This paper presents an investigation of ISAR image classification based on a comparison of range-Doppler imagery to 3D ship reference models. This comparison is performed in the image domain by estimating the motion of a sequence of ISAR images, generating 3D reference models corresponding to the same motion and matching the models with the given ISAR images. The effect of estimation error in the motion parameters was also investigated, and it was found that the accuracy of the yaw motion estimate is critical; the technique can tolerate a relative larger error of the roll/pitch motion.

Key Words: ISAR image, ship motion estimation, automatic target recognition

1. INTRODUCTION

Most traditional methods for the classification of ISAR image frames are implicitly two dimensional, and focus on extracting features or structures of the ship under the assumption that the image displays only the height structure of the ship. However, any sequence of image frames is effectively a time-varying projection from 3D onto a 2D plane, and will also contain horizontal azimuth information. The added 3D content of the image may be used to improve classification in two different ways. The first is to classify the entire image sequence by using it to reconstruct a 3D model [4], [5], and then directly compare the resulting 3D models [6]. An alternative method is to compare the model to the observations in the image domain by estimating the target motion, and using this to synthesise 2D ISAR images from the 3D library models. Similar techniques have already been applied for recognition of stationary land targets in SAR imagery but, to our knowledge, little has been done in the same area for ISAR imagery.

This paper is effectively a “proof of concept” for the comparison of a 3D model with a 2D ISAR image to obtain classification. The results are sufficiently good for the method to merit further investigation. Section 2 gives an overview of the various stages of the algorithm, which are discussed in more detail in Sections 3 and 4. Some numerical classification results based on simulated ISAR imagery of nine different ships (scaled to be equal length to make classification more difficult) are then described in Section 5, finally ending with some discussion and conclusion.
2. ALGORITHM

The model based classification process is shown in block diagram in Figure 1. The input to the process is an ISAR image sequence, which for this paper have been simulated in ISARLAB [3]. Each image is then preprocessed to remove speckle noise and streaking artifacts. Then the motion of the ship during the ISAR image formation is estimated. There are two rotational motions of interest in an ISAR image: the yaw, and a certain combination of pitch and roll which emphasises the height profile in the resulting image. Two methods have been studied for the estimation of these parameters. The first was obtained as a by-product of previous work [4, 5], which extracted a 3D model for a ship from a sequence of ISAR images. The second method is largely heuristic based, and treats each of the motion parameters separately. By assuming that the ship is mostly linear in structure, a fairly accurate estimate for the yaw based on the Radon transform can be found. The pitch/roll motion parameter is related to the size of the height profile, and a crude method for estimating this is described in Section 3.

![Block Diagram](image)

**FIG. 1.** Model Based Classification

Based on the estimated motion, the corresponding 3D library models are used to generate approximate ISAR images. A number of these images are generated for each model. These models use a range of motions around the estimate, so that the effect of the estimation error is reduced. The normalised cross-correlation is applied between the image to be classified and each of the reference model images. The ship is then classified as being the ship whose model image gives the highest match score.

2.1. Image preprocessing

Although many methods are available for removing noise from images prior to classification, the initial approach taken here is similar to that of [7]. The first step is a global threshold, which is calculated based on a noise estimate obtained from vertical strips at the left and right of the image, which are assumed to contain noise only. Next, to remove vertical stripe artifacts, two regions at the top and bottom of the image are used to estimate the noise in each of the columns, so that a separate threshold may be applied to each column.

3. MOTION ESTIMATION

If the target motion parameters [8] are known, the same motion can be induced in each of the reference models to produce a set of corresponding reference ISAR images. The motion components of interest for ISAR image generation are based on a coordinate system different from the standard roll, yaw and pitch axes. These components are the rotational motions which emphasise the height and the horizontal components of the ship’s structure respectively. When the look-down angle of
the radar is relatively shallow (so air-borne rather than satellite ISAR), the velocity which emphasises the horizontal azimuth will be roughly equal to the yaw velocity \( \phi(t) \), while the remaining component will be a linear combination of the pitch and roll, depending on the ship aspect angle.

In most real cases, the motion of the ship is unknown and must be estimated. Accuracy in the target motion estimation is a critical part of classification. Two methods to estimate ship motion were investigated. One is based on some 3D model estimation code, while the other one is based on single 2D images.

