtering[7][10] [11] process. KF is a two-step process: Predict and Update. Kalman filter[13] [14] performs predict-update steps in an iterative fashion.

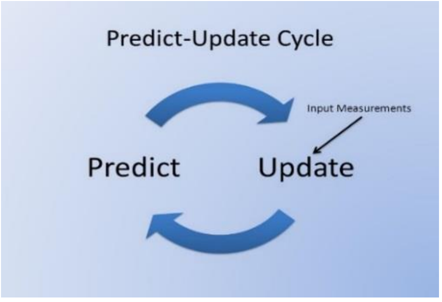

Figure 2: Predict-Update Cycle

Prediction phase: Prediction as shown in figure 2 is done by using the timestep of the previous state to yield the estimate at the current timestep of the system. This predicted estimate is termed as "priori" state estimate.

Update phase: Updation is termed as "posteriori" state estimate. The priori state estimate is amalgamated with observations to process the state estimate.

Kalman filter also provides state estimates of the various measurements such as speed, velocity, acceleration,yaw-rate, etc. These are measurements obtained from IMU which are considered as factors for their estimation. Kalman filter algorithm can be roughly organized under the following:

Prediction of states is made based on previous values and models. The measurement of states is obtained. Updating our prediction, based on the errors and Repeat. First, in Kalman filter, prediction update, pre-error calculation is being made and previous and present error will be calculated. The Kalman gain lies between zero and one. Kalman gain equal to one means good in accuracy of prediction data and zero means bad inaccuracy of prediction data. So, whenever we want to predict a new value, previous value plus Kalman gain into the measurement of the previous value is done. Following these, will give us the new estimate/prediction of positions i.e new latitude and longitude values.

4. Simulation Results:

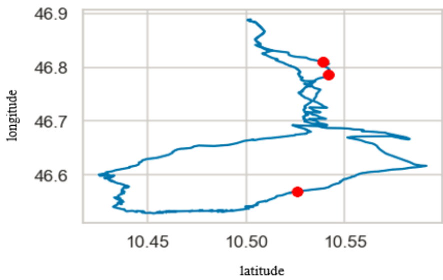

Fig 3(a): Missing GPS data's

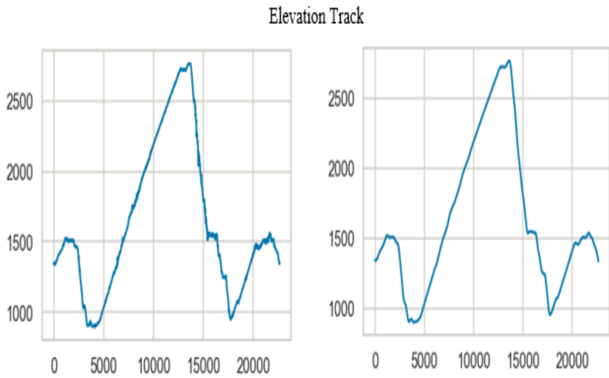

Fig 3(b): Elevation of GPS track
Fig 3(c): Smoothened Elevation track

In Figure 3(a) red dots show places where GPS data's have been lost. The data will not be time equally divided and the values will be rounded off to the next nearest values and when a graph is plotted with these rounded off values one can observe the places where the data have gone missing.

Figure 3(b) and 3(c) shows the elevation of a GPS track with x-axis denoting time and y-axis denoting elevation. It can be observed that figure 6(b) has variations and noises and Figure 3(c) shows a smoothened version of the previous graph. Here, Kalman filter [8] smoothing is used to rule out variations and noises to get a smooth track.

