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

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Abstract

This paper offers the TRAM-FPV Racing open database. It results from indoor flights with five (5) racing drones at Cranfield University (UK). Strictly, at the Flight Arena. It is one of the largest indoor flight fields in the world for research goals. The flight data were recorded using an optical measurement system (OMS). The position and orientation info in the vector space of the drone models can be found in the database. It has readings from accelerometers and gyroscopes. Besides this, the heading angles recorded by inertial unit (IMU) sensors are in it. The most frequent use is to fit the data output by sensor fusion. At the same time, those are used to develop sensors. Also, those are embodied in the drones to estimate their current state vector. However, their scope is vast. It can be used, for example, to design nonlinear mathematical models or forge trajectories. This paper was published in the Jornadas XLIII de automática 2022/Spain. The author's version, translated into Spanish, can be found at the references [77].

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

1 Introduction

A wide variety of databases hold info from flight tests of drones. They are often used for machine learning. Strictly, the data is used to tune algorithms. For example, to estimate vehicle states. Also, for the guidance and control of the aircraft.

Table 1: Other datasets

Datasets	**BD1**	**BD2**	**BD3**	**BD4**	**BD5**
Airframe type	Quad SY130	Hexa SY300	Quad SY-MAV	Quad SY	Quad SY250
Quantity of models	1	1	1	1	1
Sequences	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	$3,0x1.5\ m^2$

Table 1 shows multiple databases. These have several discerning features. The Blackbird database (BD1) [2] stores details on aircraft with medium speeds of close to 7.0 (m/s). The EuRoC data (BD2) [7] makes unique use of a laser system for vehicle tracking. The Urban Mav (BD3) [44] data comes from flights in urban areas. At the same time, the KumarRobotics data (BD4) [68] holds a Matlab file that aligns its GPS measures with an odometry system. Finally, the UZH-FPV (BD5) [15] data stores info from FPV cameras built into racing drones.

The flight records in these databases are usually made with only one kind of drone. It mainly holds data from satellite signals. Also, it has readings from inertial sensors and systems outer to the drone [8, 26, 30]. The drones are often for general goals. It means they are not designed for a clearly defined application. However, this kind of racing drone has burst onto the scientific scene. Nowadays could find multiple studies focus on their fast motion [9, 41]. These studies have linked the shape of the airframe. Also, flight dynamics, in general, are pretty attractive to researchers. In addition, this leads to autonomous control and machine learning approach: Situations with static or dynamic obstacles. Thus, new sorts of databases have started to be worked. Those take into account data on a racing drone. Their fast and aggressive motion [58] makes them distinct from classic drones.

This paper presents the open database TRAM-FPV Racing. It is created to study the motion of racing drones. Section 2 briefly explains the vision system used to capture motion. Also, to obtain the 3D orientation of the body. Section 3 defines the calibration of the Flight Arena. The racing drones used for testing flight are presented. In addition, basic control methods that combine these drones are shown. Section 4 details the flight process to record the data. Section 5 describes the database structure. Finally, section 6 presents the most relevant conclusions of the work.

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

An autonomous aerial vehicle can: Plan its flight path. Handle it later without human action. It must act under clear safety rules [10]. In addition, it must guide itself in some instances. It means, on trajectories, it must be able to: Detect objects. Avoid likely collisions. Recalculate them when doing so and assess them in the flight plan [4]. In this way, mixing info from multiple sensors is crucial. That is to mix the data between sensors to estimate their states constantly[21, 69]. In addition, this sensor fusion is vital for training vehicle control and aircraft guidance [34, 61].

The databases hold info from the Global Positioning System (GNSS). It occurs when flights have been made in open space. In addition, they hold records from the inertial navigation system (IMU) sensors. Images or videos on board attend these flight tests to guide the aircraft [17, 29, 49]. They also cover info from other kinds of sensors. For example, when flights are made in GPS-denied areas. Also, laser or ultrasonic sensors are included to detect objects or markers around the flight space [46]. Some of the sensors used are listed below:

- The Global Positioning Systems (GNSS) send radio signals (EMS) [45]. It estimates the time it takes for the wave to reach an open receiver. Thus, it is doable to define a position of an object [42, 45, 72]. However, the reliability of the data is faked by some factors. Signal noise affects the precision of the reading [27, 35, 52]. NAVSTAR-GPS, GLONASS, IRNSS, GALILEO and BEI-DUO are samples of these systems.

