Ship Size and Heading Angle Estimation in Range-Doppler Domain and in Focused SAR/ISAR Images

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Abstract

Ship size estimation is a prerequisite for ship classification. In this paper an eigenvalue decomposition-based ship size estimation method is proposed. The method uses the eigenvalue information of the detected ship pixels and fits an ellipse for estimating the length, width and heading of the ship. The algorithm operates in the range-Doppler domain on coarse resolution image sequences for obtaining rough ship extents as well as on focused high-resolution ISAR and SAR images for more accurate estimations. The proposed method is compared with state-of-the-art algorithms. Airborne and satellite radar data containing real ships are used for evaluating the proposed method.

1 Introduction

Marine target detection and monitoring is important to ensure safety and security at the open sea [1]. For this purpose the Microwaves and Radar Institute of DLR is currently developing a MMTI (maritime moving target indication) processing framework suitable for airborne radar sensors [2]. This framework will also be installed on the onboard computer of the compact HAPSAR radar sensor [3]. HAPSAR itself will be integrated as payload in the DLR HAP [2], which is expected to have a much longer endurance than conventional aircrafts making continuous monitoring of important hotspots feasible.

For achieving fast processing times on low-cost single board computers, instead of using fully-focused synthetic aperture radar (SAR) images the processor will operate directly on range-compressed radar data (cf. **Figure 1** top). This reduces the overall processing time significantly and will pave the way for future real-time monitoring systems [4].

One of the components of the MMTI processor is the ship classification. For classifying the ships at least their size, i.e. their length and width/beam have to be estimated. There exists several methods in the open literature for ship size estimation. One classical method, for instance, is based on the Radon transform. It is an image-based approach which is used for object rotation and size estimation [5]. Another widely used approach is elliptical fitting to the periphery of the detected ship pixels. For this, first the target is detected using some statistical model followed by a morphological operation, e.g., a dilation and erosion for removing the distortion. Afterwards an ellipse is fit using the edge pixels of the ship [6, 7]. However, if the edge pixels are noisy and sparse it may lead to an overestimation of the target size.

There are also deep learning-based approaches which could accurately estimate the ship size, however, they are computationally very intensive and requires a large volume of ship ground truth data for training [8].

In this paper we propose a comparatively fast eigenvalue decomposition-based ship size estimation method. Like the elliptical fitting method discussed previously the proposed method also fits an ellipse to the target. However, instead of taking just the boundary pixels of the ship, it takes into account all the detected pixel positions of the ship and use them for length, width and heading estimation.

The proposed method can be applied on range-Doppler image sequences with coarse resolution (cf. **Figure 1**) for obtaining rough ship size estimates as well as on high-resolution focused ISAR and SAR images for getting more accurate estimation results.

Real range-compressed airborne radar data acquired with DLR's DBFSAR system [9] as well as ground truth AIS (automatic identification system) data are used for the investigations.

2 Processing Framework

Figure 1 shows the processing structure for the size estimation using range-Doppler images of short CPIs (coherent processing intervals), focused SAR and ISAR images as input.

For the processing chain based on short CPIs (cf. left side of **Figure 1**, the range-compressed data is partitioned into smaller CPIs and each CPI is transformed to range-Doppler domain via an azimuth fast Fourier transform (FFT). A CFAR-based detection is then carried out for obtaining the binary detection map (= slant range and Doppler positions of the detected ship pixels) [10, 11].

For the SAR/ISAR-based processing chain as shown in the right side of the figure, a focused SAR/ISAR amplitude image is needed as input. Note that for the Radon-based size estimation method, detection is not necessarily needed since the method is applied directly on the amplitude image.

