Development of Methods and Algorithms for Improving Accuracy of Integrated INS/GPS Systems for Vehicles

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Abstract

Background: This article reviews the integration of INS with a differential global positioning system using a specific mathematical tool for simultaneous processing of both system measurements and namely the Kalman filtering. The article also includes the algorithms for increasing INS accuracy. Method: The first part of the article describes the mathematical positioning methods using the inertial sensors and the odometer. The second part is devoted to the description of methods and algorithms intended to eliminate errors in the INS mathematical programming software. The third part provides a mathematical model for positioning an object by means of an integrated inertial satellite system. The fourth part lists the experimental results and the conclusions based on the results of this experiment. Findings: The authors of this article made the main research contribution by carrying out experiments and processing relevant data when studying the integration of the inertial navigation and the global positioning systems. Applications/Improvements: The article reports on the results of the described experiments with several significant conclusions concerning the studied direction of the inertial navigation and global positioning systems theory.

Keywords: Accelerometer, Complementary Filter, Exponential Filter, Global Positioning, Gyroscope, Inclinometer, Inertial Navigation, Inertial Sensors, Kalman Filter, Odometer, Orientation

1. Introduction

GPS data is the main source of the navigation information for autonomous vehicles since it provides a moving vehicle with a sufficiently accurate real-time georeferencing technology without time-dependent degradation of its accuracy.

GPS is a system designed to determine the exact location of an object on the Earth at any place, at any time and under any weather conditions, which is based on a constellation of 24 satellites. It is an accurate and specific method for positioning a vehicle. To accurately determine the actual position \((x, y, z)\) of an object in three-dimensional space \((3D)\) with an error of less than 20 meters, the GPS-receiver requires signals from at least 4 satellites. In addition, the mode of the so-called differential correction \((DGPS - Differential GPS)\) allows for the error reduction to 2 and less centimetres using at least 5 satellites. However, the automobile navigation system with GPS has one major drawback: The presence of obstructions (trees, tunnels, buildings) can cause signal blocking for an indefinite period of time, which leads to the loss of information and vehicle operation failure. The optimal solution is to integrate the GPS data with the inertial system.

The Inertial Navigation Systems (INS) predated the Global Positioning Systems (GPS) and they are widely used in the navigation of ships and aircraft, geodesy, space and rocket technology. The INS serves to position vehicles by measuring linear acceleration and angular velocity exerted on the system in the inertial reference system using the Inertial Measurement Units (IMU).
is a measurement system consisting of angular velocity sensors and accelerometers. Using the IMU data and anodometer it is possible to determine the actual location of a vehicle if its initial position is known, wherein the accuracy of navigation does not depend on the external signals. Although INS is able to calculate the location of moving objects without any additional navigation data received from other devices, it is prone to the random errors accumulated over time that result in a considerable deviation of the final result when positioning the object. Therefore, the best practice is to improve navigation results by integrating INS with another navigation system.

The integrated inertial navigation and Global Positioning Systems (INS/GPS) are the most promising class of all currently existing navigation systems that allow the combination of the advantages and the compensation for the shortcomings inherent in the INS and the GPS if taken separately. The advantages of the INS/GPS as compared to the conventional GPS are the signal continuity (successful operation in the absence of GPS signals), the possibility of calculating the angular orientation of an object and the high frequency of the navigation data reception. The integrated systems provide for the use of a low-cost, lightweight and space-saving INS constructed on the basis of Microelectromechanical (MEMS) sensors. A stand-alone use of such INS is complicated due to the instability of system performance in MEMS gyroscopes and accelerometers that lead to a rapid accumulation of errors when determining the navigation data.

1.1 Objectives and Problem Statement
The objective of this study is to develop mathematical programming software for the INS/GPS vehicle positioning and to compare the test results under different conditions, as well as to test different methods and algorithms for the improvement of the INS/GPS system accuracy.

2. Positioning by Means of INS and Odometry

The Inertial Navigation Systems (INS) serve to position vehicles by measuring linear acceleration and angular velocity exerted on the system within the inertial reference system by means of the inertial Measurement Units (IMU). (The principle of inertial navigation is to measure the object motions characterized by changes in the time of its acceleration, velocity and coordinates by using the spatial displacement sensors). The IMU is a measurement system consisting of angular velocity sensors and accelerometers. Using the IMU data and odometer it is possible to determine the actual location of a vehicle if its initial position (condition) is known, wherein the accuracy of navigation does not depend on the external signals. On the other hand, the dependence on proper initialization can induce an unlimited growth of errors in vehicle positioning. In addition, the inertial systems are associated with dead reckoning systems. This means that their accuracy degrades with time.

