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Measurement Differencing Approach Based Kalman Filter Applied To INS Error Compensation

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Abstract: The Modified Optimum Discrete Kalman Filter with Inertial Navigation System (INS) error compensation is developed in this study. The proposed filter is designed for the case of correlated system and measurement noise and it is based on the measurement differencing approach. Measurement differences are used in the filter for the solution of the state estimation problem. The proposed measurement differencing approach based Kalman filter is applied to multi-input multi-output model of an aircraft. A conventional and proposed Kalman Filters have been applied for flight dynamics estimation of an aircraft in the case of biased INS measurements. The comparison of the estimates obtained via conventional and proposed filters is fulfilled. This approach can provide autonomous navigation for real-time applications without using a global positioning system.

Keywords: Inertial Navigation; Kalman filters; Difference analysis; Estimation; Error compensation; Aerospace.

1. INTRODUCTION

Inertial navigation uses gyroscopes and accelerometers to maintain an estimate of the position, velocity, attitude, and attitude rates of the vehicle in or on which the Inertial Navigation System (INS) is carried, which could be a spacecraft, missile, aircraft, surface ship, submarine, or land vehicle (Grewal et al., 2001).

After compensation for sensor errors and gravity, the accelerometers outputs are integrated once and twice to obtain velocity and position, respectively. The velocity errors are excited by accelerometer errors (primarily bias and scale factor) and imprecision in knowing local gravity, and the attitude errors are significant due to gyro precession.

Dominant INS errors are caused by imperfect knowledge of initial conditions (for example, those existing after alignment) and by error propagation in time. The nine, nonlinear differential navigation equations – three from the fundamental equation of navigation, three from integrating velocity to get position, and three from the equation for direction cosine matrix rate of change – can be perturbed by a wide variety of error sources, not only those resulting from incorrect initial conditions (Biezad,1999). The actual differential equations for INS operation are nonlinear, but the error equations are valid for linearized versions of these differential equations; hence, the requirement for the errors themselves to remain small, otherwise a linear analysis is not valid.

For many vehicles requiring a navigation capability, there are two basic but conflicting requirements to be considered by the designer, namely those of achieving high accuracy and low cost. Many works (Grewal et al., 2001; Zhukovskiy and Rastorguev, 1998) examine the scope satisfying these demanding requirements by using integrated navigation systems, in which inertial navigation systems are used in conjunction with other navigation aids.

To compensate inertial sensors errors, INS can be aided with information obtained from external sensors. For this purpose integrated navigation systems with INS may be used. In such way aided inertial system, one or more of the inertial navigation system output signals are compared with independent measurements of identical quantities derived from an external source. Corrections to the inertial navigation system are then derived as functions of these measurement differences. By judicious combination of this information, it is possible to achieve more accurate navigation than would be achieved using the inertial system in isolation. Navigation aiding of this type may be provided by baro or/and radar altimeters, Doppler radar, airspeed indicators, GPS, magnetic sensors, star sensors, etc. (Zhukovskiy and Rastorguev, 1998; Hajiyev and Saltoglu, 2004; Hajiyev, 2012; Badshah et al., 2015). Such sensors may be used to provide attitude, velocity or position updates, any of which may be used to improve the performance quality of the inertial navigation system.

The Differential Inertial Filter (DIF) for estimation of the local misalignment angle components is presented in (Carlson et al., 1994). The DIF estimates the in-flight alignment of mission sensors and weapons mounted on modern aircraft with dynamically flexing structures. Sensor/weapon attitude is defined by the instrument frame of a local inertial measurement unit (IMU). Misalignments are defined relative to the instrument frame of the reference INS. Differences between the IMU and INS accelerometer and gyro outputs provide a measure of the IMU/INS angular misalignment. The DIF is a Kalman filter that employs accelerometer and gyro difference measurements to estimate the local misalignment angle components. This approach requires an inertial hardware redundancy.

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Compensation of output errors of inertial sensors can be performed via calibration procedure. Integrated GPS/INS applications effectively perform sensor error model calibration “on the fly” using sensor error models , sensor data redundancy, and a Kalman filter. A Kalman filter algorithm may be used for the integration of different measurement data with inertial measurements. As a result, it may be possible to allow some minor relaxation in pre-flight alignment accuracy and in the precision of the inertial sensors. Such techniques can be extended to achieve a measure of sensor calibration as part of the aiding process. The Kalman filter forms estimates of the errors in position, velocity and attitude, as well as inertial sensor biases, scale-factor errors and misalignments (Wang et al., 2008; Rapoport, et al., 2010; Falco, et al. 2012; Chiang et al., 2013).

