Tracking and Classification of Drones and Birds at a Far Distance Using Radar Data

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ABSTRACT

The challenge in industry and academia nowadays is to classify small drones and distinguish them from the birds at distances where technologies like radar micro-Doppler, visual, acoustic and radio-frequency sensing systems are not able to detect. The paper presents a method for target tracking and classification of objects in ranges greater than 500 m. We discuss the overall architecture of the system including tracking and initial model for classification. The initial experiment and simulation show very good classification accuracy.

1.0 INTRODUCTION

Recently, the availability of small and light drones has remarkably increased to society due to low cost and ease of operational complexity. The drones can be used for many applications including filming, environment monitoring, disaster management, agriculture and many such applications. However, there can be potential misuse involving drones, as filming restricted areas, invading personal privacy, collision hazard with aircraft and transport of explosive materials. At low elevation, flying birds are the principal low speed, small targets in addition to drones. To classify drone and flying bird targets, it is customary to identify their signatures. The flying birds have similar radar cross section (RCS), same velocity range, similar signal fluctuation, and approximate signal amplitude to drones [1]. The similarity between small drones and birds present major challenges in class separation.

Present-day, existing technologies on drone target detection include radar, radio detection, acoustics and visual [2]. The visual-based methods have advantage of low cost cameras with existing state of the art object detection techniques. However, their performance depends on weather conditions and gets worst during the periods of fog and rain [3-4]. The acoustic-based methods do not require line of sight and work in low visibility environments. But they are very sensitive to ambient noise and required a database of acoustic signature for different types of drones and birds [5-6]. Radio-frequency (RF) based techniques have long detection range with low cost RF sensors but not suitable for autonomous flying drones [7-8]. Many researchers have discriminated drones and flying birds using the micro-Doppler characteristics of the target [9–11]. But this method is only applicable for metal-rotor drones and at distance more than 500 m radar micro-Doppler is not detectable. Novel approaches include using deep learning LSTM networks for learning the maneuvering models instead of applying traditional IMMs [12]. That work was based only on simulation data. Recently, a probabilistic model has been proposed for joint target tracking, classification and intent inference of the airplanes [13]. Two intents (cruise and attack) were classified using simulated data. Markov blankets for joint tracking and inferring intent (intended destination and arrival time) were developed in [14] with an example of maritime surveillance. Motion detection combined with the SURF (Speed Up Robust Features) algorithm can properly detect drones while successfully ignoring other flying objects [15]. A Hidden Markov model-based and an adaptive Bayesian classifier was used for classification of synthetic data that represented UAVs and birds [16].

In this paper, a method is proposed for classification using features from interacting multiple models (IMM) tracking filters and flight trajectories that uniquely describe the flight of each target.

2.0 METHODOLOGY

The proposed system is divided into four blocks: radar data acquisition, target tracking with interacting multiple model filters, feature extraction and classification as shown in Figure 2-1.

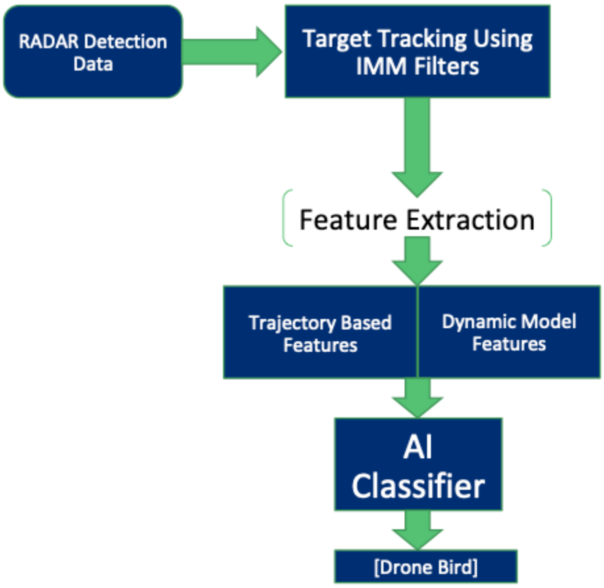


Figure 2-1: The overall system architecture for classification of flying bird and UAV.

2.1 Target Tracking with Multiple Models

For manoeuvring target tracking, one single motion model does not represent the behaviour of the target at all times [17]. Figure 2-2 describes the general structure of the interacting multiple model filters. The state vector $X(k)$, $Z(k)$ observation vector and $\mu(k)$ model probability are input to the IMM filter. The observation $Z(k)$ contains the x-y-z coordinates of the radar detected flying target. At every sampling instance, each tracking filter estimates the state of the flying target as per the respective motion model and resultant state estimate is the combination of all state estimates.

Our IMM filter uses a set of liner (Kalman Filter) and nonlinear (Extended Kalman Filter) filters with respective motion models to capture the complex flight behaviour of the target. The motion model includes Constant Velocity (CV), Constant Acceleration (CA), Horizontal Coordinated Turn (HCT) and 3D Coordinated Turn (3DCT) which can accurately represent target manoeuvres. The purpose of the IMM tracking is not only to improve the tracking accuracy but also to adopt them for the classification of the targets in ranges greater than 500m.

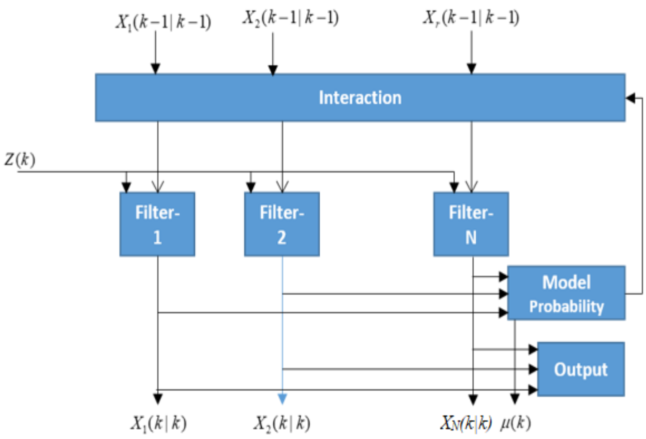


Figure 2-2: A framework of the interacting multiple model (IMM) filter.

2.2 Feature Extraction

Several existing studies on birds flying behaviour motivate us to analyse birds and drone flights [18-19]. In general, the manoeuvrability of the flying bird target is usually higher than the small UAVs at low altitude flights. We began by analysing the variation of speed, acceleration, and curvature of the flight trajectories during relatively straight and turning segments. There is a significant difference among the distribution of these parameters for the bird and drone flights. This is due to the inherent difference in the kinematics of their flights. Besides, we analysed the variation of the tracking filter probabilities during the relatively straight and turning segments. It is observed that the tracking filter for birds' frequently changes motion models compares to the UAV flight tracker. Figure 2-3 shows the block diagram of the feature extraction before the classification. Besides tracking IMM filter smoothen trajectories to accurately get trajectory-based features.

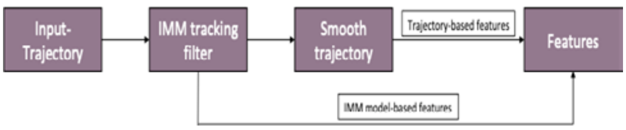


Figure 2-3: A block of feature extraction before the AI classifier.

Table 2-1 shows the potential features to be used for classification. The IMM filter produces estimates of the velocity (v_x, v_y, v_z), acceleration (a_x, a_y, a_z) and turn rate (ω) at every sampling instance. Based on these estimates the statistical features are directly calculated. The IMM model probabilities play an important role in identifying flying targets. Based on the filtered results, the average model conversion frequency F is calculated as,

$$F = \frac{1}{n}\sum_{i=1}^{n} Var\{\mu_i^k \mid k = 1, 2, \cdots, T\}$$

Where μ_i^k is the transition probability of the i^{th} filter at a k^{th} time instance as shown in Figure 2-2. It captures information about the target's flight dynamics.

During our initial study, we extracted 2D and 3D turn; maneuvering points and calculated the model conversion frequency for bird flight. Figure 2-4 shows these maneuvering points for a pigeon flight. These points were extracted using tracking using IMM filters by putting threshold on horizontal and vertical turning rates for the flying target. These points are one of the important features to classify between a bird and drone trajectory.

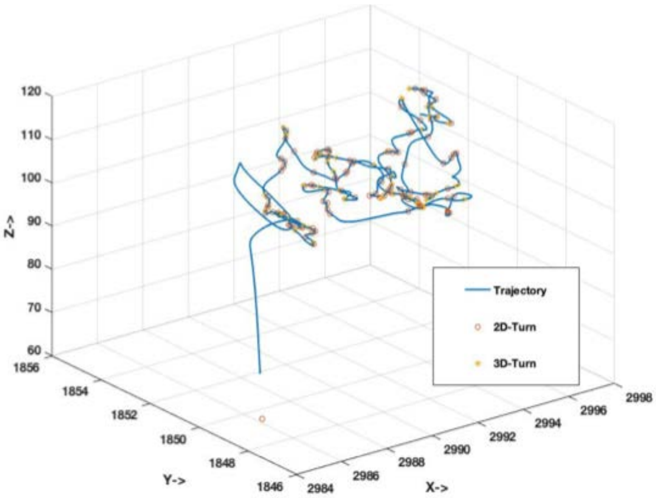


Figure 2-4: Extracting maneuvering points during tracking from the trajectory.

