Michal REINSTEIN

Czech Technical University in Prague

Evaluation of Fine Alignment Algorithm for inertial navigation

***Abstract**. This paper describes results obtained during evaluation of a fine alignment algorithm for inertial navigation. The fine alignment algorithm is based on a full-state error model for extended Kalman filter and its purpose is to estimate random errors in accelerometers and angular rate sensors signals to improve the precision of determination of initial attitude angles. Precise determination of initial attitude is important in inertial navigation, since it is one of the most crucial sources of error during inertial data integration, which is performed to obtain velocity and position information.*

***Streszczenie.** Opisano zastosowanie algorytmu dokładnego wyrównania (fine alignement) do nawigacji inercyjnej. Algorytm ten wykorzystuje filtr Kalmana i jego celem jest wyznaczenie błędu przypadkowego przyśpieszeniomierza oraz zmianę kąta w celu precyzyjnego wyznaczenia kątów i początkowej wysokości. (**Ocena możliwości zastosowania metody dokładnego wyrównania w nawigacji inercyjnej**)*

Keywords: extended Kalman filter, inertial navigation, initial alignment.
Słowa kluczowe: filtr Kalmana, nawigacja inercyjna.

Introduction

The traditional concept of inertial navigation usually exploits an Inertial Measuring Unit (IMU), which consists of three accelerometers to measure translational acceleration (can further be integrated to obtain velocity and position), and three angular rate sensors to measure rotational motion in order to get attitude information [1]. It was well proven in [2], [3] that this concept has to be enhanced by both advanced signal processing methods for sensor errors compensation [4], [5], as well as by additional sensors to provide aiding to the navigation system [6], [7]. Inertial navigation in general finds use in many fields of research, but mainly it concerns new sensor concepts [8] and algorithms for autonomous navigation in automotive [9], [10], submarine and airborne applications [11].

Results and conclusions presented in this paper are direct continuation of the research published already in [12], and [13], which concerned inertial sensor errors and advanced signal processing methods. Furthermore, this paper aims to extend the concept of the coarse alignment algorithm derived in [14]. The algorithm presented in [14] was designed to compute initial attitude angles using inertial sensors and magnetometer measurements from the ADIS16405 unit. The fine alignment algorithm introduced in this paper exploits the extended Kalman filter (EKF) [15] to further refine the raw attitude results computed by this coarse alignment algorithm. Hence, the major aim of this paper is to show the relevance in combining both alignment algorithms to obtain more reliable inertial navigation.

Evaluation of the proposed fine alignment algorithm was performed using MicroStrain 3DM-GX2 inertial measurement unit (for details see Fig. 1), which provided raw inertial and magnetometer data.

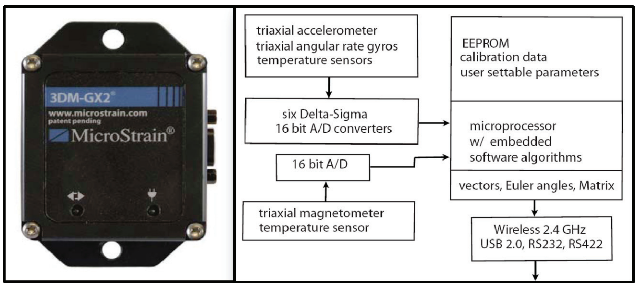


Fig.1.MicroStrain 3DM-GX2 inertial measurement unit.

The strapdown mechanization algorithm (already published in [13]) was used to compute the position, velocity and attitude vectors in real-time during a series of dynamic motion field-tests. The unit was evaluated as stand-alone, i.e. without any external reference such as GPS, therefore the drift in the integrated velocity and position was expected to manifest. In final, all the expectations were confirmed and the errors due to ill-estimated initial angles were clearly minimized due to the fine alignment algorithm.

