Visual Odometry Data Fusion for Indoor Localization of an Unmanned Aerial Vehicle

Saptadeep Debnath
Department of Electrical & Electronics Engineering,
BITS Pilani, Dubai Campus,
Dubai-345055, UAE
f2014061@dubai.bits-pilani.ac.in

Jagadish Nayak
Department of Electrical & Electronics Engineering,
BITS Pilani, Dubai Campus,
Dubai-345055, UAE
jagadishnayak@dubai.bits-pilani.ac.in

Abstract—This research aims at design and development of an Unmanned Aerial Vehicle which is spatially aware in an indoor environment devoid of GPS and SLAM algorithms. The sensor readings used for the indoor localization were fused by using an onboard autopilot system called Pixhawk. The presented work aims at enhancing the performances and optimizing the existing state estimation codes to get better results, in an indoor environment.

Keywords—Pixhawk; Quadrotor; UAV; PX4Flow; LIDARLite; Optical Flow

I. INTRODUCTION

In the recent times, there is an increase in the research and development of unmanned aerial vehicles (UAV), especially of type quadcopter, due to high stability (than the tricopter and hexcopter) and high maneuverability in comparison to the fixed wing planes. With an increasing research and study being done on developing UAVs, people have been working on making the UAVs robust in an unknown environment. This includes improving the design of the UAV as well as improving the control aspect of the system. The most widely used technique for stabilizing a UAV in an unknown indoor environment and is done via optical flow.

There has been an exponential growth in the research and development of quadcopters. Zingg et al. [1] have reported the designing of Unmanned Aerial Vehicle of the type quadrotor, and designing a PD control for the autonomous navigation in an indoor environment. This work done in Autonomous Systems Lab, ETH Zurich, Switzerland, in the year 2010, paves the way for the use of optical flow data to be used for various purposes. Using optical flow algorithm, and with a help of a fisheye lens camera, the team was able to detect obstacles and avoid it, while flying it through an indoor corridor. The inertial and measurement unit (IMU) data was used to compensate for the rotational effect caused by the movement of the UAV.

An optical flow sensor was also reported [2] that was designed to meet the needs of indoor micro aerial vehicles (MAVs). The sensor offers real-time, multi-directional optical flow data in a miniature package suitable for MAVs, demonstrating high degree of accuracy in real indoor environments. A new vision-based obstacle avoidance technique for indoor navigation of Micro Aerial Vehicles has been presented in another research paper [3]. The Depth Map

of the surrounding environment has been constructed using only visual and inertial measurement, with the help of absolutescaled Optical Flow. Based on the map a safe navigation control has been proposed, which able to avoid lateral obstacles.

A research [4] carried out by Pastor –Moreno et al., in the year 2011, has presented a new framework that utilizes an optical flow camera and an IMU as a main source of information. The results showed that it is possible to navigate only with optical flow and the necessity of the localization module to recover from camera failures. The recovery is limited to previously visited places and it recovers the past optical flow position at the specific bag of words match, therefore, the error for long-term navigation is bounded with the inter-image distance.

A simple method for rich and high frequency vehicle state estimation fusing low-cost inertial and smart optical flow measurement units for a MAV was reported by Santamaria -Navarro et al. [5]. A large amount of variants for nonlinear KF have been benchmarked, revealing that, for such a basic setup, with high input data rates, the plain EKF filter performs equivalently to other, more sophisticated options. Li et al., in 2016 presented the autonomous control of a fully customized quadrotor MAV in GPS-denied environments based on onboard visual odometry. They achieved the best integration and efficiency of the MAV hardware system by optimizing the mechanical frame, propulsion system, flight controller, visual sensor and also developed the optical-flow module with the low-cost and small-scaled visual sensor as well as height estimation. They also did autonomous path tracking from the fusion of corresponding sensing feedback with proper design of a Kalman Filter. In a recent paper by Liu et al., 2016, motion estimation was studied using optical flow sensors and rate gyros. They after establishing the measurement equations using an Unscented Kalman Filter (UKF), estimated the flight states of the MAV [7]. In another similar research by McGuire et al., 2016 the stereo-based distance estimates are used to scale the optical flow in order to retrieve the drone's velocity at the same time this method allowed the MAV to control its velocity and avoid obstacles [8]. The challenges of the present day arise from less accuracy and noisy data of the MicroElectroMechanical System (MEMS) technology, which is the basis of modern, miniaturized inertial sensors [9]. So they proposed in 2015 a unique complementary filter for MAVs that fuses together gyroscope data with accelerometer and magnetic field readings.