- The inertial navigation systems (INS) are on board the vehicle. It uses inertial units or sensors (IMU) to report angles rate [16, 53, 59]. Also, it reports some forces. In addition, it could be reported body position. An accelerometer forms it to compute the change in speeds. Also, it has gyroscopes to define object orientation. In addition, it has magnetometers to specify the strength of the signals. However, they must be fused with other algorithms to resolve the position of a body.

- Data from image processing systems (IMS) are on board the vehicle. It uses cameras to provide the position of the object. It can also predict the orientation. The sensors sense both motions through a series of filtered images. Thus, they are handled in digital form using a mix of methods [5, 28, 73]. Thus, real-time images ought robust and high-quality cameras.

- Data from acoustical systems (UMS) has two pieces: The receiver is on board the vehicle. The transmitter is fixed at any point in the navigation area. It defines the object's location via ultrasonic waves [19, 63]. The waves travel through the air until they find the transmitter.

- Data from systems combining optical and electronic sensors (OMS) have two pieces. The cameras are in the flight arena. The marker is on board the vehicle. In addition, they are coated with luminescent textiles. In this way, the cameras can catch the light. Two cameras are needed to rebuild the vehicle's location [20, 25]. The number of cameras defines the trustworthiness of the data. Also, their height in the place and the light power inside it are essential factors [12, 31].

OMS systems are used in pressing cases. An example of this is in places without GPS access [1, 11, 40]. Also, in those where high dynamic motion is the guide of research [14, 60, 67]. Likewise, it offers high measurement accuracy due to the fast dynamics of racing drones [37, 50].

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

Three vital factors for a proper flight series: The test room must be prepared. The related measuring tools must be calibrated. In addition, the drone models must fit the sizes of the flight arena.

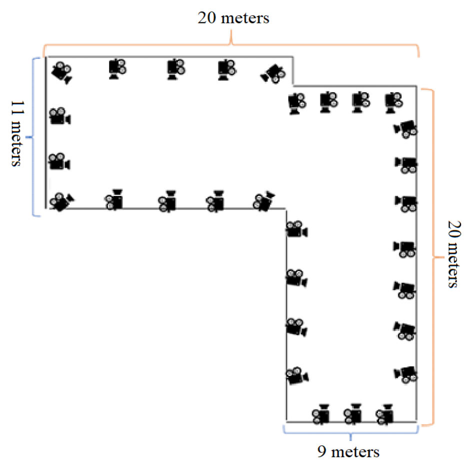

Figure 1: *Flight Arena.* Cranfield University

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 flight arena has 30 Vicon cameras [75]. The set of cameras is located at a height of 10 meters. In addition, they are 1.5 metres apart from each other. The data are transmitted via Ethernet. This way, the software *tracker* uses the TCP/IP communication protocol [74].

3.1 Description and configuration of the flight arena.

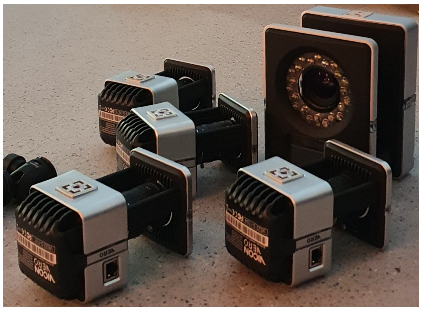

Figure 2: Cameras Vicon. Vantage and Vero

The cameras are Vicon Vantage and Vero (see fig 2). They can capture motion between 250 and 1070 FPS. Also, the field of view is around 40 and 57 degrees. On the other hand, the resolution ranges between 1.3 and 5.0 megapixels. It depends on the volume calibration, the proper flight area and the number of frames per second needed for the flight test.

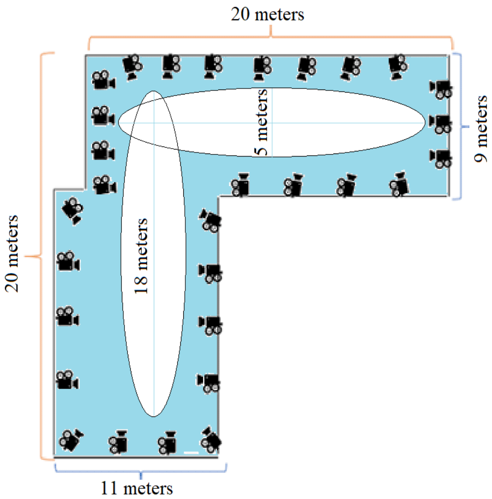

Figure 3: Effective flight area for the flight test.

