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A Two-Stages Unsupervised/Supervised Statistical Learning Approach for Drone Behaviour Prediction

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Abstract— **Drones are prone to abuse due to their low cost and their pool of potential illegal applications that can compromise safety of national infrastructures and facilities. Hence, drone detection and predict its behaviour is crucial to ensure smooth operation of services. In this paper, an unsupervised/supervised statistical learning algorithm for drone behaviour prediction is proposed. The algorithm is based on drone detection data collected from any radar or RF- sensor. The architecture of the approach is comprised of two stages: i) the first stage attempts to study the drone detection data using either unsupervised or supervised learning methods to model low dimensional expert's features, and ii) in the second stage a real time drone behaviour predictor model is proposed based on the Kolmogorov-Smirnov and Wasserstein distances. Simulation studies using synthetic data obtained from the AirSim simulator are given to provide the evidence-base for future improvements in the field of drone behaviour prediction.**

I. Introduction

The aerospace industry is witnessing a rapid growth in unmanned aerial vehicles (UAVs) technologies. With ever increasing advantages of UAVs in many fields like agriculture, security, search and rescue, surveillance, etc., this technology is increasingly irreplaceable. However, the threat space is also increasing since many incidents have been reported where drones perform some anomalous activities, e.g., operating in private and other restricted places without prior permissions [1]. To deal with this issue, significant advances in drone detection have been developed using a wide variety of sensors and multi-sensor fusion [2]–[5]. However, pure detection does not serve as a preventive measure of a potential drone's malicious activity [6]–[8], because these sensors capture instantaneous information of the drone, e.g., positions and velocities, that do not inform the hidden drone's intention [9]. Hence, there is need to develop a real-time system to identify the potential malicious drones out of all-other regular drones operating in a particular geographic zone before they execute any illegal activity.

A. State of the Art & Gaps

Recent studies have focused on drone's short-time trajectory prediction to classify the drone's potential risk of entering to a restricted area. The most common methods used in the literature are linear models based on Kalman-filter or state-estimation techniques [10], support vector regression (SVR), deep neural networks [11], recurrent neural networks [12]–[14], and their variants. However, this simplistic geometric approach does not exhibit significant changes in terms of the algorithm in use and may produce a high-number of false positives. Table I summarizes some of the advantages and disadvantages of some recent works in intent prediction and the embedded sensor. Authors in [15], [16] have done attempts to identify the type, payload weight and flight mode of drones, though it was not mentioned clearly whether it was used to classify the intent or not. However, these approaches may provide a motivation to analyse the flying patterns associated to malicious and non-malicious drones behaviours which is exploited in this paper.

TABLE I
Previous works in Drone Behaviour Analysis: Pros and Cons.

Methods	Sensor	Pros	Cons
Bayesian Kalman-filter based linear prediction [17]	Radar	Simple implementation Memory-less prediction No Historical dataset	Inference based on trajectory intersection with restricted area Less reaction time for preventive control
SVR, Kinematics linear motion equations [18]	Radar	Better performance than a linear model	Inference based on trajectory intersection with restricted area Less reaction time for preventive control
Deep Neural Network [15]	RF-sensor	Analysis of RF signals of drones	Inference limited to identifying drone type, payload, and flight mode prediction
Encoder-Decoder [19] transformer model neural network	Optical (camera)	Only rely on optical sensor data	Inference based on trajectory intersection with restricted area Visual trajectory prediction suffers from large inaccuracies Less reaction time for preventive control
Gradient Boost Classifier [20]	Radar	Use historical data	Not applicable for real-time intent classification
GRU time series prediction [21]	Radar	Better prediction of short-time flight path in comparison to linear models	Inference based on trajectory intersection with restricted area Less reaction time for preventive control
Softmax regression LSTM [16]	Radar, Acoustic	Better prediction of short-time flight path in comparison to linear models	Inference based on identifying the formation prediction of a group of drones and payload weight prediction

The majority of the above approaches are biased towards using the short time trajectory prediction as the main basis for drawing the inference of malicious and non-malicious drones [22]. The research work [23] has made a good attempt to use a different approach by using drone's RF and acoustic signatures to make predictions regarding the payload and flight mode. Drawing the motivation from this work, an attempt was made to look for more works on this approach, but nothing very promising could be found out. However, in the car driving field, several research works [24], [25] have been found where different approaches are developed to assess and classify the different driving behaviours and styles.

