

Signal feature extraction for rain clutter mitigation in surveillance radar

Vitor H. Duque, Pedro Sega, Neuton Severo, Leandro Pralon

Abstract—Rain clutter can significantly degrade the performance of surveillance radars by generating false detections and masking returns from genuine targets. In single-polarization architectures, this challenge is amplified by the absence of polarimetric signatures, and existing single-attribute approaches may not reliably separate target and clutter returns. This paper investigates an offline approach for discriminating target and rain clutter echoes using real-world single-polarization measurements acquired with the SABER M200 VIGILANTE S-band surveillance radar. The proposed classifier combines complementary Doppler-domain and spatial-coherence attributes derived from the Spectral Peak-to-Average Ratio (SPAR), pairwise inter-receiver coherence, and background-region Spectral Flatness Measure (SFM) statistics. The dataset comprises measurements collected under different rainy-weather conditions and acquisition scenarios, including situations in which target and rain clutter returns coexist. To evaluate generalization, entire measurement days are reserved exclusively for testing on a per-class basis, ensuring that training and test data never share the same day and class. Under this evaluation, the method achieves average recall values of 0.94 for target returns and 0.97 for rain clutter echoes. These results support the use of complementary signal-derived attributes for offline rain clutter discrimination in single-polarization surveillance radar measurements.

Keywords—rain clutter, surveillance radar, feature extraction, classification.

I. INTRODUCTION

In surveillance radar systems, precipitation echoes severely compromise target detection by generating dense false detections, initiating spurious tracks, and masking legitimate targets located within or behind rain cells. This problem is particularly relevant in air-defense and border-surveillance applications, in which persistent detection capability and reliable track formation are operational requirements. Unlike meteorological radars, where precipitation is the signal of interest, surveillance radars must suppress or classify weather-related returns while preserving echoes produced by genuine targets.

Rain clutter mitigation has traditionally been addressed through statistical modeling, filtering, and clutter-classification approaches. Early studies characterized weather clutter through non-Gaussian amplitude models, including the Weibull distribution [1]. With the advent of high-resolution radars, it became increasingly evident that traditional Rayleigh models failed to accurately capture the extended tails of empirical clutter amplitude data [2], [3]. To address this,

researchers expanded these early characterizations to include other highly flexible non-Gaussian models [3], [4]. In more recent applications, distributions such as the Nakagami-m [2] and Gamma models [5] have also been validated as highly suitable for accurately modeling rain and weather clutter across various modern radar bands. In ground-based coherent radars for air traffic control, spectral features and statistical or neural classifiers were investigated to discriminate weather echoes from other clutter classes and target-related returns [6]. More specifically, rain clutter suppression in surveillance radar data has been investigated using spectral-shape filtering and time-scale representations, including slope-based filters and discrete wavelet transforms [7], [8]. These works indicate that weather echoes exhibit statistical and spectral characteristics that can be exploited for clutter discrimination and suppression.

While the advanced statistical models and spectral classifiers discussed above are highly effective, many of these techniques assume the availability of multi-dimensional data or complex hardware configurations. Consequently, rain clutter mitigation is particularly challenging in single-polarization radar architectures, where polarimetric signatures are not available for discrimination. In this context, attributes extracted directly from the spectral and spatial behavior of the received signal provide an attractive alternative, since they can be evaluated without requiring additional polarimetric channels. Previous work investigated the use of the Spectral Flatness Measure (SFM) for rain clutter mitigation in real surveillance radar data, showing the discriminative potential of spectral information for distinguishing weather echoes from target returns [9]. However, spectral flatness alone captures only one aspect of the clutter discrimination problem. It characterizes the overall spectral shape of the received signal but does not explicitly quantify the concentration of energy around dominant Doppler components nor the spatial consistency across multiple receiver channels. Since rain clutter and target returns may overlap in any single feature dimension, a multi-attribute approach that combines complementary signal characteristics is expected to improve discrimination reliability. Addressing this limitation is relevant for improving rain clutter mitigation in single-polarization surveillance radars, where reliable target discrimination under adverse weather conditions remains an operational need.

Building upon these observations, this paper investigates an offline approach for discriminating genuine targets from rain clutter in real-world single-polarization surveillance radar measurements. Three feature families are considered: the Spectral Peak-to-Average Ratio (SPAR), pairwise inter-receiver coherence, and background-region SFM statistics

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computed across receiver channels. The SPAR characterizes the concentration of energy in the Doppler spectrum, the pairwise coherence values describe spatial consistency between receiver channels, and the mean and variance of the background-region SFM characterize spectral behavior and its variability across receivers.

The proposed analysis uses real-world data collected by the SABER M200 VIGILANTE S-band surveillance radar under rainy conditions. To evaluate generalization, the dataset is partitioned so that, for each class, entire measurement days are reserved exclusively for testing, ensuring that the classifier is never trained and tested on data from the same day and class. The results show that the joint attribute space enables supervised discrimination between target and rain clutter returns on previously unseen measurement days.

II. RADAR SYSTEM AND MEASUREMENT DATASET

The measurements analyzed in this work were acquired with the SABER M200 VIGILANTE, a ground-based S-band active phased-array surveillance radar developed for air-defense applications [10]. The analyzed data correspond to radar returns available after processing stages involving range compression and Doppler-domain processing.

The dataset comprises measurements collected over multiple acquisition days under different rainy-weather conditions and scenarios, including cases in which target returns and rain clutter echoes coexist. Target-return samples are available from four acquisition days, denoted by A, B, C, and D, whereas rain clutter samples are available from two days, denoted by B and D. In total, the dataset contains 128720 target-return samples and 249353 rain clutter samples. Target and rain clutter labels were assigned through manual inspection, in which an expert analyst examined target trajectories in the raw data and classified each detection according to its spatial and temporal behavior.

The test subsets are defined on a class-specific per-day basis. In each experiment, all target-return samples from one target day and all rain clutter samples from one rain day are reserved for testing, while the remaining samples are used for training. The four target days and two rain clutter days result in 8 test pairings, which assess generalization across distinct acquisition conditions despite the availability of rain clutter samples only from days B and D.

III. FEATURE EXTRACTION

Rain clutter and target returns originate from distinct scattering mechanisms. While genuine targets are generally associated with reflections from spatially localized objects, rain clutter results from the superposition of echoes produced by multiple distributed scatterers within the illuminated volume. Consequently, the corresponding received signals may differ in their spectral energy concentration, spectral structure, and spatial coherence across receiver channels.

Based on this physical motivation, three complementary feature families are investigated in this work. The SPAR characterizes the concentration of reflected energy in the Doppler spectrum by comparing the dominant spectral component

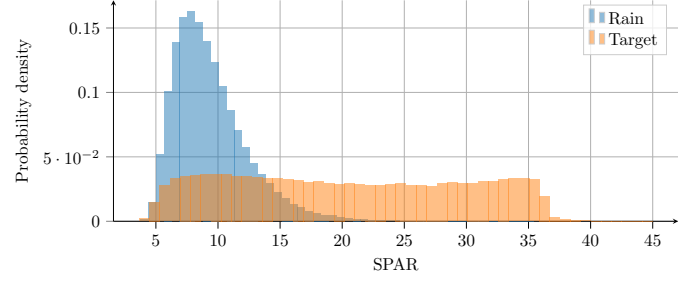


Fig. 1. Empirical normalized distributions of the SPAR for target and rain clutter returns.

with the average spectral power. The inter-receiver coherence evaluates the similarity of complex spectra acquired by distinct receiver channels. Finally, statistics derived from the background-region SFM characterize the spectral distribution outside the dominant return region and its variability across receiver channels. All attributes are extracted offline from the available measurements and subsequently used as inputs to the supervised classifier.

A. Spectral Peak-to-Average Ratio

The Spectral Peak-to-Average Ratio (SPAR) quantifies the concentration of reflected energy in the Doppler spectrum by comparing the maximum spectral power to the average spectral power over the analyzed frequency interval, similar to what the peak-to-average power ratio does in the time domain [11]. For a power spectrum $P[k]$ composed of K samples, the SPAR is computed as

$$\text{SPAR} = \frac{K \max_{1 \leq k \leq K} |P[k]|^2}{\sum_{k=1}^K |P[k]|^2}. \quad (1)$$

Large SPAR values indicate that most of the signal energy is concentrated in a small number of frequency bins, whereas lower values correspond to a more distributed spectral power distribution. In the considered application, target returns often produce stronger localized spectral components associated with reflections from spatially concentrated objects. Rain clutter results from the superposition of echoes generated by a large number of distributed scatterers, which may lead to a broader distribution of power across Doppler frequencies. Therefore, the SPAR is evaluated as a spectral-domain descriptor for distinguishing target and rain clutter returns.

Figure 1 presents the empirical normalized distributions of the SPAR for target and rain clutter returns. For the analyzed measurements, rain clutter samples are predominantly concentrated at lower SPAR values, whereas target samples tend to exhibit higher values. This behavior indicates that the SPAR provides discriminative information for the considered classification task.

B. Spectral Windowing Strategy

The coherence- and SFM-based descriptors are computed from selected regions of the frequency-domain representation of each measurement. Let $P[k]$ denote the power spectrum employed to identify the dominant spectral component of a given detection, and let $\mathcal{K}$ denote the complete set of analyzed frequency bins. The bin associated with the maximum spectral power is defined as

$$k_p = \arg \max_{k \in \mathcal{K}} P[k]. \quad (2)$$

A rectangular peak-region window centered at k_p is then defined as

$$\mathcal{W}_p = \{k \in \mathcal{K} : |k - k_p| \leq K_w\}, \quad (3)$$

where K_w denotes the half-width of the selected spectral region. The complementary background region is defined as $\mathcal{W}_b = \mathcal{K} \setminus \mathcal{W}_p$.

The same spectral-windowing rule is applied to all evaluated measurements. The peak-region window $\mathcal{W}_p$ is used in the computation of the inter-receiver coherence, since this descriptor is intended to evaluate spatial similarity in the frequency interval containing the dominant reflected energy. Conversely, the background region $\mathcal{W}_b$ is used in the calculation of the SFM-derived descriptors, allowing the spectral behavior surrounding the dominant return component to be analyzed separately.

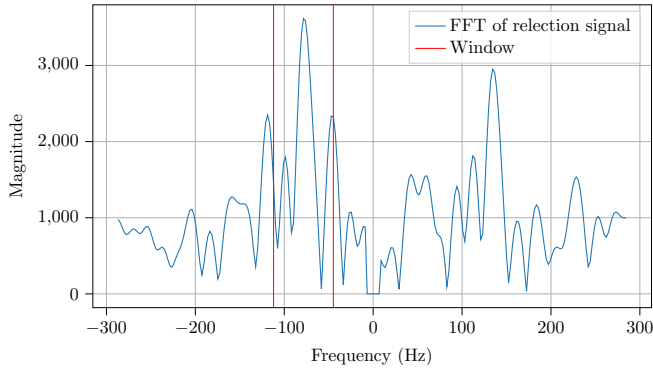


Fig. 2. Example of the peak-region spectral window centered at the dominant energy component, located at approximately -78 Hz.

Figure 2 illustrates the adopted spectral-windowing strategy for a representative measurement. In this example, the dominant return component is located around -78 Hz, and the surrounding spectral regions are separated according to their use in the coherence- and SFM-based descriptors.

C. Inter-Receiver Coherence

The inter-receiver coherence quantifies the similarity between complex spectra acquired by distinct receiver channels. Since target and rain clutter returns originate from different scattering mechanisms, their spatial consistency across the receiving array may also differ. In this work, the coherence is computed within the peak-region window $\mathcal{W}_p$, where the dominant reflected energy is concentrated.

Let $X_i[k]$ and $X_j[k]$ denote the complex spectra acquired by two distinct receiver channels i and j . Their pairwise inter-receiver coherence is computed as

$$\hat{\gamma}_{i,j} = \frac{\left| \sum_{k \in \mathcal{W}_p} X_i[k] X_j^*[k] \right|}{\sqrt{\left(\sum_{k \in \mathcal{W}_p} |X_i[k]|^2 \right) \left(\sum_{k \in \mathcal{W}_p} |X_j[k]|^2 \right)}}. \quad (4)$$

The coherence value lies in the interval $[0, 1]$. Values close to one indicate high similarity between the complex spectral responses of the considered receiver channels within the dominant spectral region, whereas values close to zero indicate low similarity [12].

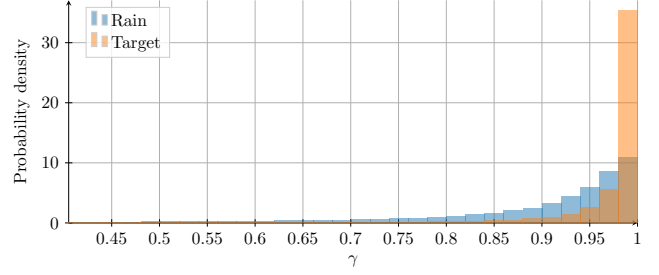


Fig. 3. Empirical normalized distributions of the pairwise inter-receiver coherence for target and rain clutter returns.

Since multiple receiver channels are available, the coherence is computed for all distinct receiver-channel pairs. For M receiver channels, the number of pairwise coherence descriptors is $N_p = \frac{M(M-1)}{2}$.

Rather than aggregating the pairwise coherence values into a single statistic, all values $\hat{\gamma}_{i,j}$, for $1 \leq i < j \leq M$, are individually supplied to the classifier. This representation preserves the spatial information associated with different receiver-channel pairs and allows the classifier to exploit pair-dependent differences between target and rain clutter returns.

Figure 3 presents the empirical normalized distributions of the pairwise inter-receiver coherence values for target and rain clutter returns. The observed difference between the distributions indicates that spatial consistency across receiver channels provides information complementary to the energy concentration attributes captured by the SPAR.

D. Spectral Flatness Measure

The Spectral Flatness Measure quantifies how uniformly power is distributed over a spectral region. It is defined as the ratio between the geometric and arithmetic means of the power spectrum. Values close to one indicate a relatively flat spectral distribution, whereas values close to zero indicate a spectrum dominated by a smaller number of spectral components.

The SFM has previously been investigated as a detection statistic in spectrum sensing applications [13], where noise-only observations tend to present flatter spectra than signals containing structured spectral components. Its use for rain clutter discrimination in surveillance radar data was subsequently investigated in [9]. In the present work, the SFM analysis is extended by evaluating background-region statistics across the available receiver channels.

Let $S_r[k]$ denote the power spectrum associated with the r -th receiver channel. For a set of frequency bins $\mathcal{W}$, the SFM is computed as

$$\text{SFM}_r(\mathcal{W}) = \frac{\exp\left(\frac{1}{|\mathcal{W}|} \sum_{k \in \mathcal{W}} \ln S_r[k]\right)}{\frac{1}{|\mathcal{W}|} \sum_{k \in \mathcal{W}} S_r[k]}. \quad (5)$$

In this work, the SFM is computed over the background spectral region $\mathcal{W}_b$, defined as the frequency bins outside the dominant peak-region window introduced in Section III-B. Thus, for the r -th receiver channel, $\text{SFM}_{r,b} = \text{SFM}_r(\mathcal{W}_b)$.

Rather than using the background-region SFM from an individual receiver, two statistics are extracted across the M available receiver channels. The mean background-region SFM

is defined as

$$\mu_{\text{SFM},b} = \frac{1}{M} \sum_{r=1}^M \text{SFM}_{r,b}, \quad (6)$$

whereas its variance across receiver channels is computed as

$$\sigma_{\text{SFM},b}^2 = \frac{1}{M-1} \sum_{r=1}^M (\text{SFM}_{r,b} - \mu_{\text{SFM},b})^2. \quad (7)$$

These two statistics characterize complementary aspects of the background spectral behavior. The mean quantifies the typical spectral flatness outside the dominant return region, whereas the variance measures the variability of this behavior across receiver channels. For distributed rain clutter returns, the background spectral distribution and its variability across receivers may differ from those associated with spatially localized target returns.

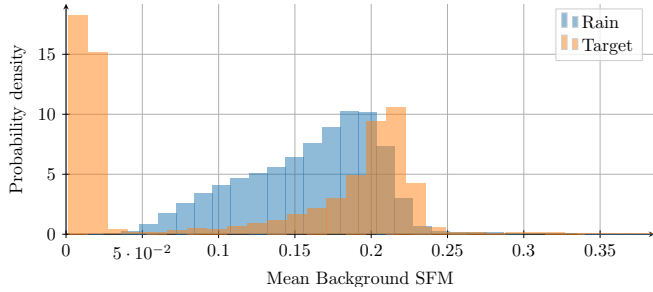


Fig. 4. Empirical normalized distributions of the mean background-region SFM across receiver channels for target and rain clutter returns.

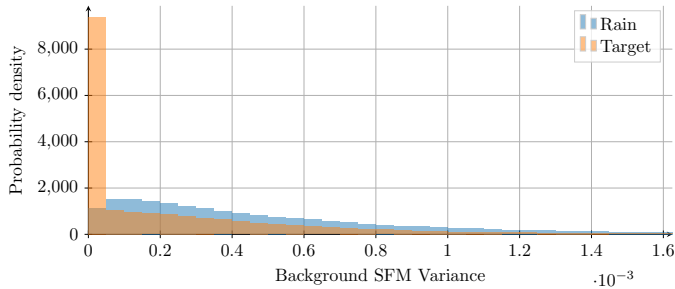


Fig. 5. Empirical normalized distributions of the background-region SFM variance across receiver channels for target and rain clutter returns.

Figures 4 and 5 present the empirical normalized distributions of the mean and variance of the background-region SFM, respectively. For the analyzed measurements, the mean background-region SFM provides visible separation between target and rain clutter returns, although partial class overlap remains. The variance descriptor further characterizes differences in the variability of the background spectral behavior across receiver channels.

IV. CLASSIFICATION METHOD

The feature extraction procedure described in Section III provides complementary information regarding the spectral energy concentration, spatial-coherence, and spectral-domain behavior of the radar returns. Nevertheless, the empirical distributions of the individual attributes exhibit partial overlap between target and rain clutter samples. Therefore, classification is performed in the joint feature space defined by

the feature vector that groups the signal features rather than through independent thresholding of a single descriptor. For each evaluated detection, the input feature vector supplied to the classifier must be defined according to the implemented pairwise coherence representation. It can be written as

$$\mathbf{z} = [\text{SPAR}, \gamma^T, \mu_{\text{SFM},b}, \sigma_{\text{SFM},b}^2]^T, \quad (8)$$

where

$$\gamma = [\hat{\gamma}_{1,2}, \hat{\gamma}_{1,3}, \dots, \hat{\gamma}_{M-1,M}]^T \in \mathbb{R}^{N_p} \quad (9)$$

contains all pairwise inter-receiver coherence attributes. Therefore, Although the classifier input comprises multiple scalar attributes, these attributes correspond to three complementary feature families: the SPAR, pairwise inter-receiver coherence, and background-region SFM statistics.

A k -Nearest Neighbors (KNN) classifier is employed to discriminate target returns from rain clutter echoes. KNN is a non-parametric classification method that assigns a label to an unknown feature vector according to the labels of its k closest training samples in the feature space [14].

Since the attributes composing $\mathbf{z}$ have different physical meanings and numerical scales, each feature dimension is standardized before classification using the mean and standard deviation estimated exclusively from the training set. The same transformation is subsequently applied to the test samples.

Let $\tilde{\mathbf{z}}$ denote a standardized feature vector associated with an evaluated detection and let $\tilde{\mathbf{z}}_\ell$ denote the standardized feature vector of the ℓ -th training sample. The Euclidean distance is computed as

$$d_\ell = \|\tilde{\mathbf{z}} - \tilde{\mathbf{z}}_\ell\|_2. \quad (10)$$

The k training samples associated with the smallest values of d_ℓ define the neighborhood of the evaluated sample. Considering the two classes $\mathcal{C} = \{\text{target}, \text{rain}\}$, the predicted class is obtained by majority voting:

$$\hat{c} = \arg \max_{c \in \mathcal{C}} \sum_{\ell \in \mathcal{N}_k(\tilde{\mathbf{z}})} \mathbb{1}\{c_\ell = c\}, \quad (11)$$

where $\mathcal{N}_k(\tilde{\mathbf{z}})$ denotes the set of indices of the k nearest training samples, c_ℓ is the label of the ℓ -th training sample, and $\mathbb{1}\{\cdot\}$ is the indicator function. The value of k is selected using only the training data and is then kept fixed during evaluation on the test subsets.

The KNN classifier is adopted because it can exploit local class structure in the joint feature space without imposing a predefined linear decision boundary. This property is appropriate for the considered problem, in which the individual feature distributions partially overlap and discrimination relies on their combined behavior.

V. EXPERIMENTS AND RESULTS

As described in Section II, the test subsets are defined on a class-specific per-day basis. For each experiment, target returns from one target acquisition day and rain clutter returns from one rain clutter acquisition day are reserved for testing, while the remaining available samples are used for training. This procedure evaluates the classifier across different held-out target and weather-return conditions, but does not constitute a complete leave-one-acquisition-day-out evaluation.

TABLE I
KNN PERFORMANCE ACROSS HELD-OUT CLASS-DAY PAIRS.

Target day	Rain day	Prec. _T	Rec. _T	Prec. _R	Rec. _R	N _T	N _R
A	B	0.69	0.95	0.99	0.96	17366	171590
A	D	0.90	0.92	0.98	0.98	17366	77763
B	B	0.52	0.97	1.00	0.95	9543	171590
B	D	0.84	0.95	0.99	0.98	9543	77763
C	B	0.67	0.92	0.99	0.96	15565	171590
C	D	0.90	0.88	0.98	0.98	15565	77763
D	B	0.89	0.97	0.99	0.94	86246	171590
D	D	0.97	0.96	0.96	0.97	86246	77763
Mean	–	0.80	0.94	0.99	0.97	–	–

The spectral peak-region window defined in Section III-B contains $L = 9$ frequency bins, corresponding to a half-width of $K_w = 4$ bins around the dominant spectral component. The KNN classifier uses $k = 5$ neighbors. Since the considered attributes have different numerical scales, the feature vectors are standardized using the mean and standard deviation estimated exclusively from the training data, and the same transformation is subsequently applied to the test samples.

Classification is performed using distance-weighted voting. The voting weight assigned to the ℓ -th neighbor is defined as

$$w_\ell = \frac{1}{d_\ell + \varepsilon}, \quad (12)$$

where ε is a small positive constant introduced to avoid numerical instability when a test sample coincides with a training sample. The predicted class is obtained as

$$\hat{c} = \arg \max_{c \in \mathcal{C}} \sum_{\ell \in \mathcal{N}_k(\tilde{\mathbf{z}})} w_\ell \mathbb{1}\{c_\ell = c\}, \quad (13)$$

where $\mathcal{C} = \{\text{target}, \text{rain}\}$ and $\mathcal{N}_k(\tilde{\mathbf{z}})$ denotes the set of the k nearest training samples.

The results are summarized in Table I. Acquisition days are represented by letters. For each test pairing, Prec._T and Rec._T denote the precision and recall of the target class, whereas Prec._R and Rec._R denote the corresponding metrics for the rain clutter class. The quantities N_T and N_R indicate the number of target and rain clutter test samples, respectively.

The classifier exhibits high recall for both classes across the evaluated held-out acquisition-day pairings. rain clutter recall ranges from 0.94 to 0.98, while target recall ranges from 0.88 to 0.97, with an average value of 0.94. Therefore, most genuine target returns are correctly retained by the classifier across the evaluated configurations. This behavior is particularly relevant in surveillance applications, since missed targets directly compromise detection capability.

The main performance limitation is associated with the precision of the target class, which ranges from 0.52 to 0.97. The lowest values occur in configurations presenting a strong imbalance between rain clutter and target supports. For example, in the B/B experiment, the test set contains 171590 rain clutter samples and only 9543 target samples. In such a scenario, even a small fraction of rain clutter samples incorrectly classified as targets produces a significant number of false target declarations, thereby reducing target precision despite the high recall values observed for both classes.

Overall, the results indicate that the joint use of spectral energy concentration, inter-receiver coherence, and background spectral-flatness descriptors enables effective offline

discrimination between target and rain clutter returns in real-world single-polarization surveillance radar measurements. The class-specific day-separated evaluation further indicates that the extracted attributes retain discriminative capability across held-out target and rain clutter acquisition conditions.

VI. CONCLUSION

This paper investigated an offline approach for rain clutter discrimination in real-world single-polarization surveillance radar measurements. The proposed method combines the SPAR, pairwise inter-receiver coherence, and background-region SFM statistics to capture complementary Doppler-domain spectral-concentration, spatial-coherence, and spectral-shape characteristics of target and rain clutter returns. Using class-specific acquisition-day subsets reserved for testing, the distance-weighted KNN classifier achieved average recall values of 0.94 for targets and 0.97 for rain clutter, indicating that the selected attributes remain discriminative across the evaluated held-out target and rain clutter conditions.

The main limitation was the reduction of target precision in highly imbalanced test scenarios, where a small fraction of rain clutter misclassifications can produce a significant number of false target declarations. Future work should investigate additional acquisition conditions and classification strategies aimed at improving false-alarm control under class imbalance.

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