The correction part of the filter is based on the method described above and works for both IMU (Inertial Measurement Unit) and MARG (Magnetic, Angular Rate, and Gravity) sensors. Tsai et al., 2016 studied and prepared a design for indoor hovering that is more precise than using GPS positioning is design is safer, cheaper, and easier for users to control the MAV flight [10].

This research is aimed at developing a quadcopter type UAV, spatially aware in an unknown GPS-denied indoor environment. The existing algorithms used for estimating the state of the system in an unknown environment are studied and implemented on the research platform. This research is carried out in two folds. First, is the initial testing and calibration being performed on the sensors. Second, enhancing and optimizing the performance of the used estimator. Thus the steps included performance enhancement and optimization of the used algorithms. PX4Flow Camera will be used with LIDARLite to increase its potential, and thus get better results.

II. METHODOLOGY

A. System Setup

The vehicle used as the research platform is a multirotor of the type quadcopter, fully customized vehicle, built upon on a UFO frame. This frame limits the propellers with a certain range and to obstruct anything coming towards the propellers, thus increasing the safety of bystanders. The propulsion and lift system of the vehicle include four motors, propellers and ESCs. The motors used are 120 W 2150KV brushless DC out runner motors in combination with 12A ESCs. A 6-inch length and 3-inch pitch (0630), two blade propellers, made the quadcopter more durable and stable. The vehicle is powered by an 11.1V Lithium Polymer battery, having a capacity of 5000 mAh at a discharge rate of 25C. This configuration (Fig. 1A) provides a flight time of about 10 minutes.

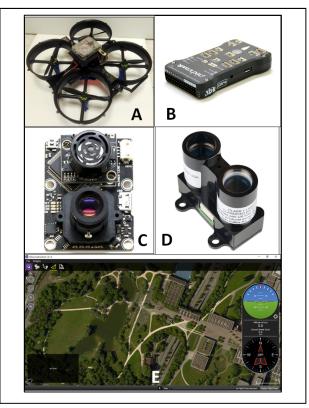
• Pixhawk

The task of controlling unmanned quadcopters is rather complicated in the presence of parametric uncertainties and measurement noises. It is essential that the flight control system of an unmanned quadcopter should be endowed with well-suited automatic capabilities to carry out complex flight missions. Our vehicle uses an off the shelf flight controller, the Pixhawk flight controller an open-source hardware project by 3D Robotics uses a wide sensor suite to achieve the desired attitude and altitude. The Pixhawk (Fig. 1B) uses 2 level PID controller to control the motor speeds to achieve the desired attitude (the roll, pitch and yaw) and altitude, and removes the hassle of dealing with the dynamic nonlinear complexities of the quadrotor system allowing us to focus on the autonomy of the quadrotor itself.

a. Guidance Navigation and Control

OGroundControl

QGround Control is an operator control unit / ground control software (Fig. 1C) for micro air vehicles. It allows instant visualization and control of micro air vehicles during development and operation, both indoors and outdoors. With



flexible software architecture, it supports multiple MAV types/autopilot projects. QGC runs on Windows, OS X, Linux, iOS and Android tablets.