Many studies were devoted to the inertial navigation consisting of an accelerometer and gyroscopes. Therefore, since this article is devoted to the integration of INS with GPS, it is advisable not to be distracted from the topic and to distinguish only the key insights. An odometer - a set of built-in sensors on the car wheels - is used to improve accuracy.

2.1 Odometry

Odometry, which is a set of built-in sensors on the car wheels, is used to improve accuracy.

In particular, the wheel speed data is used to find the distance \( d_a \) using the following formula: 1.

\[
d_a = o\text{Speed} \cdot \Delta t
\]

where the \( o\text{Speed} \) value is obtained directly from the wheel tyre in m/s, \( \Delta t \) is the time between two consecutive measurements; dimension of \( d_a \) — meters. The same value will be used to create the Kalman Filter for mutual correction of the GPS and INS data.

3. INS Errors

If we consider an autonomous operation of the INS consisting of only one accelerometer and one gyroscope, then the error in navigation inclusive of all possible sources of sensor faults can be estimated using the following expression:

\[
p(t) \approx p_0 + v_0 \Delta t + b_a \frac{\Delta t^2}{2} + b_g \frac{\Delta t^2}{6} + \alpha_g \frac{\Delta t^2}{2} + A_z \cdot \Delta t + V \Delta t + SF_s \cdot f \frac{\Delta t^2}{2} + SF_s \cdot A_z V \Delta t,
\]

where

\[
p_0 \text{ is a positioning error at the initial time } t_0;\]
\[
v_0 \text{ is a velocity error at the time } t_0;\]
$\Delta t$ is a time interval from the start of data acquisition; 

$b_a$ is an accelerometer bias error at the time $t_g$; 

$\alpha_g$ is an error in the misalignment of INS axis at the bank and attitude angles with the axis of a local coordinate system; 

$A \cdot V \Delta t$ is an INS misalignment error according to the azimuth angle from the local coordinate system multiplied by the distance travelled; 

$SF_a$ is a scale factor for the accelerometer; 

$SF_g$ is a scale factor for the gyroscope; 

$f$ is the apparent acceleration; 

$g$ is the gravitational acceleration.

From (1) it can be seen how the error of object positioning using the INS increases proportionally to the square of time due to the accelerometer parameters (the bias ($b$) and the Scale Factor ($SF$)) and to the cube of time due to the gyroscope bias. The following formula can be chosen as a model for the MEMS sensor signals:

$$I_{w,a}(t) = x(t) + b_{w,a} + SF_{w,a} x(t) + N_{w,a} x(t) + \varepsilon_{w,a}(t),$$

Where:

$x(t)$ is the actuating quantity vector: either of the angular velocity $\omega(t)$ or of the acceleration $a(t)$; 

$I_{w,a}(t)$ are the sensor signals ($\omega(t)$ or $a(t)$); $b_{w,a}$ is the bias; 

$SF_{w,a}$ are the matrices of scale factors, 

$N_{w,a}$ is a matrix of the sensors cross-axis sensitivity with respect to the axis $X$; 

$\varepsilon_{w,a}(t)$ are the transducer noises.  

### 3.1 SPM Calibration of Sensors

Information in the inertial navigation systems is formed on the basis of sensor readings. The readings of these sensors contain errors that will eventually lead to the accumulation of errors in positioning and determining of velocities and angles of the object orientation. Thus, one way to improve the accuracy of navigation is to evaluate the instrumental errors and to introduce the relevant amendments to the sensor readings. The determination of these errors is called calibration.

The following methods of laboratory calibration have been recently proliferated: A Six-Position Method (SPM), a Modified Six-Position Method (MSPM), a Multi-Position Method (MPM) and a Modified Multi-Position Method (MMPM). The study focuses on the SPM and MMPM methods.

The SPM method allows the assessment of bias ($b$) and Scale Factors ($SF$) of sensors by using simple ratios given in to carry out measurements in six positions.

