SIMULATED ANNEALING CFAR THRESHOLD SELECTION FOR SOUTH AFRICAN SHIP DETECTION IN ASAR IMAGERY

†‡C. P. Schwegmann,†‡W. Kleynhans,*‡B. P. Salmon

†Department of Electrical, Electronic and Computer Engineering, University of Pretoria, South Africa

‡Remote Sensing Research Unit, Meraka Institute, CSIR, Pretoria, South Africa wkleynhans@csir.co.za

*School of Engineering, University of Tasmania, Australia

ABSTRACT

Synthetic Aperture Radar images are able to detect ships that would be hidden to tradition ship tracking methods due to their transponders being turned off. Using a SAR image as input, the CFAR method can highlight these ships given a correctly chosen threshold value. Typically, the threshold value is chosen as a single floating value for all positions creating a flat threshold plane. This study introduces a novel method of creating a threshold plane which is adapted using Simulated Annealing. This non-flat threshold allows different areas of the image to have different threshold values thereby improving the overall performance of the ship detection system. It was found in our experiments that the proposed method improves upon the false alarm rate of the flat threshold plane CFAR method whilst keeping a similar level of detection accuracy.

1. INTRODUCTION

The detection and tracking of ships at sea is an international priority. Establishing control over ones Exclusive Economic Zone (EEZ) is an important requirement for a country's maritime domain awareness (MDA). Every country bordering the sea requires some form of ship monitoring to maintain and safely police its own waters. Ships within and around the EEZ are usually tracked with ship-based transponder systems. Under international agreements it is mandatory for certain types of ships to carry transponders [1]. When a ship cannot be detected using transponders it is known as a "dark" target. An additional, remote method of observing an area known as Synthetic Aperture Radar (SAR) can be used to identify these types of targets. SAR satellites have large swath widths allowing for the viewing of much of the ocean in a single image. They can view the ocean day or night, in almost any weather condition and the images produced by these satellites can be processed in order to detect ships at sea (irrespective of transponder status) [2, 3].

This study aims to highlight a unique manner of combining a conventional ship detection method with the usage of Long Range Identification and Tracking (LRIT) data and a probabilistic global optimisation methods to improve ship detection accuracy and system flexibility. This study is an extension of a previous study which used the vessel distribution map to select a single threshold [4]. This study differs from that one in that here we aim to set a non-flat, 2D plane of thresholds using the vessel distribution map.

2. DATA DESCRIPTION

### 2.1. Long Range Identification and Tracking Data

The Long-Range Identification and Tracking (LRIT) is a global transponder based ship tracking system. The International Maritime Organization (IMO) coordinates the usage of LRIT data and most countries have signed agreements related to the deployment of these transponders [1]. Approximately 400 000 reported ship locations from the LRIT data for the period 2011/03 to 2012/03 were used. These positions were used to estimate a ship distribution map which covered most of the South African EEZ.

2.2. SAR Data

Six Advanced Synthetic Aperture Radar (ASAR) ENVISAT Wide Swath Mode (WSM) images that covered the South African coastal waters were used as testing and training data. The six ASAR images each had a spatial resolution of 75 m × 75 m and were taken over the period of 2012/01 and 2012/03. Each of the six images were expertly analysed and 135 ships were identified across the six images.

3. METHODOLOGY

The proposed system works by initially pre-screening the input image using a low-threshold, Constant False Alarm Rate (CFAR) method to identify candidate ships. Thereafter, a second CFAR stage is used as a ship discrimination step to select ships from the candidates that are deemed ships. The threshold selection of the second stage of CFAR uses Simulated An-
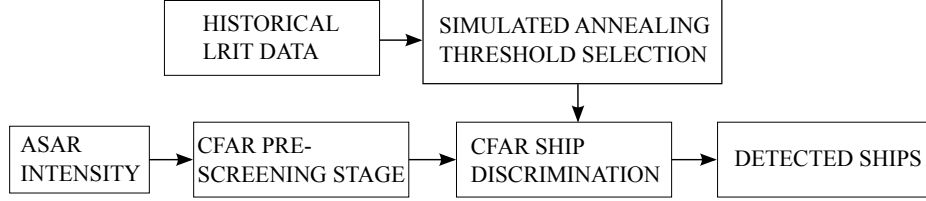
Fig. 1. Ship detection system used for this study. The CFAR pre-screening stage feeds candidate ships into a second CFAR stage where a threshold plane is generated using simulated annealing by making used of historical LRIT data.

nealing to gradually decrease the threshold in areas that have a high probability of ships within them (using the LRIT ship distribution map as a training data). The configuration of the system can be seen in Fig. 1.

3.1. CFAR with a low threshold value

Ships within SAR images typically have a higher than average background radar backscatter and appear as bright pixels within SAR images. A cell averaging Constant False Alarm Rate (CFAR) pre-screening method can be used to identify these ships if it is assumed that the ocean noise can be approximately modelled by a K-distribution [3]. The CFAR pre-screening method employs a local window configuration which includes a target, guard and background windows to detect ships. A ship can be detected using the following

$$\text{Ship Detected} = \begin{cases} \text{true,} & \text{if } x_t > \mu_b T(x,y) \\ \text{false,} & \text{if } x_t < \mu_b T(x,y), \end{cases} \quad (1)$$

where x_t is the target window's backscatter pixel value, $T(x,y)$ is the threshold value plane and μ_b is the mean backscatter pixel value within the background window. Essentially, if a pixel at coordinate (x,y) is $T(x,y)$ times above the background mean at that target window, then the target window is marked as a ship. Setting $T(x,y)$ determines the Detection Accuracy (DA) and False Alarm Rate (FAR) of the ship detection system. In this study we use an initial CFAR pre-screening stage with a low threshold value for the entire threshold plane such that $T(x,y) = 1.0$. This is to ensure that as many candidate ships are selected as possible. It should be noted that the pixels identified in this stage are grouped into clusters and the centre of the clusters are both found using the Mean Shift algorithm to ensure ships of different sizes are weighted equally in the following stages [5].

3.2. Mean probability per ship

The LRIT data is used to generate a probability distribution function called the vessel or ship distribution map (denoted **V**). Every pixel position within the 2D distribution map indicates the likelihood of a ship being found at that position. High probability areas of the map indicate areas of the sea

Low to High Vessel Probability

CFAR Detected Vessel
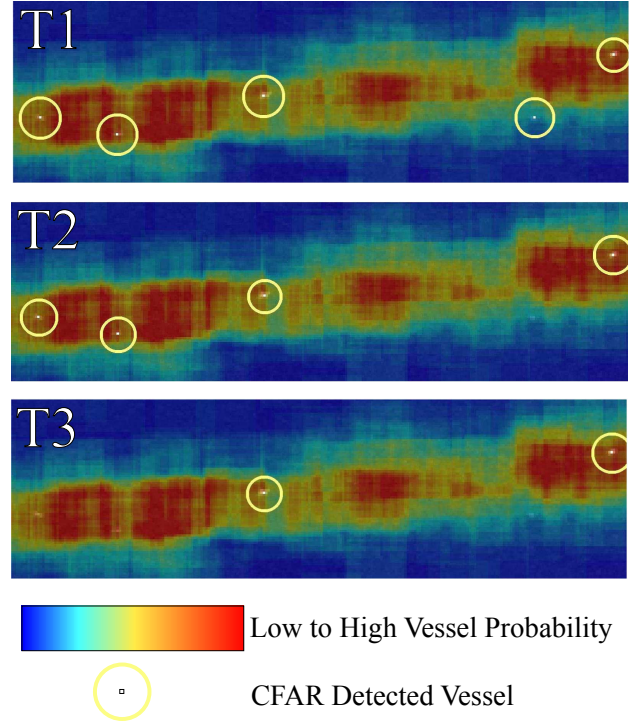
Fig. 2. Ship distribution map **V** overlaid with three CFAR pre-screened images. T1 through T3 indicate flat threshold planes such that $T_i(x,y) = \{1.0, 2.0, 3.0\}$ for $i = \{1, 2, 3\}$. At each threshold the value of β is calculated such that $\beta = \{0.495, 0.490, 0.385\}$. The large change from T_2 to T_3 is due to the removal of two ships in high probability areas. This large change indicates a threshold that is less useful and the previous threshold T_2 is selected as the better, highest threshold.

