Maritime Automated Targets Recognition Algorithm Test Bed for High Resolution ISAR Imagery

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Abstract—A maritime automatic target recognition system is under development to perform ship classification using images from inverse synthetic aperture radar (ISAR) systems. This work will describe the algorithm framework for feature extraction, classification, and aim-point recognition. ISAR systems produce two-dimensional images of ships from the periodic motion inherent to all maritime objects and can be used to distinguish objects of interest for Homeland Security. There is a need for real-time classification of these objects. This work extends the state of the art in two ways: One – current maritime classification focuses on satellite ISAR, creating latency for classification [1]; and Two – work with Homeland Security ISAR radar systems is focused on concealed weapon detection [2,3]. This work uses localized ISAR images from stationary radars to classify maritime objects. Since the aspect and cross-range scale factor are continually changing, ISAR images form distinct representations unique to each object under observation. These distinct representations are analogous to visual images in many ways. They have unique shapes and areas of strong return, much in the same way objects in passive images have unique sizes and colors. However, ISAR images are synthetic portrayals of scattered field data from active sensor RF sensors whereas visual images are observations of passive sensors. This distinction must be considered as a design constraint in the classification system – each feature employed must be exhaustively examined regarding its physical counterpart. Within that constraint, ISAR synthetic imagery feature extraction techniques can leverage from previous work developed for passive sensors. This is especially the case of High Range Resolution (HRR) ISAR systems. After extraction from ISAR prototype images, a set of representative features will be used to train a support vector machine (SVM) classifier, a supervised learning model capable of pattern recognition.

Keywords— Inverse synthetic aperture radar, high resolution, automated target recognition

I. INTRODUCTION

The automated recognition of maritime targets based on inverse synthetic aperture radar systems (ISAR) has many applications including weapon systems and homeland security surveillance. Previous systems have been investigated [1]-[8]. While, Synthetic Aperture Radar (SAR) assumes stationary targets viewed by travelling radars, ISAR is the reverse. While both systems analyze differences in Doppler due to relative motions, the unknown motions of the target add a level of complexity for ISAR target recognition, especially in maritime environments [4]. The range – range rate (Doppler) technique is used to process the received data and large bandwidth coded

signals achieves high resolution in the range coordinate and coherent integration of echoes collected at different viewing angles are used to achieve high cross-range resolution.

In this paper, we focus on the classification ISAR images of maritime targets exhibiting various motions with respect to the radar in a variety of sea states. An advantageous feature of maritime ISAR is, while the velocity of the target may be relative slow, the consistent pitch and roll motion due to external ocean forces intensifies the Doppler signal revealing physical features, such as mast and other superstructure forms. Another feature of maritime images is the ever present whitewater; whitecaps, propeller wash, and bow wakes. Whitewater can either help or hinder the classification of maritime objects. On one hand, bow wakes greatly aid in the detection and other phases of automated recognition [7-9], i.e. given a wake there must be a maritime object. Conversely, whitewater can distort the resultant ISAR images leading to misclassification [10]. This research has developed an effective means of whitewater detection and mitigation.

In order to classify maritime targets each image must be processed by a sequence of algorithms [4]. This research, while building upon previous work, deviates through expansion of the proposed features sets and more in-depth range profiling. Referring to Fig. 1, the following parameterized functions are user-selectable in the algorithm chain:

- Preprocessing
 - Set the image threshold;
 - Blur the image; and
 - Identify and mitigate streaks.
- Segmentation
 - Connect ship regions;
 - Identify and mitigate whitewater; and
 - Calculate the ship mid-line.
- Image transforms
 - Apply affine transforms;
 - Split the image about mid-line; and
 - Define ship sections (bow, mid, stern)
- Extract features for classification or training purposes

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Fig. 1. Data flow diagram of algorithm chain.

The ship ISAR image is preprocessed producing an image that then can be segmented into regions yielding a hard body representation as well as wake locations. The hard-body and wake segments are ready for applicable image transformations. The selectable transforms are the final image enhancements prior to feature extraction. The features extracted are based on geometric properties (length, area, etc.) wake identification; and range profiling. The features are then used to either establish a training database or be used to classify objects using models in said database.

