# Chebychev moments based Drone Classification, Recognition and Fingerprinting

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***Abstract:*** *This paper introduces the use of a Chebychev moments' based feature for micro-Doppler based Classification, Recognition and Fingerprinting of Drones. This specific feature has been selected for its low computational cost and orthogonality property. The capability of the proposed feature extraction framework is assessed at three different levels of major classification steps, namely classification, recognition and fingerprinting, demonstrating the effectiveness of the proposed approach to discriminate drones from birds, fixed wings from multi-rotors and drones carrying different payloads on real measured radar data.*

**Index terms:** Drones, UAVs, micro-Doppler, classification, recognition, fingerprinting, ATR , image moments.

## 1. Introduction

Counter drones is an area of growing interest within the radar community, due to the exponential growth in the use of this family of devices for both commercial and leisure as well as to the exploitation of drones for malicious use such as smuggling drugs into prisons or causing disruption on airport traffic. This led both industry and academia to investigate solutions to detect, track, classify and disable drones in order to mitigate possible hazards and threats.
Drones or UAVs represent a particularly challenging class of targets due to their small radar cross section and the fact that it is comparable with a large number of targets that could fall within a mainlobe or sidelobe of a counter drone radar. Example of targets that could lead to 'false alarms' if present in the radar mainlobe are birds, while ground vehicles are examples of targets that could deceive if appearing in a sidelobe. As the coexistence with drones will become more a reality, there will be the growing need to be able to have a higher degree of understanding of the characteristics of the target, with the challenge moving from the simple bird vs drone case


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to more detailed challenges such as fixed wing vs multi-rotor (recognition) and understanding if the drone carries a more or less heavy payload (fingerprinting). The recognition task will be relevant if for example a countermeasure has to be deployed, such as a drone equipped with a net to disable the threat, as knowing the degree of agility of the target drone increases the kills per shots rate. Understanding whether a drone is equipped with a specific payload, or a payload of a specific weight, can provide extremely useful insights on what and how dangerous the intent of the drone could be. For instance, a drone used for non-professional application equipped with a camera only would have a much lighter payload than the same drone used to smuggle phones, weapons and drugs in a prison.

The task of classifying micro-Doppler signatures of drones has been investigated with a number of approaches, such as the use of features extracted from the received I/Q radar signal using empirical mode decomposition (EMD) [1] as well as extraction of features from both high resolution range profiles and Doppler [2]. Recently, the latest deep learning frameworks have been also investigated for this challenge as in [3] that demonstrated how multi-layers perceptron can provide high classification rates of drones with different propellers, while the method proposed in [4] has shown how deep learning can be useful to denoise the micro-Doppler signature before a classification stage. In [5], the first investigation on the effect of different payloads was performed, proposing additional strategies to classify the radar returns in a multi-static radar system. While in [6] the payload recognition is addressed by using a spectral kurtosis based approach, interestingly other payload types have been also investigated in the literature recently such as dynamic payloads in [7]. As a matter of fact, micro-Doppler, that can be seen as additional frequency modulations induced by small displacement, rotation or vibration of secondary parts of the object under observation, have been widely exploited for target classification and micro-motion analysis, including hand-gesture, over the last decade [8–11].

In such a context, this paper proposes a method capable of automatically classifying radar signals related to drones exploiting their intrinsic micro-Doppler signature. In particular, following the line of reasoning of [8], the method extracts the Chebychev moments [12] from the cadence velocity diagram (CVD) obtained from the short time Fourier transform (STFT) of each recorded signal. The choice of using these image moments is motivated within the radar context for their useful characteristics. In fact, Chebychev moments, differently from Zernike [13], are directly defined on a discrete set, therefore no approximations are needed in their implementation. Additionally, they are characterized by their symmetry property that can be properly exploited to reduce both the computational time as well as the required storage in the database. The analyses are performed on two challenging datasets and show promising capabilities in terms of target classification, recognition and fingerprinting. The remainder of the paper is organized as follows. Section 2 introduces the proposed feature-based algorithm. The method is validated and the results discussed in Section 3. Finally, Section 4 concludes the paper.

