

Automatic Ship Detection on Volga River Using Sentinel-1 Data

Research Project

Prepared by:

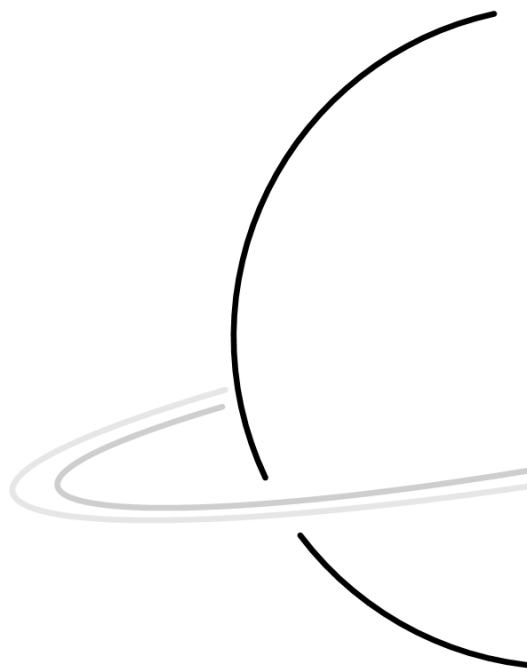
VASILII MOSIN

Checked by:

Approved by:

Space Center
Skoltech
Moscow, Russia

•
02/02/2018



Contents

Acronyms	2
References	2
List of Figures	3
List of Tables	3
1 Introduction	4
2 Driving Technical Requirements	4
2.1 Sentinel-1 Data	5
3 Approach and Implementation	5
3.1 Preliminary Objects Detection	5
3.2 Additional Objects Classification	7
4 Results and Discussion	7
5 Conclusion	9

Acronyms

AIS Automatic Identification System. 4

AoI Area of Interest. 3–7, 9

CFAR Constant False Alarm Rate. 6, 9

CNN convolutional neural network. 4, 5, 7–9

ESA European Space Agency. 5

GRDH Ground Range Detected High. 5

PDF Probability Distribution Function. 6

SAR Synthetic Aperture Radar. 4–7

SNAP Sentinel Application Platform. 5–7, 9

References

- [1] Copernicus Open Access Hub. URL: <https://scihub.copernicus.eu>.
- [2] I. D. Negula, V. D. Poenaru, V. G. Olteanu, and A. Badea. Sentinel-1/2 data for ship traffic monitoring on the danube river. English. In *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, volume 41, pages 37–41, 2016. URL: www.scopus.com.
- [3] R. Pelich, N. Longepe, G. Mercier, G. Hajduch, and R. Garelo. Performance evaluation of sentinel-1 data in sar ship detection. English. In *International Geoscience and Remote Sensing Symposium (IGARSS)*, volume 2015-November, pages 2103–2106, 2015. URL: www.scopus.com. Cited By :6.
- [4] C. P. Schwegmann, W. Kleynhans, B. P. Salmon, L. W. Mdakane, and R. G. V. Meyer. Very deep learning for ship discrimination in Synthetic Aperture Radar imagery. In *IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, pages 104–107, July 2016.

List of Figures

2.1	Regions of Area of Interest (AoI)	4
3.1	Original (left) and Masked (right) Images of the AoI	6
3.2	Adaptive Thresholding	6
3.3	Example of the Training Data (first row - ships, second row - ship-like areas)	7
4.1	Examples of the Detected Objects	8
4.2	Location of the Detected Ships (red: Image1, green: Image2, blue: Image3)	8

List of Tables

1	Images Information	5
---	------------------------------	---

1 Introduction

Synthetic Aperture Radar (SAR) satellite imagery has many different applications nowadays. For example, it is used a lot for ship traffic monitoring, what is demonstrated by enormous number of recent works in this field. However, there are not much articles like [2], where satellite data applied for ship detection on rivers. This task is more difficult because of the complicated landforms around the river waters. Moreover, there are not much available Automatic Identification System (AIS) open data from rivers' harbors, which is also a problem for automatic ship detection.

