SURVEY ON ANALYSIS OF INS PARAMETERS AND ERROR REDUCTION BY INTEGRATING GPS AND INS SIGNALS

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Abstract

In recent days navigation system has been receiving high demand for several kinds of applications. In the navigation system Inertial Navigation System (INS) and Global Positioning System (GPS) are most popular. In paper [1], the author briefs us that the Inertial Navigation system is combined with other navigation supports like GPS, which has gained importance due to enhanced navigation and inertial reference performance. The INS itself can compute the position of the device without any help from the outside world. However, a huge number of errors are introduced by a sensor which gives rise to an unacceptable drift in the output. So, a GPS is used to help the INS, using a Kalman filter which helps in estimating the errors in the INS and thus updating position to improved accuracy. The author in paper [2] gives us a brief view of extended Kalman filtering-based attitude tracking algorithm is presented. The star sensor is modelled as a nonlinear stochastic system with the state estimate providing the three degree-of-freedom attitude quaternion and angular velocity. In paper [3], the author conducts performance evaluation for the ultra-tight integration of Global positioning system (GPS) and inertial navigation system (INS) by use of the fuzzy adaptive strong tracking unscented Kalman filter (FASTUKF). In paper [4], a 15-state Extended Kalman Filter is designed to integrate INS and GPS in a flexible way compared with many conventional integration.

Keywords: Inertial navigation system (INS), Global Positioning System (GPS), Kalman Filter, GPS-INS Integration, Navigation System. GPS ·INS· Ultratight integration· Strong tracking filter· Fuzzy logic· Unscented Kalman filter

Introduction

GPS and Inertial Navigation Systems (INS) are increasingly used for positioning and attitude determination in a wide range of applications. The integration of GPS and INS is usually achieved using a Kalman filter which is a sophisticated mathematical algorithm used to optimize the balance between the measurements from each sensor. The measurement and process noise matrices used in the Kalman filter represent the stochastic properties of each system. The primary advantage of using GPS includes its ability to provide absolute navigation information, and the long-term accuracy in the solution. Although the solution provided by GPS is sufficiently accurate (especially when used in differential mode), it is unable to fulfil the requirements of continuity and reliability in many situations. Being a satellite-based navigation system, GPS requires line-of sight (LOS) between the receiver antenna and the satellites. However, in the case of a land vehicle, the LOS criteria may not always be met, because a land vehicle typically moves in urban and under dense foliage environments which prevent signals from reaching the antenna. Thus, signal interruption is one of the primary reasons which affects the continuity and reliability of the navigation solution from GPS. GPS cannot be solely used for navigation, especially in urban environments. Unlike GPS, an INS is a self-contained DR (Dead Reckoning) navigation system which provides position and velocity information through direct measurements from an IMU (Inertial Measurement Unit). The advantage of INS over GPS is its independence from external electromagnetic signals, and its ability to operate in all environments.

This allows an INS to provide a continuous navigation solution, with excellent short term accuracy. However, the INS suffers from time-dependent error growth which causes a drift in the solution, thus compromising the long term accuracy of the system. The drift of high quality inertial devices is small, and can fulfil the accuracy requirement in land applications for longer periods. However, there are two specific limitations for their use in general applications, such as LVNS. One is their price (over US $90,000 for a high-end IMU and over $10,000 for medium grade IMUs), and the other is the regulation by the governments against their unrestricted use. Due to these limitations, the use of INS has generally been confined to only high accuracy navigation and geo-referencing applications. Recently, with advances in Micro Electro-Mechanical Systems (MEMS) technology, low cost MEMS-based inertial sensors are available. The immediate start-up time, low power consumption, weight and cost of these sensors meet the specifications and requirements needed for commercial applications, like vehicle navigation. The errors of even today's most accurate INS (based on high end IMUs) would become unacceptably large after several minutes. It therefore becomes necessary to provide an INS with regular updates in order to bind the errors to an acceptable level. The powerful synergy between the GPS and INS, and the availability of low cost MEMS sensors, makes the combination of these two navigation technologies a viable positioning option for LVNS. Their combination not only offers the accuracy and continuity in the solution, but also enhances the reliability of the system. GPS, when combined with MEMS inertial devices, can restrict their error growth over time, and allows for online estimation of the sensor errors, while the inertial devices can bridge the position estimates when there is no GPS signal reception. Also, the use of inertial components allows the GPS measurements to be compared against statistical limits and reject those measurements that are beyond the limits, thus enhancing the reliability and integrity of the system. Ultimately, the navigation solution derived from a GPS/INS system is better than either standalone solution. As GPS/MEMS INS systems constitute an increasingly attractive low cost option, it is of significant importance to evaluate their performance. Thus, the broad aim is to evaluate the performance of a GPS/MEMS INS integrated system, and to develop a system capable of providing an accurate navigation solution, reliably and continuously for land vehicle navigation application.