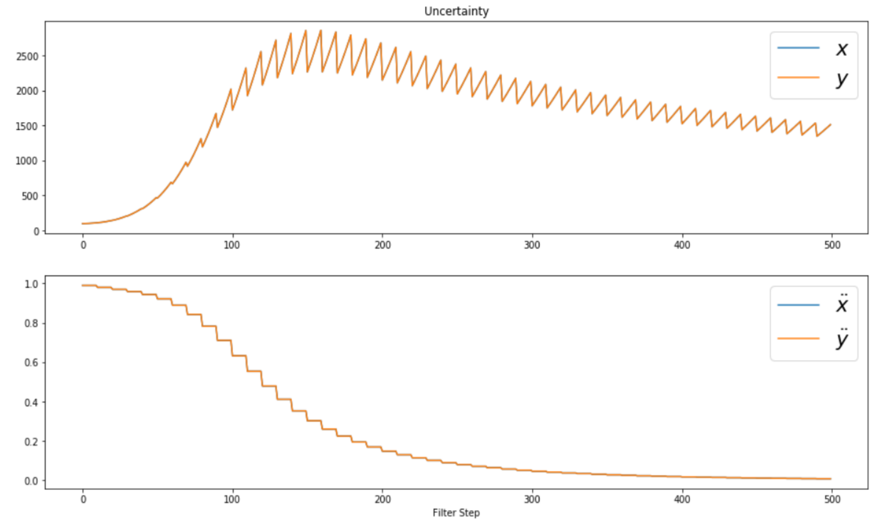

Fig 3(d): Uncertainties of various measurements

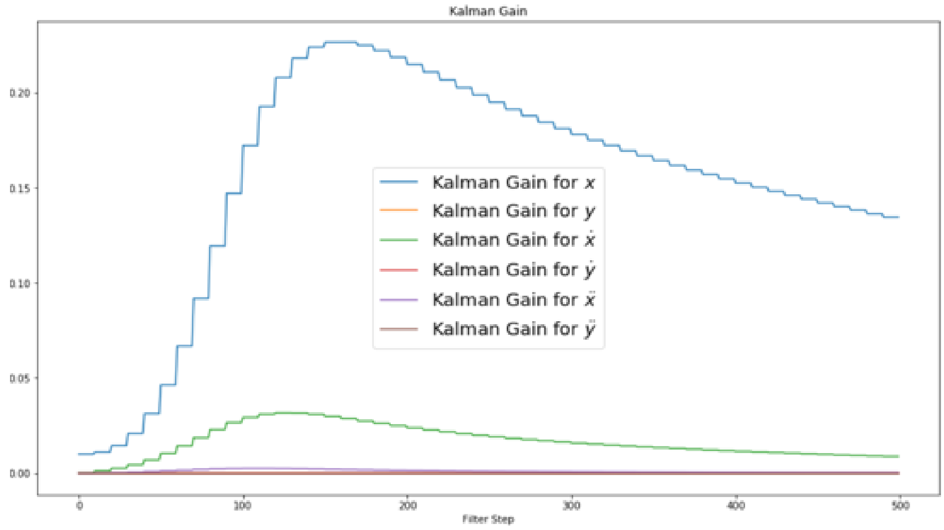

Figure 3(e): Kalman Filter Gains

The Figure 3(d) shows the unfeasibility to exactly describe the existing states.

Figure 3(e) shows the Kalman gain for different measurements such as apposition, acceleration and velocity. It concludes that the lower the Kalman gain the more efficient or fulfilling the prediction will be.

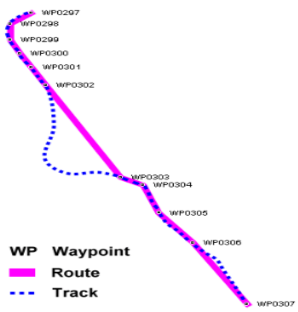

Figure3 (f): Waypoint of the track

Figure 3(f) shows the course of the vehicle, it tells the course traveled by a vehicle from one waypoint to another.

