A GPS-aided Inertial Navigation System in Direct Configuration

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ABSTRACT
This work presents a practical method for estimating the full kinematic state of a vehicle, along with sensor error parameters, through the integration of inertial and GPS measurements. This kind of system for determining attitude and position of vehicles and craft (either manned or unmanned) is essential for real time, guidance and navigation tasks, as well as for mobile robot applications.

The architecture of the system is based in an Extended Kalman filtering approach in direct configuration. In this case, the filter is explicitly derived from the kinematic model, as well as from the models of sensors error. The architecture has been designed in a manner that it permits to be easily modified, in order to be applied to vehicles with diverse dynamical behaviors.

The estimated variables and parameters are: i) Attitude and bias-compensated rotational speed of the vehicle, ii) Position, velocity and bias-compensated acceleration of the vehicle and iii) bias of gyroscopes and accelerometers.
Experimental results with real data show that the proposed method is enough robust for its use along with low-cost sensors.

Keywords: Inertial Navigation, Sensor Fusion, State Estimation.

1. Introduction

The process for autonomously estimating the state of a vehicle (e.g position, velocity, orientation, etc.), while it is maneuvering along a trajectory, is often referred as navigation.

The autonomous navigation is an important capability for both manned and unmanned vehicles. In our context the term "autonomous" refer to the capacity of the system for estimating the state of the vehicle without the aid of a human operator. Often, the autonomous navigation is a prerequisite for control tasks.

The Inertial Navigation System (INS) is one of the most widely used dead reckoning systems. A typical INS fuses sensory information taken from inertial sensors (accelerometers) and rotational sensors (gyroscopes) in order to continuously estimate position and orientation of the body (vehicle). Because different sources of sensor errors are integrated over time, an INS can provide correct and high frequency (typically in the range of 100 to 200 Hz) information but only for short term. This fact is especially notorious when low-cost sensors are used. On the other hand, a Global Positioning System (GPS) provides global-referenced position and velocity estimations at low rate (typically in the range of 1 to 4 Hz). The integration of both systems (INS and GPS) can generate a navigation system capable of exploiting the advantages of both, and also limits the drawbacks of the systems viewed by separate. Thus, a GPS-aided INS can produce estimates of the full state of the vehicle, both at high frequency as drift-free.

The integration of inertial sensors with GPS is broadly classified as follows [25]:

• *Loosely coupled system.*

• Tightly coupled system.

• Ultra-tightly coupled system

In loosely coupled systems [8-13],[16],[18] and [19], the GPS data (e.g. position velocity, etc) are fused explicitly with INS data. This kind of systems is significantly dependent on the availability of GPS data.

In tightly coupled systems [6] and [13], the GPS raw measurements (e.g pseudo ranges) are fused directly with the INS data. The main advantage of this kind of methods is that the system can carry out GPS measurement updates, even if there are less than four satellites available. Their downside has to be with the increase of complexity.

In Ultra-tightly coupled systems [26], the INS output (position, velocity and attitude) is used as an external input to the GPS receiver. The INS output aid in prepositioning calculation for faster signal acquisition and in interference rejection during signal tracking. The implementation of this kind of systems is often complicated because access to the GPS's firmware is required.

Different techniques of state estimate have been used for integrating INS and GPS. Schemes presented in [1] and [2] are based in techniques of linear Kalman filtering. The Kalman filter (KF), commonly used in estimating the system state variables and suppressing the measurement noise, has been recognized as one of the most powerful state estimation techniques. The KF allows to merge information obtained from different sensor sources in a structured manner. For example in [29], a KF-based method for estimating position is presented, this approach combines visual data with wireless sensors network information. Commonly methods based on linear filtering utilize simplified (linearized) models. Thus, some computational time is saved, but at the cost of some decrease in performance. However, the wide variety of processing devices currently available makes feasible the implementation of complex algorithms in order to improve performance.

Due to the nonlinear nature of the problem, the nonlinear version of the Kalman Filter (The Extended Kalman Filter or EKF) has been the technique typically used to compute the GPS-INS solution. There are two basic ways for implementing the EKF:

• Indirect formulation.

• Direct formulation.

The EKF in Indirect formulation (also referred as the error state space formulation), estimates a state vector which represents the errors defined by the estimated state and the estimated nominal trajectory. An error model for each component of the state is needed in order to estimate the measurement residual. The measurement in the error state space formulation is made up entirely of system errors and is almost independent of the kinematic model. Most of the approaches found in literature are based in this kind of configuration [3-13].

The EKF in Direct configuration (also referred to as total state space formulation) updates the vector state implicitly from the predicted state and the measurement residual (the difference between the predicted and current measurement).

Method	Integration type	Estimated errors	Attitude	Estimation technique
[16]	Loosely	G_b,G_s,A_b,A_s	Quat.	I-EKF (Unscented)
[19]	Loosely	No	Euler	Neural Networks
[6]	Tightly	G_b,A_b	Euler	i-EKF (Quadratic)
[9]	Loosely	G_b	Quat.	i-EKF
[8]	Loosely	G_b,A_b	DCM	i-EKF
[10]	Loosely	G_b,A_b	Euler	i-EKF
[18]	Loosely	No	Euler	Particle Filter
[11]	Loosely	A_b	Euler	i-EKF
[12]	Loosely	*	*	i-EKF
[13]	Tightly	G_b,A_b,T_b	Quat.	i-EKF
This work	**Loosely**	**G_b,A_b**	**Quat.**	**d-EKF**

Table 1. Resume of Methods. *Not specified. For "Estimated errors" column: G = gyroscope, A = accelerometer, T = GPS time, b = bias, s = scale, (e.g. Gb means gyro bias). For "Attitude" column: DCM means Direction Cosine Matrix, and Quat. is the abbreviation of quaternion. For "Estimation Technique" column, i-EKF = Extended Kalman Filter in indirect configuration, d-EKF = Extended Kalman Filter in direct configuration. In parentheses are indicated.

In this kind of EKF configuration, the system is essentially derived from the kinematics. One of the characteristics of the direct configuration is its conceptual clarity and simplicity. A review on the EKF and its configurations can be found in [14].