Automatic Target Recognition of Surface Vessels Using SAR/ISAR Imagery

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INTRODUCTION

Automatic Target Recognition has come to refer to techniques used in the development of automated classification systems and decisions aids. The issue of ever-increasing amounts of radar imagery versus the cost and availability of manpower to review that imagery is well known and calls for automated methods of searching through data for specific targets.

ATR techniques are becoming a routine inclusion in the processing chain of various data such as seismic, acoustic, EO, and SAR/ISAR imagery. Note that each of these data types exists in distinctly different bands of interest with different bandwidth and dynamic range requirements. For example seismic data are typically acquired with sensors covering a band from 1 to 100 Hz; Side-scan sonars operate in narrow bands between 100 and 500 kHz, while Airborne EM systems employ signals in the visible spectrum, near infrared, and microwave bands. In most cases, each system and sensor provides the operator with a display; often an actual target image.

ATR is cognizant but not confounded by the physics of acoustic or EM wave propagation. In contrast to strictly physic-based approaches, ATR generally assumes all physical phenomena have been exploited at the point of image display. Consequently ATR moves beyond that point using science and solutions no less challenging, but different with respect to the tools and techniques applied.

This white paper explores ATR focused broadly on the extraction of image features and measurements that aid in the classification of surface ships from processed SAR/ISAR data acquired by airborne platforms which employ SAR and ISAR technologies. The discussion begins at a point where the displays have been corrected using all available metadata. In the following sections a review of current SAR/ISAR processing capabilities is offered, followed by a short description of potential extensions and enhancements that may further the state-of-the-art using novel ATR techniques SAIC has developed and applied to other data types (e.g., ocean bottom surface modeling, and acoustic target recognition, nuclear monitoring, etc.).

1 Previous Work

1.1 Review

Synthetic-aperture radar (SAR) is a form of radar whose defining characteristic is its use of relative motion between an antenna and its target region to provide distinctive long-term coherent-signal variations that are exploited to obtain finer spatial resolution than is possible with conventional beam-scanning means. It originated as an advanced form of side-looking airborne radar (SLAR).

ATR within the context of SAR/ISAR imagery is a broad topic with many of its current implementations sharing a consistent top-level approach including in a limited sense, the application of

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image processing schemes (e.g., segmentation, parameter extraction) and machine learning techniques (clustering algorithms, MLP classifiers, Bayes nets, etc.)

In a more specific sense, SAR/ISAR includes a sequential set of operations.

- Automatically detect and segment targets within an image
- Extract image parameters including the length, width and height of each detection.
- Train classifiers on subsets of reviewed detections to automatically classify detections as a particular ship class or category
- Provide the analyst with candidate classifications and uncertainty metrics

SAR is usually implemented by mounting, on a moving platform such as an aircraft or spacecraft, a single beam-forming antenna from which a target scene is repeatedly illuminated with pulses of radio waves at wavelengths anywhere from a meter down to millimeters. The echo waveforms received successively at the different antenna positions are coherently detected and stored and then post-processed together to resolve components in an area of the target region.

Inverse synthetic aperture radar (ISAR) is a technique to generate a two-dimensional high resolution image of a target. ISAR technology utilizes the movement of the target rather than the emitter to create the synthetic aperture. ISAR radars have a significant role aboard maritime patrol aircraft to provide them with radar image of sufficient quality to allow it to be used for target recognition purposes. In situations where other radars display only a single unidentifiable bright moving pixel, the ISAR image is often adequate to discriminate between specific target classes. An ideal example is shown in Figure 1. However, airborne systems require high precision motion compensation to overcome the defocusing and mislocation effects resulting from path deviations caused by vibration, atmospheric turbulence, and winds. These effects are much reduced or absent in space borne systems, although platform orbit and attitude must still be carefully controlled.