## 2. Chebychev Feature Extraction Based Algorithm

This section explains the considered micro-Doppler signatures classification procedure, whose main steps are graphically illustrated in the block-scheme of Figure 1. This approach uses the

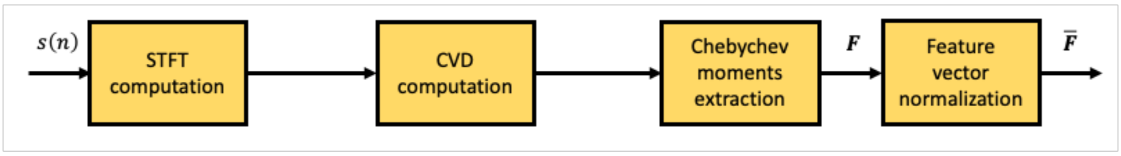


Figure 1: Block scheme of the proposed micro-Doppler hand-gesture signatures classification algorithm.

same line of reasoning of that proposed in [8,9], and replacing the pseudo-Zernike/Krawtchouk moments with the Chebychev ones. Full description of the Chebychev's moments can be found in [12]. Starting from the I/Q signal the spectrogram is computed in order to obtain a 2D real valued image. Then, to increase Signal to Noise Ratio and highlight periodical components in the micro-Doppler signature the Cadence Velocity Diagram (CVD) is computed by applying a discrete Fourier transform in the time direction for each Doppler bin. The absolute value of the CVD is then projected on the Chebychev Polynomial basis extracting a 1-D feature vector that undergoes a linear normalization stage that removes the mean of the feature vector and scales it by its standard deviation in order to avoid biases. The extracted features can be then fed as input to a classifier to predict the class of the target. Remarkably, this approach is characterized by a low computational cost, as the computation of the moments has a complexity of $\mathcal{O}(M \times N)$, with $M$ and $N$ being the dimensions of the CVD.

## 3. Performance Assessment

The aim of this section is to demonstrate the effectiveness of the proposed procedure based on the exploitation of the Chebychev moments to recognize different drones at various level of classification. To do this two datasets have been used. A Ku band dataset, containing returns from 10 (1 bird, 3 fixed wing and 6 multi rotor) types of targets and acquired by Plextek DTS, is used for the Drone vs Bird and Fixed Wing vs Multi Rotor tasks, while the dataset collected by the University College London comprising loaded and unloaded drones using the S-band radar system NetRAD [14] is used to assess the capability to discriminate between loaded/unloaded drones and discriminating the payload weight. Details of the Ku band dataset are reported in Table 1, while in [6, 14] can be found the details of the NetRAD data. To evaluate the effectiveness of the classification procedure proposed in Section 2, the considered figure of merit for the Ku band dataset are the accuracy and the average F1-score, which results to be more reliable when dealing with unbalanced datasets, while accuracy only is considered for the S-band data. Furthermore, the moments of the orders are considered from order 2 to order 18. Finally, three

Table 1: Ku Band Dataset Composition

| **Target Type** | **# of 1s long observations** |
|---|---|
| Fixed Wings | 1743 |
| Multi-Rotors | 4354 |
| Birds | 504 |

different classifiers have been used, a K-Nearest Neighbours ($k = 7$), a Support Vector Machine (with Gaussian kernel) and a Random Forest classifier [?]. The first set of results are reported in Figure 2, showing both the accuracy and the average F1 scores for the Chebychev and the Krawtchouk based approach proposed in [9], showing the performance when the classification challenge is Bird Vs Drone. From the results it can be seen that in this case the Krawtchouk based approach shows a better accuracy, however this result is not confirmed by the average F1 score, suggesting that, in reality, is the Chebychev based approach that achieves the best performance when used in combination with a Random Forest Classifier, achieving an F1 score of $0.85$, and meaning that the high performance achieved by the Krawtchouk based approach is strongly biased by the unbalance in the dataset. The second set of results is shown in Figure

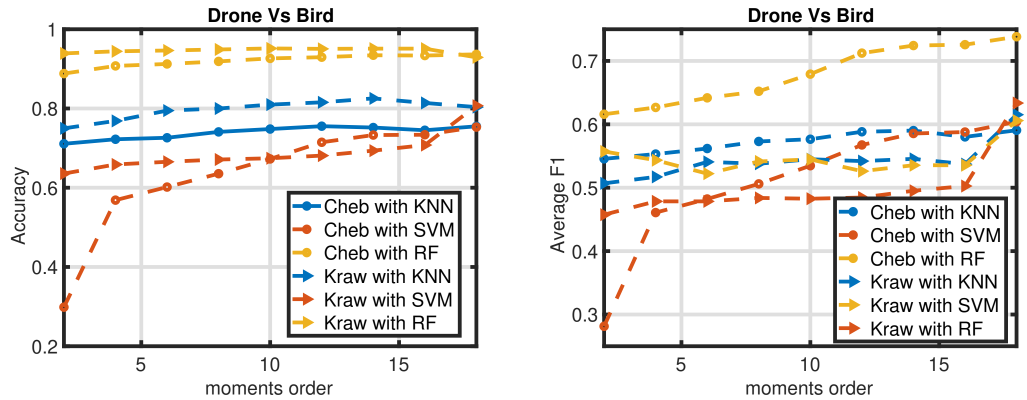


Figure 2: Accuracy (left) and average F1 score (right) for the Drone Vs Bird Classification challenge.