For both the processing chains ground and cross-range

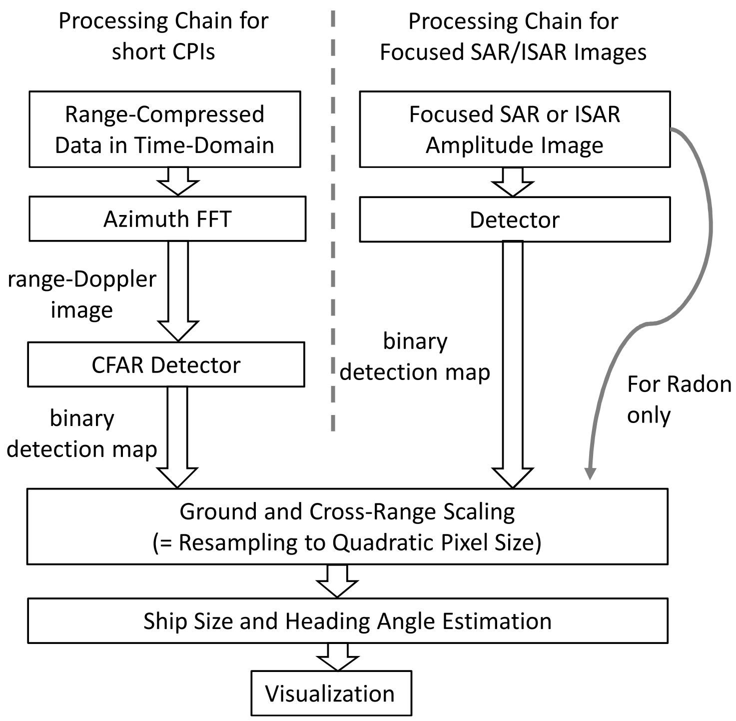


Figure 1 Processing framework for ship size estimation. Coarse resolution range-Doppler image of short CPIs (left processing chain), as well as focused SAR and ISAR images (right processing chain) can be used as input.

scaling (or resampling) are carried out for ensuring equal pixel spacing on ground in ground range and cross-range or azimuth direction. This is necessary for obtaining reliable size and angle estimation results. For ground range scaling, incidence angle is used and for the cross-range scaling of range-Doppler images, the following equation for computing the cross-range resolution of a Doppler bin is used [12]:

$$\delta_{\mathrm{cr}} \approx \frac{\lambda\, r}{2\, v_{\mathrm{p}}\, T_{\mathrm{CPI}}}, \tag{1}$$

where $\lambda, r, v_{\mathrm{p}}$ and T_{CPI} are the radar wavelength, target range, platform velocity and the coherent integration time, respectively. Note that for conventionally processed SAR images the azimuth or cross-range resolution is already known so that δ_{cr} needs not to be computed.
After these pre-processing steps the ship size and heading angle on ground can be estimated, as shown at the bottom of **Figure 1**.

3 State-of-the-Art Estimation Methods

For ship size and heading angle estimation three state-of-the-art methods are presented in the following.

3.1 Rectangular fitting

In this method a rectangle is fit to the set of 2D points in the binary detection map. The maximum and minimum positions in ground and cross-range are used to determine the length and width of the target, respectively. Note that this approach does not estimate the heading of the target [10].

3.2 OpenCV library of Python

This library has an in-built function called **cv2.fitEillipse**. This function fits an ellipse to a set of 2D points using a least-square method. To use this method, the border points of the ship need to be first extracted. For this, a convex hull is created for extracting the edge-points. These edge-points are then given as an input to the **cv2.fitEillipse** function. As output the center, major and minor axes of the ellipse and its orientation is obtained. The major and minor axes of the ellipse corresponds to the target extents [13].

3.3 Radon Transform

It integrates the intensity of a 2D image along different angles, known as projection angles. The angle with the highest intensity represents the width and heading angle, the angle orthogonal to that gives the length of the object [14]. The Radon transform is implemented using the **skimage.transform.radon** python function [15].

4 Proposed Eigen-based Method

As a first step a covariance matrix is computed using the target's ground and cross range positions from the ground projected binary detection map. Then, the eigenvalues and eigenvectors are estimated after performing the eigenvalue decomposition (EVD) of the covariance matrix.

