IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received August 30, 2016, accepted September 16, 2016, date of publication September 21, 2016,
date of current version October 15, 2016.

Digital Object Identifier 10.1109/ACCESS.2016.2611492

Automatic Target Recognition in Synthetic Aperture Radar Imagery: A State-of-the-Art Review

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This work was supported in part by the Research and Development Corporation of Newfoundland and Labrador, in part by the Atlantic Innovation Fund, and in part by the Natural Sciences and Engineering Research Council of Canada.

ABSTRACT The purpose of this paper is to survey and assess the state-of-the-art in automatic target recognition for synthetic aperture radar imagery (SAR-ATR). The aim is not to develop an exhaustive survey of the voluminous literature, but rather to capture in one place the various approaches for implementing the SAR-ATR system. This paper is meant to be as self-contained as possible, and it approaches the SAR-ATR problem from a holistic end-to-end perspective. A brief overview for the breadth of the SAR-ATR challenges is conducted. This is couched in terms of a single-channel SAR, and it is extendable to multi-channel SAR systems. Stages pertinent to the basic SAR-ATR system structure are defined, and the motivations of the requirements and constraints on the system constituents are addressed. For each stage in the SAR-ATR processing chain, a taxonomization methodology for surveying the numerous methods published in the open literature is proposed. Carefully selected works from the literature are presented under the taxa proposed. Novel comparisons, discussions, and comments are pinpointed throughout this paper. A two-fold benchmarking scheme for evaluating existing SAR-ATR systems and motivating new system designs is proposed. The scheme is applied to the works surveyed in this paper. Finally, a discussion is presented in which various interrelated issues, such as standard operating conditions, extended operating conditions, and target-model design, are addressed. This paper is a contribution toward fulfilling an objective of end-to-end SAR-ATR system design.

INDEX TERMS SAR, radar, target, classification, recognition, features, model.

I. INTRODUCTION

As early as 1886, Heinrich Hertz demonstrated the reflection of radio waves from solid objects. However, the first use of radio waves to detect the presence of distant metallic objects was first patented in 1904 by Christian Hulsmeyer of Germany. In 1925, Breit and Tuve of the Carnegie Institution of Washington introduced pulsed transmissions (1 ms) for ranging. Before World War II, researchers in countries such as France, Britain, Germany, Soviet Union, United States and Japan worked independently and secretly on developing technologies that led to modern day version of radar. In 1934, American Robert M. Page of the Naval Research Laboratory demonstrated the first radar as a pulsed system. In 1934, the British were the first to fully exploit radar as a defense against an aircraft attack. Radar is an acronym for radio detection and ranging that was coined in 1940 by the United States Navy [1].

The development of modern high-resolution synthetic aperture radar (SAR) was led by three key innovations. The first of these was pulse compression which enabled radars to range-resolve closely spaced targets. The most widely used pulse compression technique is linear frequency modulation (LFM), also known as chirp modulation, which was introduced in the early 1950s. Second, by 1951, it was possible to resolve closely spaced targets in angular position relative to the antenna beam center of side looking airborne radars. This was achieved through Doppler filtering which was pioneered by Carl Wiley of Goodyear Aircraft Corporation.

Finally, high-resolution SAR was enabled through the advent of a technique to synthesize a long aperture for storing the magnitude and phase of successive radar returns along the platform trajectory. The integration of these innovations led to the formation of the first focused SAR image at the University of Michigan in 1957 [2], [3].

SAR is an active remote sensor (i.e., it carries its own illumination and it is not dependent on sunlight) which makes it functional in all-weather and day-and-night operating conditions (OCs). Focused SAR images are different from their optical counterparts in many aspects. Some distinctive characteristics of SAR images include (1) a target size does not vary with the distance between the SAR sensor and the target, (2) the information about the imaged scene is carried in the magnitude of the radar backscatter (i.e., for a single-channel SAR),[1] (3) large specular reflections pertaining to a microwave mirror-like behavior result from man-made scenes and some natural objects (e.g., rocks), and (4) high sensitivity to the very small changes in the target's pose and configuration for various reasons including: the shadowing effect, the interaction of the target's backscatter with the environment (e.g., clutter, adjacent targets, etc.), projection of the 3-D scene (including the target) onto a slant plane (i.e., SAR's line of sight (LOS)), and a noise-like phenomenon known as speckle due to the backscatter's dependence on the coherent combination of returns from points in the imaged scene.

There are various types of SAR sensors in the literature. These sensors can be broadly classified into three main categories: space-borne SAR, air-borne SAR and ground-based SAR (GB-SAR). Different SAR sensors, including within the same category, can have different sensor properties such as: frequency/wavelength, polarization, imaging mode (i.e., Stripmap SAR, Spotlight SAR, ScanSAR, Inverse SAR, Bistatic SAR and Interferometric SAR (InSAR), etc.), antenna dimensions (i.e., real aperture), synthetic aperture, resolution (i.e., resolution in the range and the cross-range directions), and focusing algorithm (e.g., range Doppler algorithm (RDA), chirp scaling algorithm (CSA), Omega-K algorithm (ωKA, also known as the range migration algorithm (RMA)), and the SPECAN algorithm, etc.), among others [10], [11]. These factors add to the distinctiveness of SAR imagery.

From the perspective of polarization of the microwave signals, a SAR system can use linear horizontal (H) and/or vertical (V) polarization.[2] Accordingly, the following channels may be formed, for transmit and receive, respectively: HH, VV, HV and VH. The former two polarization modes are commonly known as co-polarized or like-polarized. The latter two are typically known as cross-polarized. Depending on the level of polarization complexity supported, the image produced by the SAR system can be any of (1) single polarized, meaning that the SAR sensor only supports a single polarization from among the abovementioned four (i.e., HH, or VV, or HV/VH). This is also known as a single-channel SAR, (2) dual polarized, meaning that the SAR sensor supports a pair of polarization combinations from among the four abovementioned (i.e., HH and VV, or HH and HV, or VH and VV). This is also known as a dual-channel SAR, and (3) quad polarized, meaning that the SAR sensor offers support for the four channels (i.e., HH, VV, and HV/VH). This is also known as polarimetric SAR. Typically, for (a low-to-medium resolution) single-channel SAR, often the magnitude information is utilized, and the phase content is discarded. However, for dual-channel or quad-channel SAR, besides the magnitude information, the phase difference between the channels is typically utilized as it carries important information about the imaged scene.

Automatic target recognition (ATR) deals with the use of computer processing capabilities to infer the classes of targets (i.e., objects of interest) in the sensory data, and to characterize the desired OCs. ATR technology originated in the military but today it is of paramount importance in both the military and civilian applications [19]. In the literature, there is a wide range of ATR applications varying from recognizing a pre-known signature in homogeneous clutter to recognizing the source of the signature that varies considerably with pose and configuration, and is located in a highly heterogeneous and probably occluded scene [20]. Due to the unique characteristics of SAR images, it is not feasible to interpret them by the most sophisticated ATR systems, let alone the trained eye [21]. An end-to-end ATR system for SAR imagery (SAR-ATR) is typically multistaged to handle the SAR imagery in a divide-and-conquer approach. Subsequently, SAR-ATR is a difficult and diverse problem that continues to receive increasing attention from researchers around the globe. This is evident from the overwhelming number of open-literature research articles published on the subject. Different researchers tend to approach the topic from various perspectives. This makes it even more challenging and time consuming to relate the various research findings and to grasp the relationship between those various approaches. This motivates the need for a survey that offers an umbrella under which various research activities in the field are broadly probed and taxonomized. In this paper, our attention is restricted to single-channel SAR. This is because the development of this survey is motivated by our endeavor to develop SAR-ATR algorithms for Spotlight SAR data [22]. However, the topics addressed in this paper are either applicable or extendable to multi-channel SAR systems. Readers exclusively interested in multi-channel SAR processing are referred to pertinent references [23]–[29].

[1] Note that while this statement is applicable to medium-to-low resolution SAR imagery, it is not the case for extended targets. It is shown in the literature that the phase in single-channel high-resolution SAR imagery carries important information due to nonlinear phase modulation induced by cavity-like reflectors in man-made targets (both stationary and moving) such as vehicles and airplanes. For a synopsis on the subject see [4]. For an in-depth discussion see [5]–[9].

[2] Note that while the focus here is on the common linear polarization, there are SAR systems that utilize circular polarization [12], [13]. Moreover, another relatively recent advancement in nonlinear polarization, which is receiving increasing attention from the radar community, is the orbital angular momentun [14]–[18].

The remainder of this paper is organized as follows. In Section II, the topic of ATR is overviewed in the context of SAR imagery. In Section III, the taxonomy and architecture of the SAR-ATR methods are introduced. In Section IV, a comprehensive survey and comparison between various SAR-ATR methods are presented. In Section V, a benchmarking scheme for evaluating existing SAR-ATR systems and motivating new system designs is described. The proposed scheme is applied to the SAR-ATR systems surveyed in Section IV. In Section VI, important issues pertinent to the design of the SAR-ATR system are discussed. First, the reasons for variability of the target signature in the SAR image are elaborated. Second, the OCs, in the context of SAR-ATR, are characterized. Third, a methodology to differentiate between the various target-models is presented. Fourth, relevant methods for superresolving the radar cross section (RCS) in the SAR target chip are surveyed. Fifth, respective methods for 3-D SAR image reconstruction are reviewed. Sixth, the competitive advantage of the model-based SAR-ATR approach is highlighted. Conclusions appear in Section VII. A list of the acronyms used throughout this paper is provided in the Appendix.

II. AUTOMATIC TARGET RECOGNITION IN THE SAR CONTEXT (SAR-ATR)

ATR deals with the information output from one (or more) sensor(s) aimed at a scene of interest. It generally refers to the use of computer processing capabilities to infer the classes of the targets in the sensory data, and to (optionally) characterize some attributes of interest such as articulation, orientation, occlusion, sub-class and so on, without human intervention. The term ATR originated in the military in the early 1980s under the Low Altitude Navigation and Targeting Infrared for Night (LANTRIN) program [19]. Today, ATR technology is important in both military and civilian applications. The ATR problem is a part of the general broad problem of machine vision; namely, *how can computers be configured to do what humans do efficiently and naturally?*

Target, clutter and noise are three terms of military origins associated with ATR and are dependent on the application of interest. In the case of SAR imagery, target refers to object(s) of interest in the imaged scene. Clutter refers to either man-made (e.g., building, vehicles, etc.) or natural objects (e.g., trees, topological features, etc.) which tend to dominate the imaged scene. Noise refers to imperfections in the SAR image which are result of electronic noise in the SAR sensor as well as computational inaccuracies introduced by the SAR signal processor. In the literature, there is a spectrum of ATR problems ranging from classifying a pre-known signature in a well-characterized clutter to recognizing the source of signature that varies greatly with pose and state, and is located in a highly complex and probably occluded scene [20].

STRUCTURE OF AN END-TO-END SAR-ATR SYSTEM

The general structure of an end-to-end SAR-ATR system as reported in the literature is depicted in Figure 1.

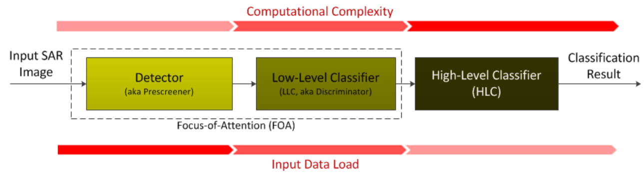

FIGURE 1. General structure for an end-to-end SAR-ATR system.

To counter the prohibitive amounts of processing pertaining to the input SAR imagery, the strategy is to divide-and-conquer. Accordingly, the SAR-ATR processing is split into three distinctive stages: detection (also known as prescreening), low-level classification (LLC, also known as discrimination), and high-level classification (HLC) [30]–[38]. The first two stages together are commonly known as the focus-of-attention (FOA) module. While this is the most common structure reported in the literature, it should be highlighted that (theoretically) there is no restriction on the number of stages.

As depicted in Figure 1, the input SAR image possesses an extremely high computational load due to its high-resolution and/or the presence of various clutter types and/or objects. As the SAR data progresses throughout the SAR-ATR processing chain, its load is reduced. The HLC stage deals with SAR data that have relatively lower computational load. On the contrary, the computational complexity of the SAR-ATR chain increases as the SAR data progresses from the front-end stage towards the back-end stage. In the next sections, the main functionalities of the three blocks depicted in Figure 1 are briefly reviewed.

A. FOCUS-OF-ATTENTION (FOA)

The FOA module is a significantly important stage in the SAR-ATR processing chain. It interfaces with the input SAR image and outputs a list of potential targets. The output list from this stage is passed in to the back-end HLC stage. Typically, the FOA module is comprised of two blocks: a front-end detector (also known as prescreener) and an intermediate low-level classifier (LLC). The significance of the FOA module lies in that it should efficiently handle the input SAR data and effectively identify the potential targets. Failure or degradation in the robustness of this stage has a direct impact on the performance of the back-end HLC stage. Here, we briefly review the functionalities of the detector and the LLC classifier constituents of the FOA module, which are the

1) DETECTION (ALSO KNOWN AS PRESCREENING)

Detection is the front-end stage in any SAR-ATR processing chain. It is a relatively computationally simple algorithm that passes all potential targets and eliminates only obvious clutter. Preprocessing is usually required to optimize the computational efficiency and increase the detection accuracy. The detector interfaces with the input SAR image to identify all regions of interest (ROIs). Thus, ROIs can be passed in to the LLC stage. One may think of the detector as a dimensionality reduction scheme that appropriately reduces the dimensionality of the SAR data. The detector should be designed to balance the trade-off between computational complexity, detection efficacy and outlier rejection. On the one hand, it is required that the detector is relatively computationally simple and thus operate in real-time or near real-time. On the other hand, it is required that the detector enjoys a low probability of false alarm (PFA), and a high probability of detection (PD). Indeed, these often conflicting factors distinguish one detector from another. Simply put, if the detector fails to perform its functionality, the subsequent stages in the SAR-ATR processing chain will follow suit and eventually fail. There are numerous methods reported in the literature for implementing the detector. The reader is referred to a state-of-the-art review pertaining to the front-end stage, which is complementary to this paper [39].

2) LOW-LEVEL CLASSIFICATION (LLC, ALSO KNOWN AS DISCRIMINATION)

The LLC stage involves processing the detections output from the front-end stage (i.e., ROIs). Both the computational complexity and the data load pertaining to this stage are relatively intermediate when compared with the preceding and the succeeding stages. In this stage, the following functionalities are typically performed. First, the position and orientation of a relevant detected object from the first stage are determined. Second, discrimination features of interest are computed from the detected object and are then properly combined. Next, these features are input to the pre-trained LLC classifier for it to decide whether the detection is a candidate, or it is a non-target (i.e., clutter) and is thus rejected. The candidates are treated as potential targets and passed in to the third stage in the SAR-ATR processing chain for HLC classification. Obviously, the aim of the LLC stage is to refine detections output from the front-end stage, and to identify all the potential targets of interest and discriminate them from clutter. These candidate targets can belong to different target-classes, and the target classification process is performed in the succeeding stage. The classifier in the LLC stage is often feature-based and is typically implemented either as a one-class classifier (i.e., anomaly detector) trained only on the target-class features, or as a two-class dichotomizer trained on features extracted from both the target-class and the clutter (further discussion on this is found in Sections III and IV-A).

B. HIGH-LEVEL CLASSIFICATION (HLC)

The HLC classifier is the back-end stage in the SAR-ATR processing chain. It receives the candidate targets output from the preceding stage, and classifies them to recognize potential classes. We taxonomize the various methods for implementing the classification stage in general (i.e., both LLC and HLC) into three taxonomies: feature-based, model-based and semi-model-based (see more on this in Sections III and IV). The feature-based approach is a multi-class classifier that can be implemented as a single multi-class classifier, a combination of two-class dichotomizers, or a combination of one-class classifiers. Despite its relative simplicity and popularity, the feature-based approach may be overwhelmed to cope with the 'combinatorial explosion' of the target signature variations pertaining to extended operating conditions (EOCs; see Sections VI-A and VI-B). Model-based and semi-model-based approaches are aimed at circumventing this drawback. This is accomplished at the expense of increased SAR-ATR system complexity. Depending on the design requirements, candidate targets can be classified into classes (between-class classification) and subclasses (within-class classification), or identified as confusers (i.e., objects of no interest) and thus rejected. Regardless of the classification approach used, features utilized for this stage should be chosen to capture the between-class and (if desired) the within-class variations.

III. THE SAR-ATR APPROACHES: TAXNONOMY AND COMPARISON

While the front-end stage in the SAR-ATR system depicted in Figure 1 identifies ROI(s) in the input SAR image, the subsequent LLC and HLC stages are concerned with classification. A suitable classifier is required in each of these two stages. Given its position in the SAR-ATR processing chain, the LLC stage typically utilizes a relatively simple classifier when compared to the HLC stage. In this section, we taxonomize the various methods for SAR-ATR reported in the open literature from the perspective of classification. The taxonomy proposed can be applied to both the LLC stage as well as the HLC stage. As it will be apparent soon, the LLC stage tends to follow a certain taxon (i.e., feature-based) given its constraint on computational complexity. Conversely, the HLC stage allows for more flexibility in the choice of the classification taxon. However, this is accomplished at the expense of increased complexity. This section is organized as follows. In subsection III-A, the various methods pertaining to classification in SAR-ATR are broadly taxonomized as feature-based, model-based or semi-model-based. Further, a concise description for the main methods and relevant architectures under each taxon is provided. Finally, in subsection III-B, a comprehensive comparison between various aspects of the three taxonomies is presented.

A. TAXONOMY OF THE SAR-ATR APPROACHES

From the perspective of classification, ATR algorithms can generally be broadly taxonomized into two distinctive taxa based on their implementation approach: pattern recognition (PR) and knowledge-based (KB) [40]. The latter also goes by other names including artificial intelligence (AI) based, expert system, rule-based and model-based approach. In the context of SAR-ATR, we refer to techniques that solely rely on feature vectors (including representative templates as a kind of feature vectors) as feature-based methods, and those methods that incorporate intelligence into the design as model-based methods. These two taxa are distinguished by the motivation of the feature generation technique utilized, and whether the system training is classifier-oriented

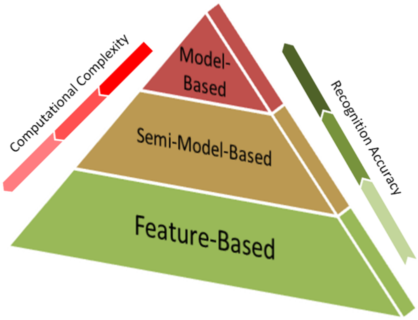

FIGURE 2. Taxonomy of the SAR-ATR approaches.

or target-model-oriented. A careful examination of the literature pertinent to SAR-ATR reveals that a third taxon of methods falling between feature-based and model-based taxa emerges. We refer to this taxon as a semi-model-based. What distinguishes this taxon from the earlier two is that although it solely relies on features, it somehow incorporates intelligence into the SAR-ATR system design. For an end-to-end SAR-ATR system, the feature-based taxon is extensively used in the literature for both LLC and HLC classification. The semi-model-based and model-based taxa are primarily used for HLC classification. Figure 2 depicts the three taxa proposed. The feature-based taxon is placed at the base of the pyramid because it is the most common in the literature. As one ascends from the base of the pyramid to the top of the pyramid a better recognition performance is attained. Conversely, as one descends from the top of the pyramid to the base of the pyramid, the computational complexity of the SAR-ATR system decreases. Obviously, these are design trade-offs that need to be appropriately accounted for.

In the next subsections, a concise description for each taxon is provided. Typically, regardless of the taxon in question, there are two phases involved: offline classifier training (for the feature-based taxon), or offline model construction/ training (for the model-based and the semi-model-based taxa, respectively); and online prediction and classification. First, the feature-based taxon is presented in subsection III-A1. Second, the model-based taxon is discussed in subsection III-A2. Finally, the semi-model-based taxon is described in subsection III-A3. The issues addressed under each section include: generic description, architecture(s), major challenges, advantages and disadvantages.

1) FEATURE-BASED TAXON

The feature-based taxon is a PR approach that relies solely on features to represent the target. These features can be either image target templates or feature vectors extracted from the targets of interest (i.e., SAR target chips). Feature-based approaches assume that the features of targets from different classes lie in separable regions of the multidimensional feature space, while features from the same class cluster together. The process of recognition in the feature-based approach involves two distinctive phases: an offline classifier training and online classification. The classifier training phase is performed entirely offline as depicted in Figure 3. One has to have an extensive set of target chips pertaining to all the targets of interest. From the target chips, features of choice are extracted and preprocessed. Then, these features are used to train the classifier of choice.

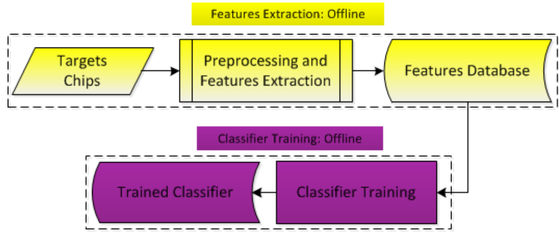

FIGURE 3. Classifier training for the feature-based approach.

In the classification phase, features are extracted online from the input SAR chip to be classified, and fed to the previously trained classifier as depicted in Figure 4. Obviously, the classification result relies solely on the choice of the training features and their uniqueness to abstract the target(s) of interest.

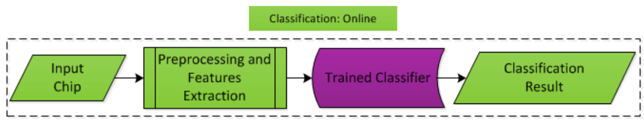

FIGURE 4. Classification in the feature-based approach.