### 3.1. 3D Motion Estimate

[4] describes a method for reconstructing a 3D scatterer model from a sequence of ISAR images. A by-product of this result is an estimate for the motion of the ship (the translation toward the radar, and two rotational velocities) for each of the image frames. The motion estimate is based on a set of Doppler measurements extracted from the imagery, and the formula

\[

\nu_i(t) \approx h_i \hat{\theta}(t) + x_i \hat{\phi}(t) + \tau(t) \quad \text{for small angles.} \tag{1}

\]

where \( \hat{\theta}(t) \) and \( \hat{\phi}(t) \) are ship rotation velocities, \( \tau(t) \) is the translation in the direction of the radar, \( h_i \) and \( x_i \) are the height and horizontal positions of the \( i \)th scatterer, and \( \nu_i(t) \) is the Doppler of the \( i \)th scatterer in the \( t \)th ISAR image from the sequence. Equation (1) does not have a unique solution, and as a result there will be some ambiguity in the estimated motion. For instance, a vessel that is twice as fast, but rotating half as quickly will produce identical Doppler measurements, so there is some unknown scaling factor (which may be negative) between the actual and estimated ship motions. This scale ambiguity may be overcome by ensuring that the estimated 3D model has the same linear dimensions as the model to which it is being matched. In this paper, the scaling factor for each image sequence was found manually, and a comparison of the true motion with the 3D estimated motion for some ISARLAB simulated sequences is given in Figure 2. Some of the ships with very little height structure produced very poor roll/pitch motion estimates.

![FIG. 2. Comparison 3D estimated motion with true motion, horizontal axis is the number of the images, the vertical axis is rad/sec (ship 4-6)](image-url)
3.2. 2D Motion Estimation

There are only two rotational motion components that affect the observed ISAR image, as is described by equation (1). Each of the two motions emphasises a different projection of the ship structure in the azimuth direction, and knowledge about the general morphology of a ship is required to separate the two. Although more accurate results might be achieved using the available detailed knowledge of the ship scatterer positions, the following sections describe very fast and simple heuristic motion estimates.

For air-borne ISAR, the yaw velocity is the component of the motion which emphasises the horizontal azimuth structure of the ship. Because ships are generally long and thin, this means that when the ship is not broadside, the Doppler due to the yaw will be dominated by the part which is linear in range. An estimate for the magnitude of the yaw can thus be achieved by finding the slope of the line of scatters associated with the hull of the ship in the range Doppler image. This can be done using a number of methods (e.g., linear regression, etc.) but the approach adopted in the current study locates the centre-line based on the Radon transform [1, 2].

3.2.1. Radon Transform

The Radon transform of a function \( f(x, y) \) is defined as the integral along a straight line defined by its distance \( \rho \) from the origin and its angle of inclination \( \theta \), a definition very close to that of the Hough transform

\[
r(\rho, \theta) = \int \int f(x, y) \delta(x \cos \theta + y \sin \theta - \rho) dx dy,
\]

where the delta function defines integration only over the line. The range of \( \theta \) is limited to \( 0 \leq \theta \leq \pi \). The Radon operator maps the spatial domain to the projection domain, in which each point corresponds to a straight line in the spatial domain. Local maxima of the pixel intensity identify straight line segments in the original image space.

3.2.2. Centre-line

Here, the centre-line is determined by the maximum in the Radon transform of the cleaned image. The slope of the centre-line in a given image frame will be proportional to the ship yaw velocity. Figure 3 (a) and (b) show the “ddg171” and “oiler” yaw motion estimates.

In this paper, the constant of proportionality was obtained by comparing the estimate for each frame in the sequence to the corresponding true yaw velocity. Thus a single scaling factor was manually chosen by the best fit compared to the true velocity. In practice, this scaling factor could have been determined analytically based on estimates of the ship’s aspect coming out of the radar target tracking system (assuming an accuracy < 5 degrees in the heading estimates).

The other required component of the motion is the combination of roll and pitch motions, which emphasise the ship height structure. This motion is less trivial to estimate from the imagery since the observed Doppler displacement of scatters in the image caused by the roll or pitch motion of the ship is partly dependent on the height structure of the ship, which is unknown. Here we present two slightly different approaches based on the observed height structure in the Doppler image which
might be used to approximate the roll velocity. The first approach is employed since it provides slightly better estimate.

