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# MACHe - Model-Based Algorithm for Classification of Helicopters

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**Abstract**—Secondary motions of a target, such as rotating blades of a helicopter’s main rotor, induce a Doppler modulation around the main Doppler shift. This represents a unique feature of the target itself, known as micro-Doppler signature, and can be used for classification purposes. In this student research highlight a model-based automatic helicopter classification algorithm is presented. It is a parametric classification approach based on a sparse signal recovery method and it is independent of both the initial position of the blades and the aspect angle. The algorithm is tested on simulated and real data.

## I. INTRODUCTION

The Doppler effect is the change in frequency of a wave (sound or electromagnetic wave) radiated, reflected or received from a moving object. It arises in radar systems when there is a relative motion between the radar and the target. In particular, depending on whether the illuminated target is approaching or receding the radar, the Doppler frequency shift is positive or negative, respectively.

In many cases targets exhibit additional movements to the bulk motion, such as swinging limbs of a human walking or rotating blades of a helicopter’s main and tail rotors. These secondary motions induce a Doppler modulation around the main Doppler shift known as micro-Doppler (mD) effect [1]. The maximum mD frequency shift of a rotating object depends on its tip velocity. Thus the mD frequency shift induced, for example, by a wide set of helicopters, can reach values as high as 13 – 15 kHz at the X-band [1]. Therefore, it is easily detectable and can be exploited for civil and military purposes.

In the last decade several mD-based radar techniques have been reported [2]. The challenging problems of human gait classification and human behaviours recognition in a cluttered urban environment or in presence of vehicles have been widely addressed by mD techniques. These are mostly based on the extraction of information from a time-frequency distribution, such as the Short Time Fourier Transform (STFT) and the Cadence Velocity Diagram [3]. Similar techniques have been applied for the challenge of helicopters classification [4], where it was demonstrated that the return signal from propeller blades depends on the number, the length and the rotation speed of the blades themselves and generates a distinctive mD signature. Classic approaches to the helicopter classification problem are based on the computation of the  $L/N$ -quotient [5], where  $L$  is the length of the main rotor blades and  $N$  is the number of blades. However, it is evident that two different models that share the same  $L/N$ -quotient cannot be distinguished. More recent methods attempt to solve this problem

by exploiting information extracted from the spectrogram of the radar signal [6], [7]. Nevertheless, this adds significant computational and algorithmic complexity to the process.

In the remainder of this article, a novel algorithm for helicopter classification is presented. Performance results are given using simulated and real data.

## II. CLASSIFICATION ALGORITHM

The helicopter classification method presented in [8] is an iterative automatic algorithm that is independent of both the initial position of the blades and the aspect angle (i.e. the angle between the line-of-sight and the perpendicular to the plane in which the blades lie). It does not need any signal-dependent tuning parameter, as it may be the window size used to compute the spectrogram in a STFT based method. Moreover, it is a parametric classification approach [9] that does not require any prior information about the target (i.e. samples acquisitions) but its model of rotating blades [1]. The idea is to model the received radar signal in a sparse domain, and then retrieve such a sparse representation in order to estimate the helicopter’s parameters.

Figure 1 shows the block diagram of the proposed classification algorithm. Firstly, the received signal of the detected helicopter is pre-processed by subtracting its mean and normalizing it to its maximum absolute value. This is done in order to remove the strong return from the fuselage of the aircraft and to make the algorithm independent of the radar cross section (RCS) of the target, respectively. Secondly the synchronisation step ensures that the algorithm is also independent of the initial position of the blades. The red box in Figure 1 represents the iterative procedure steps used to estimate the parameters of the helicopter, namely the rotation speed,  $R$ , the length of the blades,  $L$ , and the number of blades,  $N$ . These steps implement a modified version of the Pruned Orthogonal Matching Pursuit (POMP) presented in [10], which is the combination of the iterative OMP with a pruning process aimed to solve a parametric sparse representation problem. Note that the rotation speed of the main rotor,  $R$ , is a distinctive feature of the helicopter, since it is constant in a normal operational mode [11]. However the estimate of the length of the blades,  $L$ , is not used in the final classification step, since it is strongly affected by the aspect angle, thus it does not represent a reliable feature. Finally, the classification is carried out by finding the entry in a look-up table that corresponds to the minimum Euclidean distance with the estimated couple  $(N, R)$ .

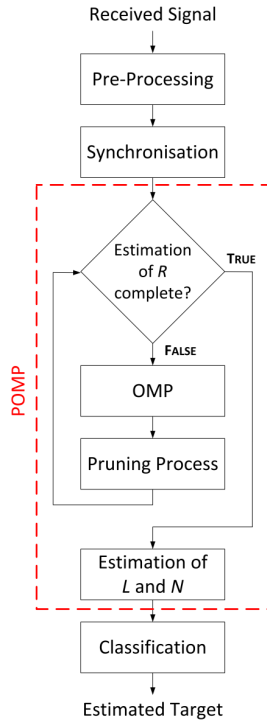


Fig. 1. Block diagram of the proposed classification algorithm.

### III. RESULTS

The algorithm has been tested on both simulated and real data, the latter acquired in our EM anechoic laboratory environment using a real scaled helicopter. The simulated dataset is a collection of signals scattered by 9 different helicopters, 100 realizations for each of them. The performance, on varying the  $SNR$  and for each target, is shown in Figure 2. At 0 dB,

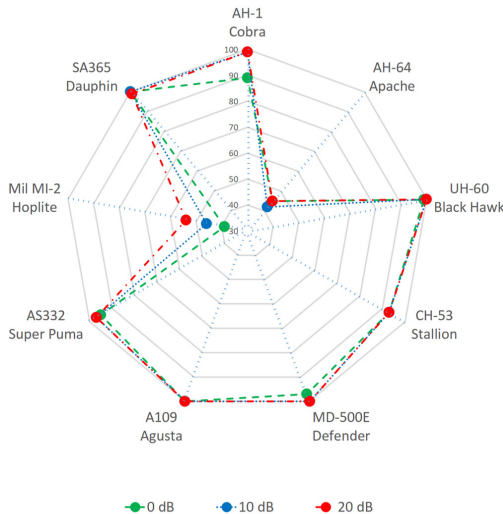


Fig. 2. Performance on simulated data in terms of percentage of correct classification, for each target on varying the  $SNR$ .

the percentage of correct classification is equal or greater than 90% for 7 out of 9 targets. The *Apache* and the *Hoplite* present the lowest performance: the former is misclassified with the

*Cobra*, which has a similar rotation speed. For the latter the algorithm estimates 6 blades rather than 3, which makes it close, in terms of Euclidean distance, to the *Stallion*. The validity of the approach is confirmed by the results obtained on the real dataset, which is a collection of signals acquired with a 24 GHz Continuous Wave (CW) radar and scattered from a two-bladed helicopter scale model GAUI X3, whose main rotor is made to rotate at three different speeds. The GAUI X3's main blade length is 36 cm, which corresponds to a small helicopter, with blade length of about 290 cm, in a real scenario with an *S*-band radar (3 GHz). In order to test the robustness and reliability of the algorithm, 8 confusers are introduced in the classification look-up table; the performance shows an overall 82.44% of correct classification.

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His research interests include micro-Doppler based and SAR based classification and identification, Compressive Sensing based radar techniques and MIMO radar signal processing.