Technische Universiteit Delft

Thales Nederland B.V.

Master Thesis

Faculty: EEMCS
MSc: Electrical Engineering
Track: Wireless Communication and Sensing
Group: Microwave Sensing, Signals and Systems (MS3)

Classification of Birds and Drones Exploiting Kinematic Properties for Surveillance Radars Using Machine Learning Techniques

TU DELFT Supervisor: Dr. Francesco Fioranelli

THALES Supervisor: Ronny Harmanny
THALES Supervisor: Dr. Lorenzo Cifola

Georgios Tsakirakis
5388538

Date of Defence: September 19th, 2022

Approval Internship report/Thesis of:

Georgios Tsakirakis

Title: **Classification of Birds and Drones Exploiting Kinematic Properties for Surveillance Radars Using Machine Learning Techniques**

Educational institution: TU Delft

Internship/Graduation period: January 2022 – September 2022

Location/Department: Delft, Advanced Development & Study (435) – LAS-SRA

Thales Supervisor: Ronny I. A. Harmanny

This report (both the paper and electronic version) has been read and commented on by the supervisor of Thales Netherlands B.V. In doing so, the supervisor has reviewed the contents and considering their sensitivity, also information included therein such as floor plans, technical specifications, commercial confidential information and organizational charts that contain names. Based on this, the supervisor has decided the following:

- ○ This report is **publicly available (Open).** Any defence may take place publicly and the report may be included in public libraries and/or published in knowledge bases.

- ● This report and/or a summary thereof is **publicly available to a limited extent (Thales Group Internal)**. It will be read and reviewed exclusively by teachers and if necessary by members of the examination board or review committee. The content will be kept confidential and not disseminated through publication or inclusion in public libraries and/or knowledge bases for the duration of 2 years starting from the date of submission. Digital files are deleted from personal IT resources immediately following graduation, unless the student has obtained explicit permission to keep these files (in part or in full). Any defence of the thesis may take place **in public to a limited extent**. Only relatives to the first degree and teachers of the MS3 department may be present at the defence.

- ○ This report and/or a summary thereof, is **not publicly available (Thales Group Confidential)**. It will be reviewed and assessed exclusively by the supervisors within the university/college, possibly by a second reviewer and if necessary by members of the examination board or review committee. The contents shall be kept confidential and not disseminated in any manner whatsoever. The report shall not be published or included in public libraries and/or published in knowledge bases. Digital files shall be deleted from personal IT resources immediately following graduation. Any defence of the thesis must take place **in a closed session** that is, only in the presence of the intern, supervisor(s) and assessors. Where appropriate, an adapted version of report must be prepared for the educational institution.

Approved: Harmanny

(Thales Supervisor)

Approved:

(Educational institution)

Delft, 8th September 2022

(city/date)

(copy security)

Acknowledgements

Delft, September 2022

I would like to thank the following people without whom I could not have done this research. I would like to sincerely thank my TU Delft professor, supervisor and chair of my committee Dr. Francesco Fioranelli, as well as my supervisors at Thales Nederland B.V., Ronny Harmanny and Dr. Lorenzo Cifola, who guided me through this research with their insight and knowledge of the subject matter.

My deepest gratitude goes to my partner Eftychia Tsapanou-Katranara and my family, Zisis Tsakirakis, Dimitra Dovri and Eleni Tsakiraki, for all the support they have given me during this research. Their belief in me has kept me focused and motivated throughout this process.

This master thesis was implemented as part of my master degree in Electrical Engineering following the Wireless Communication and Sensing track at Delft University of Technology. The master thesis was done in the Microwave Sensing, Signal and Systems group of TU Delft in combination with the company Thales Nederland B.V.

'To my partner Eftychia Tsapanou-Katranara and my family, Zisis Tsakirakis, Dimitra Dovri and Eleni Tsakiraki'

Summary

Small UAVs and in particular the class of micro-UAVs, whose mass is below 2 kg, are constantly rising in popularity for personal as well as professional use, since they are beneficial in many fields such as defense, transportation, monitoring and agriculture. In spite of their advantages, UAVs can be used for terrorist attacks to fly over restricted areas, transport illegal materials or cause an accident in crowded areas. Thus, in the event of non-cooperative drone users, radars can be ideal detection devices, due to their capability to operate day and night in all-weather conditions. However, due to birds and UAVs having similar altitude, speed and radar cross section, many false alarms can occur. For this reason, it is urgent to develop techniques to distinguish UAVs and birds amongst other radar contacts that may be present.

The classification of drones and birds is not unprecedented. Plenty of acoustic, camera and radar solutions are available in the market today. Radar applications frequently rely specifically on the differences in micro-Doppler signature between these two classes. However, limited solutions exist based on the differences in flight behavior, which is referred as "track behavior" in the radar domain. Assuming that drones and birds have different kinematic characteristics, the question arises, whether these can be tracked by surveillance radars in such a way that radar processing can recognize either or both, based on a given tracking time interval. In particular, possible methods include the exploration of the flights of drones and birds, the kinematic features extraction from tracking their trajectories, their implementation to machine learning models in order to classify these two flying objects, as well as the evaluation of their classification accuracy.

The methodology of this thesis project is divided into two parts. First, a 6-Degree-of-Freedom quadcopter simulator is used to generate drone trajectories, while the bird data are created from real bird GPS tracks. These simulated drone and real bird trajectories are compared to distinguish them in an initial feasibility study, by examining observations such as feature importance, the total trajectory observation time and the time between two continuous tracks. The classification accuracy is more than 95%, as it is observed that birds and drones have different track behaviors.

The second part of the work classifies real bird and drone trajectories tracked by a man-portable scanning surveillance radar. In this way, the kinematic features that are reliable for the classification of the flying object have been identified. The raw data include pedestrians, cars and ocean waves targets that are not useful for that classification problem. So, data filtering is applied to remove all different to bird and drone targets. Moreover, as the labels are missing, unsupervised learning techniques are used to create bird and drone clusters.

In conclusion, it is derived that birds and UAVs have different flight behaviors. The current research can provide valuable information for the development of classification algorithms for existing radars, and fill the gaps for future efforts to improve the classification of birds and drones.

Contents

SUMMARY ..... **V**

CONTENTS ..... **VI**

LIST OF TABLES ..... **VIII**

LIST OF FIGURES ..... **IX**

LIST OF ACRONYMS ..... **XI**

NOMENCLATURE ..... **XII**

1 INTRODUCTION **1**

1.1 Problem Definition 1
1.2 Contribution of the thesis research 3
1.3 Structure of the thesis 4

2 BACKGROUND INFORMATION **5**

2.1 Unmanned Aerial Vehicles (UAVs) 5
2.2 Birds 6
2.3 Surveillance Radar 8
2.4 Existing Flying Targets Classification Techniques and their Limitations 9
2.5 Existing Publications in Kinematic Signatures to Classify Birds and Drones 14
2.6 Classification using Machine Learning 15
2.7 Gaps in the Literature - Novelty 18
2.8 Summary of the chapter 18

3 PROBLEM ANALYSIS **20**

3.1 Extracted Kinematic Features of Low-Slow-Short (LSS) Targets Tracked by Surveillance Radars 20
3.1.1 Average Speed 21
3.1.2 Standard Deviation of Speed 21
3.1.3 Average Heading 22
3.1.4 Standard Deviation of Heading 22
3.1.5 Maneuverability Factor 22
3.1.6 Average Displacement 23
3.1.7 Standard Deviation of Displacement 23
3.1.8 Average Acceleration 24
3.1.9 Standard Deviation of Acceleration 24
3.1.10 Average Curvature 25
3.2 Kinematic Features Processing 25
3.3 Summary of the chapter 27

4 CLASSIFICATION OF SIMULATED DRONES AND REAL BIRDS TRAJECTORIES DATA **28**

4.1 Methodology and Design 28
4.2 6-Degree-of-Freedom Quadcopter 29
4.3 Birds MOVEBANK Dataset 31
4.4 Time Interval Between Tracks and Total Trajectory Duration 31
4.5 Simulations 33
4.6 Classification and Evaluation 35
4.7 Clusters Generation for Drones with different mass values 40

4.8 SUMMARY OF THE CHAPTER 41

5 CLASSIFICATION OF REAL DRONES AND BIRDS TRAJECTORIES TRACKED FROM TNL RADAR........................ 42

5.1 METHODOLOGY AND DESIGN 42
5.2 TNL SURVEILLANCE RADAR AND DATA ACQUISITION 43
5.3 DATA FILTERING FROM DIFFERENT TO BIRDS OR DRONES TARGETS 43
5.4 CLUSTERS GENERATION AND EVALUATION 44
5.5 DISCUSSION 49
5.6 SUMMARY 49

6 CONCLUSION AND RECOMMENDATIONS 51

6.1 CONCLUSION 51
6.2 FUTURE WORK 53

REFERENCES.. 54

List of Tables

TABLE 1: DRONES AND BIRDS DETECTION TECHNOLOGIES WITH ADVANTAGES AND DISADVANTAGES..3
TABLE 2: UNMANNED AIRCRAFT CLASSIFICATION GUIDE (WCG: WEIGHT CLASSIFICATION GROUP, AGL: ABOVE GROUND LEVEL, (B)LOS: (BEYOND) LINE-OF-SIGHT) [13]. 6
TABLE 3: SUMMARY OF THE MOST RELEVANT EXISTING PUBLICATIONS THAT USE THE KINEMATIC SIGNATURE FOR CLASSIFICATION OF DRONES AND BIRDS WITH ANALYSIS OF ADVANTAGES AND DISADVANTAGES. BY KINEMATIC FEATURES IT IS MEANT THE EXTRACTION OF FEATURES FROM THE POSITION AND VELOCITY RADAR TRACKS. 19
TABLE 4: A SUMMARY OF THE GENERATED TRAJECTORIES FOR THE THREE DIFFERENT 'TIME INTERVALS BETWEEN TWO CONSECUTIVE TRACKS (1S, 2S AND 4S)' CASES. THE TRAJECTORY DURATION, THE NUMBER OF THE GENERATED BIRD AND DRONE TRAJECTORIES, AND THE NUMBER OF TRACKS IN EACH OF THEM ARE PRESENTED. 35
TABLE 5: SUMMARY OF THE EXTRACTED KINEMATIC FEATURES, THAT ARE USED FOR THE CLASSIFICATION OF THE SIMULATED DRONE AND THE REAL BIRD DATA. 36
TABLE 6: CLASSIFICATION OF BIRDS AND DRONES USING THE DECISION TREE AND THE KNN MODELS. THE TIME INTERVAL BETWEEN TWO CONSECUTIVE TRACKS IS 2 SECONDS AND THE MODELS ARE TRAINED AND TESTED 5 TIMES. THE CLASSIFICATION ACCURACY EACH TIME AND THEIR AVERAGE CLASSIFICATION ACCURACY ARE ALSO PRESENTED...37
TABLE 7: BIRDS AND DRONES CLASSIFICATION ACCURACY BY APPLYING EACH KINEMATIC FEATURE SEPARATELY TO THE DECISION TREE AND KNN CLASSIFIERS. THREE CLASSIFICATION CASES ARE PRESENTED, CONCERNING THE TIME INTERVAL BETWEEN TWO CONSECUTIVE TRACKS (E.G. 1S, 2S AND 4S). TRACKS ARE USED TO GENERATE THE KINEMATIC FEATURES OF TABLE 5. THE CLASSIFICATION ACCURACY OF THIS CASE IS USED TO EVALUATE THE IMPORTANCE OF EACH FEATURE. 38
TABLE 8: THE AVERAGE ACCURACY OF ALL THREE 'TIME INTERVALS BETWEEN TWO CONSECUTIVE TRACKS (1S, 2 S AND 4S)' CASES, FOR BOTH THE DECISION TREE AND THE KNN CLASSIFIERS OF TABLE 7. THE OVERALL ACCURACY FOR EACH KINEMATIC FEATURE PRESENTS ITS QUANTITATIVE EVALUATION IN THE SIMULATED DRONE AND REAL BIRD CLASSIFICATION CASE...40
TABLE 9: RAW DATA CLEANING PARAMETERS AND ASSUMPTIONS. OBJECTS THAT ARE DIFFERENT FROM BIRDS AND DRONES ARE REMOVED. THE FILTERING CHARACTERISTICS ARE PRESENTED IN THE FIRST COLUMN AND THEIR NUMERICAL VALUERS IN THE SECOND. 44
TABLE 10: CLUSTERS GENERATION OF THE TRAJECTORIES OF BIRDS AND DRONES, AND THEIR COMPARISON WITH KNOWN DRONE TRAJECTORIES. THE SECOND COLUMN SHOWS THE GENERATION OF THE DIFFERENT NUMBERS OF BIRD AND DRONE CLUSTERS USING THE K-MEANS ALGORITHM. THE THIRD COLUMN PRESENTS THE KNOWN DRONE TRAJECTORIES IN THE LIGHT GREY COLOR ON TOP OF THE GENERATED CLUSTERS. 47
TABLE 11: THE NUMBER OF THE TRAJECTORIES OF THE WHOLE DATA SET AND THE KNOWN DRONE TRAJECTORIES THAT WERE USED FOR THE EVALUATION OF THE CLUSTERS. THE FINAL BIRDS CLUSTER CONTAINS 749 TRAJECTORIES AND THE DRONES CLUSTER 2609 TRAJECTORIES. 49

List of Figures

Figure 1: Modified drone carrying a grenade [4]. 1
Figure 2: Drone crashed into the Pisa landmark [5]. 2
Figure 3: Drone appearance at Gatwick airport [6]. 2
Figure 4: Radar detection threshold [courtesy of TNL]: here it can be seen that UAVs and birds detection is overlapped, therefore there is a problem to classify them. 2
Figure 5: Birds passive and active flight modes [19]. 7
Figure 6: Birds movement forces [19]. 7
Figure 7: Micro-Doppler signature of a helicopter rotor with two blades [7]. 9
Figure 8: Black knight UAV detection radar. A surveillance radar from the company IDS in Italy in combination with an Electro-Optical sensor (camera) [32]. 10
Figure 9: Jet engine: The front of the engine contains the compression stage rotor blades, which generate the jet engine modulation spectrum when illuminated by radar [33]. 10
Figure 10: Helicopter main rotor blade flashes - Time domain data (pulse-to-pulse) [33]. 11
Figure 11: Spectrogram of 1 helicopter blade [34]. 11
Figure 12: Drone spectrogram with 5ms window [34]. 11
Figure 13: Drone spectrogram with 100ms window [34]. 12
Figure 14: Spectrogram of a DJI Phantom drone [34]. 12
Figure 15: Spectrogram of a barn owl [34]. 12
Figure 16: Ducted fan design drone [38]. The blades are covered by conducting materials and the micro-Doppler effect is not examined. 13
Figure 17: Supervised Learning: the system sees the feature, that indicates if the flying object is either a bird or a drone (label), and learns how to classify an unknown object. 16
Figure 18: Unsupervised Learning: a training set with birds and drones. The clustering algorithm aims to group them into categories based on certain criteria (e.g. RCS; velocity; altitude flight etc.). The algorithm creates boundaries between the clusters. 17
Figure 19: A geometry of the radar plus a drone. Angles a and b are the radar azimuth and elevation angles respectively. The reference is (X,Y,Z=0). 21
Figure 20: Block diagram of the data processing. The raw data are filtered from different bird and drone flying objects. These data are used to generate kinematic features for each trajectory of the flying objects. Scaling, division of the training and test sets, and the PCA technique are applied to the kinematic features before their application to ML models. 27
Figure 21: Methodology of classification between the simulated quadcopter and real bird data. The drone simulated and real bird data are used to extract kinematic features, that are applied to the KKN and decision tree classifiers. The classification accuracy of the models and the importance of the features are evaluated. 28
Figure 22: The 6-DoF physical quadcopter model, that is used for the generation of the simulated drone trajectories [55]. 29
Figure 23: Block diagram for the generation of trajectories using the 6-DoF quadcopter model. The random waypoint generator is used to create plenty of different trajectories. 31
Figure 24: Classification accuracy concerning the total flight time. The classification accuracy of the simulated quadcopter and the real bird flights is observed in 5 different ‘flight duration’ scenarios (4s, 8s, 15s, 20s and 30s). The accuracy of each of them is higher than 98%. 32
Figure 25: Drones trajectories with 1 second time interval between two consecutive tracks. 33
Figure 26: Birds trajectories with 1 second time interval between two consecutive tracks. 33
Figure 27: Drones trajectories with 2 seconds time interval between two consecutive tracks. 34
Figure 28: Birds trajectories with 2 seconds time interval between two consecutive tracks. 34
Figure 29: Drones trajectories with 4 seconds time interval between two consecutive tracks. 34

Figure 30: Birds trajectories with 4 seconds time interval between two consecutive tracks...34
Figure 31: Drone clusters generation using the K-means classifier and the kinematic features of Table 5. Each cluster contains a drone class with different weights (3.5kg, 3.6kg, 3.7kg, 3.8kg and 3.9kg). 41
Figure 32: Methodology of the real bird and drone classification, using data that were received from a TNL surveillance radar. 42
Figure 33: The average speed, the associated plot number that indicates the interpolated tracks, the time validity which is the time of the measurement, and the RCS values of the tracks of the surveillance radar are presented in blue dots. These tracks are filtered with the average speed, RCS, time validity between consecutive tracks and interpolated tracks methods. 44
Figure 34: The block diagram of the bird and drone clusters generation. The heading and curvature kinematic features application to the K-means classifier creates the bird and drone clusters. 45
Figure 35: The block diagram for the evaluation of the drone and bird generated clusters. The known drone trajectories are compared with the generated clusters, in order to create the final bird and drone clusters. 45
Figure 36: Known drone trajectories in red color and unknown flying object trajectories in green color. The distinction is implemented in regards to whether the velocity is received from one or more objects that are closely spaced and have multiple velocities. The probability, that the velocity of a drone is received from a group of closed spaced objects, is higher. 48
Figure 37: Generation of the final clusters of drones in red and birds in green color. In the case of 17 clusters in Table 10, the clusters that contain known drone trajectories integrate the drone cluster (red). The rest clusters, which do not contain known drone trajectories, are incorporated into the bird cluster (green). 48

List of Acronyms

AGL - Above Ground Level
BLOS - Beyond Line of Sight
CNN - Convolution Neural Networks
DASR - Raytheon Digital Airport Surveillance Radar
DC - Direct Current
DoF - Degree of Freedom
EM - Electromagnetic
EO - Electro-Optical
FMCW – Frequency Modulated Continuous Wave
HERM - Helicopter Rotation Modulation
ID - Identity
JEM - Jet Engine Modulation
KNN - K-Nearest Neighbors
LOS - Line of Sight
LSS - Low Slow and Small
ML - Machine Learning
MLP - Multilayer Perceptron
NATO - North Atlantic Treaty Organization
NCTR - Non-Cooperative Target Recognition
PID - Proportional Integral Derivative
Radar - Radio Detection and Ranging
PCA - Principal Component Analysis
RCS - Radar Cross Section
RF - Radio Frequency
RNN - Recurrent Neural Network
STARS - Standard Terminal Automation Replacement System
STFT - Short Time Fourier Transform
SVM - Support Vector Machine
TOT - Time on Target
TNL - Thales Nederland B.V.
TWS - Track while scan
UAS - Unmanned Aircraft Systems
UAV - Unmanned Aerial Vehicles

NOMENCLATURE

a – acceleration [meters/square meter]
d - displacement [meters]
F - force [newton]
f_d - Doppler frequency [hertz]
f_r - received frequency [hertz]
f_t - transmitted frequency [hertz]
G_t - antenna gain factor on transmit [unitless]
h - heading [unitless]
M - torque [newton-meter]
mf - maneuverability factor [meters/seconds/degree]
P_t - transmitted power [watts]
R - maximum detection range [meters]
s - speed [meters/seconds]
t_d - time delay [seconds]
v - velocity [meters/seconds]
W - angular velocity [radians per second]
ΔR - range resolution [meters]
θ - curvature [unitless]
σ - radar cross section [decibels per square meter]
τ - pulse length [seconds]

1 Introduction

In this chapter, the research problem of this thesis is introduced and the relevant research questions are formulated and discussed. Section 1.1 describes the problem definition of the classification of drones and birds, considering the gaps in the literature and the existing research studies. Section 1.2 indicates the contribution of this thesis and formulates the research question. Finally, section 1.3 presents the structure of the report.

