A Cognitive SAR Concept for Ship Detection using Support Vector Machines

Jan Meyer[a,b], Kay Glatting[a], Sigurd Huber[a], and Gerhard Krieger[a]
[a]German Aerospace Center (DLR), Oberpfaffenhofen, Germany
[b]jan.meyer@dlr.de

Abstract

Cognitive radar is a new acquisition technique that forms a closed loop between radar receiver, radar transmitter and environment, similar to the perception-action cycle in human cognition. The continuous adaptation of the acquisition parameters based on previously acquired information also harbours great potential for future SAR missions. As an example, this paper presents a spaceborne cognitive SAR concept for ship detection. The concept foresees a two-stage process to improve the overall ship detection probability compared to conventional approaches. First, a wide-swath mode with coarse resolution is utilized to cover a large maritime area. From these SAR data, the positions of potential ships shall be detected, however, due to the low signal-to-clutter ratio, with a high false alarm rate. In the second step, a high-gain mode with fine resolution is used to look at the presumed ship positions and either confirm or reject the presence of ships with high fidelity. This radar concept could be realized on a single platform using a hybrid mode. In the context of this investigation, the cognitive functionality is distributed on two separate SAR satellites operated in a convoy configuration, where the leading satellite performs the first coarse-detection step and the companion satellite implements the high-fidelity detection step including intelligent digital beamforming of one or more spotlight beams accessible via phased array antennas.

1 Introduction

The general motivation behind synthetic aperture radar (SAR) is always some form of information extraction from a scene. A lot of effort is made to continuously improve the information gain for different scenarios. In principle, retrieving optimal information from a scene via SAR can be understood as a complex optimisation problem with multiple degrees of freedom as well as physical and technical constraints. To optimize the radar acquisition for a specific scenario, in the following, spaceborne ship detection, considering the radar transmission process is crucial. It affects all steps from the concept and design of a radar system over hardware choices (e.g. bandwidth) to the actual operation.
Detecting the position of ships and their trajectories is of high interest for different reasons. Examples include typical reconnaissance missions, detection of waste dumps, tug boats or investigations regarding the 'Nord Stream' pipeline explosion. However, detecting ships of unknown positions in large maritime areas is currently not feasible reliably due to the bad signal-to-clutter ratio of wide-swath low-resolution modes respecting limitations of onboard resources.
Cognitive Radar, a term coined by Simon Haykin, is a promising SAR concept that can alleviate many issues traditional SAR operations face. He suggested a theoretical concept for a radar system that dynamically adapts its active illumination to an observed environment in a feedback loop via Bayesian inference from the received radar echo[1]. Moreover, he references similar behaviour in the echolocation of some bats and argues that they face related challenges when searching for food. When assuming objects in the near distance certain bats change their transmission from single to multiple clicking sounds, thus generating a richer neural response [1][2].
Similarly, modern phased array antennas allow a fast adaptation to dynamic scene changes through digital beamforming (DBF) on transmit and receive and thus, an adaptive radar acquisition, in principle. Utilizing DBF, sophisticated hybrid acquisition modes can be realized as described, e.g., in [3]. Consequently, the aforementioned optimisation task can be faced by switching between these hybrid modes, mimicking the bat. DBF introduces many degrees of freedom for possible adaptations of the radar illumination to the scene which becomes crucial for more complex and dynamic scenes, e.g., a varying number of active spotlight beams. Furthermore, feature extraction and subsequent mode change seem tractable via modern machine learning methods. Both tasks can be addressed with a variety of algorithms, some of which are too difficult to implement on classical computers in a reasonable time. This may be different on modern quantum computers due to possible algorithm scaling advantages.