In this work the combined approach for automatic ship detection on river waters is described and implemented. The main idea is to use the conventional algorithm for preliminary objects detection on the river followed by additional classification of the detected objects by means of convolutional neural network (CNN). Also, experiment setup and results are provided. The region of Volga river near Kazan was selected as the AoI because this project is considered as the exploratory step for the current cooperative program of Skoltech and Inopolis university. This work is continuation of the previous research project in which basics methods and tools for sea ship detection were explored.

2 Driving Technical Requirements

The goal of this project is to explore the possibility of the usage of the SAR satellite imagery for ship detection on Volga river. Three regions inside the AoI were chosen for the experimental part (Figure 2.1): there are one smaller and two bigger regions (Table 1). The



Figure 2.1: Regions of AoI

whole procedure should be fully automated and developed using existing libraries and tools.

Experiment setup and results discussion should be clearly represented to analyze how well the presented approach works on the images of AoI.

Image	Sensing Date	Region
Image1	2017-06-02T03:04:13.563Z	small
Image2	2017-07-08T03:04:15.560Z	big
Image3	2017-08-13T03:04:17.691Z	big

Table 1: Images Information

2.1 Sentinel-1 Data

This project is focused on using Sentinel-1 data as the main source of SAR satellite imagery. Sentinel-1 is a space mission carried out by European Space Agency (ESA) within the Copernicus Programme, consisting of a constellation of two satellites. The payload of Sentinel-1 is a Synthetic Aperture Radar in C band that provides continuous imagery (day, night and all weather). First Sentinel-1A satellite was launched on 3 April 2014. The images from Sentinel-1A used in this work are Ground Range Detected High (GRDH) resolution class imagery. GRDH images have a resolution of 50 x 50 m and pixel spacing of 25 x 25 m (in range and azimuth respectively). Sentinel-1 data can be accessed from the open data source within the Copernicus Programme [1].

Performance evaluation of Sentinel-1 data in SAR ship detection was done in [3]. Results seem to be promising as the ship detection on Sentinel-1 images yields better performance compared to some of the analogue satellites' image datasets.

3 Approach and Implementation

As it was mentioned above, the main idea of the project is to use the standard tools for objects detection on the river and then apply CNN for classification of detected objects.

3.1 Preliminary Objects Detection

All preliminary objects detections were made in Sentinel Application Platform (SNAP). This software has a built-in ship detection module. Before applying this module in order to avoid detection of false targets (ships) on land it is needed to perform a land masking. The Land/Water Algorithm in SNAP takes the geographic bounds of the input image and creates the new image covering the same area. The output image contains a single band, which indicates if a pixel is a land or water. Example of the original and masked images of the AoI is shown on Figure 3.1.

The masking operation is not very accurate because of complicated landforms in the AoI, which will be the reason of false detections further.



Figure 3.1: Original (left) and Masked (right) Images of the AoI

For object detection SNAP uses adaptive thresholding algorithm. Adaptive thresholding is a frequently used method for target detection in SAR imagery. The underlying assumption is that targets appear bright on dark background. The adaptive thresholding algorithm is applied in moving window. For each pixel under test (central pixel) a new threshold value is calculated based on the statistical characteristics of its local background: if the pixel value is above the threshold the pixel is classified as target pixel.

The specific type of adaptive thresholding algorithm used in the SNAP is a Two-Parameter Constant False Alarm Rate (CFAR) Detector. The user defines the parameters of the moving window (Figure 3.2) where the Target cell corresponds to one or multiple pixels under test; the Buffer window prevents contamination of the background values by the target pixels; the values within the Background window represent the local background and are used to determine the Probability Distribution Function (PDF) of fitted Gaussian distribution. The threshold value is then calculated as shown on the right side of the Figure 3.2.

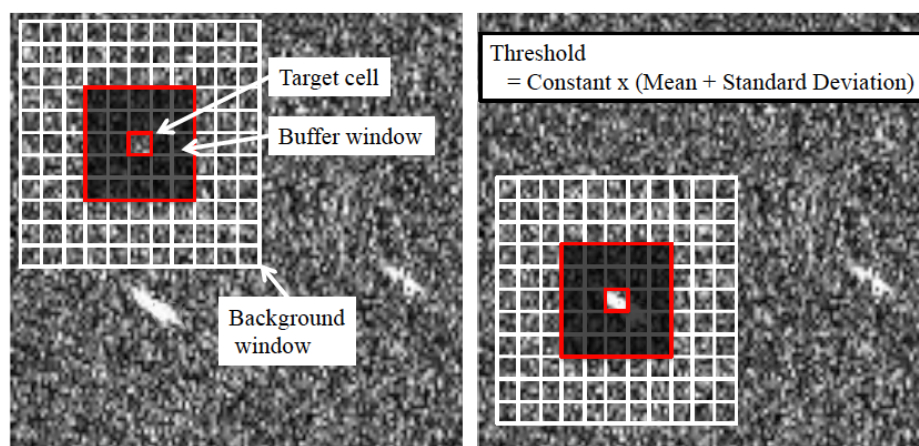


Figure 3.2: Adaptive Thresholding

3.2 Additional Objects Classification

Built-in objects detection algorithm in SNAP produces a lot of false ships detection, especially near the coastal region. So, the further step is to classify whether the detected object is a ship or not. For this, it is proposed to use a simple CNN. Architecture of the CNN used in this project can be found in the accompanying Jupyter Notebook. To build and train the glsenn Keras with TensorFlow stack was being used in a Python language environment.

The dataset that is described in [4] was selected as the training data. It contains 1596 SAR images of the ships and 6384 SAR images of the false positives (ship-like) areas. Each image in this dataset has the size of 51 x 51 pixels (Figure 3.3).

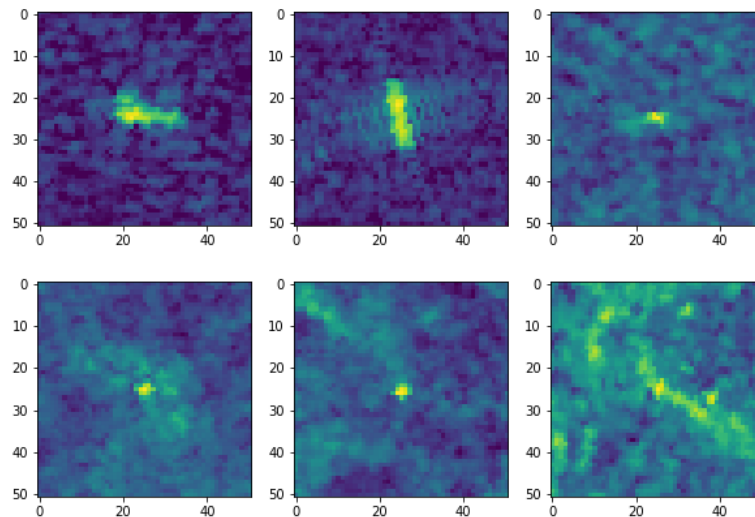


Figure 3.3: Example of the Training Data (first row - ships, second row - ship-like areas)

4 Results and Discussion

The CNN has achieved the 0.98 accuracy score on the train set and 0.97 accuracy score on the validation set. To be able to apply the trained CNN, the images of the detected objects should have the 51 x 51 pixel size. So, the images of the appropriate size with the centroid in coordinates of the detected objects were cropped from the original SAR image. The 63 objects in total were detected during preliminary stem using SNAP application for the one small region of the AoI, where 17 objects are the true ships and 46 objects are false positives coastal areas. After the second step of the additional objects classification using CNN 16 objects were classified as ships, where 15 objects are true ships (Figure 4.1 a, b) and 1 object is false positive coastal area (Figure 4.1 c). Accordingly, 47 objects were classified as non-ships, where 45 objects are true non-ships (Figure 4.1 d, e) and 2 object is a ship (Figure 4.1 f).