1.1 Problem Definition

The operational flexibility and variety of applications in which drones can be beneficial have increased their use remarkably. In particular, some of these examples include filming, environmental monitoring, materials transportation and agriculture. However, their increased popularity comes with associated safety risks to the public and their properties. Such possible risks involve privacy violations, transport of illegal materials and the risk of collisions with obstacles or other low-flying objects, such as birds [1] [2].

An occasion where micro-UAVs, both hobby type as well as military are used, is the Ukraine-Russia war. Micro-UAVs mass is below 2 kilograms, their maximum operational altitude and radius are 70 meters and 5 kilometers, respectively. Micro-UAVs are used by both sides for surveillance, reconnaissance, but also to attack targets, as Figure 1 shows [3]. For example, on March 18, 2022, a modified commercial drone dropped a grenade on a civilian car in Ukraine, causing an explosion [4].

Figure 1: Modified drone carrying a grenade [4].

In addition, two unwanted civilian drone usages are presented in the following examples. On April 23, 2020, a tourist crashed his drone into the Pisa landmark, as Figure 2 shows. Fortunately, no one was injured and the monument remained unscathed [5]. Another unwanted drone flight occurred on December 10, 2018, when a drone appeared near the runway of Gatwick Airport near London, England. It flew for a while, then disappeared and when the runway was about to open, it reappeared. The drone in Figure 3 caused disruption for nearly 33 hours, affecting 140.000 passengers and 1.000 flights, with fears of a possible terrorist attack causing additional problems [6]

Figure 2: Drone crashed into the Pisa landmark [5].

Figure 3: Drone appearance at Gatwick airport [6].

As Figure 4 presents, the radar detection threshold has to decrease, in order to detect flying objects which are small and fly with low speed. In the same area on the size-speed plot, birds are also observed. As the different types of UAVs and birds are confused by radars, the importance of their distinction is examined.

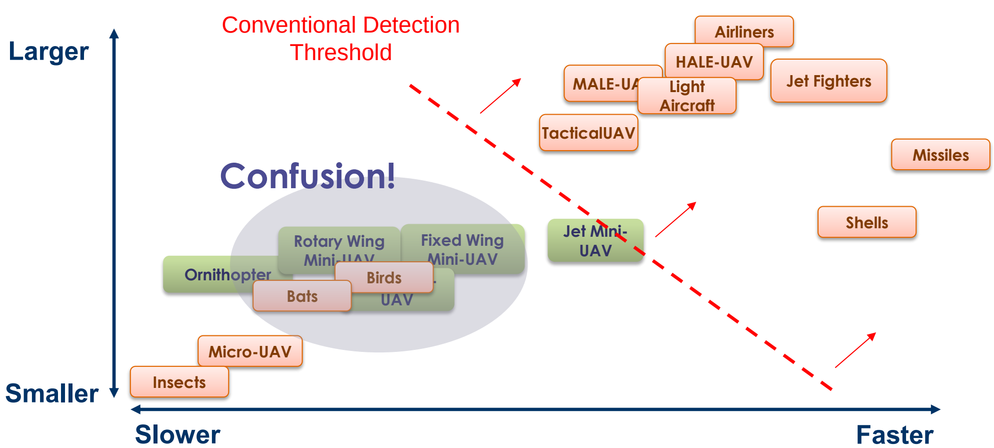


Figure 4: Radar detection threshold [courtesy of TNL]: here it can be seen that UAVs and birds detection is overlapped, therefore there is a problem to classify them.

While the detection of birds and UAVs has been studied and analyzed at a high level in the literature through radar technology and the micro-Doppler signature, the classification of them relative to the invention of radar is fairly new, as it is analyzed in more detail in the literature review of Chapter 2. Specifically, many studies in the literature use the micro-Doppler signatures for the classification of drones, as the rotation of their blades provides additional frequency modulation to the constant Doppler frequency shift induced by the bulk motion [7] [8].

Thus, the existing technologies are proven and operate with sufficient performance in most situations, but the classification of Low-Slow-Short (LSS) targets, such as birds and drones at large radar distances, is not assured. Therefore, it is important to explore and analyze a different approach to fill this gap and recognize the type of flight targets before applying the micro-Doppler effect. Analyzing the birds and drones flight behaviors, by tracking them and observing if they change their flight direction in different ways, is the approach that will be researched in this master thesis.

1.2 Contribution of the thesis research

Existing technologies for detecting and classifying birds and drones rely on radar technology, acoustics and visual methods. All of these proven methods have specific situations in which the classification of birds and drones is not guaranteed. In particular, the radars have a large detection range and use the micro-Doppler effect to distinguish drones and birds. The disadvantage of this method is that in long detection distances, the reflected signal from the drone rotor blades and the bird wings is weak. In addition, the non-conducting materials of the drone rotor blades and the fact that birds do not always flap their wings to fly, provide very less micro-Doppler information. Thus, the spectrograms that are generated by applying Short Time Fourier Transform (STFT) to the received signal do not assure the presence of the birds and drones micro-movements. Moreover, acoustic methods do not require line of sight detection and work well in environments with poor visibility. However, they are very sensitive to ambient noise. Finally, visual methods have the advantage of using cameras with high angular resolution that visualize the flying object type. A major problem is though, that their performance depends on weather conditions and degrades in fog and rain as the visibility decreases, while they do not provide range or Doppler information [1] [9] [10]. The advantages and disadvantages of the small flying object detection technologies are summarized in Table 1.

Technology	Advantages	Disadvantages
Radar	-Scan large volumes in less time -Independent on: *weather conditions* *visibility* *noise* -Spectrograms *classification features* -Simulated drone data *accurate classification*	-Plastic rotor blades *weak reflected signal* -Detection range multiple targets *drones and birds swarms* -Real birds and drones data *inaccurate classification in long detection ranges*
Acoustics	- Work well in environments with poor visibility	-Sensitive to ambient noise
Visual	-Visualize the flying object	-Weather conditions

Table 1: Drones and birds detection technologies with advantages and disadvantages.

The analysis of birds and drones flight behavior by tracking their trajectories and extracting kinematic features represents an approach that could benefit this classification problem. The kinematic features should be applied as input to machine learning models, in order to classify birds and drones [11] [2]. Thus, the main research question that arises is the following.

How can birds and drones tracking provide kinematic features that contribute to the classification of birds and drones and provide additional information to the existing radar classification methods?

Besides the above main question, the following sub-questions are derived:

1. Is the classification of birds and drones using radars entirely explored, by the existing proven methods?

2. What observations can be examined from the classification of drones and birds, using simulated trajectories data by applying supervised learning and how can they be used in real case scenarios?

3. What are the kinematic features that provide enough information to distinguish drones and birds?

4. What are the limitations of using kinematic properties to classify drones and birds?

1.3 Structure of the thesis

The remainder of this report is organized as follows. Chapter 2 presents the background information, about UAVs, birds, surveillance radars and the existing birds versus UAVs classification techniques. A literature review, on the state-of-the-art publications about the classification of birds and drones using their kinematic properties is also provided. Additionally, in Chapter 2, the machine learning application in these flying targets classification case, as well as the gaps in the literature and the novelty of this master thesis research are examined. The following Chapter 3 presents the extracted kinematic features of Low-Slow-Short (LSS) targets, that are tracked by surveillance radars and their preprocessing. Furthermore, Chapter 4 analyzes the classification between a 6-DoF quadcopter simulation model and real bird GPS flight tracks. Chapter 5 investigates the classification of real bird and drone data received from a TNL surveillance radar. The missing labels lead to the usage of unsupervised machine learning models to generate bird and drone clusters, while the created clusters and the evaluation of which of them contain bird and which drone trajectories are also presented in Chapter 5. The final Chapter 6 provides the conclusion and recommendations for future research.

2 Background Information

In this chapter, the background information is presented. Sections 2.1 and 2.2 present the UAVs and birds flight behaviour. Sections 2.3 and 2.4 examine the theory of surveillance radars and the existing flying targets classification techniques. The next Section 2.5 analyses the existing publications of bird and drone classification using their kinematic signature, while Section 2.6 provides the machine learning applicability in this classification case. The last Section 2.7 shows the novelty and gaps in the literature that motivated the implementation of this master thesis.

2.1 Unmanned Aerial Vehicles (UAVs)

According to NATO, UAVs can be divided into three main classes in terms of weight, with each class containing sub-classes. UAVs are informally known as drones and include all of the aircrafts shown in Table 2. In this master thesis, both real and simulated UAVs belong to the category of MICRO and CLASS I because their weight is less than 2 kg. Therefore, drones are defined as these UAV types for this research [12]. In Table 2 the NATO 2.1 Unmanned Aerial Systems (UAS) classification system is implemented for military UAVs, whereas all other types of commercial or personal UAVs are also considered drones. The Above Ground Level (AGL) is the height measured from the underlying ground surface. The Line of Sight (LOS) is the distance between the transmitting and receiving antenna at which they can see each other and the Beyond Line of Sight (BLOS) is the propagation that occurs outside of the typical LOS between the transmitter and receiver.

UNMANNED AIRCRAFT CLASSIFICATION TABLE						
Class	**Category**	**Normal Employment**	**Normal Operating Altitude**	**Normal Mission Radius**	**Civil Category (UK CAA)**	**Example Platform(s)**
Class I < 150 kg	Nano < 250 gr	Platoon / Squad, Sect, Individual (hand launch)	Up to 200 ft AGL	< 2 km (LOS)	WCG 1 Small Unmanned Aircraft (< 20 kg)	Black Hornet
	Micro < 2 kg	Tactical Platoon, Sect, Individual (single operator)	Up to 200 ft AGL	5 km (LOS)		Black Widow
	Mini 2-20 kg	Tactical Sub-Unit (manual launch)	Up to 3000 ft AGL	25 km (LOS)		Scan Eagle, Skylark, Raven, DH3
	Small > 20 kg	Tactical Unit (employs launch system)	Up to 5000 ft AGL	50 km (LOS)	WCG 2 Light UAV (20 >< 150 kg)	Luna, Hermes 90

Class II 150 to 600 kg	Tactical	Tactical Formation	Up to 10,000 ft AGL	200 km (LOS)	WCG 3 UAV (> 150 kg)	Sperwer, Iview 250, Hermes 450, Aerostar, Watchkeeper
Class III > 600 kg	Medium-Altitude Long-Endurance (MALE)	Operational/ Theatre	Up to 45,000 ft AGL	Unlimited (BLOS)		Predator A & B, Heron, Hermes 900
	High-Altitude Long-Endurance (HALE)	Strategic/ National	Up to 65,000 ft AGL	Unlimited (BLOS)		Global Hawk
	Strike / Combat	Strategic/ National	Up to 65,000 ft AGL	Unlimited (BLOS)		

Table 2: Unmanned Aircraft Classification Guide (WCG: Weight Classification Group, AGL: Above Ground Level, (B)LOS: (Beyond) Line-of-Sight) [13].

Multicopters use their blade rotors to obtain lift and control their various maneuvers, such as hovering, moving in a specific direction and accelerating or decelerating. In addition, the aerodynamics of drones with fixed wings are affected by their shape and design, while the copter aerodynamics are not necessarily affected by their shape, because they have more degrees of freedom [14]. Quadcopters can be precisely navigated and remotely controlled over long distances. They are electronic and mechanical flying machines that follow the principles of aviation, while their precise automatic control is achieved by PID controllers. Modeling and trajectory generation is developed using kinematic equations. In this way, UAV tracking is also efficiently and accurately achieved through a set of nonlinear equations that can be transformed into linear equations. Thus, the PID controllers can design a linear approximate model describing the quadcopter trajectories. This dynamic model is described by the variation of the torque and thrust of the quadcopter. Thee 6-DoF quadcopter consists of four DC motors with fixed dimensions [15] [16].

Finally, since drone trajectories are based on their kinematic properties, it is possible to create drone trajectories simulations derived from their mathematical equations that explain their physical meaning. The derivation of drone flights kinematic equations is out of the scope of this master thesis.

2.2 Birds

There are about 11000 species of birds [17]. Birds are vertebrates with wings and feathers that vary greatly in anatomy, physiology and behavior, depending on the species. Most birds fly, while each bird flight is unique and adapted to a specific habit. Birds fly to migrate, to prey, to survive, or to find a place to nest. Their flight modes can be passive, as they do not flap their wings. Such types of flights include gliding, in which birds exchange altitude to maintain forward speed and soaring, in which birds use the wind to maintain or gain altitude. The second type of flight is called active because the birds flap their wings to fly. In addition, there is a combination of passive and active flights called interval flight, in which birds combine their wing flapping with passive flight [18]. All of these flight types are shown in Figure 5 and in Figure 6 [19]. There are many different types of birds with many flight behaviors and it is difficult to categorize them. Thus, in this master thesis, all types of birds will be referred to as 'birds'.

Furthermore, the physical and mathematical explanation of bird flights is a crucial topic, the modelling and simulation of which present many difficulties. One approach to representing how birds fly is based on the Newtonian mechanism. During their flight, birds flap their wings through a mass of air and as this air is accelerated backward and downward, a force is created. According to Newton, this motion creates an opposing and equal force that causes both the forward motion of the bird and the vertical lift. As the wings push the air backward and downward, the bird is pushed forward and upward by the reaction of the air force [19].

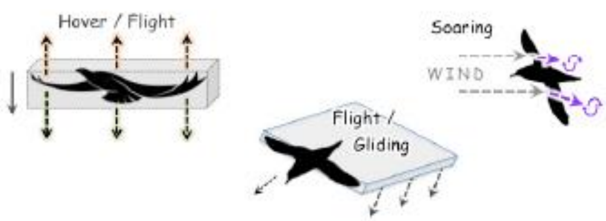


Figure 5: Birds passive and active flight modes [19].

Figure 6: Birds movement forces [19].

According to the following publications, the physics of bird flights is controversial and unproven, as there are no conclusive experiments that prove a theory or equation. Specifically, Landell-Mills [19] supports that it is still unknown how birds fly exactly. William [20] examines that there are still many unresolved questions about how birds fly with flapping wings. Diana and David [21] also claim that flapping flight is not fully understood. Finally, Kristen and Brett [22] support that evidence that flapping contributes to force production is increasing, but the aerodynamic and kinematic mechanisms are still unknown. As current theories and studies are unable to explain how birds fly, simulation models that exist today cannot sufficiently generate trajectories of birds. Specifically, the bird simulations are not accurate enough because they do not approach the aerodynamic and kinematic characteristics of real birds [23] [24].

Bird real flight datasets are frequently used to create an accurate trajectory of a bird, as the simulated bird data are not similar enough to the real ones. Therefore, in research [11] the received bird data are from real bird trajectories. In that way, it is decided to use trajectories and kinematics of birds from real GPS data in Chapter 4 of this master thesis. In particular, the MOVEBANK [25] dataset contains many different types of bird trajectories.

2.3 Surveillance Radar

Radar, short for Radio Detection and Ranging is a measuring principle based on echo location using EM waves (or 'radio waves').

The following equation (2.1), that provides the distance between the radar and the object, is called range [m]. Additionally, t_d is the time delay [s] until receiving the backscattered signal and c [m/s] is the propagation speed of the EM transmission, which approaches the speed of light in a vacuum.

$$\mathrm{R} = \frac{\mathrm{t_d c}}{2} \quad (2.1)$$

The power of the received signal is provided in the following equation (2.2)

$$P_r = \frac{P_t G_t A_e \sigma}{(4\pi)^2 R^4} \quad (2.2)$$

where P_t is the transmitted power, G_t is the antenna gain factor on transmit, A_e is the antennas effective area on receive, R is the maximum detection range and σ is the average radar cross section [26].

Surveillance radars scan a large volume and have limited dwell time on the target because they scan the field with a narrow beam [27]. These radars are used to detect targets and measure their range and velocity indirectly through tracking or directly through Doppler, while the presence of the target and its reflected signal at the antenna is called detection. Space is scanned mechanically by rotating a fixed antenna or electronically with a phased array antenna. Surveillance radars detect targets, while other echoes such as ground or precipitation echoes are also present [28]. Tracking moving targets with surveillance radars is called 'Track while scan' (TWS). Tracks are consecutive target detections that are combined and provide the total target trajectory. The trajectory is defined as the path that a moving target has followed during the period that is detected from the radar. The observation time of the target is the total duration in which the target is detected until tracking is terminated as no more target detection is provided [29]. So, surveillance radars are used for tracking targets and not for examining the micro-Doppler signature of the flying objects, as they have a limited dwell time.

The Doppler effect is the basis for detecting the velocity of moving targets and is presented first. The Doppler effect is the change in frequency of a wave as the source moves. The transmitted electromagnetic waves reflect a shifted frequency signal when the detected object moves. The frequency change of the backscattered signal is used to measure radial velocity. Equation (2.3) gives the received signal frequency. The Doppler frequency shift is the frequency difference between the transmitted signal and the received signal, "$f_d = f_t - f_r$". The received velocity is positive when the object moves away from the radar [30].

$$f_r = f_t \frac{1+\frac{v_r}{c}}{1-\frac{v_r}{c}} \quad (2.3)$$

$$f_d = -\frac{2v_r}{\lambda} \quad (2.4)$$

In the equations (2.3) and (2.4) f_r, f_t and f_d are the received, the transmitted and the Doppler frequencies in Hz, whereas v_r is the radial velocity of the target in m/s.

When a single target has additional rotational or vibratory motion besides the main bulk, additional frequency modulation is observed. These motions are referred to as micromotions and the additional Doppler modulation is referred to, as the micro-Doppler component [31]. The micro-Doppler signature is associated with the micro-Doppler effect for a specific target and is visualized from the spectrogram. The micro-Doppler signature of a helicopter rotor with two blades is presented in the Figure 7.

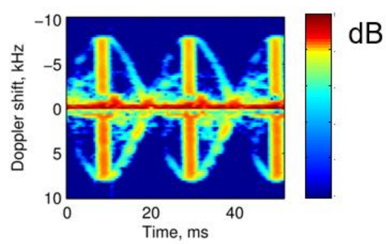


Figure 7: Micro-Doppler signature of a helicopter rotor with two blades [7].

Spectrogram is the visualization of the spectral density of a signal that varies over time and it is calculated from the squared absolute value of the Short-Time Fourier Transform (STFT). STFT is the application of Fourier transform on a short-time window that shifts on the entire signal [30].

2.4 Existing Flying Targets Classification Techniques and their Limitations

There are proven operational products, which use surveillance radars that scan an area to track flying targets in combination with other sensors, such as the Electro-Optical (EO) cameras, in order to classify them. For example, as Figure 8 shows, the ‘‘Black Knight UAV detection radar’ from the company IDS in Italy is a radar-based system, that incorporates an optimal EO camera and is used for the detection and classification of unmanned aerial vehicles [32].

Figure 8: Black knight UAV detection radar. A surveillance radar from the company IDS in Italy in combination with an Electro-Optical sensor (camera) [32].

Despite the existing solutions that surveillance radars with integrated sensors provide in the classification of flying targets, this master thesis focuses on a single surveillance radar solution by researching the possibility of classifying flying targets only by tracking them.

In the radar domain, the techniques that are used to classify targets are called Non-Cooperative Target Recognition (NCTR). Some of these NCTR aircraft recognition existing techniques for ground-to-air or air-to-air activities are the Jet Engine Modulation (JEM), the HERM (Helicopter Rotation Modulation) line, the micro-Doppler signature and the RCS.

JEM is one type of NCTR technique that recognizes the jet engine type and is based on the spectrum analysis from the reflected signal. JEM is used for air targets identification due to their rotating compressor blades, through the modulation imposed on the radar echo. The contribution of rotors provides a unique spectrum that is able to recognize the engine type and thus the aircraft. This technique is applied to recognize a helicopter due to the rotation of the main and the tail rotor [33].

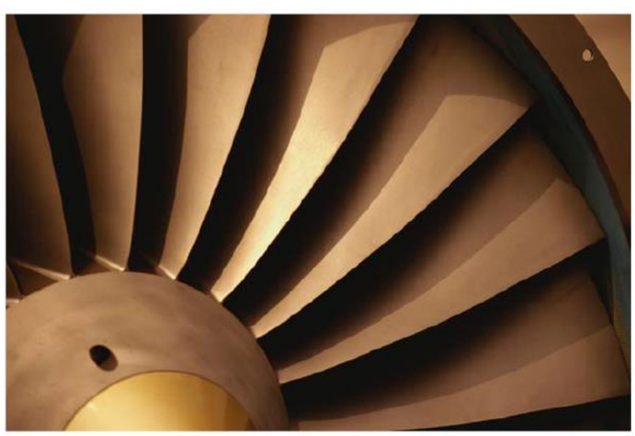


Figure 9: Jet engine: The front of the engine contains the compression stage rotor blades, which generate the jet engine modulation spectrum when illuminated by radar [33].