Fine Alignment Algorithm

Initial alignment algorithm for inertial navigation is a mathematical procedure for determining the initial attitude information between the body frame and the navigation frame [1], [6] of the navigated object. There exist various algorithms for initial alignment, each suitable under different circumstances. According to [3], these algorithms can be divided into:

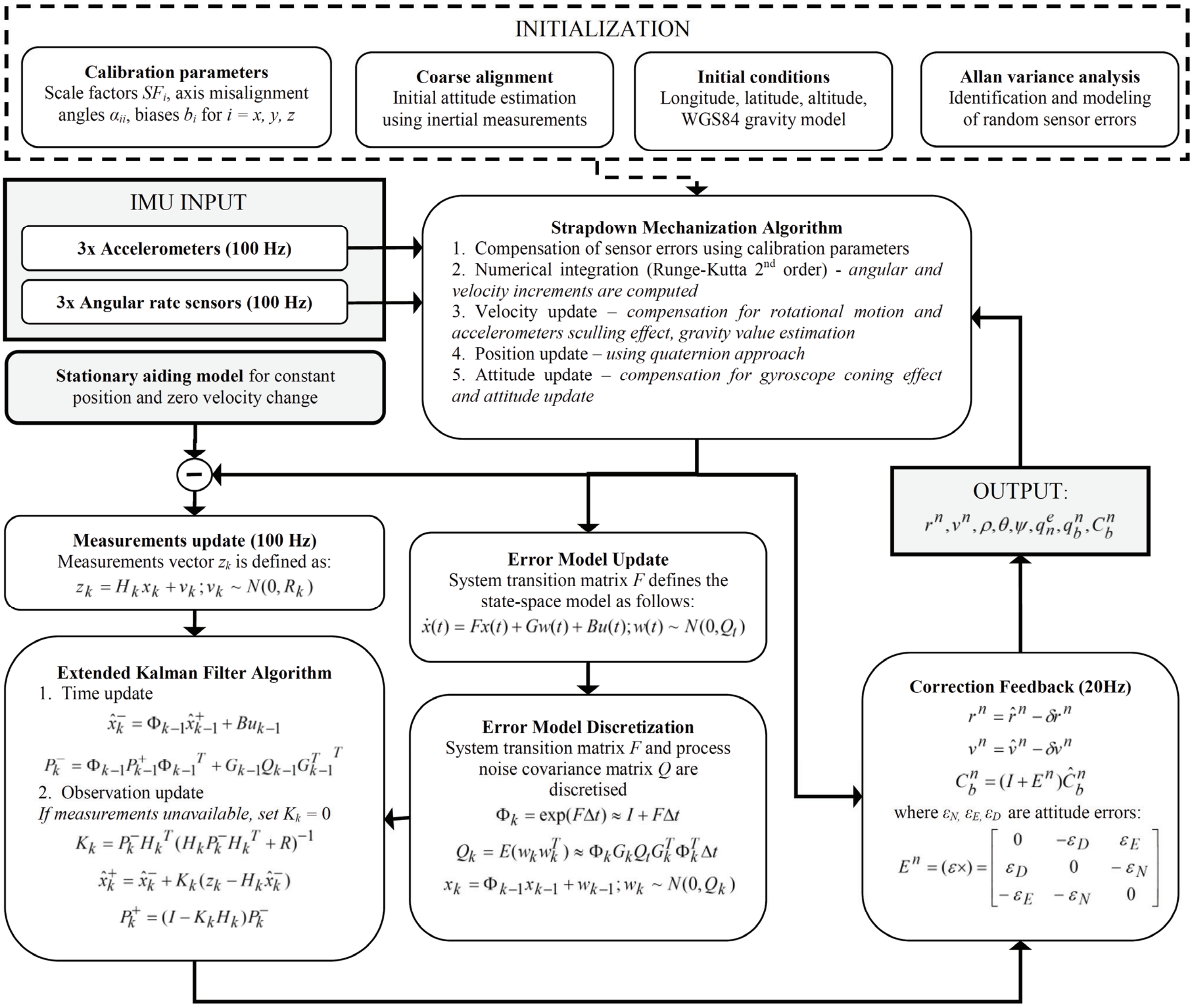
1. coarse / fine alignment - according to the amount of attitude error that has to be dealt with,
2. static / in-motion alignment - according to the dynamics of the navigated object during the procedure.