Accelerometers are typically calibrated by measuring the gravity. The accelerometer is fixed on a swivel rotary table for calibration and the sensitive axis is aligned vertically upwards. The information is collected for 10–15 minutes and the $f_{\text{up}}$ value is counted by averaging the data obtained. Then, the same is done by aligning the sensitive axis vertically downwards and the data obtained is averaged to find the $f_{\text{down}}$ value.

Figure 1 shows that the $f_{\text{up}}$ and $f_{\text{down}}$ values can be represented as follows:

$$f_{\text{up}} = b_a + (1 + SF_a) g$$

$$f_{\text{down}} = b_a - (1 + SF_a) g$$

The accelerometer bias $b_a$ is calculated by adding these two equations:

$$b_a = \frac{f_{\text{up}} + f_{\text{down}}}{2};$$

Besides, the scale factor $SF_a$ will equal to,

$$SF_a = 1 - \frac{f_{\text{up}} - f_{\text{down}}}{2g}.\quad (5)$$

Figure 1. The calibration of an accelerometer with a sensitive OZ axis aligned upwards and downwards.

The considered method for finding the accelerometer bias is not particular about the initial orientation of the sensitivity axis (the same cannot be said for the calculation of the scale factor), which greatly simplifies its implementation. The described sequence of actions shall be carried out for each of the accelerometer’s sensitive axes.

The drift and the scale factor of a gyroscope can be determined in a similar manner. The angular velocity of
the Earth’s rotation is a sufficiently weak signal and can be used only to calibrate the high-precision and expensive INS systems, in which the noise level of an angular velocity sensor is below the reference signal value. To calibrate the INS gyroscopes of medium and low accuracy classes, which include the MEMS-based INS systems, it is required to use an auxiliary pivot mechanism that can provide a stable reference rotation rate⁴⁻⁶.

3.2 Complementary Filter

As noted above, the MEMS gyroscope has one insidious drawback called zero drift. The essence of this drawback is in that the gyroscope will still show a nonzero value even after the stop of its rotation. One more drawback of this solution is the use of discrete integration, which inherently provides for an inaccurate result. The third problem is expressed in the gradual accumulation of calculation errors because of the limited accuracy of the microcontroller variables.

At rest, the accelerometer can also be used to determine the orientation angles of bank and attitude. To find the inclination angles with the accelerometer, it is enough to apply simple geometric transformations to its readings. As long as it is not exposed to the external forces, the device will present the value of the gravitational acceleration projection on the observed axis. In Figure 2 the accelerometer readings for axis \( x \) are marked as \( A_x \). If \( g \) and \( A_x \) are known, it is possible to calculate the angle of accelerometer deviation from the horizontal position—\( \alpha \):

\[
\sin(\alpha) = \frac{A_x}{g}, \\
\alpha = \arcsin\left(\frac{A_x}{g}\right).
\]  

(6)

Figure 2. The gravitational acceleration projections to the axis \( x \) and \( y \).

In making these calculations, it is important to bear in mind that \( X \) and \( G \) should be measured in the same units. For example, if the accelerometer readings are converted into the units of gravity, in other words \( g = 1 \) Earth’s gravity, then the expression for the \( \alpha \) angle takes the following form:

\[
\alpha = \arcsin(A_x).
\]  

(7)

Thus, based on only one accelerometer is it also possible to build an inclinometer in a quite simple way. Unfortunately, the exposure to any external force introduces an error into these calculations. This external force may be, for example, the vibration from the UAV engines or a sudden wind gust. This effect can be partially removed by means of a low-Pass Filter (LPF). However, such signal processing has a side effect, which is a strong decrease in the speed of inclinometer response.

As a result, there are two devices, each of which allows the calculation of inclination angles relative to the Earth surface. However, in the case of the gyroscope, the accuracy of such calculations is reduced due to the zero drift and the integration errors. In the case of the accelerometer, the sensitivity to external exposures is too high.

It is possible to combine the readings of these two devices by using a complementary filter, the operation of which is determined by a fairly simple equation:

\[
\alpha = (1-K)\alpha_{gyr} + K\alpha_{acc},
\]  

(8)

Where,

- \( \alpha \) is a filtered, resulting angle of inclination;
- \( \alpha_{gyr} \) and \( \alpha_{acc} \) are the values of inclination angle obtained by means of the gyroscope and the accelerometer;
- \( K \) is a complementary filter factor.

