UAV navigation using opto-electronic and inertial means in GNSS-denied environment

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Abstract. The article presents an approach to improving navigation solution of unmanned aerial vehicle in GNSS-denied environment by means of optoelectronic and inertial measurements. An approach is based on locating and tracking keypoints on the underlying surface to correct inertial system errors. The approach is based on EKF-SLAM and can be applied both in the presence and in the absence of a terrain map. The simulation results of the optical-inertial navigation system readings are presented.

1. Introduction

Unmanned aerial vehicles (UAV) are currently widely used to solve various problems, such as disaster relief, border surveillance, terrain mapping and others. Medium-altitude long-range (MALE) UAVs [1] are among the most popular UAV types with typical flight duration exceeding 10 hours. The core components of the UAV’s navigation system typically are: a global navigation satellite systems (GNSS) receiver, an inertial navigation system (INS), a radio and barometric altimeters.

Despite the fact that the technology is well studied and has been in use for many years, significant problems arise during the GNSS signals outage, which can occur due to natural (multipath, ionospheric, tropospheric and other delays [2]) or artificial (Jamming, Spoofing [3]) interference. Hardware [4] and software GNSS-based solutions [5], widely used on modern aircrafts, add some level of noise immunity and perform continuous integrity monitoring, but in the event of GNSS failure or unavailability, cannot provide a reliable navigation solution. In practice, GNSS outages do not frequently occur, but for critical applications, such as autonomous UAV flight, an ability to provide non-GNSS navigation solution is more and more needed. One way to approach this problem is incorporating an optoelectronic system (OES) as a secondary INS corrector.

At present, a large number of publications are devoted to studying the use of OES as a source of navigation information. Such approaches include the use of neural networks [6]; use of environmental models and correlation methods [7]; use of SLAM algorithms (RTAB-Map, EKF-SLAM, DPSLAM and others) [8] and others.

UAV’s navigation in case of GNSS outage for the proposed approach is demonstrated in figures 1 and 2.
The video image of the earth's surface obtained by the OES usually contains many keypoints. The selection and tracking of these points are carried out by special algorithms – detectors [9] and descriptors [10]. At the moment $t_1$, if there is information about UAV’s coordinates and attitude, it is possible to calculate the coordinates of the keypoints detected on the camera image and locate these points in Earth Centered Earth Fixed (ECEF) coordinate system. Position of detected keypoints on the next video frame at time $t_2$ can be predicted based on the INS measurements. The difference between actual and predicted position of the keypoint at time $t_2$ contains INS errors that have accumulated over time $t_2 - t_1$. Estimates of these errors can be used to correct the INS readings in the case of GNSS outage.

Equation (1) makes it possible to predict the keypoint displacement in ECEF coordinate system. To calculate the coordinates of the keypoint on video frame, the equation opposite to equation (1) is used.
Rotation Matrix $A$ links the camera-associated coordinate system to the ECEF coordinate system as shown in figure 3 and is the product of multiple rotation matrices.

![Figure 3. Coordinate systems transformations.](image)

2. INS correction algorithms

Figure 4 shows the proposed algorithm structure (when the GNSS signals are available), which utilizes a Kalman filter to estimate INS errors. A tightly coupled scheme was chosen, that in future will allow to perform integrity monitoring.

![Figure 4. INS correction algorithm structure.](image)

where

- $\bar{Y}_I = \{\lambda^I, \varphi^I, V_{e}^I, V_{n}^I, \gamma^I, \psi^I, \theta^I\}$ - INS output parameters;
- $\lambda^I, \varphi^I$ - INS longitude and latitude;
- $V_{e}^I, V_{n}^I$ - INS east and north ground speed projection;
- $\gamma^I, \psi^I, \theta^I$ - INS roll, yaw and pitch;
- $\bar{Y}_G = \{\rho_1^G, \rho_2^G, ..., \rho_m^G, \rho_1^G, \rho_2^G, ..., \rho_m^G\}$ - GNSS output parameters;
- $\rho_1^G, \rho_2^G, ..., \rho_m^G$ - GNSS pseudoranges;
- $\rho_1^G, \rho_2^G, ..., \rho_m^G$ - GNSS pseudoranges variation;
- $m$ - number of tracked satellites;
- $\bar{Y}_O = \{P_{1x}^O, P_{1y}^O, P_{2x}^O, P_{2y}^O, ..., P_{nx}^O, P_{ny}^O\}$ - OES output parameters;
- $P_{1x}^O, P_{1y}^O, P_{2x}^O, P_{2y}^O, ..., P_{nx}^O, P_{ny}^O$ - keypoints coordinates on the video frame;
- $n$ - the number of used keypoints;
- $\bar{Z} = \{\bar{Z}_{I/O}, \bar{Z}_{I/O}\}$ - combined measurements for Kalman filter input;
The well-known Kalman filter main equation has the following form:
\[
\begin{align*}
\dot{X} &= F \cdot \dot{X} + G \cdot \dot{W}, \\
\dot{Z} &= H \cdot \dot{X} + V,
\end{align*}
\] (2)

where
\[
\dot{X} - \text{system state; } F - \text{system dynamics matrix; } G - \text{system noise matrix; } \dot{W} - \text{system noise vector; } Z - \text{measurement vector; } H - \text{matrix of connection between the state vector and the measurement vector; } V - \text{measurement noise vector.}
\]