The coarse alignment, which requires static inertial data, can be implemented in two ways as:

1. combination of leveling to obtain pitch and roll angles, and gyro compassing for heading determination (usually using magnetometer) [14],
2. analytic coarse alignment, which exploits the property of orthogonality between acceleration and angular rate signals [2, pp. 68].

However, the analytic approach can only be used with precise gyroscopes that are able to sense the speed of rotation of the Earth, which is usually below the noise level in low-cost angular rate sensors.

The fine alignment uses the EKF to refine the attitude angles determined initially using coarse alignment [2, p. 72]. The EKF estimates the random sensor errors, which are then utilized to provide a correction feedback. This approach was implemented in the form of a complementary filter as explained in [13, p. 244] and is thoroughly described in Fig. 2. If there is a GPS signal to the disposal, the alignment can be implemented as in-motion by means of velocity matching. In such case, the EKF with large heading uncertainty model is used together with lever arm compensation for the GPS antenna placement. However, since standalone IMU with magnetometer was evaluated, static fine alignment was implemented instead. For this reason, the complementary filter scheme was enhanced by a stationary aiding model (implemented as non-holonomic constraints [16]) to provide constant position and zero velocity signals during the stationary initialization phase.



F, Φ – The system transition matrix continuous time and discrete
G – The process noise coupling matrix
H – The measurement sensitivity matrix
B – The control matrix
Q – The covariance matrix of process noise
R – The covariance matrix of measurement noise
x – The system state vector (15 states: errors in position, velocity, attitude, errors of accelerometers and angular rate sensors)
z – The measurement vector
k – The discrete time-step
ρ, θ, ψ - Roll, pitch and yaw angles

q_b^n, C_b^n - Quaternion and corresponding Direction Cosine Matrix (DCM) for transformation from body frame (BF) to navigation (NED) frame
q_n^e, C_n^e - Quaternion and corresponding DCM for transformation from navigation (NED) frame to Earth-centered Earth-fixed (ECEF) frame
$r^n = [\varphi \quad \lambda \quad h]^T$ – The position vector [latitude, longitude, altitude]
$v^n = [V_N \quad V_E \quad V_D]^T$ – The velocity vector due to North, East, Down
$\hat{r}^n$ $\hat{v}^n$ $\hat{C}_b^n$ - Navigation variables computed by mechanization
δr^n δv^n E^n - Errors estimated by the EKF as the part of state vector

Fig.2. Data fusion scheme for fine alignment algorithm based on EKF and stationary inertial data.

The scheme in Fig. 2 shows the real-time implementation of the developed fine alignment algorithm. At first, the algorithm is initialized with coarse alignment procedure to compute raw attitude angles as described in [14]. Furthermore, during the initialization phase the initial position, calibration parameters for the inertial sensors, and parameters for random sensor errors modeling (determined using Allan variance analysis as described in [12], [17], [18]) are supplied. After the initialization ends, raw inertial data enter the strapdown mechanization algorithm, which proceeds with all the integrations and transformations necessary to provide position, velocity and attitude vectors in the navigation frame (quaternion approach was exploited for attitude representation). At each time-step, the error model, which is described well in detail in [2, pp. 35-41], [19, pp.24-30], is updated and the measurements vector is formed using the stationary aiding model. This is done in such a way, that the differences in position and velocity between the stationary aiding model and the strapdown mechanization outputs can enter the EKF algorithm as measurements. Then the error model is discretized and the EKF proceeds at 100 Hz with estimation of the state vector. The state vector contains the estimated errors, which are used to provide feedback to the strapdown mechanization to correct the position, velocity and attitude vectors.

Results and Evaluation

For the purpose of experimental evaluation of the proposed fine alignment algorithm, conventional pendulum experiment was performed. The 3DM-GX2 MicroStrain was mounted at the end of a hand-held pendulum to capture the motion dynamics in 3D. The aim was to generate such motion, which could easily be identified on the velocity / position / attitude graphs and distinguished from the influence of drift and error integration. Zero position change during the stationary phase and periodic position change during the motion were expected for the ideal case. However, precise position estimation without additional external aiding (such as GPS) was not reachable. On the other hand, precise attitude determination was expected; especially the roll angle was meant to capture the close-to-sinusoidal motion dynamics.