2 Problem Description

The acquisition of SAR data is constrained by power, illumination time, computation speed, heat generation as well as ambiguities induced by the use of multiple channels [3]. Originating in Küpfmüller's uncertainty principle, the re-

lation $\frac{W_g}{\delta_{az}}$ between swath-width on the ground W_g and azimuth resolution δ_{az} is subject to an upper bound for the established SAR acquisition process, such that a well-known trade-off between swath-width and resolution in azimuth arises [4, p.4 & 16-20].
The main challenge for ship detection is that ships are small compared to the ocean and that ocean waves generate a lot of clutter when reflecting radar signals. Effectively, a threshold of the signal-to-clutter ratio must be overcome to sense them reliably. As a consequence, a useful radar acquisition must reach the necessary resolution and power which is not feasible for large areas concerning the physical and technical limitations of present SAR satellites. Therefore, possible solution paths consist of increasing the efficiency of different aspects of the acquisition process. A simple but promising idea is to limit the area that has to be searched with sufficient resolution (for small ships) in the first place, thus reducing resource usage. This allows for the illumination of the remaining area with higher gain and therefore improved local information retrieval. Prior information is crucial, to reduce the area of interest and its acquisition process contributes to the overall resource demand. This idea could take shape when the search space can be limited geographically, e.g., in the following concept: By only considering those locations motivated by the coarse detection step, for high-resolution acquisitions, the effective area to be searched for ships with high resolution can be reduced.

3 Methods

As a suitable setup to test our hypothesis we suggest the detection of an unknown number of ships in the ocean using two SAR satellites in a convoy configuration as shown in Fig. 1. To simplify the operational complexity and the management of resources the following assumptions are made here: The leading satellite is continuously scanning the ocean in a low-resolution wide-swath (ScanSAR) mode and the companion satellite uses a high-resolution hybrid spotlight mode, with one or more active beams repeatedly switching illumination to the position of maximum detection likelihood of unknown ships. All accumulated SAR data from both satellites are taken into consideration to continuously update a growing probability density map of ship detection for the whole scene. The detection algorithm on the leading satellite is then adjusted to estimate a high number of falsely positive but almost no falsely negative ship detections. The companion satellite, with high resolution and gain, then validates the possible detection area with high fidelity.
Since different currently operational spaceborne systems seem to converge to the upper limit for $\frac{W_g}{\delta_{az}}$ [4] and with the additional assumption of different acquisition modes converging to the same limit, we consider cognitive radar as a process of assigning a limited number of high-resolution cells to a scene. From this perspective, it conceptually seems comprehensive to distribute resolution as a form of attention to different positions in a scene, hence, improving the overall information extraction and saving resources.

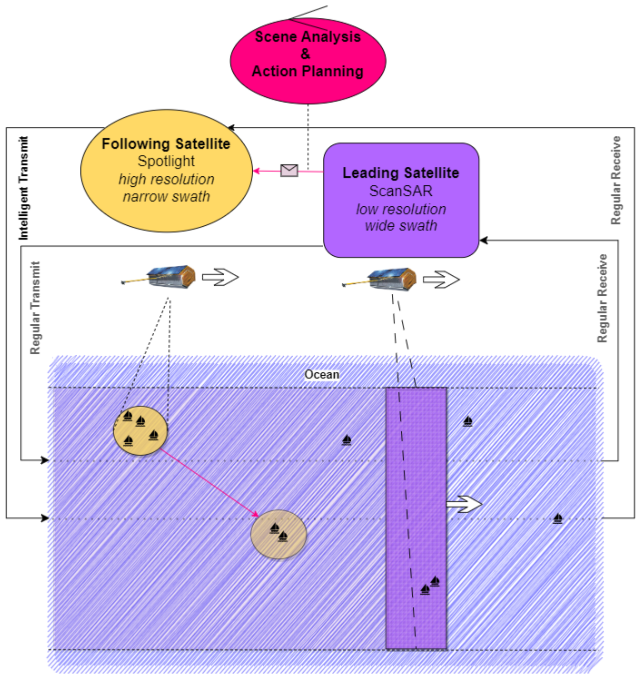

Figure 1 Cognitive radar concept consisting of a feedback loop of a leading scanning satellite with a high false alarm rate tasking another to validate possible ship detections with higher resolution but smaller swath-width by relocating its spotlight to the most promising positions in the ocean based on the current state of accumulated SAR data. The spotlight repositioning and the underlying decision process are both denoted in pink. Multiple such beams could be active at the same time.

The cognitive aspect of this distribution process can be divided into firstly analyzing the scene from the received radar echo and secondly planning an action, in our scenario the positioning of the spotlight beams. Effectively, a cognitive radar introduces (computational) complexity to save resources where high gain would not be useful. This allows higher resource usage for locations of more promising information content leading to an expected detection advantage based on a useful choice of resolution distribution. Binary classification based on the high-resolution data allows a final detection step for that area. Proper implementation of cognitive radars seems to have remained a major challenge in the last years. This could be due to the necessary algorithm complexity of an effective cognitive radar as well as the limited onboard processing capabilities. Typically the hardware on board is not capable of reconstructing the final SAR image directly which is a useful representation of the collected data for scene analysis as it contains the received radar signal focused to the corresponding positions in the scene.
Therefore in this paper, the further assumption is made, that enough computational power was accessible for the SAR image reconstruction as well as the optimisation of the adaptive transmission of the spotlight satellite. To reduce computational demand, a combination of efficient algorithms and sufficient computational power becomes obligatory and possible speedups could be based on di-

verse hardware choices. Many machine learning algorithms are highly parallelizable and therefore profit drastically from using graphical processing units (GPUs) and related tensor cores. Especially for large amounts of data, e.g., from scanning a large area for ships, the scaling of algorithms becomes important. Moreover, some (quantum machine learning) algorithms are expected to have scaling advantages when scheduling subroutines on proper quantum computers which extend the classical Turing model of computation [5][6][7]. As quantum computers will not likely be onboard of satellites soon, more realistic scenarios would involve information transmission to a ground station, e.g., using geostationary relay satellites.

3.1 Scene Analysis and Feature Extraction

A good scene analysis includes extraction of useful features, in our example at least an estimation of likely ship positions, based on the low-resolution acquisition of the leading satellite and builds the backbone for the subsequent intelligent adaptation step. Depending on the task other information could be useful. Prior information about, e.g., the type of ships of interest, an estimated number thereof or their size and possible trajectories could be beneficial for detection. Such additional information is not considered here.

One of many effective machine learning architectures for regression and classification are support vector machines (SVMs) that are useful for spaceborne ship detection on real SAR images [8]. Moreover, in 2014 Rebentrost et al. [6] presented a quantum SVM which can achieve an up to exponential speedup in computation time compared to the classical SVM in the number of features and the training size. Given some conditions, the time complexity of their quantum SVM algorithm only scales polynomially in the logarithm of the input data size on a quantum computer.

Since a lot of area has to be classified quickly and therefore efficiently based on the SAR data of the leading satellite an exponential scaling advantage makes quantum SVMs a promising subroutine for cognitive radar. More precisely, the ScanSAR acquisition leads to a roughly constant information inflow that needs to be processed in real time such that the spotlight satellite can optimally relocate its beam just in time. For constant speed and distance between both satellites, the upper bound for the available computation time would remain constant as well.

In [8] the authors report a low number of falsely negatively classified ships using SVMs compared to convolutional neural networks. Since the spotlight satellite depends on prior detection by the scanning satellite, this observation aligns well with our chosen cognitive radar concept as it also should result in a low number of overall falsely negative detections of the combined acquisition.

3.1.1 Support Vector Machines

After supervised training, support Vector Machines (SVMs) allow binary classification of contiguous regions in input data d [9], such as reconstructed SAR images, containing information $d(a, r)$ for each point in the space spanned by the position in azimuth a and position in the

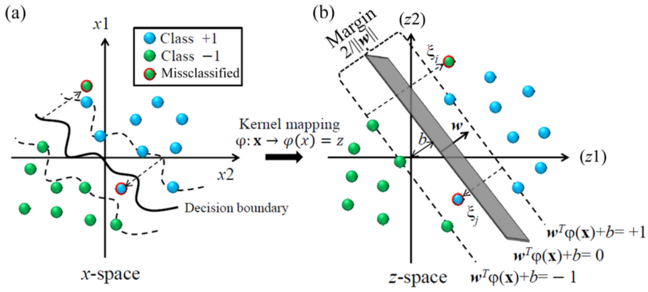

Figure 2 Schematic description of the binary classification procedure of a support vector machine (SVM) (a) in the original space $\boldsymbol{x}$ and (b) the non-linear kernel mapping $\boldsymbol{z} = \varphi(\boldsymbol{x})$ where the two classes are separable via the hyperplane determined by the support vector $\boldsymbol{w}$. The image is taken from [9].

range r, in our scenario the classification into ship and background. Thus, regions containing ships can be separated from regions containing no ships in principle. An illustration is given in Fig. 2. Trained SVMs allow for the classification of points and by construction also contiguous regions of points into different categories. In our case, the resolution cells belonging to the same ship build such a contiguous region labelled into the same class = +1, corresponding to ship detection instead of background detection (class = -1). By construction (eq. 1) other cells can be labelled the same way individually and consequently different ships are labelled into the same class.

Typically, the regions corresponding to two classes cannot be separated by a flat surface or straight line. Therefore, one transforms the data, e.g., the SAR image, through a so-called kernel map φ into a typically higher-dimensional space $\boldsymbol{z} = \varphi(\boldsymbol{x})$ in which a classification above and below a correspondingly dimensional hyperplane is possible. This hyperplane is uniquely described by its normal vector w and the calculation in $\boldsymbol{z}$ instead of $\boldsymbol{x}$ is known as 'kernel trick' [6][9]. The classification of whether a point belongs to a region containing ships is then done by the sign of the scalar product of the transformed input data (the SAR image) with the high dimensional support vector and the scalar bias b, both determined during training on labelled data

$$\text{class} = \text{sign}\left\{\boldsymbol{w}^T\varphi(\boldsymbol{x}) + b\right\} \tag{1}$$

and hence is also efficiently computable for new data. Different choices of the transformation φ are common and shall be tested for our scenario. Determining w typically involves minimising an Euclidean norm respecting all data points.

For classification problems that are more complex than binary, e.g., different ship types, multiple classifiers could be logically linked to map into more complex classes, yet inducing overhead. For our detection scenario binary classification is sufficient.

The scalar product of high dimensional vectors (in eq. 1) is native to quantum computers such that the kernel evaluation can be done directly in the high dimensional (quantum) state, allowing for an up to exponential speedup in time complexity [6].

3.2 Action Planning

Using extracted features to find an optimal exploration policy is a highly nontrivial task in general. Effective algorithms, involving an agent making systematic choices, live in the overlap between machine learning (ML) and artificial intelligence (AI).

In contrast to supervised learning (e.g. for training SVMs), with explicit labels for the desired output, there are reinforcement learning (RL) procedures involving an 'agent' making decisions that ideally maximize an (overall) reward when interacting with its environment. By trial and error, it learns successful policies. This mimics the way intelligent biological systems typically learn in nature. The agent could be any form of network capable of decisions and learning. One could couple a reward to successful information retrieval and thereby implicitly teach said agent to use its actions, dependent on its state, in a way that maximizes his reward and thus, our information gain about the scene. In our scenario, the detection of one or more ships should lead to a reward for the RL agent if the ship was not detected before. Punishing resource inefficiency with a negative reward should be useful for training as well. Depending on the complexity, a large number of simulations will be necessary for the agent to learn to steer one or more beams effectively in terms of detection success. The most prominent algorithms involve a discretization of the accessible state-action space and a subsequent visit of all its elements for global optimisation which is infeasible for many practical applications. The agent could, e.g., randomly choose where to locate the spotlight beam by sampling from a uniform distribution, or better, the predestined probability density map. The actor-critic class of algorithms also allows continuous-state reinforcement learning based on gradient evaluation, rather than trying every possible solution, with possible advantages from hybrid quantum-classical ML models. In [10] a hybrid version of actor-critic is used for proton beam target steering at CERN which could also be applicable to digital beam forming to steer, e.g., the spotlight beams of our second satellite. Especially exploring large state-action spaces seems well suited for exploiting the superposition of different states in a quantum computer. In [11] a quantum actor-critic network is reinforced to plan flight trajectories of a (simulated) UAV to support independent moving smartphone users with an optimal wifi connection between buildings and to save resources. Like other authors, they report faster convergence and better expressibility of variational quantum circuits over classical neural networks. Similar approaches could be very useful for the action planning step in our concept where possible quantum advantages would be most important and plausible, alike.

Many different reinforcement learning algorithms are explored in active research, e.g., for detection and tracking using multi-function radars [12]. Possible quantum advantages could apply to many of them, with strong implications for the effectiveness and efficiency of our cognitive radar concept. Especially if the quantum computer is located at a ground station it would be easier to send the current probability density map to a ground station in real-time than the whole SAR data, making the planning step better suited for practical quantum advantages in the future. Regarding our explicit detection scenario in Fig. 1, we will start with less complex, reliable algorithms in future work.

The spotlight satellite could centre its beam(s) on the coarse resolution cells of the leading satellite in descending order of the estimated likelihood of ship detection. A next step could be to consider the flight direction as an additional constraint. The relation between classification and probability can be fitted via Platt scaling (logistic regression and cross-validation) [13]. Consequently, the primary satellite should have a high number of false positive estimations, such that as few ships as possible are neglected.

Moreover, using a high-gain spotlight for the validation of most likely ship positions might not be ideal regarding resource usage compared to the actual information gain. Formulating a generally optimal exploration strategy a priori might not be feasible as it could sensitively depend on the particular scenario. For example, increasing the number of active spotlight beams and (heterogeneously) reducing their individual resolutions drastically increases the complexity and degrees of freedom leading to possibly very different optimal strategies than with just one beam.

Ideally, future systems could autonomously self-organize the beam-steering as well as the number of active beams and their corresponding resources, likewise. Not only is agent-based self-organization interesting in itself in these scenarios from a complex systems perspective, but also potent regarding highly dynamic adaptation capabilities in future SAR missions with a better trade-off between information retrieval and resource usage.

For many scenarios, e.g., a mostly empty ocean, the expected increase in detection performance using a (simple) cognitive radar compared to established SAR acquisition modes should be worth its computational cost.

4 Results

In the following, we show first results for the scene analysis step using support vector machines. Figure 3 shows the support vector machine based pixel-wise classification of a maritime scene. Given an unknown preprocessed SAR image from the public SARscope dataset [14], a probability for the presence of a ship is calculated for every resolution cell. The resolution in the dataset ranges between 0.5 and 3 m. The segmentation on the right has the same origin and is used as ground truth to quantify the prediction accuracy. A sliding window of seven resolution cells, in azimuth and range each, is used as feature space for the support vector classifier (SVC) to predict a class for the centre of the window. This way the scene can be analyzed and a probability density map estimated for each resolution cell and thus the whole scene. Based on such a map subsequent beam-steering could follow in future work. Exemplary for a larger window size of 31×31 resolution cells some windows are shown in Fig. 4. For the training, validation and test dataset of processed images and their segmentation in

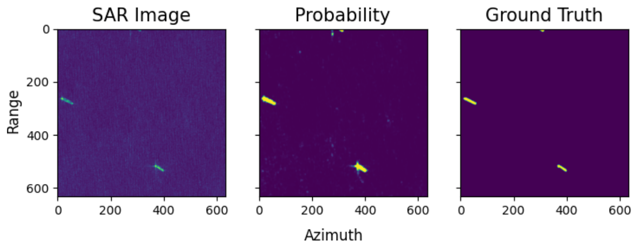

Figure 3 Left: Image from the test set in [14], Middle: Estimated pixel-wise ship detection probability predicted by a support vector classifier utilizing a sliding window of size 7×7 as feature-space, Right: Segmentation from [14]

[14] such windows were built and the SVC trained on those originating from the training set. To guarantee parity of the classes many windows without a ship in their center were discarded. The SVC was implemented using the 'scikit-learn' python package [15] with a Gaussian radial basis function (RBF) for the kernel mapping φ in equation 1. It estimates a class label and its corresponding probability via Plattscaling of cross-validation. The accuracy of the trained classifier on the aforementioned windows is shown in Fig. 5 for different window sizes.