Figure 3 shows the proper flight area. It is after a successful calibration. The ASTM E3064 relates to the ability of the cameras to process the images. They are without filtering mainly. Also, without post-processing the data. Suppose this is the case and the test values match the reference values of the standard. In that case, the Tracker software can capture data at 41993 FPS with an accuracy of 0.017 mm. In addition, it sets the accordance between different test results acquired by the standard test method. They must be under defined states. In this way, it levies the performance of optical tracking systems. These systems gauge six degrees of freedom of position and orientation.

The relative error between the position of the cameras and the origin of the effective flight area relies on two factors. The first factor is the calibration process. It is done by catching the light by moving a rod in front of the camera. The second factor is the intensity of the ambient light. A space without reflective lights and darker is preferred. Based on these factors, an error of 0.1 millimetres is sufficient for each axe (X, Y, Z).

3.2 Description and configuration of the racing drones used.

In this database, five kinds of racing drones have been used. The main distinction between them is their geometric shape. Thus, they develop dynamic behaviours based on their shape [9]. It is called a symmetric (SY) airframe, non-symmetric (NSY) or hybrid (HS).

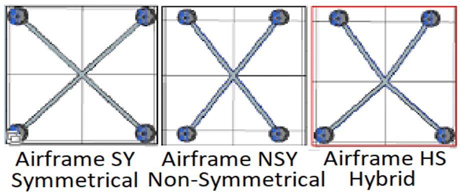

Figure 4: Kinds of airframe for racing drones

In figure 4, the SY airframe has angular distances equal to 90 degrees. In addition, the wheelbase of 210 and 250 mm. The NSY airframe has a range of 80 and 65 degrees. Also, a wheelbase of around 210 and 230 mm. The HS airframe has an angular distance between the upper arms equal to 80 degrees and lower arms of 90, while the wheelbase is 250 mm.

Table 2: Component Descriptions

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	Linear Emax
Battery	6s - 4s
Propellers	5147 - Tmotor
Motors - Tmotor	F60PRO 1950-2550 Kv
Firmware	Betaflight

On the other hand, all racing drones were fitted with the same electronic parts, motor group and power supply, as shown in Table 2. In addition, the control gain values are the same for all airframes. Also, the stability control aids were left as default[9].

Figure 5: Hybrid structure - HS.

Figure 6: Symmetrical Structure - SY.

Figure 7: Non-Symmetrical Structure - NSY.

Figures 5, 6 and 7 show the kinds of drones used for the flight test. It should be noted that the geometric settings of these model racing drones were written on the firmware of each flight controller. In addition, the settings linked to the travel of the radio-control levers were set to their default values.

Figure 6 also shows the position of the markers. Each ball has 14 mm in diameter. Also, they are dressed in fluorescent textiles. In addition, they are placed in non-symmetrical locations with a gap of 10 mm. It is so that the OMS system can more quickly rebuild the position of the markers during motion.

3.3 Control scheme of the drones used

TRAM-FPV Racing are integrated between the control levels. It is to merge with the other sensor readings. Thus, it could be to train the motions of racing drones. Also, to test a motion in confined spaces under certain safety conditions. [23, 32, 36].

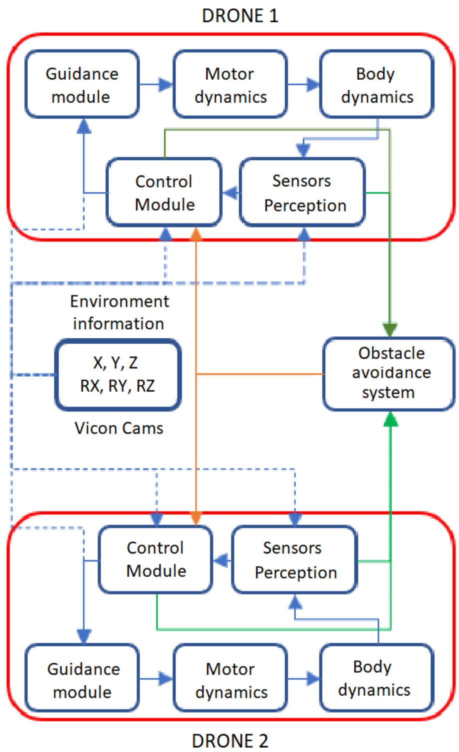

Figure 8: Alternatives with Vicon system

Figure 8 shows a basic control scheme of two racing drones. They are in a safe area with a Vicon control system. It shows how the OMS data replace the GPS data for autonomous navigation. In addition, the blue arrows show this data's feasible relations in the control loop. Mainly, the green ones are to detect or avoid collisions. In the case of racing drones, they could pass through obstacles and evade them.

