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Department of Mathematics and Physics
Master of Data Science

Drone Flight Performance Evaluation Methodology based on Data Science

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THESIS to obtain the **DEGREE** of
MASTER OF DATA SCIENCE

A thesis presented by:
Adrián Homero Moreno García

Thesis Advisors:
Dr. Luis Fernando Luque Vega

Tlaquepaque, Jalisco, April, 2022

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Author: **Adrián Homero Moreno García**

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Thesis Advisor, **Dr. Luis Fernando Luque Vega**

Thesis Reader, **Dr. Riemann Ruíz Cruz**

Thesis Reader, **Dr. Carlos Augusto Arellano Muro**

Academic Advisor, **Mtro. Juan Carlos Martínez Alvarado**

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Drone Flight Performance Evaluation Methodology based on Data Science

Adrián Homero Moreno García

Abstract

Nowadays Unmanned Aerial Vehicle (UAV) consist of collaborators for hazardous jobs like deliveries, from commerce to clients, and emergency scenarios, like fire fighting and rescue humanitarian jobs. The pilot's responsibility has increased as the new requirements settle for new applications, so in this way, they need to have enough capabilities to perform this valuable work. However, this required knowledge, skills, and attitudes not provided in a formal educational institute with an established process. Therefore, there is no method defined to know the level of performance of a Pilot, and this is essential before giving a duty as valuable of delivery.

This thesis presents an effort to establish a detailed structured methodology for evaluating a pilot's ability to coordinate psycho-motor and evaluate this determined pilot's learning rate in a sequence of flights. Furthermore, to generate a predictive model representing this learning for a specific pilot and give formal evidence of the improvement in the near future and which orientation coordination ability can improve.

Contents

List of Figures

List of Tables

Acronyms

BNOF Back Nose Orientation Flight. 10, 40

CI Confidence Interval. 71–73

CRISP Cross Industry Standard Process for Data Mining. 32

EMCF Educational Mechatronics Conceptual Framework. 26

FNOF Front Nose Orientation Flight. 9, 38

LNOF Left Nose Orientation Flight. 9, 39

MoCap Motion Capture. 9, 26, 30, 31, 38, 41

NFPA National Fire Protection Association. 23

NIST National Institute of Standards and Technology. 7, 9, 19, 20, 23, 24, 36, 37

Ph.D. Doctor of Philosophy. 26, 29

PI Prediction Interval. 71–73

PoE Power over Ethernet. 30

RNOF Right Nose Orientation Flight. 9, 39

RPAS Remotely piloted aircraft system. 19

SE Standard Error. 57, 58, 63, 64, 70–73

sUAŠ Small Unmanned Aircrafts. 23

TDSM Team Data Science Methodology. 9, 29, 32, 36, 79

UAV Unmanned Aerial Vehicle. 5, 7, 20, 21, 23, 26, 29

Dedicated to my family, my beloved parents Homero, Maria del Pilar and my little sister Iris...

Also to the Advisor of this Thesis, Dr. Luis Fernando Luque Vega for all his time and effort to guide this research...

1 Introduction

Contents

1.1 Background

Canada public safety agencies have made an enormous effort to introduce Remotely piloted aircraft system (RPAS) in their activities for situational awareness scenes of wildland fires and unnatural disasters. This includes high response time and effective management for invading hot zones and giving adequate evacuation during dangerous scenarios. In addition, Transport Canada has done an excellent job in crafting regulations that include several basic examination knowledge of areas like air traffic rules and procedures; after this, the candidate can download the certificate for basic operations. Therefore, Canadian Fire Agencies require a standardized sequence of tests in a more practical reinforcement, as firefighters' present situations are risky.

On the other hand, the National Institute of Standards and Technology (NIST) in the United States, who has several expert engineers in the field, is implementing new and better performance tests that evaluate pilot proficiency capabilities. All test methods are available, free of charge, so in this way, other agencies or companies can regulate their operations for aircraft[1]. The best part is that the material used for the different tests scenarios can be acquired and assembled in any supplier store. Figure 1.1 depicts the differences between these two mentioned types of evaluation scenarios, the one from Canadian

[1] Alan Frazier. Evaluating drone pilot skills, Nov 2020. URL https://www.firefightingincanada.com/evaluating-drone-pilot-skills/

Fire Agency and the one from NIST. Finally, it is essential to mention this effort's importance that even the Civil Air Patrol© uses this Unit Accreditation Program for their pilots; this is a massive success on this effort for standardized aircraft, and its the inspiration and base of this work. Please find Figure 1.1 the represents mentioned above.

Figure 1.1: (Left) Evaluating flight abilities for Drone pilots by Canadian Fire Agency, (Right) NIST: National Institute of Standards and Technology in the United States, Methods for Test Flight.

1.2 *Justification*

The responsibility of a drone pilot involves the manipulation of the aircraft previously, during, and after the flight, every time it serves in many activities immerse in society when performing several applications. That is why, it is necessary the creation of standardization flight tests and an evaluation framework for drone pilots that includes the pilot capabilities diagnostics and an estimate of their learning rate progress. This will allows the drone pilot to build confidence and accomplishes the abilities necessary for performing their designated tasks in a safely manner for himself, the people and objects around the drone.

1.3 *Problematic*

As discussed in the Background section, drones have specific applications; some are complex and require a certain level of accuracy on their flights. In addition, the creation of various types of drones with different sizes and weights makes their management even more challenge. Therefore, it is a reality that risks must be mitigated or at least reduced at its minimum when dealing with these aircrafts. Citing some examples, Amazon Prime Air Unmanned Aerial Vehicle (UAV) drone can carry a package weighing 2.5 kg and travel up to 24 km. On the other hand, DHL's ® Parcelcopter brings a box of up to 2 kg with a travel range of 16 km[2]. It is worthwhile to mention that regulations

[2] Gohram Baloch and Fatma Gzara. Strategic network design for parcel delivery with drones under competition. *Transportation Science*, 54(1):204–228, 2020

require that a UAV must be monitored by a certified operator, even though some drones can fly in automatic mode. In case of failure on the autopilot system, the drone pilot needs to take the intervention of the aircraft and be capable of handling it into safe destiny. We cannot ignore that collisions can happen between aircraft, terrestrial structures, people, birds, interference, and failed in critical activity (see Figure 1.2). So in this way, the responsibility of an operator that controls the flight is essential. That is why drone pilots need to have enough capabilities to perform this valuable work. This raises the following question: How can a drone pilot be evaluated to know if he/she has the necessary skills to be reliable when performing a specific type of flight depending on the application?

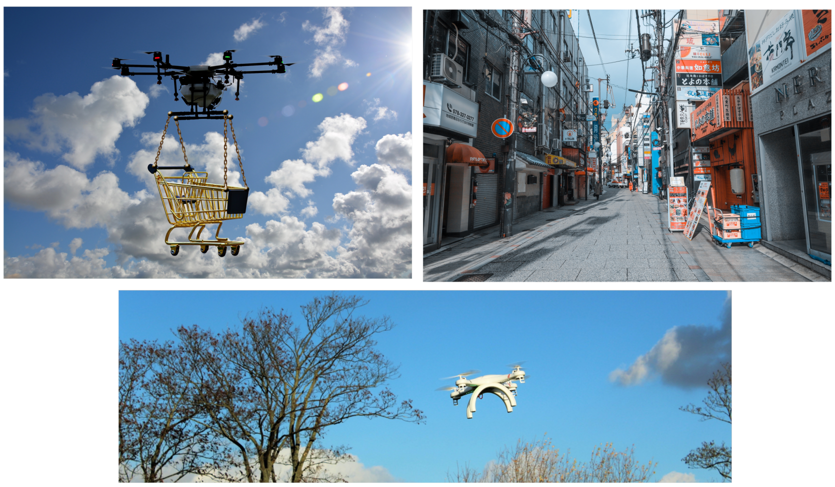


Figure 1.2: (Left-Top) Drone delivery representation. (Right-Top) Street view perspective with all the obstacles for free flight. (Down) Drone in an open field with trees surrounding.

1.4 *Hypothesis*

Creating an evaluation system for drone pilots flight abilities will enable the creation of a Benchmark of flight drone performance in specific tasks from basic to advanced flight. This system will be able to diagnose the technical skills of a drone pilot, making him aware of his strengths and weaknesses. Then, an estimate on the required time to improve their flight skills to a point in which it is ready to perform safety flight and tasks will be given to the pilot. In this way, civilians and enterprises will have the confidence that a capable pilot is in charge of the drone.

1.5 Objectives

1.5.1 General Objective

Generate a benchmark capable of evaluating drone pilots' flight. Also, analyze and give feedback about the evolution of the learning rate of the pilot, generating a system capable of predicting the number of flights needed for reaching a certain level of experience.

1.5.2 Specific Objective

- Establish a sequence of tests for pilots for a different level of experience.
- Generate a Database by using the data thrown by the simulator, virtual or real.
- Generate a model that defines the trend line evolution of the determined pilot and, based on this, estimates their learning rate of a specific flight.
- Evaluate models and determine their accuracy for the results, standardizing the process for certificate a pilot drone.

1.6 Scientific Innovation, Techonological and Contribution

This project promises to generate tangible results to interpret as a level of confidence that a pilot can bring; this by itself is an innovation combined as an automatic tool built with Software and Data Science. The actual process of evaluating a pilot consists of a manual process, written tests, sequences of flights, and some performance with the help of visible markers. However, there are few related works in the extensive scientific research to automate these auto-evaluations for pilots. Indeed, in this thesis are mentioned some related results, where we can see that innovation goes forward in the scientific and technological contribution. The creation of this project works under the different designed tests for the auto-evaluation; the scheduled manual mainly focuses on developing knowledge (previous co-related work)[3], and the methodology applied to achieve this goal. This work ensures that the process and the different tools used are references for future research.

[3] Luis F. Luque-Vega, Emmanuel Lopez-Neri, Carlos A. Arellano-Muro, Luis E. González-Jiménez, Jawhar Ghommam, and Rocío Carrasco-Navarro. Uav flight instructional design for industry 4.0 based on the framework of educational mechatronics. In *IECON 2020 The 46th Annual Conference of the IEEE Industrial Electronics Society*, pages 2313–2318. IEEE, 2020

2 Related Work

Contents

This Chapter mainly emphasizes the related work that directly or indirectly impacts this research, also as evidence of the investigation done of previous works. Additionally, it remarks on this community's effort to formalize the educational format for piloting a drone's learning and evaluation process. As stated before, it is essential for the actual society. The study of these related works helped this research adapt or even improve with its focus on the pilot evaluation flight.

2.1 The initiative of NIST

NIST© effort to develop a set of flight tests for Drone Pilots that yields quantifiable metric results to evaluate them.[1] This Institute created test methods for Small Unmanned Aircrafts (sUAŠ) referenced some of them as Job Performance Requirements in the National Fire Protection Association Standard for Small Unmanned Aircraft System Used For Public Safety Operations (National Fire Protection Association (NFPA)© 2400). These methods are the opening of this work which creates an open window to take this reference and adapt into the necessities. However, first, introducing these methods primarily for vertical takeoff and landing systems with an onboard camera and remote pilot display. In general, these tests focus on Maneuvering and Payload Functionality taking proficiency tests for:

- Position (hold position and rotate, climb and descend, fly straight and level, move and rotate and land Accurately) and manipulates traverse, orbit, spiral, and recon flights.

[1] Jonathan Griffin. Nist performance tests for aerial response robots become national standard, May 2021. URL https://www.nist.gov/news-events/news/2018/12/nist-performance-tests-aerial-response-robots-become-national-standard

- Avoid obstacles that pass through doors and windows.

Now, for being specific in each kind of test, below are the details[2]:

- Maneuvering Tests (Man)©: Align with 20 buckets along the flight paths. The pilot will identify continuous rings inside the bucket using its camera; the aligned image is considered a point. Five minutes per test in 30 minutes total time. Score up to 20 points each, 100 points in total.

- Payload Functionality Tests (Pay)©: Align with 20 buckets along the flight paths. The pilot will use the camera to identify continuous rings inside the bucket, but it will capture a full zoom showing the ring and a small concentric C gap inside the bucket. Ten minutes per test in 60 minutes total time. Score up to 100 points each, 500 points in total.

[2] National Institute of Standards | NIST, Technology, and Adam Jacoff. National institute of standards and technology | nist. URL https://www.nist.gov/system/files/documents/2019/08/21/nist-astm-nfpa_standard_test_methods_for_suas_-_maneuvering_and_payload_functionality_overiew_v2019-08-20v2.pdf

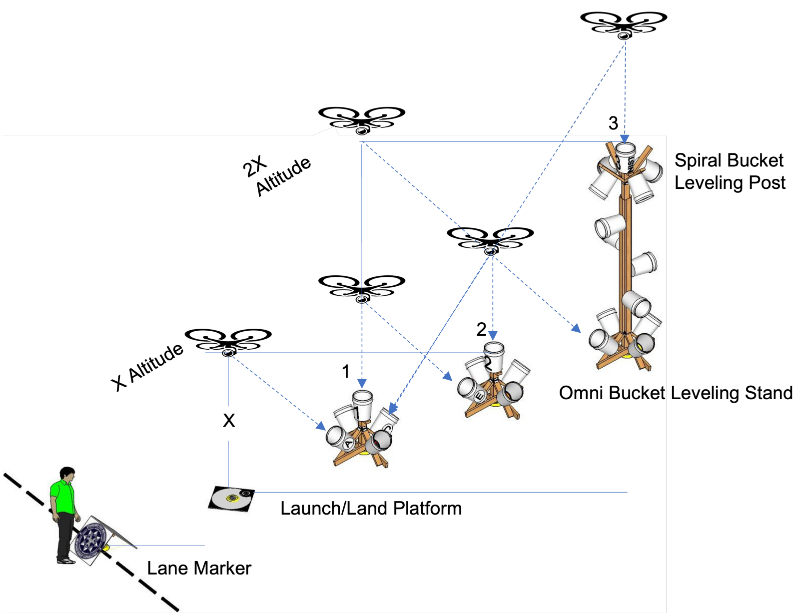


Figure 2.1: Scalable Test Lane Route for Maneuvering and Payload Functionality.

Figure 2.2: (Left) MAN test type bucket aligned to see the entire inscribed ring inside the bucket. (Right) As mentioned before, PAY test type bucket with the increasingly small concentric C gap.

This work done by NIST© opens new opportunities to improve and apply this test concept to more specific purposes.

2.2 State of Art related with Pilot Evaluation using Data Science

On this section purpose is for put some of the effort from different researches that are applying Data Science for Evaluate Drone Pilot Evaluation.

Starting with *Visual attention prediction improves performance of autonomous drone racing agents* its a very interesting paper that studies how neural networks can be trained to imitating a human race drone. Part of the hypothesize is about the gaze-based attention can be predicted in a model. They do it in base of raw image inputs and image-based abstractions. To be more specific the first consists of the mean attention map over training set. The second, shuffle ground-truth attention map samples within each lap of the race tack in the test set, retaining the same distribution across the lap , but disconnecting the attention output from the RGB input. The results demonstrate that human visual attention prediction improves the performance of autonomous vision-based drone, having some results with (88% success rate) outperforms the RGB-image.[3] An extend of this work is expressed on an article named *Human-Piloted Drone Racing: Visual Processing and Control* which collected a multi modal data set from 21 experienced drone pilots using a highly realistic drone racing simulator. They found a strong correlation between pilots eye movements and the commanded direction of quadrotor flight, with an average visual-motor response latency of 220 m. In Conclusion they revealed a strong relationship between eye gaze behavior, quadrotor control, and flight performance.[4]

[3] Christian Pfeiffer and Davide Scaramuzza. Human-piloted drone racing: Visual processing and control. *IEEE Robotics and Automation Letters*, 6(2):3467–3474, 2021

[4] Christian Pfeiffer, Simon Wengeler, Antonio Loquercio, and Davide Scaramuzza. Visual attention prediction improves performance of autonomous drone racing agents. *arXiv preprint arXiv:2201.02569*, 2022

The second one presents an article that evaluates the potential of flight simulators in the process of pilot training to enhance the flying precision as piloting errors may negatively influence air traffic safety. They focus in a designed rout which is a maneuver 180° climbing/descending turn, but this limited the results, so in future studies they want to experiment with other types of maneuvers in order to obtain different error ratios. In the other hand there is an intention of optimize the effectiveness of flight simulators parameters that determine the levels of mental stress impacting the piloting precision. So in conclusion the objective is providing correct flying habits, eliminating errors, teaching flight procedures etc.[5]

[5] Vladimr Socha, Lubos Socha, Karel Szabo, Stanislav Hana, J Gazda, Iveta Kimlickova, M Vajovaa, A Madoran, Lenka Hanakova, V Nemec, et al. Training of pilots using flight simulator and its impact on piloting precision. In *Transport Means 2016, Proceedings of the International Conference*, pages 374–379, 2016

2.3 UAV Flight Instructional Design for Industry 4.0 based on the Framework of Educational Mechatronics

It is essential to mention this co-related work; which author is the director of this thesis Ph.D. Luis F. Luque Vega. The cited work's purpose is the present a Framework with a structural design for teaching [6] Unmanned Aerial Vehicle (UAV) flight based on the Educational Mechatronics Conceptual Framework (EMCF). So this will be constructed in different macro-process levels: concrete, graphic, and abstract, which will generate a learning construction to pilot a drone.