Figure 1: Inverse-SAR ship image from Northrop Grumman's MFAS prototype ²

Inverse synthetic aperture radar (ISAR) is a technique to generate a two-dimensional high resolution image of a target. ISAR technology utilizes the movement of the target rather than the emitter to create the synthetic aperture. ISAR radars have a significant role aboard maritime patrol aircraft to provide them with radar image of sufficient quality to allow it to be used for target recognition purposes. In situations where other radars display only a single unidentifiable bright moving pixel, the ISAR image is often adequate to discriminate between specific target classes. An ideal example is shown in Figure 1. However, airborne systems require high precision motion compensation to overcome the defocusing and mislocation effects resulting from path deviations caused by vibration, atmospheric turbulence, and winds. These effects are much reduced or absent in space borne systems, although platform orbit and attitude must still be carefully controlled.

Although unrelated to the present ship classification topic, interferometric synthetic aperture radar, also abbreviated InSAR or IfSAR, is another radar technique used in remote sensing. In this technique, two SAR images are differenced to detect changes in a particular region or geodetic scene (Figure 2). The technique is very powerful if the application involves change detection. However, ever present are typical problems of co-registration as in multi-spectral satellite data analysis, although change detection algorithms have recently been implemented by SAIC to alleviate these problems.

![Figure 2: SAR (a) and ISAR (b) Terrestrial Example](image)

1.2 Noise Effects

Admittedly, many practical issues make automatic ship recognition a very complex problem, in particular for Synthetic Aperture Radar (SAR) imagery:

- uncontrolled environment
- variable 3-D image acquisition geometry and resolution
- image blurring due to target motion
- high noise level (speckle)
- dependence of radar scattering to ship orientation
- operator requirements (up the 1000 ships in database)
- difficulty of accessing real image data due to potential strategic interest

As a result SAR and ISAR images are subject to a number of effects that can reduce image resolution and obscure target recognition. For example, targets can disappear because they are masked

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(“shadowing” effect). The eccentricity of a target largely due to azimuthally dependent interference is calculated and serves as one screening step to discard objects that are not elongated enough due to possible image artifacts or blurring. Speckle noise is a granular noise that inherently exists for a ship on the ocean surface and degrades the quality of the active radar and synthetic aperture radar (SAR) images. This phenomenon and others are evident in Figure 1, and also in simulations shown in section 1.3. Models exist that include the ship on ocean scenario, but other models simply ignore the interaction between the ship-like target and the ocean surface.

There are numerous other phenomena that affect the quality of SAR imagery. Although not completely understood, the vertical line appearing in Figure 1 can obscure and/or corrupt target features. A plausible explanation might be a return glint of high intensity which does not appear across the entire aperture of the survey. A pre-processing technique is discussed in section 2 which might be employed to filter its affect on feature extraction.

1.3 Simulations

Use of computer-based ship SAR/ISAR image simulation enables a database of images to be generated. Numerous images can be produced for numerous ship motions and orientations. This simulation facility provides an effective method of acquiring radar images when compared to the alternative methods of acquiring real images, using either full sized vessels or scaled ship models. It also enables extensive testing of automatic ship classification algorithms and noise reduction techniques (Figure 3 and Figure 4). In their 1998 paper, Gagnon and Klepko described the state-of-the-art at that time.

The ship classes included in their simulated SAR data set are listed in Table 1.

<table>
<thead>
<tr>
<th>Class</th>
<th>Class Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Destroyer</td>
</tr>
<tr>
<td>2</td>
<td>Cruiser</td>
</tr>
<tr>
<td>3</td>
<td>Destroyer</td>
</tr>
<tr>
<td>4</td>
<td>Supply ship</td>
</tr>
<tr>
<td>5</td>
<td>Aircraft carrier</td>
</tr>
<tr>
<td>6</td>
<td>Cruiser</td>
</tr>
<tr>
<td>7</td>
<td>Aircraft carrier</td>
</tr>
<tr>
<td>8</td>
<td>Frigate</td>
</tr>
</tbody>
</table>

At that time only a handful of simulated measurements at a limited set of ranges, source frequencies, aspect angle, and other data acquisition geometries were explored. The primary obstacle the authors

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encountered was the intensive processing required to simulate the few examples in their training set. However, much of their 4-step approach based on model simulations still applies.