HERM is a technique used to find the blade flashes from a large manned helicopter. The plot of the reflected signal from the helicopter rotors by applying FT visualizes the blade flashes when there is a specular reflection at the approaching and receding points of the blades Figure 10. The micro-Doppler of the helicopter with one blade is provided in Figure 11 .

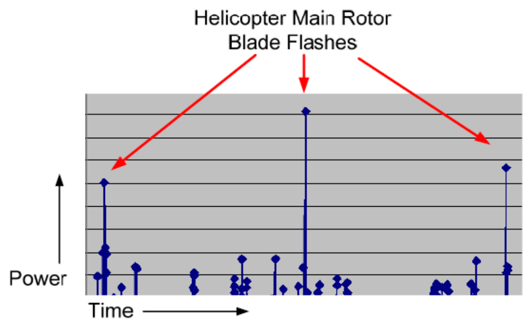


Figure 10: Helicopter main rotor blade flashes - Time domain data (pulse-to-pulse) [33].

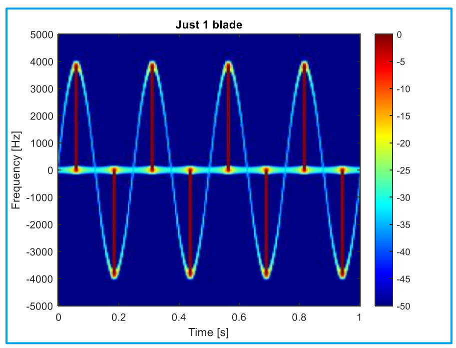


Figure 11: Spectrogram of 1 helicopter blade [34].

Multicopters fly using multiple blades, which create overlapping in their signature and they are less reflective than helicopter blades, because they are made from plastic materials. By examining the spectrogram of drone blades using a short window, vertical lines similar to the helicopter flashes are provided in Figure 12. However, by increasing the spectrogram window, the signature of the blades consists of horizontal lines that are called HERM (Helicopter Rotation Modulation) lines as Figure 13 shows.

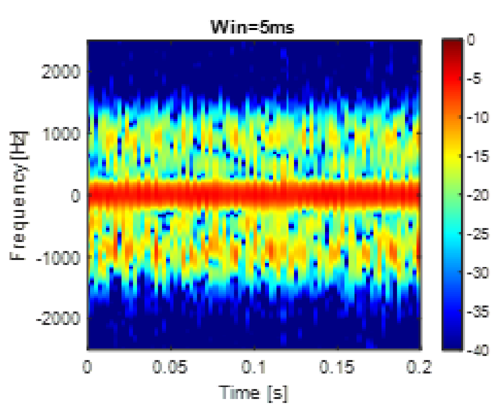


Figure 12: Drone spectrogram with 5ms window [34].

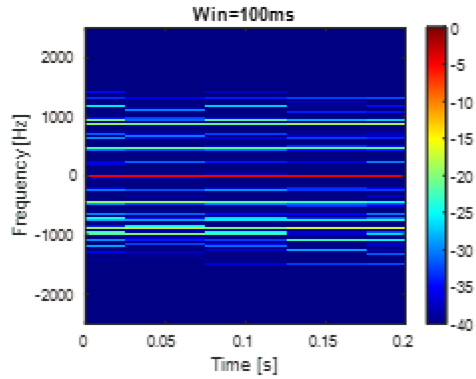


Figure 13: Drone spectrogram with 100ms window [34].

As drone blades rotate faster than the helicopter ones, they are visualized as HERM lines rather than clear blade flashes in the micro-Doppler. Thus, the classification of drones from helicopters can be achieved [34].

The Radar Cross Section (RCS) of the target is a measure of power reflected back to the radar. The definition of the Radar Cross Section of a target is the area intercepting that amount of power which, when scattered equally in all directions, produces an echo at the Radar equal to that from the target [35]. RCS can be used as a feature for the classification of flying objects, as the larger shape ones have higher RCS values [33].

However, the only proven radar technique mentioned in the literature that has been used to classify birds and drones utilizes the micro-Doppler signature. The micro-Doppler signature of a drones rotating blades is provided in Figure 14, whereas the micro-Doppler signature of a barn owl bird flapping its wings is seen in Figure 15 [34].

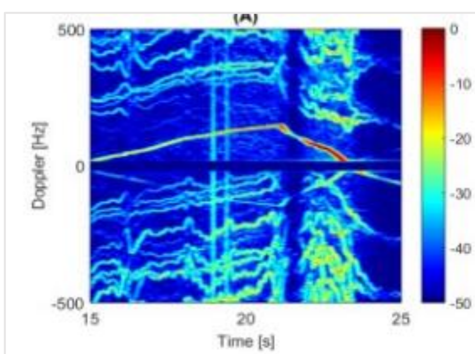


Figure 14: Spectrogram of a DJI Phantom drone [34].

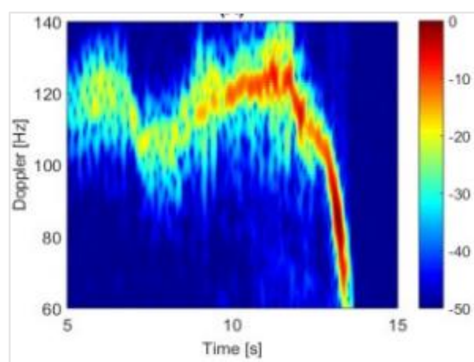


Figure 15: Spectrogram of a barn owl [34].

Despite the functionality of the micro-Doppler effect to classify birds and drones, it has its limitations. The first constraint is the range dependency. The drone blades are smaller than the UAV, as a whole. Therefore, as a function of increasing range, the micro-Doppler will not be detectable anymore earlier than the complete aircraft at long detection ranges [1] [36]. Another restriction can occur when in certain drones, blades are placed on the back side of the aircraft or the blades are covered by conducting materials, through which EM waves hardly penetrate, as Figure 16 shows. Thus, the rotation of their blades is not visible from the radars. In addition, birds also provide passive flights without moving their wings. In that way, they do not fly by flapping their wings and their micro-Doppler signature is not examined. Finally, surveillance radars also introduce several downsides in examining the micro-Doppler effect, as their time on target (TOT) is limited, hence the bird wingbeats and the drone blades rotation movements are not assured [37]. In the above cases, the Doppler effect is visible but the micro-Doppler information is missing.

Figure 16: Ducted fan design drone [38]. The blades are covered by conducting materials and the micro-Doppler effect is not examined.

Apart from the micro-Doppler proven method to classify birds and drones, there is the kinematic signature approach that is used by surveillance radars to track the flying targets, by extracting differences in their flight behavior.

The subfield of physics that describes the motion of a system, a body or a point without considering the forces that cause them to move, is called kinematics. In order to analyze motion, kinematic quantities such as position, velocity and acceleration are used [39]. The body motion is represented using a coordinate system, which is used as a basis for all the kinematic quantities. The coordinate vector from the origin of the reference coordinate system is the position of the body.

Velocity of a body is the vector quantity that indicates the magnitude and the direction of its motion. Velocity is defined as the rate of change of position as the equation (2.5) indicates. In addition, the absolute value of velocity is called speed.

$$\vec{v} = \frac{\Delta\vec{r}}{\Delta t} \quad (2.5)$$

Where Δr is the change in the position of the radius vector $\vec{r} = \overrightarrow{OP}$, that represents the position point P(x, y, z) with respect to the origin 0.

The state-of-the-art existing publications about the classification of birds and drones using their kinematic signatures are presented in the following literature review Section 2.5. The kinematic features that are used in these researches will be analyzed in Section 3.1.

2.5 Existing Publications in Kinematic Signatures to Classify Birds and Drones

The classification of birds and drones, by tracking their trajectories and creating kinematic features from their speed and position data, is an approach in which research is at early stages and publications are very few. The already implemented researches existing in the literature [1], [2], [11], [40], [41], [42] and [43] are discussed below.

As part of the research [11], the Hybrid Digital Radar Twin, which is a radar simulator that generates Doppler signatures for different types of UAVs, was developed. In this way, many kinematic simulation data for different types of drones were used to generate realistic drone trajectories. In addition, drone flight trajectories were created using the autopilot software tool PAPARAZZI UAV. All these simulated drone flight data were compared with the flight trajectories of real birds from the MOVEBANK database [25]. The MOVEBANK datasets contain the timestamped position and speed of real bird flights recorded using GPS recorders. Thus, in this research the drone data were simulated, while the bird data were received from GPS. The classification of birds and drones using their kinematic features was implemented using the decision tree and random forest algorithms, while the research purpose was to enhance the classification of the flying target, based on the micro-Doppler signature.

J. Liu et al. [43] present a bird surveillance radar system working at S-band frequencies (2 to 4 GHz), whereas the rotational speed is 2.4 seconds/scan. The data for this experimental research collected in the FuCheng airport in BeiHai city, where many local birds fly and during hours at which no airplanes fly were scheduled to avoid receiving signal from such big aircrafts. In addition, after 6 radar tracks for a drone hovering over 15 seconds in the air, the drone tracking stopped. This research uses the PCA technique to reduce the number of features and the supervised machine learning random forest model to classify birds and drones, while the accuracy level of the classification is around 85%. According to J. Liu et al., the RCS maybe is the missing feature that can be considered in such false alarm cases in order to make a difference and increase the classification accuracy.

Another research implemented to classify birds and drones from the kinematic properties was implemented by N. Mohajerin et al. [40]. The Raytheon Digital Airport Surveillance Radar, the Standard Terminal Automation Replacement System and simulated drone trajectories combined in order to classify birds and drones. The Raytheon Digital Airport Surveillance Radar operates at S-band with 2.5 GHz, while the pulse repetition frequency is 800 Hz. The received data is a mixture of birds, aircraft and simulated UAV tracks. So, statistical kinematic features are applied as input to a standard Multilayer Perceptron (MLP) Neural Network to classify birds and UAVs. Similarly, to the previously discussed publications, the data of drones are not only based on real UAVs trajectories, but they are simulated data. The ML classification accuracy is 99%. So, the authors claim that experimental flights should be performed to create more representative datasets for future work.

The literature of the next study [2] shows that the trajectory-based kinematic features and target RCS features provide classification results with an accuracy of 99.3%. The drone flights generated data are simulated with a model following constant speed and acceleration, while the drone directions change, based on only two-dimensional x-y space. The kinematic features of speed and acceleration are used as input to the Recurrent Neural Network (RNN) model to classify birds and drones. Zhang Xu et al. support that the classification results on simulated data-set provide enough evidence to apply this method on real radar tracks. The classification evaluation is almost perfect but, in this scenario the data are simulated and not real.

The next publication implemented dealing with tracking and classifying drones and birds using their kinematic features was presented by V. Mehta et al. [1]. In this research, the combination of real and simulated data was used, whereas the real drone trajectories had a flight duration of 5 seconds. The statistical kinematic features of speed, acceleration, turn rate, curvature and heading are used as input to the Bayesian, SVM and Decision Tree classifiers to evaluate the performance of the classification of birds and drones. The decision tree model classification accuracy is 83.33%. The trajectories data are synthetic as both real and simulated data are used. Mehta Varun et al. support that both real data and simulations show promising results in terms of classification accuracy, but to further validate this conclusion, it is important in the near future to use only real track data and increase the different flying targets trajectories scenarios.

Another research on drone and bird classification which is generally related to the combination of micro-Doppler and kinematic features was implemented by T. B. Sarikaya et al. [41]. In this publication, SVM supervised learning and the PCA technique are used to reduce the features in order to separate in classes the flying objects. The classification accuracy is more than 90%. Moreover, the data collection for this literature review approach is implemented using a Ku-band (12–18 GHz) surveillance radar. The kinematic features are extracted from velocity, acceleration and turn rate, whereas the RF characteristic are extracted from the received signal, but they are not further analysed and presented in the publication.

2.6 Classification using Machine Learning

The classification of birds and drones from their kinematic features is implemented with machine learning techniques. The need to classify data in order to create patterns, that can provide important information about the structure of the data and the features that they represent, has driven the development of machine learning technology. Machine learning is the scientific study and development of algorithms and statistical models, that perform a specific task without being explicitly programmed, while they are used in many applications. These types of algorithms improve computer systems and use the known data to create patterns and predict information from unknown received data after training the model [44] [45].

Data types differ on many different occasions and there is no specific algorithm for all types that is capable of solving every problem. Therefore, the nature of the problem and the known data determine the type of algorithm that can be used on that particular occasion. Consequently, machine learning is divided into three main categories: supervised, unsupervised and reinforcement learning [46].

The first category of machine learning is supervised learning, which uses functions that map an input to a specific output, based on the input-output pairs used to train the ML model. The supervised machine learning category uses data that is tagged with a set of labels. Labels can be defined as a target variable that is numeric, and each label characterizes a class. More specifically, labels are defined based on a feature that is different for each class. The patterns learned from the training dataset are applied to the test dataset to make a classification or prediction, as Figure 17 shows. Certain supervised ML models are the Decision Tree and the KNN [44].

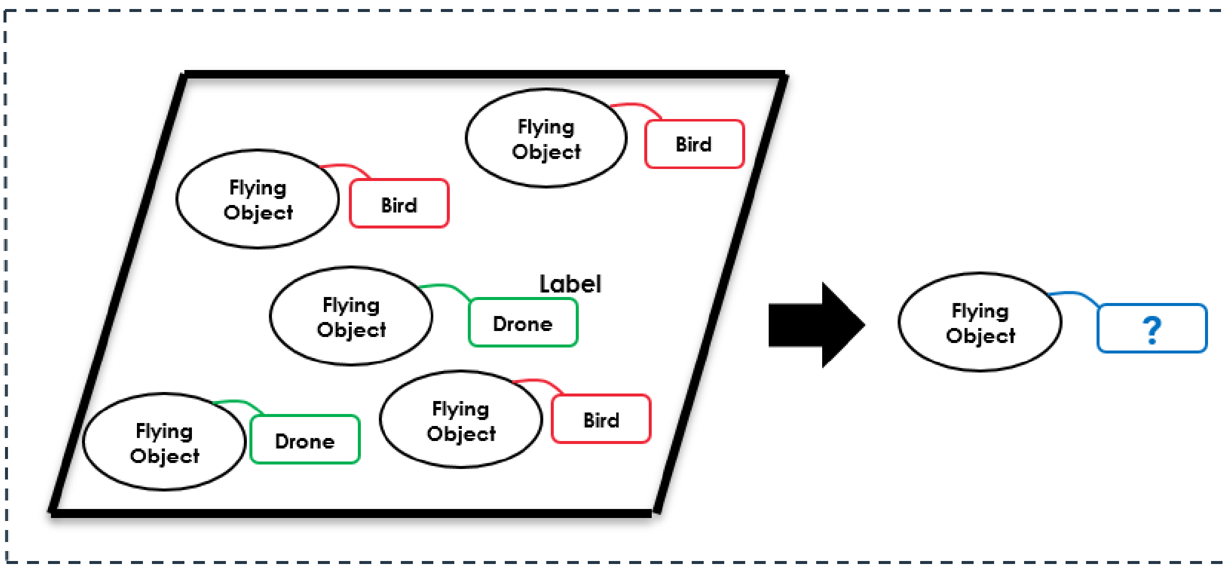


Figure 17: Supervised Learning: the system sees the feature, that indicates if the flying object is either a bird or a drone (label), and learns how to classify an unknown object.

Decision tree is a machine learning algorithm that explores decisions, choices and outcomes in a tree representation. The nodes and edges in the graph represent the decision tree, which are the events or choices and the decision rules or conditions. In this way, the classification is implemented and the model is trained to classify new unknown feature data into each class [46].

The KNN classifier is a supervised machine learning method that uses distance metrics to classify the new unknown object class. The Euclidean distance between the new data and the neighbors is calculated, while the K neighbors with the smallest distance are selected. The new data is assigned to the class in which the majority of the neighbors belong. The number of neighbors is selected with respect to the study case. The KNN classifier can be applied to multi-class problems, and predict to which of these classes a new unknown object belongs to [47].

In most cases, datasets do not have predefined labels, so supervised learning is not applicable. In this case, unsupervised learning is used because the data are first classified into different groups and then labels are assigned to these groups. Unsupervised learning is the second category of machine learning and there are no feature labels or input-output relationships to extract classification patterns and train the model. However, the unsupervised learning algorithms discover and create structures from the dataset and create clusters based on these discovered patterns. The division into different clusters is achieved by metrics, such as the distance to the classes, i.e. how close the features data are to the data of each class. In this way, the data is assumed to belong to the class, whose data have the smallest distance. Clustering is then implemented by separating the different classes presented [44] [48].

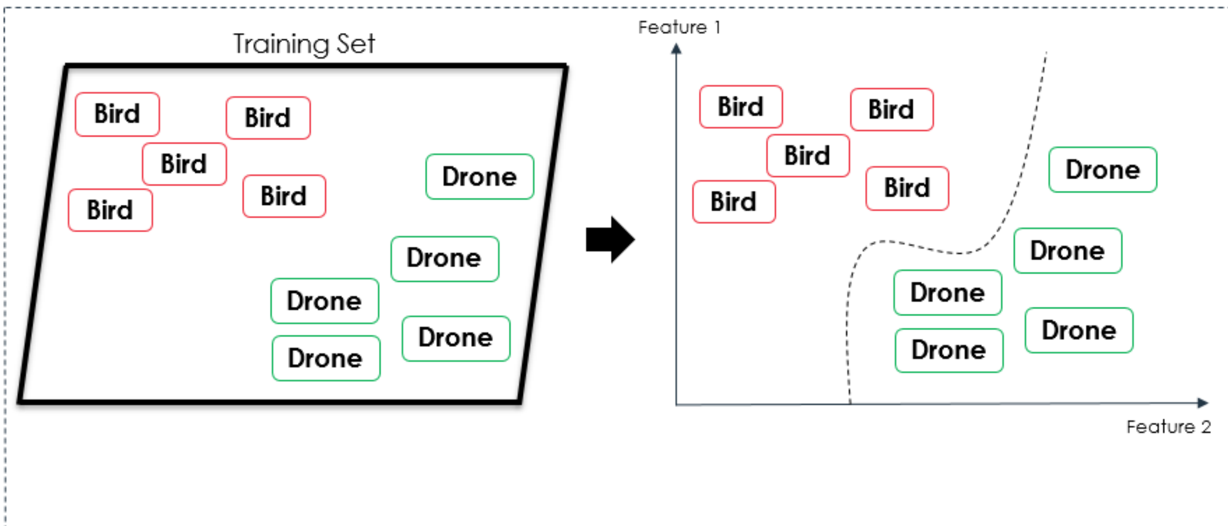


Figure 18: Unsupervised Learning: a training set with birds and drones. The clustering algorithm aims to group them into categories based on certain criteria (e.g. RCS; velocity; altitude flight etc.). The algorithm creates boundaries between the clusters.

K-means is an unsupervised learning technique that uses the training dataset to classify the data, into a specified number of clusters. The K-means algorithm predefines the k centers and a different class will be created around each center. The best classification is achieved when the centers are far from each other to avoid overlapping. As the number of clusters is defined in advance and their centers are randomly selected, the data are assigned to the closest center. The center is moved to the new center of the newly created cluster. This process continues until the clusters and their centers are no longer reassigned. In this way, the final clusters are created using distance metrics and contain data with similar characteristics [44] [49].

A machine learning technique that imitates the way humans naturally learn by example is called deep learning. Deep learning models are trained to perform the classification directly from images, sound and text by using a broad set of unstructured data and multilayer neural network architectures. Two significant categories of neural networks that lay the foundation for most pre-trained models in deep learning are the Convolution Neural Networks (CNN) and Recurrent Neural Networks (RNN) [50].

Deep learning models are not fully interpreted and are often referred to as ‘black boxes’. For this reason, when the importance of features needs to be examined, classic machine learning algorithms are used. Furthermore, in cases where the data amount is small, deep learning is also not so effective, because it requires extremely large data sets to accomplish high performance. Such enormous datasets are not easily collected [51]. On the other hand, classical ML algorithms such as KNN and random forest often outperform deep networks for smaller datasets. Thus, in the classification of birds and drones, where the dataset is limited and the importance of feature have to be observed, classic machine learning techniques are preferred.

2.7 Gaps in the Literature - Novelty

In the radar domain, there are many techniques that classify flying objects, such as the HERM and JEM, but they are not applicable to the classification of birds and drones. The only existing bird and drone classification methods depend on the micro-Doppler effect, but they have some limitations to provide the micro-Doppler signature of birds that do not flap their wings, drones that have covered blades and flying objects at long detection ranges.