As can be seen, the final value of the inclination angle is the sum of the integrated gyroscope value and the instantaneous accelerometer value. In fact, the main task of the complementary filter is to level the gyroscope zero drift and the errors of discrete integration. This is what the above expression exactly performs. At each step of the integration, the inclination angle integral is adjusted by using the accelerometer readings. The strength of this correction is determined by the filter factor \( K \).

The choice of the \( K \) factor depends on the gyroscope zero drift value, on the rate of computation error accumulation and on the computer use environment.
Thus, a too high $K$ value results in that on the vibration of the vehicle body will impose a strong impact on the operational result of the filter. At the same time, a too low $K$ value may be insufficient to eliminate the gyroscope zero drift. Typically, the complementary filter factor is selected manually for each inclinometer based on the above conditions. For example, in amateur multi-copters the $K$ value can range from 0.05 to 0.01.

Figures 2 and 3 present the gradual adjustment of the angle integral by using the readings of one accelerometer axis of the actual inertial system.

The use of complementary filter does not require a large processing power of a machine controller and provides for a sufficiently high stabilization quality of flight or balancing.

![Figure 3. The angles of rotation around the axis OX obtained by the gyroscope (top) and the accelerometer (bottom).](image)

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![Figure 4. The result of using the complementary filter with the 0.03 parameter.](image)

Figure 4. The result of using the complementary filter with the 0.03 parameter.

### 3.3 Exponential Smoothing of Noises

The MEMS accelerometer readings are subject to a sufficiently strong noise, which urgently necessitates the smoothing of noises. One way to deal with the noisy data is to use a filter. The positioning task of the device imposes one important requirement to the filter, which is the requirement of maintaining the performance sufficient to use the filter in real-time and with minimal latency. Of course, a great advantage of the filter is the proximity of values to the initial ones.

The exponential filter is one of the simplest and most common recursive algorithms, which is widely used for the analysis of time series, especially for their forecasting. The exponential filter’s output parameter is a weighted sum of the filter’s output parameter in the previous instant of time and the current value of the input parameter taken with certain weight coefficients. The main advantage of the forecasted model based on the exponential smoothing is that it is able to adapt sequentially to the new level of a process without a significant response to the random deviations.

The exponential smoothing can be represented as a data filter, the input of which successively receives the outgoing series members and at the output the exponential average values are formed.

The data from the inertial sensor can be represented in the form of a time series:

$$A = (a_1, \ldots, a_t),$$

The exponential smoothing can be written as follows:

$$a'_i = (1-\gamma)a'_{i-1} + \gamma a_i$$  \hspace{1cm} (9)

where

- $a'_i$ is the acceleration (angular velocity) after processing the current point in time;
- $a'_{i-1}$ is the acceleration (angular velocity) after processing the previous point in time;
- $a_i$ is the initial acceleration (angular velocity);
- $\gamma$ is a filter parameter which is selected experimentally.

Figure 5 shows a flowchart of the data-filtering algorithm using the exponential smoothing developed on a basis of the mathematical model shown in the Equation (9).

In practical use of the exponential smoothing method, two problems arise: Selecting the smoothing coefficient $\gamma$, which largely influences the results and determining the initial $a_i$ value. On the one hand, to smooth the random deviations, the $\gamma$ value should be reduced. On the other hand, to increase the weight of new measurements, it should be increased.
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Figure 5. The data-filtering algorithm using exponential smoothing.

The exponential average \( a'_i \) has the same mathematical expectation as the original series, but smaller dispersion. At a high \( \gamma \) value, the dispersion of the exponential average is slightly different from the \( a \) series dispersion. The smaller \( \gamma \) is, the greater the dispersion of the exponential average is reduced (i.e. the fluctuations in the original series are suppressed). In other words, the smaller the value of the filter coefficient we choose, the more noise is suppressed, but the stronger the sensitivity of the accelerometer is reduced.\(^6\)

Figures 6 a) and b) present the work log of a real inertial system with an accelerometer, which noises are smoothed based on the exponential filter. This illustration makes it possible to easily compare the noise level of the accelerometer signal before and after exposure with the coefficients \( \gamma = 0.1 \) and \( \gamma = 0.5 \).\(^6,8\)

(a)

(b)

Figure 6. The accelerometer signals before and after exponential smoothing:

4. Integrated Inertial Navigation and Global Positioning System

This part of the article is dedicated to the Kalman filtering. However, the synchronization problem should be solved first, since the frequency of signals receipt from different sensors differs. For example, for the sensors of a Cybus intelligent vehicle manufactured by INRIA (Paris, France): the GPS frequency of 5 Hz, the wheel sensors (odometer) provide data every 25 ms and the IMU frequency is above 100 Hz. The high accuracy of the GPS frequencies enables its use as a chronometric control system. The GPS frequency will be used to perform position calculations and the Fourier filter - to determine the angular velocity. The Fourier filter provides for a smooth value in measuring angular velocity and reduces the drift error.\(^2\)

When calculating the vehicle position with the help of the inertial sensor data, it is impossible to take into account the small perturbations that act on it. Therefore, the calculated velocity will not be accurate and has a certain error. Consequently, the vehicle motion equation can be written as follows:

\[
x_{k+1} = x_k + v_k \cdot \Delta t + \xi_k
\]

(10)

where \( x_k \) is a real vehicle coordinate, \( v_k \) is the vehicle velocity calculated according to the inertial sensors, and \( \xi_k \) is a random value (a sensor error).
A car-mounted GPS sensor measures the vehicle coordinate with an error $\eta$, that also has a random value. As a result, the sensor provides erroneous data:

$$Z_k = x_k + \eta_k \quad (11)$$

Then, the best approximation to the true coordinate is as follows:

$$x_{k+1}^{opt} = K_k \cdot z_{k+1} + (1 - K_k) \cdot (x_k^{opt} + v_k \cdot \Delta t) \quad (12)$$

where, $0 \leq K \leq 1$ is the Kalman factor. To find the exact value of the Kalman factor $K$, the error should be simply minimized:

$$e_{k+1} = x_{k+1} - x_{k+1}^{opt} \quad (13)$$

Minimizing the average value of the squared error, the following formula is derived:

$$e_{k+1}^{opt} = \frac{\sigma_\eta^2 + (\epsilon_k^{opt})^2 + \sigma_\xi^2}{\sigma_\eta^2 + (\epsilon_k^{opt})^2 + \sigma_\xi^2} \quad (14)$$

$$K_{k+1} = \frac{(e_{k+1}^{opt})^2}{\sigma_\eta^2}$$

where, $\sigma_\eta^2$ is the dispersion of GPS errors, $\sigma_\xi^2$ is the dispersion of errors $d_\xi$, which can be easily calculated by comparing them to the RTK DGPS data$^9,10$.

5. Experimental Results and Conclusions

The data received from the Cybus automated vehicle sensors manufactured by INRIA (Paris-Rokenkur, France) and the data from the KITTI website (the Karlsruhe Institute of Technology, Germany). http://www.cvlibs.net/datasets/kitti/index.php were used as the database for testing.

5.1 The Results of the Experiment Conducted by the Author Ibraev A. S. during his Foreign Internships in the INRIA Research Centre (Paris, France). The GPS-receiver Ashtech Z-xtreme located on the Cybus automated vehicle manufactured by INRIA (Paris-Rokenkur, France) was used as the source of GPS data for tests. Using the Ashtech Z-xtreme, the data were collected in two modes: The RTK DGPS (RTK correction) and the GPS (without differential correction) modes. Since the coordinates calculated in the RTK DGPS mode feature high accuracy (1–2 cm), they can be regarded as the real coordinates of the receiver. In this part, the task is to assess the accuracy of the vehicle positioning in the GPS mode with regard to the location calculated in the RTK DGPS mode (real coordinates).

The main entrance gate of the INRIA Company was chosen as the reference point. The OX direction is from west to east and the OY direction is from south to north.

The motion trajectory charts drawn in MATLAB of the intelligent vehicle in these two modes are as follows:

Figure 7. The coordinates (in meters) determined in the GPS (green) and the RTK DGPS (blue) modes.

Since the frequency of data reception in these modes differs (also due to the presence of various disturbances, these frequencies are not always constant), the data synchronization software has been developed. For this purpose, the closest possible time of data receipt in the RTK DGPS mode if determined for each time of data reception in the GPS mode and only the following values of RTK DGPS are considered (GPS frequency - 2 Hz, RTK DGPS frequency - 10 Hz). Using the synchronized data, the difference between the GPS and the RTK coordinates is calculated:
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The mean-square deviation of coordinates in a simple GPS mode = 8.8775 m^2 as calculated from the above mentioned data.