While this method is the most common in the literature, it can become overwhelmed when faced with (substantial) variations in the input chip signature (i.e., extracted features) due to factors such as clutter heterogeneity and/or EOC(s). Thus, the major drawback of this method is that it has limited knowledge and almost no intelligence and reasoning capability to learn from the dynamic environment and adapt to it. Further details on the various methods for implementing this taxon are surveyed in Section IV-A. For additional details on the supervised classification and statistical PR problem in general, the reader is referred to standard reference textbooks on the subject [41], [42].

2) MODEL-BASED TAXON

Unlike the feature-based taxon, the model-based taxon handles the recognition problem in a bottom-up fashion. In other words, the recognition process in the model-based approach begins with a simple feature extraction operation from the input SAR chip. Then, the extracted features are compared against feature hypotheses derived on-the-fly from (offline) pre-designed models of the target(s) of interest and the SAR sensor. Typically, there exists one such model per each target of interest. By contrast, the feature-based taxon is a top-down approach in that it attempts to capture multiple aspects of the target variations and to represent them in the form of features, after which these features are used to produce a trained classifier. Indeed, the debate on the preference of the bottom-up approach over the top-down approach originated in the field of computer vision. It was professor Rodney A. Brooks of Massachusetts Institute of Technology (MIT) who showcased the superiority of the bottom-up approach in relation to the top-down approach through explaining that ATR system design should focus on actions and behavior rather than representation and function [43]. ACRONYM was the first model-based system for target recognition introduced by R. A. Brooks in the early 1980s [44].

Model-based approaches combat the major challenges of the feature-based approach through incorporating prior knowledge into the design. Thus, the model-based approach utilizes some of the techniques used in the feature-based approach and builds on them. Model-based approaches represent a spectrum of attempts steered towards the characterization of the physical structure of the target-classes of interest. Typically, the model-based approach is comprised of two distinctive phases: an offline target-model construction, and an online prediction and classification. These two phases resemble the feature-based approach but with two major differences. Firstly, the offline model-construction is a major task in the model-based approach which focuses on building (a) holistic and generic physical model(s) for the target(s) of interest. This is different from the feature-based approach where, in this phase, a classifier of choice is merely trained based on an ad hoc selection of (training) target features. Secondly, unlike the feature-based approach where the online classification is merely based on extracting certain features from the input SAR chip and determining where the extracted features fit in the feature space of the offline-trained classifier(s), the model-based approach hypothesizes relevant attributes in the input SAR chip and based on these attributes it produces certain predictions on-the-fly from the offline-constructed target-model. The online classifier then looks for the hypothesis prediction that yields close resemblance to the input SAR chip.

Multiple methods pertaining to offline target-model construction are reported in the literature. Regardless of the method used, the online classification phase for all methods has similar structure with a few minor differences. Here, some of the major methods reported in the open literature for offline target-model construction is summarized. This is followed by a description of the online prediction and classification process. In the first method [45], only a 3-D CAD model for each target of interest is designed offline and stored in the system's database. This process is depicted in Figure 5. These 3-D CAD models are used for online prediction and classification in the second phase.

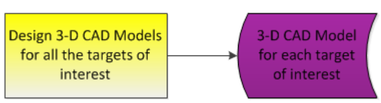

FIGURE 5. The first model-based method for offline target-model construction.

In the second method [46], [47], similar to the first, 3-D CAD models are designed for all the targets of interest. Then, a so-called global scattering center model is generated for each target of interest using a suitable electromagnetic (εM) prediction tool. These 3-D global scattering center models are stored offline in the training database, and used for the online prediction and classification. The process of offline target-model construction is depicted in Figure 6.

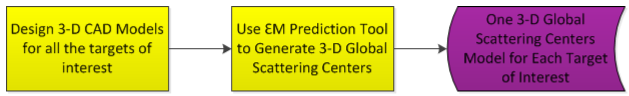

FIGURE 6. The second model-based method for offline target-model construction.

In the third method [48], similar to the first, a 3-D CAD model for each target of interest is designed offline. An εM prediction tool is used to generate 2-D target templates at uniformly sampled azimuth angles. Then, for each template, a dictionary of invariant histograms is generated. These 2-D target templates and corresponding dictionaries are stored offline in the target-model database. This database is used during the online prediction and classification phase. The process of offline target-model construction is depicted in Figure 7.

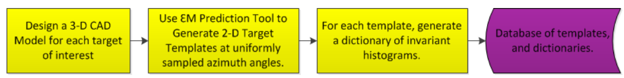

FIGURE 7. The third model-based method for offline target-model construction.

In the fourth method [49], [50], unlike the previous three methods, no CAD models are utilized. Rather, for each target of interest, a set of target chips that covers the span of the azimuth angles from 0° to 360° is required. Scattering centers are extracted from each chip. These scattering centers are used to produce a 3-D target-model comprised of a number of N primitives each of which is characterized by a canonical primitive type, a 3-D location of the primitive and a set of continuous-valued descriptors. This process is shown in Figure 8. These 3-D target-models are stored offline in the target-model database and invoked on-the-fly during the online classification phase.

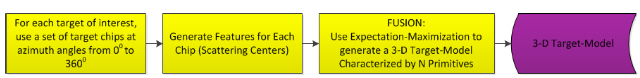

FIGURE 8. The fourth model-based method for offline target-model construction.

In the next phase, an online prediction and classification is performed. This is depicted in Figure 9. Two distinctive sub-stages are executed in parallel. In the first sub-stage, pertinent features are extracted from the input SAR chip and fed to the *hypothesis verification unit*. In the second sub-stage, certain parameters are extracted from the input SAR chip

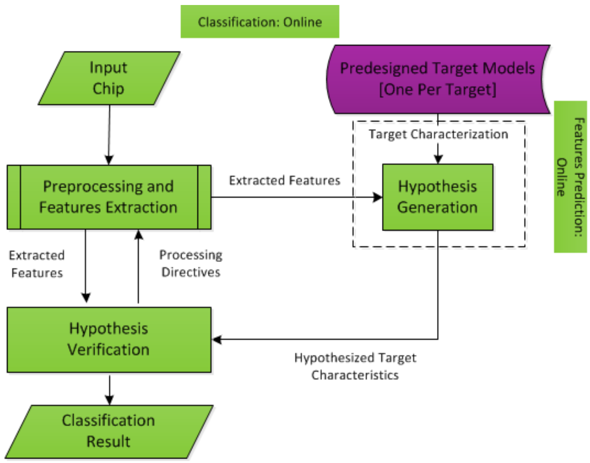

FIGURE 9. **The online model-based prediction and classification.**

and fed to the *hypothesis generation unit*. Depending on the method used for target-model construction (e.g., methods #1 through #4), the functionality of the hypothesis generation unit may vary from retrieving an εM prediction tool (i.e., to generate prediction hypotheses based on the extracted parameters from the input SAR chip) to simply retrieving relevant entries in the target-model database and characterizing them based on the extracted parameters from the input SAR chip. This process is often referred to as *indexing*. Typically, the output from the hypothesis generation unit is a set of arbitrary feature-vector predictions pertinent to various target-classes, poses and the EOCs of interest. All the predicted feature hypotheses are fed to the hypothesis verification unit. Finally, the classification of an input chip is performed by searching over the hypothesis space for the set of possible combinations of the target-class, pose and relevant EOCs (if any) that yield a predicted observation close to the actual observation. The feature-vector prediction that scores the highest match, typically within some predefined threshold constraint, is chosen. Being a function of the target-class, pose and relevant EOC(s), matched features reflect the recognized target and its corresponding pose and EOC(s). The pre-designed threshold constraint is used to reject the non-target confusers so that no forced recognition is allowed.

From the earlier description it is obvious that regardless of the method used for target-model construction, the generic structure of the online model-based prediction and classification phase is similar for all methods. For the four methods described, the hypothesis generation unit is used to hypothesize feature predictions that are fed to the hypothesis verification unit for feature matching that yields a classification result. However, depending on the target modeling method utilized, additional operation(s) may need to be incorporated into the hypothesis generation unit. It should be highlighted that while methods 1, 2 and 4 for target-model construction yield 3-D target-models, method 3 yields a 2-D target-model which presumably handles the 3-D space. This makes method 3 cumbersome when compared to the other three methods. The challenge of the model-based method is that the identification, design and incorporation of pertinent knowledge are major tasks that introduce additional complexity to the SAR-ATR system. Thus, there always exists a trade-off between system complexity and performance that needs to be carefully accounted for in the target-model design process.

3) SEMI-MODEL-BASED TAXON

In the literature, there is a class of approaches to the SAR-ATR problem that are neither strictly feature-based nor explicitly model-based. It differs from the feature-based approach in that it does not solely rely on an ad hoc selection of feature-vectors for offline classifier training, and thus it is not strictly classifier-oriented. It deviates from the model-based approach in that it does not tightly follow the online classification regime prescribed in the previous subsection. In this paper, we refer to the approaches that are neither feature-based nor model-based as a semi-model-based. This SAR-ATR taxon loosely fits between the feature-based and model-based approaches that were described earlier.

In this section, we opt for two such methods from the literature to depict the spectrum of this approach. For each method, the major steps in the offline target-model training are described. The term 'target-model' training is used to distinguish this approach from the target-model construction process utilized under the model-based taxon. This is followed by details on the online classification process.

In the first method [51]–[55], an extensive set of target chips that covers the span of uniformly sampled azimuth angles from 0° to 360° is utilized. After a certain preprocessing, the variance for each target chip is estimated. The variances for the various target chips are stored in the target-model database as a function of the target-class and pose angles. The process of offline target-model training is depicted in Figure 10. There exists one such target-model for each target of interest. These variances are utilized during the online classification phase.

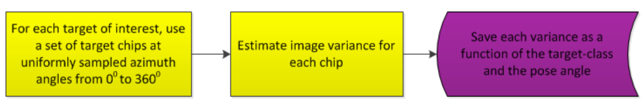

FIGURE 10. **The first semi-model-based method for the offline model-training.**

In the online classification phase, a complex Gaussian probability density function (PDF) is utilized. Note that a suitable PDF model other than the Gaussian can also be used. The PDF model is parametrized by the pixel values of the preprocessed input (test) SAR chip as well as the target-model variances drawn from the database of variances pertaining to the different targets and corresponding pose angles that are constructed offline. A generalized likelihood ratio test (GLRT) is used to search for the variance value that maximizes the likelihood test. Provided that the GLRT test exceeds some predetermined threshold, the variance value that achieves the highest score over all other variances is declared.

The corresponding parameters of the declared variance (i.e., target-class and pose) represent the classification result. If the GLRT is found to be less than the pre-determined threshold over the space of all variances, the input SAR chip is declared as a non-target confuser. The online classification process pertaining to three target-classes is depicted in Figure 11.

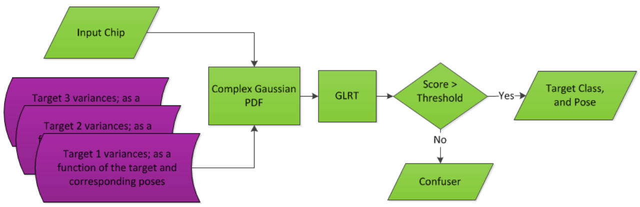

FIGURE 11. The first semi-model-based method for the online classification. In this example, only three targets of interest are depicted.

In the second method [40], [56]–[65], similar to the first method, an extensive set of SAR target chips at uniformly sampled azimuth angles from 0° to 360° is required. For each chip, the N strongest scattering centers are sought (these are from $p = 1$ to N), and their pixel values S, along with the corresponding range location R and cross-range location C are determined. This yields triples, (R, C, S), which are arranged in a descending order based on the pixel value S. Then, an origin pair (R_o, C_o) is chosen from the N pairs (R, C). Further, dR and dC are calculated as

$$dR = R_p - R_o, \quad dC = C_p - C_o. \tag{1}$$

Accordingly, a look-up table (LUT) in which (x, y) addresses are (dR, dC) is constructed, and its corresponding entries are $(Object\ Class, R_o, S_o, S_p)$. This process is repeated N times where for each time a unique origin (R_o, P_o) is chosen from the tuple (R, C) from $p = 1$ to N. The results are stored in the LUT. There is one such LUT for each target-class of interest. The process of LUT construction is depicted in Figure 12.

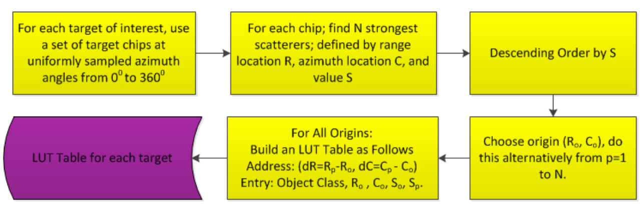

FIGURE 12. The second semi-model-based method for the offline model-training.

In the online classification phase, similar features as those described above in the offline phase are extracted and arranged in a descending order based on the pixel value S. Then, the distances DR and DC are calculated as

$$DR = dR - 1 : dR + 1, \quad and\ DC = dC - 1 : dC + 1. \tag{2}$$

A weighted vote is defined. Moreover, a transition limit as well as a magnitude limit is introduced. These limits serve as thresholds for rejecting the non-target confusers. Then, a search is performed over all the pre-constructed LUTs pertaining to the target-classes of interest. The value that achieves the highest score over all the LUTs is declared, provided that it exceeds the abovementioned thresholds. Corresponding entries in the relevant LUT represent the target-class and its respective pose. This process is depicted in Figure 13 for three target-models (i.e., three LUTs).

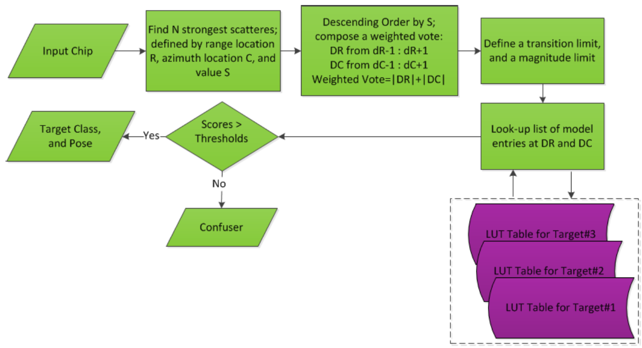

FIGURE 13. The second semi-model-based method for the online classification. In this example, only three targets of interest are depicted.

B. COMPARISON

In this section we provide a general comparison between the feature-based, semi-model-based and the model-based taxa. The feature-based taxon is relatively less-complex and less-computationally demanding when compared to the model-based taxon. However, the major drawback of the feature-based taxon is that it does not have intelligence or reasoning capability which causes it to be overwhelmed when faced with features (substantially) variant from those used in the offline training phase. On the other hand, the model-based taxon embeds knowledge into the design which makes it more flexible and capable to cope with various OCs. However, it should be noted that this capability is conditional upon the generality of the target-model design which, unlike for optical imagery, is a major challenge in the case of SAR imagery (and radar imagery in general). Further, a major drawback of the model-based taxon is the design complexity as well as the computational complexity involved. Thus, there always exists a trade-off between the (design and computational) complexity and classification accuracy. The feature-based taxon is less complex but may yield less accurate results depending on how variant are the online OCs from those that were prevalent during the offline classifier training. Conversely, the model-based taxon is relatively more computationally complex but yields classification results with higher accuracy conditional on the target-model as highlighted above. To balance this complexity-accuracy trade-off, the feature-based taxon is typically used for LLC classification while the model-based/semi-model-based taxon is utilized for the more computationally expensive HLC classification.

In the LLC classification stage, one is interested in rejecting the clutter in the SAR image, and extracting and passing-in candidate targets to the back-end HLC classifier. Typically, this problem can be looked at from two different perspectives as either a two-class classification problem or a one-class classification problem. The two-class classification problem is the traditional statistical PR problem, where a certain dichotomizer is selected and trained offline with exemplar features of the two classes (i.e., target-class and clutter-class). In the online classification phase, the classifier uses the features extracted from the input (test) SAR chip, and decides into which class of the two the input chip should be classified.

In one-class classification [66], only features from the target-class are used. The other class (i.e., clutter) is treated as an outlier and the information available about it is not considered. The boundary between the target-class and the outliers is estimated from the genuine class (i.e., target-class). The classifier is trained offline so that, when put online, it defines the boundary around the target-class and minimizes the chance of accepting outliers. Note that the HLC classification problem can also be treated from similar perspectives. In other words, HLC can be considered as a multi-class classification problem which can be handled using either a multi-class classifier, or properly combining a suitable number of dichotomizers. Conversely, a suitable number of one-class classifiers can be properly combined to perform multi-class classification. In this case, each one-class classifier is trained only on a single genuine target-class, while the other target-classes are considered as outliers. Similar procedure is repeated for all the target-classes of interest. Obviously, this is a sub-optimal approach given that the one-class classifier is an anomaly detector [66].

A comprehensive comparison between the feature-based, semi-model-based and model-based taxa is presented in Table 1. Naturally, the model-based taxon is expected to be superior in terms of classification accuracy (conditional upon the target-model). The semi-model-based taxon tends to be closer to the feature-based taxon in that it should be fed with all the expected EOCs during the offline training phase, and thus the target-model can neither be (completely) generic nor holistic. Subsequently, from this perspective, the semi-model-based taxon shares many of the pitfalls found in the feature-based taxon. This conclusion will be clear when a few semi-model-based methods are surveyed and compared in Section IV-C.

IV. SURVEY OF THE SAR-ATR TAXA

In this section, a comprehensive survey for a selection of SAR-ATR systems is presented. Although the systems considered in this section far from exhaustively cover the numerous research activities published on the subject in the open literature, the choice is carefully made to serve the purpose of this paper, and represent the wide spectrum of the SAR-ATR methods. The survey arrangement is based on the three SAR-ATR taxa presented in the previous section. Firstly, a survey of selected methods pertaining to the feature-based taxon is considered in subsection IV-A. Due to the broad spectrum of methods under this taxon, a classification methodology is introduced first, along with a selection of pertinent SAR-ATR systems under each class. This is followed by a tabular comparison between relevant issues for the various feature-based methods considered. Secondly, a selection of multiple model-based SAR-ATR systems (i.e., those introduced under Section III-A2) is provided in subsection IV-B. This is followed by a tabular comparison between the selected model-based methods. Finally, pertinent semi-model-based SAR-ATR systems are surveyed (i.e., those introduced under Section III-A3) in subsection IV-C. Similarly, this is followed by a tabular comparison pertinent to the semi-model-based examples considered.

A. FEATURE-BASED TAXON

The feature-based taxon relies on an ad hoc selection of target features to train the classifier of choice. There are numerous methods for feature generation. The preference of certain features depends on the user's choice and experience. Classifier preferences are also user-dependent. In subsection IV-A1, we first introduce a classification methodology for the various methods that fall under the feature-based SAR-ATR taxon. This is followed by a survey of selected examples under each class, introduced in subsection IV-A2. Finally, a tabular comparison of relevant issues between the various methods is presented in subsection IV-A3.

1) MOTIVATIONS AND CLASSIFICATION METHODOLOGY

Any supervised PR (i.e., feature-based) system can be viewed as a set of discriminant functions

$$g_i(x) :\in \{1, \ldots, C\}, \tag{3}$$

where C is the number of target-classes and x is the features vector of dimension D. The classifier assigns a feature-vector x to class ω_i if $g_i(x) > g_j(x)$ for all $j \neq i$. Thus, the classifier is viewed as a machine that computes C discriminant functions, and selects the class category that corresponds to the highest discriminant. This is depicted in Figure 14 [41].

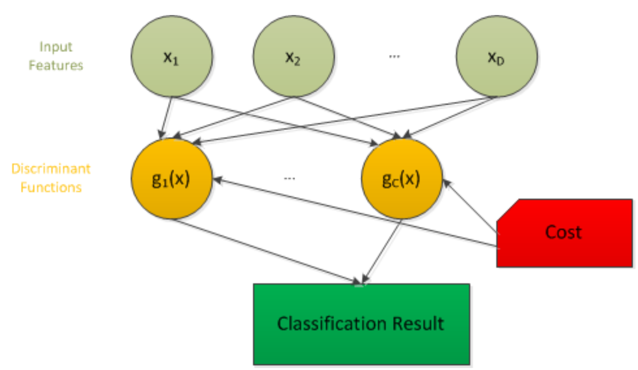

FIGURE 14. The classifier as a set of discriminant functions [41].

From a PR perspective, there exists many ways in which the function $g_i(x)$ can be expressed and learned. The various categories through which the discriminant function can be

TABLE 1. Comparison between feature-based, semi-model-based and model-based SAR-ATR systems. [OAFB] denotes the comment is Only Applicable to Feature-Based Taxon. [AASMB] denotes the comment is Also Applicable to Semi-Model-Based Taxon.