We have calculated model conversion frequency separately for bird and drone for the GPS trajectories. Table 2-2 shows the model conversion frequency for bird (pigeon) and drone (DJI Phantom 3) flights. We can observe that the higher value of F for birds than drone this is due to the manoeuvrability of the flying bird target is usually higher than the small drone.

Table 2-1: Feature set used for classification

IMM Filter based Features	**Trajectory Based Features**
Mean and variance of velocity along x, y, and z	Mean and variance of curvature
Mean and variance of acceleration along x, y, and z	Mean and variance of slope along z-x and z-y
Mean and variance of turn rate	
IMM filter model transition probabilities	

The directional bearings, another significant feature of the target's flight can be measured using curvature. The curvature of the trajectory is calculated as,

$$\kappa = \frac{\sqrt{(z^{''}y^{'} - y^{''}z^{'})^2 + (x^{''}z^{'} - z^{''}x^{'})^2 + (y^{''}x^{'} - x^{''}y^{'})^2}}{(x'^2 + y'^2 + z'^2)^{\frac{3}{2}}}$$

Where prime denotes the differentiation with respect to time.

Table 2-2: Comparison of model conversion frequency for bird and drone.

Bird flight #	Bird (Pigeon)	Drone flight #	Drone (DJI Phantom 4)
1	0.5038	1	0.3218
2	0.6245	2	0.3248
3	0.6122	3	0.4465

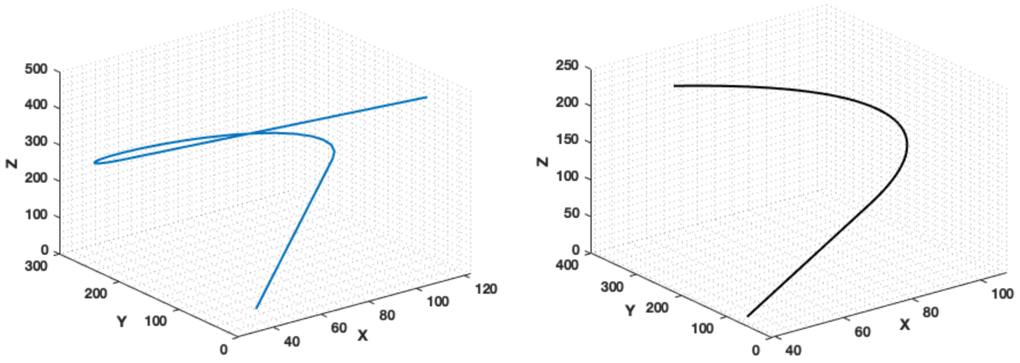
3.0 RESULTS AND DISCUSSION

The section describes the synthetic and real radar data collection, target tracking and classification.

3.1 Synthetic Data

We have used the flying pigeons [20] and drone (Phantom-2) GPS data in the simulation. The dataset contains 11 free flights of the flocking birds and 11 free flights of the drones, each flight with an average duration of 75 mins and 20 mins respectively. The pigeon trajectories were recorded at high resolution at 5 samples/sec by miniature GPS devices. The drone GPS data were re-sampled and converted to x, y and z coordinate using the flat Earth approximation.

Due to limited amount of GPS data, we have synthetically generated trajectories comparable to drones and birds for the experiment. To generate each trajectory, we have used a combination of 3D kinematics models with different parameters for birds and drones. UAV mainly undertakes the transportation of package and area surveillance; it usually has the predefined route. Because of safety, it generally maintains a stable flight with fewer manoeuvres. Whereas Bird is flexible, it can fly from very low altitude to high altitude. Also, it can perform some unique manoeuvres. Table 3-1 shows the motion parameters used for trajectory generation for each target class. The parameters are normally distributed, and it covers a wide range of manoeuvring situations for each target. Figure 3-1 shows the sample of synthetically generated trajectories.



(a) (b)

Figure 3-1: Sample of the generated trajectory for bird (a) and drone (b) respectively.

We computed both types of features separately for bird and drone trajectories and prepared a feature set. It is divided into two sets, one for training and one for the test. The ratio of these sets is chosen to be 80% and 20%; respectively. Total, 584 tracks are randomly chosen for training purpose and 146 tracks are chosen for testing purposes out of 730 tracks. We consider three classifiers, the Bayesian, Kernel Support Vector Machine (K-SVM) and Decision Tree to evaluate the performance of the proposed method. Also, a 5-fold cross-validation method is applied to this classification problem.

Table 3-1: Parameters values used for trajectories generation.

