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Analysis of sensor data and estimation output with configurable UAV platforms

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Abstract— This paper presents a methodology to assess the performance of sensor fusion in UAVs based on PixHawk flight controller and peripherals to create ad-hoc unmanned vehicles and his adequacy to create different projects based on his architecture. The selected platform is described with stress on available sensors and data processing software, and the experimental methodology is proposed to characterize sensor data fusion output.

Keywords— UAVs sensor fusion, IMU, GPS, Real Data Analysis

I. INTRODUCTION

Unmanned aerial systems (UAS) have evolved recently thanks to development of technologies in navigation, sensing and obstacle avoidance (“Sense&Avoid”). The research has focused in getting higher degree of autonomy thanks to enhanced navigation, and also in robust methods to protect missions against intended attacks, mainly interference (jamming) and supplant (spoofing) of GNSS signal.

The main navigation problem focuses on improving GPS with the ability to provide accurate navigation output when GPS data is unavailable due to unexpected outages or intentional problems (jamming or spoofing) in certain environments. Therefore, an approach based on the fusion of complementary sensors is essential, resorting to the fundamental equations of navigation and characterization of the errors committed by each Source. This area has become popular due to the ubiquity of GPS and the availability of inexpensive micro electromechanical (MEMS) inertial sensors [1], [2], [3]. The integration of these complementary technologies will allow compact and robust navigation solutions to determine orientation and location, so that the vehicle can determine its state in a robust way and use appropriate control techniques for autonomy. Other more drastic options for non-dependence on the GPS signal involve the deployment of autonomous localization systems such as the recognition of the environment by artificial vision [4] or location by means of electromagnetic beacons [5], with the associated cost of developing a complementary infrastructure.

In a complementary way to the navigation methods, the use of the radar in combination with other sensors (video, laser, sonar), allows to extend the navigation conditions and the evasion of obstacles. In the air vehicles (UAVs), the integration requirements (consume, weight, dimensions) are much more restrictive, even so, it is a line in continuous development [6],[7],[8].

Regarding spoofing protection, there is also a noticeable research activity. These techniques include diverse strategies from simple actions such as monitor the communication channel, to cryptographic authentication, discrimination based on the level of signal, time of arrival, multi-antenna systems, wave polarization, Doppler shift and arrival angle, etc., as described in [9],[10].

Therefore, the research of robust and general techniques of integrating complementary data sources has become essential for this type of systems. In addition to theoretical developments, it is of vital importance the availability of equipment and experimental environments to validate the robustness of the solutions in real conditions. This paper presents the selected environment and a selection of available data sources and effects of data processing techniques on the quality of the navigation solution. The main contribution of this paper is the briefing of the methodology that we have use for our experimentation, and the further systematic analysis of acquired real data. Section II introduces the selected working platform, detailing the architecture of its software and the vehicles we have made to test its capacities and collect data. Section III explains experimental methodology, the data characterization and the analysis of the PixHawk and Px4 system filter and fusion algorithms. Section IV contains the conclusions.

II. THE PIXHAWK AND PX4 UAV SYSTEM

A. Architecture

Every unmanned vehicle that may be able to control its own attitude and position using automatic control algorithms, are always controlled by a computer that integrates data from some electro-mechanical sensors and any local or global positioning system, and applies any output control system to change its location using any locomotion system. This controller is usually an embedded microcontroller that performs the core of all vehicle components.

This research is based in the study of the PixHawk flight controller performance. An open-hardware computer designed by 3D Robotics specifically to create autopilot vehicles, that arises from the combination of PX4FMU and PX4IO boards. Both cards, from their version v2, are integrated in the same PCB (Printed Circuit Board) giving origin to PixHawk.

B. Sensors and data sources

The PixHawk board has several sensors integrated, shown in Table I, which serve as data sources to the PX4 stack.

