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AN INTEGRATED AIRCRAFT NAVIGATION SYSTEM WITH OPTICAL HORIZON SENSOR

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Abstract. An integration algorithm for a strapdown inertial navigation system with optical horizon sensor based on Kalman filtering is presented. It allows the accuracy of the estimation of aircraft motion parameters to be improved. A self-contained horizon recognition algorithm for the video sequence that enables real-time aircraft attitude determination relative to the horizon line is developed. A scaled-down simulation and performance analysis of the operation of the integrated navigation system is carried out.

Keywords: navigation system, optical sensor, horizon recognition algorithm, computer vision.

1. Introduction

Because of weight, size or cost requirements, integrated inertial satellite navigation systems (ISNS) based on low-cost MEMS sensors are often used for unmanned air vehicles (George, Sukkarieh 2005; Plekhanov *et al.* 1998). Such navigation systems mostly provide medium or low accuracy of navigation parameters. A trouble spot of such systems is that the inertial part is the only source of information about an object's angular attitude. It is therefore necessary to improve the accuracy of ISNS by introducing additional sensors based on physical principles other than the primary system (Winkler *et al.* 2004).

A lot of modern UAVs are used to obtain real-time images of the environment. For this purpose, optical equipment is installed on board. The image from the on-board camera carries enough information for estimation of aircraft attitude. The displacement and angle of the horizon line in a video frame from an on-board video camera can inform us about the attitude of the camera and hence of the aircraft relative to the surface of the ground. Some difficulties arise during the automation of this process, for example, detecting exactly the horizon line from numerous lines on an image. Such a problem requires the use of computer vision methods further adapted to specific conditions.

Some research uses various computer vision techniques for horizon line recognition for the purpose of partial micro air vehicle attitude determination (Ettinger *et al.* 2002; Dusha *et al.* 2007; Malysheva 2008; Zbrutsky *et al.* 2012). Another study (Cornall, Egan 2005) also has practical results under certain weather conditions. In this paper, the application of a horizon line recognition algorithm via computer vision technique is also considered. This self-contained algorithm can be used in the airborne computer. The research concerns the use of this recognition algorithm for the development of an optical horizon sensor. This paper also discusses the development of the main features of an algorithm for the integration of strapdown inertial navigation system (SINS) and optical horizon sensor.

2. Horizon formation by the optical sensor

Let us consider the initial image in figure 1. Investigation of the colour components of an RGB image shows that the horizon line can be identified in all three colour channels. Processing is therefore applied in parallel to each of the colour channels of the initial image to obtain more information about the position of the horizon line.

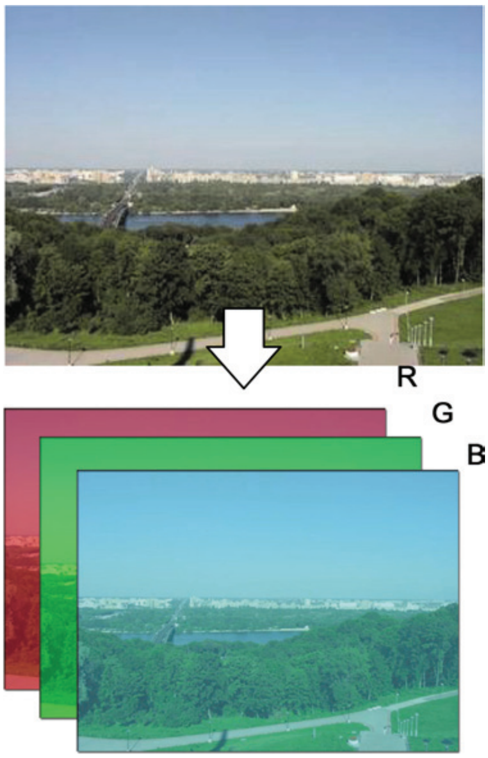

Fig. 1. Initial image and its RGB colour channels

As the first step of processing, an edge detection procedure via a predefined set of morphological operators and then the Sobel operator are performed (Gonzalez, Woods 2002). The advantage of using morphological operators over linear low-frequency filters is that they better preserve the magnitude and position of the various edges. This is an essential condition to ensure accurate edge estimation. Figure 2 shows the corresponding view of all three image channels after the first step of processing.