As the micromovements of birds and drones are not captured by the radar, the need to explore different approaches is generated. Specifically, tracking flying objects, in order to observe possible differences in their flight behavior, is a relatively new approach and very few researches are published. Moreover, the majority of these researches use simulated or hybrid and not real bird and drone data. The real bird and drone data have limitations, such as the labels that indicate the class of the objects are not provided, or the fact that many different to birds and drones data are involved in the raw data.

Thus, the few publications on flying objects track analysis and kinematics to classify birds and drones are not fully explored, while the realistic cases that use real tracks from radars are also not examined. Further investigation of bird and drone classification using their kinematic signature, which is little explored, is the gap in the literature that this master thesis examines.

2.8 Summary of the chapter

This chapter examines an analysis of birds and drones, their tracking with surveillance radars and the existing flying targets classification techniques. The most relevant state-of-the-art publications regarding their classification are also provided and they are summarized in the following Table 3. The machine learning adequacy to the classification of birds and drones in contrast to other techniques, such as deep learning, is also presented. Finally, the gaps in the literature that motivated the implementation of this research are analyzed.

Reference	Features	Advantages	Disadvantages
[11]	Kinematic Signature and Micro-Doppler Signature	-Good classification performance -Many types of drones used to generate data	-Classification with simulated data, while real case scenarios did not research -Kinematic features are not presented
[43]	Kinematic Signature	-High classification accuracy of 85% -Real bird and drone data were used	-Precipitation data are similar and overlapped with bird data -Speed and position data are not separated on x, y and z axes -Curvature and acceleration features are not used
[40]	Kinematic Signature and RCS related	-Classification evaluation for each feature (indicate each feature importance) -Classification accuracy of 100%	– The received data is a mixture of bird, aircraft and simulated UAV tracks.
[2]	Kinematic Signature and RCS related	-Classification accuracy of 99.3%	-Both kinematic and RCS features used for classification -Simulated data used for the classification
[1]	Kinematic Signature	-Classification accuracy of 83.33%	-Combination of real and simulated data
[41]	Kinematic Signature And RF related	-Classification accuracy higher than 90% -Real bird and drone data were used	-Features used for the classification are not presented -Data cleaning process before applying unsupervised machine learning to generate clusters is not provided -The evaluation procedure of the cluster reliability is not presented

Table 3: Summary of the most relevant existing publications that use the kinematic signature for classification of drones and birds with analysis of advantages and disadvantages. By kinematic features it is meant the extraction of features from the position and velocity radar tracks.

3 Problem Analysis

This chapter presents an analysis of the kinematic features that are used for the classification of birds and drones. The extracted kinematic features of Low-Slow-Short (LSS) targets tracked by surveillance radars are presented in Section 3.1, while an analysis of how these features are processed is provided in the next Section 3.2.

3.1 Extracted Kinematic Features of Low-Slow-Short (LSS) Targets Tracked by Surveillance Radars

Tracking a target with surveillance radars can provide kinematic features, that can be created from position and velocity data of the target trajectory. Feature reduction techniques are applied since certain features can provide similar information, because they are derived from position and velocity measurement data. The generated kinematic features are used as input to machine learning classification algorithms to classify birds and drones and evaluate the accuracy of their discrimination [41].

Moreover, feature information is contained in each tracking point, while birds and drones have a flight speed of around 20m/s and they can be properly detected by radars even several kilometers away. In particular, according to the literature researches [1], [2], [40], [41], [42] and [43] the following features can provide birds and drones kinematics information. So, they can be used to generate kinematic features that are able to efficiently distinguish birds from drones. The statistical values of the mean and standard deviation parameters of the speed, acceleration and displacement, as well as the heading and curvature are the extracted kinematic features. These kinematic features are presented and analyzed below. The coordinate system in which these kinematic features are applied has as origin the surveillance radar. The coordinate axes are the x, y and z as Figure 19 shows.

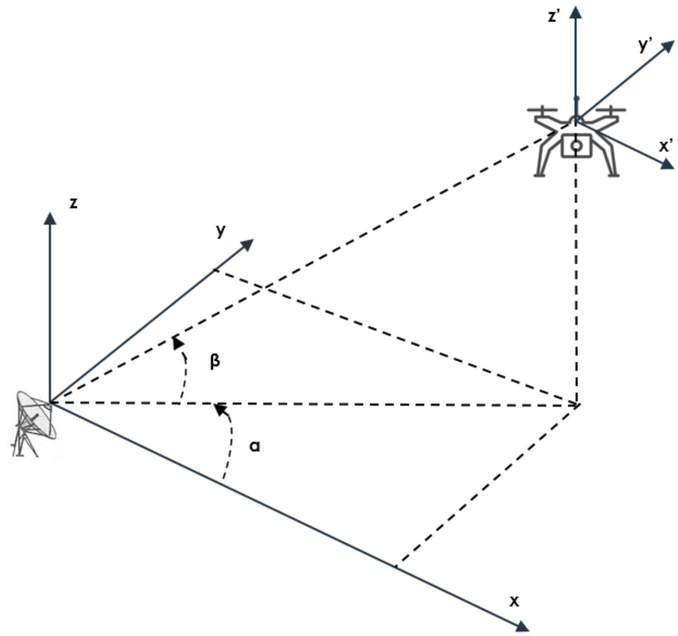


Figure 19: A geometry of the radar plus a drone. Angles α and β are the radar azimuth and elevation angles respectively. The reference is (X,Y,Z=0).

3.1.1 Average Speed

The average speed of the selected trajectory duration time interval is one of the most important features because it is used as a common feature to create other ones. In this way, the average speed is a classification feature that provides direct information to drones and birds. Average speed is also fundamental and dominant [2].

$$u_{mean} = \frac{1}{N}\sum_{i=0}^{N} u_i \quad (3.1)$$

The above equation (3.1) describes the average speed of the total target observation time. N defines the total number of tracks and u_i the measured speed at each track.

3.1.2 Standard Deviation of Speed

The speed deviation along the x, y and z axes, as well as the total standard deviation of the speed magnitude, indicate information between different flying objects and their behavior. In particular, the standard deviation indicates if the speed values of the trajectory tracks deviate from the mean speed value. The below equation (3.2) describes the standard deviation of speed for the selected trajectory observation time [43].

$$u_{std} = \sqrt{\sum_{i=1}^{N} \frac{(u_i - u_{mean})^2}{N}} \quad (3.2)$$

3.1.3 Average Heading

The average heading is relevant to a specific flying object trajectory. The flight direction changes of the bird and drone trajectories can be different, especially when the flying objects deviate from straight line flights. According to [42] drones can have either very small or very big changes in their turn rate. Thus, drones heading values can be either very small or very big, whereas birds have smaller heading values in a wider range. Concerning the bird and drone behavior, the heading feature can provide important information to classify them, whereas heading can be applied also in the 2-dimensional x-y space. This is an important advantage, as many radars such as the TNL surveillance one, that was used for this master thesis, do not provide the altitude z-axis information. The following equation (3.3) presents the average heading of the selected trajectory tracks i to N.

$$h_{mean} = \frac{1}{N}\sum_{i=0}^{N} \tan^{-1}\frac{y_i - y_{i-1}}{x_i - x_{i-1}} \quad (3.3)$$

The above equation (3.3) examines how smoothly a flying target changes its direction. In the case where two consecutive tracks have the same x and y position tracks, the heading takes the zero value.

3.1.4 Standard Deviation of Heading

The standard deviation of the heading indicates the spatial deviation from the average heading value. As a result, the behavior and purpose of each flight can lead to different heading deviations, which is an important feature for the classification of these two flight targets [43].

$$h_{std} = \sqrt{\sum_{i=1}^{N}\frac{\Delta_h(i)}{N}} \quad (3.4)$$

This equation (3.4) describes the standard deviation of heading, whereas Δ_h is defined as:

$$\Delta_h(i) = \begin{cases} (h_i - h_{mean})^2, |h_i - h_{mean}| \le \delta_h \\ (|h_i - h_{mean}| - 360)^2, |h_i - h_{mean}| > \delta_h \end{cases} \quad (3.5)$$

h_{mean} is the average heading whose computation considers the relationship between 0° and 360°, while h_i is the heading value at each measurement. Moreover, δ_h is the threshold for heading deviation and it is empirically set to 90° according to [43].

3.1.5 Maneuverability Factor

While the standard deviation of the heading indicates the position changes of the flight target, it does not provide timing information. In contrast, the speed mean value and standard deviation provide information in the time domain, while the spatial information is weak. Therefore, the maneuverability factor is a feature that links the spatial and temporal characteristics, to determine whether a high-speed target can have large heading information [43].

$$\mathrm{mf} = \frac{\mathrm{v_{mean}}}{\mathrm{h_{std}}} \quad (3.6)$$

Equation (3.6) presents the maneuverability factor, which unit is {m/s/deg].

3.1.6 Average Displacement

Average displacement is the mean absolute value of the difference between two consecutive tracks. This feature can provide useful information for identifying objects, since drones and birds change altitude in very different ways. In particular, a drone can keep its altitude constant, whereas migratory birds change their position on the z-axis during long flights. In addition, drones can create trajectories with high maneuvers and thus change their position on the z-axis very quickly, or have a constant altitude when they hover. Therefore, the average displacement, especially on the z-axis, can provide important information for detecting flight targets. The following equation (3.7) presents the average displacement [40].

$$\mathrm{d_{mean}} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i=0}}^{\mathrm{N}} |\mathrm{d_{i+1}} - \mathrm{d_i}| \quad (3.7)$$

d_i is defined as: $\mathrm{d_i} = \sqrt{\mathrm{x_i}^2 + \mathrm{y_i}^2 + \mathrm{z_i}^2}$

The average displacement can also be measured on each axis as the following equations (3.8), (3.9) and (3.10) provide:

$$\mathrm{x_{mean}} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i=0}}^{\mathrm{N}} |\mathrm{x_{i+1}} - \mathrm{x_i}| \quad (3.8)$$

$$\mathrm{y_{mean}} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i=0}}^{\mathrm{N}} |\mathrm{y_{i+1}} - \mathrm{y_i}| \quad (3.9)$$

$$\mathrm{z_{mean}} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i=0}}^{\mathrm{N}} |\mathrm{z_{i+1}} - \mathrm{z_i}| \quad (3.10)$$

3.1.7 Standard Deviation of Displacement

The standard deviation of displacement provides the deviation of x, y and z axes position values, during the selected trajectory time of an object. Since drones can have very large or almost no changes in their altitude values, the deviation of their position can be either large or small. However, position changes on the z-axis for bird flights could cover a wider range.

$$\mathrm{d_{std}} = \sqrt{\sum_{\mathrm{i=1}}^{\mathrm{N}} \frac{(\mathrm{d_i} - \mathrm{d_{mean}})^2}{\mathrm{N}}} \ (3.11)$$

$$\mathrm{x_{std}} = \sqrt{\sum_{\mathrm{i=1}}^{\mathrm{N}} \frac{(\mathrm{x_i} - \mathrm{x_{mean}})^2}{\mathrm{N}}} \ (3.12)$$

$$\mathrm{y_{std}} = \sqrt{\sum_{\mathrm{i=1}}^{\mathrm{N}} \frac{(\mathrm{y_i} - \mathrm{y_{mean}})^2}{\mathrm{N}}} \ (3.13)$$

$$\mathrm{z_{std}} = \sqrt{\sum_{\mathrm{i=1}}^{\mathrm{N}} \frac{(\mathrm{z_i} - \mathrm{z})^2}{\mathrm{N}}} \ (3.14)$$

The above equations (3.11), (3.12), (3.13) and (3.14) provide the standard deviation of the displacement on the x, y and z axes, as well as the average standard deviation of the displacement [40].

3.1.8 Average Acceleration

The average acceleration feature provides the way a flying object changes its speed over time. Comparing the simulated data in Chapter 4, the acceleration values of drones are higher than those of birds because they change direction very quickly. Thus, this function could provide useful classification information about birds and drones, while the equation (3.15) represents the average acceleration [40].

$$a_{mean} = \frac{1}{N} \sum_{i=0}^{N} \frac{v_{i+1} - v_i}{t_{i+1} - t_i} \ (3.15)$$

3.1.9 Standard Deviation of Acceleration

The standard deviation of acceleration indicates the deviation of acceleration values from the mean value. The flying objects whose acceleration deviate from the mean acceleration have more random trajectories. Thus, the standard deviation of acceleration provides individual information about birds and drones when the flying objects do not fly at constant flight speed. In addition, this feature can also be separated along each x, y and z axes, while the equation (3.16) indicates the standard deviation of acceleration [40].

$$a_{std} = \sqrt{\sum_{i=1}^{N} \frac{(a_i - a_{mean})^2}{N}} \quad (3.16)$$

3.1.10 Average Curvature

The curvature θ is a feature that measures if a flight trajectory deviates from a straight-line path. The trajectories that are close to straight flights or do not provide changes in their direction have curvature values near zero, whereas when a flying object changes its directory and deviates from the straight-line path, the curvature feature increases. The important advantage of this feature is that it can be calculated in two-dimensional space. As many radars do not provide altitude information on the z-axis, the curvature characteristic can be examined on the x-y plane. The mathematical equation (3.17) indicates the curvature of the selected trajectory tracks [42].

$$\theta = \frac{1}{N} \sum_{i=0}^{N} \cos^{-1} \frac{a^2 - b^2 - c^2}{2bc} \quad (3.17)$$

In the above equation (3.17) a, b and c are the Euclidian distances from (x_{i+1}, y_{i+1}) to (x_{i-1}, y_{i-1}), from (x_i, y_i) to (x_{i-1}, y_{i-1}) and from (x_{i+1}, y_{i+1}) to (x_i, y_i) respectively.

3.2 Kinematic Features Processing

The surveillance radar provides tracks, and specifically the position and velocity information, at each detection of the trajectory of the flying objects. The tracks of each trajectory are applied to the already mentioned kinematic formulas, in order to extract the kinematic features for each selected trajectory. By applying this procedure to all trajectories that are detected from the radar, the entire dataset is generated.

Tracks preprocessing, is an important preliminary step for extracting the kinematic features that will be used to train the ML model [52]. For example, in the study case of the classification of birds and drones with data received from the TNL surveillance radar, targets with RCS and speeds values above -5dB and 40m/s respectively are removed, because the raw data includes pedestrians, cars and ocean waves that are not useful for that classification problem. The filtered data are applied to the equations of Section 3.1, in order to generate the kinematic features.

Features scaling is an essential step during the pre-processing of data, before entering the ML model. Scaling is a process of normalizing features in the same range, since they may have data at different numerical scales. One of the most common techniques for features scaling is the normalization, which bounds the features values between two numbers such as 0 and 1. For example, in the case of the classification of birds and drones, the heading and the average speed features have different values range, as mean velocities values are from 0 to 40, whereas the heading values are in the range from 0 to 80. Therefore, it is urgent to scale the features in the same range to not affect the classification results [52].

In the validation state, the entire data set is divided into a training set and a test set. In the training set, the features will be used to train the ML model and create different classes based on the features. The test data set will be used as input to the ML model, as it should predict in which class the test data belong to. In this way, the accuracy of the model will be estimated. The training and the test dataset are randomly selected to observe and evaluate the accuracy of the model [49].

The kinematic features for each trajectory that will be applied as input to machine learning classifiers are generated from the velocity and position tracks. Thus, they can be correlated, as their information could be overlapped. To minimize and select the useful features for classifying drones and birds, Sarikaya et al. [41] propose Principal Component Analysis (PCA). PCA is a dimensionality reduction method that transforms the data from a higher-dimensional space to a lower-dimensional space. Thus, PCA reduces the feature space to a smaller set that can classify the different objects. More specifically, the PCA space contains orthogonal and uncorrelated principal components. The direction of the PCA space is the variance between the given features data and the individual information each feature contains [53] [54].

The preprocessed kinematic features are applied to machine learning models in order to classify birds and drones. Their classification is divided into two parts. In the first part, simulated drone trajectories are generated using the 6-DoF quadcopter [55], while migratory bird trajectories GPS data are collected from the MOVEBANK database [25]. Both simulated quadcopter and real bird features have labels. Thus, the KNN and decision tree supervised machine learning algorithms are used in this case. This classification scenario will be analyzed in Chapter 4. The next case is to classify real data of birds and drones from a TNL surveillance radar. Since, a limitation in this study is the lack of labels, the unsupervised machine learning K-means algorithm will be applied to generate bird and drone clusters, as presented in Chapter 5. Figure 20 presents the block diagram of the data processing.

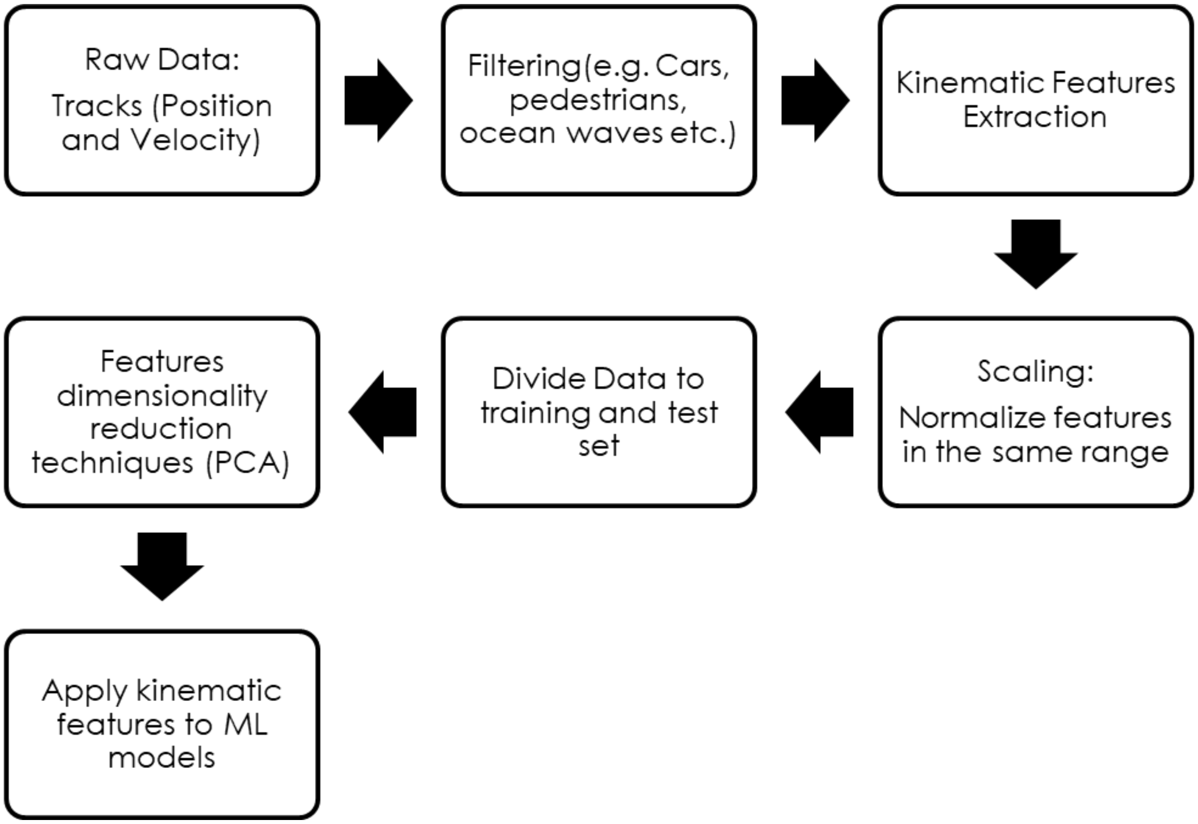


Figure 20: Block diagram of the data processing. The raw data are filtered from different bird and drone flying objects. These data are used to generate kinematic features for each trajectory of the flying objects. Scaling, division of the training and test sets, and the PCA technique are applied to the kinematic features before their application to ML models.

3.3 Summary of the chapter

In this chapter, the kinematic features that exist in the state-of-the-art publications, are collected and presented. Their mathematical equations are also provided, as they will be used in the bird and drone classification cases, in Chapters 4 and 5. The surveillance radar tracks for the trajectories of each flying target will be applied to the formulas of Section 3.1, in order to examine the kinematic features for the selected trajectory. The data preprocessing is significant, as the data filtering from irrelevant to the bird and drone tracks will increase the classification accuracy. The procedures of scaling the features in the same range, as well as splitting them into training and validation sets, are steps that have to be implemented before applying them to ML algorithms. Finally, the PCA importance is analyzed, as the features are extracted from position and velocity tracks. Thus, they are possible to contain overlapped information. The two classification scenarios, of the 6-DoF quadcopter versus the bird MOVERBANK trajectories and the real bird and drones tracked by a TNL surveillance radar, are also presented and will be further investigated in the following chapters.