[6] Luis F. Luque-Vega, Emmanuel Lopez-Neri, Carlos A. Arellano-Muro, Luis E. González-Jiménez, Jawhar Ghommam, and Rocío Carrasco-Navarro. Uav flight instructional design for industry 4.0 based on the framework of educational mechatronics. In *IECON 2020 The 46th Annual Conference of the IEEE Industrial Electronics Society*, pages 2313–2318. IEEE, 2020

Everything starts by practicing basic drone flight movements (basic maneuvers) using remote control in a simulated environment. Then, the pilot will perform some accurate flights; this covers the concrete level.

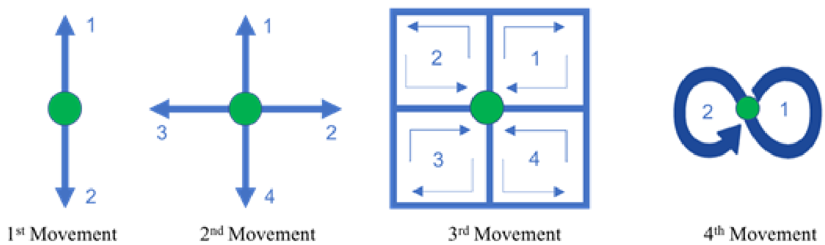


Figure 2.3: Basic Maneuvers: Go forward, backward, rightward and leftward, accomplishing a back and forth displacements of the drone, a cross movement, an square array movement and a lemniscate movement.

Then comes the Graphic Level, which covers the construction level. This stage aims to show the participant the relevant flight dynamics variables like position and orientation, then perform a flight connected to the PC with a Motion Capture (MoCap) System© (This system is explained in subsequent Chapters.) The intention is that the participant can understand the variables and data behavior while performing the flight.[7]

[7] Luis F. Luque-Vega, Emmanuel Lopez-Neri, Carlos A. Arellano-Muro, Luis E. González-Jiménez, Jawhar Ghommam, and Rocío Carrasco-Navarro. Uav flight instructional design for industry 4.0 based on the framework of educational mechatronics. In *IECON 2020 The 46th Annual Conference of the IEEE Industrial Electronics Society*, pages 2313–2318. IEEE, 2020

To finalize the construction level based on an abstract stage represented from a mathematical model and established in a control scheme where the participant can understand the rules that control the flight of the quadrotor using Simulink© , called Control Scheme.

Mentioning this related work is so valuable because it opens the gate to many applications. For example, once the participants have experienced this process for getting the knowledge in different levels for learning how to pilot a drone, now it is possible to reference this and recreate a model to evaluate the abilities acquired for beginners and advanced pilots. Also, this framework's knowledge helped the principal author of this thesis to understand all the variables involved in a drone flight and the behavior. The tools used in this related work helped during the acquisition process to retrieve the data, so they match as a perfect complement to this work.

3 Materials and Methodology

Contents

This Chapter presents the materials and Methodology selected for constructing this project. The main intention is to find the equipment and a step-by-step process with clear stages to define and organize the work appropriately. The Methodology is based on the Team Data Science Methodology (TDSM) proposed by Microsoft® , which is an agile, iterative data science methodology that delivers predictive analytics solutions and intelligent applications efficiently. It is focused on teams but can also be applied for co-individual research. The following sections present this information in a detailed manner.

3.1 Materials

3.1.1 DJI Panthom 4

DJI Phantom 4© is a quadcopter equipped with a collision-avoidance system, called Obstacle Sensing System©, which uses two forward-facing cameras to detect obstacles as far as 49.5 feet (15 m) ahead of the drone.[1] The drone comes, mainly with a remote controller, camera and gimbal as in Figure 3.1

[1] Phantom 4 - dji manual. URL https://www.dji.com/mx/phantom-4

3.1.2 MoCap© System

First, as was introduced in Chapter 1.6, one of the co-related projects by Ph.D. Luis F Luque Vega started a UAV Instructional Design effort where process learning works on different construction levels. Finally, it is good to mention that this study uses the same systems approaches used for data acquisition.

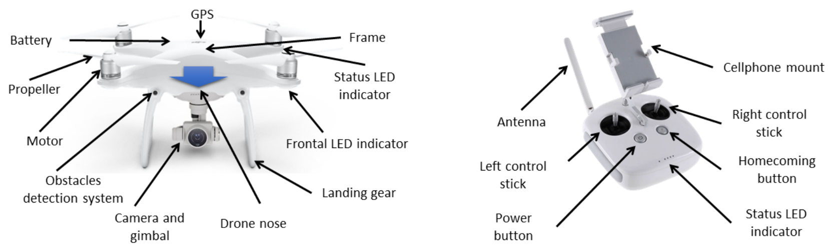


Figure 3.1: Drone Control

Digitally capturing the movement of humans can be done in many ways. There exist different techniques for doing this, using Motion Capture (MoCap)© systems that are marker-based. This system works between 6 and 50 cameras placed in the walls and ceils of a recording studio. There is competence between commercial systems to be the precursors on this field, some of them there already leading as Vicon Motion Systems® and Motion Analysis Corp® .[2]

So, for this work, the MoCap© system used comes from Vicon Motion Systems® and consists of the following elements:

[2] Chris Bregler. Motion capture technology for entertainment [in the spotlight]. *IEEE Signal Processing Magazine*, 24(6):160–158, 2007

- Eight Vantage V16, each camera contains a thermal sensor to detect changes in temperature that could affect the system status.
- Lock Sync Box connects and synchronizes the cameras with the Vision Tracker® through Poe Switch.
- Power over Ethernet (PoE) switch, where power and connectivity are through PoE + protocol by CISCO Systems® .
- PC with Vicon Tracker Software® , created by Vicon Systems® , is a motion tracking software application that is easy to learn and use.[3] Designed specifically for engineering requirements and its workflows are based on an analysis of the needs of typical engineering users. Some features to mention like: tracking multiple objects, single-camera tracking, and real-time system modeling with Simulink®.

[3] VICON. *Vicon Tracker User Guide - Prophysics*, Sep 2020. URL https://www.prophysics.ch/wp-content/uploads/2017/06/Vicon-Tracker-User-Guide.pdf

The setup mentioned above gives the necessary setup for obtaining the position and orientation of the drone in real-time and the data stored from the flight. Figure 3.2 of a Drone in MoCap System©. In Figure 3.3 there is a representation of the communication between PC-Drone, MoCap and the PC-MoCap.

The test flights executed for the acquisition data were executed Laboratory for Capture Movement, located in the University of the Valley of Mexico campus in Guadalajara South, which contains all the setup mentioned above in a closed- environment. As in Figure 3.4

Figure 3.2: Drone in the MoCap System©

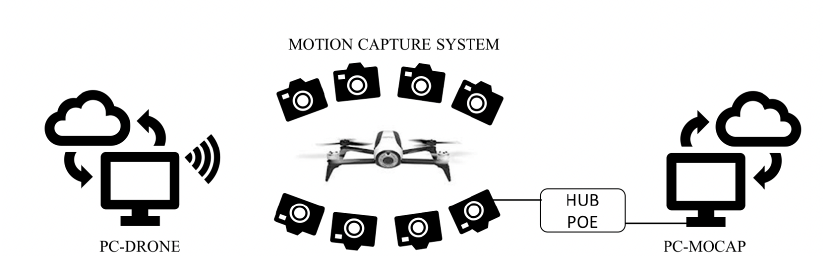


Figure 3.3: Dron-PC to Dron-MoCap©

there is a example of a Real Flight practice in inside the installation of Laboratory for Capture Movement. [4]

Flight data acquired by MoCap© are some variables collected as position, velocity, linear acceleration, and angular acceleration. During the testing of the defined trajectory, takes data such as $\psi, \dot{\psi}, z, \dot{z}, x, \dot{x}, y, \dot{y}$ (Control Position, Angular Speed) [8 Variables] also the time the duration of the flight at each point. For each flight, store sensor values and store system output.

[4] Luis F. Luque-Vega, Emmanuel Lopez-Neri, Carlos A. Arellano-Muro, Luis E. González-Jiménez, Jawhar Ghommam, and Rocío Carrasco-Navarro. Uav flight instructional design for industry 4.0 based on the framework of educational mechatronics. In *IECON 2020 The 46th Annual Conference of the IEEE Industrial Electronics Society*, pages 2313–2318. IEEE, 2020

3.2 *Teams Data Science Methodology (TDSM)*

The importance of data science is increasing while the main complexity of projects is getting more sophisticated. There is a necessity to employ a methodology that contributes to the improvement to get step-by-step

Figure 3.4: Real flight practice.

approaches that can help us to improve the goals of a specific Data Science Project. Therefore, the visual representation of the proposed methodology in this thesis, based on the TDSM© , is shown in Figure 3.5 and it is called Team Data Science Methodology (TDSM) since .

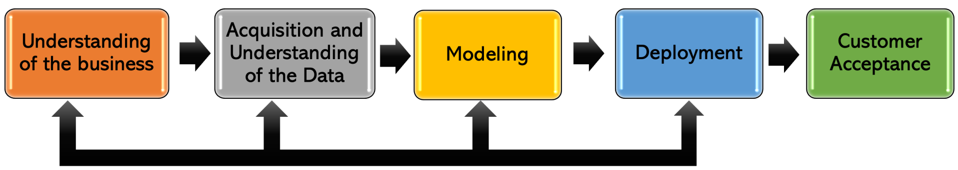


Figure 3.5: Team Data Science Methodology (TDSM)© .

Methodology TSDP improves the team collaboration and learning. So it includes best practices from Microsoft and other industry players to help successfully implement a data science project. TDSM© combines the Cross Industry Standard Process for Data Mining (CRISP)-inspired process into a down iterative five stages, stories (life-cycle substages), and tasks ("assignable code or document work items in order to complete a specific data science story"), this is designed to follow a scrum-like framework.[5]

[5] MicrosoftDocs. Architecture-center at main microsoft docs. URL https://github.com/Azure/Microsoft-TDSP

TDSM© also describes a life cycle for a data science project, defining the following phases: business understanding, data acquisition, and understanding, modeling, deployment, and customer acceptance. These phases will be described in the next lines with more detail on how to execute certain steps and what outputs they produce. The five steps of Microsoft´s® *TDSM©* life cycle include:

1. **Understanding of the business:** The goal of this phase is to reveal the business objectives, stakeholders, and business questions, also to identify the correct variables and analysis needed to meet the project's purpose.

2. **Acquisition and Understanding of the Data:** The goal is to reproduce clean data, high quality for target variables, also include a strategy of developing a pipeline to regularly have refresh data to the model in the next phase.

3. **Modeling:** The modeling stage has the determination of having the optimal data features like *algorithm, model building, model training, and validation* ready for the next Deployment stage.

4. **Deployment:** Once the model is ready is time to deploy it with an automated pipeline job into production, this has to be efficient for every time it is needed.

5. **Customer Acceptance:** At last, this goal is to confirm the data pipeline, model, and deployment into production, giving the different results we are meeting the customer's acceptance.

Finally, following this methodology will ensure to extract the valuable knowledge of data, formulating the solutions, and evaluating the results involving thinking carefully the *context* in which is used, as it is specified below for this specific project.

4 Drone Flight Performance Evaluation Methodology based on Data Science

Contents

This Chapter has the intention of explain all the methodology of TDSM applied for this study case, to evaluate the ability of flight that a determined pilot has. As follows, this also gives a step-by-step of this process in all the stages using the methodology in Chapter **??**.

4.1 *Understanding of Drone Flight Performance Evaluation*

The previous tests described were the first point in touch to qualify a pilot's performance for this work. The objective of NIST© is to gather the performance-based of point, but is it possible to evaluate this performance from metrics thrown by the drone? In this case, is it possible to recreate some scenarios taking the drone's position and angular movements? Maybe yes, and following the same methodology, but let us understand the external involved to define this. So, primarily in NIST© tests, we have external conditions like wheater, which can partially affect the results; for example, given different wind speed conditions, this might make more difficult the manipulation of the drone. If there is an intention of capturing the learning rate of a specific pilot, then it is needed to limit this external variable like weather conditions. On the other hand, a critical aspect to consider is the defined route for the pilot; this is a perfect point to consider to prepare some specific scenarios for this work. A defined route helps define a specific scenario and limit the areas where the flight could be measured. Resuming what is explained before, for this work, there are some things defined for sure:

- A closed environment without weather conditions can affect the test.
- Position and angular metrics captured in real-time through the drone are the most convenient for this work.
- The pilot will need to accomplish a defined, specific, and straightforward route.

From here, there is also another thing to consider, and it is about measuring the metrics obtained during the flight. In the case of NIST© , there is using a system point gain in the base of the zooming of the drone's camera. For this work, is proposed position metric, so an area error is convenient to implement as a list of errors in a determined distance during the route, defined as how much the drone is away from the mainline route the defined scenario, theoretically. In this way, it is possible to measure the learning rate behavior between a timeline of flight of a specific pilot and visualize this distance error during each flight.

4.2 *Acquisition and Understanding Data of the Flight Evaluation*

4.2.1 *Designed Experiment*

These flights had executed by eight pilots, and the route designed is as represented in Figure 2.3, described in words consists of a zone considered as "Home" where the drone is its starting point and "Landing" which is the endpoint for arrival, which marks the end of the route. The drone should start from the "Home," elevating up to 1 meter in y-axis only; after this, it should advance 4 meters on the x-axis, it should go down 1 meter in the y-axis until it reaches the "Landing" zone. Below Figure 4.1 represents this scenario.

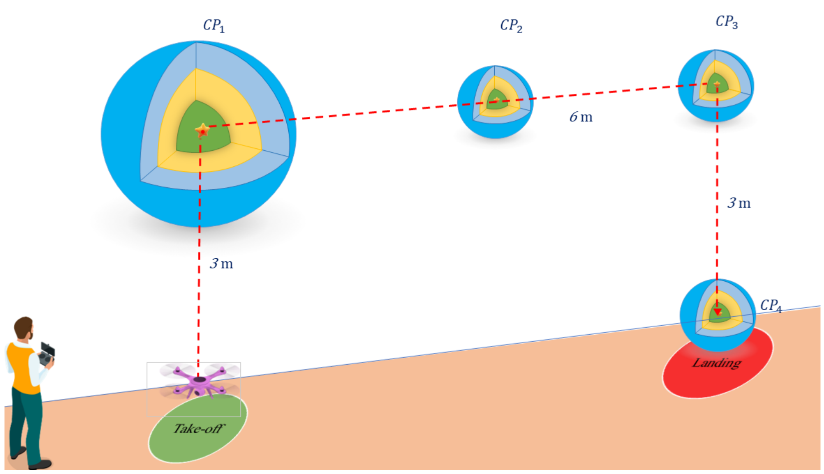


Figure 4.1: Scenario Flight Test

For this route (*please refer Figure 4.2 the origin coordinates*) mentioned above was the reference for each test flight which each pilot executed this order of set flight like next,

Set of Flights:

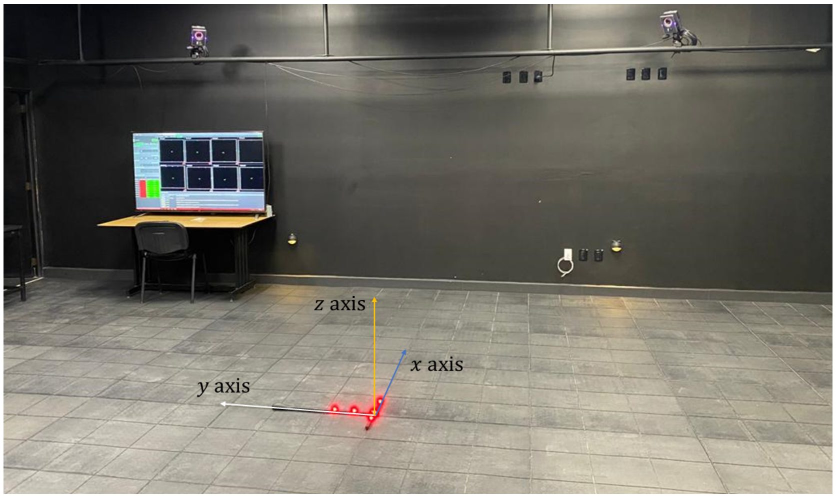


Figure 4.2: Origin set up of the MoCap System© workspace.

