THE TRAM-FPV RACING Open Database. Sequences complete indoor flight tests for the study of racing drones.

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Abstract

This paper presents the TRAM-FPV Racing open database, generated from a set of indoor flights performed with five racing drones at Cranfield University (UK), specifically at the Flight Arena, one of the largest indoor flight fields in the world for research purposes. The database incorporates the position and orientation information in the space of five racing drone models using an optical measurement system (OMS). It includes readings from accelerometers, gyroscopes, and heading angles recorded by inertial unit (IMU) sensors. These databases are frequently used to develop and adjust the sensor fusion algorithms incorporated in the drones to estimate their current state vector. However, their field of application is vast, being able to be used, for example, for the development of the nonlinear mathematical models of drones or the generation of trajectories.

Keywords: Racing drones, Database, Trajectory, Guidance, GPS-denied, IMU, Navigation, Autonomous, Simulation.

1 Introduction

Multiple databases incorporate experimental data from flight tests of autonomous vehicles, generally referred to as drones. The available experimental data are often used to develop, adjust and validate such devices' estimation, control, guidance and navigation algorithms.

Table 1: Other datasets

Datasets	**BD1**	**BD2**	**BD3**	**BD4**	**BD5**
Airframe type	Quad SY130	Hexa SY300	Quad SY-MAV	Quad SY	Quad SY250
Cantidad de vehículos	1	1	1	1	1
Number of vehicles	186	11	1	4	27
Indoor/sensors	IMU/OMS	IMU/OMS	NO	NO	IMU/OMS
Outdoor/sensors	GPS	NO	GPS/IMU	GPS/IMU	GPS/IMU
Video/image capture	Yes	Yes	Yes	Yes	YES
Size room	$11,0X11,0\ M^2$	$1,5x1,0\ m^2$	Urban place	Outdoor	$3,0x1.5\ m^2$

The databases in table 1 have several differentiating characteristics, such as Blackbird (BD1) [2], which stores information from aircraft with average flight speeds close to $7.0\frac{m}{s}$. The EuRoC (BD2) [7] database is notable for using a laser system to track vehicles and improve measurements. The Urban Mav (BD3) [44] has the peculiarity that its data comes from flights in urban areas. At the same time, the KumarRobotics (BD4) [68] database (BD71) contains a Matlab file that aligns its GPS measurements with an odometry system. Finally, the UZH-FPV (BD5) [15] is characterised by the inclusion of information from the FPV cameras incorporated in the racing drones.

The measurements in these databases are usually made with only one type of drone, mainly recording information from satellite signals and readings from inertial sensors and measurement systems external to the drone [8, 26, 30]. Also, the drones are often general-purpose and are not usually customised for a clearly defined application. However, racing drones have burst onto the scientific scene, and we can find numerous studies on their dynamic behaviour[9, 41]. These studies confirm the existence of open questions in their structural design, flight dynamics and autonomous control in environments with static or dynamic obstacles. Therefore, new databases have started to be developed with information on this specific type of drone, mainly characterised by their fast and aggressive dynamics [58] compared to traditional drones.

This paper presents the open database TRAM-FPV Racing, created to study the dynamic behaviour of racing drones. Section 2 briefly introduces the vision system used for 3D motion and orientation sensing. In section 3, the calibration and configuration of the Flight Arena are described, together with the racing drones used and the description of the primary control schemes that integrate these drones. Section 4 details the flight procedure, while section 5 describes the database structure. Finally, section 6 presents the most relevant conclusions of the work.

2 Sensor systems for 3D positioning and orientation of drones.

A system endowed with the capability to plan its flight trajectory and subsequently execute it without human intervention, according to specific safety standards, is an autonomous air vehicle[10]. If, in addition, during these autonomous trajectories, the aerial vehicle detects objects, avoids possible collisions and re-calculates its trajectory by carrying out different flight manoeuvres, then the vehicle is said to navigate autonomously [4]. In order to make an air vehicle behave autonomously, it is necessary to combine measurements from different types of sensors, generally referred to as sensory fusion [21, 69]. This combination of information is necessary for state estimation, control and stabilisation, navigation and guidance of the aircraft [34, 61].