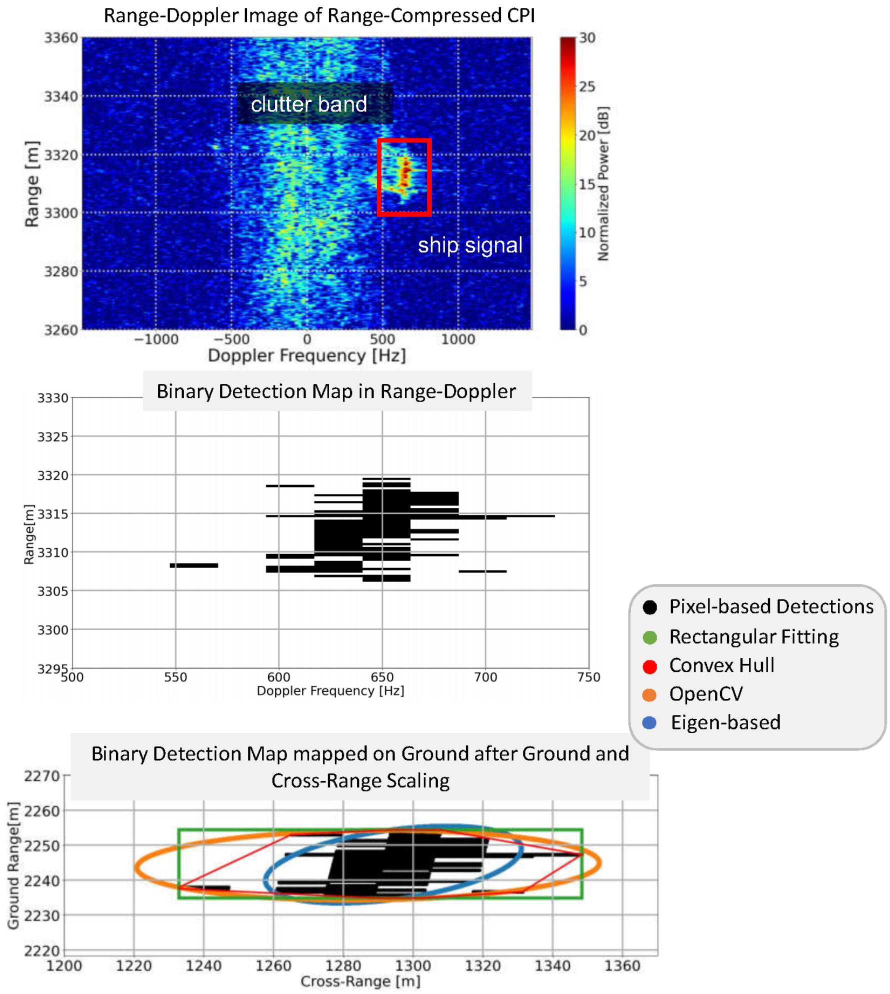


Figure 2 Ship size estimates in range-Doppler domain in a single CPI using real X-band VV polarized DBFSAR airborne radar data. Top: Range-Doppler image with the clutter band and the ship signal outside the clutter band. Middle: CFAR-based binary detection map in range-Doppler. Bottom: Binary detection map on ground after ground range and cross-range scaling overlaid with the estimation results using different methods.

The EVD of the covariance matrix $\mathbf{C}_{\mathrm{rd}}$ is given as [16]

$$\mathbf{C}_{\mathrm{rd}} = \mathbf{V}\lambda\mathbf{V}^{-1}, \tag{2}$$

The terms $\mathbf{V}$ and λ are the eigenvectors and eigenvalues, respectively. The largest and smallest eigenvalues correspond to the semi-major and semi-minor axes of the ellipse, respectively, and the eigenvector corresponding to the largest eigenvalue gives the orientation of the ellipse. For instanace, python function **numpy.cov()** can be used for computing the covariance matrix and **numpy.linalg.eig()** for computing the eigenvalues and eigenvectors of the estimated covariance matrix.