	Feature-Based/Semi-Model-Based	Model-Based
Underpinnings	- A top-down approach,	- A bottom-up approach,
	- Founded on emulation of biological perception,	- Founded on extensive knowledge of the targets of interest and the sensing physics,
	- Representation and function (i.e., classifier) oriented.	- Actions and behavior oriented.
Features	- Various feature generation methods have been utilized to generate features [OAFB],	- Feature choice is motivated by the model design, and thus features are often generated based on the nature of the sensor and the radar target signature [AASMB],
	- Features are often chosen on an ad hoc basis [OAFB].	- Typically, scattering centers or high resolution range profiles (HRRPs) are often used (i.e., radar (SAR)-specific features) [AASMB].
Training	-Training is a classifier-oriented,	-Training is a target-model-oriented,
	- Maintains a large database of exemplar feature vectors (or templates) for all the targets of interest. Depending on the classification method used, the database either needs to be maintained throughout the online classification process, or it can be discarded upon completion of the classifier training,	- Maintains a database of (physical/conceptual) models; one model for each target of interest, -Phenomenologically/conceptually motivated feature-vectors are extracted from the chips of the target of interest,
	- The target training features are extracted offline from real or synthetic SAR target chips, typically at a number of different OCs (e.g., different poses, deployments, viewing configurations, etc.),	- The matching features are predicted on-the-fly from a real-world or synthetic SAR target-model,
	- The classifier is trained (offline) on the feature database, and then utilized in the online classification phase,	- Predictions are generated from hypotheses based on relevant attributes extracted from the input SAR chip to be classified. Clearly, relevant EOCs of interest can be accounted for,
	- No classifier manipulation (i.e., retraining) is permitted online (i.e., during the classification phase).	-The target-model is constructed (offline), and utilized in the online classification phase, - The target-model is manipulated on-the-fly (online) to predict feature-vectors for targets in arbitrary poses, deployment conditions, and viewing configurations.
Classification	- Classification is achieved through inputting the feature-vectors, extracted from the input SAR chip, to the trained classier,	- Classification is achieved by extracting feature-vectors, and intelligently refining the models of the targets to the indexed attributes from the input chip,
	- The classifier's decision solely relies on the resemblance between the extracted feature-vectors and those used for training the classifier (i.e., within the decision boundaries between the target classes).	- This yields multiple predicted feature-vector hypotheses, - The classifier's decision depends on the match between the extracted features vector from the SAR chip and the predicted ones from the target models.
Publicity	- Traditionally, feature-based approach has found wider use than model-based approach. This is evident from the numerous number of works published on the topic [OAFB].	- In recent years, there has been an increasing interest in model-based approach due to its apparent advantage as well as computational advances that facilitated its implementation.
Advantage	- Relative ease of deployment due to the availability of various techniques and implementations,	- Incorporates knowledge into the target-model design,
	- Relatively less demanding for computational power (when the dimensionality of the database is properly designed) [OAFB].	- Provides the capability of part analysis for the target signature which provides the potential for robustness with respect to dealing and coping with some EOCs (e.g., partial occlusion of target and cluttered background),
		- Offers more general framework and more compact training methodology,
		- Less prone to the curse-of-dimensionality*[41],
		- Less prone to bias in feature selection (Ugly Duckling theorem**[41]) [AASMB],
		- Less prone to classification bias (No-Free-Lunch theorem [41], see Section IV-A3b).

*"The fundamental reason for the curse-of-dimensionality is that high-dimensional functions have the potential to be much more complicated than low-dimensional ones, and that those complications are harder to discern. The only way to beat the curse is to incorporate knowledge about the data that is correct."

**"Roughly speaking, the Ugly Duckling theorem states that in the absence of assumptions there is no privileged or 'best' feature representation, and that even the notion of similarity between patterns depends implicitly on assumptions which may or may not be correct."

Table 1. *(Continued.)* **Comparison between feature-based, semi-model-based and model-based SAR-ATR systems. [OAFB] denotes the comment is Only Applicable to Feature-Based Taxon. [AASMB] denotes the comment is Also Applicable to Semi-Model-Based Taxon.**

<table>
<tr><th></th><th>Feature-Based/Semi-Model-Based</th><th>Model-Based</th></tr>
<tr><td rowspan="7">Disadvantages</td><td>- It does not incorporate intelligence into the design,</td><td>- Unlike optical imagery under which the model-based approach originated, the design of a general and holistic target-model is a challenging task in the case of radar imagery (i.e., see Section VI-A and Section VI-B),</td></tr>
<tr><td>- The training database is sparse and the representative features are often chosen ad hoc based on the experience of the designer,</td><td>- Relative computational complexity pertaining to model manipulation, hypothesis generation, and feature prediction in real-time,</td></tr>
<tr><td>- Prone to the curse-of-dimensionality [41],</td><td rowspan="5">- Number of available model-based implementations in the open literature is relatively limited when compared to the feature-based approach [AASMB].</td></tr>
<tr><td>- Prone to bias in the process of feature choice (Ugly Duckling theorem [41]) [OAFB],</td></tr>
<tr><td>- Prone to classification bias (No-Free-Lunch theorem [41], see Section IV-A3b): Discrete selection imposed by the structure of the feature-based framework greatly renders the performance,</td></tr>
<tr><td>- It is impractical to capture and include an exemplar feature pertaining to all EOCs,</td></tr>
<tr><td>- This renders it incapable to cope with the simplest EOCs that may not be included in the database.</td></tr>
<tr><td rowspan="6">Challenges</td><td>- Balance should be sought between various issues including feature choice, classifier choice and dimensionality,</td><td>- The challenge of conceptual model choice/design, implementation, and intelligence incorporation,</td></tr>
<tr><td>- Being done on an ad hoc basis, feature choice is a cumbersome task that introduces bias (i.e., Ugly Duckling theorem [41]),</td><td>- Model choice/design: How to model the target features in the target-model; 3-D models are more complex but more compact when compared to 2-D models,</td></tr>
<tr><td>- Incorporating features for all EOCs is impractical,</td><td>- Model training: based on CAD $/\varepsilon M$ prediction (i.e., facetization) is questionable (see Discussion under Section IV-B5, and Section VI-E), various real-world target chips at different aspect angles. Can we use a hybrid of both? Or rather, can one construct a real-world 3-D target-model?</td></tr>
<tr><td>- The more one incorporates features to describe the target, the more the dimensionality increases (i.e., curse-of-dimensionality [41]),</td><td>- Feature choice: scattering centers attributed scattering centers, geometric invariants, canonical reflective primitives (e.g., flat plates, tophats, dihedrals, and trihedrals) [AASMB],</td></tr>
<tr><td>- Use of dimensionality reduction techniques (i.e., feature extraction and feature selection) can introduce additional bias into the process [67],</td><td rowspan="2">- How to make the model more robust in relation to various EOCs?</td></tr>
<tr><td>- Choosing a proper classifier can be a daunting task (i.e., No-Free-Lunch theorem [41]).</td></tr>
</table>

learned are summarized in Figure 15. Despite these many options for the discriminant function, the decision rules remain equivalent. The effect of any decision rule is to split the feature-space into C decision regions: $R_1, R_2, \ldots, R_C$. If $g_i(x) > g_j(x)$ for all $j \neq i$, then x is in R_i, and the decision rule calls to assign x to ω_i. The regions in the feature space are separated by decision boundaries [42].

In the next section, a brief review for the classes listed in Figure 15 is provided. Under each class, a selection of examples pertaining to SAR-ATR is presented. It should be highlighted that some of the examples provided are for LLC while some others are for HLC classification. The subsequent section provides a tabular comparison between various aspects pertaining to these examples.

2) FEATURE-BASED METHODS: A SURVEY

The main categories for learning the discriminant function are depicted in Figure 15. First, a brief description for each category is provided. Then, under each category, some relevant SAR-ATR examples are carefully chosen from the literature. It should be highlighted that there are numerous research works published on the topic. Accordingly, this survey is not meant to be exhaustive but rather it aims at reflecting the broad spectrum of the various methods available in the literature.

a: TEMPLATE-MATCHING

Template matching is one of the simplest approaches for PR. First, all known patterns for a target of interest are stored into templates. Such patterns can be either a 2-D SAR chip or a prototype of the pattern in the SAR chip. The process of constructing such templates and properly storing them represents the offline training phase. During online classification, patterns to be recognized (i.e., templates) are appropriately matched with all the stored templates based on some similarity measure (i.e., template matching/matched filtering or another relevant similarity measure). In cases where deformation cannot be explained, deformation template-models or rubber sheet deformations can be exploited for pattern matching [68].

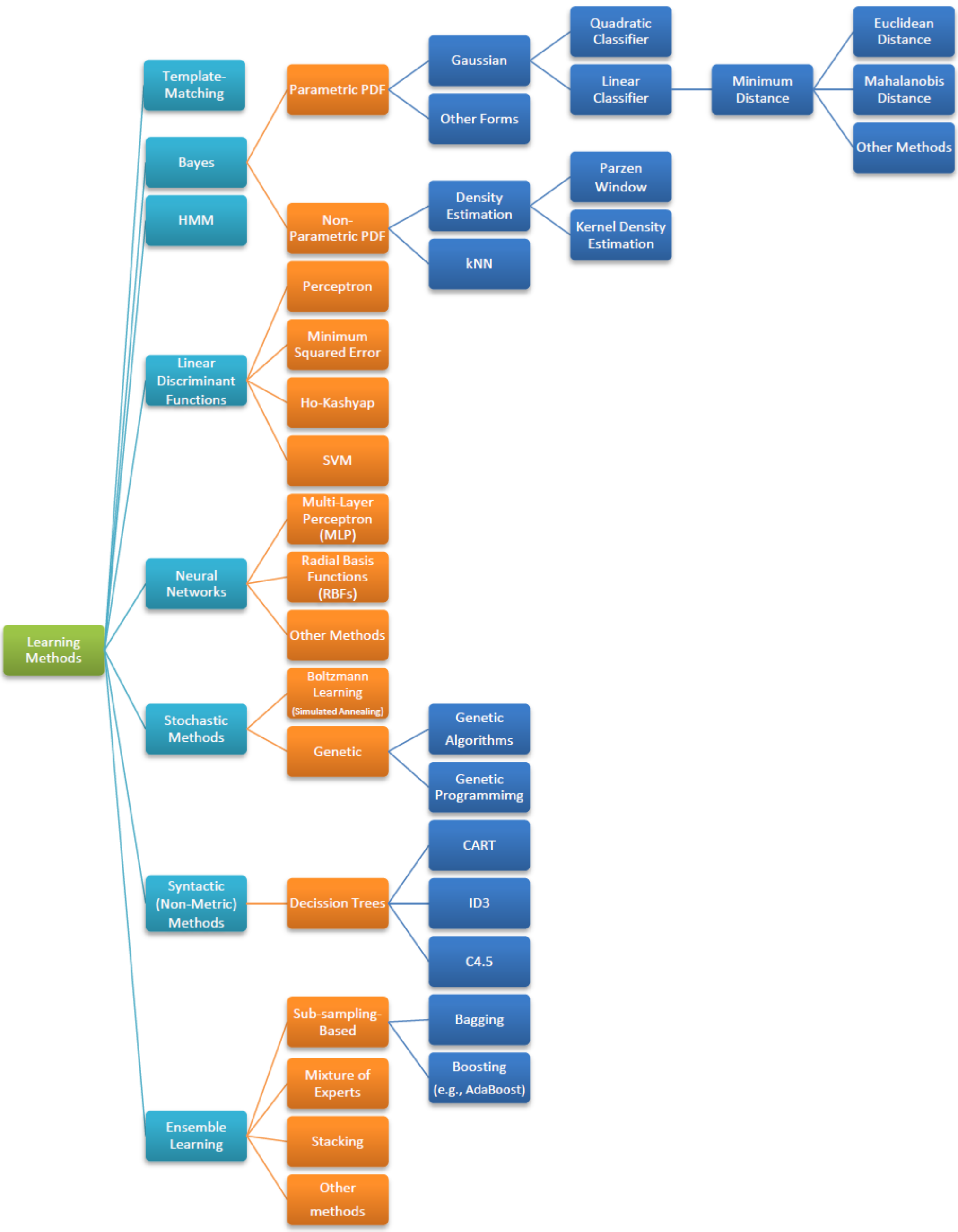

FIGURE 15. Categories of the various feature-based learning methods.

A few representative examples of this method are referenced. Theory of the ideal target detection for SAR-ATR based on adaptive matched filtering (AMF) as well as other relevant techniques is provided in [69]. A review of correlation techniques as well as implementation of template matching based on Mahalanobis distance is given in [70]. Another relevant work on template matching based on the squared-Mahalanobis distance is given in [71].

b: THE BAYES CLASSIFIER

The Bayes classifier is based on the Bayesian decision theory. For a set of C target-classes, $\{\omega_1, \omega_2, \ldots, \omega_C\}$, each of which has a likelihood PDF function $p(x|\omega_j)$, and a prior $P(\omega_j)$. The posterior probability is

$$P(\omega_j|x) = \frac{p(x|\omega_j)P(\omega_j)}{p(x)}, \tag{4}$$

where $p(x)$ is the evidence which is given by

$$p(x) = \sum_{j=1}^{C} p(x|\omega_j)P(\omega_j). \tag{5}$$

In the field of PR, it is well-known that the Bayes decision procedure provides the optimal decision rule [41]. The parametric sub-class shown in Figure 15 assumes that the likelihood function of the target-class $p(x|\omega_j)$ has a pre-known form, and the training feature vectors are used to estimate the parameters of the distribution. Assume that the PDF (i.e., the likelihood) of the classes follows a Gaussian distribution. Estimating the parameters of the Gaussian distribution (i.e., mean and covariance matrix) for each class from the relevant training feature-vectors yields a *quadratic* decision boundary. Thus, this classifier is referred to as a *quadratic classifier*. Depending on the type of covariance matrix, multiple simplified versions of this classifier are obtained as follows. First, for equal priors, and when all the target-classes have a covariance matrix of the form $\Sigma_i = \sigma^2 I$ (where σ^2 is the variance, I is the identity matrix). This yields the *Euclidean distance classifier*. Second, when the covariance matrix is diagonal, where $\Sigma_i = \Sigma$. This results in a *linear classifier*. Third, assuming equal priors, and when the covariance matrix is a non-diagonal $\Sigma_i = \Sigma$. This leads to the *Mahalanobis distance classifier*. Fourth, when $\Sigma_i = \sigma_i^2 I$, this yields a *quadratic classifier*. The generic case is when $\Sigma_i \neq \Sigma_j$, which yields the generic quadratic classifier as explained earlier in this section. Obviously, the *minimum distance classifiers* (i.e., Euclidean and Mahalanobis distance classifiers) are special cases of the Gaussian quadratic classifier.

Representative examples on using the Gaussian classifier for SAR-ATR are provided in [30], [31], [34], [72], and [73]. As depicted in Figure 15, a variant to the parametric method is the non-parametric method where it directly infers the likelihood functions $p(x|\omega_j)$ of the target-classes from the training dataset, without pre-assuming any particular form. There are two methods for performing the estimation: kernel density estimation (KDE) and k-nearest neighbor (kNN). In KDE, a kernel function centered at the origin with a fixed volume $V = h^D$, where h is the side length and D is the dimension of the training feature-vectors, is typically used. The kernel function is sequentially slid on the training points in the feature-space and the corresponding number of feature points k encompassed by V is tracked. This is equivalent to histogramming the feature space except that the dataset is used to determine the bin locations. A special case of the kernel function is the Parzen window, which has the shape of a unit hypercube. Because of its rectangular shape, the Parzen window can yield discontinuities in the estimation process. To fix this problem, the hypercube Parzen window is typically replaced with a smooth kernel such as the Gaussian kernel. In the kNN method, unlike KDE estimation, the number of data points k is predetermined and fixed. Then, the likelihood density function is estimated based on the volume V in the feature-space that encompasses k. A representative example of using the Parzen window method for estimating the performance bounds in a SAR-ATR system is given in [74]. Another representative example for the kNN classifier is provided in [75].

c: HIDDEN MARKOV MODELS (HMM)

A hidden Markov model (HMM) is a stochastic Markov model in which the SAR chips or representative features being modeled (i.e., the target) are assumed to constitute a Markov process with hidden states. An HMM can be considered as the simplest dynamic Bayesian network. Similar to other PR approaches, there are two phases involved. In the offline training phase, a finite number of HMM states is specified with some initial probabilities. Then, certain ad hoc features, presumably invariant to translation and rotation, are extracted from the SAR chips for the target of interest. Typically, these features are sought for an individual target at various orientations or other desired OCs. Then, using the Expectation-Maximization (EM) algorithm, the parameters of the model (i.e., transition probabilities) are estimated. This process is repeated for all the targets of interest to produce the HMM-based (so-called) target-models (see Section VI-C for a discussion on differentiating between the target-models). In the online classification phase, similar features are extracted from the input chip, and the Viterbi algorithm is used to find the single best state sequence that corresponds to a target-model according to a maximum likelihood criterion.

Representative examples of an HMM classifier used for SAR-ATR can be found in [76]–[78]. Moreover, in [79]–[81] an HMM classifier for SAR-ATR based on HRRP profiles is described in detail. The classifier utilizes the code from the toolkit in [82]. Another relevant example based on this HMM classifier for HRRP profiles is provided in [71].

d: DISCRIMINANT FUNCTIONS (DFs)

In the Bayes classifier described above, it was assumed that the underlying probability densities were known (or could be inferred), and the target features were used to estimate the parameters of the densities (i.e., train the classifier). However, discriminant function (DF) methods do not require knowledge of the underlying probability distributions, they rather assume that the proper forms of the discriminant functions are known, and the target feature-vectors are used to train the classifier. Discriminant functions are attractive because they are relatively easy to compute and they have important principles that are exploited for neural networks (NNs). Assuming a two-class problem and a linear discriminant function (LDF), the objective of the training procedure (i.e., parameter estimation) is to learn the parameters of the function as,

$$g(x) = w^T x + w_o, \text{ where: } \left\{ \begin{array}{l} g(x) > 0 \; for \; x \in \omega_1 \\ g(x) < 0 \; for \; x \in \omega_2 \end{array} \right\}. \quad (6)$$

This process is depicted in Figure 16 for a two-class problem in a 2-D vector-space, which can be easily extended to multi-class problem and/or multidimensional vector-space. Amongst the methods used to learn the discriminant function are: perceptron, minimum-squared error (MSE), Ho-Kashyap, and support vector machines (SVMs), among others. For details on these methods, the reader is referred to texts on PR and machine learning such as [41] and [42]. The perceptron algorithm has the advantage that it is capable of always finding a solution if the target-classes are separable but it suffers from the limitation that it cannot converge if the target-classes are nonlinearly separable. The MSE method

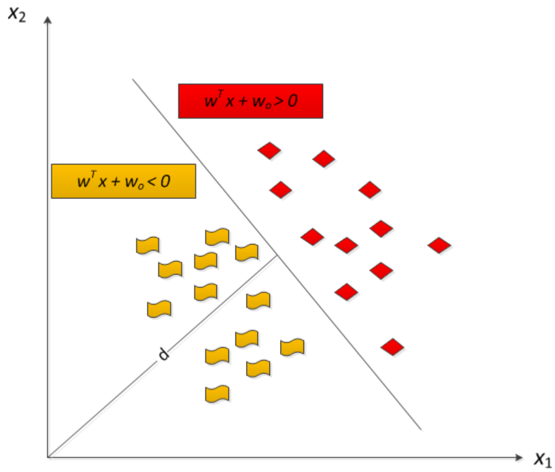

FIGURE 16. The process of learning the LDF. The process entails finding the parameters of the straight line (i.e., $g(x) = 0$) separating between the two-classes shown in red and orange.

remedies this constraint through guaranteeing convergence but it has the limitation that it may fail to find a separating hyper-plane for linearly separable classes. The Ho-Kashyap procedure extends the MSE method to guarantee convergence. SVMs are motivated by similar considerations but for nonlinear cases. Prior to the process of parameter estimation, SMVs preprocess the data to represent the patterns in (a much) higher dimension than the original space. In the high dimensional space, data from two-classes can always be linearly separated by a hyper-plane. After determining the linear decision boundary, the data are then projected back to the original dimension of the feature-space. This procedure is motivated by *Cover's theorem* which states that: *"A complex pattern-classification problem, cast in a high-dimensional space nonlinearly, is more likely to be linearly separable than in a low-dimensional space, provided that the space is not densely populated*" [83].

Representative examples pertaining to SAR-ATR for the MSE classifier are given in [32], [33], and [84]. A representative example of the Ho-Kashyap procedure is given in [85]. Representative examples of the SVM classifier are given in [86] and [87]. Further, additional examples on linear discriminants can be found in [34].

e: NEURAL NETWORKS (NNs)

Neural networks (NNs) are typically implemented using multi-layer perceptrons (MLPs), radial basis functions (RBFs), and holographic neural network (HNN), among other methods. MLPs are simple processing units comprised of feed-forward networks with one or more hidden layers that partition the feature-space with hyperplanes. In the hidden layer, hidden neurons compute the inner product between an input feature-vector (to be classified) and a corresponding weight vector. These weight vectors are estimated, during the offline (classifier) training, from the training dataset of the target feature-vectors. The hidden units include a nonlinear activation function which acts as a threshold that determines when the neuron fires. Unlike the MLP-based NN and similar to SVM, the RBF-based NN implements Cover's theorem quite directly through the so-called *kernel trick* which offers an implicit mapping to higher dimensional space without having to address the mapping details. This is achieved through a proper choice of the RBF function. RBF-based NN is typically comprised of a hidden layer for nonlinear transformation of the input space, and an output layer to predict the target-classes. Unlike, the MLP-based NN, the RBF-based NN computes the Euclidean distance between an input feature-vector (to be classified) and the RBF centers. Further, the RBF-based NN exhibits significantly faster training, and the decision boundaries for the RBF-based NN are hyper-ellipsoids.

In contrast to conventional NN, HNN is comprised of a simple topology, information is represented by complex numbers within two degrees of freedom, and offline training is accomplished by a means of direct (almost non-iterative) algorithms [88]. Through contrasting the SVM approach with the NN approach it is noticed that in SVM, the decision boundary that gives the best generalization is sought and learned. However, the NN approach in general seeks to learn the decision boundary that minimizes the empirical error. Representative examples of MLP-based and Holographic NN for SAR-ATR can be found in [89]. Examples of RBF-based NN can be found in [90].

f: STOCHASTIC METHODS

The previous techniques either assume that the target-classes follow a certain distribution, and use the training features to estimate the distribution parameters, or utilize techniques such as gradient descent to calculate the decision boundary. In high-dimensional and complicated models, there are multiple maxima which force us to utilize certain techniques to overcome such problems. The general technique is to bias the search to regions where the solution is expected and to somehow allow randomness to help establish parameters [41]. There exist two approaches to handle this problem, the first being Boltzmann learning which is based on concepts and techniques from statistical mechanics. This approach has a highly developed and rigorous theory. The second approach, involving genetic algorithms is based on concepts from the mathematical theory of evolution. The latter approach is more heuristic, yet it affords flexibility and can be attractive when adequate computation resources are available. Moreover, genetic programming shares the algorithmic structure of the basic genetic algorithms but differs in representation in each classifier. For more details the reader is referred to [41, Ch. 7]. A survey of the implication of Boltzmann-type machines for SAR data processing is given in [91]. A representative example for genetic programming for SAR-ATR is provided in [92].

g: SYNTACTIC (OR NON-PARAMETRIC) METHODS

In the previous methods, the feature-vectors were always discrete real or complex numbers. In the syntactic method for PR, the classification problem involves nominal data represented by a list of attributes. One approach to represent the values of a fixed number of properties is by using a property D-tuple. Another approach is to represent the pattern by a variable length string of nominal attributes. A syntactic PR system is comprised of two major parts, those being analysis and recognition. The analysis part aims at choosing the primitives and the formation of a grammar. Through grammars or syntax rules, the structural relations of the patterns can be described. Grammatical inference is the problem of learning grammar from a set of sample sentences. The syntactic PR system performs the classification process through selecting the primitives that properly represent the sub-patterns which, in turn, represent the complex pattern [41], [93]. Decision trees classify a pattern through a sequence of (yes/no) questions. The answer to the current question determines the next question to be asked. Among the commonly used methods for induction of decision trees for classification are the CART, ID3 and C4.5. More information can be found in [94]. A representative example for syntactic PR pertaining to SAR-ATR is provided in [93].

h: ENSEMBLE LEARNING

In ensemble learning, a mixture of a finite number of multiple classifiers is combined to learn a target function. The classifiers are individually trained and combining them yields improvement in the overall predictive performance. Depending on the underlying technique used for constructing the ensemble classifier, ensemble learning can go by various names such as classifier fusion, mixture-of-expert models, modular classifiers, or pooled classifiers [41]. Results show performance gains when significantly diverse classifiers are utilized in the ensemble [95]. On the one hand, this motivated researchers to utilize random algorithms such as random decision trees to produce a powerful ensemble [96]. On the other hand, it has been shown that using a mixture of various strong models is more effective than using techniques that attempt to establish diversity through degrading the model [97]. There are various methods to construct the ensemble classifier, amongst which are sub-sampling-based, mixture of experts, and stacking. In the subsampling-based method, individual classifiers are trained on subsamples of a common training dataset of features. The resampling is typically performed using either bagging or boosting. A popular example of boosting is known as adaptive boosting or AdaBoost [41]. In the mixture-of-experts method, the training dataset is partitioned into multiple different regions using some gating network. An individual component classifier in the ensemble is assigned to each region. In the stacking method (also known as stacked generalization), a second-level expert is used to accept the output from an ensemble-of-experts [98]. For more information on the topic including additional combining (i.e., fusion) strategies the reader is referred to books on the topic such as [41] and [42]. A representative example for ensemble learning in SAR-ATR using AdaBoost is presented in [99]. Another example, in which the classifier fusion strategy shown to outperform AdaBoost, is given in [75].

3) COMPARISON BETWEEN FEATURE-BASED METHODS

In this section, a tabular comparison between selections (i.e., from amongst those cited earlier) of feature-based methods is provided in Table 2. The comparison is arranged based on the classification for the feature-based learning methods depicted in Figure 15. A brief discussion is provided after the table.

DISCUSSION

a: MSTAR DATASET

In many of the surveyed feature-based systems (and also for the other two taxa), it is noticeable that the *moving and stationary target recognition* (MSTAR) SAR dataset is utilized. MSTAR is a freely and publicly available dataset from the Sensor and Data Management System (SDMS) of the United States Air Force. Extensive research work based on this dataset is available in the literature. Because of this dataset, researchers can test the performance of their own classifiers and compare it with previously published results. The MSTAR dataset can be retrieved from the link in [100].

b: CLASSIFIER CHOICE

In the surveyed feature-based SAR-ATR systems, researchers tend to choose a particular classifier to the exclusion of others. Thus, natural questions to ask are, *is there a solid motivation for preferring one classifier over another? and, is there a superior classification method over random guessing?* As shown in [41], the answer to these questions and other related questions is *'no'* as explained by the so-called No-Free-Lunch (NFL) theorem. The NFL theorem simply explains that, *"if the goal is to obtain good generalization performance there are no context-independent or usage-independent reasons to favor one learning or classification method over another. If one algorithm seems to outperform another in a particular situation, it is a consequence of its fit to the particular pattern recognition problem, not the general superiority of the algorithm"* [41]. Thus, one concludes the lack of inherent superiority of any classifier.

c: DESIGN CYCLE: OVERFITTING vs. GENERALIZATION

The design cycle of the feature-based classifier in the SAR-ATR system is summarized in Figure 17. The first step in the design cycle is the SAR data collection. This is the most time consuming step since an extensive set of target-class exemplars (i.e., chips) is typically required. Then, for each target-class of interest, target-class features are generated. Additionally, depending on the type of the feature generation method(s) utilized, the features are properly rescaled/normalized, and then suitably combined to form the class exemplars dataset. Further, depending on the dimensionality of the feature-space (i.e., number of features in each exemplar), a suitable dimensionality reduction technique may need to be utilized (see for example [67]).

Table 2. Comparison between feature-based SAR-ATR methods.

	Refs	Classifier Type	Level	Training/ Test Dataset	Features	Motivation(s) of feature choice	Decision Boundary	Comments
Template Matching	[70]	Template matching (based on the Mahalanobis distance)	HLC	DCS Sensor with HH and VV polarizations. X-band; similar to MSTAR	High resolution range profiles (HRRPs)	Based on literature review that found HRRP profiles account for 90% of the target energy	Nonlinear	C-class targets. 724 chips for each target (HH and VV) target type cover the 360^oazimuth angles
Bayesian	[30, 31, 72]	Gaussian	LLC	Lincoln Laboratory MMW SAR	A choice of the best discriminative features among 15 various features	Experimental analysis of discrimination ability	Nonlinear (Quadratic)	One-class [outlier detector], trained only on target features
	[34]	Gaussian	LLC	INGARA SAR	Radon-transform based, and others	Presumably, rotation and translation invariance	Nonlinear (Quadratic)	Two-class [target/non-target]
	[73]	Gaussian (linear discriminant)	LLC	INGARA SAR	Brightness, size of the target, among others	The assumption that the target features are discriminative	Linear	Two-class [target /non-target]
	[74]	Bayesian	HLC, performance bounding	MSTAR	PCA-based features	Based on the wish for dimensionality reduction	Nonlinear	Two-class, and C-class. Not as successful for C-Class
	[75]	kNN	HLC	MSTAR	PCA-based features	Ad hoc	Nonlinear	C-class. Two additional classifiers are considered
HMM	[76, 77]	HMM	HLC	MSTAR	Radon transform	The assumption of invariance to translation and rotation	Nonlinear	C-class [targets]. It is assumed that the target-class can be modeled by the HMM
	[78]	HMM	HLC	MSTAR	Windowed DFT for HRRP profiles of complex-valued signal			
Discriminant Functions	[32, 33, 84]	MSE	LLC and HLC	MSTAR	Target chip templates (72 templates per target)	The assumption that the templates cover the desired OCs	Linear	C-class [targets]. A superresolution technique is utilized
	[85]	Ho-Kashyap	LLC (parameter estimation)	XSAR	Image pixels	Ad hoc	Nonlinear	Used for parameter estimation in an MRF model

Table 2. ***(Continued.)*** **Comparison between feature-based SAR-ATR methods.**

	Refs	Classifier Type	Level	Training/ Test Dataset	Features	Motivation(s) of feature choice	Decision Boundary	Comments
	[86]	SVM	HLC	MSTAR	Elliptical Fourier descriptors for the target outline	Based on the assumption that features are discriminative between target-classes	Nonlinear	C-class. An ensemble of SVM classifiers is used
Neural Networks	[89]	MLP	HLC	MSTAR	Invariant Fourier features.	Discrimination and invariance assumption	Nonlinear	3-class targets. NN has 2 hidden layers
	[89]	HNN	HLC	MSTAR	Features based on Haar wavelet, and Zernike moment invariants	Discrimination and invariance assumption	Nonlinear	3-Class targets
	[90]	RBF/MLP	LLC/HLC	Own dataset from Ultra High-Resolution Radar (UHRR)	Ratio of length /width, standard deviation, maximum brightness, compactness, complexity, mean contrast, contrast ratio, bright pixel ratio, and difference of means	Ad hoc choice followed by feature selection	Nonlinear	C-class targets. RBF NN used for LLC, while MLP-NN for HLC. Two-hidden layers
Syntactic	[92]	Genetic programming	Feature selection, LLC, and HLC	DARPA ADTS	Blob mass, diameter, inertia, contrast max, mean, brightness; standard deviation, fractal dimension count, and weighted-rank fill ratio. Additional features are used for HLC	Ad hoc choice followed by feature selection.	Nonlinear	2-class target [for LLC], and C-class target [for HLC]
	[93]	Syntactic [similarity metric; minimum distance classifier]	HLC	DCS SAR data (X band, HH)	Peaks of the HRRP profiles	Ad hoc choice	Nonlinear	C-class targets [15 targets]. Note that there is a total of 724 SAR images over the 360^o azimuth span

Table 2. *(Continued.)* Comparison between feature-based SAR-ATR methods.

	Refs	Classifier Type	Level	Training/ Test Dataset	Features	Motivation(s) of feature choice	Decision Boundary	Comments
Ensemble Learning	[99]	AdaBoost	HLC	MSTAR	Magnitude of the 2-D DFT coefficients and pixel values in an 80×80 window positioned on the center of the target chip	2-D DFT is shift invariance and eliminates the 180^o inherent uncertainty in the pose estimation	Nonlinear	C-class targets. RBF network is proposed as the base learner. The classifier is compared with other classifiers including: template matching, SVM and NN
	[75]	Classifier fusion	HLC	MSTAR	Elliptical Fourier descriptors (EFD), PCA and 2-D Fourier coefficients	Ad hoc	Nonlinear	C-class. Three classifiers: SVM, kNN and Minimum Noise and Correlation Energy (MINACE) filter

The next stage is to choose and train a classifier. Typically, the features dataset is partitioned into two partitions (i.e., one partition for training and the other for testing the classifier) using some resampling technique such as cross-validation or bootstrapping [41], [42]. Note that there can be multiple splits in each partition depending on the resampling method used. In the next stage, the classifier performance is evaluated based on the test dataset just described. Note that if the classifier is trained on the whole feature dataset and tested on the same dataset, it can appear to achieve optimal performance. However, this is misleading because such a classifier will not generalize when applied to a new dataset. This problem is known as *overfitting*, and should be appropriately accounted for, as described above, through resampling. This design cycle may need to be repeated more than once depending on the performance of the classifier.

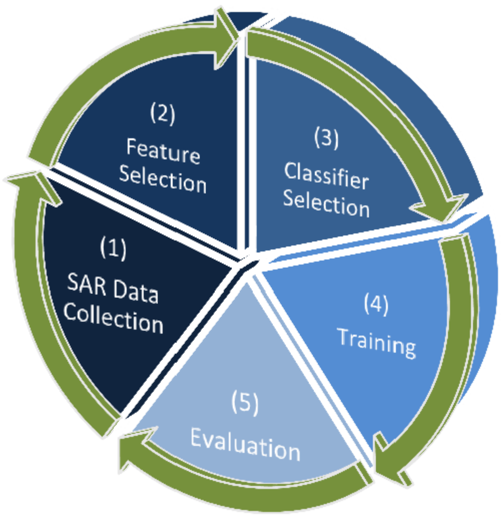

FIGURE 17. The design cycle of a feature-based classifier.

d: FEATURE-BASED TAXON, A FINAL WORD

As depicted in Figure 1, the front-end stage in the SAR-ATR processing chain is the detector. The detector is typically designed to be relatively non-computationally intensive, and to identify ROIs in the input SAR image. Due to this computational constraint, detections output from this first stage are naturally prone to false alarms (i.e., relatively high PFA). Accordingly, the LLC classifier in the intermediate stage handles these false alarms, and further refines the detections. Obviously, either a one-class classifier or a binary classifier (i.e., dichotomizer) can be used to perform this task. Further, the features used in the classifier should be properly chosen such that they are orthogonal and discriminative from the perspective of LLC classification (i.e., for target-class and non-target (clutter)-class).

Various feature generation methods are proposed in the literature for this task. For examples on features for LLC classification, the reader is referred to Table 2. Naturally, the choice of suitable features for this stage is dependent on the type of target(s) of interest as well as the environment in which the target(s) is/are embedded. In most cases, the choice of features in the LLC stage should be motivated by some form of a prior knowledge about the scene and/or the target(s) of interest. Indeed, some researchers refer to the LLC classifier that incorporates such knowledge into the process of feature choice as a knowledge-based classifier. For example, in [101], a prior knowledge in that the targets of interest exist in groups is used to extract features that are utilized in a weighted quadratic discriminant binary classifier (i.e., trained on both target and clutter). The typical quadratic discriminant classifier is weighted by a weight matrix that weighs the features based on the significance of their contribution from the perspective of redundancy (i.e., the percentage of correlation among features). This weight matrix is derived based on a feature selection scheme that uses a genetic algorithm. A variant example that utilizes group detection is reported in [102]. Another relevant form of knowledge utilization that can be used for both detection (i.e., front-end stage) and discrimination (i.e., intermediate stage) is reported in [21] and [103]. In the log-domain, the PDF of man-made objects and (natural) clutter returns exhibit opposite skewness. The PDF for man-made objects returns tend to have right tails whereas natural clutter returns have heavy left tails. This knowledge is captured in a skewness metric that is used to differentiate man-made objects from natural clutter. In [21], this feature is used for target detection and discrimination.

Another relatively recent and ongoing research into feature-based classification is that motivated by the so-called 'sparse representation' originally proposed in [104], and applied to the SAR-ATR problem in [105] and [106]. Its aim is to handle two crucial issues with conventional methods including feature extraction and robustness to occlusion. It is argued that if sparsity in the classification problem is properly harnessed, the choice of features is no longer critical. What is critical, however, is whether the number of features is sufficiently large and whether the sparse representation is correctly computed. Finally, another recent development is the utilization of the so-called all-convolutional networks (A-ConvNets) [107]. A-ConvNets are convolutional networks (ConvNets) [108] consist of sparsely connected layers, without fully connected layers being used. The idea is that instead of relying on an ad-hoc choice of features, the process of feature generation is conducted automatically by learning hierarchical features from the SAR dataset. The effectiveness of A-ConvNets is demonstrated on the MSTAR dataset.

In conclusion, the LLC stage in any SAR-ATR system is exclusively handled using a suitable feature-based classification method as shown in Table 2. Conversely, the HLC stage can be handled using one of feature-based, model-based or semi-model-based taxa. Due to its relative simplicity of implementation, methods based on the feature-based taxon are widely reported in the literature. However, due to its drawbacks (see Table 1), more noticeably in handling the EOCs, multiple research attempts that utilize model-based and semi-model-based taxa are reported. Examples for model-based and semi-model-based taxa are surveyed in the next two sections.

B. MODEL-BASED TAXON: A SURVEY

In Section III-A2, it was shown that the model-based taxon is comprised of two distinctive phases, namely, offline target-model construction, and online prediction and classification. Based on the method used for constructing the offline target-model, a selection of four methods for target-model construction was briefly provided. In this section, these methods are reviewed in some detail. First, in subsection IV-B1, the model-based method based on the 3-D CAD model is reviewed. Second, in subsection IV-B2, the method based on the 3-D global scattering center model is considered. Third, in subsection IV-B3, the method based on the database of templates and dictionaries is approached. Fourth, in subsection IV-B4, the method based on 3-D model for target primitives is reviewed. Finally, a table of comparison between the four methods along with a brief discussion are presented in subsection IV-B5.

1) METHOD #1: 3-D CAD TARGET-MODEL

This method is developed by Randolph L. Moses, Lee C. Potter, and their colleagues at the Ohio State University [45], [109]–[116]. The method is based on an online attribution of the scattering centers present in the input SAR chip to be classified and the corresponding SAR chips predicted from relevant 3-D CAD models. The process of attributing the scattering centers is achieved through parametrizing some stochastic model. The overall procedure pertaining to this method is summarized below.

DESCRIPTION

- There are two distinctive phases, namely, an offline phase for 3-D CAD target-model construction, and an online phase for stochastic models training, prediction and classification.
- The stochastic models trained online are models for the attributed scattering centers (i.e., features) extracted from both the input SAR chip (to be classified) and the chips hypothesized on-the-fly from the 3-D CAD model(s) based on an εM prediction tool.
- The classification process simply consists of matching the stochastic model pertaining to the input SAR chip with the hypothesized stochastic models from the 3-D CAD models.
- Attributed scattering centers are phenomenologically (i.e., physically) based features.
- The stochastic model can utilize either focused SAR chips, or the complex-domain raw data.
- Except for the design of the CAD models which is performed offline, all the computation is done online during the classification process.

PHASE #1: OFFLINE 3-D CAD MODEL CONSTRUCTION

- The target-model assumes a prior knowledge of the targets of interest. This knowledge is initially incorporated through predesigned 3-D CAD models, with one such CAD model for each target of interest.

PHASE #2: ONLINE STOCHASTIC MODEL TRAINING, PREDICTION AND CLASSIFICATION

- There are two sub-stages executed in parallel under this phase. This is followed by the classification process.

- Sub-stage #1
  - Extract features (i.e., attributed scattering centers) from the input target chip (i.e., measurement U). The output is the extracted features vector Y.
  - Based on the stochastic (attributed scattering centers) model, estimate the model parameters from the extracted features (i.e., attributed scattering centers) $f(Y|U)$. Then, use these estimated model parameters as an input to the Indexer (Sub-stage #2), and hypothesize the possible target-classes and poses.
- Sub-stage #2
  - Indexer: based on the available predesigned 3-D CAD target-models, use the stochastic model parameters estimated online to generate a hypothesis list (H) of target signatures using an εM prediction tool.
  - Feature Predictor: Extract features (X^k) from the hypothesized target signatures/poses to parametrize the stochastic attributed scattering center model $p(X^k|H_k)$. This is summarized as follows:
    * [Input] List of hypothesized target-class/pose (H_k) $\Rightarrow$ [εM prediction engine (black box)] $\Rightarrow$[output] predicted feature-vectors (X^k) and associated feature uncertainty $f(X^k|H_k)$.
- Classification
  - Search for a (Bayes) match [ΛH_k] between the extracted features from the input SAR chip [$Y, f(Y|U)$], and those predicted for various hypotheses, $X^k, f(X^k|H_k)$. This is implemented as a Bayes classifier.
  - Take the score that has the highest match within some predefined prerequisite (if any); otherwise, reject the input SAR chip as a confuser.

The parametric stochastic model for the scattering centers provides phenomenological characterization of the SAR chip for the target(s) of interest. It is based on the geometric theory of diffraction (GTD) and physical optics, and describes an MLE algorithm. A GTD scattering model is presumably accurate for targets of remarkably small electrical size $\frac{L}{\lambda}$ where L is the object length and λ is the radar wavelength. Further, the total response from a complex target is approximated as the sum of responses for the individual scattering centers. Scattering centers, as described by estimated attributes, offer a set of discriminating features for SAR-ATR. Attributes for each scattering center include high-resolution downrange and cross-range locations, amplitude, frequency dependence (partially characterizing scattering center geometry) and polarimetric properties. However, it is denoted in [45] that such features have limitations and cannot serve as the only vocabulary for SAR-ATR. Scattering centers should be augmented by additional features describing, for example, shadow, context and image texture behavior, which are not incorporated in the scattering center model. In addition, parametric scattering center extraction is computationally more demanding than traditional image formation and it is therefore inappropriate for prescreening [45]. For a description of the feature extraction and classification procedure, the reader is referred to [114]. For an in-depth description the reader is referred to [110].

2) METHOD #2: 3-D GLOBAL SCATTERING MODEL

This method is developed by Zhou Jianxiong and his colleagues at the National University of Defense Technology in China [46]. Primarily, this method is based on matching the scattering centers extracted from the input SAR chip to be classified with the corresponding 2-D scattering center predictions generated on-the-fly from the offline predesigned 3-D global scattering center models. The overall procedure pertaining to this method is summarized below.

DESCRIPTION

- There are two distinctive phases, namely, an offline phase for 3-D global scattering center target-model construction; and an online phase for training, prediction and classification.
- The offline phase involves the construction of 3-D global scattering center models for the targets of interest.
- Target-models can be modified to predict features for various target configurations.
- The online classification process is achieved through matching the scattering centers extracted from the input SAR chip with multiple corresponding 2-D SAR chips predicted on-the-fly from pertinent 3-D global scattering center models.
- The two phases of this method are described below.

PHASE #1: OFFLINE MODEL CONSTRUCTION

- The target-model assumes a prior knowledge of the targets of interest. This knowledge is initially incorporated through predesigned 3-D CAD models. There is one such CAD model per each target of interest.
- Then, using a suitable εM prediction tool, a 3-D global scattering center model is generated offline using range profiles at multiple viewing angles.
- One such model is generated for each CAD model.
- These models are stored in the target-model database.

PHASE #2: ONLINE MODEL TRAINING AND CLASSIFICATION

- There are two stages executed in parallel under this phase. This is followed by the classification process.
- For the input chip, extract a certain number of the strongest scattering center features as well as the whole region of interest.
- Two levels of features are introduced: a coarse regional feature, [F_o: masking matrix of ones and zeros identifies the ROI]; and fine regional features, [F_n : a number of n features describe the position of the n strongest scatterers in the ROI defined by F_o].
- Regional features are extracted from the input SAR chip by thresholding and morphological operations.

