Radar Recognition of Multi-Propeller Drones using Micro-Doppler Linear Spectra

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***Abstract* — This paper proposes to perform radar recognition of multi-propeller drones using micro-Doppler linear spectral pattern in long Doppler coherent processing interval (CPI) circumstances. It focuses on the investigation of the influence of geometry design and motion variables, such as blade number, blade shape, drone's design geometry and propeller synchronisation, on the micro-Doppler spectral pattern. We propose suitable scalar features for the characterisation of these patterns measured within a long (relatively to propellers rotation period) CPI. A thin-wire model was used to simulate drones micro-Doppler spectra for various input variables. Proposed features are extracted from the simulated micro-Doppler spectra for further processing in a support vector machine (SVM), with the purpose of demonstrating the radar recognition of multi-propeller drones based on these features.**

***Keywords* — radar, drone, micro-Doppler, feature, CPI**

I. Introduction

Last years multi-propeller drones have widely spread to civil and industrial domains. The improper use of them harms flight safety and civil security. To evaluate and eliminate these threats, radar systems are used for the detection and classification of such targets.

Traditionally, the analysis of micro-Doppler patterns of radar data has been used to classify drones. In [1], the authors merged a drone micro-Doppler image with its cadence-velocity diagram and performed classification using convolutional neural networks (CNN). In that work, the link between the micro-Doppler images, drone's motion properties and its influence on classification results were undisclosed. De Wit et al. in [2] extracted micro-Doppler features using the singular value decomposition (SVD) technique. These features of SVD components were proposed for characterisation of the periodic quasi-sinusoidal micro-Doppler patterns. In [3], the author extracted physical features from time-velocity diagrams, i.e. micro-Doppler image, such as base velocity, total Doppler bandwidth, and cadence frequency. In these works, micro-Doppler features were based on clear periodic quasi-sinusoidal patterns. However, the periodic micro-Doppler pattern presenting the propeller rotation in detail is a result of a Doppler CPI much shorter than propeller rotation period, so that in each time interval of integration the propellers orientation angles do not change too much.

Drone's micro-Doppler linear spectral pattern is commonly observed by radar systems with low pulse repetition frequency (PRF) and/or high Doppler resolution. In these systems, to achieve a good signal-to-noise ratio (SNR), long CPI equal to several propeller rotation periods is used for Doppler processing, smearing periodic micro-Doppler pattern into linear pattern [4]. It is important to study and understand the relation between the observed micro-Doppler linear patterns and the characteristics of multi-propeller drones, radar signals and processing configurations. For the efficient implementation of radar recognition, it is also important to propose a set of suitable scalar features to characterise the micro-Doppler linear patterns, which can be used in recognition algorithms.

The paper is organized as follow. Section II presents the micro-Doppler linear spectral patterns of multi-propeller drones simulated by a thin-wire model in relation to the input variables of drone parameters. In Section III, micro-Doppler features are proposed based on the understanding of the input variables' influence. Section IV applies the proposed features to drone classification within simulated scenarios of different drones in various flight modes. Section V concludes the paper and formulate plans for future work.

II. Influence of design and motion variables

In order to investigate the influence of drone's design and motion variables on micro-Doppler patterns, a thin-wire model [4] that simply represents a propeller blade as two thin wires was proposed to calculate the reflected on a multi-propeller drone electromagnetic (EM) signal in time domain (see Fig.1b). The phase of the reflected in the drone propellers' rotation plane signal is given by (1). Symbol $\sim$ indicates proportionality. Parameters $\eta = 120\pi$ and $k = 2\pi/\lambda$ are the intrinsic impedance of air and the wavenumber of EM signal. P, B and W are the numbers of propellers, blades per propeller, and of thin wires per blade, correspondingly, in the simplified model. Variables r_p and r_0 indicate the distance from the p^{th} propeller's rotation centre and the the centre of drone's geometry design to an observation point. Element

Table 1. Input Variables of Drone Properties in Thin-Wire Simulations

Variable combination	(a)	(b)	(c)	(d)	(e)	(f)
Blade number B	2	3	2	2	2	2
Blade length l [m]	0.11	0.11	0.22	0.11	0.11	0.11
Prop. initial angle θ_0	0	0	0	random	0	0
Prop. number P	4	4	4	4	6	4
Prop.velocity shift (from 4000 rpm)	0	0	0	0	0	20%

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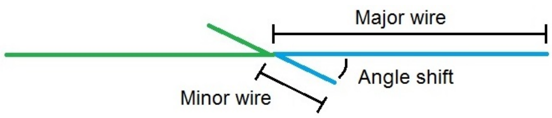
$dz'_{p,b,w}$ is the length of infinitesimal dipole along the z-axis at the distance $z'_{p,b,w}$ along the w^{th} wire of the b^{th} blade of the p^{th} propeller in the rotation plane. $l_{p,b,w}$ is the length of this wire, and parameter $\theta_{p,b,w}(t)$ gives the rotation angle of this wire at time t: $\theta_{p,b,w}(t) = \theta^0_{p,b,w} + \Omega_p t$ as a function of its angular velocity Ω_p and initial angle $\theta^0_{p,b,w}$ relatively to the LOS at time $t = 0$.

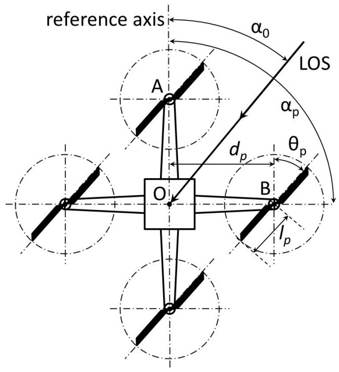
$$\begin{aligned} E^{drone}(t, r_0) &\sim \sum_{p=1}^{P} E_p^{prop}(t, r_p, \theta_{p,b,w}, l_{p,b,w}) \\ &= \sum_{p=1}^{P}\sum_{b=1}^{B}\sum_{w=1}^{W} E^{wire}_{p,b,w}(t, r_p, \theta_{p,b,w}, l_{p,b,w}) \\ &= \sum_{p=1}^{P}\sum_{b=1}^{B}\sum_{w=1}^{W} \int_0^{l_{p,b,w}} j\eta \frac{ke^{-jkr_p}}{4\pi r_p} \times E^{in}_{r_0}(t) \\ &\times \sin\theta_{p,b,w}(t) \times e^{j2kz'_{p,b,w} cos\theta_{p,b,w}(t)} dz'_{p,b,w} \end{aligned} \tag{1}$$

Micro-Doppler patterns of specific drones were simulated by applying short-time Fourier transform (STFT) to the model-based signal series using corresponding input variables. In the simulations, the geometry of a popular drone, DJI Phantom 4 was taken as an example [5]. Its propeller blades were simplified as two thin wires of 11.43 cm and 2.29 cm in length, shifted of 15°. The distances from the propeller rotation centre to the centre of drone geometry design was set as 0.175 m, imitating the DJI Phantom 4 drone. The radar parameters were set the same as for the PARSAX system [6], with single carrier frequency f_c=3.315 GHz, sampling frequency f_s=PRF=1 kHz, and CPI=512 ms for Doppler processing with 256 ms overlapped. These setups are quite common for S-band radar systems.

Various combinations of other variables (see Table 1) were used in the simulations, in order to discuss their influence on the simulated micro-Doppler patterns. In real practice, these variables are related to drone types and flight attitudes. The bottom row in Table 1 indicates the variety of propellers rotation periods around the mean value of 15 ms in the simulations. In this circumstance, the CPI is much longer than the propeller rotation period, thus giving linear micro-Doppler patterns of interest.



(a)



(b)

Fig. 1. Thin wire model of propeller and multi-propeller drone used in micro-Doppler pattern simulation: (a) propeller, (b) multi-propeller drone

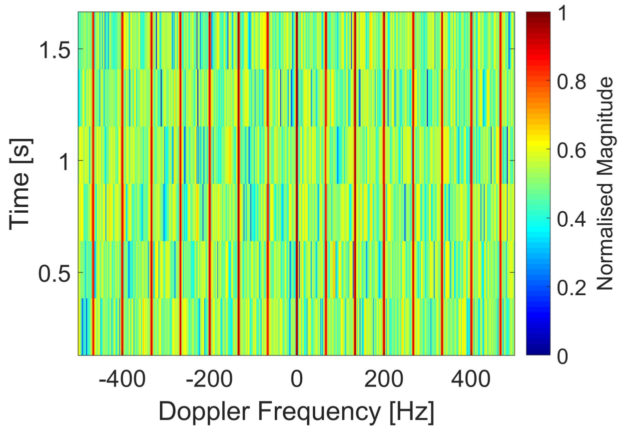


Fig. 2. Simulated micro-Doppler pattern for the variables combination (a) in Table 1