- A set of 10 flights with the nose of the drone pointing to the front view from the pilot is situated; this type of flight is called Front Nose Orientation Flight (FNOF) as data variable. Figure 4.3

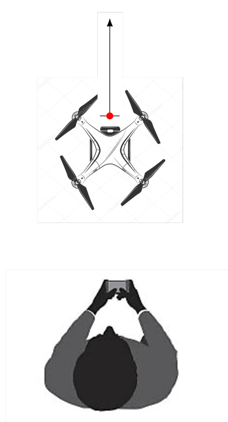


Figure 4.3: Flight with Nose oriented to Front. *In data we can find as FNOF*

- A set of 10 flights with the nose of the drone pointed to the right-hand direction from the pilot is situated; this type of flight is called Right Nose Orientation Flight (RNOF) as data variable. Figure 4.4

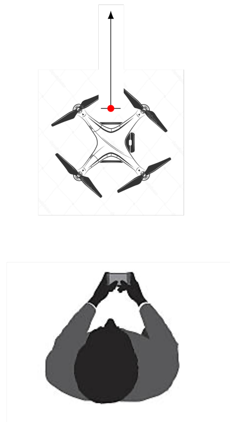


Figure 4.4: Flight with Nose oriented to Right. *In data we can find as RNOF*

- A set of 10 flights with the nose of the drone pointed to the left-hand direction from the pilot is situated; this type of flight is called Left Nose Orientation Flight (LNOF) as data variable. Figure 4.5

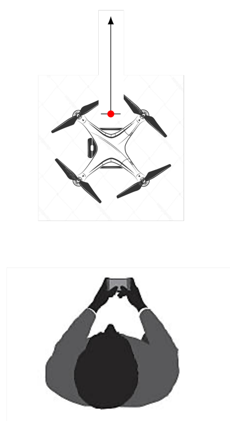


Figure 4.5: Flight with Nose oriented to Right. *In data we can find as LNOF*

- A set of 10 flights with the nose of the drone pointed to the backward view from the pilot is situated (nose will be face-to-face to pilot); this type of flight is called Back Nose Orientation Flight (BNOF) as data variable. Figure 4.6

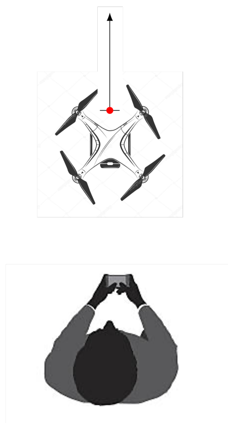


Figure 4.6: Flight with Nose oriented to Right. *In data we can find as BNOF*

Each set of ten flights is performed with different nose orientations of the drone to find this weakness-strongest response from the psychomotor abilities of pilots. One of the objectives mentioned in Chapter 1.5 is studying the learning rate of the pilots between a set of flights and the abilities that need reinforcement.

4.2.2 Data Acquisition

As mentioned in subsection 3.1, values captured such as control position and angular speed from the drone using the Motion Capture (MoCap) System and stored as a .csv file for each flight. A brief description of this type of file canes as follows, it consists of the columns: *Frame (sequential number), Sub Frame, RX, RY, RZ (angular speed as radians), TX, TY, TZ (control position as millimeter), Time (seconds), Euclidean Angle (radians), and Euclidean Distance (millimeter).* In Figure 4.7 there is a representation of the Drone Trajectory in 3d graph and in Figures 4.7 and 4.8 are the representation of the flight in a spatial graph in respect with the ground truth trace-line, and the behavior of the position of *x*, *y*, *z* in time.

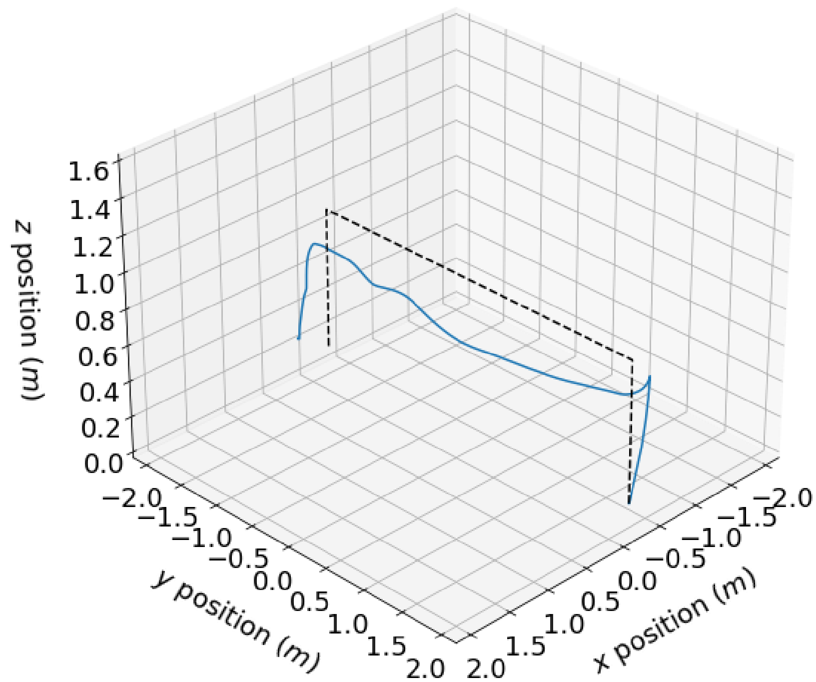
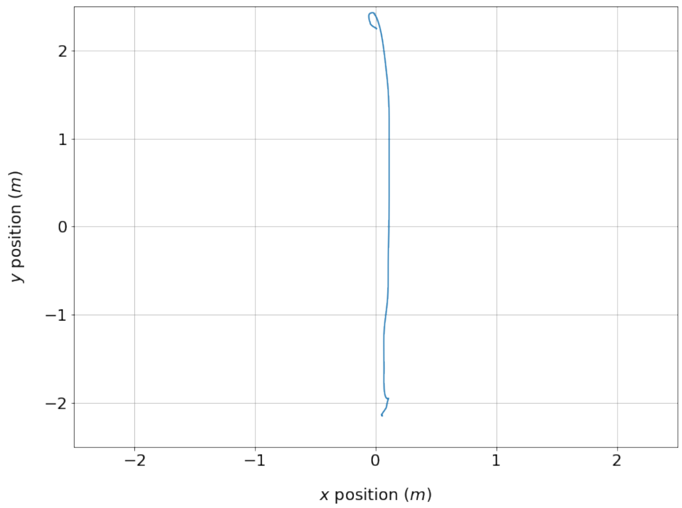
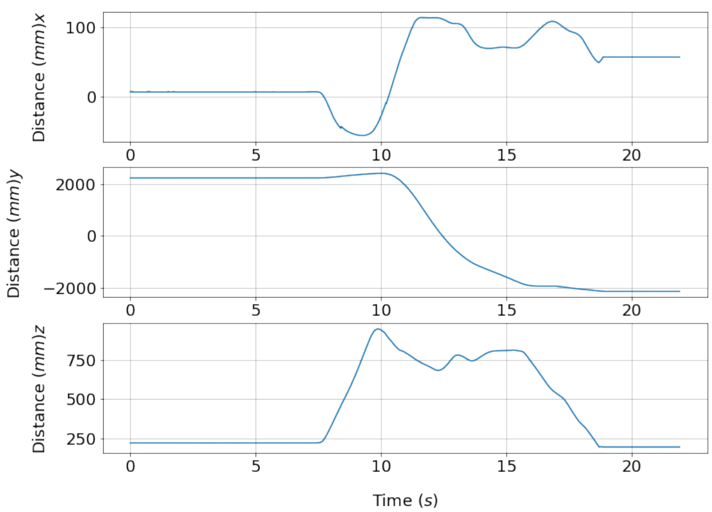


Figure 4.7: Graphic Representation of Drone trajectory in *blue line* vs. the defined route as ground truth with *dotted black line*.



(a)



(b)

Figure 4.8: Flight #1 with Nose in Front Orientation, *(a) represents the movement between x position in relation with y position, (b) represents the timelines behavioral positions for x, y and z positions.*

In Figure 4.8 *(a)* represents the visualization of the drone flight from sky down view perspective in order to see the variation of the flight when the drone reaches the top of the trace and travels to the opposite side of the marked area. Please follow this explanation using Figure 4.7 for a better visualization.
In Figure 4.8 *(b)* is reflected that in the intervals of seconds 0 to 10 the position in y starts with 200 mm, meanwhile x remains with 0 mm and z starts with 250 mm, this is the first part of the Flight, when the Drone tries to go up 1 $meter$. The second part of the flight consists

from seconds 10 to 16 approximately when z position is elevated to 800 mm an it tries to maintain during this time with some variations, meanwhile y position value goes down from 2000 mm to -2000 mm because is the part when the drone travels 2 meters to the other side of the trace, and x position has little variations which is expected. Finally during seconds 17 to 19 the drone has a quick descending, this can be reflected with position z how this value goes down until it reaches the start point from 750 mm to 250 mm approximately, meanwhile y position reaches the opposite side of the marked trace. Please follow this explanation using Figure 4.7 for a better visualization.

In Tables 4.1 and 4.2 there is an extract of a set of data captured specifically for *Flight #1 with Drone Nose in Front Orientation*.

Table 4.1: Part I: Extract of File Generated by MOCAP System for Front Flight #1

Objects							
100							
	Sub	DJI_1:DJI_1					
Frame	Frame	RX	RY	RZ	TX	TY	TZ
		rad	rad	rad	mm	mm	mm
1	0	-116.239	-240.183	-159.317	739.496	2245.51	223.694
2	0	-106.326	-237.183	-158.309	745.372	2245.55	223.69
3	0	-106.394	-235.396	-156.306	746.144	2245.59	223.705
4	0	-107.128	-199.088	-193.631	690.471	2246.29	223.392
5	0	-230.902	-205.318	-19.534	689.285	2246.28	223.354
6	0	-277.058	-201.255	-196.545	692.621	2246.23	223.354
7	0	-235.616	-168.467	-287.347	752.951	2244.83	223.677
8	0	-214.263	-170.587	-287.915	759.278	2244.88	223.727
9	0	-195.135	-175.381	-281.537	757.763	2244.96	223.72
10	0	-147.038	-198.618	-191.917	690.118	2246.3	223.409
...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...
...	...	...	...	...	..	...	...
2190	0	-360.886	217.624	-341.503	569.667	-2147.9	197.26
2191	0	-348.314	215.974	-341.596	569.418	-2147.88	197.453

For the processing part after all this analysis of the data collected as mentioned in subsection 1.5.1 we want to calculate on first hand, how separated was the pilot trace flight with the ground truth, obtain a metric that can distinguish how distance was in total in the flight, and after this for all flight with this metric find a model that interprets for all flights the behavior of this distance error from the pilot flight to the ground truth, and predicts if possible what would be this distance error in a specific future flight and type flight with the nose orientation of the drone specified.

In the first part its necessary to design a *methodology* for calculate this distance error explained before, it need to exact, and covers all the possible critical sides of the trace. So in this way we can evaluate the most accuracy way possible the pilot ability. In next

Objects		
100		
	Ángulo	Distance
Time (s)	Euclideana (¡)	Euclidieana (mm)
0.01	3.107.753	2.256.636.624
0.02	30.433.983	2.256.676.223
0.03	30.193.133	2.256.717.538
0.04	27.792.762	225.738.132
0.05	28.433.493	2.257.367.573
0.06	28.266.787	2.257.317.921
0.07	33.392.301	2.255.958.737
0.08	3.353.417	225.601.366
0.09	3.322.685	225.609.252
0.1	27.658.172	2.257.392.943
...	...	...
...	...	...
...	..	...
21.9	342.214.735	2.157.691.155
21.91	342.295.789	2.157.688.242

Table 4.2: Part II: Extract of File Generated by MOCAP System for Front Flight #1

subsection is explained *Methodology* proposed for this work, and the designed *checkpoints* for measure this metric, and then in Chapter 4.2.4 in specifically in Table 4.6 in column *DEE* is the Distance Euclidean Error for all this checkpoints error for each flight.

4.2.3 Assignment Checkpoints Convention

This methodology was created with the intention to give a step by step details process of how assigned checkpoints will be located in a specific route depending of the number of direction changes and longitude measurement. The idea of this methodology is to being generic for other types of flights in order to convey a general way to apply this for other levels of experience pilot tests too. Also this Checkpoints will establish the error distance that the pilot miss over the trace in an exact measurement.

1. We locate a Checkpoint CP_1 *(3)* at home position, then we locate the Checkpoints at the points where there will be a change of direction CP_{i+1} up to $CP_{\#CDD}$ *(4)*, and finally another Checkpoint on landing position CP_n. *(5)*

   Refer to Figure 4.9 as visual representation.

   A checkpoint is a defined sphere in space with a defined radius rCP_i Moreover, its center had defined with coordinates:

$$CP_i = (x_i, y_i, z_i) i = 1...n \tag{4.1}$$

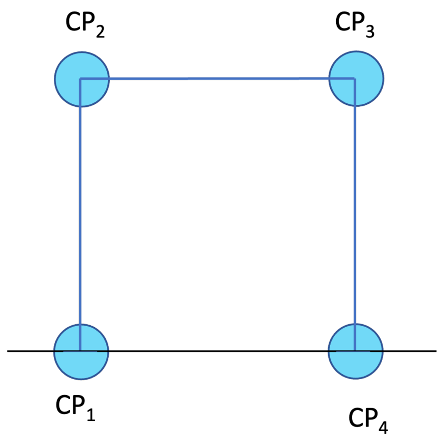


Figure 4.9: Locating initial Checkpoints *(Home, Landing, Change of Direction).*

The change in any axis of the path either x, y, z is defined as a change of direction where:

$$\#CDD = \# \text{ address change number} \tag{4.2}$$

The home is where the drone had located when it is ready for takeoff, and there we label the CP_1.

$$H = CP_1 \text{ at home plate position} \tag{4.3}$$

Once the drone takes off, we assign a CP to each change of direction.

$$CP_{i+1} \text{ to } CP_{\#CDD} \text{ where } i = 1...\#CDD \tag{4.4}$$

Once we are in the last change of direction before landing. The landing had defined as:

$$L = CP_n \text{ at landing position} \tag{4.5}$$

And finally n is defined as the total number of checkpoints which is defined as:

$$n = H + \#CDD + L \tag{4.6}$$

2. For each position CP_i generate a uniform random number ECP_i *(7)* within a range $(0 - rCP_i)$

$$ECP_i = random.generator(CPi, (0 - rCP_i)) \tag{4.7}$$

3. We assign the trace T_i between CP_{i+1} and CP_i and calculate its length.

   Each trace is defined as:

$$\vec{T_i} = \overrightarrow{CP_iCP_{i+1}} \tag{4.8}$$

And its length as:

$$\left|\overrightarrow{T_i}\right| = \text{span length} \tag{4.9}$$

Applying to the case:

$$\overrightarrow{T_1} = \overrightarrow{CP_1CP_2} = \overrightarrow{OCP_2} - \overrightarrow{OCP_1} = (0,0,1) - (0,0,0) = (0,0,1)$$

$$\overrightarrow{T_2} = \overrightarrow{CP_2CP_3} = \overrightarrow{OCP_3} - \overrightarrow{OCP_2} = (1,0,1) - (0,0,1) = (1,0,0)$$

$$\overrightarrow{T_3} = \overrightarrow{CP_3CP_4} = \overrightarrow{OCP_4} - \overrightarrow{OCP_3} = (1,0,0) - (1,0,1) = (0,0,-1) \tag{4.10}$$

The visual representation of traces looks like Figure 4.10 in red arrows.

