Classification of Bird and Drone Targets Based on Motion Characteristics and Random Forest Model Using Surveillance Radar Data

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ABSTRACT Accurate detection and tracking of birds and drones are of great significance in various low altitude airspace surveillance scenarios. Radar is currently the most proper long range surveillance technology for this problem but also challenged by various difficulties on effective distinguishing between birds and drones. This paper explores the inherent flight mechanic and behavior mode of birds and drones. A target classification method is proposed by extracting target motion characteristics from radar tracks. The random forest model is selected for target classification in the new feature space. The proposed method is verified by real bird surveillance radar systems deployed in airport region. Classification results on birds, quadcopter drones and dynamic precipitations indicate that the proposed method could provide good classification accuracy. The Gini importance descriptors in random forest model provide extra reference on motion characteristic evaluation and mining. High sample flexibility and efficiency make the classification system capable of handling complicated low altitude target surveillance and classification problems. Limitations of the existing method and potential optimization strategy are also discussed as future works.

INDEX TERMS Target detection, radar tracking, target classification, feature extraction, machine learning.

I. INTRODUCTION

Unmanned Aerial Vehicle (UAV) achieve booming developments in recent years. As a dominant branch in UAV family, multi-rotors drones possess unique platform advantages. They provide innovative solutions in various application scenarios [1]. However, benefits like small size, low costs and flexible deployments also result in non-negligible and unpredictable safety threats in specific regions. Effective monitoring of non-cooperative drones become necessary for safety consideration [2], [3].

Low altitude surveillance radar is considered as the most suitable technical solution for long range UAV monitoring [4]. It possesses advantages like long range detection, tracking and all weather operational functions. However, unlike conventional noncooperative targets, drones are small and made of non-metallic materials. These result in small radar cross section (RCS) values. The low altitude flying

capabilities also make them possess very low radar detectability [5], [6]. In many representative surveillance environments, there exists another type of low altitude noncooperative targets: birds. Existing works demonstrate high radar echo similarities for drones and birds [7]–[9]. The high similarity brings great difficulties in distinguishing drones and birds from radar viewpoint. Moreover, interference from ground clutter, multipath effects and precipitations further elevate the difficulty of drone target classification [10]–[12]. Therefore, in practical surveillance scenarios, effective noncooperative drone target surveillance requires capabilities of accurate distinguishing among drones, birds and environmental interferences like static and dynamic clutters.

Relative works found moving parts of aircrafts like propeller could modulate radar echoes in amplitudes and phases. The Micro Doppler Signature (MDS) could be extracted from this modulated signal as an extra feature for radar targets [13], [14]. Simulation results discover the clear MDS from quadcopter drone echo as a representative target

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signature. Relative works [5], [15]–[18] utilize MDS to extract target representative features like mean spectrum, the first left singular vector of singular value decomposition (SVD), the mean cadence velocity diagram (CVD). These features are combined with common classifiers like SVM to achieve effective drone target recognition. The wing flapping from nonrigid bird targets also modulates radar echoes and produces MDS. Birds particular flapping pattern results in distinctive MDS which could be utilized for target classification [19]–[21]. However, existing achievements based on MDS are mostly based on theoretical simulation, indoor measurement or outdoor measurement in close range (<200m). In practical surveillance scenarios, the effective extraction of MDS in long range is still controversy. Experiments also indicate that gliding birds and plastic-rotor UAVs present insignificant MDS and poor RCS modulation. For grouped targets like swarm drones or bird flocks, their mutual couplings within radar scanning volumes further complicates radar echo signatures in amplitudes and phases modulations, which is very difficult for effective MDS extraction. An extra limitation of MDS is its long dwelling time requirements over a specific target for sufficient coherent integration [22]. This is conflict with radar scanning mode for multiple target detection and tracking. Therefore, MDS is a promising radar target signature but its application significance in practical surveillance scenarios needs more improvements. As current MDS technology is still in question for long range drone monitoring, the target classification problem needs contribution from other target signatures. Besides RCS, the polarimetric signature is also a representative radar target characteristics for narrowband radar. In [23] nine polarimetric features are extracted and a nearest-neighbor classifier is adopted to achieve effective target classification. However, this work is based on simulation results and its practical performance needs further verification from field experiments. Moreover, the cross polarization measurement also complicates the hardware requirement of radar system. The trade off between system complexity and surveillance performance enhancement still need to be balanced.

Even birds and drones reflect high similarity in transit radar echo signatures, they still present intrinsic differences in flight mechanics and maneuvering patterns. Therefore, flight motion characteristics might provide extra information for target discrimination [24]. In radar system viewpoint, target motions are discretely represented by tracks. Each plot of the track contain spatial, temporal, signal intensity and doppler information. Existing works based on simulation platform have initially verify the possibility of distinguishing birds and drones using statistical features of radar tracks [25]. Recent works based on field experiment further verify the potential of discriminating targets based on new feature space composed of dynamic descriptors [26]. Therefore, track motion characteristics is promising for drone recognition but current methods are mostly based on simulation or ideally sampled target tracks. Environmental robustness and adaptability to high sample quality uncertainty still need to be explored in

classification method development to guarantee its application significance.

In this paper, a drone target classification method using motion characteristics extracted from tracks is introduced. Flight mechanic and behaviour mode difference between birds and drones are explored. Five dynamic descriptors are proposed for target feature description. The random forest model is applied in classification among drones, birds and dynamic precipitation clutters. The method is verified by field experiment datasets collected from a bird surveillance radar system deployed in BeiHai airport by CAAC (China Academy of Civil Aviation Science and Technology). The overall rate of correct classification for three target types is larger than 85%. The proposed method does not require additional modification on radar hardware or signal processor, which makes the method possess great flexibility and generality in various radar surveillance systems. RCS and MDS signatures are not adopted in classification. This makes the method independent of radar calibration, radar operating mode and other environmental interference factors. The low computational complexity guarantees the real-time classification performance. The Gini importance descriptor in random forest model provides extra reference information to evaluate descriptor contributions in classification. This is constructive for target motion characteristics understanding and descriptor developing.

The paper is organized as follows: section II discusses flight mechanism and behaviour modes differences between birds and drones to support motion characteristics mining. Five descriptors are introduced in section III to construct a new feature space for target classification. The reason of selecting random forest model as the classifier and the experiment setups are described in section IV. Section V discusses classification results from various aspects and existing problems of the proposed method.

II. FLIGHT MECHANIC AND BEHAVIOUR ANALYSIS
Even birds and drones present high similarity in flying speed and radar echo signatures, their flying patterns are still different from the viewpoint of visual observation. This visual difference is derived from their intrinsic difference in flight mechanic and behaviour modes. In the radar system, a flying target is depicted by a track containing spatial and temporal information. The target motion characteristics is discretely represented by a series of target detection plots. In this section, a preliminary discussion on flight mechanic and behaviour modes for birds and drones is provided to support the following feature mining.

A. FLIGHT MECHANIC
Drones get lifting power from blade rotor controlling to achieve different maneuverings like moving forward and backward, ascending, descending, hovering, and so on. Aerodynamic is considered in shaping design but for copter drones aerodynamic is not as dominant as in fixed wing drone designing. In contrast, birds are nonrigid and get power by
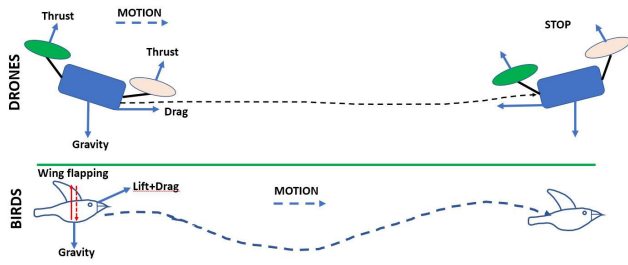
FIGURE 1. Graphic illustration of flight mechanics for birds and drones.
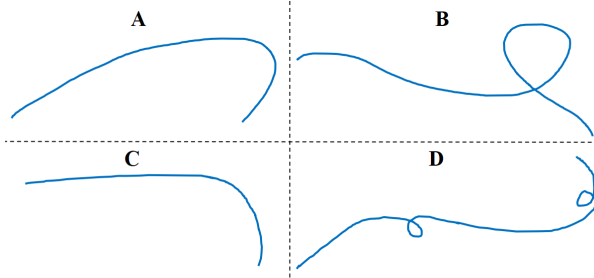

FIGURE 2. Representative flight trajectory projection of drones.

flapping wings. They achieve maneuverings by adjusting shapes, attitudes and wing flapping patterns. Aerodynamic is dominant in birds maneuvering and usually more complicated than drones due to their nonrigid property. Figure 1 presents an intuitive demonstration about flight mechanics. Theoretically drones could achieve more complicated maneuvering patterns due to its higher degree of freedom in rotor blades controlling. Birds usually present smooth flight trajectory. Their hovering in the air occasionally happen under specific strong wind conditions. Therefore, even birds and drones have similar flight speed, inherent flight mechanic differences make them could hardly reproduce each other's particular maneuvering patterns. Figure 2 illustrate ground projections of four representative flight trajectories of drones in a few general operating scenarios. Spatial information is provided by GPS equipment. Obviously trajectories B and D are regular maneuvering patterns for drones but challenging for birds.

B. BEHAVIOUR MODE
From the viewpoint of behavior mode, drones are artificial targets and their flight is motivated by serving specific duties like surveillance and delivery. Therefore, the behaviour mode of drones is a combination of duty and pilot controlling preference. In contrast, birds are typical noncooperative targets with self-intelligence. Their behaviors have close relevance with their habits and species. For example, migrant and local birds have distinctive behaviour mode differences. Birds of the same specie could also present diverse maneuvering patterns in food hunting, roosting, etc. Therefore, considering the large species number and their diverse habits, birds possess much more abundant behaviour modes than drones. This abundance is reflected from various motion characteristics in plots spatial-temporal information and could hardly be reproduced by drones neither.

In conclusion, drones present higher degree of freedom in maneuvering, but birds possess much more complicated behaviour modes. This makes it difficult for birds and drones to totally reproduce each other's flying pattern, and their differences are reflected from motion characteristics contained in radar tracks. The spatial and temporal information contained within each detection plot provides a possibility of motion characteristics mining.

III. MOTION CHARACTERISTIC MODELLING AND EXTRACTION FROM RADAR TARGET TRACKS
In surveillance radar systems, a track is the most fundamental element to describe a detected moving target. A track is initiated when enough detections are accumulated (in our system 3 out of 4 consecutive scans initiates a track). During tracking association, a track could include "misses" termed as coasted targets which maintain a tentative track. The system software allows for up to 3 consecutive misses. If a target is missed during 4 consecutive scans the track is terminated. Each track is assigned with a track ID and each plot of the track contains time and position information. Target heading direction and corresponding flying speed information could be deduced from neighboring track plots. Even with deviation, deduced speed and direction information from discrete track plots could still be a good approximation for target motion description if high radar scanning rate could be guaranteed.

However, the direct application of speed and heading information has following limitations: (1) There usually exists great variations among track length (plot number). This results in inconsistent feature vector dimension. (2) Speed and heading direction describes the first order motion features in spatial and temporal dimension independently. Therefore, motion characteristics hidden in track's spatial-temporal information need to be further explored to construct a new feature space with uniform dimension.

This paper introduces five descriptors extracted from speed and heading information of tracks. A new feature vector composed of five descriptors is defined and applied in the learning machine to achieve the target classification. A track composed of N plots could be mathematically described by a vector $\mathbf{Z} = [Z_1, Z_2, \ldots, Z_N]$. The symbol Z_i indicates the ith plot. Corresponding speed and heading direction information is presented in vector form as $\mathbf{V} = [v_1, v_2, \ldots, v_N]$ and $\mathbf{H} = [h_1, h_2, \ldots, h_N]$. Units for speed and heading are m/s and degree respectively. The 0 degree is the north direction and 90 degree indicates east direction. Five descriptors are defined in following subsections.

A. AVERAGE SPEED
The average speed is defined as:

$$v_{\text{mean}} = \frac{1}{N} \sum_{i=1}^{N} v_i \qquad (1)$$

The average speed describes the overall speed level of the track. It is the most fundamental motion descriptor. Birds and

drones usually have close average speed except for hovering. The speed of precipitation clutter is dependent on wind profile and precipitation intensity, which is usually slower than birds. The average speed is suitable for discriminating targets with distinctive speed difference like birds and ground vehicles. However, this descriptor usually does not play a dominant role in target classification. Generally It is adopted as a fundamental descriptor for joint description with other motion descriptors.

B. STANDARD DEVIATION OF SPEED

Most tracks usually present speed deviations among plots. The degree of deviations indicates the spatial and temporal uncertainty of target motion. The standard deviation of speed for a track is defined as:

$$v_{std} = \sqrt{\sum_{i=1}^{N} \frac{(v_i - v_{mean})^2}{N}} \qquad (2)$$

The larger standard deviation value indicates a higher speed uncertainty. Bird tracks usually present small speed variations and the probability of high speed uncertainty is rare. The speed of precipitation clutter is consistent with wind profile. In most cases the corresponding speed profile is smooth. Drones could present a wider range of speed deviation pattern due to its high maneuverability flexibility. They demonstrate smooth speed patterns in cruising mode, but are also capable of presenting large speed uncertainty in many scenarios. Pilots operating preference also have impacts on speed features. Therefore, the intrinsic motion differences between birds and drones make speed uncertainty contain more distinctive features.

C. STANDARD DEVIATION OF HEADING

Unlike the speed information, the average heading direction of a track has little relevance with target motion. However, the heading deviation pattern could be utilized to describe target's relative spatial uncertainty. The standard deviation of heading is defined to quantify this uncertainty as:

$$h_{std} = \sqrt{\sum_{i=1}^{N} \frac{\Delta_h (i)}{N}} \qquad (3)$$

Considering the definition of heading, the Δ_h is defined as:

$$\Delta_h (i) = \begin{cases} (h_i - h_{mean})^2 & |h_i - h_{mean}| \leq \delta_h \\ (|h_i - h_{mean}| - 360)^2 & |h_i - h_{mean}| > \delta_h \end{cases} \qquad (4)$$

In which the symbol h_{mean} is the average heading direction. Its computation considers the relationship between 0 degree and 360 degree. δ_h is the threshold for heading deviation. It is empirically defined as 90 degree. The heading deviation of birds is more related with their behaviors. Local birds usually present larger spatial uncertainty than migrants. Considering the maneuverability of birds, their overall heading deviation is smaller than drones. Drones sometimes present specific maneuverability which birds could hardly reproduce

and corresponding heading deviations are distinctive. Most precipitation tracks present consistent heading variations with small standard deviation. Abrupt heading changes are rare except for the condition of gust interference.

D. MANEUVERABILITY FACTOR

The standard deviation of heading degrees describes target's spatial uncertainty, but its correlation with time information is weak. The speed features describe target's scalar variation in temporal domain but their relevance with target spatial uncertainty is unclear. Therefore, previous three descriptors represent target motion characteristics within respective dimensions independently. Based on massive analysis, it was noticed that targets present diverse heading variations with speed. A target presents strong maneuverability if it can make large heading deviation under high speed. This maneuverability is a joint dimensional description of target motion. A maneuverability factor is defined as:

$$\sigma = v'_{mean}/h'_{std} \qquad (5)$$

The unit of maneuverability factor is m/sec/deg, it describes the target motion speed under unit heading deviation. Considering the prominent numerical difference between speed and heading deviation, v'_{mean} and h'_{std} are normalized values based on predefined value ranges. According to existing track samples, value ranges for average speed and heading deviations are (2-20) m/s and (0-90) degrees. According to equation (5), a target reflects strong maneuverability if it could make large heading deviations under high speed, and the corresponding σ value locates within a specific small value range.

The bird maneuverability has close relevance with species and behaviour modes. Migrating birds usually do not make abrupt motions and present weaker maneuverability. Local birds have more diverse behaviour modes. Birds could present occasional strong maneuverability during hunting, roosting, and so on. As drones could hover in the air, their maneuverability factors have a larger variation range and closely related with duties. The maneuverability for precipitation tracks are totally dependent on wind profiles. In most cases the maneuverability of tracks from dynamic precipitation clutters is weak. Numerical results indicate that the σ value distributes within a specific range for both high and low speed targets with different heading deviation features. This is beneficial for separating targets with different maneuverability patterns in the feature space. However, it should be noticed that this maneuverability description is based on a specific target track, and it does not represent target's essential maneuverability property.

E. OSCILLATION FACTOR

The oscillation factor further complete the maneuverability factor by providing more comprehensive dynamic feature description. It is motivated by a distinguishing confusion problem for two tracks whose ground projections are projected in Figure 3(a) and Figure 3(b). Track-1 and Track-2
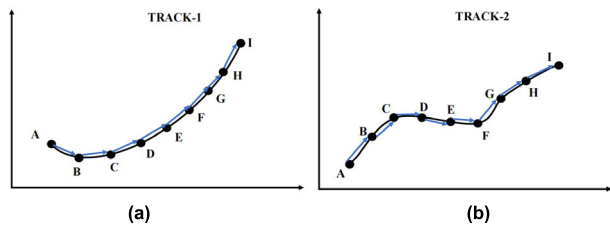
FIGURE 3. Track projection presentations with distinctive motion patterns-(a) Track-1 (b) Track-2.

TABLE 1. Weight factor definition.

Oscillation number	Weights
1	1
2	1.5
3	2
4	3
≥5	5

are all composed of nine plots marked from A to I. Track-1 is representative for most bird tracks with smooth and consistent dynamic features. Track-2 is rare for bird and precipitation tracks due to its complicated oscillation pattern, but it is not challenging for drones and this oscillation pattern presents frequently under unpredictable environmental interferences. However, this prominent difference is not comprehensively reflected from descriptors defined in previous subsections. The contradictory is caused by absolute value operator in standard deviation. The absolute value describes a scalar variation quantity without variation directions. The summation of absolute deviation confines the motion description in local scale. Heading oscillations caused by alternative deviation directions could not be effectively reflected. Therefore, an oscillation factor is developed to complement the heading deviation description.

The computation of oscillation factor starts from getting heading deviation direction information. The deviation direction is determined from the symbol of heading angle difference between neighboring plots, which is defined as $\tau_h(k) = h_{k+1} - h_k$. A threshold value δ_e is defined as 0.5 by considering radar measurement error. For a detection plot Z_k, its heading deviation symbol is defined as:

$$X_h(k) = \begin{cases} 1 & \tau_h(k) > \delta_e \\ 0 & |\tau_h(k)| \leq \delta_e \\ -1 & \tau_h(k) < -\delta_e \end{cases} \quad (6)$$

A heading deviation symbol vector could be constructed from (6) and denoted in the form like $\mathbf{O} = [1, -1, 0, 1, \ldots]$. Two oscillation modes are defined from vector $\mathbf{O}$:

Mode1: $\mathbf{O}(i\text{-}1) + \mathbf{O}(i) = 0$ and $\mathbf{O}(i\text{-}1) \neq \mathbf{O}(i)$;

Mode2: $\mathbf{O}(i\text{-}1) + \mathbf{O}(i+1) = 0$ and $\mathbf{O}(i\text{-}1) \neq \mathbf{O}(i+1)$, $\mathbf{O}(i) = 0$;

The traversing procedure is restarted from the initial detection plot, if there exists one of the two oscillation models, the oscillation counter is added by one and the corresponding heading deviation is recorded as $\tau_h(k)$. If there exists K ($K > 0$) oscillations in a track, the corresponding oscillation factor is calculated as:

$$\zeta = \sum_{k=1}^{K} w(k) \times |\tau_h(k)| \quad (7)$$

In equation (7) the symbol $w(k)$ is the weighing factor for the kth oscillation and its definition is in Table 1. For a specific track, more oscillations generally indicate a more intensive oscillation pattern. The weighing factor is defined to indicate the growing impact of oscillation times. Its application on heading deviation angles interprets the overall degree of track oscillation. The unit of oscillation factor is degree and the larger value indicates more intensive track oscillation. It should be noted that in Table 1, the oscillation number k indicates the kth oscillation rather than the total number of oscillations. For example, the oscillation number 3 indicates the third oscillation in current track traversing, and the weighing factor 2 is multiplied with the corresponding heading deviation angle at the third oscillation. The increasing weighing factor indicates a growing impact of the oscillation times. However, current weighing factor definition is empirical and subjective biased. In future works, weight factor could be more reasonably defined through numerical regression or statistical fitting.

IV. SUPERVISED LEARNING MODEL AND EXPERIMENT SETUP

A. RANDOM FOREST CLASSIFICATION MODEL

According to descriptors defined in section III, a target track could be represented by a new feature vector:

$$\mathbf{S} = [v_{mean}, v_{std}, h_{std}, \sigma, \zeta] \quad (8)$$

This feature vector contains target motion characteristics from various aspects. The uniform dimension makes it suitable to be applied in the learning machine model for target classification. In this paper, labelled feature vectors from radar observation data are selected to construct a training database, and the supervised learning strategy is taken. The unknown target track is converted in to the feature vector (8) and applied on the trained classifier to determine the target type. Therefore, it is necessary to select a proper learning machine. There are lots of popular existing models available like Support Vector Machine (SVM) and Artificial Neural Networks (ANN). However, the selection of learning machines should consider intrinsic properties of the specific classification problem and feature vectors. The random forest model is taken as the learning machine in this paper.

Random forest model is a representative machine learning technique [27]. It is an ensemble classification strategy based on multiple decision trees. The basic principle of random forest is building multiple decision tress by randomly selecting partial features from the feature space. Decision procedures of trees are independent and the final decision is made
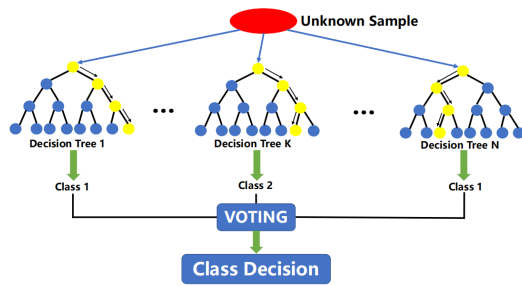
FIGURE 4. Graphical description of random forest model.

through weighed integration of all trees. This procedure could be graphically demonstrated in Figure 4.

The principle and implementation of random forest model is simple. The classification platform development is not challenging for our problem. However, there is the necessity to give comprehensive explanations about reasons of selecting random forest as the learning machine.

1. Unlike other machine learning techniques which operate in a complete feature space, feature selection and tree construction strategies in random forest make it possess good noise tolerance capability and lower chance of overfitting [28]. In our problem, even though radar system could detect and track birds accurately, environmental interference and tracking algorithm's uncertainty make training database partially contain low quality non-bird tracks which are categorized as noise interference. Therefore, the random forest model is suitable for our problem to handle training database with sample quality uncertainties.

2. Five descriptors are integrated into a feature vector as in equation (8). However, these descriptors are inherently independent. There exists distinctive dimension and physical meaning inconsistency. This might result in inconvenience on other learning machines but not a problem for random forest model. As the basic component, a decision tree could naturally accustom to quantitative and qualitative features without feature normalization. Therefore, the random forest model performs well for inconsistent feature space. An extra benefit is its flexibility on feature variation when additional target features are introduced or rearranged.

3. The computational and memory consumption of random forest model is lower than many popular machine learning techniques. Due to great diversity in bird species and behaviour patterns at different season and locations, it is necessary to frequently adjust training database in diverse scenarios. Random forest model's efficiency and flexibility advantages are suitable for these requirements.

4. The Gini importance is an important reason of selecting random forest model. As a quantitative descriptor of feature importance, Gini importance provides useful references in feature selection [29]. In our problem, even five descriptors are proposed, their contributions in classification lack quantitative evaluators for verification. As a complement, the Gini importance could intuitively interpret relative importance quantitatively as feature selection reference.

FIGURE 5. Bird surveillance avian radar systems developed by CAAC.

B. EXPERIMENT SETUP

The radar data comes from the bird surveillance radar system developed by CAAC as presented in Figure 5. The system is composed of a climate-controlled cabin housing the computer systems, data processors, wireless data transmitters, and 2 towers mounting the dual-scanning array antennas with both vertical and horizontal scanning. The radar works at S band. The horizontal scanning antenna is mounted on a tower with adjustable heights. Solid state amplifiers are adopted for both vertical and horizontal scanning with peak power of 0.4KW. the rotational speed is 25 revolutions per minute (2.4s/scan). Bird detection and tracking algorithms are developed with real time visualization function [30].

The radar is deployed in FuCheng airport in BeiHai city, GuanXi Province in China. Deployment details are presented in Figure 6. Region A and B are dense regions for local birds activity and the major source of radar observation data. Region C is selected as a test field of drone flights. Data collection was conducted from early September to the end of October in 2019. Bird observation data is collected from 7:00 to 19:00 in local time under good weather conditions with cross validations from visual observations. Drone tracks come from practical drone flights in area C. To maximally reduce the potential risk, all drone flight experiments were conducted at early morning or night hours when there was no airplane landing or taking off. The model of drones is DJI Phantom 3. Drone flight plans are designed to simulate various working modes like video taking, cruising, multi-aspect photo taking, hovering and so on. According to GPS information, it was found that a radar track would stop association if a drone hovers in the air over 15 seconds (6 radar scans). In other cases when drones present different maneuvering patterns the system could effectively capture drones and generate tracks. In our experiments a single drone is considered as a medium sized bird by the radar system. Historical observation data indicates precipitations moving with wind might generate large amount of false bird tracks [31]. Precipitation tracks are collected in two selected days in September with medium level precipitation. Observations indicate that when precipitation moves in a uniform pattern, dense precipitation volumes with sufficiently large echo intensity are considered
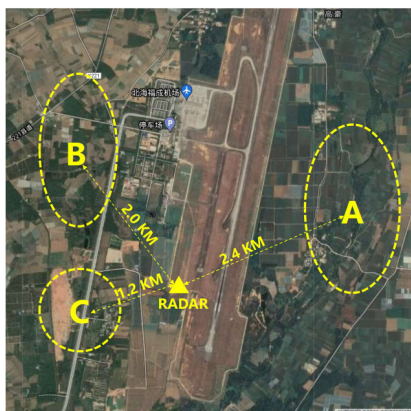
FIGURE 6. Geography illustration of radar deployment in BeiHai Airport.

FIGURE 7. Principal components distribution for three types of targets.

FIGURE 8. Confusion matrix for five-fold self-validation experiment.

as birds flying in consistent speed and direction [32]. During data collection the wind speed is around 10m/s. Field observation during precipitation data collection confirmed negligible bird activities.

The track pre-processing on target tracks is required. Short tracks (shorter than 4) are neglected. Long tracks (longer than 20) are rare and sometime possess low quality due to incorrect plot association. They are filtered out either. Tracks with too many oscillations are mainly caused by clutter interference and tracking algorithm association error. Therefore, the upper oscillation time is set to 7. Tracks with average height lower than 50 meters are removed due to building sheltering and clutter interference. Training and testing databases are constructed using a random selecting algorithm with no repeated samples. Sample amounts for birds, drones and precipitation tracks in training database are 927, 635 and 1385. The corresponding numbers for testing database are 217, 184 and 239. The non-repeating sampling strategy provides 0% repetition rate.

V. RESULTS AND DISCUSSION
A. SEPARABILITY ANALYSIS
The training sample separability is firstly verified to explore the potential of classification performance. As the feature space is five dimensional, it is difficult to intuitively observe the sample separability in the original feature space. Therefore, the principal component analysis (PCA) technique is taken to extract first two dominant principal components from feature vectors. Figure 7 demonstrates the projection of first two principal components for three types of target feature vectors. Separability among three target types could be visually observed. The most distinctive separability is between drone and precipitation tracks, which represents the intrinsic motion feature difference between drones and winds. Bird samples present broader distribution in Figure 7 indicating their more abundant motion diversity.

There also exists overlapping samples between bird and drone/precipitation tracks. These samples are extracted for further exploration. Bird tracks overlapping with precipitations present simple flying trajectories and they could be categorized as small flocks. Bird tracks overlapping with
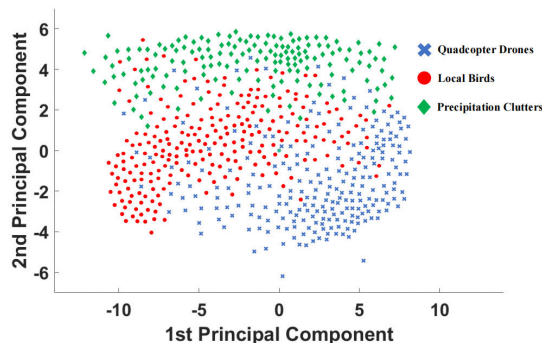
drones possess high maneuverability with slight oscillation. Moreover, it could be observed that bird and drone samples in Figure 7 present clustering patterns. The clutter centre for each type could be found using k-means algorithm. Samples surrounding drone clutter centre are mostly tracks presenting maneuverability like track B and D in Figure 2. These tracks are from drones performing video/photo collections. Therefore, separability analysis presented in Figure 7 consolidates confidence in effective target classification using the random forest model.

B. SELF VALIDATION
It is necessary to verify the quality of the trained classifier before its application for unknown sample classification. The five-fold cross validation strategy is usually taken for this verification. Figure 8 presents a confusion matrix with contents representing the rate of correct classification in cross validation. The green block indicates the correct classification and red ones denote misclassification. The accuracy could provide rate of correct classification over 85% indicating the acceptable quality of the constructed random forest classifier.

In many areas dynamic precipitation clutter interferences are minor. Therefore, the classifier's capability of merely distinguishing drones and birds is more attractive in more general surveillance scenarios. To verify this performance, the training database is reconstructed by excluding precipitation tracks. A new random forest model is trained. The corresponding confusion matrix is presented in Figure 9. There reflects slight variations on the rate of correct classification. The overall quality of the classifier is still good enough to provide satisfied classification accuracy.

FIGURE 9. Confusion matrix for self-validation excluding precipitation.

FIGURE 10. Confusion matrix for classification of three target types.

FIGURE 11. Confusion matrix for birds and drones classification.

FIGURE 12. Confusion matrix from self-validation by merging testing and training database.

C. ACCURACY AND EFFICIENCY DISCUSSION

In the proposed classification system, an unknown target track is represented by five descriptors in a feature vector. This vector is applied on the random forest model to get the target type determination. The classification accuracy is still quantified by the rate of classification in the confusion matrix, as illustrated in Figure 10. The average rate of correct classification for three target types is larger than 85%, and this could basically satisfy application requirements. The misclassification rate between drones and precipitation tracks is close to zero, which is consistent with their prominent difference as presented in Figure 7. Misclassified bird and drone tracks demonstrate smooth motion characteristics and their ground projection trajectories are highly similar with track C as in Figure 2. They reflect little distinctive features for effective classification.

Further explorations on distinguishing capabilities between birds and drones are provided by excluding precipitation samples. The confusion matrix in Figure 11 reflects negligible variation on the rate of correct classification compared with Figure 10. This also indicates that birds are major sources of interferences in drone target recognition problem. Moreover, according to Figure 6, all tracks are sampled at the radar detection range larger than 1km. This proves that the proposed method is capable of long range drone recognition under radar surveillance mode.

Unlike drones, the motion characteristics of birds and precipitations are closely related to dynamic environments. Therefore, even under the same surveillance region, they may present varying behaviour patterns under different seasons. This requires the surveillance system to properly adjust the training database for accurate motion pattern modelling. The

classification model needs to possess a good adjustability to training database modifications. To verify this, the training and testing databases are merged to construct a new database for random forest modelling. The five-fold cross validation experiment is also conducted for verification, as presented in Figure 12. There is minor variation on classification performance. This indicates the good robustness of the random forest model. However, it should be noted that this robustness verification is not very comprehensive due to limited samples.

The efficiency performance in classification is critical for a non-cooperative drone monitoring system. The low complexity of the random forest model and the feature vector dimension make the classification system possess the capability of efficient target classification. The random forest model adopted in this paper is developed by Python language. The computer is configured with Intel i5-7500 CPU with 16GB RAM. Due to the limited amount of training sample, it only costs 17.1 seconds in training procedure. For a single target track the system takes 0.27 seconds to make the target class evaluation. Therefore, the system could basically achieve the real-time target recognition. Results on accuracy, robustness and efficiency indicate the proposed classification model possess good application significance.