In paper [1], the author explains that for any automatic machines, be it robots, aircraft or other autonomous vehicles, navigation is of extreme importance. Various systems are used in navigation of aircraft, like inertial navigation systems (INS), global positioning systems (GPS), air-data dead reckoning systems, radio navigation systems, Doppler heading reference systems, are few among them. Our interest is in integrating both the GPS and the INS to provide the best possible estimate of the aircraft position in terms of the longitude, latitude and height above the surface of the earth. The INS gives us the position, velocity and attitude of the aircraft but it is included with errors due to the fact that any small drift error can grow the error with time. Hence, an update or position fix is considered from the GPS and using a Kalman filter we can estimate the errors in both the GPS and the INS, thus giving the better position information. Applications are not limited to aircraft alone. Although these integrated systems find extensive usage in airborne vehicles, they have also been used in the navigation of cars, ships, satellites and many other vehicles. There are many advantages in developing this kind of a navigation system as compared to the ones used earlier in terms of size and speed. GPS chips and Micro- gyroscopes can be integrated on a small board and can effectively give the position of the vehicle. With the advantage of MEMS technology, all this can be done at high levels of accuracy and at very lower costs. The objective of the author was to develop the GPS-INS integrated system so that it can be implemented on real time hardware like a microcontroller, microprocessor or a digital signal processor. Even though high accuracy sensors like gyroscopes and accelerometers are available, their costs are higher. Usage of low cost and low accuracy sensors may find application where high accuracy is not compulsory. First the simulation of the whole navigation system would be done on a computer, where given the initial state of the vehicle and regular updates from the sensors (INS) and the GPS, the program will return the estimated position of the vehicle. Eventually this simulated model would be implemented on real hardware.

In paper [2], the author widely uses Star sensors for attitude determination in both orbiting and interplanetary spacecraft. A star sensor typically operates in two modes: initial acquisition and tracking mode. The difference between them is whether the approximate attitude is known. In initial acquisition without a-priori attitude input, stars inside the whole field of view (FOV) are acquired and mapped to the matching stars in the sensor's star catalogue by a search over the whole celestial sphere. In the case sufficient stars have been identified, the star sensor starts the calculation of attitude and goes into tracking mode. In contrast to initial acquisition mode, the sensor performs an attitude tracking and not a star tracking in tracking mode. The current attitude and angular rate is used to determine an expected attitude for the following measurement frame.

The sensor uses this expected attitude and on board star catalogue to determine the star track windows to get the stars to be measured and evaluated. This method shortens the time to find the measurement stars and will also to eliminate spurious objects. Tracking mode is more efficient and reliable than initial acquisition mode and is the key operation mode in the lifetime of a star sensor. Attitude Tracking Algorithm directly affects the star sensor's performance. If there is only one observed star in the window, the star is matched with the reference star corresponding to the track window. The radius of the window is in proportion to star sensor's angular rate. The larger the radius is, the more stars will be observed in one track window. In that case the angular distance between the observed stars and reference stars are used to find the correct match which is complicated and time consuming. In order to speed up the accessing the catalogued stars to identify the stars which enter or exit the sensor FOV, assigned the catalogued stars into sub-catalogue. A partition table including all sub-catalogues is generated which is memory-consuming. Finally, according to stars transformation between inertial-based coordinate system and image plane, the star sensor's attitude is calculated by QUEST algorithm.