The information in these databases usually contains Global Positioning System (GNSS) data when flights have been conducted in open space, as well as records of the inertial navigation system sensors and even video sequences for the autonomous guidance of the aircraft [17, 29, 49]. Similarly, some databases incorporate information from other types of sensors, for example, laser or ultrasonic sensors, to detect objects or markers in the navigation environment [46]. Some of the sensors used to measure aircraft position and orientation, both on-board and external to vehicles, are detailed below:

- Global Positioning Systems (GNSS). These are made up of artificial satellites (constellation of satellites) that send radio signals (EMS) [45]. These systems calculate the time it takes for the wave to reach a receiver to determine its position [42, 45, 72]. However, the reliability of the data is affected by some factors, with noise in the signal increasing significantly [27, 35, 52]. These systems include NAVSTAR-GPS, GLONASS, IRNSS, GALILEO and BEI-DUO.

- Information from inertial navigation systems (INS). These systems are on board the vehicle and use inertial units or sensors (IMU). They are composed of an accelerometer, gyroscopes and magnetometers [16, 53, 59]. To determine position and orientation, measurements from these sensors are combined using different algorithms, e.g. Extended Kalman Filter (EKF).

- Information from image processing systems (IMS). These systems are on board the vehicle and use different types of cameras to estimate the position and orientation of the object. Camera sensors capture the displacement by employing sequences of images digitally processed and analysed using different methods or algorithms [5, 28, 73]. Consequently, real-time image recognition requires high definition, high speed and high-resolution cameras.

- Information from acoustical systems (UMS). The system has two components: The receiver is on board the vehicle, and the transmitter is fixed at any point in the navigation environment. These systems determine the object's location utilizing ultrasonic waves travelling through the air [19, 63].

- Information from systems combining optical and electronic sensors (OMS). These systems are composed of a set of cameras and markers. The cameras are located in the navigation environment, not on-board the vehicle, and detect light from a marker coated with luminescent material and attached to the vehicle. A minimum of two cameras is required to estimate the position and orientation of the object, i.e. as long as two sensors (cameras) detect or recognise the marker. It is possible to reconstruct the position of the vehicle [20, 25]. The number of cameras determines the reliability of the data. In addition, their location and the light intensity in the environment [12, 31].

It should be noted that in situations where there are no GNSS measurements [1, 11, 40], or in contexts that demand high dynamic performance [14, 60, 67] with high positioning and orientation accuracy, OMS systems are used [3, 18, 24, 48]. Likewise, due to the fast dynamics of racing drones, using OMS systems is essential to study their behaviour accurately [37, 50].

3 Configuration of measurement systems for the TRAM-FPV RACING database.

In order to perform a flight sequence accurately, the preparation of the flight arena, the respective measurement equipment and the drone models are necessary to be used for the flight tests.

The test room is the *Flight Arena* at Cranfield University in the UK. The plan dimensions of the arena are shown in figure 1, with a maximum height of 10 m throughout the enclosure.

On the other hand, the enclosure is equipped with 30 Vicon cameras[75]. The set of cameras is located at the height of 10 meters and separated by approximately 1.5 meters. The data are transmitted via Ethernet, using the TCP/IP communication protocol managed by the software *tracker* [74].