4 Classification of Simulated Drones and Real Birds Trajectories Data

In this chapter, the classification between a simulated 6-DoF quadcopter and real MOVEBANK bird trajectories is performed. Section 4.1 describes the methodology and design of this classification case, while the 6-DoF quadcopter model and the MOVEBANK bird dataset are presented in Sections 4.2 and 4.3. The next Section 4.4 shows the importance and applicability of different time intervals between two consecutive tracks and the total duration of the trajectory. Sections 4.5 and 4.6 present the simulations, as well as the classification of birds and drones, respectively. The next Section 4.7 provides the clusters generation case of drones with different mass values.

4.1 Methodology and Design

The methodology of the classification between the simulated quadcopter and real bird data is shown in Figure 21. The first task is to create the simulated trajectories with the 6-DoF quadcopter and separate the real bird data from the MOVEBANK dataset in shorter duration trajectories, as the whole dataset contains GPS tracks received over a long period of several days. The next step is to derive the u_{mean}, u_{std}, d_{mean}, d_{std}, a_{mean}, a_{std}, h_{mean} and θ kinematic features from the trajectories data. The kinematic characteristics are also calculated separately for each axis, since important flight differences can be observed on each of them. These features are applied as input to the supervised machine learning KNN and decision tree algorithms. Finally, the classification evaluation indicates the importance of each feature used to classify birds and drones.

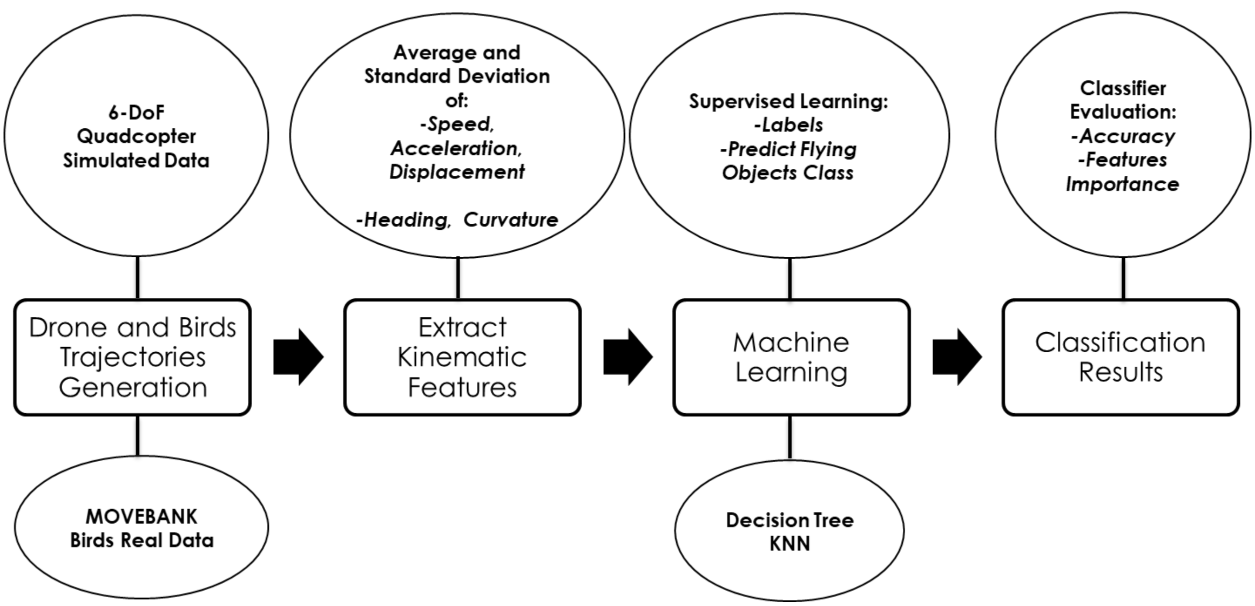


Figure 21: Methodology of classification between the simulated quadcopter and real bird data. The drone simulated and real bird data are used to extract kinematic features, that are applied to the KKN and decision tree classifiers. The classification accuracy of the models and the importance of the features are evaluated.

4.2 6-Degree-of-Freedom Quadcopter

The 6-DoF quadcopter is the simulation model used to generate drone trajectories in this chapter. According to Ahmed et al. [55], 6-DoF quadcopter is a drone simulation model that can perform similar results to a real drone. The six degrees of freedom are the movements along the x, y and z axes, as well as the roll, pitch and yaw rotation of a quadcopter. The 6-DoF model is implemented in MATLAB™ and Simulink™. Moreover, the control of the flight maneuvers is achieved by a PID controller and the mass values of the rigid body can be adjusted by the model user [55].

The dynamics of the 6-DoF quadcopter are explained by Newtons laws. The end point of each drone arm has a motor, so 4 motors drive the quadcopter model. The center of gravity of the model is the midpoint connecting all four arms of the drone and the length of the arm is the distance between the center of gravity and the endpoint where the motor is located, as Figure 22 shows. Each motor generates a thrust u and a torque t. Thus, the 4 motors generate the thrusts u_1, u_2, u_3 and u_4 and the torques t_1, t_2, t_3 and t_4. The following equations (4.1) and (4.2) describe the dynamics of the 6-DoF quadcopter, where $\mathrm{F_b}$ is the total force, $\mathrm{M_b}$ is the total torque, $\mathrm{V_b}$ is the velocity and $\mathrm{W_b}$ is the angular velocity on the rigid body frame [55].

$$\overrightarrow{\mathrm{F_b}} = \mathrm{M}\left(\frac{\mathrm{d}\overrightarrow{\mathrm{V_b}}}{\mathrm{dt}} + \overrightarrow{\mathrm{W_b}} + \overrightarrow{\mathrm{V_b}}\right) \quad (4.1)$$

$$\overrightarrow{\mathrm{M_b}} = \mathrm{I}(\frac{\mathrm{d}\overrightarrow{\mathrm{W_b}}}{\mathrm{dt}}) + \overrightarrow{\mathrm{W_b}} \times \left(\mathrm{I}\overrightarrow{\mathrm{W_b}}\right) \quad (4.2)$$

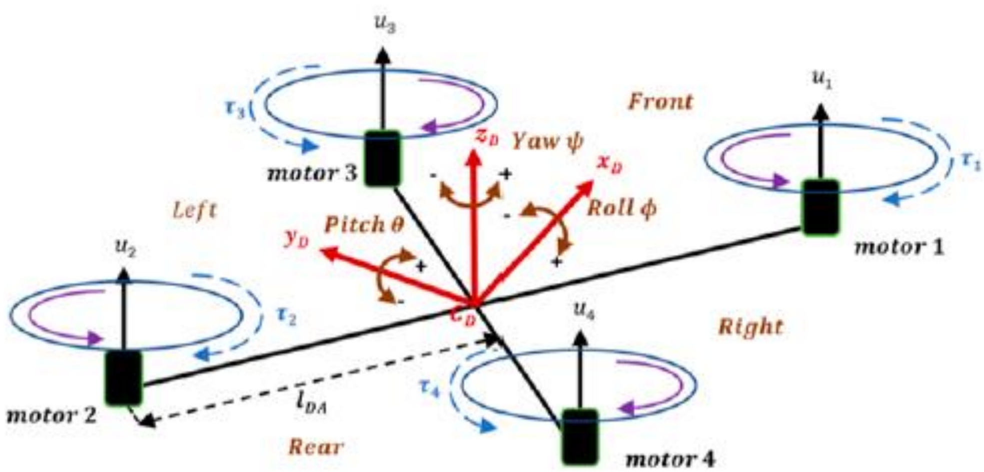


Figure 22: The 6-DoF physical quadcopter model, that is used for the generation of the simulated drone trajectories [55].

Ahmed et al. [55] present the circular motion of the spacecraft which is described in equation (4.3). A quadcopter has to overcome its gravity and this force acts only on the z-axis. Equations (4.4) and (4.5) give the force and torque of the quadcopter. Equation (4.5) shows that a constant torque is required along the x-axis when I_z is not equal to I_y. This torque is required to maintain the roll angle of the quadcopter, which in turn provides the centrifugal force for circular motion. In most cases, I_z is not equal to I_y for a quadcopter, since the inequality (4.6) holds for a t-shaped UAV object. In this way and in term of quadcopter dynamics, the 6-DoF model is implemented to generate drone trajectories.

$$F_x = mR\dot{\omega} \quad (4.3)$$

$$F_y = mR\omega^2 \quad (4.4)$$

$$M_x = \omega^2 \sin(a)\cos(a)\left(I_z - I_y\right) \quad (4.5)$$

$$I_x < I_y < I_z \quad (4.6)$$

Finally, the uniform motion in 3D space can be represented by the 3D coordinated turn model. The received measurements of the state space model of the trajectory are defined as the feature vector f_i, where $f_i = [x, u_{x_i}, a_{x_i}, y, u_{y_i}, a_{y_i}, z, u_{z_i}, a_{z_i}, \omega_i]$, is the features target state at each track i. The measurements contain the position, velocity, acceleration in the x, y and z axes as well as the turn rate [2].

The input to the 6-DoF quadcopter model is the waypoints of the flight path at a given time. By simulating the model, the drone trajectory is generated while the position and velocity information is obtained as output. The structure of the trajectories' generation is shown in the following Figure 23. For this master thesis, a script was developed to generate random trajectory waypoints, in order to create a user-specified number of trajectories. Since the speed of birds in MOVEBANK datasets is about 20m/s, the random waypoint generator examines drone trajectories with similar speeds, while the data are received every 0.01 seconds. The mass value of the rigid body can be adjusted by the model user [55].

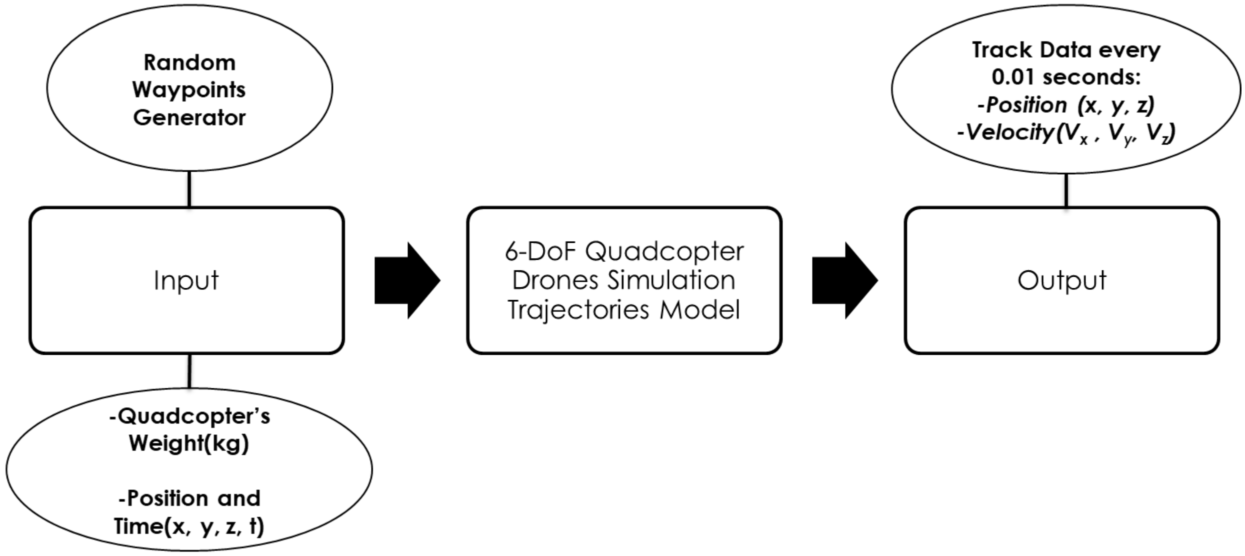


Figure 23: Block diagram for the generation of trajectories using the 6-DoF quadcopter model. The random waypoint generator is used to create plenty of different trajectories.

4.3 Birds MOVEBANK Dataset

As was concluded in Section 2.2, there is no realistic approach to generating simulated bird flight trajectories. The literature study [11] that classifies birds and drones uses simulated drone and real bird data from a bird flights MOVEBANK dataset [25]. In that way, for this chapter, the bird trajectories from the MOVEBANK dataset are also examined. Birds position and velocity data in the MOVEBANK database are collected from GPS attached to birds, while most birds are migratory. In addition, few datasets contain altitude axis information, as most of the data from GPS contain only x and y axes velocity and position information. Therefore, the flight path data of a pigeon bird flying over Germany was used for this master thesis, because this dataset also provided information about the altitude axis. The data are received every 1 second, while the total data from GPS are received over many days. Thus, there are enough data to create trajectories of shorter duration.

4.4 Time Interval Between Tracks and Total Trajectory Duration

The time interval between two consecutive tracks in the 6-DoF model is 0.01 and is predefined. In real case scenarios and specifically the received data from the TNL surveillance radar, the tracks data are received almost every 2 seconds. In this way, the simulations are divided into three different categories where the time interval between two consecutive tracks is 1, 2 and 4 seconds. The reason for this selection is that the optimistic scenario of the time interval between two consecutive tracks is 1 second, which is rarely observed in real cases. The selection to measure a new trace every 4 seconds is a pessimistic scenario, which is also very rare, but could be observed in some measurements. The time interval between two consecutive measurements is 2 seconds in the third case, as this is a realistic scenario and it is verified from the real TNL radar data. Since the simulations are intended to be as close to reality as possible, it is important to investigate whether all three cases provide similar results in the classification evaluation.

Another important simulation parameter is the total trajectory time. In the real bird and drone classification case of Chapter 5, it is observed that the majority of trajectories duration is between 10 seconds to 35 seconds. There are also a few trajectories, with longer or shorter duration of this time interval. In that way, it was decided to analyze these time intervals at the simulated and real bird flights in this chapter, in order to observe if the different trajectories duration affect the classification results.

Specifically, Figure 24 shows the different flight durations of birds and drones with respect to the accuracy provided by the decision tree classifier. The specific observation time intervals are 4, 8, 15, 20, and 30 seconds. It can be observed that the accuracy for all 5 different time intervals is around 98%. In that way, it is examined that the different trajectories duration in the time interval from 5 seconds to 35 seconds do not affect the classification results. The 4-seconds trajectories provide the highest classification accuracy but are also very similar to the other trajectories. The reason is that drones, as shown in Figure 25, Figure 26, Figure 27, Figure 28, Figure 29 and Figure 30, have trajectories with high maneuverability along all x, y, and z axes, while birds have smoother trajectories that do not deviate along all axes, because they are migratory birds. In this way, the speed values are similar, but the displacement and acceleration of drones are higher as they change their direction and position in small time intervals, while birds have very constant trajectories in only 4 seconds. For this reason, the 4-seconds flight has slightly higher accuracy.

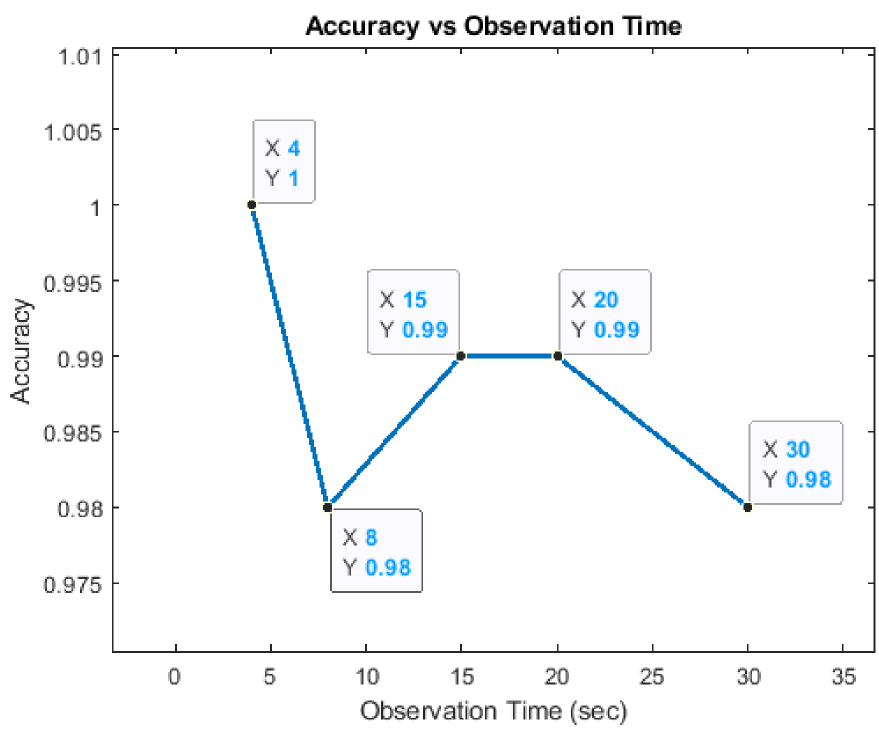


Figure 24: Classification accuracy concerning the total flight time. The classification accuracy of the simulated quadcopter and the real bird flights is observed in 5 different 'flight duration' scenarios (4s, 8s, 15s, 20s and 30s). The accuracy of each of them is higher than 98%.

4.5 Simulations

The simulations in the following Figure 25, Figure 26, Figure 27, Figure 28, Figure 29 and Figure 30 below show the trajectories of the 6-DoF quadcopter and the trajectories of a bird from the MOVEBANK dataset. The simulations are divided into 3 categories in terms of the time interval between two consecutive tracks. The trajectories of the 6-DoF quadcopter last 34 seconds and the flight duration of the pigeon from the MOVEBANK dataset is 30 seconds.

The time interval between two consecutive tracks for the first category is 1 second. Since the data from the 6-DoF quadcopters are received every 0.01 seconds, the track update rate is downsampled towards 1 second. For the bird data, which are received every second, all consecutive data are considered for the trajectory path. Thus, the drone and the birds have 34 and 30 tracks, respectively.

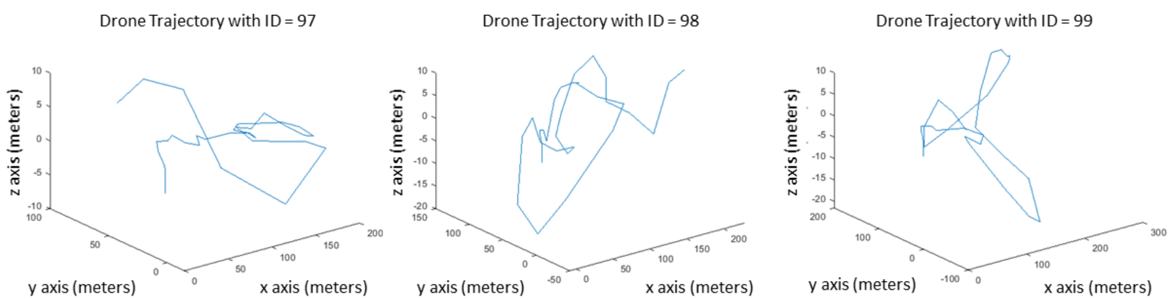


Figure 25: Drones trajectories with 1 second time interval between two consecutive tracks.

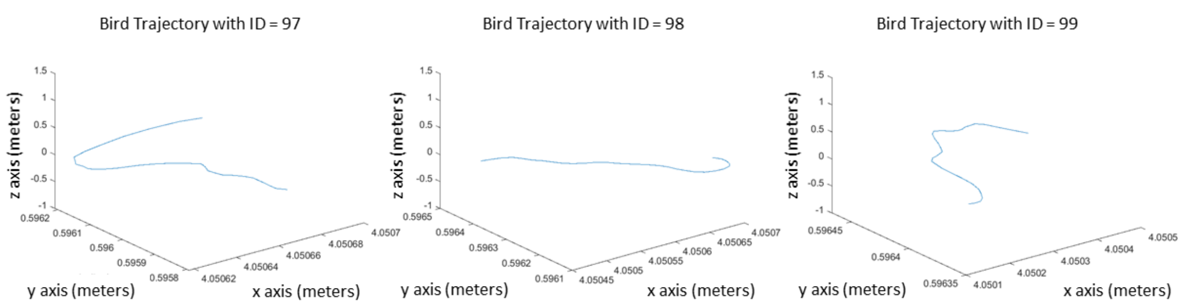


Figure 26: Birds trajectories with 1 second time interval between two consecutive tracks.