	Bird	Drone
Velocity (m/s)	N (11,5)	N (16,4)
Acceleration (m/s^2)	N (6,2)	N (8,4)
Turn rate (rad/s)	N (0.3,0.15)	N (0.05,0.02)

During training, a test trajectory with added noise is passed through the IMM tracker. The filtered trajectory after tracking is used for feature extraction. The algorithm updates the classification score at every 30-sec interval. Finally, Table 3-2 summarises the classification accuracy of different classifiers with GPS data and synthetically generated data. The general performance and false alarm rate are considered, the decision tree algorithm performs better than others. The decision tree classifier has a 97% true positive rate and a 3% false-negative rate. In these 3% cases, a bird track with low manoeuvrability similar to that of UAV causes false alarm and sometimes a UAV track gets miss classified as bird due to its unstable flight because of environmental conditions. The main hypothesis is that each target has its unique flight property, which controls its trajectory. The length of the trajectory is an important factor while training the classifier as too short a trajectory may miss the import manoeuvres for classification and too long trajectory may dilute the important features for classification.

Table 3-2: Classification accuracy for different classifiers.

Data	**Bayesian**	**K-SVM**	**Decision Tree**
GPS data	89.4%	86.4%	97.4%
Synthetic data	90%	97%	97%

3.2 Real Radar Data

After getting convincing results on the synthetic dataset, we have conducted few experiments to collect real radar data. In each experiment, there were around 20 flights with average duration of 15 min per flight. The experiments were conducted with electronically scanning radar. The radar creates separate track for each of the detected targets and streams the target coordinates and other target parameters at sampling rate of 10 samples/s.

Figure 3-2 shows the sample of the real radar trajectory for bird and drone. We can observe that birds have more complex manoeuvres than drone at low altitude flights. We also observed significant difference in the turning rate among the bird and drone flights in the collected data.

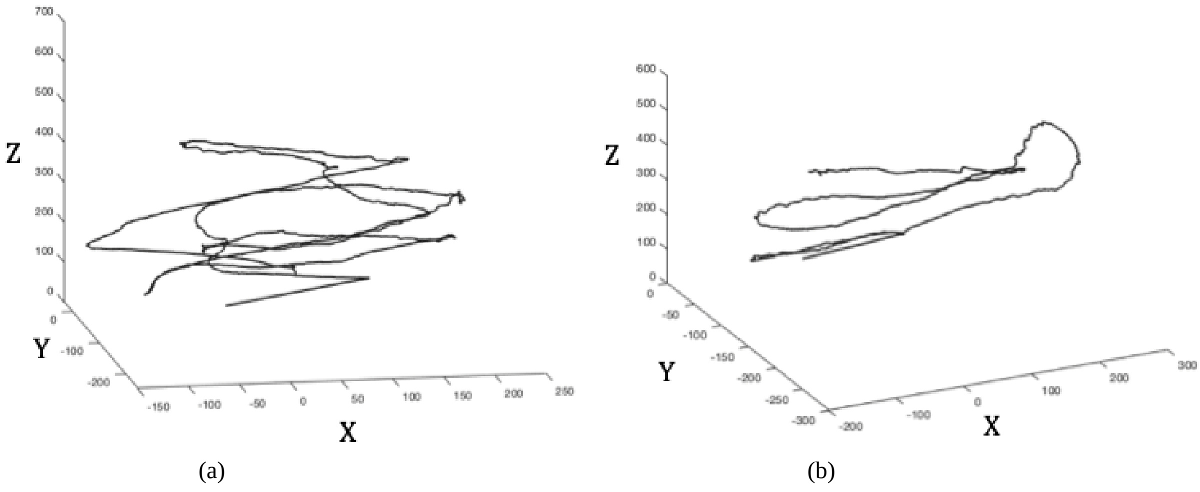


Figure 3-2: Sample radar trajectory for bird (a) and drone (b) respectively

We build the 2-class (Bird, UAV) classifier using collected data. There were around 4671 tracks in total with each track of 5 sec duration. We divided into two classes, (1) Bird (2) UAV. There were 1038 and 3115 tracks for bird and UAV respectively. Then, we further divided the tracks into two sets, one for the training and one for the testing. The ratio of these sets was chosen to be 80% and 20%; respectively. Before training, the tracks were first divided into small sub-tracks of 5 sec duration (50 samples) each and passed through the IMM filter for feature extractions. Then, model is trained using extracted features and a 5-fold cross-validation method was applied. We achieved a good classification accuracy of 83.33% with decision tree classifier on real radar data.

4.0 CONCLUSIONS AND FUTURE WORK

In this work, initial synthetic tracks generation and models for tracking, feature extraction and classification are developed. The classification is mainly based on the flight's kinematics and tracking models features which are independent of the target distance from the radar. The initial experiments and simulations show promising results in terms of classification accuracy. To further validate this conclusion, we will train and test these models with real radar tracks of different type of targets with different scenarios in the near future.

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