In presented approach, the INS error model is chosen, proposed in [12]. The INS errors vector of this model has the form:
\[
\begin{align*}
\tilde{X}_I &= \begin{bmatrix} x_1, x_2, x_3, x_4, \alpha, \beta, \gamma, \Delta \Omega_x, \Delta \Omega_y, \Delta \Omega_z, \Delta K_{\Omega_x}, \Delta K_{\Omega_y}, \Delta K_{\Omega_z}, \Delta n_x, \Delta n_y, \Delta n_z \end{bmatrix}^T.
\end{align*}
\] (3)

where
\[
\begin{align*}
x_1, x_2 &- \text{longitude and latitude error expressed in meters; } \\
x_3, x_4 &- \text{east and north ground speed projections errors; } \\
\Delta \Omega_x, \Delta \Omega_y, \Delta \Omega_z &- \text{angular velocity sensors biases; } \\
\Delta K_{\Omega_x}, \Delta K_{\Omega_y}, \Delta K_{\Omega_z} &- \text{angular velocity sensors scale factors errors; } \\
\Delta n_x, \Delta n_y, \Delta n_z &- \text{accelerometer biases; } \\
\Delta K_{n_x}, \Delta K_{n_y}, \Delta K_{n_z} &- \text{accelerometer scale factors errors; } \\
\alpha, \beta, \gamma &- \text{INS orientation errors.}
\end{align*}
\]

These errors are related to the INS errors in determining the roll, yaw and pitch angles as follows:
\[
\begin{align*}
\begin{bmatrix} \delta \psi \\ \delta \theta \\ \delta \gamma \end{bmatrix} &= \begin{bmatrix} \sin \psi \tan \nu & \cos \psi \tan \nu & -1 \\ \cos \psi & -\sin \psi & 0 \\ \sin \psi / \cos \nu & \cos \psi / \cos \nu & 0 \end{bmatrix} \cdot \begin{bmatrix} \beta \end{bmatrix},
\end{align*}
\]

where \(\psi, \nu, \gamma\) – ideal values of the current yaw, pitch and roll angles;
\[
\delta \psi, \delta \theta, \delta \gamma - \text{errors in determining the corresponding angles.}
\]

The state vector, which includes the GNSS errors and included in system state, has the form:
\[
\dot{X}_G = \begin{bmatrix} [\delta \rho^c_{xI}, \delta \rho^c_{yI}] \end{bmatrix},
\] (4)

where
\[
\begin{align*}
\delta \rho^c_{xI} &- \text{receiver clock error; } \\
\delta \rho^c_{yI} &- \text{receiver clock drift.}
\end{align*}
\]

There are various ways of representing the OES errors [13], but generally they can be represented as a sum of high-frequency and low-frequency components. In this paper, the high-frequency component of OES error is considered Gaussian random process or so-called white noise. The model of OES errors has been constructed to solve the problem posed, built on the basis of equation (1):
\[
\begin{align*}
\begin{bmatrix} \delta p^x_{xI} \\ \delta p^y_{yI} \end{bmatrix} &= \frac{1}{N} A^T \begin{bmatrix} \delta R^0_{1I} - \delta R^1_{1I} \\ \delta R^0_{2I} - \delta R^1_{2I} \\ \delta R^0_{3I} - \delta R^1_{3I} \end{bmatrix} + \frac{1}{N} M^T \begin{bmatrix} 0 & 0 & \alpha \\ \beta & -\alpha & 0 \end{bmatrix} C^T C_1 \begin{bmatrix} \delta R^0_{1I} - \delta R^1_{1I} \\ \delta R^0_{2I} - \delta R^1_{2I} \\ \delta R^0_{3I} - \delta R^1_{3I} \end{bmatrix} + \\
&+ \frac{1}{N} M^T \begin{bmatrix} 0 & 0 & \beta_1 \\ \beta_1 & -\gamma_1 & 0 \end{bmatrix} C^T C_1 \begin{bmatrix} \delta R^0_{1I} - \delta R^1_{1I} \\ \delta R^0_{2I} - \delta R^1_{2I} \\ \delta R^0_{3I} - \delta R^1_{3I} \end{bmatrix} + (-1) \frac{1}{N^2} A^T \Delta N,
\end{align*}
\]

where
\[
\begin{align*}
\Delta N &= \begin{bmatrix} \Delta n_x \\ \Delta n_y \\ \Delta n_z \end{bmatrix},
\end{align*}
\]