After determining the largest and smallest eigenvalues, the length, width(or beam), and the orientation of the fitted ellipse (ship in our case) w.r.t. the cross-range or azimuth axis can be written, as

$$\hat{l}_{\mathrm{ship}} = 2\sqrt{k\lambda_1}, \tag{3}$$

$$\hat{b}_{\mathrm{ship}} = 2\sqrt{k\lambda_2}, \tag{4}$$

$$\hat{\theta}_{\mathrm{ship}} = \arctan 2\left(\frac{V_{1,\mathrm{gr}}}{V_{1,\mathrm{cr}}}\right). \tag{5}$$

where $\theta \in [-\pi, \pi]$, k is the scale factor and $\mathbf{V}_1$ is the eigenvector that corresponds to λ_1. The terms $V_{1,\mathrm{gr}}$ and $V_{1,\mathrm{cr}}$ are the ground range and cross-range components of $\mathbf{V}_1$.

The scale factor k= 3.21 corresponding to the 80% confidence interval is used to take into account the uncertainty in the 2D positions of the ship and is found suitable for the investigated data.

5 Experimental Results

5.1 Range-Compressed CPIs as Input

In this section experimental results using real ships detected in DBFSAR range-compressed airborne radar data are shown. In November 2019, a multichannel flight campaign was carried out in the North Sea near the town Cuxhaven. The data were acquired in stripmap mode in X-band with a PRF of 3KHz, chirp bandwidth of 500 MHz and with a flight altitude of 2400 m above mean sea level. More details about the campaign can be found in [17]

Table 1 True RMSE and mean value estimates of length and beam for ship AURORA and ship FAIR LADY. Ships' moving directions and size on ground shown in the table are obtained from the AIS receiver onboard the aircraft.

Ship	Moving Direction w.r.t. the aircraft [°]	Size on ground (length/beam) [m]	Size Estimation Methods	Estimated Length [m]	True RMSE in Length [m]	Estimated Beam [m]	True RMSE in Beam [m]
AURORA	≈ 104	20 x 6	Eigen-based	19.29	3.41	84.75	88.05
			OpenCV	26.34	14.5	165.59	206.97
			Rectangle	25.23	10.04	125.49	131.33
FAIR LADY	≈ 4	68 x 10	Eigen-based	248.75	240.37	16.12	6.88
			OpenCV	446.32	540.45	33.11	31.68
			Rectangle	355.26	368.08	32.14	27.73