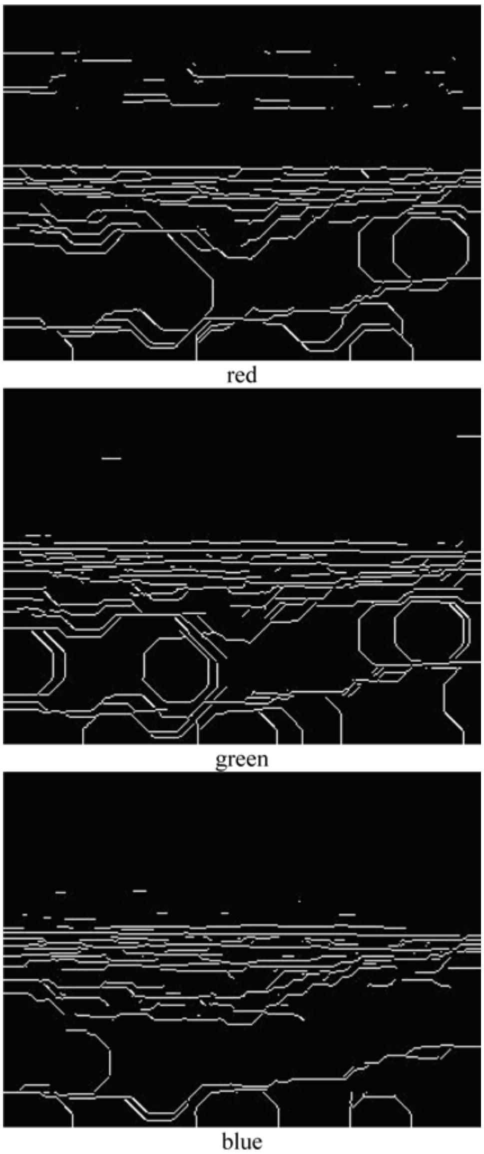

Fig. 2. View of red, green and blue image channels after first step of processing

Examination of the camera lens distortion model shows that the pixels in the image corners are distorted the most. To eliminate this effect, a binary circular mask is added when the results of the first step are combined by means of a logical AND operation (Fig. 3). It should be noted that it is not the image centre but the lens optical centre projected on the image plane that is selected as the circular mask centre.

Fig. 3. Result of application of logical AND operation with circular mask

Line extraction from the processed image is carried out via the Hough transform (Gonzalez, Woods 2002).

Figures 4–6 show the result of applying the recognition algorithm to the initial image and two other test images that present a different weather condition and view of the sky. One can see that the algorithm has sufficient accuracy to detect the horizon line.

Fig. 4. Result of application of horizon recognition algorithm to the initial image

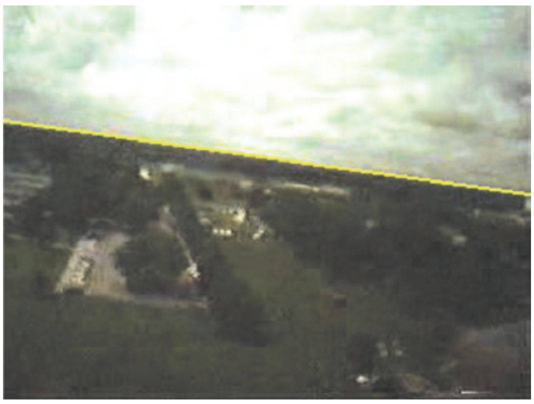

Fig. 5. Result of application of horizon recognition algorithm to image demonstrating cloudy weather

Fig. 6. Result of application of horizon recognition algorithm to image demonstrating sky with a drop in intensity

Real-time estimation of two aircraft attitude angles, i.e. roll and pitch, by means of a web camera and the horizon recognition algorithm implemented in MatLab Simulink is demonstrated in figure 7. Information from the on-board camera installed on a moving object enters the airborne computer, which determines the roll and pitch values.

3. Integrated navigation system

The aircraft navigation algorithm is based on optimal error estimation of the subsystems, such as SINS, GPS receiver, an optical horizon sensor, and a magnetometer. The purpose of this feature is to compensate the errors of the subsystems in an integrated system (Fig. 8). The SINS is considered the main navigation system. It consists of three accelerometers and three single-component angular rate sensors.

The algorithm of integrated navigation data processing is based on the generation of difference measurements. In such measurements, the navigation parameters are excluded. Thus the problem of gauges error estimation can be solved. As an invariant estimation algorithm, the optimal Kalman filter is applied.