Fig.2 presents the normalised simulation result of micro-Doppler pattern using variable combination (a) in Table 1. In this figure, the normalised magnitude of background noise is about 0.5, while the micro-Doppler pattern peaks appearing at several frequencies have the normalised magnitude close to 1. The pattern shown in Fig.2 can be further averaged over the time interval of 1.5 seconds, during which the fluctuations of the patterns observed in real open air scenario due to air disturbance can be averaged. Such averaged over time result of the micro-Doppler linear pattern in Fig.2 is shown in Fig.3, together with the averaged over time results for other combinations of variables (see Table 1) evaluated using the same simulation method.

As can be seen from the comparisons of sub-figures in Fig.3, the number of blades per propeller has a strong influence on the micro-Doppler pattern, by introducing different harmonic components of Doppler spectra. The length of blades slightly influences the bandwidth of each Doppler pattern peak. The change of rotation velocity due to blade length is small and does not affect much the resulting pattern. The synchronisation of propellers in rotation angle influences the micro-Doppler pattern obviously, since the phase of backscattered signal series is modulated by the angle shift between rotating propellers, together with the geometry design of the drone, eliminating the symmetry of micro-Doppler spectra around zero frequency. The synchronisation of propellers in rotation period complicates the micro-Doppler pattern by introducing more velocity components, and the pattern shifts away from zero frequency due to the radial velocity of the whole drone. The number of propellers does not influence the micro-Doppler pattern alone, but coupling with other variables.

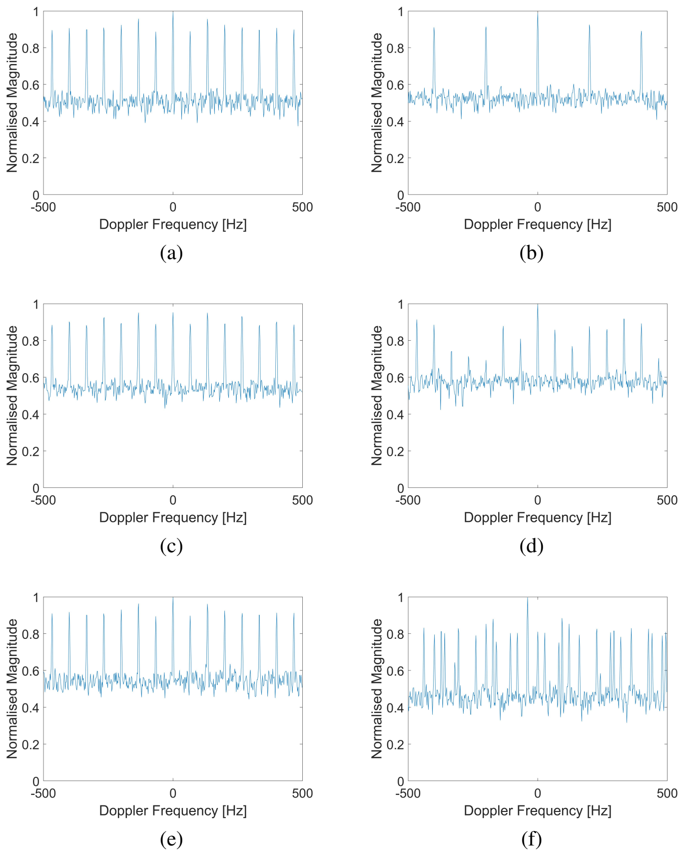


Fig. 3. Averaged over time simulated micro-Doppler spectra patterns using various combinations of variables: (a)-(f) correspond to variable combination (a)-(f) in Table 1

Overall, these variables of the blade properties, propeller synchronisation and drone geometry design together influence the linear micro-Doppler pattern in terms of the frequency where pattern peaks appear and the relative magnitudes of the peaks.