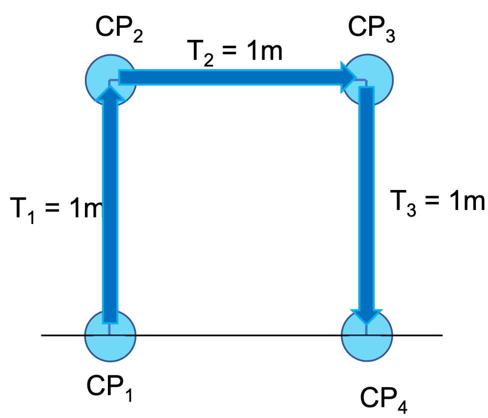


Figure 4.10: Assignment of the Traces.

4. Calculate the maximum number of intermediate checkpoints per trace:

$$\#CPI_{T_i} = \frac{\left|\overrightarrow{T_i}\right| - rCP_i}{2 * rCP_i}, \quad i = 1, \ldots, n-1 \tag{4.11}$$

Where applying to the case we have:

$$\begin{array}{lll} i = 1 & \#CPI_{T_1} = \frac{1-2(0.1)}{2(0.1)} = 4 \\ i = 2 & \#CPI_{T_2} = \frac{1-2(0.1)}{2(0.1)} = 4 \\ i = 3 & \#CPI_{T_3} = \frac{1-2(0.1)}{2(0.1)} = 4 \end{array} \tag{4.12}$$

5. Calculate the position of the intermediate checkpoints $PCPI_jT_i$ *(13)*:

$$\mathrm{CPI}_j\, T_i = j\Delta_{(i,j)}\overrightarrow{T_i} \quad \text{where } \Delta_{(i,j)} = \frac{\left|\overrightarrow{T_i}\right|}{j+1}\left\{ \begin{array}{l} i = 1, \ldots, n-1 \\ j = 1, \ldots, k \quad [\textit{ where the value of } k = \#CPI_{Ti}] \end{array} \right. \tag{4.13}$$

Applying to the case:

For T_1

With 1 intermediate checkpoint ($k = 1$) at T_1 ($i = 1$)

$$\begin{gathered} \Delta_{(1,1)} = \frac{\left|\overrightarrow{T_1}\right|}{1+1} = \frac{1}{2} \\ CPI_1T_1 = 1\Delta_{(1,1)}\overrightarrow{T_1} = (0, 0, 0.5) \end{gathered} \tag{4.14}$$

With 2 intermediate checkpoints ($k = 2$) in T_1 ($i = 1$)

$$\begin{gathered} \Delta_{(1,2)} = \frac{\left|\overrightarrow{T_1}\right|}{2+1} = \frac{1}{3} \\ CPI_1T_1 = 1\Delta_{(1,2)}\overrightarrow{T_1} = \frac{1}{3}(0, 0, 1) = (0, 0, 0.\widehat{333}) \\ CPI_2T_1 = 2\Delta_{(1,2)}\overrightarrow{T_1} = \frac{2}{3}(0, 0, 1) = (0, 0, 0.\widehat{666}) \end{gathered} \tag{4.15}$$

With 3 intermediate checkpoints ($k = 3$) in T_1 ($i = 1$)

$$\begin{gathered} \Delta_{(1,3)} = \frac{\left|\overrightarrow{T_1}\right|}{3+1} = \frac{1}{4} \\ CPI_1T_1 = 1\Delta_{(1,3)}\overrightarrow{T_1} = \frac{1}{4}(0, 0, 1) = (0, 0, 0.25) \\ CPI_2T_1 = 2\Delta_{(1,3)}\overrightarrow{T_1} = \frac{2}{4}(0, 0, 1) = (0, 0, 0.5) \\ CPI_3T_1 = 3\Delta_{(1,3)}\overrightarrow{T_1} = \frac{3}{4}(0, 0, 1) = (0, 0, 0.75) \end{gathered} \tag{4.16}$$

With 4 intermediate checkpoints ($k = 4$) in T_1 ($i = 1$)

$$\begin{aligned}
\Delta_{(1,4)} &= \frac{\left|\overrightarrow{T_1}\right|}{4+1} = \frac{1}{5} \\
CPI_1T_1 = 1\Delta_{(1,4)}\overrightarrow{T_1} &= \frac{1}{5}(0,0,1) = (0,0,0.2) \\
CPI_2T_1 = 2\Delta_{(1,4)}\overrightarrow{T_1} &= \frac{2}{5}(0,0,1) = (0,0,0.4) \\
CPI_3T_1 = 3\Delta_{(1,4)}\overrightarrow{T_1} &= \frac{3}{5}(0,0,1) = (0,0,0.6) \\
CPI_4T_1 = 4\Delta_{(1,4)}\overrightarrow{T_1} &= \frac{4}{5}(0,0,1) = (0,0,0.8)
\end{aligned} \tag{4.17}$$

For T_2

With 1 intermediate checkpoint ($k = 1$) in T_2 ($i = 2$)

$$\begin{aligned}
\Delta_{(2,1)} &= \frac{\left|\overrightarrow{T_2}\right|}{1+1} = \frac{1}{2} \\
CPI_1T_2 = 1\Delta_{(2,1)}\overrightarrow{T_2} &= (0.5,0,0)
\end{aligned} \tag{4.18}$$

With 2 intermediate checkpoints ($k = 2$) in T_2 ($i = 2$)

$$\begin{aligned}
\Delta_{(2,2)} &= \frac{\left|\overrightarrow{T_2}\right|}{2+1} = \frac{1}{3} \\
CPI_1T_2 = 1\Delta_{(2,2)}\overrightarrow{T_2} &= \frac{1}{3}(1,0,0) = (0.\widehat{333},0,0) \\
CPI_2T_2 = 2\Delta_{(2,2)}\overrightarrow{T_2} &= \frac{2}{3}(1,0,0) = (0.\widehat{666},0,0)
\end{aligned} \tag{4.19}$$

With 3 intermediate checkpoints ($k = 3$) in T_2 ($i = 2$)

$$\begin{aligned}
\Delta_{(2,3)} &= \frac{\left|\overrightarrow{T_2}\right|}{3+1} = \frac{1}{4} \\
CPI_1T_2 = 1\Delta_{(2,3)}\overrightarrow{T_2} &= \frac{1}{4}(1,0,0) = (0.25,0,0) \\
CPI_2T_2 = 2\Delta_{(2,3)}\overrightarrow{T_2} &= \frac{2}{4}(1,0,0) = (0.5,0,0) \\
CPI_3T_2 = 3\Delta_{(2,3)}\overrightarrow{T_2} &= \frac{3}{4}(1,0,0) = (0.75,0,0)
\end{aligned} \tag{4.20}$$

With 4 intermediate checkpoints ($k = 4$) in T_2 ($i = 2$)

$$\begin{aligned}
\Delta_{(2,4)} &= \frac{\left|\overrightarrow{T_2}\right|}{4+1} = \frac{1}{5} \\
CPI_1T_2 = 1\Delta_{(2,4)}\overrightarrow{T_2} &= \frac{1}{5}(1,0,0) = (0.2,0,0) \\
CPI_2T_2 = 2\Delta_{(2,4)}\overrightarrow{T_2} &= \frac{2}{5}(1,0,0) = (0.4,0,0) \\
CPI_3T_2 = 3\Delta_{(2,4)}\overrightarrow{T_2} &= \frac{3}{5}(1,0,0) = (0.6,0,0) \\
CPI_4T_2 = 4\Delta_{(2,4)}\overrightarrow{T_2} &= \frac{4}{5}(1,0,0) = (0.8,0,0)
\end{aligned} \tag{4.21}$$

For T_3

With 1 intermediate checkpoint ($k = 1$) in T_2 ($i = 3$)

$$\begin{aligned}
\Delta_{(3,1)} &= \frac{\left|\overrightarrow{T_3}\right|}{1+1} = \frac{1}{2} \\
CPI_1T_3 = 1\Delta_{(3,1)}\overrightarrow{T_3} &= (0,0,-0.5)
\end{aligned} \tag{4.22}$$

With 2 intermediate checkpoints ($k = 2$) in T_2 ($i = 3$)

$$\begin{aligned}
\Delta_{(3,2)} &= \frac{\left|\overrightarrow{T_3}\right|}{2+1} = \frac{1}{3} \\
CPI_1T_3 = 1\Delta_{(3,2)}\overrightarrow{T_3} &= \frac{1}{3}(0,0,-1) = (0,0,-0.\widehat{333}) \\
CPI_2T_3 = 2\Delta_{(3,2)}\overrightarrow{T_3} &= \frac{2}{3}(0,0,-1) = (0,0,-0.\widehat{666})
\end{aligned} \tag{4.23}$$

With 3 intermediate checkpoints ($k = 3$) in T_2 ($i = 3$)

$$\begin{aligned}
\Delta_{(3,3)} &= \frac{\left|\overrightarrow{T_3}\right|}{3+1} = \frac{1}{4} \\
CPI_1T_3 = 1\Delta_{(3,3)}\overrightarrow{T_3} &= \frac{1}{4}(0,0,-1) = (0,0,-0.25) \\
CPI_2T_3 = 2\Delta_{(3,3)}\overrightarrow{T_3} &= \frac{2}{4}(0,0,-1) = (0,0,-0.5) \\
CPI_3T_3 = 3\Delta_{(3,3)}\overrightarrow{T_3} &= \frac{3}{4}(0,0,-1) = (0,0,-0.75)
\end{aligned} \tag{4.24}$$

With 4 intermediate checkpoints ($k = 4$) in T_2 ($i = 3$)

$$
\begin{aligned}
\Delta_{(3,4)} &= \frac{\left|\overrightarrow{T_3}\right|}{4+1} = \frac{1}{5} \\
CPI_1T_3 = 1\Delta_{(3,4)}\overrightarrow{T_3} &= \frac{1}{5}(0,0,-1) = (0,0,-0.2) \\
CPI_2T_3 = 2\Delta_{(3,4)}\overrightarrow{T_3} &= \frac{2}{5}(0,0,-1) = (0,0,-0.4) \\
CPI_3T_3 = 3\Delta_{(3,4)}\overrightarrow{T_3} &= \frac{3}{5}(0,0,-1) = (0,0,-0.6) \\
CPI_4T_3 = 4\Delta_{(3,4)}\overrightarrow{T_3} &= \frac{4}{5}(0,0,-1) = (0,0,-0.8)
\end{aligned}
\tag{4.25}
$$

Figure 4.11 represents graphically how the trace looks with the middle checkpoints and the initial ones, after it finishes all iterations.

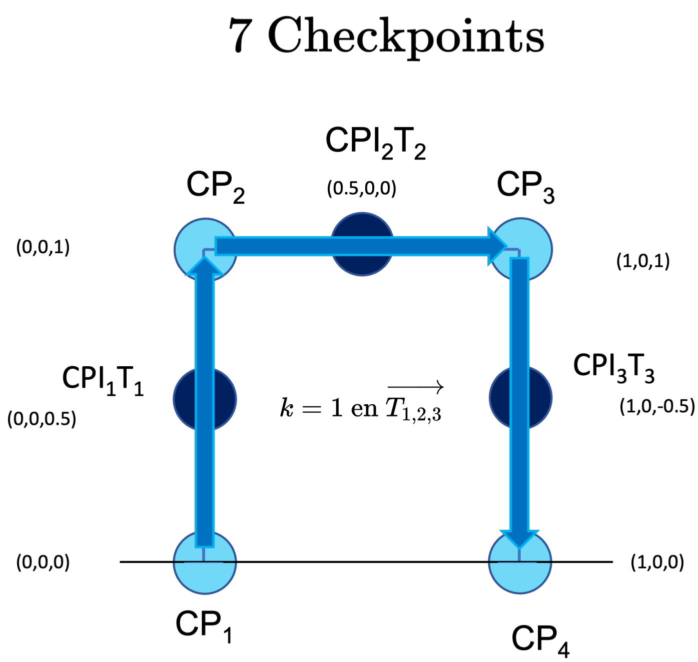


Figure 4.11: Final iteration remaining with initial and one intermediate checkpoints per trace.

4.2.4 Processing Checkpoints in Data

	Distance CP 1	Time CP 1	Distance CP 1,1	Time CP 1,1	Distance CP 2
DJI_1.csv	0	0	0.09422685123	10.39	0.1230964143
DJI_1 1.csv	0	0	0.1072618008	10.63	0.1679795491
DJI_1 2.csv	0	0	0.1222917882	6.01	0.0448231698
DJI_1 3.csv	0	0	0.2022566183	8.28	0.04551918453
DJI_1 4.csv	0	0	0.173967196	5.38	0.1471906894
DJI_1 5.csv	0	0	0.07374948072	8.45	0.1536095659
DJI_1 6.csv	0	0	0.07664092966	6.91	0.080878208
DJI_1 7.csv	0	0	0.08266311678	5.77	0.05126018525
DJI_1 8.csv	0	0	0.0962524878	5.28	0.0743017463
DJI_1 9.csv	0	0	0.1462147332	5.43	0.1958881472
...	...	...	...	...	...
...	...	...	...	...	...
DJI_right 10.csv	0	0	0.193896614	2.9	0.1470736674

Table 4.3: Part I: Extract of Data with distance error for checkpoint calculated,*(including time)* in Front Flight #1

Time CP 2	Distance CP 2,1	Time CP 2,1	Distance CP 2,2	Time CP 2,2
13.06	0.1063482472	13.99	0.1234759725	14.77
10.52	0.2830023798	11.51	0.3349848237	12.24
7.75	0.0388972473	9.15	0.08810078142	10.07
8.55	0.2853162584	9.92	0.328282967	11.07
7.38	0.1370842097	8.5	0.1212568685	9.44
10.03	0.03059313731	12.56	0.1874753611	13.44
7.24	0.1904778006	9.3	0.2001255687	10.08
6.38	0.07254837434	8.68	0.09209649279	9.77
6.29	0.1309726603	7.62	0.08980766257	8.53
5.89	0.1057668385	8.21	0.1034246115	9.03
...	...	...	...	...
...	...	...	...	...
4.49	0.1142192847	5.35	0.2179864112	6

Table 4.4: Part II: Extract of Data with distance error for checkpoint calculated,*(including time)* in Front Flight #1

Distance CP 2,3	Time CP 2,3	Distance CP 3	Time CP 3	Distance CP 4
0.07591725505	15.78	0.1264816041	16.81	0.2618491739
0.2445824942	13.18	0.2007087463	15.34	0.3397884757
0.1144959564	11.08	0.1114939063	12.23	0.4146496652
0.3214861791	12.2	0.09669152362	15.13	0.1261417144
0.1174594085	10.46	0.1110417164	11.72	0.332883812
0.2063493372	14.29	0.05853862507	15.64	0.3573431177
0.1498789631	10.93	0.1277228716	12.34	0.4048202144
0.01871915043	10.78	0.04128619501	11.86	0.4679391111
0.09830709231	9.52	0.08221410745	10.74	0.3168416638
0.1058873561	9.77	0.05274039016	10.73	0.392489008
...	...	...	...	...
...	...	...	...	...
0.2335362941	7.04	0.1006436762	8.33	0.1789560913

Table 4.5: Part III: Extract of Data with distance error for checkpoint calculated,*(including time)* in Front Flight #1

The explained methodology in subsection 4.2.3 was coded using Python Language, please find the code developed of on this link repository `http://t.ly/FGtk` there is a Google Colab. file with name *checkpoints-methodology-assignment.py*. This code takes data from tables 4.1 and 4.2 and after processed we will have an extract data as for example in tables 4.3, 4.4 and 4.5. So going in detail in table 4.3 focusing in the first row this is the extract of Flight #1 with Front Nose Orientation and the Checkpoint Error Distance and Time, for each one, so its mentioned as Distance *CP* ***ID*** and Time *CP* ***ID*** and so on. In Figure 4.12 is the visual representation of the flight with the checkpoints were considered specific flight, in repository `http://t.ly/FGtk` there are the rest of all graphs for each flight as reference. For finalize this Chapter, and as introduction of Chapter 4.2.4 in table 4.6 is the finished data set after processing, with the column *DEE* as this is equal to the Euclidean Distance for all the Checkpoints error for the specific flight.

