



Recognizing impurities of Micro Doppler Signals and determination of the target

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ABSTRACT

This paper addresses the problem of recognizing and mitigating impurities in micro-Doppler signals to improve target classification accuracy. Micro-Doppler signatures capture fine movements of objects, but noise, clutter, and environmental interference introduce impurities that degrade classification performance. We propose a hybrid approach combining advanced signal processing and machine learning to detect impurities, filter out interference, and accurately determine the target. Experiments demonstrate the effectiveness of our method on both synthetic and real-world datasets, with improved classification performance in noisy environments.

Keywords: Micro-Doppler, radar, deep learning, feature extraction, machine learning, pattern recognition, classification algorithms.

1 Introduction

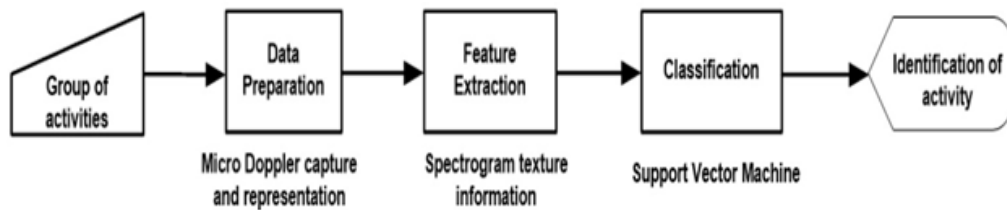
The use of first operational radar for remote sensing of targets dates back to the Second World War in which ‘Chain Home’ radar network was used by the Royal Air Force to provide early warning about detection of enemy aircraft [1]. The need for automatic target recognition was felt at the earlier stages of radar development and since then it has remained an active area of research. It was as early as 1937 when the target recognition experiments were carried out by adding resonant dipoles to friendly aircraft for their discrimination from enemy aircraft [2]. Secondary Surveillance Radars (SSR) were then introduced to achieve target classification using Identification of Friend and Foe (IFF) transponders. However, this technique was dependent on the target transmitting the required information. In 1980, Merrill Skolnik presented certain approaches in his famous book [3], which can be employed for target recognition. One of the approaches was the Jet Engine Modulation (JEM), which deals with engine induced frequency modulation on the echo signal of radar.

In many scenarios, the sub-components of a target exhibit micro-motions such as rotation, vibration, tumbling, and coning, in addition to the target’s “bulk motion”. Examples of such micro motions include rotating blades of a helicopter or multicopter, rotating blades of propeller of a fixed wing aircraft, swinging arms and legs of a pedestrian, and rotation of wind turbines. In war time scenarios, rapid and robust target classification is vital as it can help in generating appropriate response according to the type of threat being identified. With the deployment of radars in cluttered urban scenarios and prompt availability of many commercial off-the-shelf



(COTS) drones, there is a growing need for detection and classification of smaller targets like humans, drones, bicycles, birds, etc. That is why the velocity and Radar Cross Section (RCS) thresholds need to be lowered for detection of smaller targets. This invites a large number of target signatures, which if not discerned, may lead to loss of situational awareness. Thus, target classification has become critical

Architecture design / diagram



2 Recent Works

In the recent work, to perform target recognition based on the micro-Doppler effect, certain discriminating features are usually extracted. The accuracy of the classifier is dependent on the robustness of the selected features and its relevance to the dataset. Micro-Doppler returns from a target depend on its RCS, radar operating frequency, and aspect angle. Therefore, extracted features should be robust enough against variations caused by these factors. Feature extraction for micro Doppler-based classification can be divided into two categories depending upon the type of classifier employed.

First is to directly use the micro-Doppler signature images as features for classification. These images can be in the form of spectrograms [21–23], CVD [24], cepstrograms or a combination of these micro-Doppler signature images [24]. This is particularly used when Deep Convolutional Neural networks (DCNNs) are employed as the classifier [21–25].

Second approach is to extract statistically uncorrelated or independent features from micro-Doppler signature using methods like Singular Value Decomposition (SVD) [26, 27], Principal Component Analysis (PCA) [28] and Independent Component Analysis (ICA) [29]. Empirical Mode Decomposition (EMD) has also been successfully employed for extracting micro motion features generated by rotating or vibrating structures [30–32]. An algorithm proposed in [7], extracts four micro Doppler features from spectrograms and cepstrograms, to discriminate between UAVs and birds. Cadence Velocity Diagram Frequency Profile (CVDFP) and Mean CVD are used as features for micro-Doppler classification in [28, 33] respectively.