The second dataset provides a time interval of 2 seconds between two consecutive tracks. In this way, the tracks for the 6-DoF quadcopter are examined every 200 measurements, since the model provides tracks information every 0.01 seconds. The same procedure is used for the bird data, as the track update rate is downsampled towards 2 seconds. In this category, the total trajectory time is 34 seconds for the drone and 30 seconds for the bird, while the time interval between consecutive tracks is 2 seconds, giving 17 tracks for the drone and 15 for the bird.

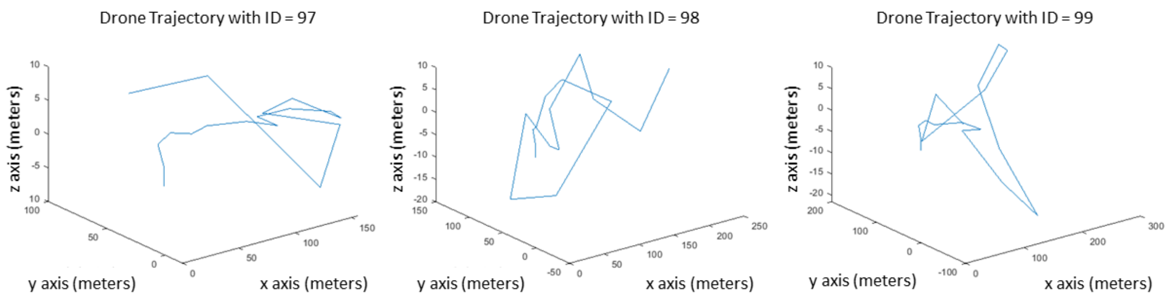


Figure 27: Drones trajectories with 2 seconds time interval between two consecutive tracks.

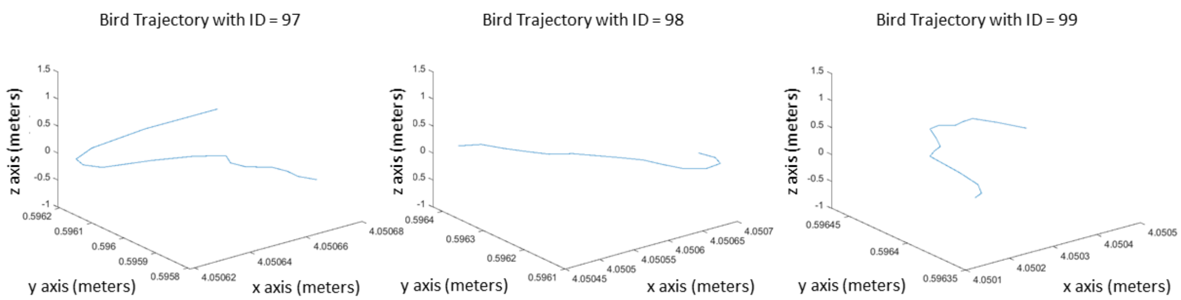


Figure 28: Birds trajectories with 2 seconds time interval between two consecutive tracks.

The last category consists of received data from the bird and the drone every 4 seconds. In this way, all tracks within the time interval of 4 seconds are discarded for both 6-DoF quadcopter simulations and real bird data sets. In this scenario, the tracks for the drone trajectory are 8 and for the birds are 7, as data are received every 4 seconds for the 34 seconds drone trajectory and every 30 seconds for the trajectory of the bird.

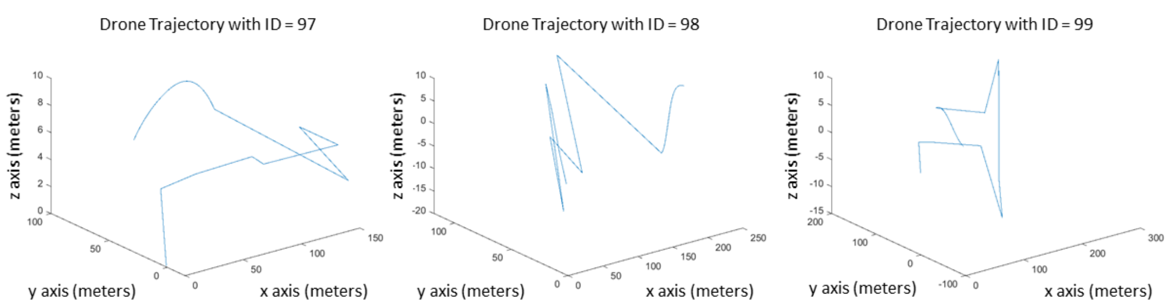


Figure 29: Drones trajectories with 4 seconds time interval between two consecutive tracks.

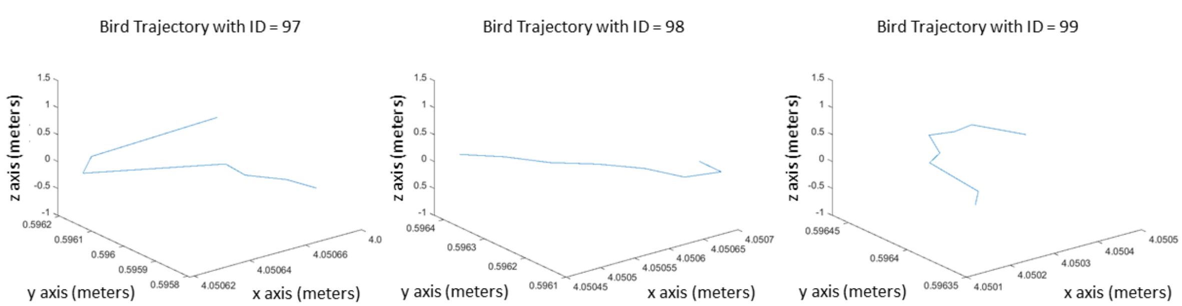


Figure 30: Birds trajectories with 4 seconds time interval between two consecutive tracks.

The following Table 4 summarizes the three different categories and the time interval between the measurements of the trajectories, as well as the total number of different trajectories generated, in order to obtain a large number of trajectories for feature extraction, as input to the machine learning models.

	1s Time interval Between 2 Consecutive Track updates	**2s Time interval Between 2 Consecutive Track updates**	**4s Time interval Between 2 Consecutive Track updates**
6-DoF Quadcopter Simulations			
Total Trajectory Time Interval	34 seconds	34 seconds	34 seconds
Number of Generated Trajectories	250	250	250
Number of Tracks	34	17	8
Real Bird MOVEBANK Dataset			
Total Trajectory Time Interval	30 seconds	30 seconds	30 seconds
Number of Generated Trajectories	250	250	250
Number of Tracks	30	15	7

Table 4: A summary of the generated trajectories for the three different 'time intervals between two consecutive tracks (1s, 2s and 4s)' cases. The trajectory duration, the number of the generated bird and drone trajectories, and the number of tracks in each of them are presented.

4.6 Classification and Evaluation

The u_{mean}, u_{std}, d_{mean}, d_{std}, a_{mean}, a_{std}, h_{mean} and θ kinematic features were extracted from the simulated drone and the real bird trajectories. They are summarized in the following Table 5. The PCA technique was also applied to these features. The maneuverability and standard deviation of heading features are not applied to this classification scenario, as the azimuth and elevation angles information is not provided by the GPS MOVEBANK dataset.

Kinematic Feature	Symbol
Average Speed	u_{mean}
Standard Deviation of Speed	u_{std}
Average Displacement	d_{mean}
Standard Deviation of Displacement	d_{std}
Average Acceleration	a_{mean}
Standard Deviation of Acceleration	a_{std}
Average Heading	h_{mean}
Average Curvature	θ

Table 5: Summary of the extracted kinematic features, that are used for the classification of the simulated drone and the real bird data.

The input features to the machine learning classifiers are the kinematic features presented in Table 5. These features are examined for each of the 250 bird and 250 drone trajectories. The kinematic features for the total 500 trajectories are used as input to the supervised machine learning KNN and Decision Tree classifiers, while the data are divided into a training and a test set. The training data set accounts for 80% of the total input data and the data are randomly selected, while the remaining 20% of the total input data are used to test the accuracy of the models.

All classification cases, for both the decision tree and the KNN classifiers, were tested 5 times, in order to evaluate the precision of the classification accuracy of the models. It is observed that each time the classifier provided similar classification results. Specifically, Table 6 presents the classification accuracy for the decision tree and the KNN models, for the 2 seconds time interval between two consecutive tracks. The average accuracy of the 5 times that the models were trained, is also estimated.

	2 seconds Time interval Between 2 Consecutive Tracks	Average Accuracy across Time	2 seconds Time interval Between 2 Consecutive Tracks	Average Accuracy across Time
Classifications Times	5		5	
Classifier	Decision Tree		KNN	
Features				
PCA	-100% -100% -100% -100% -100%-	100%	-100% -100% -100% -100% -100%-	100%
Average Displacement	-77% -74% -77% -73% -76%-	75.4%	-80% -79% -75% -74% -74%-	76.4%
Standard Deviation of Displacement	-88% -91% -88% -87% -88%-	88.4%	-97% -96% -92% -91% -92%-	93.6%
Average Speed	-73% -70% -71% -70% -74%-	71.6%	-82% -79% -78% -78% -84%-	80.2%
Standard Deviation of Speed	-99% -96% -97% -97% -99%-	97.6%	-99% -100% -99% -99% -98%-	99%
Average Acceleration	-100% -100% -100% -100% -100%-	100%	-100% -100% -100% -100% -100%-	100%
Standard Deviation of Acceleration	-100% -100% -100% -99% -100%-	99.8%	-100% -100% -100% -100% -100%-	100%
Average Displacement at each x, y, z axes	-96% -97% -93% -93% -91%-	94%	-91% -92% -92% -94% -89%-	91.6%
Standard Deviation of Displacement at each x, y, z axes	-97% -95% -97% -96% -94%-	95.8%	-94% -89% -89% -86% -87%-	89%
Curvature	-95% -94% -95% -97% -94%-	95%	-98% -94% -96% -97% -98%-	96.6%
Heading	-80% -84% -83% -85% -84%-	83.2%	-81% -87% -84% -87% -85%-	84.8%

Table 6: Classification of birds and drones using the decision tree and the KNN models. The time interval between two consecutive tracks is 2 seconds and the models are trained and tested 5 times. The classification accuracy each time and their average classification accuracy are also presented.

Table 7 shows the results of the classification study case for the simulated quadcopter and the real bird flights, by applying the extracted kinematic features of Table 5 to the KNN and the decision tree classifiers, in order to examine the importance of the kinematic features. As the accuracy of the models was examined in Table 6, this classification case will be tested once, because the goal is to analyze the significance of each feature for the classification of birds and drones. The classification accuracy is provided for all three 'Time interval Between 2 Consecutive Tracks' cases.

Time interval Between 2 Consecutive Tracks	1 Second	2 Seconds	4 Seconds	1 Second	2 Seconds	4 Seconds
Classifier	Decision Tree	Decision Tree	Decision Tree	KNN	KNN	KNN
Features						
PCA	100%	100%	100%	100%	100%	100%
Average Displacement	72%	74%	69%	75%	77%	70%
Standard Deviation of Displacement	91%	89%	91%	95%	94%	91%
Average Speed	77%	75%	70%	83%	80%	78%
Standard Deviation of Speed	99%	98%	97%	98%	99%	98%
Average Acceleration	99%	100%	100%	100%	100%	100%
Standard Deviation of Acceleration	100%	100%	100%	99%	100%	99%
Average Displacement at each x, y, z axes	94%	95%	98%	95%	96%	98%
Standard Deviation of Displacement at each x, y, z axes	96%	95%	91%	98%	91%	93%
Curvature	95%	96%	95%	96%	97%	95%
Heading	78%	81%	84%	83%	85%	86%

Table 7: Birds and drones classification accuracy by applying each kinematic feature separately to the Decision Tree and KNN classifiers. Three classification cases are presented, concerning the time interval between two consecutive tracks (e.g. 1s, 2s and 4s). Tracks are used to generate the kinematic features of Table 5. The classification accuracy of this case is used to evaluate the importance of each feature.

The evaluation of the classification study for the simulated 6-DoF quadcopter and the real MOVEBANK bird flights provided high accuracy results. By applying PCA the accuracy is 100%, because the features with the important information are used to distinguish the flight targets, examined from a drone with high maneuverability trajectories and a migratory bird with straight line flights. Therefore, the reason for this high accuracy is explored by applying inverse engineering techniques. Specifically, the classification accuracy of each feature was presented, as it is possible to determine which of these features are responsible for providing classification information for birds and drones. As Table 7 shows, the mean and standard deviation of speed provide classification with an accuracy of about 70% to 99%. The reason for these results is that the flight speed of both birds and drones is about 20 m/s, but birds have more constant speed values between 16 and 19 m/s, while drones have speeds between 14 and 30 m/s. Thus, the standard deviation of speed provides high classification accuracy.

The next observation is that the acceleration statistics features classify birds and drones with 100% accuracy. The reason is that drones have trajectories with high acceleration, while birds have smoother trajectories without changing their flight direction. Therefore, the acceleration related features provide higher values for drones and smaller ones for birds, which is responsible for the 100% classification accuracy. This difference between the acceleration related features of birds and drones is observed by comparing the simulated quadcopter and real bird data. The acceleration related features have to be explored in real case scenarios.

Another observation is that separating the displacement features on each x, y and z axes increases the accuracy by more than 91%, since bird trajectories do not show significant displacement differences, especially on the altitude axis, while drones change their position along all axes and especially along the z-axis.

In addition, the heading and curvature features provide classification accuracy from 78% to 97%, because birds fly close to straight lines and change smoother their direction as they are migratory, while drones deviate from straight trajectories and have many changes in their directions. The curvature feature provides a classification of around 96%, as the simulated drones deviate from the straight trajectory, whereas birds fly close to the straight line, as the above Figure 25, Figure 26, Figure 27, Figure 28, Figure 29 and Figure 30 show. The heading feature examines classification accuracy of around 83%, which is lower than this of the heading feature. The reason is that drones change their direction very often, while birds do not, but there are many drone direction changes, which are not as strict as the above classification results examine. These two features are promising to classify real birds and drones.

The last observation in the classification evaluation is that the classification results are similar in all different time intervals between two consecutive tracks as Table 7 presents. This is useful for real scenarios since the time interval between two tracks is about 2 seconds for the real TNL radar data, while it can be observed that the time interval can sometimes take values close to 1 or 4 seconds. Since the accuracy of the results for all 3 scenarios is in the same range, similar results can be expected for the real case.

The average accuracy values for each kinematic feature across all ML classifiers and all time intervals between two consecutive tracks from Table 7 are presented in Table 8. The reason is to provide an overall classification accuracy value for each kinematic feature and thus the significance of each one of them, in the classification of the simulated quadcopter and the real bird trajectories. Specifically, as it can be seen in Table 8, the average classification accuracy of the kinematic features of curvature and heading is 95.66% and 82.83%, respectively. Thus, these features will be further investigated in the real case scenarios of Chapter 5.

Feature	Average Classification Accuracy for each row of Table 7
Average Displacement	72.83%
Standard Deviation of Displacement	91.83%
Average Speed	77.16%
Standard Deviation of Speed	98.16%
Average Acceleration	99.83%
Standard Deviation of Acceleration	99.83%
Average Displacement at each x, y, z axes	96%
Standard Deviation of Displacement at each x, y, z axes	94%
Curvature	95.66%
Heading	82.83%

Table 8: The average accuracy of all three 'time intervals between two consecutive tracks (1s, 2 s and 4s)' cases, for both the decision tree and the KNN classifiers of Table 7. The overall accuracy for each kinematic feature presents its quantitative evaluation in the simulated drone and real bird classification case.

4.7 Clusters Generation for Drones with different mass values

The mass values of the 6-DoF quadcopter can be changed by the user. The equations (4.4) and (4.5) indicate that the force and torque are responsible for the motion of the quadcopter. As they also depend on the mass values, it is expected that drones with different mass values and the same waypoints will have different trajectories at certain times. The input to the 6-DoF quadcopter simulation model is the waypoints that the quadcopter follows in a given time. The waypoints were generated using the random waypoint generator, which was presented in Section 4.2, by using drones with 5 different mass values for each waypoints input. The generated simulated data for drones with different weights are used to create the kinematic features of Table 5. These kinematic features are applied as input to the unsupervised learning K-means classifier, which was explained in Section 2.6. The output is the creation of 5 clusters, one for each mass class, which is visualized in Figure 31. Additionally, 5 centers were chosen to be generated, as the quadcopter trajectories were created for 5 different mass values. The reason for the unsupervised machine application is to examine the significance of the clusters generation when the labels are missing, because in the real case scenario in Chapter 5 the birds and drones labels are not provided in the raw data. The following Figure 31 shows the 5 different weight clusters in the weight range from 3.5kg to 3.9kg. The same waypoints were used for all 5 different quadcopter weights. Numerous trajectories were generated using the random waypoint generator.

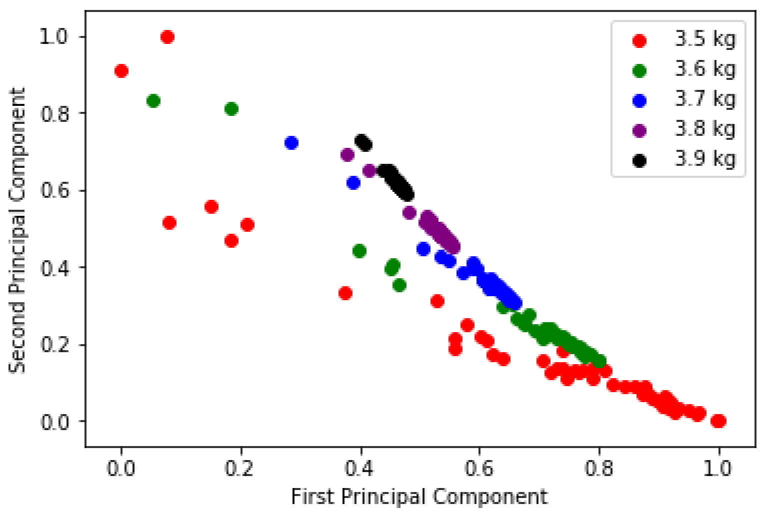


Figure 31: Drone clusters generation using the K-means classifier and the kinematic features of Table 5. Each cluster contains a drone class with different weights (3.5kg, 3.6kg, 3.7kg, 3.8kg and 3.9kg).

4.8 Summary of the chapter

In this chapter, the classification of simulated 6-DoF quadcopter and real MOVEBANK bird trajectories is analyzed. The simulated quadcopter model and bird flight dataset were presented, while the importance of the time interval between two consecutive tracks and the time interval of the whole trajectory was also analyzed. The extracted kinematic features were applied as input to the KNN and decision tree ML algorithms which classified the birds and drones with 100% accuracy. The reason for the high accuracy of the classification results is that the 6-DoF quadcopter simulation models produce trajectories with high maneuverability, as the quadcopter changes direction very quickly. On the contrary, the bird data provide straighter trajectories since it is a migratory bird. The importance of features and the generation of clusters were also examined. In the next Chapter 5 the classification of unlabeled real birds and drones will be investigated.

5 Classification of Real Drones and Birds Trajectories Tracked from TNL Radar

In this chapter, the classification of real birds and drones tracked by a TNL surveillance radar is performed. Section 5.1 describes the methodology of this classification study, while Section 5.2 provides the characteristics of the surveillance radar and the data acquisition. The next Section 5.3 presents the data filtering from different bird and drone targets, while Section 5.4 examines the clusters generation and evaluation. Section 5.5 provides a discussion of the results.

5.1 Methodology and Design

In this chapter, the classification case of real birds and drones is analyzed using data from a surveillance radar. The methodology is divided into 5 different steps, as Figure 32 shows. The first part is the data acquisition from the surveillance radar and their conversion into usable matrices forms, while the second step is the data cleaning, as the raw data do not contain information that is entirely related to bird and drone tracks. In particular, the tracks could include various moving targets. The third part of the methodology is the heading and curvature features extraction from the cleaned data, which will be used by the unsupervised machine learning K-means algorithm to generate bird and drone clusters. The final step is the evaluation of these clusters and specifically, the flying objects contained in each cluster.

