An Integrated and Vision Aided GPS/INS Navigation System for Ultra-low-cost MAVs

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Abstract

Today's MAV navigation systems take advantage of GPS in combination with an IMU to derive velocity and position as well as attitude and heading. Ultra-low-cost systems ($<$ 500$) for unstable flight vehicles, with their restricted hardware abilities and low measurement quality, use GPS information to determine the position and inertial measurements for stabilization control only. This paper presents an integrated closed-loop navigation system with ultra-low-cost MEMS inertial sensors using a complementary Kalman filter approach, which fuses GPS and IMU data in a loosely-coupled-system to improve position and velocity information. Therefore, sophisticated approaches from high-end UAVs have been adapted for usage in very cheap MAV navigation systems. As further improvement, this paper introduces additional aiding by computer vision and a smooth operating mode switching concept. This concept allows seamless switching between different modes of operation, which are selected depending on the availability of visual information and GPS data. Correct attitude information needed for stabilization control can be guaranteed also in case of permanent GPS and/or visual data loss. Implemented on a tiltwing MAV, this solution is also capable of dealing with both flight modes. The approach is evaluated by simulation, based on empirically captured real-world data.

1 Introduction

During the last years small, light and inexpensive micro aerial vehicles (MAVs) have been developed. Many of these vehicles are not of type fixed-wing and have the ability to hover, to move close to the ground and to maneuver precisely between obstacles. One challenge in this context is the development of adequate navigation systems for these types of vehicles. Most of them are inherent unstable and depend on accurate attitude information that have to be all-time available for stabilization control. A simple solution to improve navigation and stabilization of the vehicle would be to use high quality inertial measurement units (IMUs), however, with an increasing quality, the price rises exponentially. Since our goal is an ultra-low cost navigation system for MAVs, we focus on ultra-low-cost IMUs. In MAVs, inertial sensors of MEMS-type have to be used instead, which are small, light and inexpensive but suffer from significantly larger errors. These errors cause a drift in the strapdown solution that leads to unusable results if it is not constantly aided by measurements of other sensors. But also within the class of MEMS-IMUs there are significant differences between sensors of higher and lower price levels. Satellite navigation is a widely-used possibility to determine position, velocity and even attitude and heading of an aerial vehicle [1]. GPS-receiver have become less expensive and meet all the requirements of MAV navigation and due to simplicity, many MAVs use only GPS-information for outdoor navigation. But satellite navigation alone is not a satisfying solution for all problems of MAV navigation. Attitude information can be collected by multi-antenna-systems and is not reliable enough for stabilization control of an inherent unstable MAV. Gaining heading information by observing the velocity is possible if the flight direction of the vehicle corresponds to a fixed axis of the vehicle, which is the case in fixed-wing MAVs. The heading of MAVs with the ability to hover is not observable this way. Evaluating GPS pseudo-range and delta-range measurements are often the only possibility to get absolute position and velocity information, but they are not precise and reliable enough to maneuver close to obstacles or to the ground. Additionally, it is possible to use these measurements to calibrate the inertial sensors so that the performance of the inertial solution improves.

Navigation by computer vision is quite a new approach compared to inertial and satellite navigation. In recent years, embedded computers have become smaller and less expensive while memory and computational power increased. Due to these developments, it is possible to use computer vision for MAV navigation [2]. The CMOS-camera systems are cheap and vision-aided navigation does not rely on the availability of GPS signals and is, therefore, also suitable for indoor navigation. But the computational effort of image processing is high and the required data for navigation carries delays. Due to lower data rates than IMU sensors, vision alone is not suitable for stabilization of MAVs with high dynamics. Furthermore, due to the high diversity in the environment of an outdoor MAV, the availability and integrity of the solution from video-aided navigation cannot be guaranteed all

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the time. Another aspect of video-aided navigation is the increased weight of the vehicle, due to the requirement for more computational power.

Because every type of sensor offers useful information, but suffers from specific disadvantages, sensor data has to be fused in a way that leads to the best possible navigation solution.