3, reporting the case of classification of Fixed Wing vs Multi Rotor. In this case the superiority of the proposed approach is evident and confirmed in both accuracy and average F1-score. In particular, both accuracy and average F1 score achieve values constantly above $0.8$ for the three classifiers and all the order of the moments considered in the analysis. Last set of results

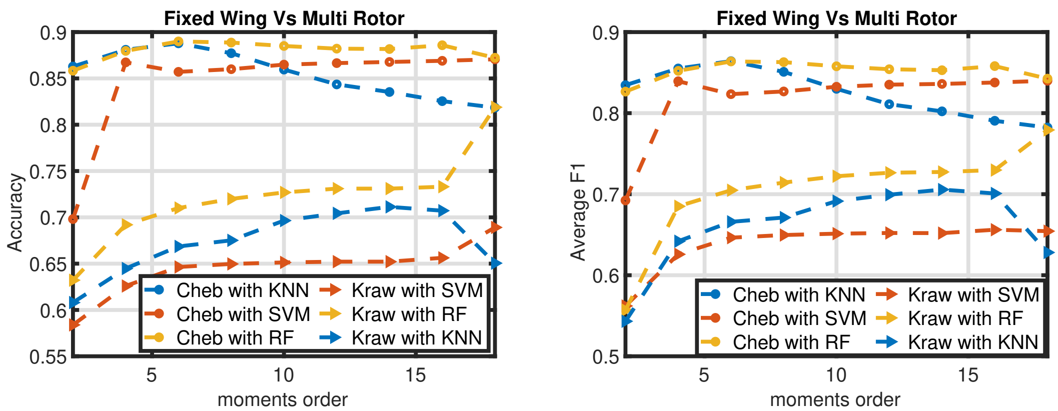


Figure 3: Accuracy (left) and average F1 score (right) for the Fixed Wing Vs Multi-Rotor challenge.

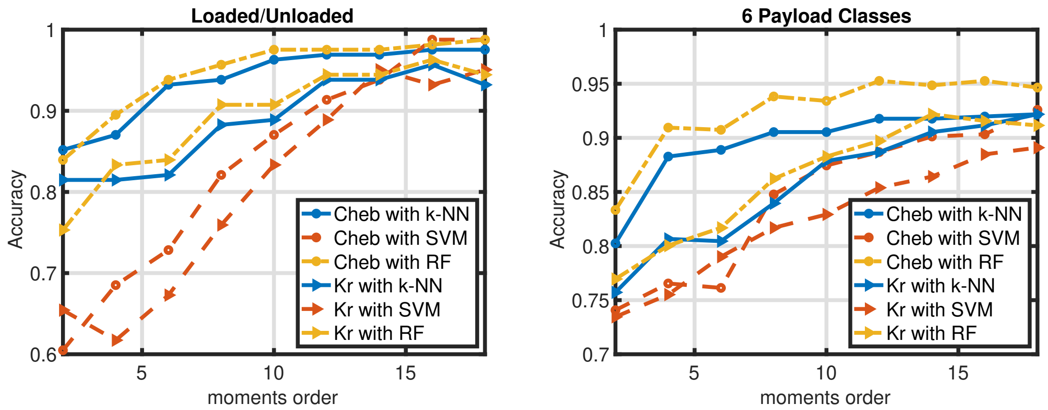


Figure 4: Performance on the Loaded/Unloaded payload classification challenge (left) and of the classification of the 6 payloads (right).

investigates the performance when the S-band dataset containing acquisitions with different payloads is considered. Figure 4 shows the performance obtained when the discrimination is limited to the binary classification Loaded Vs Unloaded as well as when a finer fingerprinting is investigated with 6 different payload weights considered with [0, 200, 300, 400, 500, 600] grams of additional payload. In both cases it can be seen how the Chebychev based approach is still able to provide the best performance, and also in this case the performance obtained when considering the Random Forest classifier are the best. In particular a remarkable $95\%$ of accuracy is achieved in the 6 classes payload discrimination challenge vs $\approx 90\%$ achievable with Krawtchouk moments.

## 4. Conclusions

This paper has investigated the challenge of Classification, Recognition and Fingerprinting of drones by using an approach exploiting the Chebychev moments as features to discriminate the various classes. The approach has been tested on real data and has demonstrated to perform well and more importantly it has shown to be reliable when applied to different classification challenges and datasets. Given its low computational cost and portability, this approach can be a candidate for implementation on mobile platforms. Extensions of this work would include the analysis taking into account different SNR levels and Doppler resolutions, the investigation of different representations of the micro-Doppler signature other than the CVD as well as the integration of the method in an heterogeneous processing pipeline able to integrate multiple approaches and fuse decisions at various levels of the processing chain.

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