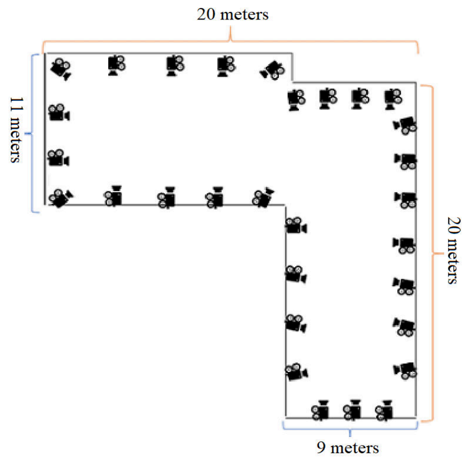

Figure 1: Scheme. *Flight Arena* - At the Cranfield University

3.1 Description and configuration of the flight arena.

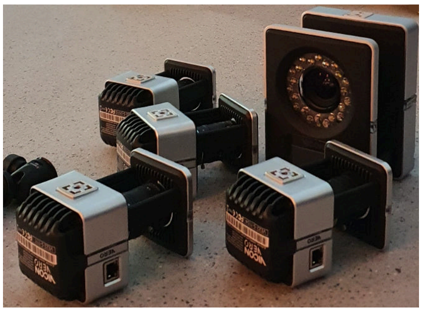

Figure 2: Cameras Vicon. Vantage and Vero

The cameras are Vicon Vantage and Vero (see figure 2). These cameras can capture motion between 250 and 1070 FPS, with the field of view being between 40 and 57 degrees. On the other hand, the resolution ranges between 1.3 and 5.0 megapixels, depending on the volume calibration, the effective flight area and the number of frames per second required for the experiment.

Figure 3 shows the effective measurement area after calibrations have been performed. It should be noted that ASTM E3064 relates to the ability of the cameras to process the images without filtering or post-processing the data when it agrees with a test result and the accepted reference values so that Vicon-tracker software can capture 41993 FPS, with an accuracy of 0.017 mm. It considers the agreement between independent test results obtained under stipulated conditions (as per $ISO3534 : 2014$) and according to the standard test method for evaluating the performance of optical tracking systems that measure six degrees of freedom of position and orientation (ASTM E3064).

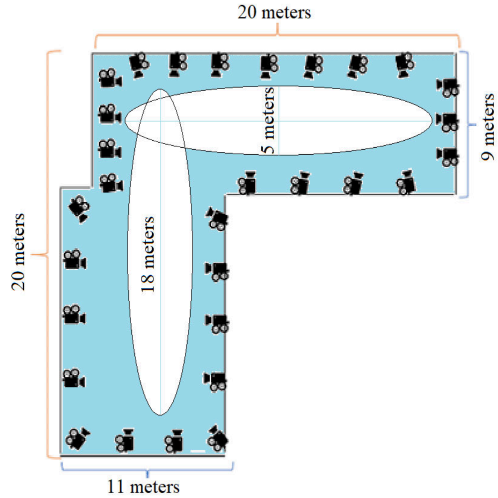

Figure 3: Effective flight area for the experiments

However, the calibration process and the ambient light conditions during the tests give the relative error between the position of the cameras and the origin of the effective flight area. Considering the conditions under which the experiments were conducted, an average range of 0.1 mm for each coordinate axe was accepted.

3.2 Description and configuration of the racing drones used.

In this database, the geometric structure of 5 types of racing drones has been taken into consideration. These drones have different dynamic behaviours depending on their geometry (airframe) [9], which are defined as symmetric (SY), non-symmetric (NSY) or hybrid (HS).

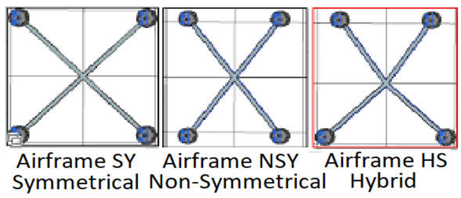

Figure 4: Airframe geometry of racing drones

Table 2: Configuration of the flight platform

Components	Description
Airframe geometry	SY, NSY, HS
ESC	55 mA - Tmotor
Flight controller	F7 - Tmotor
Video transmitter	VTX Viva FPV - Tbs
Radio receiver	R-XSR - FrSKY
Antennas	Emax lineales
Battery	6s - 4s
Propellers	5147 - Tmotor
Motors - Tmotor	F60PRO 1950-2550 Kv
Firmware	Betaflight

In figure 4, the symmetrical geometries (SY) represent an angular distance between upper and lower arms equal to 90 degrees and motor centre distances equal to 210 and 250 millimetres (mm).

The angular distance of non-symmetrical structures (NSY) is between 80 and 65 degrees, and the motor centre-to-centre distance is between 210 and 230 mm. Hybrid structures have an angular distance between upper arms equal to 80 degrees and lower arms of 90, while the wheelbase is 250 mm. Moreover, all racing drones were equipped with the same electronic components, motor group and power supply as shown in table 2.

Figure 5: Hybrid structure - HS.

Figure 6: Symmetrical Structure - SY.