where many ships have traversed. Using this map and the previously CFAR pre-screened image an estimation of the mean probability per ship β is calculated using

$$\beta = \frac{\text{Total probability using } \mathbf{V} \text{ and all ships detected}}{\text{Number of ships detected}}. \quad (2)$$
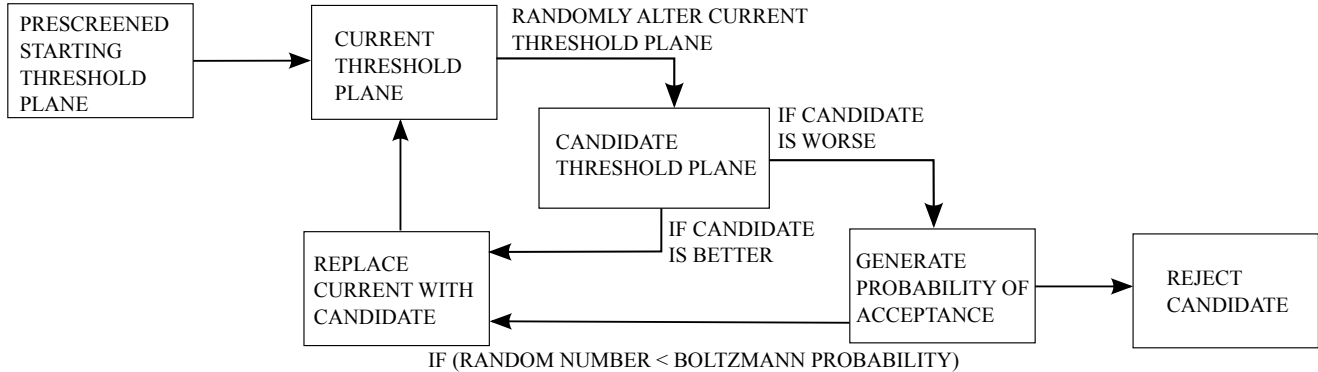
Fig. 3. The iterative procedure of Simulated Annealing. Starting at some initial threshold plane $T_i(x,y)$ each iteration tests if the new solution T is better than the previous best solution $T_b(x,y)$. A possible "bad" candidate can replace the current best due to the Boltzmann probability.

A new threshold plane $T_b(x,y)$ is defined which is mapped to the 2D distribution map to improve upon the flat threshold plane $T(x,y)$. The change in β is used when estimating $T_b(x,y)$. When $T_b(x,y)$ is altered, the value of β changes because the number of detected ships either decreases or increases. A large change in β indicates that too many ships were removed (or added) and so the changes should be reverted and another threshold plane should be created. An illustration of the threshold plane optimisation procedure is shown in Fig. 2.

3.3. Simulated Annealing

Simulated annealing is an algorithm used to meta-optimise a set of parameters [6]. The algorithm mimics the physical process of letting a heated material cool slowly by lowering the temperature to decrease the abnormalities in an object. It proceeds by altering a currently accepted solution randomly and then testing the candidate solution to see if it is better in some way than the best solution. In this study, the change in β is the cost function D. A significant change D indicates a worse threshold plane. If the current solution is not better than the previous best then it can still be accepted using the following

$$e^{-\frac{\Delta D}{\gamma}} > R. \tag{3}$$

Where ΔD is the change in cost between the current solution and the best solution, γ is the current temperature of the solution and R is a random real number in the range $[0,1]$. While simulated annealing is unlikely to find the optimum solution for such difficult problems it can often find a more than acceptable solution. Fig. 3 shows the general steps used in the Simulated Annealing process.

