SARAI | CPL-RO-SARAI-EXS-10705-1.0

EXECUTIVE SUMMARY REPORT

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INTRODUCTION TO WORK

Earth observation (EO) and remote sensing are pivotal in various domains such as climate monitoring, disaster response, asset management, and security, with Synthetic Aperture Radar (SAR) data being particularly valuable. SAR's ability to create dense time series, unaffected by cloud cover or darkness, makes it ideal for monitoring applications. The commercial SAR sector has seen significant growth recently, with advancements in the quantity, quality, frequency, and dissemination of data through new instruments and missions. However, these technological strides have introduced challenges, especially in data management. The volume of data captured by modern SAR instruments and constellations is immense, and satellite downlink capacities will not keep pace with this data explosion. This has resulted in a bottleneck, hindering high-value data from reaching end-users efficiently.

In response, this project took a novel approach, focusing not on on-board data analysis but on enhancing raw data compression using machine learning (ML) models. These models are designed to select the most effective compression algorithms based on the content inferred from the raw data. This strategy not only conserves bandwidth but also improves overall system performance. It demonstrates the feasibility of gleaning useful insights directly from raw SAR data, an innovative step in satellite data processing.

Processing SAR data on-board satellites is traditionally challenging due to the high computational complexity. This project's ability to infer information from data without creating SAR images is a significant breakthrough. This method could potentially extend to other applications like target detection or change detection in the future.

Designing and implementing an ML model to operate within the constrained, low-power computing environment of a satellite presents unique challenges. The model must be trained on representative data and must function effectively within these limitations. Access to true raw SAR data is rare, as it is typically compressed immediately upon acquisition due to difficulties in lossless compression.

The Adaptive SAR Signal Compression Through Artificial Intelligence (SARAI) project explored solutions for on-board ML to enhance raw SAR data compression. It covered data handling, machine learning methodologies, software development, and included a proposed hardware roadmap for future initiatives. This report provides a comprehensive summary of the SARAI project's activities and findings, showcasing its contribution to addressing the critical challenge of efficient satellite data management in the era of rapidly expanding SAR capabilities.

DATASETS AND ALGORITHMS REVIEW AND FINDINGS

Review

A review of the datasets available to perform raw SAR data compression experiments and the algorithms used for on-board SAR data compression was performed and documented over the first several months of the activity. The review looked at:

- The available sources of raw SAR data.
- The availability of existing datasets.
- The main on-board compression algorithms currently used.
- Algorithm implementation

Findings

The review work resulted in the following key findings across the assorted topics:

- There are currently no raw SAR datasets available from SAR satellites. There is raw SAR *data* available, but no *datasets*.
- Few tools are openly available for working with raw SAR data e.g. to focus into SAR images.
- SAR compression algorithms rely heavily on specific statistical assumptions made about the data. These same assumptions have been used since the late 1970s with incremental improvements in algorithms.

Data Availability

Data sources were identified in the form of freely available data (Seasat, ERS-1 and ERS-2, ENVISAT and Sentinel-1), data where access is dependent on successful proposal submission and a fee may be charged (JERS-1, TerraSAR-X, Tandem-X, Radarsat-1/2, Radarsat Constellation, ALOS/ALOS-2, CosmoSkyMed, SOACOM, Kompsat-5), and data from commercial providers (Iceye, Capella, Umbra, SSTL).

Of the publicly accessible SAR data available at the time of the survey[1], each source was analysed to identify its suitability for being used to perform raw SAR data compression experiments. As a result of the survey, Sentinel-1 Strip Map mode was chosen as the best data source for the further work. A summary is presented in Table 1.

[1] Since this work concluded in March 2023, the availability of raw SAR data has increased with both commercial operators Umbra and Capella starting Open Data Programs.

Table 1 - Available mission data summary

Mission	Raw (L0)	SLC (L1)	GRD (L2)	Raw decoder	Global coverage raw data	Multi Pol
Seasat	F	T	T	F	F	F
ERS-1	T	T	F	T	F	F
ERS-2	T	T	F	T	F	F
ENVISAT	T	T	F	T	F	T
Sentinel-1	T	T	T	T	T	T
RADARSAT-1	F	T	T	F	T	T
RADARSAT-2	F	T	T	F	T	T
CosmoSkyMED	F	T	T	F	T	T
TerraSAR-X	F	T	T	F	T	T
Iceye	F	T	T	F	F	F
Capella	T	T	T	T	F	F
Umbra	T	T	T	T	F	F
SSTL NovaSAR	F	T	T	F	F	F

Raw SAR Data Compression Methodology

The survey of SAR data compression algorithms was used to make a sub-selection of algorithms to utilise during the AI/ML Demonstrator Development stage of the activity. The standard algorithm in the field of raw SAR data compression is Block Adaptive Quantization (BAQ). The benefits of using BAQ as a base algorithm are that it is simple to implement in hardware, well tested and documented.