The two estimators are:

\[
v_{rp}(t) = \frac{1}{a} \left[ \sum (s(x_i, h_i, t) > \text{centreLine}(x_i, h_i, t)) - \sum (s(x_i, h_i, t) < \text{centreLine}(x_i, h_i, t)) \right]
\]

(2)

or

\[
v_{rp}(k) = \frac{1}{a} \left( \sum \left[ \text{Var}(s(x_i, h_i, t) > \text{CentreLine}(x_i, h_i, t)) \right] - \sum \left[ \text{Var}(s(x_i, h_i, t) < \text{centreLine}(x_i, h_i, t)) \right] \right).
\]

(3)

where \( s \) is the Doppler from a point scatterer at position of \((x_i, h_i)\) and time \( t \), \( a \) is a scaling factor which dependent on the aspect angle and the height structure of the target.

Both of these heuristic methods are expected to increase with the roll velocity, and should be approximately zero when the roll/pitch velocity is zero (i.e. when there is no height profile). There is no guarantee that the relationship is even linear however, so the motion estimate is likely to be crude. The motion was made to be at least approximately equal to the true velocity by the introduction of a scaling factor, which was chosen manually as was done for the yaw velocity estimate. In practice, the best scaling factor to use will be difficult to determine without prior knowledge of the ships height structure. However, some assumption of the range of possible scatterer heights could be made in order to constrain the range of potential roll velocities. An improved roll/pitch velocity might also be achieved by identifying the taller height structures from the range-Doppler image and using these instead of the overall variance to estimate roll/pitch velocity, in which case by (1) the relative Doppler displacement of the scatterer from the hull is strongly coupled to the scatterers height and the roll/pitch velocity.

Figure 4 presents the estimated velocities comparing to the true corresponding velocities. The top plot is the yaw motion and the bottom is the roll/pitch motion. The red-dotted line is the true motion and the other colour lines are the estimated
motion from Ship 1 to 9. The figure shows that the estimated yaw velocities are fairly accurate except for Ships 7 and 5. These ships are much wider than the rest ships, so it is harder to obtain accurate centre-line. Although the estimated roll/pitch motion are crude the trend of the plots roughly following the true motion.

![Image](image1.png)

**FIG. 4.** 2D estimated motion with true motion

4. MODEL MATCHING

Once motion estimates have been obtained, the next step is to produce corresponding ISAR images for each of the reference ships so that a comparison can be made in the image domain.

An ISAR image, which is effectively a range-Doppler plot, is first initialised to zero. Then for each scatterer, the motion estimates obtained from the previous section are used with equation (1) to generate the Doppler. Since the range of the scatterer is already known, the contribution of this point can be added to the image by adding the scatterer backscatter intensity (also specified by the reference model) to the range-Doppler plot. Because the phase of the scatterer return has not been calculated, the addition of scatterer returns that overlap must be done incoherently. The resulting approximate ISAR image still strongly resembles the actual image, as can be seen from the examples in Figure 5 (b).

In order to obtain an objective measure of match between two images, the normalised cross-correlation was used. The peak correlation score in each image will be the match score between the target image and the corresponding reference model. For this example, peak values of each correlation coefficient matrix are listed in Table 1. The highest correlation coefficient is 0.6463, which is the match score for ship 2. This means that the received image has been correctly classified.

5. SIMULATION RESULTS

All of the experiments performed are based on a set of nine point scatterer models provided by DSTO which, for the purposes of classification, have been assigned to
different classes of ships. A set of semi-realistic ISAR images were then generated for the nine different image sequences of 50 frames each. Based on these images, the target motion was estimated, then the known models were given the same motion as that of the target. The most likely class ship is identified based on correlation coefficients of each ISAR image and the known models.

5.1. The ISARLAB Data

ISARLAB [3] is a MATLAB program for realistically simulating ISAR images from a point scatterer model. It contains many of the sources of noise that would be present in real imagery, including speckle noise, sidelobes and motion blurring. The radar configuration parameters were set as follows: Pulse frequency: 9.375 GHz; Bandwidth: 150 MHz; Pulse width: 8 μs Pulse repetition frequency: 512 Hz; Sampling frequency: 20 kHz; Samples per pulse: 256; Pulses per image: 256; Signal to noise: 70dB; which means that each frame in the sequence corresponds to about half a second, and the range resolution is 1 m. The ships were imaged at an aspect angle of 220° and were subject to an induced sinusoidal motion corresponding to wave action. The roll, yaw and pitch amplitudes were 3°, 1° and 1°, with their respective periods being 10.1, 6.7 and 8.3 seconds. A total of nine ship models (supplied by DSTO based on CAD models and radiometric measurements) were used for simulating ISAR image sequences of 50 image frames.

