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Validation of nonlinear integrated navigation solutions

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ABSTRACT

There exist numerous navigation solutions already implemented into various navigation systems. Depending on the vehicle in which the navigation system is used, it can be distinguished in most cases among; navigation, tactical, and commercial grade categories of such systems. The core of these systems is formed by inertial sensors, i.e. accelerometers and angular rate sensors/gyros. Navigation and tactical grade systems commonly rely on fiber optic/ring laser gyros and servo/quartz accelerometers with high resolution, sensitivity, and stability. In the case of cost-effective navigation systems, for example piloted light and ultralight aircraft, usually use commercial grade sensors, where the situation differs. The sensor outputs are less stable and sensitive, and suffer from manufacturing limits leading to temperature dependency, bias instability, and misalignment which introduces non-negligible disturbances. These conditions commonly limit the applicability of the navigation solution since its stand-alone operation using free integration of accelerations and angular rates is not stable. This paper addresses a cost-effective solution with commercial grade inertial sensors, and studies the performance of different approaches to obtain navigation solution with robustness to GNSS outages. A main goal of this paper is thus comparison of a nonlinear observer and two extended Kalman filter solutions with respect to the accuracy of estimated quantities and their sensitivity to GNSS outages. The performance analyses are carried out on real flight data and evaluated during phases of the flight when the solutions are challenged by different environmental disturbances.

1. Introduction

Cost-effective MEMS (Micro-Electro-Mechanical System) based inertial measurement units (IMU) aided with GNSS (Global Navigation Satellite System) based positioning have become common for applications in broad areas of interest, such as piloted light and ultralight aircraft, unmanned aerial, terrestrial, and water vehicles. For a strapdown navigation solution an inertial navigation system (INS) consisting of tri-axial accelerometer (ACC) and tri-axial angular rate sensor (ARS) aided with GNSS receiver is used for position, velocity and attitude (PVA) estimation. There are various methods for INS aiding with using GNSS based measurements based on un-coupled (Savage, 1998a,b), loosely coupled (Wolf, Eissfeller, & Hein, 1997), tightly coupled (Li, Wang, Rizos, Mumford, & Ding, 2006), and ultra-tightly coupled (Babu & Wang, 2009) integration schemes. A variety of the mentioned integration schemes integrates IMU measurements with GNSS based ones in order to provide a stable and robust navigation solution regardless of the condition of operation. MEMS based IMUs are compact, lightweight, and cost-effective thus offering a cheap solution. However, at the same time they suffer from bias instability, insufficient sensitivity, noise etc. That presents significant challenges in data processing which has to be dealt with in the data fusion process. Moreover, the vibration imposed by vehicle or engine motions often dominates and corrupts ACC measurements (Alam & Rohac, 2015) as well as ARS readings depending on g- and g^2-sensitivity parameters. On the other hand, accuracy of the single point GNSS based measurements can degrade due to ionospheric or tropospheric refraction, multipath, and/or weak/blocked GNSS signal. However, by fusing available data these disadvantages of both individual systems can be reduced, and thereby the resultant system can provide a robust navigation solution under all environmental conditions even when GNSS signal is temporally unavailable or it suffers from increased level of error. The accuracy of the GNSS based measurements can be further improved with satellite-based augmentation system (SBAS) corrections and/or Real-Time-Kinematic (RTK) solutions down to the order of cm-level precision.

There are several approaches for fusing INS/GNSS in order to obtain PVA estimates, such as temporally interconnected ob-

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Nomenclature

EKF	Extended Kalman Filter
NO	Nonlinear Observer
GNSS	Global Navigation Satellite System
ACC	Accelerometer
GYR	Gyroscope/angular rate sensor
BF	Body frame (b – frame)
NED	North-East-Down referential coordinate frame (n – frame)
ECEF	Earth-Centered-Earth-Fixed coordinate frame (e – frame)
ECI	Earth-Centered-Inertial coordinate frame (i – frame)
PVA	Position, Velocity, and Attitude
LP filter	Low-Pass filter
RMSE	Root Mean Square Error
TMO	Translational Motion Observer
$\boldsymbol{C}_b^n$	Transformation matrix from the BF to NED
$\boldsymbol{f}^b$	Vector of specific force expressed in the BF
$\boldsymbol{\omega}_{ib}^b$	Vector of angular rate between the BF and ECI expressed in the BF
$\boldsymbol{a}^b, \boldsymbol{v}^b$	Vectors of acceleration and velocity expressed in BF,
$\boldsymbol{g}^n$	Vector of gravitational acceleration expressed in NED,
$\boldsymbol{ACF}$	Vector of anti-centrifugal force,
$\boldsymbol{\Theta}$	Vector of Euler angles - (ϕ, θ, ψ),
$\boldsymbol{p}_{GNSS}^n$, $\boldsymbol{v}_{GNSS}^n$	Vectors of position and velocity from GNSS expressed in NED,
$\boldsymbol{b}_g, \boldsymbol{b}_a$	GYR and ACC bias vectors in BF,
$\hat{\boldsymbol{x}}_k$	State vector estimate at a time instance k,
$\boldsymbol{z}$, $\hat{\boldsymbol{z}}_k$	Measurement vector, expected measurement vector formed based on $\hat{\boldsymbol{x}}_k$,
T	Sampling period,
$\Vert \cdot \Vert_2$	Euclidean norm of the vector,
$(\cdot \times)$	Skew-symmetric matrix of the vector.