TABLE I
SENSORS INTEGRATED IN THE PIXHAWK BOARD

Sensor	Type	Axes	Scale	ADC accuracy	Data rate
L3GD20H	gyroscope	3	2000 dps	16 bits	760 Hz
LSM303D	accelerometer / magnetometer	6	± 16g / ± 12gauss	16 bits	1600 Hz / 100 Hz
MPU-6000[1]	accelerometer / gyroscope	6	± 16g / 2000 dps	16 bits	1000 Hz / 8000 Hz
MS5611	barometer	1	1200 mbar	24 bits	1000 Hz

[1]MPU-6000 includes a Digital Motion Processing (DMP) with programable LPFs

C. Connectivity and external sensors

Besides, PixHawk counts with high connectivity for external devices and peripherals that may increase the vehicle capabilities. By one side, there are some specific connectors for certain peripherals, such as: 2 connectors for telemetry communication, 1 for GPS, and 1 Spektrum receiver socket. By other side, there are some general purpose ports and buses like: 2 UART ports, 2 SPI, 1 I2C connector, 1 USB connector, 1 CAN bus connector and 3.3V and 6.6V ADC connectors.

The standard configuration of a PixHawk UAV counts with some external sensors that we have specified into the next table:

TABLE II
ADDITIONAL SENSORS WIRED TO THE PIXHAWK

Sensor	Type	Interface	range	accuracy	Data rate
Ublox Neo 6M	GPS	GPS port	x	2 5m	<3s
HMC5883[1]	Magnetometer	I2C	± 16G	±12MG	1600 Hz
Flow Sensor shield	Optical flow/ gyroscope	I2C	x	<0.5m	250Hz
Range finder	Ultrasonic sonar	I2C	0-6m	0.5cm	1000 Hz
Lidar lite	Pointer lidar	I2C	0-40m	±2.5cm	1-500Hz

[1] The GPS sensor and the HMC magnetometer are integrated in the same external shield.

These sensors allow enhancing navigation capabilities and increase the accuracy of the stabilization system measurements, what is quite important when we want to create an unmanned vehicle, because allows a more faithful image of the flying environment.

The following diagram shows the main configuration of sensors used in our researching vehicles:

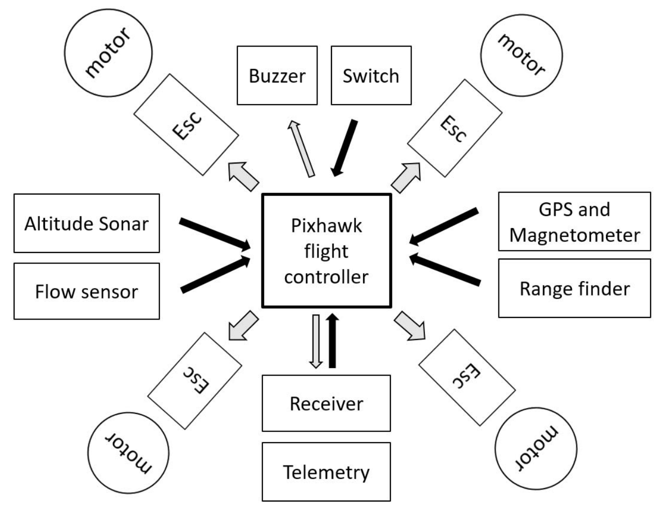

Figure 1: UAV components schema

D. Software for Flight Control and Data Processing

PX4 is the control software of PixHawk. It is an operating system based on NuttX and consists of two main layers: PX4 Flight Stack and PX4 Middleware.

PX4 Flight Stack is the complete collection of applications embedded in PixHawk hardware for drone control, while PX4 Middleware is the interface that allows the flow of data from sensors to applications through a publish/subscribe system called uORB. uORB allows to publish the data coming from the sensors and make them available to the applications of the Flight Stack, obtaining a reactive system and totally parallelized. The outstanding modules are flight controller and sensor data processing [12].