III. The features for drones recognition

Understanding the influence of drone variables on the micro-Doppler patterns in terms of the frequency and relative magnitudes of micro-Doppler pattern's peaks, it is a natural choice to extract features from these two aspects. In the averaged over time simulated micro-Doppler spectra, the location of frequencies where pattern peaks appear f_1^l is proposed as a feature. f_1^l is defined as a vector of s entries, where s is the number of frequency points over Doppler bandwidth. The ith entry of f_1^l is set to be 1 if a linear pattern peak appears at the ith frequency, or otherwise 0. The mean f_2^m, the standard deviation f_3^{sd} and the entropy f_4^e of the magnitudes of pattern peaks are computed as additional features, since these values illustrate the distribution of the magnitudes of peaks linear pattern in a statistic way. Fig.4 shows the frequency points of value 1 in blue ellipse on the horizontal axis and the magnitudes of pattern peaks in red ellipse on the vertical axis.

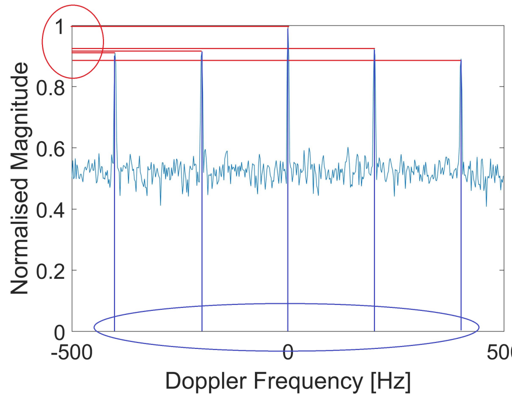


Fig. 4. Magnitudes and frequencies of pattern peaks in the averaged over time simulated micro-Doppler spectra pattern

The final feature list z is given as

$$z = [f_1^l \quad f_2^m \quad f_3^{sd} \quad f_4^e] \tag{2}$$

and combines the proposed above features. They are derived from the frequencies and magnitudes of the peaks of linear micro-Doppler spectra, thus containing the information of drone properties.

IV. An example of drones recognition

Support vector machines (SVM) separate different classes of data with hyperplanes giving the largest margin and demonstrate good results in micro-Doppler targets recognition [7] [8]. In this article, a binary SVM classifier offered by MATLAB R2017b as $fitcsvm$ and $predict$ functions was used to validate the proposed micro-Doppler features, with the SVM parameters of $KernelFunction$ and $Standardize$ set as rbf and $true$. There are more sophisticated techniques to solve this classification problem, but in this paper was selected a simple method with the aim of validating the proposed features for characterising linear micro-Doppler spectra patterns.

The data of linear micro-Doppler spectra averaged over the time of 1.5 seconds was achieved from simulations of thin-wire models of a quadcopter DJI Phantom 4 and a hexacopter DJI Matrice 600 [9]. The variables of blade properties and drone geometry designs were chosen according to real drones, while the propellers were given random initial angles at start time t=0. The drones were assumed in hovering and maneuvering flight attitudes with propellers synchronous and asynchronous in velocity. In maneuvering flight attitudes, the drones were supposed moving radially towards the radar Tx/Rx antennas, with half of the propellers rotating faster than the rest. The velocity difference varied randomly within $\pm$50% of the standard rotation velocity. In the simulations, radar parameters were set the same as in the PARSAX system. Fig.5 illustrates the data set of the averaged over time linear micro-Doppler spectra patterns simulated for these drones and flight attitudes. For each simulation result, the proposed features were extracted and used in the SVM classifier, and 40% of the total data were used to train the SVM classifier, while the rest 60% - for tests.