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where
\[ \delta P_{X1}, \delta P_{Y1} \] – the error in predicting the position of the keypoint in the coordinate system associated with the camera;
\[ \delta R_{111}, \delta R_{211}, \delta R_{311} \] – keypoint location error in ECEF during initialization phase, caused by an initial INS error at the moment of observing the keypoint for the first time;
\[ \delta R_{111}, \delta R_{211}, \delta R_{311} \] – INS position errors in ECEF;
\[ \delta N \] – scale factor error;
\[ l \] – keypoint number;
\[ \alpha_1, \beta_1, \gamma_1 \] – INS orientation errors;
\[ M \] – a rotation matrix from a camera-associated coordinate system to an aircraft-associated coordinate system;
\[ C \] – a rotation matrix from an aircraft coordinate system to an East, North, Up (ENU) coordinate system;
\[ C_1 \] – rotation matrix from ENU coordinate system to ECEF (matrices \( M, C, C_1 \) are used to construct the matrix \( A \)).

The state vector, including the measurement errors of the OES, has the form:
\[
\bar{X}_0^T = [\delta R_{111}, \delta R_{211}, \delta R_{311}, \ldots, \delta R_{1n}, \delta R_{2n}, \delta R_{3n}]^T,
\]  
(5)

Here \( n \) – the number of used keypoints.

Thus, the base vector of the state of the system includes vectors (3), (4), (5) and has the form:
\[
\bar{X}^T = \begin{bmatrix}
    x_1, x_2, x_3, x_4, \alpha, \beta, \gamma, \Delta \Omega_x, \Delta \Omega_y, \Delta \Omega_z, \Delta K_{nx}, \Delta K_{ny}, \Delta K_{n2}, \Delta n_x, \Delta n_y, \Delta n_z, \\
    \delta \rho_{\phi}, \delta \rho_{\theta}, \\
    \delta R_{111}, \delta R_{211}, \delta R_{311}, \ldots, \delta R_{1n}, \delta R_{2n}, \delta R_{3n}
\end{bmatrix}
\]

3. Results and discussion
As part of the work, a software was developed for simulating the readings of the UAV. This software contains the following components: UAV trajectory generation along the given coordinates; GNSS/INS measurements simulation; constructing projections of ground keypoints on the camera image; implementation of the proposed approach.

Simulation of developed algorithm was performed in GNSS-denied environment without a digital terrain map on board the UAV. Figure 5 shows the result of simulation of the UAV flight trajectory with randomly "scattered" keypoints on the earth's surface.

The trajectory shown in figure 5 is divided into 10 sections and built in such a way that the UAV flies over the same section twice (sections 1 and 5, 4 and 9). This leads to previously observed keypoints reappear in camera’s field of view. Two options for constructing measurements of the OES are considered:

1) After a keypoint disappears from the camera's field of view, all information associated with it is erased. If this point is observed again, it is considered a new keypoint;
2) Information about keypoints (coordinates in ECEF coordinate system and keypoint descriptor) is stored in memory and can be used when keypoint is observed again.
During the simulation, the digital terrain map was not included in the available navigation information. Figure 6 shows INS position errors in autonomous mode (without correction from GNSS and OES).

Figures 7, 8 show the results of developed algorithm simulation in GNSS-denied environment without using the points that have reappeared in camera's field of view.
Simulation of the developed algorithm yielded the following results:

Figures 9, 10 show the results of developed algorithm simulation in GNSS-denied environment with the reuse of previously observed keypoints.

Simulation of the developed algorithm yielded the following results:
8

- the error in determining coordinates when using the OES as an INS corrector without using previously observed keypoints was 0.2% of the distance traveled under the given initial conditions;
- INS error standard deviation, calculated by the filter, shows that the quality of the estimate increases when the UAV maneuvers;
- the proposed method allows to reduce errors of the INS in determining the orientation angles of the UAV. It was also observed, that for an effective correction of the heading channel, change of course is required;
- the use of previously observed keypoints greatly reduces accumulated coordinate errors, but does not have an effect on orientation accuracy.

4. Conclusion
An approach was presented which allows to improve navigation solution of unmanned aerial vehicle in GNSS-denied environment by means of optoelectronic and inertial measurements. Simulation has proven the operability of the developed algorithms. A number of tests under different initial conditions showed a decrease in the coordinate errors by a factor of 10-15 compared to autonomous INS operation. Reuse of previously observed keypoints further improved the accuracy of the navigation solution.

However, it should be noted that in reality the result will depend on a number of random factors: the geometry of keypoints constellation on the video frame, the quality of keypoint detection and extraction algorithms, and others. Further software deployment on a real UAV requires the following tasks to be performed, which fall out of the scope of this article: camera calibration, calculation of camera position and orientation with respect to the UAV. The performed simulations did not use digital terrain map, but if such map was available, then the achievable accuracy of the algorithm would also depend on the errors of the map itself.

The described approach can be applied not only as part of the navigation solution of MALE class UAVs, but also for a number of other objects: small UAVs, ground vehicles, ships and underwater vehicles (when using sonar equipment), and so on.

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