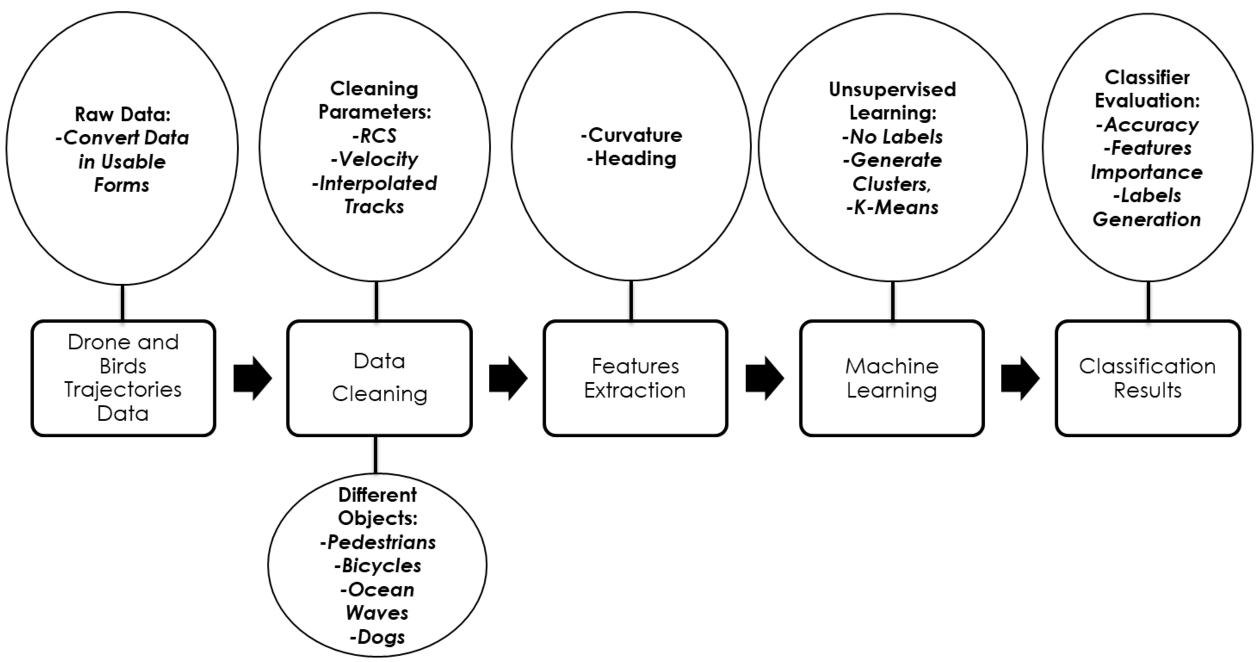


Figure 32: Methodology of the real bird and drone classification, using data that were received from a TNL surveillance radar.

5.2 TNL Surveillance Radar and Data Acquisition

The TNL radar used for the classification of birds and drones of this master thesis is an FMCW, X-band surveillance radar. The data that have the same track ID must be sorted from the initial to the final of the measured time values, to generate the trajectory in the correct order. Moreover, the data do not contain z-axis information, whereas the labels that indicate the class in which the tracks belong to are missing. These measurements were taken over a very long period of several days. So, it was impossible to indicate next to each track whether it was a bird or a drone, because this method requires a person to be present throughout the experiments, to observe the class of each track.

5.3 Data Filtering from Different to Birds or Drones Targets

The data cleaning process is a very important step, as the quality of the data used to extract the kinematic features, affects the classification accuracy. The tracks may be pedestrians, bicyclists, dogs, ocean waves or other moving objects, while the labels of the objects are missing. So, the filtering of birds and drones from other objects must be implemented. The cleaning procedure that aims to include only the bird and drone trajectories, relies on the RCS, speed, and interpolated tracks data. Since the RCS values of birds and drones are between -10dB and -25dB [56] [57], it is decided to exclude all the trajectory data with RCS values below -30dB and above -5dB, to have a margin of 5dB for possible radar error in RCS measurements. The next feature that affects the data cleaning is the speed values, as drones and birds can have a wider speed range from 0m/s to 40m/s. Therefore, tracks with speed values higher than 40m/s are removed from the raw data. The next characteristic that is responsible for data cleaning is the interpolated data. It is possible that certain consecutive tracks do not correspond to detected tracks, as they are interpolated. So, trajectories with more than 3 consecutive interpolated tracks are discarded.

The last characteristic of the data cleaning process is the total observation time. The approach of this research is to observe tracks between the short-term and long-term analysis. Thus, the trajectory time interval is selected between 10 and 35 seconds. All trajectories with a total trajectory time of fewer than 10 seconds are removed from the raw data, while all trajectories with a total observation time of more than 35 seconds are split into smaller trajectories with different track IDs. All these cleaning procedures, that are applied to the raw data, are listed in Table 9. Figure 33 shows the tracks from the surveillance radar at which the above-mentioned filtering methods are implemented. Specifically, this figure plots the characteristics of the detected target cornering their track ID. These characteristics are the RCS, the average speed, the measured time and the internal classification of each track.

Characteristic	Remaining Data after Filtering
RCS	-5 dB to -30 dB
speed	0 m/s to 35 m/s
Interpolated Tracks	Number of Interpolated Tracks ≤ 4
Time Interval between Consecutive Tracks with the Same Track ID	Smaller of Equal to 6 seconds
Total Observation Time	10 seconds to 35 seconds

Table 9: Raw data cleaning parameters and assumptions. Objects that are different from birds and drones are removed. The filtering characteristics are presented in the first column and their numerical valuers in the second.

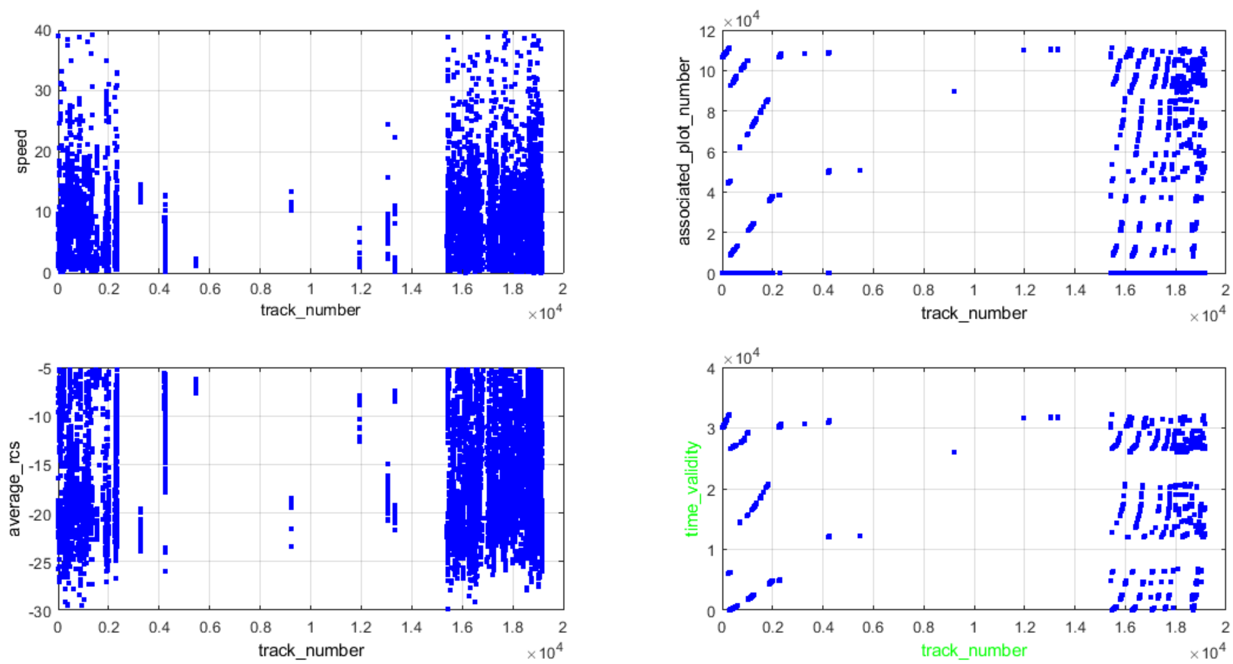


Figure 33: The average speed, the associated plot number that indicates the interpolated tracks, the time validity which is the time of the measurement, and the RCS values of the tracks of the surveillance radar are presented in blue dots. These tracks are filtered with the average speed, RCS, time validity between consecutive tracks and interpolated tracks methods.

5.4 Clusters Generation and Evaluation

During data cleaning, the goal was to remove all different to bird and drone tracks. The remaining bird and drone data are used to generate kinematic features that are used as input to the unsupervised machine learning K-means algorithm. In the previous Chapter 4, the importance of the kinematic features due to the classification accuracy was analyzed. A very important observation was that birds and drones show flight behavior differences along the altitude axis in the simulated case. Also, the heading and curvature features indicated high accuracy classification results.

However, in real scenarios, the received data are not as optimistic as these of the 6-DoF model and the MOVEBANK dataset. As the speed and position tracks are provided only on the x and y axes, the altitude information that could provide birds and drones classification is missing. The mean and standard deviation of speed, acceleration and displacement kinematic features, that are used in real scenarios, cannot be separated in each of the x, y and z axes. Therefore, the heading and curvature features examined in Section 3.1 are two features that could provide classification in this case.

Furthermore, as the labels are missing, unsupervised machine learning techniques are used to generate bird and drone clusters. The curvature and heading kinematic features are applied to the K-means classifier and the clusters are evaluated. Figure 34 shows the process used to create the bird and drone clusters, while the total number of trajectories of the flying objects is 3359.

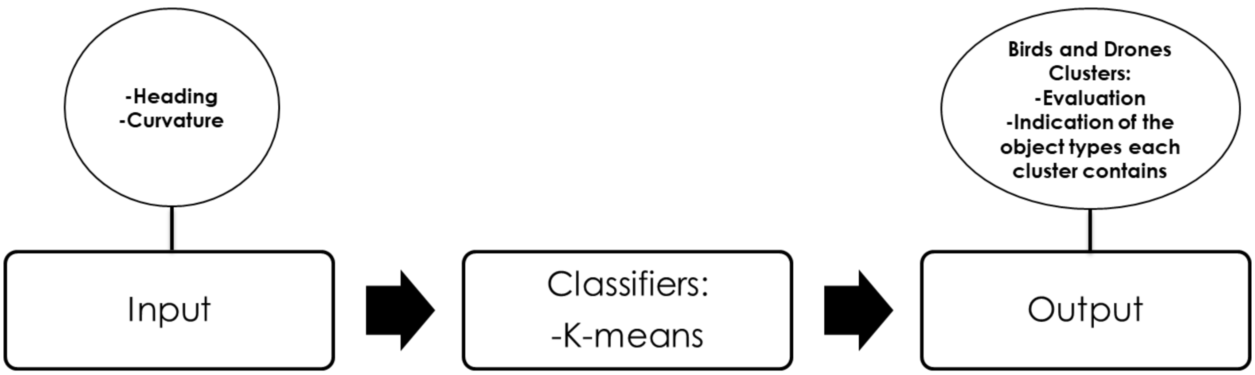


Figure 34: The block diagram of the bird and drone clusters generation. The heading and curvature kinematic features application to the K-means classifier creates the bird and drone clusters.

Two clusters have to be created, as one cluster contains the drones and the other cluster the bird trajectories. In addition, the clusters must be labeled and accurately indicate the type of flying objects they contain. However, the whole dataset is divided into several smaller clusters. Combining these smaller clusters, a large drone cluster and a large bird cluster are examined.

The evaluation of the clusters and their separation into bird and drone clusters is a procedure that shows the accuracy of the generated clusters. The evaluation of the reliability of the generated clusters is shown in Figure 35.

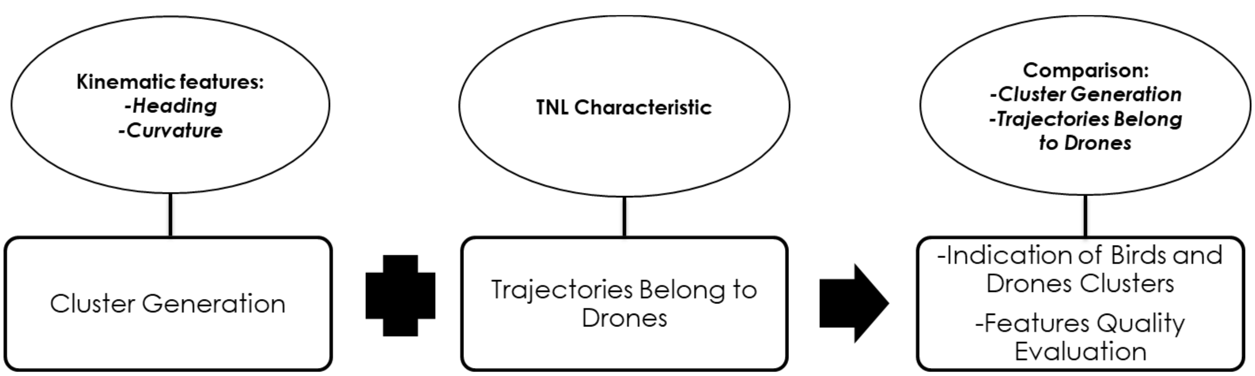
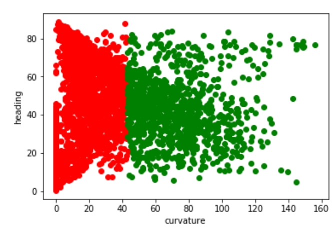
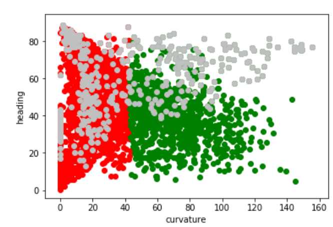
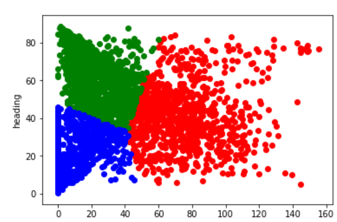
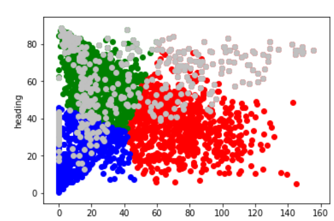
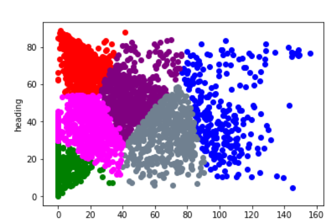
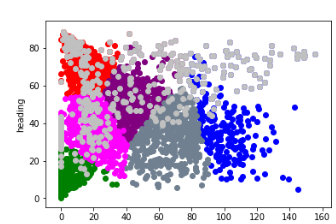


Figure 35: The block diagram for the evaluation of the drone and bird generated clusters. The known drone trajectories are compared with the generated clusters, in order to create the final bird and drone clusters.

The characteristic, which is used for the evaluation of the generated clusters of this master thesis, is related to whether the velocity is received from one object or a group of objects that are closely spaced and have multiple velocities. Drones have high blade rotation speed in addition to directional speed. Thus, the TNL characteristic with values higher or equal to 0.3 increase the probability of drone presence, since such values cannot be measured for birds. In that way, it is assumed that all trajectories that provide values above 0.3 for this related to wide velocity spectrum characteristic belong to drones. These known drone trajectories are used for the characterization of the drone and bird clusters, as Table 10 presents, as well as for the evaluation of the heading and curvature features accuracy to classify these two flying objects.

The 'Cluster Visualization' column of the following Table 10 shows the generation of the different numbers of clusters using the K-means algorithm. The trajectories with the TNL characteristic values above 0.3, which are known as drone trajectories, are presented in the light grey color on the 'Clusters and Known Drones Trajectories Visualization' column. The class of the flying objects of the rest trajectories is unknown. Each dot on the plots shows the heading and curvature values for each trajectory for the entire data set.

Number of Clusters	**Clusters Visualization**	**Clusters and Known Drones Trajectories Visualization**
2		
3		
6		

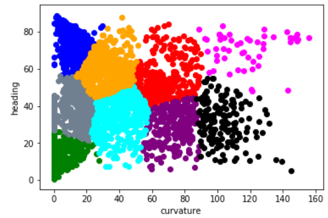
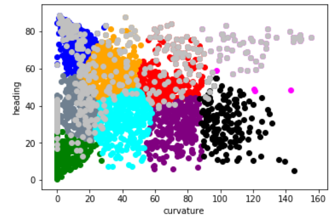
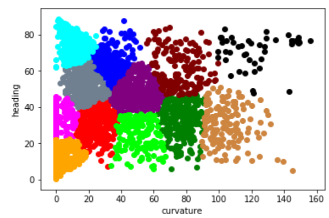
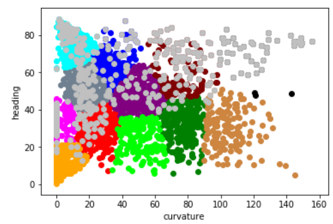
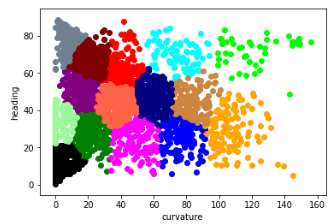
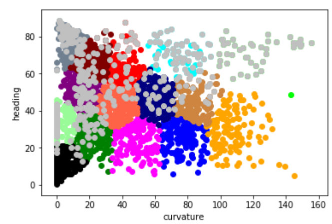
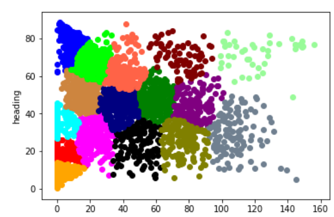
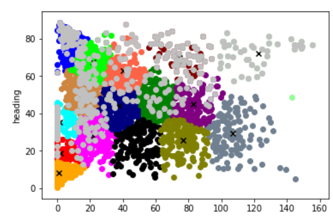
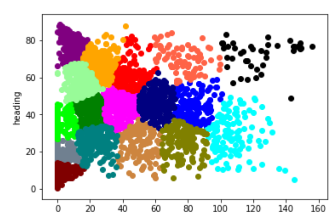
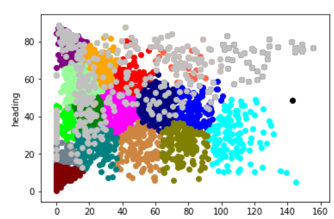
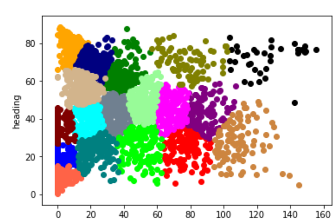
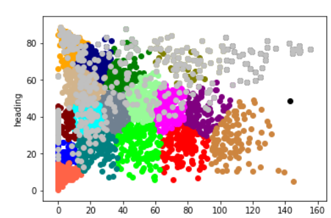
9		
12		
15		
16		
17		
18		

Table 10: Clusters generation of the trajectories of birds and drones, and their comparison with known drone trajectories. The second column shows the generation of the different numbers of bird and drone clusters using the K-means algorithm. The third column presents the known drone trajectories in the light grey color on top of the generated clusters.

Since the light gray trajectories belong to drones and they are contained in certain clusters, it is assumed that these clusters contain drone trajectories. Specifically, Figure 36 shows in red color the known drone trajectories, while the remaining trajectories, colored in green have no specific information indicating whether they represent trajectories of drones or birds.

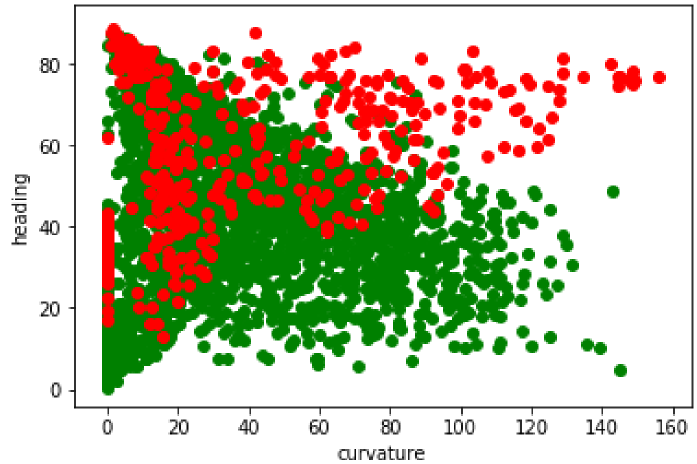


Figure 36: Known drone trajectories in red color and unknown flying object trajectories in green color. The distinction is implemented in regards to whether the velocity is received from one or more objects that are closely spaced and have multiple velocities. The probability, that the velocity of a drone is received from a group of closed spaced objects, is higher.