There are evolutions on the BAQ technique such as Entropy Constrained Block Adaptive Quantization, Block Adaptive Vector Quantization, Flexible Block Adaptive Quantization, and others, visualized in Figure 1. They all improve the basic BAQ technique but at the price of added complexity, which is a significant concern when considering future hardware implementations.

Following the survey, the following algorithms were then implemented and analysed:

- BAQ
- FBAQ
- FFT-BAQ

A set of statistical metrics was used to assess the performance of compression methods on raw SAR data. These include dynamic range (ratio of brightest vs darkest pixel), and for magnitude and phase of the raw data: mean, standard deviation, skewness, kurtosis and entropy.

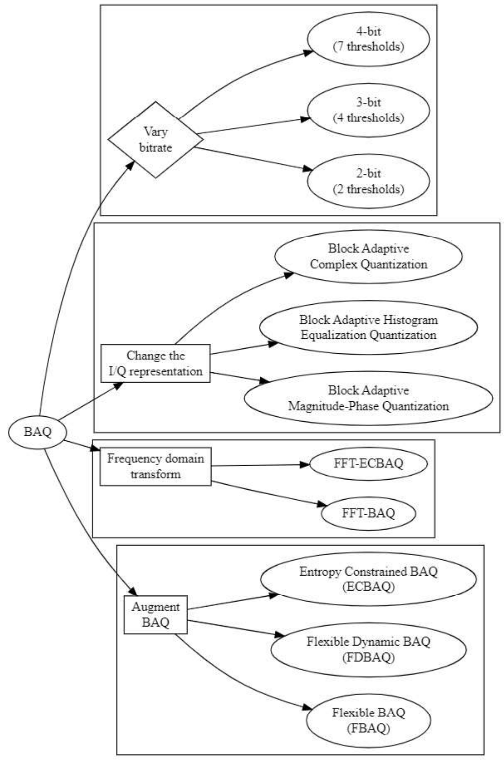

Figure 1 - Algorithm taxonomy

The methodology for evaluating the performance of the selected compression algorithms against raw SAR data, using both image domain and statistical metrics, is shown in Figure 2.

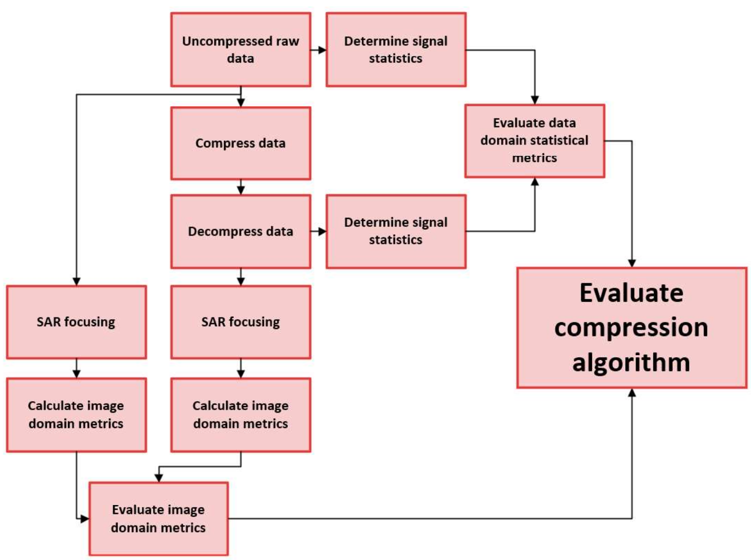

Figure 2 - Compression algorithm evaluation methodology

AI/ML DEMONSTRATOR DEVELOPMENT, TESTING AND FUTURE HARDWARE ROADMAP

A software-based demonstration was developed that creates features from range lines of raw SAR data, runs inference on these features, and predicts the chosen target metric of signal-to-quantisation-noise-ratio (SQNR). A short study was then performed on what future developments would be required to implement such a scheme on on-board hardware, and a roadmap set out to this effect.

Development

An ML model was developed and used to predict the signal-to-distortion noise ratio (SDNR) of the focused images during each decision window for each compression algorithm as outlined in Figure 3.