Regarding the data processing, Px4 implements a navigation system called AHRS that implements different algorithms to estimate the local and global position, the vehicle attitude and creates a direction vector that allows the unmanned displacement. In this section we will explain the main real time data transformation algorithms that runs into the vehicle during the flights.

a) Direction Cosine Matrix (DCM)

This program allows the analysis of the triaxial linear accelerometers and gyroscopes to obtain a Direction Cosine Matrix. Making possible the conversion of the real time measurements into instant orientation parameters of the vehicle like Roll, Pitch and Yaw angles or variations:

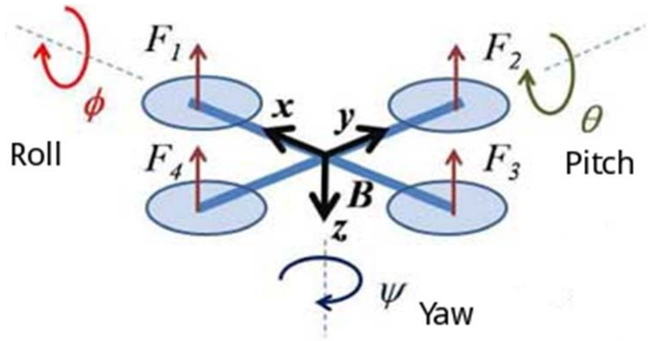

Figure 2DCM inertial measurement conversion

b) Inertial Navigation System (INS)

This algorithm calculates the trajectories and corrections that allows the vehicle to move between single points using the DCM data. It is used to estimate the vehicle attitude with high frequency, so it is especially useful to complement the global position obtained from the GPS data.

c) Extended Kalman Filter (EKF)

It is important to take into account that all measurements are affected by noise that can reduce the efficiency of the attitude estimation based in DCM matrix. To reduce the effect of this noise, the Px4 system counts with an Extended Kalman Filter algorithm that process all sensor data in a compensation function that depends of the specific noise and accuracy characterization of each sensor, throwing high accuracy estimations of the vehicle attitude. The Px4 application counts with the possibility of applying different EKF solutions running in parallel, using different sensor measurements and states. With this implementation, it is possible to increase the accuracy and the consistence of the attitude estimation even if the vehicle loss the GPS signal in a few time interval. Next table shows the three different EKF modes:

TABLE II
PX4 EXTENDED KALMAN FILTERS

Name	Specification
EKF1	Only use the DCM for attitude control and the Inertial nav for ahrs reckoning for position control
EKF2	Use the GPS for 3D velocity and position. The GPS altitude could be used if barometer data is very noisy.
EKF3	If there is no GPS, it can use optical flow to estimate 3D velocity and position.

AHRS is able to select the best EKF mode for each situation and execute both EKF1 and EKF2 in parallel if there is necessary

III. EXPERIMENTAL METHODOLOGY

A. Data acquisition

The process of data acquisition it's being supported by several flight test missions that have taken place on the circuit specified on the Figure 3:

Figure 3: Test circuit diagram

For each mission, we have applied different configuration parameters in order to analyze the performance differences between each setting up. The flight controller was always logging data which was saved together with the configuration settings to be analyzed in the results presented later.

TABLE III
TEST PERFORMED OVER THE SAME CIRCUIT

Name	Specification
Static test without propellers[1]	Accelerometers and gyroscopes, noise
Static test on idle	Accelerometers and gyroscopes, noise
Unmanned flight test	GPS, inertial navigation system
Unmanned hold test	GPS, Flow Sensor, DCM
Manual flight test	PID and configuration parameters

[1]The static test have been performed on the floor to avoid displacements and vibrations that could disturb the readings.

B. Data characterization

Before exploiting sensor data for navigation enhancement, it is important to know the behaviour, limitations and main characteristics of the data we are working with, to establish a measure of the confidence and the consistence of the data. This properties became determined by the sensor and the measurement algorithm. The logged data can be useful to debug the estimation algorithms and the flight performance but, in this work we will only pay attention to those data that could explain the local position estimations, the navigation system performance or the filter capabilities. Table IV shows the data analysis for the main data sources available[11].