A widely-used and well known approach of sensor data fusion for integrated navigation systems is the Kalman filter [3, 1, 4, 5, 6]. The Kalman filter is a linear quadratic estimation algorithm that calculates a statistically optimal estimate of system states by processing noisy measurements. The expensive navigation systems of many UAVs of great dimensions use sophisticated Kalman filters to estimate their navigation solution with high precision by fusion of inertial and GPS data which have complementary properties. Inertial solutions are very precise for a short period of time and GPS data guarantees long term stability. In case of GPS loss, the navigation solution is propagated by inertial measurements from high quality IMUs with low error rates.

This paper describes the development of an integrated navigation system for a tilt-wing-MAV using an ultra-low-cost MEMS-IMU, a small commercial GPS-receiver and a camera for computer vision. Further sensors include a magnetometer and a barometer. Several operating modes of the navigation system are established, depending on the one hand on the availability of GPS and/or visual information and, on the other hand, on the flight mode of the MAV (hover or fixed-wing). We choose a closed-loop indirect Kalman filter formulation, estimating the errors of the total state containing position, velocity, attitude, heading and the bias errors of the inertial sensors and the level of air pressure. In every mode those states are estimated, that are still observable. Other states are either reset or frozen to get the best estimate without losing filter stability. Switching between operating modes is implemented without any evitable discontinuities. Correct attitude information needed for stabilization control is guaranteed also in case of temporarily or permanent GPS and/or visual data loss by determining the local gravity vector. Our work shows, that the stability, the average accuracy and the maximal error of the navigation solution can be improved, compared to every single sensor information, although ultra-low-cost MEMS sensors are used. The improvement in the accuracy of position compared to GPS alone will make it possible to accomplish precise maneuvers (e.g. flying through an arch) that would otherwise be impossible or too dangerous.

The remainder of the paper is organized as follows. In the next section some of the related work on this area is listed. Section 3 introduces the MAVs system design and hardware architecture, into which the navigation system is integrated, while Sec. 4 describes the development of the navigation system itself. In the following section the results of the simulation using captured real-world data are presented and discussed. Finally, Sec. 6 concludes this work.

2 RELATED WORK

The fusion of data from inertial and satellite navigation by Kalman filtering is widely-used and well known. INS/GPS-navigation systems are used in many aerial and other vehicles and have proven their abilities [3, 1]. They have also been applied to different kinds of UAVs [4, 6]. INS/GPS-systems using low-cost MEMS sensors have also been developed [5]. Different types of Kalman filter approaches were applied to those systems using MEMS sensors, most of all extended Kalman filter in error-state- or total-state-space formulation but also Sigma-Point Kalman filter which did not show significantly better results [7]. Wendel et al. [5] developed an integrated GPS/MEMS-IMU navigation system using a Kalman filter approach for an autonomous helicopter with two operating modes that is capable of dealing with GPS outages by determining earth gravity vector in order to aid roll and pitch information to stabilize the MAV. Different approaches of aiding by computer vision have been presented in the last years. One possibility is to use feature points whose positions and orientations are known a-priori. Wu et al. [6] developed an extended Kalman filter that fuses data from inertial sensors and from camera pictures with this a-priori-knowledge. Another possibility is to use the horizon line extracted from camera images to aid the attitude [8]. But in our approach aiding of position and heading by visual data is of main interest. If the horizon line is not visible, the attitude of the vehicle, which is crucial for unstable MAVs, would not be observable.

Our work is based on the GPS/INS-navigation system approach for autonomous helicopters presented by Wendel et al. [5], extended by adding new operating modes, integrating image processing and aiding by computer vision similar to the processing proposed by Wu et al. [6]. It is adapted for a tilt-wing MAV, which is capable not only of hovering, but also of fixed-wing flight. Thus it is a more general approach that covers many different types of MAVs. In our work, we use *ultra-low-cost* MEMS-sensors, differing from *low-cost* sensors in their significantly lower performance and price. Sometimes even IMUs of tactical grade are called low-cost [4] or MEMS sensors are generally called low-cost in comparison to IMUs consisting of much more expensive fiber optic gyroscopes (FOG) or ring laser gyroscopes (RLG) and high-quality accelerometers. In our experimental setup we use complete MEMS-IMUs with a price of less than 100 USD and a poor performance, e.g. with a bias stability (one sigma) of several hundred to thousand degrees per hour.