Fig. 1. System set up and sensor modules of the quadcopter. A. Quadcopter platform for research; B. Pixhawk Autopilot; C. LIDARLite Range finder; D. PX4Flow Camera; E. QGroundControl user interface on Window 10.

b. Sensor Modules

PX4Flow Camera

The PX4FLOW Optical flow sensor (Fig. 1D) is an open-source instrument which helps to hover a UAV in an indoor environment. The flow estimation is based on SAD block matching. The position of the minimum SAD block value out of the 81 candidates is taken as the flow value at the corresponding sample point. 64 sample points is processed per frame. A subsequent histogram filter takes into account every sample point and chooses the histogram bin with the highest value. As the processing is being done on histograms, the lamination of the environment doesn't make much difference in the readings. In addition to this the board is capable of computing with 120Hz speed in dimmer environment without the need of LED lamination. This property along with its ability to be reprogrammed made it an essential choice.

The sensor on the board is attached in such a way that the camera faces downwards, which helps in calculating the optical flow and determines aircraft ground velocity.

• LIDARLite Rangefinder

Pulsed Light provides one of its kind, low-cost optical distance measurement solution, the LIDARLite Rangefinder (Fig. 1E). It is a compact 48mm x 40mm x 20mm module with a 40m measuring range. This LiDAR allows the UAV to calculate the optical distance thus providing the distance from the ground at any point in time. The laser has a range of 0-40m, and provides an accuracy of +/- 2.5cm at distances greater than 1m. The low power consumption (<140mA) is also an added to increase our flight time. The newer version of this 1-D module, which is used for this project, has, new signal processing improvements, which offer 5X faster measurement speed. The communication protocol for LIDARLite is I2C, with assignable I2C addressing.

B. Estimators

a. Introduction to Estimators

• Kalman Filter

A Kalman filter is an optimal (linear) estimator or optimal recursive data processing algorithm. Kalman filters are ideal for systems, which are continuously changing. They have the advantage that they are light on memory (they do not need to keep any history other than the previous state), and they are very fast, making them well suited for real time problems and embedded systems. You can use a Kalman filter in any place where you have uncertain information about some dynamic system, and you can make an educated guess about what the system is going to do next. Even if messy reality comes along and interferes with the clean motion you guessed about, the Kalman filter will often do a very good job of figuring out what actually happened. Computations done in this type of filter belongs to the state space model (time domain) compared to frequency domain. Some major components include: system's dynamics model, control inputs, and recursive measurements (include noise).

A typical Kalman filter block diagram looks as is shown in Fig. 2A. The control values are fed into the system, which is vulnerable to the error sources, which in turn produces the system states. The states thus produced from the system are desired but not known, for which the measurement devices are connected to measure the states. The observed measurements are sent to the Kalan Filter, which in turn tries to minimize the error and optimize the output and gives it as an estimate of the system. The Kalman filter also has a memory, which helps it estimate the output state. This estimate is in-turn fed into the system via the controls.

estimation
$$\hat{X}_k = K_k \cdot Z_k + (1 - K_k) \cdot \hat{X}_{k-1}$$

$$\text{Kalman Gain}$$

$$\text{Estimate error covariance}$$

$$K_k = P_k^- H^T (H P_k^- H^T + R)^{-1}$$

$$= \frac{P_k^- H^T}{H P_k^- H^T + R} \qquad \text{measurement error covariance}$$

$$(2)$$

A typical Kalman Filter estimator works to bring the output value as close to the desired value over certain duration of time. An example of such an estimator can be seen in the Fig. 2B.

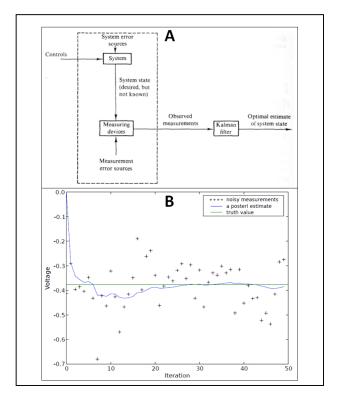


Fig. 2. Estimators: A. Kalman Filter block diagram; B. Kalman filter result.