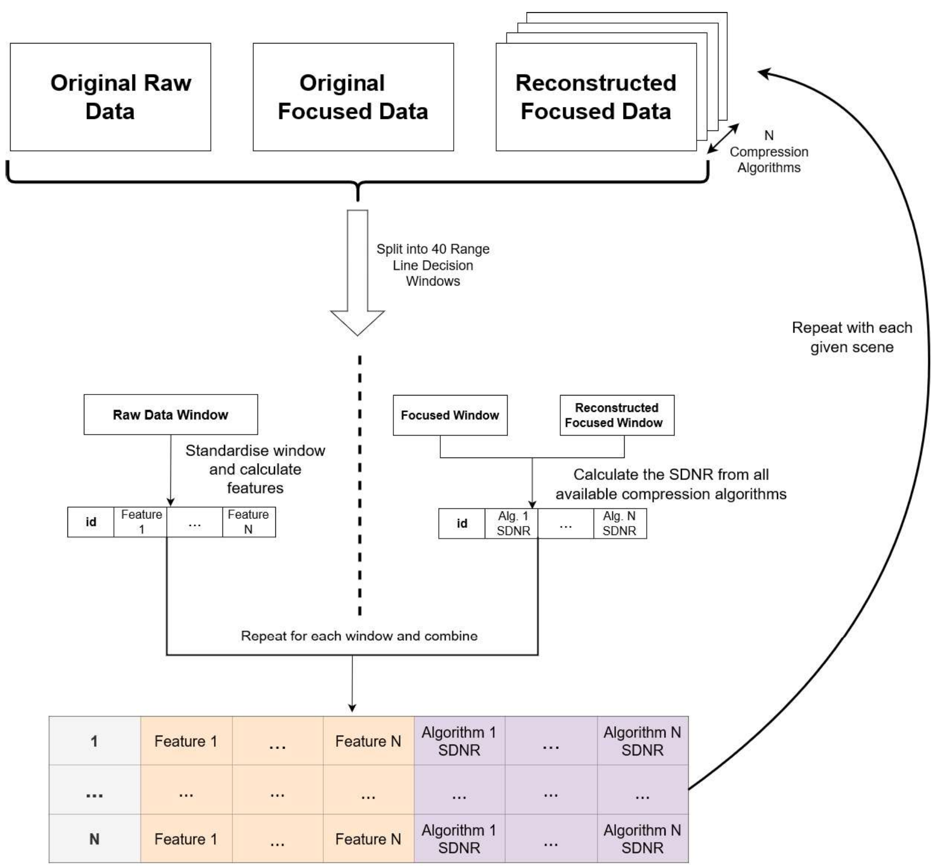

Figure 3 - ML dataset generation methodology

To achieve the desired bitrate, logic was implemented to simply choose the lowest bitrate compression algorithm that meets the SQNR threshold. In this way, the bitrate is kept to a minimum within the integer bitrate choices available. The interfaces of the decision module are shown in Figure 4.

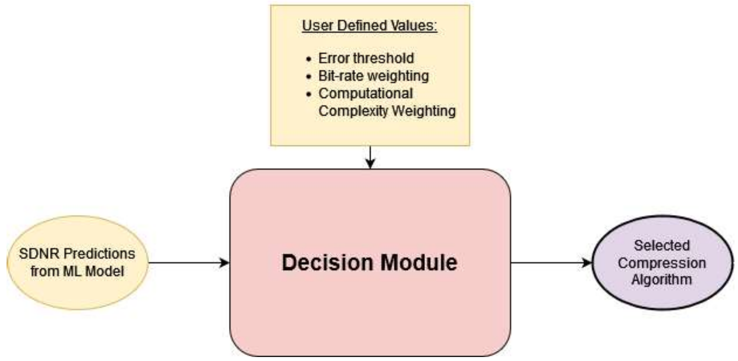

Figure 4 - Decision model inputs and outputs

Demonstration & Testing

The ML enabled decision module was deployed against various test scenes, with different user defined parameters set. The results for 3 scenarios are included below, demonstrating the module's selection of the most appropriate compression algorithm in each case.