- Step 1: Target segmentation (threshold detection and merging of small region)
- Step 2: Ship length estimate, length and eccentricity tests (estimating the ship center-line from the maximum peak of the Hough transform of the segmented image)
- Step 3: Ship category and ship type declarations
- Step 4: Ship class declaration

Figure 3: Simulated SAR images. Each row contains images of one ship class obtained at different aspect angles.
Clearly the most widely used target features in processed SAR/ISAR images are their length and shape (Table 1), and various databases and catalogues contain these features, and also sample images for a variety of specific targets. The Generalized Hough Transform or GHT, introduced by D.H. Ballard in 1981, is the modification of the Hough Transform using the principle of template matching (Step 4).

<table>
<thead>
<tr>
<th>Table 2: Detailed ship length estimation (meters)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adams (D-133)</td>
</tr>
<tr>
<td>Amazon (F-117)</td>
</tr>
<tr>
<td>Belknap (C-167)</td>
</tr>
<tr>
<td>Boxer (F-145)</td>
</tr>
<tr>
<td>Bremen (F-130)</td>
</tr>
<tr>
<td>Chilkin (O-162)</td>
</tr>
<tr>
<td>Coontz (D-156)</td>
</tr>
<tr>
<td>Donatto (M-145)</td>
</tr>
<tr>
<td>Farland (M-272)</td>
</tr>
<tr>
<td>Geestbay (M-159)</td>
</tr>
<tr>
<td>Grisha (F-73)</td>
</tr>
<tr>
<td>Invinc (A-206)</td>
</tr>
<tr>
<td>Irogo (O-159)</td>
</tr>
<tr>
<td>Iroquois (D-130)</td>
</tr>
<tr>
<td>Jross(O-95)</td>
</tr>
<tr>
<td>Kara (C-174)</td>
</tr>
<tr>
<td>Kiev (A-270)</td>
</tr>
<tr>
<td>mckenzie (F-112)</td>
</tr>
</tbody>
</table>

However, an approach using synthetic images still appears to offer a promising means of developing effective processing, display, and classification schemes which are complete in the phenomena they include. In the past they have been severely limited due to their processing requirements, and consequently only a handful of target classes at a comprehensive set of ranges, source frequencies, aspect angle, and other data acquisition geometries could be obtained synthetically.

Today however, advances in multi-processor and parallel computing capabilities could provide realistic images of the multitude of ship classes and categories of interest. Without these advances in computer technology, surface ship characterization has been essentially limited to an often crude estimation of target dimensions. High fidelity models have been developed over the years to simulate nearly every aspect of the ship-on-ocean imaging problem, and the practical implementation of these composite models should enable the use of advanced multiprocessors in conjunction with more sophisticated image processing and enhancement techniques as well as multivariate classification schemes.
2 Preliminary Work

ATR is a broad topic with many of its applications sharing a consistent top-level approach involving the integration of image processing schemes (image representation, segmentation, parameter extraction) and machine learning techniques (clustering algorithms, template matching, MLP classifiers, Bayes nets, etc.) A few interesting examples of ATR are applied here to the example ISAR image in Figure 1 to illustrate potential extensions to the previous work. These examples employ

Figure 4: The simulated SAR images of Figure 3 after applying a local-statistics speckle reduction algorithm. Each row contains images of one ship class obtained at different aspect angles.
various algorithms drawn from systems developed by SAIC to support sonar surveillance systems, comprehensive test-ban treaty monitoring, and a recent IR&D effort to support SAIC’s Newport NOAA sponsored survey operations to detect and classify small objects on the ocean bottom from analysis of sides can sonar data. All employ techniques that come under the general category of ATR, although the specific algorithms have been modified to extract the most effective target features. Advances in ATR as applied today have generally been enabled by advances in a number of different areas such as:

- Knowledge Acquisition: especially the transition of neural-network “black boxes” into thoroughly understood processes
- Software: in particular MATLAB’s suite of specialized signal processing, image processing, and database toolboxes, and real-time C++ conversion from prototypes to operationally deployable systems. Also there are excellent open source libraries available for commercial use such as those listed in Section 5
- Computational Resources: computer clusters, multiprocessors, FPGAs, and parallel computing capabilities – all making possible the generation of high-fidelity synthetic data examples from existing models

In the following sections, several elements of ATR are applied to the ISAR image in Figure 1 that draw from the areas of SAIC’s current and ongoing research efforts in this field.