• Extended Kalman Filter (EKF)

In simple cases, such as the linear dynamical system just, exact inference is tractable; however, in general, exact inference is infeasible, and approximate methods must be used, such as the extended Kalman filter. Unlike its linear

counterpart, the extended Kalman filter in general is not an optimal estimator, non-linear in nature as well.

$$x_k = f(x_{k-1}, u_k, w_{k-1})$$
 (3)

To summarize, if all noise is Gaussian, the Kalman filter minimizes the mean square error of the estimated parameters. It is convenient for online real time processing, as the processing needed for this type of method is much less. Kalman Filter in general is much easy to formulate and implement given a basic understanding. To enable the convergence in fewer steps, just a few steps need to be kept in mind; modelling the system more elegantly and estimating the noise more precisely.

b. Estimators on QGroundControl

The main reason behind choosing the QGroundControl as the primary control unit on the ground station is the availability of state estimators available in its firmware. The estimators available in this software are Q attitude estimator, INAV position estimator, LPE position estimator, EKF2 attitude, position and wind states estimator.

- Q attitude estimator The attitude Q estimator is a very simple, quaternion based complementary filter for attitude. The quaternion is a number system which extends from the complex numbers. It is mostly applied in mechanics for a three dimensional system, which is apt for the system in question.
- INAV position estimator The INAV position estimator is a complementary filter for 3D position and velocity states.
- LPE position estimator The LPE position estimator is an extended Kalman filter for 3D position and velocity states
- EKF2 attitude, position and wind states estimator -EKF2 is an extended Kalman filter estimating attitude, 3D position / velocity and wind states.

The difference between LPE and EKF2 lies in its usage. LPE is generally used for a generally sterile environment, i.e. denied of wind, etc. Whereas EKF2 estimator can also be used in extreme windy conditions. As can be seen from the descriptions of the different attitude estimators, most of them depend on the general Extended Kalman Filter. For this research a combination of Q attitude estimator and LPE position estimator is used in combination.

A. Initial Testing and Calibration

A set of tests are carried out to ensure that the sensors are properly calibrated. The calibration result is also verified by running dry tests.

LIDARLite Rangefinder

The LIDARLite Rangefinder was tested on an Arduino Uno board before connecting it to the Pixhawk board. The connection was done through the PWM ports on the Arduino Board according to the Fig. 3A.

The quadcopter fitted with the sensor facing downwards was lifted about 90 cm and the following results were obtained (Fig. 3B).

• PX4Flow Camera

The PX4Flow Camera was calibrated using the QGroundControl software. The camera was focused on the height of flight, which is chosen to be 1.5 m.

B. LPE Parameters

On the ground control software, certain LPE parameters are changed from their default values. These values include the LIDAR_Z_OFFSET and the LPE_FUSION.

• LPE LDR OFF Z (FLOAT)

This parameter defines the z-offset of the Lidar Rangefinder. Lidar is placed at a height of 11 cm above the ground, therefore the LPE_LDR_OFF_Z so the default ('0') value is changed to 0.11 (i.e. 11 cm from the ground).

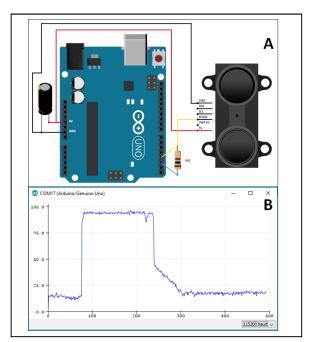


Fig. 3. Initial testing and calibration of the quadcopter. A. Connection Diagram for LIDARLite to Arduino Uno; B. testing results on LIDARLite

• LPE FUSION (INT32)

The LPE_FUSION is the most distinct parameter in the Local Point Estimator framework. It is an 8-bit binary value which defines how the different sensors work collectively. An Integer bitmask controlling data fusion. Bitmask used is as shown in Table 1 and Table 2.