Scenario 1: Error Threshold

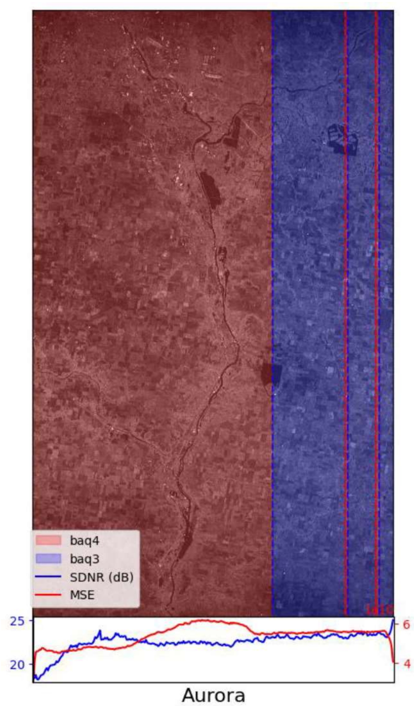

Figure 5 – Compression algorithm selection across Aurora test scene

In the scenario shown in Figure 5, a test was carried out to show that the predictor and decision function could switch compression algorithm while maintaining an overall SDNR figure above the set threshold. It would also give an indication of where and how switching would occur, with the initial hypothesis that the algorithm would switch to lower bitrates in area with less cultural clutter. The decision function parameters used for this test were:

Error threshold = 15dB Complexity weight = 0 Bit-rate weight = 0

Over regions in the Aurora test scene where there is greater cultural clutter (and more heterogeneity) present in the data, the BAQ4 algorithm has been selected. Over more homogeneous regions (where fields can be seen in the data), the BAQ3 algorithm has been selected. In conclusion, the decision module has selected a more complex algorithm (BAQ4) for the job of compressing a heterogeneous scene, and a less accurate algorithm (BAQ3) for compressing a homogeneous scene to achieve the same SDNR in both cases.

Scenario 2: Weighted Bitrate

This scenario tested the decision module in meeting multiple constraints: a minimum error threshold had to be maintained (as in Scenario 1) while also maintaining a maximum average bitrate. This was designed to exercise the use of more computationally complex algorithms which could meet these dual constrains of minimising both error and bitrate whilst trading off on increased computation. The decision function parameters were set to:

- Error threshold = 15dB Complexity weight = 0 Bit-rate weight = 4.5

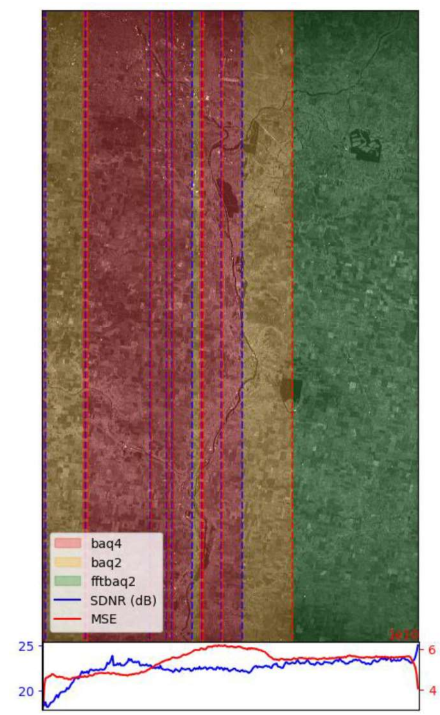

Figure 6 - Compression algorithm selection across Aurora test scene when decision module prioritises lower bit rate

It is shown that the higher bit rate algorithms are selected for the job of compressing regions with most cultural clutter.

In conclusion, the decision module has penalised higher bit rate algorithms when meeting this user set constraint. This scenario also highlights the use of the FFTBAQ algorithms being used as they can achieve a higher accuracy whilst maintaining a lower bitrate, although this comes at the cost of higher computational complexity. Where FFTBAQ was used here, it was predicted to still meet the set error threshold of 15dB whereas BAQ2 was not.

Scenario 3: Error Threshold with Clear Target

In the scenario a test was carried out to show that the predictor and decision function could switch compression algorithm while maintaining an overall SDNR figure above the set threshold. This time a completely unseen island region is used to demonstrate algorithm selection by the decision module. The parameters used for this test were:

Error threshold = 18dB   Complexity weight = 0   Bit-rate weight = 0

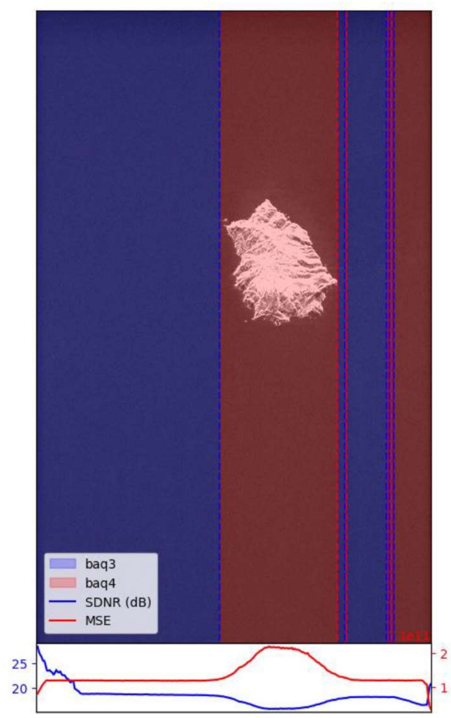

Figure 7 - Compression algorithm selection across St Helena island test scene

It is shown that the decision module selects higher bit rate algorithms for the job of compressing the land region, and lower bit rate for the surrounding sea. The selection of BAQ4 at the right side of this scene is due to ocean current that can be seen in the VV and VH dB image causing greater backscattering and thus a higher bit rate selection.

