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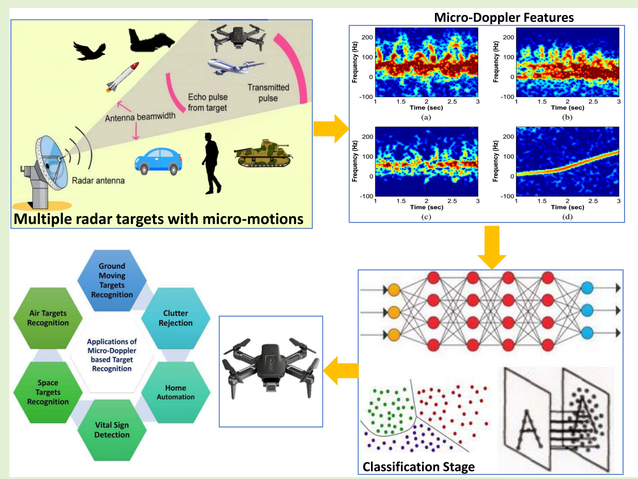
Micro-Doppler Based Target Recognition With Radars: A Review

Ali Hanif, Muhammad Muaz, Azhar Hasan, and Muhammad Adeel

***Abstract*—With the deployment of radar in versatile scenarios and a wide variety of potential targets, demand for automatic classification of various targets is increasing. The wide variety of radar signatures from physically smaller targets due to lower velocity / radar cross-section thresholds and the increased deployment of radar-based sensors do crowd the radar screen with misinterpreted targets. Micro-Doppler signatures have been widely employed by researchers for the recognition of those targets that exhibit micro-motions. This review article presents the evolution and recent advances in radar micro-Doppler based signature analysis and feature extraction. A review of the micro-Doppler-based target classification techniques along with their applications in defense and commercial sectors, has also been presented. This article provides the first review paper in the open literature that systematically covers the major steps along with the adopted practices in micro-Doppler based target recognition. Moreover, the limitations and future trends in the field are also discussed.**



***Index Terms*—Micro-Doppler, radar, deep learning, feature extraction, machine learning, pattern recognition, classification algorithms.**

I. 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 multirotor, rotating blades of propeller of a fixed wing aircraft, swinging arms and legs of a pedestrian, and rotation of wind turbines. The micro-motions induce Doppler modulations on the received signal known as micro-Doppler effect [4]. Micro-Doppler effect was first introduced in coherent laser detection and ranging systems [5]. Due to these modulations, sidebands are generated about the target's Doppler frequency shift. The micro-Doppler signature is the characteristic to a particular target's micro-motion and hence it can be exploited for classification of different targets [4]. Figure 1 shows the simulated micro-Doppler signature of a running human with a radial speed of 2 m/s [6].

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

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TABLE I
COMPARISON WITH EXISTING REVIEW ARTICLES

Review Article	Year	Scope of Work	Remarks
[8]	2003	Review of micro-Doppler effect, maths of micro-Doppler effect, micro-Doppler signature analysis and potential applications	No coverage of feature extraction, classification techniques, datasets and limitations for micro-Doppler based target recognition
[9]	2008	Review of micro-Doppler signature analysis, feature extraction, applications and future directions	No coverage of classification techniques, datasets and limitations form micro-Doppler based target recognition
[10]	2014	Review of advances in extraction and applications of radar micro-Doppler signatures	No coverage of feature extraction, classification techniques, datasets and limitations for micro-Doppler based target recognition
[11]	2015	Review of micro-Doppler effect, micro-Doppler signature analysis, applications and future research	No coverage of feature extraction, classification techniques and datasets for micro-Doppler based target recognition
[12]	2018	Review of radar signals in terms of Doppler tolerance, time-sidelobe level and immunity against jamming	No coverage of micro-Doppler signature analysis, feature extraction, classification techniques,applications and datasets for micro-Doppler based target recognition

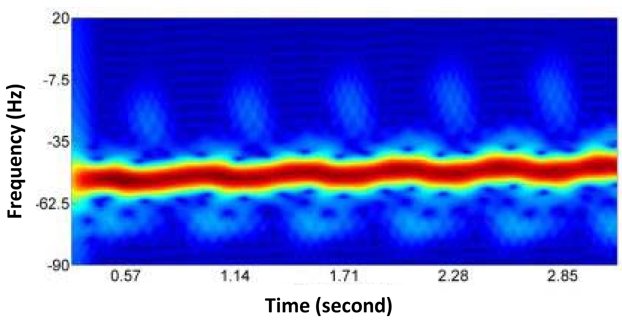

Fig. 1. Micro-Doppler signature of a running human [6]. Used under CC license.

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 for filtering out irrelevant targets [7]. Detection and classification of drones is also crucial in current times for avoiding their misuse for activities like espionage and terrorism. Micro-Doppler signatures have emerged as a useful tool for radar target recognition in such scenarios.

A comparison of our article with existing review articles on the topic [8]–[12] is presented in Table I. The remaining paper is arranged as follows: micro-Doppler signature analysis is covered in Section II. Section III covers the micro-Doppler-based feature extraction techniques. Section IV summarizes the micro-Doppler-based classification approaches and dataset generation is covered in Section V. Section VI presents important applications of micro-Doppler-based target recognition. Section VII discusses limitations and possible future directions in the field. The paper is concluded in Section VII.

II. 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]:

A. Instantaneous Frequency Analysis

For a non-stationary signal, instantaneous frequency is defined as:

$$f(t) = \frac{1}{2\pi}\frac{d}{dt}\Phi(t), \tag{1}$$

where $\Phi(t)$ is the phase function of the analytic signal $z(t) = a(t)\exp[\Phi(t)]$. The limitation of this method is that it only provides a single frequency at any time instant. Therefore, it cannot be used for analysis of multi-component signals, like the micro-Doppler signature of a target, containing multiple frequencies at a given time instant. For applying this method on multi-component signals, they need to be decomposed into constituent mono-component signals, using techniques such as Empirical Mode Decomposition (EMD) [13], which can then be analyzed using instantaneous frequency analysis.

B. Joint Time-Frequency Analysis

Joint time-frequency analysis is used for analyzing the time dependent spectral content of micro-Doppler signals. It can be applied to mono-component as well as multi-component signals. Its techniques are classified into linear time-frequency transforms and bilinear time-frequency transforms.

1) Linear Time-Frequency Transforms: Short Time Fourier Transform (STFT) is the commonly used linear time-frequency transform for micro-Doppler signature analysis. STFT is expressed mathematically as follows:

$$X(\tau, \omega) = \int_{-\infty}^{\infty} x(t)w(t-\tau)\exp(-j\omega t)\,dt, \tag{2}$$

where $x(t)$ is the signal to be transformed and $w(\tau)$ is the window function. Major pitfall of STFT is that there is a trade-off between time resolution and frequency resolution [14].

TABLE II
BILINEAR TIME-FREQUENCY TRANSFORMS [14]

Time-Frequency Transform	Mathematical Form	Kernel Function
Spectrogram	$\lvert \mathrm{STFT}(\mathrm{t},\omega)\rvert^2$	-
Cohen Class	$\int\int\int \Phi(\theta,\tau)s(u+\ \tau/2)s^*(u-\ \tau/2)e^{j\theta t\ -\ j\Omega\tau\ -\ j\theta u}dud\tau d\theta$	$\Phi(\theta,\tau)$
Wigner-Ville	$\int s(t+\frac{\tau}{2})s^*(t+\frac{\tau}{2})\exp(-j\omega\tau)d\tau$	$\Phi(\theta,\tau)=1$
Pseudo Wigner (PWD)	$\int h(\tau)s\left(t+\frac{\tau}{2}\right)s^*\left(t+\frac{\tau}{2}\right)\exp(-j\omega\tau)d\tau$	$\Phi(\theta,\tau)=h(\tau)=\exp\left\{j\alpha\tau^2/2\right\}$
Smooth Pseudo Wigner-Ville	$\int s(t-u)\ \mathrm{PWD}(\mathrm{t},\omega,\alpha)\mathrm{du}$	$\Phi(\theta,\tau)=h(\tau)=\exp\left\{j\alpha\tau^2/2\right\}$
Choi-Williams	$\int\int K_{CW}(u-t,\tau)s\left(u+\frac{\tau}{2}\right)s^*\left(u+\frac{\tau}{2}\right)e^{-j\omega\tau}dud\tau$	$\Phi(\theta,\tau)=K_{CW}(\theta,\tau)=\frac{\exp\left\{-\theta^2\tau^2/\sigma\right\}}{4\pi^{3/2}\sqrt{\tau^2/\sigma}}$
Cone Kernel	$\int\int\int K_{CK}(t-u,\tau)s\left(u+\frac{\tau}{2}\right)s^*\left(u+\frac{\tau}{2}\right)e^{-j\omega\tau}dud\tau$	$\Phi(\theta,\tau)=K_{CK}(t,\tau)=\begin{cases} g(\tau); & \lvert t/\tau\rvert<1/2 \\ 0; & \lvert t/\tau\rvert>1/2 \end{cases}$

2) Bilinear Time-Frequency Transforms: In order to improve the resolution of linear time-frequency transforms and to better analyze the micro-Doppler modulations, bilinear or quadratic time-frequency transforms have been applied. They provide good time-frequency resolution but increase the computational cost and also suffer from the phenomenon of "cross-term interference" [4]. The cross-term gives wrong spectrum distribution and blur the characteristics of the time-frequency signals, thus affecting the physical explanation of bilinear time-frequency transform [15]. Some of the commonly used bilinear time-frequency transforms are listed in Table II, along with their respective kernel functions for reducing the cross-term interference [14]. Any of the bilinear time-frequency transforms can be used for analyzing micro-Doppler signals as long as it satisfies the requirements of high time-frequency resolution and minimum cross-term interference [14]. Other important representations widely used for micro-Doppler signature analysis are Cadence Velocity Diagram (CVD) [16] and Cepstrogram [17], both of which are computed from the spectrogram. The relationship between STFT, spectrogram, CVD and cepstrogram is depicted in Fig. 2.

Generally the radar data is first represented in the form of range-Doppler to extract the range and velocity of the targets of interest. Clutter cancellation and detection is performed subsequently. Once the range bins of the targets of interest are identified, then the micro-Doppler signature analysis is done using appropriate time-frequency transforms as discussed earlier. The information from range-Doppler representation can also be used in combination with micro-Doppler features for target recognition such as in [19], where selected kinematic features extracted from 4-D data matrix (range, azimuth, elevation and Doppler) of a 3-D staring radar are used along with micro-Doppler information to train a decision tree.

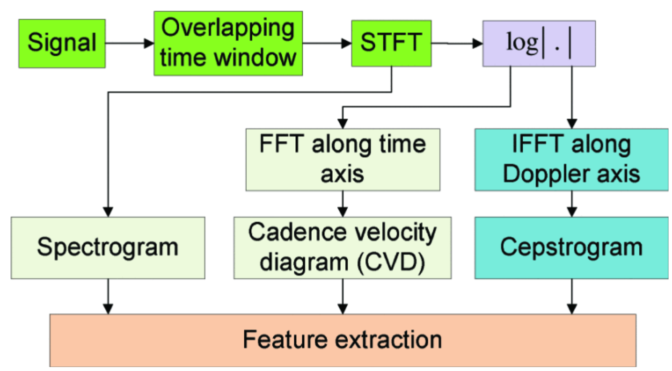

Fig. 2. Relationship between STFT, spectrogram, CVD and cepstrogram [18]. ©2019 EuMA.

For radars having sufficiently high range resolution (HRR), the displacements caused by the target's micro-motion may become observable from the 'macro-range' response. These responses are termed as micro-range signatures [20]. The combination of micro-range and micro-Doppler signatures can be helpful in analysis and recognition of complex motions like human motion where it can be used to isolate the micro-motions from individual body parts leading to improved target detection, classification and discrimination. An algorithm for automated micro-range-micro-Doppler target signature decomposition has been presented in [20].

III. FEATURE EXTRACTION FROM MICRO-DOPPLER SIGNATURES

To perform target recognition based on the micro-Doppler effect, certain discriminating features are usually extracted from the micro-Doppler signature of targets. 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.

The above mentioned methods decompose micro-Doppler signature into components that are uncorrelated or independent, but they are not necessarily linked to motion of individual body parts. In the case of complex motion like human walking or running, the first step is to decompose the micro-Doppler signature into components related to the individual body parts or structures [4]. Such a methodology is proposed in [34], [35]. However, it covered signature decomposition for human walking and running only. In the same context, Viterbi algorithm is also applied for decomposition of micro-Doppler signatures and estimation of hidden state in joint time-frequency domain [36].

Table III lists down the features employed ('Features' column) in a variety of works on micro-Doppler radar target recognition. The above listed feature categories are also evident from the information presented in Table III. Feature extraction is done automatically in the case of deep learning classifiers such as CNNs. However, manual feature extraction has to be done for conventional classifiers such as SVM and Naïve Bayes. Manual feature extraction offers more control over the classification process and can prove beneficial in certain scenarios where we want to give more weight to particular features. On the other hand, automatic feature extraction by deep learning classifiers may extract certain important features that may otherwise be missed during the manual feature extraction [21]. Feature selection for different applications is peculiar to problem and depends on factors such as the environment, type of radar and characteristics of target. However, based on the literature, following general guidelines may be used to select the features:

- Selected features should provide information about physical target parameters such as rotation rate, blade flash frequency, number of rotor blades, etc.
- Features should be discriminative between concerned target classes e.g., the bulk velocity can be a discriminative feature for classifying between drone and non-drone but it can't be for mini-UAV and birds as both have velocities in the same range [37]. The discrimination between the classes can also be quantitatively verified by separability measures like Jefferies-Matusita distance, Transformed Divergence, etc.
- Selected features should be robust with respect to target type, radar settings, background environment and measurement parameters such as operating frequency, aspect angle and polarization [37].
- When the targets differ in their rate of micro-motions, micro-Doppler periodicity feature can be used because it represents the rotation rate. This feature has been used in classifying drones from birds [37]. The rotation rate is higher in case of drones as compared to birds. The wing beat frequency of birds is between 2 and 20 beats per seconds [37].
- When the ratio of the maximum velocity of micro-motions to the main velocity of a target is different than that of the other targets, micro-Doppler spectrum width may be employed as a discriminating feature. This feature is being utilized in [33], [37] to classify birds and drones.
- Spectrogram symmetry can also be used for differentiating between targets that differ in the symmetry of their micro-motions. For instance, birds and drones (with even number of blades) can be distinguished using this feature as birds have an asymmetric spectrogrm [37].
- Important features used for classification of humans and human gait are torso Doppler frequency and bandwidth, total Doppler bandwidth, offset of the total Doppler, Doppler bandwidth without micro-Doppler effect, period of limb motion, average radial velocity and normalised standard deviation of Doppler signal strength [38], [39]. These features are extracted from the micro-Doppler signature by computing the mean, minimum and maximum of lower and upper envelopes of spectrogram, mean Doppler, torso bandwidth, total bandwidth and outer bandwidth [38], [40].
- In case of multi-feature integration, dimensionality reduction techniques such as PCA, can be employed to remove redundancy between different feature vectors and to reduce features dimensionality [41].

IV. Micro-Doppler-Based Target Classification Algorithms

For classification of different radar targets based on their micro-Doppler features, different types of classification algorithms have been used in the open-literature. These approaches can be broadly classified into model-based and data-driven methods [42], [43].

TABLE III

COMPARISON OF DATASETS, CLASSIFICATION APPROACHES AND FEATURES USED FOR MICRO-DOPPLER BASED TARGET RECOGNITION

References	Year	Radar	Classification Approach	Target Classes	Features	Samples per Target Class	Environmental Scenario	Classification Accuracy (%)
[50]	2013	CW	Linear SVM/ Nonlinear SVM/ Naïve Bayes	Birds, Stationary Rotor, Mini Quadcopter, Mini Helicopter, Mini Fixed-Wing Plane	Transformed Eigenvectors and Eigenvalues	7500[a]	Outdoor	94.91 / 95.39 / 93.6
[41]	2013	Pulse [67]	Nonlinear SVM	Human Walking (different speeds), Horse with Rider (different speeds), Both	SFP[b], CVDFP[c], SFP-CVDFP-PCA	28, 112 (For last class only)	Outdoor	> 90
[7]	2015	CW	Min Error Rate	Large Man-made, Bio Life, Small Multicopter, Small Heli, Small Fixed-Wing	Mean RCS, Target Velocity, micro-Doppler Periodicity and Spectrum Width	Hand-drawn likelihood curves used	Outdoor	Not Provided
[68]	2015	CW	Naïve Bayes / Shape Spectrum	Humans	Shape spectrum features based on CVD	240	Indoor	> 90
[40]	2015	Pulse	Two-Nearest Neighbor	Human Activity	Mean,min and max of lower/upper spec -trogram envelope, Mean doppler,Torso, total and outer BW	1680	Indoor	> 88
[22]	2016	CW	DCNN	Human, Dog, Horse, Car / Human Activity	Automatic feature extraction by CNN from spectrograms	40 / 144	Outdoor	97.6 / 90.3
[33]	2017	CW	SVM	Drones, Birds (Simulated)	Mean micro-Doppler spectrogram, Mean CVD, 1st left singular vector	80	Outdoor (for Drones only)	96 - 100
[24]	2017	FMCW	GoogLeNet CNN	Drones	Automatic feature extraction by CNN from merged images	50,000 (Chamber) 10,000 (Outdoor)	Anechoic Chamber/ Outdoor	94.7 / 100
[56]	2017	CW	LSTM	Upto 3 Human Gaits	Automatic feature extraction by RNN from spectrograms	3235 - 9889	Outdoor	89.1
[32]	2018	CW	Nonlinear SVM	Birds, Stationary Rotor, Mini Quadcopter, Mini Helicopter, Mini Fixed-Wing Plane	08 statistical and geometrical features extracted from IMFs[d]	1129 - 3617	Outdoor	> 90
[62]	2018	FMCW	CNN / Residual Network / CNN-LSTM	Single and Two Person, Bicycle, Car	Automatic feature extraction by CNN / RNN from spectrograms	60 and 44, 22, 60	Outdoor	98-100 (Two Class), 79-93 (Three Class)
[55]	2018	CW	Convolutional Autoencoder (CAE)	12 Human Activities	Automatic feature extraction by CAE from spectrograms	50 - 149	Indoor	94.2
[25]	2020	FMCW	Light CNN	Drones , Noise	Automatic feature extraction by CNN from improved spectrograms	700	Outdoor	97.14
[69]	2020	CW	DCNN-6 and GANs / AlexNet and VGG-16	Human Activity	Automatic feature extraction by CNN from spectrograms	144 (Actual) + 1440 (Using GANs)	Outdoor	97.6 / 95.56
[63]	2020	FMCW	Hybrid SVM-CNN	Human, Vehicle	Range extension/ variance, Velocity, Velocity ext/var	2500 (Vehicle) 500 (Human)	Outdoor	96
[70]	2020	CW	Dictionary Learning	Mini Helicopter, Quadcopter and Hexacopter (Single and Multiple Targets)	Dictionary features extracted using K-SVD algorithm on CVDs	200	Indoor	93.38
[21], [71]	2020	FMCW	GoogLeNet CNN / Series Network	Drone, Birds, Clutter, Noise	Automatic feature extraction by CNN from spectrograms	600	Outdoor	99 / 94.4
[19]	2020	Pulse	Two Stage Decision Tree	Drone, Non-Drone	RCS, Velocity, Height, Kinematic and micro-Doppler information	4622 (Drone) 9244 (Non-Drone)	Outdoor	85.02 (TPR[e]) 0.37 (FPR[f])

[a] Calculated indirectly. Not explicitly stated in paper, [b] Spectrogram Frequency Profile, [c] Cadence Velocity Diagram Frequency Profile.
[d] Intrinsic Mode Functions, [e] True Positive Rate, [f] False Positive Rate.

A. 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 [44], and Vignaud model for human running [45]. 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 [46], 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 non-convergence for large number of parameters [43].

B. 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.

1) Template Matching: Template matching methods perform classification by matching the input data to a signature database or reference library. The library contains the reference signatures of all possible target classes. A class is assigned based on the confidence level of its matching with a certain reference signature. In [47], [48], micro-Doppler classification has been achieved using Dynamic Time Warping (DTW), which is a template-based classification technique. DTW is a technique used in speech recognition and it can measure the similarity between two time series with varying speeds. In performance comparison with k-Nearest Neighbors (k-NN), another template-based technique, has also been provided in [48]. k-NN classifier is also used in [29], [49] for radar micro-Doppler-based target classification. These methods are simpler to implement as compared to model-based and supervised learning techniques. However, for large databases, these methods can be time-consuming as the input data has to be compared with all possible entries in the reference library. Moreover, larger libraries also require more memory as these are needed during classification, in contrast to supervised learning, where training data is used offline.

2) Conventional ML Classification Algorithms: Conventional ML classifiers that have been employed for micro-Doppler-based classification include linear and non-linear Support Vector Machines (SVM) [28], [32], [33], [49], [50], naïve Bayes [50], [51], Maximum A Posteriori (MAP) [7], subspace reliability analysis [52], discriminant analysis [53], and decision trees [19], [54]. These classifiers have achieved good results with classification accuracies of 90% and above on their acquired datasets under different experimental scenarios. The advantages of these conventional ML techniques over deep learning are the requirement of less amount of training data, especially if the dimension of the feature space can be reduced using signal processing techniques such as SVD or PCA [42]. The overall computational complexity of these classifiers is less than deep learning based classifiers, thus they are much faster and less complex. A comparison of both types of classifiers in terms of computational complexity is provided in [55]. The total time for the SVM classifier is reported to be 99 seconds, whereas it is 157 seconds and 241 seconds for a CNN and convolutional autoencoder, respectively.

3) Deep Learning Classification Algorithms: Deep learning (DL) based classification approaches have certain inherent advantages over conventional ML approaches. They are less dependent on domain knowledge as they can automatically extract the features as well as classification boundaries from the micro-Doppler signatures [22], [24]. Due to the elimination of feature extraction step, they can save the processing time required by feature extraction algorithms [21] as well as avoid human errors in making the right choices. Deep learning classifiers are also reported to learn the clutter and noise patterns during training e.g., during the convolution filtering process in CNNs. Clutter has a significant impact on the performance of other classifiers, in which such deep learning architectures may be useful by the automatic capability of clutter cancellation [40], [55]. Moreover, deep learning architectures can extract certain important features, which may otherwise be missed by the manual feature extraction process in case of ML based approaches [22].

Deep Convolutional Neural Networks (DCNNs) have been applied for radar micro-Doppler-based classification [21]–[25]. However, DCNNs have certain drawbacks: they require input data in the form of images and require diverse training sets for better classification. As the input to DCNNs is in the form of micro-Doppler signature images, accuracy can reduce if there are variations in micro-Doppler signature due to irregularities in the micro-motion dynamics of a target [22]. Moreover, the training and validation process needs to be rigorous and diverse for better classification and to avoid overfitting [21].

In addition to DCNNs, Recurrent Neural Networks (RNNs) have also been exploited for target classification based on micro-Doppler effect [56]–[60]. Out of different RNN types, Long Short-Term Memory (LSTM) networks are popular, as they can overcome the issue of vanishing/exploding gradient problem [61] and are able to learn both long and short data sequences compared to other RNN architectures [62]. Use of RNNs bring the advantages of classifying measurements with variable observation time and can also deal with measurements that include transitions between classes over time.

A deep Convolutional Autoencoder (CAE), that essentially combines the benefits of Autoencoder and CNN, is proposed in [55] to classify 12 types of aided and non-aided human activities with an accuracy of 94.2%. Researchers have also employed hybrid classifiers for micro-Doppler-based target classification, that combine both the conventional ML and DL classifiers to take advantages of both techniques [63].

V. 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. Due to relatively low PRF/SRF of pulse-Doppler and FMCW radars, Doppler fold-over may occur for high-speed targets [64], but this should not affect their suitability in applications like human gait analysis, where the velocity of micro-motions is generally low.

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 [65]. 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 [65], [66]. 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]. However, the number of GANs being used increase with the increase in target classes, and training of large number of GANs is challenging [69]. Transfer learning has been employed for micro-Doppler-based classification using DCNNs [21], [24], [66]. In [66], unsupervised pre-training is implemented through the use of convolutional autoencoder and a comparison with the transfer learning approach is presented. Table III presents a summary of various types of datasets, classification methodologies and features adopted in the literature for micro-Doppler-based target recognition.

An important practical issue arises when all the radar data is not available beforehand for training the model, rather data is arriving sequentially as learning continues. In such scenarios, if the model is retrained from scratch every time on the arrival of new data, it can result in huge computational cost. On the other hand, if the model is simply updated with new data, it can result in catastrophic forgetting of past learned tasks [74]. A comparative study of continual learning methods for micro-Doppler-based human activity classification has been presented for the first time in [75]. The authors have considered two continual learning scenarios of domain incremental learning (DIL) and class incremental learning (CIL), for comparing the performance of regularization- [76]–[78] and exemplar-memory-based continual learning methods [79]–[81].

VI. Applications and Practical Implementations

Micro-Doppler-based target recognition has found applications in a variety of defense as well as commercial fields. Some important areas of application are depicted in Fig. 3.

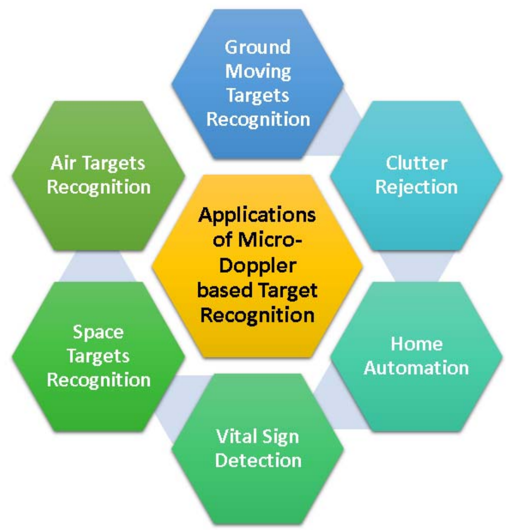

Fig. 3. Applications of micro-Doppler-based target recognition.

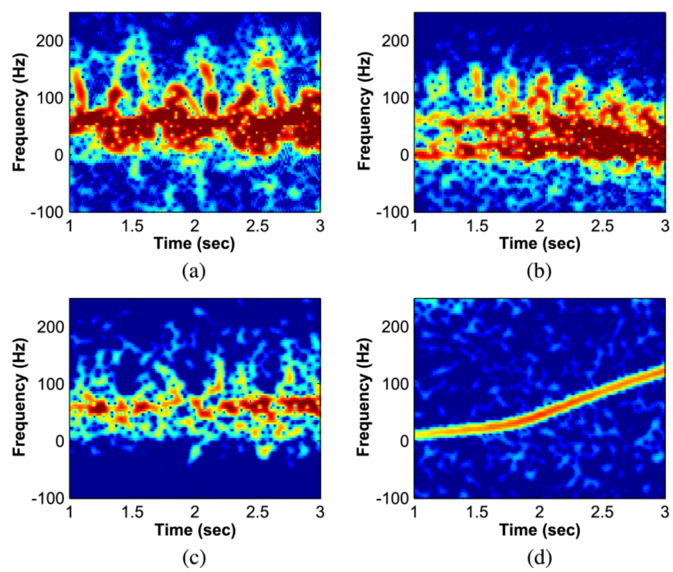

Fig. 4. Sample spectrograms from [22]. (a) Human. (b) Dog. (c) Horse. (d) Car. ©2016 IEEE.

A. Ground Moving Targets Recognition

Classifying ground moving objects such as humans, roadway vehicles, and animals are important for applications like perimeter security, intelligent transportation system, surveillance, human gait analysis, etc. Micro-Doppler effect has been successfully employed for recognition of ground moving targets. In [22], four types of ground moving targets were classified based on micro-Doppler spectrogram images using DCNN. In addition to target recognition, seven types of human activities were classified such as walking, running, crawling, and boxing. The authors achieved classification accuracies of 97.6% and 90.9% for target recognition and human activity classification respectively on their acquired datasets. Figure 4 shows the extracted spectrogram images of four types of ground targets from [22] whereas spectrograms of four human activities are shown in Fig. 5 [22].

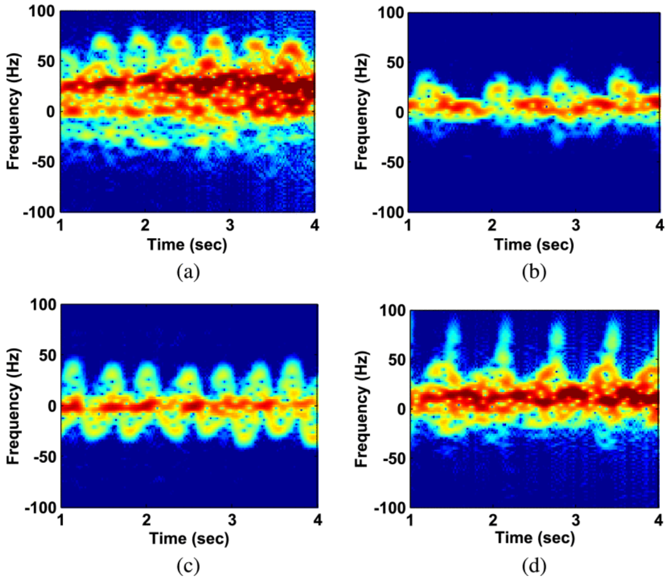

Fig. 5. Sample spectrograms of four human activities from [22]. (a) Running. (b) Crawling. (c) Boxing still. (d) Boxing forward. ©2016 IEEE.

Six different types of pedestrian movements have been classified in [82] using a Support Vector Machine (SVM) classifier; the dimensions of which were reduced using Principal Component Analysis (PCA) applied on "aligned" spectrograms. Classification of ground vehicles, as wheeled or tracked vehicles, has been done in [27]. The classification was performed using an SVM classifier based on micro-Doppler features and SVD. Micro-Doppler-based target recognition has also found applications in the field of automotive industry and road safety. An approach for joint estimation of tracks and micro-Doppler signatures in a real-time multi-target scenario has been presented in [83]. The authors have proposed to use the algorithm for driver assistance to avoid crashes with other vehicles and obstacles, for intelligent traffic light systems to monitor traffic participants at pedestrian crossings, and for intelligent street light systems.

Micro-Doppler-based target recognition have also been used for perimeter security and surveillance of critical infrastructures such as military bases, airports, dams and grid stations [83], [84]. It has the potential to replace infrared-based motion sensors, which have a high false alarm rate because the infrared sensors can create alarms even for moving foliage and roaming animals. For perimeter security, the humans, vehicles, and animals are automatically differentiated [22].

B. Air Target Recognition

Primary purpose of radars, which also triggered their invention, is the detection of air targets such as aircraft, helicopters, and drones. Recognition of air targets can give an edge to military forces over their adversary. Incorrect classification of air targets can result in friendly fires and can even change the outcome of a conflict.

Micro-Doppler effect can be used for recognition of air targets as these targets possess micro-motion dynamics such as rotation of propellers of fixed wing aircraft, rotation of fan

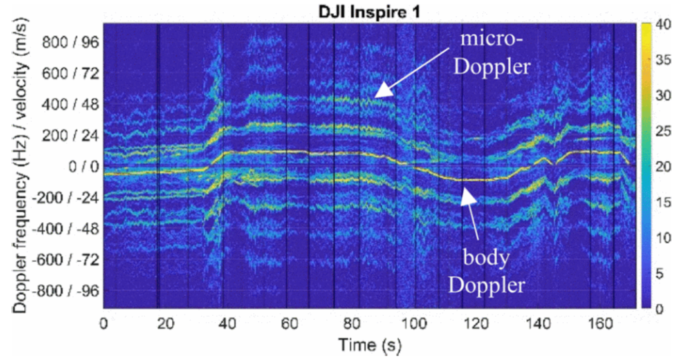

Fig. 6. Example spectrogram from DJI Inspire 1 with the Gamekeeper staring radar. [19]. ©2020 IEEE.

and turbine in case of jet engines, rotation of helicopter blades, and rotation of rotors in case of drones [4]. Plenty of research has been done for recognition of drones based on micro-Doppler effect [7], [19], [23], [25], [30]–[32]. Micro-Doppler-based target recognition is also employed for classification of loaded and unloaded drones [51], to differentiate birds from drones [21], [50], and for classification of propeller based aircraft [85]. Micro-Doppler signatures from helicopter rotor blades have been studied in [86]–[88]. The research in this field has also resulted in useful commercial products for drone surveillance and security, and for unmanned air system traffic management [89]. One such product, named "Gamekeeper 16U" [89], used for detection, tracking, and classification of Unmanned Air Systems (UAS) is shown in Fig. 7a. It is currently deployed at various airports as part of their counter-UAS strategies for ensuring security and aviation safety [89]. A two stage decision tree approach has been proposed in [19] to classify drones from other confuser targets using the Gamekeeper 16U radar. Sample spectrogram of DJI Inspire I quadcopter obtained with the Gamekeeper 16U radar is shown in Fig. 6.

C. Clutter Rejection From Wind Turbines

Countries around the world are installing large number of wind farms to generate clean and green electricity. However, these wind farms are a major source of clutter for nearby radars due to their large RCS and time varying Doppler return. A typical wind turbine could have a RCS of the order of 60 dBsm at X-band [90]. The impact of such wind farm clutter on the performance of aviation radars was studied in [91]. Negative effect of wind turbine clutter on weather radars has also been reported in [92], [93]. Due to their time varying Doppler return, wind turbine clutter cannot be mitigated using classic ground clutter cancellation techniques [94].

Micro-Doppler signature of wind turbines have been studied in [95], [96]. Micro-Doppler signature identification in the presence of wind turbine clutter for airborne pulse-Doppler radar is presented in [97]. Mitigation of the radar imprints from wind turbines using a combination of CNN and Multilayer Perceptron (MLP) is presented in [98]. The classification of wind turbines was done based on target's attributes and high resolution Doppler spectrum. A commercial radar, named

(a) Aveillant's Gamekeeper 16U counter-UAS radar [89].

(b) Aveillant's Theia 16A wind farm tolerant radar [89].

Fig. 7. Aveillant's Gamekeeper 16U and Theia 16A commercial radars using micro-Doppler phenomenon [89].

"THEIA 16A", designed by Aveillant (Thales company) for wind farm clutter mitigation is shown in Fig. 7. It uses the micro-Doppler effect to classify between aircraft and wind turbines, and can present an uncluttered picture of airspace to air traffic controllers by minimizing the number of false tracks.

D. Space Targets Recognition

Distinctive micro-Doppler signatures result from various types of micro-motions exhibited by space targets. These micro-motions include precession, nutation, spinning, and wobbling. Micro-motion parameters such as spin rate, precession rate, inertia ratio, and nutation angle can be extracted from the micro-Doppler signatures of these space targets, which can be used for their classification. Distinction of a ballistic missile warhead from other confusing space targets is paramount because of higher cost of interceptors and minimum reaction time [99]. Tactical Ballistic Missile (TBM) has to be intercepted during its mid-course phase. However, in this phase, separation of multiple boosters from the missile takes place, which results in interfering targets for classification. Warhead of a ballistic missile undergoes precession and nutation motions whereas wobbling motion is exhibited by a decoy. This difference is depicted in their respective micro-Doppler signatures and can be employed to discriminate between ballistic missiles and decoys. In [99], authors have presented an approach based on micro-Doppler effect for classification of space targets into warhead and confusing target classes. The two target classes are shown in Fig. 8. Micro-Doppler signature extraction from ballistic targets is considered in [100]. Micro-Doppler signature resulting from precession motion of warhead is shown in Fig. 9. Other works on micro-Doppler-based recognition of ballistic targets include [101]–[107].

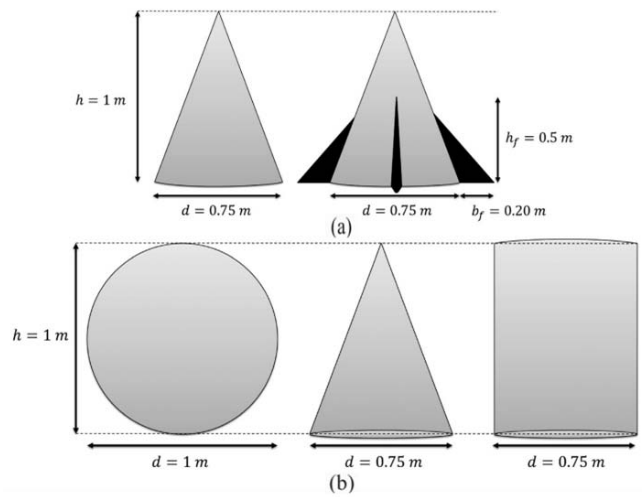

Fig. 8. Two target classes along with their subclasses. (a) Warheads. (b) Confusing objects. [99]. Used under CC license.

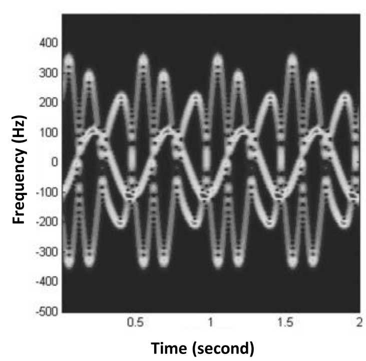

Fig. 9. Precession induced micro-Doppler signature [100]. ©2010 IEEE.

E. Home Automation

Concept of smart homes is gaining popularity with the evolution of Internet of Things (IoT). One aspect of home automation is security such as access control and alarm systems, where the micro-Doppler-based target recognition offers a promising solution. Gesture recognition and control can also be achieved using micro-Doppler features. Radars do not require any tag attached to human hand, can penetrate through materials, and are more robust to variations in light, distance, etc. [4]. Hand gesture recognition based on micro-Doppler signatures has been covered in [108]–[112].

Another aspect of home automation is the indoor monitoring of inhabitants, especially those who have a medical condition to cater for any health emergency situation. As per the statistics of U.S. Center for Disease Control and Prevention (CDC), the death rate in older adults increased by 30% from 2007 to 2016 [113]. Radar-based human gait monitoring

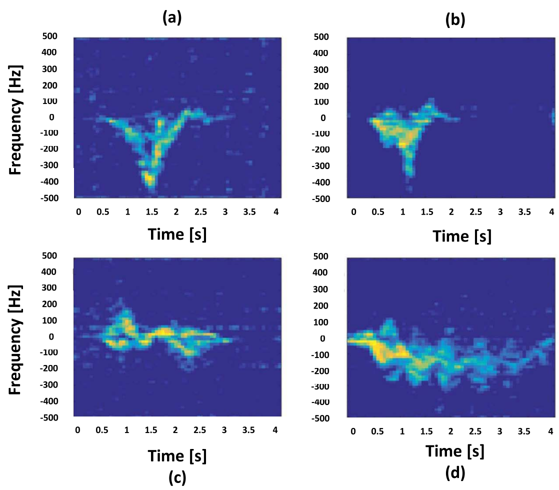

Fig. 10. Spectrograms of four human motions [116]. (a) Fall. (b) Sit. (c) Bend. (d) Walk. ©2018 IEEE.

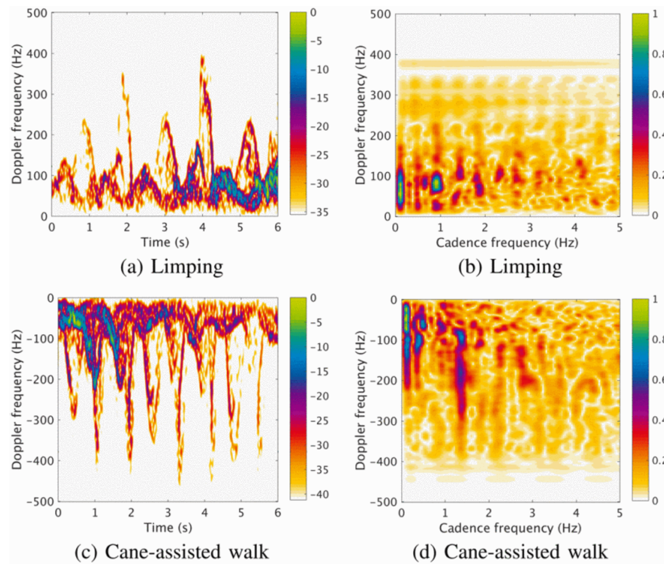

Fig. 11. Spectrograms and cadence velocity diagrams of different types of human gaits from [118]. ©2018 IEEE.

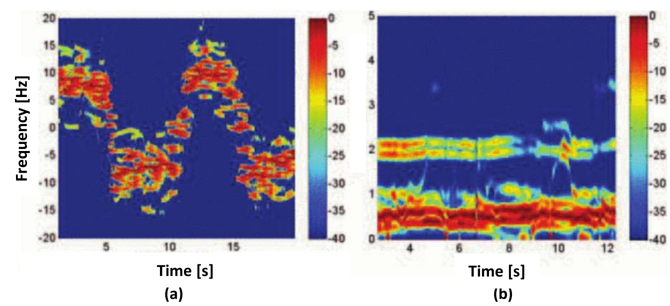

Fig. 12. (a) Spectrogram of human walking towards and away from radar. (b) Extracted micro-Doppler trajectory of respiration [124]. ©2016 IEEE.

offers certain advantages like it is contactless and it doesn't violate the privacy of an individual. Micro-Doppler effect has been exploited for monitoring of abnormal human activities inside homes, offices, etc. [4]. Human motion consists of periodic movements such as walking, running, and non-periodic movements such as falling, kneeling. These aperiodic movements can be an indication of a health related emergency such as heart attack, unconsciousness or a severe fall. Analysis of micro-Doppler signatures of various human body parts can give an indication of such situations and can be used for indoor monitoring of habitats [39], [114], [115]. Spectrograms of various human motions used for fall detection in [116] are shown in Fig. 10. Micro-Doppler signatures have been used in [117] for in-home aided and unaided gait recognition with multiple radar and sonar systems.

Subspace classification of five types of human gaits using radar micro-Doppler signatures have been presented in [118]. These gaits include normal walking, limping with one leg, limping with both legs, cane-assisted synchronized walk and cane-assisted unsynchronized walk. Few sample spectrograms of these gaits from [118] are shown in Fig. 11.

F. Vital Sign Detection

Vital signs, such as heart rate and respiratory rate, are important indications of human health. These signs are also being used in search and rescue operations for detection of survivors trapped in rubble. Micro-motions resulting from heartbeat and breathing have distinctive micro-Doppler signatures, which can be used for vital sign detection of humans [119]–[123]. Figure 12 shows the micro-Doppler signature for respiration of a walking human obtained using an ultra wideband radar [124]. Micro-Doppler based vital sign detection offers certain advantages due to being a contactless technique. This edge provides a more convenient way for accurate patient's examination, especially in cases where the patient cannot be reached (for survivors trapped in rubble) or touched (e.g., burn wounds). It is also a desirable method when long duration and repeated measurements are required for continuous monitoring of patients and when privacy of patients is required. Moreover, it can also be used for vital sign detection behind obstacles. The challenges faced by radar-based vital sign detection are the electromagnetic interference, random body movement (RBM) of the subject, separation of heartbeat signal from respiration signal, and power consumption [125]. A comprehensive and latest review of human vital signs detection methods and potentials using radars is presented in [125].

VII. Limitations and Future Trends

There are research avenues related to micro-Doppler-based target recognition that needs further exploration. In addition to this, certain limitations also exist. One of the important limitations for micro-Doppler-based radar target recognition is that there is no widely-accepted open-source benchmark dataset that can be used to check the evolution of micro-Doppler based target recognition methodologies. As discussed in Section V, researchers have developed and used their own datasets for testing the classification performance of their proposed algorithms. However, each dataset is different in terms of type of radar used, number and type of targets considered, diversity (in terms of changing frequency, aspect angle, polarization etc.), number of training samples, and environmental scenario. Recently, one such public dataset named 'UWB-Gestures' has been presented in [126] for hand gesture recognition. It is the first public dataset of twelve dynamic hand gestures acquired with three ultra-wideband impulse radars.

As discussed in Section V, dataset creation for micro-Doppler-based target recognition is a cumbersome task. Radar-based data gathering requires expensive equipment and extensive labour. In order to overcome the scarcity of training data, several solutions have been proposed in the literature [42]. These include generating synthetic micro-Doppler data from model based simulations, using GANs, unsupervised pre-training and transfer learning. However, none of these is the generalized solution valid for all sorts of target scenarios [42].

Micro-Doppler signature is a multi-component signal formed by the superposition of constituent mono-component signals. The decomposition of a micro-Doppler signature into components associated with individual structural parts of a target is still a challenge. Methods such as EMD can decompose a multi-component micro-Doppler signal into constituent mono-components. However, these decomposed signals have no association with any structural part of the target. An effective decomposition algorithm that can perform physical component based decomposition of micro-Doppler signature will lead to improvement in target classification, recognition, and identification. It may also help in identifying and predicting the behaviour, emotions, and intentions of human targets [4].

Polarimetric micro-Doppler analysis can also aid in separation of different components of human motion. The double bounce of radar signal from dihedral joints like elbow and knees, can be separated from planar body surfaces by measuring the phase difference between HH and VV [127], [128]. Use of dual polarization radar can be used to improve the classification accuracy for body gesture recognition, by combining the micro-Doppler signatures obtained using HH and HV [129]. Different types of polarimetric parameters have been used in [130] for classification of UAVs and birds using a S-band quadrature polarization radar.

Use of multistatic radars for capturing micro-Doppler returns is another research avenue that needs further exploration. A multistatic radar has spatially diverse transmitter/receiver nodes having a shared coverage area [131]. Use of multistatic radars offer certain advantages over monostatic radars, which include improvement in target detection, enhanced information about the target due to multiple aspect viewing, reduced vulnerability of the receiver to jamming, wider coverage, and use of clutter tuning for increased sensitivity [42], [132], [133]. Multistatic micro-Doppler signature is dependent on system topology, and the motion and location of the target [1]. By using the micro-Doppler information received from multiple channels, radar-based target classification can be improved as indicated in [51], [53], [134], [135].

The micro-Doppler signatures may be communicated to an operator or classification algorithm for a human-like experience. This can be in the form of aural signals or any other visual representation. Aural signal classification has been employed in sonar signal classification [136]. Advantage of aural classification is the robustness of human auditory classification process to noise. An audio depiction of micro-Doppler signal may help a human listener to differentiate between different human movements or between different target types [20]. Aural classification can be applied to micro-Doppler signatures by conversion of baseband micro-Doppler signal into an audio signal for training listeners [4]. Work on meaningful visual depictions of micro-Doppler data is also important for conveying useful information to the operator. Visual depiction can take the form of range-Doppler movies, as the processing speed has now improved to near real-time [137]–[139].

Another important research trend is augmenting micro-Doppler information with other forms of information from radar data, such as range, velocity, height, and direction of arrival information. With the development on millimeter wave radars with several GHz of bandwidth, returns from multiple targets and various parts of an object can be resolved in range. Use of micro-range micro-Doppler features can improve the classification performance and can also help in mapping motion components to individual body parts [42]. In [19], height, RCS, and velocity information is used in conjunction with micro-Doppler to achieve robust drone classification. In [140], micro-range micro-Doppler has been used to differentiate a single person from a group of people walking towards radar. Micro-Doppler and range-Doppler analysis has been used in [141] for detection of potential active shooter.

Wrong predictions in a real-time radar classification system can result in catastrophic outcomes. For example, confusing a bird with a drone can mistakenly trigger the air defense system in case of a military scenario. Hence, with regards to the classification approaches discussed in Section IV, there is a need to take into account the factors of data bias and uncertainty, as these approaches are data-driven. Is our training dataset labelled properly? Is our training dataset diverse enough to be free from data bias? How confident our classifier is about its predictions? Can we trust the predictions of our classifier on unseen data? Current work on micro-Doppler-based classification have not addressed these important questions.

VIII. Conclusion

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 trade-off 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, health sector, 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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