Let us describe the system dynamics by the differential equations in matrix form (Matveev, Raspopov 2009):

$$\begin{aligned}&\dot{X}(t) = A \cdot X(t) + G \cdot U(t) + B \cdot W(t);\\ &Y(t) = C \cdot X(t) + V(t),\end{aligned} \tag{1}$$

where $X(t)$ is the system state vector; $U(t)$ is the known input vector (including control signals); $W(t)$ is the random input vector; $A(t), B(t), G(t)$ are the state matrix, the control matrix, and the input matrix respectively; $Y(t)$ is the measurement vector; $C(t)$ is the transition matrix of $X(t)$ and $Y(t)$; and $V(t)$ is the random measurement noise vector.

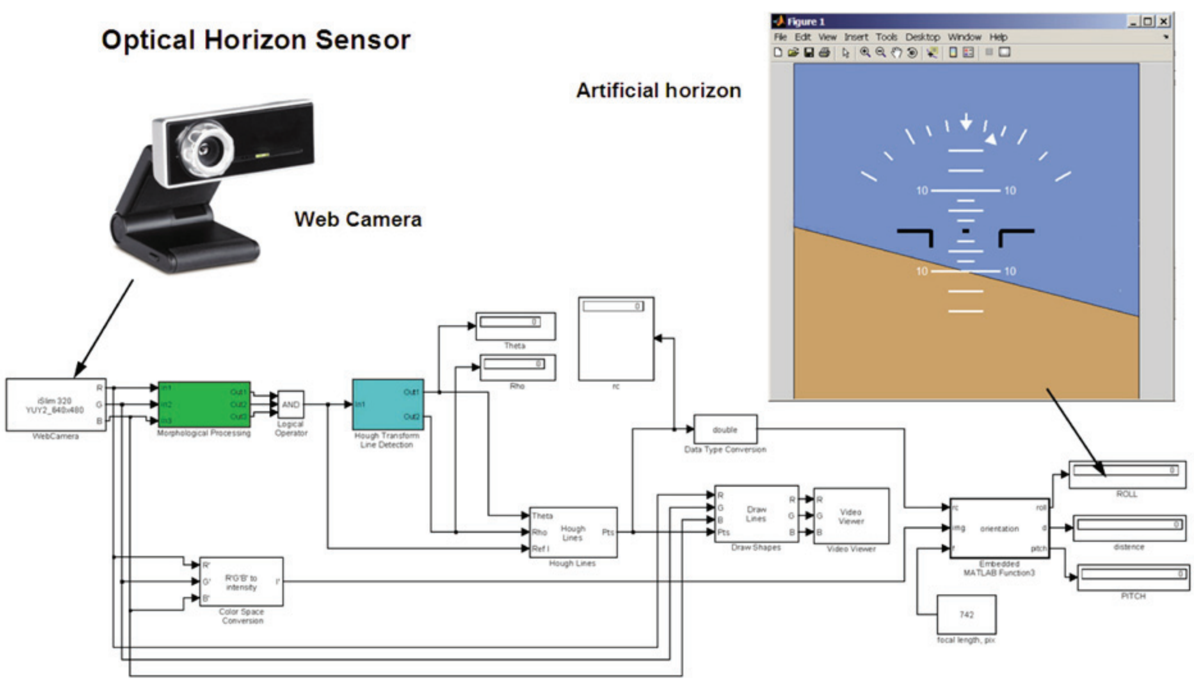

Fig. 7. Implementation of attitude estimation algorithm in MatLab Simulink

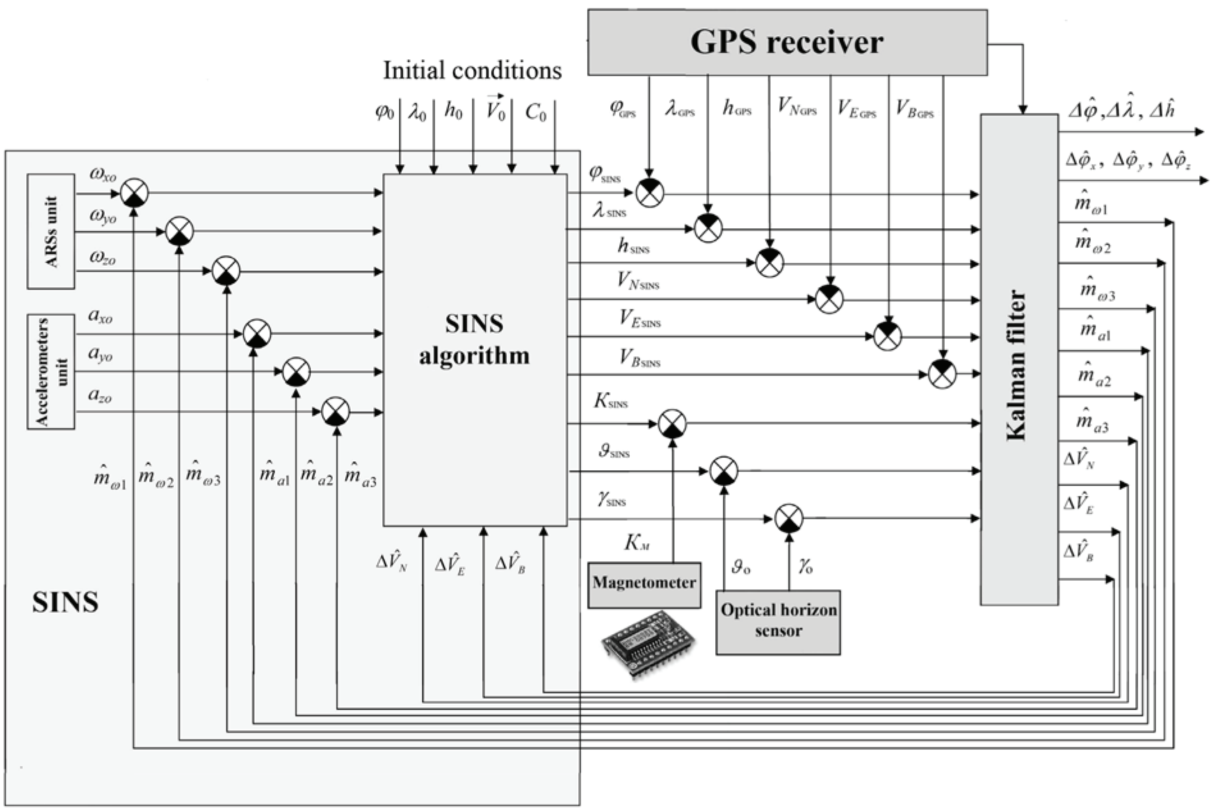

Fig. 8. Block diagram of integrated aircraft navigation system

The state vector:

$$X = [\Delta\xi\ \Delta\eta\ \Delta\zeta\ \Delta V_\xi\ \Delta V_\eta\ \Delta V_\zeta\ \ldots \quad (2)$$
$$\Delta\varphi_x \Delta\varphi_y \Delta\varphi_z m_{ax}\ m_{ay}\ m_{az}\ m_{\omega x}\ m_{\omega y}\ m_{\omega z}\ ]^T,$$