3.4. Adaptation of the threshold plane

3.4.1. Initial threshold plane

To begin the process of adapting the threshold plane an initial flat threshold plane is created. All pixel values within the plane is initialised to a low value.

When the input SAR image is processed at the first CFAR stage a binary image indicating where the possible ships are in the image is generated. This binary image is then used as auxiliary information to determine the areas of the current SAR image that contains ships. The areas of the threshold plane that correspond to the areas of the pre-screened image that do not contain ships are increased to have a threshold that is considered very high. This creates a threshold plane with two levels: areas with possible ships (low threshold) and areas without ships (high threshold). This reduces processing significantly as areas with a high threshold are ignored for the rest of the threshold adaptation process.

3.4.2. Gradual adaptation of threshold plane

Each ship detected in the initial CFAR stage has a corresponding threshold plane value. Initially, each ship's threshold plane value will be 1.0, but as the Simulated Annealing method progresses these values are increased by a random amount to form a candidate new threshold plane. The schema for adapting a threshold plane value at a specific ship's position is simple: ships have their threshold plane value increased by a uniform random number inversely proportional to the number of ships in the area (25×25 for instance). This ensure that areas with a high number of ships will have their threshold value gradually increased whereas areas with fewer ships will have their thresholds increased more substantially. A gradual increase of threshold plane values around areas with ships will highlight subtle changes in β. Conversely, larger increases of threshold plane values in areas with fewer

Table 1. Detection Accuracy (DA) and False Alarm Rate (FAR) results for a CA-CFAR using a single valued (flat) threshold plane and a Simulated Annealing generated plane.

METHOD	CD	FAR
Flat-threshold	91.11%	1.7×10^{-7}
Simulated Annealing Non-flat threshold	85.19%	1.01×10^{-7}

ships will quickly indicate solitary ships that are removed in high probability areas (Fig. 2).

3.4.3. Candidate selection

The current temperature γ used in the simulated annealing process is equal a 100 divided by the mean threshold value of the areas of the threshold plane that are initially said to contain ships (initially $\gamma = 100$ but decreases with each epoch). The cost D of the current threshold plane compared to the best one is used to check if the current threshold plane is a better candidate. Finally, if the Boltzmann probability is calculated using eq. 3 and a random number is selected that is larger than this probability, then the "worse" threshold plane replaces the best candidate plane. This part of the Simulated Annealing algorithm is implemented to improve solution diversity. Finally, the Simulated Annealing ceases when the change in temperature over a number of epochs becomes constant. This produces the final threshold plane which is then used in the second CFAR stage to threshold the binary CFAR image for a final time.

4. RESULTS

The results of applying a flat threshold plane and adapted threshold plane on the six ASAR images is shown in Table. 1. The adaptive plane had a 6% reductions in overall DA when compared to the CFAR using a flat threshold plane. However, the adaptive threshold plane approach does boast a 40% reduction in FAR when FAR when compare to the same flat threshold plane approach. With further investigation the Simulated Annealing non-flat threshold plane could provide optimal results due to the fact that it can be altered in such a way to adapt to different input images and thus provide better generalisation and overall performance compared to the non-adaptive flat-threshold method.

5. CONCLUSION

This study proposed a new ship detection system configuration that utilises a CFAR method as a pre-screening and a ship discrimination stage. The Simulated Annealing process is used to create a 2D threshold plane for the ship discrimination stage that can allow for improved ship detection and accuracy. The 2D adaptive threshold plane allows for improved ship detection accuracy as it can allocate different thresholds to different geographical regions. The proposed ship detection system was able to detect ships with a detection accuracy of 85% with a corresponding false alarm rate of 1.01×10^{-7}. The proposed system extends the CFAR method to have complex threshold planes for different geographical areas and thus provides a powerful tool for threshold selection. Using the correct cost and update functions, the Simulated Annealing non-flat threshold method could provide a threshold plane that would allow for very high detection accuracies and corresponding low false alarm rates.

6. REFERENCES

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