The pendulum experiment was repeated several times. Selected set of results is presented in the following figures: Fig. 3 and Fig. 4 show the estimated random errors of the inertial sensors. The most significant error was detected in the vertical channel, i.e. the z-axis accelerometer. Correction of this channel proved to be the most beneficial; the corrections of angular rate sensors were the least influential, but still necessary.

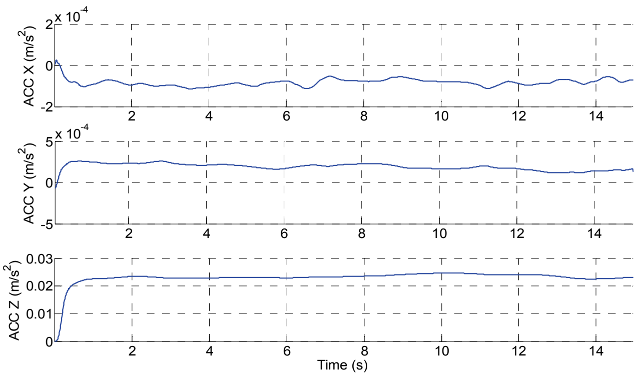


Fig.3. Accelerometers random errors estimated by the EKF.

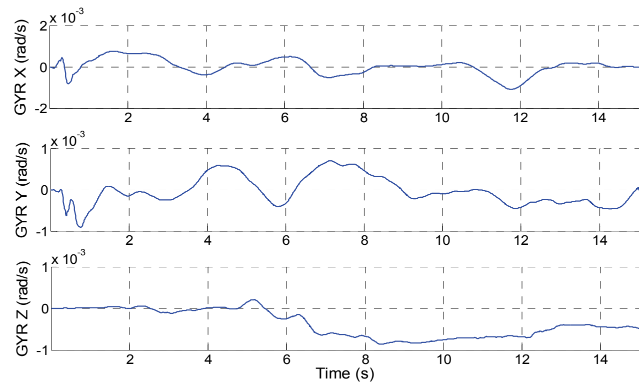


Fig.4. Angular rate sensors random errors estimated by the EKF.

Fig. 5 and Fig 6 present results for the case, where the fine alignment algorithm was not applied; initial attitude was estimated using only the coarse alignment algorithm. The deterioration in precision of velocity and position estimates is due to the integration of drift and mostly gravitational acceleration, which is introduced into each measurement axis due to errors in initial attitude values. For comparison, Fig. 7 and Fig. 8 show results regarding the same data as for Fig. 5 and Fig. 6, but with fine alignment algorithm applied. Clearly the errors are compensated to some extent and both position and velocity dynamics are captured correctly at least for some time (highlighted in Fig. 7. and Fig. 8.).

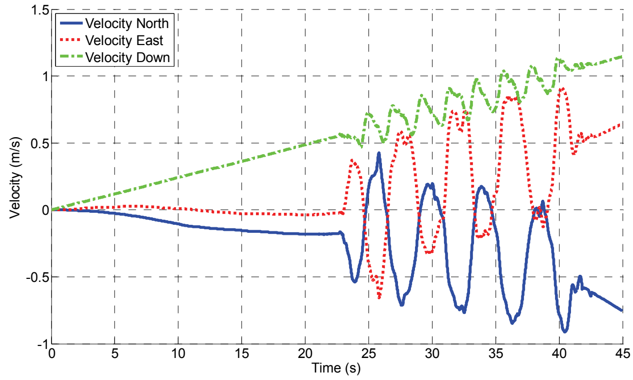


Fig.5. Velocity signals computed without the fine alignment.

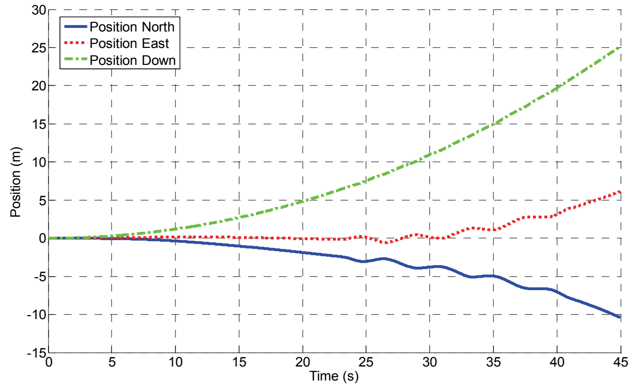


Fig.6. Position signals computed without the fine alignment.