5.2 Inertial Unit
The Crossbow Nav440 located on-board the Cybus intelligent vehicle with the calibrated zero bias and sensitivity was used as the inertial module. An odometer - a set of built-in sensors on the car wheels - is used to improve accuracy.

The results of determining the coordinates based on the inertial unit consisting of a three-axis accelerometer, a gyroscope and an odometer that were pre-calibrated using GPS data (the permanent components of the sensor system errors are calculated by comparing to DGPS) are as follows:

This is the result of the Kalman filtering:

![Figure 8](image1.png)
Figure 8. The deviation of the calculated coordinates along the axes OX and OY in the GPS mode from the real values (in meters), (time scale - in seconds).

![Figure 9](image2.png)
Figure 9. The coordinates calculated using the data from the gyroscope and the odometer before and after the gyroscope data calibration (red line) in comparison with the GPS data (blue line) (scale - in meters).

![Figure 10](image3.png)
Figure 10. The blue line shows the coordinates for RTK DGPS, the red line shows the coordinates for INS/GPS (the Kalman filtering result), (scale - in meters).
The mean-square deviation of coordinates in the simple GPS and INS/GPS modes from the real coordinates equal to 8.8775 m^2 and 3.3755 m^2, respectively.

5.3 The Results of the Kalman Filtering according to the KITTI Data (the Karlsruhe Institute of Technology, Germany)

The start point of motion (measuring) was chosen as the reference point. The OX direction is from west to east and the OY direction is from south to north.

5.3.1 City

While driving along the even city streets, the motion trajectory can be regarded as a broken line. The task is to determine the turning point (at junctions) by measuring the vehicle orientation via GPS and to build the broken line as the target motion trajectory to determine the coordinate dispersion via GPS (Figure 12). The real GPS coordinates cannot be used to estimate the GPS error dispersion, as in real life they will be unknown. The INS accuracy is known according to the measuring sensor characteristics.

Figure 11. The GPS readings and the broken line (scale - in meters).

Figure 12. a) The coordinates according to odometer (green), INS (red) and the actual coordinates (scale - in meters). b) The actual coordinates (blue), according to odometer + INS, the GPS receiver readings, and the results of the Kalman filtering (scale - in meters).

As it is seen from Figure 12, the integration resulting in obtaining a very good accuracy.

5.3 Roadway

If a vehicle moves along the roadway, the above mentioned (city) method of GPS dispersion assessment is unusable.
Therefore, the exponential smoothing of GPS noises should be chosen as the target trajectory.

The dispersion of the INS/GPS error is 0.640738 m^2.

6. Conclusion

The use of global positioning systems in the automated vehicles is a powerful technology that allows for the absolute positioning of high accuracy. The disadvantage of this method is that in the presence of obstacles (a tunnel, trees, tall buildings, GPS signal silencers, etc.) the GPS signals are lost or severely distorted. Therefore, controlling a vehicle requires a different navigation system.

Using the INS consisting of a three-axis accelerometer and a gyroscope makes it possible to control the vehicle motion at a temporary GPS signal blockage. Besides, the odometer data was used to adjust the INS data, thus tenfold improving the positioning accuracy. The test results show that this mathematical model of positioning by means of INS and odometer allows for a sufficiently accurate vehicle positioning for a long period of time. The INS ensures the highest accuracy on smooth roads.

To solve the problems of error accumulation over time and of accuracy loss in a short period of time due to the IMU sensitivity to various kinds of disturbances a mathematical programming software for mutual INS and GPS data correction was developed, which provides for a good precision of positioning.

The developed algorithms for filtering and calibration of signals from the three-axial MEMS gyroscopes and accelerometers make it possible to significantly improve the accuracy of spatial object positioning. At the same time, the use of the complementary filter to interconnect angles calculated according to the data from the accelerometer and the gyroscope ensures the integration error compensation for the angles of bank and attitude.

All the presented methods are reasonably accurate, computationally stable and easy for practical implementation. The experimental data for the methods of improving the INS accuracy were obtained via the inertial navigation system consisting of a three-axis MEMS accelerometer LSM303DLH and a gyroscope L3G4200D. The data for integrating the INS and the GPS systems were collected from the Cybus vehicle sensors manufactured by the INRIA Research Centre (Paris, France) and the KITTI data (Karlsruhe, Germany).

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