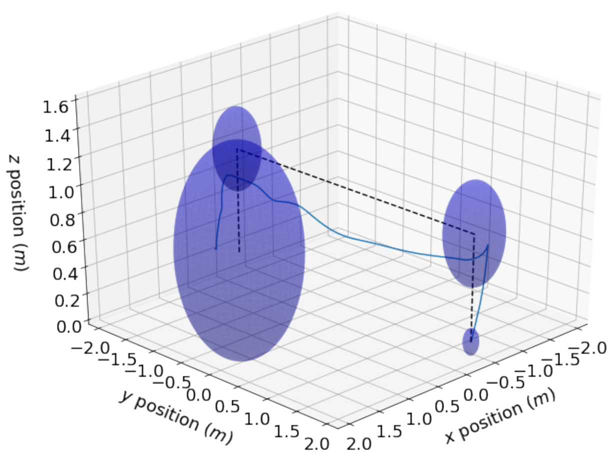


Figure 4.12: Graphic Rperesentation of Drone Trajectory in *blue line* vs the defined route as ground truth with *dotted black line* **and including in purple ovals considered as checkpoints counting the error distance.**

4.3 Drone Flight Performance Evaluation Model

This section presents all the process that involves analyzing, modeling, and predicting the final data after being processed. The main intention, as mentioned before, is first to have an analysis of the behavior of the dependent and independent variables in each category. Then have a precise examination of the variance between the different category flights, then propose a model that can predict the distance error in future flights for this selected pilot.

4.3.1 Data for Analysis

Next subsection explores the data set that has been processed, and describes in first place the columns that are composed with, the behavior of the data using scatterplots, and self-organized way to add some dummy data in order to categorize the types of flights orientation.

4.3.2 Analysis for the final data after Processing for Modeling

In the first column of final data in Table 4.6, the ID Flight, which is a variable that increments by, is the sequence that the pilot is performing over and over to an expected less error distance, represented with column DEE. This ID Flight resets the "Category Flight." As was already mentioned, we have four types of flight; it depends on the nose orientation of the drone to qualify the different psycho-motor abilities of the pilot. Therefore, columns RNOF, LNOF, and BNOF are dummy variables to get the best-categorized separation in the dataset for analysis and modeling; the meanings are Right Nose Orientation Flight, Left Nose Orientation Flight, and Back Nose Orientation Flight consecutively. An explanation of dummy variables is in subsection 4.3.7.

The scatterplot Analysis, beginning with Front and Back Flights, has unambiguous evidence that the Distance Euclidean Error decreases the ID Flight. The relation between both variables is relational inverse, in Figures 4.13 and 4.14, as mentioned before; expected because it shows the evidence that this learning rate the causes the decrements of Error during the Flight. Left Flight, Figure 4.15 seems to have the most dispersed data behavior; it doesn't have a particular behavior sometimes; it increments and decrements, even though there are some outliers data. Finally, Right Flight in Figure 4.16 has this behavior explained as learning where the Error goes down as starting, but the #6 flight before this data is not predictable. Left and Right Flights can affect a model, assuming from here this dispersion may conflict some accuracy, but first, let's introduce with variance analysis.

ID Flight	Type Flight	RNOF	LNOF	BNOF	DEE
1	Front	0	0	0	0.985675149
2	Front	0	0	0	1.806739288
3	Front	0	0	0	1.047604871
4	Front	0	0	0	1.528641891
5	Front	0	0	0	1.234495717
6	Front	0	0	0	1.174186399
7	Front	0	0	0	1.343742274
8	Front	0	0	0	0.962990611
9	Front	0	0	0	0.972933571
10	Front	0	0	0	1.210365933
1	Back	0	0	1	2.365307062
2	Back	0	0	1	2.329833631
3	Back	0	0	1	1.052362288
4	Back	0	0	1	1.939221534
5	Back	0	0	1	1.992030662
6	Back	0	0	1	1.281841702
7	Back	0	0	1	1.387536712
8	Back	0	0	1	1.666399614
9	Back	0	0	1	1.645480065
10	Back	0	0	1	1.063678058
1	Left	0	1	0	1.694682341
2	Left	0	1	0	1.402926549
3	Left	0	1	0	1.342333974
4	Left	0	1	0	2.07969051
5	Left	0	1	0	1.534874568
6	Left	0	1	0	1.756106841
7	Left	0	1	0	0.974873673
8	Left	0	1	0	1.034750899
9	Left	0	1	0	2.01350065
10	Left	0	1	0	1.677935904
1	Right	1	0	0	1.771016853
2	Right	1	0	0	1.2398286
3	Right	1	0	0	2.084629454
4	Right	1	0	0	1.33609378
5	Right	1	0	0	1.35132887
6	Right	1	0	0	1.384263872
7	Right	1	0	0	1.411525773
8	Right	1	0	0	1.581860767
9	Right	1	0	0	1.461563516
10	Right	1	0	0	1.274292183

Table 4.6: Data Table after processed, used for the modeling. Columns shorted for the width page, which follows: ID Flight, Type Flight, RNOF (Right Nose Orientation Flight), LNOF (Left Nose Orientation Flight), BNOF (Back Nose Orientation Flight), DEE (Distance Euclidean Error)

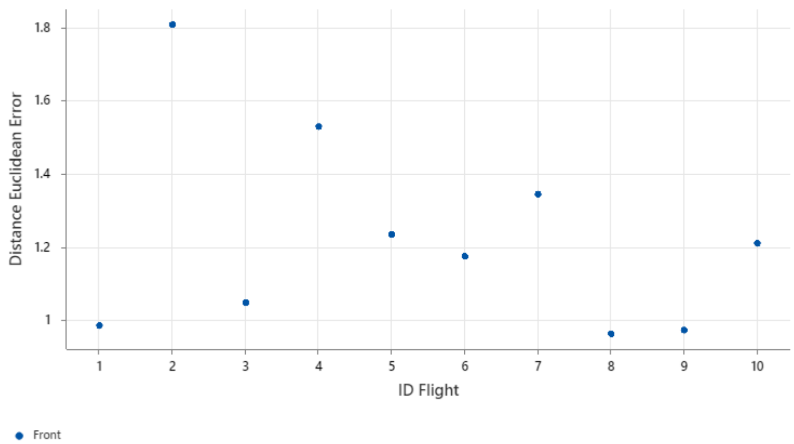


Figure 4.13: Graphic Scatterplot for Front Nose Orientation Flights

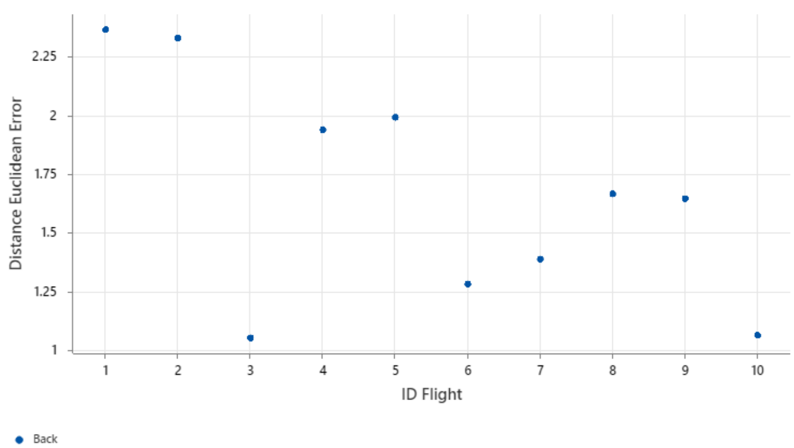


Figure 4.14: Graphic Scatterplot for Back Nose Orientation Flights

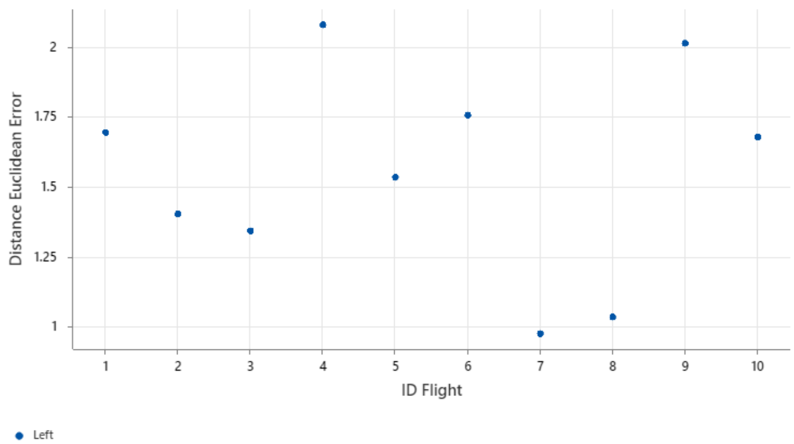


Figure 4.15: Graphic Scatterplot for Left Nose Orientation Flights

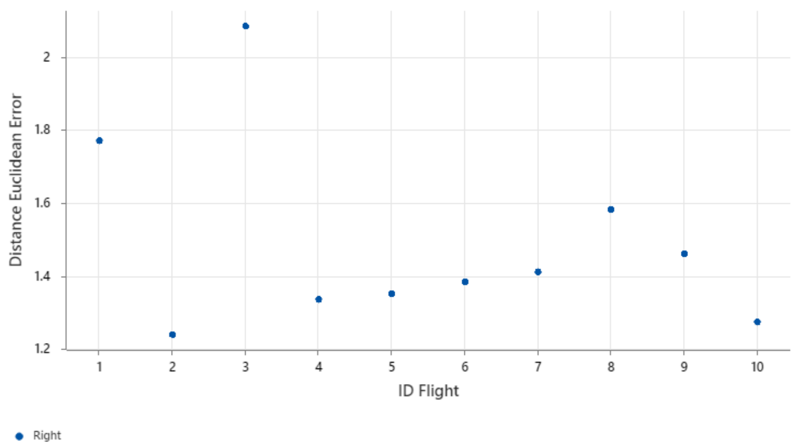


Figure 4.16: Graphic Scatterplot for Right Nose Orientation Flights

4.3.3 *Diagnosis of the Pilot Abilities in Flight Performance with different Oriented Positions*

Next subsection remarks all the variation between data with different categories in order to do a diagnosis of what is the behavior of the pilot while doing different orientations; in order to group the data and how similarities can have. This subsection focus in the average for the different types of flights, minimum and maximum values.

4.3.4 *Tukey HSD Test. Multiple Comparisons method.*

- For *Back Nose* Orientation we have the maximum value of Euclidean Distance Error with **2.365**m, and has also the most highest mean of Distance Euclidean Error with **1.2267**m from all the types of flights, means that this was the flight with more difficulty to follow the trace line. Also has the highest Standard Deviation with a value of **0.480** which means that for this type of flight the Distance Euclidean Error for the 10 flights is the most dispersed data in relation to the mean.

- For *Front Nose* Orientation we have the minimum value of Distance Euclidean Error with **0.9630**m, and has also the minimum mean of Distance Euclidean Error from all the types of flights with **1.2267**m, means that this was the flight most controlled with the lowest Distance Euclidean Error, so it was more near to the following trace line.
- For *Left Nose* Orientation we have the second highest mean of Distance Euclidean Error with **1.551**m, the values from minimum and maximum comes from **0.975**m to **2.080**m which it makes sense because we have the second highest Standard Deviation in the Distance Euclidean Error, so data has extensive range for each flight. But it is the second hardest orientation for the pilot to be controlled.
- For *Right Nose* Orientation we have the second lowest mean of Distance Euclidean Error with **1.4896**m, so at simple view, can be say that this is the second most controlled orientation for the pilot, and this particular Type of Flight has the lowest Standard Deviation with a value of **0.2606**, so the dispersed Distance Euclidean Error in relation to the mean is less than the other types of flight.

In conclusion, with this simple metrics it can be said that the pilot has more domain in this orientation in order as follows, Front and Right, but its more difficult to maintain a control in the drone when the nose is oriented to Left and Back towards the pilot. So the pilot need to work more on this orientations that will help in his psychometric control. Now, lets compare this means to see if there is an "honestly significant difference" from one type of flight to the other, or maybe can be found that means are almost same there is no difference, but this needs to be proved with the help of Tukey Test. [1]

[1] Douglas C Montgomery, Elizabeth A Peck, and G Geoffrey Vining. *Introduction to linear regression analysis*. John Wiley & Sons, 2021

Variable	Drone Nose Orientation	Total Count	Mean	SE Mean	StDev	Min	Max
Distance Euclidean Error	Back	10	1.672	0.152	0.480	1.052	2.365
	Front	10	1.2267	0.0862	0.2725	0.9630	1.8067
	Left	10	1.551	0.117	0.371	0.975	2.080
	Right	10	1.4896	0.0824	0.2606	1.2398	2.0846

Table 4.7: Descriptive Statistics: Distance Euclidean Error in base of Type of Flight

Tukey Test is based in a Pair Wise Comparison this means determine if the relationship between two sets of data is statistically significant, this is part of the ANOVA analysis which is created a confidence intervals

for all pair wise differences between the factor level (Types of Flights) means while controlling also the family error rate to a specified level. This study is based on the alpha value and a independent P value, which comes from compares the differences between means and then taking the absolute value of the this difference and dividing it by the standard error of the mean (SE) as determined by a one-way ANOVA test. The SE is in turn the sqaure root of (variance divided by sample size).
Following the next steps:

1. **Method**
   Null hypothesis: All means are equal
   Alternative hypothesis: At least one mean is different
   Significance level: $\alpha = 0.05$ *(Equal variances were assumed for the analysis)*[2]

   From the result of one way ANOVA can be demonstrated that **P** value is **0.055** which means that there is not a significant difference exist in the Type of Flight with the different Drone Nose Orientation. Plot 4.17 explains by itself that the mean values for the four groups interval distributed not too far from their respective means. Using Table 4.13 and Figure 4.17 it is identified that ANOVA detect not a significant effect Type of Flight between the groups. Lets going deep maybe it should be a remarked difference between pair of groups of flights. In this case the pair wise multiple comparisons test, also called as post hoc test, can explain us the mean differences with a more detailed way, between groups, using *Tukey Pair wise Comparisons.*

[2] William Mendenhall, Terry Sincich, and Nancy S Boudreau. *A second course in statistics: regression analysis*, volume 6. Prentice Hall Upper Saddle River, NJ, 2003

Table 4.8: Factor Information

Factor	Levels	Values
Drone Nose Orientation	4	Back, Front, Left, Right

Table 4.9: Analysis of variance table

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Drone Nose Orientation	3	1.062	0.3540	2.78	0.055
Error	36	4.591	0.1275		
Total	39	5.653			

2. **Tukey Pair wise Comparisons**

   The Tukey simultaneous with different error rate (90, 95 and 99%)

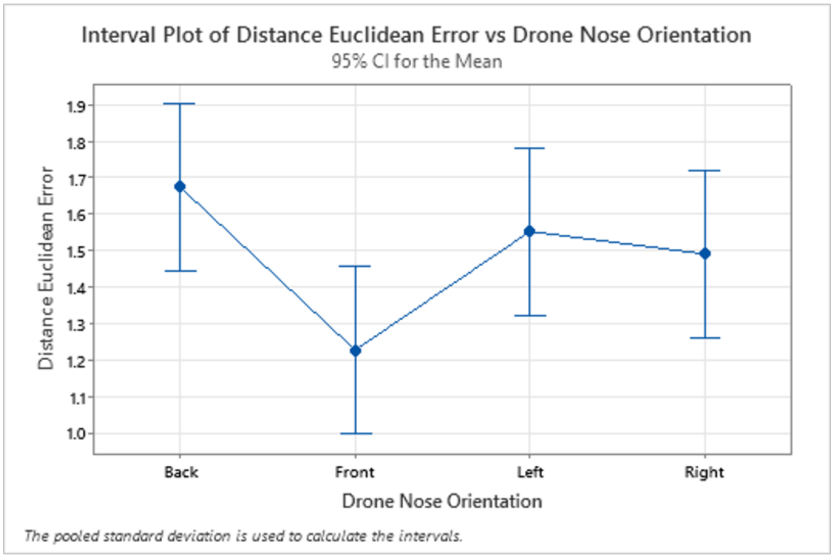


Figure 4.17: One way ANOVA plot of Distance Euclidean Error vs Drone Nose Orientation (4 groups with 95% CI for the mean)

Grouping information using the Tukey Method and 95% confidence			
Drone Nose Orientation	N	Mean	Grouping
Back	10	1.672	A
Left	10	1.551	A B
Right	10	1.4896	A B
Front	10	1.2267	B
Grouping information using the Tukey Method and 99% confidence			
Drone Nose Orientation	N	Mean	Grouping
Back	10	1.672	A
Left	10	1.551	A
Right	10	1.4896	A
Front	10	1.2267	A
Grouping information using the Tukey Method and 90% confidence			
Drone Nose Orientation	N	Mean	Grouping
Back	10	1.672	A
Left	10	1.551	A B
Right	10	1.4896	A B
Front	10	1.2267	B

Table 4.10: Grouping information (4 groups) using the Tukey Method with 90%, 95% and 99% confidence

is presented in Table 4.10 and Table 4.11. So going forward in the interpretation of the results in Table 4.10 highlights the significant and non-significant comparisons for any pairs of groups subsist or not. The Grouping column presented with alphabetical letters that group the factor levels. Groups that do not share a letter have a mean difference that is statistically significant. In Table 4.10 for *90% and 95%* there is the same grouping, in Left and Right Nose Oriented flights have both letters, so between this two types flights mean is almost not significant different between them, but in Back and Front flights does not share letter so this are significant different between each other. In the 99% confidence level it was observed that in all the types of flights are significantly different, it might be due to selection of 1% error rate, so this makes more sensitive detective differences. For this part in the moment, definitely can we conclude that Front and Back are kindly opposite abilities for the pilot means are so distinct and that is why there is a great significance difference. For Left and Right there is not much difference between this means so those are maintained with both letters, it can be seen like next, this two types of flights are almost in same difficulty level for Pilot.