D. DISCUSSION ON GINI IMPORTANCE

Extra discussions on Gini importance are necessary for its significant contribution in feature selection. Figure 13 and Figure 14 present Gini importance distribution in different classification problems. Larger numerical values indicates higher degree of feature importance. The maneuverability factor with largest Gini importance indicates targets distinctive maneuvering capability difference in both classification
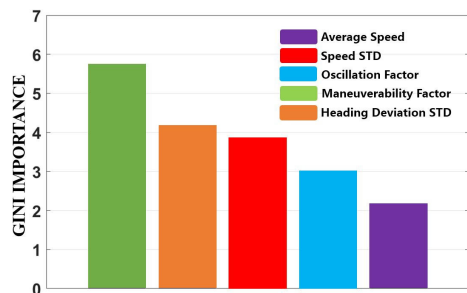
FIGURE 13. Gini importance in classifying birds-drones-precipitation.
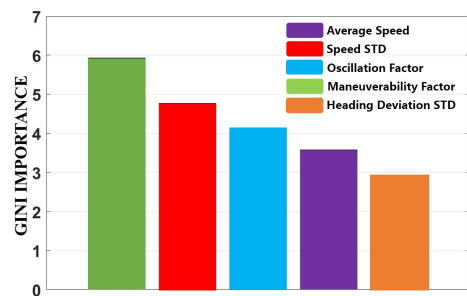

FIGURE 14. Gini importance in classifying birds-drones.

problems. In contrast, the average speed presents its minor contribution in classification, which is consistent with our empirical analysis.

Gini importance evaluation excluding precipitation clutters are conducted and presented in Figure 14. Compared with Figure 13, the prominent difference is the standard deviation of heading, which becomes least important. This indicates the dominant role of heading deviation in discriminating precipitation and other two types of targets. On the other hand, birds and drones could all make large heading deviations during flight, but their deviation patterns could hardly be reflected from standard deviation of heading. This results in its importance degradation in random forest. In contrast, this deficiency is complemented by the oscillation factor, whose Gini importance is promoted in the distinguishing between bird and drone targets.

Above discussions indicate that the Gini importance description on motion characteristic present consistent conclusions with empirical evaluations. The quantitative property of Gini importance is helpful for further understanding of target motion features and providing references on new feature's mining.

E. PROBLEMS AND FUTURE WORKS
Results in this section verify the effectiveness of the proposed feature extraction and classification method. However, existing works still have limitations with improvement potentials.

1. Target motion characteristics extracted from track information are highly dependent on tracking accuracy. Analysis on existing database indicates tracks might present distortions when large scale flocks crossing many resolution cells fly in nonuniform patterns. This might cause association algorithm error during tracking. Distorted tracks usually present inconsistent motion patterns resulting in adverse impact on classification accuracy. A potential solution to this problem is transferring focuses from a single track to group tracks. The extraction and utilization of multi-scale motion characteristics related to group targets might improve tracking and classification performance.

2. The proposed method in this paper only utilizes target motion characteristics for feature description. Radar echo signatures like RCS are not adopted. This facilitates the method applicable to other radar systems which could not provide RCS due to data security concern or access limitation. However, for systems whose RCS data is available the adoption of RCS information is beneficial. The relevance mining between motion and radar echo characteristic has the potential of further enriching target signature description. This topic would also be a major concern in our future works.

3. Misclassified tracks analysis indicates that the existing method have difficulty to distinguish tracks with smooth and consistent motion patterns. These tracks present high similarity in both radar echo and motion signatures. Other information sources need to be introduced to distinguish these highly similar tracks. One possible solution might be correlating the track information with surveillance environments. A joint probability distribution function could be modelled to describe bird activities. This probability distribution function could be utilized as an auxiliary decision making model to determine if a presented target a bird or something else (probably a drone). This is related with cognitive radar theory and might be another technique routine for low altitude airspace surveillance.

VI. CONCLUSION
The UAV technologies booming brings potential threats in many areas. This elevates the thinking of non-cooperative drone surveillance. Radar is the most proper technique solution for long range drone surveillance. However, low altitude airspace interference like birds and environmental clutters make accurate drone target recognition difficult and challenging within large surveillance area. This paper explores the motion characteristics of drones, birds and precipitation clutters. Five descriptors are proposed as target motion descriptor. The random forest model is selected as the learning machine for supervised learning due to its peculiar advantages for our problem. The proposed method is verified through a field experiment with target track information collected from a bird surveillance radar system deployed in the airport region. Results indicate acceptable classification accuracy, sample robustness as well as the high efficiency. Extra discussions on Gini importance distribution reflect good consistency with empirical analysis. The quantitative property of Gini importance also provides useful references in feature understanding and mining. Problems about the proposed method are also addressed. Multi-scale group target tracking, feature fusion with radar echo signature and the association with cognitive radar theory are three possible routes to further enhance the recognition accuracy in noncooperative drone target surveillance.

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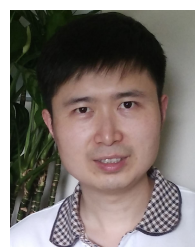
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