- Further, multiple poses of the input SAR chip are estimated using a box enclosing method for pose estimation.
- Pose estimates along with the sensing geometry are used to project all the 3-D global scattering center target-models into a 2-D ground-plane.
- Sub-stage #1: Indexer
  - Based on the features extracted from the input chip, and available 3-D global scattering center models, a list of prediction hypotheses is generated.
- Sub-stage #2: Feature Predictor
  - Based on the list of hypotheses generated from the Indexer, suitable 3-D scattering center models are projected to 2-D ground plane.
- Classification:
  - Prior to classification, the scattering centers in the predicted 2-D models are registered with the input SAR chip to account for any misalignment shifts.
  - This is a region-to-point registration wherein the extracted regional features in the input SAR chip are registered to the corresponding points in the 2-D predicted scattering centers from the target-models.
  - A matching technique between the extracted regional features and the predicted scattering center features is devised.
  - The prediction that achieves the maximum match, provided that it exceeds some predefined threshold, is declared. Corresponding target-class and pose represent the classification result.
  - Otherwise, the input SAR chip is rejected as a confuser. No forced recognition is imposed.

The major drawbacks of the target-model in this method follows. First, εM prediction (similar to other CAD-based methods) does not incorporate the ground and the target's side plate backscattering. Second, the target shadow is not considered. Third, when the target-model is tested for configured targets (i.e., for EOCs), the recognition performance is found to decrease. Finally, the recognition performance decreases when the resolution of the input SAR chip is lowered.

3) METHOD #3: GEOMETRIC-INVARIANT HISTOGRAMS-BASED MODEL

This method was developed by Katsushi Ikeuchi and his colleagues at the Carnegie Mellon University [48]. In the offline phase, an εM prediction tool utilizes a 3-D CAD model to generate uniformly sampled (i.e., covers the full span of azimuth angles) 2-D SAR chips. A dictionary (i.e., database) of so-called invariant histograms (and corresponding target templates) that relates the histograms/templates to their azimuth angles is constructed and stored. In the online phase, invariant histograms and corresponding templates are generated from the input SAR chip. These invariant histograms are used to poll (i.e., predict) pertinent histograms of the target-models stored in the database. The classification process entails matching the templates corresponding to the polled histograms from the target-model database with those generated on-the-fly from the input SAR chip. The overall procedure pertaining to this method is summarized below.

DESCRIPTION

- This method utilizes the so-called invariant histograms for feature representation, and template matching techniques for classification.
- An invariant histogram is a histogram of translation invariant values defined by geometric features such as points and lines in SAR chips.
- Strong invariants vs. weak invariants: strong geometric invariants are geometric invariant features that are extracted directly from the SAR chip and used as features, and they can be matched with their counterparts based on correspondence. However, weak invariants are defined by the relationship between a pair of features (i.e., distance in this work).
- It is assumed that the SAR target signature is translation invariant while it is rotation variant.

PHASE #1: OFFLINE MODEL CONSTRUCTION

- A 3-D CAD model for each target of interest is used as an input to an XPATCH SAR simulator [117] (i.e., εM predictor) to generate SAR images at uniform samples of 10° over the whole azimuth span from 0° to 360°. Thus, there are 36 target chips per each target.
- Three model invariant histograms and three corresponding templates are generated for each chip. Thus, there are 36×3 invariant histograms and 36×3 corresponding templates.
- The three translation invariants used are: Point-Point (P-P) histogram, Line-Line (L-L) histogram, Point-Line (P-L) histogram; the distance and direction (angle) of these histograms are used to construct three histograms. For each interval, the average and variance histogram is computed.
- The three types of templates corresponding to invariant histograms are:
  - Two non-deformable templates (coarse/medium-level templates): These are binary templates. They capture the shape and approximate shape of the target. They can be generated via a suitable filter in which a binary mask is used.
  - One deformable template (fine-level template): These are binary templates. They capture the strong scatter centers in the SAR chip. They account for typical perturbations in SAR images.
  - An additional [optionally deployed] so-called difference template is introduced to handle the ambiguity arising with 180° rotations. This template suppresses similar parts in the image pair and emphasizes conflicting parts.
- Thus, the offline training yields a dictionary comprised of the invariant histograms as well as corresponding templates.

PHASE #2: ONLINE PREDICTION AND CLASSIFICATION

- Sub-stage #1: Indexer
  - For an input SAR chip, the following are calculated: three geometric invariant histograms (P-P, L-L, and P-L) and three templates (coarse, medium level, and fine).
- Sub-stage #2: Feature Predictor
  - Based on a (similarity) minimum distance measure, this predictor is used to compare the input (three) histograms with the histograms in the dictionary and to find multiple candidates (hypotheses). These candidates could be from one target in the dictionary at multiple orientations (10° or multiples of 10°) and/or from multiple target-models.
- Classification
  - In this sub-stage, the process of matching or verification is performed. The templates (also known as *potential fields*) generated from the input SAR chip are matched with the templates indexed in Sub-stage #1. The target candidate that yields the highest match above a predetermined threshold is selected as the classification result. Otherwise, the input SAR chip is classified as a non-target confuser.

4) METHOD #4: 3-D TARGET-MODEL BASED ON REFLECTOR-PRIMITIVE PARAMETRIZATION

This method was developed by John A. Richards and his colleagues at MIT [49], [50]. The work published under this method is primarily focused on the target-model design, and the online classification process is not explicitly addressed. However, one can easily infer that the generic model-based SAR-ATR classification scheme introduced earlier is applicable to this method. This method is similar to the previous model-based methods in that it aims at building a 3-D global target-model. However, this method differs from earlier methods in that no 3-D CAD models are used in the model construction phase. Rather, an extensive set of real-world SAR target chips are utilized for this purpose. The overall procedure pertaining to this method is summarized below.

DESCRIPTION

- Unlike earlier methods, no CAD model is required; however, an extensive set of SAR target chips pertaining to the same target at multiple poses (azimuth and elevation) angles is required to generate a 3-D target-model. Complex phase history (i.e., raw SAR data) pertaining to the target chips can also be used.
- A 3-D target-model consists of spatial collections of reflector primitives (i.e., physical-optics-based), each of which is described in terms of a few parameters, including a discrete index indicating basic scattering type and several continuous parameters including location and pose, and other information relevant to describing the scattering signature of the overall target.
- Such reflector primitives include cylinders, tophats, dihedrals and trihedrals. To clarify, extracted scatterers from each SAR chip are represented (modeled) based on these reflector primitives.
- The target-model is a parametrized description of the target in terms of its N component reflector primitives. Thus, each reflector primitive is described by vectors of parameters that describe the scattering behavior given any imaging geometry.
- Note that the online classification (i.e., phase 2) is not explicitly addressed in this work.

PHASE #1: OFFLINE MODEL CONSTRUCTION

- Fusion via Expectation-Maximization (EM):
- Target-model generation is cast as a parametric estimation problem in which a description of the target is sought in terms of its component reflector primitives given a set of features extracted from SAR chips pertaining to the same target.
- First, target features $[Z]$ in each chip are extracted (based on available peaks, i.e., scatter centers).
- The target-model is characterized by the parameter matrix $\theta = [\theta_1, \theta_2, \ldots, \theta_N]$ which yields a total number of N estimated reflector primitives.
- Target-model parameter estimation is a fusion process achieved through using an EM method developed for this task.
- E Step:
  - Each SAR image is compressed into a set of augmented detections consisting of relevant information about significant scattering responses in each image including location and other data extracted (from focused images or phase history).
- M Step:
  - Compressed representations are then fused to estimate the 3-D locations and characteristics of the target primitives.
- From this model it is feasible to calculate the log-RCS $A(\theta_i, \varphi_k, \phi_k)$ for a given relative pose angles (azimuth and elevation).
- The algorithm selects a model order (number of reflector primitives N) and operates without supervision.
- Extensions of the model to some EOCs are presented (e.g., partial occlusions, and non-canonical primitive responses).

Reflective primitives are presumably more stable and potentially more informative than full facetization or CAD models. Reflective primitive types considered in this study are restricted to cylinders, tophats, dihedrals and trihedrals. Target-model generation is a fusion process performed through the EM algorithm. Various additional issues pertaining to initialization, termination and order reduction of the model are discussed by the authors. The proposed model construction algorithm is applied to X-band SAR data generated using an XPATCH SAR simulator. Note that no description is provided for the classification procedure [49], [50].

5) COMPARISON BETWEEN MODEL-BASED METHODS

In Table 3, we provide a comparison between multiple aspects in the four aforementioned model-based methods. This is followed by a brief discussion of some important issues.

DISCUSSION

Based on the comparison provided in Table 3, the following conclusions are reached. First, scattering centers are primarily used as features in model-based SAR-ATR systems. This is a natural choice motivated by the prior knowledge on the nature of SAR target signatures. Second, most works published on the model-based taxon in the open literature are based on either the MSTAR dataset, or simulated data generated with some εM prediction tool using 3-D CAD models (e.g., XPATCH [117]). Regardless of the target-model construction method utilized, there is a resemblance in the structure of the online classification phase in all the model-based methods.

Despite the presumed advantages of the model-based SAR-ATR taxon, methods surveyed in this section have their own drawbacks. In method #1, representing the scattering centers by only dihedrals, corner reflectors and cylinders constrains the model's ability to generalize to real-world complex target signatures. In method #2, simplified representations of SAR target signatures were used to construct the target-model. This has the disadvantage that the model cannot generalize when applied to real-world SAR target chips. In method #3, the assumption that the scattering centers in the SAR target signatures are translation invariant is impractical since real-world SAR target signatures are translation variant. In method #4, restricting the scattering center representation to only four primitives (i.e., cylinders, tophats, dihedrals and trihedrals) makes this model incapable to handling real-world SAR target chips that contain complex signatures (e.g., vehicles and airplanes).

Finally, most of the methods presented here incorporate an εM prediction tool into the process of target-model construction. This has the following disadvantages. First, in most cases, the process of εM prediction does not incorporate the ground, the target's side plate backscattering, or the target's shadow. Second, the effect of speckle is ignored in most cases. Third, generating the target signature based on an εM prediction tool entails facetization of a 3-D CAD model. The accuracy of design and facetization of such CAD models is always questionable, more pronouncedly, at high-resolutions [4]–[6]. Subsequently, the model-based systems that overlook these factors are prone to small changes in OCs, and they are rendered impractical for real-world target recognition. This motivates a need for designing models that combat all these drawbacks. For example, such a model can be constructed entirely based on real-world SAR imagery as shown in method #4 (see Section VI-E for a discussion on relevant methods for 3-D target reconstruction). However, in real-world scenarios, the challenge is to obtain such an extensive set of SAR target chips that cover the whole span of pose angles and desired EOCs.

C. SEMI-MODEL-BASED TAXON: A SURVEY

In III-A3, it was shown that the semi-model-based taxon is comprised of two distinctive phases: offline target-model training and online classification. However, unlike the model-based methods which tend to follow a similar structure for the online classification phase, semi-model-based methods remove this restriction and tend to be lenient on the structure of the online classification phase. Under this section, two such methods (i.e., those introduced earlier in Section III-A3) are surveyed. First, in subsection IV-C1, the DeVore-O'Sullivan method is reviewed. Second, in subsection IV-C2, the Bhanu et al. method is examined. Finally, a table of comparison between the two methods is presented in subsection IV-C3. This is followed by a brief discussion.

1) METHOD #1: DeVore-O'SULLIAVAN METHOD

This method, developed by Michael D. DeVore, Joseph A. O'Sullivan, and their colleagues from Washington University and Johns Hopkins University [51]–[55], involves estimation of variance images at uniformly sampled pose angles, in the offline target-model training phase. These variance images are estimated from an extensive set of SAR chips pertaining to the target to be modeled. In the online classification phase, the SAR chip to be classified is used as an input to a conditionally complex Gaussian PDF model. A GLRT test is performed to look for the variance target-model pertinent to a corresponding pose angle in the training database that maximizes the PDF model. The overall procedure pertaining to this method is summarized below.

DESCRIPTION

- Neither CAD models nor εM prediction tools are required.
- This method models the RCS (i.e., the input SAR chip after clutter suppression) based on a set of real-world target chips at different azimuth angles.
- Target-models are based on stochastic modeling of SAR imagery that attempts to capture the complexity of SAR returns through conditionally Gaussian PDFs.
- Target-models are used to predict statistical properties of radar images of targets at arbitrary poses relative to the radar platform.
- This method can be viewed as a hybrid between feature-based (i.e., particularly, template-based because the training entails a number of target chips (templates) that cover the span of 360° in azimuth), and model-based (i.e., in the sense that a complex Gaussian PDF is used for modeling the input SAR chip, and for classification).

OFFLINE MODEL TRAINING

- The model training is entirely performed offline.
- For each target of interest, it is assumed that an extensive set of (training) target chips at properly (uniformly)

Table 3. Comparison between the model-based SAR-ATR methods.

Comparison Aspect	Method #1	Method #2	Method #3	Method #4
Offline Tasks	3-D CAD modeling	3-D CAD modeling + 3-D global scattering center modeling (generated using an εM prediction tool)	3-D CAD modeling + dictionary of invariant histograms and binary templates generated using an εM prediction tool	Extensive set of 2-D SAR chips at various pose angles are used to generate a 3-D log-RCS target-model
Online Tasks	Training (i.e., parameter estimation), prediction, and classification	Training (i.e., feature extraction and registration), prediction, and classification	Training (i.e., feature extraction), prediction, and classification (also known as verification)	Not considered. Only offline target-model construction is addressed
Model Type	Stochastic model	3-D global scattering	Dictionary (i.e., database) of invariant histograms, and templates	3-D log-RCS
Model Motivation	εM theory, optics theory, and GTD theory	εM prediction, compactness, and globalism (i.e., freedom from being tied to radar system parameters)	The assumption that the target signature is translation invariant, while it is rotation variant	Physical optics
Model Validity	Presumably accurate for targets of remarkably small electrical size $\frac{L}{\lambda}$ where L is the object length and λ is the wavelength	The assumption that predicted target signatures using some εM prediction tool resembles real-world SAR signatures	The assumption that real-world target signatures will resemble those predicted using εM tool. And the assumption of translation invariance	Primitive types (in this study) are restricted to only four (i.e., cylinders, tophats, dihedrals, and trihedrals)
Modeling Phenomenon	Scattering centers from the input SAR chip and the CAD models. Two models are considered; localized and distributed	Scattering centers from the input SAR chip and the CAD models	Histograms are generated based on the distance and angle of the scattering centers in the target chip between: Point-Point, Line-Line, and Point-Line	Scattering centers are treated as belonging to one of four primitives (i.e., cylinders, tophats, dihedrals, and trihedrals), and modeled accordingly
Scattering Center Segmentation	Modified watershed segmentation	Coarse and fine regional thresholding	Coarse and fine regional thresholding	Reflector primitives are used to approximate the scattering centers based on an EM algorithm
Model Parameters	Six attributes per each single scattering center: $\theta_k = [Rx_k, Ry_k, A_k, \alpha_k, L_k, \phi_k], k = 1, \ldots, p$; is the total number of scattering centers in the SAR chip	Predicted scattering centers defined by: $S = \{x_n^k, y_n^k, A^k\}$, $k \in k(\theta, \gamma)$ and extracted regional features F_n	Histograms of the target signature are generated based on the distances and angles between: point-point, line-line, and point-line	Target-model is characterized by N primitives each of which is specified by three parameters: $\theta_i = [\theta_i^t, \theta_i^x, \theta_i^d]$. These depend on additional parameters: scattering centers, elevation angles, etc
Parameters Estimation	Through minimization of a cost function represents difference between the simulated model and the actual response	Through estimating a number of poses from the input chip. These pose along with the sensing geometry are used to project the 3-D scattering centers to the 2-D plane	Through using a set of 36 chips (i.e., 10° uniform samples), per each target. These are used to generate invariant histograms and corresponding templates	Through an EM algorithm

Table 3. *(Continued.)* **Comparison between the model-based SAR-ATR methods.**

Comparison Aspect	Method #1	Method #2	Method #3	Method #4
Characterization of Parameter Estimation Accuracy	Characterized by PDFs; $f(Y\|U)$, and $f(X_k\|H_k)$	N/A	N/A	Split into a coarse and fine. Coarse uncertainties are characterized by λ_k, and fine uncertainties are characterized by the PDF, $p(\lambda, Z\|\theta) = p(Z\|\lambda, \theta)p(\lambda\|\theta)$
Characterization of primitive scattering geometries	Yes; dihedrals, corner reflectors and cylinders are distinguishable by their $(\lambda,\ L)$ parameters	N/A	N/A	Yes; handled in the parameters of the log-RCS, $A(\theta_i, \varphi_k, \phi_k)$
Handling Extracted vs. Predicted Scattering Centers	Many-to-one mapping	Region(many)-to-point (one) mapping	Compacted in the histograms which are used to index predictions	Not addressed. As only the offline model-construction phase is presented
Classifier	Bayesian matching between θ_k estimated from the input SAR chip, and those estimated from predictions	Minimum distance score (matching between extracted features from input SAR chip, and predicted ones from target-models)	Template matching	Not addressed. Only the offline model-construction phase is presented
Various EOC Handling	Not explicitly addressed	Some EOCs are addressed (configured input and/or lower resolution)	Occlusion and camouflage are tested	Not explicitly addressed
Model Complexity	Extremely complex	Relatively less complex	Relatively less complex	Relatively complex
Type of SAR Data Tested on	MSTAR (X-band), and simulated SAR chips	MSTAR (X-band), and simulated SAR chips (C-band)	Tested only on simulated SAR data (using XPATCH)	Tested only on simulated SAR data (using XPATCH)
Comments	XPATCH is the εM prediction tool used. Note that $\theta_k = X_k$ or Y, depends on how it was generated (i.e., extracted or predicted)	εM prediction does not incorporate the ground and target's side plate backscattering; and target shadow. Recognition performance decreased when standard model was tested on configured input chip and/or lower resolution	The system is not tested on real-world data. Thus, the assumptions of target-signature invariance is not accurate. Further, εM prediction used does not seem to account for real-world phenomenon such as speckle	This work does not address the classification phase. Further, primitive types (in this study) are restricted to only four (i.e., cylinders, tophats, dihedrals, and trihedrals). Additionally, it is not tested on real-world SAR chips

sampled azimuth angles in the span of 0° to 360° are available.
- Then, the variance in each chip is estimated.
- These variances are stored in the training database as a function of the target-class (a) and the azimuth angle (ϕ) [more generally the pose angle, Θ], $\sigma_i^2(a, \Theta)$.
- This process is performed for all the targets that one wishes to model (i.e., considered for recognition).

ONLINE CLASSIFICATION

- The online classification process for an input SAR chip is performed through a modified GLRT test pertaining to a complex Gaussian PDF used to model the input SAR chip.
- Thus, the classification of an input SAR chip is performed by maximizing the (log) likelihood of the observation over all possible target-classes and poses.
- The inputs to the complex Gaussian PDF are the pixel values of the input SAR chip (to be classified) as well as the variance taken from the training database.
- The GLRT search is performed over all variances in the training database, and the variance that maximizes the complex Gaussian PDF is declared as the recognition output provided that it scores a value above some predetermined threshold.
- The parameters of the winning variance (a, Θ) are the classification result; i.e., target-class (a) and target-pose (Θ), respectively.

- If the winning variance is less than the predetermined threshold, then, the detection result is declared as a confuser and thus is rejected.

For a detailed description of this method the reader is referred to [51] and [52]. Besides the complex Gaussian target-model mentioned here, some other models are tested. For detailed description, the reader is referred to [55].

2) METHOD #2: Bhanu et al. METHOD

This method was developed by Bir Bhanu, Grinnell Jones III, and their colleagues at the University of California [40], [56]–[65]. As with other SAR-ATR systems, this method is characterized by two phases. In the offline model training phase, quasi-invariant local features including relative locations of the radar scattering centers are used to characterize the target in the training SAR chips in order to build a suitable target-model. Obviously, an extensive set of such training chips is required. Extracted features are used to build a target-model stored in the form of an LUT. This process is performed for all the targets of interest. In the online recognition phase, similar features are extracted from the input SAR chip to be classified and matched with those stored in the LUTs pertaining to the relevant target-models. The entry in the LUT that achieves the highest match, within some predefined threshold, is declared as the classification result. The overall procedure pertaining to this method is summarized below.

DESCRIPTION

- This method uses inexact matching of local features to handle EOCs with object configuration variants, articulations and occlusions.
- The processes of offline model training and online classification is described below.

OFFLINE MODEL TRAINING

- Quasi invariant local features in the SAR target chips are determined from the N strongest local peaks (i.e., scattering centers).
- The locations and magnitudes of a significant number of SAR scatterers are (presumably) quasi-invariant with target configuration variations and articulations. These are used as features.
- The target-model is designed (offline) as an LUT comprised of these quasi invariant local features with the addresses of the entries in the LUT are the relative locations to the scattering centers. The N strongest scattering centers are used as the reference points for these relative locations.
- The training phase (i.e., model build-up) is the process of building-up this LUT based on distinctive local features. This is accomplished through using geometric hashing.
- Obviously, the model requires an extensive set of training target chips for the target of interest.
- This process is performed for all the targets of interest.

ONLINE CLASSIFICATION

- The recognition process is a search for positive evidence.
- The model gains recognition improvement through exploitation of knowledge of model similarity (i.e., among models of different targets) and through integration of multiple recognizers at different look angles.
- The similarities between target-models can be quantified using histograms of collisions in feature-space to improve performance.
- Experiments demonstrate that SAR recognition results at different azimuth angles are independent, even for small azimuths such as one degree. Thus, the fundamental azimuthal variance of SAR scatterer locations can be used as the basis for a multiple-look-angle SAR recognition approach.
- Using decision level fusion of two observations (or more), at different look angles, can substantially increase the recognition performance for target configuration variants.
- The algorithm was tested on the MSTAR dataset.

The fact that the SAR scatterer locations do not persist over azimuth angles as small as one degree strongly indicates that the observations at different azimuth angles are independent. Thus, recognition performance can be improved by integrating the results of SAR observations at multiple look angles [60].