Analyzing Table 4.11 and Figure 4.18 there are some items to discuss:

i. The 95% simultaneous confidence level indicates that only this groups contain the true differences: *Front-Back, Left-Back, Right-Back, Right-Left* while *Left-Front and Right-Front* doesn't presents any significance difference at all. This also applies for 99% and 90% confidence levels.

ii. The 95% confidence level for the difference between means of: *Left-Back, Right-Back, Left-Front, Right-Front, Right-Left* extends from *-0.551 to 0.309, -0.613 to 0.248, -0.106 to 0.755, -0.167 to 0.693, -0.492 to 0.369*, as this ranges includes zero, indicates that the difference between these means is not **statistically** significant.

iii. Also in the %95 confidence level for the difference between the means of *Front-Back* which extends in range from *-0.876 to -0.0.15* does not include zero that means, for this special levels is a **statistically** significant difference.

iv. For the 99% confidence level the differences between means of *Left-Back, Right-Back, Left-Front, Right-Front, Right-Left*, includes the zero in their respective range, so this indicates that for this means there is **not** a **statistically** significant difference between them.

v. However, in Table is also observed that in 99% confidence level the adjusted P value for the following group: *Front-Back* is *0.040*, which is lesser than the selected significance level $\alpha = 0.05$. This P value confirms in a more stronger sense that there is a significant difference between this groups.

vi. In the 90% confidence level there is a conflict between groups *Front-Back* this because the range of the CI Values comes from *-0.980 to 0.089* range and because this range include *0* it can be interpreted that doesn't has a level significance, however in the Adjusted P-value can be seen that *0.040* which is lower than

$\alpha = 0.05$ shows the opposite, that there is a significant difference. This is caused as by the probability of a type I error (false positive) in 90% as consequence for a very low simultaneous confidence level.

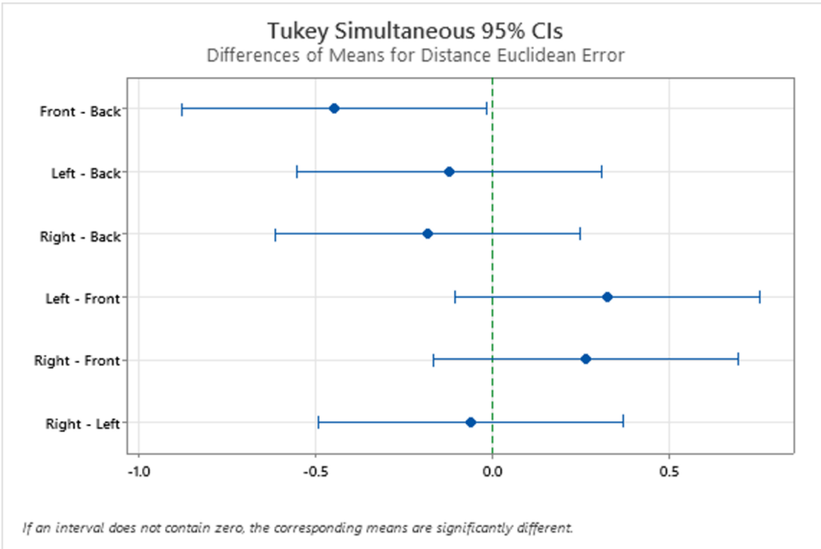
So, it was identified that with 95% and 99% error rate or confidence level the probability of committing type I error is less. However in 90% a type I error was observed. The probability of committing a type I error depends of the number of groups, so if groups to compare increases the difference between experiment wise error proportions increases, so with a lower level confidence there is a gap that can carry to have a type I error. The selection of error rate or the confidence level plays a significant role while performing HSD test in pair groups, and for this data we can conclude that 95% and 99% are the best options.

3. As conclusion, this analysis for this point was conducted for obtained raw data and sequential approach using Tukey's HSD test to find the suitable confidence level to minimize the type I error, which is the rejection of a true null hypothesis (false positive). The error was calculated and then significant of different significance level was explained using P valueof ANOVA test. So, this study confirms that there is a conflict results using 90% confidence for *Front-Back* grouping, due to the lower individual confidence level. For the other levels 95% and 99% can be concluded that *Front-Back* differences are significant such as it can be considered as opposite, and also that *Back* type flight has mean difference with the rest of the types of flights orientation.*Front* type of flights is lightly similar with *Right and Left* type of flights, but this was not confirmed by the P- value, perhaps it can be said that least this two types of flights are more similar of Front than from Back flight.

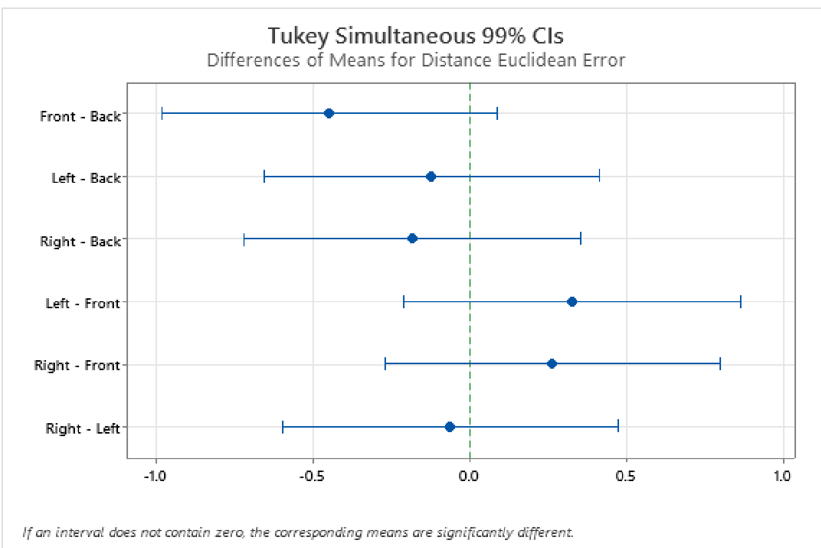
4.3.5 *Kruskal-Wallis*

Null hypothesis H_0 : All medians are equal Alternative hypothesis H_1 : At least one median is different

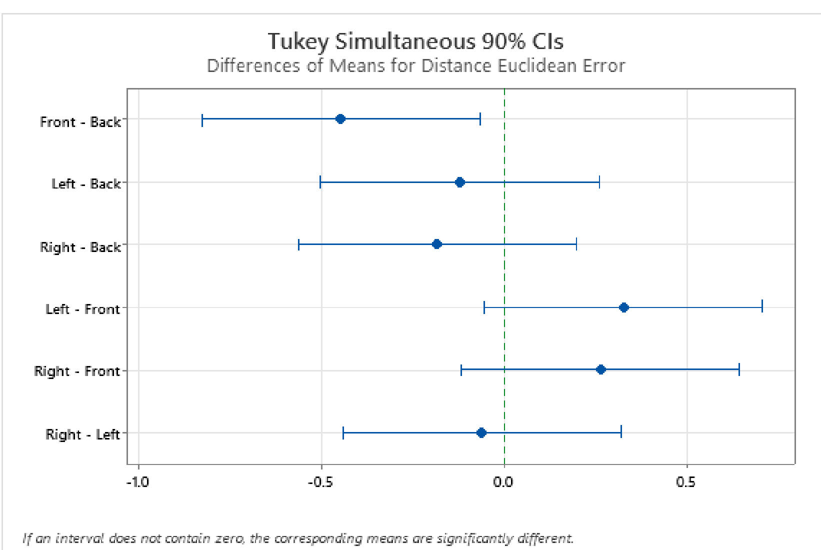
As for the data in table 4.6 column *DEE* is considered as a **Dependant** variable, sometimes called as *response*, this is the metric that express evaluation flight of a determined pilot. So, as there are other variables includes it was decided to judge into this relation between *x with y*, and formulate a multiple regression analysis that can help also in order to predict this DEE metric in near future for next flights that can perform, the pilot. In this way, we will have an idea of a range of Euclidean Distance Error will he pilot have in the next flights, during the learning progress.



(a)



(b)



(c)

Figure 4.18: Tukey Simultaneous test for differences of mean of score for 3 groups with (A) 95% CI (B) 99% CI and (C) 90% CI

Tukey simultaneous tests for differences of means for 95% confidence level					
Difference of Levels	Difference of Means	SE of Difference	95% CI Value	T-value	Adjusted P-value
Front - Back	−0.446	0.160	(−0.876, −0.015)	−2.79	0.040
Left - Back	−0.121	0.160	(−0.551, 0.309)	−0.76	0.872
Right - Back	−0.183	0.160	(−0.613, 0.248)	−1.14	0.665
Left - Front	0.324	0.160	(−0.106, 0.755)	2.03	0.196
Right - Front	0.263	0.160	(−0.167, 0.693)	1.65	0.367
Right - Left	−0.062	0.160	(−0.492, 0.369)	−0.39	0.980
Tukey simultaneous tests for differences of means for 90% confidence level					
Difference of Levels	Difference of Means	SE of Difference	90% CI Value	T-value	Adjusted P-value
Front - Back	−0.446	0.160	(−0.980, 0.089)	−2.79	0.040
Left - Back	−0.121	0.160	(−0.655, 0.413)	−0.76	0.872
Right - Back	−0.183	0.160	(−0.717, 0.351)	−1.14	0.665
Left - Front	0.324	0.160	(−0.210, 0.859)	2.03	0.196
Right - Front	0.263	0.160	(−0.271, 0.797)	1.65	0.367
Right - Left	−0.062	0.160	(−0.596, 0.473)	−0.39	0.980
Tukey simultaneous tests for differences of means for 99% confidence level					
Difference of Levels	Difference of Means	SE of Difference	99% CI Value	T-value	Adjusted P-value
Front - Back	−0.446	0.160	(−0.825, −0.066)	−2.79	0.040
Left - Back	−0.121	0.160	(−0.501, 0.258)	−0.76	0.872
Right - Back	−0.183	0.160	(−0.562, 0.197)	−1.14	0.665
Left - Front	0.324	0.160	(−0.055, 0.704)	2.03	0.196
Right - Front	0.263	0.160	(−0.117, 0.642)	1.65	0.367
Right - Left	−0.062	0.160	(−0.441, 0.318)	−0.39	0.980

Table 4.11: Tukey simultaneous tests differences means 95%, 90% and 99%

Drone Nose Orientation	N	Median	Mean Rank	Z-Value
Back	10	1.65594	25.2	1.47
Front	10	1.19228	11.7	−2.75
Left	10	1.60641	23.3	0.87
Right	10	1.39789	21.8	0.41
Overall	40		20.5	

Table 4.12: Analysis of variance table

DF	H-Value	P-Value
3	7.98	0.046

Table 4.13: Analysis of variance table

RNOF	LNOF	BNOF	Regression Equation
0	0	0	DEE $= 1.446 - 0.0399$ ID Flight
0	0	1	DEE $= 1.892 - 0.0399$ ID Flight
0	1	0	DEE $= 1.771 - 0.0399$ ID Flight
1	0	0	DEE $= 1.709 - 0.0399$ ID Flight

Table 4.14: MINITAB© Regression Equations output.

4.3.6 *Predictions in the Error Distance of Future Flights for Pilot*

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	1.446	0.149	9.69	0.000	
ID Flight	−0.0399	0.0188	−2.13	0.041	1.00
RNOF	0.263	0.152	1.72	0.093	1.50
LNOF	0.324	0.152	2.13	0.040	1.50
BNOF	0.446	0.152	2.92	0.006	1.50

Table 4.15: MINITAB© Coefficients output.

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	4	1.5874	0.3969	3.42	0.018
Error	35	4.0659	0.1162		
Total	39	5.6533			

Table 4.16: MINITAB© Analysis of Variance output.

S	**R − sq**	R − sq(adj)	R − sq (pred)
0.340834	28.08%	19.86%	5.22%

Table 4.17: MINITAB© Model Summary

4.3.7 *Drone Flight Performance Evaluation Model: First-order model, constant differences between all types of flights*

$$E(y) = \overbrace{\beta_0}^{\substack{\text{Base Level}\\ \text{Front Flight}}} + \overbrace{\beta_1 x_1}^{\substack{\text{Flight ID}\\ \text{value}}} + \overbrace{\beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4}^{\substack{\text{RNOF, LNOF}\\ \text{BNOF types of flights}}}$$

Writing a model relating $E(y)$ to Type Flight. Since the qualitative variable of interest, type of flight, has four levels, we must create $(4-1) = 3$ dummy variables. First, select one of the levels to be the base level- say Front Nose Flight (because it is the natural way to pilot a drone).[3] Then each of the remaining levels is assigned the value 1 in one of the three dummies variables as follows:

[3] William Mendenhall, Terry Sincich, and Nancy S Boudreau. *A second course in statistics: regression analysis*, volume 6. Prentice Hall Upper Saddle River, NJ, 2003

$$x_2 = \begin{cases} 1 & \text{if Right Nose Flight} \\ 0 & \text{if not} \end{cases} \qquad x_3 = \begin{cases} 1 & \text{if Left Nose Flight} \\ 0 & \text{if not} \end{cases}$$

$$x_4 = \begin{cases} 1 & \text{if Back Nose Flight} \\ 0 & \text{if not} \end{cases}$$

(Note that for the base level, Front Nose Flight, $x_2 = x_3 = x_4 = 0$).) The values of x_2, x_3 and x_4 for each flight are given in Table 4.6. Also, consider that $x1$ values is the ID Flight which is an incremental value from 1..10 for each type of flight. Then the appropriate model is:

$$E(y) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4$$

4.3.8 Drone Flight Performance Evaluation Model: Interpreting the estimated β coefficients in the model.

To interpret the β's, first, it explains the mean of the Distance Euclidean Error $E(y)$ for every four types of flights as a function of the β's:

Right Nose Flight $(x_2 = 1, x_3 = 0, x_4 = 0)$:

$$E(y) = \beta_0 + \beta_2(1) + \beta_3(0) + \beta_4(0) = \beta_0 + \beta_2 = \mu_R$$

Left Nose Flight$(x_2 = 0, x_3 = 1, x_4 = 0)$:

$$E(y) = \beta_0 + \beta_2(0) + \beta_3(1) + \beta_4(0) = \beta_0 + \beta_3 = \mu_L$$

Back Nose Flight$(x_2 = 0, x_3 = 0, x_4 = 1)$:

$$E(y) = \beta_0 + \beta_2(0) + \beta_3(0) + \beta_4(1) = \beta_0 + \beta_4 = \mu_B$$

Front Nose Flight $(x_2 = 0, x_3 = 0, x_4 = 0)$:

$$E(y) = \beta_0 + \beta_2(0) + \beta_3(0) + \beta_4(0) = \beta_0 = \mu_F$$

Then we have

$$\beta_0 = \mu_F (\text{ Mean of the base level})$$
$$\beta_2 = \mu_F - \mu_R$$
$$\beta_3 = \mu_F - \mu_L$$
$$\beta_4 = \mu_F - \mu_B$$

Note that the β's associated with the non-base levels of types of flights(Right, Left, and Back) represents differences between a pair of means. β_0 represents a single mean response for the base level flight (Front). Now, the estimated β's (highlighted on the MINITAB© [4] printout in Table 4.15) are:

$$\hat{\beta}_0 = 1.446, \quad \hat{\beta}_2 = 0.263, \quad \hat{\beta}_3 = 0.324 \quad \hat{\beta}_4 = 0.446$$

Note taking the constants of the single regressions equations of table ref 4.2, its explained that the estimated mean Distance Error for Front Nose Flight ($\hat{\beta}_0$) is 1.466 meters; the difference between the estimated Distance Error for Front and Right Nose Flight ($\hat{\beta}_2$) is $1.709 - 1.446 = 0.263$; the difference between the estimated Distance Error for Front and Left Nose Flight ($\hat{\beta}_3$) is $1.771 - 1.446 = 0.324$ and the difference between the estimated Distance Error for Front and Back Nose Flight ($\hat{\beta}_4$) is $1.892 - 1.446 = 0.446$. Finally the ($\hat{\beta}_1$) with value -0.0399 this is the Distance Error decreasing after each new flight, this is applied generally for most of all flights and remains as a constant in the linear regression equation. Now Table 4.15 with estimated coefficients makes sense and how are calculated.