II. METHODOLOGY

The input to the overall automated recognition algorithm chain is a sequence of ISAR image with each image portrayed is in the slant-range and Doppler-frequency domains. The original image (Fig. 2) while information rich needs preprocessing to augment desirable features (i.e. hull shape, mast locations, and spinning antenna returns) while abating other effects (i.e. speckle-like noise, white water and wake

returns). The next subsections will discuss the technical approach and justification for key algorithms.

Fig. 2. ISAR image highlighting areas of concern.

A. Detect and Mitigate Vertical Streaks

ISAR imagery usually contains vertical streaks as seen in Fig. 2. These vertical streaks, several pixels wide, originate from either internal motion on the ship (e.g., spinning antennas) or multiple-bounce scattering from white water returns have adverse effects on hard-body segmentation [5]. MATRAT reduces the streaks by removing the mean or median value from each range bin. The removed streaks are then set aside for further feature extraction (Note: this is a future improvement still under design). Figure 3 depicts streak reduction in while retaining the overall range profile. The resulting image is available for segmentation

Fig. 3. Reducing streaking of ISAR image. (a) input image; (b) image with reduced streaking

B. Initial Segmentation

Segmentation partitions the image into multiple segments in order to more easily identify regions of relevance in the ISAR image (i.e. background, hull, or wakes, etc.). Edges in an ISAR scene are caused by changes physical properties of the scene, such as illuminating power, aspect angle, distance and radar cross section, etc. Therefore, direct relationships exist between the edges and the physical properties of the scene, and critical information can be recovered from the edge

image [13]. The MATRAT system uses the MATLAB function `bwlabel` to label a binary representation of the ISAR image [26]. The general procedure outlined in [14] is as follows:

- Run-length encodes the input image;
- Scan the runs, assign preliminary labels and recording label equivalences in an equivalence table;
- Resolve the equivalence classes; and
- Relabel the runs based on the resolved equivalence classes.

Figure 4 demonstrates the result of initial segmentation.

Fig. 4. Segmentation: (a) input image; (b) labeled segments

C. Wake Identification and Mitigation

While segmentation is a primary purpose of separating the hard-body from other regions, it sometimes necessary to apply a further wake segmentation algorithms. Figure 5 illustrates such a case; a wake is still attached to the hard-body after initial segmentation, distorting the image, and eventually, misclassification.

Fig. 5. Attached wakes after initial segmentation.

Attached wakes are separated from the hard-body through an image erosion technique [15]. Erosion simply ‘pares’ the image along the outermost path leaving the erosion outline and an image containing the hard-body and wake remnants. Figure 6 illustrates the erosion technique.

Fig. 6. Eroding the ISAR image to separate wakes from the hard-body.

The subsequent relabeling produces multiple regions and a method is needed to select the most hard-body like region. In order to facilitate selection local features are calculated for each region. Table 1 show an example feature set for a relabeled ISAR image. Typical features include:

- Region area, in pixels;
- Euclidian distance of the region to the image center, in pixels;
- Solidity, a scalar specifying the proportion of the pixels in the convex hull that also included in the region. The convex hull is defined as the smallest convex polygon that can contain the region;
- The maximum, minimum and sum of intensities of the region;

TABLE I. REGION STATISTICS

Label	Area	Distance	Solidity	Max	Min	Sum
0	16482	206.334	0.414	4.313	1.402	16010.217
1	216700	12.315	0.896	3.610	1.175	13013.108
2	7261	110.914	0.872	5.729	2.883	20214.026
3	1308	149.196	0.916	3.077	1.486	1507.073

Rules for selection are as follows:

- The selected region cannot have the lowest solidity ratio, eliminating the erosion outline from consideration.
- The selected region cannot have pixels in any corners, eliminating the background. Merge all "similar" select regions. A nominal similarity, S , is defined as a normalized score

$$S = \sqrt{(Max)^2 + (Mean)^2} \quad (3)$$

- Any region with a normalized score within ten percent of the highest scoring region is determined to be similar and merged with the highest scoring region. The merged region is designated as the hard-body and will dilated by the same amount as the preceding erosion (Fig 7).