Whilst driving a car is completely different from piloting

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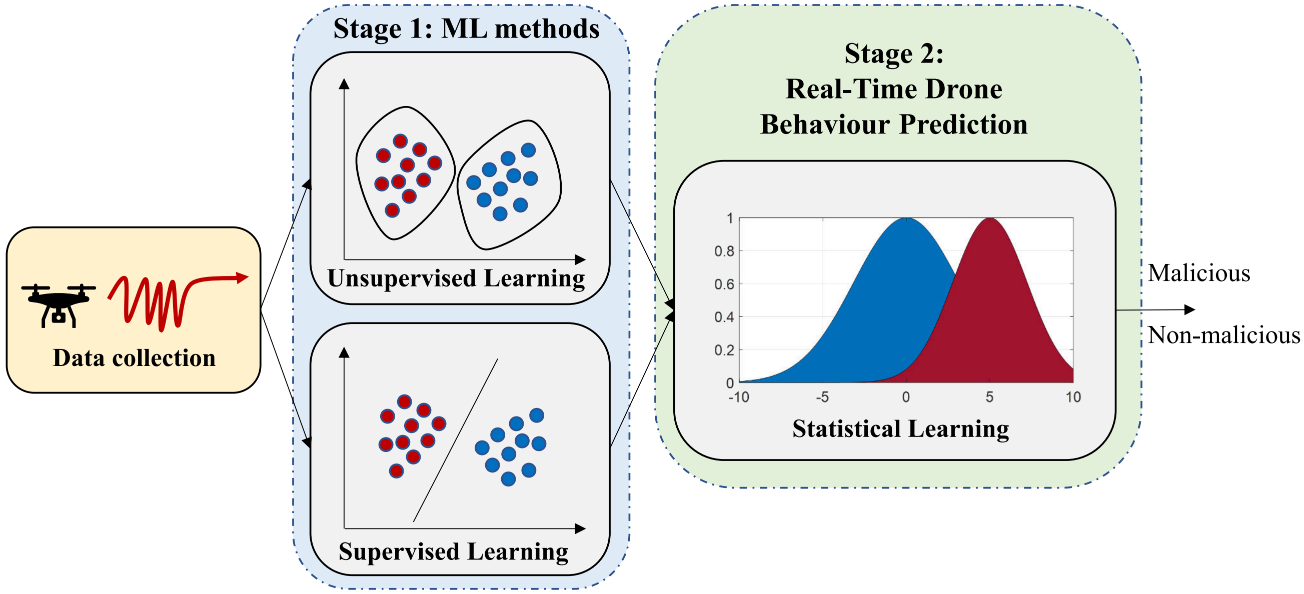


Fig. 1. Proposed methodology for drone's behaviour prediction

a drone, the humans' typical signatures are always attached to the way in how they perform the controlling actions [26], [27], that is, the way a person drives a car is always somewhat different from any other person that drives the same car due to differences in: i) the acceleration pattern used, ii) frequency of breaks applied or iii) relative distance maintained with the vehicle ahead. Similarly, two operators piloting a drone in similar conditions will use the similar controlling actions, that is, the way that the drone has been kinematically moved throughout the trajectory [28], the sharpness of the turns while changing direction, the adopted altitude variation, etc. Hence, the exploitation of the humans' driving signatures have been used to classify the driving behaviours and styles. Therefore, a similar approach is adopted in this paper to study and classify drones behaviours by analysing the kinematic variables recorded in the historical drone detection datasets.

All the drone detection techniques discussed previously have one common objective, that is to detect and track the drone in real-time and provide the trajectory data [29] which should be as accurate as possible. The accuracy of the technique being used may depend on the location, surroundings, type of drone being tracked, etc. For the scope of this research, the drone detection technique to be focussed upon is either a radar or a cooperative RF sensor like DJI Aeroscope which can track the drone in real time.

B. *Innovation*

The proposed high level system architecture is shown in Fig. 1. The system basically works in two stages. First stage of the system aims to use either unsupervised or supervised learning methods to classify malicious and non-malicious trajectories. In the case of unsupervised learning methods, they utilise unlabelled drone detection datasets to obtain two clusters to classify drones' behaviour. On the other hand, supervised learning methods use labelled data extracted from the incident reports and also by the knowledge of the experts of concerned agencies to train an efficient machine learning model. The second stage is based on a statistical learning model trained with the outcome of stage 1 for real-time drone behaviour prediction.

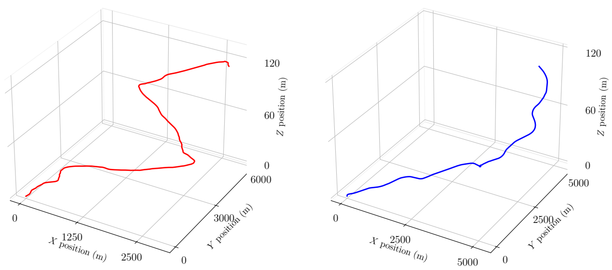
II. Methodology

Drones are used for a wide range of applications due to their different sizes and workloads, e.g., in surveillance, navigation, etc. Drones used in these applications exhibit specific trajectory patterns (e.g., altitude variations, acceleration and velocity values) which are usually smooth trajectories with small abrupt changes in the kinematic variables. On the other hand, drones used for criminal and other malicious activities (e.g., surveillance of restricted spaces, spying, suicide, etc.) may exhibit flying patterns that are entirely different from regular ones. This is because criminals are usually in a different state of mind caused by emotional factors [30]–[32] such as: state of anxiety, guilty feeling, emotion of crime, depression, fear and anger.

The flying patterns associated to malicious drones can be observed from the drones kinematic variables, i.e., velocity and acceleration values, altitude variations, hovering durations and the randomness of the trajectory. However, from the basic knowledge of the drone's flight mechanisms, it can be observed that the kinematic variables (speed, position) are governed by the longitudinal, lateral and vertical accelerations values. So, the drone's behaviour can be inferred from the acceleration patterns which gives an initial insight for the data collection.

A. *Synthetic Data Generation*

The AirSim platform is used to simulate the drone trajectories due to the unavailability of open-source real-world drone detection datasets. A total of 369 trajectories are generated where 79 are an attempt to represent malicious drone's behaviours and 290 trajectories represent non-malicious drone's behaviours. Fig. 2 exhibits two representative trajectories. Table II defines low dimensional expert's features that serve as guidance for data collection. In addition, specifications of the four most used drones are compared (see Table III) to adopt the average technical specifications for the trajectories simulations.



(a) Potential malicious flight (b) Potential non-malicious flight

Fig. 2. Sample trajectories of the Data Generation

TABLE II
DISSIMILARITY BETWEEN MALICIOUS AND NON-MALICIOUS DRONES

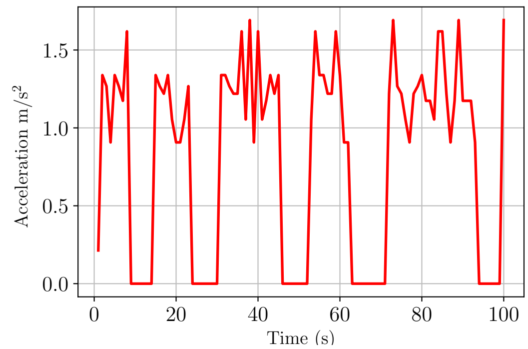
Malicious Drones	Non-Malicious Drones
Higher frequency of occurrence of abrupt acceleration & deceleration throughout the flight	Very low frequency of occurrence of abrupt acceleration & deceleration throughout the flight
Zig-zag flight path in most of the trajectories	Smoother flight paths
Higher number of altitude limit violations	Minimum occurrence of altitude limit violations
Flying at higher velocities during most of the flights	Flying at normal velocities most of the times