Some of the drones used for the experiments are shown in figures 5, 6 and 7. It should be noted that the geometric parameters of these model racing drones were entered into the firmware of each of the 5 flight controllers. The navigation aids and stability control were configured under the same conditions to perform the experiments[9]. In addition, the settings related to the travel of the radio-control levers were set to their default values.

Figure 7: Non-Symmetrical Structure - NSY.

Figure 8: Location of the markers on the Drone

In order to capture the flight trajectories most accurately, five 14 mm diameter spherical and luminescent markers were placed on each of the airframes as shown in figure 8. In addition, they were placed in non-symmetric positions with a minimum distance of 10 mm, which ensures that the OMS system can more quickly reconstruct the position of the markers during movement.

3.3 Control scheme of the drones used

Databases like TRAM-FPV Racing are integrated between various control levels to merge with the different sensor readings, which is to train the motions of autonomous racing drones or to validate their behaviour in enclosed spaces under certain safety conditions. [23, 32, 36].

Figure 9 shows a basic control scheme or architecture for two racing drones in a controlled environment. It shows how the translation and rotation information obtained from the optical systems (Vicon cameras) replaces the information usually provided by a more inertial satellite system for autonomous navigation. In addition, it shows the possible interactions of this data with the control architecture modules in an environment to detect, evade or pass through obstacles and avoid collisions.

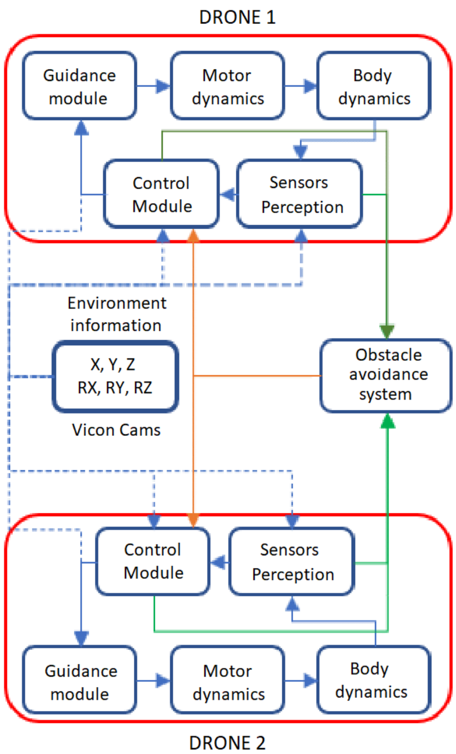

Figure 9: Alternatives with Vicon system

In general, using the direct data from the vision system is a recurrent use [51, 70, 71], this allows the management of possible obstacles [39, 55, 56] either to detect and/or evade them during a flight path. Some of the algorithms related to these obstacle management strategies are precise localisation, simultaneous localisation with imagery (SLAM), LiDAR, odometry and others that include the classification and extraction of images preloaded in databases for the recognition of dynamic environments.

4 Flight sequences.

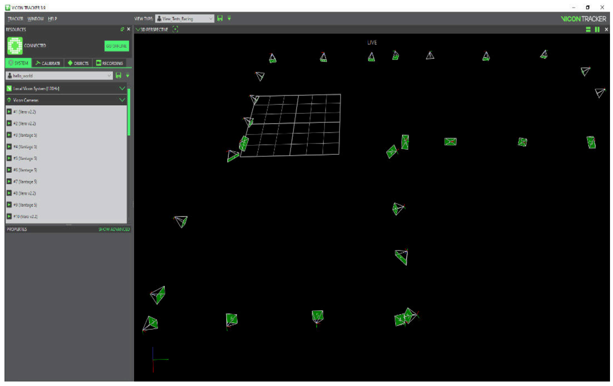

Figure 10: Software - Vicon Tracker.

First of all, before starting the flights, it is necessary to adjust the sampling frequencies of the Vicon camera sensors and the inertial sensors (IMU) according to the effective flight area (see figure 3), as well as the relative measurement errors.

In the case of the Vicon cameras, the flight sequences were captured at 250 FPS, while the capture of data collected by the inertial sensors (IMU) of the controller embedded in the racing drone was performed at 500 Hz. This calibration was performed every ten flights, and a calibration error of less than 0.1% was allowed, and these flight sequences were synchronised with video recordings for each test.