3) COMPARISON BETWEEN SEMI-MODEL-BASED METHODS

In Table 4, a comparison between the two aforementioned semi-model-based methods is provided. The comparison aspects are similar to those introduced in the comparison between model-based methods. This enables the reader to compare the methods reported here with their model-based counterparts. Table 4 is followed by a brief discussion on some important related issues.

DISCUSSION

Based on the comparison presented in Table 4, the following conclusions are reached: (1) As with the model-based SAR-ATR, scattering centers are primarily used as features in semi-model-based SAR-ATR taxon. (2) Again, as with the model-based SAR-ATR, most works published for the semi-model-based taxon in the open literature are based on either the MSTAR dataset or a synthetic data generated with some εM prediction tool using 3-D CAD models. (3) in the works considered here, unlike the model-based SAR-ATR, the offline model training process does not entail using an CAD/εM prediction tool. Rather, the model training process depends solely on an extensive set of real-world SAR target chips. Further, unlike the model-based taxon, there is no resemblance in the structure of the online classification phase between the semi-model-based methods.

Despite the advantages of the semi-model-based SAR-ATR taxon, methods reported in this section have their

Table 4. Comparison between the semi-model-based SAR-ATR methods.

Comparison Aspect	Method #1	Method #2
Offline Tasks	Estimation of variance images from target chips cover the span of azimuth angles in $[0^o, 360^o]$	Construction of an LUT for each target of interest based on SAR target chips. One target chip at each 1^o azimuth in $[0^o, 360^o]$ is included
Online Tasks	Perform classification based on an GLRT test pertaining to a stochastic model parametrized by the input SAR chip and the target variances in the target-model database	Perform classification based on matching the input SAR chip to be classified with the LUTs pertaining to all the target-models
Model Type	Stochastic model	LUT
Model Motivation	The assumption that the pixels in the target signature can be modeled by a complex Gaussian model, and that they are independent and identically distributed	The assumption that a target of interest can be uniquely characterized by local quasi invariant features pertaining to the strongest scattering centers, and the distance between them
Model Validity	The model assumes that the PDF of radar's RCS is a complex Gaussian. Further, it assumed that the target pixels are independent and identically distributed	The model assumes that the capability of the amplitude scattering centers as well as the relative distance between them to characterize targets
Modeling Phenomenon	RCSs in the SAR chip are represented by a variance image	$[S_1 \, to \, S_N]$ is the descendingly ordered strongest target scatter centers, S_p; consecutive choice of origin (reference) center, $S_o = S_1 \, to \, S_N$; and relative distance between scattering centers in both range (i.e., R_p) and cross-range (i.e., C_p) $[dR = R_p - R_o, dC = C_p - C_o]$. LUT entries: $[R_o, \, C_o, \, S_o, \, S_p]$; and LUT entry index $[dR, \, dC]$
Scattering Center Segmentation	Information-theoretic segmentation utilizes a null-hypothesis distribution	Speckle suppression using Crimmins algorithm, thresholding at the mean plus two standard deviations, dilating to fill small gaps among regions, eroding to have one large ROI and little regions, discarding the small regions with a size filter and dilating to expand the extracted ROI. The scattering centers are extracted from the SAR magnitude data (within the boundary contour of the ROI) by finding local eight-neighbor maxima. The parameters used in extracting ROIs are held constant for all the results reported
Model Parameters	Target chip variance, $\hat{\xi}_l(a, \theta_k)$ as a function of the target-class a, and azimuth angle θ_k	Both the LUT entry index $[dR, \, dC]$, and the LUT entry, $[R_o, \, C_o, \, S_o, \, S_p]$. There are multiple such entries per each target
Parameters Estimation	MLE estimation of the image variances	N strongest scatter centers, alternative choice of origin, and relative distance between scatter centers and the chosen origin. The same procedure is repeated for all scatter centers
Characterization of Parameter Estimation Accuracy	N/A	N/A
Characterization of primitive scattering geometries	N/A	N/A
Handling Extracted vs. Predicted Scattering Centers	N/A	The concern here is that the scattering centers extracted from two or more different targets could have the same target entry index to the LUT $(dR, \, dC)$. A constraint (threshold) on the magnitude difference between two such targets is used to refine some of such similarities
Classifier	GLRT test	An implicit minimum distance classifier based on the relative distance between scatter centers. A constraint is imposed on the amplitude values

Table 4. *(Continued.)* **Comparison between the semi-model-based SAR-ATR methods.**

Comparison Aspect	Method #1	Method #2
EOC Handling	Not explicitly addressed. Some EOCs can be handled if the training chips account for the EOC of interest	Some EOCs are considered. Pertinent target chips have to be included in the LUT
Model Complexity	Relatively complex	Relatively complex
Type of SAR data tested on	Only MSTAR (X-band) dataset	MSTAR (X-band) dataset and synthetic dataset
Comments	The assumption that the pixels in the target chip are independent and identically distributed can be problematic given the nature of neighboring pixel correlations in SAR imagery. Further, the assumption that the target signature is restricted to a single region is impractical. For example in high-resolution Spotlight Radarsat-2 imagery, a single vehicle may show-up as two or more blobs	For each target of interest, this method requires a set of real SAR target chips that cover the span of azimuth angles from 0^o to 360^o. Practically, this may be infeasible depending on the available resources. Further, the assumption that the distance between scatter centers can discriminate between target-classes is inaccurate. Indeed, in this study, it is reported that there is an extensive overlap between such distances pertinent to multiple target-classes. Finally, the method is not extensively tested on real-world SAR data

own drawbacks. In method #1, the assumption of independence amongst target pixels in the SAR chip overlooks the correlative nature of the speckle present in real-world SAR imagery. In method #2, the assumption that the distance between the strongest scattering centers in the SAR chip can uniquely characterize the target of interest is an oversimplification given that multiple targets can have similar distances. In both methods considered, the assumption that one has access to an extensive set of real-world SAR chips pertaining to the target(s) of interest can be impractical in real-world scenarios. The reader is referred to Table 1 for comparison between the semi-model-based taxon and the other taxa.

V. DESIGN CHALLENGES, EVALUATION CRITERIA, AND BENCHMARKING

In this section, some important design challenges and evaluation criteria pertinent to the SAR-ATR system are pinpointed. From the perspective of design, these are design challenges that should be accounted for in the design process of a successful SAR-ATR system. From the perspective of evaluation, these criteria present a benchmarking scheme that can be applied to evaluate existing SAR-ATR systems. First, our proposed design challenges and evaluation criteria are presented in subsection V-A, along with a brief description for each criterion. Then, in subsection V-B, the proposed criteria are applied to the SAR-ATR systems surveyed in Section IV, and are used to evaluate them accordingly.

A. DESIGN CHALLENGES AND EVALUATION CRITERIA

Our proposed design challenges and evaluation criteria are depicted in Figure 18. This is followed by a brief description for each criterion.

1) AN END-TO-END SYSTEM DESIGN

The generic framework for an end-to-end SAR-ATR system is depicted in Figure 19. The purpose of the design is to reduce the complexity of the input SAR data as it moves from the front-end stage (i.e., Detector) to the back-end stage (i.e., HLC). Conversely, the design complexity of the pertinent stage in the SAR-ATR chain decreases as one moves from the back-end stage towards the front-end stage. From the perspective of (composite) engineering system design [118], this SAR-ATR design strategy offers a means for decomposing the complex end-to-end SAR-ATR problem into less complex and more manageable stages.

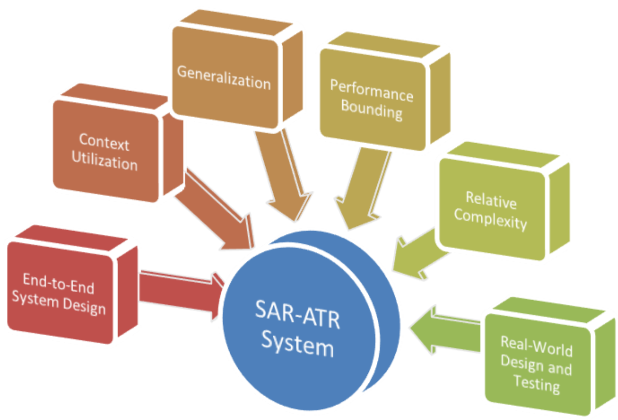

FIGURE 18. Proposed design challenges and evaluation criteria of a SAR-ATR system.

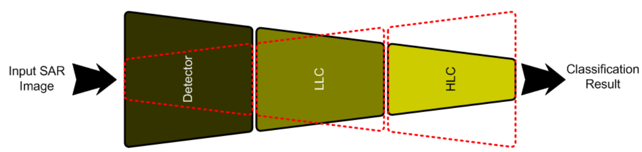

FIGURE 19. SAR-ATR system when viewed as a composite system.

Approaching the stages of the SAR-ATR system in isolation from each other is typically based on incorporation of simplifying assumptions. For example, a system design exclusively concerned with the HLC classification stage, in isolation from the preceding stages, typically assumes the presence of ready-to-classify SAR chips (i.e., the output of the LLC stage). Obviously, the performance of such system can be dramatically different if the output of the LLC stage cannot produce the presumed SAR chips with the desired quality. A successful SAR-ATR system design that aims at HLC classification should approach the ATR problem from a holistic end-to-end perspective. This offers a means for smooth integration of the system stages. Further, from the perspective of reliability engineering [119], this allows for the development of performance measures that both predict and gauge the system's performance on the intra-stage level, inter-stage level and for the end-to-end SAR-ATR system.

2) CONTEXT UTILIZATION

In SAR-ATR jargon, context refers to the utilization of information from sources other than the SAR sensor in use [20]. Context utilization is the process of incorporating a prior-knowledge into the SAR-ATR system to handle the variability of the SAR target's signatures. This variability is an intrinsic characteristic of SAR images for a target viewed at different OCs. The process of prior knowledge incorporation can be attained for one or more of the stages in the SAR-ATR system. Examples of such other information sources can include terrain maps, road locations, operational information and previous surveillance missions. The task entails addressing two central issues: (1) what are the suitable other information sources, and (2) how to properly integrate such context information into the design of the SAR-ATR system so that the recognition process can be consistently and robustly aided [20]. Obviously, a system design that properly incorporates prior knowledge into all the stages pertaining to the SAR-ATR processing chain has the upper hand when compared to a system that blindly performs recognition without taking advantage of such prior knowledge.

3) GENERALIZATION

A closely related (but more holistic) criterion to context utilization is generalization. Indeed, context utilization is one way to achieve generalization. Generalization refers to the ability of the SAR-ATR system to perform accurately on unseen SAR datasets that are different from that/those used for designing the SAR-ATR system. In other words, generalization-oriented SAR-ATR system design offers a means for adaptation. As explained in a later section (see Section VI-B), OCs dominant during the SAR imaging process play a significant role in dictating the way that a target signature manifests itself in the SAR image. Under particular OCs, a certain target signature from a particular target-class may look completely different, or it can even resemble another target signature from a different target-class. The design process for all the stages in the SAR-ATR processing chain involves some degree of training. The training process can be relatively indirect as in the front-end stage, wherein the design of the detector involves proper choice and tuning of certain model(s) and/or parameters. Or it can be direct as in training the LLC and HLC the classifiers. A SAR-ATR system that is solely designed based on specific OCs (i.e., top-down approach) will fail when faced with OCs (substantially) different from those were prevalent in the training phase. In order for the SAR-ATR system to generalize, the SAR-ATR problem may need to be approached from a bottom-up perspective. For example, in the HLC stage, a model-based HLC classifier based on properly designed 3-D target-models enables the HLC stage to migrate from specialization to generalization. Obviously, understanding the underlying variables pertaining to the EOCs is a key to the development of a generalizable SAR-ATR system design.

4) PERFORMANCE BOUNDING

Performance bounding (also known as performance modeling) generally refers to the ability to predict (or estimate) the limits (i.e., the performance bounds, whether it is the upper bound or lower bound) pertinent to various performance metrics of the SAR-ATR system for given OCs. The goal is not to estimate the performance for a given dataset, but rather to understand the performance bounds over various situations. The SAR-ATR performance is generally measured in terms of the PD, PFA and the confusion matrix. Additional application-specific measures are usually built on top of these measures [120]. The performance is typically modeled by developing bound estimates of these metrics as a function of various parameters of interest such as certain EOC(s), target-type, target-class, etc.

From the perspective of performance engineering, there are many advantages that can be realized from estimating the performance bounds of the SAR-ATR system. Probably the most important three are that performance modeling (1) enables the incorporation of the performance as a feature in the system design process and not merely a last minute afterthought, (2) allows one to predict the expectations and the limitations of SAR-ATR system, and (3) enables benchmarking the performance of the SAR-ATR system design, and allows for understanding and improving the system's performance, thus time and money can be saved [121]–[123]. Generally, approaches for optimal performance bounding in SAR-ATR can be broadly classified as heuristic (also known as empirical) or theoretic (i.e., statistical) [120]. These classifications are summarized in Figure 20. The heuristic class can be sub-classified into Monte Carlo simulation based (i.e., based on synthetic dataset) and large real-world dataset based. The drawback of the heuristic class is that it fails to predict the performance bounds in situations not represented in the training datasets. The heuristic approach is typically used when the theoretic approach is analytically intractable.

The theoretic class utilizes a statistical framework to directly predict the performance pertaining to certain data models. This class can be further sub-classified into the Bayesian approach and the information theoretic approach. These two approaches do not compete but rather complement each other [120]. The Bayesian approach uses the

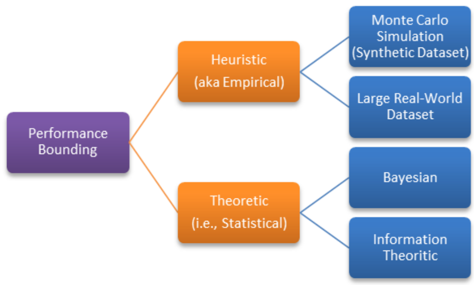

FIGURE 20. **Summary of methods for performance modeling in SAR-ATR.**

Bayesian rule for probability distributions that are built on certain simplifying assumptions to infer the performance bounds. The information-theoretic approach views the recognition problem as a communication process where the SAR image is dealt with as a message received through a potentially lossy and noisy communication channel. Accordingly, the information-theoretic approach infers the performance bounds through utilizing the concepts of entropy and mutual information to quantify the information loss in the SAR-ATR processing chain. Naturally, the theoretic class has the drawback that it suffers from inherent errors due to the simplifying assumptions typically made in the statistical modeling process. Depending on how these assumptions deviate from the real-world scenario, the error can vary from minor to major [120], [124], [125]. Note that as reported in [126], it is possible to estimate the performance bounds based on a hybrid of the heuristic and theoretic approaches.

5) SYSTEM DESIGN COMPLEXITY

As discussed earlier (see Figure 19), the design complexity of the SAR-ATR system increases as the SAR data moves from the front-end stage to the back-end stage. Obviously, the increase in the complexity of the system design yields an increase in the computational complexity. This is depicted by a red dotted line in Figure 19. A successful SAR-ATR system design should appropriately account for this design constraint. This criterion is related to the end-to-end system design criterion introduced earlier. Obviously, approaching the design problem from the holistic end-to-end perspective allows for an understanding of the interrelations amongst the stages in the SAR-ATR processing chain, and a proper balancing of the complexity constraint.

6) REAL-WORLD DESIGN AND TESTING

In order for a certain SAR-ATR system to be applicable for real-world testing, it should be designed based on a dataset representative of real-world scenarios. Further, a realistic SAR-ATR system design should also be based on realistic design assumptions. SAR-ATR systems built on simulated SAR signatures tend to suffer from various drawbacks relative to their counterparts built on real-world SAR data. Moreover, incorporation of simplifying assumptions into the process of design may render the SAR-ATR system impractical when applied to real-world scenarios. Additionally, real-world SAR data should offer a means for evaluating the performance of the SAR-ATR system. This is typically achieved through the process of ground-truthing the targets of interest. A successful design strategy of the SAR-ATR system should properly account for these requirements and properly balance the pertinent design trade-offs.

B. EVALUATION OF THE SURVEYED SAR-ATR SYSTEMS

The result of applying the evaluation criteria introduced in Section V-A to the SAR-ATR systems surveyed in Section IV is presented in Table 5. This is followed by comments on the evaluation result pertaining to the feature-based methods introduced in Table 6. Then, relevant comments on the evaluation of the model-based methods are presented in Table 7. Further, comments on the evaluation pertinent to the semi-model-based methods are provided in Table 8.

CONCLUDING REMARKS

Based on the abovementioned evaluation, the following conclusions are drawn. First, an end-to-end design strategy of the SAR-ATR system allows for a holistic understanding of the design requirements. Second, embedding the generalization capability into the SAR-ATR processing chain allows the system to account for and adapt to various EOCs. In the front-end stage, this can be accomplished through adopting system design strategy that accounts for context utilization. In the intermediate stage, context utilization can also be used to guide the choice of features and the choice/design of the LLC classifier. Similarly, in the back-end stage, design of the HLC classifier should offer a means to allow for the training dataset or the target-model to be relatively independent of the constraining OCs prevalent during SAR image acquisition. Third, modeling the performance of the SAR-ATR system allows for understanding the capabilities and limitations of system design under the desired OCs. Thus, a timely and objective design can be attained. Fourth, the accuracy-complexity trade-off should be handled from two perspectives: local (i.e., on the stage-level) and global (i.e., on the end-to-end system level). The front-end stage entails relatively less complex design which yields relatively high PFA. Conversely, the back-end stage entails a high classification accuracy which leads to relatively complex design. Fifth, if the SAR-ATR system design is based on garbage, it will naturally produce garbage (i.e., garbage in garbage out, GIGO). From this perspective, two factors of importance can be identified: (1) the quality of the dataset used for training the SAR-ATR system, and (2) the underlying assumptions used to design the stages and phases in the SAR-ATR system. As to the former factor, one or more realistic datasets that reflect the standard OCs (and all the desired EOCs) of real-world scenarios should always be sought. As to the latter factor, reasonable design assumptions that allow for implementing the SAR-ATR system without rendering

Table 5. Evaluation of the surveyed SAR-ATR systems based on the proposed benchmarking scheme. √ denotes the criterion is fully supported. + denotes the criterion is partially supported. × denotes the criterion is not supported. - denotes that presence/absence of the criterion is not known/not explicitly addressed. ↑, I and↓ denotes high, intermediate and low complexity, respectively. PS≡Pre-Screener (Detector). LLC≡Low-Level Classifier. HLC≡High-Level Classifier. TM≡Template Matching. DF≡Discriminant Function. NN≡Neural Network.

Taxon	Sub-Taxon	SAR-ATR System	End-to-End System Design			Context Utilization			Generalization			Performance Bounding			Relative Complexity			Real-World Design and Testing		
			PS	LLC	HLC	PS	LLC	HLC	PS	LLC	HLC	PS	LLC	HLC	PS	LLC	HLC	PS	LLC	HLC
Feature-Based	TM	[70]	×	×	√	×	×	+	×	×	×	×	×	+	×	×	I	×	×	√
	Bayesian	[30, 31, 72]	√	√	×	×	+	×	+	√	×	-	-	×	I	I	×	√	√	×
		[34]	√	√	×	×	+	×	+	√	×	-	-	×	I	I	×	√	√	×
		[73]	×	√	×	×	+	×	×	√	×	×	√	×	×	I	×	×	√	×
		[74]	×	×	√	×	×	×	×	×	×	×	×	+	×	×	↓	×	×	+
	HMM	[76, 77]	×	×	√	×	×	×	×	×	×	×	×	-	×	×	I	×	×	+
		[78]	×	×	√	×	×	+	×	×	×	×	×	-	×	×	I	×	×	+
	DF	[32, 33, [84]	√	√	√	×	√	+	×	√	+	-	-	-	↓	↑	I	+	+	+
		[85]	+	+	×	+	+	×	+	+	×	-	-	-	I	I	×	+	+	×
		[86]	×	×	√	×	×	×	×	×	×	-	-	-	×	×	I	×	×	+
	NN	[89]	√	√	√	-	-	×	-	-	×	-	-	-	-	-	I	-	-	+
		[90]	√	√	√	+	+	×	+	×	×	-	-	-	I	I	I	√	√	√
	Syntactic	[92]	×	√	√	×	+	×	×	+	×	×	-	-	×	I	I	×	×	+
		[93]	×	×	√	×	×	+	×	×	+	×	×	-	×	×	I	×	×	+
	Ensemble	[99]	×	×	√	×	×	+	×	×	×	×	×	-	×	×	I	×	×	+
		[75]	×	×	√	×	×	×	×	×	×	×	×	-	×	×	I	×	×	+
Model-Based	Method#1	[45, 109–116]	×	×	√	×	×	√	×	×	√	×	×	√	×	×	↑	×	×	+
	Method#2	[46]	×	×	√	×	×	√	×	×	√	×	×	+	×	×	↑	×	×	+
	Method#3	[48]	×	×	√	×	×	√	×	×	√	×	×	-	×	×	↑	×	×	×
	Method#4	[49, 50]	×	×	√	×	×	√	×	×	√	×	×	-	×	×	↑	×	×	×
Semi-Model- Based	Method#1	Method #1 [51–55]	×	×	√	×	×	√	×	×	+	×	×	√	×	×	↑	×	×	+
	Method#2	Method #2 [56–65]	×	×	√	×	×	√	×	×	+	×	×	√	×	×	↑	×	×	+

its performance in real-world scenarios should be adopted. Finally, thanks to the availability of ready-to-classify candidate targets output from the LLC classifier, additional means for context utilization and generalization can be embedded into the design of the HLC classifier. Obviously, design of the HLC classifier guided by the model-based taxon may offer a competitive means to achieve this goal. However, proper caution should be taken in the process of target-model design and the choice of the underlying assumptions.