In paper [3], the author states that although the Global Positioning System (GPS) is capable of providing accurate position information, the data is prone to jamming or being lost due to the limitations of electromagnetic waves, which form the fundamental of their operation. The inertial navigation system (INS) is a self-contained system that integrates three acceleration components and three angular velocity components. However, the error in position coordinates increases unboundedly as a function of time. Due to the inherent complementary operational characteristics of GPS and INS systems, the synergy of both systems has been widely explored. The GPS/INS integrated navigation system is the adequate solution to provide a navigation system that has superior performance in comparison with either GPS or INS stand-alone system. Traditional GPS/INS integration designs use a loosely or a tightly coupled architecture. The loosely coupled integration uses the GPS derived position and velocity as the measurements. In this paper the author has explained about the drawbacks of using Unscented Kalman Filter. To fulfil the requirement of achieving the filter optimality or to preventing divergence problems, the adaptive Kalman filter (AKF) approach has been one of the promising strategies and has been widely explored. The method is developed based on the combination of UKF and STA, which has several important merits, including (1) strong robustness against model uncertainties; (2) good real-time state tracking capability, no matter whether the system has reached steady state or not; (3) moderate computational load. In the STUKF, the softening factor is introduced to provide better state estimation smoothness. Traditional approach for determining the softening factors heavily relies on personal experience or computer simulation using a heuristic searching scheme. The application of fuzzy logic to engineering applications has been very popular, especially in the field of adaptive control for dealing with nonlinear systems with dynamical uncertainties. The fuzzy logic reasoning system based on the model is incorporated into the STUKF for obtaining suitable softening factors according to the time-varying change in dynamics by monitoring the innovation information.

In paper [4], the author explains the integration of GPS and INS, the Kalman filter plays a significant role. Being a recursive estimator, a Kalman filter can process the linear model and estimate the state vector which has a minimum variance based on the information at the moment and its prior value in the past. In INS/GPS integration system the Kalman filter combine the navigation signal from both GPS and INS, estimate the errors then compensate back to the original input. The distinction of Kalman filter is that: it uses only navigation state at the present and previous, hence it costs less memory than traditional filters. Besides that, a Kalman filter could use one of little measurement information (e.g. position) to estimate to provide additional information (heading, pitch, roll, etc...) which is useful for semi-automated navigation. In reality, the navigation process is always non-linear. However this problem can be solved by the Extended Kalman Filter. Integration of GPS with an inertial Navigation System improves the quality and integrity of each navigation system: use of GPS permits calibration of inertial instrument biases, and the INS can be used to improve the tracking and reacquisition performance of the GPS receiver.

METHODOLOGY

In paper [1], the author describes that a single-frequency civilian user can obtain three types of measurements from the currently available GPS signal. These are: (1) Code phase (pseudo range) measurement; (2) Carrier phase measurement; and (3) Doppler/incremental phase measurement. The carrier phase measurement is the most precise measurements available to GPS users, and is typically used in high-accuracy (cm level) application such as geodetic surveying, and automatic vehicle applications. However, typical accuracy requirements in land vehicle navigation application are on the order of few meters.

In an open area environment, GPS pseudo range measurements can provide accuracies better than 5 m in differential mode for a baseline length of 50 km from reference station. The code pseudo range measurement represents the apparent distance between the GPS satellite and the receiver antenna. These measurements are derived from the PRN codes, by measuring the amount of time shift required to align the PRN-code replica generated at the receiver with the one received from the satellite. Using this information the GPS receiver determines the time required for the signal to propagate from the satellite to the receiver, which when scaled by the speed of light provides the pseudo range measurement. These measurements are termed as pseudo ranges instead of ranges because the clocks of the satellites and the receiver are not perfectly synchronized to GPS time. The measurements therefore contain clock biases; hence, the term pseudo. The true pseudo range is the pseudo range in the idealized error-free condition, which includes the true range and the clock error bias. However, in real measurements there are random noise effects, and various propagation and system specific errors.