3 SYSTEM DESIGN

This section provides an overview of the entire system, starting with the architecture and closing with the navigation system.

3.1 Sensors and GPS-Receiver

The Ardupilot Mega Oilpan provides an ultra-low-cost sensor system, based on MEMS sensors. The hardware mainly consists of acceleration sensors, gyroscopes and a pressure sensor. To measure the acceleration, the *ADXL335* three axis accelerometer is mounted on the board. Furthermore, the rotational speed in horizontal directions is measured by the *IDG-500* gyroscope with a hardware integrated amplifier and low pass filter. Regarding the z-direction, the *ISZ-500* gyroscope is a dedicated piece and provides an integrated amplifier and low pass filter, as well. Finally, the *BMP085* pressure sensor resides on the hardware, allowing to estimate the current pressure. The magnetic field can be estimated by adding a further sensor, the *HMC5843* compass, providing a three dimensional magnetic field sensor. For satellite navigation, a u-blox *LEA 5H* GPS receiver is attached to the aerial computer, allowing to estimate the position and the three dimensional speed by taking advantage of the Doppler effect.

3.2 Embedded Processing Hardware

Regarding the aerial computer, we use our concept from our participation in the IMAV 2011 [2]. An arduino-based hardware and IMU with an integrated barometer form the main controller of the vehicle. The arduino-based processing unit has a clock frequency of 16MHz and 512KB static RAM. All analog sensors, such as the gyroscopes and accelerometers are connected to an eight channel and 12 bit analog digital converter, in this case the ADS7844. Digital sensors, such as the magnetometer and barometer are connected via the two wire I^2C-bus. Finally, the GPS is connected via the serial interface. With an attached gumstix module, the computation for the vision-aided navigation system is possible. The communication between both processors, the ATMega2560 on the arduino board and the OMAP3 processor, is realized using the serial interface. Providing more computational power than the ATMega2560, the OMAP3 processor has a frequency of up to 1GHz and additionally 512MB static RAM. For the video processing, a *Caspa FS* module, implementing the MT9V032 CMOS sensor, is directly attached to the OMAP3 processor. Note, a CMOS sensor has been chosen, due to the low prices of such camera systems, while CCD technology would perform better in the given scenario. For controlling ArduPilot software has been taken as a basis and extended for tilt-wing airframes and the Kalman filter based navigation system. The Angstrom Linux distribution has been chosen as an operating system for the gumstix module.

4 Integrated Navigation System

The navigation system is an essential component of the tilt-wing MAV. It has to determine attitude information that are needed by the stabilization controller and also heading, position and velocity information for flight control and guidance. It consists of an inertial measurement unit in MEMS technology that measures accelerations and angular rates of the body frame, a GPS-receiver that delivers 3d-position and 3d-velocity information, a magnetometer measuring a 3d-magnetic field and a barometer to determine air pressure. A camera, connected to its own processing unit, is able to process visual data. Figure 1 presents the process.

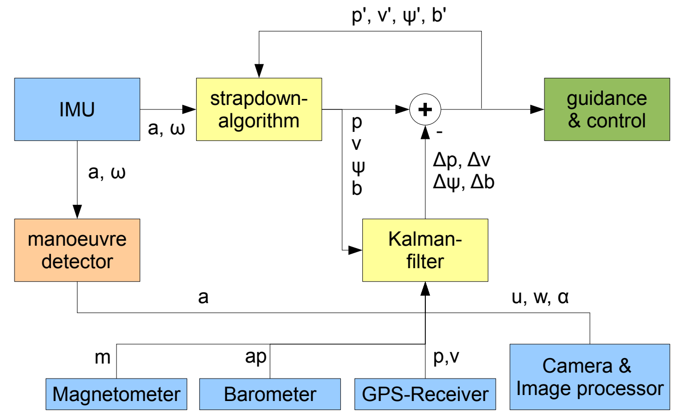

Figure 1: Sensor and Data Flow

4.1 Inertial Navigation

The strapdown algorithm determines a new navigation solution by propagating the solution at the last time step using measured angular rates and accelerations. The change of attitude and heading is calculated by solving Bortz' differential equation for small angles [3]. Earth rotation, transport rate and Coriolis accelerations are neglected because those effects are much smaller than the expected IMU measurement noise. Thus, the differential equations to propagate attitude, heading, velocity and position become quite simple. A complete derivation can be found in literature, e.g. in Titterton and Weston [3].