TABLE I. LPE _FUSION INTEGER BIT MASK

Bit	Data
0	Fuse GPS, requires GPS for alt.init
1	Fuse optical flow
2	Fuse vision position
3	Fuse vision yaw
4	Fuse land detector
5	pub agl as lpos down
6	Flow gyro compensation
7	Fuse baro

TABLE II. LPE_FUSION CHOSEN BIT VALUES

Bit	Value	Reason
0	0	Since vehicle is being operated in a GPS –denied indoor
		environment, GPS is not used on the vehicle
1	1	The PX4 Flow sensor is an optical flow sensor which is
		included in the vehicle
2	0	These values are used when a downward facing vision
3	0	system is implemented for state estimation and
		localization
4	1	The land detector when enabled publishes a data when the
		system has landed.
5	1	Publishes the local position downward
6	1	The optical flow gyro is compensated within the PX4Flow
		board
7	1	The barometer /sonar reading from the PX4Flow are also
		fused into the Lidar reading to achieve higher accuracy on
		the height readings

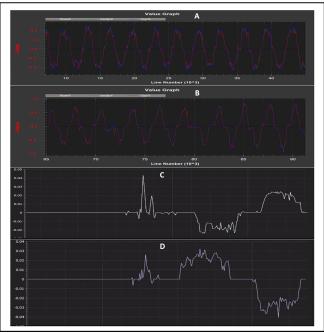


Fig. 4. Performance of the proposed estimation method; A. X –axis result; B. Y-axis result C. Optical flow X axis result; D. optical flow Y-axis result.

III. RESULTS AND DISCUSSION

In this section, we evaluate the performances of the proposed estimation method and the parameters involved with the same. At first the vehicle is being held and moved along a square path, whereas in the second part of the testing the quad in flown in two flight modes namely Stabilized Mode and Position Hold Mode.

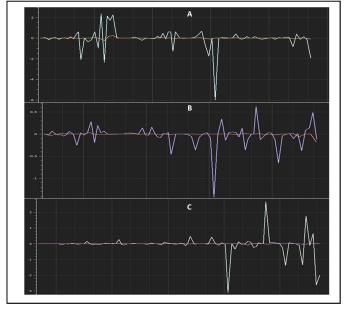


Fig. 5. Performance of the proposed estimation method; Comparative gyro results in, A. Y-axis, B. X-axis, C. Z-axis

As the primary trial of a series of tests, the vehicle is held and moved along a square path. The results as shown in the Fig.3 reveal that the errors between the gyro readings and the optical flow readings are minuscule. This initial testing proved that the results that will be achieved later on when the UAV will be flown will be accurate. The graphs have a steady rise and fall due to the fact that the motors are not turned on during this phase of testing, and the vibrations thus created during the flight due to the propulsion systems are thus negated in this process.

During the second phase of trials the UAV is flown and two sets of readings are taken:

- Optical Flow x and y values
- IMU Gyro and Optical Flow Gyro (x, y and z)

The UAV is flown in stabilized mode to achieve the following results. As can be seen from the graphs obtained, the value keeps on fluctuating when it reaches the set-point. The reason for this condition as discussed previously is because of the vibrations caused during the flight and the external forces that act in this system, having a dynamic nature. The Inertial Measurement Unit (IMU) of a quadcopter consists of basically three types of attitude sensors, Gyroscope, Magnetometer and Compass. The IMU of a UAV is the basic attitude sensor responsible for its motion. The next set of results was obtained by comparing the IMU gyroscope readings with the optical flow gyroscope readings, which gave a very distinct set of outcomes.

It was observed that as the IMU of the UAV as described above is prone to vibrations in the vehicle, on contrary to that, the gyroscope reading of the optical flow sensor wasn't so. The IMU gyroscope readings showed a huge amount of peaks and troughs, these were actually noises that were being generated as the IMU is prone to the vibrations in the system. But in contrast to that the readings acquired from the optical flow gyroscope had minimal (or no) noise.