Pseudo range measurements are useful in determining a user's position in terms of latitude, longitude, and height. These three unknowns combined with the receiver clock error term, results in a total of four unknown parameters. Thus, independent GPS navigation requires signals from at least four satellites for computation of a complete position solution. However, with clock aiding, it is possible to navigate with less than four satellites. Augmenting GPS with clock and height aiding requires only as few as two satellites measurements to provide the navigation solution.

MEMS accelerometers are typically a pendulous/displacement mass type system that uses capacitive sensing to provide a measure of acceleration. It consists of a proof mass located at the center of two electrodes, each made of silicon. The deflection of the proof mass leads to the change of capacitance which is used to measure the amplitude of the force that led to displacement of the proof mass. This method is generally termed as an open loop mode of operation. Another mode is the closed loop, where the counteracting force required to keep the proof mass at zero-deflection point is measured, to provide a measure of acceleration .These silicon accelerometers are being developed for a wide range of applications commercially such as automotive air bags, as well as autonomous vehicle markets. The majority of MEMS-based gyroscopes currently under development operates in a vibratory mode and measures the angular rate instead of the absolute angle .These gyros consist of a sensing element vibrating with constant amplitude controlled by a vibrating motor that maintains the oscillation at constant amplitude. When this system is rotated around any axis other than the axis of its internal in-plane vibration, the Coriolis force causes the element to oscillate out of the plane. This oscillation is picked-up by the sensing capacitors and is used to provide a measure of angular rate.

The integration of the raw data obtained from the IMU is done in two steps. In the first step, the body sensed angular rates are integrated to compute the transformation matrix (rotation matrix) from b-frame to e-frame. A gyro senses the angular rates due to Earth rotation and the rotation due to vehicle movement. To get the actual vehicle angular velocity, Earth rotation rate should be transformed into the body frame, and removed from the measured angular rates. Once the angular rate is obtained, a transformation matrix can be computed using a quaternion approach.
In the second step, the computed transformation matrix is used to rotate the measured specific force from the b-frame toe-frame. The output of an accelerometer represents the sum of actual vehicle acceleration and the gravity. The sensed acceleration information must therefore be compensated for gravity in order to determine the total acceleration of the vehicle. This acceleration can then be integrated to obtain vehicle velocity, which when integrated provides the vehicle position.

KF is a very effective and versatile procedure for combining noisy sensor outputs to estimate the state of a system with unsure dynamics. Noisy sensor outputs include outputs from the INS and GPS; state of the system might include position, velocity, attitude and attitude rate of a vehicle or an aircraft; and uncertain dynamics includes unpredictable disturbances in the sensor parameters or disturbances caused by a human operator or a medium (like wind). The KF is used to calculate the errors introduced into the unaided INS system due to the gyros and accelerometers. These errors form the state vector k and the measured values of the state vector from the GPS forms the measurement vector z. After modeling the errors, the KF loop, is implemented after giving the initial estimates of the state vector and its covariance matrix at time t = 0. This makes the GPS-aided INS system configuration, and the errors are either compensated by the feed forward or the feedback mechanism as shown in the figure below.

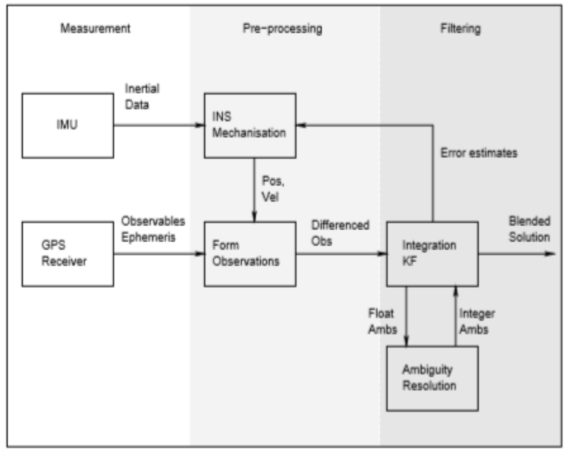

Figure 1: Integration of GPS and INS signals using Kalman filter[6].