3 Proposed Work Explanation

Designing a system for recognizing impurities in micro-Doppler signals and determining target characteristics requires a multi-step approach to process, analyze, and classify signals with high precision. Micro-Doppler signatures are small variations in frequency caused by minor target movements (e.g., body or limb motion) that are captured by radar systems. Detecting



impurities in these signals and correctly identifying targets involves several critical stages.

3.1 Micro-Doppler Signature Analysis

Fourier transform does not provide time dependent frequency information. Hence, it is not suitable for the analysis of micro-Doppler signals since the spectral content of these signatures vary with time [4]. Time-frequency analysis techniques do provide spectral and temporal information of the micro-Doppler signal simultaneously, in which the following methods are employed [4]:

3.2 Model-based Classification Approach

Model-based methods rely on the parametric models of the dynamic and kinematic properties of targets for classification. Examples of such models are the Thalmann model for human walking [43], and Vignaud model for human running [44]. These methods estimate the probability of radar data to fit a predefined model by simulating the data with different input parameters of the model, and find out the parameters that minimize the difference between the simulated and real data. In [45], a model-based classification of human motion is proposed by applying particle filtering to micro-Doppler spectrum of targets. Particle filters are a set of Monte Carlo algorithms that use a set of particles with associated weights to represent the required posterior density and to compute estimates. Model based classification methods can provide useful information regarding the current dynamic state of target by providing estimates of target's motion parameters. However, these methods require high processing power due to model calculations for different parameters, generalized models, and tackling the problem of nonconvergence for large number of parameters [42].

4 Data-driven Classification Approach

Data-driven classification methods can be further categorized into template matching, conventional Machine Learning (ML) techniques and Deep Learning (DL) techniques.

4.1 Dataset Generation for Data-Driven Algorithms

Any coherent Doppler radar such as pulse-Doppler, Continuous Wave (CW), or Frequency-Modulated Continuous Wave (FMCW) can be employed for capturing micro-Doppler returns from the targets. CW radar offers advantages of high sampling rates and longer integration times whereas pulse-Doppler / FMCW radar can calculate target range; thus improving the Signal to Noise Ratio (SNR) of micro-Doppler returns. However, pulse-Doppler and FMCW radars have relatively low Pulse Repetition Frequency (PRF) / Scan Repetition Frequency (SRF), which can result in major Doppler fold-over [63].

Collecting real data for the radar micro-Doppler-based target recognition is laborious and expensive. However, diversity in the limited training dataset can be enhanced by generating additional data with Generative Adversarial Networks (GANs) and model-based simulations [64]. Additionally, transfer learning and unsupervised pre-training methods can also be used in case of low training sample support, thus preventing the models from over-fitting [64, 65].



GANs have been used in the literature for generating additional training samples from the actual data because they have the ability to synthesize data whose distribution is very close to the real-world datasets [69,72,73].

5 Performance Metrics

We evaluate the system using accuracy, precision, recall, and F1- score to measure the effectiveness of impurity recognition and target classification.

Metric	Without Filtering	With Filtering
Accuracy	78.5%	92.3%
Precision	75.2%	90.1%
Recall	76.8%	91.5%
F1-Score	76.0%	90.8%

The results indicate a significant improvement in target classification after filtering impurities, highlighting the importance of impurity recognition in micro Doppler analysis.

6 Results and Discussion

The results demonstrate that our approach successfully mitigates the impact of noise and clutter on micro-Doppler signals, improving classification accuracy. The use of CNNs for both impurity recognition and target classification ensures robust performance in diverse conditions. However, the framework's performance can degrade in extreme noise conditions, suggesting the need for further research into more adaptive filtering techniques. Future work could explore real-time processing and multi-target scenarios

7 Conclusions

With ever increasing applications of radar for remote sensing applications, there is a need for classification and recognition of different types of radar targets. Micro-Doppler signatures have emerged as the popular choice for classification of a wide range of air, ground, and space targets. Joint time-frequency techniques are used for micro-Doppler signature analysis since the spectral content of these signals vary with time. Linear time-frequency transforms have a tradeoff between time and frequency resolution while bilinear transforms suffer from the phenomenon of cross-term interference. DCNNs directly use micro Doppler signature images as inputs for classification while conventional ML based classifiers require manual feature extraction step using different methods like EMD, SVD, PCA or ICA. Deep learning classifiers offer inherent advantages over conventional ML classifiers, but they require large and diverse training datasets for better classification performance. Micro-Doppler effect has found numerous applications in various fields like military, automotive industry, healthsector, home automation and security, search and rescue, vital sign monitoring, and clutter rejection from wind turbines. There is a need of further work in this area, specifically in creation of



standardized datasets by adopting the best practices, effective micro-Doppler signal decomposition, polarimetric and multistatic micro Doppler analysis, optimization of feature extraction methods, addressing issues of uncertainty, and continual learning for practical systems.

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