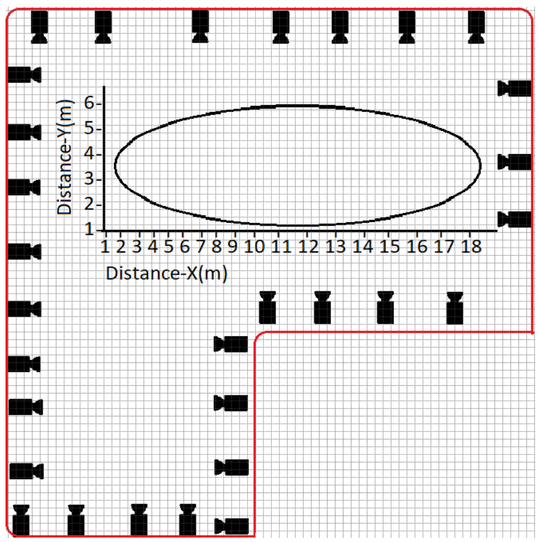

Figure 11: *Flight Arena* Cranfield University. Distances and trajectories covered.

It should be noted that the Tracker software (see Figure 10) was used to match the reference system of the object with the inertial reference system of the sand volume. The origin of coordinates of the object was adjusted according to NED coordinates concerning the reference system of the cameras.

Recording of the data can start after calibration of the effective flight area. The calibration procedure depends on the light conditions and the camera parameters and is effective when the software tracker registers the acceptable error margins. Subsequently, the pilot will activate the IMU sensors of the drone to start the flight test.

Each test lasted between 2.5 and 3.0 minutes of flight time. 30 tests were performed for each drone used, for a total of 150 tests, equating to a range between 75 and 90 hours of flight time for each drone used. These data are stored in the TRAM-FPV database.

All cameras in the flight arena (figure 11) were directed toward the trajectories performed by the racing drone so that at least three cameras could detect a marker during rotations or turns at the end of the 18 metres performed and at the start of the trajectory.

5 Structure of the TRAM-FPV dataset.

The data from the experiments were stored in a database hosted in a dedicated repository at Cranfield University. This database is open and available at the bibliographic reference [76].

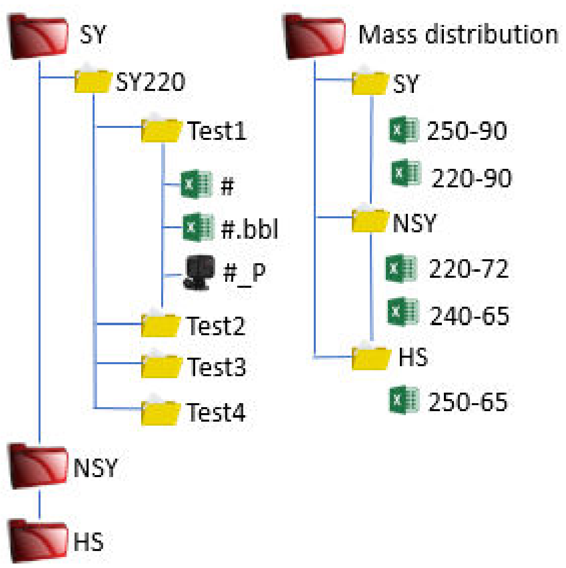

Figure 12: Map tree of the TRAM-FPV Racing dataset.

The TRAM-FPV Racing database is composed of 3 folders segmented by the geometry of the racing drones (SY, NSY and HS). An additional folder that relates the mass distributions and different moments of inertia of each of the models used is also organised in three sub-folders segmented by the geometries of the drones (Ver figura 12).

Inside the first three folders, SY, NSY and HS, there are three other sub folders called test1, test2, and test3, except for the SY folder, which is composed of 4 tests. Likewise, inside each test subfolder, there are three files: a video file in WEBM format and two excel - CSV files. The battery number calls the CSV files produced by the Vicon software from zero to 9, and the CSV files produced by the IMU are also called by the battery number and the acronym bbl.