Because of the poor performance of the IMU, the errors of this propagated navigation solution increase within seconds out of reasonable bounds.

The main error sources of the MEMS inertial sensors that are considered during data fusion, as shown later, are bias error, bias drift and angular/velocity random walk caused by sensor noise. Scale factor errors, non-linearities and sensor misalignment are neglected in this approach.

4.2 Kalman Filter

An extended Kalman filter is established to continuously correct the propagated states using noisy measurements of GPS and other sensors. An indirect Kalman filter formulation is chosen which is also known as error-state or complementary Kalman filter. The propagation of the total states is done by the strapdown algorithm, the Kalman filter does not estimate the states themselves but the errors of these states. This formulation is often used in navigation system because it offers several advantages. Kalman filters can only estimate the state of linear systems in an statistically optimal way. Extended Kalman filters linearize those systems analytically and deliver suboptimal estimations. Linearizing the error propagation equations will lead to better results than linearizing the total equations [9]. Another advantage of the error-state formulation is the possibility to process the time-update-step of the Kalman filter at a lower frequency because only the covariances and not the total states are propagated. These are propagated by strapdown-algorithm with the same update rate as the IMU measurements are read. The total state vector consists of seventeen states: Position (latitude, longitude, altitude), 3d-velocity, attitude/heading (quaternion), 3 gyroscope bias errors, 3 accelerometer bias errors and bias error of the air pressure level. The attitude/heading information is stored in form of a quaternion and not in roll-pitch-yaw angles because quaternion description does not suffer from singularities or ambiguities. The estimated bias errors of the inertial sensors are subtracted from measured angular rates and accelerations during the processing of the strapdown-algorithm.

The error-state-vector of the Kalman filter consists only of sixteen states. The errors of attitude/heading are calculated as roll-pitch-yaw angles. Because those angles will be small there will not be any problems as discussed before and the dimension of the filter is smaller. This reduces the computational effort.

The system equations of the error-state formulation are well-known [1] and their complexity is significantly reduced if the system in simplified similar as in strapdown-algorithm. A further state containing the bias error of the air pressure level is added,

$$\frac{d}{dt}\begin{pmatrix}\delta p^n\\ \delta v^n\\ \delta\psi^n\\ \delta b_\omega\\ \delta b_a\\ \delta b_{ap}\end{pmatrix} = \begin{pmatrix}0 & I & 0 & 0 & 0 & 0\\ 0 & 0 & -a^n\times & 0 & -C_b^n & 0\\ 0 & 0 & 0 & -C_b^n & 0 & 0\\ 0 & 0 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 0 & 0\end{pmatrix}\begin{pmatrix}\delta p^n\\ \delta v^n\\ \delta\psi^n\\ \delta b_\omega\\ \delta b_a\\ \delta b_{ap}\end{pmatrix}$$

where δp^n, δv^n, $\delta\psi^n$ are the position, velocity and attitude/heading errors in the navigation frame coordinate-system and δb_ω, δb_a and δb_{ap} are the gyroscope, accelerometer and air pressure bias errors. Finally, a^n is the acceleration in the navigation-frame and C_b^n the direction-cosine-matrix transforming from body- to navigation-frame.

The deviations of bias errors which are caused by bias drift of the inertial sensors also have to be modeled. According to the expected performance of the IMU the bias drift is modeled as a random walk process. The bias drift of air pressure level depending on weather changes is also assumed to be a random walk process. The bias of the barometer is not observable, because it interferes with the change of pressure at main sea level.

Furthermore, the sensor noise is considered as process noise during time-update of the Kalman filter. To calculate the error-states and correct the total states, the differences between the actual measurements and the expected measurements based on the total-state are processed. For every type of measurement, an equation and information about the expected noise are needed to calculate error-states and correct the covariances. If states are not related to any measurement, they become unobservable and their variances grow out of reasonable bounds. It is generally advantageous to process all measurements in one step to consider any correlations between the measurements. In this approach measurements of different sensors are processed individually, because it is impossible to receive them with the same frequency at the same time.