TABLE III
TECHNICAL SPECIFICATIONS OF COMMONLY USED DRONES

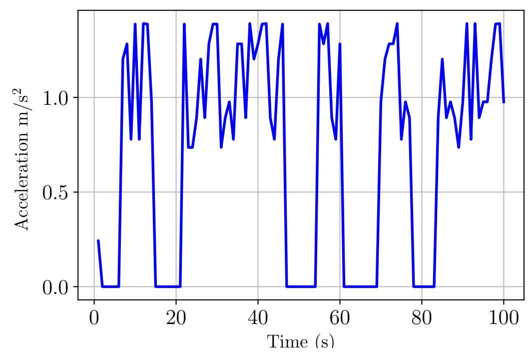
Specifications	**Four Most Commonly Used Drones**				
	DJI Mini 2	**DJI Matric 300 RTK**	**DJI Mavic Air 2**	**DJI Air 2S**	**Average**
Max Ascend Speed	5 m/s	6 m/s	4 m/s	6 m/s	**5.25 m/s**
Max Descend Speed	3.5 m/s	5 m/s	3 m/s	6 m/s	**4.375 m/s**
Max Horizontal Speed	16 m/s	23 m/s	19 m/s	19 m/s	**19.25 m/s**
Max Flight Time	31 min	55 min	34 min	31 min	**37.75 min**

Each drone flight trajectory was performed for a duration of 600 seconds. The sampling rate for data extraction was kept as 1 second and in each time-stamp, the following information was extracted and stored for each flight: coordinates X, Y, Z (which represents Longitude, latitude and Altitude), velocities V_x, V_y, V_z (which represents velocity in longitudinal, lateral and vertical directions), accelerations A_x, A_y, A_z (which represents acceleration in longitudinal, lateral and vertical directions). These data define the information that we expect that the drone detection systems like radars or RF sensors like DJI Aeroscope can provide after data processing.

Fig. 3 depicts the acceleration pattern of a time window of 100 seconds. Notice that for malicious drones, the acceleration pattern presents high variations in comparison to the non-malicious behaviours which gives an insight of how abruptly changes of the acceleration can be related to drone's misbehaviours.



(a) Malicious



(b) Non-malicious

Fig. 3. Acceleration pattern of different drones' behaviour

B. Stage 1: Unsupervised and Supervised Learning Methods

The aim of this stage is to tackle two different scenarios for classification of misbehaviour, that is, when the available drone detection data is either not labelled or labelled.

When the data provided by the detection system is not labelled, then unsupervised learning methods are used to classify the data in two clusters, i.e., malicious and non-malicious drone trajectories. In this case, the data generated through simulation is treated as unlabelled data and the quality of the computed clusters is verified with respect to the real ground truth labels. The unsupervised machine learning methods used in this scenario are: K-means clustering [33], hierarchical clustering, K-means clustering based on the dynamic time warping (DTW) distance [34], and principal component analysis (PCA) [35].

When the data is labelled, then supervised learning methods are used to obtain a binary classifier of the drone's behaviours. Here, the supervised-learning classifier aims to obtain a behaviour classifier that considers the low-dimensional expert's features of Table II and Table III with high accuracy. The classifier should guarantee small false positive and negative rates to avoid disruption and potential attacks on national infrastructures and facilities. In other words, we seek a supervised learning model which has good recall and a reasonable F-1 scores. The supervised learning methods used in this scenario are: support vector machines (SVM), logistic regression, Gaussian Naive Bayes, and decision trees.

C. Stage 2: Statistical Learning methods

This is the most important stage of the proposed system architecture and require good classification capabilities of the stage-1. Previous works [24]–[26], classify the driving styles of different drivers using off-line data, that is, they are not real-time. Hence, it is easy to implement any supervised or unsupervised learning classifiers based on these independent data by fixing the trajectories length and size. However, for drone's behaviour prediction, the algorithm needs to be fast in predicting the drone's intention using a small proportion of the on-line flight data.