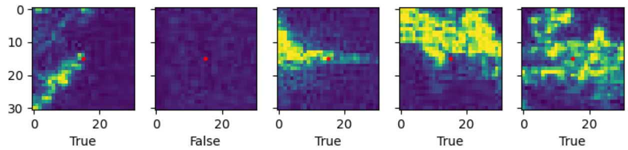

Figure 4 Examples of windows of 31×31 resolution cells in azimuth and range with a label below stating whether their center-pixel (red) belongs to a ship.

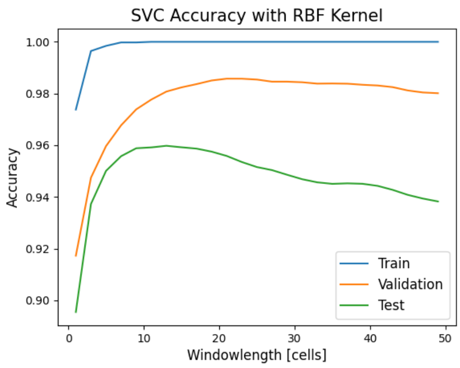

Figure 5 Classification accuracy on sliding (square) windows for different sets of the SARscope dataset [14] and different lengths of a square window. For all sets, empty windows were randomly discarded such that half of the remaining windows were centred on pixels belonging to ships.

5 Discussion

The results show that a support vector classifier can be used for ship detection that is translation invariant regarding the detection performance and the ship's position due to the sliding window approach. It suppresses moderate levels of ocean clutter and finds practically all ships in the [14] dataset. Fig. 3 suggests that even very small ships would be detected given the high resolution. While the SVC's nonlinear sensitivity to intensity seems promising, its sensitivity to shapes is not sufficient such that other objects, e.g., in harbours are falsely positively classified as ships. This problem can be addressed by additional edge detection filters or intensity gradients of the windows similar to [8].

We also implemented quantum support vector classifiers via the 'qiskit' python package [16] that simulates a quantum kernel mapping using one simulated qubit per feature. Outside of the kernel mapping it relies on the 'scikit-learn' SVC implementation and can therefore also estimate a class probability. While its possible scaling advantage remains interesting for the analysis of large scenes using many features, e.g., large sliding windows, windows of size 3×3 (nine qubits) seem practically infeasible on a simulated quantum computer using this implementation. This is due to the large Hilbert Space spanned by the quantum encoding and probably partly to scikits missing GPU support which typically speeds up the multiplication of large matrices utilising parallelisation.

6 Outlook

In future work, we will demonstrate the action planning aspect of our cognitive radar concept by reducing the image quality of high-resolution data to simulate the scanning satellite. Then we will estimate a probability density map as in this work and further use it to simulate the intelligent steering of one or more spotlight beams of the second satellite that would then locally grant access to higher resolution and allow us to quantify the concept's effectiveness on real data.

We plan to implement reinforcement learning routines to steer the spotlight beam(s), utilizing and continuously updating a probability density map. Furthermore, phased array antennas and possibly multiple satellites allow us to extend our concept to arbitrary complexity, in principle, e.g., by switching between the hybrid acquisition modes described in [3], and possibly to adapt to complex dynamical scene changes. Thus, better information retrieval and resource demand reduction compared to established SAR operations should be achievable in these scenarios. Nevertheless, effectiveness, efficiency and especially reliability of the action planning routine will be crucial for the usefulness of any cognitive radar.

Acknowledgement

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7 Literature

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