4.3 Satellite Navigation

One of the best and easiest possibilities to get absolute position and velocity information during outdoor navigation is satellite navigation using GPS. There are different ways to integrate inertial and satellite navigation systems [1]. In our approach, a loosely-coupled system is established. The navigation filter uses position and velocity information, delivered by the GPS-receiver. Other possibilities are tightly-coupled systems, which process pseudo-range, delta-range and or carrier-phase measurements delivered by the GPS-receiver or deeply-coupled systems (GPS-filter is integrated in navigation filter). The loosely-coupled approach is the easiest to implement, because of the low integration depth. However, aiding is only possible with at least four visible satellites. The estimated variances of the GPS-measurements are transmitted by the GPS-receiver. Unfortunately, the GPS-receiver used in our experimental setup does not transmit further information about covariances. GPS measurements of absolute position and 3d-velocity can be used to observe all states. Nonetheless, the yaw angle (heading) is only observable if horizontal accelerations are measured. If the MAV hovers or flies at a straight level, the yaw angle is unobservable. In case of fixed-wing mode, the yaw angle is approximately close to the direction of the horizontal component of the measured velocity-vector. In general the lever arm of the GPS-antenna also has to be considered. In this approach this lever arm is neglected, because of its small dimensions.

4.4 Aiding by Gravity

In case of GPS loss all states become unobservable if there are no other measurements related to them. Because of poor IMU performance, the error of the navigation solution grows within seconds out of reasonable bounds. If aiding by computer vision is also not available, there is no possibility to estimate horizontal position and velocity. But, as required, reliable attitude information (roll and pitch) have to stay available for stabilization control.

In this case gravity vector based aiding can be applied. The direction of gravity vector can be determined by measured accelerations and thereby it is possible to calculate the attitude of the body-frame with respect to the navigation frame. Equation (1) is the corresponding measurement equation for the Kalman filter, as presented by Wendel et al. [5], where $\hat{C}_b^n$ is the estimated direction-cosine-matrix transforming from body- to navigation-frame, a_{ib}^b is the measured accelerations in body frame coordinate-system, g_l is the local gravity vector, $\delta\psi^n$ is the attitude/heading error in navigation frame coordinate-system and finally υ_a is the measurement noise.

$$\hat{C}_b^n a_{ib}^b + g_l = [g_l \times]\delta\psi^n + \upsilon_a \tag{1}$$

Errors in roll and pitch angles are related to measurements of the accelerometers, however, yaw angle is still unobservable, because the rotation axis is parallel to the direction of gravity vector. Changes of yaw angle do not affect these measurements. Since errors in yaw angle are not relevant for stabilization control, the requirements are not violated, however, constraining the error is necessary, to avoid numerical problems among others.

Aiding by gravity vector is applicable if gravity is dominating the measurements of the accelerations. This is the case if the MAV is hovering and not accelerating. Generally accelerations may corrupt the integrity of the navigation solution if they are processed as measurements of the gravity vector. This problem is even more severe, because bias errors of the gyroscopes are also estimated using these measurements, causing a possible divergence of the filter. A maneuver-detector is used to decide whether gravity is dominating (no-maneuver-zone) or accelerations of the MAV may interfere (maneuver-zone) [1]. During maneuvers, particularly appearing in fixed-wing mode for short-time periods, no aiding by gravity vector is performed. The decision is made by defined limits for measured angular rates and accelerations.