2.1 Feature Extraction

One of the most important elements of ATR following detection stage is the extraction of salient features. The image feature set may capture shapes, textures and statistical moments of the detected targets. Consequently, an important step in feature extraction is the isolation of the target image window typically within a larger detection window. These windows are based on the automated analysis and thresholding of the detection window resulting in bounding regions, in which the target can be isolated and analyzed. In the SAIC application support SAIC’s Newport survey operations, the moment and texture parameters extracted from these windows were used successfully for classifier training and target measurements.

In that case a global image threshold using Otsu's method was used to compute a global threshold (LEVEL) that can be used to convert an intensity image to a binary image. LEVEL is a normalized intensity value that lies in the range [0, 1]. The algorithm uses Otsu's method, which chooses the threshold to minimize the intraclass variance of the thresholded black and white pixels and constrain region of interest based on feature extent. The raw moments listed in Table 3 are also returned. Unlike the well known watershed algorithm and numerous others, Otsu’s method is a particularly flexible and intuitive approach that can be adapted to segment an arbitrary image.

2.2 Moment Calculations

At each threshold, a set of image properties is produced efficiently by the MATLAB function `getregionprops`, defining the size of the target and scatters within its perimeter. A set of properties is

7 MATLAB Image processing toolbox documentation
assigned for each labeled region in the image. The list ranges from simple measurements such as orientation and eccentricity to more complex geometric properties.

<table>
<thead>
<tr>
<th>Table 3: Image properties for each region in a labeled image</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area</td>
</tr>
<tr>
<td>BoundingBox</td>
</tr>
<tr>
<td>Centroid</td>
</tr>
<tr>
<td>ConvexArea</td>
</tr>
<tr>
<td>ConvexHull</td>
</tr>
<tr>
<td>ConvexImage</td>
</tr>
<tr>
<td>Eccentricity</td>
</tr>
<tr>
<td>EquivDiameter</td>
</tr>
</tbody>
</table>

![Figure 5: gray-level co-occurrence matrix](image)

**2.3 GLCM**

The gray-level co-occurrence matrix (GLCM) can reveal certain properties about the spatial distribution of the gray levels in the texture image. An explanation of the elements of the matrix is illustrated in Figure 5. For example, if most of the entries in the GLCM are concentrated along the diagonal, the texture is coarse with respect to the specified offset. In the output GLCM, element (1, 1) contains the value 1 because there is only one instance in the input image where two horizontally adjacent pixels have the values 1 and 1, respectively. glm (1, 2) contains the value 2 because there are two instances where two horizontally adjacent pixels have the values 1 and 2. Element (1, 3) in the GLCM has the value 0 because there are no instances of two horizontally adjacent pixels with the values 1 and 3.

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8 MATLAB Image Processing Toolbox Documentation.
Image textures derived from the GLCM are listed in Table 4. These measures can be extracted from an image once the target has been properly segmented.

### 2.4 Textons

Due to noise sources and data artifacts, there is some degree of 2-D filtering required before an image is passed through feature extraction algorithms such as the ones mentioned above. Textons which reveal textures as well as the directionality and intensity of a target and its components offers another potential approach. In this section, we introduce a rotationally variant filter bank that can be used by a feature extraction algorithm to provide input to a target classification scheme. In this approach the filter bank, which contains filters at multiple orientations, produce output images that are collapsed...
across all orientations. This achieves rotation invariance which is an important quality of classifier input.

The Leung-Malik set selected for its diversity in directionality, consists of 48 filters, partitioned as follows: first and second derivatives of Gaussians at 6 orientations and 3 scales making a total of 36; 8 Laplacian of Gaussian filters; and 4 Gaussians.