The core issue in the implementation of any supervised machine learning model for prediction is the use of distance metrics. The most common distance metrics used in machine learning models like Euclidean, Minkowski, Manhattan and Hamming cannot be used for real-time prediction due to the uneven length of the feature vectors. However, from Fig. 3 we can observe that the acceleration is not an ever increasing or a decreasing feature, instead is a pattern which is composed of smaller patterns that the drone creates throughout the flight trajectory in a repeated manner. Hence, the acceleration pattern followed by the drone throughout the trajectory may be regarded as a distribution. A fixed length acceleration pattern observed during the flight of the drone may be considered as a sample drawn from the acceleration distribution of a completed flight of a particular drone. Therefore, any distance that enables the comparison of distributions may be used for the design of the real-time drone behaviour prediction algorithm. Here, the best methods that fits the scope of the approach are: the Kolgomorov-Smirnov test (K-S test), and the Wasserstein distance.

The Kolmogorov-Smirnov statistic measures the separation between the empirical distribution functions of two samples, or between the empirical distribution function of the sample and the cumulative distribution function of the reference distribution. The two sample K-S test is one of the most helpful and broad non-parametric approaches for two samples comparison. On the other hand, the Wasserstein distance measures how far apart two probability distributions are from each other.

III. Results

The available data is a matrix of size 369×6000 where each row vector represents a flight trajectory. However, it is decided to remove the geographic coordinates data from the dataset because the machine learning models tend to learn the geographic information from it. This learning tendency may cause that the geographic area to be specific and may not be useful in a general implementation scenario. Hence, the final data is a matrix of 369×3600.

A. Stage 1: Unsupervised and Supervised Learning Methods

PCA is used to reduce the dimensionality of the data and observe if it is possible to observe a tendency to classify drones behaviour using only the first two principal components (PC). Here, two scenarios are considered: i) features composed by the velocity and acceleration patterns, and ii) features composed by only acceleration patterns. The results are exhibited in Fig. 4. PCA analysis suggests that the acceleration patterns give a better visualization to classify drone's behaviour. On the other hand, using both the velocity and acceleration patterns makes difficult to visualize a boundary to classify drone's behaviour. Notice that the non-malicious trajectories are close together and verifies the assumptions of Table II. The results of the clustering methods are summarized in Table IV.

TABLE IV
STAGE 1: UNSUPERVISED LEARNING ACCURACY RESULTS

Algorithm	**Accuracy %**	
	Features $(V_x, V_y, V_z, A_x, A_y, A_z)$	**Features** (A_x, A_y, A_z)
K-Means (Euclidean distance)	64.4	91.0
Hierarchical Clustering (Agglomerative)	63.4	88.0
K-Means (DTW)	58.8	**93.7**

It can be observed that the classification results are notably improved when only acceleration patterns are used. This means that the velocity features add redundancy to the data which compromises the accuracy results. These results allow to conclude that the acceleration patterns are the most informative feature for behaviour classification. In addition, the distance metric is a factor that can improve the accuracy results. Here, DTW distance outperforms the results of the Euclidean distance by considering larger trends for comparison amongst the trajectories.

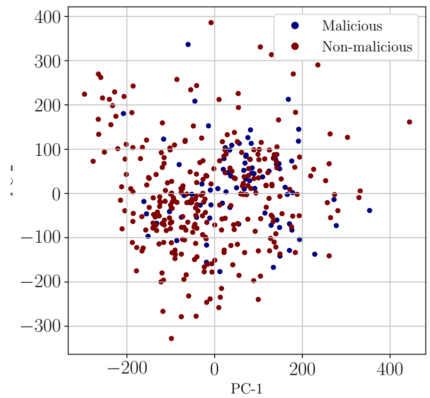
The results of the supervised learning case are shown in Table V. Here, the Gaussian Naive Bayes model has the most promising recall and relatively good F1-score. However, the unsupervised learning results outperforms the supervised learning models. Hence, the unsupervised learning models are used for the prediction purposes of stage 2.