includes SINS and its sensor errors: $\Delta\xi$, $\Delta\eta$, $\Delta\zeta$ are the object coordinate estimation errors in an inertial frame $O_1\xi\eta\zeta$ with origin at the centre of the Earth (the axis $O_1\zeta$ along the axis of the Earth's rotation axis is directed); ΔV_ξ, ΔV_η, ΔV_ζ are the object rate estimation errors; $\Delta\varphi_x$, $\Delta\varphi_y$ are the SINS vertical line analytical modelling errors; $\Delta\varphi_z$ is the meridian direction estimation error; and m_{ai}, $m_{\omega i}$ are slowly varying random components of the accelerometers zero offset and angular rate sensors drift.

The measurement vector $Y(t)$ for the optimal Kalman filter is generated from the differences in the coordinate, rate and rotation angle measurements provided with the SINS on the one hand and the GPS-receiver, optical sensor, and magnetometer on the other. Taking into account expression (2), we obtain:

$$Y(t) = C \cdot X(t) + V(t) =$$
$$[\Delta\xi + \nu_1, \Delta\eta + \nu_2, \Delta\zeta + \nu_3, \quad (3)$$
$$\Delta V_\xi + \nu_4, \Delta V_\eta + \nu_5, \Delta V_\zeta + \nu_6,$$
$$\Delta\gamma + \nu_7, \Delta\vartheta + \nu_8, \Delta K + \nu_9]^T.$$

Such a system is completely observable and controllable.

The optimal Kalman filter application allows the problem of state vector recovery from noisy measurements $Y(t)$ to be solved in real time, providing an estimation of minimum mean square error of the state variables $x_i(t)$.