VI. DISCUSSION

Under this section, we discuss important issues pertinent to SAR-ATR. First, the underlying reasons for variability in the SAR target signature are introduced in subsection VI-A. Second, the operating conditions (OCs) and their characterization to standard operating conditions (SOCs) and extended operating conditions (EOCs) are discussed in subsection VI-B. Third, a methodology to differentiate between the various target-models is presented in subsection VI-C. Fourth, the topic of superresolution and its relevance to SAR-ATR is overviewed in subsection VI-D. Fifth, the problem of reconstructing 3-D SAR imagery from 2-D SAR chips is reviewed in subsection VI-E. Finally, a brief discussion on the advantages and challenges of the model-based approach for HLC classification is presented in subsection VI-F.

A. UNDERSTANDING THE VARIABILITY OF THE TARGET SIGNATURE IN SAR IMAGERY

A major challenge to any SAR-ATR system is the target signature variability which is attributed to the properties of the SAR sensor used, the condition(s) of the target being imaged and the mechanism of the SAR imaging process. This variability is related to the OCs as discussed in the next section. We broadly classify the underpinning reasons for this

Table 6. Comments on feature-based methods evaluated in Table 5.

	Ref	Comments
TM	[70]	This is primarily concerned with HLC classification. Partial context utilization is achieved via utilizing HRRP profiles as features. The algorithm cannot generalize in EOCs. Performance estimates from empirical dataset (i.e., receiver operating characteristic (ROC) curves) are used to approximate the performance bounds. The algorithm has relatively intermediate complexity. Finally, the method is trained and tested on real-world dataset.
Bayesian	[30, 31, 72]	This is primarily concerned with the FOA module. No context information is explicitly utilized in the front-end stage. Context is partially utilized in the LLC stage through opting for features that achieve a form of prior knowledge incorporation (e.g., a choice of Lincoln Laboratory discriminant features). Given that the detector is designed to handle a specific type of clutter (i.e., homogeneous), without incorporation of inherent means for context utilization, it is hard for the detector to generalize to a variant clutter environment. Conversely, the features used in the LLC classifier possess the qualities of orthogonality and discriminability, and they are more likely to generalize. While the performance of the FOA module is evaluated, the issue of performance bounding (i.e., modeling) is not explicitly addressed. The FOA module enjoys relatively intermediate complexity. Finally, the FOA module is trained and tested on real-world dataset.
	[34]	Similar to [30, 31, 72], this work is primarily concerned with the FOA module. No context utilization explicitly considered in the front-end stage. A selection of features is used in the LLC classifier to partially achieve a form of context utilization. Additional comments are similar to those given for [30, 31, 72] above.
	[73]	This work primarily focuses on the LLC stage. Context utilization is partially considered in the form of features used for training the LLC classifier. The features used possess the qualities of orthogonality and discriminability, and they are more likely to generalize. Performance bounding of the LLC classifier is addressed in the form of an optimal ROC curve derived theoretically. The LLC classifier enjoys a relatively intermediate complexity. Finally, the LLC classifier is trained and tested on real-world dataset.
	[74]	This work focuses on the HLC stage. The issue of context utilization is not explicitly addressed given that a set of (principal component analysis) PCA-based features are utilized. The algorithm is incapable of handling more than two classes which makes it unable to generalize. Performance bounding for the HLC classifier is partially addressed through using a non-parametric Bayes error estimate based on Parzen window. The HLC classifier has a relatively low complexity. Finally, the HLC classifier is trained and tested only on the real-world MSTAR dataset.
HMM	[76, 77]	This work focuses on the HLC stage. The issue of context utilization is not explicitly addressed given that Radon-transform-based features are utilized. The classifier's ability to generalize is questionable in EOCs. The issue of performance bounding is not explicitly addressed. The relative complexity of the HLC classifier is intermediate given that it utilizes HMMs. The classifier is tested on the MSTAR dataset. No other real-world datasets are used.
	[78]	This work is concerned with the HLC stage. Context utilization is partially considered through using the radar-motivated features of the HRRP profiles. The algorithm cannot generalize in EOCs. The issue of performance bounding is not explicitly addressed. The relative complexity of the HLC classifier is intermediate given that it utilizes HMMs. The classifier is tested on the MSTAR dataset. No other real-world datasets are used.
Discriminant Function	[32, 33, 84]	This is an end-to-end SAR-ATR system. No context utilization is reported in the front-end stage. Further, context is utilized in the LLC stage in the form of terrain delimitation, object-level change detection, cultural-clutter identification, and spatial clustering. Moreover, the HLC stage partially utilizes context in the form of using 72 templates per each target for the classifier training. Thanks to prior knowledge utilization, the LLC classifier possesses an inherent ability for generalization. Further, the HLC classifier has a limited ability to generalize given that it is tied to the training chips, more pronouncedly when it is faced with variant EOCs. The front-end stage has relatively low complexity. However, the LLC classifier has relatively high complexity. Further, the HLC classifier possesses an intermediate complexity (i.e., for the offline training phase). Finally, the classifier is trained and tested on real-world MSTAR dataset. No additional real-world tests are reported.
	[85]	This work is primarily concerned with parameter estimation for SAR image segmentation which can be used in both detection and LLC classification. Context utilization is incorporated through using Markov random fields (MRFs). The parameter estimation method proposed can generalize. The issue of performance bounding is not explicitly addressed. The complexity of the method proposed is relatively intermediate. The proposed method is tested on a real-world XSAR dataset.
	[86]	This work is concerned with the HLC stage. Being the classifier is trained on elliptical Fourier descriptors for the target outline generated from representative target chips, the process of context utilization (i.e., knowledge incorporation) is partially exploited. Further, given the nature of SAR target signatures, the method cannot generalize under EOCs. The issue of performance bounding is not explicitly addressed. The complexity of the method is relatively intermediate. Finally, the method is tested only on real-world MSTAR dataset.
Neural Networks	[89]	This is another work that addresses the end-to-end SAR-ATR system. However, no detailed information is provided on the implementation process. For the online training phase (and for online classification), the algorithm utilizes features based on wavelet/Haar transform, Zernike moments, and Fourier coefficients. Given the nature of SAR imagery, this renders the proposed algorithm incapable neither to utilize context nor to generalize under EOCs. The issue of performance bounding is not explicitly addressed. The HLC algorithm has an intermediate level of complexity. Finally, the algorithm is tested on the real-world MSTAR dataset.

Table 6. ***(Continued.)*** **Comments on feature-based methods evaluated in Table 5.**

	Ref	Comments
	[90]	This is another work addresses the end-to-end SAR-ATR system. The detection stage deploys a form of context utilization via wavelet-based multiresolution analysis. The features used for classification include: ratio of object length/width, standard deviation, maximum brightness, compactness, complexity, mean contrast, contrast ratio, bright pixel ratio, and difference of means. Obviously, in the context of HLC classification for SAR-ATR, these features do not offer a means neither for context utilization nor for generalization under EOCs. The issue of performance bounding is not explicitly addressed. Further, the algorithm has a relative intermediate complexity. Finally, the training and testing process is performed on own data generated from an ultra high-resolution radar (UHRR).
Syntactic	[92]	This work is primarily concerned with LLC classification and HLC classification. Among the features used for LLC classification are: blob mass, diameter, and inertia; contrast max, mean, and brightness; standard deviation, fractal dimension count, and weighted-rank fill ratio. Obviously, these features allow the LLC classifier to account for generalization (to some extent). For the HLC classifier, two additional correlation-based features are used in conjunction with the abovementioned features. Obviously, these features do not offer a means for generalization in the HLC classifier under EOCs. The issue of performance bounding is not explicitly addressed. Further, the relative complexity of the classifiers utilized is intermediate. Finally, the DARPA ADTS real-world dataset (SAR chips) is used for training and classification.
	[93]	This work is primarily concerned with the HLC stage. HRRP profiles pertaining to a total of 724 SAR images over the $[0^o, 360^o]$ azimuth span is used to construct a language and train a syntactic classifier. Thanks to the extensive dataset used in the classifier training phase as well as using the radar-motivated features of HRRP profiles, this method offers a means for context utilization and partial generalization. However, the classifier cannot generalize under EOCs variant from those used in the offline training phase. The issue of performance bounding is not explicitly addressed in this work. Further, the classifier introduced has relatively intermediate complexity. Finally, the training and testing is based on the real-world DCS SAR dataset.
Ensemble Learning	[99]	This work is concerned with the HLC stage. The features used are based on the coefficients of Fourier transform (i.e., Fourier descriptors). Obviously, the classifier cannot generalize to EOCs other than those considered in the offline training phase. Despite this drawback, a form of context utilization is adopted through the deployment of an ensemble classifier based on adaptive boosting (AdaBoost). AdaBoost is built on an ensemble of RBF NNs. The issue of performance bounding is not explicitly addressed in this work. The classifier's complexity is relatively intermediate given its position in the SAR-ATR chain. Finally, the HLC classifier is trained and tested only on the MSTAR dataset.
	[75]	This work focuses on the HLC stage. The features used for offline training are PCA-based. The classifier cannot generalize to conditions (i.e., EOCs) other than those considered in the offline training phase. A form of context utilization is adopted through the deployment of ensemble classifiers. The issue of performance bounding is not explicitly addressed in this work. The classifier's complexity is relatively intermediate given its position in the SAR-ATR chain. Finally, the HLC classifier is trained and tested only on the MSTAR dataset.

variability into two main categories: inter-sensory reasons and intra-sensory reasons.

Inter-sensory reasons for target signature variability result from the discrepancy in the properties of two or more SAR sensors used for imaging the same scene, either a particular SAR sensor when used at different imaging modes/operation properties (e.g., Radarsat-2 used in Spotlight and Stripmap modes), or different SAR sensors with different sensor properties (e.g., Radarsat-2 and Envisat). The inter-sensory reasons for target signature variability include frequency/wavelength, polarization (HH, HV, VH, VV, dual, or quad), imaging mode (e.g., Stripmap, Spotlight, ScanSAR, etc.), and resolution.

Intra-sensory reasons for target signature variability are attributed to specific variables pertinent to a particular SAR sensor and the imaged target. We broadly classify these reasons into three main categories: intrinsic reasons, extrinsic reasons and a hybrid of intrinsic-extrinsic reasons. *First*, intrinsic reasons for target signature variability may be classified as sensor-oriented or target-oriented. Sensor-oriented intrinsic reasons for signature variability may be classified as geometry-related or noise/calibration-related. Geometry-related reasons are those pertinent to the acquisition geometry. The SAR sensor's line-of-sight (LOS) is the slant-rage, wherein the backscattered waves from 3-D real-world objects are projected into a 2-D SAR image. Geometry-related reasons include squint angle, depression angle and all-target aspects (i.e., aspect angle and elevation angle). Noise-related reasons are due to the noise introduced by the radar imaging process (transmitter/receiver), as well as the intrinsic errors introduced by the focusing algorithm used to process the raw radar data. Calibration-related reasons account for whether the SAR sensor is calibrated or not, and whether there are calibration errors involved. Target-oriented intrinsic reasons for signature variability are due to the target state variations, and they include articulation and alternative configurations of the target. *Second*, extrinsic reasons for target signature variability may be classified as clutter-oriented or target-oriented. Clutter-oriented reasons are those related to the type of the background (i.e., homogenous, nonhomogenous and heterogeneous), and the proximity of the target to other objects that can interact with the incident/backscattered radio waves from the SAR sensor and the target, respectively. Target-oriented reasons

Table 7. **Comments on model methods evaluated in Table 5.**

	Ref	Comments
Method#1	[45, 109–116]	This method is primarily concerned with the HLC classification stage. The method captures prior knowledge about the target of interest in the form of a 3-D CAD model. This allows for generalization under various EOCs. However, one should be cautious as this generalization is limited by the accuracy of the 3-D CAD models as well as the εM prediction tool utilized. Analytical performance bounds are derived in terms of the Cramér-Rao bound. The method possesses a high level of complexity more pronouncedly in the online (i.e., on-the-fly) training (i.e., verification) phase. The method is tested on synthetic SAR dataset as well as the real-world MSTAR dataset.
Method#2	[46]	This method is primarily concerned with the HLC classification stage. Initially, prior knowledge concerning the target of interest is captured in the form of a 3-D CAD model. However, unlike the previous method, 3-D scattering center model is generated offline from the CAD model. Obviously, this process shifts the high computational complexity from the online phase (i.e., during the classification phase) to the offline phase (i.e., during the model construction phase). Similar to the previous method, this method allows for context utilization and generalization but this is constrained by the accuracy of the 3-D CAD model as well as the εM prediction tool utilized. An estimate of the performance bound is empirically devised. The method is tested on both synthetic dataset generated using some CAD models and εM prediction tool, as well as the real-world MSTAR dataset.
Method#3	[48]	This method is primarily concerned with the HLC classification stage. Similar to the abovementioned model-based methods, prior knowledge about the target of interest is captured through using a 3-D CAD model. Similar to Method #2, a relevant target-model is built offline from the CAD model. Unlike Method #2, the target-model is a dictionary of invariant histograms and binary templates generated using an εM prediction tool. This allows for generalization under various EOCs. However, similar to Method #2, one should be cautious as this generalization is limited by the accuracy of the 3-D CAD models, as well as the εM prediction tool utilized. The issue of performance bounding is not explicitly addressed. The method possesses a high computational complexity, more pronouncedly in the offline model construction phase. Finally, the method is tested on a simulated SAR dataset.
Method#4	[49, 50]	This method is primarily concerned with the HLC classification stage. Although this method closely follows the structure of the model-based taxon, only the process of target-model construction is addressed in this work. Extensive set of 2-D SAR chips at various pose angles are used to generate a 3-D log-RCS target-model. The process of model construction is purely motivated by physical optics. The issue of performance bounding is not addressed. Similar to other methods, although a means for context utilization and generalization are offered, these means are constrained by the underlying assumptions/simplifications used for building-up the model. The method is tested only on a simulated SAR data.

Table 8. **Comments on semi-model methods evaluated in Table 5.**

	Ref	Comments
Method#1	[51–55]	This method is primarily concerned with the HLC stage. The method captures prior knowledge about the target of interest through generating variance images estimated from 2-D real-world SAR target chips which cover the span of azimuth angles in $[0^\circ, 360^\circ]$. This allows for context utilization. However, this method possesses a relatively limited generalization capability. Similar to relevant feature-based taxon, this method cannot generalize when faced with EOC(s) extensively variant from those utilized in the model training phase. Moreover, the limited generalization capability of this method is further constrained by the underlying assumptions used in constructing the target-model. Relevant analytical performance bounds are described in [51–55]. The method possesses a high-level of complexity both in the offline model training phase as well as the online classification phase. The method is tested only on the real-world MSTAR dataset.
Method#2	[56–65]	This method is primarily concerned with the HLC stage. The method captures prior knowledge about the target of interest through forming a target-model in the form of an LUT based on the scattering centers extracted from the 2-D real-world target chips that cover the span of azimuth angles in $[0^\circ, 360^\circ]$. This allows for context utilization. However, similar to method #1 above, this method possesses a relatively limited generalization capability. Similar to relevant feature-based taxon, this method cannot generalize when faced with EOC(s) extensively variant from those utilized in the model training phase. Additionally, the limited generalization capability of this method is further constrained by the underlying assumptions used in constructing the target-model. Relevant analytical performance bounds are described in [120, 124, 125]. The method possesses a high-level of complexity both in the offline model training phase as well as the online classification phase. The method is tested only on the real-world MSTAR dataset.

for signature variability include obscuration (including occlusion and layover) and camouflage of the target. Third, the interaction between the intrinsic and extrinsic reasons yields a noise-like phenomenon known as speckle. Speckle is not precisely a noise. It is rather a product of the coherent nature of radiation that, when it illuminates the scene and backscatters, it interferes destructively and constructively.

Figure 21 depicts a summary of the abovementioned reasons for target signature variability. Obviously, there always exists an interaction between all of these factors which makes the target signature very sensitive to the smallest variations. This explains the uniqueness of the SAR-ATR problem and poses a real challenge to any real-world SAR-ATR system. The reasons for variability presented here are from the perspective of the target signature. In the next section, these reasons are viewed from the perspective of the SAR-ATR system design. This perspective is important because it allows for understanding and characterizing the relevant parameters of the SAR-ATR system.

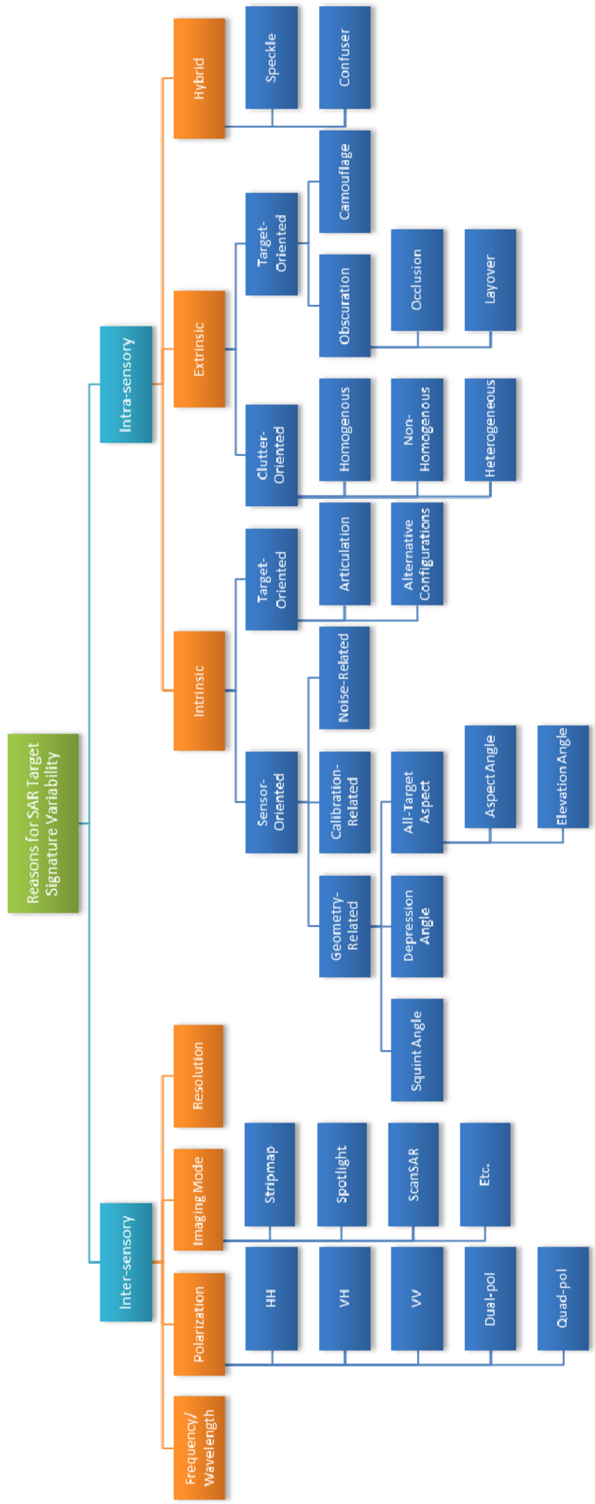

FIGURE 21. Summary of the reasons for target-signature variability, a target-signature perspective.

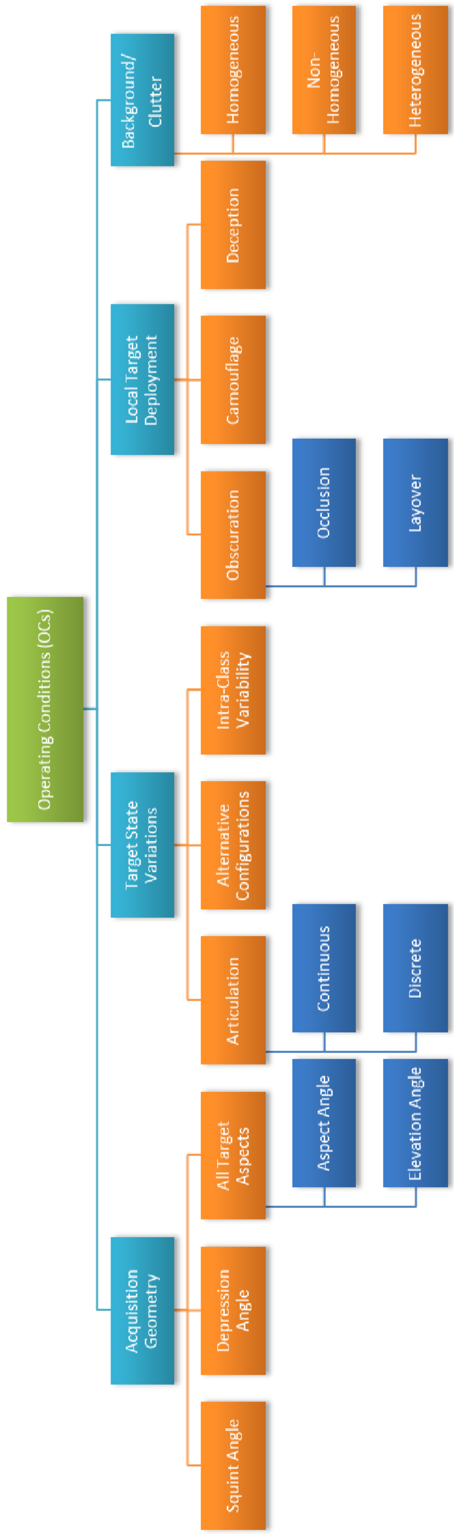

FIGURE 22. Summary of operating conditions (OCs), a SAR-ATR system design perspective.