[4] Barbara F Ryan, Brian L Joiner, and Jonathan D Cryer. *MINITAB handbook: update for release*. Cengage Learning, 2012

4.3.9 *Drone Flight Performance Evaluation Model: Conducting the F-Test for overall model utility using $\alpha = .05$, and explaining the practical significance result.*

The F-Test for overall model utility tests the null hypothesis

$$H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$$

Note that $\beta_2 = 0$ implies that $\mu_F = \mu_R$, $\beta_3 = 0$ implies that $\mu_F = \mu_L$ and $\beta_4 = 0$ implies that $\mu_F = \mu_B$. Therefore, $\beta_2 = \beta_3 = \beta_4 = 0$ implies that $\mu_F = \mu_L = \mu_B = \mu_R$

$$H_0 : \mu_F = \mu_L = \mu_B = \mu_R$$

From the MINITAB© printout, Table 4.18, $F = 3.42$. Since the p-value of the test (0.018) is less than $\alpha = .05$, the null hypothesis is rejected. Thus, there is evidence of a difference between any three of the four mean Distance Error, that is Type of Flight is useful predictor of Distance Error in a flight.

4.3.10 *Drone Flight Performance Evaluation Model: Detecting Residual Correlation: The Durbin-Watson Test.*

There is a variable on this set of data that is an observation that occurs in an interval, which is called **time serie.** Regression models of time series may pose a special problem. Introducing that this variable is time t is an indicative of its same value at time $t+1$. So in this way, the value of time series at time t is **correlated** with its value at time $(t+1)$. [5] The problem here is that this will generate random errors correlated, and of consequence *standard errors of the $\beta -$ estimates that are seriously the underestimated.* Considering our practical problem, following next there is a variable which is $\beta_1 t$ called as **Flight ID**, an incremental value pointing in time, as its reflects flights in sequence while the increments of each one its a consequence a progress in time. As remarking the regression equation it looks like, where $x_1 = t$:

[5] William Mendenhall, Terry Sincich, and Nancy S Boudreau. *A second course in statistics: regression analysis*, volume 6. Prentice Hall Upper Saddle River, NJ, 2003

$$E(y) = \beta_0 + \beta_1 t + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4$$

As mentioned before, in last before steps the model seems to fits, since the *F-value* (3.42) in table 4.18 that tests the adequacy of the model is significant. The hypothesis that the coefficient β_1 is positive is accepted at level $alpha = .001$. The residuals $\hat{\epsilon} = y - (\beta_0 + \beta_1 t + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4)$ are plotted in Figure 4.19. Residuals variate into positive and negative, so if the residual for a Flight ID t is positive, there is a tendency for the residual for Flight ID $(t+1)$ to be positive. As starting point lets consider to test the null hypothesis:

$$H_0 : \text{No Residual correlation}$$

against the alternative

$$H_a : \text{Positive residual correlation}$$

The presence of residual correlation is determined as ***d statistic*** as Durbin-Watson as:

$$d = \frac{\sum_{t=2}^{n} (\hat{\varepsilon}_t - \hat{\varepsilon}_{t-1})^2}{\sum_{t=1}^{n} \hat{\varepsilon}_t^2}$$

where n is the number of observations, and $\hat{\varepsilon}_t - \hat{\varepsilon}_{t-1}$ represents the difference between a pair of successive residuals. Durbin-Watson value is mentioned in Table 4.19 and to determine the correlation if exists in the population of residuals, its necessary to find the rejection region for the test. Using table of Durbin-Watson, for determine the limits using $\alpha = .05$, and for this example having $k = 5$ independent variables and $n = 39$ observations. Using $\alpha = .05$ for the one-tailed test for positive residual correlation, the table values are $d_L = 1.22$ and $d_U = 1.79$.

Table 4.18: MINITAB© Analysis of Variance output.

n	$k=1$		$k=2$		$k=3$		$k=4$		$k=5$	
	d_L	d_U	d_L	d_U	d_L	d_U	d_L	d_U	d_L	d_U
31	1.36	1.50	1.30	1.57	1.23	1.65	1.16	1.74	1.09	1.83
32	1.37	1.50	1.31	1.57	1.24	1.65	1.18	1.73	1.11	1.82
33	1.38	1.51	1.32	1.58	1.26	1.65	1.19	1.73	1.13	1.81
34	1.39	1.51	1.33	1.58	1.27	1.65	1.21	1.73	1.15	1.81
35	1.40	1.52	1.34	1.58	1.28	1.65	1.22	1.73	1.16	1.80
36	1.41	1.52	1.35	1.59	1.29	1.65	1.24	1.73	1.18	1.80
37	1.42	1.53	1.36	1.59	1.31	1.66	1.25	1.72	1.19	1.80
38	1.43	1.54	1.37	1.59	1.32	1.66	1.26	1.72	1.21	1.79
39	1.43	1.54	1.38	1.60	1.33	1.66	1.27	1.72	1.22	1.79
40	1.44	1.54	1.39	1.60	1.34	1.66	1.29	1.72	1.23	1.79

Durbin-Watson Statistic	2.38714

Table 4.19: Extract of part of Durbin-Watson Statistic Table with ($\alpha = .05$)

TWO-TAILED TEST H_0 : No residual correlation H_a : Positive or negative residual correlation

Rejection region:

$$d < d_{\mathrm{L},\alpha/2} \quad \text{or } (4-d) < d_{\mathrm{L},\alpha/2}$$

Nonrejection region:

$$d > d_{\mathrm{U},\alpha/2} \quad \text{or } (4-d) > d_{\mathrm{U},\alpha/2}$$

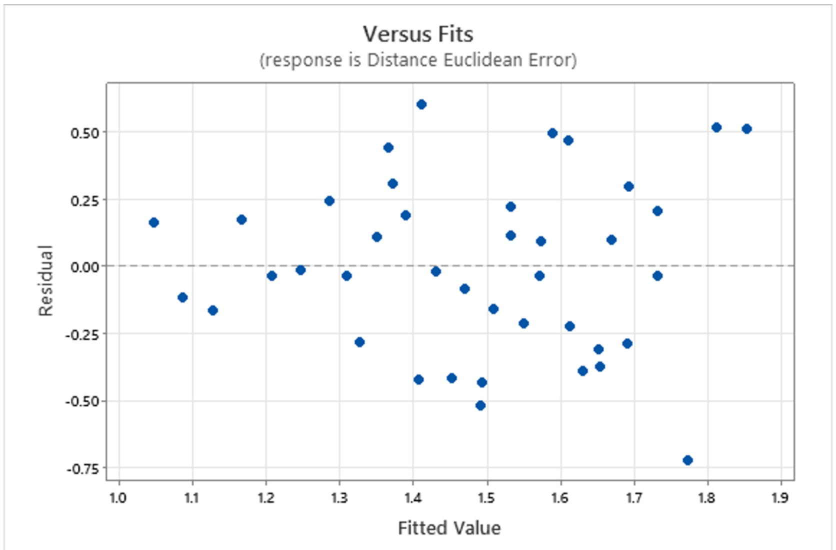


Figure 4.19: Residuals- Fitted Values Model I.

Inconclusive region: Any other result where $d_{L,\alpha}$ and $d_{U,\alpha}$ are the lower and upper tabulated values, respectively, corresponding to k independent variables and n observations. Assumption: The residuals are normally distributed.

Applying first for *Rejection region*, this is rejected because $d = 2.38714$ is greater than d_L=*1.22*, even $4 - 2.38714 = 1.6128$ is still greater than d_L. For the *Non-Rejection region*, is accepting that $d = 2.38714$ is greater than $d_U = 1.79$ this is an evidence we are in the non-rejection region, even that for $4 - 2.38714 = 1.6128$ is less than $d_U = 1.79$, so this puts an evidence an acceptance to the H_0, so here is a prove that there in the time series the residuals are not correlated. So this is a good point for this model, and increments the confidence to this model.

4.3.11 *Drone Flight Performance Evaluation Model: Summary Model & Conclusions*

In the model summary Table 4.17 can be interpreted as next:

1. **S**, represents the standard deviation, which is measured in the units of the response variable and revealed how distant the data values fall from the fitted values. A lower value results to have a better fit, and higher values indicates a worse fit, in this case *0.340834* means a that model is meeting the model assumptions, however checking the residual plot in Figure 4.19 it can be improved for having residuals more equally dispersed, for this is described in **Model II**, because **S** value can improve.

2. **R-sq**, is the percentage of variation in the response that is explained by the model, its determine how well the model fits the data, a higher

value leads to have a better adjustment of the model in the data, in this case having a 28.08% is not as higher as expected, but considering that there is a small sample of data and few predictors, its high for this scenario, and its one measure of how well he model fits the data, but we can consider other metrics to make an assumption is a good model.

3. **R-sq (adj)**, this percentage express the variation in the response that is explained by the model, adjusted for the number of predictors in the model relative to the number of observations. For this reason if it is added a predictor to the model then this metric will increase, even if there no real improvement into it. In this is understandable to have lower value of **19.86%** as we have one predictor which is the Flight ID, and three categorical ones, which are few to be considered.

4.3.12 Model Predictions & Interpretations

Table 4.20: Predictions for Front Nose Orientation Flights.

ID Flight	Drone Nose Orientation	RNOF	LNOF	BNOF
11	Front	0	0	0
12	Front	0	0	0
13	Front	0	0	0
14	Front	0	0	0
15	Front	0	0	0
20	Front	0	0	0
25	Front	0	0	0
35	Front	0	0	0
50	Front	0	0	0

Fit	SE Fit	95%Cl	95% PI
1.00729	0.149216	(0.70437, 1.31022)	(0.25196, 1.76263)
0.96739	0.162757	(0.63698, 1.29781)	(0.20062, 1.73416)
0.92749	0.177252	(0.56765, 1.28733)	(0.14759, 1.7074)
0.88759	0.192485	(0.49683, 1.27836)	(0.09295, 1.68224)
0.84769	0.208295	(0.42483, 1.27056)	(0.03678, 1.65861)
0.6482	0.292626	(0.05414, 1.24226)	(−0.26376, 1.56016)
0.4487	0.38141	(−0.3256, 1.22301)	(−0.58972, 1.48712)
0.04971	0.563884	(−1.09504, 1.19445)	(−1.2879, 1.38732)
−0.54878	0.84185	(−2.25783, 1.16027)	(−2.39258, 1.29502)

As Tables 4.20 there are some predictions using Model explained in past subsection for future flights considering from #11 to #50 flights in order to see the Euclidean Distance Error behavior in future. So starting with Fit Column which estimates the mean of the response for given values predictors, this works as the entering x-values into the model equation for a response variable, it can be seen how it started by flight 1.00729 meters and how this goes down until -0.5 meters of error. So its notable this decrements of error and proves an expected learning.

Table 4.21: Predictions for Back Nose Orientation Flights.

ID Flight	Drone Nose Orientation	RNOF	LNOF	BNOF
11	Back	0	0	1
12	Back	0	0	1
13	Back	0	0	1
14	Back	0	0	1
15	Back	0	0	1
20	Back	0	0	1
25	Back	0	0	1
35	Back	0	0	1
50	Back	0	0	1

Fit	SE Fit	95%CI	95% PI
1.45292	0.149216	(1.15, 1.75585)	(0.69759, 2.20826)
1.41302	0.162757	(1.08261, 1.74344)	(0.64625, 2.1798)
1.37312	0.177252	(1.01328, 1.73296)	(0.59322, 2.15303)
1.33323	0.192485	(0.94246, 1.72399)	(0.53858, 2.12787)
1.29333	0.208295	(0.87046, 1.71619)	(0.48241, 2.10424)
1.09383	0.292626	(0.49977, 1.68789)	(0.18187, 2.00579)
0.89433	0.38141	(0.12003, 1.66864)	(−0.14409, 1.93275)
0.49534	0.563884	(−0.6494, 1.64009)	(−0.84227, 1.83295)
−0.10315	0.84185	(−1.81219, 1.6059)	(−1.94695, 1.74065)

Meanwhile in SE Fit which is the standard error of the fit to measure the precision of the estimate mean response, if it becomes smaller the SE more precise the predicted mean response will be. Also with the fitted value, it is used the standard error of the fit to create the intervals for the mean response. The value of SE Fit is smaller almost near to 0 in some cases, that will react directly into the 95% CI which is the confidence interval that proved the range of likely value we have 95% confidence will be, so still ranges sometime variate even from a range of 20% of its Fit value, but sometimes this standard error Fit value is higher in the #35 and #50 flights, as those are the most far future flights and its understandable, so also confidence level will impact. The PI which is the prediction intervals can be more wider ranges because is including this uncertainty involved in predicting, which in this case for Front Flight for more of the half range is wider.

Table 4.22: Predictions for Left Nose Orientation Flights.

ID Flight	Drone Nose Orientation	RNOF	LNOF	BNOF
11	Left	0	1	0
12	Left	0	1	0
13	Left	0	1	0
14	Left	0	1	0
15	Left	0	1	0
20	Left	0	1	0
25	Left	0	1	0
35	Left	0	1	0
50	Left	0	1	0

Fit	SE Fit	95%Cl	95% PI
1.33172	0.149216	(1.0288, 1.63465)	(0.57639, 2.08706)
1.29182	0.162757	(0.96141, 1.62224)	(0.52505, 2.05859)
1.25192	0.177252	(0.89208, 1.61176)	(0.47202, 2.03183)
1.21202	0.192485	(0.82126, 1.60279)	(0.41738, 2.00667)
1.17212	0.208295	(0.74926, 1.59499)	(0.36121, 1.98304)
0.97263	0.292626	(0.37857, 1.56669)	(0.06067, 1.88459)
0.77313	0.38141	(−0.00117, 1.54744)	(−0.26529, 1.81155)
0.37414	0.563884	(−0.77061, 1.51888)	(−0.96347, 1.71175)
−0.22435	0.84185	(−1.9334, 1.4847)	(−2.06815, 1.61945)

For Table in 4.22 SE also maintains similar ranges as Front flight, in the same range of future flights, this explains that for this up the moment the model seems to be consistent in predictions, also the Fit values are decrements as expected, meanwhile the 95% CI range values varieties sometimes in half of meter from lower boundary to upper boundary. And PI range goes wider in the flights more extends to future like flights IDs #20, #25, #35 and #50.

Table 4.23: Predictions for Right Nose Orientation Flights.

ID Flight	Drone Nose Orientation	RNOF	LNOF	BNOF
11	Right	1	0	0
12	Right	1	0	0
13	Right	1	0	0
14	Right	1	0	0
15	Right	1	0	0
20	Right	1	0	0
25	Right	1	0	0
35	Right	1	0	0
50	Right	1	0	0

Fit	SE Fit	95%CI	95% PI
1.27019	0.149216	(0.96727, 1.57312)	(0.51486, 2.02553)
1.2303	0.162757	(0.89988, 1.56071)	(0.46352, 1.99707)
1.1904	0.177252	(0.83056, 1.55024)	(0.41049, 1.9703)
1.1505	0.192485	(0.75973, 1.54126)	(0.35585, 1.94514)
1.1106	0.208295	(0.68774, 1.53346)	(0.29969, 1.92151)
0.9111	0.292626	(0.31704, 1.50516)	(−0.00086, 1.82306)
0.7116	0.38141	(−0.0627, 1.48591)	(−0.32681, 1.75002)
0.31261	0.563884	(−0.83213, 1.45736)	(−1.025, 1.65023)
−0.28588	0.84185	(−1.99492, 1.42317)	(−2.12968, 1.55792)

For Table in 4.23 and 4.22 Fit values come similar in a decrements error over each ID Flight, even the same case is negative in the #50 flight and ranges comes wider for CI and PI ranges.