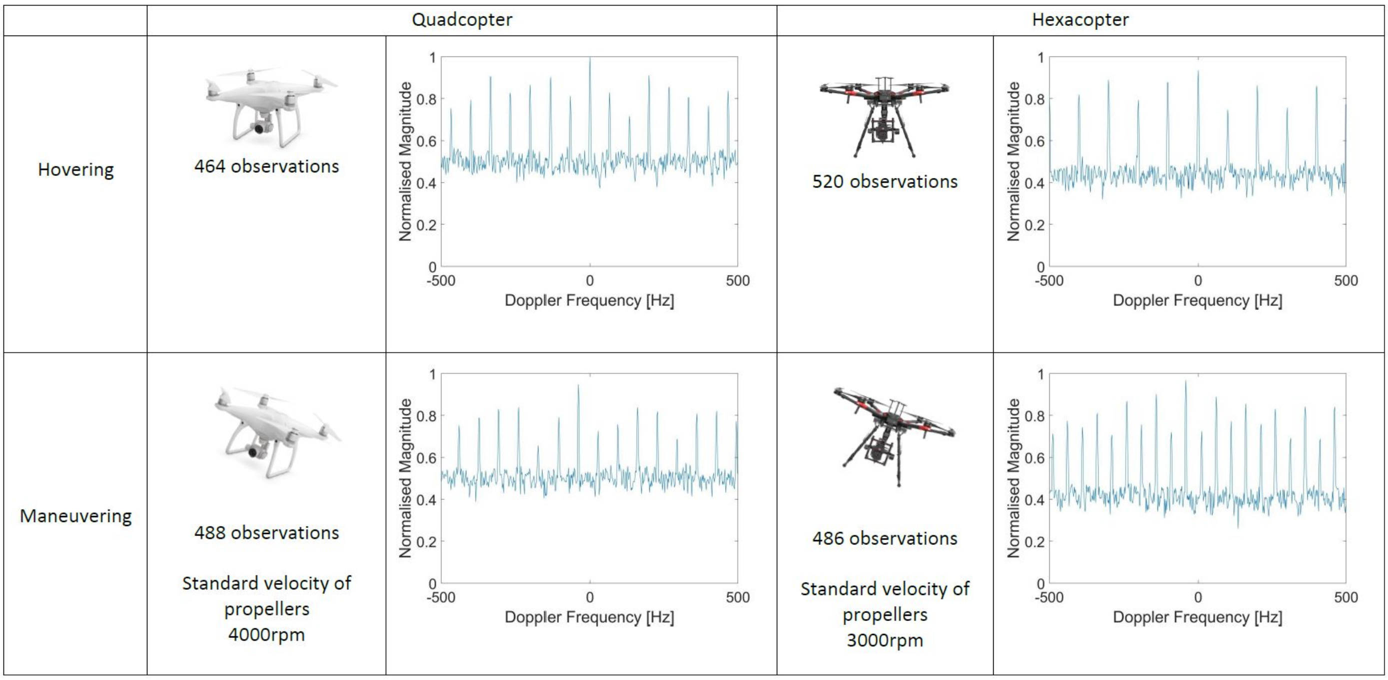


Fig. 5. Simulated data set of micro-Doppler linear spectra: two drones in two flight attitudes

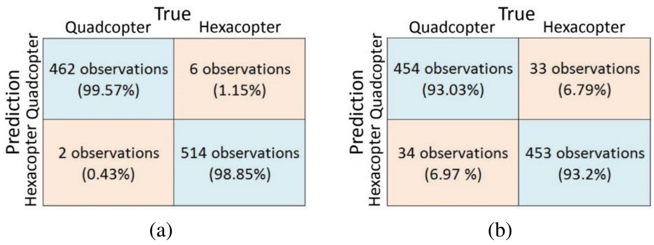


Fig. 6. Results of drone recognition accuracy using proposed features on simulated linear micro-Doppler spectra patterns: (a) Hovering flight attitude, (b) Maneuvering flight attitude

Fig.6 summarises the classification results. The SVM gives good classification accuracy using the proposed features. Maneuvering flight attitude achieves slightly lower accuracy due to additional variables of propellers synchronisation in velocity. The results validate that the proposed features are appropriate to characterise linear micro-Doppler spectra patterns in long CPI circumstances.

V. Conclusions

In this paper, the influence of drone's parameters, such as blade properties, propellers synchronisation and drone geometry design, on the micro-Doppler linear spectra were investigated using thin-wire model simulations for a long CPI circumstances. Based on the observed frequency peaks amplitudes and locations in the micro-Doppler linear spectra were proposed efficient features for the recognition of drones. Their efficiency has been validated using good classification results for the simulated quadcopter and hexacopter data. Applications of the proposed features on the real data of flying drones observed by radar systems will be a following research step in future, with the aim of confirming these features' robustness under different real circumstances, including different types of drones, flight scenarios and radar setups, in order to perform the detection and recognition of multi-propeller drone using radar systems with low/medium PRF and long CPI.

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