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GPS/BDS/INS tightly coupled integration accuracy improvement using an improved adaptive interacting multiple model with classified measurement update

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Abstract An Extended Kalman Filter (EKF) is commonly used to fuse raw Global Navigation Satellite System (GNSS) measurements and Inertial Navigation System (INS) derived measurements. However, the Conventional EKF (CEKF) suffers the problem for which the uncertainty of the statistical properties to dynamic and measurement models will degrade the performance. In this research, an Adaptive Interacting Multiple Model (AIMM) filter is developed to enhance performance. The soft-switching property of Interacting Multiple Model (IMM) algorithm allows the adaptation between two levels of process noise, namely lower and upper bounds of the process noise. In particular, the Sage adaptive filtering is applied to adapt the measurement covariance on line. In addition, a classified measurement update strategy is utilized, which updates the pseudorange and Doppler observations sequentially. A field experiment was conducted to validate the proposed algorithm, the pseudorange and Doppler observations from Global Positioning System (GPS) and BeiDou Navigation Satellite System (BDS) were post-processed in differential mode. The results indicate that decimeter-level positioning accuracy is achievable with AIMM for GPS/INS and GPS/BDS/INS configurations, and the position accuracy is improved by 35.8%, 34.3% and 33.9% for north, east and height components, respectively, compared to the CEKF counterpart

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for GPS/BDS/INS. Degraded performance for BDS/INS is obtained due to the lower precision of BDS pseudorange observations.

1. Introduction

During the past two decades, the positioning and navigation technologies have been extensively researched and applied to many applications, such as vehicle navigation, personal positioning, and mobile surveying. The rapid development of the market for Location Based Service (LBS) has made the positioning and navigation technologies more important and attractive.[1] Traditionally, the Global Positioning System (GPS) has been an important tool for navigation in the open sky environment. However, GPS can only provide reliable solutions when the number of the visible satellites is larger than four and the measurement noise is not significant. This can be a major drawback when GPS operates alone.[2]

The satellite based navigation has experienced dramatic changes with the rapid development of multi-Global Navigation Satellite System (GNSS).[3] The fusion of multi-GNSS can bring significant improvement on satellite visibility, accuracy and reliability. In particular, the Chinese BeiDou Navigation Satellite System (BDS), which was established independently in China, has begun to provide positioning service in the Asia-Pacific region in December 2012, and is pacing steadily forward towards its global coverage.[4] BDS based Real Time Kinematic (RTK) positioning,[5] Precise Point Positioning (PPP)[6] and Precise Orbit Determination (POD)[7] have been investigated recently.

When the solution availability and update rate are stringent requirements, the GNSS alone may not provide satisfactory results in constrained environments, such as urban canyons and open pits. For the modern navigation technologies, two or more systems are usually integrated together to improve the navigation performance, among which the Inertial Navigation System (INS) has become one fundamental adding system. The integration of GNSS and INS has been widely deployed due to their complementary characteristics.[8,9] Especially when the low-cost inertial sensors are available in the market, the GNSS/INS integration becomes more attractive due to the fact that it can provide superior performance compared to GNSS or INS standard-alone system.

Conventionally, the Extended Kalman Filter (EKF) algorithm is commonly applied to fuse the outputs from GNSS and INS, namely position and velocity estimates in Loosely Coupled (LC) mode or pseudorange, Doppler and carrier phase observations in Tightly Coupled (TC) mode.[8] However, the EKF requires that the dynamic model noise covariance and measurement model noise covariance are known exactly in a priori.[10] Inaccurate knowledge on the statistical properties to both dynamic noise and measurement noise will result in degraded performance or even cause divergence problem. However, in real environments, using a pre-specific constant noise for such applications is not suitable. Various adaptive Kalman filtering strategies have been proposed to overcome the problem of uncertainty in noise statistics for both dynamic and measurement models. The Innovation-based Adaptive Estimation (IAE) method has been widely used for adjusting covariance matrix on line.[11] In addition, the residual sequences can also be used to adapt the stochastic properties of the filter on line.[12] The adaptive filtering with fading memory algorithm has been developed to improve the estimation accuracy.[13] To improve the robust and adaptive capability of the filter, optimal adaptive factors are derived to improve the filtering results.[14]

Another major adaptive estimation strategy is multiple model adaptive estimation. As a probability switching approach, the Interacting Multiple Model (IMM) algorithm has the structure for dynamically selecting a large set of filters, which actually performs well in many cases. The IMM algorithm has originated from tracking applications,[15] and now been extended to multi-sensor fusion applications.[16,17] Simulation results have proved its good performance. However, real tests were seldom carried out to validate its effectiveness. In this work, an improved Adaptive IMM (AIMM) algorithm is developed and tested with real data.

The remainder of this paper is organized as follows. The tightly coupled integration strategy for GPS/BDS/INS is briefly introduced first. Then the proposed sensor fusion algorithm is provided, and the field test used to evaluate the performance of various integration strategies is described. Finally, conclusions are given.

2. Tightly coupled integration of GPS/BDS and INS

The complementary characteristics of GNSS and INS have made them well-suited to integration. In particular, INS obtains better short-term accuracy; however GNSS can provide navigation solution with long-term stability. In this research, the tightly coupled mode, which is believed to obtain advanced performance compared with loosely coupled mode, will be adopted by using an EKF. The mathematical details of integration system are examined.

2.1. Dynamic system model

The inertial sensors can measure the specific force and angular rates, and strapdown INS mechanization process then transforms the raw inertial outputs into navigation solutions. The navigation equations parameterized in the north-east-down navigation (n-)frame can be written as[18]

$$\dot{\boldsymbol{r}}^{\mathrm{n}} = -\boldsymbol{\Omega}^{\mathrm{n}}_{\mathrm{en}}\boldsymbol{r}^{\mathrm{n}} + \boldsymbol{v}^{\mathrm{n}} \tag{1}$$

$$\dot{\boldsymbol{v}}^{\mathrm{n}} = \boldsymbol{f}^{\mathrm{n}} - (2\boldsymbol{\Omega}^{\mathrm{n}}_{\mathrm{ie}} + \boldsymbol{\Omega}^{\mathrm{n}}_{\mathrm{en}}) + \boldsymbol{g}^{\mathrm{n}} \tag{2}$$

$$\dot{\boldsymbol{C}}^{\mathrm{n}}_{\mathrm{b}} = \boldsymbol{C}^{\mathrm{n}}_{\mathrm{b}}\boldsymbol{\Omega}^{\mathrm{b}}_{\mathrm{ib}} - \boldsymbol{\Omega}^{\mathrm{n}}_{\mathrm{in}}\boldsymbol{C}^{\mathrm{n}}_{\mathrm{b}} \tag{3}$$

where $\boldsymbol{r}^{\mathrm{n}}$ and $\boldsymbol{v}^{\mathrm{n}}$ are position and velocity vector in the n-frame, respectively; $\boldsymbol{f}^{\mathrm{n}}$ and $\boldsymbol{g}^{\mathrm{n}}$ are the specific force and gravity vector in the n-frame, respectively; $\boldsymbol{\Omega}$ represents the skew-symmetric