4.4 Deployment

The intention in this subsection is to emphasize that after the complete process of developing the model, now its time to demonstrate some results in a customer front-end user, without technicism, and to be clear. The idea presenting is that after an evaluation of any pilot a system can generated this typo graphics in Figures 4.20, 4.21, 4.22 and 4.23. The technology can be a dashboard built in Grafana®using some special builder with the predictions, in order to remarks, the Flights done by the user, and the future flights with the estimations of the distance error euclidean. In the graphs it can be showed a drone mark under the x-axis over the 0 value, this means when the pilot just accomplish the learning rate as expected and can perform a zero error flight, this means is a perfect flight in order to the trace. Also there is a trend line the shows the descending value of the error that proves the learning behavior. After this it can be delivered to customer a special report paragraph using IPython® or Jupyter Notebook© with the interpretation of the results almost same as in next paragraph of *Customer Acceptance*.

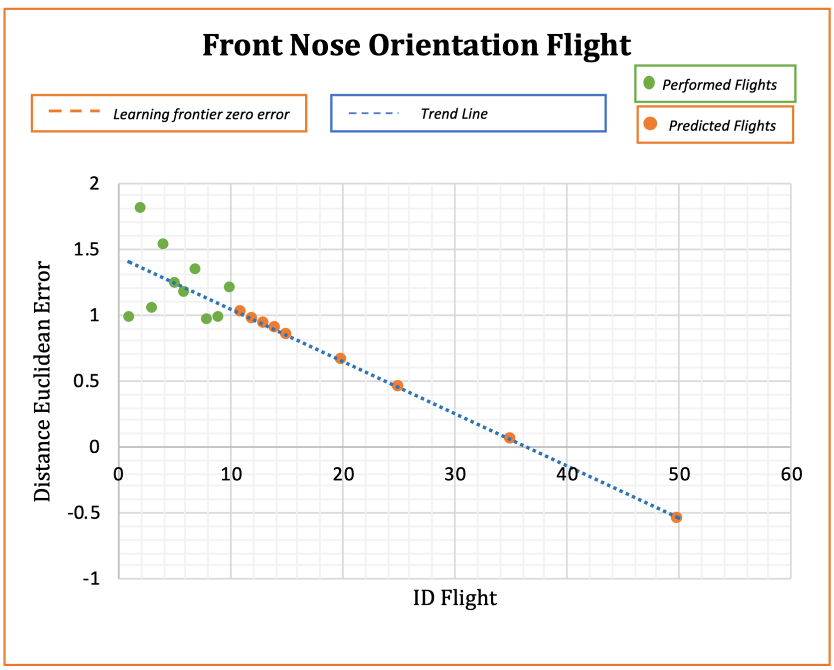


Figure 4.20: Front Flight Graph Results.

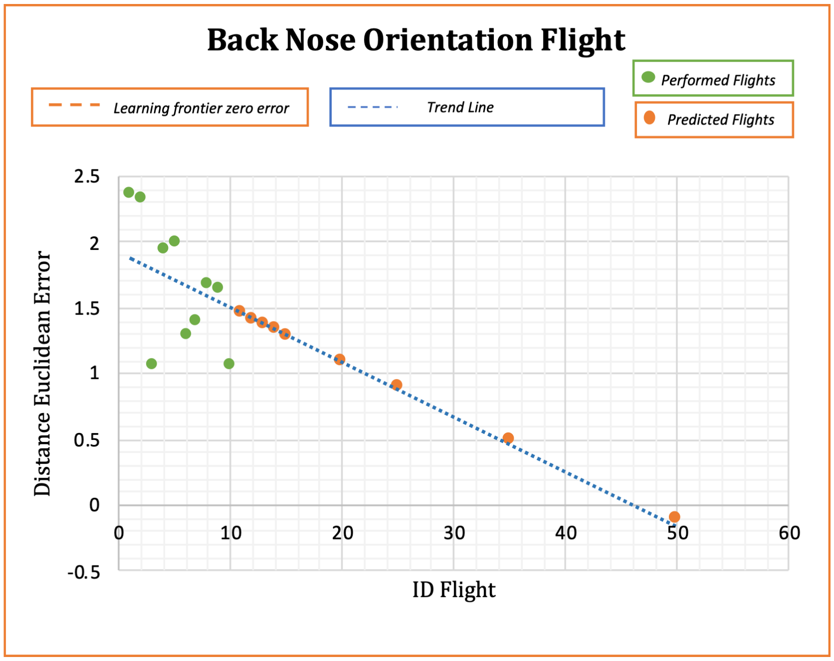


Figure 4.21: Back Flight Graph Results.

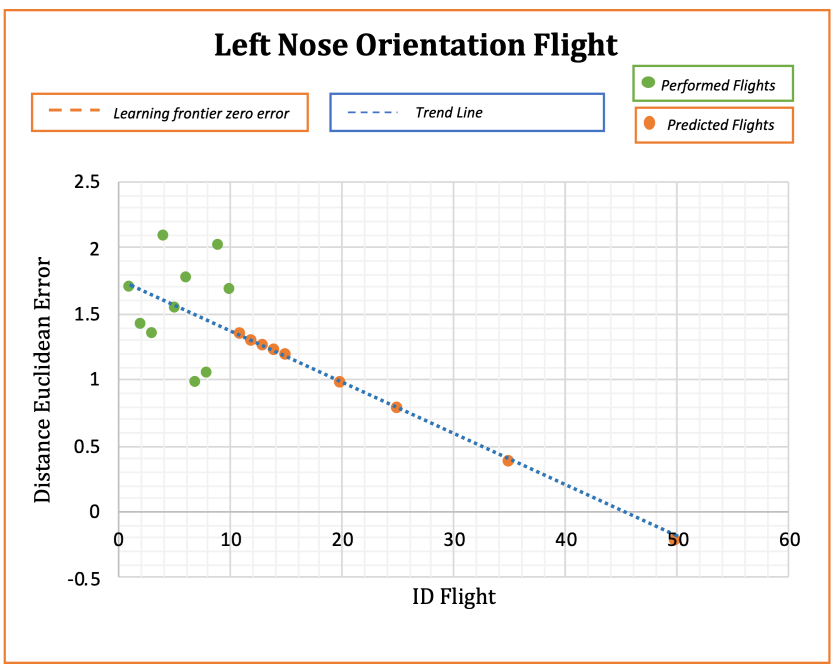


Figure 4.22: Left Flight Graph Results.

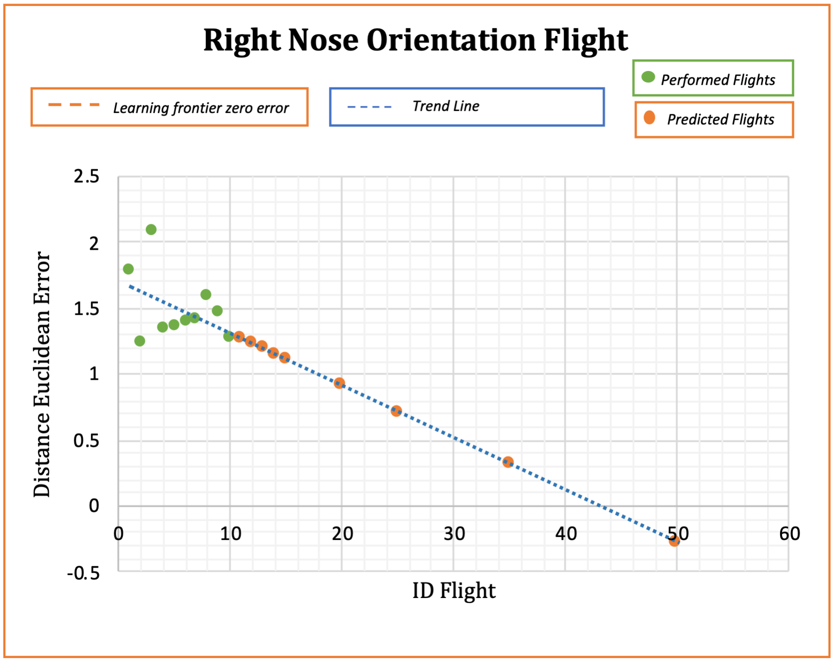


Figure 4.23: Right Flight Graph Results.

4.4.1 *Drone Pilot Diagnosis*

In Figure 4.24 represents the values of the distance error flight for *Front, Left, Right & Back*, with the average values. Lastly the average marks the error distance for each flight so in the Figure can be representative of the initial diagnosis of the first set of flights.

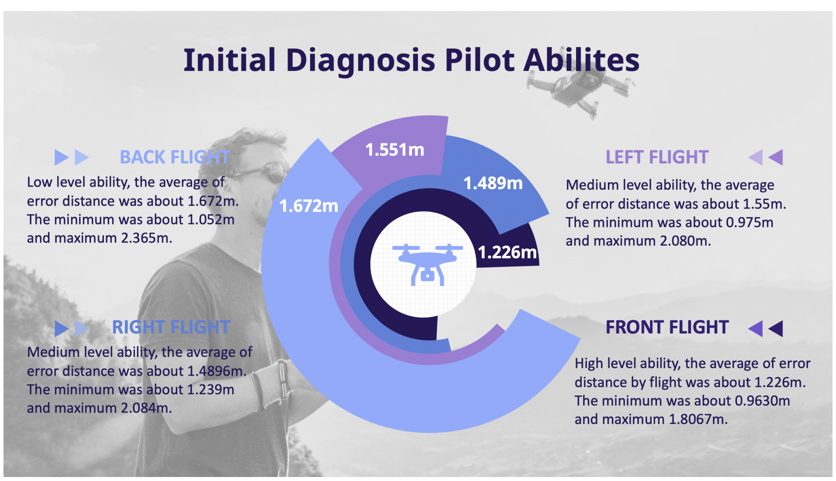


Figure 4.24: Initial Diagnosis for Pilot in Flight.

4.4.2 *Drone Pilot Flight Improvement Estimation*

After this there is a Figure as referenced as 4.25 which is the representation of the flights currently made by the pilot and for each category how many are missing to do in order to have less than 0.05 m of error distance considering the complete flight.

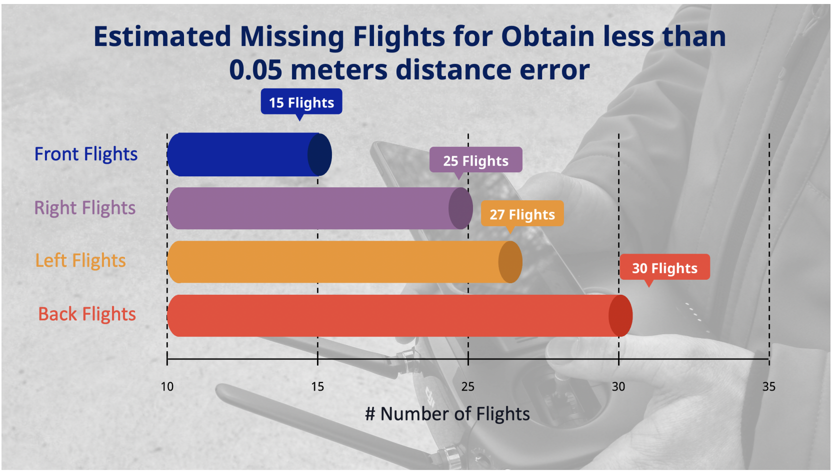


Figure 4.25: Missing Flights for obtain a distance error less than 0.05 meters.

4.5 *Customer Acceptance*

The results delivered to this determined pilot, first as an analysis of the data generated from its flights, are generated in a data table with the euclidean distance in determining points of the routing scenario. And with it, the first analysis of the primary skill is with Front Flights, with a minimum mean distance error of 1.22 m over the ten flights. In the second place, the ability is Right Flights with a very similar value then Left Flights which are also at the same level with an average error of 1.48 m and 1.51 m, consecutively. And in the last place, the ability that needs more practice is the Back Flight with a mean of 1.672 m, closer to Right Flight Error but too remote from Front Flight. The minimum error in the 40 flights was in the Front Flight, to be precise, in-flight #8 with a 0.96 m value. Instead, the higher error distance value was in the #1 Back Flight with an almost 2.35 m value.

Now, grouping the flights based on level of experience would be as follows: Front (high experience level), Left & Right (middle experience level), and Back (low experience level). The pilot has an average rate of learning of 4% in each flight, which means that 0.04 m error decrements on average for any new flight in any category. In the worst cases, after ten flights, the pilot would increase the precision and reduce the error to 0.4 m, generally independently of the category.

For Front flights, the prediction will start with 1.446 m, impossible based on the statistics to get an error higher than this for this category, and with this value starting point, the error will go down. As a result, flight #15 expects to get 0.84 m to value, and in its #35 flight value, the learning curve will be overshooting with a minimum error of 0.04 m, so it is an invisible error.

Predictions for Left and Right flights are almost similar because they are considered a group with nearly the same variance and range of error. So approximately at flight #35, it would be a minimum error of 0.37 m value.

Predictions for Back Flights explains that approximately after 35 flights, the error would be half of a meter that would be 0.5 m.

Recommendation for the pilot to first level left and right flights in the same domain as the front flight. Then practice the back flight to have a middle experience level, which this one will be the hardest.

So it consists of executing a range of 25 to 35 flights more than the initial set performed, with left and right orientation to domain this ability. So then, for back flights, having an entire domain with a minimum zero error will consist of 35 to 45 extra flights. And if the pilot wants to improve the front ability in the route entirely, it will only need a range of 15 to 20 flights additional to have a zero error in front flights. So, in conclusion, this pilot will need, in total, counting all categories, a set of special training of 80 flights to have an entire domain with zero error in this route with all the types of flights that can schedule in a month of intensive training.

The importance is to make the pilot aware of its progress so that the learning involved by practice and practice is visible and tangible in metrics and graphics. This project is an auxiliary for the pilot to consciously obtain this learning and see the behavior of improvement in real-time. In addition, predictor gives pilots a future scenario of the goals to achieve specific knowledge.

5 Conclusions & Future Work

Contents

In this Chapter, the intention is to remark where the results can lead to going forward and if there are other questions your results raise. The idea is to set a way to sort of "claim" an area of research, so in this way, people know what you're thinking of doing next, and they may ask to collaborate if your future research area crosses over theirs.

After this, the conclusion subsection reviews the main points of the thesis and the importance of the work suggesting applications and extensions. Finally, it highlights the significant accomplishments and remarking how this research ties to the "real world."

5.1 Future Work

This work can extend to many horizons. However, it starts with the point that gives the initiative from defining a Methodology for calculating a valuable metric of the flight evaluation in a defined route trace in a drone flight. This methodology determines the error distance in the flying done by Checkpoints that work with any shapes and critical positions. So in one part, this gives a starting point to establish a better adequate methodology for other types of flights traces with more complex transitions. The main idea has been presented in this thesis. On the other hand, after the complete application of TDSM for this particular case and a single pilot gives an entry opportunity to perform this for a group of pilots categorized in different experience levels. This new experiment will generate a complete diversification of a model that can establish conclusions more generalized about pilots and their behavior after repeating a trace over and over and how this learning impacts their abilities. So in this way, after a segmented grouping of how different pilots can learn, a new form established format for the learning process will lead the learning process for pilots to improve their abilities in manual flights.

5.2 Conclusions

Humans acquire knowledge that implies "learning" is a complex process that assumes a lot of variables, and more if there is involved psychomotor variable in our body as a response for that learning. However, there are standardized methods/forms for evaluating machine performance, even human effort quantified, for many applications and areas. This thesis intends to bring this effort of establishing and giving tangible metrics for an evaluation pilot flight using Data Science. The evidence proved in this work shows how a drone flight evaluation presented in the way of metrics and a standardized method is possible. Also, a predictive model can explain the behavior of the learning process of an individual by tracking with data the performed action of piloting a drone, which is the main objective of data science. Indeed the complexity of this problem was to establish a format for capturing the data and then processing it, and then find if there is any logic in the data behavior. This thesis presents that giving the correct format to data and establishing cautious processing for expressing the data positions in distance error using mathematic models is possible even to predict the data. In this way, indicating the learning rate of piloting a drone for a single individual is an excellent step of initiative that it's essentially innovative, and no other projects handle this. This thesis concludes that this particular pilot has a more developed psychomotor ability than others, which can be categorized to be improved by the way, and as the data expressed itself. The learning proved by itself with only ten flights; it's mainly probably to give a quantified metric of the absolute knowledge.

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Index