The scale of the filters range between \( \sigma = 1 \) and \( \sigma = 10 \) pixels. They are shown in Figure 6. When applied to the ISAR image in Figure 1 and then collapsed over various moments (mean, median, min, max, variance), the ISAR image are enhanced in different ways that accentuate the outline of the target and also reveals the distribution of scatters within the perimeter of the target relative to the centroid of the ship are shown in Figure 8. This can provide a rich and diverse feature set used to support confident classification.

In Figure 7 the collapsed images have been quantized. However there are a number ways the images can be manipulated to accentuate different features (e.g., SVD reduced rank). Of particular importance is the resultant normalization of images to enable comparison among the multitude of ship classes available. Figure 8 identifies the location of maxima in the texton variance image in Figure 7.

In all, the previous feature extraction algorithms offer a wealth of information that can be exploited in various ways to isolate and characterize target images of surface vessels in terms of textures, directionality, and moments which apply to the whole target and features within.

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Figure 7: Texton filtered versions of the original image collapsed over different moment where image quantization at probability 0.05.
3 TARGET CLASSIFICATION

The design sensitivity of the detector typically ensures a high probability of detection often at the cost of a large number of false detections. However, this does not necessarily degrade the target identification capability when an effective classification scheme is employed.

3.1 Candidate Classifiers

Recommended classifiers are two supervised machine learning algorithms referred to as the Multilayer Perceptron (MLP) and Bayes belief nets. The simplified concepts and requirements underlying each are:

- Multi layer Perceptron (MLP): requires an extensive ground truth data set
- Bayes belief nets: examine the available data and form target/parameter associations by way of estimated probability distributions.
They are both supervised learning algorithms that require a set of training examples representative of all targets of interest. Both are essentially acyclic graphs whose structure is illustrated concurrently in Figure 9, although the operations performed at each node and the error minimization algorithms are unique. In the MLP case, the nodes represent network weights, and in the Bayesian case, a priori distributions. The learning algorithms used by each are extensively documented in the open literature, although some continue to be characterized as “black box” implementations without optimized configuration.

3.2 Confidence Metrics and Generalization Testing

Ultimately, any target classification algorithm must provide some measure of confidence. The MLP algorithm provides a formal error analysis which includes confidence metrics and performance evaluation based on the beta distribution of class probabilities.\[\frac{1}{B(\alpha,\beta)} x^{\alpha-1}(1-x)^{\beta-1}\]

In addition, generalization testing and the application of adaptive learning techniques are critical to the future success of any classification system if it is to be deployed in different environments. A key point often absent in past discussions is the fact that all ATR implementations require analyst supervision, i.e., they cannot duplicate the role of a trained analyst, but rather can assist their function and hopefully reduce the often overwhelming burden of the review process. In the case of active learning, automation is possible, but largely supported by ongoing analyst review and the effective archiving of information.

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\[\text{10} \text{ The receiver operating characteristic (ROC) can be obtained by integration of the beta CDF.}\]
4 SUMMARY

Automatic methods for the interpretation of SAR/ISAR imagery containing ship patterns have been proposed in recent literature. However, due to the increasing technological advance of airborne-based imaging sensors, design and implementation of automatic ship recognition systems are receiving much more interest in the scientific and engineering communities. Despite the fact that automatic ship recognition presents profoundly interesting scientific challenges, very few practical results are reported in the open literature\textsuperscript{11}. Previous results in this area have either considered ship classification under simplifying assumptions, or have been concerned solely with ship detection rather than ship classification.

The MLP algorithms developed in support of SAIC’s ATR applications generally address the binary class problem, although they can easily be adapted to multi-class surface ship recognition. These algorithms further provide a realistic measure of confidence based on detection scores that represent real probabilities drawn from a realistic distribution. As such these Target classification paradigms provide a much needed measure of confidence. Nearly as important as the feature extraction and selection process SAIC’s ATR applications include innovative generalization tests to ensure confident classification in previously unseen environments.

The image filtering, feature extraction, and adaptive learning schemes proposed throughout this discussion hopefully present the enormous diversity of options available for further investigation and research in this area.

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The Netlab Toolbox Version 3.3.1

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