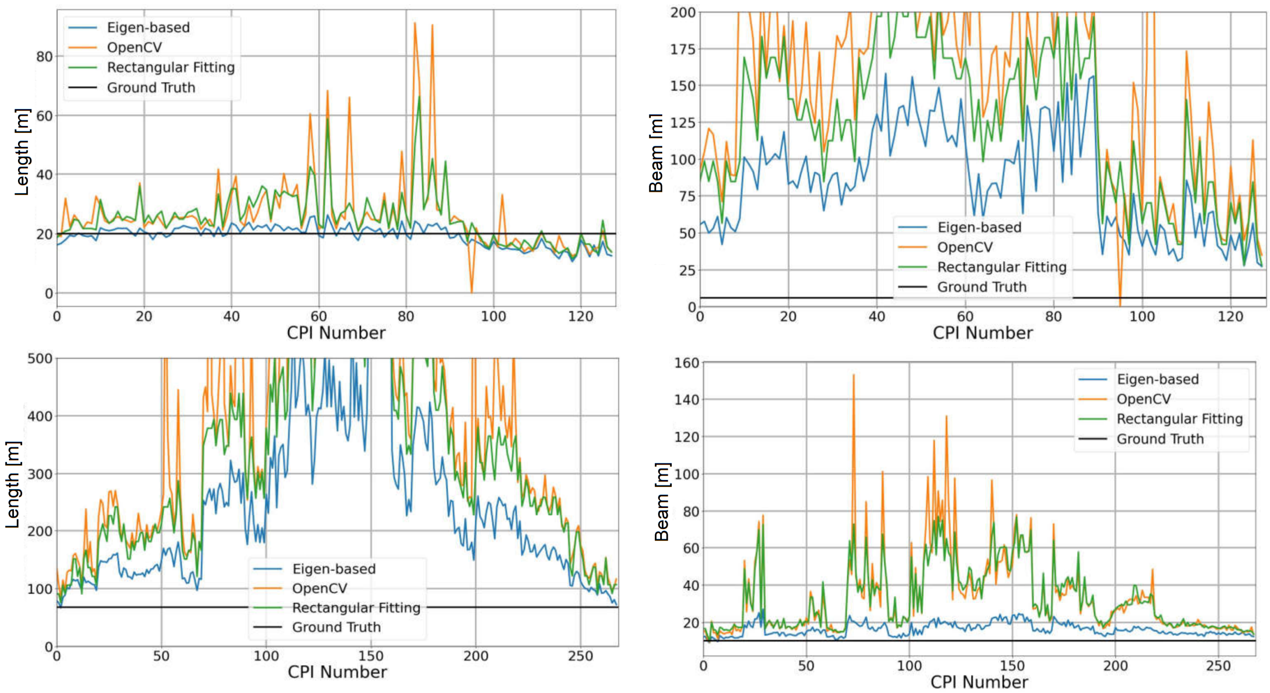


Figure 3 Length and beam estimates over CPIs obtained using different methods for ship AURORA (top) and ship FAIR LADY (bottom). For visualization purposes the beam of AURORA and length of FAIR LADY are truncated to 200 m and 500 m, respectively.

In this campaign several ships of opportunities were observed. The AIS receiver onboard the aircraft received the AIS signals from ships, which are considered as ground truth for the following investigations, with distances up to 200 km away from the aircraft.

For the investigation in this section we have selected two ships, the AURORA and the FAIR LADY. The AURORA is moving almost perpendicular and the FAIR LADY almost parallel w.r.t the flight direction. The dimensions and moving directions of the ships are listed in Table 1. **Figure 2** shows one result obtained for the ship AURORA.

Figure 3 shows the length and beam estimates of AURORA and FAIR LADY over several successive CPIs. As it can be seen from **Figure 3** top left that in comparison to other methods, the estimated length of ship AURORA using the eigen-based approach match very well with the ground truth data of 20 m with a mean value of 19.29 m and true root mean square error (RMSE) of 3.41 m. The OpenCV-based approach is the worst of all with a mean value of length as 26.34 m and the true RMSE of 14.5 m. Similarly, for the ship FAIR LADY with 10 m beam as the ground truth data, the eigen-based approach gives the best results with a mean value of 16.12 m and true RMSE of 6.88 m (cf. Table 1).

By looking at the beam estimates of AURORA and length estimates of FAIR LADY, it is found that there is an overestimation. There are two main reasons for that, first is due to the worse Doppler resolution (or cross-range resolution) of the data compared to its ground range resolution. For an integration time of 43 ms (128 azimuth samples) as shown in **Figure 2** top, the cross-range resolution of the image (in meters) is approximately 14 m which is computed using (1).

The second reason is due to the ocean wave-induced ship motion. Such motion can cause the ship to shake which introduces an additional Doppler shift of the target. Depending on the shake severity and sea state, this may lead to a further overestimation of the target size in the cross-range direction. Please note that the comparatively large errors in **Figure 3** top right and bottom left in fact corresponds only to a few pixels in Doppler (e.g., 7 pixels for $\approx$ 100 m). This can however, be minimized by motion-adapted refocusing, i.e., by using refocused high-resolution ISAR images instead of coarse resolution CPIs. Also with fully focused SAR images such large errors will not occur. The errors of length and width will be in the same order, as can be seen in **Figure 4**. Nevertheless, here also, the eigen-based approach performs better than other methods.