Furthermore, instead of the creation of two clusters, one containing drone and the other bird trajectories, more clusters are formed. Specifically, 17 smaller clusters are generated and compared with the known drone trajectories. From Table 10 it is observed that 17 clusters are many to generate smaller bird and drone clusters. Therefore, the clusters that contain certain known drone trajectories are referred to as drone clusters, while the remaining clusters that do not have known drone trajectories are referred to as bird clusters. Figure 37 is the final clusters generation, in which all the smaller drone clusters are combined in one, while all the rest clusters are combined in one bird cluster. The drones cluster contains the trajectories in red color, while the green cluster contains the bird trajectories.

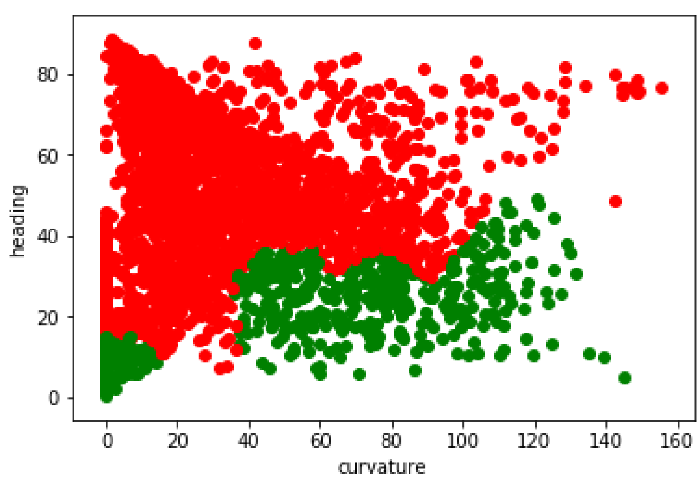


Figure 37: Generation of the final clusters of drones in red and birds in green color. In the case of 17 clusters in Table 10, the clusters that contain known drone trajectories integrate the drone cluster (red). The rest clusters, which do not contain known drone trajectories, are incorporated into the bird cluster (green).

As Table 11 shows, the total number of trajectories is 3358, while the known drone trajectories are 452. After the final clustering generation, which can be seen in above Figure 37, the drone trajectories in red are estimated to be 2609, while the bird trajectories are shown in green and are 749.

	Number of Trajectories
Entire Dataset	3358
Known Drones Trajectories	452
Drones Trajectories after Cluster Generation	2609
Birds Trajectories after Cluster Generation	749

Table 11: The number of the trajectories of the whole data set and the known drone trajectories that were used for the evaluation of the clusters. The final birds cluster contains 749 trajectories and the drones cluster 2609 trajectories.

5.5 Discussion

The clusters generation and their comparison with the known drone trajectories examined the bird and drone clusters in Figure 37. The evaluation of the birds and drone curvature and heading features is that they provide information to classify birds and drones, as the known drone trajectories are placed in a specific area in the curvature-heading plot as Figure 36 presents. The flight behaviors of birds and drones and the way they change their direction place them at different positions in that visualization space. So, the heading and curvature information about how smooth or strict birds and drones change their direction, as well as how they deviate from the straight flight path, can be used to classify bird and drone clusters. The known drone trajectories are compared with the generated clusters in the 'Clusters and Known Drones Trajectories Visualization' column of Table 10. It is observed that 17 clusters are plenty to generate smaller bird and drone clusters, which are combined to create the two final birds and drone clusters. From Figure 37 it can be observed that when drone trajectories have low curvature values, their heading feature covers a wide range from low to high values. When the drone curvature values increase their heading is also rising. On the other hand, the trajectories of the birds with a low heading, have curvature values in the whole curvature interval, while as the heading increases, their curvature takes higher values. It is also observed in Figure 37 that drones tend to have higher heading values than birds.

5.6 Summary

The classification of real birds and drones using data from a TNL surveillance radar, is the main challenge of this master thesis. The kinematic features that can distinguish birds and drones in a realistic scenario were examined. The first task was the data acquisition and filtering. The received signal contained detection from many different bird and drone targets. Pedestrians, ocean waves, cars, and bicycles were included in the raw data. The kinematic features that were used in this classification scenario were the heading and curvature. The clusters generation was achieved by applying them to the K-means algorithm, while the bird and drone clusters were characterized using the known drone trajectories. The heading and curvature importance and accuracy in classifying birds and drones were also examined, as the trajectories of these two flying objects have a different place in the curvature-heading plot. Their flight behavior provides differences in the way they change direction or deviate from the straight flight path. In that way, the classification of birds and drones was achieved.

6 Conclusion and Recommendations

6.1 Conclusion

This thesis goal is to investigate the classification of birds and drones using their kinematic features. The flying targets are tracked by a TNL surveillance radar, while the importance of the kinematic features that provide their classification is evaluated via an analysis of experimental data. These data contain information in regards to whether the velocity is received from one or more objects that are closely spaced and have multiple velocities. The main content is summarized below as a contribution to answering the research sub-questions set in the introduction.

1. Is the classification of birds and drones using radars entirely explored, by the existing proven methods?

- In the radar domain literature, the micro-Doppler signature is the only proven existing method that classifies birds and drones. Micro-Doppler signature has certain limitations, as it is not visible in long detection ranges, due to the weak reflected signal from the micromovements of the birds and drones. The covered from conducting materials rotor blades and the bird passive flights are additional downsides to the micro-Doppler extraction. A gap filler in the occasions, when the micro-Doppler is not assured, is tracking the flying targets with surveillance radars and observing the difference in their kinematic behavior. The existing publications that examine kinematic features from bird and drone tracks, in order to classify them are few. In addition, they use simulated or hybrid data, which provide very high classification accuracy. This is controversial in real data cases. In that way, the classification of birds and drones using their kinematic properties needs further investigation, in order to provide additional information when the birds and drones classification is not settled.

2. What observations can be examined from the classification of drones and birds using simulated trajectories data by applying supervised learning and how can they be used in real case scenarios?

- The simulated 6-DoF quadcopter versus the real birds MOVEBANK trajectories classification scenario showed that the separation of the mean and standard deviation values of speed and displacement at each x, y and z axes, could classify birds and drones with accuracy from 70% to 99%. It was observed that these flying targets change their altitude position in different ways. Thus, their z-axis information could be valuable to classify them. Furthermore, the heading and curvature features provided classification with accuracy from 78% to 97%. The importance of these features was observed in the simulated data classification scenario in Chapter 4 and was evaluated in the real data classification case in Chapter 5.

- The simulated 6-DoF quadcopter generates trajectories that have high maneuverability, whereas the migratory birds follow straight flight paths with almost constant speed. Thus, the 100% classification accuracy related to acceleration features is too optimistic, as in real data scenarios birds and drones have similar average acceleration.

- The time interval between two tracks is about 2 seconds for the real TNL radar data, while that time interval can take values close to 1 or 4 seconds. Since, the accuracy of the simulated drone versus real bird trajectories for all these 3 scenarios examined similar classification results, it is expected that the time interval between consecutive tracks in real scenarios does not affect the classification accuracy.

3. What are the kinematic features that provide enough information to distinguish drones and birds?

- The clusters generation of the real bird and drone data in Chapter 5 was compared with the known drone trajectories. It was observed that these known trajectories were in a specific space on the heading-curvature plot in Figure 36. So, the combination of the drone known clusters and the generated clusters in Table 10, was used to create the complete bird and drone clusters in Figure 37. The features that were used for the generation of these clusters were the heading and the curvature, while their importance in classifying birds and drones was also examined. The different ways birds and drones change their direction, and the way their trajectories deviate from the straight line, were observed as well. Thus, these differences in their flight behavior which are translated in numbers from the heading and curvature features, were used to classify birds and drones.

4. What are the limitations of using kinematic properties to classify drones and birds?

- Many surveillance radars lack the capability to estimate the altitude position and the velocity in the vertical direction, while only the two-dimensional x and y axes data are received. In the absence of the altitude axis information, the average speed, displacement and acceleration features cannot be used to extract useful information on the two-dimensional x-y space.

By combining the sub-questions, the main research question '**How can birds and drones tracking provide kinematic features that contribute to the classification of birds and drones and provide additional information to the existing radar classification methods?**' is also answered.

Essentially, the observations from both classification study cases in Chapters 4 and 5, showed that tracking birds and drones with surveillance radars and extracting the kinematic features of curvature and heading, is a method that can classify these two flying objects. In that way, valuable information can be added, benefitting those cases when the classification of birds and drones with existing radar methods is not guaranteed.

6.2 Future Work

Although this research examined the heading and curvature kinematic features importance to classify birds and drones, there are shortcomings, that are analyzed in Section 6.1. The main focus of the thesis is to extract the kinematic features that are able to classify birds and drones in real case scenarios, by tracking targets with surveillance radars. On basis of the results, specific directions in which the research can be taken forward are mentioned below:

- The labels that indicate the class in which each track belongs to are missing in the available experimental data. Specifically, only a few known drone trajectories are provided to characterize and evaluate the birds and drones generated clusters. In addition, the altitude information is also not provided. Thus, the separation of the mean and standard deviation of speed, displacement and acceleration features on z-axis cannot be applied to the real case scenarios. So, the different ways birds and drones change their direction along the altitude axis cannot be examined in this research. Moreover, the dataset contains different targets from only birds and drones. The cleaning process does not assure the removal of all irrelevant to this classification case targets. Thus, a dataset with labeled data, velocity and position information on the altitude axis, that contains exclusively bird and drone tracks, would be significant for a more advanced study of the features proposed in this thesis.

- This research uses classic machine learning algorithms such as the KNN, decision tree and K-means. A potential future approach to perform the bird and drone classification is to use deep learning models by using a broad set of unstructured data and multilayer neural network architectures. Such models are the Convolution Neural Networks (CNN) and the Recurrent Neural Networks (RNN). Specifically, bird and drone trajectories data could be applied as input to deep learning techniques in order to observe the classification accuracy. However, deep learning is not so effective when the data amount is small, because it requires extremely large data sets to accomplish high performance. Thus, enormous bird and drone labeled datasets need to be collected for their classification using deep learning techniques.

References

[1] V. Mehta, M. Bolic, I. Mantegh and C. Vidal, "Tracking and Classification of Drones and Birds at a Far Distance Using Radar Data," *S&T Organization,* p. 152–1510, 2021.

[2] X. Zhang, V. Mehta, M. Bolic and I. Mantegh, "Hybrid AI-Enabled Method for UAS and Bird Detection and Classification," *IEEE International Conference on Systems, Man, and Cybernetics,* no. 11-14, pp. 2803-2807, 2020.

[3] H. Astier, "BBC," BBC News, 07 August 2022. [Online]. Available: https://www.bbc.com/news/world-62225830. [Accessed 08 August 2022].

[4] H. Kesteloo, "DroneXL," 18 March 2022. [Online]. Available: https://dronexl.co/2022/03/18/modified-dji-drone-grenade-car-ukraine/. [Accessed 8 August 2022].

[5] B. Livia, "CNN Travel," 27 April 2022. [Online]. Available: https://edition.cnn.com/travel/article/tourist-drone-incidents-rome-pisa/index.html. [Accessed 25 July 2022].

[6] S. Samira, "The Guardian," 19 December 2018. [Online]. Available: https://www.theguardian.com/uk-news/2020/dec/01/the-mystery-of-the-gatwick-drone. [Accessed 25 July 2022].

[7] P. Molchanov, R. Harmanny, J. De Wit, K. Egiazarian and J. Astola, "Classification of small UAVs and birds by micro-Doppler signatures," *International Journal of Microwave and Wireless Technologies,* vol. 6, p. 435–444, 2014.

[8] S. Rahman and D. Robertson, "Radar micro-Doppler signatures of drones and birds at K-band and W-band," *Nature Scientific Reports,* vol. 8, no. 17396, pp. 1-11, 2018.

[9] J. Patel, F. Fioranelli and D. Anderson, "Review of radar classification and RCS characterisation techniques for small UAVs or drones," *IET Journals - The Institution of Engineering and technology,* vol. 12, no. 9, pp. 911-919, 2018.

[10] P. Wellig, P. Speirs, C. Schuepbach, R. Oechslin, M. Renker, U. Boeniger and H. Pratisto, "Radar Systems and Challenges for C-UAV," *19th International Radar Symposium (IRS),* pp. 1-8, 2018.

[11] F. Barbaresco, D. Brooks and C. Adnet, "Machine and Deep Learning for Drone Radar Recognition by Micro Doppler and Kinematic Criteria," *IEEE 17th European Radar Conference,* no. 13-15, 2021.

[12] T. Fell, M. D. White, M. Jump and I. Owen, "Sensitivity study of a small maritime rotary UAS operating in a turbulent airwake," *JO-Annual Forum Proceedings-AHS International,* vol. 3, pp. 1-9, 2015.

[13] NATO JAPCC, "Strategic concept of employment for unmanned aircraft systems in NATO," January 2010. [Online]. Available: http://www.japcc.org/wp-content/uploads/UAS_CONEMP.pdf. [Accessed 16 September 2020].

[14] S. Abdelhay and A. Zakriti, "Modeling of a Quadcopter Trajectory Tracking System Using PID Controller," *The 12th International Conference Interdisciplinarity in Engineering,* p. 564–571, 2019.

[15] G. Ganga and M. M. Dharmana, "MPC Controller for Trajectory Tracking Control of Quadcopter," *International Conference on circuits Power and Computing Technologies,* 2017.

[16] L. M. Argentim, W. C. Rezende and P. E. S. and, "PID, LQR and LQR-PID on a Quadcopter Platform," *IEEE,* 2013.

[17] F. Gill, D. Donsker and P. Rasmussen, "IOC World Bird List," Worldbirdnames, 2021.

[18] G. Ruaux, S. Lumineau and E. d. Margerie, "The development of flight behaviours in birds," *Royalsocietypublishing,* pp. 1-9, 2020 .

[19] N. Landell-Mills, How Firds Fly According to Newtonian Physics, London: Indigo Press, 2019.

[20] W. Thielicke, "The flapping flight of birds," University of Groningen/UMCG research database, Groningen, 2014.

[21] D. D. Chin and D. Lentink, "Flapping wing aerodynamics: From insects to vertebrates," *Journal of Experimental Biology,* vol. 219, no. 7, pp. 920-933, 2016.

[22] K. E. Crandell and B. W. Tobalske, "Kinematics and aerodynamics of avian upstrokes during slow flight," *The Company of Biologists ,* vol. 218, pp. 2518-2527, 2015.

[23] B. Parslew, "SIMULATING AVIAN WINGBEATS AND WAKES," The University of Manchester-School of Mechanical, Aerospace and Civil Engineering, Manchester, 2012.

[24] Z. Lin-Lin, G. Hui and W. Chui-Jie, "Three-dimensional numerical simulation of a bird model in unsteady flight," *Springer,* vol. 58, pp. 1-11, 2015.

[25] I. Schiffner and R. Wiltschko, "MOVEBANK - Behavioural traits of individual homing pigeons, Columba livia f. domestica, in their homing flights.," MOVEBANK, Frankfurt, 2012.

[26] M. A. Richards, J. A. Scheer and W. A. Holm, Principles of Modern Radar: Basic Principles, SciTech Publishing, 2010.

[27] G. Oswald, "Holographic surveillance radar," vol. 7308, pp. 1-9, 2009.

[28] M. Skolnik, Radar Handbook, Third Edition, McGraw-Hill Education, 2008.

[29] S. Harman and B. I. Ahmad, "The Need For Simultaneous Tracking And Recognition In Drone Surveillance Radar," *The International Radar Symposium IRS,* no. 21-23, 2021.

[30] V. C. Chen, The micro-Doppler effect in radar, Artech House, 2011.

[31] C. .. C., W. J. Miceli and D. Tahmoush, Radar micro-Doppler signatures: processing and applications, The Institution of Engineering and Technology, 2014.

[32] IDS, "IDSCorporation," IDS Ingegneria Dei Sistemi S.p.A., 2019. [Online]. Available: https://www.idscorporation.com/pf/black-knight/. [Accessed 30 August 2022].

[33] D. Blacknell, "RADAR Automatic Target Recognition (ATR) and Non-Cooperative Target Recognition (NCTR)," NATO - Sensors and Electronics Technology Panel, London, Hengelo, Lisbon, Dayton, Ohio, 2011.

[34] F. Fioranelli, "Object Classification with Radar (EE4675)," EWI-MS3, Delft, 2021.

[35] A. Yarovoy, ET4169 - Radar I: From Basic Principles to Applications, TU Delft- MS3, 2021.

[36] O. Beom-Seok, G. Xin and Z. Lin, "A UAV classification system based on FMCW radar micro-Doppler signature analysis," ELSEVIER, Singapore, 2019.

[37] R. Harmanny, J. De Wit and G. Premel Cabric, "Radar Micro-Doppler Feature Extraction Using the Spectrogram and the Cepstrogram," *11th European Radar Conference,* pp. 165-168, 2014.

[38] S. Headrick, "DIYDRONES," NING, 3 February 2015. [Online]. Available: https://diydrones.com/group/arducopterusergroup/forum/problems-with-ducted-fan-design-with-standard-pids. [Accessed 30 August 2022].

[39] E. T. Whittaker, A Treatise on the Analytical Dynamics of Particles and Rigid Bodies, Cambridge : Cambridge University Press, 1904.

[40] N. Mohajerin, J. Histon, R. Dizaji and S. L. Waslander, "Feature Extraction and Radar Track Classificatio for Detecting UAVs in Civillian Airspace," *IEEE,* 2014.

[41] T. B. Sarikaya, D. Yumus, M. Efe and G. Soysal, "Track Based UAV Classification Using Surveillance Radars," *ResearchGate 22nd International Conference on Information Fusion,* 2019.

[42] S. Sutthiphong, H. C. Kim and M. D. L. P. R. Denzel, "Drone versus Bird Flights: Classification by Trajectories Characterization," *Annual Conference of the Society of Instrument and Control Engineers of Japan,* pp. 343-348, 2020.

[43] J. Liu, Q. Y. Xu and W. S. Chen, "Classification of Bird and Drone Targets based on Motion Characteristics and Random Forest Model using Surveillance Radar Data," *IEEE Access,* vol. 9, pp. 160135-160144, 2021.

[44] B. Mahesh, "Machine Learning Algorithms - A Review," *International Journal of Science and Research,* vol. 9, no. 1, pp. 381-386, 2018.

[45] M. Torres, G. Hart and T. Emery, The DSTL Biscuit Book - Artificial Intelligence, Data Science and Machine Learning, Nottingham: Defence Science and Technology Laboratory, 2019.

[46] T. Hastie, R. Tibshirani and J. Friedman, The Elements of Statistical Learning - Data Mining, Inference, and Prediction, Springer, 2017.

[47] O. Kramer, Dimensionality Reduction with Unsupervised Nearest Neighbors, Oldenburg: Springer, 2013.

[48] G. Z. Sevgi, Deep Neural Network Design for Radar Applications, Croydon: SciTech - The Institution of Engineering and Technology, 2020.

[49] A. Geron, Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow, O'Reilly Media, Inc., 2019.

[50] Y. LeCun, Y. Bengio and G. Hinton, "Deep learning," *NATURE,* vol. 436, pp. 1-9, 2015.

[51] J. Petch, S. Di and W. Nelson, "Opening the Black Box: The Promise and Limitations of Explainable Machine Learning in Cardiology," *ELSEVIER,* vol. 38, pp. 204-213, 2022.

[52] K. Jolly, Machine Learning with scikit-learn Quick Start Guide, Packt Publishing, 2018.

[53] A. Herve and J. W. Lynne, "Principal component analysis," *WIREs Computational Statistics,* vol. 2, pp. 433-459, 2010.

[54] R. Thippa, K. R. Praveen, L. Kuruva, K. Rajesh, S. R. Dharmendra, S. Gautam and B. Thar, "Analysis of Dimensionality Reduction Techniques on Big Data," *IEEE Access,* vol. 8, pp. 54776-54788, 2020.

[55] S. Ahmed, B. Qiu, C.-W. Kong, H. Xin, F. Ahmad and J. Lin, "A Data-Driven Dynamic Obstacle Avoidance Method for Liquid-Carrying Plant Protection UAVs," *IEEE,* vol. 12, no. 4, pp. 1-15.

[56] V. Semkin, J. Haarla, T. Pairon, C. Slezak, S. Rangan, V. Viikari and C. Oestges, "Analyzing Radar Cross Section Signatures of Diverse Drone Models at mmWave Frequencies," *IEEE Access,* vol. 8, pp. 48958-48969, 2020.

[57] B. Torvik, ,. K. E. Olsen and H. Griffiths, "X-band measurements of radar signatures of large sea birds," *Norwegian Defence Research Establishment-International Radar Conference,* pp. 1-6, 2014.