5.2. The effect of image cleaning

The ISARLAB image sequence files were rather large so, to conserve space, the images were automatically cropped close to the edges of the ship. This was done by first estimating the mean μ and variance σ² of the noise floor, and using a global threshold of μ + 4σ. To remove most of the Doppler extent of the vertical

Table 1

<table>
<thead>
<tr>
<th>Mod 1</th>
<th>Mod 2</th>
<th>Mod 3</th>
<th>Mod 4</th>
<th>Mod 5</th>
<th>Mod 6</th>
<th>Mod 7</th>
<th>Mod 8</th>
<th>Mod 9</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.4618</td>
<td>0.6463</td>
<td>0.5911</td>
<td>0.5046</td>
<td>0.3872</td>
<td>0.5381</td>
<td>0.4229</td>
<td>0.4971</td>
<td>0.4003</td>
</tr>
</tbody>
</table>
streaks (so that the image could also be cropped in Doppler), the same process was individually applied to the columns of the image with a threshold of $\mu + 3\sigma$. Extra speckle noise was removed by performing an erosion followed by a dilation. The above processes were not intended to remove imaging artifacts however, and so streaking in the vertical and horizontal directions is still quite pervasive, and may reduce the classification performance of the 2D model matching. To assess the effect of these artifacts, two scenarios were simulated. One was the normalised two-dimensional cross-correlation applied to the original image and the known models. The other one used preprocessed (cleaned-up) images with the known models. Both simulations are based on true yaw and roll/pitch velocities.

Figure 6 shows the simulation results. It is clear that the performance of the cleaned image matching is much better than that of the original image matching. Therefore, the remaining experiments are based on the cleaned image correlation.

![Confusion Matrix](image.png)

**FIG. 6.** Performance comparison with the original or cleaned image matching

Section 3 shows that there is discrepancy between estimated velocities and the true velocities in both 3D and 2D estimation. To improve the classification performance we search a range based on the estimated velocities.

### 5.3. Motion estimate sensitivity

Any estimate of the motion is likely to contain errors, which may significantly reduce the match score between the model generated image and the real image. This reduction in performance can be decreased by searching to find the motion estimate giving the best match between the model and the image. The overall computational cost of the match however will be roughly proportional to the number of search values required to be tested. To determine the best trade-off between performance and speed, it is useful to know how accurately the motion parameters need to be known before the performance degrades significantly. Thus in this section, the robustness of the 2D model matching system to yaw and roll/pitch estimation errors is determined.
Classification corresponding to different error in the roll/pitch velocity (the true yaw velocity is used) are investigated. The results (Fig 7 (a)) indicated that the performance degrade significantly at about 50% error (peak to peak), which means that the classification can tolerate the reasonably large errors in roll/pitch velocity, that is, the performance is not highly sensitive to the roll/pitch velocity.

This experiment was repeated again using the true roll/pitch velocity, and a fixed error in the yaw velocity. The results indicate that the classification is sensitive to the yaw velocity. Therefore, the accuracy of the yaw velocity is crucial in the model based classification. Fortunately, the yaw velocity estimator by using Radon Transform is reasonably accurate.

Finally, both 3D and 2D estimated yaw and roll/pitch motion are employed in the following simulation. The yaw velocity search is [-10 -5 0 5 10]% and the roll/pitch search is [-20 -10 0 10 20]%.

**FIG. 7.** Performance with estimated motion error

![Confusion Matrix](image1.png)

(a) 50% roll/pitch error (d) 15% yaw error

![Confusion Matrix](image2.png)

(b) 15% roll/pitch error (e) 15% yaw error

**FIG. 8.** Performance of 3D estimated motion

![Confusion Matrix](image3.png)

(a) 3D with both yaw and roll search (b) 2D with yaw search only
The results show that both 3D and 2D perform well and with 3D classification being better than that of 2D. However, 2D motion estimation is much simpler than 3D. Ship 7 is much wider than the rest ships, it is harder to obtain accurate centre-line. This is the reason that Ship 7 is difficult to identify.

6. CONCLUSIONS

The paper has presented a simple method of model based classification as an alternative to the feature based classification studied in previous work. The technique is based on estimating a ship's motion from the image sequences and using the estimated motion to construct hypothesis images of the models under consideration. The hypothesis images are then matched to the real imagery to estimated the likely ship class. This approach has been implemented and tested. The simulation results have shown that the proposed approach is feasible.

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