5.2 Focused SAR and ISAR Amplitude Images as Input

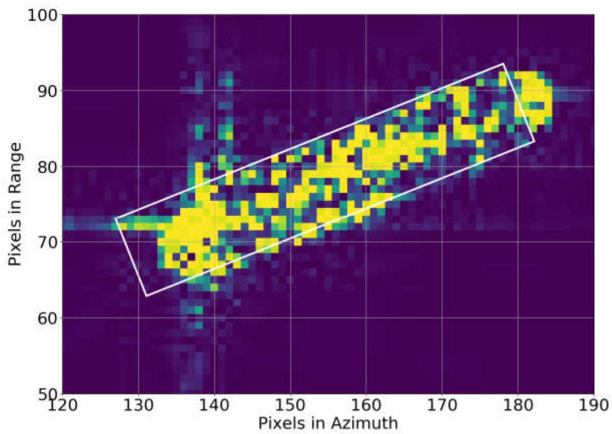
The proposed eigen-based approach was also applied on focused SAR images acquired with the Sentinel-1 radar satellite and the estimation results were compared with the state-of-the-art Radon transform (cf. Section 3). One image of a freely available SAR dataset [18] was used for this investigation where the results are shown in **Figure 4**.

This figure shows the size estimation results obtained from the Radon transform and the eigen-based method with 80% confidence interval. The length, beam (in pixels) and orientation of the ship using eigen-based and Radon transform methods are estimated as 58, 12, 22.05°, 55, 11 and 21.7°, respectively. Visually both methods appeared to fit well with the ship shape. Unfortunately, no ground truth data are available for the used SAR image.

Furthermore, a processing time comparison was also carried out. The algorithms were executed hundred times and their corresponding average processing times were computed. It was found that for a image patch of 256 x 256 pixels, the proposed eigen-based, OpenCV, rectangular fitting and Radon approaches takes approximately 70 μs, 20 μs, 0.13 ms and 0.5 s, respectively. The Radon method is the slowest of all. It takes $\approx$ 6000 times larger than the proposed eigen-based method. This is because the proposed method is applied on the pixel-based detections whereas, the Radon transform needs the entire image patch for its calculations. Thus, for real-time applications, the use of the proposed eigen-based is advantageous. Furthermore, for fully focused ISAR images with quadratic pixel size, the method works similar as with the SAR images.

6 Conclusion

In this paper a novel eigenvalue decomposition-based ship size estimation method is proposed. Range-Doppler and focused SAR images were used for the investigations. In comparison with the state-of-the-art methods, the proposed eigen-based approach was found to be more stable and accurate in the coarse resolution range-Doppler CPIs, especially along the ground range dimension. Furthermore, an overestimation of the target extent in the cross-range direction was observed but this was expected for the Doppler



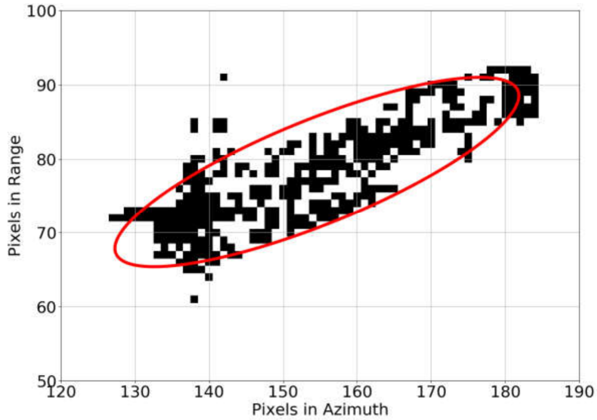


Figure 4 Top: Fitting results based on Radon transform (white) on a ship image. Bottom: Binary detection map of the ship obtained after applying the Otsu's thresholding method and the fitted ellipse (red). The image has originally 256 x 256 pixels, it is truncated for visualization purposes

direction. The Doppler smear or ship shaking, leading to this overestimate can be significantly reduced by proper motion-adapted refocusing in a further pre-processing step. The proposed method was also compared with the state-of-the-art Radon transform. The dimensions and the angle calculated by both the methods were found to be almost similar. However, in terms of computation time, the proposed method is significantly faster, for the example shown in Section 5.2 by a factor of 6000, making it a suitable choice for future real-time ship monitoring applications.

7 Literature

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