A nine state Kalman filter is designed and implemented using the perturbation theory model for position, velocity and attitude. The accuracy of the results obtained was better than the accuracy given by the GPS and INS as individual systems. The accuracy can be further improved if we increase the states of the filter and model for the scale factors, biases and non-orthogonally of the sensors. The program of integration of the INS and GPS using Kalman filtering was run on the DSP simulator software and the computation time was well within the requirements of 10ms.

In paper [2], the author describe the tracking model of the star sensor. We then provide some implementation details, particularly on attitude estimation, star catalog partition and initial angular velocity estimation. Firstly, the EKF algorithm for attitude estimation is designed. Secondly, a novel star catalog partition method is presented to speed up accessing the cataloged stars while having a small memory requirement. Thirdly, the initial angular velocity estimation algorithm is described.
Tracking Models after a full-sky star identification is finished to establish an initial attitude and angular velocity, the star sensor

enters the tracking mode and recursively performs the following three steps as shown in Figure 2.
(i)From EKF the attitude quaternion and its error covariance is extrapolated to the next frame in EKF. The expected attitude is used to access on board partition table and star catalog by spherical polygon approach to determine the centers of the star track windows. Meanwhile, the error covariance is used to determine the radius of the track windows. (ii) Get the stars to be measured and evaluated in the track windows of star image. If there is only one star in a reference stars neighborhood, the star in star image is matched with the star in reference star image. Further, the match can be checked by the inter-star angles between the reference stars and the observed stars. (iii) The coordinates of the matched stars in the observation star image are used as the measurements for EKF to estimate the optimal attitude quaternion of current frame and the angular velocity.

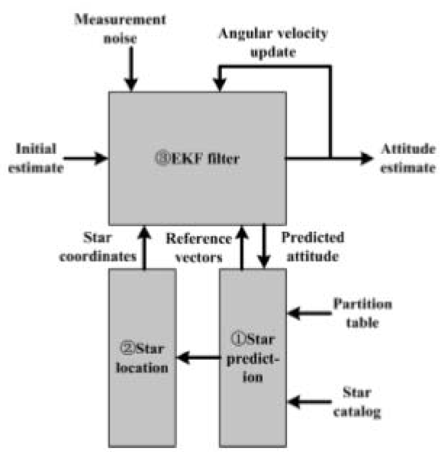

Figure 2: Tracking Model of Star Sensor[2]

To improve the performance of star sensor in case of high attitude dynamics, a novel attitude tracking algorithm based on extended Kalman filter is presented. The approach model the star sensor as a nonlinear stochastic system with the state estimate providing the three degree-of-freedom attitude quaternion and angular velocity based on the extended Kalman filter (EKF). From EKF the attitude quaternion and its error covariance are extrapolated to the next frame used to predict the centers and radius of the star track windows. In order to speed up the prediction a star catalogue partition method by an inscribed regular icosahedron is introduced for a fast search of the star catalog while having a small memory requirement. Then the matched stars in the track windows of star image are measured and used as the measurements for EKF to estimate the optimal attitude quaternion of current frame and the angular velocity.