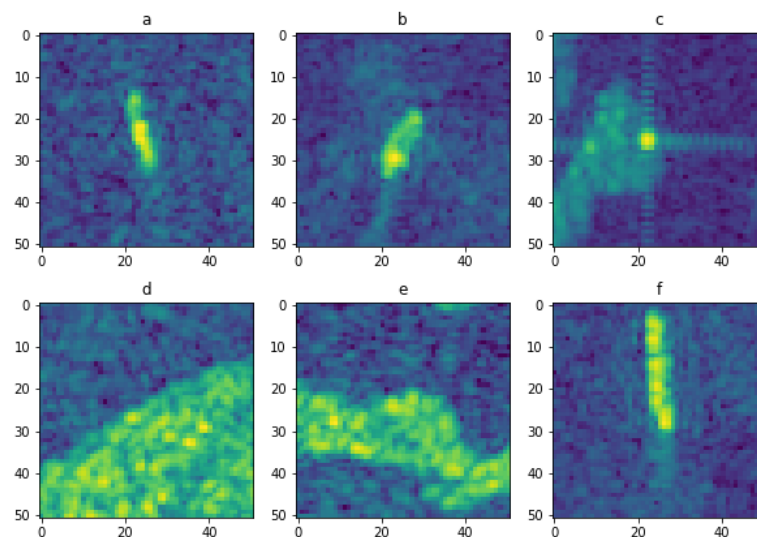


Figure 4.1: Examples of the Detected Objects

So, the overall quality of the proposed approach is quite good. The additional objects classification step using CNN allowed to get rid of 45 false positive detections out of 46, while losing only 2 real ships.

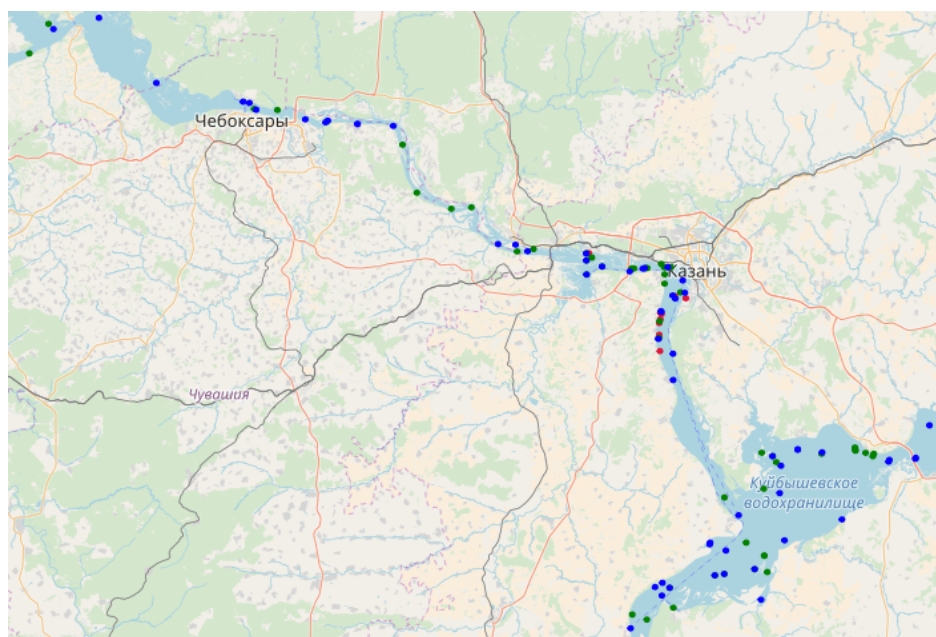


Figure 4.2: Location of the Detected Ships (red: Image1, green: Image2, blue: Image3)

For further improvement of the classification step one can collect and use bigger and more relevant training dataset for CNN. One of the reason that the accuracy of the CNN is high on the train and validation data, but not very good for test data, is that the dataset from [4]

was collected using not only Sentinel-1 satellite and there are not so much examples of the false positives coastal areas, which are arising very frequently during ships detection on the rivers.

The same experiment was done also for two bigger regions of the AoI, where 459 and 440 objects were detected in SNAP application, among which 52 and 59 objects were classified by CNN as ships. The all ships that were detected and classified are shown on the geographical map (Figure 4.2).

5 Conclusion

The proposed two-steps approach for ships detection on river waters in this project improves the results of the original CFAR algorithm. In particular, it can be used effectively for removing a large number of false positive detections from the observation. Experiment done in this work on the area of the Volga river showed that the approach is reasonable, but still requires further improvements. Collecting more relevant raining data for CNN can be considered as one of the first future steps for this project.

VASILII MOSIN
Moscow, 02/02/2018