4.5 Magnetometer and Barometer

A magnetometer has to be embedded in the MAV, because heading is not observable during GPS outages or when the MAV is hovering and visual aiding is not available. A magnetometer delivers 3d-measurements of the local magnetic field. In general the complete attitude and heading information can be obtained by this measurements. But the quality of these measurements is low and may be disturbed by other magnetic fields. For that reason, only yaw angle is corrected by magnetometer measurements. A possible corruption of attitude information concerning roll and pitch angles has to be avoided. The according Kalman filter measurement equation can be found in [5]:

$$\tilde{h}^b - \hat{C}_b^{n,T} h^n = -\hat{C}_b^{n,T}[h^n \times]\delta\psi^n + \upsilon_m$$
$$\text{with } \delta\psi^n = (0, 0, \gamma)^T$$

Where $\tilde{h}^b$ is the measured magnetic field vector in body-frame coordinate-system, h^n is the magnetic field vector in navigation-frame coordinate-system, υ_m is the measurement noise and γ is the yaw angle error. Barometer measurements are used to aid vertical position and velocity. This way, these states stay observable in case of GPS loss. Unfortunately, the general air pressure level drifts, depending on weather changes. Estimating the bias error of air pressure level with GPS altitude measurements compensates this drift. If visual aiding and GPS data are not available, the altitude and vertical velocity information shows a drift and cannot be stable for a long time-period. This may cause problems, because these information are needed for height control. The measurement equation is the well-known barometric formula, which has to be linearized at the working point:

$$\frac{dap}{dh} = -\frac{Mg}{RT}(ap_0 + b_{ap})e^{-\frac{Mg}{RT}h}$$

4.6 Aiding by Computer Vision

Some typical missions for MAVs require more precise position, velocity and heading information for navigation than those provided by GPS navigation systems. Aiding those states by computer vision allows to accomplish missions like maneuvering close to obstacles. The accuracy of GPS position measurements of the used civil GPS-receiver, for example, is denoted as 2.5 meters (circular error probability). By fusing data of IMU, GPS-receiver and camera system more accurate navigation solutions can be estimated and used by the aerial computer. Additionally, in case of GPS loss, all states stay observable if visual information is still available. Our approach to process visual information is limited to special missions. Feature points of a-priori known position and orientation are used to observe the attitude and position of the MAV. Position and heading information is used for navigation, attitude information concerning roll and pitch angles is used for integrity monitoring and not for aiding those states. As it is a requirement of the navigation system, that roll and pitch angles have to be accurately estimated all the time, those states can be compared to the derived attitude data from computer vision. If the difference is too significant, the visual measurements are rejected to assure the integrity of the navigation solution in case of erroneous object recognition.

The measurement model depends on the type of object to be recognized. A model for an object with the outline of a square with known area, position and orientation is presented in [6]. This measurement model is also used in our experimental setup because the computational effort is low and it actually may be relevant in real missions of the MAV. Measurement models for other types of objects can easily be developed, although the number and type of states that are observable may differ with respect to the properties of the object type.

One challenge of vision aided navigation is the computational load of image processing and object recognition which leads to a significant delay of several hundred milliseconds. This delay has to be considered in the Kalman filter update.

States	I	I/G	I/V	I/G/V
Horizontal Position	N	O	O	O
Vertical Position	O	O	O	O
Horizontal Velocity	N	O	O	O
Vertical Velocity	O	O	O	O
Attitude	O	O	O	O
Heading	O	O	O	O
Gyroscope Biases	O	O	O	O
Accelerometer Biases	N	O	(O)	O
Air Pressure Bias	N	O	O	O
Air Pressure	A	A	A	A
GPS-Position		A		A
GPS-Velocity		A		A
Gravity	A		A	
Magnetic Field	A	A	A	A
Visual Data			A	A

Table 1: Observable(O), not observable(N) states and sources of aiding(A) for combinations of INS(I), GPS(G) and vision(V) based navigation systems

For that reason data of all states is buffered for an appropriate period of time and the error between the expected and the actual measurement is determined at the time of validity of the measurement. This solution is easy to implement, but neglects the influences on the covariance propagation. More complex and accurate approaches are to be found in [10]. Following the delay, the lever arm of the camera, which is not fixed in the centre of the MAV but at its nose, is considered, as well.