In recent years there has been a major upsurge of interest in the integrated INS/celestial navigation system (CNS) as a cost-effective way of providing accurate and reliable navigation aid for civil and military vehicles (ships, aircraft, land vehicles and so on). One of the disadvantages of INS is its errors will grow unbounded. In (Zhao and Guo, 2005 and Badshah et al., 2015) the CNS was used to improve position estimation resulting from INS measurement. An error model developed earlier is used for CNS/INS filter (Kalman filter) mechanization. The tests carry out with this system show that system will get accurate navigation information, but this approach is very expensive duo to the usage of celestial navigation system.

It is apparent from foregoing statements that an INS requires some type of aiding and updating in the long term to remain valid. In many applications for purpose of INS’s error compensation its integration by GPS is preferred. Thus, if the aircraft contains an integrated INS-GPS navigation system, this will generally provide a more accurate reference than a pure INS. However, when GPS signals are suddenly re-acquired after a period of jamming (e.g. if the jammer is destroyed) the transient in the aircraft velocity solution as GPS corrects the inertial drift can disrupt the transfer alignment process. Furthermore, a low cost INS may not sustain prolonged GPS signal losses which frequently occur in indoors, foliages, urban environments etc. The upcoming applications such as Location Based Services (LBS) require positioning systems to work in all these environments and this stimulates the interests in developing alternative INS’s error compensation methods.

In this study the Modified Optimum Discrete Kalman Filter with INS’s error compensation schema is developed to solve this problem. The proposed filter is designed for the case of correlated system and measurement noise and it is based on the measurement differencing approach, where measurement differences are used in the filter for the solution of the state estimation problem. The proposed method does not require any hardware redundancy and enables to solve the INS’s error compensation problem using sensor error models, and a Kalman filter based on the measurement differencing approach. This method is very important for autonomous navigation in real-time applications without using a global positioning system.

2. PROBLEM STATEMENT

The model of system is as follows

$$x(k) = Ax(k-1) + Bu(k-1) + Gw(k-1) \tag{1}$$

$$z(k) = Hx(k) + v(k) + \lambda(k) \tag{2}$$

where $x(k)$ is an N-dimensional vector of system state; A is the $N\times N$ transition matrix of the system; B is the $N\times p$ control distribution matrix; $u(k)$ is the p-dimensional deterministic control input vector; $w(k)$ is a random N-dimensional vector of disturbances; G is the $N\times N$ transition matrix of disturbances (of system noise); $z(k)$ is the n-dimensional vector of measurements; H is the $n\times N$ matrix of measurements of the system; and $v(k)$ is a random n-dimensional vector of measurement noise, $\lambda(k)$ is an n-dimensional random INS errors process.

Assume that random vectors $w(k)$ and $v(k)$ are a Gaussian white noise. Their mean values and covariance are determined by the expressions

$$\begin{aligned} &E\left[w(k)\right] = 0; E\left[v(k)\right] = 0; \\ &E\left[w(k)w^T(j)\right] = Q_w(k)\delta(kj); \\ &E\left[v(k)v^T(j)\right] = Q_v(k)\delta(kj). \end{aligned} \tag{3}$$

Here E is the operator of statistical averaging; T is the sign of transposition; and $\delta(kj)$ is the Kronecker delta symbol. Note that $\{w(k)\}$ and $\{v(k)\}$ are assumed mutually uncorrelated.

To simulate the INS errors the $\lambda(k)$ is assumed by (Brown and Hwang, 1997)

$$\lambda(k) = A_n\lambda(k-1) + B_nU(k-1) . \tag{4}$$

Here A_n and B_n are the matrices of appropriate dimensions, $U(k-1)$ is the independent Gaussian random vector sequence with zero mean and covariance Q_U :

$$\begin{aligned} &E\left[U(k)\right] = 0; \\ &E\left[U(k)U^T(j)\right] = Q_U(k)\delta(kj) \end{aligned} \tag{5}$$

Equations (1), (2) and (4) do not yet compose a suitable form of linear optimum Kalman filter for state estimation. It is required to modify the optimum discrete Kalman filter to solve this problem.

3. MEASUREMENT DIFFERENCING APPROACH BASED KALMAN FILTER DESIGN

In order to make the system suitable to formulate the linear optimal Kalman filter, the measurement differencing approach (Rao, 1998) is used for INS error compensation purpose. As a result, a linear combination of measurements $z(k+1)$, and $z(k)$ which does not contain $\lambda(k)$ is obtained. The proper linear combination is taken in the following form: