Radar Target Detection Using Target Features and Artificial Intelligence

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***Abstract*— A new type of radar target detection approach based on target features and artificial intelligence techniques is proposed and investigated in this work. Traditional radar target detection in clutter and interference is achieved by removing clutter and interference through filtering prior to target detection. The novel approach, keeping both targets and interferences, recognizes and detects targets using artificial intelligence techniques based on distinguishable target and interference features. The proposed approach is equally effective and more robust to environmental changes and could replace the traditional filtering-based detection methods for all radar platforms.**

Keywords—target detection; clutter and interference; artificial intelligence; target features.

I. INTRODUCTION

Radar target detection is a critical part of radar functions. Targets can be reliably detected if the signal-to-noise ratio (SNR) is sufficiently large [1]. Numerous techniques such as increasing transmitting power, pulse compression and coherent processing can be used to enhance target signals and thus to improve detection SNR. However, if radar echoes contain interferences such as clutter and jammers as well as thermal noise, the interferences are considered to be a part of "color" noise and must be removed or significantly suppressed through filtering to have a large enough signal-to-interference plus noise ratio (SINR) for reliable target detection. Therefore, traditionally optimum target detection can be achieved by filtering out interferences such as clutter and jammers using the optimum filter. Typically, MTI radars use a filter to remove any stationary clutter with zero or near-zero Doppler frequencies. Airborne Pulse Doppler (PD) radars employ a stopband filter to remove ground clutter from specific Doppler frequency bands. Airborne radars equipped with a Space-Time Adaptive Processing (STAP) system eliminate ground clutter by using a space-time adaptive filter. However, all current filtering-based target detection schemes require accurate knowledge of the interferences such as their power spectra or covariance matrices for effective interference removal; incomplete or slightly inaccurate interference information may lead to a significant processing loss [2].

In this work, we propose a new type of radar target detection method based on distinguishing target and interference features without removing interferences from the radar receiver. Typically radar targets possess isolated-point features in space domain; and no-zero single or congregated frequencies in Doppler domain. Clutter are normally extended in space domain, close to zero (for ground radar) or extended (for airborne radar) in Doppler domain. For jammers, normally they are extended in Doppler domain and isolated in space domain. With these distinguishing features, targets will be automatically detected from interferences using artificial intelligence techniques. With recent advances in computing, VLSI, and machine learning, artificial intelligence techniques are increasingly mature and feasible for radar target detection. Numerous artificial intelligence techniques such as decision trees, feature vectors and machine-learning classifiers are used for smart target detection in this work.

The rest of the paper is arranged as follow. Radar target and interference features will be discussed for various radar platforms in section II; several artificial intelligence techniques and schemes will be introduced for smart radar target detection in section III; and finally some preliminary results are presented in section IV.

II. TARGET AND INTERFERENCE FEATURES FOR VARIOUS RADAR APPLICATIONS

The extraction of discriminating features is crucial for target detection using artificial intelligence algorithms. Generally, some kinds of transforms are needed to generate favorable discriminating features under certain application scenarios. We will consider selecting target and interference features and their extraction methods in several typical radar applications.

A. Surface-Based MTI/MTD Radars

For surface-based MTI/MTD radar, the ground clutter is stationary with zero-Doppler frequency. The Doppler frequencies of the weather clutter might be nonzero, but are relatively small. The clutter is extended in space domain (continuous in adjacent range bins). The target is pointed in space domain (occupying one or two range bins); and pointed in Doppler domain with a value that is much higher than

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clutter Doppler frequencies. The clutter and target features in space and Doppler domains for ground-based MTI/MTD radars are shown in Fig. 1.

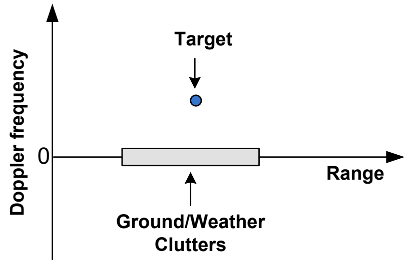


Fig. 1. Clutter and target features for MTI/MTD radars

Target and clutter are separate in range-Doppler domain and have different shape-features. The targets are detectable based on their unique features.

B. *Airborne Pulse Doppler (PD) Radars*

For traditional airborne PD radars, high PRF waveforms are used to separate various kinds of ground clutter and targets for clutter suppression filtering processing and target detection. The clutter and target features for PD radars are shown in Fig. 2.

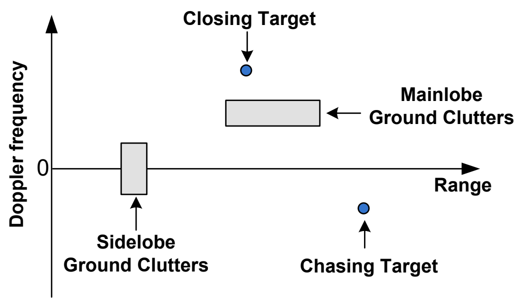


Fig.2. Clutter and target features for airborne PD radars

The ground clutter and targets in Fig.2 are well separated in range-Doppler domains. Because clutter is extended in either Doppler or range domain, they can be identified and differentiated from targets based on their different features.

C. *Airborne Adpative Radars*

Airborne adaptive radars such as space-time adaptive processing (STAP) radars allow low PRF waveforms to be used for adaptive suppression of ground clutter [3]. Therefore, the covariance matrix of the ground clutter must be accurately estimated for adaptive processing. Alternatively, clutter, jammers and targets can be transformed to Doppler-angle domains for target detection based on their different features. The features of clutter, jammers and target are shown in Fig. 3. The ground clutter for airborne radar in angle-Doppler domains is extended in a tilted direction since the clutter Doppler frequency changes with its angle. Wideband jammer signals are extended in Doppler domain and pointed in angle domain. Target is pointed in both Doppler and angle domains. Therefore, target can be detected based on its distinguishing features without adaptive filtering.

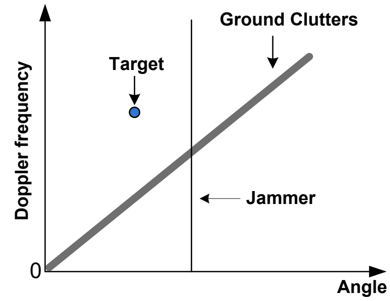


Fig. 3. Clutter, jammer and target features in angle-Doppler domain for airborne adaptive radars

D. *Other Clutter and Deceptive Jammers*

Discrete ground clutters generated by isolated scatters such as ground medal towers are pointed in feature domains, but they are recognizable as clutter since they are stationary. In addition, deceptive jammers are normally difficult to recognize by regular radars, but can be identified easily in feature spaces using artificial intelligence techniques.

III. FEATURE-BASED TARGET DETECTION SCHEMES USING ATIFICAL INTELLIGENCE TECHNIQUES

Since radar echoes contain interferences such as clutter and jammers as well as targets and thermal noise, target signals should be enhanced through integration processing to ensure a large enough SNR prior to any feature-based detection for reliable target detection regardless of various interferences. In addition, radar echo samples should be transformed to a multi-dimensional signal domain (range/angle/Doppler) for a desired feature recognition result. Thermal noises are still independent in any transformed domains. Normally SNR is enhanced through the same data transform; and thermal noise is removed by hard-thresholding processing of the transformed radar echoes prior to feature-recognition processing for target detection. The general feature-based detection scheme for radar target is shown in Fig. 4.

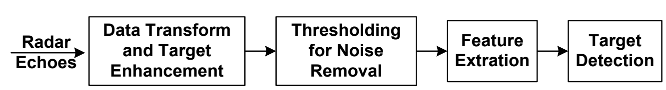


Fig. 4. Feature-based target detection

The keys to the feature-based target detection schemes are feature extraction and target detection methods. Typical features differentiating a target and clutter or jammers are the received signal shape in the transform domain. We will define the feature based on serval concepts firstly developed by ourselves. The target detection schemes designed using artificial intelligence techniques include decision-tree based detector, feature parameter or vector based detector; and machine-learning classifier. These detection schemes are detailed as follows.

A. Target Detection Using a Decision Tree

Target detection decision tree is a target-or-no-target classifier of a hierarchical tree structure evaluating multiple features based on training data or analysis results using a divide-and-conquer strategy. Fig. 5 is a decision tree for MTI/MTD radar target detection using the features in Fig. 1. The feature data used for the detection are feature block sizes and their Doppler centers.

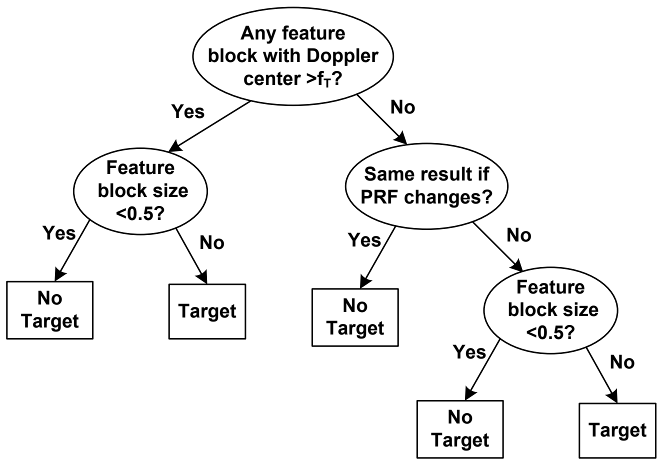


Fig. 5. A decision tree for feature-based target detection with MTI/MTD radars

In Fig. 5 target feature sizes are set to be between 1 and 3. If the size of a feature is less than 0.5 with a large Doppler frequency, it is generated from a random noise spike. Similar decision trees can be constructed for target detection with other radar platforms or applications. This approach is simple, straightforward and normally accurate.

In order to construct a decision tree in Fig. 5, we need to use the following definition of feature block size. *Feature block size* is defined as the maximum distance between two any pixels in a feature block [4]. If a feature block contains only one pixel, the size is defined as zero. The feature blocks are generated from the thresheld image data in Fig. 4 using a region growing algorithm [5].

B. Target Detection Based on Feature Vector Distances

Another useful target detection approach is based on the distance between the data feature vector and the mean feature vector of typical targets. Assume we use the feature vector **x** containing N components, which are likely to be feature block size, Doppler frequency of the block center, Doppler spread, range spread, and etc.

$$\mathbf{x} = [x_1, x_2, \cdots, x_N]^T \quad (1)$$

For typical radar targets and clutter, using training data we can calculate the mean feature vectors for target and clutter, respectively, as:

$$\boldsymbol{\mu}_T = [\mu_{t1}, \mu_{t2}, \cdots, \mu_{tN}]^T \quad (2)$$

and $$\boldsymbol{\mu}_C = [\mu_{c1}, \mu_{c2}, \cdots, \mu_{cN}]^T \quad (3)$$

Similarly we can calculate the variances of the feature vectors for targets and clutter using training data. The standard deviations of the target and clutter feature vectors can be expressed, respectively, as:

$$\boldsymbol{\sigma}_T = [\sigma_{t1}, \sigma_{t2}, \cdots, \sigma_{tN}]^T \quad (4)$$

and $$\boldsymbol{\sigma}_C = [\sigma_{c1}, \sigma_{c2}, \cdots, \sigma_{cN}]^T \quad (5)$$

We define the weighted distance between the data and the target as:

$$D_{x,T} = \sqrt{\sum_{i=1}^{N} (x_i - \mu_{ti})^2 / \sigma_{ti}^2} \quad (6)$$

Furthermore, the weighted distance between the data and clutter is defined as:

$$D_{x,C} = \sqrt{\sum_{i=1}^{N} (x_i - \mu_{ci})^2 / \sigma_{ti}^2} \quad (7)$$

Subsequently, target detection is based on the following rule:

If $D_{x,T} < D_{x,C}$, a target is declared for the data; otherwise, no target is declared.

For this approach, we generally require that the feature vector components are statistically uncorrelated.

C. Target Detection Using Machine-Learning Classifiers

Even more useful approach is to design a machine-learning classifier using radar training data by establishing a hyperplane boundary between the target subspace and clutter subspace. The boundary is formulated in the space with the feature vector components we select for the classification of the radar data as either target or interference. If the training data are available, the boundary can be formulated by using an artificial neural network [6] or a support vector machine (SVM) [7]. The advantage of this approach is that the different feature vector components do not need to be independent.

IV. PRELIMINARY RESULTS

We have achieved some preliminary target detection results using the proposed artificial intelligence approaches. We applied the decision-tree approach and the one using the feature vector distances to the simulated radar data with some very promising results obtained.

A. Target Detection Results Using A Decision Tree for A MTI Radar

We simulated aground MTI radar in C- band with 6000 datasets with half of them containing a moving target. The waveform bandwidth is 1MHz, the radar PRF is 5kHz, the number of coherent pulses during a beam dwelling is 16, the SNR for received pulses is 0dB and CNR=40dB. The target Doppler frequency is randomly selected between 0 and 5kHz for each CPI and the clutter Doppler frequency is zero. Using the decision tree algorithm in Fig.5, the detection result is displayed in Table I. Some misdetections of targets shown in the Table are due to the fact that the Doppler frequency of targets was randomly selected to be zero or close to zero.

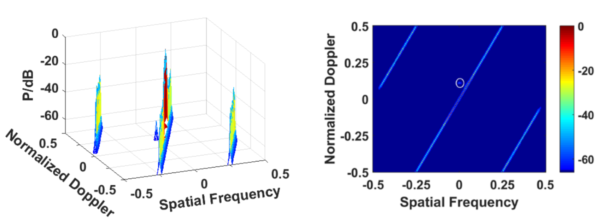
TABLE I. CONFUSION MATRIX FOR CLUTTER/TARGET RECOGNITION

		Declared signal	
		Clutter	Target
Actual signal	Clutter	100%	0%
	Target	0.2%	99.8%

Other than some target misdetections, the feature-based target detection results using the decision tree were almost perfect.

B. Target Deteciton Results Using Feature Vector Distacnes

For this approach, we used one feature vector with only one component, i.e., the feature block size. The radar data are simulated from an airborne STAP radar with a 16-element array for beamforming processing. The target and clutter data are generated in space-time domain, but their distinguishing features are obtained in the angle-Doppler domain through basis transformation. In the feature domain, the target and interference features, defined as feature blocks, must be separated. Therefore, the feature blocks are either targets or interferences such as clutter or jammers. The feature blocks for airborne radar generated using a region growing algorithm and thresholding processing are shown Fig. 6(a, b).



(a) (b)

Fig. 6. Feature blocks generated in Doppler-angle domain for airborne radar (a) 3-D plot; and (b) 2-D plot.

The only feature parameter used for target detection in this application is the feature block size. We define the feature block size as the maximum size of any two image pixels inside the feature block.

The feature vector distances generated from the four feature blocks and the corresponding detection result are shown in Table II. From the table, we can find both target and clutter are detected correctly based on the proposed algorithm.

TABLE II. FEATURE BLOCKS GENERATED FROM FIG. 6 AND DETECTION RESULTS

Feature Block	$\mathbf{B}_1$	$\mathbf{B}_2$	$\mathbf{B}_3$	$\mathbf{B}_4$
$D_{x,T}$	52.2	85.6	4.2	58.9
$D_{x,C}$	10.5	5.7	92.1	12.6
Target?	No	No	Yes	No

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