4.7 Operating Modes

The operating mode of the navigation system depends on the availability of sensor information and the flight mode of the UAV (hover or fixed-wing). Modes differ in number and types of observable states and the use of aiding information. The system model in every mode is a subset of the described system with seventeen total states and sixteen error-states. There are four main modes depending on available sensor data: INS, INS/GPS, INS/Vision and INS/GPS/Vision. The data of the barometer and the magnetometer is expected to be always available. Furthermore, the flight-mode of the MAV is used to determine a sub-mode with the same state vector and system. It provides additional information, that can be used for different aiding, e.g. the yaw angle can be estimated by GPS-measurements in fixed-wing mode in most cases. In Table 1, an overview of the observable(O) and not observable(N) states and the used sources of aiding for given combinations of the Kalman filter is presented. The first column(I) describes the case, in which only the INS is used for navigation. In the second and third column GPS(I/G) and Vision(I/V) is added to the available data sources, while in the last column all data is available from INS, GPS and Vision(I/G/V).

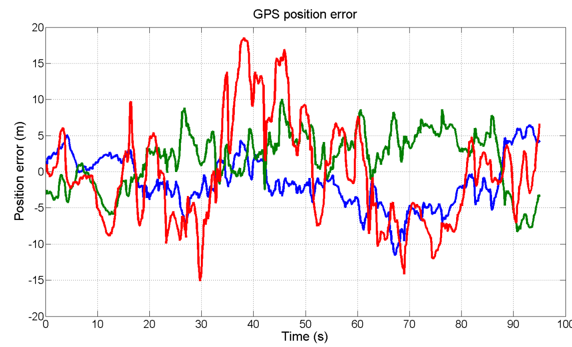

Figure 2: Position error (m) - GPS

The main operating mode is switched, if required sensor measurements are not available for a period of time, depending on IMU quality. It is important, that switching the operating mode does not require all states to converge again as far as it is evitable. For that reason, rules for every transition are established concerning total states and the covariance matrix. Estimation of bias errors are frozen and stored if they become unobservable. Total states of position and velocity are reset to unknown state. All known covariances are used in case of operating mode switching. To avoid extreme corrections directly after switching the operating mode, it is necessary to reduce the weighting of measurements by Kalman Gain in the first updates. A smooth operating mode switching is achieved by continuously linearly increasing the weighting with every measurement update. Particularly the estimations of bias errors have to be corrected carefully after switching, because inappropriate estimations may cause the filter to diverge. Permanent switching of operating mode may lead to suboptimal results. For that reason, it is supervised how often switching was necessary because of GPS outages and because of loss of visual aiding within the last ten seconds. If this number exceeds defined limits, the operating mode will not switch back to a mode that depends on availability of this data for an appropriate time period.

5 Evaluation

This section covers the explanation of a test setup and the results of the test for the navigation filter.

5.1 Test Setup

The performance of the navigation system was tested in simulation using captured real-world data. This way it was possible to test different operating modes on identical sensor data. Data was recorded on the aerial computer of the tilt-wing MAV. The test was realized outdoors with cloudy weather and suboptimal GPS signal reception. A white panel with a dimension of 0.65m x 0.50m was fixed in a distance of 6m to the MAV and was used as a feature point with known position and orientation for computer vision. The MAV was in hovering mode at a fixed position. The initial position,

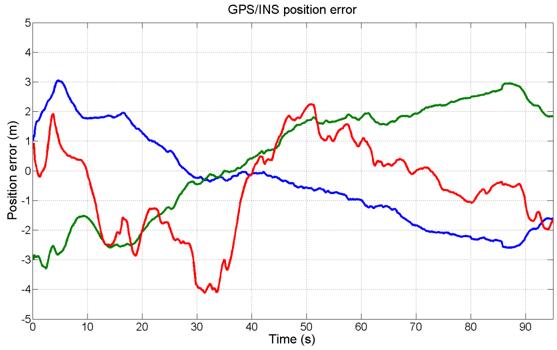

Figure 3: Position error (m) - GPS/INS

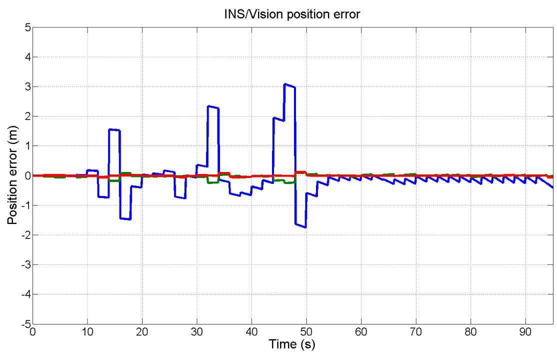

Figure 4: Position error (m) - INS/Vision

Figure 5: Position error (m) - GPS/INS/Vision

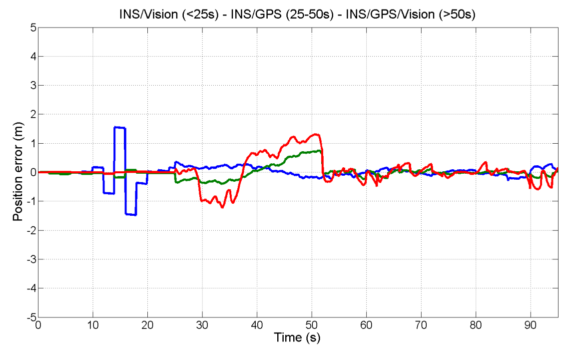

Figure 6: Position error (m) - operating mode switching

attitude and orientation was determined by averaging sensor measurements over a period of several minutes. Four different test cases were simulated: INS with aiding by GPS, INS with aiding by computer vision, INS with aiding by GPS and computer vision and switching between these operating modes

5.2 *Test Results*

First of all, the navigation system performed well in all test scenarios. The system has proven stability and accurate attitude information was available all the time. One important goal of the development of this navigation system aside stability is to improve the position and heading information. Particularly the estimation of the position improved significantly, compared to pure GPS data. In figures 2 to 5, the error in position of the different systems is shown, in which the horizontal position error along the main axis of the MAV is drawn blue, the horizontal position error across the main axis is drawn green and the vertical error is drawn red. Pure satellite navigation is outperformed, considering the error in position achieved by the INS/GPS-system. The maximal error in horizontal position components of less than 3.5 meters (INS/GPS) is satisfying for a MAV in most situations, whereas a maximal error of more then 10 meters in horizontal position (GPS) may be critical. With visual aiding becoming available, the performance drastically improves. If the known feature point is recognized correctly (INS/Vision), the resulting error in position is less than one meter. But the results for the horizontal position component, which is observed by the size of the object, is always less accurate than the other ones. Figure 4 also shows the importance of integrity monitoring particularly if computer vision is the only source of aiding. Some measurements show a significantly bigger error, because object recognition did not perform well. They may cause problems, since they violate the assumption of additive white Gaussian noise. Another disadvantage is the low frequency of measurements, caused by the computational effort of image processing. The combination of aiding by GPS and computer vision shows the most satisfying results as expected. After some seconds the filter needs to converge, the maximal error in the horizontal position components is permanently below one meter. An improvement in the accuracy of heading cannot be observed, because the state was dominated by the measurements of the magnetic field, which has not been disturbed during the experiments. In case of disturbances, navigation, aided by computer vision, may show better results. This has to be investigated in further research. The switching between different operating modes did not cause any problems and did not endanger the stability of the filter. Figure 6 shows the result of switching from the system aided by computer vision (0-25s) to the one aided by GPS (25-50s) and eventually to the combined system (50-95s). All operating modes have been tested in hovering mode. An experimental investigation of the performance in fixed-wing mode and during transition is subject of further research.

6 Conclusion

This works presents an integrated INS/GPS navigation system using ultra-low-cost inertial sensors for MAVs with the ability to hover and/or to switch their flight mode. The system is additionally aided by computer vision including an approach for integrity monitoring of visual data. We have shown by simulation, using captured real-world data, that this system is capable of providing position information that are significantly more accurate than GPS data. Thus, precise maneuvers near obstacles are possible, which would otherwise be impossible or too dangerous. The navigation system including all sensors is small, light, inexpensive and suitable for application in MAVs. A smooth operating mode switching concept is presented that assures stability of the filter and of the possibly inherent unstable vehicle by providing attitude information also in case of GPS loss. Attitude is determined by gravity vectors using a maneuver-detector to assure the integrity of the navigation solution. A magnetometer is embedded to limit the error of heading and to avoid corresponding problems in the filter. The presented navigation system can be applied to different types of MAVs and can be easily extended or adapted depending on available sensors.

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