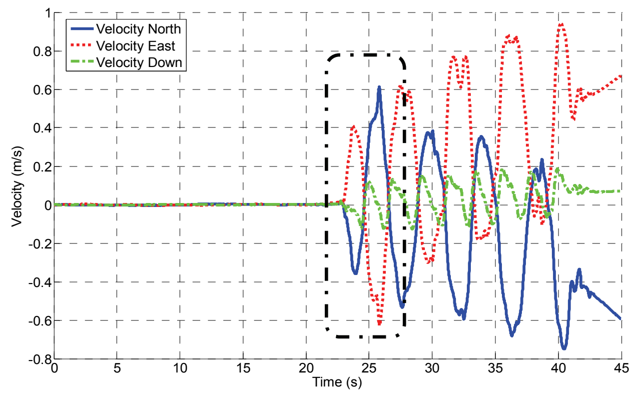


Fig.7. Velocity signals computed with the fine alignment algorithm.

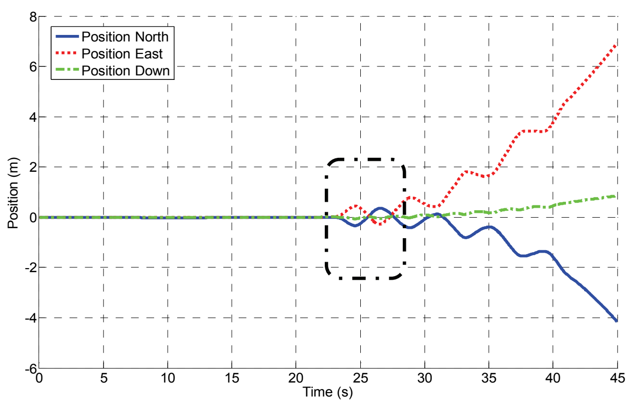


Fig.8. Position signals computed with the fine alignment algorithm.

However, the position and velocity estimates are still subjected to errors due to integration since no aiding is applied and the correction feedback is terminated when the fine alignment algorithm stops as the motion starts. Nevertheless, as shown in Fig. 9, the attitude signals capture the dynamics as desired; it is visible especially in the roll angle signal.

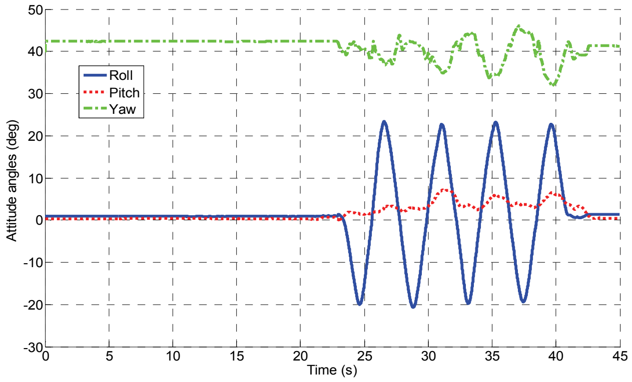


Fig.9. Attitude angles computed with application of the fine alignment algorithm to correct the random sensor errors.

Conclusions

This paper comments on the importance of application of the fine alignment algorithm for inertial navigation. In [14] the coarse alignment was presented and hence the main aim was to extend this concept and show, how it can be further improved regarding not only attitude determination but also the influence on velocity and position estimation.

The real-time implementation of the fine alignment algorithm is presented together with results from pendulum experiments. The results confirm the importance of fine alignment, especially for low-cost inertial sensors, since badly determined initial attitude angles are one of the major sources of error in inertial navigation.

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***Authors**: Ing. Michal Reinštein, E-mail: reinsmic@fel.cvut.cz, Czech Technical University in Prague, Faculty of Electrical Engineering, Technická 2, 166 27 Prague, Czech Republic.*