On the other hand, using direct data from OMS is regular use [51, 70, 71]. Some of the algorithms are to manage obstacles. Other uses take into acound precise and simultaneous localisation. The most classic can be SLAM, LiDAR or odometry [39, 55, 56]. Other kinds include tagging and dragging images. They are preloaded in databases to place the motion of objects. The latest progress has to do with the machine learning app.

4 Flight sequences.

There are three essential parts before starting the flight tests. The first is to adapt the sampling frequencies of the Vicon camera. Secondly, the IMU has to be also set. It is preferred that those settings are according to the flight arena (see figure 3)). Finally, relative size errors are vital to be known.

In the case of the Vicon cameras, the flight sequences were captured at 250 FPS. In contrast, the IMU was performed at 500 Hz. This calibration of the cams was performed every ten flights. Also, the calibration error of less than 0.1% was allowed. Thus, flight sequences were synchronised with video recordings for each test.

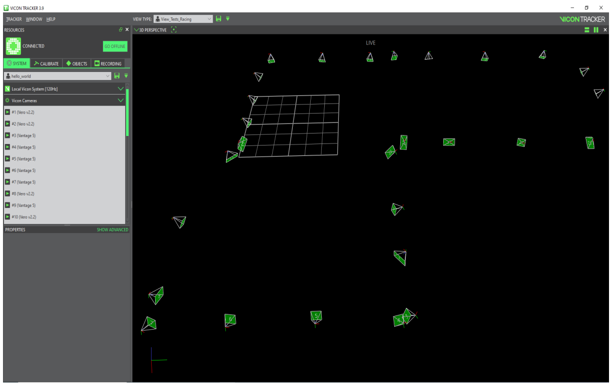

Figure 9: Software - Vicon Tracker.

The Tracker software (see Figure 9) matched the frame systems. It is the object origin with a frame system of the flight arena. The origin of the object is according to NED coordinates. So, NED has to match the frame system of the cameras.

Recording of the data can start after the calibration of the flight area. It depends on the light conditions. Also, the camera positions are essential to catch the motion. It is ready when the software tracker records acceptable error margins. Later, the pilot will start 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 pointed(see figure 10) toward the tra-

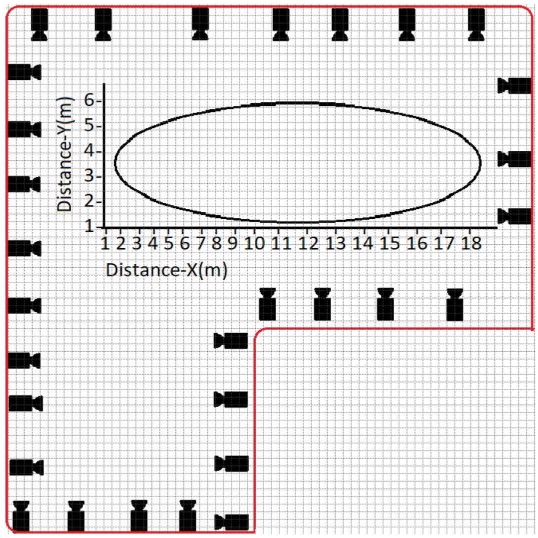

Figure 10: Distances and trajectories covered.

jectories performed by the racing drone. They must be positioned in such a way that they cover the dead spots of the turns. Thus, at least three of them could detect a marker. This way, rotations on turns are captured. These special cares are due to the ends of the trajectory.

5 Structure of the TRAM-FPV dataset.

The database is kept in a storage repository at Cranfield University. It is open and can be accessed through the bibliographic link [76].