IV. CONCLUSIONS

In this paper we have explored the idea of designing and developing a UAV in a GPS denied indoor environment. A mutirotar of the type quadcopter was built on a UFO frame. Algorithms used for estimation were of the type Kalman Filter and Extended Kalman Filter, the research platform and the sensor suite installed on the UAV. We hoped to fabricate the UAV after the sensor modules were calibrated and initial testing was done on it before installing it on the UAV. The initial tests included, getting the correct height readings from the LIDARLite Rangefinder and calibrating the PX4Flow Camera according to the height of the flight, which is chosen to be 1.5m. The subsequent section dealt with installing the sensor suite on the UAV and gets the initial results from the PX4Flow Camera.

The latter half of the study dealt with the results obtained from the tests performed using the parameters as discussed. The results achieved from the tests are then analyzed accordingly and conclusions are drawn from them. A major conclusion which was observed from the tests was, though the vibration caused due to the propulsion system increases the noise in the

readings from the IMU of the UAV, but rather doesn't seem to affect the gyroscope readings from the optical flow sensor.

Acknowledgment

The authors would also like to express his heartfelt gratitude to the Director of BITS Pilani, Dubai Campus, who has always motivated him, provided them facility to perform this work and helped in keeping their spirits high. The authors would also like to thank Dr. Abdul Razzak Instructor-in-Charge of Design Projects, for his time and support for the project.

References

- S. Zingg, D. Scaramuzza, S. Weiss, and R. Siegwart, "MAV navigation through indoor corridors using optical flow," in Proc. IEEE Int. Conf. Robot. Autom. (ICRA), May 2010, pp. 3361–3368.
- [2] D. Watman and H. Murayama, "Design of a miniature, multidirectional optical flow sensor for micro aerial vehicles," in Robotics and Automation (ICRA), 2011 IEEE International Conference on. IEEE, 2011, pp. 2986– 2991
- [3] V. Lippiello, G. Loianno, and B. Siciliano, "MAV indoor navigation based on a closed-form solution for absolute scale velocity estimation using optical flow and inertial data," in IEEE Int. Conf. on Decision and Control/European Control Conf., pp. 3566–3571, December 2011.
- [4] D. Pastor-Moreno, H. S. Shin and A. Waldock, "Optical flow localisation and appearance mapping (OFLAAM) for long-term navigation," 2015

- International Conference on Unmanned Aircraft Systems (ICUAS), Denver, CO, 2015, pp. 980-988.
- [5] A. Santamaria-Navarro, J Sola, and J. Andrade-Cetto, High-frequency MAV state estimation using low-cost inertial and optical flow measurement units." in Intelligent Robots and Systems (IROS), 2015 IEEE/RSJ International Conference. 2015, pp. 1864-1871
- [6] K. Li, K. Zhang, and B. M. Chen. "On-board visual odometry and autonomous control of a quadrotor micro aerial vehicle." 12th IEEE International Conference on Control & Automation (ICCA) Kathmandu, Nepal, June 1-3, 2016, pp. 68-73
- [7] X.Liu, Xiaoming, Z. Chen and W. Chen, and X. Xing "Motion estimation using optical flow sensors and rate gyros." IEEE International Conference on Mechatronics and Automation, 2016 DOI: 10.1109/ICMA.2016.7558821
- [8] K. McGuire, G. de Croon, C. De Wagter, K. Tuyls, and H. Kappen, "Efficient Optical flow and Stereo Vision for Velocity Estimation and Obstacle Avoidance on an Autonomous Pocket Drone." arXiv preprint arXiv:1612.06702, 2016.
- [9] R. G. Valenti, G. Roberto, I. Dryanovski, and J. Xiao, "Keeping a good attitude: A quaternion-based orientation filter for IMUs and MARGs." Sensors (2015), 15:19302-19330
- [10] E. Tsai and S. H. Zhuang, "Optical flow sensor integrated navigation system for quadrotor in GPS-denied environment," 2016 International Conference on Robotics and Automation Engineering (ICRAE), Jeju, 2016, pp. 87-91.