TABLE IV
DATA CHARACTERIZATION

Sensor	Source	range	Accuracy	Data rate
Raw X,Y,Z accelerometer[1]	L3GD20H MPU-6000	[-32768, +32767] DoT[2]	± 7 DoT[2]	8000Hz
Raw X Y Z gyroscope	L3GD20H MPU-6000	[±2000] deg/s	± 3deg/s	8000Hz
Roll, Pitch, Yaw	DCM over Accel/Gyro	[0,180]	± 0.05deg	1600Hz
Heading	DCM over magnetometer	[0,360]	± 1.5deg	1000 Hz
Atm. Pressure	MS5611	[10,1200]HPa	± 1.2Hpa	1000Hz
Sonar Floor		[0,6]m	± 0.02m	
Estimated local position terms	INS	Different[2]		1000Hz
Estimated speed	Optical flow sensor	[0,16]m/s	± 3.5m/S	760 Hz
SpeedN/E	GPS	[0, 999 mph	5%	<3s
Global position[3]	GPS	Lat[-90,90] Lon[-180,180]	3m	<3s

[1]Note that these raw data are not filtered data and always have a lot of noise
[2]There are a lot of variables fpr X,Y,Z axes, velocities and planes, each one has different scales and ranges.
[3]The main problem with this data is the data rate. The INS works to increase the precision of the attitude and global position between GPS refresh.

C. Data analysis

1) Data filtering evaluation

The main problem that we have to solve when using this low-cost MEMS is be able to discriminate between the sensor errors and the environment noise. Px4 implements some complementary filters that decrease the error of the estimation despite this situation:

a) Low Pass Filter (LPF)

A direct and effective way to eliminate the noise of the system is applying a low pass filter that gets only those data with an oscillation frequency that underneath the cutoff barrier and discard all data with a higher frequency. This approach works based in the principle that the vehicle movements that we wish to register, never surpass a certain speed, and those that overtake it can be directly considered as environment noise and vibrations.

Use this complementary filters may be do not increase the accuracy of the estimation but it helps to improve the efficiency of the system by reducing the amount data that the other algorithms like the EKF and the INS would have to deal.

Due to this relevance, during the configuration and calibrating process of our vehicles, we have performed an analysis of the max motor vibration frequency and those perturbations that travel through the frame of the multicopter up to the flight controller sensors. After this analysis we have tested the performance with different cutoff values to optimize the adjustment of the Low Pass Filter and ensure not to acquire useless data.

The following image shows the band of dominant frequencies collected by the gyroscope sensor during an real flight. At lower frequencies we can observe the vehicle intentioned movements with frequencies that oscillate between [0-2]Hz, then with values that reach 90Hz are the movements produced by the fast speed corrections that are made on each motor to maintain the stability of the vehicle. The higher values than this frequency performs the vibration noise, introduced by the small unbalances of the motors, the propeller turbulence shocking with the chassis and a phenomenon of resonance between propellers denominated propwash.

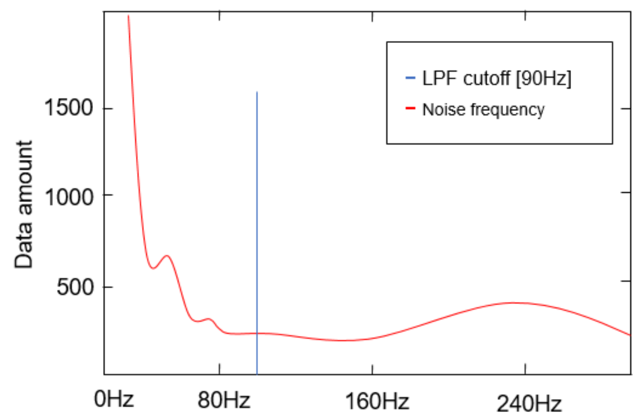

Figure 4: Gyroscope data frequency analysis (y-axis is amount of data)

b) EKF data performance:

To reduce the effect of the environment noise, the Px4 system counts with some Extended Kalman Filter algorithm that process all readed data using estimation states that increases the precision of the data thanks to the application of specific corrections on each measure based in known characteristic error of the sensors.