Hardware Roadmap

With SAR instruments acquiring data at rates of Gbps when observing, on-board data handling and downlinking through the space-ground link is a challenge. Any effort to reduce this on-board will provide increases in system capacity. The motivations for better on-board compression of raw SAR data are therefore:

- The low duty cycle of SAR instruments
- Lowering on-board storage requirements or increasing amount that can be stored on-board
- Lowering the amount of data that needs to be downlinked

Considering the feasibility of deploying the ML-enabled decision module onboard, the ML model that has been generated uses a small number of statistical metrics as input features. Many of these would be calculated anyway for the standard onboard compression algorithms, so it follows that these features or similar can be generated from the raw data on-the-fly at the rate of data acquisition (if need be).

Onboard inference could be implemented on FPGA using tools like Vitis AI. It has been demonstrated that inference of SDNR in the image domain is possible from features derived from statistics in the raw data domain. A neural network (as a universal function approximator) could be trained to map these features to SDNR. Neural networks have a well-trodden path to implementation on hardware and there are software/hardware development toolchains available for further optimization of the onboard implementation e.g. weight quantization, connection pruning.

Another aim of the hardware roadmap development was to compare two approaches to the hardware architecture, runtime compression versus offline compression. NovaSAR-S was considered as a potential future target hardware system. It provides a good candidate for comparing a runtime compression mode with an offline compression operating mode, as it currently operates runtime compression and SSTL (Surrey Satellite Technology Ltd) are actively exploring offline on-board payload data processing architectures. One such project is the Incubed funded Flexible Intelligent Payload Chain (FIPC) where SSTL partnered with Craft Prospect Ltd and University of Surrey as application developers for an offline on-board processor designed to integrate the platform to process data from optical EO payloads. Offline compression modes were found to be the preferred option, at least initially as they required the least modification of radar backend architectures like Airbus DS NIA Radar Backend (as used on NovaSAR).

CONCLUSIONS

The SARAI activity demonstrated that the execution of machine learning models working on raw SAR data to perform predictions of reconstruction error in the image domain with various raw SAR data compression algorithms is feasible, albeit with a limited number of end-to-end solutions available when compatibility of all the elements is considered and many iterations of refinement required before an optimal solution can be found.

The achievements in the activity have applications across several ESA programmes. On-board processing to improve onboard data compression has many benefits to the EOEP in terms of eliminating or reducing data bottlenecks in EO missions, improving on-board data management, and reducing operational and infrastructure costs. This also benefits Science and Robotic Exploration missions (such as future interplanetary exploration missions with radar payloads), as better data compression can increase the possible scientific return of the mission. The activity also developed a machine learning ready raw SAR dataset and a pipeline for generating further datasets, which could be adapted to other applications to enable rapid prototyping of new machine learning methods in the raw SAR domain.

Much further development is expected in this area. In future work, the demonstrated algorithms could be embedded in a more realistic mission concept and demonstrated in simulation, with requirements preferably solicited from stakeholders with real use cases. The suggestions of the Hardware Roadmap, created under this activity, should be further assessed, and followed to demonstrate the scheme on representative flight hardware. The demonstrator should explicitly address compliance with requirements on end benefits as defined by a relevant stakeholder. Completion of this work to address an end user application on representative flight hardware is estimated at €250k over fifteen months. This estimate is based on similar projects developing hardware testbeds with representative simulated scenarios representative of flight.

A flight demonstration of the developed technology is a highly feasible mid-term goal. This is estimated at €2M total to develop flight models of an application demonstrator (ML technology fully integrated with a modified SAR instrument radar backend). This can then be integrated with a Smallsat bus and tested in-orbit. Clear requirements can be solicited from end users engaged through this and other parallel activities, resulting in a demonstration mission with measurable end benefits to these users. The compression demonstration would likely be part of a larger demonstrator mission. The work is estimated at eighteen months, using the TRL 6 milestone as a starting point.