Fig. 7. Final hard-body ISAR image after segmentation, erosion and dilation: (a) original image; (b) hard-body ISAR image.

D. Length Estimation

True length is a very powerful discriminator between classes of maritime targets. Very accurate a priori information is available regarding most major commercial and naval vessels [18]. ISAR images can accurately measure the apparent length of maritime targets but the calculation of true length requires the ISAR/target aspect angle. MATRAT has the ability to estimate the true length. True length is computed by taking the difference in meters between the bow edge bin and the stern edge bin. This distance is then divided by the cosine of the estimated aspect angle, producing an estimate of the true length. If the aspect angle is not provided then the apparent length will be used in a relative sense, i.e., *the target is the longest object in the mission*. This requires contextual discrimination and is future work.

E. Range Profiling

Range profiling, in this context, is defined as Doppler returns per range bin and are a key component in the classification of the target [17]. Figure 8 shows an ISAR image and three proposed profile measures.

Fig. 8. Doppler image and different range profiles; (a) original image; (b) total intensity per range bin (c) extent (width) of Doppler returns by range bin; (d) the product of (b) and (c) The proposed profiles reflecting of the hard-body ship are defined as follows:

- Total Doppler intensity of each range bin – indicative of strong radar reflectors;
- The Doppler extent, also known as the Doppler width – indicative of taller structures on the target; and

- The product of the total Doppler and the Doppler extent – indicative of the tallest and strongest reflectors.

MATRAT calculates these profiles per image as available features for training and classification. In addition, all features are calculated for the total ship and three other sections; bow, midship, and stern.

Current Doppler feature suites used in this evaluation are shown in Fig. 9:

- Total number of significant total intensity peaks per section;
- The distance of the peak extents from the bow edge per section

Fig. 9. Range profile features (a) original image; (b) significant peaks in total intensity per range bin by section (c) the distance of the peak extents from the bow edge per range bin by section.

F. Features and Feature Selection

There are many types of surface ships, both commercial and naval combatants. In general, naval ships are bulkier than merchant ships, having flowing lines and usually less deckhouse and superstructure [22]. In addition, each of the classes have specialized purposes and as such have differing image shapes. For that reason, MATRAT calculates all features by section (bow, mid, and stern). While having a rich feature set can aid in classification, care should be exercised regarding the dimensionality of the feature vector used in the classification process. The curse of dimensionality refers to problems when analyzing data in high-dimensional spaces leading to the possibility of overfitting the data, leading to incoherent classification [25]. Users of MATRAT can select from a rich feature set and quickly determine which features have the most impact to the classification and help alleviate the problem of over-fitting. Table 2 lists all available features by category and section. Currently, the feature categories are unweighted geometric features, weighted geometric features, length features, and Doppler features (Table II).

TABLE II. FEATURES BY CATEGORY BY SHIP SECTION

Unweighted		
Area	Length	Perimeter
<i>All</i>	<i>All</i>	<i>All</i>
<i>Bow</i>	<i>Bow</i>	<i>Bow</i>
<i>Mid</i>	<i>Mid</i>	<i>Mid</i>
<i>Stern</i>	<i>Stern</i>	<i>Stern</i>

Weighted			
Centroid	Mean Intensity	Max Intensity	Sum of Intensities
<i>All</i>	<i>All</i>	<i>All</i>	<i>All</i>
<i>Bow</i>	<i>Bow</i>	<i>Bow</i>	<i>Bow</i>
<i>Mid</i>	<i>Mid</i>	<i>Mid</i>	<i>Mid</i>
<i>Stern</i>	<i>Stern</i>	<i>Stern</i>	<i>Stern</i>

Range Profile	
# of Significant Peaks	Distance of Maximum Extent
<i>All</i>	<i>All</i>
<i>Bow</i>	<i>Bow</i>
<i>Mid</i>	<i>Mid</i>
<i>Stern</i>	<i>Stern</i>

a) *Unweighted features*: These are features that do not involve intensity measurements and calculated for all four sections. The current unweighted features are:

- Area is the number of image pixels;
- Perimeter is a measure of Doppler variation; and
- Length is the difference in range of the sections.

b) *Weighted features*: These are features that incorporate intensity measurements and calculated for all four sections. The current weighted features are:

- The maximum intensity;
- The mean intensity;
- The sum of intensities; and
- The centroid.

c) *Range profile features*: These are features that characterize the Doppler measurements of the range profile. The current range profile features are:

- The number of significant peaks in the sum of intensities range profile; and
- The ratio of the distance from the largest extent to the bow edge;

G. Classification

In automated target recognition classification is the problem of identifying to which of a set of classes, an real observation belongs, on the basis of a training set of data containing observations (real or modeled) whose class membership is known. MATRAT uses a support vector machine (SVM) classifier. SVMs have already been applied in other radar target recognition problems for ground, air and

maritime targets [19-21]. The support-vector is a learning machine for two-group classification problems. The machine conceptually implements the following idea: non-linearly mapped to a very high dimension feature space. In this feature space a linear decision surface is then constructed and subsequent observations are classified [25].

III. RESULTS

A. Current Data Sets

Current data sets are comprised of three ships, one automotive carrier (the Auriga Leader), one cruise ship (Ms. Zandaam), and an unknown fishing vessel. All ISAR images have unknown aspect angles, but the Doppler and range bin sizes are known. While the current data sets do not pose a difficult classification problem, they were well suited for MATRAT algorithm prototype design, especially in wake and streak mitigation.

B. High Fidelity Models Data set

Due to cost and classification restrictions it is impractical to secure adequate amounts ISAR data to further develop the ATR capabilities of MATRAT. However, with the advent of faster computers it possible to improve the MATRAT by generating ISAR images from highly detailed maritime models. With these inexpensive models, we can push MATRATs capabilities especially in classification of populated maritime scenes. Current plans include the ISAR imaging of ten models of modern combatants in realistic scenarios.

C. Introducing Random Bias and Noise into Features Extracted from Current Data Set

While the limited data set was adequate for feature extraction, it posed no stressing scenarios regarding classification. In order to test the prototype SVM classifier in the design phase, we introduced bias and increased noise to ensure scenes in which the maritime objects had overlapping features, specifically estimated length and total number of significant peaks. Figure 10 contrasts the original scenario and the obvious separation and the scenario with additional random bias and noise.

Fig. 10. ISAR 2-D Feature sets (a) original features; (b) features with additional random bias and noise.

Another reason for choosing these features, previous work has shown good classification results using length and number of peaks as primary features [17]. While this sparse feature space has shown good results in classifying distinct classes, we believe expanding the feature sets to include sectional features. This allows us to begin to see the benefit of this approach. While many combatant ships have similar lengths, each class of combatant ship has a specialized purpose, leading to differing range profiles. We believe the expansion to sectional features will exploit these differences.

D. Results

a) Two overlapping features performance: Referring to Table III, the SVM classifier was present three classes (Faux Car Carrier -CC, Faux Cruise Ship - CS, and Fishing Boat - FB) and two features (Estimated Length and # of Significant Peaks - ALL). As expected the results of the SVM classifier were not very good with each car carrier object being miscassified as a cruise shi resulting in an overall performance of Accuracy = 66.67% total classification accuracy

b) Sectional Features Performance: By replacing the total number of signicant peaks of all sections two the number of significant peaks per section the performance increases to 100% total classification accuracy.

Granted this is a straightforward example, clearly it illustrates the advantage of the sectional featuresh. We expect to see improvement in interclass classification of maritime combatants with this methodology.

IV. CONCLUSIONS

A test bed for maritime automated ISAR image recognition has been developed, with detailed discussion of each of the current algorithm components. Special emphasis was placed on the mitigation of wakes and streaks from the ISAR images. In additional, the efficacy of expanding the features to a sectional approach was shown to have a real potential in future systems. Finally, future work was outlined to generate adequate amounts of relevant ISAR imagery using high fidelity commercial to further advance the MATRAT

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