The following figure shows the UAV data acquired during a vertical descent test and illustrates the behavior of the output values of the EKF2 implementation implemented in the PX4 System. It is a simulation applied on real data of a vertical descent.. The green curve shows the raw altitude data based in the embedded barometer sensor, and the red one the estimated measurement after apply the second Extended Kalman Filter of the Px4:

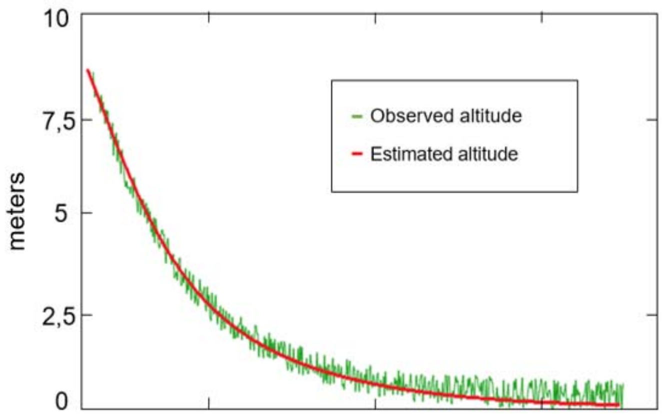

Figure 5: EKF noise filtering

Note that the deviations are greater as the rate of the landing decreases, This is consequence of the action of the corrections that the flight controller makes when it deal with lateral wind gusts or little unbalances when the vehicle is close to the ground. Despite this, the output filtered altitude value is smooth and does not present any noise, so it can be used safely to know the local position of the vehicle and even perform automatic landing maneuvers without GPS positioning, something useful in jamming situations. As we can see, the result of applying this filters to the raw data is very efficient. The results are quite consistent, giving high confidence stabilization to the final system even though the noise conditions are very variable depending of the environment conditions.

2) Raw vs Estimated altitude values:

The height value can be recovered from multiple sensors, like the barometer, the GPS and the range finders. The figure 6 is a plot based on real logged data from out flights. It shows the estimated value from the UAV altitude starting from the data given by the GPS and the barometer. Notice that, the GPS value describes a discrete scale with high precision but low resolution and a large latency. On the other side, the barometer measurement allows high resolution data but it has much more noise and a calibration error.

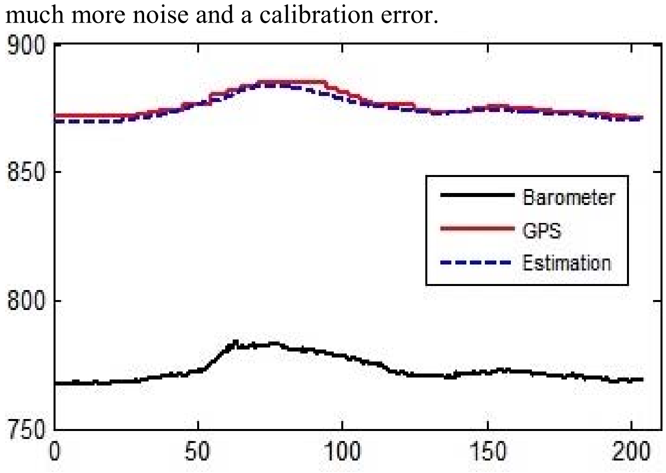

Figure 6: Altitude result after de data fusion

Our flight field is situated at 960 meters' height, that is why the barometer has a derivation, due to a bad calibration with regard the typical atmospheric pressure. However, the system y capable of ignoring this error and only use the variations for the estimation. The result of the fusion process throws an estimated value with the accuracy benefits of both measurements, allowing a consistent altitude.

This measurement does not use data from the range finders because these presents some significant problems such as the short range of lectures or the errors introduced when the vehicle changes its angle to make any displacement. That is why the height calculation is made only using the data from the barometer and the GPS, and the measurement of the ground sensors is used only in landing and takeoff procedures.