B. CHARACTERIZING THE OPERATING CONDITIONS (OCS) FOR SAR-ATR

OCs refer to the conditions that are prevalent during the image acquisition process by the SAR sensor. There are various OCs for any image acquisition system. However, in the case of SAR, typically those conditions which, when varied, alter the target signature, are considered. We summarize the most relevant OCs in Figure 22. These reasons were adopted from [127], and slightly modified to fit our generic perspective. It is assumed here that a single particular SAR sensor with a non-variable set of sensor properties (i.e., frequency/wavelength, polarization, imaging mode and resolution) is used during both training and classification. If more than one different SAR sensor is involved, or the same sensor with varying sensor properties (e.g., different polarizations, different imaging modes or different resolutions) is utilized, then relevant inter-sensory reasons explained in the previous section have to be included under the OCs because these will alter the way the target signature manifests itself in the SAR image.

As explained earlier in Section III, any classification system (i.e., be it LLC or HLC) pertaining to SAR-ATR has two phases: the offline training (also known as model construction, for model-based systems), and the online classification. To characterize the OCs of the classification phase in reference to the training (or model construction) phase, two terms are often used in the literature. These are standard operating conditions (SOCs) and extended operating conditions (EOCs). The term SOCs is utilized when the OCs during image acquisition for online classification are similar or very near to those conditions during offline training [128]. Conversely, if the OCs during online classification are different from those prevalent during offline training (or model construction), the term EOCs is used. Obviously, in any real-world scenario, SOCs will not often persist. This yields an alteration in the signature of the target of interest. Depending on the OCs and the type of target, the target signature can vary significantly and may even resemble the signature of a different target-class acquired at some other OC(s). A major design challenge for SAR imagery (and for radar imagery in general) is to design the SAR-ATR system in such a way that handles the desired EOCs.

C. DIFFERENTIATING BETWEEN THE MODELS

There are various research works in the open literature on the utilization of certain stochastic models for SAR-ATR. These models can be broadly classified as texture-oriented or target-oriented. In this section, we show how these models drastically differ from the model-based approach for SAR-ATR introduced in Section III and Section IV. We also explain that, while the name target-model (for the target-oriented class) is often used, this class of methods is simply feature-based. It assumes that the SAR target can be uniquely represented by certain ad hoc features and builds a model for these features rather than physically modeling the target itself.

To differentiate between the various models one needs to examine whether the target-model construction process follows a top-down approach or a bottom-up approach. The bottom-up approach is the strategy used in all the methods pertaining to the model-based taxon as explained in Section III.

Texture-oriented models aim at capturing the statistical characteristics of the texture in the SAR image, and they are used for texture synthesis, feature extraction, and image segmentation. Examples of these models include Markov random field (MRF) [129]–[134], fractal models [38], [135]–[138], autoregressive (AR) models [139], autoregressive moving average (ARMA) [140], log-normal random field (LN-RF) [141], among others.

Target-oriented models aim at modeling the target of interest through a stochastic characterization. The underpinning assumptions are that the target chip can be well represented by certain choice of ad hoc features, the features can be well characterized as a parametric random process, and the parameters of the stochastic process can be estimated precisely. Obviously, this is a top-down approach in that the features generated from the target chips under certain OCs are used to represent the target and build-up the (so-called) target-model. The DeVore-O'Sullivan complex-Gaussian model [53] presented earlier, and related stochastic models presented in [54], loosely fit under this category (see Section IV-C1), although those models account for a comprehensive set of OCs (i.e., extensive training set of SAR target chips at various OCs) more so than traditional stochastic models, and thus were classified earlier as a semi-model-based.

Another example of target-oriented models is the hidden Markov model (HMM). It is well known in the field of pattern classification that HMM is a PR [41] (also known as feature-based) approach. However, for SAR-ATR, HMM is often presented in the literature as a target-model [76], [78], [142]. As explained in Section IV-A2c, the process of building-up the HMM model is based on certain choices of ad hoc features generated from the chips of the target of interest that one wishes to model. Obviously, this method follows a top-down approach, does not resemble the model-based taxon, and shares the limitations of the feature-based approach.

Other limitations specific to the HMM method include the assumption that successive observations are independent, the underlying constraining assumption that the distributions of individual observation parameters can be well represented as a mixture of Gaussian or autoregressive densities, and the Markov assumption per se which assumes that the probability of being in a given state at time t only depends on the state at time $t-1$ [76], [78], [142].

To conclude, there are various methods for SAR-ATR presented in the literature as model-based. Based on the classification methodology presented in this paper, closer investigation reveals that many of these methods are indeed either feature-based or semi-model-based. Thus, they all share the pitfalls of these two taxa as explained in this section. It is stressed that one needs to be cautious about the naming terminology. A model-based SAR-ATR system should closely follow the structure of the model-based taxon as presented in Section III-A2.

D. SUPERRESOLVING RCS IN THE SAR CHIPS

Superresolution techniques enhance the process of ATR through superresolving the radar's RCS in the SAR image. These techniques utilize signal processing methods to perform an extrapolation in spatial frequency beyond the resolution suggested by the Rayleigh resolution criterion. Given the parameters of the SAR system (i.e., wavelength, bandwidth and aperture), the Rayleigh resolution limit defines the minimum distance that makes two point scatterers resolvable by the SAR system. In case of SAR, there are two such resolution limits, one being in the slant-range direction and the other in the cross-range direction [143]. In the slant-range, the resolution limit is defined by

$$\triangle r_s \approx \frac{c}{2B}, \tag{7}$$

where c is the speed of light, and B is the bandwidth of the transmitted signal. In the cross-range, the resolution limit is defined by

$$\triangle r_a \approx \frac{\lambda}{2\Psi_a} = \frac{d_a}{2}, \tag{8}$$

where λ is the radar wavelength, Ψ_a is the azimuth beamwidth, and d_a is the length of the antenna in the azimuth direction. Obviously, besides their dependence on the radar parameters, the resolution limits are altered due to the focusing methods used to convolve the backscattered signals (i.e., SAR phase history, which is also known as SAR raw data or SAR signal data) with the point spread function (PSF) of the system (i.e., PSFs for range and cross-range). Examples of popular SAR focusing algorithms include the range Doppler algorithm (RDA), chirp scaling algorithm (CSA), Omega-K algorithm (ωKA), SPECAN algorithm, among others [10], [11]. In all such methods, windowing is typically applied to the SAR phase history. Besides the impact of windowing on the resolution limit (i.e., windowing causes broadening that reduces the spatial resolution), the focusing process is further impacted by the finite number of discrete samples used in the calculation. Further, the focused image output from the SAR processor is complex-valued. In most works on SAR-ATR, the complex-valued SAR image is often detected prior to utilizing it. It is well known that power detection degrades the spatial resolution of the complex-valued SAR image by a factor of two while magnitude detection degrades it by a factor greater than two [144].

The SAR chips to be classified are normally acquired under conditions better described as variant and non-ideal. When the resolution of such chips is compared with the target chips used during the training phase, be it for feature synthesis or target-model construction, it is most probable that discrepancy between the two resolutions will be found. Herein lies the benefit of superresolution techniques in matching the resolution of the test chips with that of those used for training. Thus, the ATR performance can be improved, or at least retained. There are various superresolution techniques. Superresolution techniques were originally designed to enhance the resolution of the RCS in 1-D datasets [145]. Then, these techniques were extended to handle 2-D data [146]. Further extension of these techniques deals with 3-D [147], [148], and even higher dimension data [149], [150]. As explained in the next section, superresolution techniques have also been extended for 3-D target reconstruction from a relatively limited number of SAR target chips.

Superresolution techniques can be broadly classified into two classes, non-parametric and parametric. Examples of the non-parametric class include CLEAN, its variants, and RELAX. Examples of the parametric class include PRONY, MUltiple SIgnal Classification (MUSIC), and Estimation of Signal Parameters by Rotational Invariance Techniques (ESPRIT) [151], [152]. An introduction to the concept of superresolution for SAR imagery can be found in [143]. Some interesting observations using MUSIC and ESPRIT for SAR imagery are provided in [153]. A comprehensive literature review on the superresolution techniques for SAR-ATR, along with a brief description of their advantages and disadvantages, is provided in [152].

E. RECONSTRUCTING A 3-D SAR IMAGE

In the surveyed SAR-ATR methods pertaining to the model-based and semi-model-based taxa, the target-model construction process is based on either one of two methods. In the first method, a predesigned 3-D CAD model for a target of interest is input to an εM SAR simulation tool (e.g., XPATCH [117]) from which either a 3-D SAR target-model is generated or 2-D SAR chips for the parameters of interest are simulated. In the second method, extensive set of SAR images for a target of interest that covers the span of azimuth angles $[0°, 360°]$ are used to estimate certain pose-dependent parameters that were used during the online classification phase. However, none of the surveyed SAR-ATR methods utilized SAR images for a target of interest to explicitly construct a 3-D SAR target-model. Obviously, one limitation of the CAD/εM simulation-based method is that such simulators do not provide accurate estimations of real-world targets due to the inaccuracies in the CAD model design that impacts the simulation of the εM facetization process. Furthermore, it is imperative for a SAR simulator to handle the radar wave interactions between the target, adjacent objects, heterogeneous clutter, speckle, and multi-bounce effects pertaining to the geometry of the target and surroundings involved. Indeed, the accuracy of εM simulation tools is questionable, particularly at high resolutions and for complex man-made targets such as vehicles and airplanes [4]–[6]. On the other hand, the second method requires an intensive sets of SAR chips for the target of interest and this will be impractical to collect in most real-world cases.

In this section, some methods for 3-D target reconstruction from 2-D SAR images are briefly reviewed. Given a relatively limited set of 2-D SAR images for a target of interest in the $x-y$ plane, the goal is to estimate the radar backscatter in the elevation plane (i.e., z-direction). One major advantage of such methods is that they require a relatively smaller number of SAR images (when compared to the second method discussed above) to construct the 3-D SAR target. Another advantage is that such methods are based on real-world SAR images which make them less prone to estimation inaccuracies when compared to their simulation-based counterparts. However, it should be stressed that, while these methods enable the estimation of 3-D SAR targets, they are based on a relatively limited number of 2-D SAR images representative of a limited number of perspectives. The question arises is 'how accurate is this method'? We are not aware of publications in the open literature that explicitly address this issue. It is certainly worthwhile to investigate the applicability of such methods for 3-D target-model construction.

In the literature, there are two major classes of methods for 3-D SAR image reconstruction. The first class is the surface-constrained approach, and the second is the spectral approach. We briefly review these two classes (in subsection VI-E1 and subsection VI-E2, respectively) and present some of the methods available under each of them. A brief description of the associated advantages and disadvantages is also presented.

1) SURFACE-CONSTRAINED APPROACH

This class of methods implicitly assumes that the scene being imaged is a surface rather than a volume. Two popular schemes are stereo and interferometry. However, due to the surface-constrained assumption, when applied to SAR imagery, these methods fail to account for the multiple reflectors at different elevation levels (i.e., in the z-direction) at the same point in the $(range, cross - range)$ plane, which are characteristics of many man-made targets. Despite their lack of utility, the two methods are briefly reviewed for the sake of completeness.

a: STEREO

This method requires only two images taken from two different perspectives. However, regardless of its success for optical imagery, this method fails to handle the unique correspondence problem characteristic of SAR imagery which is a result of the strong dependence of the SAR reflectivity on the observation angle [154].

b: INTERFEROMETRY

Interferometry relies on phase unwrapping where at least two pair of images taken from slightly different elevation angles is required. One such method is the dual antenna interferometric SAR where a 3-D digital elevation map (DEM) can be created using only the two SAR images gathered by the two antennas. However, this method suffers from sensitivity to variations in the platform altitude (in the case of airborne SAR), is error prone to abrupt changes in elevations, and is impractical at handling small man-made targets such as vehicles [154], [155].

2) SPECTRAL APPROACH

The spectral approach is the most convenient for 3-D SAR image reconstruction. Under this section, we briefly review two approaches. The first approach is the brute force direct inversion approach, and the second approach covers a class of methods that are based on high-resolution spectral estimation. It is shown that the first approach is suitable when an extensive set of SAR chips is available, while the second approach is the most convenient for 3-D SAR image reconstruction from a relatively limited number of SAR chips.

a: BRUTE FORCE DIRECT FOURIER INVERSION

In this method, an inverse Fourier transform is applied to a volume of Fourier data pertaining to an extensive number of 2-D SAR chips for the target of interest taken from many passes at varying radar elevations. Obviously, due to the impracticality of collecting such an intensive dataset in many cases (e.g., for space-borne SAR), this method fails to achieve high-resolution in the elevation direction (i.e., $z - axis$). However, the method finds success in elevation-circular SAR (E-CSAR) due to the nature of the imaging process where reflectors are available at different elevations (i.e., altitudes) in the SAR data [156], [157].

b: HIGH-RESOLUTION SPECTRAL ESTIMATION METHODS

Unlike previous methods, this approach is the most relevant for 3-D SAR target-model reconstruction from a relatively limited number of SAR chips. This class of methods directly accounts for the presence of multiple radar reflectors in the target elevation direction (i.e., $z - axis$). Most of these methods employ a process of decoupled parameter estimation or decomposition in the 3-D $(range, cross - range, elevation)$ space. Particularly, for each relevant $(range, cross - range)$ point in the 2-D SAR plane, the following three parameters are estimated: the number of reflectors in the elevation (i.e., $z - axis$) direction for a $(range, cross - range)$ location, the amplitude of each reflector, and the relative elevation for each reflector in the z-direction.

Typically, the estimates in the elevation (i.e., $z - axis$) direction are superresolved through utilizing some suitable superresolution technique. This explains the relationship between spectral-based superresolution techniques (discussed in Section VI-D) and the spectral estimation methods for 3-D target reconstruction. It also explains the reason for the similarity between the names of some of the 3-D reconstruction algorithms with those used for superresolution. In the literature, there is a variety of methods proposed for 3-D target reconstruction based on spectral estimation. Some popular methods include the relaxation algorithm (RELAX) [154], [158], [159], CLEAN [160]–[162], Estimation of Signal Parameters via Rotational Invariance Techniques (ESPRIT), and Decoupled Least Squares (DLS) [163]. There are other methods that build on one or more of these algorithms such as the shadow-based spectral estimation method presented in [164].

The RELAX algorithm [154], [158], [159] is probably the most popular. It iteratively estimates the individual reflectors at specific $(range, cross - range)$ points through an accumulative energy process that continues until the total energy exceeds some arbitrary noise threshold. The remaining energy from the original frequency samples is assumed to be due to noise and is thus discarded. Thanks to the ability of the technique to operate in such a noise-type irrelevant manner, it can be effective in various noise environments.

The CLEAN algorithm [160]–[162] was first introduced in radio astronomy [161], and later utilized for radar imaging [160]. Indeed, the CLEAN algorithm and its variants [162] are instances of the RELAX algorithm. If the number of reiterations in each step of the RELAX algorithm is set to zero, then the RELAX algorithm reduces to the CLEAN algorithm [159]. ESPRIT is another method used to estimate the 3-D scattering center but it differs from RELAX and CLEAN in that it is parametric [148]. It is shown that RELAX outperforms CLEAN, ESPRIT, and their variants [159], [165].

Decoupled Least Squares (DLS) is presented in [163]. This method forms a 3-D SAR image from a small number of 2-D SAR images pertaining to different elevation passes. The modeling process is based on the assumption that point scatterers in the imaged scene are finite, isotropic and independent; and embedded in an additive white Gaussian noise (AWGN). Based on decoupled least squares, the method provides estimates to superresolve scatterers in elevation (height) at a particular $(range, cross-range)$ location out of the slant-plane. One obvious disadvantage of this technique in relation to RELAX is that it is not designed to cope with non-AWGN noise.

Another relevant method is presented in [164]. Based on target shadows and the corresponding beam depression angles, the physical target heights along the range axis are computed. Then, elevation data extracted from multiple SAR images for the same target are fused together to construct the 3-D target. Despite the advantage of the spectral estimation approach, after-all it performs 'estimation' for 3-D image reconstruction. Hence, the accuracy of the estimation process is solely dependent on the quality and number of the 2-D SAR chips used in the reconstruction process, and whether the utilized algorithm can accurately estimate the 3-D image. Obviously, the brute-force inversion utilized in E-CSAR outperforms spectral estimation methods.

F. MODEL-BASED APPROACH: ADVANTAGES AND CHALLENGES

From the perspective of HLC classification, the model-based approach enjoys unique advantages that make it a competitive candidate of choice. One key advantage is that the model-based taxon caters to a wide range of EOCs without offline algorithm retraining. This is because the model-based strategy is designed to adapt and generalize to various scenarios on-the-fly during the online classification phase. Conversely, feature-based and semi-model-based taxa lack this characteristic which renders them incapable of coping with EOCs variant from those used in the offline training phase.

However, a major challenge to the model-based approach is the design of the target-model. Obviously, a 3-D reconstruction of scattering centers offers a means to build a global 3-D target-model. The 3-D global target-model is a near-optimal model in the sense that it represents the target in the standard operating conditions, and it allows for hypothesizing the desired EOCs. In Section III and Section IV, some popular methods for constructing such model have been surveyed. Most notably, methods based on 3-D CAD models and εM prediction tools are among those widely reported in the open literature. However, as discussed earlier, despite their advantage, these methods have some major drawbacks, particularly at high resolution and for complex man-made targets (e.g., vehicles and airplanes) [4]–[6]. Further, methods based on 3-D SAR image reconstruction from 2-D real-world SAR chips provide an alternative to the less realistic 3-D CAD model based methods. However, the challenge in real-world scenarios is to obtain an extensive set of SAR chips under the appropriate OCs so that the 3-D target-model can be reconstructed accurately. The efficacy of 3-D real-world target-model reconstruction methods for SAR-ATR warrants an in-depth investigation, which to our knowledge, is presently lacking in the literature.

VII. CONCLUSIONS

This paper presented a comprehensive state-of-the-art review for automatic target recognition in synthetic aperture radar imagery (SAR-ATR). An end-to-end SAR-ATR system is typically multistaged to handle the SAR image in a divide-and-conquer approach. The front-end stage in the processing chain is referred to as the detector (also known as prescreener). The intermediate stage is known as the low-level classifier (LLC) or the discriminator. Finally, the back-end stage is described as the high-level classifier (HLC). As the input SAR data progresses from the front-end toward the back-end stage, the system design aims at reducing the data load while increasing the complexity of the pertinent stage. From the perspective of target classification, we broadly taxonomized the various SAR-ATR systems into three major taxa: feature-based, model-based and semi-model-based. The feature-based taxon is characterized as a top-down approach that relies solely on representative features. The model-based taxon is a bottom-up approach that allows for intelligent knowledge incorporation into the system design. The semi-model-based taxon lies between the aforementioned two taxa, and shares many of the pitfalls in the feature-based taxon.

We carefully opted for twenty-four representative SAR-ATR systems and taxonomized them accordingly. Additionally, a two-fold benchmarking scheme for evaluating existing SAR-ATR systems and motivating new system designs was proposed. The benchmarking scheme was applied to the SAR-ATR works surveyed in this paper and was used to evaluate them accordingly. Our findings convey that the LLC stage is typically implemented as a feature-based classifier while the HLC stage is based on one of the three aforementioned taxa. Although the inherently complex model-based taxon for HLC classification allows for context utilization and generalization, in contrast to optical imagery where the model-based approach originated, target-model design in the case of radar imagery is a major challenge. Finally, motivated by our holistic perspective for an end-to-end SAR-ATR system design, various interrelated issues were addressed including the underlying reasons for variability in the SAR target signature, the OCs and their characterization into standard OCs and extended OCs, differentiation between the various target-models, the topic of superresolution and its relevance to SAR-ATR, and the problem of reconstructing 3-D SAR imagery from 2-D SAR chips.

APPENDIX

LIST OF ACRONYMS

ϵM	electromagnetic
AASMB	Also Applicable to Semi-Model-Based
AI	artificia intelligence
AMF	adaptive matched filtering
AR	autoregressive
ARMA	autoregressive moving average
ATR	automatic target recognition
AWGN	additive white Gaussian noise
CSA	chirp scaling algorithm
DEM	digital elevation map
DF	discriminant function
DLS	Decoupled Least Squares
E-CSAR	elevation-circular SAR
EM	Expectation Maximization
EOCs	extended operating conditions
ESPRIT	Estimation of Signal Parameters by Rotational Invariance Techniques
FOA	focus-of-attention
GB-SAR	ground-based SAR
GLRT	generalized likelihood ration test
H	horizontal
HLC	high-level classification
HMM	hidden Markov model
HNN	holographic neural network
HRRPs	high resolution range profiles
InSAR	Interferometric SAR
KB	knowledge-based
KDE	kernel density estimation
kNN	k-nearest neighbor
LANTRIN	Low Altitude Navigation and Targeting Infrared for Night
LDFs	linear discriminant functions
LFM	linear frequency modulation
LLC	low-level classification
LN-RF	log-normal random field
LOS	line of sight
LUT	look-up table
MIT	Massachusetts Institute of Technology
MLPs	multi-layer perceptrons
MRF	Markov random field
MSE	minimum-squared error
MSTAR	moving and stationary target recognition
MUSIC	MUltiple SIgnal Classification
NFL	No-Free-Lunch
NNs	neural networks
OAFB	Only Applicable to Feature-Based
OCs	operating conditions
PD	probability of detection
PDF	probability density function
PFA	probability of false alarm
PR	pattern recognition
PSF	point spread function
RADAR	Radio Detection and Ranging
RBFs	radial basis functions
RCS	radar cross section
RDA	range Doppler algorithm
RELAX	relaxation algorithm
ROIs	regions of interest
SAR	synthetic aperture radar
SAR-ATR	ATR in SAR imagery
SDMS	Sensor and Data Management System
SVMs	support vector machines
V	vertical

ACKNOWLEGMENT

The authors would like to thank Dr. Paris Vachon from Defence R&D Canada (DRDC Ottawa) who provided advice and oversight to the project team for the last five years.

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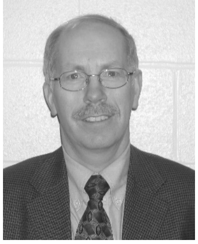

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