Measurement 42 (2009) 577–582

Contents lists available at ScienceDirect

Measurement

journal homepage: www.elsevier.com/locate/measurement

A consistent and robust Kalman filter design for in-motion alignment of inertial navigation system

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ARTICLE INFO

Article history:
Received 3 August 2008
Received in revised form 8 October 2008
Accepted 10 October 2008
Available online 17 October 2008

Keywords:
Inertial navigation
In-motion alignment
Robust Kalman filter
GPS

ABSTRACT

The necessity recurrently comes up to align a strapdown inertial navigation system (SINS) in a moving vehicle to avoid a long run-up of the inertial system before a start or launch command is issued. This in-motion alignment is therefore achieved by integrating SINS data with some external aiding source such as the Global Positioning System (GPS) by using some form of measurement matching method. Consequently, this paper illustrates a reliable in-motion alignment scheme for a low-cost strapdown inertial measurement unit (SIMU) using a consistent and robust Kalman filter (RKF) structure. An error model of the SINS is derived and the state vector comprises attitude, velocity, position and sensor errors. Velocity information from the GPS with maneuvering is employed as a measurement to the filter. Experimentation results show that the proposed filter is less sensitive to impulsive noise and gives better estimates of the navigation parameters.

1. Introduction

Aligning a strapdown inertial navigation system (SINS) sets up a relationship among coordinates of the body and a local level navigation reference frame. The initial alignment of the SINS is completed prior to the vehicle's motion. On the other hand, this initialization method necessitates some considerable amount of time and the vehicle must be in static condition. For a time, there is not adequate time to bring the vehicle to a standstill at the starting point. Moreover, after the initial alignment, the resulting navigation states errors grow up due to initialization and sensor inaccuracies. Consequently, in large navigation errors because of the poor orientation or the growing sensor error, SINS often needs to be re-aligned by correcting for navigation states [1–3]. Accordingly, it is induced to build up the in-motion orientation scheme.

The navigation states for in-motion orientation can also be acquired by integrating the SINS data with an independent navigation data, such as the Global Positioning System (GPS). Furthermore, in-motion orientation entails putting together the SINS error equations with the sensors' errors. These errors can be developed in the navigation system states via a variety of sources. The calculated states for the initial values will by no means precisely equal the actual navigation states. For that reason, it is significant to comprehend the dynamic behavior of the navigation system errors [4–7].

The Kalman filter is an accepted tool in managing estimation problems [8,9]; however, its optimality critically depends on the linearity. It has set up remarkably expansive range of applications, not only for estimating the state of a dynamic system in the presence of process and observation noise, but also for concurrently estimating model parameters. On the other hand, the Kalman filter goes wrong in the presence of outliers [10]. Even unusual happenings of abnormally large observations severely degrade its performance, resulting in poor state estimates and worthless conclusion. A robust version of the Kalman filter would have to satisfy two objectives: be as nearly optimal as possible when there are no outliers; and be resistant to outliers when they do occur [11,12]. Robustness of the alignment algorithm is a stringent requirement. In order to realize the accuracy,

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doi:10.1016/j.measurement.2008.10.002

Nomenclature

B	noise input matrix	$\bar{w}_{\varepsilon}$	gyros' white noise along x, y and z axes
C_b^n	matrix for transformation between b and n-frame	$\bar{w}_{\nabla}$	accelerometers' white noise along x and y axes
D	diagonal matrix	$\bar{x}$	state vector
G	diagonal matrix	$\bar{z}$	measurement vector
H	measurement sensitivity matrix	c	threshold parameter
I	identity matrix	h	height above mean sea level
K	Kalman gain matrix	J	cost function
P	state covariance matrix	R_{λ}	radius of curvature of the reference ellipsoid in the east–west direction
Q	process noise covariance matrix	R_{φ}	radius of curvature of the reference ellipsoid in the north–south direction
R	measurement noise covariance matrix	ω_{ie}	Earth's rate with respect to i-frame
0	zero matrix	φ	geodetic latitude
$\bar{f}$	specific force vector	κ	significance level of the test
I_n	innovation vector	Φ	state transition matrix
$\bar{r}$	position vector	λ	terrestrial longitude from Greenwich
$\bar{v}$	velocity vector		
$\bar{\vartheta}$	measurement noise vector		

rapidness, and robustness of the in-motion alignment filter design, innovative concept and an efficient technique is brought together to solve the underlying problem.

Systems that rely on high quality sensor data are highly susceptible to observation or measurement that lies outside some overall pattern of distribution [13]. While a data from sensors are effortlessly interpretable in their noise characteristics, other sensors such as visual systems, the GPS devices and sonar sensors are frequently endowed with measurements settled with uncertainties. Accordingly, robust, consistent handling and barring of uncertainties is vital so as to process these kinds of data. Therefore, in this paper, interest lies in making the Kalman filter more consistent and robust to the uncertainties in the observations.

The information such as position, velocity and attitude obtained from the SINS, composed of gyro and accelerometer, is very accurate for short time intervals. However, because of gyro characteristics, the system drifts at a slow rate. All INS information has errors that grow slowly with time, and errors are unbounded. Therefore, those errors must be removed by using external measurement with the long-term accuracy. In this proposed effort, it is presumed that merely initial position is set by the GPS navigation data and initial orientation errors are small. Fig. 1 depicts the conceptual arrangement for the in-motion alignment problem.

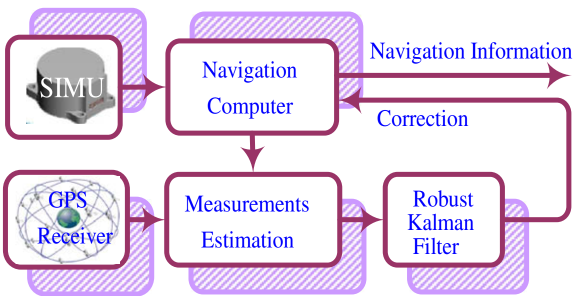

Fig. 1. SINS/GPS loose integration for in-motion alignment.

It is well known reality that the Kalman filter state estimate is optimal when the system and measurement noises are both Gaussian, where optimal means minimum mean-squared error among all linear and non-linear filters. When the measurement noise has a contaminated normal or other heavy-tailed non-normal distribution, the realized values of noise will contain uncertainties and hence so will the observations [14]. Since the Kalman filter is linear, such uncertainties can have an arbitrarily adverse effect on the state estimate. A single uncertainty at time step k_0 can spoil not only the estimate $\hat{x}_{k_0}$ but also many of the subsequent estimates of the state vector.

In the in-motion alignment application, it will be fairly essential to have good robust substitutes available. Consequently, this problem provides motivation for determining how to design robust Kalman filter and the pursuit of this goal is initiated in this paper.

2. Robust Kalman filtering

The key setback of Kalman filter is the divergence caused by the inexact depictions of system equations and its statistic properties, plus the divergence caused by observations. Attempts have been made to robustify the operation of Kalman filtering [11].

The weighted least-squares criterion employed in the Kalman filter derivation is [15]

$$J = (z_k^i - Hx_k)R^{-1}(z_k^i - Hx_k) + (x_k - \bar{x}_k)^T P^{-1}(x_k - \bar{x}_k) \quad (1)$$

The standard derivation of the Kalman filter minimizes Eq. (1) but unluckily does not spell out how the measurement noise covariance is to be found. A familiar option is to employ a constant matrix or even a constant scalar. Making it constant though decreases the Kalman filter estimates to be standard least-squares estimates. It is recognized that least-squares estimation is very vulnerable to outliers or gross errors, i.e., data points that lie far-off from the bulk of the observed data [16]. For instance, in