TABLE V
METRIC RESULTS OF THE SUPERVISED LEARNING METHODS

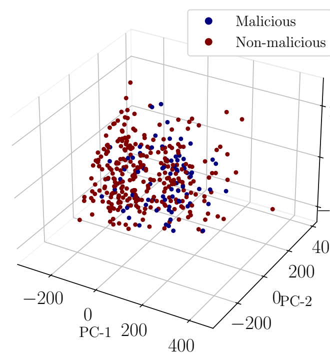
Algorithm	**Metric Results**				
	Class	**Precision**	**Recall**	**F1-score**	**Accuracy**
SVM	Malicious	1.00	0.42	0.59	0.86
	Non-Malicious	0.85	1.00	0.92	
Logistic Regression	Malicious	0.89	0.62	0.73	0.89
	Non-Malicious	0.89	0.98	0.93	
Gaussian Naive Bayes	Malicious	0.74	0.88	0.81	**0.90**
	Non-Malicious	0.96	0.91	0.93	
Decision Tree	Malicious	0.79	0.58	0.67	0.83
	Non-Malicious	0.88	0.95	0.92	

B. Stage 2: Statistical Learning Methods

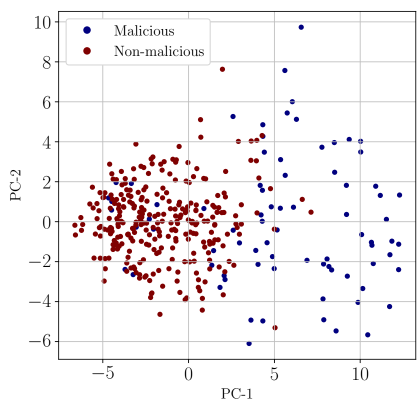
The k-nearest neighbours algorithm [36] is used to apply the Kolgomorov-Smirnov test and Wasserstein distance as distance metrics. The complete dataset of 369 flight trajectories is divided into training and test subsets. Here, the



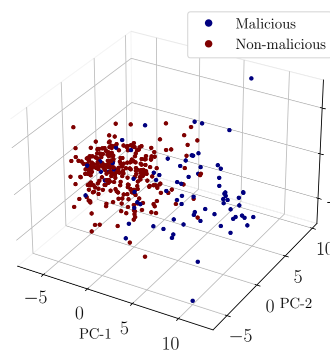
(a) PCA with 2 PC using velocity components



(b) PCA with 3 PC using velocity components



(c) PCA with 2 PC without velocity components



(d) PCA with 3 PC without velocity components

Fig. 4. Stage 1 Unsupervised Learning Results

prediction accuracy is verified on the test subset using only the first 100 seconds of each flight trajectory.

TABLE VI
METRIC RESULTS OF THE STAGE 3- STATISTICAL LEARNING

Algorithm	**Metric Results**				
	Class	**Precision**	**Recall**	**F1-score**	**Accuracy**
Kolmogorov-Smirnov test	Malicious	1.00	0.82	0.90	0.97
	Non-Malicious	0.97	1.00	0.98	
Wasserstein Distance	Malicious	1.00	0.76	0.87	0.96
	Non-Malicious	0.96	1.00	0.98	

The performance of the prediction models are depicted in Table VI. Both distance metrics have good accuracy results. A low number of false positives is crucial to avoid economic damage and closing national infrastructures. On the other hand, a low number of false negatives is required to avoid damage in national facilities. Whilst the precision results show zero false positives, the recall results show some number of false negatives. This results are informative since there are some malicious trajectories that are considered non-malicious which require further analysis to overcome any false positives problem.

IV. CONCLUSIONS

In this paper a two-stages drones behaviour prediction algorithm is proposed. The first stage is given by either a supervised or unsupervised machine learning method to classify malicious and non-malicious trajectories in accordance to expert's low dimensional features associated to kinematic values and constraints. The second stage is given by a statistical learning method based on the Kolgomorov-Smirnov test and the Wasserstein distance to predict in real-time the drone's potential malicious activity. The results show good accuracy results using these low dimensional features, however, further work will analyse the study of high-dimensional features to improve the prediction accuracy of methods in stage 1 and hence, increase the reliability of stage 2. In addition, the complementary merits from both expert systems with deep patterns is topic of our future work.

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