servers (Bristeau & Petit, 2011), complementary filters (Reinstein & Kubelka, 2012) or Kalman filters (KF) with various architectures (Alam, Moreno, Sipos, & Rohac, 2016; Farrell, 2008; Rezaeian et al., 2013; Simanek, Reinstein, & Kubelka, 2014; Simon, 2010; Zihajehzadeh, Loh, Lee, Hoskinson, & Park, 2015), eXogenous Kalman Filters, nonlinear observers (Johansen & Fossen, 2016), unscented Kalman filters (UKF) (Gustafsson et al., 2002; Ristic, Arulampalam, & Gordon, 2004) and particle filters (PF) (Sotak, Sopata, & Kmec, 2006). Due to the dynamic motion of the majority of the vehicles being highly nonlinear, the most commonly used approaches utilize nonlinear observers and extended Kalman filter (EKF). Much attention is also paid to UKF and PF, but their applicability is limited by high computational loads. In the following sections only EKFs and nonlinear observers are studied for the estimation algorithm and compared, where each approach has its own advantages.

The KFs generally provide estimates as well as the estimated uncertainty of the state vector based on a recursive algorithm (Bar-Shalom, Li, & Kirubarajan, 2004). It is a well-established state estimation approach for a linear or nonlinear state space model which works on the assumption that the inputs are normally-distributed and characterized by their mean and covariance values. The weakest point of the KF (and EKF) is calculation of the inverse covariance matrix of the measurement vector due to round-off errors when implemented into microcontrollers and its high computational cost. There are several methods to solve this problem for instance Modified Cholesky factorization (UD decomposition)

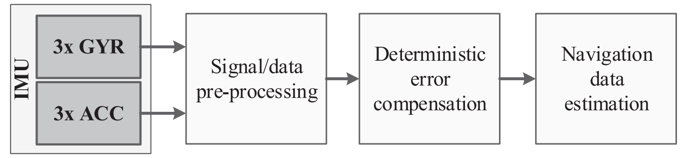

Fig. 1. Block scheme of processes required for position, velocity, and attitude estimation.

or sequential approaches, for more details see (Grewal & Andrews, 2001). Nonlinear observers are based on a deterministic approach, contrary to the stochastic approach of the KF, motivated by the higher computational load of KFs when applied to nonlinear systems. When designing nonlinear observers, the stability properties should be determined explicitly, whereas the optimality of the KF ensures stability in linear systems, while having no stability guarantee for nonlinear systems. In recent years, nonlinear observers have been proposed in various fields, where attitude estimation has had extensive research; for instance, see (Batista, Silvestre, & Oliveira, 2011a; Batista, Silvestre, & Oliveira, 2011b; Crassidis, Markley, & Cheng, 2007; Grip, Fossen, Johansen, & Saberi, 2012; Hamel & Mahony, 2006; Mahony, Hamel, Trumpf, & Lageman, 2009; Salcudean, 1991; Thienel & Sanner, 2003; Vik & Fossen, 2001). A common approach to determine attitude is to compare corresponding vectors in two coordinate frames, e.g. (Salcudean, 1991). These vectors can be based on e.g. gyroscopic data, (Vik & Fossen, 2001), magnetometer or velocity measurements, (Hamel & Mahony, 2006). A modular observer structure consisting of an attitude observer and translational motion observer was proposed in Grip, Fossen, Johansen, and Saberi (2013). Here the advantage is that the observer gains can be fixed or slowly time-varying leading to a decrease in computational load, compared to the KF gain estimation which is carried out at every iteration.

A main contribution of this paper lies in a providing a detailed performance analysis of loosely coupled navigation solutions, where a nonlinear observer and two EKF solutions with different architectures/models incorporated are in focus. For the EKFs two different architectures are presented, one with a 21-state single-stage and the other with a multi-stage configuration. The estimation algorithms are verified on real flight data from a Slingsby T67C aircraft, detailed in Section 4. This paper thoroughly investigates the robustness of the individual estimation approaches with respect to GNSS outages.

The paper is organized as follows: Section 2 outlines the estimation approaches used in the paper to estimate PVA. Section 3 presents a complete description of a sensor assembly and related description for flight experiments. Section 4 presents experimental verification, robust performance analysis and comparison of each estimation techniques with respect to GNSS outages when compared to the referential positioning system using RTK based GNSS positioning. Section 5 concludes the paper with final remarks.

2. Principles and models used

Navigation systems are primarily supposed to provide PVA estimates. The navigation data are typically estimated by a chain of processes schematically shown in Fig. 1.

Signal/data preprocessing can differ according to vehicle dynamics and types of sensors utilized. The sensors might have analog as well as digital outputs. In the case of analog outputs, the preprocessing requires A/D conversion. The LP filter is then used for both high-frequency components reduction and as an anti-aliasing filter. When the outputs are in digital form then a digital LP filter is utilized only. It is very important to choose the cut-