In paper [3], the design of GPS/INS integrated navigation system heavily depends on the design of sensor fusion method, which is typically carried out through the extended Kalman filter (EKF) . The EKF not only works well in practice, but also it is theoretically attractive because it has been shown to be the filter that minimizes the variance of the estimation mean square error (MSE). Unfortunately, the fact that EKF highly depends on a predefined dynamics model forms a major drawback. To achieve good filtering results, the designers are required to have the complete a priori knowledge on both the dynamic process and measurement models.
The UKF is superior to EKF not only in theory but also in many practical situations to address nonlinear state estimation in the context of control theory, the UKF is a nonlinear, distribution approximation method that uses a finite number of carefully chosen sigma points to propagate the probability of state distribution.
The UKF made a Gaussian approximation with a limited number sigma points through the Unscented Transform (UT). Through the nonlinear dynamics of system, the true mean and covariance of the Gaussian random variable (GRV) are completely captured with a minimal set of samples. The basic premise behind the UKF is it is easier to approximate a Gaussian distribution than it is to approximate an arbitrary nonlinear function. The posterior mean and covariance can be captured accurately to the second order of Taylor series expansion for any nonlinear system. One of their markable merits is that the overall computational complexity of the UKF is the same as that of the EKF. To fulfil the
Requirement of achieving the filter optimality or to preventing divergence problems, the adaptive Kalman filter (AKF) approach has been one of the promising strategies and has been widely explored.

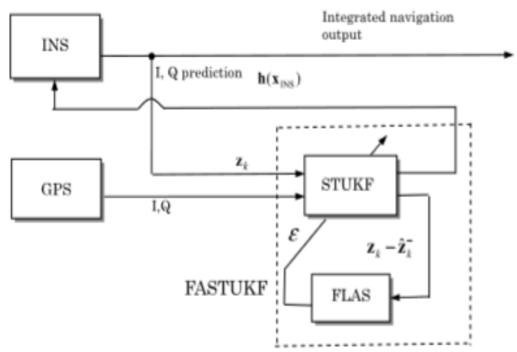

Figure 3: Configuration of the ultra-tightly coupled feedback integrated navigation using the FASTUKF[3]

The application of fuzzy logic to engineering applications has been very popular, especially in the field of adaptive control for dealing with nonlinear systems with dynamical uncertainties. Recently, application of fuzzy logic to adaptive Kalman filtering has been becoming popular. Sasiadek, Wang, and Zeremba introduced the Fuzzy Logic Adaptive System (FLAS) for adapting the process and measurement noise covariance matrices in navigation data fusion design. Incorporation of the FLAS for dynamically adjusting the softening factors based on the fuzzy rules so as to enhance the estimation accuracy results in an approach called the fuzzy adaptive strong tracking unscented Kalman filter (FASTUKF).

The UKF has been presented to be superior to the EKF, due to the fact that the UKF is able to deal with the nonlinear formulation. The UKF ensures better description on the vehicle dynamics and shows superior navigation accuracy when compared with EKF since the series approximations in the EKF algorithm can lead to degraded representations of the nonlinear functions and probability distributions of interest. Determination of the softening factors in the STUKF through the use of fuzzy logic has been employed. The FLAS has been incorporated in to the STUKF as a mechanism for timely detecting the dynamical changes by the DOD parameters and implementing the on-line determination of softening factors by monitoring the innovation information and accordingly improve the navigation accuracy at the high dynamic regions without sacrificing the precision at the lower dynamic regions. For trajectories with sharp turns or an abrupt maneuver involved, the performance improvement becomes obvious.

In paper [4], the author explains that there are three main types of INS/GPS integration: loosely-coupled, tightly-coupled and ultra-tightly coupled. In loosely-coupled integration, the position and velocity output of the GPS receiver and inertial sensors data are integrated in a Kalman filter. Tightly-coupled integration uses an estimation technique to integrate inertial sensors readings with raw GPS data (i.e. pseudoranges and pseudorange rates) to get the vehicle position, velocity, and orientation. For the ultra-tight-coupled integration, there is a basic difference in the architecture of the GPS receiver compared to those used in loose and tight integration. Here, the receiver comprises a bank of single vector delay lock loop instead of a bank of independent code and carrier tracking loops. The information from INS is used as an integral part of the GPS receiver, thus, INS and GPS are no longer independent navigators, and the GPS receiver itself accepts feedback.