The state vector estimation algorithm by optimal Kalman filter equation is described (Brammer, Siffling 1982):

$$\dot{\hat{X}}(\mathrm{t}) = A(\mathrm{t}) \cdot \hat{X}(\mathrm{t}) + B(t)U(\mathrm{t}) + K(\mathrm{t}) \cdot \left(Y(\mathrm{t}) - \hat{Y}(\mathrm{t})\right); \quad (4)$$
$$\hat{Y}(\mathrm{t}) = C(\mathrm{t}) \cdot \hat{X}(\mathrm{t}),$$

where $\hat{X}(t)$, $\hat{Y}(t)$ are the estimations of state and measurement vector respectively.

To reduce SINS errors, the influence of the slowly varying random components of the accelerometers zero offset and angular rate sensors drift is compensated by the estimations of zero offset $\hat{m}_{\mathrm{ai}}$ and drift $\hat{m}_{\grave{u}\mathrm{i}}$.

4. Simulation results of the integrated navigation system with a horizon optical sensor

Simulation is carried out in the MatLab Simulink software environment. The assumption of object immobility relative to the Earth is considered. Figure 9 demonstrates an aircraft attitude estimation error. The optical horizon sensor and magnetometer integration decreases the SINS vertical line analytical modelling errors $\Delta\varphi_x$, $\Delta\varphi_y$ and the meridian direction estimation error $\Delta\varphi_z$ respectively. Thus the object attitude error estimation is about $2.16 \cdot 10^{-4}$ rad in course, $2.05 \cdot 10^{-5}$ rad in pitch, and $3 \cdot 10^{-7}$ rad in roll.

Other simulation results show that the coordinate determination errors of a moving object in all three coordinates is less than 1 m, and the error standard deviation of the determination of object linear rates is on average 0.0052 m/s.

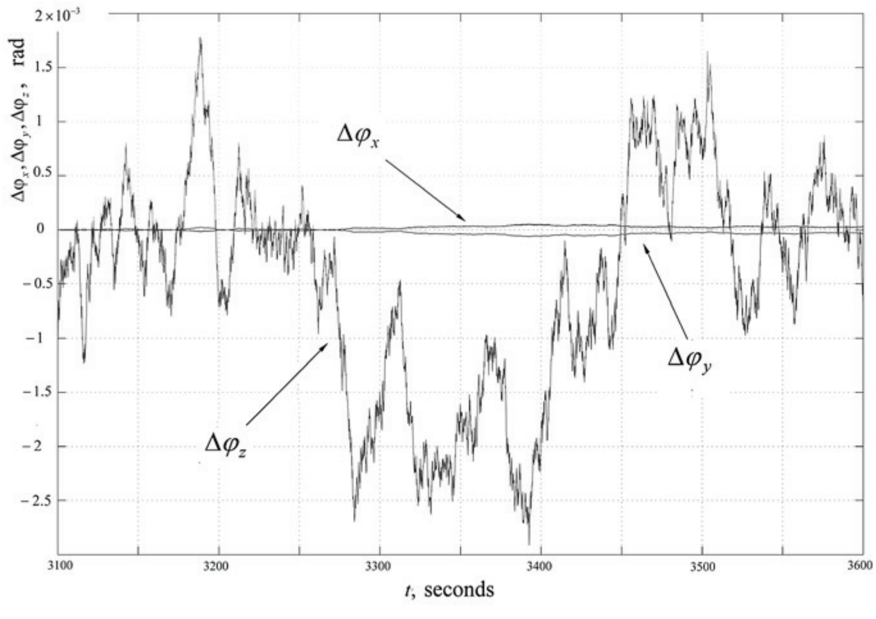

Fig. 9. Aircraft attitude estimation error $\Delta\varphi_x$, $\Delta\varphi_y$, $\Delta\varphi_z$, rad

5. Conclusions

It can therefore be concluded that the proposed SINS and optical horizon sensor integration algorithm enable the improvement of determining the accuracy of aircraft motion parameters and provide the utilisation of SINS based on MEMS sensors during an unlimited period of time as long as the horizon is in the field of view.

In this research, a self-contained horizon recognition algorithm for video sequence is developed. It allows real-time aircraft attitude relative to the horizon line to be determined.

A scaled-down simulation of system operation confirmed its high accuracy and reliability and also showed the high efficiency of SINS, GPS, optical sensor, and magnetometer integration via the Kalman filter to create intelligent UAV on-board systems.

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