The CSV-IMU files contain 11 columns by approximately 90000 rows and are organised as in the table 3. This table describes three rotations, three accelerations and 3 heading angles according to the coordinate axes (X, Y Z). On the other hand, it must be taken into consideration that the magnitudes of the accelerations and the heading angle are raw values (RAW) according to the travel of the stick, so their equivalences are: 2048 units of accelerations is equivalent to one unit of gravity (1g). In addition, the data is smoothed by a low-pass filter, where one unit of Heading is equivalent to 58.1 degrees.

Table 3: Dataset - IMU

Row	Description	Magnitude	Error (%)
1	loopIteration	$< 1.284.656$	
2	Local Time	µs	
3	Roll axis rotation	deg/s	$< 0,01$
4	Pitch axis rotation	deg/s	$< 0,01$
5	Yaw axis rotation	deg/s	$< 0,01$
6	X-axis acceleration	raw	$< 0,1$
7	Y-axis acceleration	raw	$< 0,1$
8	Z-axis acceleration	raw	$< 0,1$
9	Roll-Heading	raw	$< 0,09$
10	Pitch-Heading	raw	$< 0,09$
11	Yaw-Heading	raw	$< 0,09$

Table 4: Dataset OMS-Vicon

Row	Description	Magnitude	Error (%)
1	Frames	fps	< 0.017
2	Subframes	0	NA
3	RX X-axis rotation	rad	$0.397 - 0.79$
4	RY Y-axis rotation	rad	$0.397 - 0.79$
5	RZ Z-axis rotation	rad	$0.397 - 0.79$
6	TX X-axis translation	mm	$< 0,149$
7	TY Y-axis translation	mm	$< 0,149$
8	TZ Z-axis translation	mm	$< 0,149$

The CSV-Vicon files contain 8 columns with approximately 50000 rows and are organized as shown in the table 4. This table contains three rotations and translations, plus the data capture rate or FPS. Note that the rotation order is helical, i.e. the rotation is relative to the position of the marker at different time instants (roto-translation) and can be transformed to any other type of non-instantaneous rotation such as Euler or quaternion expressions. The errors in the table are percentage coefficients of variations given by the tracker software. For more precise measurements, please consult [48].

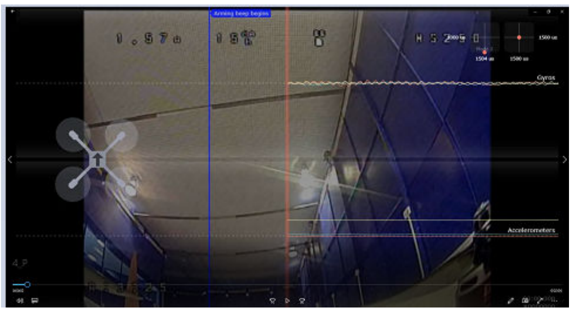

Figure 13: IMU readings synchronized with video

In the WEBM video files (figure 13), it is possible to visualise the behaviour of the gyroscopes at the top and the accelerometers at the bottom while the flight tests were performed. These video sequences have been synchronised, and the changes in the angle signals can be seen in a synchronised manner.

6 Conclusions

This paper presents the TRAM-FPV database containing accurate flight information of 5 racing drone models. The diversity of data related to mass distributions, together with position and rotation information, makes it one of the complete sources of information found in open repositories (see table 5). It guarantees the integrity and consistency of data since it incorporates 30 flight sequences for each model used, for a total of 150 between all the models.

Table 5: Características de la Base de datos

Base de datos	**TRAM-FPV Racing**
Tipo de chasis	SY, NSY, HS
Cantidad de vehículos	5
Secuencias de vuelo	150
Interior/sensores	IMU/OMS
Exterior/sensores	NO
Captura vídeo/imagen	Sí
Área utilizada	20x20 metros

The incorporation of 5 models contributes to a more accurate characterisation of the different design approaches in which the TRAM-FPV RACING database can be employed. Approaches based on the geometry of their structures to implement control algorithms allow the characterisation and development of aerodynamic models for racing drones.

This database aims to continue expanding interest in developing sensors for autonomous racing drones. Sensors capable of sensing the typical dynamics of a radio-controlled racing drone can be implemented in autonomous racing drones.

Finally, the large volume of data, together with their present accuracy, allows them to be used for the design and adjustment of models, estimation algorithms, navigation and guidance.

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