The integration of GPS and INS in this paper based on loosely-coupled approach. The input of Kalman Filter is the mixed of GPS and INS errors. After the filtering process, the random noises mostly come from GPS are removed, the remained INS errors are added to INS output to get the correct navigation value. Another concern in commonly INS/GPS system is the difference in each system's update rate. An INS system always has higher update rate than a GPS system that means from time to time, the system has to operate without the presence of GPS information. Moreover, GPS signal could suffer from external environment and may lost, causing an absence of GPS in relative long time.

To deal with these situations, we use the configuration with the ability to switch back and forth between feed forward mode and feedback mode.

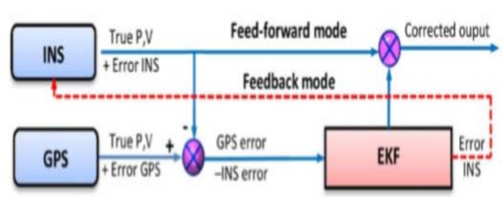

Figure 4. Feedback and feed-forward mode [4].

Feedback mode: Assume when GPS signal is lost, since there is no presence of GPS information, the Kalman Filter block enable prediction mode which use the last corrected value to estimate the current state using a dynamic model. Since the measurement signal is interrupted, all the measurement equation and Kalman gain computation are obsoleted. Feed-forward mode when GPS has its signal back, the feedback is removed, the Kalman Filter block enable feed-forward mode which use INS and GPS information to process as usual.

A configuration of INS/GPS integrated system is given for compensating the limitation of using each navigation system separately. With the system integrated using this configuration, it's possible to navigate with relative high accuracy when GPS signal is presented and continue to keep a good track even when the GPS signal is lost. In order to achieve this performance, a 15-state Extended Kalman Filter is implemented to deal with the non-linear issue of the system dynamic. Besides that, a linear Kalman filter is also presented and operated when the GPS outage occur. Along with two filtering scheme, a switching mechanism is given to brings the feature of automatically switch from the extended Kalman filtering scheme to the linear Kalman filtering scheme whenever GPS signal is lost, and switch back to the extended Kalman filtering scheme on condition that the system receive GPS information.

COMPARISON TABLE

Table 1: Comparison Table

YEAR	TOPIC	OBJECTIVE	CHANLLEGES
2013	Design of Inertial Navigation System using Kalman Filter	To integrate GPS and INS signal using a nine state kalman filter	Accuracy can be increased by increasing the state of kalman filter.
2017	An Extended Kalman Filter-Based Attitude Tracking Algorithm for Star Sensors	The star sensor is modelled as a nonlinear stochastic system with the state estimate providing the three degree-of-freedom attitude quaternion and angular velocity where	Efficiencyandreliabilityarekeyissueswhenastars ensoroperatesintrackingmode.
2013	Performance enhancement for ultra-tight GPS/INS integration using a fuzzy adaptive strong tracking unscented Kalman filter	An ultra-tight GPS/INS integration architecture involves fusion of the in-phase and quadrature components from the correlate of the GPS receiver with the INS data. These two components are highly nonlinearly related to the navigation states.	Low accuracy, expensive.
2015	15-State Extended Kalman Filter Design for INS/GPS Navigation System	Based on the loosely coupled GPS/INS integration, the proposed scheme can switch back and forth between feed forward and feedback aiding methods. The system can reduce the position and velocity errors compared to conventional integration method.	The disadvantage is that the result that accuracy is less and switching mechanism happens between EKF to linear KF whenever GPS signal is lost.

Conclusion:

In paper [1], the accuracy can be increased by increasing the state of kalman filter. In paper [2], efficiency and reliability are key issues when a star sensor operates in tracking mode. In paper [3], low accuracy and design and development of Ultra Tight GPS and INS integration is expensive. In paper [4], the disadvantage is that the result that accuracy is less and switching mechanism happens between EKF to linear KF whenever GPS signal is lost. The extended Kalman filter in general is *not* an optimal estimator another problem with the extended Kalman filter is that the estimated covariance matrix tends to underestimate the true covariance matrix. Thus the design of integration Architecture should be such that the accuracy, reliability and continuity is improved.

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