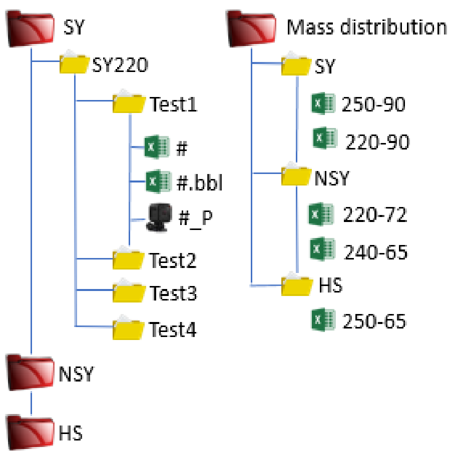

Figure 11: TRAM-FPV files.

The TRAM-FPV Racing database consists of three folders. These have been labelled according to the geometry of the racing drones (SY, NSY and HS). In addition, a fourth folder has been included. It is about each model's mass distributions and moments of inertia. It is also tagged into three sub-folders according to the names of the airframes (see figure 11).

Within the SY, NSY and HS folders, there are three subfolders. These have been named test1, test2 and test3. However, the SY folder has been added to a fourth 4 test. Thus, an extra subfolder (test4) will be found there. Also, within each test subfolder, there are three files: a video file in WEBM format and two excel - CSV files. The CSV files labelled with the battery number (from zero to nine) are the data from the OMS system. So the CSV data from the IMU is also called by the battery number plus the acronym bbl.

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	$< 0,09$

The CSV-IMU files hold 11 columns by 90.000 rows. They are sorted as in table 3. Mainly, it describes three rotations, three accelerations and 3 heading angles. The frame reference for the motion is X, Y, and Z. The data values of the accelerations and the heading angle are raw values (RAW). Also, they are based on the stick's travel. The equivalences are: 2048 units of acceleration is equal to one unit of gravity (1g). In addition, the data is smoothed by a low-pass filter. Thus, one unit of Heading is equal to 58.1 degrees.

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 hold eight columns by 50000 rows. They are sorted as shown in table 4. Mainly, it has three rotations and translations. Also, it has the rate of data capture or FPS. The rotation order is helical. It means that the rotation is relative to the position of the marker at various time instants. It is also called roto-translation. These kinds can be transformed into any other type of non-instantaneous rotation, such as Euler or quaternion terms. The errors in the table are ratio coefficients of variations. The tracker software gives them. For more exact measures, please consult [48].

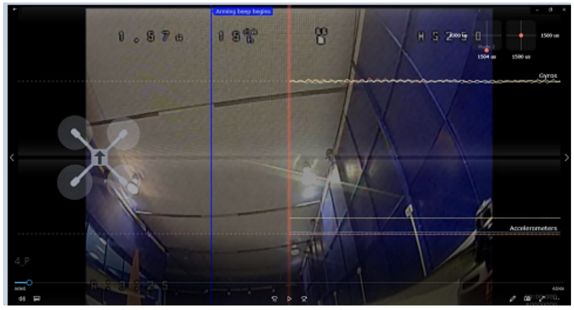

Figure 12: IMU readings synchronized with video

Figure 12 shows the WEBM video files. In-flight on the screen, it is feasible to watch the motion of the gyroscopes at the top. Also, the motion of accelerometers is at the bottom. The video images have been matched with the behaviour of the sensors. Thus, varied sorts of comparisons are possible.

6 Conclusions

This paper presents the TRAM-FPV racing database. It stores dynamic flight data for the study of racing drones. In this way, the position and rotation motion is in it. Also, it holds the mass distribution of the models. This mix of data makes it unique (see table 5). It incorporates 30 flight sequences for each model used. It means a total of 150 flight tests.

Table 5: Database features

Base de datos	TRAM-FPV Racing
Kind of airframe	SY, NSY, HS
Quantity of models	5
Flight sequences	150
Indoor/sensors	IMU/OMS
Outdoor/sensors	NO
Video cam/image	Yes
Rffective flight area.	20x20 meters

The database holds details on five kinds of racing drones. This range of choices makes it the only one of its class. It is made to study the motion of racing drones. However, other types of studies could be done with it. The aerodynamic models based on the database are highly relevant. Also, studying cross-modal performance by analysing big data is an exciting topic. Specific uses like machine learning training are feasible yet.

On the other hand, the database aims to continue the growing interest in designing sensors. Mainly for the field of autonomous racing drones. They will have to sense the usual motion of a radio-controlled racing drone.

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