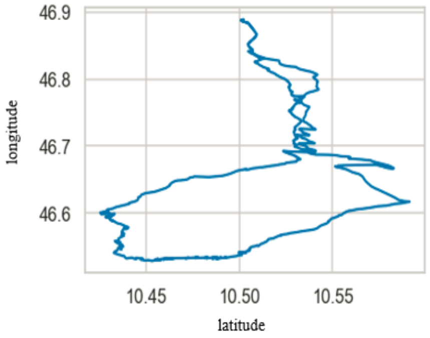

Fig 3(g): Prediction of missing data

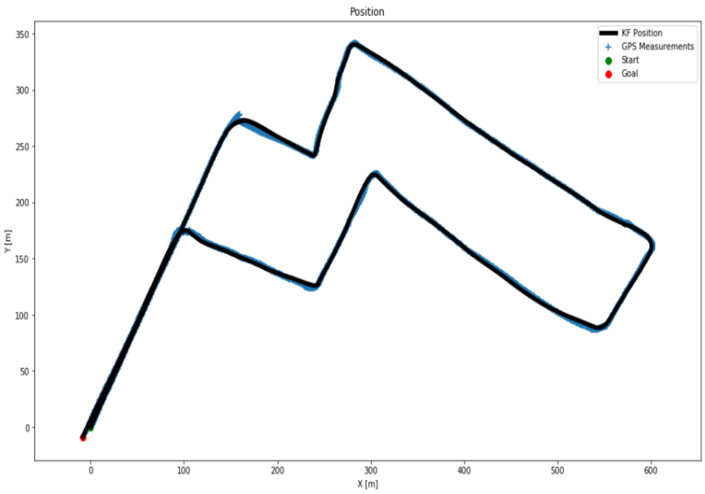

Fig 3(h): Trajectory of a vehicle

Figure 3(g) shows the positions that have been predicted to provide a barrier-free navigation solution. Figure3(g) and Figure3(h) show the navigation track of a vehicle the blue line shows the original path traveled by the vehicle the black line notifies the Kalman filter estimate, green dot denotes the start point of the vehicle and the red dot is the destination/goal of the vehicle. From the simulation results, it is observed that the positions which were lost due to GPS outages have been predicted to offer a good navigation solution.

Table 1: Not assigned data's

Time	idx	Lat	lon	ele
04:57:17	NaN	NaN	NaN	NaN
04:57:18	NaN	NaN	NaN	NaN
04:57:19	NaN	NaN	NaN	NaN
04:57:20	NaN	NaN	NaN	NaN
04:57:21	NaN	NaN	NaN	NaN

NaN in Table 1 stands for "not assigned" data values. When variations occur the latitude longitude, idx (index number) data values get automatically assigned to NaN concerning each time frame. Generally, the data will not be equally divided based on time leading to variations and such variations are rounded off to the next nearest value and during rounding off, the data will sometimes be missed and will be automatically assigned as NaN(not assigned).

Table 2: Range of measurements before and after filters.

	Speed	Acceleration	Altitude
Without Filter	2.452	0.2647	111.5246
With Kalman Filter	2.4201	0.2555	111.5137
With Extended Kalman filter	2.390	0.2461	111.3014

Table 2 shows different measurements before and after applying Kalman and Extended Kalman filter. Kalman filter provides precise results for linear systems whereas Extended kalman filter provides accurate results for non-linear systems.

5. Conclusion

In this paper with regards to land vehicle applications, a system has been developed which can predict and update GPS positions accurately using Kalman filter. A semi-supervised machine learning technique is used to increase the data size when adequate resources are not available during training. Pre-processing of the dataset is carried out before applying the Kalman filter. The pre-processed measurements of the Global Positioning System are taken as input and pre-processed measurements of the Inertial Navigation System are taken as additional information for estimation of state variables. Kalman filter performs predicted of lost GPS positions keeping various factors in track. Here, the KF approach is used as it is a simple and easy approach saving with competitive performance figures. Uncertainties related to the Global Positioning System and Inertial Navigation System has been investigated. Simulation results show that the system was able to predict and update the future position values with the help of the filters to offer good navigation solution with any hindrance. Ranging from the study of initial calibration to minimizing the cost of the merger of the two for the prominent estimation of the navigation solution Kalman filter has been used substantially In the GPS/INS navigation system. Several areas are worth exploring in the future as this paper scores the surface of IMU/GPS. A higher-order integration method can be used to improve prune error. Various sources of data, estimate the error as states, and formulation of minimum variance solution for random errors that are associated with the environment can be combined with Kalman filter. Also, a variety of methods can be made use of for the integration of GPS/INS, and also various other filters can also be used based on the ease of use for estimation.

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