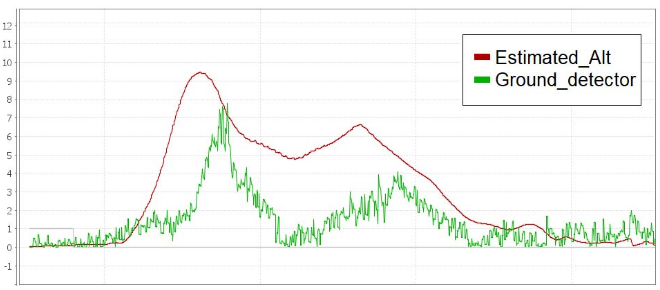

Figure 7: Estimated altitude and range finder data comparison

3) GPS and INS local position integration:

One of the most interesting works performed by the data fusion process of the Pixhawk is the attitude estimation using accelerometers and GPS data (EKF2), the figure 8 shows the result of the position estimation on the planes X and Y Using the integrated speed respect to the North and East coordinates. We can see how the attitude changes in a superposition of the X and Y projections, especially on the last values. It is possible to explain the position estimation changes with the value of the :X and :Y plane of the Inertial Navigation System input, but always near to the global position data.

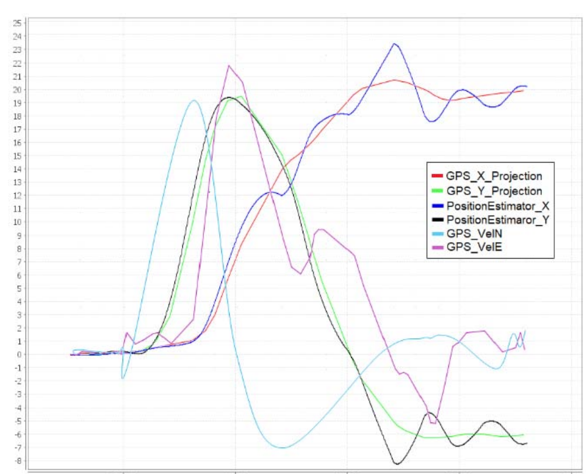

Figure 8:Attitude estimation though GPS and INS data fusion

On the other hand, the INS is able to obtain the same local position using an integration data from accelerometer and gyroscope into X and Y planes velocity, like it is able to see on The Figure9 that it's showing a shorter time interval of the same database, allowing to see how affects the velocity variations to the local position estimation of the vehicle.

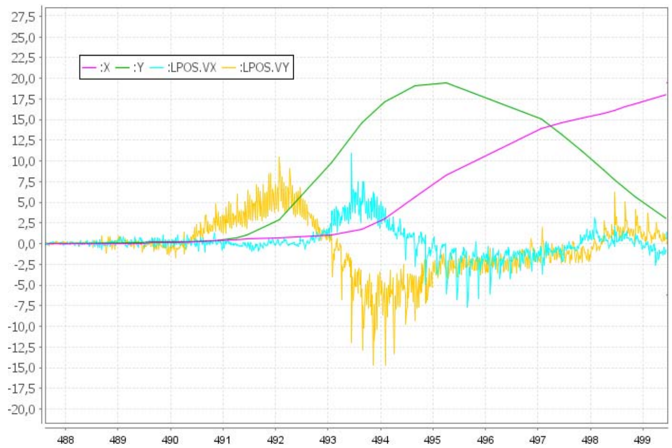

Figure 9:Attitude estimation though INS velocity integration

IV. Conclusions

This paper presented a platform (Pixhawk PX4) and methodology to experiment with real data for UAV navigation. Based on data analysis and characterization the algorithms can take advantage of available sources. The three processing algorithms, DCM, LPF and EKF, can be configured to exploit the data in the appropriate way considering the output of the analysis.

The analysis of real data in a systematic way will allow successive improvements and parametrization, considering, among others, the following aspects:

- Data filtering to reduce perturbations and remove outliers
- Quality analysis to weight data uncertainty
- Analysis of biases and calibration previous to fusion
- Parameter adjustment to optimize performance (PID gains, filter parameters, observation and plant noises, etc.)

V. Acknowledgments

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